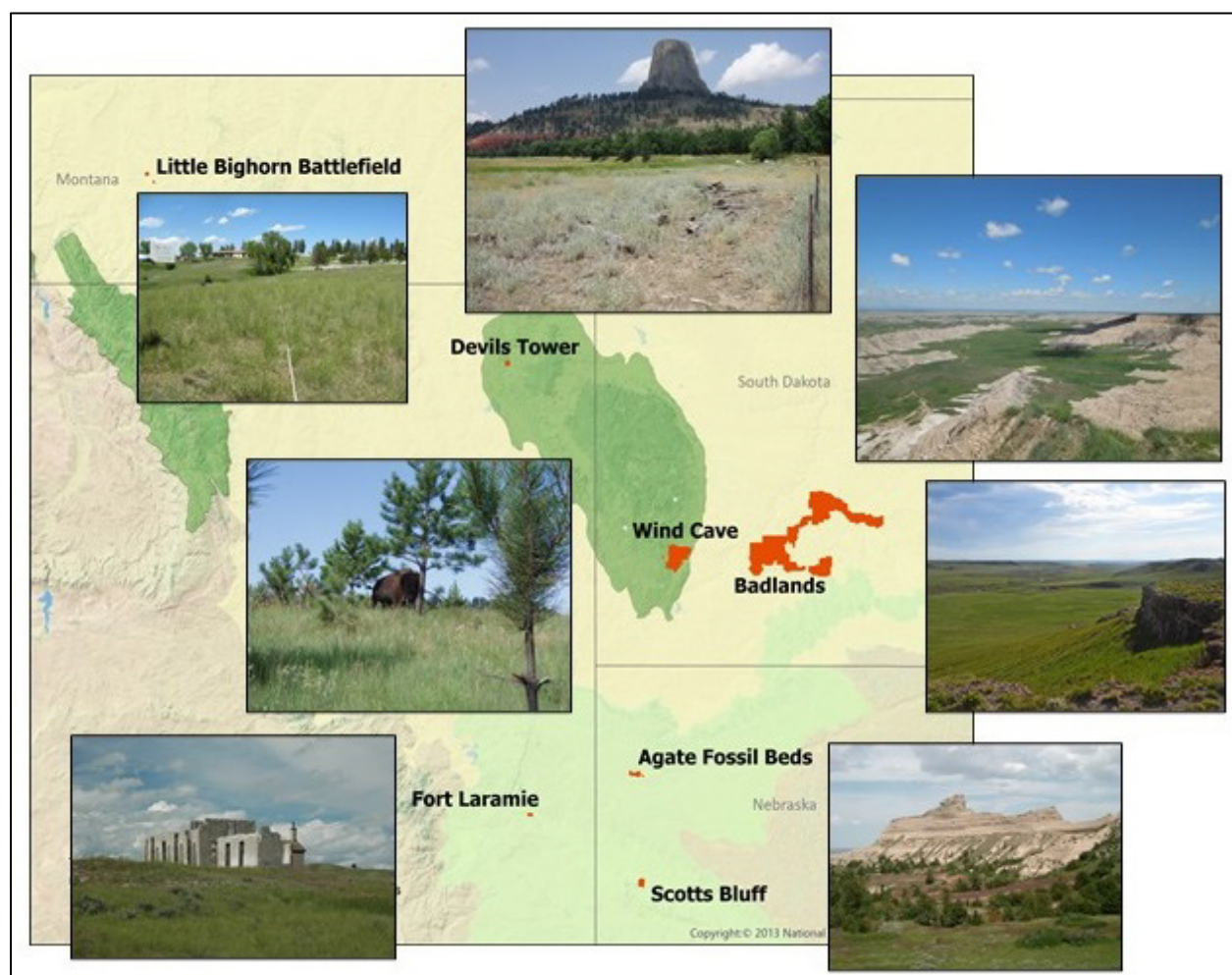




Adaptive Management Framework and Decision Support Tool for Invasive Annual Bromes in Seven Northern Great Plains National Park Service Units

Natural Resource Report NPS/NGPN/NRR—2022/2381





ON THIS PAGE

The Annual Brome Adaptive Management framework aims to shift areas dominated by invasive annual brome grasses (top; USGS) to grasslands with few exotic species and a high diversity of native species (bottom; NPS).

ON THE COVER

The Annual Brome Adaptive Management framework is built around a consortium of seven National Park Service units in the northern Great Plains. Clockwise from top center: Devils Tower National Monument (USGS / AMY SYMSTAD), Badlands National Park (NPS), Agate Fossil Beds National Monument (NPS), Scotts Bluff National Monument (USGS / AMY SYMSTAD), Fort Laramie National Historic Site (NPS), and Little Bighorn Battlefield National Monument (NPS)

Adaptive Management Framework and Decision Support Tool for Invasive Annual Bromes in Seven Northern Great Plains National Park Service Units

Natural Resource Report NPS/NGPN/NRR—2022/2381

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Executive Summary

National Park Service (NPS) units in the northern Great Plains (NGP) were established to preserve and interpret the history of the United States, protect and showcase unusual geology and paleontology, and provide a home for vanishing large wildlife. A unifying feature among these national parks, monuments, and historic sites is northern mixed-grass prairie, which not only provides background scenery and habitat but is the foundation of many park missions. As recognition of the prairie's importance to park fundamental resources and values has grown, so too has the realization that invasive plants threaten these values by reducing native species diversity, altering food webs, and marring the visitor experience. Cheatgrass (*Bromus tectorum*) and Japanese brome (*Bromus japonicus*)—collectively referred to as “annual bromes”—are of particular concern because of their documented increase through time, and their association with lower native plant diversity, in NGP parks. A variety of grazing, herbicide-application, and prescribed-fire experiments have shown promising short-term results for controlling annual bromes in research-scale plots in the NGP, but it is unclear whether these management actions will be as effective at the larger spatial and longer temporal scales relevant to park management. When uncertainties about the effectiveness of different management actions cannot be answered with traditional research approaches in time to prevent resource degradation, yet recurrent management decisions must be made, an adaptive management approach may be appropriate. Thus, in 2017, we began to develop the ABAM—Annual Brome Adaptive Management—framework. The aim of this framework is to reduce uncertainties about methods for controlling annual bromes in seven NGP parks through a formal process of learning from the application of on-going management. A uniform framework across seven parks provides greater opportunities for reducing these uncertainties compared to a single park acting alone or to multiple parks using different adaptive management frameworks.

This technical report details the development and expected implementation of the ABAM framework. After briefly introducing the issue (Section 1) and describing the context in which the framework was developed (Section 2), the report describes how a structured decision-making process was used to frame the problem, determine concrete objectives, and decide the alternative actions for achieving those objectives that the framework would be designed around (Section 3). Then the report describes the process used to develop the ABAM decision support system (Section 4). At the core of this system is the ABAM decision support tool, a Bayesian decision network built on nearly two decades of vegetation monitoring data from NGP parks, as well as current literature and ABAM-specific experiments. This tool, referred to as the ABAM model by its intended users, is built to work with the existing vegetation monitoring, prescribed fire, and invasive plant management programs that support the seven ABAM parks. In Section 5, the report describes how output from the ABAM model is produced and used in annual vegetation management decision making. It describes the *ABAM* R package (Baldwin et al. 2021) and an example R script that leads a user through an annual workflow using the model and the package. This workflow updates the model with information from new monitoring events following management actions of prescribed fire, herbicide application, or a combination thereof. With the updated model, data describing the current condition of vegetation in park management units, and current data for environmental factors included in the model (soil texture, slope, weather, and grazing), the user then runs the model to predict future vegetation

conditions—and managers’ happiness with the outcome—in response to each of 10 management actions for each management unit in each park. These predictions inform managers’ decisions regarding locations and types of management actions to apply in the upcoming year.

The ABAM framework is in its infancy, and the report concludes (Section 6) with a discussion of its longer-term viability. Successful adaptive management requires commitment for the long term, likely decades. Currently, the predictions of the decision support tool are not expected to be highly accurate, but they ideally will improve over time as more management actions are applied and their outcomes are captured by monitoring. We designed the ABAM decision support tool to work with the existing management and monitoring resources in ABAM parks to maximize the sustainability of the model’s use, but the ABAM framework requires more than the model. Because this application of an adaptive management framework supported by a quantitative decision support tool to guide vegetation management is unique within the NPS (to our knowledge), institutional knowledge and mechanisms for long-term implementation of the ABAM framework do not exist within the agency. Additionally, the ABAM model and the data that inform it could be improved in a variety of ways. Thus, this report concludes with a discussion of ways to both sustain and improve upon the work completed so far.

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The ABAM project is nominally a collaboration among parks, programs, and agencies, but in reality, it is a collaboration among people. We are especially thankful for the commitment of the ABAM “tech team” of NPS staff: D. Swanson, I. Ashton, S. Bekedam, E. Borgman, C. Davis, S. Rockwood, and K. Paintner-Green. J. Mills provided helpful FFI and R advice, and A. Jarding and C. Serratos provided GIS support. G. Eckert, T. Hogan, C. Wienk and C. Thomson have championed the project. C. Wienk’s vision for something like NGP CALM long before ABAM was conceived produced the close collaboration between NGP fire and NGPN vegetation monitoring that made ABAM possible. Park staff have shown the open-mindedness needed to learn and accept a new way to approach management decision making. We especially recognize D. Morford, E. Childers, M. Slovek, M. Haar, R. Ohms, M. Evans, C. Mather, M. Doane, R. Manasek, G. Schroeder and T. Richardson. We thank D. Blumenthal, J. Ott, L. Porensky, T. Seastedt, and L. Vermeire for their insights and input. We also thank J. Booker and C. Dixon for their facilitation, patience, insight, and guidance on structured decision making and real-world adaptive management of invasive species. Finally, we thank I. Ashton, E. Borgman, D. Blumenthal, and J. Cronin for their constructive comments on earlier versions of this report. Funding for this work was provided by the National Park Service Natural Resource Science and Stewardship Directorate and the U.S. Geological Survey. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

1. Introduction

National Park Service (NPS) units (“parks”) in the northern Great Plains (NGP) were established to preserve and interpret the history of the United States, protect and showcase unusual geology and paleontology, and provide a home for vanishing large wildlife. A unifying feature among these national parks, monuments, and historic sites is northern mixed-grass prairie, which not only provides background scenery but is the foundation of many park missions. As recognition of the prairie’s importance to park fundamental resources and values has grown, so too has the realization that invasive plants threaten these values by reducing native species diversity, altering food webs, and marring the visitor experience. Two invasive plant species are of particular concern: cheatgrass (*Bromus tectorum* L.) and Japanese brome (*Bromus japonicus* Thunb. ex Murray) (hereafter collectively referred to as “annual bromes”). Both species are Eurasian, cool-season, annual grasses that are widespread in many NGP parks. Vegetation monitoring data from seven NGP parks has shown that (1) annual bromes are abundant in some NGP parks, having more than doubled in abundance since 1998 in one park and invaded parks where they were once rare (Figure 1.1a, b), and (2) that native plant species richness is negatively associated with annual brome abundance (Figure 1.1c; Ashton et al. 2016).

Annual bromes have been a part of the NGP landscape for more than a century, but their invasion in the region has accelerated since 1950 (Douglas et al. 1990, Schachner et al. 2008). Despite their long residence in the NGP, most of the information about these species—particularly for cheatgrass—comes from the Intermountain West, where invasive annual grasses are well known for increasing the frequency of fires, leading to widespread replacement of fire-intolerant, native sagebrush-bunchgrass steppe with fire-prone annual grasslands (D'Antonio and Vitousek 1992, Balch et al. 2013, Brooks et al. 2016). In contrast, annual brome invasion has not demonstrably changed fire regimes in the NGP (Porensky and Blumenthal 2016). This could be because the region’s continuous grassy fuels have long supported frequent fires (pre-settlement mean fire return interval 4–18 yr; Higgins 1986, Guyette et al. 2012, 2015), rapid wildfire suppression in a fragmented landscape, or both. However, annual bromes adversely affect NGP grasslands in other ways. Their early phenology gives them a head start in competing for moisture and nutrients with native species, thereby reducing native production and nutritional content of forage (Haferkamp et al. 1997, 2001), and their early senescence compared to native grasses adversely affects forage availability later in the growing season (Ogle et al. 2003).

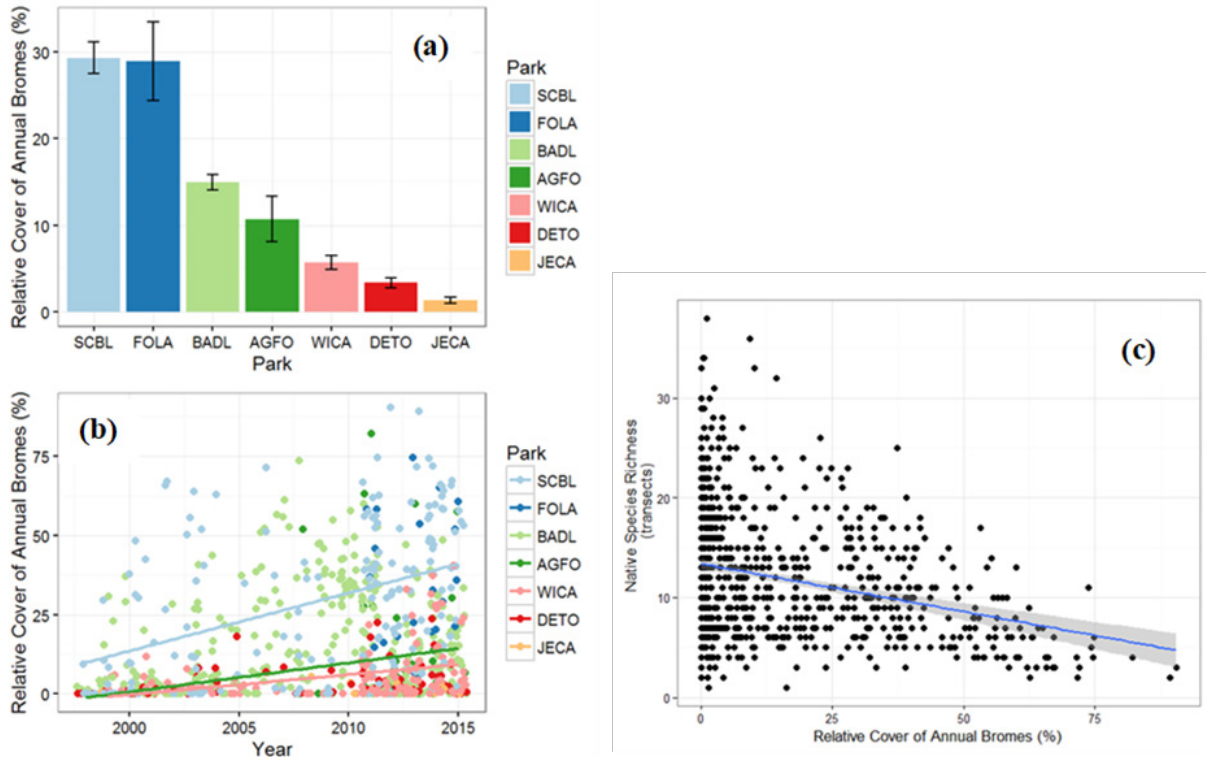


Figure 1.1. Status, trends, and impacts of annual bromes in Northern Great Plains (NGP) parks. (a) Mean (± 1 standard error) percentage of total plant cover comprised of annual bromes in six NGP parks over 1998–2015. (b) Relative cover of annual bromes has increased significantly ($P < 0.05$) from 1998 to 2015 in three NGP parks (trend lines for AGFO, WICA, and SCBL); dots are individual monitoring events. (c) Native plant species richness is significantly negatively correlated with annual brome cover in NGP park grasslands. Results and figures from Ashton et al. (2016; reproduced under open access Creative Commons license). AGFO = Agate Fossil Beds National Monument (NM), BADL = Badlands National Park (NP), DETO = Devils Tower NM, FOLA = Fort Laramie National Historic Site, LIBI = Little Bighorn Battlefield NM, SCBL = Scotts Bluff NM, WICA = Wind Cave NP.

Until recently, annual bromes received little management attention in NGP parks. Ashton et al.’s (2016) analysis of NGP park vegetation monitoring data strongly suggests that continued lack of intervention will result in further increase in annual brome abundance and the accompanying degradation of resources. A variety of grazing, herbicide-application, and prescribed-fire experiments have shown promising short-term results for controlling annual bromes in research-scale plots in the NGP (e.g., Whisenant and Uresk 1990, Haferkamp et al. 2001, Harmony 2007, Symstad et al. 2021), but it is unclear whether these management actions will be as effective at larger scales. Land-use history, topo-edaphic factors, and recent fire and grazing history likely influence annual brome abundance across the landscape (Hulbert 1955, Gundale et al. 2008, Lovtang and Riegel 2012, Reisner et al. 2013, Bansal and Sheley 2016). These factors—which either directly or indirectly influence brome abundance—could also impact the effectiveness of management actions on annual brome control, but this has not been investigated. Temporal variability in the effectiveness of management actions is also likely, given the NGP’s naturally high interannual climate variability (Borchert 1950) and the tendency of annual brome populations to respond quickly to weather

fluctuations (Mack and Pyke 1983, Ashton et al. 2016). Finally, the short-term nature of most research precludes understanding how long various management actions remain effective.

When uncertainties about the effectiveness of different management actions cannot be answered with traditional research approaches in time to prevent resource degradation, yet recurrent management decisions must be made, an adaptive management approach may be appropriate. Thus, in 2017, we began to develop the ABAM—Annual Brome Adaptive Management—framework. The aim of this framework is to reduce uncertainties about methods for controlling annual bromes in seven NGP parks through a formal process of learning from the application of on-going management. A uniform framework across seven parks provides greater opportunities for reducing these uncertainties compared to a single park acting alone or to multiple parks using different adaptive management frameworks.

In developing the ABAM framework, we followed the process outlined in Williams et al. (2009), which includes two phases. In the set-up phase, structured decision making (SDM, also known as decision analysis; Gregory et al. 2012) is used to understand the structure of the decision problem, develop management objectives, create management alternatives, and specify the main uncertainties that make predicting management effectiveness difficult. A model is developed to evaluate the consequences—or predict the outcomes—of specific decisions, and to express the uncertainties of those predictions. In the implementation phase, a cycle of applying management actions, monitoring the effects of management, and using monitoring data to update the predictive model is repeated; learning occurs through this cycle (Runge 2011, Figure 1.2).

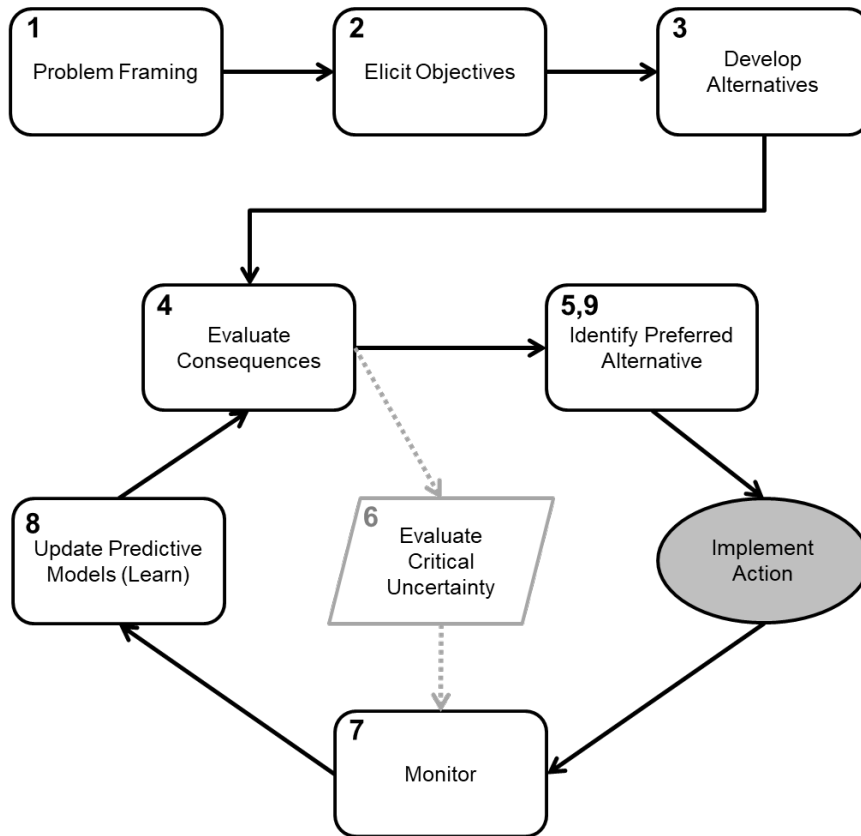


Figure 1.2. Adaptive management in a structured decision-making framework (Runge 2011; figure in public domain). Steps 4–9 represent the iterative approach to learning that occurs by updating a model with new information to improve the model’s predictions of management action outcomes.

This report details the development and expected implementation of the ABAM framework. After explaining the ecological and managerial context the framework was developed to operate in, we describe the outcomes of the first three steps in the process outlined in Figure 1.2. Next, we describe the development of the ABAM decision support tool—the predictive model at the core of the ABAM framework. This model is the instrument used to complete the fourth step in Figure 1.2, predicting the outcomes and evaluating consequences of alternative actions. We then explain how this model is used in the framework and how the framework is implemented (steps 5–9). Finally, we end by discussing how to sustain implementation over the long term.

2. Context

The seven parks in the ABAM consortium are Agate Fossil Beds (AGFO) and Scotts Bluff (SCBL) National Monuments in western Nebraska, Badlands (BADL) and Wind Cave (WICA) National Parks in western South Dakota, Devils Tower National Monument (DETO) and Fort Laramie National Historic Site (FOLA) in eastern Wyoming, and Little Bighorn Battlefield National Monument (LIBI) in southeastern Montana (Figure 2.1). Thus, in this report, when we refer to NGP, we are specifically referring to the area encompassing these parks. As mentioned above, the unifying vegetation context across these parks is northern mixed-grass prairie that is invaded to varying degrees by annual brome grasses. Two ABAM parks in the Black Hills—DETO and WICA—also have substantial areas of ponderosa pine (*Pinus ponderosa* Douglas ex P. Lawson & C. Lawson) woodland. Because the understory vegetation in these woodlands is similar to northern mixed-grass prairie, and because the prairie-woodland ecotone is dynamic, these woodlands are included in the ABAM framework.



Figure 2.1. Locations of ABAM parks. Note that only the North Unit of Badlands National Park is shown, as only that unit is included in the ABAM consortium.

2.1. Ecological Context

In this section, we provide a general overview of the ecological context of the ABAM framework. Detailed descriptions of the native vegetation in ABAM parks are provided in Appendix A. The northern mixed-grass prairie of ABAM parks is dominated by a mixture of perennial, cool- and warm-season grasses. Forbs contribute substantial diversity but relatively little production, and shrubs are generally a minor component of diversity and production. Although annual and biennial species—especially forbs—are an important part of the native vegetation, the vast majority of plant production comes from perennial grass species. Annual grasses typically contribute a tiny portion of

plant production in native northern mixed-grass prairie, and most of these annual grasses are warm-season; only one native, cool-season, annual grass (*Vulpia octoflora*, six-weeks fescue) is even occasionally encountered in NGP parks. Thus, the lifecycle of cool-season, annual brome grasses differs from that of most native plant species in ABAM parks.

Zouhar (2003), Howard (1994), and Beck (2009) summarized the lifecycle and regeneration of cheatgrass and Japanese brome as follows. The predominant lifecycle of both species is to germinate in the fall, overwinter in semi-dormancy as a small rosette, grow rapidly in early spring when soil temperatures get above freezing, then produce mature seed and senesce by early summer. Cheatgrass typically matures and senesces roughly two weeks earlier than Japanese brome in the NGP (Symstad, pers. obs.). However, the timing of cheatgrass germination is highly variable, with seedlings observed throughout the year and the plants from these seedlings producing viable seed as long as they are not frost- or drought-killed before that. Cheatgrass seeds fall to the ground soon after maturing, then require a 1- to 4-week period of after-ripening in warm to hot temperatures—conditions typical in NGP summers—after which they are capable of germinating at a wide range of temperature and soil moisture conditions. Published literature states that Japanese brome seeds are often retained on the plant until fall or winter, then require a summer of after-ripening to germinate under field conditions, leading to most fall-germinating Japanese brome seedlings being from the previous year's crop (Howard 1994, Beck 2009). However, current-year seeds often dehisce and germinate in the fall in the NGP (Symstad, pers. obs.) Japanese brome appears to be more restricted to fall germination and to require more consistent fall soil moisture than cheatgrass (Beck 2009), but much less research has been done on Japanese brome than cheatgrass. Both species produce copious amounts of seed, and many of these seeds germinate soon after the required after-ripening period. However, seeds that do not germinate at this time will remain dormant and viable in the soil or litter seedbank for at least 2 years, and up to 5 years for cheatgrass; again, less information is available for Japanese brome's seed longevity.

Three major factors—climate, fire, and grazing—shaped the evolution of northern mixed-grass prairie and Black Hills pine woodlands, and these factors remain important in their management today. This region of cold winters and hot summers has a strong, unimodal precipitation pattern, with a large portion of each year's moisture falling in spring (Figure 2.2a). Overall, the climate is semi-arid, with evapotranspiration generally exceeding precipitation on an annual basis. However, as with the Great Plains as a whole, there is high interannual variability in precipitation, leading the vegetation in the region to continually face shifts between states of water limitation and water abundance (Knapp and Smith 2001; Figure 2.2b). Consequently, the native vegetation is adapted to this variation, and annual production responds strongly to spring precipitation (Yang et al. 1998, Smart et al. 2007, Petrie et al. 2018). Annual bromes also respond strongly to each year's weather (Klemmedson and Smith 1964), though the most important components of weather that affect brome fluctuations in the NGP seem to vary geographically (Ashton et al. 2016). Anthropogenically driven climate change will warm the region by 4–5 °F by the middle of the 21st century (compared to 1975–2000 annual average temperature), and projections generally suggest that winter and spring precipitation will increase on average (USGCRP 2017). Together, these projections suggest that, on average, moisture available for plant growth will be lower in the future than in the recent past in the

summer, in the NGP (Adler and Hostetler 2013, Mankin et al. 2017, USGCRP 2017, Adhikari et al. 2019), although the effects of rising atmospheric CO₂ concentration on plants' water use efficiency complicates this prediction (Blumenthal et al. 2018). The effects of these changes on northern mixed-grass prairie and woodlands are difficult to predict, as their interacting effects with increased atmospheric CO₂ concentration, longer growing seasons, and altered precipitation patterns are complex and will impact each species differently. However, cheatgrass' positive response to experimental warming in NGP grasslands (Blumenthal et al. 2016), combined with the projected higher winter and spring precipitation and cheatgrass' positive response to that (Prevéy and Seastedt 2015), certainly suggest that climate change will not alleviate the annual brome issue in NGP parks.

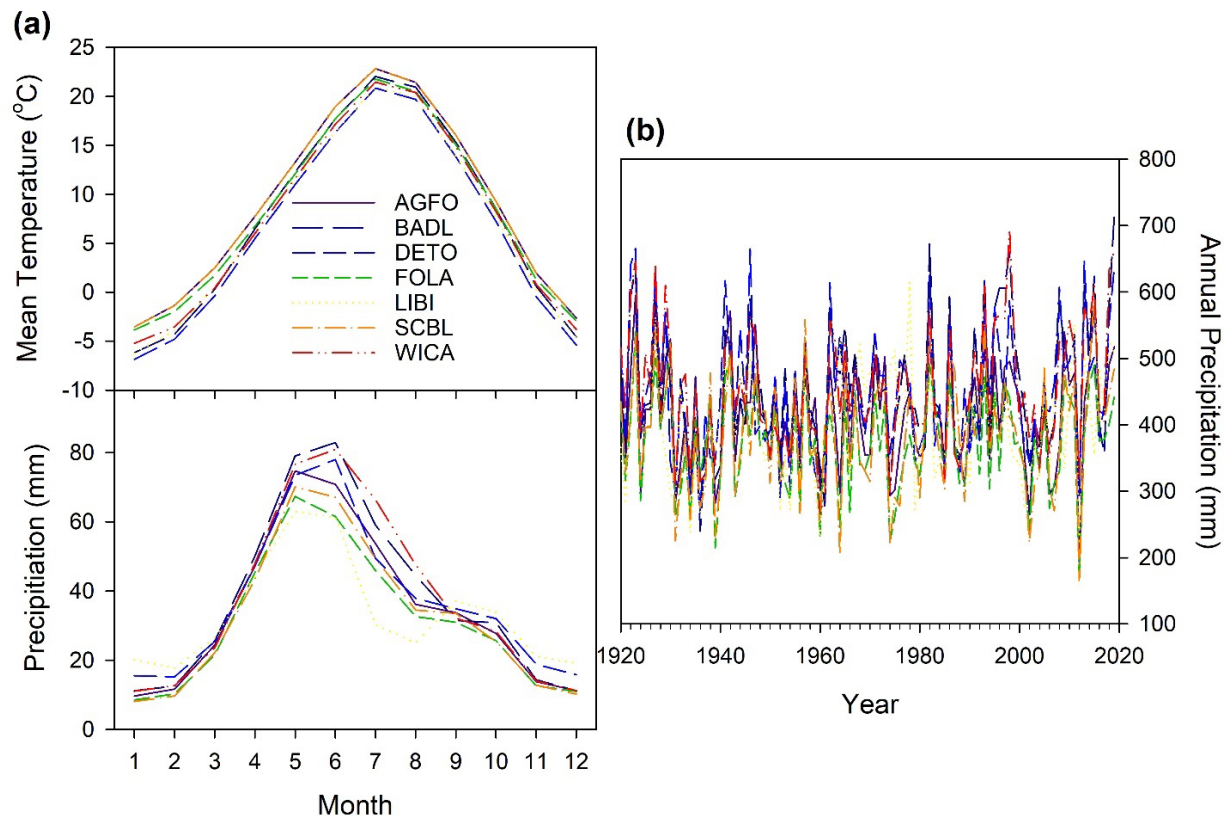


Figure 2.2. Weather patterns in the ABAM parks. (a) Average (1920–2019) monthly mean temperature (top) and total precipitation. (b) Annual precipitation from 1920 to 2019. Data for each park is for the county in which the park lies and comes from NOAA National Centers for Environmental information, Climate at a Glance: County Time Series, published July 2020 (<https://www.ncdc.noaa.gov/cag/> retrieved on July 29, 2020). AGFO = Agate Fossil Beds National Monument (NM), BADL = Badlands National Park (NP), DETO = Devils Tower NM, FOLA = Fort Laramie National Historic Site, LIBI = Little Bighorn Battlefield NM, SCBL = Scotts Bluff NM, WICA = Wind Cave NP.

The adaptation of northern mixed-grass prairie to a relatively frequent natural fire return interval (Higgins 1986, Guyette et al. 2012, 2015) is reflected in the minor response of herbaceous vegetation production and composition to a single fire in comparison to weather-driven interannual variations

(Vermeire et al. 2011, Vermeire and Russell 2018). The response of annual bromes to fire in the NGP is more pronounced, with many studies showing consistent and substantial reductions in annual bromes 1–2 years after a single fire (Gartner et al. 1986, Whisenant and Uresk 1990, Vermeire et al. 2011, Vermeire and Russell 2018, Symstad et al. 2021). Experimental research on longer-term effects of a single fire is rare, but the little that does exist suggests that these effects on annual bromes in NGP grasslands do not extend beyond the second growing season (Whisenant and Uresk 1990). In contrast, an observational study in the western portion of the region found lower cheatgrass and Japanese brome cover in areas burned once by wildfire regardless of time since fire (Porensky and Blumenthal 2016). We could find no published reports on the effects of fire return interval on annual bromes in northern mixed-grass prairie, but the assertion that these species (especially Japanese brome) fare better when litter loads are higher because the litter retains soil moisture (Evans and Young 1970, Whisenant 1990, Whisenant and Uresk 1990) has led some to assume that the lack of fire is one reason for the increase of these species in this ecosystem (e.g., USDA-NRCS 2011). The asserted role of litter also suggests that shorter fire return intervals would more effectively control annual bromes than longer intervals in this ecosystem. Although the ponderosa pine woodlands of parks in the Black Hills had slightly longer historical fire return intervals than their neighboring prairies (10–25 years; Brown and Sieg 1999, Stambaugh et al. 2008), these intervals were (and still are) necessary for maintaining their characteristic low tree density, open canopy, and robust grassy understory. NPS has recognized the importance of fire to northern mixed-grass prairie and ponderosa pine woodlands for decades (Wienk et al. 2009). A prescribed fire program aims to maintain historical fire return intervals in many ABAM parks, but this goal is rarely achieved. Similarly, in the NGP as a whole, the number of large fires and area burned by large wildfires has increased since 1985 in the NGP as a whole (Donovan et al. 2017), but fire return intervals remain far longer than before widespread fire suppression.

Grasslands of the NGP are also highly tolerant of grazing, much more so than the more arid shrub steppe to the west (Milchunas et al. 1988). Like fire, grazing reduces the buildup of dead plant material on the soil surface and recycles nutrients in aboveground plant material into forms accessible to plant roots. If not too severe, grazing also stimulates some native grass species to produce more tillers, resulting in higher density of grass stems within a given area (Eneboe et al. 2002). Because NGP grasslands evolved with grazing, its absence is often seen as more of a disturbance to the system than its presence (Vermeire et al. 2008). In fact, many ecological site descriptions for NGP grasslands written by the Natural Resource Conservation Service include an assumption that lack of grazing or fire results in a condition of cool-season exotic grass invasion associated with excessive plant litter (e.g., Miller et al. 2017). This assumption is drawn largely from professional experience, but decades-long grazing exclosure studies from areas with vegetation similar to that in ABAM parks show increases in annual bromes when grazing does not occur (Porensky et al. 2016). However, a shorter-duration study also showed that the effect of grazing on annual bromes depends on the timing of that grazing (Vermeire et al. 2008). Movements of bison herds that roamed the Great Plains until the 1880s were governed by climate, fire, hunting, disease, and predation, likely resulting in large interannual fluctuations in the timing and intensity of grazing that occurred in a given location. Between the 1880s and the establishment of each park in the ABAM consortium (or even after their establishment), grazing by domestic livestock may have

occurred within the current park boundaries, but records regarding the intensity and type of this grazing are minimal or non-existent. After parks solidified their control over the land within their boundaries with fences, the grazing history of each park followed a unique path (see Modlin and Symstad 2018 and Section 2.2). As a whole, though, grazing outside of prairie dog towns in ABAM parks has been light to nil for at least the past three decades and usually much longer.

Other factors influencing the grassland and woodland vegetation in ABAM parks include topographic position, soil characteristics, soil disturbance, and atmospheric nitrogen deposition. Topographic position (slope, aspect, and elevation with respect to surroundings) affects air and soil temperature and soil moisture. Soil characteristics, including depth, texture (percent sand, silt, and clay), and parent material, affect water and nutrient availability and their daily and seasonal dynamics. These characteristics also determine physical properties, such as shrink-swell behavior as moisture changes, that affect plant growth. Soil disturbance occurs at many spatial and temporal scales, from individual small-mammal excavations less than a square meter in size and occurring just once in a given location, to repeated anthropogenic cultivation in fields tens to hundreds of hectares in size. All soil disturbance kills, injures, or buries existing vegetation, and the exposed soil and released nutrients offer opportunities for new plant species to become established. Species that produce large numbers of seeds that remain dormant in the soil until exposed to sunlight or that are widely dispersed are often the first to take advantage of these disturbances (Pickett and White 1985, Grime et al. 1997). Natural atmospheric nitrogen (N) deposition is very low in the NGP, but anthropogenic sources have increased this to 3–9 kg N·ha⁻¹·yr⁻¹ (NADP 2020) and could further increase the deposition by 0–5 kg N·ha⁻¹·yr⁻¹ by 2050 (Ellis et al. 2013). Because plant growth is generally co-limited by water and N in the NGP, adding N to the system could alter the competitive interactions among plant species, potentially favoring those adept at using available nutrients to grow rapidly. A recent study in two ABAM parks suggests that N deposition from the recent past and currently could be contributing to the increase in annual bromes seen in some ABAM parks (Symstad et al. 2019).

Every plant species tolerates and thrives in different ranges of these factors. Invasive species often tolerate and thrive in a wide range of conditions and are adept at using available nutrients to grow quickly (van Kleunen et al. 2010, Drenovsky et al. 2012). A variety of studies have attempted to predict the presence and/or abundance of annual bromes from such factors (e.g., Lovtang and Riegel 2012, Reisner et al. 2013, Bansal and Sheley 2016, Porensky and Blumenthal 2016, Ashton et al. 2016). Although each study generally yielded a different set of predictors, due not only to different suites of factors considered but also due to the different geographical areas covered by each study, the general pattern of their results is one of complexity. No single factor strongly determines annual brome invasion; instead, abiotic (climate, weather, soil texture, aspect, etc.) factors interact with processes (grazing, fire, and soil disturbance) to influence biotic factors (resident plant composition and structure). Together, these factors and processes directly and indirectly influence annual brome invasion. This complexity is the ecological context in which ABAM parks must operate when trying to control annual bromes.

2.2. Management and Monitoring Context

A variety of constraints and opportunities provide the management and monitoring context in which we developed the ABAM framework. We describe them here because new resources for management and monitoring specifically for ABAM were not expected. Thus, the framework's design had to work with existing monitoring programs' number of plots and revisit design, as well as the types of management actions realistically achievable in these parks.

ABAM parks range in size from 310 to 94,659 ha and were established as early as 1879 and as recently as 1997. Their primary reasons for establishment include historic events or landmarks, fossil and geological feature preservation, and wildlife conservation (Table 2.1). The land use history of the parks varies substantially (Modlin and Symstad 2018). Some parks (FOLA, SCBL) had portions of their landscape cultivated or otherwise severely disturbed before becoming part of the park; many of these areas were planted with native species after park acquisition. Other parks (BADL, WICA) had scattered homesteads and associated, but usually undocumented, livestock grazing and cultivation. BADL and WICA have bison herds; BADL expanded the portion of the park accessible to bison in 2019, and WICA expects to do so by 2021. WICA also had a large elk population decades ago and in the recent past, but its size has decreased dramatically in the past 5 years. BADL, DETO, SCBL, and WICA have prairie dog colonies. FOLA has approximately 20 horses grazing its vegetation in the winter and a few year-round resident horses. Mule deer, white-tail deer, and pronghorn occur in all ABAM parks but have a small impact on herbaceous vegetation compared to bison, elk, horses, and prairie dogs.

Table 2.1. ABAM parks' size, establishment date, and primary reasons for establishment.

Park	Size (ha)	Year of establishment (and border extensions)	Primary reason(s) for establishment ^b
Agate Fossil Beds NM (AGFO)	1,238	1997	Fossils, history
Badlands NP (BADL)	94,659 ^a	1939 (1952, 1957, 1968)	Fossils, geological features
Devils Tower NM (DETO)	545	1906 (1955)	Geological feature
Fort Laramie NHS (FOLA)	351	1938 (1960, 1978)	History
Little Bighorn Battlefield NM (LIBI)	310	1879 (1886, 1926)	History
Scotts Bluff NM (SCBL)	1,217	1919 (1924, 1932, 1940, 1961)	Geological feature, history
Wind Cave NP (WICA)	13,734	1903 (1931, 1935, 1946, 1978, 2005)	Geological resource (cave), large wildlife

^a 44,305 ha are in the North Unit, which is the only portion of BADL involved in ABAM; the remainder of BADL is managed by the Oglala Lakota Tribe.

^b According to each park's Foundation Document

Only three ABAM parks (BADL, DETO, and WICA) currently have full-time, permanent natural resource management positions, and these parks usually hire seasonal staff specifically to manage invasive plants. SCBL and AGFO plan to share a permanent natural resource manager beginning in 2021. At the other parks, natural resource management is a collateral duty for staff with other primary duties and seasonal staff are occasionally hired to perform some natural resource management activities. In addition to these park staff, natural resource management in all ABAM parks is supported by three programs: an Invasive Plant Management Team (IPMT), a Fire Management office, and an Inventory and Monitoring (I&M) network.

An IPMT travels to each park within its jurisdiction to treat—usually with chemical herbicides but sometimes with biological control agents or mechanical treatments—and/or map invasive plants in areas selected by the park and the IPMT staff. Chemical treatments are applied on foot with backpack sprayers, from an all-terrain or utility vehicle with hand-held wands or via boom sprayers, or from the air via airplane or helicopter. Aerial applications are completed through contracts overseen by the IPMT and/or a park resource management specialist. All treatments are mapped as polygons or points. The time an IPMT spends in each park each year depends on park needs and resources available. Funding for IPMT labor and travel comes from the IPMT program, but parks often provide funds for herbicides. LIBI is served by the Northern Rockies IPMT; all other ABAM parks are served by the NGP IPMT.

Fire management offices oversee wildfire suppression and, in some cases, implement prescribed fires in the parks in their jurisdiction, with personnel for both coming from NPS fire management offices, parks, and other agencies as needed. At the writing of this report, five ABAM parks (AGFO, BADL, DETO, SCBL, and WICA) had active prescribed fire programs and associated vegetation monitoring overseen by the NGP Fire Management Office; FOLA and LIBI had no prescribed fire history or current activity, but both were considering adding prescribed fire to their fire management plans at the writing of this report. FOLA is served by the Grand Tetons Fire Management Office, and LIBI is served by the Yellowstone Fire Management Office. Parks work together with their fire management office to prioritize the location and season of prescribed fires to occur over the next ~5 years. Prescribed fires are conducted in spring and fall. Wildfires can occur any time of year but are most common in late summer and early fall. ABAM parks suppress all wildfires except those occurring naturally (ignited by lightning) in the wilderness area of BADL. Prescribed fires are “prescribed” in that they are conducted according to a written plan that specifies the objectives of the burn (e.g., reduce fuel loads, achieve 85% mortality of ponderosa pine seedlings, reduce exotic grasses) and the conditions needed to achieve those objectives safely (e.g., fuel moisture conditions, weather at the time of the fire).

Fire management offices include fire ecology programs. In the NGP Fire Management Office the fire ecology program (“NGP Fire”) monitors vegetation in areas burned by prescribed fires in order to determine whether each fire achieved its objectives. NGP Fire uses a point-intercept method to measure plant species composition (cover of each species) and structure (herbaceous layer height). They also measure the density and diameter of each tree species. Data are collected up to two growing seasons before a prescribed fire, then one, two, five, and ten growing seasons following the

fire. Monitoring plots are installed in a burn unit before the prescribed fire then maintained in the same locations until they are deemed no longer necessary. Locations are selected randomly within the prescribed fire unit following pre-established rejection criteria (e.g., must have a minimum vegetation cover), and the number of plots varies with the size of the area to be burned.

Six ABAM parks are served by the NGP I&M network (NGPN); LIBI is served by the Rocky Mountain I&M network (ROMN). Both of these networks collect plant species composition and structure data using the same (NGPN) or very similar (ROMN) point-intercept protocol as the NGP fire ecology program. NGPN and ROMN also measure plant species richness by recording the identity of all species in ten 1-m² quadrats in each monitoring plot. Inventory & Monitoring plots are permanent and were established to evaluate, using a statistically robust sampling design, the status and trends of vegetation condition of each park as a whole. Plots are monitored in a rotating panel design, with the number of plots in each panel varying according to the size of the park (Figure 2.3). Symstad et al. (2012) provides details on the NGPN vegetation monitoring protocol, and Manier et al. (2011) and Borgman and Schweiger (2016) describe ROMN vegetation monitoring at LIBI. NGP Fire and NGPN work closely together in two important ways relevant to the ABAM framework. First, when establishing new monitoring plots in a burn unit, NGP Fire draws their sample from the random draw of sampling locations that NGPN used to establish their monitoring plots. Second, the two programs store their vegetation monitoring data in the same FFI database¹ and share quality assurance procedures in entering, checking, and maintaining the data in FFI. ROMN has its own database and quality assurance procedures.

¹ 'FFI' stands for FEAT-FIREMON Integrated, where FEAT is Fire Ecology Assessment Tool and FIREMON is Fire Monitoring.

Northern Great Plains Network

Year	Panel				
	1	2	3	4	5
1	X				X
2	X	X			
3		X	X		
4			X	X	
5				X	X
6	X				X

Park	# Plots per Panel (X)
Agate Fossil Beds NM	3
Badlands NP*	10
Devils Tower NM	4
Fort Laramie NHS	2
Scotts Bluff NM	4
Wind Cave NP	9

Little Bighorn Battlefield NM

Year	Plots Monitored
1	33, 34, 36, 37, 38, 40, 43, 50, 1, 4
2	1, 4, 5, 6, 7, 8, 9, 10, 11, 12
3	11, 12, 15, 16, 17, 18, 20, 21, 22, 23
4	22, 23, 24, 25, 26, 27, 28, 32, 33, 34
5	33, 34, 36, 37, 38, 40, 43, 50, 1, 4

Figure 2.3. Plot revisit designs of Northern Great Plains (NGPN) and Rocky Mountain (ROMN) Inventory & Monitoring Networks. (Top left) The basic revisit design of NGPN vegetation monitoring. Two panels of plots are monitored each year; all plots within a panel are monitored two years in a row, then “rested” for three years (a [2–3] revisit design). (Top right) The number of plots per panel varies by the size of the park. *BADL differs from the other NGPN parks in that it began in 2011 with 5 panels, then transitioned during 2016–2021 to 10 panels. In 2022, the final 10-panel, [2–8] revisit design will be implemented. See Symstad et al. (2012) for details. (Bottom) Vegetation monitoring plot revisit design of ROMN at Little Bighorn Battlefield NM. Ten plots are monitored each year, with two of these plots overlapping with those monitored in the previous year (coloration). Thus, 4 plots in each panel are visited in a [2–2] schedule, and the other 6 plots in each panel in a [1–3] schedule. NM = National Monument, NP = National Park, NHS = National Historic Site. Data shown in this figure are presented in Appendix J, Table J1.

The NPS mission “to preserve unimpaired the natural and cultural resources and values of the national park system for the enjoyment, education, and inspiration of this and future generations” influences the options available for managing invasive plants in ABAM parks. Three aspects of this mission and the agency’s resulting policies are particularly relevant to ABAM. First, preserving unimpaired natural resources translates into the policy that “exotic species will not be allowed to displace native species if displacement can be prevented” (section 4.4.4. in National Park Service 2006). Following this policy, parks also generally strive to restore native species and communities. Second, even though domestic livestock were part of the history that some parks seek to preserve (AGFO, FOLA, SCBL), they are generally not considered a viable management tool, either because of a general public and agency perspective that domestic grazing is an unnatural disturbance or for logistical reasons. Finally, NPS policy also states that “natural processes will be relied upon to maintain native plant and animal species... The Service may intervene to manage populations or individuals of native species only when such intervention will not cause unacceptable impacts ... to other components and processes of the ecosystems that support them” (section 4.4.2 in National Park Service 2006). Therefore, purposely directing bison grazing to specific locations with internal fences

or mineral lures, for example, is generally unacceptable. In contrast, conducting a prescribed fire in a specific area with the expectation that bison would preferentially graze that area in the following growing season is acceptable, since the fire-grazing interaction is a natural process.

3. Problem, Objectives, and Alternatives of the Annual Bromes Adaptive Management Framework

We coordinated and facilitated a workshop following the structured decision-making (SDM) process (Runge 2011) in April 2017 to formally establish an adaptive management program for annual bromes in ABAM parks. The goal of this workshop was to work through the first three steps in the process laid out in Figure 1.2. Participants in this workshop were NPS staff with technical and management expertise from each of the seven ABAM parks, NGPN, ROMN, NGP Fire, NGP IPMT, and the national office of the NPS Natural Resources Stewardship and Science Directorate. Staff from the U.S. Geological Survey (USGS) provided additional technical expertise and workshop facilitation. During and soon after the workshop, participants refined and finalized a problem statement, defined and categorized objectives, specified metrics for those objectives, described a preliminary set of vegetation states, and listed potential management options.

3.1. Framing the Problem

Articulating the nature of any decision problem includes specifying the decision or decisions that need to be made; identifying the primary decision makers, constraints, relevant policies and laws; and determining whether there are related decisions (Gregory et al. 2012). Additionally, the framing step includes detailing the spatial scale at which management actions are applied, the frequency of deciding which actions to apply, and other aspects of the problem that may influence decision making (Runge 2011). The workshop participants began with describing the management problem that ABAM parks face:

How do we strategically manage annual bromes and other exotic annual grasses with seasonally applied actions in ABAM parks to improve the likelihood that we attain desired vegetation conditions, while accounting for limited budgets and potential impacts on other park resources? In the short term, we would like to improve the effectiveness of management by resolving the uncertainties that impact our management decisions. In the longer term, we want to maintain vegetation in our parks closer to our desired conditions.

The decision problem was extended to include all exotic annual grasses, not just annual bromes, because other invasive species with similar life histories and potentially more damaging effects (e.g., *Taeniatherum caput-medusae* and *Ventenata dubia*) are known to occur in the greater NGP. However, for brevity, we continue to refer simply to “annual bromes”. The decision problem also accounts for the potential that management actions that influence annual bromes could influence other exotic species positively or negatively. Workshop participants also agreed that burn units (areas in which a single prescribed fire is conducted) provided a reasonable spatial scale for management because they provide spatial divisions within a park that are small enough to be managed with single management strategies and large enough to capture variation in vegetation within each park. The temporal resolution was described by the fact that management actions would be applied to a burn unit no more frequently than every three to five years, but that management decisions for a whole

park would occur annually. For parks without defined burn units (LIBI and FOLA), areas of size comparable to burn units would be designated as management units.

3.2. Eliciting Objectives

Following the development of the problem statement, workshop participants considered potential management objectives, where a management objective is defined as an object of interest and a preferred direction of change (i.e., maximize or minimize; Clemen and Reilly 2000). An initial list of objectives was organized into topic areas and objective type (fundamental, means, strategic, or process; sensu Keeney 1992). Fundamental objectives are ends in themselves and measure the performance of a management action. Means objectives are how fundamental objectives are achieved and not necessarily measured to determine performance. Strategic objectives are high-level, desired outcomes and typically help to define the range of fundamental objectives. Process objectives typically specify desired steps, or a preferred process, to reach a decision. The main concern at this step of the process was to classify the objectives in the initial list to identify the fundamental objectives.

Workshop participants refined the initial objectives for the problem down to two fundamental objectives: 1) maintain high-quality, native, herb-layer vegetation and 2) maximize cost-efficiency of management actions. The first objective was meant to describe what parks hoped to achieve in terms of desired vegetation conditions. The second objective was meant to describe the desire of applying effective management actions that are least expensive. When building the model, the technical team decided to reframe this objective as “minimize cost”. This meant that, all else being equal, managers would prefer applying management actions that cost less. The participants deemed many of the other objectives, such as societal or wildlife benefits, as directly related to successful vegetation management outcomes or as outside the scope of this problem.

3.2.1. Vegetation Desired Conditions and Their Attributes

The first fundamental objective requires a quantitative description of “high-quality, native, herb-layer vegetation.” Aside from providing a concrete, specific goal, this description serves two purposes. First, it identifies attributes of herb-layer vegetation that define its condition. These attributes are the key ecological attributes critical to the persistence of northern mixed-grass prairie and Black Hills ponderosa pine woodland. Second, it specifies the values of those attributes that constitute the desired condition. By extension, then, the description provides a means for quantifying how different the current vegetation condition is from the desired condition, as well as the nature of difference.

Even before we formally framed the problem of annual brome management in consortium parks, we recognized the importance of a clear, concrete, quantitative description of the vegetation that each park desired to achieve or maintain. Thus, before the SDM workshop, we worked with each consortium park to develop vegetation desired conditions specific to ecologically distinct portions of each park; these are presented in Appendix A. It is important to note that the desired conditions we developed were driven strongly by the concept of ecological integrity. They do not strictly adhere to NPS guidance on desired conditions (National Park Service 2009) in that it is not clear whether they are achievable, even in the long term. Rather, they were developed specifically for the ABAM framework to provide a reference for high-quality vegetation.

In these desired conditions, the key attributes of the vegetation are exotic species, cool-season native graminoids (grasses, sedges, and rushes), warm-season native grasses, native forbs, shrubs, trees¹, and litter. The desired conditions of specific attributes are described in terms of herb-layer canopy cover and height; ground-layer cover of litter and bare ground; litter depth; relative canopy cover of exotic species, native graminoids, forbs, and shrubs; native species richness in 1 m², 1,000 m², and the whole park; and density of trees in various size classes. These metrics—specifically, cover rather than biomass or production of herbaceous species—were used because they are compatible with what is measured by the monitoring programs supporting ABAM. Moreover, abundance of each broad plant category is described in terms of relative cover (percent of total canopy cover) rather than absolute cover (percent of area covered by the canopy) because the former more intuitively depicts the dominance hierarchy of a plant community (e.g., whether desired species are more abundant than undesired species). The desired conditions descriptions also include lists of native species expected to occur in certain areas (soil types, topographic positions) or under different conditions (e.g., heavy vs. light grazing), but species-level composition is not described because variability in the factors that influence this composition is a natural, and therefore desired, aspect of this ecosystem.

3.2.2. Preliminary Vegetation “States”

In no ABAM park does the vegetation of the whole park currently exist in the desired condition. Departures of current vegetation from the desired conditions vary not only among locations within and among parks, but the nature of those departures also varies. Most commonly, exotic species relative cover is higher than desired. However, other types of departures occur, such as native species richness being lower than desired. Different types of departures may require different types of management to rectify, and they vary in their acceptability to managers. To quantify these departures, workshop participants divided the first fundamental objective into two sub-objectives and then used the desired conditions descriptions and their professional experience and knowledge to develop field-measurable metrics for specific attributes related to each of those sub-objectives (Table 3.1).

Different management actions not only are needed to rectify different types of departures from the desired condition, but they also may affect each attribute of the vegetation in different ways – potentially with tradeoffs between desired attributes. For example, fire may reduce annual bromes but, at least temporarily, stimulate some exotic forbs. Quantifying and confronting these tradeoffs are essential pieces of SDM. To make this problem more tractable, workshop participants developed a set of preliminary “vegetation states.” These vegetation states are distinct combinations of different levels of attribute metrics that workshop participants have observed in ABAM parks and that are relevant to vegetation management and the fundamental objective of maintaining high-quality vegetation. Their key characteristics are described in Table 3.2 and photographic representations of the states envisioned when developing these characteristics are in Figure 3.1. A notable uncertainty arose during the construction of these descriptions. Workshop participants agreed that exotic perennial grass or exotic forb relative cover $\geq 20\%$ constituted a strong-enough management challenge to use that value as a threshold to distinguish among states. However, they could not agree

¹ Exotic shrubs and trees are very rare in ABAM parks.

on a similar threshold for annual brome (exotic annual grass) cover, with some arguing that a grassland with up to 50% annual brome relative cover could be restored relatively easily (compared to grassland with >20% exotic perennial grass cover), but others arguing that the threshold should be the same as for exotic perennial grasses.

Table 3.1. Sub-objectives of the first fundamental objective, attributes relevant to the sub-objectives, and the field-measurable scale of each attribute (“metric”). All metrics assume point-intercept cover and species richness measurement methods followed by NGPN and ROMN.

Sub-objective	Attribute	Metric (Attribute scale)
Decrease exotic vegetation	Extent of annual brome presence	Percent of plots with any annual brome
	Extent of annual brome dominance	Percent of plots dominated by (≥50% relative cover) annual brome
	Annual brome relative abundance	Annual brome relative percent cover
	Exotic perennial grass relative abundance	Exotic perennial grass relative percent cover
	Other exotic plant relative abundance	All other exotic relative percent cover
Maintain or improve native vegetation structure and diversity	Graminoid relative abundance	Native graminoid relative percent cover
	Forb relative abundance	Other native relative cover
	Litter depth	Litter + duff depth
	Shrub cover	Shrub absolute cover
	Tree density	Stems/acre of trees with dbh ^a >15 cm
	Alpha diversity	Native species richness in 1 m ²
	Beta diversity	Native species richness in 10 1-m ² frames
	Conservatism	Mean Coefficient of Conservatism ^b

^a dbh = diameter at breast height, where breast height is 137 cm from ground level.

^b Coefficient of Conservatism is a value between 0 and 10 that represents an estimated probability that a plant is likely to occur in a landscape relatively unaltered from what is believed to be pre-European settlement condition. A value of 0 indicates a species is highly tolerant of environmental degradation, whereas a value of 10 indicates a species that is nearly always restricted to a high-quality remnant natural area.

Table 3.2. Preliminary vegetation states identified in the structured decision-making workshop and the levels of the attribute metrics that define them.

Preliminary State	Description
High-quality prairie	Annual bromes occur in <20% of the plots in a management unit, and no plots dominated by (i.e., >50% relative cover) annual bromes. Average relative cover of all exotic species <5%. Native forb relative cover 5–25%. High native species richness and mean coefficient of conservatism high. Low shrub cover and tree density (<10% and <5 stems/acre, respectively).
High-quality woodland	Same as high-quality prairie, but shrub cover up to 50% and tree density ≥5 stems/acre.
Simplified grassland	Relative cover of all exotic species <20%, native forb relative cover ≤15%, native species richness low, shrub cover and tree density low.
Exotic annual grassland	Relative cover of annual bromes ≥ either 20% or 50%. Tree density <5 stems/acre.
Exotic annual woodland	Relative cover of annual bromes ≥ either 20% or 50%. Tree density ≥5 stems/acre.
Exotic perennial grassland	Relative cover of exotic species other than annual bromes ≥20%, with ≥50% of that being perennial grasses. Tree density <5 stems/acre.
Exotic perennial woodland	Relative cover of exotic species other than annual bromes ≥20%, with ≥50% of that being perennial grasses. Tree density ≥5 stems/acre.
Weedy forb mess	Relative cover of exotic species other than annual bromes ≥20%, with <50% of that being perennial grasses.
Low-quality prairie	Prairie with too much annual brome or other exotic cover to be high quality, but not meeting the definitions of the other states.
Low-quality woodland	Woodland with too much annual brome or other exotic cover to be high quality, but not meeting the definitions of the other states.

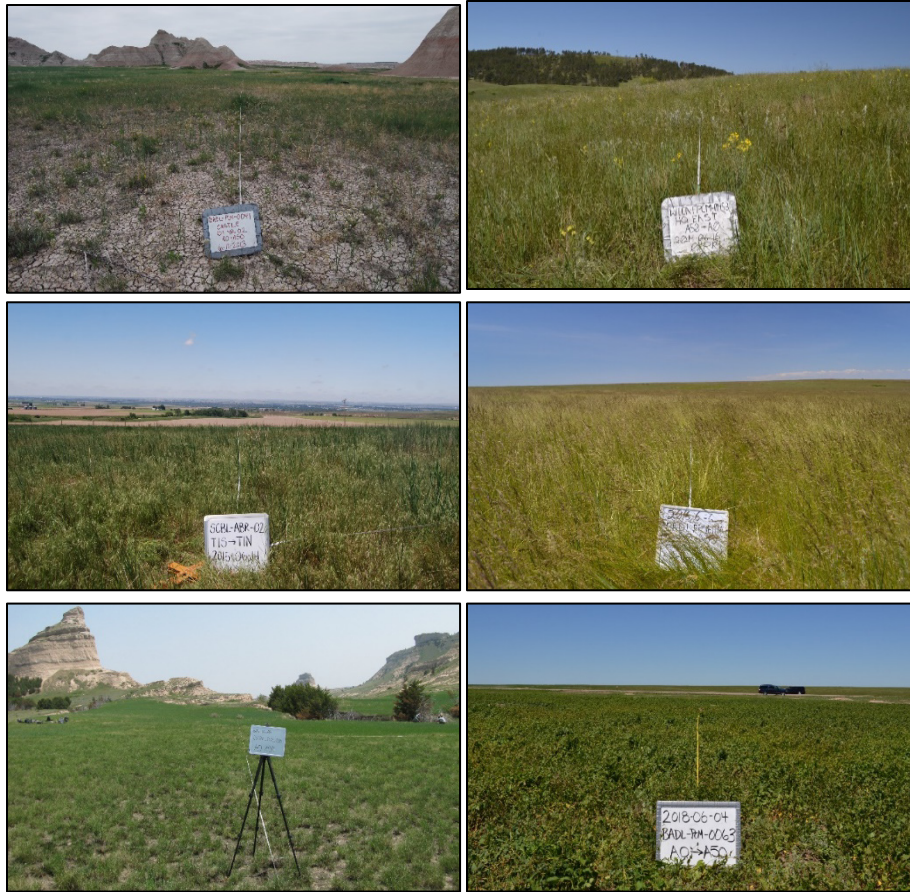


Figure 3.1. Monitoring plots with the characteristics described for some preliminary vegetation states. High-quality prairies at Badlands (top left) and Wind Cave (top right) National Parks have a high diversity of native species, are dominated by native grasses, and low exotic cover (all exotic species together comprise <5% of total plant cover). Exotic annual (middle left) and perennial (middle right) grasslands have at least 20% relative cover of their namesake exotic species. Simplified grassland (bottom left) is strongly dominated by native graminoids and has low diversity. Weedy forb mess (bottom right) has high cover of exotic forbs and often occurs in disturbed areas such as prairie dog towns. All photos NPS.

The states described in Table 3.2 served as the starting point for the states we ultimately developed to use in the ABAM decision support tool, which is structured as a state-and-transition model (see Section 4.1). However, the combinations of metrics arrived at are not necessarily “states” in the sense commonly used in ecological, and especially rangeland ecology, literature. In that literature, transition from one vegetation state to another requires long-term and/or unusually strong management action or disturbance (Westoby et al. 1989, Bestelmeyer et al. 2003). Clear evidence for the existence of such states in northern mixed-grass prairie does not exist. Whether this is because the system does not behave this way (see Porensky et al. 2016) or because of the lack of long-term data to evaluate the system’s dynamics is unknown. Indeed, the lack of understanding of how difficult it is to restore prairie invaded by various species and to various degrees is one of the reasons for developing the ABAM framework. Thus, to avoid the specific connotations of the term “state”,

hereafter we refer to our distinct, management-relevant combinations of attribute values as “vegetation conditions”. This terminology is also consistent with the term “desired conditions”.

3.3. Developing Alternatives

The establishment of preliminary vegetation conditions, and the departures from desired conditions that they represented, aided discussion of potential management options. Workshop participants created a menu of options that included a broad array of actions including prescribed fire, livestock grazing, microbial herbicides, mowing, over seeding, soil amendments, and various chemical herbicides. However, the group quickly determined that policy constraints and uncertainty about experimental approaches made most of these options infeasible. In the end, the group determined that the most feasible options for parks would be to use prescribed fire, chemical herbicide, or some combination of the two. Much of the rationale for this determination is based on current NPS management capacity. The existence of the fire management programs and IPMTs makes these options the most feasible, whereas the dearth of native grazers in many ABAM parks, shortage and expense of appropriate native seed supplies, and the large areas to be treated limit the feasibility of other options considered. Table 3.3 briefly describes the management actions ultimately selected to be included in the ABAM decision support tool. We fully describe the management options considered for inclusion and our justification for our selections in Appendix B.

Table 3.3. Full list of management actions in the Bayesian Management Network (BMN) described in section 4.4.3. Fire-herbicide combinations must occur within a single year, and between vegetation monitoring events, to be considered a single management action. See Table B.2 for detailed description of timing associated with each action.

Management Action Name	Description
none	No management action taken within the year
fall burn	Fire in September–February
spring burn	Fire in March–May
indaziflam only	Indaziflam applied any time of year; no fire in the same year
imazapic–indaziflam	Imazapic–indaziflam mixture applied any time of year; no fire in the same year
fall burn then imazapic	Fire in September–February followed by imazapic application through following March
fall burn then indaziflam	Fire in September–February followed by indaziflam application before veg monitoring
fall burn then imazapic–indaziflam	Fire in September–February followed by application of an imazapic–indaziflam mixture through following March
spring burn then indaziflam	Fire in March–May followed by indaziflam application before veg monitoring
indaziflam then spring burn	Indaziflam after veg monitoring followed by fire in March–May

3.4. Evaluation of Consequences and Identification of Uncertainties

Despite the capacity of the NPS to apply fire and chemical herbicides, assessing their consequences on annual bromes and other aspects of the vegetation proved difficult. As described in Section 2.1, fire's control of annual brome invasion appears to be short-lived, but little is known about the relative effectiveness of fire among and within seasons, or about the effect of fire return interval. According to research and expert opinion, the general consensus is that spring fire (Sather 1987, 1996; Willson and Stubbendieck 2000; D. Swanson, NGP Fire Program, oral comm., 2019) and spring fire in conjunction with heavy grazing (C. Dixon, U.S. Fish and Wildlife Service, written comm., 2017) are the most effective means of reducing exotic perennial grass invasion in tall- and mixed-grass prairies. There is currently little information about how spring fire impacts annual bromes in northern mixed-grass prairie.

Given that fire alone appears to be insufficient for long-term control of annual bromes, chemical herbicides are likely to be necessary. Two herbicides are considered in the ABAM framework because they have shown some promise for controlling annual bromes. Imazapic has been shown to reduce annual brome cover for 1–3 years (Morris et al. 2009, Kyser et al. 2013, Mangold et al. 2013). Indaziflam is expected to have variable control of annual brome cover the first year but much higher control in later years because, once bound to the soil, it controls seedling emergence for up to four years (Sebastian et al. 2016, 2017a, b). This expectation, though, is generally based on small-plot field tests in more arid and more heavily grazed areas than ABAM parks. In ABAM parks, where greater litter depth and plant production may interfere with herbicide contact with the soil, pre-herbicide fire may be necessary to reduce this interference, but we are unaware of information about the potential effects of combined herbicide and fire treatments on both exotic and native plant species.

Workshop participants identified the likely impacts of the different management actions as the primary uncertainty that made choosing a management action difficult. To be more specific, they were unsure whether the effects of burning or spraying herbicide would have positive or negative effects on specific attributes of the vegetation. Furthermore, they were concerned that burning or spraying in a particular season or in a particular combination might inadvertently facilitate the spread of exotic species and further reduce vegetation quality. They also felt that the potential effects of these management actions might be exacerbated by different weather conditions, soil composition, and native grazing. Because managers are likely to apply management to a given unit infrequently (at least a 5-year interval), there was also some interest in understanding what the effects of different management strategies would be over different time periods after application.

Given these uncertainties, we decided to build a model to predict the consequences of different management actions on annual bromes and other attributes of the vegetation. Given the need to keep making vegetation management decisions while these uncertainties remained, we had to build a model that would reduce the uncertainties as more data become available or, in other words, support adaptive management. In order to aid managers in their decision making (i.e., to become a decision support tool), the model would need to be coupled with manager preferences for different vegetation

conditions and the relative importance they placed on the vegetation and cost objectives identified for the framework. We describe our process for developing this tool in the next section.

4. Development of the Annual Brome Adaptive Management Decision Support Tool

Developing the ABAM decision support tool consisted of the steps outlined in Figure 4.1. In the first step we selected the general form of a model that managers could use to predict and understand the relationship between vegetation management, vegetation ecology and manager preferences for different vegetation conditions (section 4.1). Second, we built a conceptual model based on expert input to determine which variables to include when estimating the model's structure, then compiled available data for those variables (section 4.2). Third, we defined vegetation conditions that reflected the management objectives for the parks (section 4.3). Fourth, we estimated the model's structure using an algorithm that statistically determined the relationships among the vegetation, environmental, management, and time variables (section 4.4). Fifth, we estimated the model's parameters – the values that will be updated with each year of learning that occurs through adaptive management (section 4.5). Finally, we turned the ecological model into a decision support tool by incorporating manager preferences for different levels of performance on their management objectives (section 4.6).

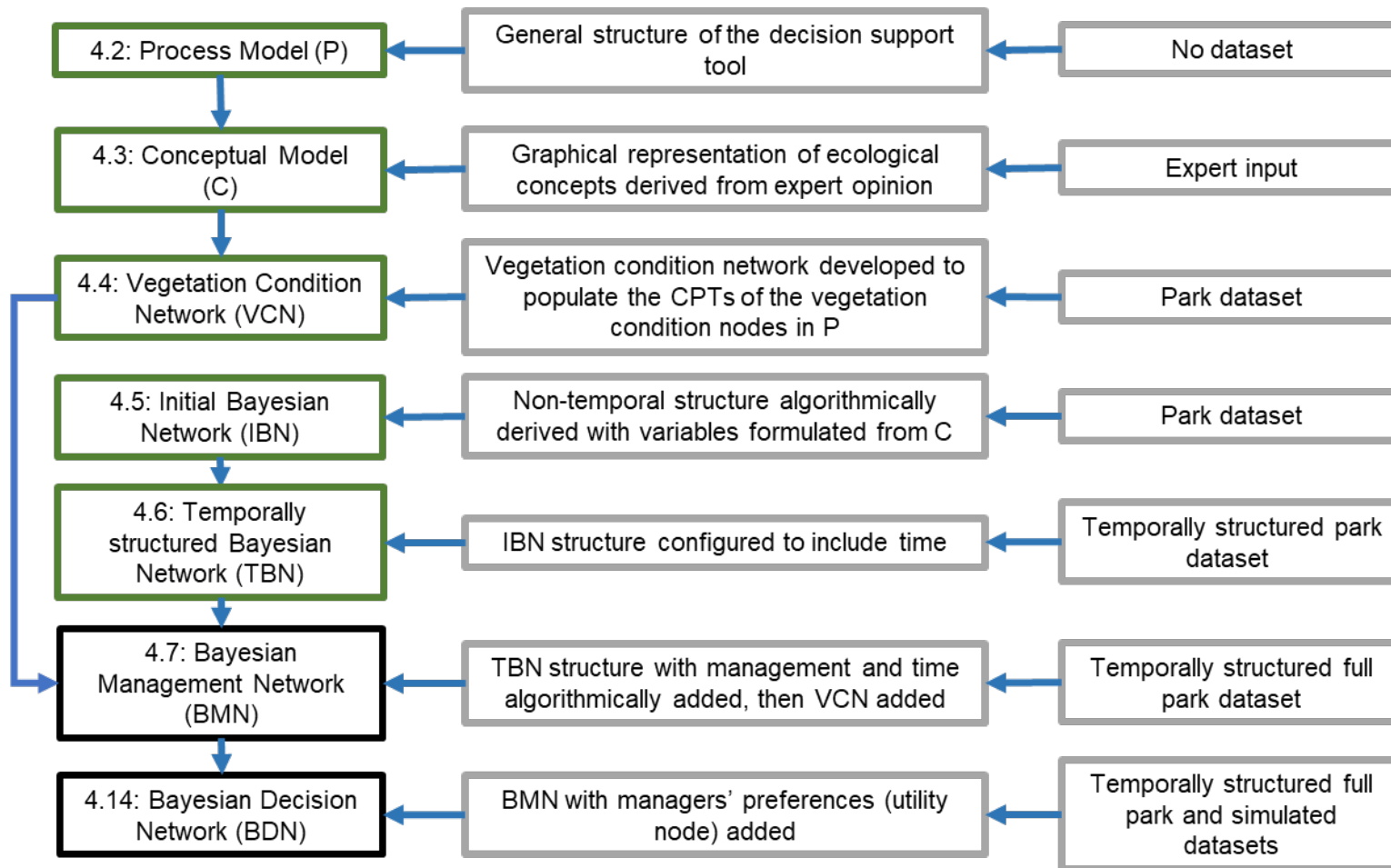


Figure 4.1. Overview of steps taken to develop the ABAM decision support tool. The left column lists the term we use to refer to the interim model resulting from each step and references the figure showing the structure of each of these interim models (e.g., Figure 4.6 for the TBN). The center column provides a brief description of the model in the left column. The right column lists the information used in the step. CPT = conditional probability table.

4.1. General Form of the Decision Support Tool

We built the ABAM decision support tool as a Bayesian Decision Network (BDN) with an underlying state-and-transition model (Rumpff et al. 2011; Figure 4.2). A Bayesian network (BN) is a probabilistic model that is composed of a set of nodes, which represent model variables, and a set of arcs, which represent hypothesized causal relationships between the nodes, in the form of a directed acyclic graph. Conditional dependencies among the nodes are quantified in the conditional probability table (CPT) associated with each node. We chose to use a BN for a few reasons. First, BNs let analysts and managers explicitly and transparently represent complex systems of interacting variables. Because plant communities are complex, with multiple native and exotic components that potentially interact, we felt a BN was most appropriate. Second, BNs can be built using available field data while also including prior information from other sources, such as published literature. In our case, we have both types of information. Third, the managers we worked with would like to reduce uncertainties over time through learning following management. Bayesian network parameters are relatively easy to update with new information using Bayes Theorem (Marcot et al. 2006; Marcot 2012, 2017; Marcot and Penman 2019).

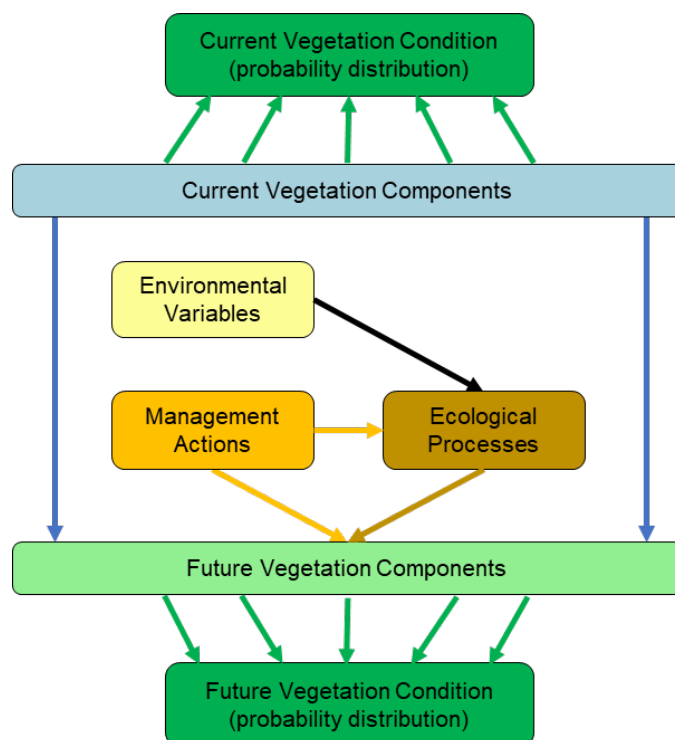


Figure 4.2. General structure of the Bayesian Decision Network. The structure shows how current vegetation components (aspects of the plant community) are used to determine the probability distribution of being in various current vegetation conditions, and how management, environmental variation, and other processes will impact the future values of those components and conditions.

4.2. Conceptual Model and Selection of Relevant Variables

The main challenge with using Bayesian network models for management problems is building a model structure that adequately represents the processes and patterns that managers would like to

affect. Often, there is little empirical data available with which to build such models (Marcot et al. 2006). In those cases, models are built on the basis of expert opinion, and there are many successful applications of this approach available in the scientific literature (e.g. Marcot et al. 2006). When data are available; model structure can be learned using algorithms that are applied in machine learning contexts (Nagarajan et al. 2013). We began with expert input to determine which variables to test for inclusion in the model, but we relied on statistical techniques to build the model structure (Figure 4.1). All our analyses and modeling were performed in the R programming environment (R Core Team 2019).

As mentioned previously, BN models used for decision making are often built with decision-maker or technical-expert input because data are not available (Marcot et al. 2006, Rumpf et al. 2011). Thus, estimates and structures derived from expert opinion need to be conducted in a structured framework (Kuhnert et al. 2010). Because our approach relies on an already existing monitoring program, we opted to build our model with available monitoring data (see 4.2.4). Before we could begin this process, we needed to determine which variables to include in the model-structuring process. We solicited input from technical experts by building a conceptual model (or influence diagram) using an approach similar to the one outlined in Gregory et al. (2012). These experts were one university researcher, four USDA researchers, one USGS researcher, and five ecologists from NPS (all NPS experts were members of the ABAM team). The participants had diverse expertise in NGP plant ecology and invasive species, the state of vegetation within ABAM parks, and use of management tools such as herbicide and prescribed fire. We built the conceptual model through an informal discussion via teleconference after first providing participants with background material via email. In the discussion, we presented participants with a diagram consisting of management objectives on one side and management options on the other. We then began asking the technical experts to list variables that would be important to consider in predicting the effects of management on the objectives. While the experts discussed these variables, we added nodes and arcs to the diagram to reflect their discussion. We then confirmed with the experts whether the arcs we drew represented their expectations about potential ecological relationships. The participants identified the primary variables driving annual brome invasion as being features of native vegetation, slope and aspect, precipitation and temperature, disturbance, time since burn, soil texture, and litter (Figure 4.3).

Based on this discussion, we then conducted a literature review on the topic of annual brome invasion in western North America, with an emphasis on the NGP. Many studies have assessed the factors that drive brome invasion (e.g., Miller et al. 2006, Chambers et al. 2007, Lovtang and Riegel 2012, Reisner et al. 2013, Bansal and Sheley 2016, Porensky and Blumenthal 2016, Ashton et al. 2016). Although these may vary across systems, or are species-specific, they largely confirmed the components of the conceptual model developed with the technical experts we spoke with (see section 2.1). The literature review also provided guidance on how to format our available data to be used in learning the structure of our model. Although the conceptual model and literature review provided the list of variables and their format to include in the structure-learning process, they did not constrain the relationships among those variables to those depicted in the conceptual model (arrows in Figure 4.3).

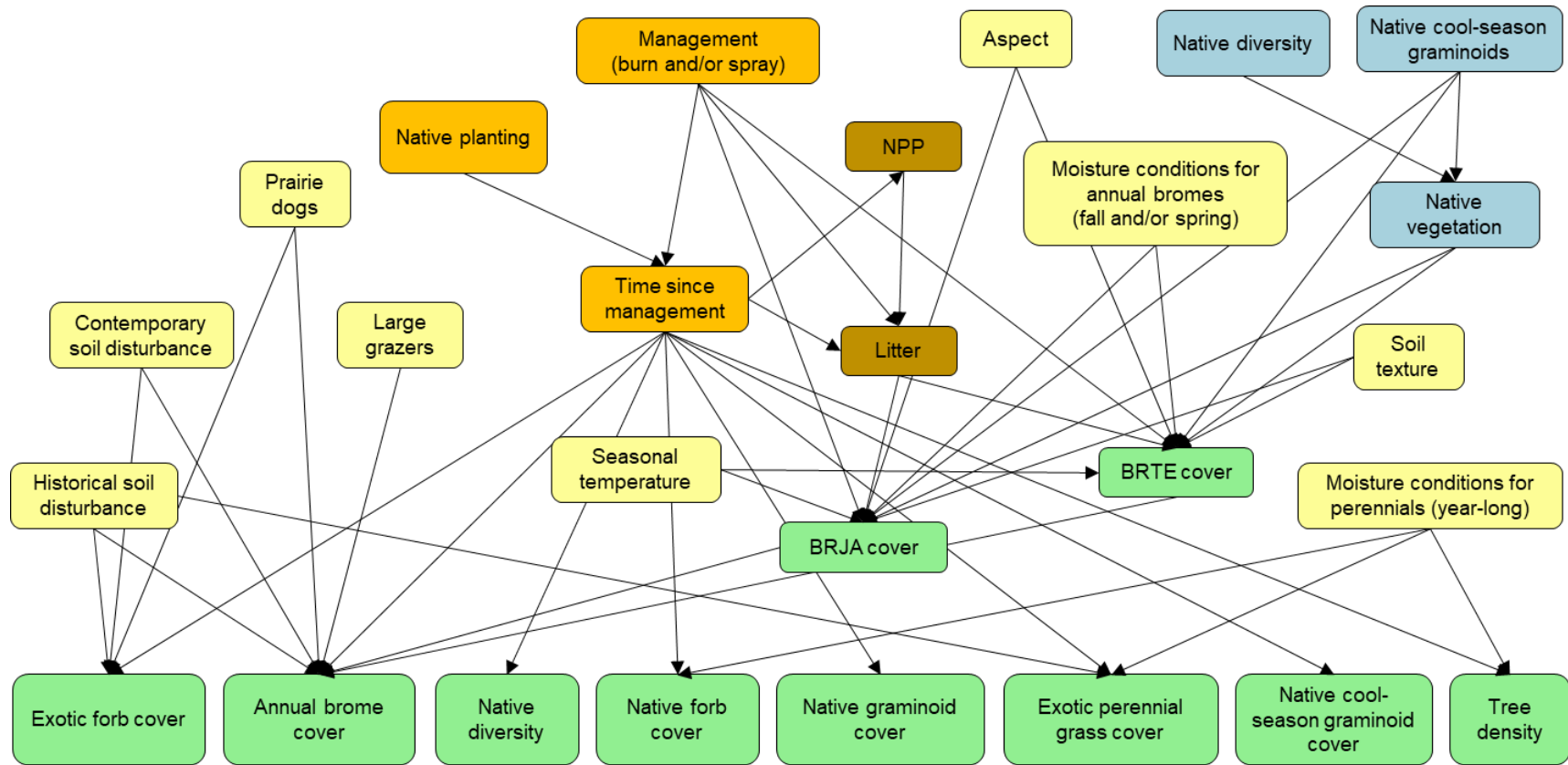


Figure 4.3. The conceptual model developed from expert input. Current native vegetation (blue boxes), environmental factors (yellow boxes), ecological processes (brown boxes), and management (orange boxes) affect future vegetation components (green boxes) directly, whereas others have indirect effects through annual bromes (BRTE = *Bromus tectorum*, BRJA = *B. japonicus*). NPP = net primary production.

4.2.1. Data Assembly and Variable Descriptions

To build the IBN and TBN model structure, we assembled a dataset composed of most of the variables depicted in the conceptual model (Figure 4.3). We refer to this dataset as the ‘park dataset’. In the following subsections we define the vegetation composition and structure variables (section 4.2.1.1) and the environmental variables (section 4.2.1.2) and describe how we derived them from available data. In Appendix C, we explain why we included (or excluded) specific vegetation and environmental variables and forms of those variables in the full park dataset. In section 4.4, we describe how we incorporated the management and time variables in Figure 4.3 into the park dataset. Note that one management type appearing in the conceptual model – native plantings – was not included in this dataset because it was deemed infeasible by the participants of the 2017 workshop. In assembling the park dataset, we also considered the attributes and metrics developed in that workshop to describe vegetation conditions.

The dataset drew primarily from monitoring observations from 1998 to 2018 by NGPN, NGP Fire, and ROMN within ABAM parks. Additional data came from herbicide trial plots at WICA and annual brome research plots at BADL and SCBL (Appendix D). Monitoring plots within sparsely vegetated badlands areas, wetlands, and the NGPN riparian sampling strata at AGFO and FOLA were excluded from the dataset because their environmental conditions (lack of soil development in badlands areas, temporarily saturated soil in wetland and riparian areas) and vegetation differ strongly from the northern mixed-grass prairie or woodland targeted by the ABAM framework and represented by the large majority of monitoring plots. This resulted in 1,497 sample events from 489 unique plots relevant to this project.

4.2.1.1. Vegetation Composition and Structure Variables

We assembled 13 variables to represent vegetation composition and structure. All but tree density were derived from the point-intercept method of measuring plant foliar cover and ground cover used by NGPN, ROMN, and NGP Fire in their vegetation monitoring plots. The same method was used in the USGS experimental plots. In this method, a 0.8-cm diameter pole was inserted through the plant canopy to the ground at points arranged at a fixed interval along one or more transects in a plot. At each point, each species that intercepts the pole in the canopy was recorded, as was the ground-level substrate (e.g., bare soil, litter, rock). The number of points per transect, number and spatial arrangement of transects within a plot, and the size and shape of each plot varied among the different programs and experiments. However, calculation of the variables (in **bold** in the following bullets and thereafter) from the raw data was the same across the programs and experiments. Except for the native diversity variable, the variation in sampling details does not bias the value of the variables. We address the bias in that variable in its description below.

- **Litter cover** is the percentage of points at which litter was the ground-level substrate.
- **Total cover** is the number of intercepts summed over all points in a plot divided by the number of points in a plot, expressed as a percentage. Because of layering of the vegetation, total cover can be over 100%. Total cover is a surrogate for net primary productivity (NPP).

- Relative percent cover (“rpc”) of an individual species is the number of points at which that species was intercepted divided by total cover, expressed as a percentage. Relative percent cover cannot exceed 100%. The **BRTE rpc** and **BRJA rpc** (*Bromus tectorum* and *B. japonicus*, respectively) variables were calculated this way.
- Relative percent cover of a group of species (such as exotic annual graminoids¹) is the sum of the relative percent covers of its constituent species. **Exotic annual graminoid rpc** (sum of **BRTE rpc**, **BRJA rpc**, and rpc of any other exotic annual graminoids), **exotic perennial graminoid rpc**, **exotic forb rpc**, **native graminoid rpc**, **native forb rpc**, and **woody rpc** (includes shrub and tree species) were calculated this way.
- **Native diversity** is the number of native plant species intercepted across all points in the plot. This index is not independent of the number of points sampled or the size of the plot across which the points were spread, with more points and larger plots expected to produce higher native diversity. We followed NGPN² in assuming that 100 points adequately represent the diversity of a plot and did not adjust diversity for plots with more than 100 points when constructing the dataset. However, we do account for the greater number of points in the ROMN sampling design (216, vs. NGPN’s 100) in the conditional probability table for vegetation condition (section 4.3, Appendix E)
- **Percent cool-season** is the percentage of **native graminoid rpc** comprised of cool-season (C₃ photosynthetic pathway) species.
- In each plot, the number of trees with diameter at breast height (1.38 m) >15 cm is recorded in a fixed area. These data were used to calculate **tree density** as the number of trees per acre.

Three of these variables – **litter cover**, **total cover**, and **percent cool-season** – were eliminated during preliminary data investigation and not included in the park dataset (see Appendix C), resulting in 10 vegetation variables in the dataset.

4.2.1.2. Biotic and Abiotic Environmental Factors

We assembled 21 variables to represent biotic and abiotic environmental factors hypothesized to influence vegetation components’ dynamics (yellow boxes in Figure 4.3).

Contemporary Soil Disturbance

The NGPN and ROMN vegetation monitoring protocols document a variety of disturbances at the time of each sample event. Five of these indicate substantial soil disturbance: erosion, prairie dog

¹ Graminoids are grasses (family Poaceae) and grass-like plants, including sedges (Cyperaceae) and rushes (Juncaceae). We use the term graminoids, as opposed to grasses, for variables in the park dataset because of the way plant growth forms are categorized in the database where NGPN and NGP Fire store their monitoring data. In reality, though, the only annual graminoids in ABAM parks are grasses.

² In the first few years of its monitoring, NGPN sampled 200 points per plot. They reduced this to 100 points per plot after their analysis of their data indicated that the additional information provided by the higher number of points was minimal compared to the effort required to sample with that intensity (I. Ashton, NGPN, oral comm., 2018).

activity, other small mammal activity, bison wallowing, and burned woodpile. The NGPN protocol notes whether each type has occurred and, for some types, records the area of the plot impacted by the disturbance. The ROMN protocol records whether each type is present and the degree of impact on the plot according to a categorical scale. In addition, some parks use standard protocols (Plumb et al. 2001, Northern Great Plains Network 2019) to map the extent of prairie dog towns at irregular intervals, providing a longer-term record of the potential influence of prairie dog activity (burrowing, clipping vegetation) than that provided by the vegetation monitoring protocols. Specifically, prairie dog town perimeter data were available for BADL in 2000–2017, DETO in 1975–2016, SCBL in 1996–2017, and WICA in 1982–2016. The data were not complete enough to determine the age of active prairie dog towns or identify locations of abandoned prairie dog towns. The quality and quantity of data available for each park vary substantially. For example, it appears that towns that are more accessible or are associated with black-footed ferret (*Mustela nigripes*) home ranges have been surveyed most frequently.

We used these two sources of information to develop the categorical **contemporary soil disturbance** variable, which has four levels: *yes* (soil-disturbance recorded at time of vegetation monitoring event), *past* (soil disturbance recorded in past vegetation monitoring event or indicated by location within prairie dog town mapped at any time in the past, but no disturbance recorded at current monitoring time), *none* (neither current nor past soil disturbance recorded), and *not known* (not in previously mapped prairie dog town and disturbance information not collected as part of vegetation monitoring).

Historical Soil Disturbance

Historical soil disturbance captures events of significant soil disturbance where the vegetation and soil are expected to have been affected on a scale much larger than the size of a plot, and that usually occurred before the park was established. Significant disturbance of topsoil destroys biological, chemical, and physical properties of the soil that may take decades or centuries to recover in semiarid grasslands (Burke et al. 1995). It also opens large areas to invasion by weedy species. We developed the Historical Land Use (**HLU**) variable to represent historical soil disturbance from a land-use history spatial database created specifically for this project (Modlin and Symstad 2018). Types of land use in this database are cultivation, grazing, seeding, existing structures, excavation, and other.

We did not expect grazing to have long-lasting impacts on vegetation condition. Therefore, this category was excluded as land use when assigning one of two values to the **HLU** variable: *yes* (vegetation monitoring plot falls within polygon with a history of land use) and *none known* (vegetation monitoring plot falls outside all polygons indicating historical land use).

Grazing

Grazing reduces aboveground biomass more selectively than fire and stimulates both above- and belowground plant growth and nutrient cycling. To capture the various grazing situations in ABAM parks (see Section 2.2), we developed the **grazing** variable, which has three levels: *freerange_bison_other* (bison ranging freely in the area of the park where the monitoring plot lies, plus other wildlife ranging freely within and across park boundaries), *freerange_wl_no_bison* (only

non-bison wildlife ranging freely within and across park boundaries), and *freerange_other* (non-bison wildlife ranging freely within and across park boundaries, plus seasonal grazing by horses).

Slope and Aspect

We included two variables to represent the topographical context. Percent slope is the grade (rise over run) as measured in the center of the plot. Aspect is the compass direction a sloped plot faces. If slope and aspect were not recorded in the field, we extracted aspect and slope values for NGPN park from the 2011 National Elevation Dataset. For parks in ROMN we extracted these values from the USDA data gateway (USDA 2018). To calculate a value representative of the whole plot, we used bilinear interpolation over all cells adjacent to the cell in which the plot's centroid fell. NoData values were ignored in the interpolation unless all adjacent cells are NoData.

Slope is a numeric vector that ranged from 0 to 60.

Aspect is a numeric vector that ranged from 0° to 360°.

Soil Texture

Soil texture is described by the relative amount of soil particles of three different sizes, designated as sand, silt, and clay. Because these percentages sum to 100%, only two variables are needed to represent soil texture; we selected silt and clay. We downloaded the gSSURGO database (USDA 2018) for Nebraska, South Dakota, Wyoming, and Montana. In this raster database, each cell has a map unit key (mukey) that serves as a link between the cell and the attribute tables containing information about the soil types ('components') in the database. Almost all map units include more than one component; the 'component' table, which is specific to each state, describes these one-to-many relationships, referring to each component with a component key (cokey). Each component has many horizons (soil layers); the 'chorizon' table is specific to each state and describes these one-to-many relationships, referring to each horizon with a 'chkey', and provides soil composition data (% clay, silt, and sand) for each horizon. Thus, to calculate soil composition variables for each monitoring plot, we first assigned mukey values to each plot based on its geographic location. We then imported this plot-mukey table and the component and chorizon tables into R to (1) determine the components relevant to that plot from the mukey-cokey relationship; and (2) use the cokey-chkey relationships to calculate the average % clay and % silt over the A and B horizons and the relevant components. We acknowledge that the data in the SSURGO database are not meant to be used at the fine spatial scale at which we applied them (~0.1 ha), but field-collected soil data are not available for the monitoring plots in all parks but LIBI. However, we included the variables derived from them in the database because we assumed that the discretization of the variables would prevent over-emphasizing any fine-scale relationships between soil texture and vegetation variables. The Wyoming gSSURGO database does not include soil texture information for the region where FOLA lies. Thus, at this point we left the soil texture variable for all FOLA sample events empty.

Percent clay ranged from 5.5% to 44.6%

Percent silt ranged from 3.9% to 70.2%

Weather

We created 14 weather variables from data downloaded from the PRISM monthly climatologically aided interpolation (CAI) modeling database (PRISM Climate Group 2021). These were **fall temperature, winter temperature, spring temperature, fall precipitation, winter precipitation, spring precipitation, SPEI fall-r, SPEI winter-r, SPEI spring-r, SPEI previous growing season-r, SPEI fall-g, SPEI winter-g, SPEI spring-g, and SPEI previous growing season-g**. For these, we defined fall as September–November, winter as December–February, and spring as March–May. Temperature variables are the average (over the three months in the season) mean temperature, and precipitation variables sum precipitation over the three months in the season.

SPEI is the Standardized Precipitation-Evapotranspiration Index, which uses both temperature and precipitation to compute a water balance index in which a value of 0 is the long-term mean (Vicente-Serrano et al. 2010). It is scaled to a specific timeframe, as indicated by, for example, SPEI fall. Our **SPEI growing season** variables include the month in which a plot was sampled through the previous growing season (e.g., March of previous year to June of sampled year: 16 months). A rectangular (**r**) distribution is used to weight all months in an SPEI calculation equally, whereas a Gaussian (**g**) distribution weights the earlier months in the SPEI calculation heavier than the later months. To calculate SPEI, we first used the *SPEI* R package (Beguería and Vicente-Serrano 2017) to calculate potential evapotranspiration using the Hargreaves method (Hargreaves and Samani 1985), which is derived from temperature data and can be just as accurate as more complex methods when applied in semi-arid systems (Hargreaves and Allen 2003). We then used the *SPEI* package to calculate the **r** and **g** forms of each **SPEI** variable.

Some weather variables are highly correlated (Appendix C). For example, winter precipitation has a strong negative correlation with winter temperature, and SPEI has a strong negative correlation with winter and spring temperature. To reduce the risk of these correlations confounding model results, we divided the dataset into four weather variable groups (Table 4.1), each of which included different ways of representing the three weather concepts in the conceptual model (Figure 4.3): seasonal temperature, moisture conditions for annual bromes (shorter-term conditions), and moisture conditions for perennial species (longer-term conditions). We ran the algorithm to estimate model structure five times, once using all weather variables together, and once each using only the weather variables in each group, in our process of selecting the final model structure (section 4.4).

Table 4.1. Weather variable groups used in model structure learning analyses. SPEI = standardized precipitation-evapotranspiration index, -g = Gaussian distribution, -r = rectangular distribution.

Group 1	Group 2	Group 3	Group 4
spring precipitation	spring precipitation	spring temperature	spring temperature
spring temperature	spring temperature	winter temperature	winter temperature
winter precipitation	winter precipitation	fall temperature	fall temperature
winter temperature	winter temperature	SPEI spring-r	SPEI spring-g
fall precipitation	fall precipitation	SPEI winter-r	SPEI winter-g
fall temperature	fall temperature	SPEI fall-r	SPEI fall-g
SPEI previous growing season-r	SPEI previous growing season-g	SPEI previous growing season-r	SPEI previous growing season-g

4.2.2. Discretizing Continuous Data

In the R programming environment (R Core Team 2019), variables can be represented within Bayesian network nodes in two ways, as either Gaussian or discrete distributions (Scutari and Denis 2015). Gaussian models are appropriate when variables follow a Gaussian (i.e., normal) distribution, whereas discrete distributions are appropriate when variables follow any other distribution. Upon inspection of our data, we determined that discrete distributions were the most appropriate to describe our data. Determining the number of discrete levels for each variable requires balancing the need to properly represent patterns in the data with the practical considerations of model complexity, and the potential to overfit the data resulting in estimates that are not generalizable enough to make predictions in novel situations.

There are numerous methods available to define categorical levels. We relied upon the Hartemink pairwise mutual information method (Hartemink 2001) in the *bnlearn* package (Scutari 2010). This method uses a discretizing algorithm that operates over an entire dataset. This dataset includes the continuous form of all variables to be included in a model. The algorithm determines cutoff values for all of the variables in a way that preserves as much information in the data set as possible. For each continuous variable, we used the Hartemink algorithm to discretize variables to 2 and 3 levels. This small number of levels at first appears to limit the model to relatively simple behavior, such as representing annual bromes' response to above- vs. below-average winter temperature, rather than representing a linear or even curvilinear response. However, because the algorithm minimizes loss of information about relationships between variables, this concern is reduced. Furthermore, the multidimensionality of a BN ensures that the complex interrelationships among variables is captured even when continuous variables are discretized.

We used the breakpoints produced by the Hartemink algorithm for the vegetation component variables to aid in translating the vegetation condition descriptions in Table 3.2 into a discrete node representing vegetation conditions. This process is described in Section 4.3. We also used the breakpoints produced by the Hartemink algorithm to compare the predictive accuracy of IBN

structures estimated using all two-level environmental variables to those estimated using all three-level environmental variables to inform our decision on the structure of the Initial Bayesian Network (IBN) and the number of levels for the environmental variables. This process is described in Section 4.4.1.

4.3. Translating Management Objectives into Vegetation Condition Node

Translating the management objectives and thoughts of managers regarding various vegetation conditions (section 3.2.2, Table 3.2) into a discrete vegetation condition node could not be purely data-driven because the vegetation conditions described, and differently valued, by the managers are neither discrete nor objectively defined entities. Thus, we used a combination of quantitative analyses and expert knowledge to complete this step.

We began by examining the breakpoints produced by the Hartemink algorithm for five different variable sets. Each of these sets included all vegetation component variables, all edaphic variables, and either one of the weather variable groups in Table 4.1 or all weather variables. The resulting breakpoints are shown in Appendix E. Based on the information in Table 3.2 and the vegetation desired condition descriptions in Appendix A, we decided that three levels of most vegetation variables were necessary to distinguish among the ten vegetation conditions in the vegetation condition node. The exception to this rule was **tree density**. This variable is used solely to distinguish between grassland and woodland conditions with similar other vegetation components (e.g., low-quality grassland vs. low-quality woodland), for which a simple presence/absence of trees is adequate. We then selected preliminary breakpoints for each variable from those produced by the Hartemink algorithm based on their proximity to thresholds described for exotic vegetation components in Table 3.2 and native vegetation components in Appendix A.

Next, we built a small BN (Vegetation Condition Network, or VCN, in Figure 4.1) with arcs drawn from a vegetation condition node, whose levels are the ten vegetation conditions in Table 3.2, to each of the vegetation component nodes. We then assigned probabilities to the CPT for each vegetation component node in this BN based on how much the levels of those components contributed to the vegetation condition definition in Table 3.2, as well as our own knowledge of the system. We then reversed the direction of the arcs, which had the effect of populating the vegetation condition node's CPT (Figure 4.4). This outcome required further refinement.

We adjusted the breakpoints between levels of the vegetation component variables after examining the behavior of the vegetation condition node under different combinations of vegetation component node levels. During this process, we decided that a fourth level was needed for the **exotic annual graminoid rpc** variable to anticipate greater exotic annual grass invasion that may occur in the future and because evidence from an experiment suggested this is an important threshold for exotic annual grass management (Symstad et al. 2021). We added a breakpoint for this level based on the results of the Hartemink algorithm run to produce four levels; this additional breakpoint was close to the 50% threshold described in Table 3.2. The final breakpoints for the vegetation variables are shown in Table 4.2. Finally, we adjusted the CPTs for each vegetation component node in VCN until the behavior of the network adequately met our expectations. These final CPTs are in Appendix E. To distinguish between the continuous variables and their discretized counterparts that appear as nodes

in BNs described in subsequent sections, we refer to the discrete nodes by shortened names, which are also shown in Table 4.2.

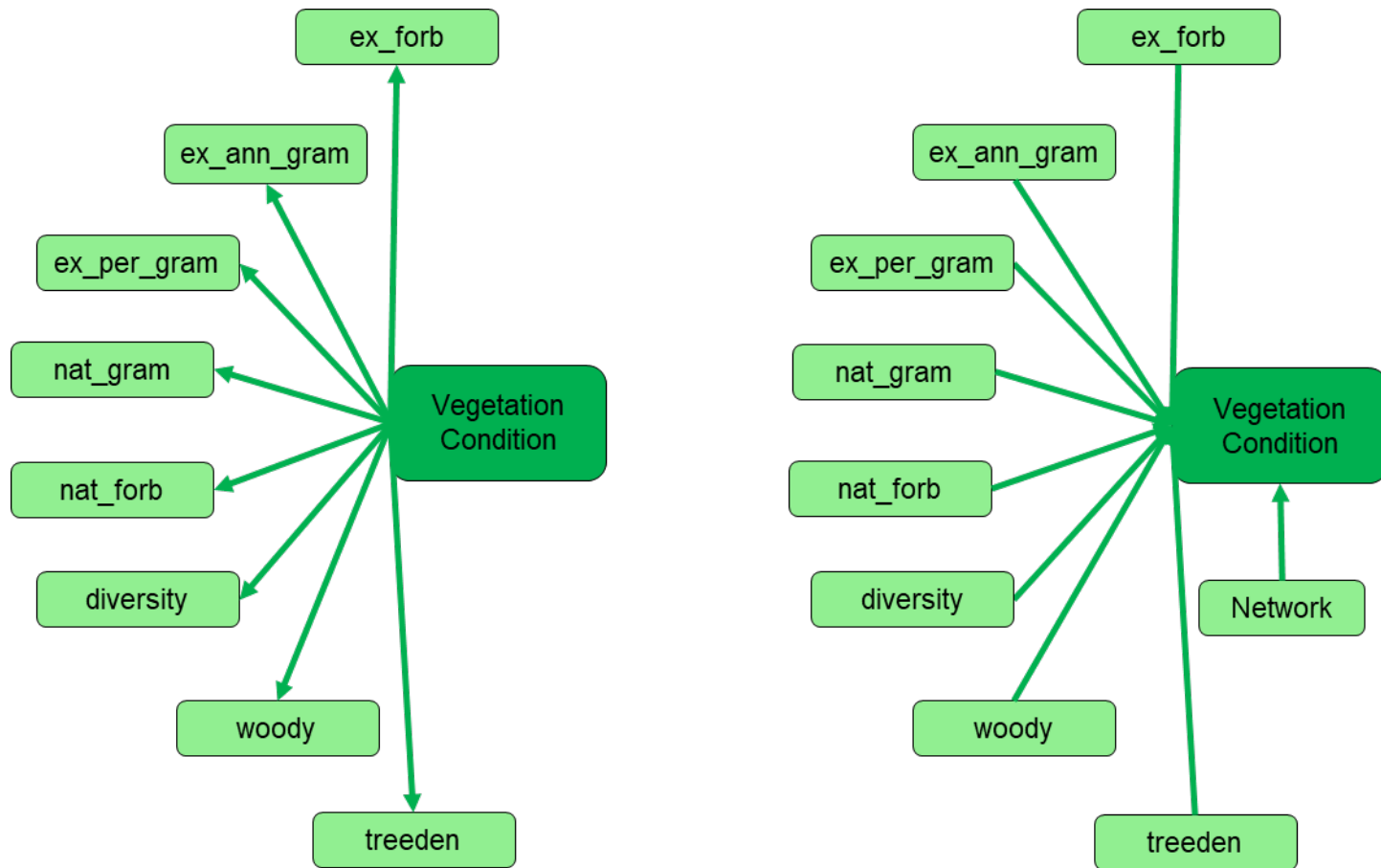


Figure 4.4. The two forms of the Vegetation Condition Network (VCN) used to populate its conditional probability tables (CPTs). We began with the one on the left, populated the CPTs in each of the vegetation component (light green) nodes, then reversed the links to produce the configuration on the right. Doing this created the large CPT we needed for the vegetation condition node on the right. See Table 4.2 for meaning of node names. The Network node distinguishes between vegetation condition characteristics applicable to Little Bighorn Battlefield National Monument (ROMN) versus the other parks (NGPN).

Table 4.2. Final breakpoints for vegetation component variables and the names used for the discrete form of these variables in the rest of this report. BRTE = *Bromus tectorum*, BRJA = *B. japonicus*, rpc = relative percent cover.

Variable	Breakpoint 1	Breakpoint 2	Breakpoint 3	Discrete Name
exotic annual graminoid rpc	1	12	48	ex_ann_gram
BRTE rpc	1	19	–	brte
BRJA rpc	1	12	–	brja
exotic perennial graminoid rpc	2	18	–	ex_per_gram
exotic forb rpc	1	14	–	ex_forb
native forb rpc	1	4	–	nat_forb
native graminoid rpc	69	92	–	nat_gram
native diversity	12	18	–	diversity
woody rpc	0.5	12	–	woody
tree density	0	–	–	treeden

4.4. Estimating the Bayesian Management Network Model Structure

In this section we describe the process we used to estimate the model structure of the BMN. By “model structure” we are referring to the model’s topology, which is a visual representation of variables (in the form of nodes, or colored boxes) and the presence of a statistical relationship between those nodes (in the form of directional arcs, or arrows). We describe the process in detail below, but in general, we began by estimating the structure of Initial Bayesian Networks (IBNs), which captured relationships between vegetation components and a suite of environmental variables. Using the structures of the IBNs, we produced Temporally structured Bayesian Networks (TBNs) by adding a set of nodes to represent current vegetation variables and a set of nodes to represent future vegetation variables. We then selected one of these TBNs, to which we added management and time-scale nodes and estimated where the arcs between these nodes and the rest of the nodes in the TBN lie. This model structure is the Bayesian Management Network (BMN). Finally, we added the vegetation condition and utility nodes to the BMN. This model structure is referred to as the Bayesian Decision Network (BDN; Figure 4.1).

4.4.1. Estimating Initial Bayesian Networks (IBNs)

The intent of the IBNs was to capture relationships between vegetation components and environmental variables independent of management effects. Therefore, when estimating the IBNs, we worked with a subset of the park dataset described in section 4.2.1. Specifically, we excluded all sample events that occurred less than five growing seasons after a management action (fire and/or herbicide application). We also excluded all data from FOLA. This is because the algorithm we used to estimate model structure (described in next paragraph) requires observations to have no missing information, yet as noted in section 4.2.1.2, not all environmental data were available at FOLA. Thus, we only incorporated FOLA data for parameterization (Section 4.5.1). As described in section

4.2.1.2, we grouped weather variables to reduce the number of spurious relationships between variables. First, we created five sets of variables by combining the vegetation component data with each of the four weather variable groups shown in Table 4.1, and one set including all weather variables. Next, we created two versions of the five variable sets, one with the two-level forms of the environmental variables and one with the three-level variables (Table 4.3). Breakpoints between these levels were those resulting from the Hartemink algorithm run on the variable set including all weather variables (Table 4.4). As with the vegetation component variables, we distinguish between the continuous variables and their discretized counterparts that appear as nodes in BNs by referring to the discrete nodes by shortened names shown in Table 4.4. We then used the same algorithm with each of the ten variable sets to estimate ten competing model structures.

Table 4.3. Components of the ten variable sets used to estimate competing model structures to produce the Initial Bayesian Network (IBN). The levels of the vegetation components remained the same for all variable sets (Table 4.2); the number of levels changed for only weather and edaphic variables.

Variable Set	Weather Variable Group	Levels in Weather and Edaphic Variables
G1.2	Group 1	2
G2.2	Group 2	2
G3.2	Group 3	2
G4.2	Group 4	2
ALL.2	All	2
G1.3	Group 1	3
G2.3	Group 2	3
G3.3	Group 3	3
G4.3	Group 4	3
ALL.3	All	3

Table 4.4. Breakpoints for environmental variables in two- or three-level discretization and names of discrete forms of those variables. Investigatory analyses indicated that breakpoints produced by the Hartemink algorithm for the variable set including all weather variables (ALL.2 and ALL.3 in Table 4.3) were valid for all other variable sets. Thus, those breakpoints are shown and were used for all variable sets. “Variable range” is the range of the variable’s values in the park dataset. “–” indicates that breakpoints in the three-level solution were so close together as to indicate that three levels were unnecessary to describe the variable’s relationship with other variables. SPEI = standardized precipitation-evapotranspiration index, -g = Gaussian distribution, -r = rectangular distribution.

Variable	Breakpoint 1	Breakpoint 2	Variable Range	Discrete Name
percent clay	13 ^a	23	6 – 45%	clay_pct
slope	1.2	13 ^a	0 – 60%	slope
aspect	260 ^a	–	0 – 360°	aspect
fall temperature	8.5	9.6 ^a	5.3 – 13.8° C	temp_fall
winter temperature	-4.0 ^a	-2.6	-8.2 – -0.7° C	temp_winter
spring temperature	8.3	8.7 ^a	4.3 – 13.1° C	temp_spring
fall precipitation	150 ^a	–	24 – 260 mm	precip_fall
winter precipitation	60 ^a	–	2 – 127 mm	precip_winter
spring precipitation	124	212 ^a	33 – 317 mm	precip_spring
SPEI fall-r	-0.20	0.70 ^a	-2.30 – 2.21	SPEI_fall_r
SPEI winter-r	-0.40	0.57 ^a	-2.40 – 2.35	SPEI_winter_r
SPEI spring-r	-0.40	0.58 ^a	-2.41 – 2.19	SPEI_spring_r
SPEI previous growing season-r	-0.50	0.84 ^a	-2.53 – 2.14	SPEI_pregr_r
SPEI fall-g	-0.30	0.64 ^a	-2.45 – 2.71	SPEI_fall_g
SPEI winter-g	-0.80	0.75 ^a	-2.64 – 2.53	SPEI_winter_g
SPEI spring-g	-1.00	0.25 ^a	-2.43 – 2.15	SPEI_spring_g
SPEI previous growing season-g	0.04	0.85 ^a	-2.53 – 2.29	SPEI_pregr_g

^a The breakpoint in the two-level discretization, also shown in italics.

We used the hill-climbing algorithm (Russell and Norvig 2009) in the R package *bnlearn* (Scutari 2010) to estimate where arcs should be drawn between the variables within each variable group. The hill-climbing algorithm performs a greedy search of possible arcs between nodes. It works by iteratively adding, removing, and reversing arcs while scoring each new change to the model using the model likelihood given the dataset. It also iteratively restarts the search to avoid getting trapped in local optima. To determine the relative importance of any arcs identified by this algorithm, we used a bootstrapping procedure that randomly proposes an initial model structure and then runs the hill-climbing algorithm. We ran the bootstrapping approach with 10 random restarts. For each restart,

we allowed the algorithm to attempt 10 random arc proposals. The hill-climbing search was then run for 1,000 iterations. IBN fit was scored using the Akaike Information Criterion (AIC).

As part of the analysis, we established a ruleset to ensure that the algorithm produced relationships that were ecologically sensical. In this ruleset, we considered variables to be either dynamic or static, with values of dynamic variables expected to change on an annual basis but static variable values to be consistent for at least a decade. Thus, dynamic variables were vegetation components, contemporary soil disturbance, and weather variables, whereas static variables were those representing soil texture, aspect, slope, grazing, and historical land use. The ruleset was as follows: (1) dynamic variables cannot influence static variables; (2) static variables cannot influence weather variables; (3) and static variables cannot influence each other. When running the algorithm, we translated these rules as restrictions on arcs between variables – an arc could not be drawn from a variable to another variable the rules set it could not influence.

The results from the bootstrapping procedure included every arc considered over the 1,000 iterations. Some of these arcs do not show up frequently, which suggests that those arcs are not as important in the IBN structure. Thus, we needed to decide which arcs should be dropped. We used the results from the bootstrapping procedure to calculate the probability that an arc occurred in the IBN. We used these probabilities to perform model averaging in which we chose a threshold probability value, above which arcs should remain in the IBN. The bootstrapping procedure produced a significance value, which we used as a guide to determine a threshold probability value. Among the IBNs, the significance thresholds ranged from 0.45 to 0.54; we felt these were overly conservative after inspecting the probability values for the remaining arcs. Therefore, we lowered the threshold value for inclusion of an arc in the averaged model to 0.25. This means that any arc that appeared less than 25% of the time was dropped from the IBNs considered for further investigation. Based on our inspection of the resulting structures and arc probabilities, as well as consideration of the input from experts reflected in the conceptual model (Figure 4.3), we found that a threshold of 25% allowed for more model complexity but also removed a number of arcs with very low probabilities. Our rationale for wanting a more complex model at this stage was motivated by the fact that we did not want to completely discount the input from our experts in terms of the number of variables and relationships we included in our IBN. We found that **contemporary soil disturbance** and **aspect** did not occur with probabilities high enough to remain in any of the competing IBNs. **Grazing, clay_pct, slope,** and weather variables generally had probabilities above the 25% cut-off, but their inclusion in the final set of arcs varied among variable groups.

As a reminder, we estimated 10 model-averaged IBNs. We compared our 10 competing IBNs by inspecting their predictive accuracy. We used K-fold cross validation, described in detail in Section 4.6.2, to calculate predictive accuracy in the form of classification error (CE). Classification error values range from 0 to 1 and are the frequency with which predictions are incorrect. For example, a CE of 0.20 means that the predicted class (level of a node, for example) was accurate for 80% of the observations. We report the CE for each vegetation component in each of the 10 IBN structures in Table 4.5. We also computed two overall CEs for each IBN as the weighted average of the CE values over all vegetation components, where weights were either equal among components or based on

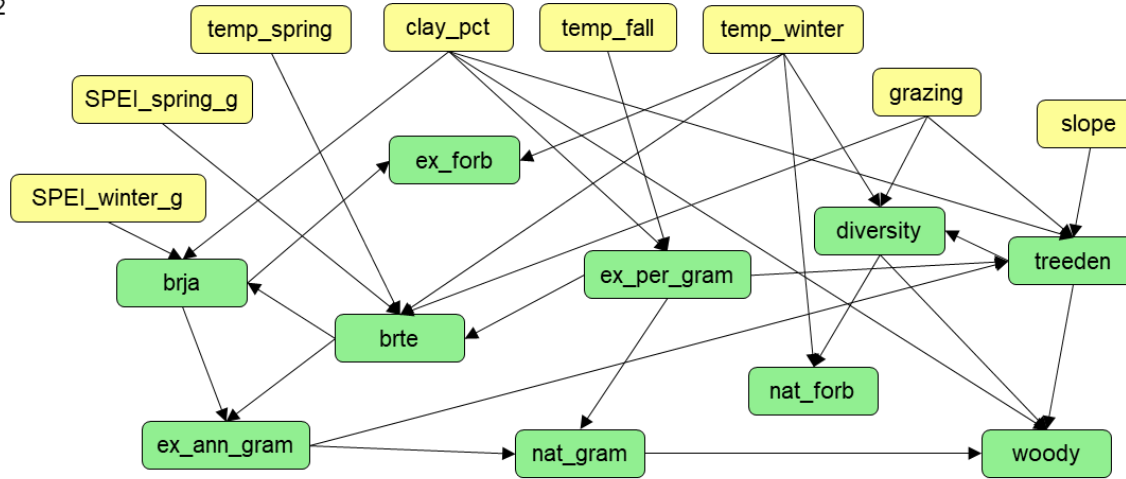
sensitivity values. A sensitivity value indicates how strongly a single node in the network is influenced by the other nodes in the network (Pearl 1988). Classification error ranged from 0.03 to 0.54 for individual vegetation components and from 0.179 to 0.261 for the weighted averages. Overall, no one model's CE was far lower than other models' CE. Therefore, from the two general groups of datasets (two- or three-level environmental nodes), we selected the model structure with the lowest overall CE for further analyses: G4.2 and G1.3 (Table 4.5, Figure 4.5).

Table 4.5. Classification Error (CE) values of competing model structures for the Initial Bayesian Network constructed from 10 variable sets. The CE is shown for each vegetation component node and overall, with overall calculated with individual components weighted according to their sensitivity (weights in bottom row) or weighted equally (weight = 0.13). A lower CE indicates higher predictive accuracy.

Variable Set	ex_ag_gram	brte	brja	nat_forb	nat_gram	ex_per_gram	ex_forb	diversity	woody	treeden	Overall CE weighted by sensitivity	Overall CE based on equal weights
G1.2	0.09	0.18	0.42	0.36	0.21	0.48	0.52	0.42	0.36	0.10	0.224	0.204
G2.2	0.10	0.25	0.51	0.36	0.18	0.52	0.43	0.46	0.37	0.14	0.239	0.212
G3.2	0.08	0.20	0.53	0.33	0.20	0.54	0.36	0.45	0.44	0.21	0.261	0.229
G4.2^a	0.06	0.26	0.43	0.26	0.23	0.46	0.47	0.43	0.38	0.14	0.219	0.195
ALL.2	0.07	0.24	0.46	0.25	0.24	0.48	0.52	0.40	0.35	0.16	0.230	0.198
G1.3^a	0.03	0.19	0.43	0.29	0.18	0.36	0.51	0.43	0.49	0.09	0.179	0.183
G2.3	0.09	0.26	0.47	0.30	0.20	0.39	0.45	0.38	0.46	0.07	0.193	0.191
G3.3	0.04	0.24	0.49	0.36	0.20	0.51	0.44	0.34	0.47	0.10	0.222	0.212
G4.3	0.03	0.22	0.41	0.26	0.20	0.53	0.48	0.40	0.39	0.11	0.216	0.194
ALL.3	0.05	0.18	0.51	0.31	0.25	0.45	0.49	0.42	0.51	0.09	0.216	0.211
Sensitivity Weight	0.16	—	—	0.10	0.17	0.20	0.13	0.11	0.03	0.26	—	—

^a Variable set used in further analyses, also shown in bold text.

G4.2



G1.3

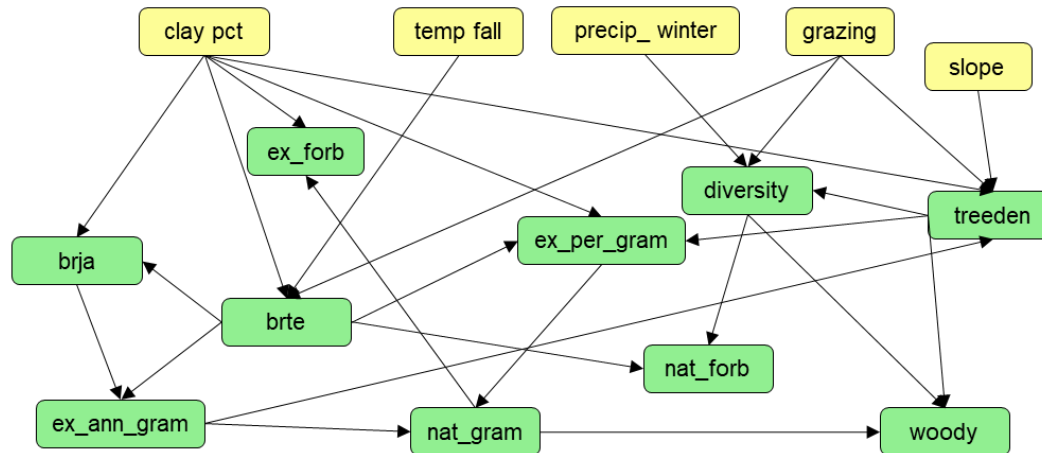


Figure 4.5. Structure of the two competing Initial Bayesian Networks (IBNs) selected for further analyses. Each structure indicates where statistical relationships occur between vegetation component nodes (green boxes) and environmental nodes (yellow boxes). The direction of an arc (arrow) can be interpreted as representing a causal effect of one node (arrow origin) on another (arrow terminus). Node names defined in Tables 4.2 and 4.4.

4.4.2. Creating the Temporally Structured Bayesian Network

Our next step was to incorporate temporal dynamics into the BN. To do this, we had to first structure the park dataset to pair sample events from the same monitoring plot and indicate the time (growing seasons) between them. In each of these pairs, the first sample event was designated as *t0* for “current” time and the second event as “*tf*” for future time. We limited these pairs to having a maximum difference in time of five growing seasons.

We then built two candidate Temporally structured Bayesian Networks (TBNs) by modifying the two IBNs we selected in the previous section. To do this, we followed the work of Rumpf et al. (2011) in that, to each IBN, we added nodes that represented current values of each vegetation component. We then connected each current vegetation component node (indicated with the notation “*t0*”) to a corresponding future vegetation component node (“*tf*”), leaving the arcs between environmental nodes and future vegetation component nodes, and among future vegetation component nodes, as identified in the IBNs. In order to select one of these TBNs to move forward with, we compared their predictive accuracy as we did with the competing IBNs (i.e., with CE). However, instead of comparing the BNs’ ability to predict vegetation component classes simply from relationships between environmental variables and vegetation components, or among vegetation components as we did for the IBNs, we now compared the BNs’ ability to predict future vegetation components from current vegetation components and the environmental variables (Table 4.6).

The CE for all vegetation components except *ex_ann_grass* and its constituent species was lower, sometimes markedly so, in both TBNs compared to their corresponding IBN (Table 4.5), indicating the more dynamic nature of the annual grasses compared to other components of the mixed-grass prairie. Once again, the overall CE values for the two competing TBNs were very close. We selected the structure built from the G4.2 variable set (Figure 4.6) because it had a slightly lower error rate and was also less complex than structure built from the G1.3 variable set. Complexity is measured by the total number of nodes and the number of levels within the nodes. Very complex models are at risk of ‘overfitting’, meaning that they predict the data used to fit them very well but do not predict outcomes from new data as well. Because our goal was to produce a model that not only captured the current conditions of NPS vegetation but also adequately predicted its dynamics for the next several years, we chose the less complex model.

Table 4.6. Classification Error (CE) values of competing model structures for the TBN constructed from two variable sets. CE is shown for each future vegetation component and overall. Sensitivity-weighted overall CE was calculated with individual components weighted as in Table 4.5. A lower CE indicates higher predictive accuracy.

Variable Set	ex_ag_gram	brte	brja	nat_forb	nat_gram	ex_per_gram	ex_forb	diversity	woody	treeden	Overall CE weighted by sensitivity	Overall CE based on equal weights
G4.2	0.04	0.24	0.34	0.24	0.18	0.24	0.39	0.34	0.20	0.00	0.119	0.116
G1.3	0.09	0.17	0.32	0.23	0.18	0.23	0.38	0.38	0.20	0.00	0.123	0.119

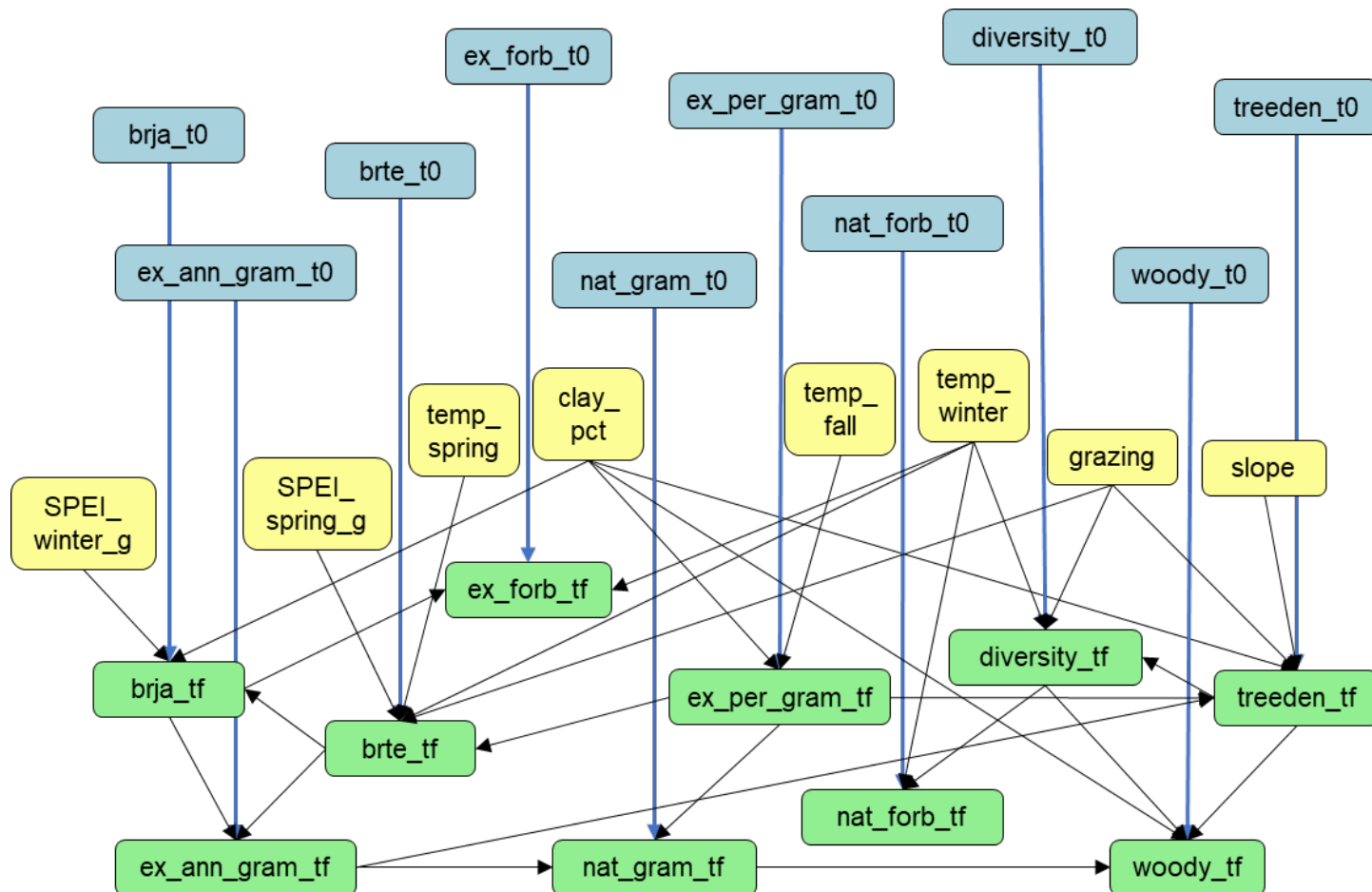


Figure 4.6. Temporally structured Bayesian Network (TBN). Blue and green boxes indicate current (t0) and future (tf) vegetation component nodes, respectively, with the blue arcs (arrows) between them indicating the influence of current on future vegetation. Effects of environmental conditions on future vegetation, and of future vegetation components on other future vegetation components, are indicated by black arcs and match those in Figure 4.5 (G2.4 structure). Node names defined in Tables 4.2 and 4.4.

At this point, the TBN did not account for the amount of time elapsed between t_0 and t_f . In order to proceed to the next step in the process of developing the BDN—incorporating the effects of management actions on vegetation—we needed to decide how to represent the potentially long-lasting effects of management actions. There are likely many ways of using a TBN for multiple timesteps, but we considered two. The first approach we considered was to treat time as a first-order Markov process. Recall that the general form we were working toward for the BDN is temporally structured with current and future sets of nodes (Figure 4.2). If we treated time as a first-order Markov process, in which the change from current to future conditions was a single year, we could simulate a longer temporal process by making recursive predictions. For the first year, we could set the CPTs of the current vegetation component nodes to some set of values based on data and then generate model outputs (i.e., future vegetation condition). For the next year, we could take that output and use it as input to generate new outputs for the next year, and so on.

There are a few problems with this approach, however. One is that it assumes that dynamics post-management are essentially the same as before the action. In other words, it assumes that the change in vegetation dynamics under a management option only occur in the year after which management was applied. The years following the action assume no management was applied, so the same set of dynamics as under no management would be applied in subsequent years. This assumption may be invalid if there are time lags in management effects, or if dynamics are different following management. However, there is some evidence that indaziflam has lingering effects beyond the year in which it was applied (Sebastian et al. 2017b), indicating that dynamics could be different for at least a few years after management.

We chose to account for these longer-term effects by adding a “time” node when constructing the Bayesian Management Network (next section, 4.4.3). This node allows the model to predict the effects of management actions for up to five years, after which we assumed dynamics would behave as in the case of no management. We discretized the associated time variable into three levels: 1, 2–3, and 4–5 growing seasons.

4.4.3. Estimating the Bayesian Management Network (BMN)

Until this point, the data used in estimating the BN structures excluded all sample events that occurred less than five growing seasons after a management action (fall or spring burn, and/or herbicide application). To estimate the Bayesian Management Network (BMN), we used all sampling events in the park dataset associated with no management, fall or spring fire, indaziflam application, and fall fire followed by imazapic. While temporally structuring these data as described in section 4.4.2, we added a variable indicating the specific management action (none, spring burn, fall burn, indaziflam-only, or fall burn imazapic) applied between the sampling events in a pair. Following our method for representing time described in the previous section (4.4.2), we then eliminated sample event pairs in which both events occurred within five growing seasons after the same management action. The number of resulting paired observations were 445 for fall burn, 244 for spring burn, 826 for none, 36 for indaziflam only, and 47 for fall burn imazapic.

We added “management” and “time” nodes to the TBN, then used the hill-climbing algorithm in the *bnlearn* package (section 4.4.1) to estimate the arcs between the management and time nodes and the

future vegetation component nodes within the structure of the TBN using either all observations or excluding observations associated with the indaziflam-only and fall burn imazapic management actions. We used the second, more restricted set of observations because we were concerned that the limited spatial and temporal extent of observations associated with these management actions could skew results. We followed the same method of including arcs with 0.25 probability or higher in the resulting structure as we used for estimating IBNs. When all observations were included, the algorithm yielded arcs between management and nat_forb_tf, and between time and brja_tf (“Algorithm 1” structure in Table 4.7). When observations for the herbicide management actions were excluded, the algorithm yielded arcs between management and brja_tf, management and ex_per_gram_tf, and time and brja_tf (“Algorithm 2” structure in Table 4.7). These results were somewhat counterintuitive, in that we expected management to also influence brte_tf, and ex_per_gram_tf and nat_forb_tf to be related to time since management. To improve our confidence in the BMN, we compared the predictive accuracy of these two structures to that of three additional structures we specified but were based on the algorithm-derived structures. These specified structures had arcs from management and time to brja_tf, ex_per_gram_tf, and nat_forb_tf (Specified 1), from management and time to brja_tf, ex_per_gram_tf, and brte_tf (Specified 2), or from management and time to brja_tf, ex_per_gram_tf, nat_forb_tf, and brte_tf (Specified 3). The ‘Specified 2’ structure had a slightly lower overall, weighted CE (0.1358) than the next lowest overall, weighted CE (‘Algorithm 1’, 0.1360), as well as lower individual CEs for ex_an_gram and ex_per_gram. Therefore, we selected it for further development. We refer to it as the ‘interim BMN’ because, at this point, it was missing two elements, which we describe in the next section.

Table 4.7. Classification Error (CE) values of three competing BMN structures. CE is shown for each vegetation component node and overall. Sensitivity-weighted overall CE was calculated with individual components weighted as in Table 4.5. A lower CE indicates higher predictive accuracy. Structures are described in the text.

Structure	ex_an_gram	brte	brja	nat_forb	nat_gram	ex_per_gram	ex_forb	diversity	woody	treeden	Overall CE weighted by sensitivity	Overall CE based on equal weights
Algorithm 1	0.10	0.20	0.28	0.19	0.21	0.26	0.39	0.30	0.26	0.01	0.136	0.130
Algorithm 2	0.11	0.19	0.28	0.28	0.21	0.25	0.37	0.32	0.25	0.01	0.145	0.141
Specified 1	0.11	0.22	0.33	0.28	0.22	0.23	0.36	0.27	0.21	0.03	0.146	0.137
Specified 2	0.09	0.16	0.30	0.26	0.23	0.23	0.36	0.32	0.25	0.00	0.136	0.134
Specified 3	0.10	0.14	0.36	0.33	0.26	0.18	0.38	0.35	0.22	0.01	0.140	0.140

4.5. Parameterizing and Adding Vegetation Condition to the Bayesian Management Network

At this point in its development, the structure of the BMN represented the ecological relationships among the vegetation composition nodes, identified which environmental drivers most strongly influence specific components of the vegetation communities, and showed which of these components are directly influenced over time by management actions. To function in the ABAM decision support tool, though, the BMN required two more elements.

First, it needed to be parameterized. In a Bayesian network, parameterizing the network means estimating a CPT for every node in the network that is influenced by another node (i.e., is a child node). Recall that parameterized CPTs are probability distribution tables with dimensions determined by the number of levels of the child node and all its parent nodes. The CPTs can be populated by entering specific values into the table. This method is often used in BNs developed through expert knowledge (e.g., as we did for the vegetation condition node, Appendix E). The CPTs can also be parameterized using a dataset, which is the approach that we used given our data-driven model development process. Second, the vegetation condition nodes needed to be added to the BMN.

In section 4.5.1 we describe our approach for parameterizing the interim BMN that resulted from the steps described in section 4.4, then adding the vegetation condition network. Then, in section 4.5.2, we briefly interpret how the BMN represents vegetation dynamics in ABAM parks.

4.5.1. Parameterization Methods

To parameterize the interim BMN, we used a combination of the park dataset¹ and an additional simulated dataset. When we estimated the interim BMN structure, the management node only included sample events in the park dataset associated with no management, fire, indaziflam-only, or fall burn then indaziflam. When parameterizing the BMN, we needed to provide information for the remaining levels in the management node. We also desired to supplement the limited information for the indaziflam-only and fall burn then indaziflam actions because the data for these came from a small number of sample events, and these had limited combinations of vegetation and environmental variable node levels. Thus, to reduce the number of scenarios with uninformed priors (i.e., those for which we had no information), we created a simulated dataset.

When building this dataset, we limited the direct effects of the two herbicides, imazapic and indaziflam, to exotic annual graminoids. This is for a variety of reasons. Although both of these herbicides affect seeds and seedlings of all species, native annual and biennial species contribute only a small amount to native cover in ABAM parks. Therefore, we assumed that the herbicides' effects on the native vegetation cover component nodes would be minimal. Annual and biennial species occasionally comprise a large portion of native diversity, but most often (88% of NGPN and NGP

¹ As noted in section 4.2.1.2, no data were available to populate the **percent clay** variable for FOLA events, and we therefore excluded FOLA observations when estimating model structure. However, because FOLA has a grazing regime unique among ABAM parks, we wished to include it for parameterization. To do this with full information for those observations, we assigned all FOLA plots to the "low" level for the Pct_Clay node based on the fact that all monitoring plots at this park are in a historical floodplain, where soils tend to be sandy rather than clayey.

Fire monitoring events) they comprise <20% of native diversity, suggesting that the herbicides' effects on the diversity node would be small. Exotic annual and biennial forbs are more common than their native counterparts, but we do not distinguish them from exotic perennial forbs in the vegetation component nodes. Moreover, the published literature on the effect of these herbicides in grasslands like those in ABAM parks provides little information about the responses of species other than the target exotic annual grasses.

We briefly describe our methods for building the simulated dataset here; the full explanation is in Appendix F. We began by simulating initial continuous values of **exotic annual graminoid rpc**. We accomplished this by randomly drawing observations from the park dataset. An observation consisted of a row from the park dataset and included observed values for all of the nodes in the BMN. The probability that we drew an observation was proportional to the frequency that specific level of **exotic annual graminoid rpc** occurred in the park dataset. This ensured that our simulated values were realistic and that patterns between exotic annual graminoid relative percent cover and other biotic and abiotic variables were retained, and that patterns of **BRJA rpc** and **BRTE rpc** within **exotic annual graminoid rpc** followed those of park observations. We then multiplied **BRJA rpc** and **BRTE rpc** in each randomly drawn observation by a randomly drawn proportion-remaining value to simulate the effect of a management action. These values were drawn from a uniform distribution using the ranges in Table 4.8, which varied according to the specific management action and time since application. The proportion-remaining values we used for indaziflam were from a study outside of the NGP (Sebastian et al. 2016), and those for fall burn then imazapic were from an experiment in NGPN parks (Symstad 2021, Symstad et al. 2021). In our simulations, we assumed that indaziflam had reduced first-year effectiveness to account for variability in activation time (D. Sebastian, Bayer United States, written communication, 2019).

Table 4.8. Proportions of initial exotic annual grass relative percent cover remaining after management action used to simulate data for herbicide actions in the Bayesian Management Network. The three timesteps in the model represent 1, 2–3, and 4–5 growing seasons following action.

Management Action	Timestep 1	Timestep 2_3	Timestep 4_5
indaziflam only; indaziflam then spring burn	0.25–0.45	0.11–0.25	0.17–0.25
imazapic-indaziflam; fall burn then indaziflam; spring burn then indaziflam	0.00–0.45	0.00–0.25	0.00–0.25
fall burn then imazapic	0.00–0.40	0.00–0.67	0.15–0.72
fall burn then imazapic-indaziflam	0.00–0.45	0.00–0.11	0.00–0.11

Next, we discretized the simulated annual brome values according to the levels shown in Table 4.2. Lacking data on the response of the other vegetation components to herbicide application, we used the BMN to simulate their response to the reduction in exotic annual grasses caused by the herbicide(s). Recall that the observations drawn from the park dataset for initial exotic annual grass

values also contained observed initial values for the other vegetation components and the environmental variables. We entered these values into the BMN, along with the simulated future impacts from herbicides, to predict future values for the other vegetation components. This prediction step involved randomly drawing a single value from the posterior predictive distributions in the BMN.

We appended all of these simulated values to the dataset, then we estimated the values of the CPTs in the BMN using the *bn.fit* function within the *bnlearn* package (Scutari 2010) with the Bayesian parameter estimation method for discrete networks. In the *bn.fit* function, we used an imaginary sample size (iss) of 10, which served as a weak, normally distributed prior. This meant that the data we used in fitting the BMN had more influence over the final CPT estimates (i.e. posterior estimates) than did the prior.

Finally, to complete the BMN, we connected vegetation component nodes in each time step to a respective vegetation condition node according to the vegetation condition network (VCN) developed in section 4.3. Recall that we had already parameterized the VCN using the CPTs depicted in Appendix E. The complete BMN is shown in Figure 4.7.

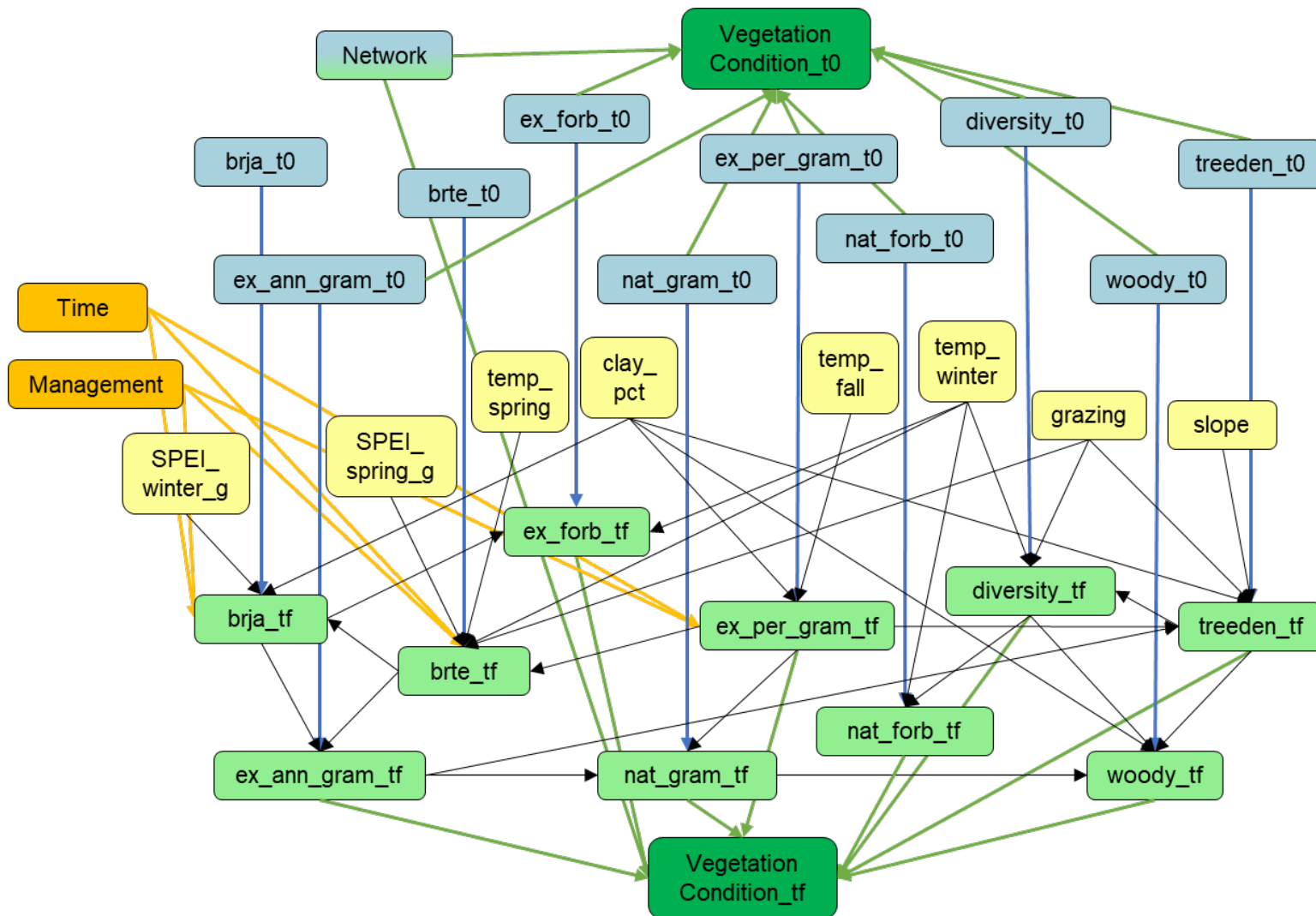


Figure 4.7. Bayesian Management Network (BMN) structure. Management and time nodes and their influences are indicated by orange boxes and arcs, respectively. Vegetation condition nodes (dark green boxes) represent the condition of the vegetation as determined by the vegetation component nodes in either NGPN or ROMN parks (Network node). Other nodes and arcs are the same as depicted in Figure 4.6.

4.5.2. Interpretation of Parameterized Bayesian Management Network

At this point it is worth examining whether the behavior of the BMN—how future vegetation component nodes respond to different values of environmental nodes and management actions given the starting condition of the vegetation components—conforms to the expectations in the conceptual model and other available information. One of the strengths of the BMN is its ability to capture complex interactions among the multiple nodes in the network. Describing these concisely is difficult, however. Thus, we concentrate our examination of BMN behavior here on the direct effect of a parent node on a child node, as these direct effects are the most relevant comparisons to the conceptual model. The behavior described in this section is for time at 1 year and management action none, unless otherwise stated. For ease of comparison to the conceptual model, in this discussion, we refer to the model's nodes by their “familiar” names (e.g., exotic annual graminoids, cheatgrass) rather than their “formal” names (e.g., *ex_ann_gram*, *brte*) used elsewhere in the report to distinguish between continuous and discrete forms of the variables.

We anticipated that vegetation component nodes would influence each other given that, for a given observation (plot and sample date), the continuous values of exotic annual graminoid, exotic perennial graminoid, exotic forb, native graminoid, native forb, and woody relative covers must sum to 100. However, only some relationships were strong enough to be included in the model. The influences of annual bromes (*ex_ann_gram*) and exotic perennial (*ex_per_gram*) grasses on native graminoids (*nat_gram*) likely reflect competition among components of the dominant growth form. When either annual bromes or exotic perennial graminoids increase, native graminoid cover decreases. Exotic annual and perennial graminoid covers are not directly connected, but instead exotic perennial graminoid cover influences only cheatgrass (*brte*), cheatgrass influences Japanese brome (*brja*), and (by definition) cheatgrass and Japanese brome influence annual brome cover. The relationship between cheatgrass and Japanese brome is complex. As cheatgrass cover increases, the probability of Japanese brome being low consistently increases. On the other hand, the probability of Japanese brome being high initially increases (when cheatgrass increases from low to medium), then this probability decreases when cheatgrass increases even more (from medium to high). Japanese brome and exotic forb (*ex_forb*) cover are positively related, whereas exotic forb and native graminoid cover are negatively related. The presence of trees (high *tree_den*) predicts a greater probability of medium and high woody cover, and the absence of trees (low *tree_den*) is slightly more probable when annual brome cover is very high compared to other levels. We expected that diversity would be positively related to native forb cover (*nat_forb*) because we assumed that native forbs contribute a large portion of native species richness. This relationship does occur in the BMN, but the direction of the arc—from diversity to native forb cover—is the opposite of what we expected. This suggests that there is a relationship between native forbs and diversity, but that native forbs alone do not cause plant diversity to be higher. For instance, the probability of native forbs being high is greater when diversity is medium than when diversity is high. This could indicate that other native vegetation components (i.e., native graminoids) are contributing a larger portion of native diversity than we expected..

The grazing node directly influences diversity, cheatgrass cover, and tree density. The effect of setting the grazing node to “freerange_other” is largely uniformed in the BMN because that type of

grazing (i.e., domestic horses) only occurs at FOLA. Thus, we only compare the other two levels of grazing, which represent bison presence and absence. Low diversity is less probable, and medium and high diversity are more probable, in areas with bison (grazing = freerange_bison_other) than in areas without them. Conversely, low cheatgrass is more probable, and high cheatgrass less probable, in bison areas. The model also implies a higher probability for trees to be present in areas with bison compared to those without bison. This could be an artefact of bison presence at WICA, a park with more trees than most other ABAM parks. Unique combinations like these may also explain why the modeling algorithm indicated relationships between other non-weather environmental nodes and vegetation metrics. Regardless, tree density did appear to be generally influenced by soil clay content and slope, with slope being the stronger predictor; the probability of some trees being present doubles when slope goes from low to high, but it decreases only slightly between low and high clay_pct. Soil clay content also appears to directly influence exotic perennial graminoids and Japanese brome; both increase with greater soil clay content. Contrary to the conceptual model (Figure 4.3), and based on the data available, contemporary soil disturbance, historical land use, and prairie dog presence (past or current) did not influence any vegetation components strongly enough to appear in the final model structure.

Of the five weather nodes in the BMN, winter temperature directly influences the most vegetation components. The model predicts that warmer winters will lead to increased cheatgrass cover, decreased exotic and native forb cover, and reduced diversity. Conversely, cheatgrass is the vegetation component influenced by the most weather nodes. Warmer springs increase the probability of medium cheatgrass, but lower probabilities of low or high cheatgrass. Higher spring moisture (SPEI_spring_g) predicts an overall increase in cheatgrass. Winter moisture (SPEI_winter_g) is the only weather variable that influences Japanese brome in the BMN, and its influence is positive. The positive effect of SPEI on the annual brome species is consistent with the conceptual model, though the expectation in that model was that spring and fall conditions, not spring and winter conditions, would be the most important (Figure 4.3). Fall conditions—specifically temperature—do influence exotic perennial graminoids, with ex_per_gram having a greater probability of being low when temp_fall is high. Contrary to the expectations in the conceptual model, season-long moisture conditions (previous-growing-season SPEI) were not found to substantially influence any of the vegetation components (Figure 4.7).

The management actions involving herbicides have the strongest negative effect on individual annual brome species, and therefore exotic annual graminoid cover, in the BMN. This is not surprising considering that this relationship strongly reflects our prior expectations (i.e., simulated data). Fall and spring burn effects on annual brome cover, which are based on empirical relationships, vary depending on the initial conditions of annual brome cover. When applied in high (13–48%) or very high (>48%) annual brome conditions, fall burn reduces the probability of annual brome cover remaining in those categories more than either spring fire or the no management action. Also, in high-very high annual brome conditions, the effect of spring burn is weaker than fall burn, but it is more effective than no management. When burns are applied to medium (1–12%) annual brome cover, the probability of transitioning to high or very high cover is roughly equal across no action and the two burn seasons, but when applied to low (<1%) annual brome cover this probability is

slightly higher for the burn actions than no action. Across all annual brome initial conditions, spring burn has a higher probability of causing a transition to or staying in low annual brome cover than fall burn does. For all but low annual brome initial conditions, fall burn has a higher probability of transitioning to low annual brome cover than no action. Fall and spring burn effects on exotic perennial grasses also vary across initial conditions. When applied to high initial exotic perennial graminoid cover (>18%), fall burn has a higher probability of transitioning to medium (2–18%) or low (<2%) exotic perennial graminoid cover than either spring burn or no action; spring burn is no more likely to result in this transition than no action. Fall burn also has a higher probability of reducing this component than spring burn or no action when applied to medium `ex_per_gram`, but in this condition spring burn is more likely to result in reduced `ex_per_gram` than is no action. In this short-term (1 year) response, no action is more likely to maintain low exotic perennial grass cover than either spring or fall burn.

4.6. Model Validation and Accuracy Assessment

At this stage of development, the BMN is not expected to be highly accurate. If it were, there would be no need for adaptive management. However, an accuracy assessment is still appropriate to identify the BMN's relative strengths and weaknesses. This can help inform decisions, especially as managers consider whether they wish to take an active or passive approach to adaptive management. An assessment at this stage also provides the baseline to which future iterations (after learning occurs) can be compared.

We used two approaches to examine the predictive accuracy of the BMN. In the first approach, we conducted k-fold cross validation (Section 4.6.2) using the function *bn.cv* in the *bnlearn* package to examine the general predictive accuracy of future vegetation component nodes over all treatments and timesteps. Thus, we interpreted the results from this approach as the confidence we have in predicted future vegetation component nodes. The second approach (Section 4.6.3) examined the predictive accuracy of future vegetation condition (i.e., the probability distribution of future vegetation condition) by comparing it to actual “future” (post-action) observations using the Bhattacharyya distance metric in the package *Compositional* (Tsagris and Athineou 2019). We interpreted this metric as the amount of confidence we have in the predicted impact of a management action's producing expected vegetation conditions over each timestep. For both of these, our confidence is influenced by the quantity or source of data used to estimate the BMN's structure and CPTs; we address this first (section 4.6.1).

4.6.1. Identification of Data Gaps

Although built with data that allowed us to explore ecological drivers of vegetation conditions, portions of the BMN are poorly informed due to a lack of data for some management actions, vegetation conditions, and time steps. Understanding these poorly informed portions of the model not only aids in interpreting the results of the accuracy assessments, but it also alerts managers using the decision support tool to its current shortcomings. In examining sample size distributions, it is important to note that the total number of observations in the temporally structured park dataset (Table 4.9) appears inflated compared to the number of unique observations reported in section 4.2.1. This is because individual observations often serve as both current and future observations.

The sample size for observations associated with the “no management” action (*none*) is almost twice that for *fall burn*, which in turn is about twice that for *spring burn* (Table 4.9). Overall, the 2–3 timestep has the fewest observations, but this is biased by the *none* action; the 4–5 timestep has fewer observations than the 2–3 timestep when observations following no management are excluded. The number of monitoring observations representing different vegetation conditions also varies considerably. Specifically, across all timesteps (t0 plus t1 timesteps 1, 2–3, and 4–5), observations in which simplified grassland (n = 257), high-quality prairie (n = 259), exotic annual grassland (n = 248), or exotic perennial grassland (n = 233) is the most probable condition are well represented. Observations with low-quality woodland (n = 24) or exotic annual woodland (n = 12) as the most probable condition are not well represented. Observations with weedy forb mess (n = 158), low-quality prairie (n = 133), exotic perennial woodland (n = 146), or high-quality woodland (n = 128) as most probably are intermediate in number. It is important to remember that these tallies should not be interpreted as the proportion of these vegetation conditions that occur in the ABAM parks for two reasons. First, they are summed over multiple timesteps so represent changes over time. Second, sample locations for NGP Fire monitoring, the WICA herbicide trial, and the BADL/SCBL annual brome research are not spatially distributed in a design conducive to park-wide inference. If desired, NGPN and ROMN data could be used to calculate these proportions because the sample distributions for these monitoring programs were designed to provide such information.

Table 4.9. Sample size and data source for each management action and timestep.

Management Action	Data Source	Timestep		
		1	2_3	4_5
none	park dataset	241	192	393
fall burn	park dataset	189	163	93
spring burn	park dataset	100	97	47
indaziflam only	park dataset (WICA Herbicide Trial)	12	24	0
indaziflam only	simulated dataset	1000	1000	1000
imazapic–indaziflam	simulated dataset	1000	1000	1000
fall burn then imazapic	park dataset (annual brome research)	19	19	9
fall burn then imazapic	simulated dataset	1000	1000	1000
fall burn then indaziflam	simulated dataset	1000	1000	1000
fall burn then imazapic–indaziflam	simulated dataset	1000	1000	1000
spring burn then indaziflam	simulated dataset	1000	1000	1000
indaziflam then spring burn	simulated dataset	1000	1000	1000

The more detailed break-down of sample sizes by management action, most probable vegetation condition before management, and time step (Appendix Table G1) reveals that far more spring burns have occurred in exotic perennial grasslands than in exotic annual grasslands. This pattern not only reflects the past assumption by managers that spring burns are more effective at reducing exotic perennial grasses than are fall burns, but it also illustrates the relative lack of information on the effect of spring burns on areas invaded by exotic annual grasses. The more numerous fall burn actions are spread more evenly among current most-probable vegetation conditions and therefore provide a better knowledge base for the BMN. The fact that burns in woodlands comprise a greater proportion of fall burns than of spring burns illustrates that management objectives not captured in the BMN contribute to decision making regarding prescribed fire seasonality. Specifically, fall's usually drier fuel conditions are more conducive to achieving objectives related to tree mortality and fuel load reduction than are spring's wetter fuels.

These sample sizes and data sources are relevant for managers' interpretation of decision support tool output for at least three reasons. First, predictions for management outcomes in management units characterized by a vegetation condition for which few observations have been made could be less reliable than for management units characterized by often-observed vegetation conditions. Bayesian networks are equipped to represent useful information from low sample sizes, but very low sample sizes are unlikely to capture the variability of vegetation condition outcomes associated with management. Moreover, when there is no information for a relationship, as occurs for some combinations of vegetation condition, management action, and timestep in the current dataset (Appendix G), a Bayesian network models this as complete uncertainty – uncertainty accounted for in the network's predictions. Second, the BMN's predictions of outcomes from management actions characterized by fewer observations may be less reliable than those for actions with more observations, though the artificially large sample sizes for herbicide actions produce a strong caveat to this general rule. Finally, as more information about the management actions applied in ABAM parks accumulates, the shortfalls of the model should diminish. Yet, it is important to monitor the rate of model learning over time to identify whether the model is no longer learning and can simply be used to support state-based management or to determine whether the model needs to be significantly modified.

4.6.2. Predictive Accuracy of Vegetation Components

Cross-validation is a technique that assesses how well a model predicts observations in an independent dataset. In general, cross-validation techniques involve splitting data into training and test sets. The model is fit to the training set then evaluated (i.e., validated) against the test set. The k-fold cross validation technique minimizes sampling bias by allowing each portion of the dataset to serve as the training and the test set. The technique works by first randomly splitting the data into subsets (folds). As an illustration of how we used cross-validation, consider a dataset randomly divided into three folds: A, B, and C. In the first round of validation, A and B serve as the training dataset to estimate a network's structure and CPTs. We can then make predictions using that network and compare the output to the observed data in fold C. Then, B and C are used to estimate the network and fold A serves as the test dataset. Finally, C and A are used to estimate the network and fold B serves as the test dataset.

We performed our cross-validation of the BMN using 10 randomly selected folds (Hastie et al. 2009). We were concerned that the BMN's fit and predictive accuracy might be notably altered by the inclusion of management options that were parameterized using simulated data. To determine if this was the case, we compared both network fit and predictive accuracy of the BMN structures estimated and parameterized with (a) observational data only (management options: none, fall burn, and spring burn) or (b) observational and simulated data (all 10 management options). We assessed network fit using the average expected loss of the BMN, where the loss function was the negative expected log likelihood of the BMN. Minimizing the average loss (or negative log-likelihood) suggests a better overall network fit. However, because this loss value is relative, we compared average loss of the two networks (fit with either 3 or 10 management actions) to a randomly generated (i.e., null) network. We then estimated predictive accuracy in terms of the proportion of classification errors for each future vegetation component node made by each network. We report classification errors that reflect predictive accuracy of each vegetation component over all timesteps and management actions. The values range from 0 to 1, and a lower value indicates a lower classification error rate.

The BMN estimated with only observational data had an overall better 'fit' than the network estimated with observational and simulated data (log-likelihood expected loss of 19.89 vs. 20.67). Both models were better than random (log-likelihood expected loss 24.39 and 23.67 for random models fit with only observational data and all data, respectively). The BMN parameterized with observational and simulated data had lower classification error rates than the BMN parameterized with only observational data for 4 of the 10 vegetation components: brte, brja, diversity, and exotic forbs (Figure 4.8). The relative values of classification error rates among the vegetation component nodes are encouraging in that our BMN focused on annual bromes and the classification error rate for the exotic annual graminoid node is the second lowest (Figure 4.8). The lowest error rate, for the tree density node, likely stems from this component having much lower interannual variability than the other components. However, the error rates also suggest that the BMN is not as skilled at predicting the other vegetation components. The values here provide a baseline for comparison in the future as more data are collected.

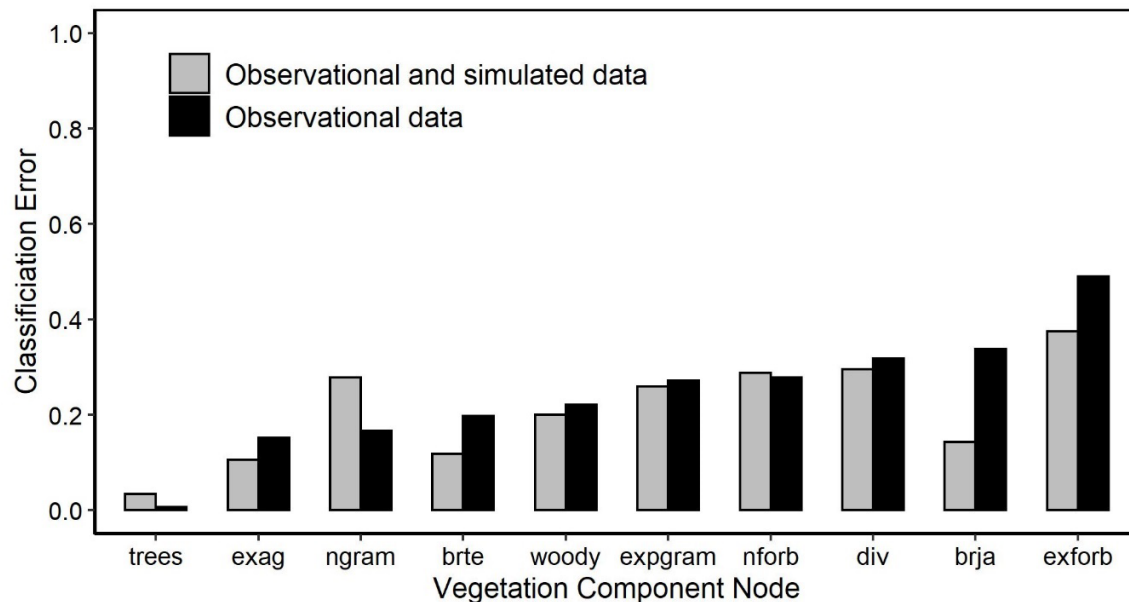


Figure 4.8. K-fold cross validation classification error scores for each vegetation component in the model fit with either all (observational and simulated) or only observational data. Classification error ranges from 0 to 1 and represents the proportion of predictions, over all timesteps and management actions, that match the test data. Lower values indicate higher predictive accuracy.

4.6.3. Predictive Accuracy of Vegetation Condition

We measured the accuracy of the BMN in predicting vegetation condition distributions by comparing predicted to observed “future” vegetation conditions. Specifically, for each pair of current (t_0) and future (t_f) observations in the park dataset (section 4.4.2), we entered the current vegetation condition distribution and the environmental conditions (e.g., weather, soil, grazing) associated with the pair’s future observation into the BMN as evidence, then recorded the vegetation condition distribution the BMN predicted from this evidence. The predictive accuracy of the BMN was calculated by comparing the vegetation condition probability distributions from the actual future observation to the predicted future observation. In this assessment we included levels of all environmental variables associated with each observation, but in practice (section 5.2), the BMN output will be reviewed each winter before some weather variables can be compiled. Therefore, accuracy of BMN predictions in practice may be lower than the values reported here.

We calculated the difference between the predicted future conditions and observed future conditions using the Bhattacharyya distance metric (Bhattacharyya 1943), which measures the similarity of two probability distributions. The distance measure ranges from 0 to 2.9, where 0 indicates identical distributions and higher values indicate more dissimilar distributions. We focus our evaluation on timestep 2–3. This is the timestep currently of most interest to managers for annual decision making because it captures longer-term responses than timestep 1 but also is based on more observations following management (i.e., excluding *none*) than are available for timestep 4–5 (Table 4.9). We present results in two different ways—summarized by management action and the current vegetation condition (Figures 4.9 and 4.10) and summarized by management action and future vegetation

condition (Figures 4.11 and 4.12)—as they provide different insights into model behavior. In these summaries, unless otherwise stated, when we refer to a vegetation condition (e.g., exotic annual grassland, high-quality prairie), we mean that is the vegetation condition with the highest probability for that observation.

Overall, Bhattacharyya distance values for the 2–3 timestep ranged from 0.0001 to 1.704. The low overall mean (0.214) and median (0.159) distance values, as well as the fact that median distance for almost all vegetation condition–management action combinations is less than 0.5 (Figures 4.9–4.12), suggest that the BMN currently produces useful predictions. However, these values must be interpreted in the proper context. Specifically, median distance values for management actions involving herbicides (bars 4–9 in Figures 4.9–4.12) are similar to or sometimes lower than those of other actions (bars 1–3) within each vegetation condition, but recall that BMN predictions for these actions are informed almost exclusively by simulated data. For example, distance values for herbicide actions involving indaziflam (bars 4, 5, 7–10) that result in exotic annual grassland (top left graph in Figure 4.12) are among the lowest distances reported. This is because the simulation explicitly stated that low exotic annual graminoid cover was highly probable—and therefore exotic annual grassland nearly impossible—at timestep 2–3 (Tables 4.9, Appendix Table G2). Thus, although the simulated data are based on observational data, predicted outcomes of the herbicide actions are still to be treated with caution until sufficient observations within ABAM parks accumulate. Predictions for exotic annual woodlands also warrant caution because of the rarity of this vegetation condition before (Appendix Table G1) or after (Appendix Table G2) any management action, which indeed prevented any accuracy assessment for this condition for management actions not informed by simulated data (Figures 4.9 and 4.11).

Probably of more interest at this time is the BMN’s prediction of vegetation condition following actions for which we have more observations (*none*, *fall burn*, and *spring burn*). Variation in the BMN’s prediction accuracy for these actions generally is not high in that, within a vegetation condition, their inter-quartile ranges of distances overlap. However, some differences in median distances are notable. Specifically, there is a small spread of distances within, but large difference of distances among, management actions for a low-quality woodland condition at either t0 or tf (Figures 4.9 and 4.11). Also, for a low-quality prairie current condition, predictability of *spring burn* outcomes is lower (distances are greater) compared with *fall burn* or *none* (Figure 4.9). These patterns of variability are likely due to small sample sizes (Appendix Table G1).

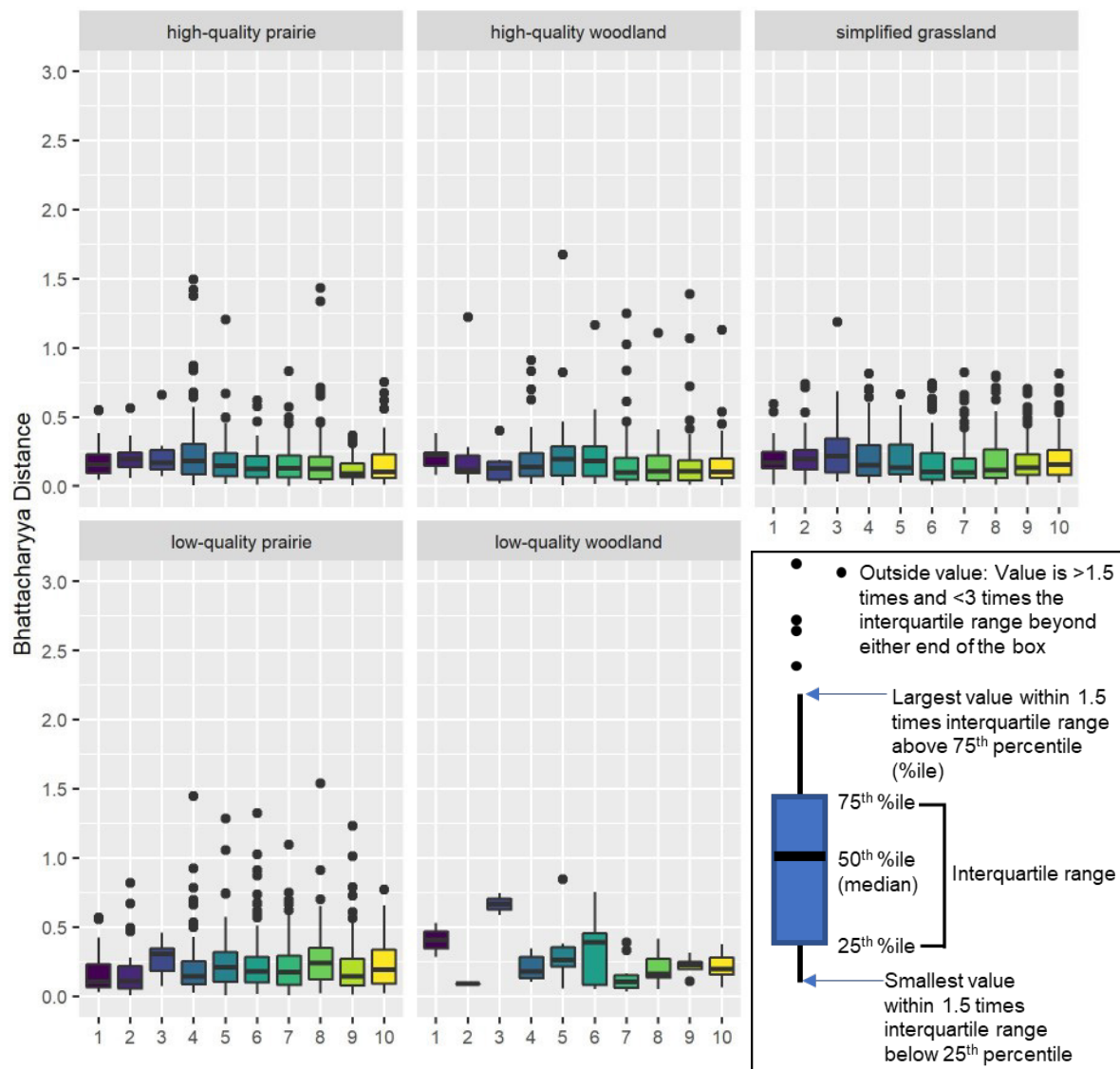


Figure 4.9. Median and distribution of Bhattacharyya distances for all management actions (x-axis), separated by highest-probability current (t0) vegetation condition (individual graphs), for conditions characterized by native species. Management actions: 1 = none, 2 = fall burn, 3 = spring burn, 4 = indaziflam only, 5 = imazapic-indaziflam, 6=fall burn then imazapic, 7 = fall burn then indaziflam, 8 = fall burn then imazapic-indaziflam, 9 = indaziflam then spring burn, 10 = spring burn then indaziflam. Distances compare predicted to actual outcome at timestep 2–3.

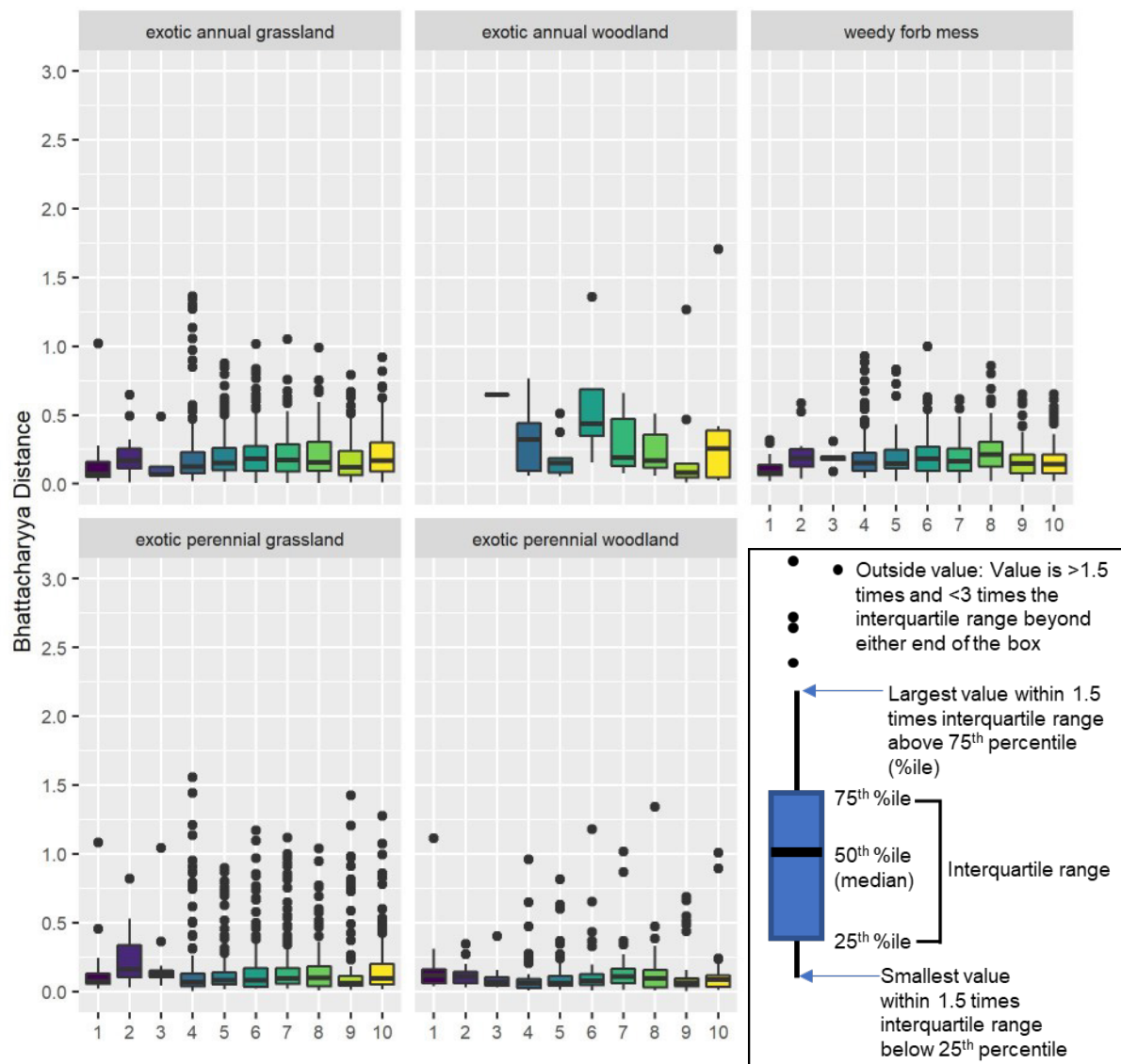


Figure 4.10. Median and distribution of Bhattacharyya distances for all management actions (x-axis), separated by highest-probability current (t0) vegetation condition (individual graphs), for conditions characterized by exotic species. Management actions: 1 = none, 2 = fall burn, 3 = spring burn, 4 = indaziflam only, 5 = imazapic-indaziflam, 6=fall burn then imazapic, 7 = fall burn then indaziflam, 8 = fall burn then imazapic-indaziflam, 9 = indaziflam then spring burn, 10 = spring burn then indaziflam. Distances compare predicted to actual outcome at timestep 2–3.

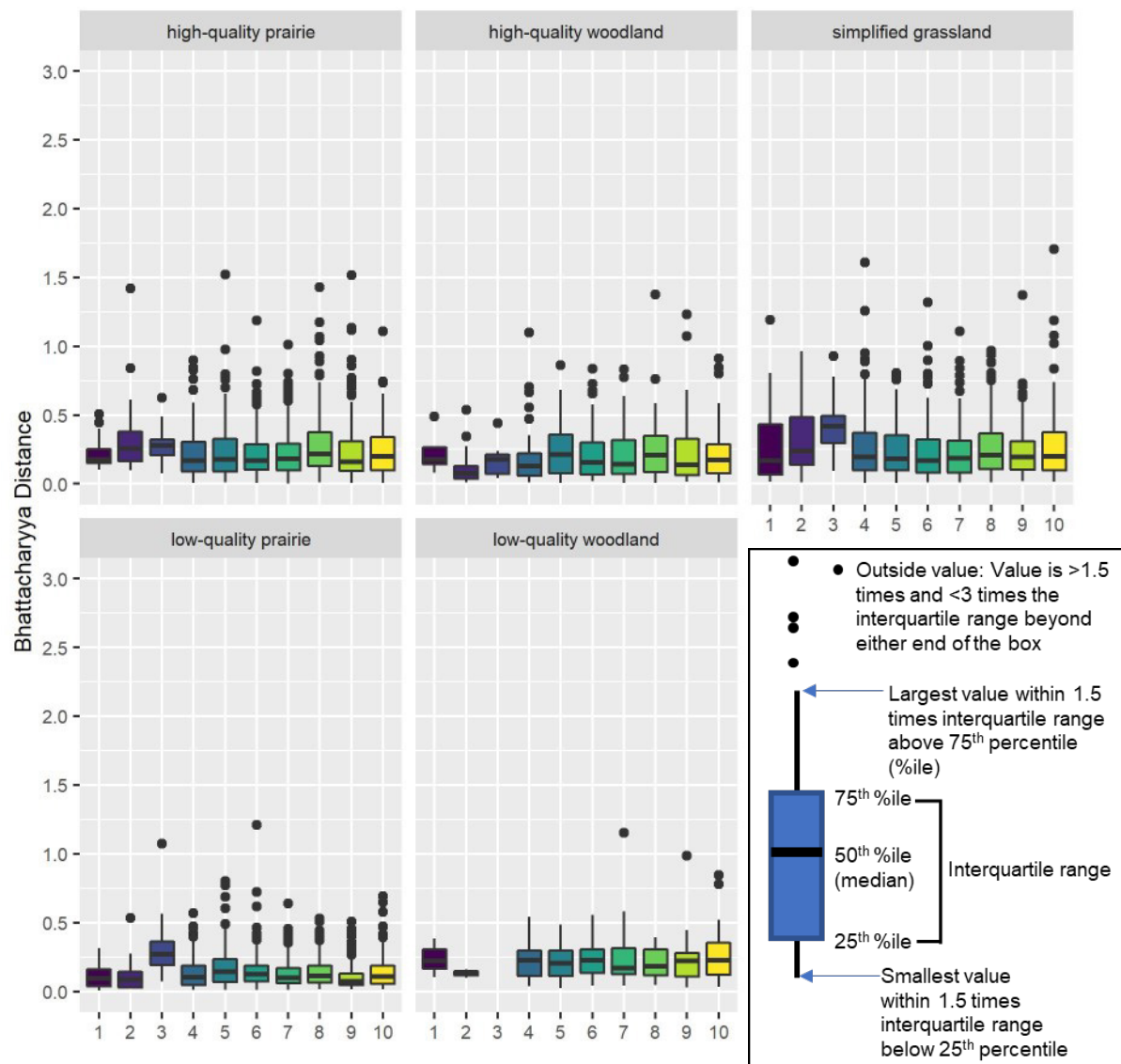


Figure 4.11. Median and distribution of Bhattacharyya distances for all management actions (x-axis), separated by highest-probability future (tf) vegetation condition (individual graphs), for conditions characterized by native species. Management actions: 1 = none, 2 = fall burn, 3 = spring burn, 4 = indaziflam only, 5 = imazapic-indaziflam, 6=fall burn then imazapic, 7 = fall burn then indaziflam, 8 = fall burn then imazapic-indaziflam, 9 = indaziflam then spring burn, 10 = spring burn then indaziflam. Distances compare predicted to actual outcome at timestep 2–3.

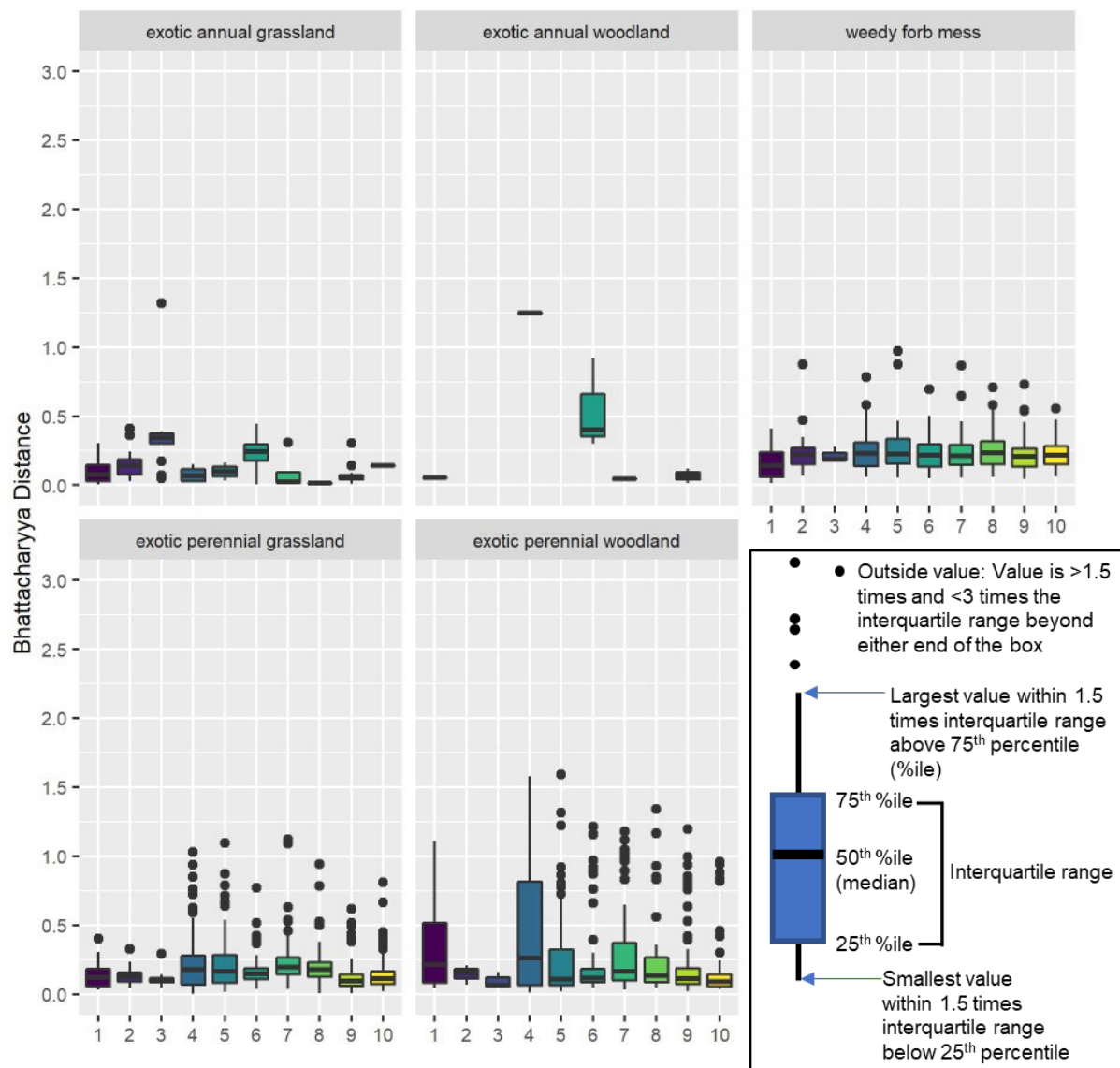


Figure 4.12. Median and distribution of Bhattacharyya distances for all management actions (x-axis), separated by highest-probability future (tf) vegetation condition (individual graphs), for conditions characterized by exotic species. Management actions: 1 = none, 2 = fall burn, 3 = spring burn, 4 = indaziflam only, 5 = imazapic-indaziflam, 6=fall burn then imazapic, 7 = fall burn then indaziflam, 8 = fall burn then imazapic-indaziflam, 9 = indaziflam then spring burn, 10 = spring burn then indaziflam. Distances compare predicted to actual outcome at timestep 2–3.

Low sample sizes do not explain other differences in predictive accuracy, such as the lower predictability of *fall burn* outcomes compared to *spring burn* outcomes when exotic perennial grassland is the current condition, or of *fall burn* compared to *none* outcomes when exotic annual grassland is the current condition (Figure 4.10). These differences may arise from the fact that outcomes, both observed and predicted by the BMN, are influenced by the whole array of vegetation conditions represented by the probability distribution, not just the vegetation condition with the highest probability. Moreover, observations represented as exotic annual or perennial grasslands in

Figures 4.9–4.12 can vary considerably in the composition of vegetation components other than those for which they are named. This is because, as shown by the CPTs for *ex_forb*, *nat_forb*, and *diversity* with respect to the vegetation condition node (Tables E8, 9, 11, & 12), these components do not contribute to defining exotic annual or exotic perennial grasslands. These components do contribute substantially to defining the overall vegetation condition probability distribution, but they are three of the four most poorly predicted components in the BMN (Table 4.7). If one or more of these components have more variable responses to *fall burn* than *spring burn* or *none*, they may be responsible for the lower predictive accuracy for *fall burn* outcomes in exotic annual and perennial grasslands.

Finally, differences in prediction accuracy for the outcomes of *fall burn*, *spring burn*, and *none* resulting in different vegetation conditions are sometimes substantial (inter-quartile ranges for distances do not overlap; Figures 4.11 and 4.12). Specifically, the BMN is more successful at predicting low-quality prairie and exotic annual grassland outcomes following *fall burn* or *none* than following *spring burn*. Reducing discrepancies in sample sizes among management action-vegetation condition combinations would improve our understanding of whether differences in predictive accuracy are driven solely by sample sizes, or whether there are inherent differences in the variability of outcomes among management actions.

4.7. Building the Bayesian Decision Network from the Bayesian Management Network

The BMN predicts the consequence of each management action as a distribution of probabilities for each of the vegetation conditions. These probabilities contain useful information about the uncertainty associated with a consequence. The relative values of the probabilities also provide some indication of the expected direction of change in condition. However, using these probabilities to assess which decision is optimal is problematic because managers may not understand how to weigh the outcomes they prefer versus those that they do not. Furthermore, these probabilities alone do not inform managers about how to make trade-offs between changes in vegetation condition and the cost of management actions. These preferences and trade-offs differ among parks for a variety of reasons. In order to use the BMN to inform these aspects of choosing an action, and to make that information relevant to individual parks—in other words, to make a decision support tool—we needed to measure and incorporate each park’s preferences among vegetation conditions and weigh their relative preferences for vegetation condition versus cost.

4.7.1. Vegetation Condition Preferences and Objective Weights

We elicited each park’s preferences for vegetation conditions as “utility values.” The scale of utility values is arbitrary, but the relative differences between those values provide a quantitative measure of the usefulness or preference of a particular outcome for the manager (Keeney 1992, Gregory et al. 2012). In our case, a value of 0 indicates a strong aversion to an outcome, whereas a value of 1 represents an extreme preference. Typically, utility values are calculated using a utility function, which maps changes in an outcome into the scale of the utility. This makes utilities comparable even on objectives measured in different units. For vegetation conditions, we used an approach to deriving utilities that entailed having managers score preferred outcomes, then normalizing those scores into utility values (see Gannon et al. 2013). The details of this approach are given in Appendix H, and the

results of the process are shown in Figure 4.13. For cost, we simply normalized the average amount of money spent per acre for each management action (Figure 4.14).

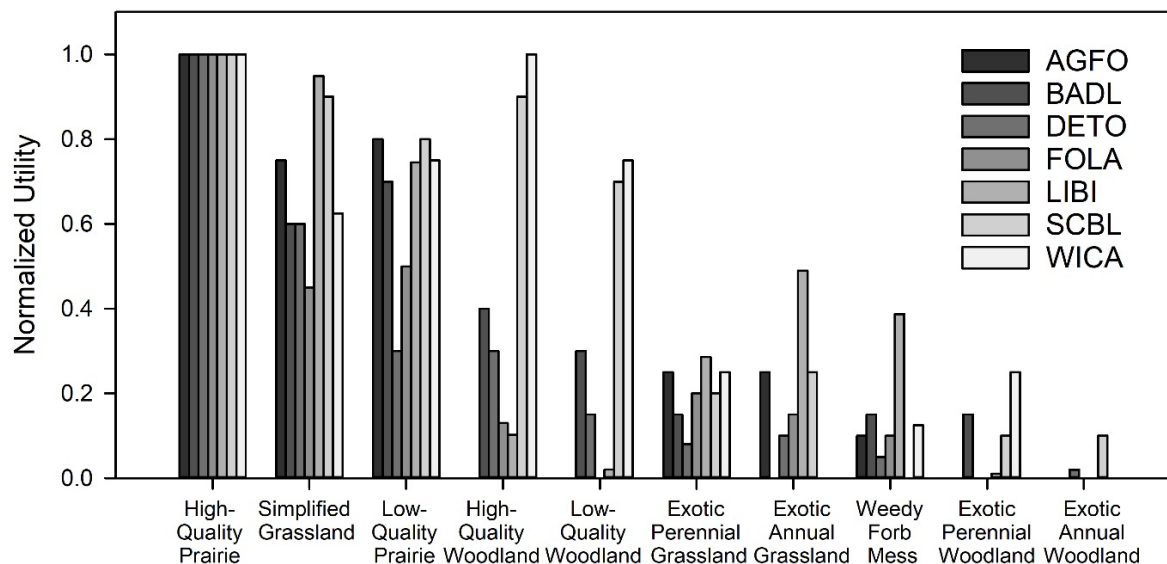


Figure 4.13. Park manager-stated normalized utilities for vegetation conditions in the ABAM decision support tool. A value of 0 indicates a strong aversion to an outcome, whereas a value of 1 represents an extreme preference. AGFO = Agate Fossil Beds National Monument (NM), BADL = Badlands National Park (NP), DETO = Devils Tower NM, FOLA = Fort Laramie National Historic Site, LIBI = Little Bighorn Battlefield NM, SCBL = Scotts Bluff NM, WICA = Wind Cave NP.

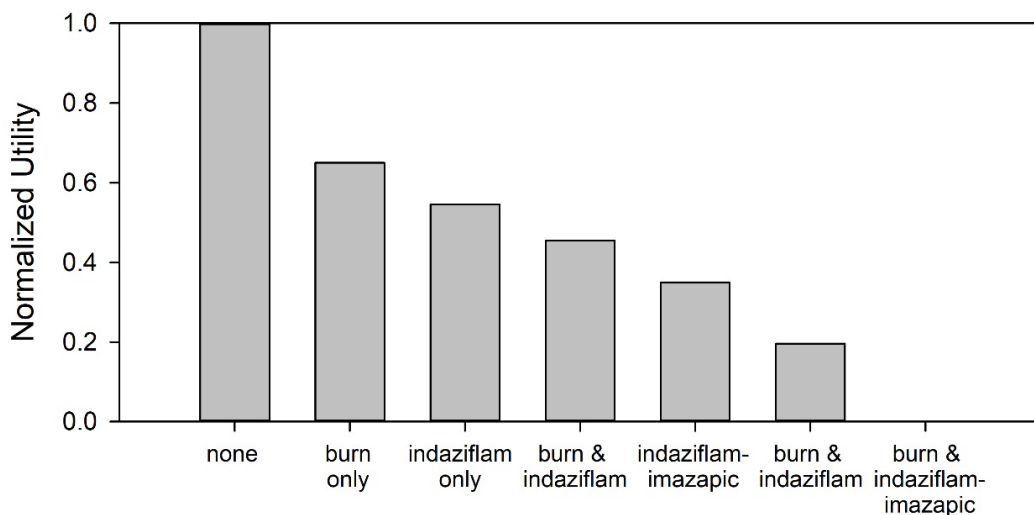


Figure 4.14. Normalized utilities for management actions in the ABAM decision support tool. A value of 0 indicates a strong aversion to an outcome, whereas a value of 1 represents an extreme preference. The normalized utilities are based on estimated short-term management costs per acre, with higher utility indicating lower cost. Timing of fire and herbicide application does not affect cost or utility.

To assess how a park manager might trade-off performance on vegetation condition for performance on cost, we asked managers at each park to put weights on both objectives. These weights express the relative importance of vegetation condition and cost when computing the optimal action (see Section 4.7.2). We used a swing-weighting exercise to elicit the weights (von Winterfeldt and Edwards 1986; see Appendix H). The resulting weights can be seen in Figure 4.15. In general, all park staff placed more weight on vegetation quality compared with cost.

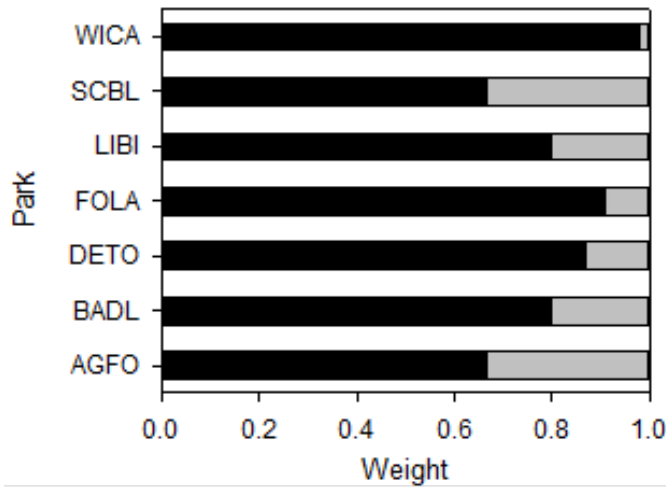


Figure 4.15. Park-specific weights on vegetation condition (black) and cost (gray). Weights are represented as values between zero and one and must sum to one across the objectives (represented by each row in the figure). WICA = Wind Cave National Park (NP), SCBL = Scotts Bluff National Monument (NM), LIBI = Little Bighorn Battlefield NM; FOLA = Fort Laramie National Historic Site, DETO = Devils Tower NM, BADL = Badlands NP, AGFO = Agate Fossil Beds NM.

4.7.2. Objective Function

In order to determine the optimal action predicted by the decision support tool, we used principles from multiple criteria decision analysis (MCDA; Keeney 1992). This entailed finding the decision with the highest total utility, given the relative preferences and weights of the decision makers (managers). We used the following equation to specify total utility:

$$U = \left(\sum_{i=1}^N X_i * p_{i,j,t} \right) * w_X + Y_j * w_Y$$

where U is total utility, X is the utility associated with the i th vegetation condition, p is the probability of the i th condition predicted by the model under the j th management action at some time t , w_X is the weight associated with vegetation condition, Y is the utility associated with the cost of the j th management action and w_Y is the weight associated with cost. We added this function to the BMN in the form of a “utility” node, which populates utility values for each level in the management node based on the probability distribution in the future vegetation condition node (Figure 4.16). So far, we

have calculated the optimal decision assuming t was set to 2–3 years in the future, but this could also be calculated by computing total utility as the sum of the utility over all time steps represented in the model.

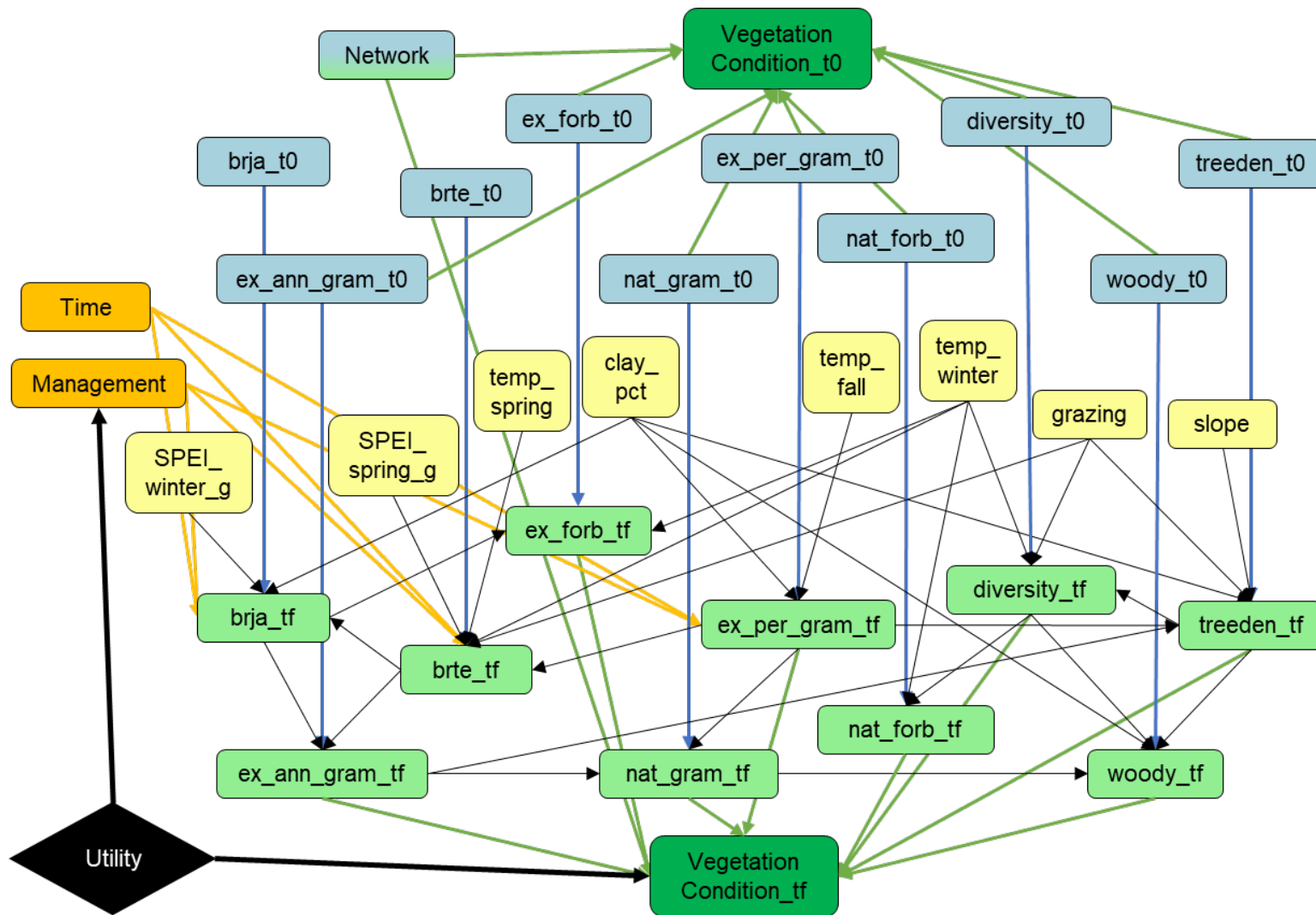


Figure 4.16. Bayesian Decision Network (BDN) structure. The utility node (black diamond) uses Vegetation_condition_tf to populate utility values for each level in the Management node (orange box). Other nodes and arcs are the same as depicted in Figure 4.7.

5. Implementation of the Annual Brome Adaptive Management Framework

The ABAM decision support tool (referred to above as the BDN and hereafter as “the model”¹) provides a scientifically rigorous, data-based, and peer-reviewed mechanism for the “evaluate consequences” portion of the adaptive management cycle illustrated in Figure 1.2. Completing the rest of the cycle requires deciding which alternative to implement and completing that action, monitoring the outcome, then using the information from the outcome to update the CPTs in the model. Successful adaptive management requires commitment to completing all of these steps repeatedly for the long term, likely decades. We designed the ABAM model to work with the existing management and monitoring resources in ABAM parks to maximize the sustainability of the model’s use, but the ABAM framework requires more than the model.

5.1. Collaborative Planning Meetings

Realizing the need for a framework implementation plan, our NPS partners and we convened a second SDM workshop in May 2019 to outline this plan. The workshop was facilitated by SDM experts not involved in ABAM. Participants were the authors of this report, the NGP plant ecologist, the NGP IMPT coordinator, the NPS regional fire ecologist, the NPS national IPMT coordinator, and the coordinator of a successful native prairie adaptive management program in national wildlife refuges. One key outcome of this workshop was the realization that the collaboration and communication among parks, monitoring, management programs, and USGS fostered by ABAM was beneficial for all aspects of vegetation management, not just that focused on annual bromes and supported by the ABAM model. Thus, participants decided to expand the communication and collaboration developed through ABAM to encompass aspects of vegetation management not directly tied to the ABAM model (e.g., rare plant monitoring, native seed production and storage). This expansion was dubbed Northern Great Plains Collaborative Adaptive Landscape Management (NGP CALM).

NGP CALM’s first manifestation was to institutionalize annual park vegetation management planning meetings, which we first implemented in January–March 2020. Participants in these meetings were, and will continue to be, park natural resource staff, representatives from the fire, invasive plant, and monitoring programs that serve the park, and USGS scientists involved in ABAM. Other park staff involved in vegetation management actions and decision making, from facilities managers to superintendents, are also encouraged to attend. The goal of these meetings is two-fold. First is to communicate everything related to recent and upcoming vegetation management, inventory, monitoring, and research. This communication—which had not existed before—ideally improves efficiencies in management (e.g., fire and IPMT programs working towards the same ends)

¹ Although “Bayesian Decision Network” (BDN) and “decision support tool” are more precise descriptions of the product we developed, the NPS staff who will use the information produced by the BDN are accustomed to referring to it as “the model”. Therefore, we adopt that convention in this and the following section, as well as in Appendix I, which we expect will be the sections of this report most used by those staff.

and monitoring (e.g., parks and programs collaborating to collect compatible information). Second is to decide vegetation management action priorities for the next one to three years. To achieve the second, a major portion of the meeting is dedicated to using the output from the ABAM model.

5.2. Using the Annual Brome Adaptive Management (ABAM) Model

To complete the ABAM decision support system, we developed the *ABAM* R package (Baldwin et al. 2021). The workflow for using the model is illustrated in Figure 5.1 and described in detail in an R vignette that accompanies the package. Appendix I of this report provides more information about functions in the package and their input and output. Briefly, the workflow includes gathering the most recently available data, relating sample events to management units, preparing vegetation and environmental data for input into the model, using the data to update the model's CPTs, running the updated model, and summarizing the output for use in the vegetation management meeting. Here we explain aspects of the workflow and model not captured in Figure 5.1 and Appendix I.

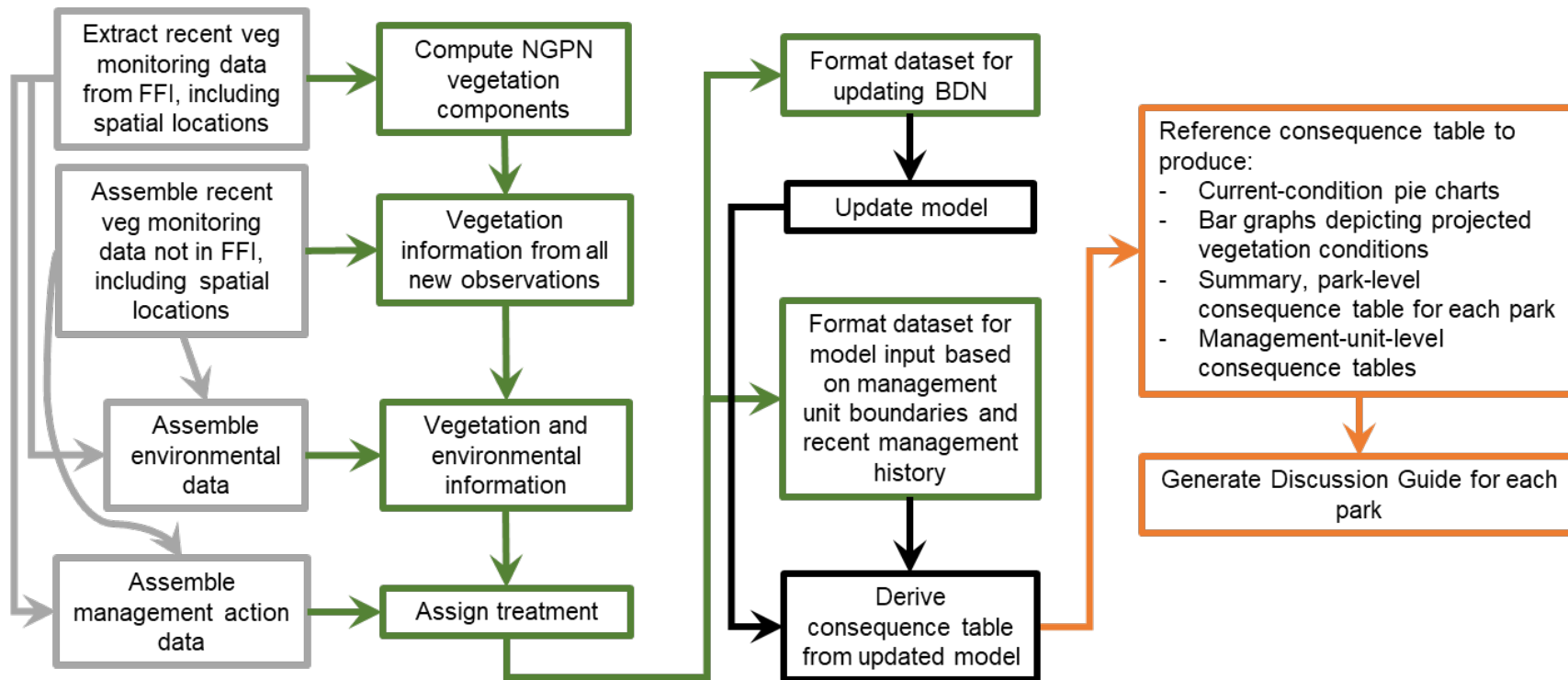


Figure 5.1. Flow diagram of steps for using the ABAM model (a.k.a. Bayesian Decision Network, BDN, or decision support tool) to produce output used in park vegetation management planning meetings. Box and arrow colors indicate four phases of the workflow: preparing data (gray), processing data (green), running the model (black), and producing communication products (orange). All phases except data preparation are completed using functions in the *ABAM* R package (Baldwin et al. 2021). “FFI” is the database where NGPN and NGP Fire vegetation monitoring data are stored.

5.2.1. Identification of Management Units

At first glance, relating sample events to management units appears relatively straight-forward, but it is, in fact, sometimes complicated. The data used to structure and parameterize the model were from individual plots ranging in size from 0.01 to 0.1 hectare. The model is, therefore, most suited to making decisions at that scale. Practically, though, management decisions and applications are not made at that scale (indeed, doing so would cause problems with the monitoring design), but instead for portions of a park ranging in size from 10s to 100s of hectares. These portions are considered “management units” in the ABAM framework. To accommodate this difference in scale, we assumed that CPTs were constant across this range of spatial scales. Although the model can be used for a subset of management units in each park, the current vision of its use is to run it for all management units in a park each year. This allows managers to better prioritize actions spatially and according to their overall vegetation management strategy, whether that be focusing limited management capabilities on keeping areas already close to or in the desired condition at that level or focusing on bringing areas in the least-desired conditions up to some minimum level of satisfaction. Thus, designating management units within parks is an important part of implementing the ABAM framework.

Participants in the 2017 SDM workshop identified burn (prescribed fire) units as a reasonable size for management units, but in the model, a management unit is simply a set of monitoring plots whose data collectively characterize the vegetation and environmental conditions of that unit. Thus, the model is not troubled by the facts that some parks do not have burn units, that the boundaries of burn units may change, and that some existing burn units have few or no monitoring plots. These facts do challenge the people using the model, though, because they require parks without burn units to consider what an appropriate management unit is, complicate the preparation of data for use in the model, and preclude applying the model to some areas of parks without additional monitoring effort.¹

In this early stage of implementing the ABAM framework, we followed the decision to use existing burn units as ABAM management units and created “placeholder” management units at the two parks that currently do not have prescribed fire. In parks where existing burn units were poorly defined or overlapping, we worked with the NGP fire ecologist to create non-overlapping units that generally covered each park. An example of the result of this process is shown in Figure 5.2. Management unit boundaries for all parks are not provided in this report because it became clear during the 2020 park vegetation management planning meetings that management units will likely change in the near future. Confronting management unit fluidity and adequate sampling will be an ongoing but not insurmountable challenge in the application of the ABAM framework.

¹ Currently, units with fewer than three monitoring events at unique plots within the five preceding years are considered inadequately sampled for model application.

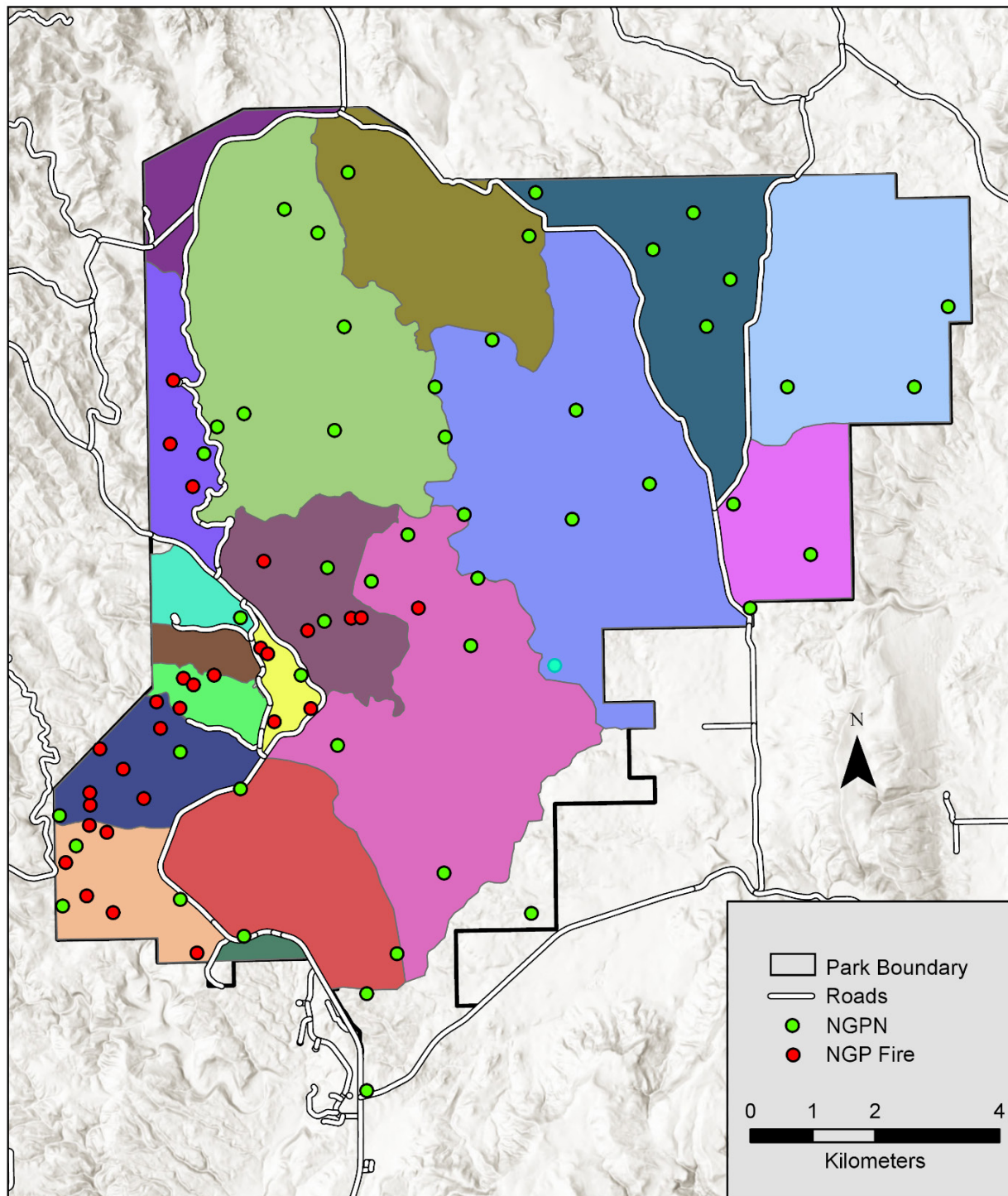


Figure 5.2. Example of management units used for running the ABAM model. Depicted here are management units (colored polygons) and monitoring plots (circles color-coded by monitoring program) used when running the ABAM model for the 2020 Wind Cave National Park vegetation management planning meeting. Management unit boundaries are often based on roads and natural features (e.g., streams or sparsely vegetated, rough terrain).

5.2.2. Compiling Input Data

The model requires ~35 input datasets. This number may vary from year to year depending on the number of parks for which tree density data are needed, whether data from experiments are available as supplemental input, and if new plots are established. However, most input files only need minor modifications each year.

To prepare the datasets, NGPN and NGP Fire vegetation monitoring data are downloaded from the FFI database. One function in the R package processes these “raw” data into the form needed for later steps in the workflow. Because LIBI data are stored in a different database, the ROMN plant ecologist completes this processing for LIBI data. The user must determine if any of the plots in these datasets are new (never monitored before) and whether they are applicable to ABAM (see Section 4.2.1). If so, these plots are added to the existing plot spatial dataset. Depending on the form of any relevant experimental data and where they are stored, they may be handled like either NGPN or LIBI data.

Weather data for ~6 years before the current year are downloaded from the PRISM website. Records for fires that occurred in the last year are obtained from the NGP Fire ecologist, and records for herbicide applications using indaziflam and/or imazapic are obtained from park and IPMT staff. Files containing bison range boundaries, vegetation condition utilities and objective weights, and management unit assignments are updated if necessary.

5.2.3. Updating the Model

After compiling each year’s monitoring and environmental data, these data are used to update the model, which occurs by updating the model’s CPTs. CPTs can be thought of as discrete distributions. Bayesian networks can be formulated to consider these distributions as multinomial distributions (Nagarajan et al. 2013). This means that these distributions can be updated using Bayes’ Theorem, which states that a posterior (i.e., updated distribution) is the product of a prior distribution and data (Clark 2007). In our case, we treat the current values of the CPTs as the prior information and data from on-going monitoring as the new information. In the case of a multinomial distribution, one can specify a Dirichlet distribution as its prior (Gelman et al. 2004). The Dirichlet distribution also has a nice property of having a fairly simple way to compute a posterior distribution when one considers it a prior to the more general categorical distribution. In this formulation, the posterior mean of a category in the distribution is

$$\frac{c_i + \alpha_i}{N + \sum_k \alpha_k}$$

where c is the count of observations in the data that belong to level i in a CPT, α functions like a prior and is a “pseudocount” of observations that are currently in the CPT (i.e. this is often referred to as the hyperprior), N is the total number of observations in the data and $\sum_k \alpha_k$ is the sum of all pseudocounts in the CPT (Gelman et al. 2004).

The strength of the prior is often an issue when dealing with posterior calculations. Most often the prior is “uninformative,” which means that a diffuse prior is chosen so as not to influence the

posterior. In our case, this posterior calculation is the mechanism for learning over time, so we would like for the prior to have some influence over the posterior. Controlling the strength of the prior using the equation above can be done by changing the size of the pseudocount by some factor. A larger α indicates more influence of the prior, whereas a small α means the new data will have more influence on the posterior. Simulations using different combinations of the hyperprior and the sample size of the new data showed that, for the amount of new information we expect each year (~100 new observations), the number of model updates required to converge on a specified true distribution was small (<2) and insensitive to values of hyperprior between 1 and 100. In circumstances where model updating is completed with a much smaller sample size (< ~25), a hyperprior value would have to be selected to appropriately reflect the user's desired relative influence of the prior and the new data.

5.2.4. Running the Updated Model

Following the updating of CPTs, the model can then be used to predict which management actions will be optimal given current vegetation conditions within management units. This requires running the model for each management option for each management unit, but the package automates this process. Two things should be considered during this part of the workflow: dynamic environmental nodes and the cost objective.

5.2.4.1. The Role of the Environmental Nodes

Before running the updated model, the user needs to carefully consider what evidence to enter in the environmental nodes' CPTs, since these nodes represent future conditions. Three of these nodes (slope, grazing, and clay_pct) are essentially static given the timeframes in the model, although changing bison range boundaries and more substantial grazing management decisions (e.g., establishing a bison herd at AGFO) could happen. Thus, the CPTs for these nodes—determined by the locations of the plots representing current vegetation condition—usually stay the same from one year to the next. In contrast, the weather nodes are dynamic. Therefore, it is important to consider what various options for entering probabilities in the CPTs for these nodes imply. One option is uniform probabilities, which would suggest complete uncertainty about future weather conditions. Another option would be to use an informed prior representing “average weather” conditions as described by the distribution of probabilities in each weather node from all the data used to inform the model so far (i.e., beginning with the earliest monitoring event). Another option would be to vary the type of informed prior among nodes. Specifically, since the model is usually run in January or February of each year, information for the fall temperature node (fall = September–November of year in which monitoring data were collected) will be available. Thus, probabilities in the CPT for this node could be set according to the fall temperatures that already occurred. Information for other weather nodes will not be complete when the model is usually run; therefore, the probabilities in their CPTs would need to be set using one of the other options described here. Finally, the model could be run assuming different combinations of high and low values for uninformed nodes in a “scenario” approach. One could achieve this by setting the desired levels to 100% in the CPTs and then running the model. This would allow for a comparison of how actions might change based on weather conditions.

When this report was written, park managers preferred that the tool be run using the “average weather” approach. Thus, we prepared the instructions for compiling data and the package for running the model according to these preferences. Using the “scenario” approach is possible, in that someone with programming knowledge can enter probabilities for these CPTs, but we hope to provide a more user-friendly method for model users to explore scenarios in the future.

5.2.4.2. Considering the Cost Objective

In our testing of the model, the effects of different management options, such as fire, were often weak. Sometimes this resulted in cases where an action resulted in a predicted change in vegetation condition, but that change did not outweigh performance on cost. Thus, we sometimes observed instances of *none* being predicted as the optimal management action despite there being some benefit in terms of improvement to the vegetation condition. Park managers felt that trade-offs with cost might be too strong at this point in the project. There are at least two solutions to this problem. One would be to elicit new weights and then rerun the analysis. Another would be to run the model without cost utilities until both more data are collected and the parametric uncertainty for the effects of management is reduced. Once there is evidence of uncertainty declining, then perhaps park managers could revisit the weights on the cost and condition objectives.

The current version of the model calculates two utility values, one with cost considered and another based only on the predicted vegetation condition. However, because park managers decided that the cost objective is of low importance at this time, the decision support system only produces summaries of the output for use in management planning meetings based on the runs that exclude the cost utilities.

5.2.5. Compiling and Interpreting Model Output

The main output for management decision making is a consequence table that depicts the probability distribution of current vegetation conditions, future conditions predicted for each management action, and their associated utilities. A consequence table is produced for each management unit. In each consequence table, the optimal management option is identified as the one with the highest expected utility—it leads to the most preferred predicted outcome when compared to the other options.

Table 5.1 is a formatted version of the consequence table output. It contains the following information:

- The second column, “Utility of Veg Condition,” conveys the park’s preference for the vegetation condition listed in the left-most column. The rows are arranged in the order of those preferences.
- The third column, “Current Condition,” shows the probability of the management unit currently being in the vegetation condition listed in the left-most column.
- The “Management Action” columns list each management action possible in the model.
 - Color shading indicates the information on which the outcome of the management action is based. This is included to show which management actions are currently largely uninformed.

- None (white), fall burn (red) and spring burn (blue) outcomes are informed by monitoring observations associated with no management action, fall fire, or spring fire, respectively.
- Treatments involving just herbicides (yellow), herbicide(s) and fall fire (orange), or herbicides(s) and spring fire (green) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.
- The last row communicates the utility, or degree of preference, associated with the outcome for each management action 2–3 years after the action. Higher utility values are indicated by darker shading.

Table 5.1. Example of formatted consequence table output depicting the probability distribution of current vegetation conditions, future conditions predicted for each management action, and their associated utilities as described in the main text.

Vegetation Condition	Utility of Veg Condition	Current Condition	Probability of Being in a Vegetation Condition									
			Management Action: None ^a	Management Action: Fall burn ^b	Management Action: Spring burn ^c	Management Action: Indaziflam only ^d	Management Action: Imazapic-indaziflam ^d	Management Action: Fall burn then imazapic ^e	Management Action: Fall burn then indaziflam ^e	Management Action: Fall burn then imazapic-indaziflam ^e	Management Action: Indaziflam then spring burn ^f	Management Action: Spring burn then indaziflam ^f
High-Quality Prairie	1.00	0.00	0.06	0.08	0.24	0.21	0.21	0.38	0.38	0.41	0.31	0.29
Low-Quality Prairie	0.80	0.76	0.59	0.71	0.30	0.76	0.75	0.59	0.59	0.57	0.60	0.64
Simplified Grassland	0.75	0.00	0.03	0.02	0.04	0.03	0.02	0.02	0.02	0.02	0.04	0.03
Exotic Perennial Grassland	0.25	0.00	0.09	0.02	0.03	0.00	0.01	0.01	0.00	0.00	0.05	0.03
Exotic Annual Grassland	0.25	0.24	0.19	0.11	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weedy Forb Mess	0.10	0.00	0.03	0.06	0.09	0.01	0.01	0.01	0.00	0.00	0.00	0.00
High-Quality Woodland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

^a None (white column heading) outcomes are informed by monitoring observations associated with no management action.

^b Fall burn (red) outcomes are informed by monitoring observations associated with fall fire.

^c Spring burn (blue) outcomes are informed by monitoring observations associated with spring fire.

^d Treatments involving just herbicides (yellow) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.

^e Treatments involving herbicide(s) and fall fire (orange) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.

^f Treatments involving herbicides(s) and spring fire (green) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.

Table 5.1 (continued). Example of formatted consequence table output depicting the probability distribution of current vegetation conditions, future conditions predicted for each management action, and their associated utilities as described in the main text.

Probability of Being in a Vegetation Condition												
Vegetation Condition	Utility of Veg Condition	Current Condition	Management Action: None ^a	Management Action: Fall burn ^b	Management Action: Spring burn ^c	Management Action: Indaziflam only ^d	Management Action: Imazapic-indaziflam ^d	Management Action: Fall burn then imazapic ^e	Management Action: Fall burn then indaziflam ^e	Management Action: Fall burn then imazapic-indaziflam ^e	Management Action: Indaziflam then spring burn ^f	Management Action: Spring burn then indaziflam ^f
Low-Quality Woodland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Exotic Perennial Woodland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Exotic Annual Woodland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Utility	–	–	0.63	0.70	0.60	0.83	0.83	0.87	0.87	0.88	0.83	0.84

^a None (white column heading) outcomes are informed by monitoring observations associated with no management action.

^b Fall burn (red) outcomes are informed by monitoring observations associated with fall fire.

^c Spring burn (blue) outcomes are informed by monitoring observations associated with spring fire.

^d Treatments involving just herbicides (yellow) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.

^e Treatments involving herbicide(s) and fall fire (orange) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.

^f Treatments involving herbicides(s) and spring fire (green) rely on simulated data, where annual brome responses are informed by publications about those herbicides and very limited field observations, and responses of other vegetation components are simulated by the model.

The information presented in a consequence table is useful for managers to compare outcomes of different treatments within a specific unit (within a table) or of the same treatment in different units (across tables). For example, the utility of the optimal action may be very similar to that of several other management actions. This can inform discussions when other factors not captured by the model influence management decisions. Such factors may include feasibility of treatment within the current management planning cycle, fuel load reduction, or other park objectives.

The consequence table includes a large amount of information, and processing all of this information for each management unit based solely on these tables can be overwhelming, especially for managers of large parks with numerous management units. When presenting model summaries to managers, the information from the consequence tables can be used to produce several forms of figures and tables to aid in the communication of model output. Code to automate the production of discussion guides is currently under development and will be a product of the next phase of the project. The discussion guides will assimilate information from model output, and spatial and tabular data associated with model input, to produce customized, park-level reports.

5.2.6. Decision Making

Limited resources and time to apply management actions allow only a small number of management actions in a park each year, so maximizing the effectiveness of management actions is a high priority for park managers. The ABAM model, as a decision support tool, provides quantitative guidance for predicting the outcomes of management decisions and a mechanism for making those predictions better over time. However, it is only a decision *support* tool; it does not make decisions. Its output can be applied in different ways, and it is only a portion of the information that managers must consider when deciding which actions to apply in which management unit each year.

One consideration is whether to emphasize learning versus management effectiveness. There are two general forms of adaptive management, active and passive (Williams 2011). Active adaptive management emphasizes both learning and accomplishment of desired outcomes. However, because both learning and resource performance are the focus, there may be cases where learning trades off against desired conditions. As described in sections 4.5.1 and 4.6.1, the model's predictions for the outcomes of herbicide applications are currently based primarily on simulated data, and predictions for outcomes of prescribed fires may be based on data skewed towards different seasons for different vegetation conditions (section 4.6.1), resulting in considerable uncertainties. Applying an active approach may result in managers choosing actions that would address information gaps to reduce those uncertainties or developing a more experimental application of multiple management actions. A potential downside to this approach, however, is that management actions may result in less desired outcomes. In contrast, passive adaptive management emphasizes the resources being managed. By applying the less risky actions (i.e., those whose outcomes are more certain), there is lower chance of undesired outcomes, but learning is much slower than in the active approach.

In addition, the same set of consequence tables may lead to different decisions depending on a park's overall approach to vegetation management. Summarizing the information in the consequence tables sometimes shows that a similar management action in two different management units would result in greater utility in the one unit, but greater *increase* in utility in the other. Thus, one question that

has repeatedly risen in the early stages of this project is whether a park will focus on maintaining already high-quality prairie (i.e., focus on utility) or focus efforts on the most degraded areas (i.e., focus on *increasing* utility). No ABAM park currently has a formal, documented vegetation management strategy that answers this question.

Finally, there are many other factors that influence management decisions that the ABAM model does not consider. For example, although the model distinguishes between prairie and woodland based on the presence of trees, it was not designed to address how specific management actions (i.e., fire) will affect woodland structure, such as density of different sizes of trees, that often concern managers. In some circumstances, these aspects of vegetation may be at least as important in decision making as the effects on the herb-layer vegetation. Practical constraints such as site accessibility in different seasons and availability of qualified personnel to implement specific actions also play a role in decision making.

5.2.7. Implementing Management and Monitoring

Once decisions are made, management actions must be applied and monitoring completed in order for learning to occur. Many adaptive management frameworks are hampered by inadequate monitoring of outcomes. The ABAM framework is unusually situated to avoid that pitfall because it is built around existing vegetation monitoring programs. However, reducing uncertainties about the effects of different management actions also requires adequate tracking of the exact nature of the management actions applied and the monitoring plots to which the actions were applied. A systematic method for tracking the details of relevant management actions does not currently exist for ABAM parks; this will be a focus of the next phase of the project.

We expect that not all actions will be implemented as planned. We constructed the model to accommodate circumstances such as an herbicide being applied later than in the optimal timeframe, but there will be circumstances in which a management action does not fit within the criteria defining any of the management actions in the model (see Appendix Table B2). In these circumstances, the user of the model must decide whether to exclude the data from monitoring events affected by that action, or how to assign those events to the most relevant option in the model. Thorough record-keeping of such decisions is necessary to maintain consistency in the way these decisions are made and would aid in changing those decisions at later dates if a need to do so is recognized.

We also expect that NGP Fire, ROMN, and NGPN will continue to follow their existing monitoring schedules as much as possible. However, if circumstances result in less monitoring being performed than usual (for example, because of a pandemic), it would benefit the ABAM framework to prioritize monitoring plots in management units with recent management actions or actions planned for the near future over those not connected to any management actions.

6. Sustaining and Improving the Annual Brome Adaptive Management Framework

The ABAM framework garners strength from the collaboration across multiple parks and networks, as information from the management actions that occur in one park is applied to all ABAM parks. However, sustaining collaborative, structured adaptive management approaches for natural resource management is challenging, and there are a limited number of successful examples to guide those embarking on such a journey (Allen and Gunderson 2011). Because this application of an adaptive management framework supported by a quantitative decision support tool to guide vegetation management is unique within the NPS (to our knowledge), institutional knowledge and mechanisms for long-term implementation of the ABAM framework do not exist within the agency. Additionally, the ABAM model and the data that inform it could be improved in a variety of ways. Thus, we conclude with a discussion of ways to both sustain and improve upon the work described in this report.

6.1. Actions to Maximize Long-Term Viability

As mentioned above, ABAM consortium members used SDM in May 2019 to work toward the fundamental objective of maximizing the viability of the ABAM framework (see Section 5.1). Four means objectives¹ were identified as essential elements of any plan to accomplish the fundamental objective (Table 6.1). *Maximizing collaboration across park units, programs, and partners* produces efficiencies not only in shared equipment, supplies, and possibly even personnel, but also in shared knowledge and experience. The latter has already proven valuable when a critical position in the NGP IPMT was vacant for an extended period. *Maximizing communications about the ABAM framework* within the consortium (e.g., to park superintendents), to regional and national NPS and USGS offices, and even to the public is necessary to maintain and build financial and institutional support for the work the consortium accomplishes through the framework. *Maximizing preconditions for management implementation* is necessary to achieve more management actions that are the foundation for improving the model's predictions *and* the vegetation conditions within the parks. This objective aims to reduce uncertainties about, and the burden of, completing regulatory requirements preceding implementation of a prescribed fire or herbicide application. Finally, *maximizing utility of the ABAM model*, by making it as easy to use as possible while producing valuable information, is necessary to ensure that NPS staff commit to its use and upkeep in the face of other demands on their time and attention. Table 6.1 highlights key proposed, planned, or already-implemented actions for each of these objectives. Most of these come from the unpublished report resulting from the May 2019 SDM exercise (available from ABAM consortium members), which contains a much longer list of actions. Other actions were identified after that report was completed.

¹ Structured decision making distinguishes between *fundamental objectives*, which reflect the desired ends of an activity, and *means objectives*, which are ways to achieve the fundamental objectives.

Table 6.1. Key actions for maximizing the viability of NGP CALM (Northern Great Plains Collaborative Adaptive Landscape Management) and the ABAM framework identified by ABAM consortium members.

Means Objective	Actions
Maximize collaboration across park units, programs, and partners	• Establish and maintain a platform (i.e., Microsoft Team) for sharing ideas, opportunities, proposals, and outcomes regarding funding for management actions and other activities to support the ABAM framework • Institute an annual NGP CALM meeting involving all consortium members to update this platform and assign tasks • Add ABAM participation and duties to team members' Employee Performance Appraisal Plans
Maximize communication about the ABAM framework	• Write official briefing statement to inform regional and national NPS and USGS administrators • Develop an "elevator speech" about the ABAM framework and NGP CALM • Publish a description of the effort in <i>Park Stewardship Forum</i> • Manage superintendent and resource management chief expectations regarding the time required for adaptive management to yield results • Create an ABAM advisory/advocacy team
Maximize preconditions for management implementation	• Conduct annual vegetation management planning meetings at each park • Create a pre-management-action checklist • Seek additional funding for management implementation across multiple parks • Incentivize management actions through recognition and informal awards
Maximize model utility	• Streamline data preparation • Automate generation of discussion guides used in annual vegetation management planning meetings • Obtain long-term quantitative support for the model (e.g., for revisions)

6.2. Actions to Improve the Model and Input Data

The ABAM model is unusual in that most of its structure and initial parameterization were derived from site-specific data, rather than expert opinion or studies conducted outside the area where the model will be used. We used the best data available to develop the variables for estimating its structure, but there is room for improvement. We discuss three aspects of the data that, if improved, we believe could improve the model's performance. A formal sensitivity analysis could quantitatively assess where more information would reduce uncertainties.

The first factor that may improve model performance is the soil texture variable. The soil maps from which this variable was derived are not intended to be used at the fine spatial resolution that we used them for (USDA–NRCS 2017). Collecting soil samples at each vegetation monitoring plot and performing standard laboratory soil analyses not only would provide more reliable data for soil texture than can be derived from soil maps but also would allow the development of other potentially relevant variables such as pH, organic matter content, and carbon-to-nitrogen ratio. Samples would only need to be collected once, as such soil properties are relatively stable through time.

Second, higher temporal resolution of the vegetation monitoring data may improve model performance. The NGPN, NGP Fire, and ROMN plot visit schedules are not ideal for filling gaps in the temporal component of the model. Supplemental monitoring visits to plots outside of these schedules when time allows would improve this aspect of the model's predictions. For example, the model currently combines the 2nd and 3rd years after a management action into the 2–3 timestep, and the 4th and 5th years into the 4–5 timestep, because the NGPN and NGP Fire plot revisit schedules yield relatively few observations for the 3rd and 4th years following management. Greater temporal resolution regarding the longevity of management action effects would require visiting plots in those years.

Finally, as noted in section 5.2.1, some of the current management units have fewer monitoring plots than the three that we arbitrarily decided were necessary to adequately describe a unit's existing vegetation conditions. NGP Fire has more flexibility in its monitoring schedule than do NGPN and ROMN and consequently may be able to add standard monitoring plots to overcome this problem in the parks that it serves when management actions are scheduled. Another proposed solution to this problem would be to increase the size of management units so that each one includes at least three vegetation monitoring plots. This should only be done, though, if it is likely that a management action could practically be applied to the whole unit and if it would make sense to do so. For example, if a management unit encompasses areas of high-quality prairie and exotic annual grassland, applying an expensive herbicide to the whole unit could be cost-prohibitive and unnecessary. (Recall that cost utility is based on a per-acre value and does not account for the area over which a management action is applied.) Many questions remain regarding how best to delineate management units for optimizing the efficiency of achieving desired conditions and the speed of model learning.

A more drastic solution to the problem of under-sampled management units would be to redesign the vegetation monitoring protocols of the monitoring programs so that more locations are monitored but less detailed vegetation information is collected at each location. We investigated the utility of one potential manifestation of this approach by conducting spatially intense (information collected every 100 m) but information-lite (broad categorical descriptions of vegetation condition with emphasis on annual brome cover) surveys of 17 management units distributed across all ABAM parks in 2017–2019. For management units in which annual brome abundance represented by the standard monitoring data and the survey data differed the most, we compared the management action identified as optimal by the model using two types of data to describe current vegetation condition. In the first, current condition was determined by the standard vegetation data (derived from NGPN, ROMN, and NGP Fire monitoring plots). In the second, survey data were combined with the standard data. This cursory analysis suggested that the survey data rarely changed the optimal management action for a management unit. However, the survey data did identify areas of high brome abundance not captured by the standard monitoring plots. Based on these results and acknowledging that redesigning the existing monitoring protocols around the ABAM model could result in loss of information used for other purposes, ABAM consortium members decided to investigate options for completing more of the surveys (e.g., perhaps with remote sensing

technology) to possibly target herbicide applications, but not to revise the standard monitoring protocols.

6.3. Revising the Model

It may prove necessary to revise the model if its performance does not improve as it is updated with new data. Revisions may include estimating model structure with an expanded set of variables, including other environmental nodes such as litter depth or fire severity, or with existing variables measured with methods more sensitive to those currently used (e.g., quadrat-based diversity measurements may be more sensitive to herbicide effects on native annual and biennial species). Model revision might also consider an alternate method to incorporate time. In an extreme case, model users might even consider changing the existing adaptive management framework altogether.

There may be a need to revisit the larger ABAM decision-making framework after participants have had some experience with current framework. In the literature, adaptive management theorists discuss the notions of *single-*, *double-* and *triple-loop learning* (Pahl-Wostl 2009). Much of what we discussed in this report so far can be described as single-loop learning: predicting, deciding, and updating. Triple-loop learning is outside the scope of this report as it pertains to high-level institutional learning, but double-loop learning could be an especially important consideration for ABAM. At least conceptually, double-loop learning consists of revisiting the steps in the set-up phase, such as assessing whether the problem was scoped correctly, the objectives reflect desired outcomes, and whether to add or remove management actions. This may be a particularly important aspect of the ABAM program considering that most consortium members were unfamiliar with the idea of quantitatively defining vegetation conditions, utilities, and objective weights. So too, if it proves that the ranges of management options in the current model are simply not very effective, or if more efficient actions become available, the ABAM consortium may need to revisit the larger range of possible options. Given the current rate at which management actions are applied in ABAM parks, as well as the 5-year revisit schedule of monitoring in six of those seven parks, we believe an assessment of model learning rate and need for double-loop learning would be warranted after 5–10 years of implementation.

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Appendix A. Desired Vegetation Conditions

This appendix contains descriptions of desired vegetation conditions, for each park in the Annual Brome Adaptive Management (ABAM) consortium, specifically for use in various stages of the ABAM project. The desired conditions do not reflect current conditions, but rather state the vegetation conditions each park would like to achieve. It is important to note that the desired conditions we developed were driven strongly by the concept of ecological integrity. They do not strictly adhere to NPS guidance on desired conditions (National Park Service 2009) in that it is not clear whether they are achievable, even in the long term. Rather, they were developed specifically for the ABAM framework to provide a reference for high-quality vegetation. Park and supporting network staff contributed to and agreed to these descriptions before the April 2017 SDM workshop.

Each description begins by describing desired conditions that apply to developed areas. The description then explains conditions applicable to the park outside of those developed areas, first addressing metrics and processes that apply park-wide, then providing more details for specific zones with distinct vegetation desired conditions. Outside of developed areas, these zones were determined by topographical and soil characteristics, as well as current distribution of general vegetation types (e.g., woodland vs. grassland). Staff at Badlands and Wind Cave National Parks felt it was necessary to describe the proportion of the park occupied by these general vegetation types, either because of the desire to maintain general current proportions (Badlands) or because of flexibility around current proportions (Wind Cave). Each description is accompanied by a map of the park indicating the general location of each vegetation zone, though the text descriptions often describe that the boundaries of these zones may be dynamic. Common names of plant taxa are used in the descriptions; scientific names are provided for all species mentioned at the end of this Appendix. Tree size is often described in terms of dbh, which stands for “diameter at breast height”, where breast height is 137 cm from ground level.

Each description is based on information from three major sources:

- **ecological site descriptions** compiled by the U.S. Department of Agriculture Natural Resources Conservation Service, which we spatially referenced within parks using NRCS soil mapping data (USDA–NRCS 2017);
- vegetation inventory maps and reports, compiled by the NPS Vegetation Inventory program, that classify **vegetation associations** according to National Vegetation Classification System standards (Aerial Information Systems 1998a, b; Salas and Pucherelli 1998; The Nature Conservancy 1998; Cogan et al. 1999; Von Loh et al. 1999; Rice et al. 2012); and
- NPS Inventory and Monitoring or Fire Ecology program data, including the number of confirmed native plant species in park plant species lists (obtained from NPSpecies, <https://irma.nps.gov/NPSpecies/>, in March 2017).

All foliar cover values assume that foliar cover is measured using the NGPN and ROMN point-intercept method (Manier et al. 2011, Symstad et al. 2012), in which total foliar cover can be greater than 100% because of layering of species within the herbaceous layer. Ground cover values also

assume the same measurement method, in which total ground cover (sum of all recorded categories for a plot) is 100%. Litter depth values are based on unpublished data (A. Symstad) collected at BADL and SCBL for two different projects following NGP Fire Ecology program fuel load measurement practices.

Agate Fossil Beds National Monument

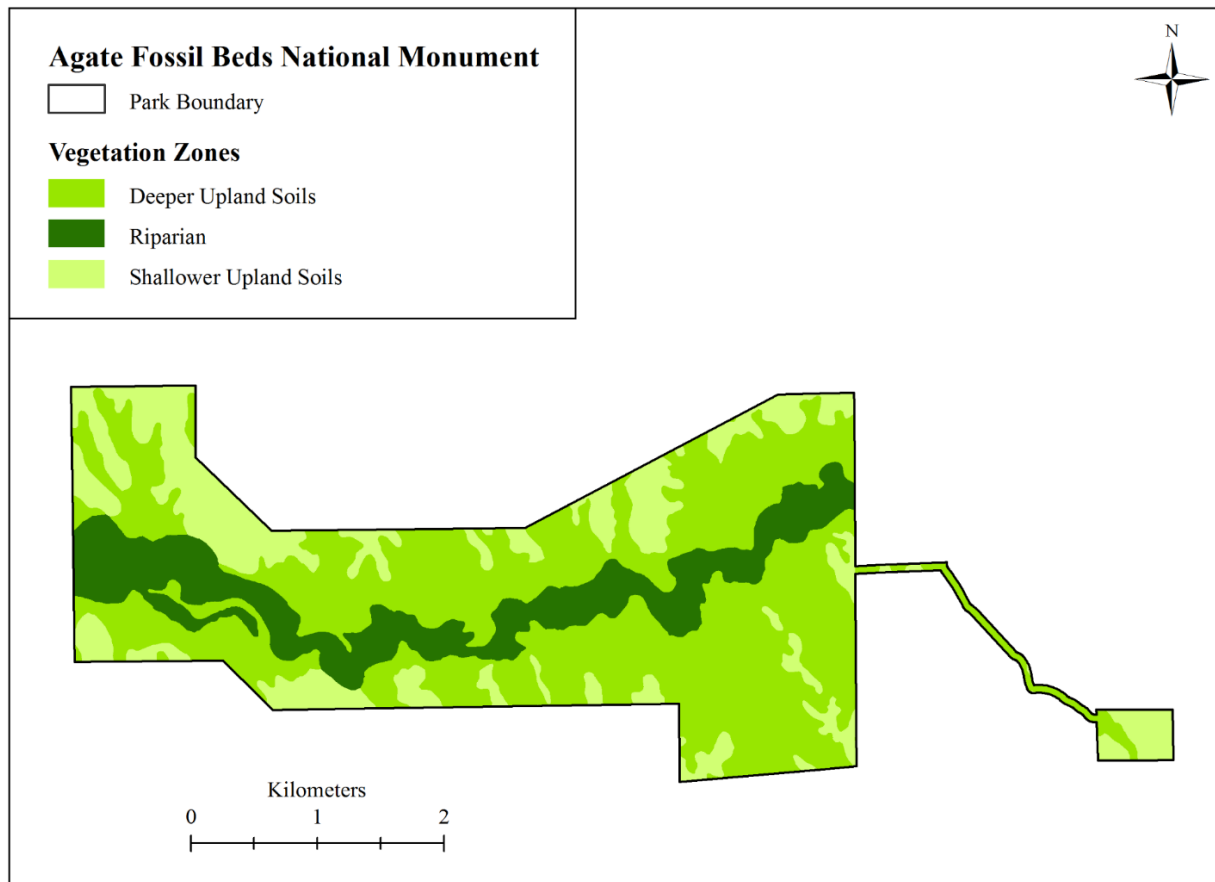


Figure A1. Vegetation zones for Agate Fossil Beds National Monument desired conditions.

Park-wide. The vegetation of the development zone (housing, visitor center, etc.) reflects that found in similar areas of the park as much as possible while maintaining historic landscapes and being sustainable in the face of the human activity it supports. Except when culturally significant, plant species are native to the central or northern Great Plains, are drought tolerant, and require little maintenance.

Outside the development zone, species composition fluctuates as climate, fire, herbivory, and other natural processes exert their individual and interactive effects on species within landscape settings described below. More than 270 native species occur in the park. Park-wide, species not native to the central and northern Great Plains comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. All parts of the burnable landscape (i.e., excluding areas that can support little or no vegetation, or that are continuously waterlogged) experience fire on average every 9–13 years (Guyette et al. 2015), with fire locations varying temporally so that the park is a mosaic of time-since-fire. Bison or cattle grazing may support the desired conditions described in this document. Native pollinators provide services that ensure seed set sufficient to

sustain native forb, shrub and tree species. Populations of species are sustained if they are culturally important to Native American tribes that consult with the park.

Deeper Upland Soils (hillsides, some flat hilltops, and non-riparian valley bottoms). The canopy is generally 60–150 cm tall, though it is shorter (<20 cm) in patches dominated by short grasses, and total foliar cover is high (average >90%). Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate (< 1.5 cm). Graminoids, forbs, and shrubs comprise 70–95%, 5–15%, and <10% of plant cover, respectively. Vegetation is dominated by a mixture of mid-height, warm- and cool-season grasses. The most abundant species are prairie sandreed and needle-and-thread, with western wheatgrass and perhaps switchgrass more common in valley bottoms. Sand bluestem, a warm-season grass common in this ecological/vegetation site elsewhere, may also occur. In some areas, particularly when heavily grazed, shorter graminoids, particularly blue grama and/or upland sedges (needleleaf, threadleaf, and sun), replace the taller grasses as dominants. A diverse array of forbs, with species that bloom throughout the growing season, occur throughout these areas. Scurfpeas, dotted blazing star, prairie sunflower, narrowleaf stone seed, spiderworts, and rush skeletonplant are some of these forbs. Woody, woody-like, and succulent plants such as skunkbush sumac, prairie sagewort, broom snakeweed, prickly-pear cactus, and soapweed yucca are a scattered, minor component of the vegetation. Local diversity is moderate, with, on average, at least 6 native species occurring in a 1 m² area, and at least 20 species in 1,000 m². Non-graminoid species comprise at least 66% of the native species richness at the 1,000 m² scale.

Based on: Loamy, Sandy, Sandy Lowland, and Sands ecological site descriptions;
Calamovilfa longifolia – *Andropogon hallii* Herbaceous and *Hesperostipa comata* –
Bouteloua gracilis – *Carex filifolia* Herbaceous vegetation associations

Shallower Upland Soils (Upper slopes and flat hilltops). Vegetation is a mosaic of grassland and sparse vegetation, with the latter in areas of little soil development and the former in areas where some soil has developed from the eroding surroundings. In the grassland patches, vegetation resembles that of deeper upland soils described above, though with more sideoats grama, and blue grama in place of prairie sandreed, and graminoids comprise less (70–85%) of plant cover. In level outcrops, plant canopy cover is highly dissected (50–80% cover), and ground cover is primarily bare soil or cryptobiotic assemblages. Sparsely vegetated areas are dominated by short, often cushion-like, perennial forbs such as Hooker's sandwort, phloxes, and buff fleabane. Plains muhly is the only common graminoid. Plant diversity is higher than in deeper soils with, on average, at least 7 native species occurring in a 1 m² area, and at least 35 species in 1,000 m².

Based on: Shallow and Thin Upland ecological site descriptions; *Schizachyrium scoparium* –
Bouteloua (curtipendula, gracilis) – *Carex filifolia* Herbaceous vegetation association

Riparian. The canopy is 50–200 cm tall, and foliar cover is very high (average >125%). Ground cover ranges from litter of a moderate (<2 cm) depth to organic muck to water. Graminoids, forbs, and shrubs comprise 80–95%, 5–10%, and <10% of plant cover, respectively. Vegetation composition varies with salinity, degree of soil saturation, and distance from water's edge, but is

dominated by a mixture of sedges, rushes, spikerushes, bulrushes, cattails, and tall and mid-height grasses. A wide range of appropriate grass species, such as prairie cordgrass, switchgrass, big bluestem, western wheatgrass, Canada wildrye, slender wheatgrass, foxtail barley, rice cutgrass, and – in more saline or alkaline spots – saltgrass and alkali sacaton, are present along with various lowland sedge species, horsetails, and Baltic rush. Western wheatgrass and sedges are more abundant in the presence of frequent, heavy grazing in the drier areas. Forbs such as white sagebrush, American licorice, Maximilian sunflower, and goldenrods occur in the drier areas, and wet meadow species such as wild mint, rough bugleweed, and blue skullcap occur in wetter areas. Shrubs such as western snowberry occur in dense but scattered patches in drier areas away from the riverbank. Dense patches of willow shrubs occur on the riverbank and in temporarily flooded areas. Scattered individuals of Plains cottonwood may occur. Local diversity is moderately high, with, on average, at least 13 native species occurring on a 50-m long, 50-point transect, but is highly variable.

Based on: Subirrigated and saline subirrigated ecological site descriptions; *Pascopyrum smithii* Herbaceous, *Typha latifolia* Western Herbaceous, *Juncus balticus* Herbaceous, and *Salix exigua* Shrubland vegetation associations

Badlands National Park (North Unit)

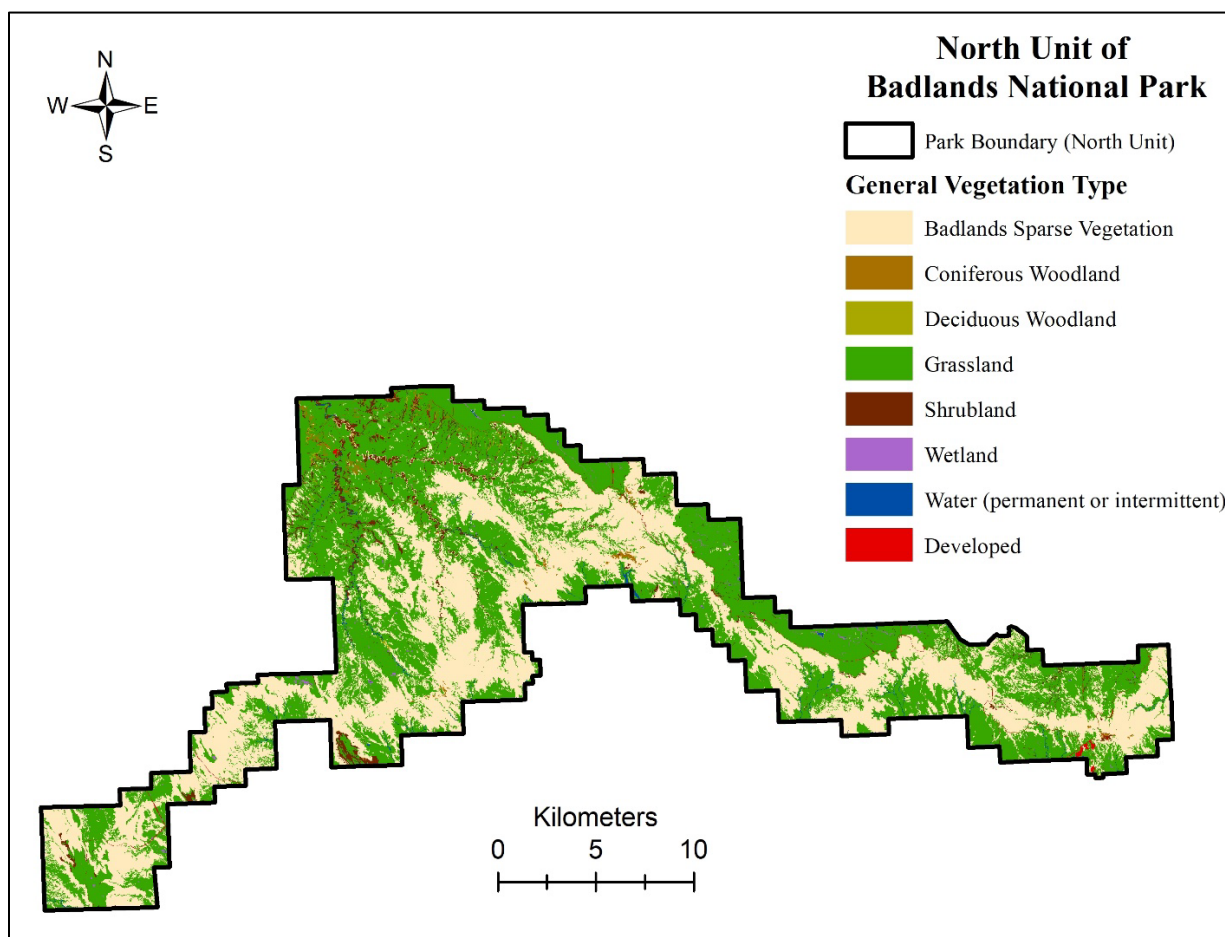


Figure A2. Vegetation zones for Badlands National Park desired conditions.

Park-wide. The vegetation in developed areas reflects that found in similar areas of the park as much as possible while maintaining historic and ethnographic landscapes and being sustainable in the face of the human activity it supports. Except when culturally significant, plant species are native to the central or northern Great Plains, are drought tolerant, and require little maintenance.

Outside developed areas, the landscape is a mosaic of vegetation types distributed according to the percentages in Table A1. Proportions of vegetation types on the landscape fluctuate within the desired proportions as climate, fire, herbivory, erosion, and other natural processes exert their individual and interactive effects on species. Species composition also fluctuates within vegetation types in response to natural processes, particularly in washout areas and in areas affected by eroding badlands features. More than 350 native species occur in the park. Local diversity is moderate, with at least 6 native species in a 1 m² area, and at least 25 native species in 1,000 m², when averaged across the park. Native forbs comprise at least 66% of the native species richness at the 1,000 m² scale. Park-wide, species not native to the central and northern Great Plains comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. Natural

processes are sustained. The burnable landscape (i.e., excluding areas with little or no vegetation) experiences fire on average every 5–15 years, with fire locations varying temporally so that the park is a mosaic of time-since-fire. Grazing by a diverse community of native wildlife (bison, pronghorn, bighorn sheep, deer, and prairie dogs) throughout the park ensures heterogeneous vegetation composition (dominant and subordinate species) and structure across the landscape. Native pollinators provide services that ensure seed set sufficient to sustain native forb, shrub, and tree species. Populations of species culturally important to tribes with which the park consults are sustained.

Table A1. Desired proportions of general vegetation types in the North Unit of Badlands National Park.

General Vegetation Type	Percentage of Park
Badlands Sparse Vegetation	40–45
Mixed-grass Prairie	50–55
Shrubland	2–3
Woodland – Deciduous	0.5–1.0
Woodland – Coniferous	<1
Wetland	0.2–0.5

Badlands Sparse Vegetation. This description applies to areas capable of supporting at least some vegetation (>10% foliar cover). This complex occurs on or at the base of rapidly (geologically speaking) eroding badlands features. Vegetation is generally short (<30 cm), and canopy cover is low (<60%). Ground cover is primarily bare (>40%), and litter, where it occurs, is very shallow (<0.5 cm deep). Species are a subset of those in mixed-grass prairie plus others (such as few-flower buckwheat, butte candle, and saltbushes) specific to sparsely vegetated areas, including some that are rare in the region as a whole (e.g., Visser’s buckwheat, Barr’s milkvetch). Forbs, subshrubs, and shrubs together comprise at least as much of the canopy cover as grasses.

Based on: *Artemisia longifolia* Badlands Sparse, *Eriogonum pauciflorum* – *Gutierrezia sarothrae* Badlands Sparse, Eroding Great Plains Badlands Sparse, and Great Plains Badlands Sparse Vegetation Complex vegetation associations

Mixed-grass Prairie. Mixed-grass prairie occurs on uplands with developed soils. Its composition varies across the landscape and is influenced by soil type, topography, slope position and aspect, time since fire, and current and historical grazing. The canopy is generally 60–100 cm tall, though it is shorter (<20 cm) in patches dominated by short grasses, and total foliar cover is high (average >100%). Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate (< 1.5 cm). Graminoids, forbs, and shrubs comprise 70–90%, 10–15%, and <10% of plant cover, respectively. Western wheatgrass is by far the most common species and may be almost a monoculture in the dense clay ecological site. Mid-height warm-season grasses

like sideoats grama and little bluestem occur along with mid-height cool-season grasses (e.g., green needlegrass, needle-and-thread) and upland sedges (threadleaf, needle leaf, and sun) on steeper slopes and in shallow soils (shallow, very shallow, and thin upland ecological sites). Mid-height warm-season grasses are less abundant, and sedges and short warm-season grasses (e.g., blue grama, hairy grama) are more prominent, in areas with a long history of heavy grazing in these ecological sites. Mid-height cool-season grasses dominate most other ecological sites (loamy, clayey, shallow loamy, shallow clay, claypan, and thin claypan ecological sites), with short grasses (e.g., blue grama and buffalograss) and sedges becoming more abundant to dominant in areas with a history of heavy grazing. Low-lying, nearly level areas along intermittent watercourses that occasionally experience sheet erosion (badlands overflow ecological site) have a mix of mid-height and tall, warm- and cool-season grasses including switchgrass, little bluestem, western and slender wheatgrasses, Indian ricegrass, and prairie sandreed. In these overflow sites, vegetation may be a mosaic of highly productive grasslands and bare soil. Prairie dog towns occur within the mixed-grass prairie; their extent does not exceed the limits stated by the park's prairie dog management plan but is large enough to support a sustainable population of black-footed ferrets. Within prairie dog towns graminoids comprise a smaller proportion of the plant community than in other prairie areas (65–70%, compared to 70–90%), and species tend to be more unpalatable or grazing- and disturbance-tolerant than those in the rest of the prairie. Examples include purple three-awn, fetid marigold, deathcamas, prairie sagewort, and broom snakeweed. Bare soil in prairie dog towns does not exceed 50% of ground cover.

Based on: Badlands overflow, clayey, claypan, loamy, shallow, shallow clay, shallow loamy, thin claypan, thin upland, and very shallow ecological site descriptions; *Calamovilfa longifolia* – *Carex inops* ssp. *heliophila* Herbaceous, *Pascopyrum smithii* – *Bouteloua gracilis* – *Carex filifolia* Herbaceous, *Pascopyrum smithii* – *Nassella viridula* Herbaceous, *Schizachyrium scoparium* – *Bouteloua (curtipendula, gracilis)* – *Carex filifolia* Herbaceous, *Bouteloua gracilis* – *Bucholoe dactyloides* Xeric Soil Herbaceous, and Blacktailed Prairie Dog Town Grassland Complex vegetation associations

Shrubland. Shrublands occur throughout the landscape, but are most consistently in draws, along intermittent watercourses, and in other mesic areas. Shrublands have 10–50% shrub cover, <10% tree cover, and a wide range (10–75%) of cover by herbaceous species. Shrub canopy height varies with the shrub species but is typically 0.6–1.5 m. Species that characterize different shrubland types include skunkbush sumac and soapweed yucca in less mesic areas; western snowberry, American plum, and chokecherry in draws and along some slumps, and silver sagebrush and sandbar willow in the most mesic areas. Herbaceous vegetation and ground cover are similar to surrounding mixed-grass prairie.

Based on: *Artemisia filifolia* / *Calamovilfa longifolia* Shrubland, *Chrysothamnus nauseosus* / *Pseudoroegneria spicata* Shrubland, *Prunus virginiana* (*Prunus Americana*) Shrubland, *Salix exigua* Temporarily Flooded Shrubland, *Symphoricarpos occidentalis* Shrubland, *Rhus trilobata* / *Carex filifolia* Shrub Herbaceous, and *Yucca glauca* / *Calamovilfa longifolia* Shrub Herbaceous vegetation associations

Woodland. Rocky Mountain juniper/eastern redcedar woodlands are confined to butte edges, slumps, and the upper portions of draws. Deciduous woodlands persist in the lower portions of draws and along perennial and intermittent streams, exhibiting recruitment sufficient to ensure their long-term viability. Herb-layer structure in woodlands resembles that of surrounding mixed-grass prairie, but its cover varies inversely with tree canopy cover. Herb-layer species composition also resembles that of mixed-grass prairie, but species that are more shade-tolerant and mesic-loving, such as Canada wildrye and meadow-rues, replace some open prairie species.

Based on: *Juniperus scopulorum* / *Oryzopsis micrantha* Woodland, *Fraxinus pennsylvanica* – *Ulmus americana* / *Prunus virginiana* Woodland, and *Populus deltoides* – (*Salix amygdaloides*) / *Salix exigua* Woodland vegetation associations

Wetlands. Wetlands – areas with saturated soils or shallow standing water on a nearly permanent basis – are small and confined to thin strips along streams, or in depressions often associated with water developments. Typical species include cattails, bulrushes, spikerushes, and prairie cordgrass.

Based on: *Spartina pectinata* – *Carex* spp. Herbaceous, *Eleocharis palustris* Herbaceous, and *Typha* spp. – *Scirpus* spp. – Mixed Herbs Great Plains Herbaceous vegetation associations

Devils Tower National Monument

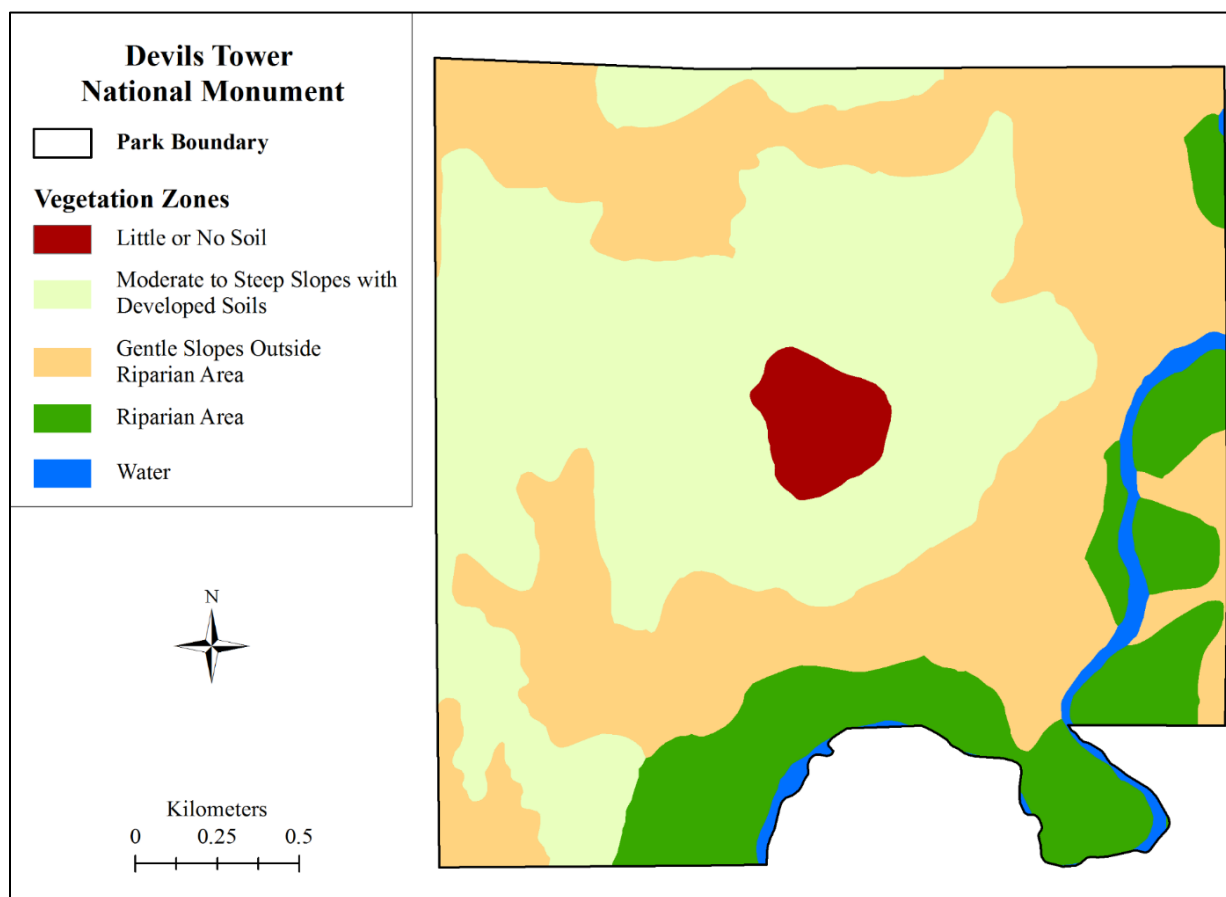


Figure A3. Vegetation zones for Devils Tower National Monument desired conditions.

Park-wide. The vegetation in developed areas (around the visitor center, campground, housing, etc.) reflects that found in similar areas of the park as much as possible while maintaining historic and ethnographic landscapes and being sustainable in the face of the human activity it supports. Except when culturally significant, plant species are native to the central or northern Great Plains (including their ponderosa pine inclusions), are drought tolerant, and require little maintenance.

Outside of developed areas, species composition fluctuates within landscape settings described below as climate, fire, herbivory, and other natural processes exert their individual and interactive effects on species. Position on the landscape of each vegetation type is also somewhat dynamic, particularly in upland areas. More than 390 native species occur in the park. Native forbs comprise at least 66% of the species richness at the 1,000 m² scale. Park-wide, species not native to the central and northern Great Plains (including their ponderosa pine inclusions) comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. Most natural processes are sustained. All parts of the upland landscape except the tower, talus slopes, and redbeds (i.e., excluding areas that can support little or no vegetation) experience fire on average every 11–32 years (Fisher et al. 1987; Stambaugh et al. 2008), with fire locations varying temporally so that the park is

a mosaic of patches with different fire histories. Native pollinators provide services that ensure seed set sufficient to sustain native forb, shrub, and tree species. Populations of species culturally important to tribes with which the park consults are sustained. Controlled flooding along the Belle Fourche River occasionally creates open patches into which Plains cottonwood recruits.

Areas with Little or No Developed Soil (tower top and sides, redbeds). Vegetative cover is sparse, ranging from <1% on the sides of the tower and in some redbeds areas to ~25% on the top of the tower. Forbs dominate on the tower sides and in the redbeds, but grasses and shrubs co-dominate on the tower's summit, where skunkbush sumac, prairie sagewort, and big sagebrush comprise the shrub component and bluebunch wheatgrass dominates the grass component. On the tower sides and tops, lichens are abundant, and mosses are abundant on the tower top.

Based on: *Rhus trilobata* / *Pseudoroegneria spicata* Shrub Herbaceous, Phonolite Porphyry Sparse, and Redbeds Sparse vegetation associations.

Moderate to Steep Slopes with Developed Upland Soils. Vegetation is a mosaic of meadows/savannas (<5/ha of tree species of any size class), woodlands ≥ 5 trees with dbh >15 cm in 1,000 m² tree and canopy cover <50%, and forests (tree canopy cover $\geq 50\%$). Ponderosa pine is the overwhelmingly dominant tree species, but bur oak comprises a significant subcanopy component on the lowermost slopes, in drainage bottoms, and in more mesic situations like northerly slopes. Quaking aspen and, in more mesic locations, paper birch, may occur in patches with little or no pine canopy, and Rocky Mountain juniper forms a moderate (<50% cover) subcanopy in limited areas. Average density of larger (≥ 30 cm dbh) ponderosa pine stems within woodlands and forests is around 50 stems/ha, but larger stem density is diverse across the landscape, ranging from 15–150 stems/ha. Ponderosa pine basal area within wooded areas averages 10–15 m²/ha, but it too is diverse across the landscape, ranging from 1 to 35 m²/ha (Brown and Cook 2006). Denser stands occur primarily on north-facing slopes. Seedling density is adequate to ensure future recruitment of mature trees but generally low. All size classes (seedling, pole, tree) of pine and oak occur at least somewhere in the park. Fuel load from woody species is at a level that supports low intensity fires (8–10 tons/acre on average), and areas of fuel load higher than this are small (<10 ha). Herbaceous layer composition in woodlands and forests varies widely, with dominant species including short shrubs (creeping barberry, common snowberry, common juniper), grasses (little bluestem, false melic, poverty oatgrass, green needlegrass), and sedges (sun, Sprengel's). Meadows, which often occur on pockets of gentle slopes within more rugged terrain, comprise at least 25% of the mosaic and their composition resembles that described for gentle slopes below, although little bluestem is more abundant on thinner soils. Local diversity is high, with, on average, at least 8 native species occurring in a 1 m² area, and more than 30 species in 1,000 m².

Based on: Devils Tower National Monument Fire Management Plan (2004); *Pinus ponderosa* / *Mahonia repens* Forest, *Pinus ponderosa* / *Carex inops* ssp. *heliophila* Woodland, *Pinus ponderosa* / *Juniperus communis* Woodland, *Pinus ponderosa* / *Pseudoroegneria spicata* Woodland, and *Pinus ponderosa* / *Quercus macrocarpa* Woodland vegetation associations.

Gentle Slopes outside of the Riparian Area. Vegetation is grassland with nearly continuous cover (foliar cover >90%) and canopy height generally 0.6–1.0 m. Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate (<1.5 cm). A mixture of warm- and cool-season, bunch and rhizomatous, mid-height grasses dominates (cover 75–85%) and a diverse array of forbs flowering throughout the season comprises 10–15% of cover. Woody plants (shrubs and trees) together comprise no more than 10% of cover. Dominant grass species include little bluestem and western wheatgrass; sideoats grama, needle-and-thread, green needlegrass, bluebunch wheatgrass, and sandberg bluegrass may also be prominent, with prairie sandreed occurring in sandy areas and blue grama sometimes as a subdominant. Big sagebrush and winterfat may comprise conspicuous portions of the shrub component. In the prairie dog town, which occupies 14–19 ha, vegetation height is low (<20 cm), but areas of bare ground are limited to the area associated with prairie dog holes. Species tolerant of very high grazing pressure dominate, including blue grama, buffalograss, purple threeawn, and bigbract vervain. Throughout the gently-sloped vegetation zone, local diversity is moderately high with, on average, at least 7 native species occurring in a 1 m² area, and at least 25 species in 1,000 m².

Based on: Clayey, Loamy, Sandy, Shallow Clayey, Shallow Loamy, Thin Upland, and Overflow ecological site descriptions; *Schizachyrium scoparium* – *Bouteloua (curtipendula, gracilis)* – *Carex filifolia* Herbaceous vegetation association, and Prairie Dog Town Disturbed Community description.

Riparian Area (stream terraces with water table usually below surface). Vegetation is a patchy woodland with tree canopy cover between 10 and 50%. The shrub layer is well developed, especially along the stream's edge. The herbaceous layer is almost continuous (total cover >90%) except in areas of dense shade or recent scouring flood. Plains cottonwood, peachleaf willow, bur oak, and boxelder occur in a variety of size classes (seedling, pole, tree). The shrub layer near stream's edge is dense with water-loving species like narrowleaf willow, whereas more upland species including chokecherry, American plum, silver buffaloberry, and western snowberry occur away from the streamside. Silver sagebrush occurs in some areas with no tree canopy. The herbaceous layer is dominated (70–80% of cover) by mesic-adapted grasses and sedges including western wheatgrass, big bluestem, switchgrass, Emory's sedge, woolly sedge, and clustered field sedge. Forbs comprise 5–15% of production and often include western yarrow, Cuman ragweed, white sagebrush, American licorice, and, closer to the river, field horsetail. A variety of disturbance-adapted annuals dominates areas recently scoured by flooding. Plant diversity is moderate with, on average, at least 6 native species occurring in a 1 m² area, and at least 20 species in 1,000 m².

Based on: Lowland ecological site description; *Artemisia cana* ssp. *cana* / *Pascopyrum smithii* Shrub Herbaceous, *Populus deltoides* – (*Salix amygdaloides*) / *Salix (exigua, interior)* Woodland, and *Fraxinus pennsylvanica* – *Ulmus Americana* / *Symphoricarpos occidentalis* Forest vegetation associations.

Fort Laramie National Historic Site

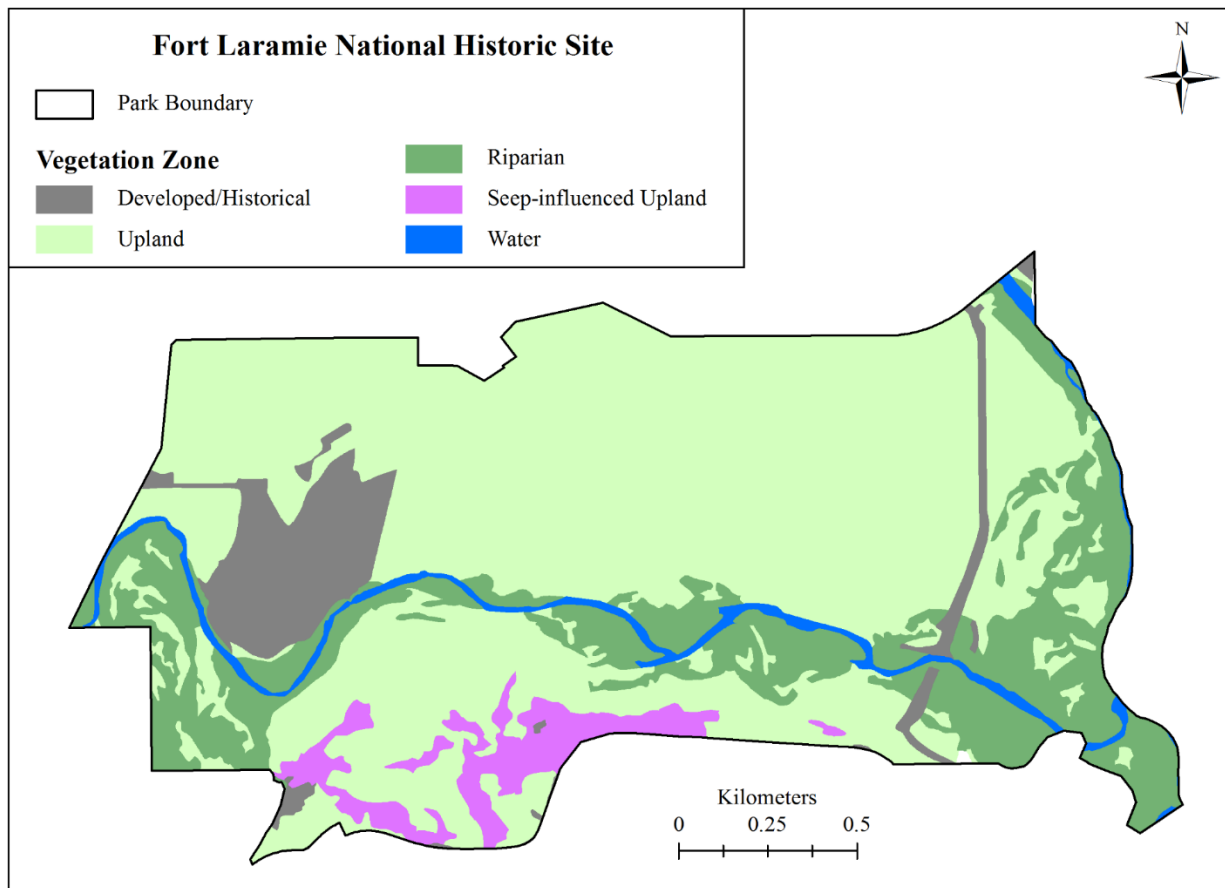


Figure A4. Vegetation zones for Fort Laramie National Historic Site vegetation conditions.

Park-wide. The vegetation of the historic parade grounds and developed areas reflects that found in similar areas of the park as much as possible while maintaining historic landscapes and being sustainable in the face of the human activity it supports. Except when culturally significant, plant species are native to the central or northern Great Plains, are drought tolerant, and require little maintenance.

Outside of the historic parade grounds and other developed areas, species composition fluctuates within landscape settings described below as climate, herbivory, and other natural processes exert their individual and interactive effects on species. More than 225 native species occur in the park. Park-wide, species not native to the central and northern Great Plains comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. Native pollinators provide services that ensure seed set sufficient to sustain native forb, shrub and tree species. Populations of species culturally important to tribes with which the park consults are sustained.

Uplands and upper floodplains outside the influence of irrigation canal seepage (soils rarely saturated). The canopy is generally 60–100 cm tall, though it is shorter (<20 cm) in patches dominated by short grasses, and total foliar cover is moderate to high (>75%). Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate (<1.5 cm). Vegetation is dominated by a mixture of short and mid-height, warm- and cool-season grasses and sedges, which together comprise 70–95% of plant cover. Common grass and grass-like species are blue grama, needle-and-thread, little bluestem, western wheatgrass, and threadleaf sedge, with prairie sandreed and sand bluestem occurring in sandier areas. Blue grama and threadleaf sedge are dominant in areas with a history of heavy grazing. A diverse array of forbs (>66% of native species at the 1,000 m² scale), with species that bloom throughout the growing season, comprise 5–15% of plant cover. Scurfpeas, dotted blazing star, scarlet beeblossom, scarlet globemallow, hairy false goldenaster, prairie clovers, and rush skeletonplant are some of these forbs. Woody, woody-like, and succulent plants such as prairie sagewort, sand sagebrush, broom snakeweed, prickly-pear cactus, and soapweed yucca comprise generally <10% of plant cover. Plant diversity is moderate, with, on average, at least 7 native species occurring in a 1 m² area, and more than 20 species in 1,000 m².

Based on: Sandy ecological site description; *Hesperostipa comata* – *Bouteloua gracilis* – *Carex filifolia* Herbaceous, and *Hesperostipa comata* – *Yucca glauca* Herbaceous vegetation associations.

Upper floodplain terrace under the influence of irrigation canal seepage (soils intermittently to frequently saturated). The canopy is generally 50–100 cm tall, and total foliar cover is high (>90%). Ground cover is dominated by litter (>90% of ground cover), and bare soil is uncommon (<10% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate to high (<3 cm). Vegetation is dominated by sedges, rushes, horsetails, cattails, and/or grasses, which together comprise 85–95% of plant cover. Nebraska sedge and smooth horsetail are common, though grasses such as alkali sacaton and saltgrass may occur in drier portions and broadleaf cattail in wetter portions. Forbs are generally uncommon (<5% of cover), as are woody species (<5% cover), though Plains cottonwood or willows may occur. Plant diversity is low to moderate, with, on average, at least 4 native species occurring in a 1 m² area, and more than 10 species in 1,000 m².

Based on: Saline subirrigated ecological site description; *Carex nebrascensis* Herbaceous and *Typha latifolia* Western Herbaceous vegetation associations.

Riparian Zone (as delineated by NGPN monitoring). Vegetation is a patchy woodland with tree canopy cover between 10 and 50% and height of 5–18 m. The shrub layer (up to 5 m tall) is diverse and variable (i.e., not continuous). The herbaceous layer (<2 m) ranges from almost continuous cover to nearly none, with the latter in areas of dense tree or shrub canopy and on recently formed or scoured sandbars. Plains cottonwood, peachleaf willow, green ash, boxelder, and other cottonwood species comprise the canopy and subcanopy, and they occur in a variety of age classes (seedling, sapling, mature). Shrub layer species include western snowberry, roses, silver sagebrush, and

narrowleaf willow. The herbaceous layer is also diverse and variable. The water's edge often supports high (>75%) cover of prairie cordgrass. Species composition on recently formed or scoured sandbars is highly dependent on the surrounding vegetation, but annual species are more common than on older surfaces. Older soil surfaces are dominated (65–85% of cover) by grasses and sedges including western wheatgrass, big bluestem, needle-and-thread, prairie sandreed, little bluestem, and slender wheatgrass. Forbs comprise 5–10% of cover and are highly variable in composition. Plant diversity is high with, on average, at least 7 native species occurring in a 1 m² area, and at least 25 species in 1,000 m².

Based on: Loamy Lowland and Sandy Lowland ecological site descriptions; *Spartina pectinata* – *Scirpus pungens* Herbaceous, *Populus deltoides* / *Symphoricarpos occidentalis* Woodland, and *Salix exigua* / Barren Shrubland vegetation associations

Little Bighorn Battlefield National Monument

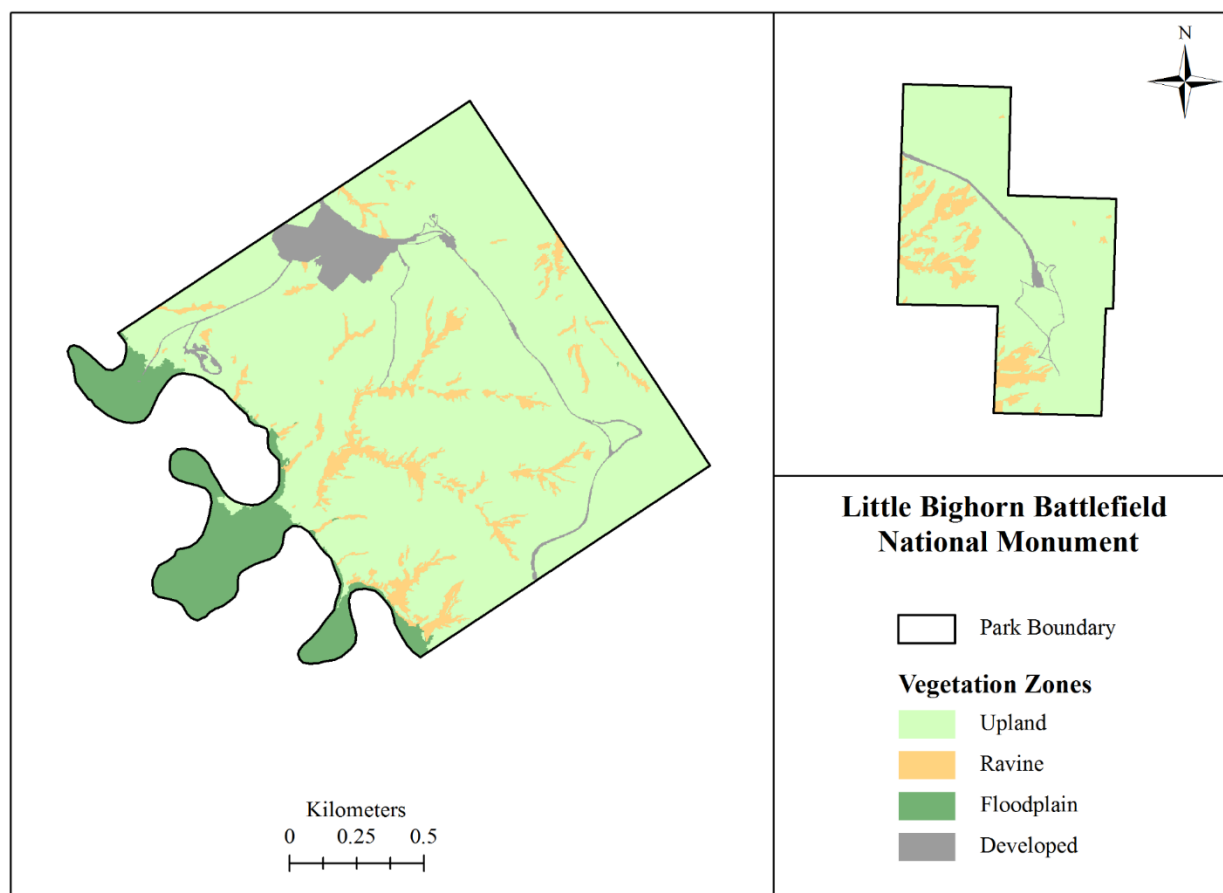


Figure A5. Vegetation zones for Little Bighorn Battlefield National Monument desired conditions.

Park-wide. The vegetation of the cemetery and developed areas reflects that found in similar areas of the park as much as possible while maintaining historic landscapes and being sustainable in the face of the human activity it supports. Except when culturally significant, plant species are native to the central or northern Great Plains, are drought tolerant, and require little maintenance.

Outside of the cemetery and other developed areas, species composition varies with position on the landscape and fluctuates within and among these positions as climate, fire, herbivory, and other natural processes exert their individual and interactive effects on species. The landscape is reminiscent of that during the 1876 Battle of Little Bighorn. It is dominated by mixed-grass prairie, with a varying shrub component, on the upland ridges and their gentler slopes and valleys. Narrow ravines (a.k.a. draws, gullies, coulees) dissecting the uplands support a variety of upland shrublands, and the Little Bighorn River floodplain supports a mosaic of riparian forest, lowland shrublands, and mesic herbaceous vegetation. More than 195 native species occur in the park. Species not native to the central and northern Great Plains comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. Populations of species culturally important to tribes

with which the park consults are sustained. Vegetation and its management ensure the protection and preservation of archeological resources.

Uplands. Mixed-grass prairie composition varies across the landscape, influenced by soil type, topography, slope position and aspect, time since fire, and current and historical grazing. The herbaceous canopy is generally 60–100 cm tall, though it is shorter (<20 cm) in patches dominated by short grasses. Canopy cover is high (>85%) and is dominated by grasses. Litter of moderate depth (<1.5 cm) covers most of the ground (50–80% of ground cover), bare soil is uncommon (5–15% of ground cover), and biological crusts are present (1–2% of ground cover). Graminoids (grasses and sedges) comprise 55–85% of canopy cover, forbs 10–25%, and smaller shrubs (e.g., prairie sagewort, soapweed yucca, and Wyoming big sagebrush) up to 20%. Trees are not present or are very rare (<0.1% canopy cover). Species composition consists of tall and medium cool-season (green needlegrass, needle-and-thread, bluebunch wheatgrass, western wheatgrass) and warm-season grasses (sideoats grama, prairie sandreed); short grasses and sedges (Sandberg bluegrass, prairie Junegrass, blue grama, threadleaf sedge); a diverse forb component (blacksamson echinacea, common yarrow, bladderpods, prairie clovers, milkvetches, scarlet globemallow); and a few subshrubs (e.g., prairie sagewort). Shrubs are generally silver or Wyoming big sagebrush but others (e.g., skunkbush sumac, greasewood, western snowberry) become more prominent near gullies. Shortgrasses and shrubs are more abundant, and tall and medium-height grasses less abundant, in areas with a history of heavy grazing, and shrubs increase with time since fire. Local native species richness is high, with at least 11 native species in one square meter, and at least 30 native species in 1,000 m², on average. Native forbs comprise at least 66% of the species richness at the 1,000 m² scale.

Based on: Clayey ecological site description; *Pascopyrum smithii* – *Nassella viridula* Herbaceous, *Pseudoroegneria spicata* – *Carex filifolia* Herbaceous, *Artemisia cana* ssp. *cana* / *Pascopyrum smithii* Shrub Herbaceous, *Rhus trilobata* / *Pseudoroegneria spicata* Shrub herbaceous, and *Sarcobatus vermiculatus* / *Pascopyrum smithii* – (*Elymus lanceolatus*) Shrub Herbaceous vegetation associations.

Ravines. Vegetation structure and composition of ravines resembles that of the adjoining prairie, but shrubs comprise a larger proportion of the canopy, averaging 10–15% of canopy cover but constituting nearly 100% in small patches. Although one shrub species may dominate the shrub layer, multiple species often occur together. Rocky Mountain juniper woodland may occur on very steep, north-facing slopes but is confined to small patches (<0.5 ha) and a very small part of the landscape (<2 ha total). Local native species richness is high, with at least 11 native species in one square meter, and at least 32 native species in 1,000 m², on average. Native forbs comprise at least 66% of the species richness at the 1,000 m² scale.

Based on: Shallow clay ecological site description; *Juniperus scopulorum* / *Pseudoroegneria spicata* Woodland, *Symphoricarpos occidentalis* Shrubland, *Artemisia cana* ssp. *cana* / *Pascopyrum smithii* Shrub Herbaceous, *Rhus trilobata* / *Pseudoroegneria spicata* Shrub herbaceous, and *Sarcobatus vermiculatus* / *Pascopyrum smithii* – (*Elymus lanceolatus*) Shrub Herbaceous vegetation associations.

Floodplain. The nearly flat terraces along the Little Bighorn River support a mixture of deciduous forest or woodland, lowland shrublands, wet prairie, and sparse floodplain vegetation. Vegetation varies with elevation above the river and time since flooding. Deciduous trees, especially Plains cottonwood and green ash, exhibit recruitment sufficient to ensure their long-term viability. The shrub layer in deciduous woodlands and forests is diverse and variable in cover and composition; species include chokecherry, western snowberry, rose, and silver buffaloberry. The herbaceous layer in riparian forests and woodlands is also diverse and variable, with upland prairie species mixed with mesic and shade-tolerant graminoids and forbs. Flood-tolerant willows (e.g., narrowleaf willow) form dense stands along the riverbanks, and other shrubs (listed above) may form shrublands with no tree canopy on higher terraces. Stands of prairie cordgrass and other tall, wet-prairie-like graminoids occur in areas with no tree or shrub canopy cover.

Based on: *Populus deltoides* – *Fraxinus pennsylvanica* Forest, *Fraxinus pennsylvanica* / *Prunus virginiana* Forest, *Salix exigua* Temporarily Flooded Shrubland, *Shepherdia argentea* Shrubland, *Symphoricarpos occidentalis* Shrubland, and Great Plains Floodplain and Riverbank Tall Herbaceous vegetation associations.

Scotts Bluff National Monument

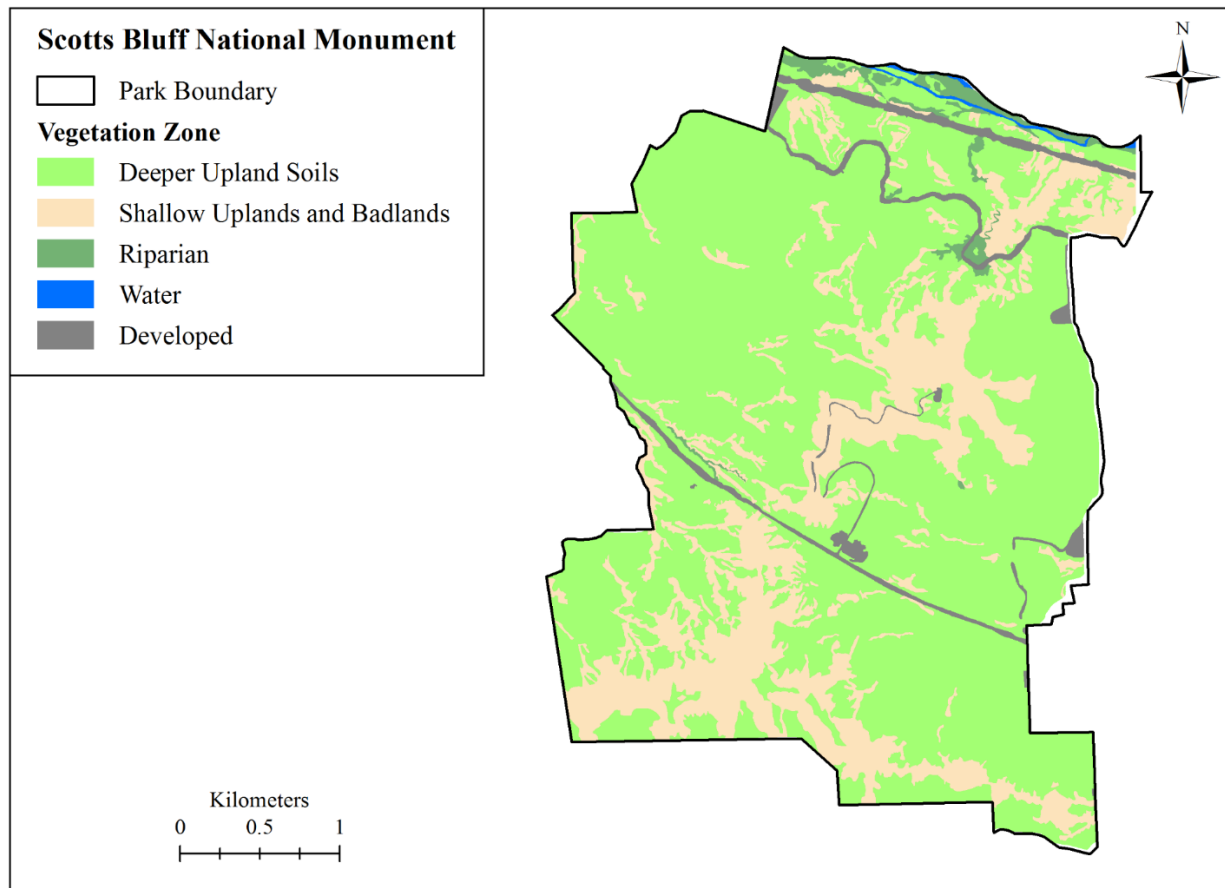


Figure A6. Vegetation zones for Scotts Bluff National Monument desired conditions.

Developed Areas. The vegetation of developed areas reflects that found in similar areas of the park as much as possible while maintaining historic and cultural landscapes and being sustainable in the face of the human activity it supports. Except when culturally significant, plant species are native to the central or northern Great Plains, are drought tolerant, and require little maintenance.

Landscape outside Developed Areas. Species composition fluctuates within landscape settings as climate, fire, herbivory, and other natural processes exert their individual and interactive effects on species. More than 280 native species occur in the park. Park-wide, species not native to the central and northern Great Plains comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. Most natural processes are sustained. All parts of the burnable landscape (i.e., excluding areas that can support little or no vegetation) experience fire on average every 9–13 years (Guyette et al. 2015), with fire locations varying temporally so that the park is a mosaic of time-since-fire. Native pollinators provide services that ensure seed set sufficient to sustain native forb, shrub and tree species. Populations of species culturally important to tribes with which the park consults are sustained.

Deeper Upland Soils (plains, hillsides, and some flat hilltops). The canopy is generally 60–150 cm tall, though it is shorter (<20 cm) in patches dominated by short grasses, and total foliar cover is high (average >90%). Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate (<1.5 cm). Vegetation is dominated by a mixture of short and mid-height, warm- and cool-season grasses and sedges, which together comprise 70–95% of plant cover. Common grass and grass-like species are blue grama, needle-and-thread, sideoats grama, western wheatgrass, and threadleaf sedge, with prairie sandreed and sand bluestem occurring in sandier areas. Blue grama and threadleaf sedge are dominant in areas with a history of heavy grazing. A diverse array of forbs, with species that bloom throughout the growing season, comprise 5–15% of plant cover. Scurfpeas, dotted blazing star, scarlet beeblossom, scarlet globemallow, prairie coneflower, prairie clovers, and rush skeletonplant are some of these forbs, with bush morningglory in sandier areas. Woody, woody-like, and succulent plants such as winterfat, prairie sagewort, broom snakeweed, prickly-pear cactus, and soapweed yucca comprise generally <10% of plant cover, though up to 15% in sandier areas where yucca is particularly noticeable. Local diversity is moderate, with, on average, at least 6 native species occurring in a 1 m² area and more than 20 species in 1,000 m². Prairie dog towns occupy <40 ha and generally occur in flat to gently sloping areas of the mixed-grass prairie. In these areas, graminoids comprise a smaller proportion of the plant community than in other prairie areas (65–70%, compared to 70–90%), and species tend to be more unpalatable or grazing- and disturbance-tolerant than those in the rest of the prairie. Examples of these species include purple three-awn, fetid marigold, prairie sagewort, and broom snakeweed. Bare soil in prairie dog towns does not exceed 50% of ground cover.

Based on: Limy Upland, Sandy, and Sands ecological site descriptions; *Andropogon hallii* – *Calamovilfa longifolia* Herbaceous, *Hesperostipa comata* – *Bouteloua gracilis* – *Carex filifolia* Herbaceous, and *Pascopyrum smithii* Herbaceous vegetation associations.

Shallow Uplands and Badlands (Steep slopes and tops of cliffs, escarpments, and outcrops; slopes of ravines that dissect plains). Vegetation is a mosaic of grassland, sparse (<50% foliar cover) herbaceous vegetation, shrubland, and, outside of the badlands, woodland. In the grassland patches, vegetation resembles that of deeper upland soils described above, though with more thickspike wheatgrass. Sparse vegetation is less dominated by graminoids compared to grasslands, with species such as tenpetal blazingstar, Hooker's sandwort, phloxes, fewflower buckwheat, and Nuttall's biscuitroot comprising the forb component and Parry's rabbitbrush, broom snakeweed, fourwing saltbrush, and rubber rabbitbrush comprising the shrub component. Regionally rare species such as double twinpod, desert wirelettuce, silverleaf phacelia, and spotted fritillary persist in the sparse vegetation or grassland patches. Bare ground cover in sparse vegetation may exceed 50% in some areas. Ponderosa pine and Rocky Mountain juniper woodlands are restricted to the tops and upper, steep, north-facing sides of bluffs or in very steep ravines. Tree canopy cover within these areas is low enough to allow for a discontinuous tree/tall-shrub subcanopy, a well-developed deciduous shrub layer (e.g., mountain mahogany, skunkbush sumac, currants), and patches of a prairie-like herbaceous stratum but with more shade-tolerant species such as littleseed ricegrass. Mountain mahogany shrublands are limited to steep, eroding slopes and include a native grass and forb

component such as sideoats grama, Indian ricegrass, and aromatic aster. Plant diversity is higher than in deeper soils with, on average, at least 7 native species occurring in a 1 m² area, and at least 35 species in 1,000 m².

Based on: Shallow, Shallow Loamy, and Loess Breaks ecological site descriptions; *Juniperus scopulorum* / *Pipatatheropsis micrantha* Woodland, *Pinus ponderosa* / *Juniperus scopulorum* Woodland, *Cercocarpus montanus* / *Bouteloua curtipendula* Shrubland, Eroding Great Plains Badlands Sparse, Siltstone – Clay Butte Sparse, Inland Siltstone Bluff / Cliff, and Eroding Great Plains Slopes Sparse vegetation associations.

Riparian (stream terraces with water table usually below surface). [Desired conditions for this general area were not determined for this project.]

Wind Cave National Park

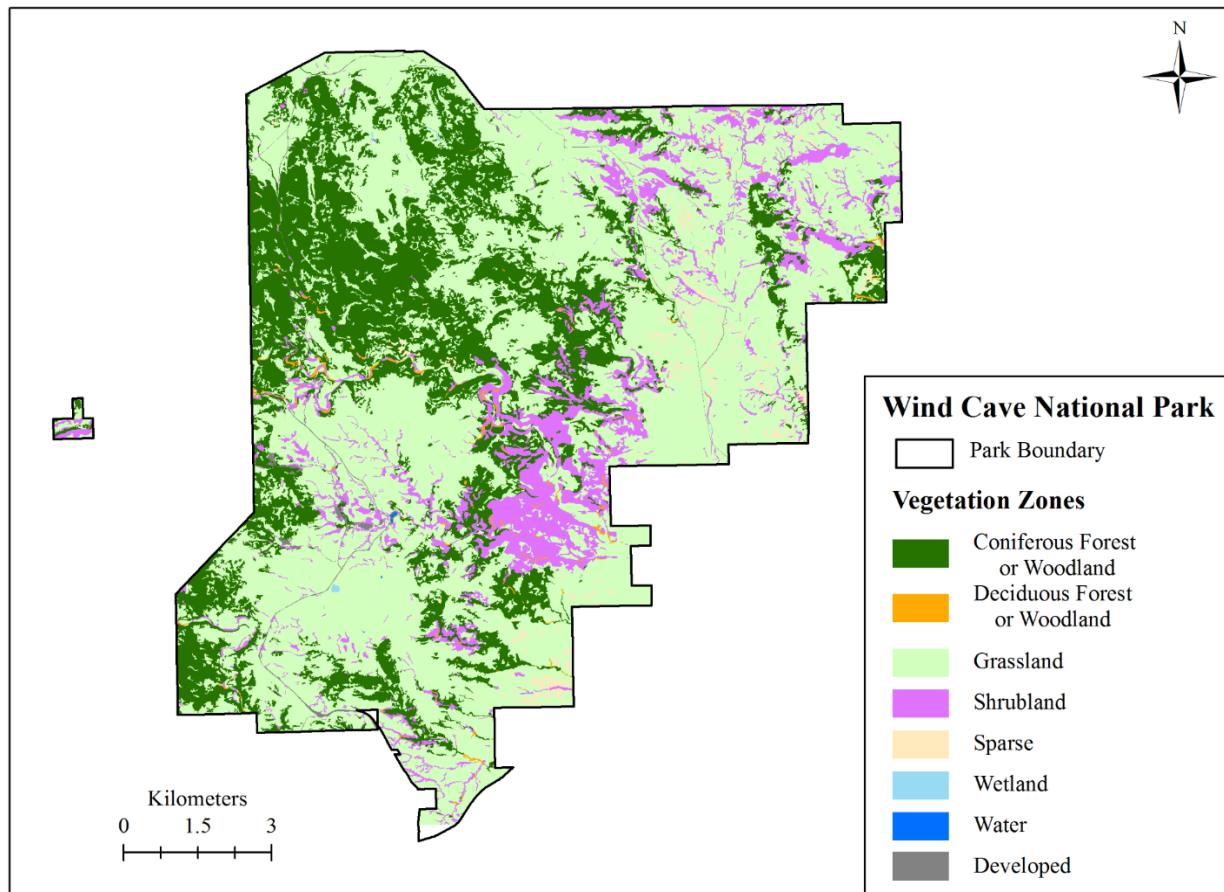


Figure A7. Vegetation zones for Wind Cave National Park desired conditions.

Park-wide. The vegetation of developed areas (visitor center, administrative buildings, housing, historic structures) reflects that found in similar areas of the park as much as possible while maintaining historic and ethnographic landscapes and being sustainable in the face of the human activity it supports. Landscaped vegetation (e.g., mowed lawns) comprises less than 0.25% of the park's area. Except when culturally significant, plant species are native to the central or northern Great Plains (including their ponderosa pine inclusions), are drought tolerant, and require little maintenance. Although listed in the park General Management Plan as a developed area, the water supply area is not managed as a developed area.

Outside of developed areas, the landscape is a mosaic of vegetation types distributed according to the percent in Table A2, with forest, woodland, and shrubland occurring primarily on steeper slopes and in the bottoms of canyons and steep valleys. Proportions of vegetation types on the landscape fluctuate within the desired proportions as climate, fire, herbivory, and other natural processes exert their individual and interactive effects on species. Species composition also fluctuates within vegetation types in response to natural processes. Position on the landscape of each vegetation type is also somewhat dynamic, particularly in upland areas. More than 450 native species occur in the park.

Local diversity is high, with at least 11 native species in a square meter, and at least 38 native species in 1,000 m², when averaged across the park. Native forbs comprise at least 66% of the species richness at the 1,000 m² scale. Park-wide, species not native to the central and northern Great Plains (including their ponderosa pine inclusions) comprise less than 5% of vegetation cover, and less than 0.5% of the landscape is dominated by exotic species. Natural processes are sustained. All parts of the landscape except rock outcrops and redbeds (i.e., excluding areas that can support little or no vegetation) experience fire on average every 10–12 years (Brown and Sieg 1999), with fire locations varying temporally so that the park is a mosaic of time-since-fire. Grazing by a diverse community of native wildlife (bison, pronghorn, elk, deer, and prairie dogs) throughout the park ensures a mosaic of herbaceous vegetation types across the landscape but especially in prairies. Native pollinators provide services that ensure seed set sufficient to sustain native forb, shrub and tree species. Populations of species culturally important to tribes with which the park consults are sustained.

Table A2. Desired distribution of general vegetation types in Wind Cave National Park.

General Vegetation Type	Percentage of Park
Mixed-grass Prairie and Savanna	60–85
Coniferous Forest and Woodland	5–20
Shrubland	5–15
Deciduous Forest and Woodland	0.5–15
Other Native Vegetation Types	–
Sparse Vegetation	<1
Wetland	0.1

Mixed-grass Prairie and Savanna. Mixed-grass prairie occurs anywhere on the landscape except in areas with saturated soils. Its composition varies with position on the landscape and is influenced by soil type, topography, slope position and aspect, time since fire, and current and historical grazing. The canopy is generally 60–100 cm tall, though it is shorter (<20 cm) in patches dominated by short grasses, and total foliar cover is high (average >100%). Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common. Litter depth is moderate (<1.5 cm). Graminoids, forbs, and shrubs comprise 70–90%, 10–15%, and <15% of plant cover, respectively. Tree species are rare, fewer than 5 per ha of any size class. Mid-height and tall warm-season grasses like sideoats grama, little bluestem, and big bluestem dominate higher, drier, steeper, rockier sites (stony hills and thin upland ecological sites). Mid-height cool-season grasses, upland sedges (threadleaf, needle leaf, and sun), and short warm-season grasses (e.g., blue grama, hairy grama) are also present in these sites and become more prominent in areas with a history of heavy grazing. Mid-height cool-season grasses like western wheatgrass, green needlegrass, and needle-and-thread dominate lower, moister, flatter, and deeper soils (loamy, clayey, and shallow loamy ecological sites), with short grasses (e.g., blue grama and buffalograss) and upland sedges becoming more abundant to dominant in areas with

a long history of heavy grazing. Prairie dog towns occupy 485–1,450 ha (~3–11%) of the park and generally occur in flat to gently sloping areas of the mixed-grass prairie. In these areas, graminoids comprise a smaller proportion of the plant community than in other prairie areas (65–70%, compared to 70–90%), and species tend to be more unpalatable or grazing- and disturbance-tolerant than those in the rest of the prairie. Examples include purple three-awn, fetid marigold, deathcamas, prairie sagewort, and broom snakeweed. Bare soil in prairie dog towns does not exceed 50% of ground cover. Savanna can occur anywhere on the landscape that mixed-grass prairie does, but it tends to be in the vicinity of more heavily wooded areas. It is essentially mixed-grass prairie with widely spaced trees (5–50 per ha of each of three dbh classes: <2.5 cm, 2.5–15 cm, and >15 cm) and low fuel loading by woody species (<5 tons per acre, <1.12 kg/m²).

Based on: Clayey, loamy, shallow loamy, stony hills, thin upland, and very shallow ecological site descriptions; *Andropogon gerardii* – *Schizachyrium scoparium* Western Great Plains Herbaceous, *Pascopyrum smithii* – *Nassella viridula* Herbaceous, *Schizachyrium scoparium* – *Bouteloua (curtipendula, gracilis)* – *Carex filifolia* Herbaceous, *Stipa comata* – *Bouteloua gracilis* – *Carex filifolia* Herbaceous, and Prairie Dog Town Grassland Complex vegetation associations

Coniferous Forest and Woodland. Rocky Mountain juniper is confined to scattered individuals on rocky outcrops. Density of larger (dbh ≥30 cm) ponderosa pine trees within wooded areas (i.e., areas with ≥50 individual trees with dbh > 15 cm per ha) is diverse across the landscape, ranging from 50 to 350 stems/ha (Brown and Cook 2006). Ponderosa pine basal area within wooded areas is diverse across the landscape, ranging from 3 to 40 m²/ha. Denser stands occur primarily on north-facing slopes. Seedling density is adequate to ensure future recruitment of mature trees but generally low; all size classes (seedling, pole, tree) are present in the park. Fuel load increases as stand density increases, but on average it is at a level that supports low intensity fires (1.8–2.2 kg/m²). Herb-layer vegetation resembles that of the mixed-grass prairie in most areas, but its cover is lower (can be <50%), less graminoid-dominated, and includes more shade-tolerant species in stands with greater tree canopy cover. A well-developed shrub layer (>25% cover) occurs in more mesic sites and may include chokecherry, common juniper, ninebark, snowberry, western poison ivy, currants and/or gooseberries. Ground cover is dominated by litter (70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common.

Based on: *Pinus ponderosa* / *Prunus virginiana* Forest, *Pinus ponderosa* / *Juniperus communis* Woodland, *Pinus ponderosa* / *Pascopyrum smithii* Woodland, *Pinus ponderosa* / *Schizachyrium scoparium* Woodland, and *Pinus ponderosa* / *Carex inops* ssp. *heliophila* Woodland vegetation associations

Shrubland. Shrublands occur throughout the landscape but most consistently occur on limestone slopes outside of conifer forest and woodlands (i.e., mountain mahogany) and in draws and drainage bottoms (e.g., chokecherry, western snowberry). Shrub foliar cover (absolute) is 20–50% and tree density is <10 stems (dbh >15 cm) in 1,000 m². Herb-layer cover ranges widely, from less than 10 to >75%, but composition resembles that of mixed-grass prairie. Ground cover is dominated by litter

(70–90% of ground cover), and bare soil is uncommon (5–15% of ground cover) except in the growing season following a fire, when bare soil is more common.

Based on: *Cercocarpus montanus* / *Bouteloua curtipendula* Shrubland, *Prunus virginiana* Shrubland, and *Symphoricarpos occidentalis* Shrubland vegetation associations

Deciduous Forest and Woodland. Deciduous forest and woodland characterized by Plains cottonwood, boxelder, green ash, American elm, or bur oak generally occur on level bottoms of drainages. Quaking aspen and paper birch woodlands or forests generally occur in previously burned areas typically occupied by ponderosa pine. Deciduous tree canopy cover is at least 10%. Total shrub cover can be >50% but is variable, as is shrub composition. Herbaceous cover is also variable in cover (usually <50%) and composition. Tree species in non-aspen or birch deciduous forests and woodlands occur in a variety of age classes that provide for sustainable, natural recruitment.

Based on: *Fraxinus pennsylvanica* – *Ulmus Americana* / *Symphoricarpos occidentalis* Forest, *Acer negundo* / *Prunus virginiana* Forest, and *Populus deltoids* / *Symphoricarpos occidentalis* Woodland vegetation associations

Other Native Vegetation Types (Wetlands, Sparse Vegetation). Other native vegetation communities are in conditions that provide for natural recruitment into appropriate habitat areas. Sparse vegetation types (<10% cover) are limited to rock outcrops and redbeds; the latter supports species rare elsewhere in the park.

Plant taxa in Appendix A

Table A3. Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by common name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Common Name	Scientific Name
alkali sacaton	<i>Sporobolus airoides</i>
American elm	<i>Ulmus americana</i>
American licorice	<i>Glycyrrhiza lepidota</i>
American plum	<i>Prunus americanus</i>
aromatic aster	<i>Symphyotrichum oblongifolium</i>
Baltic rush	<i>Juncus arcticus</i> ssp. <i>littoralis</i> (<i>Juncus balticus</i>)
Barr's milkvetch	<i>Astragalus barrii</i>
big bluestem	<i>Andropogon gerardii</i>
big sagebrush	<i>Artemisia tridentata</i>
bigbract vervain	<i>Verbena bracteata</i>
blacksamson echinacea	<i>Echinacea angustifolia</i>
bladderpods	<i>Lesquerella</i>
blue skullcap	<i>Scutellaria lateriflora</i>
bluebunch wheatgrass	<i>Pseudoroegneria spicata</i>
boxelder	<i>Acer negundo</i>
broom snakeweed	<i>Gutierrezia sarothrae</i>
buff fleabane	<i>Erigeron ochroleucus</i>
buffalograss	<i>Bouteloua dactyloides</i>
bule grama	<i>Bouteloua gracilis</i>
bur oak	<i>Quercus macrocarpa</i>
bush morningglory	<i>Ipomoea leptophylla</i>
butte candle	<i>Cryptantha celosioides</i>
Canada wildrye	<i>Elymus canadensis</i>
cattails	<i>Typha</i>
chokecherry	<i>Prunus virginianus</i>
clustered field sedge	<i>Carex praeegracilis</i>

Table A3 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by common name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Common Name	Scientific Name
common juniper	<i>Juniperus communis</i>
common snowberry	<i>Symphoricarpos albus</i>
creeping barberry	<i>Berberis repens</i> (<i>Mahonia repens</i>)
Cuman ragweed	<i>Ambrosia psilostachya</i>
currants, gooseberries	<i>Ribes</i>
deathcamas	<i>Toxicoscordion venosum</i> (<i>Zigadenus venenosus</i>)
desert wirelettuce	<i>Stephanomeria runcinata</i>
dotted blazing star	<i>Liatrus punctata</i>
double twinpod	<i>Physaria brassicoides</i>
eastern redcedar	<i>Juniperus virginiana</i>
Emory's sedge	<i>Carex emoryi</i>
false melic	<i>Schizachne purpurascens</i>
fetid marigold	<i>Dyssodia papposa</i>
few-flower buckwheat	<i>Eriogonum pauciflorum</i>
field horsetail	<i>Equisetum arvense</i>
fourwing saltbrush	<i>Atriplex canescens</i>
foxtail barley	<i>Hordeum jubatum</i>
goldenrods	<i>Solidago</i>
greasewood	<i>Sarcobatus vermiculatus</i>
green needlegrass	<i>Nassella viridula</i>
hairy false goldenaster	<i>Heterotheca villosa</i>
hairy grama	<i>Bouteloua hirsuta</i>
Hooker's sandwort	<i>Arenaria hookeri</i>
horsetails	<i>Equisetum</i>
Indian ricegrass	<i>Achnatherum hymenoides</i>
little bluestem	<i>Schizachyrium scoparium</i>
littleseed ricegrass	<i>Piptatheropsis micrantha</i>
Maximilian sunflower	<i>Helianthus maximiliani</i>

Table A3 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by common name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Common Name	Scientific Name
meadow-rues	<i>Thalictrum</i>
milkvetches	<i>Astragalus</i>
mountain mahogany	<i>Cercocarpus montanus</i>
narrowleaf stoneseed	<i>Lithospermum incisum</i>
narrowleaf willow	<i>Salix exigua</i>
Nebraska sedge	<i>Carex nebrascensis</i>
needle-and-thread	<i>Hesperostipa comata</i>
needleleaf sedge	<i>Carex duriuscula</i>
ninebark	<i>Physocarpus</i>
Nuttall's biscuitroot	<i>Lomatium nuttallii</i>
paper birch	<i>Betula papyrifera</i>
Parry's rabbitbrush	<i>Ericameria parryi</i>
peachleaf willow	<i>Salix amygdaloides</i>
peachleaf willow	<i>Salix amygdaloides</i>
phloxes	<i>Phlox</i>
Plains cottonwood	<i>Populus deltoides</i> ssp. <i>molinifera</i>
Plains muhly	<i>Muhlenbergia cuspidata</i>
Ponderosa pine	<i>Pinus ponderosa</i>
poverty oatgrass	<i>Danthonia spicata</i>
prairie clovers	<i>Dalea</i>
prairie coneflower	<i>Ratibida columnifera</i>
prairie cordgrass	<i>Spartina pectinata</i>
prairie Junegrass	<i>Koeleria macrantha</i>
prairie sagewort	<i>Artemisia frigida</i>
prairie sandreed	<i>Calamovilfa longifolia</i>
prairie sunflower	<i>Helianthus petiolaris</i>
prickly-pear cactus	<i>Opuntia</i>

Table A3 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by common name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Common Name	Scientific Name
purple three-awn	<i>Aristida purpurea</i>
quaking aspen	<i>Populus tremuloides</i>
rice cutgrass	<i>Leersia oryzoides</i>
Rocky Mountain juniper	<i>Juniperus scopulorum</i>
roses	<i>Rosa</i>
rough bugleweed	<i>Lycopus asper</i>
rubber rabbitbrush	<i>Ericameria nauseosa</i>
rush skeletonplant	<i>Lygodesmia juncea</i>
rushes	<i>Juncus</i>
saltbushes	<i>Atriplex</i>
saltgrass	<i>Distichlis spicata</i>
sand bluestem	<i>Andropogon gerardii</i> ssp. <i>hallii</i>
sand sagebrush	<i>Artemisia filifolia</i>
sandbar willow	<i>Salix interior</i>
sandberg bluegrass	<i>Poa secunda</i>
scarlet beeblossom	<i>Oenothera suffrutescens</i>
scarlet globemallow	<i>Sphaeralcea coccinea</i>
scurfpeas	<i>Pediomelum, Psoraleidum</i>
sedges	<i>Carex</i>
sideoats grama	<i>Bouteloua curtipendula</i>
silver buffaloberry	<i>Shepherdia argentea</i>
silver sagebrush	<i>Artemisia cana</i>
silverleaf phacelia	<i>Phacelia hastata</i>
skunkbush sumac	<i>Rhus trilobata</i>
slender wheatgrass	<i>Elymus trachycaulus</i>
smooth horsetail	<i>Equisetum laevigatum</i>
soapweed yucca	<i>Yucca glauca</i>
spiderworts	<i>Tradescantia</i>

Table A3 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by common name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Common Name	Scientific Name
spikerushes	<i>Eleocharis</i>
spotted fritillary	<i>Fritillaria atropurpurea</i>
Springel's sedge	<i>Carex sprengelii</i>
sun sedge	<i>Carex inops</i> ssp. <i>heliophila</i>
switchgrass	<i>Panicum virgatum</i>
tenpetal blazingstar	<i>Mentzelia decapetala</i>
thickspike wheatgrass	<i>Elymus lanceolatus</i>
threadleaf sedge	<i>Carex filifolia</i>
Visher's buckwheat	<i>Eriogonum visherii</i>
western poison ivy	<i>Toxicodendron rydbergii</i>
western snowberry	<i>Symphoricarpos occidentalis</i>
western wheatgrass	<i>Pascopyrum smithii</i>
western yarrow	<i>Achillea millefolium</i>
white sagebrush	<i>Artemisia ludoviciana</i>
wild mint	<i>Mentha arvensis</i>
willows	<i>Salix</i>
winterfat	<i>Krascheninnikovia lanata</i>
woolly sedge	<i>Carex pellita</i>
Wyoming big sagebrush	<i>Artemisia tridentata</i> ssp. <i>wyomingensis</i>

Table A4. Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by scientific name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Scientific Name	Common Name
<i>Acer negundo</i>	boxelder
<i>Achillea millefolium</i>	western yarrow
<i>Achnatherum hymenoides</i>	Indian ricegrass
<i>Ambrosia psilostachya</i>	Cuman ragweed
<i>Andropogon gerardii</i>	big bluestem
<i>Andropogon gerardii</i> ssp. <i>hallii</i>	sand bluestem
<i>Arenaria hookeri</i>	Hooker's sandwort
<i>Aristida purpurea</i>	purple three-awn
<i>Artemisia cana</i>	silver sagebrush
<i>Artemisia filifolia</i>	sand sagebrush
<i>Artemisia frigida</i>	prairie sagewort
<i>Artemisia frigida</i>	prairie sagewort
<i>Artemisia ludoviciana</i>	white sagebrush
<i>Artemisia tridentata</i>	big sagebrush
<i>Artemisia tridentata</i> ssp. <i>wyomingensis</i>	Wyoming big sagebrush
<i>Astragalus</i>	milkvetches
<i>Astragalus barrii</i>	Barr's milkvetch
<i>Atriplex</i>	saltbushes
<i>Atriplex cansescens</i>	fourwing saltbrush
<i>Berberis repens</i> (<i>Mahonia repens</i>)	creeping barberry
<i>Betula papyrifera</i>	paper birch
<i>Bouteloua curtipendula</i>	sideoats grama
<i>Bouteloua dactyloides</i>	buffalograss
<i>Bouteloua gracilis</i>	bule grama
<i>Bouteloua hirsuta</i>	hairy grama
<i>Calamovilfa longifolia</i>	prairie sandreed
<i>Carex</i>	sedges
<i>Carex duriuscula</i>	needleleaf sedge

Table A4 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by scientific name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Scientific Name	Common Name
<i>Carex emoryi</i>	Emory's sedge
<i>Carex filifolia</i>	threadleaf sedge
<i>Carex inops</i> ssp. <i>heliophila</i>	sun sedge
<i>Carex nebrascensis</i>	Nebraska sedge
<i>Carex pellita</i>	woolly sedge
<i>Carex praegracilis</i>	clustered field sedge
<i>Carex spengelii</i>	Springel's sedge
<i>Cercocarpus montanus</i>	mountain mahogany
<i>Cryptantha celosioides</i>	butte candle
<i>Dalea</i>	prairie clovers
<i>Danthonia spicata</i>	poverty oatgrass
<i>Distichlis spicata</i>	saltgrass
<i>Dyssodia papposa</i>	fetid marigold
<i>Echinacea angustifolia</i>	blacksamson echinacea
<i>Eleocharis</i>	spikerushes
<i>Elymus canadensis</i>	Canada wildrye
<i>Elymus lanceolatus</i>	thickspike wheatgrass
<i>Elymus trachycaulus</i>	slender wheatgrass
<i>Equisetum</i>	horsetails
<i>Equisetum arvense</i>	field horsetail
<i>Equisetum laevigatum</i>	smooth horsetail
<i>Ericameria nauseosa</i>	rubber rabbitbrush
<i>Ericameria parryi</i>	Parry's rabbitbrush
<i>Erigeron ochroleucus</i>	buff fleabane
<i>Eriogonum pauciflorum</i>	few-flower buckwheat
<i>Eriogonum visherii</i>	Visher's buckwheat
<i>Fritillaria atropurpurea</i>	spotted fritillary
<i>Glycyrrhiza lepidota</i>	American licorice

Table A4 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by scientific name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Scientific Name	Common Name
<i>Gutierrezia sarothrae</i>	broom snakeweed
<i>Helianthus maximiliani</i>	Maximilian sunflower
<i>Helianthus petiolaris</i>	prairie sunflower
<i>Hesperostipa comata</i>	needle-and-thread
<i>Heterotheca villosa</i>	hairy false goldenaster
<i>Hordeum jubatum</i>	foxtail barley
<i>Ipomoea leptophylla</i>	bush morningglory
<i>Juncus</i>	rushes
<i>Juncus arcticus</i> ssp. <i>littoralis</i> (<i>Juncus balticus</i>)	Baltic rush
<i>Juniperus communis</i>	common juniper
<i>Juniperus scopulorum</i>	Rocky Mountain juniper
<i>Juniperus virginiana</i>	eastern redcedar
<i>Koeleria macrantha</i>	prairie Junegrass
<i>Krascheninnikovia lanata</i>	winterfat
<i>Leersia oryzoides</i>	rice cutgrass
<i>Lesquerella</i>	bladderpods
<i>Liatrus punctata</i>	dotted blazing star
<i>Lithospermum incisum</i>	narrowleaf stoneseed
<i>Lomatium nuttallii</i>	Nuttall's biscuitroot
<i>Lycopus asper</i>	rough bugleweed
<i>Lygodesmia juncea</i>	rush skeletonplant
<i>Mentha arvensis</i>	wild mint
<i>Mentzelia decapetala</i>	tenpetal blazingstar
<i>Muhlenbergia cuspidata</i>	Plains muhly
<i>Nassella viridula</i>	green needlegrass
<i>Oenothera suffrutescens</i>	scarlet beeblossom
<i>Opuntia</i>	prickly-pear cactus
<i>Panicum virgatum</i>	switchgrass

Table A4 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by scientific name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Scientific Name	Common Name
<i>Pascopyrum smithii</i>	western wheatgrass
<i>Pediomelum</i> , <i>Psoralidium</i>	scurfpeas
<i>Phacelia hastata</i>	silverleaf phacelia
<i>Phlox</i>	phloxes
<i>Physaria brassicoides</i>	double twinpod
<i>Physocarpus</i>	ninebark
<i>Pinus ponderosa</i>	Ponderosa pine
<i>Piptatheropsis micrantha</i>	littleseed ricegrass
<i>Poa secunda</i>	sandberg bluegrass
<i>Populus deltoides</i> ssp. <i>molinifera</i>	Plains cottonwood
<i>Populus tremuloides</i>	quaking aspen
<i>Prunus americanus</i>	American plum
<i>Prunus virginianus</i>	chokecherry
<i>Pseudoroegneria spicata</i>	bluebunch wheatgrass
<i>Quercus macrocarpa</i>	bur oak
<i>Ratibida columnifera</i>	prairie coneflower
<i>Rhus trilobata</i>	skunkbush sumac
<i>Ribes</i>	currants, gooseberries
<i>Rosa</i>	roses
<i>Salix</i>	willows
<i>Salix amygdaloides</i>	peachleaf willow
<i>Salix amygdaloides</i>	peachleaf willow
<i>Salix exigua</i>	narrowleaf willow
<i>Salix interior</i>	sandbar willow
<i>Sarcobatus vermiculatus</i>	greasewood
<i>Schizachne purpurascens</i>	false melic
<i>Schizachyrium scoparium</i>	little bluestem
<i>Scutellaria lateriflora</i>	blue skullcap

Table A4 (continued). Scientific names for all common names of plant taxa mentioned earlier in this appendix are provided below, sorted by scientific name. Common names follow USDA Plants (<https://plants.usda.gov>, accessed March 1, 2021). Scientific names follow the Integrated Taxonomic Information System (ITIS, <https://www.itis.gov>, accessed March 1, 2021); when scientific names differ between USDA Plants and ITIS, the USDA Plants name follows in parentheses.

Scientific Name	Common Name
<i>Shepherdia argentea</i>	silver buffaloberry
<i>Solidago</i>	goldenrods
<i>Spartina pectinata</i>	prairie cordgrass
<i>Sphaeralcea coccinea</i>	scarlet globemallow
<i>Sporobolus airoides</i>	alkali sacaton
<i>Stephanomeria runcinata</i>	desert wirelettuce
<i>Symphoricarpos albus</i>	common snowberry
<i>Symphoricarpos occidentalis</i>	western snowberry
<i>Symphyotrichum oblongifolium</i>	aromatic aster
<i>Thalictrum</i>	meadow-rues
<i>Toxicodendron rydbergii</i>	western poison ivy
<i>Toxicoscordion venosum</i> (<i>Zigadenus venenosus</i>)	deathcamas
<i>Tradescantia</i>	spiderworts
<i>Typha</i>	cattails
<i>Ulmus americana</i>	American elm
<i>Verbena bracteata</i>	bigbract vervain
<i>Yucca glauca</i>	soapweed yucca

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Appendix B. Management Actions

This appendix provides detailed information about management actions in the Annual Brome Adaptive Management (ABAM) framework. The first section lists the general management actions initially considered to achieve the fundamental objectives of the ABAM framework and the reasons for their rejection from or inclusion in the decision support tool. The second section describes in detail the management actions included in the tool.

B.1. Full list of park management options considered

At the outset of the development of the ABAM framework, participants of the April 2017 structured decision-making workshop generated a list of potential management action types that could be applied to reduce the cover of annual bromes and the alternative actions associated with those types. As with most idea-generation exercises, feasibility was not considered until after the list was completed. At that point, workshop participants considered existing constraints on the ability of the National Park Service (NPS) to implement each action type (e.g., state of the science, size of area and terrain to be treated, availability of supplies and labor, NPS policy), as well as likelihood of the action being effective, to reduce the initial list to a subset of actions to be developed further for inclusion in the framework. Table B1 shows the outcome of these two steps.

Table B1. Initial list of management action types and associated alternative actions considered for the Annual Brome Adaptive Management (ABAM) framework; last column indicates if the type was rejected from further consideration and why. Action type groups indicate multiple components to be considered simultaneously.

Action Type Group	Action Type	Alternative Action 1	Alternative Action 2	Alternative Action 3	Alternative Action 4	Reject or Consider Further
Microbial pesticide	Microbial pesticide	<i>Pseudomonas fluorescens</i> strain ACK55	<i>Pseudomonas fluorescens</i> strain D7	“black fingers of death” (<i>Pyrenophora seminiperda</i>)	–	Rejected: still in development or demonstrated utility low (Germino and Lazarus 2020)
Fire	Fire timing	Spring	Fall	Target phenological stage	–	Consider further
	Fire type	Back	Head	Flank	–	Consider further
Managed grazing	Managed grazing species	Cattle	Goats	Bison	Horses	Rejected: Insufficient resources for necessary infrastructure and oversight; NPS preference for “natural”-appearing landscapes (native species, no internal fencing).
	Managed grazing timing	Spring	Fall	Target phenological stage	Year round	Rejected: Insufficient resources for necessary infrastructure and oversight; NPS preference for “natural”-appearing landscapes (native species, no internal fencing).
	Managed grazing intensity	Low	Medium	High	–	Rejected: Insufficient resources for necessary infrastructure and oversight; NPS preference for “natural”-appearing landscapes (native species, no internal fencing).
Herbicide	Herbicide type	Glyphosate	Imazapic	Indaziflam	–	Consider further
	Herbicide adjuvants	Many	–	–	–	Consider further
	Herbicide timing	Spring	Fall	Target phenological stage	–	Consider further

Table B1 (continued). Initial list of management action types and associated alternative actions considered for the Annual Brome Adaptive Management (ABAM) framework; last column indicates if the type was rejected from further consideration and why. Actions types groups indicate multiple components to be considered simultaneously.

Action Type Group	Action Type	Alternative Action 1	Alternative Action 2	Alternative Action 3	Alternative Action 4	Reject or Consider further
Herbicide (continued)	Herbicide concentration	Low	Medium	High	–	Consider further
Native planting	Native planting type	Seeds	Plugs	Transplants	Native hay	Temporarily rejected: Not clear whether necessary; try other actions first. Also, insufficient supply of appropriate native species and resources to self-produce them.
	Native seeding method	Drilling	Aerial broadcast	Hydroseeding	–	Temporarily rejected: Not clear whether necessary; try other actions first. Also, insufficient supply of appropriate native species and resources to self-produce them.
	Native planting style	Overseeding	Simultaneous (all at once)	Sequential	(e.g., grasses after forbs)	Temporarily rejected: Not clear whether necessary; try other actions first. Also, insufficient supply of appropriate native species and resources to self-produce them.
	Native planting timing	Spring	Fall	Dormant	Phenological stage	Temporarily rejected: Not clear whether necessary; try other actions first. Also, insufficient supply of appropriate native species and resources to self-produce them.
	Native planting composition	Infinite number of variations	–	–	–	Temporarily rejected: Not clear whether necessary; try other actions first. Also, insufficient supply of appropriate native species and resources to self-produce them.

Table B1 (continued). Initial list of management action types and associated alternative actions considered for the Annual Brome Adaptive Management (ABAM) framework; last column indicates if the type was rejected from further consideration and why. Actions types groups indicate multiple components to be considered simultaneously.

Action Type Group	Action Type	Alternative Action 1	Alternative Action 2	Alternative Action 3	Alternative Action 4	Reject or Consider further
Mechanical removal	Mechanical removal method	Hand pulling	Haying (remove clippings)	Mowing (leave clippings in place)	–	Rejected: Infeasible (all methods) and/or unlikely to be effective (haying and mowing)
	Mechanical removal timing	Spring	Fall	During a certain phenological stage	–	Rejected: Infeasible (all methods) and/or unlikely to be effective (haying and mowing)
Other	Other	Mulch	Tarp	Growing trees	Soil amendments	Rejected: Infeasible and highly uncertain effectiveness

B.2. Management actions included in the ABAM decision support tool

Prescribed fire and chemical herbicide were the two general management types considered feasible and likely to be effective for achieving the fundamental objectives of the ABAM framework. Table B2 lists the specific management actions included in the decision support tool and shows the criteria defining those actions.

Table B2. Management actions in the Annual Brome Adaptive Management (ABAM) decision support tool and the criteria defining them. “Year” in the description refers to the period (a) beginning immediately after vegetation monitoring has occurred in the park in the calendar year before the management action began (calendar year “x”), and (b) ending immediately before vegetation monitoring occurred in the park in the subsequent calendar year (“x+1”). This period is defined by the time that vegetation monitoring takes place in the park, not when a specific plot is monitored, because not all plots are monitored every year. Fire herbicide-combinations must be applied within this period to be considered a single management action. Columns 3–6 show the additional criteria used to assign management actions to one of the options in the ABAM tool. “—” indicates that a criterion is not relevant to an option. Actions that do not meet any of these sets of criteria are considered “other” actions that the ABAM tool user must either exclude from model updating or manually assign to a relevant management action option. The final column provides the exact form of the management action “level” for the management action variable in all R code used in the ABAM decision support system.

Name	Description	Earliest fire month	Latest fire month	Earliest herbicide month	Latest herbicide month	R name
none	No management action taken within the year	—	—	—	—	none
fall burn	Fire in September–February	Sep	Feb	—	—	burn.fall
spring burn	Fire in March–May	Mar	May	—	—	burn.spr
indaziflam only	Indaziflam applied any time of year; no fire in the same year	—	—	after veg monitoring in pre-treat yr (x)	before veg monitoring in yr x+1	indaz.only
imazapic–indaziflam	Imazapic–indaziflam mixture applied any time of year; no fire in the same year	—	—	after veg monitoring in pre-treat yr (x)	before veg monitoring in yr x+1	no.burn.imaz.indaz
fall burn then imazapic	Fire in September–February followed by imazapic application by following March	Sep	Feb	—	Mara	burn.fall.imaz

^a Shinn and Thill (2004) suggest that imazapic applied in the spring adversely affects native perennial vegetation. Therefore, we assume imazapic will not be applied during active spring growth, which usually occurs later than March.

Table B2 (continued). Management actions in the Annual Brome Adaptive Management (ABAM) decision support tool and the criteria defining them. “Year” in the description refers to the period (a) beginning immediately after vegetation monitoring has occurred in the park in the calendar year before the management action began (calendar year “x”), and (b) ending immediately before vegetation monitoring occurred in the park in the subsequent calendar year (“x+1”). This period is defined by the time that vegetation monitoring takes place in the park, not when a specific plot is monitored, because not all plots are monitored every year. Fire herbicide-combinations must be applied within this period to be considered a single management action. Columns 3–6 show the additional criteria used to assign management actions to one of the options in the ABAM tool. “—” indicates that a criterion is not relevant to an option. Actions that do not meet any of these sets of criteria are considered “other” actions that the ABAM tool user must either exclude from model updating or manually assign to a relevant management action option. The final column provides the exact form of the management action “level” for the management action variable in all R code used in the ABAM decision support system.

Name	Description	Earliest fire month	Latest fire month	Earliest herbicide month	Latest herbicide month	R name
fall burn then indaziflam	Fire in September–February followed by indaziflam application before veg monitoring	Sep	Feb	—	before veg monitoring in yr x+1	burn.fall.w.indaz
fall burn then imazapic–indaziflam	Fire in September–February followed by application of an imazapic–indaziflam mixture by following March	Sep	Feb	—	Mar	fall.burn.imaz.indaz
spring burn then indaziflam	Fire in March–May followed by indaziflam application before veg monitoring	Mar	May	—	before veg monitoring in yr x+1	burn.spr.w.indaz
indaziflam then spring burn	Indaziflam after veg monitoring followed by fire in March–May	Mar	May	after veg monitoring in pre-treat yr (x)	—	indaz.w.burn.spr

^a Shinn and Thill (2004) suggest that imazapic applied in the spring adversely affects native perennial vegetation. Therefore, we assume imazapic will not be applied during active spring growth, which usually occurs later than March.

B.2.1. Fire

As described in the main text (sections 2.1 and 3.4), fire is a natural part of northern mixed-grass prairie and Black Hills ponderosa pine woodland, and prescribed fire shows promise for at least short-term control of annual bromes and perhaps for exotic perennial grasses. Moreover, prescribed fire is a widely accepted tool in NPS and has been used for at least a decade in five ABAM parks. The initial list of management actions (Table B1) considered the time that a fire is applied, either by season or with respect to annual brome phenological stage, and the type of fire as potential factors influencing the effect of fire on annual bromes.

Although physically possible at any time of year that fuels are sufficiently dry, prescribed fires in the northern Great Plains (NGP) are generally conducted in spring or fall. Targeting the time to a specific (more vulnerable) phenological stage of one or more species is sometimes considered ideal for controlling exotic species (e.g., Willson and Stubbendieck 1997, 2000), but this is often difficult to achieve. Because of this difficulty, as well as the lack of information regarding fire effects on annual bromes at different stages of development, the ABAM decision support tool currently distinguishes fire management actions only by the month in which they are applied, not by annual brome growth stage (Table B2). Although prescribed fires are expected to occur in spring and fall, a management unit (or part thereof) may experience a wildfire in any season. To partially accommodate these rare instances, we included winter months in the “fall” burn definition on the assumption that a fire during those months would have similar effects on the vegetation as a fall burn. Fires occurring during summer months (June–August) are not considered management actions by the tool because this is not a viable management option and summer wildfires are rare. Although not currently included in the ABAM decision support tool, soon after the April 2017 workshop, the NGP Fire program began measuring brome phenological stage at time of fire in anticipation of including phenological stage-specific management actions in future versions of the tool.

Back, head, and flank fires could affect vegetation response because of their general differences in the degree to which they consume or heat standing vegetation, litter, and seeds in the litter or soil. Controlling fire type at the management unit scale is not feasible, and recording the type of fire that occurs at a vegetation monitoring plot during a fire is precluded for safety reasons. Therefore, we did not include anything about fire type in the decision support tool’s management action options. However, NGP fire does measure fire severity (standing vegetation and litter consumption) at each monitoring plot after a fire. We did not include it in the variables considered for determining the structure of the ABAM model but could do so in the future.

All prescribed fires are conducted under a specific “prescription.” A prescription is a set of fuel moisture and weather conditions that not only ensure firefighter and infrastructure safety, but also are assumed to be sufficient to achieve a fire’s objectives. The ABAM tool does not prescribe these conditions or keep track of the weather conditions at the time of a prescribed fire. Instead, we assume that the fire ecologist and fire management specialist will use the information about vegetation current conditions provided by the ABAM tool to write and follow a prescription conducive to a fire that will improve vegetation condition.

B.2.2. Herbicides

Many chemical herbicides (hereafter herbicides) have been tested for controlling exotic annual bromes in the western United States. One of the most widely used is Plateau® (BASF Corporation, Research Triangle Park, NC), which is registered for wildland, pasture, and rangeland use. The active ingredient is imazapic, which works by preventing the synthesis of several amino acids necessary for cell growth. The chemical targets meristematic tissue and therefore prevents new growth. Thus, it is most effective when applied shortly before seedlings emerge or soon thereafter. If applied post-emergence, the manufacturer recommends including a surfactant or methylated seed oil and that the application occur before the annual brome reaches the four-leaf stage. Others (Mealor et al. 2013) recommend application before the three-leaf stage. As with any management treatment, imazapic has shown a wide range of effectiveness in controlling annual bromes, but the general consensus is that removing litter before application increases its effectiveness (Kyser et al. 2007, Davies 2010, Kessler et al. 2015), and that its control lasts only 1–3 years (Morris et al. 2009, Kyser et al. 2013, Mangold et al. 2013).

A second herbicide showing potential for controlling annual bromes in wildland settings is Esplanade® (Bayer CropScience, Research Triangle Park, NC). Esplanade was released onto the market in 2011 for use in a variety of horticultural and agricultural systems, then in 2016 was approved specifically for invasive winter annual grass control in natural areas, open spaces, wildlife management areas, and fire rehabilitation areas. In June 2020, the U.S. Environmental Protection Agency approved Rejuvra™—essentially Esplanade with a new name and specific application rate—for controlling invasive weed species on rangeland, CRP land, and natural areas, including grazed areas on such sites (Bayer Environmental Science 2021). At the writing of this report, this formulation was not yet registered in individual states and was therefore not yet for sale. The active ingredient in Esplanade and Rejuvra is indaziflam. As a cellulose biosynthesis inhibitor, it disrupts the production of the main load-bearing structure of plant cell walls and therefore plant growth; the radicle (an embryonic root that is the first part of a seedling to emerge from a germinating seed) is particularly sensitive (Brabham et al. 2014). Indaziflam shows promise for annual brome control because annual brome seeds tend to remain viable in the soil and litter seed bank for ≤ 5 years, but the herbicide inhibits emergence of seedlings for up to four years after application (Sebastian et al. 2016, 2017a, b). Research sponsored by Bayer has shown reduction of annual brome cover up to 90% by the second year after treatment with minimal impact to native grassland plants (Clark et al. 2019b). The presumed reason for this selectivity is that the roots of perennial species that dominate NGP grasslands are deeper than the first few centimeters of soil, where indaziflam binds to organic material. As with imazapic, plant litter interferes with indaziflam's contact with the seeds it is used to inhibit (Clark et al. 2019a). It does not kill seedlings that have already emerged, and it requires sufficient precipitation after application to become active (Bayer Environmental Science no date). Consequently, annual brome control in the first year after application is not always high. Because of this, indaziflam is often applied together with another herbicide (e.g., glyphosate, rimsulfuron, imazapic) that kills emerged plants.

The management actions in the ABAM tool do not specify the application rate (e.g., 5 or 7 ounces Esplanade per acre), method (e.g., aerial vs. ground), or adjuvants for herbicides. Instead, we assume

that parks and IPMT coordinators will use the most current information to decide on these details as appropriate to each management unit. Similarly, the ABAM tool does not specify the growth stage of annual bromes at the time of herbicide application but instead accounts for expected differences in their effects depending on whether they were applied before or after annual brome emergence. We generally expect, however, that indaziflam will be used alone only when application is before annual bromes have emerged, and the combination of imazapic and indaziflam will be used only when application is after annual bromes have emerged. In the latter case, imazapic is used to provide first-year control of annual bromes when indaziflam alone is not expected to provide that control. Application rates, methods, adjuvants, and brome growth stage will be recorded and could be used in later analyses.

B.2.3. Justification for actions in the ABAM tool

Based on the information above and the experience of the IPMT coordinators in the ABAM consortium, we included the 10 management actions in Table B2 in the decision support tool. The “none” action accounts for changes in vegetation that occur through time in the absence of any of the other actions. Inclusion of the specific fire actions are justified in section B.2.2. Because litter removal prior to herbicide application improves herbicide effectiveness, we anticipate that herbicide-alone management actions will be used primarily in parks without prescribed fire programs, but they may be applicable in other situations. Without previous fire, imazapic is used only in combination with indaziflam because its demonstrated short-term effects were deemed unsatisfactory with respect to the cost of application. Fire-herbicide combinations are expected to improve vegetation conditions more than fire-alone or herbicide-alone options but are more expensive. Fire-then-herbicide actions are justified by the expectation that fire’s litter-reducing properties will substantially increase herbicide effectiveness. The indaziflam-then-spring fire action is included because herbicide applied in the growing season before the spring fire may increase the completeness of a burn (amount of litter consumed) by reducing fire-suppressing green growth in areas heavily infested with annual bromes. Fall fire following indaziflam application is expected to volatilize the applied herbicide and is therefore not included as a management action. No actions specify spring imazapic application because of its potential to adversely affect native plant species that resprout quickly after fire at that time of year (e.g., Baker et al. 2009).

Note: Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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Appendix C. Justification for Variables Included in Learning Model Structure

In section 4.2.2 we define the variables comprising the full park dataset and describe how we derived them from available data. Here, we explain why each variable or form of a variable was considered for inclusion in the dataset. We also justify our exclusion of some variables or forms of variables from the final dataset.

C.1. Vegetation composition and structure variables

Litter cover and Total cover: As described in the Section 2.1, plant litter may play a role in annual brome population dynamics through its effects on soil moisture and seed banks. The experts we consulted to develop our conceptual model disagreed as to whether litter impacts annual brome dynamics, but participants in the structured decision-making (SDM) workshop thought that litter depth was an important component of native vegetation structure (Table 3.1). As described in Appendix B, there is evidence that plant litter also impacts the effectiveness of herbicides. Litter depth and cover are two aspects of the litter condition at a given site and time, but the vegetation monitoring data available for learning model structure only contained information about litter cover (percent of the ground covered by litter). Since litter on the ground is undecomposed plant biomass from previous years, standing plant biomass in t_0 could serve as a surrogate for litter depth in $t+1$. Biomass is not measured by any of the monitoring programs, however. Thus, our best representation of plant biomass was total foliar plant cover. Standing plant biomass is itself a widely used surrogate for annual net primary productivity (NPP) in grasslands, which is an indicator of site fertility. Because site fertility and growing conditions in a given year could affect annual brome abundance directly (rather than through litter), we used separate variables for litter cover and total cover.

Litter cover was not measured in any vegetation observations before 2011, or approximately 25% of the available observations. Also, preliminary data exploration showed that litter cover was consistently high except following a fire. Given the confounding effects of fire, the missing data, and the expert opinion that litter cover was an inferior representation of litter's effects on vegetation dynamics compared to litter depth, we decided not to include **litter cover** as a variable in the full park dataset. Instead, vegetation monitoring programs began recording litter depth in 2018 for potential incorporation into later versions of the model. Preliminary model structure estimations that included **total cover** yielded models that explained total cover, rather than a model that explained the interrelations among different vegetation components. The latter was needed to relate management actions to vegetation condition. Therefore, we did not include **total cover** in the full park dataset.

Relative percent cover (rpc) as the measure of vegetation component abundance: The foliar cover of individual species or groups of species can be expressed either as absolute cover (percent of the area covered by the species) or relative cover (percent of total foliar cover). Both are affected by all of the factors that determine the plant community composition of a site at a given time (weather, grazing, fire, topographic conditions, soil characteristics, etc.), and both are important to managers. However, relative cover represents the dominance hierarchy of a plant community more directly than

absolute cover and thus is more conducive to describing the different vegetation conditions resulting from management actions. Moreover, absolute cover is more sensitive to fluctuations in weather and site conditions – factors outside of managers’ control. Thus, vegetation conditions (desired and otherwise) are expressed as relative percent cover. It is worth noting that participants in the SDM workshop expressed shrub cover as absolute cover when describing attributes relevant to the fundamental objective of high-quality vegetation. We chose to use relative cover of woody vegetation as a whole (trees and shrubs) to be consistent with the other vegetation components.

BRJA rpc and BRTE rpc: Although the two annual brome species that comprise the vast majority of exotic annual grass cover in ABAM parks are ecologically similar, their slightly different phenology, seed dynamics, and less investigated features may influence their ability to invade native grasslands in different locations and their reaction to different management actions. Thus, the experts we consulted thought it was critical to represent the species as separate objects in the model.

Extent of annual brome presence and dominance: Participants in the SDM workshop identified the extent of annual brome presence and the extent of annual brome dominance within a management unit as two attributes relevant to the ABAM framework’s sub-objective of decreasing exotic vegetation (Table 3.1). Metrics for these attributes were defined as the percent of plots in a management unit with any (>0) or $\geq 50\%$ exotic annual grass cover. However, management unit boundaries are, in practice, not static. Thus, it was impossible to run the algorithms for learning model structure at the management-unit scale, as plots within any management units we designated for this purpose may have experienced different management actions through time. Consequently, we did not include extent of annual brome presence or dominance as variables in the full park dataset, and the model necessarily represents exotic annual grass invasion with the single attribute of relative percent cover.

Native diversity: Participants in the SDM workshop identified alpha diversity (average number of native species in 1 m^2) and beta diversity (number of native species in 10 1-m^2 frames) as two attributes of native vegetation relevant to the framework’s first fundamental objective. Metrics for both of these relied on species-presence data collected in 1-m^2 frames (i.e., area based) by NGPN and ROMN but not by NGP Fire (Table 3.1). Because NGP Fire was not able to commit to collecting the area-based species-presence data in the future, we did not include beta diversity in the full park dataset. We also renamed alpha diversity as “native diversity” and redefined it as the number of native species intercepted across all points in a plot (i.e., transect based). The values obtained from the area-based and transect-based diversity measures are highly correlated (Figure C1).

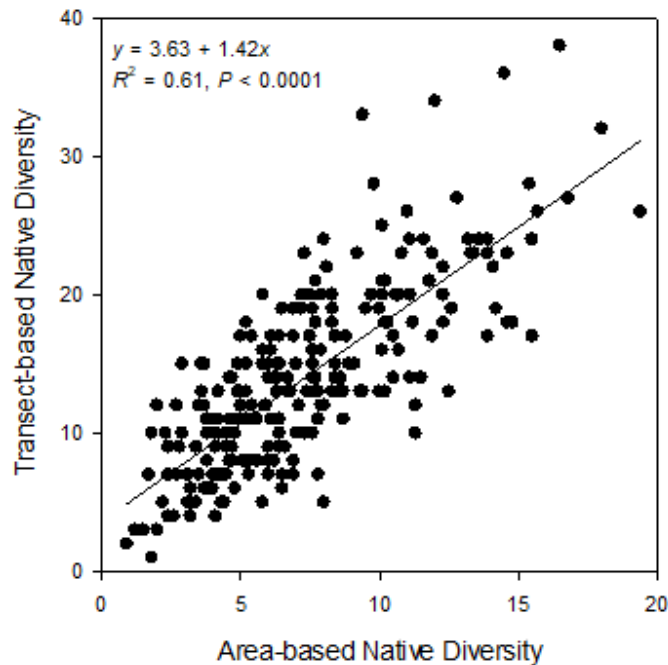


Figure C1. Relationship between diversity of native plant species derived from 10 1-m² frames (x-axis) and 100 points (y-axis) in 274 sampling events in Northern Great Plains Inventory & Monitoring Network (NGPN) parks. Area-based native diversity is the number of native species recorded in 1 m², averaged over 10 frames in a plot. Transect-based native diversity is the number of native species intercepted by 100 points along two transects in a plot.

Coefficient of conservatism: Participants in the SDM workshop identified mean coefficient of conservatism as a metric of vegetation composition and diversity. Coefficient of conservatism is a value between 0 and 10 that represents an estimated probability that a plant species is likely to occur in a landscape relatively unaltered from what is believed to be pre-European settlement condition (Swink and Wilhelm 1994, Taft et al. 1997). A value of 0 indicates a species is highly tolerant of environmental degradation, whereas a value of 10 indicates a species that is nearly always restricted to a high-quality remnant natural area. Values are assigned to each species by a panel of experts; the values are specific to a geographic region. A common use of the coefficient is to calculate its mean over all the species sampled in a site (e.g., plot). We did not include this metric in the dataset because coefficients have not been established for the regions in which some ABAM parks lie.

Tree density: Two ABAM parks (DETO and WICA) lie in the ecotone between mixed-grass prairie and Black Hills ponderosa pine woodland. Herb-layer vegetation in the woodland is similar to that in the prairie, though often with added elements. Both DETO and WICA desire to maintain both prairie and woodland within their boundaries (Appendix A). Moreover, management practices influence the balance of these two broad vegetation types. The ecotone is dynamic in that prairie transitions to woodland as tree density increases. Although climatic conditions influence the rate at which this transition occurs, frequency of fire largely determines whether or not it occurs at all (King et al. 2013). Conversely, a single fire that induces high tree mortality can transition a woodland to prairie. In some cases, exotic plant invasion accompanies the prairie-to-woodland transition. This is most

likely in areas where tree canopy cover is relatively high before the fire (Symstad et al. 2014). Thus, SDM workshop participants identified tree density as an important attribute of native vegetation (Table 3.1), with “trees” defined as tree species with stems of diameter at breast height (1.37 m) at least 15 cm. However, because the transition from prairie to woodland begins with small, young trees, not those already 15 cm in diameter, we investigated whether the density of trees and “poles” (tree species with stem diameter at breast height between 2.5 and 15 cm) was a better indicator of whether an area is (or is transitioning to) woodland. In 547 NGPN and NGP Fire sample events from 1998 to 2018 in DETO and WICA, tree and pole density were correlated ($P < 0.01$), but not strongly ($R^2 = 0.06$). Visual inspection of these data showed that total (herb-layer) cover dropped below 200% at both 150 trees/acre and 600 trees+poles/acre. Moreover, there were 46 instances of trees present with no poles, but only 3 instances of poles present with no trees. From these observations, we concluded that pole density did not add enough different information to warrant being included in the metric, particularly once the data were discretized (see Section 4.2.2).

Percent cool-season: This variable was identified as potentially important by the experts consulted for developing the conceptual model. Their logic behind this was that native cool-season graminoids growing at approximately the same time as the annual bromes would compete more strongly with the bromes than would warm-season graminoids, which generally begin growing later in the growing season than the annual bromes and the cool-season natives. We did not include this variable in the park dataset because of its low variability among plots (i.e., cool-season graminoids were $\geq 70\%$ of the graminoid cover in 80% of the observations).

C.2. Environmental variables

Grazing: Vegetation monitoring protocols record the presence of recent grazing based on whether the vegetation in a plot was cropped at the time of a sampling event. Although recent grazing may have short-term effects on relative cover of different vegetation components measured at a specific point in time, this metric does not capture longer-term effects of grazing on vegetation composition, which we expect to be more substantial (Porensky et al. 2016). For example, because annual bromes are green and palatable through much of the dormant season, large herbivores may forage on them, possibly reducing their abundance, at times that would not be captured by the monitoring protocols. Thus, we focused our grazing variable on whether a plot has the opportunity to be grazed by different types of herbivores. Because different large herbivore species have different grazing behaviors (e.g., species consumed, cropping height), our grazing variable focused on the type of large herbivores present: bison, other wild ungulates, and domestic horses. We acknowledge that the **grazing** variable is largely confounded with park and therefore may capture other park-specific factors not in our variable list that influence vegetation composition.

Contemporary soil disturbance: Although the vegetation monitoring protocols document more forms of disturbance, we included only five forms of contemporary soil disturbance (prairie dog activity, other small mammal activity, bison wallowing, erosion, and burned woodpile) in the **contemporary soil disturbance** variable based on evidence from the literature. Specifically, in a study examining relationships between the presence of exotic plant species and different forms of disturbance in NGPN parks, Larson (2003) found that both the number of exotic species and the

frequency of annual bromes were higher in and near (within 100 m of) prairie dog towns than far (>200 m) from them. Prairie dog towns occupy substantial areas of four ABAM parks and are an important source of contemporary soil disturbance in those parks (Table C1). Additionally, abandoned prairie dog towns have been found to be an avenue by which exotic species invade native grasslands (Bonham and Lerwick 1976). Prairie dog towns are a unique form of disturbance that could facilitate annual brome invasion through small-scale (contemporary) or large-scale (historical) disturbance. For these reasons, we included past and current prairie dog presence in the **contemporary soil disturbance** variable. Larson (2003) also found higher annual brome frequency within 100 m of roads than within 100 m of trails or more than 200 m from trails or roads. Thus, we did not include the trail category as a type of contemporary soil disturbance. We also did not include off-road vehicle tracks as a contemporary soil disturbance because such tracks in ABAM parks are almost exclusively from park maintenance or management activities. These tracks tend to produce much less soil disturbance than occurs with recreational off-roading, which has been shown in studies from other regions to foster invasion (Duniway et al. 2010). Other than grazing and fire, which are covered by other variables in the model, the other remaining categories are extremely rare occurrences. We do note, however, that anecdotal observations at some ABAM parks suggest that annual bromes frequently occur in areas treated with herbicides to control other invasive species, such as *Cirsium arvense* (Canada thistle), in previous years. This association likely results not from the herbicide treatment directly, but because of annual bromes' ability to quickly exploit newly available resources. We intend to investigate this relationship further in later stages of this project.

Table C1. Long-term average area (hectares) and percentage of park occupied by prairie dog towns in ABAM parks in which prairie dogs occur. Area derived from unpublished park prairie-dog-town perimeter mapping data.

Park	Average area of prairie dog towns ^a	Park area	Percent of park occupied by prairie dogs
BADL	4,556	44,490	10.2%
DETO	24	545	4.4%
SCBL	54	1,310	4.1%
WICA	1,461	13,691	10.7%

^a Badlands (BADL) and Wind Cave (WICA) National Park data provided by D. Licht (NPS Midwest Regional Office) and P. Dobesh (BADL). Devils Tower National Monument (DETO) data provided by A. Hammesfahr (DETO). Scotts Bluff National Monument (SCBL) data provided by J. Mills (NGPN). All data provided via written communication in 2018.

Historical land use (HLU): Within the Great Basin, annual brome invasion has been linked to previous land use (Stewart and Hull 1949, Elmore et al. 2006) and roads (Lovtang and Riegel 2012). To investigate whether these patterns also occur in ABAM parks, we constructed a database of land use history for the parks (Modlin and Symstad 2018). As seen in Table C2, parks with larger percentages of their area with a history of soil-disturbing land use tend to have higher annual brome abundance. Including this variable in the park dataset allowed us to investigate whether such

disturbances predict annual brome abundance at the local (plot) scale. We only included the cultivation and excavation categories because these activities result in much more substantial soil disturbance than the others do, and because monitoring plots do not occur near areas of existing structures. It should be noted, however, that only 76 of the 446 monitoring plots in the full park dataset fell within areas with historical land use.

Table C2. Area (hectares) in which specific historical disturbances were documented, percent of park area in which cultivation (C), excavation (E), and structures (S) were documented, and relative percent cover of annual bromes for each ABAM park. Cultivation, excavation, and structures are categories of disturbance that significantly disturb topsoil. AGFO = Agate Fossil Beds National Monument (NM), BADL = Badlands National Park (NP), DETO = Devils Tower NM, FOLA = Fort Laramie National Historic Site, LIBI = Little Bighorn Battlefield NM, SCBL = Scotts Bluff NM, WICA = Wind Cave NP.

Park	Culti- vation	Exca- vation	Struc- tures	Seeding	Other	Grazing	% of Park with C,E, or S	Mean (SD) annual brome cover ^a
AGFO	39	48	25	25	17	–	9%	9.4 (17.9)
BADL	1,924	272	118	–	–	23,654	5%	12.5 (14.0)
DETO	17	21	8	6	25	0	8%	2.1 (4.6)
FOLA	93	45	60	29	51	209	56%	33.8 (21.1)
LIBI	–	23	11	–	1	110	7%	21.8 (10.9)
SCBL	142	206	47	142	36	–	19%	32.2 (23.0)
WICA	2,393	120	330	2	21	13,410	19%	4.5 (7.8)

^a Calculated from 2011–2017 NGPN and ROMN observations

Slope and aspect: Evidence from the literature suggests that slope (grade) and aspect may influence annual brome abundance. Probability of *B. tectorum* and *B. japonicus* occurrence, and *B. tectorum* cover, increased with increasing slope in northeastern Wyoming (Porensky and Blumenthal 2016), and annual bromes have been found to be more abundant on south- or southeast-facing slopes (Bradley and Mustard 2006; Condon et al. 2011; Kulpa et al. 2012; Porensky and Blumenthal 2016). Southerly aspects of slopes tend to be warmer and consequently drier, and in the west-central Great Plains southeastern-facing slopes experience less snow build-up because of prevailing winter winds (Blumenthal et al. 2012).

Percent clay and percent silt: Soil composition may be an indicator of species-specific annual brome vulnerability. Various studies across western North America have identified different optimal soil textures for *B. tectorum* (Miller et al. 2006, Chambers et al. 2007, Reisner et al. 2013). In a study on the western edge of the Great Plains, however, Porensky and Blumenthal (2016) found that *B. tectorum* is more likely to occur in rocky, sandy or silty soils, whereas *B. japonicus* is more likely in areas with more clay and fewer rocks.

Weather variables: Sections 2.1 and 4.2.1.2 of the main text justify our inclusion of 15 weather variables in the full park dataset and the latter describes how we calculated those variables. Table C3 shows how these variables are related to each other.

Table C3. Spearman correlation coefficients between the 15 weather variables in the park dataset. “temp” = mean temperature, “precip” = precipitation, “SPEI” = standardized precipitation index calculated using either a Gaussian (“g”) or rectangular (“r”) weighting function, “season” for SPEI is previous growing season.

Weather Variable	spring temp	winter precip	winter temp	fall precip	fall temp	SPEI spring-g	SPEI spring-r	SPEI winter-g	SPEI winter-r	SPEI fall-g	SPEI fall-r	SPEI season-g	SPEI season-r
spring precip	-0.20	0.02	-0.06	0.24	-0.03	0.75	0.79	0.70	0.77	0.56	0.71	0.46	0.63
spring temp	–	-0.08	0.44	0.04	0.40	-0.31	-0.27	-0.28	-0.32	-0.25	-0.33	-0.13	-0.14
winter precip	–	–	-0.42	0.08	0.05	0.00	0.03	0.20	0.23	0.17	0.21	0.07	0.13
winter temp	–	–	–	-0.13	0.25	-0.16	-0.13	-0.23	-0.26	-0.22	-0.30	-0.01	-0.06
fall precip	–	–	–	–	-0.23	0.29	0.30	0.29	0.31	0.47	0.59	0.33	0.53
fall temp	–	–	–	–	–	-0.14	-0.12	-0.08	-0.11	-0.18	-0.20	-0.11	-0.11
SPEI spring-g	–	–	–	–	–	–	0.96	0.85	0.93	0.67	0.87	0.51	0.71
SPEI spring-r	–	–	–	–	–	–	–	0.88	0.96	0.70	0.89	0.53	0.73
SPEI winter-g	–	–	–	–	–	–	–	–	0.90	0.65	0.84	0.49	0.68
SPEI winter-r	–	–	–	–	–	–	–	–	–	0.72	0.92	0.53	0.74
SPEI fall-g	–	–	–	–	–	–	–	–	–	–	0.78	0.42	0.65
SPEI fall-r	–	–	–	–	–	–	–	–	–	–	–	0.56	0.81
SPEI season-g	–	–	–	–	–	–	–	–	–	–	–	–	0.65

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Appendix D. Data from Experiments Used in Decision Support Tool Development

Data for the process we used to develop the decision support tool described in Section 4 included observations from two experiments that we (A. Symstad, lead investigator) conducted in cooperation with NPS staff in three parks. Motivation for these experiments, as well as plot layout and size within the experiments, differed from those of NGPN, ROMN, and NGP Fire monitoring. Therefore, this appendix describes those experiments and how we used their data in developing the Annual Brome Adaptive Management (ABAM) decision support tool.

D.1. Wind Cave National Park (WICA) Herbicide Trial

Following the SDM workshop in April 2017, we worked with staff at WICA to establish a pilot-scale herbicide trial to compare the effects of herbicide options discussed at that workshop. The objective of the trial was to compare the effects of imazapic and indaziflam, applied in fall or spring, with or without previous vegetation and litter reduction on native and exotic plant species, including the annual bromes¹. Before beginning the trial, we used a handheld GPS to map a polygon with annual brome cover adequate for treatment ($\geq 5\%$ relative percent cover) within the general area slated for the experiment. The polygon served as the experimental site.

We established 10 m x 10 m experimental plots in random locations within the polygon in August 2017 and randomly allocated a treatment to each plot. The trial followed a Before-After-Control-Impact design, with pre-treatment data collected in August 2017, treatments applied in fall (early October) 2017 or spring (early May) 2018, and post-treatment data collected in the 2018, 2019, and 2020 growing seasons². Vegetation data were collected using the same point-intercept method used by NGPN and NGP Fire, but with a reduced number of points (64) in a different spatial configuration to accommodate the smaller plot size.

Data from four treatments, each with three replicates, in the trial were used for model parameterization: indaziflam application alone in fall or spring, and vegetation reduction followed by indaziflam application in fall or spring. Vegetation reduction was accomplished by mowing the plot area, then raking the plot area to remove the mown vegetation and the majority of already dead-and-down litter. Removed material was incinerated in the park's incinerator. Indaziflam was applied at a rate of 70 g AI/ha (5 ounces of the product Esplanade per acre) in 234 l/ha (25 gal/acre) water, using a backpack sprayer.

The vegetation reduction-then-herbicide treatments were originally included as surrogates for fire-then-herbicide treatments in the ABAM model. However, a vegetation reduction "check" treatment

¹ Because the trial was established before the list of management action options in the model was finalized, the treatments in the trial do not map completely to those in the model.

² We intend to continue collecting data until at least 2022, but only the data through 2020 were used in model parameterization.

in the trial showed minor effects on annual brome cover in the first two years post-treatment compared to fire effects in other experiments, monitoring data, and the literature. Consequently, we considered them simply herbicide treatments for model parameterization. Moreover, since the “indaziflam only” management action option in the model includes application at any time of year, the different timing of the applications in the herbicide trial were not separated in the model parameterization. Thus, the WICA herbicide trial contributed 12 plots (each with pre-, 1-year, 2-year, and 3-year post-treatment observations) to the indaziflam-only management option for model parameterization. These data are available in the data release associated with this report (Symstad 2021).

D.2. Annual Brome Research

Before the project to develop the ABAM decision support tool began, one of us (Symstad), NGP IPMT, and NGP Fire developed an experiment to compare the effects of three treatments—fire alone, fire followed by imazapic application, and fall fire followed by seeding with native grasses—over a gradient of annual brome invasion. The experiment was conducted at BADL and SCBL following a before-after-control-impact design. At each park, experimental plots were established within a prescribed fire unit and assigned a treatment in a randomized block design based on pretreatment vegetation composition. Foliar cover was measured by plant species in the central 25 x 25 m of each 50 x 50 m plot using the same point-intercept method as NGPN and NGP Fire, except that the 100 points were distributed along four, 25-m transects instead of along two, 50-m transects. Pre-treatment data were collected in June and July of 2015, treatments were implemented in October or November 2016, and post-treatment data were collected in all plots in 2017 and 2018. A detailed description of the experiment and its results through 2018 are in Symstad et al. (2021).

The experiment was designed to end in the 2018 growing season. However, to provide longer-term data for the ABAM decision support tool, we collected data in the control and fire-only plots in 2019, and the control, fire-only, and fire+imazapic plots in 2020, at SCBL¹. We included data from the control (no-treatment), fire only, and fire + imazapic plots collected in 2015, 2017, and 2018 at BADL and SCBL, as well as the data collected in 2019 and 2020 at SCBL, in the park dataset described in section 4.2.1. The number of observations contributed by this experiment to the park dataset is shown in Table 4.9, and the data from these observations are available in the data release associated with this report (Symstad 2021).

Literature Cited in Appendix D

Symstad, A.J. 2021. Vegetation composition and management action data (2015–2020) from experimental plots at Badlands National Park, Wind Cave National Park, and Scotts Bluff National Monument used to develop the ABAM model. U.S. Geological Survey Data Release. Available at: <https://doi.org/10.5066/P9Y9HZGE>.

¹ All experimental plots at BADL were burned in a second prescribed fire in fall 2018. Although we collected data in some of these plots in 2019 and 2020, the rapid-return fire treatment is not a management action in the ABAM decision support tool at this time. Therefore, we did not include these data in the park dataset.

Symstad, A. J., D. A. Buhl, and D. J. Swanson. 2021. Fire controls annual bromes in northern great plains grasslands—Up to a point. *Rangeland Ecology & Management* 75:17–28.

Appendix E. Supporting Information for Development of the Vegetation Condition Node

In Section 4.3 we describe our process for developing the vegetation condition node for the Bayesian Decision Network (BDN). The first part of this process required selecting the number of levels to which each continuous vegetation component variable would be discretized, then selecting the breakpoints between these levels. The second part of the process was to populate the conditional probability table (CPT) for each vegetation component node with respect to the vegetation condition node.

E.1. Breakpoints for Discretizing Vegetation Component Variables

Breakpoints produced by running the Hartemink algorithm (“Hartemink breaks”) for five different variable sets, and with either a two-level or three-level outcome specified, strongly guided us in making these selections. These breakpoints are shown for each vegetation component variable in Tables E1–E5. In these tables, the variable sets refer to those described in Section 4.3; each set included all vegetation component variables, all edaphic variables, and either one of the weather variable groups in Table 4.1 (e.g., “Set 1”) or all weather variables (“All”). For reference, we include threshold(s) that managers described as separating preliminary vegetation states in the April 2017 workshop (Table 3.2). If this row is blank, no preliminary thresholds were specified during that workshop. We also include the breakpoints that we selected to use going forward in the development of the decision support tool (“Final”).

Table E1. Hartemink breakpoints for the **BRTE rpc** and **BRJA rpc** (*Bromus tectorum* and *B. japonicus* relative percent cover) variables.

Number of Levels	Variable Set	BRTE break 1	BRTE break 2	BRJA break 1	BRJA break 2
2	Set 1	22	–	12	–
3	Set 1	1	22	1	12
2	Set 2	1	–	12	–
3	Set 2	1	22	1	12
2	Set 3	1	–	1	–
3	Set 3	1	22	1	8
2	Set 4	1	–	8	–
3	Set 4	1	22	1	8
2	All	1	–	8	–
3	All	1	39	1	8
–	Preliminary	–	–	–	–
–	Final	1	19	1	12

Table E2. Hartemink breakpoints for the **exotic annual graminoid rpc** and **exotic perennial graminoid rpc** (rpc, relative percent cover) variables. **Exotic annual graminoid rpc** was the only variable for which we used 4 levels.

Number of Levels	Variable Set	Exotic annual grass break 1	Exotic annual graminoid break 2	Exotic annual graminoid break 3	Exotic perennial graminoid break 1	Exotic perennial graminoid break 2
2	Set 1	12	–	–	2	–
3	Set 1	1	12	–	2	18
2	Set 2	12	–	–	2	–
3	Set 2	1	12	–	2	18
2	Set 3	10	–	–	18	–
3	Set 3	1	10	–	2	18
2	Set 4	10	–	–	18	–
3	Set 4	1	10	–	2	18
2	All	9	–	–	18	–
3	All	1	9	–	2	18
4	All	1	12	48	–	–
–	Preliminary	5	20	50	5	20
–	Final	1	12	48	2	18

Table E3. Hartemink breakpoints for the **exotic forb rpc** and **native forb rpc** (rpc, relative percent cover) variables.

Number of Levels	Variable Set	Exotic forb break 1	Exotic forb break 2	Native forb break 1	Native forb break 2
2	Set 1	2	–	3	–
3	Set 1	2	14	3	7
2	Set 2	3	–	3	–
3	Set 2	3	14	3	7
2	Set 3	3	–	2	–
3	Set 3	3	14	2	9
2	Set 4	3	–	3	–
3	Set 4	3	14	3	7
2	All	14	–	4	–
3	All	1	14	1	4
–	Preliminary	5	20	5	25
–	Final	1	14	1	4

Table E4. Hartemink breakpoints for the **native graminoid rpc** (relative percent cover) and **native diversity** (number of species) variables.

Number of Levels	Variable Set	Native graminoid break 1	Native graminoid break 2	Native diversity break 1	Native diversity break 2
2	Set 1	74	–	9	–
3	Set 1	52	74	9	16
2	Set 2	71	–	9	–
3	Set 2	44	71	9	16
2	Set 3	66	–	12	–
3	Set 3	66	92	12	21
2	Set 4	68	–	12	–
3	Set 4	68	88	12	21
2	All	69	–	12	–
3	All	69	92	12	18
–	Preliminary	multiple	multiple	multiple	multiple
–	Final	69	92	12	18

Table E5. Hartemink breakpoints for the **woody rpc** (rpc, relative percent cover) and **tree density** (in stems per acre) variables.

Number of Levels	Variable Set	Woody break 1	Woody break 2	Tree density break 1	Tree density break 2
2	Set 1	8	–	3	–
3	Set 1	0.5	8	3	50
2	Set 2	8	–	6	–
3	Set 2	0.5	8	6	50
2	Set 3	11	–	6	–
3	Set 3	0.5	11	6	50
2	Set 4	11	–	3	–
3	Set 4	0.5	11	3	50
2	All	12	–	3	–
3	All	0.5	12	3	103
–	Preliminary ^a	10	50	5	–
–	Final	0.5	12	0	–

^a expressed as absolute percent cover in preliminary discussions

E.2. Vegetation Component Node Conditional Probability Tables for the Vegetation Condition Node

We based our population of the conditional probability tables (CPT) for each vegetation component node with respect to the vegetation condition node based on our expert knowledge. These CPTs are shown in Tables E6–E13. The top two rows of each table show the levels of the node in the Bayesian Decision Network (BDN, Figure 4.16) and the range of the corresponding continuous variable assigned to that level. Note that these ranges follow the final breakpoints in Tables E1–E5. All other rows in each table indicate a vegetation condition. Each column is a level of the vegetation component node. In each CPT, the probabilities across levels for a single vegetation condition (i.e., across columns within a single row) must sum to 100. These probabilities indicate the relative probability that a monitoring plot with a given level of the variable is in the indicated vegetation condition. Thus, when the probability distribution in a row is uniform, the variable does not contribute to the description of a vegetation condition. Probability values within levels (i.e., across rows within a column) are independent from each other. To improve the numerical stability of the model, all probabilities in these tables were set to a positive (i.e., >0) value. Cells in the CPTs with the probability value 0.01 indicate instances where the level of the component in the column is not appropriate for the vegetation condition in the row; therefore, vegetation with that level of the variable has a vanishingly small (0.01%) probability of being in that condition.

In the native graminoid, native diversity, and woody CPTs, there are two rows for the same vegetation condition, one for “NGPN” and one for “ROMN”. This is because native northern mixed-grass prairie in eastern Montana, where the Rocky Mountain Inventory & Monitoring Network (ROMN) monitors Little Bighorn Battlefield National Monument, has higher forb and shrub cover than in the northern mixed-grass prairie of the parks monitored by the Northern Great Plains Inventory & Monitoring Network (NGPN). We did not make this distinction for ROMN in the native forb CPT because the highest breakpoint is too low to distinguish between ROMN and NGPN. Instead, we account for this difference in the native graminoid CPT. The “Network” node in the BDN (Figure 4.16) serves to apply the appropriate probability distribution between these vegetation component nodes and the vegetation condition node. This is the sole purpose of the Network node.

Table E6. Conditional probability table (CPT) for the exotic annual graminoid node as represented in the Vegetation Condition Network.

Vegetation Condition	Level			
	low	medium	high	very high
Exotic annual graminoid relative percent cover	<1	1 – < 9	≥9	>48
exotic annual grassland	0.01	9.99	30.00	60.00
exotic annual woodland	0.01	9.99	30.00	60.00
exotic perennial grassland	25.00	25.00	25.00	25.00
exotic perennial woodland	25.00	25.00	25.00	25.00
high-quality prairie	84.99	14.99	0.01	0.01
high-quality woodland	84.99	14.99	0.01	0.01
low-quality prairie	25.00	35.00	39.99	0.01
low-quality woodland	25.00	35.00	39.99	0.01
simplified grassland	69.98	30.00	0.01	0.01
weedy forb mess	25.00	25.00	25.00	25.00

Table E7. Conditional probability table (CPT) for the exotic perennial graminoid node as represented in the Vegetation Condition Network.

Vegetation Condition	Level		
	low	medium	high
Exotic perennial graminoid relative percent cover	<2	2 – <18	≥18
exotic annual grassland	33.33	33.34	33.33
exotic annual woodland	33.33	33.34	33.33
exotic perennial grassland	0.01	5.00	94.99
exotic perennial woodland	0.01	5.00	94.99
high-quality prairie	89.99	10.00	0.01
high-quality woodland	89.99	10.00	0.01
low-quality prairie	33.33	66.66	0.01
low-quality woodland	33.33	66.66	0.01
simplified grassland	79.99	20.00	0.01
weedy forb mess	34.00	33.00	33.00

Table E8. Conditional probability table (CPT) for the exotic forb node as represented in the Vegetation Condition Network.

Vegetation Condition	Level		
	low	medium	high
Exotic forb relative percent cover	<1	1 – <14	≥14
exotic annual grassland	33.33	33.34	33.33
exotic annual woodland	33.33	33.34	33.33
exotic perennial grassland	33.33	33.34	33.33
exotic perennial woodland	33.33	33.34	33.33
high-quality prairie	84.99	15.00	0.01
high-quality woodland	84.99	15.00	0.01
low-quality prairie	30.00	60.00	10.00
low-quality woodland	30.00	60.00	10.00
simplified grassland	84.99	15.00	0.01
weedy forb mess	0.01	5.00	94.99

Table E9. Conditional probability table (CPT) for the native forb node as represented in the Vegetation Condition Network.

Vegetation Condition	Level		
	low	medium	high
Native forb relative percent cover	<1	1 – 4	≥4
exotic annual grassland	33.34	33.33	33.33
exotic annual woodland	33.34	33.33	33.33
exotic perennial grassland	33.34	33.33	33.33
exotic perennial woodland	33.34	33.33	33.33
high-quality prairie	0.01	0.01	99.98
high-quality woodland	0.01	0.01	99.98
low-quality prairie	33.34	33.33	33.33
low-quality woodland	33.34	33.33	33.33
simplified grassland	48.00	48.00	4.00
weedy forb mess	33.34	33.33	33.33

Table E10. Conditional probability table (CPT) for the native graminoid node as represented in the Vegetation Condition Network.

Vegetation Condition	Level		
	low	medium	high
Native graminoid relative percent cover	<69	69 – <92	≥92
exotic annual grassland	49.00	49.00	2.00
exotic annual woodland	49.00	49.00	2.00
exotic perennial grassland	49.99	49.99	0.02
exotic perennial woodland	49.99	49.99	0.02
high-quality prairie (NGPN)	0.01	94.99	5.00
high-quality prairie (ROMN)	40.00	59.99	0.01
high-quality woodland	0.01	94.99	5.00
high-quality woodland (ROMN)	40.00	59.99	0.01
low-quality prairie	33.33	33.33	33.34
low-quality woodland	33.33	33.33	33.34
simplified grassland	0.01	0.01	99.98
weedy forb mess	49.99	49.99	0.02

Table E11. Conditional probability table (CPT) for the native diversity node as represented in the Vegetation Condition Network.

Vegetation Condition	Level		
	low	medium	high
Native diversity (number of species)	<12	12–18	≥18
exotic annual grassland	33.34	33.33	33.33
exotic annual woodland	33.34	33.33	33.33
exotic perennial grassland	33.34	33.33	33.33
exotic perennial woodland	33.34	33.33	33.33
high-quality prairie (NGPN)	0.01	25.00	74.99
high-quality prairie (ROMN)	0.01	10.00	89.99
high-quality woodland	0.01	25.00	74.99
high-quality woodland (ROMN)	73.00	17.00	10.00
low-quality prairie	60.00	30.00	10.00
low-quality woodland	99.98	0.01	0.01
simplified grassland	89.99	10.00	0.01
weedy forb mess	33.34	33.33	33.33

The values of native diversity within each level are grounded in the desired condition descriptions, but we had to adjust the area-based values in those descriptions to be appropriate for the point-based values used in the ABAM decision support tool (Appendix C, section C.1). ROMN is on a different scale than NGPN parks not only because of higher expected diversity in LIBI’s desired conditions (Appendix B), but because the ROMN monitoring method samples a higher number of points than in the other (NGPN) parks.

Table E12. Conditional probability table (CPT) for the woody node as represented in the Vegetation Condition Network.

Vegetation Condition	Level		
	low	medium	high
Woody relative percent cover	<0.5	0.5 – <12	≥12
exotic annual grassland	33.33	33.33	33.34
exotic annual woodland	33.33	33.33	33.34
exotic perennial grassland	33.33	33.33	33.34
exotic perennial woodland	33.33	33.33	33.34
high-quality prairie (NGPN)	47.50	47.50	5.00
high-quality prairie (ROMN)	40.00	40.00	20.00
high-quality woodland (NGPN)	33.33	33.33	33.34
high-quality woodland (ROMN)	25.00	25.00	50.00
low-quality prairie	30.00	30.00	40.00
low-quality woodland	33.33	33.33	33.34
simplified grassland	75.00	24.99	0.01
weedy forb mess	33.33	33.33	33.34

Table E13. Conditional probability table (CPT) for the tree density node as represented in the Vegetation Condition Network.

Vegetation Condition	Level	
	none	some
Tree density (stems per acre)	0	>0
exotic annual grassland	99.99	0.01
exotic annual woodland	0.01	99.99
exotic perennial grassland	99.99	0.01
exotic perennial woodland	0.01	99.99
high-quality prairie	99.99	0.01
high-quality woodland	0.01	99.99
low-quality prairie	90.00	10.00
low-quality woodland	0.01	99.99
simplified grassland	99.99	0.01
weedy forb mess	50.00	50.00

The tree density node primarily distinguishes between a woodland and grassland. Participants in the SDM workshop indicated that the breakpoint between woodland and prairie should be 5 trees per acre (Table 3.2). However, we later learned that this threshold is simply a threshold used by NGP Fire to determine whether a location has sufficient trees before a fire to install monitoring plots intended to track fire-induced tree mortality. We felt that this, as well as the definition of “wooded area” in the desired conditions as ≥ 50 trees per ha (20 trees per acre), is too high of a density of trees to be considered grassland/prairie in the model. Instead, we simplified to a presence/absence distinction.

Appendix F. Methods for Creating the Simulated Dataset

As described in section 4.5.1, we used a simulated dataset to parameterize the Bayesian Management Network (BMN) for management actions involving herbicides. This is because we currently have little or no data from Annual Brome Adaptive Management (ABAM) parks for the management actions involving herbicide application. Rather than assign uniform (uninformed) probabilities to these actions in the model, we amended the park dataset with simulated data based on other sources of information (Sebastian et al. 2016, Symstad 2021, Symstad et al. 2021).

Our process for simulating the effects of management actions involving herbicides was as follows:

1. We estimated an empirical cumulative distribution function for **exotic annual graminoid rpc** (relative percent cover) from the values of this variable in the park dataset. Using this function, we then computed the relative probability associated with each observation (row) in the park dataset.
2. Using these probabilities, we randomly sampled (with replacement) 1,000 rows from the park dataset. Each row contained one value for every node in the BMN.
3. We drew 1,000 proportion-remaining values for each timestep and management action from the ranges in Table 4.8. This resulted in 3,000 proportion-remaining values for each management action.
4. We calculated the expected future **BRJA rpc** and **BRTE rpc** resulting from a management action by multiplying their initial rpc values drawn in step 2 by the values drawn in step 3. We then computed expected future **exotic annual graminoid rpc** by summing expected future **BRJA rpc** and **BRTE rpc**. (*BRJA* = *Bromus japonicus*, *BRTE* = *B. tectorum*)
5. We discretize expected future **BRJA rpc**, **BRTE rpc**, and **exotic annual graminoid rpc**.
6. Treating the vegetation component values drawn in step two as initial values, we used the BMN to predict the distribution of effects of **exotic annual graminoid rpc** reduction on the other vegetation components. We included the environmental variables drawn in step 2, as well as the values generated from step 5, in this prediction step. We then randomly drew one value for each remaining vegetation component for each time step.
7. We appended the 21,000 simulated (3,000 x 7 management actions) data rows to the park dataset for estimating conditional probability tables (CPTs).

Literature Cited in Appendix F

- Sebastian, D. J., J. R. Sebastian, S. J. Nissen, and K. G. Beck. 2016. A potential new herbicide for invasive annual grass control on rangeland. *Rangeland Ecology & Management* 69:195–198.
- Symstad, A.J. 2021. Vegetation composition and management action data (2015–2020) from experimental plots at Badlands National Park, Wind Cave National Park, and Scotts Bluff National Monument used to develop the ABAM model. U.S. Geological Survey Data Release. Available at: <https://doi.org/10.5066/P9Y9HZGE>.

Symstad, A. J., D. A. Buhl, and D. J. Swanson. 2021. Fire controls annual bromes in northern great plains grasslands—Up to a point. *Rangeland Ecology & Management* 75:17–28.

Appendix G. Sample Sizes by Vegetation Condition, Management Action, and Timestep

An important influence on the accuracy of the Annual Brome Adaptive Management (ABAM) Bayesian Management Network (BMN) is the number of samples on which each conditional probability table (CPT) in the BMN is based. Thus, in this appendix we provide, in more detail than in the main text (Table 4.9), the sample sizes of data we used to estimate the structure of and parameterize the BMN. Table G1 shows sample sizes for all combinations of management action, timestep, and current (before management, t_0) vegetation condition because managers and monitoring programs can more purposely act to reduce data deficiencies for these combinations than they can for combinations of, say, different levels of weather and soil texture nodes. Examining this sample size distribution for future (after management) vegetation conditions provides some insight into the relative predictive accuracy of the BMN at this time (Section 4.6.3 in the main text). Therefore, we also provide sample sizes based on future condition, in Table G2. In both of these, as in the main text (section 4.6), “vegetation condition” is the most probable condition for an observation (since vegetation condition is a probability distribution, not a discrete state, in the BMN).

Sample sizes for the *none*, *fall burn*, and *spring burn* management actions are all from field observations. Sample sizes for the *indaziflam only* and *fall burn then imazapic* actions are separated into field observations and simulated data, and sample sizes for the remaining management actions are from simulated data only. Sample sizes for current vegetation condition from field observations alone (*none*, *fall burn*, *spring burn*, Table G1) highlight the uneven temporal structure of field observations. Poorly informed parts of the BMN are identified by low field observation sample sizes and simulated data.

Table G1. Sample size for each current (before management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Exotic Annual Grassland ($n=288+6,368^a$)	none	42	42	73	157
	fall burn	37	36	8	81
	spring burn	8	5	5	18
	indaziflam only	5+307 ^a	9+304 ^a	304 ^a	14+915 ^a
	imazapic-indaziflam	338 ^a	337 ^a	337 ^a	1012 ^a
	fall burn then imazapic	6+311 ^a	6+309 ^a	6+307 ^a	18+927 ^a

^a Simulated data, shown in italicized text.

Table G1 (continued). Sample size for each current (before management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Exotic Annual Grassland (n=288+6,368 ^a) (continued)	fall burn then indaziflam	301 ^a	301 ^a	300 ^a	902 ^a
	fall burn then imazapic-indaziflam	276 ^a	277 ^a	279 ^a	832 ^a
	spring burn then indaziflam	296 ^a	295 ^a	295 ^a	886 ^a
	indaziflam then spring burn	297 ^a	301 ^a	296 ^a	894 ^a
Exotic Annual Woodland (n=16+207 ^a)	none	2	0	7	9
	fall burn	3	0	0	3
	spring burn	2	1	1	0
	indaziflam only	15 ^a	15 ^a	15 ^a	45 ^a
	imazapic-indaziflam	11 ^a	11 ^a	11 ^a	33
	fall burn then imazapic	4	4	4	12 ^a
	fall burn then indaziflam	7	7	7	21 ^a
	fall burn then imazapic-indaziflam	10 ^a	10 ^a	10 ^a	30 ^a
	spring burn then indaziflam	12 ^a	12 ^a	12 ^a	36 ^a
	indaziflam then spring burn	10 ^a	10 ^a	10 ^a	30 ^a
Exotic Perennial Grassland (n=242+2,927 ^a)	none	33	29	41	103
	fall burn	18	17	15	50
	spring burn	31	26	20	77
	indaziflam only	2+130 ^a	4+130 ^a	130 ^a	6+690 ^a
	imazapic-indaziflam	139 ^a	139 ^a	139 ^a	417 ^a
	fall burn then imazapic	3+143 ^a	3+143 ^a	143 ^a	6+429 ^a
	fall burn then indaziflam	142 ^a	144 ^a	145 ^a	431 ^a
	fall burn then imazapic-indaziflam	145 ^a	146 ^a	147 ^a	438 ^a
	spring burn then indaziflam	137 ^a	136 ^a	136 ^a	409 ^a
	indaziflam then spring burn	138 ^a	137 ^a	138 ^a	413 ^a

^a Simulated data, shown in italicized text.

Table G1 (continued). Sample size for each current (before management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Exotic Perennial Woodland (n=147+1,148 ^a)	none	17	11	30	58
	fall burn	31	23	13	67
	spring burn	9	10	3	22
	indaziflam only	46 ^a	46 ^a	46 ^a	138 ^a
	imazapic-indaziflam	61 ^a	61 ^a	61 ^a	183 ^a
	fall burn then imazapic	63 ^a	63 ^a	64 ^a	190 ^a
	fall burn then indaziflam	53 ^a	53 ^a	53 ^a	159 ^a
	fall burn then imazapic-indaziflam	48 ^a	48 ^a	48 ^a	144 ^a
	spring burn then indaziflam	57 ^a	56 ^a	56 ^a	169 ^a
	indaziflam then spring burn	55 ^a	55 ^a	55 ^a	165 ^a
High-Quality Prairie (n=186+1,770 ^a)	none	33	17	65	115
	fall burn	14	9	6	29
	spring burn	16	8	6	30
	indaziflam only	4+79 ^a	8+79 ^a	79 ^a	12+237 ^a
	imazapic-indaziflam	92 ^a	92 ^a	92 ^a	276 ^a
	fall burn then imazapic	86 ^a	86 ^a	86 ^a	8+258 ^a
	fall burn then indaziflam	83 ^a	83 ^a	83 ^a	249 ^a
	fall burn then imazapic-indaziflam	97 ^a	97 ^a	97 ^a	291 ^a
	spring burn then indaziflam	81 ^a	81 ^a	81 ^a	243 ^a
	indaziflam then spring burn	72 ^a	72 ^a	72 ^a	216 ^a
High-Quality Woodland (n=117+1,030 ^a)	none	19	8	28	55
	fall burn	22	16	9	47
	spring burn	8	6	1	15
	indaziflam only	56 ^a	1+56 ^a	56 ^a	1+168 ^a
	imazapic-indaziflam	41 ^a	41 ^a	41 ^a	123 ^a
	fall burn then imazapic	50 ^a	50 ^a	49 ^a	149 ^a

^a Simulated data, shown in italicized text.

Table G1 (continued). Sample size for each current (before management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
High-Quality Woodland (n=117+1,030 ^a) (continued)	fall burn then indaziflam	50 ^a	50 ^a	50 ^a	150 ^a
	fall burn then imazapic-indaziflam	36 ^a	36 ^a	36 ^a	108 ^a
	spring burn then indaziflam	54 ^a	55 ^a	55 ^a	164 ^a
	indaziflam then spring burn	56 ^a	56 ^a	56 ^a	168 ^a
Low-Quality Prairie (n=174+3,032 ^a)	none	20	30	29	79
	fall burn	22	24	15	61
	spring burn	7	10	2	19
	indaziflam only	1+137 ^a	3+140 ^a	140 ^a	4+417 ^a
	imazapic-indaziflam	121 ^a	122 ^a	122 ^a	365 ^a
	fall burn then imazapic	4+129 ^a	4+131 ^a	3+133 ^a	11+393 ^a
	fall burn then indaziflam	158 ^a	156 ^a	156 ^a	470 ^a
	fall burn then imazapic-indaziflam	155 ^a	153 ^a	150 ^a	458 ^a
	spring burn then indaziflam	134 ^a	136 ^a	136 ^a	406 ^a
	indaziflam then spring burn	175 ^a	172 ^a	176 ^a	523 ^a
Low-Quality Woodland (n=22+138 ^a)	None	4	2	7	13
	fall burn	4	1	0	5
	spring burn	2	2	0	4
	indaziflam only	5	5	5	15 ^a
	imazapic-indaziflam	6	6	6	18 ^a
	fall burn then imazapic	7	7	7	21 ^a
	fall burn then indaziflam	10 ^a	10 ^a	10 ^a	30 ^a
	fall burn then imazapic-indaziflam	5	5	5	15 ^a
	spring burn then indaziflam	9	9	9	27 ^a
	indaziflam then spring burn	4	4	4	12 ^a

^a Simulated data, shown in italicized text.

Table G1 (continued). Sample size for each current (before management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Simplified Grassland (n=226+1,749 ^a)	none	49	25	62	136
	fall burn	18	17	11	46
	spring burn	13	24	7	44
	imazapic-indaziflam	<i>78 ^a</i>	<i>78 ^a</i>	<i>78 ^a</i>	<i>234 ^a</i>
	fall burn then imazapic	<i>75 ^a</i>	<i>75 ^a</i>	<i>75 ^a</i>	<i>225 ^a</i>
	fall burn then indaziflam	<i>77 ^a</i>	<i>77 ^a</i>	<i>77 ^a</i>	<i>231 ^a</i>
	fall burn then imazapic-indaziflam	<i>87 ^a</i>	<i>87 ^a</i>	<i>87 ^a</i>	<i>261 ^a</i>
	spring burn then indaziflam	<i>101 ^a</i>	<i>101 ^a</i>	<i>101 ^a</i>	<i>303 ^a</i>
	indaziflam then spring burn	<i>85 ^a</i>	<i>85 ^a</i>	<i>85 ^a</i>	<i>255 ^a</i>
Weedy Forb Mess (n=180+2,631 ^a)	none	22	28	51	101
	fall burn	20	20	16	56
	spring burn	4	5	2	11
	indaziflam only	<i>145 ^a</i>	<i>145 ^a</i>	<i>145 ^a</i>	<i>435 ^a</i>
	imazapic-indaziflam	<i>113 ^a</i>	<i>113 ^a</i>	<i>113 ^a</i>	<i>339 ^a</i>
	fall burn then imazapic	<i>6+132 ^a</i>	<i>6+132 ^a</i>	<i>132 ^a</i>	<i>12+396 ^a</i>
	fall burn then indaziflam	<i>119 ^a</i>	<i>119 ^a</i>	<i>119 ^a</i>	<i>357 ^a</i>
	fall burn then imazapic-indaziflam	<i>141 ^a</i>	<i>141 ^a</i>	<i>141 ^a</i>	<i>423 ^a</i>
	spring burn then indaziflam	<i>119 ^a</i>	<i>119 ^a</i>	<i>119 ^a</i>	<i>357 ^a</i>
	indaziflam then spring burn	<i>108 ^a</i>	<i>108 ^a</i>	<i>108 ^a</i>	<i>324 ^a</i>

^a Simulated data, shown in italicized text.

Table G2. Sample size for each future (after management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Exotic Annual Grassland (n=248+505 ^a)	none	39	48	81	168
	fall burn	15	22	8	45
	spring burn	5	19	6	30
	indaziflam only	4+73 ^a	1+3 ^a	11 ^a	5+87 ^a
	imazapic-indaziflam	26 ^a	2 ^a	5 ^a	33 ^a
	fall burn then imazapic	24 ^a	1+59 ^a	2+100 ^a	3+183 ^a
	fall burn then indaziflam	26 ^a	4	3	33 ^a
	fall burn then imazapic-indaziflam	38 ^a	1	1	40 ^a
	spring burn then indaziflam	25 ^a	2	4	31 ^a
	indaziflam then spring burn	70 ^a	13 ^a	12 ^a	95 ^a
Exotic Annual Woodland (n=12+37 ^a)	none	3	1	5	9
	fall burn	0	0	2	2
	spring burn	0	0	0	0
	indaziflam only	8	1	0 ^a	1+8
	imazapic-indaziflam	2	0 ^a	0 ^a	2
	fall burn then imazapic	1	3	10 ^a	14 ^a
	fall burn then indaziflam	2	1	0 ^a	3
	fall burn then imazapic-indaziflam	1	0 ^a	1	2
	spring burn then indaziflam	3	0 ^a	0 ^a	3
	indaziflam then spring burn	2	2	1	5
Exotic Perennial Grassland (n=233+3,476 ^a)	none	30	35	47	112
	fall burn	17	15	10	42
	spring burn	29	19	15	63
	indaziflam only	2+132 ^a	4+199 ^a	172 ^a	6+503 ^a
	imazapic-indaziflam	144 ^a	211 ^a	175 ^a	530 ^a
	fall burn then imazapic	4+154 ^a	3+142 ^a	1+205 ^a	8+501 ^a

^a Simulated data, shown in italicized text.

Table G2 (continued). Sample size for each future (after management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Exotic Perennial Grassland (n=233+3,476 ^a) (continued)	fall burn then indaziflam	133 ^a	151 ^a	194 ^a	478 ^a
	fall burn then imazapic-indaziflam	155 ^a	152 ^a	215 ^a	522 ^a
	spring burn then indaziflam	174 ^a	122 ^a	151 ^a	447 ^a
	indaziflam then spring burn	174 ^a	148 ^a	175 ^a	497 ^a
Exotic Perennial Woodland (n=146+1,278 ^a)	none	18	16	35	69
	fall burn	21	17	11	49
	spring burn	9	8	2	19
	indaziflam only	60 ^a	9+77 ^a	58 ^a	9+195 ^a
	imazapic-indaziflam	58 ^a	78 ^a	64 ^a	200 ^a
	fall burn then imazapic	65 ^a	69 ^a	75 ^a	209 ^a
	fall burn then indaziflam	47 ^a	50 ^a	62 ^a	159 ^a
	fall burn then imazapic-indaziflam	47 ^a	47 ^a	59 ^a	153 ^a
	spring burn then indaziflam	66 ^a	55 ^a	52 ^a	173 ^a
	indaziflam then spring burn	71 ^a	65 ^a	53 ^a	189 ^a
High-Quality Prairie (n=259+4,287 ^a)	none	41	21	66	128
	fall burn	23	23	13	59
	spring burn	24	21	8	53
	indaziflam only	5+196 ^a	8+167 ^a	196 ^a	13+559 ^a
	imazapic-indaziflam	223 ^a	213 ^a	213 ^a	649 ^a
	fall burn then imazapic	2+222 ^a	5+198 ^a	1+164 ^a	8+584 ^a
	fall burn then indaziflam	218 ^a	207 ^a	208 ^a	633 ^a
	fall burn then imazapic-indaziflam	217 ^a	238 ^a	220 ^a	675 ^a
	spring burn then indaziflam	205 ^a	203 ^a	208 ^a	616 ^a
	indaziflam then spring burn	176 ^a	203 ^a	190 ^a	569 ^a

^a Simulated data, shown in italicized text.

Table G2 (continued). Sample size for each future (after management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
High-Quality Woodland (n=128+1,229 ^a)	none	16	4	32	52
	fall burn	26	21	9	56
	spring burn	9	7	3	19
	indaziflam only	<i>50 ^a</i>	<i>1+46 ^a</i>	<i>69 ^a</i>	<i>1+165 ^a</i>
	imazapic-indaziflam	<i>52 ^a</i>	<i>55 ^a</i>	<i>59 ^a</i>	<i>166 ^a</i>
	fall burn then imazapic	<i>53 ^a</i>	<i>51 ^a</i>	<i>55 ^a</i>	<i>159 ^a</i>
	fall burn then indaziflam	<i>67 ^a</i>	<i>63 ^a</i>	<i>58 ^a</i>	<i>188 ^a</i>
	fall burn then imazapic-indaziflam	<i>44 ^a</i>	<i>51 ^a</i>	<i>50 ^a</i>	<i>145 ^a</i>
	spring burn then indaziflam	<i>70 ^a</i>	<i>69 ^a</i>	<i>73 ^a</i>	<i>212 ^a</i>
	indaziflam then spring burn	<i>63 ^a</i>	<i>63 ^a</i>	<i>68 ^a</i>	<i>194 ^a</i>
Low-Quality Prairie (n=133+3,667 ^a)	none	18	23	15	56
	fall burn	8	20	21	49
	spring burn	4	8	5	17
	indaziflam only	<i>1+170 ^a</i>	<i>214 ^a</i>	<i>185 ^a</i>	<i>1+569 ^a</i>
	imazapic-indaziflam	<i>188 ^a</i>	<i>185 ^a</i>	<i>164 ^a</i>	<i>537 ^a</i>
	fall burn then imazapic	<i>3+155 ^a</i>	<i>2+163 ^a</i>	<i>2+137 ^a</i>	<i>7+455 ^a</i>
	fall burn then indaziflam	<i>172 ^a</i>	<i>176 ^a</i>	<i>173 ^a</i>	<i>521 ^a</i>
	fall burn then imazapic-indaziflam	<i>158 ^a</i>	<i>149 ^a</i>	<i>143 ^a</i>	<i>450 ^a</i>
	spring burn then indaziflam	<i>145 ^a</i>	<i>193 ^a</i>	<i>155 ^a</i>	<i>493 ^a</i>
	indaziflam then spring burn	<i>197 ^a</i>	<i>234 ^a</i>	<i>214 ^a</i>	<i>645 ^a</i>
Low-Quality Woodland (n=24+467 ^a)	none	2	3	5	10
	fall burn	7	2	2	11
	spring burn	3	0	0	3
	indaziflam only	<i>24 ^a</i>	<i>26 ^a</i>	<i>20 ^a</i>	<i>70 ^a</i>
	imazapic-indaziflam	<i>24 ^a</i>	<i>15 ^a</i>	<i>21 ^a</i>	<i>60 ^a</i>
	fall burn then imazapic	<i>19 ^a</i>	<i>17 ^a</i>	<i>15 ^a</i>	<i>51 ^a</i>

^a Simulated data, shown in italicized text.

Table G2 (continued). Sample size for each future (after management) vegetation condition, management action, and timestep following management. Values in parentheses following the vegetation condition name are totals for that condition. Sample size is the number of data rows in the dataset used to parameterize the Bayesian Management Network. Plain text indicates field observations and italicized text indicates simulated data.

Vegetation Condition	Management Action	Time Step			
		1	2–3	4–5	Total
Low-Quality Woodland (n=24+467 ^a) (continued)	fall burn then indaziflam	26 ^a	29 ^a	26 ^a	81 ^a
	fall burn then imazapic-indaziflam	24 ^a	19 ^a	17 ^a	60 ^a
	spring burn then indaziflam	27 ^a	25 ^a	34 ^a	86 ^a
	indaziflam then spring burn	18 ^a	20 ^a	21 ^a	59 ^a
Simplified Grassland (n=257+4,427 ^a)	none	39	22	57	118
	fall burn	48	29	10	87
	spring burn	16	12	8	36
	indaziflam only	186 ^a	178 ^a	204 ^a	568 ^a
	imazapic-indaziflam	211 ^a	185 ^a	219 ^a	615 ^a
	fall burn then imazapic	8+247 ^a	5+215 ^a	3+183 ^a	16+645 ^a
	fall burn then indaziflam	231 ^a	246 ^a	203 ^a	680 ^a
	fall burn then imazapic-indaziflam	237 ^a	253 ^a	222 ^a	712 ^a
	spring burn then indaziflam	208 ^a	249 ^a	259 ^a	716 ^a
	indaziflam then spring burn	149 ^a	161 ^a	181 ^a	491 ^a
Weedy Forb Mess (n=158+1,627 ^a)	none	35	19	50	104
	fall burn	24	14	7	45
	spring burn	1	3	0	4
	indaziflam only	101 ^a	90 ^a	85 ^a	276 ^a
	imazapic-indaziflam	72 ^a	56 ^a	80 ^a	208 ^a
	fall burn then imazapic	2+60 ^a	3+83 ^a	56 ^a	5+199 ^a
	fall burn then indaziflam	78 ^a	73 ^a	73 ^a	224 ^a
	fall burn then imazapic-indaziflam	79 ^a	90 ^a	72 ^a	241 ^a
	spring burn then indaziflam	77 ^a	82 ^a	64 ^a	223 ^a
	indaziflam then spring burn	80 ^a	91 ^a	85 ^a	256 ^a

^a Simulated data, shown in italicized text.

Appendix H. Utility Elicitation Exercises

Below we describe the utility elicitation exercises completed by staff at each Annual Brome Adaptive Management park in April and May of 2018, with some revisions completed in 2020 for Fort Laramie National Historical Site and Scotts Bluff National Monument. Number of participants at each park varied from one to four, with the park's natural resource specialist always, and the park's superintendent usually, participating. We gave participants at each park an Excel spreadsheet with five exercises, each on a different page. These exercises were completed remotely, but at least two of us walked the park staff through each step to ensure consistent interpretation of the directions. Our exercises are modified from Gannon et al. (2013).

1. We asked park staff to subjectively rank each vegetation state (later renamed "vegetation condition") from 1 to 10, with 1 being the most preferred and 10 being the least preferred (Figure H1).

	A	B
1	Vegetation Condition	Rank
2	Exotic Annual Grassland	5
3	Exotic Annual Woodland	10
4	Exotic Perennial Grassland	4
5	Exotic Perennial Woodland	9
6	High Quality Prairie	1
7	High Quality Woodland	6
8	Low Quality Prairie	2
9	Low Quality Woodland	8
10	Simplified Grassland	3
11	Weedy Forb Mess	7

Figure H1. Example ranking exercise. Data shown in this figure are presented in Appendix J, Table J4.

2. Participants then calculated utilities indirectly by scoring pairwise comparisons between the states they just ranked. We asked them to find the comparison that was most difficult to make in terms of their preference. That is, which two states were most difficult to tell apart in terms of their value to the park. We had them assign this comparison a score of 1. Using the first comparison as a reference, we asked them to score each of the remaining comparisons in terms of ease in distinguishing the value between states. For example, if the value of two states in a comparison was twice as easy to distinguish, compared to the first comparison scored, they would enter "2". If the comparison was only slightly easier to distinguish, they would enter a smaller number, such as 1.2. We constrained scores to be positive (Figure H2, Tables H2, H3). We then normalized these scores to produce utilities.

	A	B	C	D	E	F	G	H
1	Comparison	Rank	Vegetation Condition	Difference Score		Rank	Condition	Normalized utility
2	1	1	High Quality Prairie	5		1	High Quality Prairie	1.00
3		2	Low Quality Prairie			2	Low Quality Prairie	0.81
4						3	Simplified Grassland	0.75
5	2	2	Low Quality Prairie	1.5		4	Exotic Perennial Grassland	0.37
6		3	Simplified Grassland			5	Exotic Annual Grassland	0.31
7						6	High Quality Woodland	0.27
8	3	3	Simplified Grassland	10		7	Weedy Forb Mess	0.15
9		4	Exotic Perennial Grassland			8	Low Quality Woodland	0.12
10						9	Exotic Perennial Woodland	0.04
11	5	4	Exotic Perennial Grassland	1.5		10	Exotic Annual Woodland	0.00
12		5	Exotic Annual Grassland					
13								
14	6	5	Exotic Annual Grassland	1				
15		6	High Quality Woodland					
16								
17	7	6	High Quality Woodland	3				
18		7	Weedy Forb Mess					
19								
20	8	7	Weedy Forb Mess	1				
21		8	Low Quality Woodland					
22								
23	9	8	Low Quality Woodland	2				
24		9	Exotic Perennial Woodland					
25								
26	10	9	Exotic Perennial Woodland	1				
27		10	Exotic Annual Woodland					
28								

Figure H2. Example comparison-scoring exercise and normalized utilities. Data shown in this figure are presented in Appendix J, Table J5 and Table J6.

3. We then presented the option of working through a free-form scoring approach. We asked participants to assign points to each state, which the spreadsheet had sorted according to their ranked preferences. They assigned 100 points to their top-ranked state. They then assigned points between (and including) 0 and 100 points to their second-ranked state, third ranked, etc. We allowed multiple states to have the same number of points. We then provided a graph of the utilities and asked whether they would like to make adjustments (Figure H3).

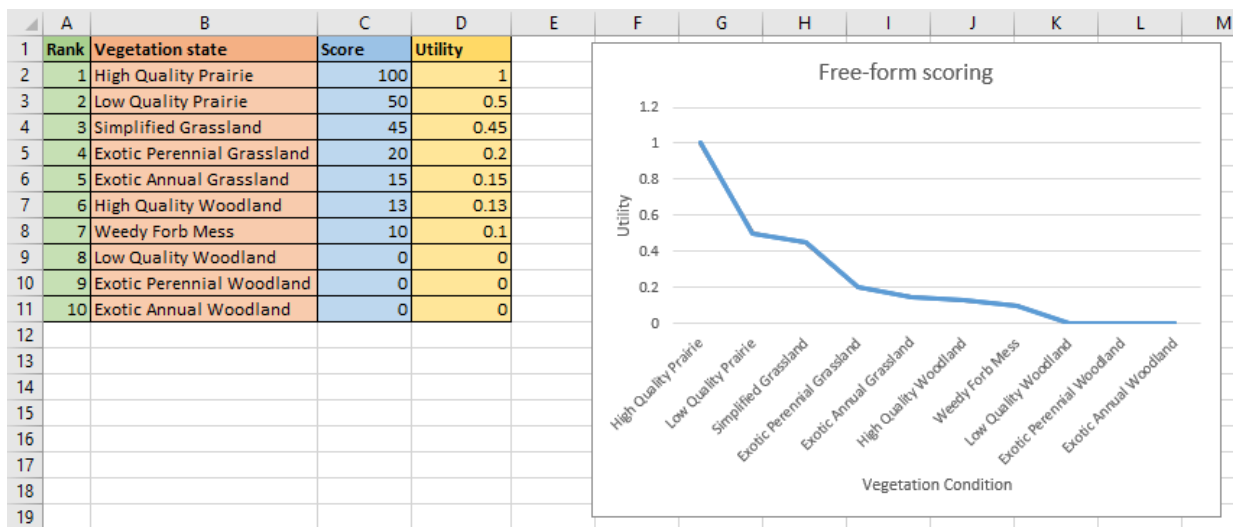


Figure H3. Example of free-form scoring exercise. Data shown in this figure are presented in Appendix J, Table J7 and Table J8.

- We next asked participants which vegetation state utilities they preferred (free-form or pairwise comparisons). We noted their answer in order to apply the correct set in the model.
- We next presented the participants with cost utilities and we explained how they were normalized based on their relative values (Figure H4).

Comparison	Rank	Cost per acre	Difference Score		Rank	Cost	Normalized utility
1	1	\$0.00	3.846		1	\$0.00	1
	2	\$50.00			2	\$50.00	0.65034965
2	2	\$50.00	1.154		3	\$65.00	0.545454545
	3	\$65.00			4	\$78.00	0.454545455
3	3	\$65.00	1		5	\$93.00	0.34965035
	4	\$78.00			6	\$115.00	0.195804196
4	4	\$78.00	1.154		7	\$143.00	0
	5	\$93.00					
5	5	\$93.00	1.692				
	6	\$115.00					
6	6	\$115.00	2.154				
	7	\$143.00					

Figure H4. Normalization of cost utilities. Data shown in this figure are presented in Appendix J, Table J9.

6. We then presented participants with a swing weighting exercise. We began by presenting participants with a benchmark, worst-case scenario, in which an action was applied but the worst performance was realized on both objectives (i.e., lowest-ranked vegetation state at the greatest cost). In the second scenario (Vegetation state), an action was applied, and the most preferred vegetation state resulted, but at the least preferred cost. In the third scenario (Cost), the opposite occurred: an applied action resulted in the least preferred vegetation state but at the most preferred cost. We then asked participants to assign their preferred scenario (between Vegetation state and Cost) a rank of 1 and assign the rank 2 to the other scenario. We then assigned 100 points to the preferred scenario and asked them to assign some lesser number of points (i.e. <100) to the second scenario. The weight in the final column was automatically calculated based on how they assigned these points.

	A	B	C	D	E	F
1	Scenarios	Resultant vegetation state	Cost	Rank	Score	Weight
2	1. Benchmark	Exotic Annual Woodland	\$115.00	3	0	0.00
3	2. Vegetation state	High Quality Prairie	\$115.00	1	100	0.91
4	3. Cost	Exotic Annual Woodland	\$0.00	2	10	0.09
5						1.00

Figure H5. Example swing-weighting exercise to derive objective weights. Data shown in this figure are presented in Appendix J, Table J10.

Literature Cited in Appendix H

Gannon, J. J., T. L. Shaffer, and C. T. Moore. 2013. Native Prairie Adaptive Management: A multi region adaptive approach to invasive plant management on Fish and Wildlife Service owned native prairies. Open File Report 2013-1279, U.S. Geological Survey, Reston, Virginia.

Appendix I. Using the Annual Brome Adaptive Management Decision Support Tool (ABAM R Package)

The ABAM decision support system consists of the ABAM decision support tool (the Bayesian Decision Network, hereafter referred to as “the model”), and the *ABAM* R package (Baldwin et al. 2021) developed for R (R Core Team 2019). The *ABAM* R package includes a vignette that leads the user through a workflow, which calls on functions in the package and on example input files (including the model) provided with the package. The README.md file accessed from the package git web page contains installation instructions and other relevant notes.

This appendix is intended to guide the user through the workflow to be performed each year for gathering input data, then updating and producing output from the ABAM model for use in annual vegetation management planning meetings. Section I.1 briefly describes the *ABAM* package and gives an overview of the workflow in tabular form. Section I.2 describes the data required for annual processing, provides a useful folder structure for the workflow, and instructs the user on how to use the *ABAM* package based on the example input files. Section I.3 describes each function in the *ABAM* package and, for each of these, provides definitions of the variables in those inputs. Section I.4 provides detailed information about the object produced by each function and the variables in those objects. Since the package facilitates a workflow, in several cases, output of a function serves as input for another function. Finally, section I.5 provides suggestions for checking work and troubleshooting problems that might occur during the workflow.

I.1. Brief Description of the *ABAM* R Package

The *ABAM* R package contains a series of functions customized for the U.S. National Park Service’s (NPS’s) Annual Brome Adaptive Management (ABAM) program. The functions are meant to run in order. The first two functions compile vegetation monitoring data from various sources into a single data frame, eliminate irrelevant observations, and process the data into the form required by later functions and the model. With the next six functions, spatial and temporal information associated with vegetation monitoring events are compiled into environmental and management history variables. Data associated with monitoring events (vegetation, environmental, and management history information) are reformatted to timestep pairs and used to update model parameters with the next two functions. Recent observations representing management units are run through the updated model to produce raw model output, which is used to produce charts and tables depicting current and predicted vegetation conditions of management units, utility of each management action in the model for those units, and model-selected optimal management actions for each unit with the next four functions. The final two functions are used to produce plot-level vegetation composition and condition information if more detailed results are desired. Table I1 lists the functions in the *ABAM* R package and shows the order in which they were designed to be run.

Table 11. Functions in the *ABAM* R package, the order in which they are intended to be used, example object representing function input (i) or output (o) in the package, example names for files that serve as raw inputs prepared by the user, and the folder in the suggested folder structure they would be called from or deposited into.

R package function	Order	Name of example object in <i>ABAM</i> package	Function input (i) or output (o)	Example name of file user creates and uses instead of object	Folder
ffi_calcs()	1	RawFFICover	i	FFI_2014_2020_AGFO.csv (pre-input format) ^a	INPUT
	1	NGP_veg_dat	o	–	OUTPUT
compilation()	2	trees	i	FFI_2014_2020_AGFO_trees.csv ^a	INPUT
	2	keepers	i	NGP_keepers_2020.csv	INPUT
	2	NGP_veg_dat	i	–	OUTPUT
	2	non_NGP_veg_dat	i	NON_NGP_observational_data.csv	INPUT
	2	compiled_veg	o	–	OUTPUT
get_spatial()	3	–	–	No example inputs for this function.	–
static_env()	4	compiled_veg	i	–	OUTPUT
	4	bison	i	ABAM_PLOTS_THRU_2020_bison.csv	INPUT
	4	–	–	–	–
	4	comps	i	component_MT.csv (compile data for each state)	SOIL
	4	hrzn	i	chorizon_MT.csv (compile data for each state)	SOIL
	4	mukey	i	ABAM_PLOTS_THRU_2020_soils.csv	INPUT
	4	slope	i	Extract from FFI vegetation export files for NGP plots, and from NON_NGP_observational_data.csv	INPUT
	4	veg_dat_s	o	–	OUTPUT

^a The user will export a file from FFI for each park separately, then merge those files to produce the function input object.

^b The user will create four folders within the PRISM folder. They are 'ppt', 'tmax', 'tmean', and 'tmin'. Within each of these four folders, PRISM data should be downloaded for each year from 1981 through May of the year in which the most recent monitoring event occurred. One zipped file is included here as an example but is not included in the *ABAM* package because of its size.

Table I1 (continued). Functions in the *ABAM* R package, the order in which they are intended to be used, example object representing function input (i) or output (o) in the package, example names for files that serve as raw inputs prepared by the user, and the folder in the suggested folder structure they would be called from or deposited into.

R package function	Order	Name of example object in <i>ABAM</i> package	Function input (i) or output (o)	Example name of file user creates and uses instead of object	Folder
PRISM_all()	5	path	i	PRISM/ppt/1981/ PRISM_ppt_stable_4kmM3_1981_all_bil.zip (unzip prior to processing) ^b	PRISM
	5	shp	i	ABAM_PLOTS_THRU_2020_XY.shp	INPUT
	5	all_prism	o	–	OUTPUT
seasonal_temps()	6	all_prism	i	–	OUTPUT
	6	veg_dat_s	i	–	OUTPUT
	6	veg_env_t	o	–	OUTPUT
seasonal_spei()	7	all_prism	i	–	OUTPUT
	7	veg_env_t	i	–	OUTPUT
	7	veg_env_p	o	–	OUTPUT
assign_mgmt()	8	veg_env_p	i	–	OUTPUT
	8	fire	i	ABAM_PLOTS_THRU_2020_fire.csv and NON_NGP_observational_data.csv	INPUT
	8	herbicide	i	ABAM_PLOTS_THRU_2020_herbicide.csv and NON_NGP_observational_data.csv	INPUT
	8	veg_env_mgmt	o	–	OUTPUT

^a The user will export a file from FFI for each park separately, then merge those files to produce the function input object.

^b The user will create four folders within the PRISM folder. They are 'ppt', 'tmax', 'tmean', and 'tmin'. Within each of these four folders, PRISM data should be downloaded for each year from 1981 through May of the year in which the most recent monitoring event occurred. One zipped file is included here as an example but is not included in the *ABAM* package because of its size.

Table 11 (continued). Functions in the *ABAM* R package, the order in which they are intended to be used, example object representing function input (i) or output (o) in the package, example names for files that serve as raw inputs prepared by the user, and the folder in the suggested folder structure they would be called from or deposited into.

R package function	Order	Name of example object in <i>ABAM</i> package	Function input (i) or output (o)	Example name of file user creates and uses instead of object	Folder
timestep()	9	veg_env_mgmt	i	–	OUTPUT
	9	all_dat_time	o	–	OUTPUT
model_update()	10	bnet	i	bnet_2019.net	MODEL_VRS
	10	all_dat_time	i	–	OUTPUT
	10	bnet_up	o	bnet_2020.net	MODEL_VRS
recent_obs()	11	unit_dat	i	assign_plots_to_unit_2020.csv	INPUT
	11	veg_env_mgmt	i	–	OUTPUT
	11	data_for_predicting	o	–	OUTPUT
opt_mgmt()	12	subset of data_for_predicting	i	–	–
	12	veg_uts	i	veg_utilities_2020.csv	INPUT
	12	cost_uts	i	management_utilities_2020.csv	INPUT
	12	weights	i	objective_weights_2020.csv	INPUT
	12	bnet_up	i	bnet_2020.net	MODEL_VRS
	12	conseq_table	o	–	OUTPUT

^a The user will export a file from FFI for each park separately, then merge those files to produce the function input object.

^b The user will create four folders within the PRISM folder. They are 'ppt', 'tmax', 'tmean', and 'tmin'. Within each of these four folders, PRISM data should be downloaded for each year from 1981 through May of the year in which the most recent monitoring event occurred. One zipped file is included here as an example but is not included in the *ABAM* package because of its size.

Table 11 (continued). Functions in the ABAM R package, the order in which they are intended to be used, example object representing function input (i) or output (o) in the package, example names for files that serve as raw inputs prepared by the user, and the folder in the suggested folder structure they would be called from or deposited into.

R package function	Order	Name of example object in <i>ABAM</i> package	Function input (i) or output (o)	Example name of file user creates and uses instead of object	Folder
current_pie()	13	conseq_table	i	–	OUTPUT
summ_optimal_mgmt()	14	conseq_table	i	–	OUTPUT
plot_cover_summary	15	veg_env_mgmt	i	–	OUTPUT
single_pie	16	conseq_table	i	–	OUTPUT

^a The user will export a file from FFI for each park separately, then merge those files to produce the function input object.

^b The user will create four folders within the PRISM folder. They are 'ppt', 'tmax', 'tmean', and 'tmin'. Within each of these four folders, PRISM data should be downloaded for each year from 1981 through May of the year in which the most recent monitoring event occurred. One zipped file is included here as an example but is not included in the *ABAM* package because of its size.

I.2. Input Data

The functions in the *ABAM* package call in and process data from several sources. Chief among them are observational data associated with individual plots. This section begins by describing those data. Before any other processing is done, a system for storing the input, intermediate products, and output must be created. The input data also need to be properly formatted. Thus, this section also suggests a folder structure and describes how the user can ensure proper file format.

I.2.1. Observational Data Required for Individual Monitoring Events

Before beginning the workflow, the user must assemble a suite of information for each monitoring event: measurements collected at the time the monitoring plot was established (coordinates and slope), data collected at each monitoring event (cover, diversity, and tree density), plot management history (fire and herbicide application), and the general grazing regime experienced by the plot. Table I2 defines the variables that provide this information to guide the user in data assembly.

Table I2. Tabular information required for individual monitoring events used in the ABAM package workflow.

Variable Name ^a	Definition
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym. NGP raw observational data extracted from FFI refers to the plot_id as the 'MacroPlot.Name'.
slope	Slope is the degree in which one portion of the plot is higher than the other.
Date	The date in year/month/day in numeric format XXXX/XX/XX. This is the form of the raw FFI output. It is not necessary for data not extracted from FFI.
day_veg	The calendar day (XX) of monitoring observation.
month_veg	The calendar month (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
ex_ann_rpc ^a	ex_ann_rpc = all exotic annual grasses
brja_rpc ^a	brja_rpc = Japanese brome (<i>Bromus japonicus</i>)
brte_rpc ^a	brte_rpc = cheatgrass (<i>Bromus tectorum</i>)
nat_forb_rpc ^a	nat_forb_rpc = native forbs (includes subshrubs)
nat_gram_rpc ^a	nat_gram_rpc = native graminoids (sedges and grasses)
woody_rpc ^a	woody_rpc = woody species including shrubs and trees

^a "rpc" in variable name stands for relative percent cover of vegetation component.

^b This variable is not required for the current ABAM model, but it is requested in anticipation of testing it for inclusion in later versions.

Table 12 (continued). Information required for individual monitoring events used in the ABAM package workflow.

Variable Name ^a	Definition
ex_per_gram_rpc ^a	ex_per_gram_rpc = exotic perennial graminoids
ex_forb_rpc ^a	ex_forb_rpc = exotic forbs
diversity	The number of native plant species intercepted across all points in the plot.
treeden	Trees per acre, where trees are woody stems with diameter at breast height >15 cm.
day_fire	The calendar day (XX) of burn.
month_fire	The calendar month (XX) of burn.
year_fire	The calendar year (XXXX) of burn.
AB_leafstage_fire ^b	Annual brome growth stage at the time of fire. Accepted levels are: “unknown” = the leaf stage of annual bromes was not determined at the time of the fire; “pre” = the fire occurred before annual brome emergence; “epost” = the fire occurred after the annual bromes emerged and the predominant stage of growth did not exceed two leaves; and “lpost” = the fire occurred after annual bromes emerged and the predominant stage of growth exceeds two leaves.
herbicide	The type of herbicide applied as all or part of a management action. Accepted levels are “none”, “indaziflam”, “imazapic”, and “imaz.indaz”.
day_herbicide	The calendar day (XX) of herbicide application.
month_herbicide	The calendar month (XX) of herbicide application.
year_herbicide	The calendar year (XXXX) of herbicide application.
AB_leafstage_herbicide ^b	Annual brome growth stage at the time of herbicide application. Accepted levels are “unknown” = the leaf stage of annual bromes was not determined at the time of herbicide application, “pre” = the herbicide was applied before annual brome emergence, and “epost” = the herbicide was applied after annual brome emerged and the predominant stage of growth did not exceed two leaves, and “lpost” = application occurred after annual bromes emerged and the predominant stage of growth exceeds two leaves.
actual_treatment	This is optional; those compiling inputs may choose to provide this to check or override the designation by the management function assign_mgmt(). Accepted management action (man_action) levels (in quotes), and the names by which they are referred to in the main text of this report (in parentheses) are: “none” (no action), “burn.spr” (spring burn), “burn.fall” (fall burn), “indaz.only” (indaziflam only), “no.burn.imaz.indaz” (imazapic-indaziflam), “burn.fall.imaz” (fall burn then imazapic), “burn.fall.w.indaz” (fall burn then indaziflam), “burn.fall.imaz.indaz” (fall burn then imazapic-indaziflam), “indaz.w.burn.spr” (indaziflam then spring burn), and “burn.spr.w.indaz” (spring burn then indaziflam). A full description of each management action is provided in Table B2.

^a “rpc” in variable name stands for relative percent cover of vegetation component.

^b This variable is not required for the current ABAM model, but it is requested in anticipation of testing it for inclusion in later versions.

Table 12 (continued). Information required for individual monitoring events used in the ABAM package workflow.

Variable Name ^a	Definition
grazing	Grazing exposure at the time of observation. Accepted levels of grazing are: “freerange_bison_other” (bison ranging freely in the area of the park where the monitoring plot lies, plus other wildlife ranging freely within and across park boundaries), “freerange_wl_no_bison” (only non-bison wildlife ranging freely within and across park boundaries), and “freerange_other” (non-bison wildlife ranging freely within and across park boundaries, plus seasonal grazing by horses).

^a “rpc” in variable name stands for relative percent cover of vegetation component.

^b This variable is not required for the current ABAM model, but it is requested in anticipation of testing it for inclusion in later versions.

1.2.2. Folder structure

The following folder and file structure is a suggestion; the user may choose an alternative structure once familiar with the workflow. The directions here are meant to help the user establish a workflow that minimizes preparation, processing, and checking. They also provide a structure that keeps files associated with each processing effort separate and well documented.

The folders described below assume that the user has established a project folder called ‘ABAM’. Within this folder, we suggest that the user create a year-specific folder (which we indicate below as ‘ABAM_XXXX’) for each iteration of the workflow, and within each year-specific folder an ‘INPUT’ and ‘OUTPUT’ folder.

ABAM/MODEL_VRS

This is where each version of the model will be saved. We suggest that the version used for a specific processing session also be stored in the session’s output folder (see below). At intervals throughout the life of the ABAM model, assessments will be made to measure the rate of learning over time. Having all of the models in a single location will make it easier to identify when and how many updates were conducted and ensure that the assessment is based on all model versions created. The updated model produced in each iteration of the workflow will be saved in the MODEL_VRS folder. It is also the folder from which the model version created in the prior year (usually the one necessary for the current year’s iteration) is called. For example, if the model version produced in the previous year was ‘bn_2019.net’, once the updating function [*ABAM::model_update()*] is run using the observations collected in 2020, the MODEL_VRS folder will also include the newly updated model named ‘bn_2020.net’.

ABAM/PRISM

Raw PRISM data can be downloaded from the PRISM Climate Group Climate Data website (<http://prism.oregonstate.edu>) or accessed via the *prism* R package (Hart et al. 2020). To calculate seasonal temperatures and standardized precipitation-evapotranspiration index (SPEI), data from all years available (1981-current) are necessary for the current workflow. To ensure that the function works properly, the PRISM folder should have the following four subfolders: ‘ppt’, ‘tmax’, ‘tmean’, and ‘tmin’, and each of these should have a subfolder for each year of data (‘1981’, ‘1982’, ... ‘2020’).

‘2021’, assuming that 2021 is current). In the example in Table I1, the PRISM data for a year is in a ‘.zip’ form, but the files need to be unzipped within the appropriate year’s folder prior to processing. It is important to note that any changes to the PRISM file structure may lead to issues when running the *ABAM::PRISM_all()* function in the R package.

ABAM/SOIL

Percent clay for each monitoring plot is usually estimated using the gSSURGO geodatabases (USDA 2018) for Nebraska, South Dakota, Wyoming, and Montana. Within each state’s respective geodatabase, mukey values can be extracted from the ‘MapunitRaster_10m’ raster, and tabular data associated with each mukey value can be gathered from the ‘component’ and ‘chorizon’ tables. Note that these files are large. At the time this document was written, the information required to estimate percent clay for FOLA was missing from the Wyoming gSSURGO geodatabase (see section 4.2.1.2). If this information becomes available or there is reason to believe that other updates to gSSURGO have been made, the data in the SOIL folder should be replaced. Or, if plot-level soil texture sampling occurs, the results may be stored here to reference in future processing.

ABAM/SPATIAL

A suite of spatial files is referenced throughout the workflow. These files include point files for plot centroids and polygon files for fire and herbicide history and bison ranges. Required variables within the attribute tables of these files are described in section I.3.

ABAM/ABAM_XXXX/INPUT

All other files that are specific to a particular run are placed within the INPUT folder. These files are listed in Table I1. Many of the files in the list must be updated each year using the information in section I.3, but all files need to be evaluated each year to determine whether modifications are necessary.

ABAM/ABAM_XXXX/OUTPUT

Processing outputs, including intermediate objects produced during the workflow, and model output are directed to the OUTPUT folder.

1.2.3. Checking file format

The *ABAM* R package includes several example objects to show what inputs for each function must include for successful processing. Table I1 lists these objects and provides example names of raw data files that contribute to each of the example objects. Section I.3 provides detailed definitions of the variables in each input file for each function. The user can examine the example objects for better understanding of their structure and content by calling them into the R Studio environment. To do this, the user should first install the *ABAM* R package with the following code:

```
install.packages("remotes")
remotes::install_gitlab("abam/abam_package",
                        host = "code.usgs.gov",
                        build_opts = c("--no-resave-data",
                                      "--no-manual"),
```

```
build_vignettes = TRUE)
```

Then load the example data with the following code:

```
inputs <- system.file("extdata",  
  "data_ABAM_input_except_soil.RData", package="ABAM")  
load(inputs)  
soil <-system.file("extdata", "data_ABAM_input_soil.RData",  
  package="ABAM")  
load(soil)  
outputs <-system.file("extdata",  
  "output_ABAM_example_products_of_functions.RData",  
  package="ABAM")  
load(outputs)
```

Some of the R base functions useful for examining each object are *class()* to identify the class of the object, *str()* to examine structure, *colnames()* to list the column names, and *head()* to observe the first five rows of most formats. The format of the R example objects will be referenced throughout section I.3.

I.3. ABAM R Package Function Descriptions and Definitions of Variables in Input Files

To aid the user in preparing the files necessary to run the ABAM tool, this section describes each function, refers to the example object(s) in the *ABAM* R package that serve as input to the function, and defines the variables in each input file used by that function. Many functions also use objects returned by previous functions. For detailed information about those objects, see section I.4 and the *ABAM* R package vignette.

I.3.1. *ffi_calcs()*

This function calculates relative percent cover for eight vegetation components (BRTE, BRJA, exotic annual grasses, exotic perennial grasses, exotic forbs, native graminoids, native forbs, and woody species) and diversity (number of native species) from point-intercept data exported from FFI. FFI is the database in which all NGPN and NGP Fire data, as well as many related experimental data, are stored¹. The output is a data frame containing 9 of the 10 vegetation components in the ABAM model.

Monitoring data collected over the previous ten years serve as the primary basis for annual model processing. At this time, the raw monitoring data that feeds into this function cannot be directly exported from FFI using an R script. This may become an option in the future. Currently, data must be exported from FFI for each park separately using FFI's "Query" process. We do not provide specific instructions for that process here. The Query process provides an option to export these data to a csv file (e.g. filename: FFI_2014_2020_AGFO.csv), which is the format assumed in the ABAM vignette. The exported file for each park should include the variables listed in Table I3. All raw FFI exports can be combined into one object for the 'dat_in' argument in *ABAM::ffi_calcs()*. The other input necessary is the date format, which allows the function to convert the single date variable in the files exported from FFI into three separate date variables (day, month, and year).

¹ FFI stands for FEAT-FIREMON Integrated, where FEAT is Fire Ecology Assessment Tool and FIREMON is Fire Monitoring.

Table 13. *ABAM::ffi_calcs()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Data exported from the 'Point-Cover (metric)' protocol in FFI for each park (package object: RawFFICover)	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	Date	The date in month/day/year in numeric format XX/XX/XXXX.
	Species.Symbol	A unique alphanumeric code representing an individual plant species
	Lifecycle	Lifecycle category appropriate for the species within the Northern Great Plains. The categories are: "Perennial", "Annual", "Biennial", and "Not Defined".
	Preferred.Lifeform	Most common lifeform of the species in the Northern Great Plains; options are: "Forb/Herb", "Graminoid", "Shrub", "Subshrub", "Tree", "Vine" and "Undefined"
	Order	Category established in FFI Query designating whether the observation was at the ground level or in the plant canopy. Levels are "ground" (order in raw data = 0) and "canopy" (order in raw data > 0).
	Cover	Percent of points at which the taxon occurred
	Native.Species	Levels "TRUE" or "FALSE" defining a species observed as native or exotic, respectively. Taxa of unknown origin (usually because not identified to species level) are assigned "FALSE".
date_format	–	The date format of the RawFFICover\$Date variable is entered as the character string "%Y/%m/%d".

1.3.2. compilation()

This function appends data to the FFI herb-layer cover and diversity variables returned by *ABAM::ffi_calcs()* and eliminates NGPN monitoring plots not appropriate for the ABAM model (e.g., riparian areas). Appended data are tree density from NGPN and NGP Fire plots, and all vegetation component variables from non-NGP plots (i.e., plots at LIBI monitored by ROMN, and experimental plots). After all vegetation data are compiled, vegetation variables are discretized (continuous data are binned into categories within each variable according to values listed in Table 4.2).

Tree density must be extracted from FFI separately from cover data. Not all parks have trees in monitoring plots, but all plots should be checked for tree occurrence every year.

Vegetation monitoring plots included in a general FFI export from the ‘Cover – Points (metric)’ protocol that have very little or no vegetation currently or potentially in the future (such as in badland areas) or that are in wetland or riparian areas are not appropriate for use in the ABAM model (see section 4.2.1). Those plots are identified in a file as in the example object 'keepers'. This file is referenced to exclude such plots from further processing, and should be maintained annually, with special focus on new monitoring plots. Specifically, if a newly established plot has <25% total vegetation cover and is in a badlands area (determine the latter by examining plot photos), the plot should be marked as “remove”. This is likely only to be relevant at BADL where a handful of new NGPN plots are still to be established. It is possible that total vegetation cover could be <25% in some heavily forested plots that NGP Fire may establish in the future, but those should be kept (marked as “yes”).

Table 14. *ABAM::compilation()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name ^a	Definition
Object produced from <i>ABAM::ffi_calcs()</i>	–	See description in section I.4.1.
Tree density data for NGP and non-NGP plots (package object: <i>all_trees</i>)	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	year_veg	The year monitoring occurred.
	treeden	Trees per acre, where trees are stems with diameter at breast height >15 cm.
List of plots to include (package object: <i>keepers</i>)	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	year_veg	The year monitoring occurred.
	keep	An indicator of plots that do not meet the criteria for model inclusion. Accepted levels are “yes” and “no”.
Vegetation metrics for non-NGP data sources (package object: <i>non_NGP_veg_dat</i>).	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym. Park is identified as the first four characters.
	year_veg	Calendar year (XXXX) of monitoring observation.
	day_veg	Calendar day (XX) of monitoring observation.
	month_veg	Calendar month (XX) of monitoring observation.
	brja_rpc	brja = Japanese brome (<i>Bromus japonicus</i>)
	brte_rpc	brte = cheatgrass (<i>Bromus tectorum</i>)
	ex_ann_rpc	ex_ann = all exotic annual grasses
	nat_forb_rpc	nat_forb = native forbs (includes subshrubs)
	nat_gram_rpc	nat_gram = native graminoids (sedges and grasses)
	woody_rpc	woody = woody species
	ex_per_gram_rpc	ex_per_gram = exotic perennial graminoids
	ex_forb_rpc	ex_forb = exotic forbs
	diversity	Native diversity is the number of native plant species intercepted across all points in the plot per observation.

^a “rpc” in variable name stands for relative percent cover of vegetation component.

1.3.3. *get_spatial()*

This function performs a simple spatial join and extracts tabular data from the attribute tables of two intersecting shapefiles, one point and one polygon. The function returns a data frame reflecting information from the attribute table of the point and polygon referenced. The function is used to populate variables whose information comes from spatial data, such as bison range, fire history, herbicide application history, and management unit for each monitoring plot.

Table 15. *ABAM::get_spatial()* input object requirements. No *get_spatial()* input objects are included in the *ABAM* R package example files.

Input Object	Definition
plot	Object of class 'sf' and 'data.frame' defining the point shapefile with plot locations. There should be one point – typically the center – representing each plot.
shape	Object of class 'sf' and 'data.frame' defining the shapefile that includes the polygon boundaries (e.g. fire, herbicide, grazing).
park	Object of class CHARACTER defining which park to subset the plot and polygons objects by. This is expressed as the four-letter park acronym and used to select plot based on the first four letters of the plot id (e.g., BADL_PCM_0001).
plot_vars	A character vector listing the variables to subset from the plot attribute table. This should include "plot_id" and any other variables needed later in the <i>ABAM</i> workflow.
shape_vars	A character vector listing the variables to subset from the shape attribute table. To record bison , the attribute table should include the columns 'park' and 'bison' (see Table 16 for definition of 'bison'). To record fire history , the attribute table should include the columns 'park', 'burn_name', 'Year', 'Month', and 'Day'. To record herbicide history , the attribute table should include the columns 'park', 'herbicide', 'year_herbicide', 'month_herbicide', 'day_herbicide', 'AB_leafstage_herbicide'. See Table 110 for variable descriptions for fire and herbicide data frames. To record management unit name , the attribute table should include 'park' and 'unit_name'.
EPSG	The EPSG code is a four- or five-digit code that represents a coordinate reference system (CRS). At the time of this publication, all federal agencies are required to use the code 6318.

1.3.4. *static_env()*

This function appends static environmental variables to the vegetation component data frame returned by *ABAM::compilation()* then discretizes them according to values listed in Table 4.4. Static environmental variables are not expected to change frequently. They are grazing, percent clay, and slope. Slope can be extracted from FFI for NGPN and NGP Fire plots when exporting herbaceous cover data for *ABAM::FFIcalcs()*. For sample event data not extracted from FFI, slope and grazing values are provided in the data file(s) provided by non-NGP data preparator(s).

Grazing is a categorical variable (3 levels) indicating the type of long-term grazing experienced by a plot. The levels are defined by the park (four letter acronym provided within the plot_id) and whether the monitoring plot is inside a bison range. Current bison range information is obtained from park staff. If this information is in spatial (e.g., shapefile or geodatabase) format, the user can create the

appropriate file using ArcPro, then convert it to the '.csv' format before using as input for this function.

Soil data are extracted from the gSSURGO geodatabases (USDA 2017) for Nebraska, South Dakota, Wyoming, and Montana. When this report was written, the data could be downloaded from the Geospatial Data Gateway (<https://gdg.sc.egov.usda.gov/>). Mukey values, and a variable defining the state the plot is located in, are extracted for each monitoring plot location. This can be accomplished using the 'Extract Multi Values to Points' tool in ArcPro (2.7.1), or likely any recent version of an Arc mapping program. Then use the field calculator to produce and populate three attribute columns called 'plot_id', 'mukey', and 'state'. Export the final table to a .csv format for model input. The function is written to extract percent clay values from the upper (A and B) soil horizons using each state's component (component_MT.csv) and chorizon (chorizon_MT.csv) tables based on the mukey value for each plot location.

The object returned by *ABAM::static_env()* should be compared to the object returned by *ABAM::compilation()* to ensure that all monitoring plots are included, and that the static environmental variables have been properly derived.

Table 16. *ABAM::static_env()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Object returned by <i>ABAM::compilation()</i> (package object: compiled_veg)	–	See description in section 1.4.2.
Exposure to bison grazing (package object: bison)	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	bison	Indicates if the monitoring plot is within the bison range (yes/no).
Slope of plot (package object: slope)	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	slope	Extracted from FFI or provided with non-FFI observational data.
Map unit key for each plot (package object: mukey)	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	state	Two-letter acronyms representing the state in which the plot is located. ABAM parks are in NE, MT, SD, and WY.
	mukey	Map unit key is a unique identifier used in the gSSURGO Database to link raster cells to attribute tables.
Compilation of ‘code key’ files downloaded from gSSURGO for each state (package object: comps).	state	Two-letter acronyms representing the state in which the plot is located. The current ABAM parks are in NE, MT, SD, and WY.
	mukey	Map unit key is a unique identifier used in the gSSURGO Database to link raster cells to attribute tables.
	cokey	Code key is a unique identifier used in the gSSURGO Database to link raster cells to attribute tables.
Compilation of ‘horizon’ files downloaded from gSSURGO for each state (package object: hrzn).	state	Two-letter acronyms representing the state in which the plot is located. The current ABAM parks are in NE, MT, SD, and WY.
	cokey	Code key is a unique identifier used in the gSSURGO Database to link raster cells to attribute tables.
	desgnmaste	The horizon of the soil layer in which the data in the row apply.
	claytotal1	Percent of clay in the soil within each horizon.

I.3.5 *PRISM_all()*

Monthly temperature (tmax, tmean, and tmin) and precipitation (ppt) are compiled for each plot location for every month from 1981 to the current year. The PRISM data are available for direct download from a website (<https://prism.oregonstate.edu/>) or via the *prism* R package (Hart et al. 2020). The spatial location of each plot, in the form of a shapefile, is required to extract PRISM values. Be sure to enter the correct projection into the function via *prism_proj* as shown in the vignette.

Table I7. *ABAM:PRISM_all()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Folder or source of PRISM files	–	Raw PRISM (bil) files from 1981 to the current observation year. See example data structure in section I.2.2 for proper setup.
shapefile with plot points (package object: shp)	plot_id	A unique identifier of a monitoring or experimental plot. The first four characters indicate park.
	Layout_PointType	Identifies point type (e.g., PC, A0, B0, A50, B50) that plot location will be based on. The center of the plot, identified as “Plot Center” or “PC” in shapefiles, is optimal. Only one point should represent each plot.
	longitude	Longitude coordinate in decimal degrees of centroid of monitoring plot.
	latitude	Latitude coordinate in decimal degrees of centroid of monitoring plot.

1.3.6. *seasonal_temps()*

Mean monthly temperature values derived from *PRISM_all()* are used to calculate seasonal mean temperatures for each monitoring observation. This function appends continuous and discretized (according to values listed in Table 4.4) temperature variables to the data frame returned by *ABAM::static_env()*.

Table 18. *ABAM::seasonal_temps()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Object returned from <i>ABAM::static_env()</i> (package object: <i>veg_dat_s</i>)	–	See description in section 1.4.3.
Object returned from <i>ABAM::PRISM_all()</i> , with column names renamed as follows: year to <i>p_year</i> , and month to <i>p_month</i> . (package object: <i>all_prism</i>)	–	See description in section 1.4.4.

1.3.7. *seasonal_SPEI()*

Seasonal SPEI values for spring and winter are calculated from monthly precipitation and temperature values gathered by *ABAM::PRISM_all()* and the mean latitude of each park (Hargreaves 1994, Beguería and Vicente-Serrano 2017). Continuous and discretized (according to values listed in Table 4.4) forms are added to the data frame returned by *ABAM::seasonal_temps()*. See the *ABAM* R package vignette for details regarding other arguments required for *ABAM::seasonal_spei()*.

Table 19. *ABAM::seasonal_spei()* input (example objects in the *ABAM* package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Object returned from <i>ABAM::seasonal_temps()</i> (package object: <i>veg_env_t</i>)	–	See description in section 1.4.5.
Object returned from <i>ABAM::PRISM_all()</i> , with column names changed as follows: year to <i>p_year</i> , and month to <i>p_month</i> (package object: <i>all_prism</i>)	–	See description in section 1.4.4.

1.3.8. assign_mgmt()

This function assigns recent management action and time since that action to each monitoring event based on the dates of the most recent observation and individual fire and herbicide events, as well as the type of herbicide applied.

The data frame returned by *ABAM::assign_mgmt()* includes a row of data for every monitoring event. Each row has variables for vegetation components, static environmental factors, weather, most recent management action, and time since management. Management actions are defined according to the criteria defined in this report (Table B2). The timing (month window) of actual management actions may not always fall within these criteria. Therefore, the user is strongly encouraged to check for management actions that do not fit within the criteria for management actions in the model and adjust accordingly (see “Assign management” in the *ABAM* R package’s vignette).

Management actions may be more effective when applied during specific growth stages of annual bromes. The leaf stage of annual bromes at the time of application does not define the management action assigned in this function. However, it is assumed that indaziflam is applied prior to the emergence of annual bromes, and that imazapic or an imazapic-indaziflam mix is applied after annual bromes have emerged. Land managers within ABAM parks have recently begun to record annual brome growth stage at the time of management. These data may be used in future analyses to assess the influence of annual brome growth stage on the effectiveness of different management actions.

At the time this report was written, the source and format of fire and herbicide information had not been finalized. The management input files described in the table below are an example of how management data can be used to define management action. Development of a dependable data source and format for this information will be addressed in the future.

Table I10. *ABAM::assign_mgmt()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Object returned from <i>ABAM::seasonal_spei()</i>	–	It includes the discretized form of vegetation component and environmental variables for each plot observation. See description in section I.4.6.
Fire history of each plot (package object: fire).	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	year_fire	The calendar year (XXXX) in which the fire event occurred.
	month_fire	The calendar month (XX) in which the fire event occurred.
	day_fire	The calendar day (XX) on which the fire event occurred.
	AB_leafstage_fire	Leaf stage of annual bromes at the time of a fire. Accepted levels are “pre”, “epost”, “lpost”, and “unknown”.
Herbicide history of each plot (package object: herbicide).	plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	herbicide	The type of herbicide applied as all or part of a management action; accepted levels are “imazapic”, “indaziflam”, and “imaz.indaz”.
	year_herbicide	The calendar year (XXXX) in which herbicide was applied.
	month_herbicide	The calendar month (XX) in which herbicide was applied.
	day_herbicide	The calendar day (XX) on which herbicide was applied.
	AB_leafstage_herbicide	Leaf stage of annual bromes at the time of herbicide application; levels are “pre”, “epost”, “lpost”, and “post”.

1.3.9. timestep()

Each row in the object returned by *ABAM::assign_mgmt()* contains information related to a single observation. The function *ABAM::timestep()* uses this object to produce a new object in which each row is a pair of monitoring events and their associated information (i.e., a variable for each node in the ABAM model) for a monitoring plot. Each pair includes information for a current (earlier) observation, a ‘future’ (later) observation, the management action (including ‘none’) separating them, and the variable ‘time’. The value of ‘time’ is either (a) the number of growing seasons between the management action and the ‘future’ observation or (b) the number of growing seasons between the ‘current’ and ‘future’ observations if no management has occurred within five years of either observation. It is uncommon to have a pre- and post-management observation within the same year, but if this does occur, the function assigns the post-action observation a time value of 1. Similarly, a monitoring event in June for a plot managed the previous August is assigned the time value of 1. The object returned by *ABAM::timestep()* serves as the ‘new’ information for ABAM model updating. The function includes an option to determine the time window in which observations should be included for this purpose. For example, the user can choose to update the model with the observation pairs associated only with data collected in the prior monitoring season, or with data collected in the prior several monitoring seasons. This is determined by the value of the object ‘keep_from’. There is an example provided in the table below and in the ABAM R package vignette.

Table I11. *ABAM::timestep()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Description
Object returned from <i>ABAM::assign_mgmt()</i>	See description in section I.4.7.
Time range of observation pairs to use for model updating (object package: keep_from)	The calendar year (XXXX) defining the most recent vegetation observations to be included in the output object. For example, if the current year is 2020, and the user only wants to update with the observations paired with data collected in 2020, the user would define it using the code ‘keep_from <- 2020’. If the user wants to update with observations pairs associated with the data collected over the last 3 years, the user will define it using the code ‘keep_from <- (2020-3)’.

1.3.10. model_update()

In this function, the data frame of paired observations returned by *ABAM::timestep()* is used to update the model. Only parameters for a subset of nodes (see description for nodes_to_update in Table I12)) are updated; this avoids modifying nodes that must remain consistent, such as Network and Vegetation Condition.

Table 112. *ABAM::model_update()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Description
BDN (package object: bnet)	The Bayesian network that is to be updated with newly collected data. The .net file is imported using the <i>gRain::loadHuginNet</i> function.
nodes_to_update	The names of the nodes to be updated. This object is expected to be the following character string: "c_temp_winter_tf", "c_temp_spring_tf", "c_temp_fall_tf", "c_SPEI_spring_tf", "c_SPEI_winter_tf", "c_brte_tf", "c_brja_tf", "c_ex_per_gram_tf", "c_treedden_tf", "c_diversity_tf", "c_ex_ann_gram_tf", "c_nat_gram_tf", "c_ex_forb_tf", "c_nat_forb_tf", "c_woody_tf", "clay_pct", "grazing", "c_slope". See the package vignette for instructions on how to prepare this input object.
Timestep dataset (package object: all_dat_time)	Object returned from <i>ABAM::timestep()</i> . See description in section 1.4.7.
n	A numeric value representing the hyper parameter, or pseudocount. It controls the strength of the influence of the prior relative to the new data. The lower the hyper parameter value, the more influence the new data will have on the updated CPT, or posterior distribution. (See section 5.2.3.)

1.3.11. recent_obs()

The current condition of a management unit is defined by observations from at least 3 plots monitored in the most recent 5 years. This function reduces the object returned by *ABAM::assign_mgmt()* to only monitoring observations from the most recent 5 years, assigns those observations to a management unit, then further reduces the dataframe to include only observations in management units with at least 3 observations. Management units are currently defined by burn unit boundaries (all parks but FOLA and LIBI) or placeholder boundaries created for this project (FOLA and LIBI; see section 5.2.1). Because the boundaries of these units are dynamic, the files used to describe management unit boundaries and plots within those boundaries need to be updated each year and then used to create the first input object for this function.

The ABAM model is currently structured based on our assumption that management induces changes in vegetation dynamics (section 4.4.2). Therefore, the current use of the decision support tool assumes that predictions for areas that have experienced management within three years is invalid. In accordance with this practice, after selecting the most recent monitoring event for each plot, this function identifies plots associated with a recent (≤ 3 years) management action by adding the suffix ".post" to the name of the management unit in which those plots occur. This allows the user to easily identify management units for which it is appropriate to calculate and communicate current conditions to managers but NOT present optimal management actions from the ABAM model output. When only a subset of plots in a management unit were treated, this action results in two entities within the same management unit that are run through the ABAM model separately (e.g. Unit.A and Unit.A.post).

The object returned by this function serves as input for *ABAM::opt_mgmt()*.

Table I13. *ABAM::recent_obs()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Object returned from <i>ABAM::assign_mgmt()</i> (package object: <i>veg_env_mgmt</i>)	–	See description in section I.4.9.
File associating each plot with a management unit (package object: <i>unit_dat</i>)	<i>plot_id</i>	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
	<i>management_unit</i>	The name of the management unit the monitoring plot is in.

I.3.12. *opt_mgmt()*

This function uses the model to predict the consequences of management actions based on current vegetation conditions and environmental conditions. Function input includes a subset of the data frame returned by *ABAM::recent_obs()*; see the vignette for instructions on how to prepare the subset. Other inputs are utilities for cost and vegetation condition, and objective weights. The example file ‘cost_uts’ includes the cost of each management action and the normalized utility for that cost (Figure H4). This file needs to be updated regularly as costs of management actions change. The ‘veg_uts’ and ‘weights’ files include the results of the elicitation exercise (section 4.7.1). Specifically, the ‘veg_uts’ file contains park-specific weights assigned to each of the 10 vegetation conditions (Figure 4.13). The ‘weights’ input file contains values for the two competing objectives in the ABAM framework assigned by each park (Figure 4.15). Over time, park managers may adjust vegetation condition utilities and objective weights; those changes should be applied and documented (i.e., new versions of files stored with other files used in the year’s processing).

Model output is produced as a series of consequence tables, one for each management unit in each park, stacked into one large table. Each consequence table, subset by park and unit, includes a series of probability distributions describing the current vegetation condition and predicted vegetation conditions at the designated timestep after management (time) for every possible management action. Utilities are also reported for current condition and each management action outcome. The utility is a score representing how satisfied the park’s managers will be with the outcome given their stated preferences for each vegetation condition and relative preference for vegetation improvement vs. cost of management. Utility values range from 0 to 1, with 1 being the highest satisfaction possible and 0 being complete dissatisfaction (section 4.7.1). Two utilities are provided in the output. One is based only on the vegetation outcome; the other accounts for vegetation outcome and the cost associated with that management action. The output is customized to each park-specific vegetation preference and objective weight.

Table I14. *ABAM::opt_mgmt()* input (example objects in the *ABAM* R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Data object prepared (from e.g., package object <i>data_for_predicting</i>) to represent the current condition of management units	–	Subset of object returned by <i>ABAM::recent_obs()</i> that has only the variables related to vegetation current conditions (i.e., vegetation components). See the vignette for instructions on how to prepare this input object.
Data object prepared (from e.g., package object <i>data_for_predicting</i>) to identify parks	–	Subset of object returned by <i>ABAM::recent_obs()</i> that has only the variable listing the park associated with each observation row. See the vignette for instructions on how to prepare this input object.
Data object prepared (from e.g., package object <i>data_for_predicting</i>) to identify management units	–	Subset of object returned by <i>ABAM::recent_obs()</i> that has only the variable listing the management unit associated with each observation row. See the vignette for instructions on how to prepare this input object.
Vector of management actions	–	A character string listing all the management actions considered in the model ("none", "burn.spr", "burn.fall", "indaz.only", "no.burn.imaz.indaz", "burn.fall.imaz", "burn.fall.w.indaz", "burn.fall.imaz.indaz", "indaz.w.burn.spr", "burn.spr.w.indaz"). This string needs to be an exact match of the levels in the <i>man_action</i> node of the model. See the vignette for instructions on how to prepare this input object.
Time step for which predictions will be produced	–	Character value of "1", "2_3", or "4_5".
Park specific utilities for each vegetation condition (package object: <i>veg_uts</i>)	Vegetation Condition	A list of the 10 vegetation conditions in the model. These are: "Exotic Annual Grassland", "Exotic Annual Woodland", "Exotic Perennial Grassland", "Exotic Perennial Woodland", "High-Quality Prairie", "High-Quality Woodland", "Low-Quality Prairie", "Low-Quality Woodland", "Simplified Grassland", and "Weedy Forb Mess".
	AGFO	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.
	BADL	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.

Table I14 (continued). ABAM::opt_mgmt() input (example objects in the ABAM R package in parentheses), variable names, and variable definitions.

Input Object	Variable Name	Definition
Park specific utilities for each vegetation condition (package object: veg_uts) (continued)	DETO	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.
	FOLA	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.
	LIBI	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.
	SCBL	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.
	WICA	Park-specific utility values between 0 and 1 representing park preferences for each vegetation condition. Higher values represent more desirable vegetation conditions.
Utilities associated with the cost of each management action (package object: cost_uts)	man_action	One of the 10 management actions considered in the model. These are: none, fall burn, spring burn, indaziflam only, imazapic-indaziflam, fall burn then imazapic, fall burn then indaziflam, fall burn then imazapic-indaziflam, indaziflam then spring burn, spring burn then indaziflam.
	cost	Estimated cost per acre for the management action.
	utility	A value between 0 and 1 calculated from cost per acre of each management action.
Objective weights for each park (package object: weights)	park	Four-letter acronym for each park. Acronyms need to be all capital letters. The parks currently enrolled in ABAM are AGFO, BADL, DETO, FOLA, LIBI, SCBL, and WICA.
	veg	The weight each park assigns to improving vegetation condition.
	cost	The weight each park assigns to cost of management action. The values for veg and cost sum to 1.
bn	—	The updated Bayesian network (i.e., the updated model), which is the object returned from ABAM::model_update().

1.3.13. current_pie()

This function produces a table and a series of pie charts and exports them to a user-specified location. The output depicts the probability distribution of the current vegetation conditions of each management unit. Inputs are the “recent_year” (e.g., 2020), the consequence table produced by *ABAM::opt_mgmt()*, and the output folder path to store pie charts.

1.3.14. summ_opt_mgmt ()

The output produced by the *ABAM::opt_mgmt()* function is a large data table. The *ABAM::summ_opt_mgmt()* function produces a summary table that organizes information pertinent to management planning from that output. This summary table lists, for each management unit in a park, the current utility; dominant vegetation condition; and future utilities associated with the model-selected optimal management action, fall prescribed fire, and spring prescribed fire.

1.3.15. plot_cover_summary ()

This function produces a stacked bar chart that shows relative percent cover of all vegetation components for a single plot over all of its observations through time. A line graph depicting diversity of the plot for each observation is overlaid on the bar chart. The figure and dataset used to produce the figure can be exported.

1.3.16. single_pie()

This function produces a pie chart representing the current condition for a specific management unit. This is similar to the function *ABAM::current_pie()*, but the output is a single object in the R environment rather than a pie chart for every management unit in a park.

I.4. Definitions of Variables in Objects Returned by Functions in the ABAM R Package

Each section below is a table describing the object(s) produced by each function in the *ABAM* R package. These objects are all R data frames containing variables; variables are listed and defined.

I.4.1. Data frame returned from *ABAM::ffi_calcs()*

Table I15. The example object provided within the *ABAM* R package is called *NGP_veg_dat*.

Variable Name	Definition
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
Date	The date in month/day/year in numeric format XX/XX/XXXX.
month_veg	The calendar month (XX) of monitoring observation.
day_veg	The calendar day (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
total.herb.cover	Total plant cover in the plot
Cover.BRJA_canopy	Absolute cover of <i>Bromus japonicus</i> in the plot
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
Cover.BRTE_canopy	Absolute cover of <i>Bromus tectorum</i> in the plot
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage
Cover.ex_ann_canopy	Absolute cover of all exotic annual grasses in the plot
ex_ann_rpc	Cover of all exotic annual grasses relative to total plant cover, expressed as a percentage
Cover.nat_forb_canopy	Absolute cover of native forb species (forb/herb and subshrub) in the plot
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
Cover.nat_gram_canopy	Absolute cover of native graminoid species in a plot
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
Cover.woody_canopy	Absolute cover of woody species (shrub and tree) in the plot
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
Cover.ex_forb_canopy	Absolute cover of exotic forb species (forb/herb and subshrub) in the plot
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
Cover.ex_per_gram_canopy	Absolute cover of exotic perennial graminoids in a plot

Table I15 (continued). The example object provided within the ABAM R package is called NGP_veg_dat.

Variable Name	Definition
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in the plot

1.4.2. Data frame returned from compilation()

Table 116. The example output provided within the *ABAM* R package is called `compiled_veg`.

Variable Name	Definition
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
month_veg	The calendar month (XX) of monitoring observation.
day_veg	The calendar day (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
ex_ann_rpc	Cover of all exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56).
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage.
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in a plot.
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
treeden	Density of trees (per acre) with diameter at breast height > 15 cm.
c_ex_ann_gram	Discretized form of ex_ann_gram_rpc. The levels are “low”, “medium”, “high” and “very high”.
c_brte	Discretized form of brte_rpc. The levels are “low”, “medium”, and “high”.
c_brja	Discretized form of brja_rpc. The levels are “low”, “medium”, and “high”.
c_nat_forb	Discretized form of nat_forb_rpc. The levels are “low”, “medium”, and “high”.
c_nat_gram	Discretized form of nat_gram_rpc. The levels are “low”, “medium”, and “high”.
c_ex_forb	Discretized form of ex_forb_rpc. The levels are “low”, “medium”, and “high”.
c_ex_per_gram	Discretized form of ex_per_gram_rpc. The levels are “low”, “medium”, and “high”.

Table I16 (continued). The example output provided within the ABAM R package is called `compiled_veg`.

Variable Name	Definition
c_diversity	Discretized form of diversity. The levels are “low”, “medium”, and “high”.
c_woody	Discretized form of woody_rpc. The levels are “low”, “medium”, and “high”.
c_treedn	Discretized form of treeden. The levels are “low” and “high”.

1.4.3. Data frame returned from static_env()

Table I17. The example output provided within the *ABAM* R package is called `veg_dat_s`.

Variable Name	Definition
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
month_veg	The calendar month (XX) of monitoring observation.
day_veg	The calendar day (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
ex_ann_gram_rpc	Cover of all exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in a plot.
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
treeden	Density of trees (per acre) with diameter at breast height > 15 cm

^a Variables added from the function `static_env()`

Table I17 (continued). The example output provided within the ABAM R package is called `veg_dat_s`.

Variable Name	Definition
<code>c_ex_ann_gram</code>	Discretized form of <code>ex_ann_gram_rpc</code> . The levels are “low”, “medium”, “high” and “very high”.
<code>c_brte</code>	Discretized form of <code>brte_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_brja</code>	Discretized form of <code>brja_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_nat_forb</code>	Discretized form of <code>nat_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_nat_gram</code>	Discretized form of <code>nat_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_ex_forb</code>	Discretized form of <code>ex_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_ex_per_gram</code>	Discretized form of <code>ex_per_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_diversity</code>	Discretized form of <code>diversity</code> . The levels are “low”, “medium”, and “high”.
<code>c_woody</code>	Discretized form of <code>woody_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_treedn</code>	Discretized form of <code>treeden</code> . The levels are “low” and “high”.
<code>grazing</code> ^a	Grazing has three levels: “Freerange_bison_other” (free range wildlife and year-round bison), “Freerange_wl_no_bison”, and “Freerange_other” (free range wildlife with seasonal grazing by horses)
<code>c_slope</code> ^a	Discretized version of slope input variable. The levels are “low” and “high”.
<code>clay_percent</code> ^a	Estimated percent clay in the soil at the monitoring plot location.
<code>clay_pct</code> ^a	Discretized form of <code>clay_percent</code> . The levels are “low” and “high”.

^a Variables added from the function `static_env()`

1.4.4. Data frame returned from `PRISM_all()`

Table I18. The example object provided within the ABAM R package is ‘`all_prism`’. Note that the user must change column names in the raw output as follows: `year` to `p_year`, `month` to `p_month`.

Variable Name	Definition
<code>plot_id</code>	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
<code>latitude</code>	Latitude coordinate in decimal degrees (DD) of centroid of monitoring plot.
<code>p_year</code>	Calendar year of precipitation value, in form XXXX.
<code>p_month</code>	Calendar month of precipitation value, in numeric form
<code>tmean</code>	Mean temperature in °C for the respective month/year.
<code>tmin</code>	Minimum temperature in °C for the respective month/year.
<code>tmax</code>	Maximum temperature in °C for the respective month/year.
<code>ppt</code>	Total precipitation in mm for respective month/year.

1.4.5. Data frame returned from `seasonal_temps()`

Table 119. The example output provided within the *ABAM* R package is called `veg_env_t`.

Variable Name	Definition
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
month_veg	The calendar month (XX) of monitoring observation.
day_veg	The calendar day (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
ex_ann_gram_rpc	Cover of all exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in a plot.
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
treeden	Density of trees (per acre) with diameter at breast height > 15 cm
c_ex_ann_gram	Discretized form of <code>ex_ann_gram_rpc</code> . The levels are “low”, “medium”, “high” and “very high”.
c_brte	Discretized form of <code>brte_rpc</code> . The levels are “low”, “medium”, and “high”.
c_brja	Discretized form of <code>brja_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_forb	Discretized form of <code>nat_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_gram	Discretized form of <code>nat_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
c_ex_forb	Discretized form of <code>ex_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
c_ex_per_gram	Discretized form of <code>ex_per_gram_rpc</code> . The levels are “low”, “medium”, and “high”.

^a Variables added from the function `ABAM::seasonal_temps()`

Table 119 (continued). The example output provided within the ABAM R package is called `veg_env_t`.

Variable Name	Definition
<code>c_diversity</code>	Discretized form of diversity. The levels are “low”, “medium”, and “high”.
<code>c_woody</code>	Discretized form of <code>woody_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_treedn</code>	Discretized form of <code>treeden</code> . The levels are “low” and “high”.
<code>clay_pct</code>	Discretized form of <code>clay_percent</code> . The levels are “low” and “high”.
<code>grazing</code>	Grazing has three levels: “Freerange_bison_other” (free range wildlife and year-round bison), “Freerange_wl_no_bison”, and “Freerange_other” (free range wildlife with seasonal grazing by horses)
<code>c_slope</code>	Discretized slope. The levels are “low” and “high”.
<code>temp_fall</code> ^a	Mean of monthly temperatures in °C for the fall months (September–November) of the year previous to the monitoring observation.
<code>temp_spring</code> ^a	Mean of monthly temperatures in °C for the spring months (March–May) of the year of the monitoring observation.
<code>temp_winter</code> ^a	Mean of monthly temperatures in °C for the winter months (December–February) previous to the monitoring observation.
<code>c_temp_fall</code> ^a	Discretized form of <code>temp_fall</code> . The levels are “low” and “high”.
<code>c_temp_spring</code> ^a	Discretized form of <code>temp_spring</code> . The levels are “low” and “high”.
<code>c_temp_winter</code> ^a	Discretized form of <code>temp_winter</code> . The levels are “low” and “high”.

^a Variables added from the function `ABAM::seasonal_temps()`

1.4.6. Data frame returned from `seasonal_SPEI()`

Table 120. The example output provided within the *ABAM* R package is called `veg_env_p`.

Variable Name	Definition
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
month_veg	The calendar month (XX) of monitoring observation.
day_veg	The calendar day (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
ex_ann_gram_rpc	Cover of exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in a plot.
treeden	Density of trees (per acre) with diameter at breast height > 15 cm
c_ex_ann_gram	Discretized form of <code>ex_ann_gram_rpc</code> . The levels are “low”, “medium”, “high” and “very high”.
c_brte	Discretized form of <code>brte_rpc</code> . The levels are “low”, “medium”, and “high”.
c_brja	Discretized form of <code>brja_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_forb	Discretized form of <code>nat_forb_rpc</code> . The levels are “low”, “medium”, and “high”.

^a Variables added from `ABAM::seasonal_SPEI()`.

Table I20 (continued). The example output provided within the ABAM R package is called `veg_env_p`.

Variable Name	Definition
<code>c_nat_gram</code>	Discretized form of <code>nat_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_ex_per_gram</code>	Discretized form of <code>ex_per_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_ex_forb</code>	Discretized form of <code>ex_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_diversity</code>	Discretized form of <code>diversity</code> . The levels are “low”, “medium”, and “high”.
<code>c_woody</code>	Discretized form of <code>woody_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_treedn</code>	Discretized form of <code>treedn</code> . The levels are “low” and “high”.
<code>clay_pct</code>	Discretized form of <code>clay_percent</code> . The levels are “low” and “high”.
<code>grazing</code>	Grazing has three levels: “Freerange_bison_other” (free range wildlife and year-round bison), “Freerange_wl_no_bison”, and “Freerange_other” (free range wildlife with seasonal grazing by horses)
<code>c_slope</code>	Discretized slope. The levels are “low” and “high”.
<code>c_temp_fall</code>	Discretized form of <code>temp_fall</code> (see I.4.5). The levels are “low” and “high”.
<code>c_temp_spring</code>	Discretized form of <code>temp_spring</code> (see I.4.5). The levels are “low” and “high”.
<code>c_temp_winter</code>	Discretized form of <code>temp_winter</code> (see I.4.5). The levels are “low” and “high”.
<code>SPEI_spring</code> ^a	The mean standardized precipitation evapotranspiration index (SPEI) for the spring months (March–May) prior to the monitoring observation.
<code>SPEI_winter</code> ^a	The mean standardized precipitation evapotranspiration index (SPEI) for the winter months (December–February) prior to the monitoring observation.
<code>c_SPEI_spring</code> ^a	The discretized form of <code>SPEI_spring</code> . The levels are “low” and “high”.
<code>c_SPEI_winter</code> ^a	The discretized form of <code>SPEI_winter</code> . The levels are “low” and “high”.

^a Variables added from `ABAM::seasonal_SPEI()`.

1.4.7. Data frame returned from `assign_mgmt()`

Table 121. The example output provided within the *ABAM* R package is called `veg_env_mgmt`.

Variable Name	Definition
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
month_veg	The calendar month (XX) of monitoring observation.
day_veg	The calendar day (XX) of monitoring observation.
year_veg	The calendar year (XXXX) of monitoring observation.
ex_ann_gram_rpc	Cover of exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in a plot.
treeden	Density of trees (per acre) with diameter at breast height > 15 cm
c_ex_ann_gram	Discretized form of <code>ex_ann_gram_rpc</code> . The levels are “low”, “medium”, “high” and “very high”.
c_brte	Discretized form of <code>brte_rpc</code> . The levels are “low”, “medium”, and “high”.
c_brja	Discretized form of <code>brja_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_forb	Discretized form of <code>nat_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_gram	Discretized form of <code>nat_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
c_ex_per_gram	Discretized form of <code>ex_per_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
c_ex_forb	Discretized form of <code>ex_forb_rpc</code> . The levels are “low”, “medium”, and “high”.

^a Variables added by the function `assign_mgmt()`

Table I21 (continued). The example output provided within the ABAM R package is called `veg_env_mgmt`.

Variable Name	Definition
<code>c_diversity</code>	Discretized form of diversity. The levels are “low”, “medium”, and “high”.
<code>c_woody</code>	Discretized form of <code>woody_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_treedn</code>	Discretized form of <code>treeden</code> . The levels are “low” and “high”.
<code>c_slope</code>	Discretized slope. The levels are “low” and “high”.
<code>grazing</code>	Grazing has three levels: “Freerange_bison_other” (free range wildlife and year-round bison), “Freerange_wl_no_bison”, and “Freerange_other” (free range wildlife with seasonal grazing by horses)
<code>clay_pct</code>	Discretized form of <code>clay_pct</code> . The levels are “low” and “high”.
<code>c_temp_fall</code>	Discretized form of <code>temp_fall</code> (see I.4.5). The levels are “low” and “high”.
<code>c_temp_spring</code>	Discretized form of <code>temp_spring</code> (see I.4.5). The levels are “low” and “high”.
<code>c_temp_winter</code>	Discretized form of <code>temp_winter</code> (see I.4.5). The levels are “low” and “high”.
<code>c_SPEI_spring</code>	The discretized form of <code>SPEI_spring</code> (see I.4.6). The levels are “low” and “high”.
<code>c_SPEI_winter</code>	The discretized form of <code>SPEI_winter</code> (see I.4.6). The levels are “low” and “high”.
<code>t.s.trt</code> ^a	The number of growing seasons since management (up to 5), or if no recent management has occurred, the number of growing seasons since last observation. The levels are “1”, “2”, “3”, “4”, “5” and “other”, where “other” is assigned for any value > 5.
<code>man_action</code> ^a	Most recent management action associated with each plot observation. The levels are: “none”, “burn.spr”, “burn.fall”, “indaz.only”, “no.burn.imaz.indaz”, “burn.fall.imaz”, “burn.fall.w.indaz”, “burn.fall.imaz.indaz”, “indaz.w.burn.spr”, “burn.spr.w.indaz”, and “other”.

^a Variables added by the function `assign_mgmt()`

1.4.8. Data frame returned from timestep()

Table 122. The example output provided within the *ABAM* R package is called `all_dat_time`.

Variable Name	Definition
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
month_veg, month_veg_tf	The calendar month (XX) of monitoring observation
day_veg, day_veg_tf	The calendar day (XX) of monitoring observation
year_veg, year_veg_tf	The calendar year (XXXX) of monitoring observation
ex_ann_rpc, ex_ann_rpc_tf	Cover of exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
brte_rpc, brte_rpc_tf	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc, brja_rpc_tf	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage
woody_rpc, woody_rpc_tf	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
nat_forb_rpc, nat_forb_rpc_tf	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc, nat_gram_rpc_tf	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc, ex_per_gram_rpc_tf	Cover of exotic graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc, ex_forb_rpc_tf	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity, diversity_tf	Total number of native species intercepted over all points in a plot.
treeden, treeden_tf	Density of trees (per acre) with diameter at breast height > 15 cm
c_ex_ann_gram, c_ex_ann_gram_tf	Discretized form of ex_ann_gram_rpc. The levels are “low”, “medium”, “high” and “very high”.
c_brte, c_brte_tf	Discretized form of brte_rpc. The levels are “low”, “medium”, and “high”.
c_brja, c_brja_tf	Discretized form of brja_rpc. The levels are “low”, “medium”, and “high”.
c_woody, c_woody_tf	Discretized form of woody_rpc. The levels are “low”, “medium”, and “high”.
c_nat_forb, c_nat_forb_tf	Discretized form of nat_forb_rpc. The levels are “low”, “medium”, and “high”.
c_nat_gram, c_nat_gram_tf	Discretized form of nat_gram_rpc. The levels are “low”, “medium”, and “high”.

Table I22 (continued). The example output provided within the ABAM R package is called `all_dat_time`.

Variable Name	Definition
c_ex_per_gram, c_ex_per_gram_tf	Discretized from of ex_per_gram. The levels are “low”, “medium”, and “high”.
c_ex_forb, c_ex_forb_tf	Discretized form of ex_forb_rpc. The levels are “low”, “medium”, and “high”.
c_diversity, c_diversity_tf	Discretized form of diversity. The levels are “low”, “medium”, and “high”.
c_treedden, c_treedden_tf	Discretized form of treedden. The levels are “low” and “high”.
grazing, grazing_tf	Grazing has three levels: “Freerange_bison_other” (free range wildlife and year-round bison), “Freerange_wl_no_bison”, and “Freerange_other” (free range wildlife with seasonal grazing by horses)
c_slope, c_slope_tf	Discretized slope. The levels are “low” and “high”.
clay_pct, clay_pct_tf	Discretized form of clay_pct. The levels are “low” and “high” and are divided at 22%.
c_temp_fall, c_temp_fall_tf	Discretized form of temp_fall (see I.4.5). The levels are “low” and “high”.
c_temp_spring, c_temp_spring_tf	Discretized form of temp_spring (see I.4.5). The levels are “low” and “high”.
c_temp_winter, c_temp_winter_tf	Discretized form of temp_winter (see I.4.5). The levels are “low” and “high”.
c_SPEI_spring, c_SPEI_spring_tf	The discretized form of SPEI_spring(see I.4.6). The levels are “low” and “high”.
c_SPEI_winter, c_SPEI_winter_tf	The discretized form of SPEI_winter (see I.4.6). The levels are “low” and “high”.
time	The number of growing seasons since management. The levels are “1”, “2–3”, and “4–5”.
man_action	Most recent management action associated with each plot observation. The levels are: “none”, “burn.spr”, “burn.fall”, “indaz.only”, “no.burn.imaz.indaz”, “burn.fall.imaz”, “burn.fall.w.indaz”, “burn.fall.imaz.indaz”, “indaz.w.burn.spr”, and “burn.spr.w.indaz”.

1.4.9. Data frame returned from `recent_obs()`

Table 123. The example output provided within the *ABAM* R package is called `data_for_predicting`.

Variable Name	Definition
park	Four-letter acronym representing each ABAM park. Levels are “AGFO”, “BADL”, “DETO”, “FOLA”, “LIBI”, “SCBL”, and “WICA”.
Network	A four-letter network acronym. The levels are “NGPN” and “ROMN”.
plot_id	A unique identifier of a monitoring or experimental plot. It must begin with a four-letter park acronym.
month_veg	The calendar month (XX) of monitoring observation
day_veg	The calendar day (XX) of monitoring observation
year_veg	The calendar year (XXXX) of monitoring observation
ex_ann_gram_rpc	Cover of exotic annual grasses relative to total plant cover, expressed as a percentage (i.e., 56, not 0.56)
brte_rpc	Cover of <i>Bromus tectorum</i> relative to total plant cover, expressed as a percentage.
brja_rpc	Cover of <i>Bromus japonicus</i> relative to total plant cover, expressed as a percentage
woody_rpc	Cover of woody species (shrub and tree) relative to total plant cover, expressed as a percentage
nat_forb_rpc	Cover of native forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
nat_gram_rpc	Cover of native graminoid species relative to plant total cover, expressed as a percentage
ex_per_gram_rpc	Cover of exotic perennial graminoid species relative to plant total cover, expressed as a percentage
ex_forb_rpc	Cover of exotic forb species (forb/herb and subshrub) relative to total plant cover, expressed as a percentage
diversity	Total number of native species intercepted over all points in a plot.
treeden	Density of trees (per acre) with diameter at breast height > 15 cm
c_ex_ann_gram	Discretized form of <code>ex_ann_gram_rpc</code> . The levels are “low”, “medium”, “high” and “very high”.
c_brte	Discretized form of <code>brte_rpc</code> . The levels are “low”, “medium”, and “high”.
c_brja	Discretized form of <code>brja_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_forb	Discretized form of <code>nat_forb_rpc</code> . The levels are “low”, “medium”, and “high”.
c_nat_gram	Discretized form of <code>nat_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
c_ex_per_gram	Discretized form of <code>ex_per_gram_rpc</code> . The levels are “low”, “medium”, and “high”.
c_ex_forb	Discretized form of <code>ex_forb_rpc</code> . The levels are “low”, “medium”, and “high”.

Table I23 (continued). The example output provided within the ABAM R package is called `data_for_predicting`.

Variable Name	Definition
<code>c_diversity</code>	Discretized form of diversity. The levels are “low”, “medium”, and “high”.
<code>c_woody</code>	Discretized form of <code>woody_rpc</code> . The levels are “low”, “medium”, and “high”.
<code>c_treedn</code>	Discretized form of <code>treeden</code> . The levels are “low” and “high”.
<code>grazing</code>	Grazing has three levels: “Freerange_bison_other” (free range wildlife and year-round bison), “Freerange_wl_no_bison”, and “Freerange_other” (free range wildlife with seasonal grazing by horses)
<code>c_slope</code>	Discretized slope. The levels are “low” and “high”.
<code>clay_pct</code>	Discretized form of <code>clay_pct</code> . The levels are “low” and “high”.
<code>c_temp_fall</code>	Discretized form of <code>temp_fall</code> (see I.4.5). The levels are “low” and “high”.
<code>c_temp_spring</code>	Discretized form of <code>temp_spring</code> (see I.4.5). The levels are “low” and “high”.
<code>c_temp_winter</code>	Discretized form of <code>temp_winter</code> (see I.4.5). The levels are “low” and “high”.
<code>c_SPEI_spring</code>	The discretized form of <code>SPEI_spring</code> . The levels are “low” and “high”.
<code>c_SPEI_winter</code>	The discretized form of <code>SPEI_winter</code> . The levels are “low” and “high”.
<code>man_action</code>	Most recent management action associated with each plot observation. The levels are: “none”, “burn.spr”, “burn.fall”, “indaz.only”, “no.burn.imaz.indaz”, “burn.fall.imaz”, “burn.fall.w.indaz”, “burn.fall.imaz.indaz”, “indaz.w.burn.spr”, and “burn.spr.w.indaz”.
<code>t.s.trt</code>	The number of growing seasons since management (up to 5), or if no recent management has occurred, the number of growing seasons since last observation. The levels are “1”, “2”, “3”, “4”, “5” and “other”, where “other” is assigned for any value > 5.
<code>management.unit</code>	The name of the management unit the plot is located within.

1.4.10. Data frame returned from `opt_mgmt()`

Table 127. This data frame is also known as the consequence table. The example output provided within the *ABAM* R package is called `conseq_table`.

Variable Name	Definition
park	Four letter acronym representing each ABAM park. Possibilities are AGFO, BADL, DETO, FOLA, LIBI, SCBL, and WICA.
unit	Management unit name
man_action	An iterative list of information for each management unit. The information provided includes the probability distribution of vegetation conditions (next 10 variables) and associated utilities for current condition and each of the following management actions: "none", "burn.spr", "burn.fall", "indaz.only", "no.burn.imaz.indaz", "burn.fall.imaz", "burn.fall.w.indaz", "burn.fall.imaz.indaz", "indaz.w.burn.spr", and "burn.spr.w.indaz".
ExoticAnnualGrassland	Probability of being in the exotic annual grassland condition
ExoticAnnualWoodland	Probability of being in the exotic annual woodland condition
ExoticPerennialGrassland	Probability of being in the exotic perennial grassland condition
ExoticPerennialWoodland	Probability of being in the exotic perennial woodland condition
HighQualityPrairie	Probability of being in the high-quality prairie condition
HighQualityWoodland	Probability of being in the high-quality woodland condition
LowQualityPrairie	Probability of being in the low-quality prairie condition
LowQualityWoodland	Probability of being in the low-quality woodland condition
SimplifiedGrassland	Probability of being in the simplified grassland condition
WeedyForbMess	Probability of being in the weedy forb mess condition
veg.cond.utility	The utility of the current condition or predicted outcome for each management action weighted only by the vegetation condition utilities of the park in which the management unit occurs.
total.utility	The utility of the current condition or predicted outcome for each management action weighted by the competing objectives of cost and vegetation improvement for the park in which the management unit occurs.

I.5. Checking Your Work and Troubleshooting

Suggested steps to identify potential pitfalls:

- Check that all relevant plot locations are within the spatial reference file for each park, and that there is only one location for each point type (e.g., A0, PC) for each plot. Some plots will have multiples because new locations were recorded with upgraded GPS technology. Keep the location that was collected most recently.
- Check that all relevant plot data are extracted properly from FFI:
 - Identify NGP MacroPlot.Names of either newly established plots or already-established plots that had vegetation transects added to them. Add those plots to the NGP_keeper_plots_XXXX.csv file.
- Ensure appropriate assignment of management actions
 - Review the object returned from *assign_mgmt*. You will want to ensure that management actions were assigned correctly and pay particular attention to any observations assigned the level of ‘other’. The level ‘other’ means that management has recently occurred at this plot, yet the date(s) of implementation do not fit within the criteria currently defined for any of the management actions. You may override the classification of ‘other’ to a management option level in the model. NOTE: You cannot add an additional management option to the model.
- Confirm that the model was updated
 - Compare the conditional probability estimates of individual nodes of the model before and after updating to ensure update was successful. The following code provides an example comparing the conditional probability estimates of the future exotic annual graminoid node (c_ex_ann_gram_tf) 2–3 years after an indaziflam-only application. The object names for the Bayesian net before and after updating are “bnet” and “bnet_up”, respectively.

```
cpdist(bnet,  
       nodes = "c_ex_ann_gram_tf",  
       evidence = list(man_action_tf = "indaz.only",  
                       time_tf = "2_3"),  
       method = "lw", n = 100000)  
cpdist(bnet_up,  
       nodes = "c_ex_ann_gram_tf",  
       evidence = list(man_action_tf = "indaz.only",  
                       time_tf = "2_3"),  
       method = "lw", n = 100000)
```

- Ensure safe keeping of your newly updated model
 - Your newly updated model produces the model predictions for the current year. It is also the model version that will be updated in the next iteration.
- Clearly identify the final set of output used to produce park reports each year

- If the data require cleaning, the user may attempt this workflow several times until satisfied with the entire workflow. When you have worked out all kinks and produced what will be deemed the final model output for the year, be sure to label it accordingly.
- Keep detailed notes that are accessible to all potential users
 - Be sure to document any helpful notes and changes you have made to any part of the workflow and save these notes in an SOP.

Literature Cited in Appendix I

- Baldwin, H. Q., M. Post van der Burg, and A. J. Symstad. 2021. ABAM. R package version 0.0.0 (provisional release). Available at: https://code.usgs.gov/abam/abam_package.git.
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- U.S. Department of Agriculture [USDA]. 2018. Gridded Soil Survey Geographic Database (gSSURGO). Available at: <https://data.nal.usda.gov/dataset/gridded-soil-survey-geographic-database-gssurgo> (accessed 9 January 2018).

Appendix J. Accessible Tables

This appendix contains accessible tables with data from figures found in the body of the report. Table captions include hyperlinks to the corresponding figures.

Table J1. Data from [Figure 2.3](#). Plot revisit designs of Northern Great Plains (NGPN) and Rocky Mountain (ROMN) Inventory & Monitoring Networks. The basic revisit design of NGPN vegetation monitoring. Two panels of plots are monitored each year; all plots within a panel are monitored two years in a row, then “rested” for three years (a [2–3] revisit design).

Year	Panel				
	1	2	3	4	5
1	X	–	–	–	X
2	X	X	–	–	–
3	–	X	X	–	–
4	–	–	X	X	–
5	–	–	–	X	X
6	X	–	–	–	X

Table J2. Data from [Figure 2.3](#). Plot revisit designs of Northern Great Plains (NGPN) and Rocky Mountain (ROMN) Inventory & Monitoring Networks. The number of plots per panel varies by the size of the park. In 2022, the final 10-panel, [2–8] revisit design will be implemented. See Symstad et al. (2012) for details.

Park ^a	# Plots per Panel (X)
Agate Fossil Beds NM	3
Badlands NP ^b	10
Devils Tower NM	4
Fort Laramie NHS	2
Scotts Bluff NM	4
Wind Cave NP	9

^a NM = National Monument, NP = National Park, NHS = National Historic Site.

^b BADL differs from the other NGPN parks in that it began in 2011 with 5 panels, then transitioned during 2016–2021 to 10 panels.

Table J3. Data from [Figure 2.3](#). Plot revisit designs of Northern Great Plains (NGPN) and Rocky Mountain (ROMN) Inventory & Monitoring Networks. Vegetation monitoring plot revisit design of ROMN at Little Bighorn Battlefield NM. Ten plots are monitored each year, with two of these plots overlapping with those monitored in the previous year (coloration). Thus, 4 plots in each panel are visited in a [2–2] schedule, and the other 6 plots in each panel in a [1–3] schedule.

Year	Plots Monitored ^a
1	33, 34, 36, 37, 38, 40, 43, 50, 1, 4
2	1, 4, 5, 6, 7, 8, 9, 10, 11, 12
3	11, 12, 15, 16, 17, 18, 20, 21, 22, 23
4	22, 23, 24, 25, 26, 27, 28, 32, 33, 34
5	33, 34, 36, 37, 38, 40, 43, 50, 1, 4

^a Plots 33 & 34 are shown in red text; plots 1 & 4 are shown in blue text; plots 11 & 12 are shown in green text; plots 22 & 23 are shown in purple text.

Table J4. Example ranking exercise data from [Figure H1](#).

Vegetation Condition	Rank
Exotic Annual Grassland	5
Exotic Annual Woodland	10
Exotic Perennial Grassland	4
Exotic Perennial Woodland	9
High Quality Prairie	1
High Quality Woodland	6
Low Quality Prairie	2
Low Quality Woodland	8
Simplified Grassland	3
Weedy Forb Mess	7

Table J5. Example comparison-scoring exercise data from [Figure H2](#).

Comparison	Rank	Vegetation Condition	Difference Score
1	1	High Quality Prairie	5
1	2	Low Quality Prairie	5
2	2	Low Quality Prairie	1.5
2	3	Simplified Grassland	1.5
3	3	Simplified Grassland	10
3	4	Exotic Perennial Grassland	10
5	4	Exotic Perennial Grassland	1.5
5	5	Exotic Annual Grassland	1.5
6	5	Exotic Annual Grassland	1
6	6	High Quality Woodland	1
7	6	High Quality Woodland	3
7	7	Weedy Forb Mess	3
8	7	Weedy Forb Mess	1
8	8	Low Quality Woodland	1
9	8	Low Quality Woodland	2
9	9	Exotic Perennial Woodland	2
10	9	Exotic Perennial Woodland	1
10	10	Exotic Annual Woodland	1

Table J6. Normalized utilities data from [Figure H2](#).

Rank	Condition	Normalized Utility
1	High Quality Prairie	1.00
2	Low Quality Prairie	0.81
3	Simplified Grassland	0.75
4	Exotic Perennial Grassland	0.37
5	Exotic Annual Grassland	0.31
6	High Quality Woodland	0.27
7	Weedy Forb Mess	0.15
8	Low Quality Woodland	0.12
9	Exotic Perennial Woodland	0.04
10	Exotic Annual Woodland	0.00

Table J7. Example free-form scoring exercise data from [Figure H3](#).

Rank	Condition	Score	Utility
1	High Quality Prairie	100	1
2	Low Quality Prairie	50	0.5
3	Simplified Grassland	45	0.45
4	Exotic Perennial Grassland	20	0.2
5	Exotic Annual Grassland	15	0.15
6	High Quality Woodland	13	0.13
7	Weedy Forb Mess	10	0.1
8	Low Quality Woodland	0	0
9	Exotic Perennial Woodland	0	0
10	Exotic Annual Woodland	0	0

Table J8. Normalization of cost utilities data from [Figure H3](#).

Comparison	Rank	Cost per Acre	Difference Score
1	1	\$0.00	3.846
1	2	\$50.00	3.846
2	2	\$50.00	1.154
2	3	\$65.00	1.154
3	3	\$65.00	1
3	4	\$78.00	1
4	4	\$78.00	1.154
4	5	\$93.00	1.154
5	5	\$93.00	1.692
5	6	\$115.00	1.692
6	6	\$115.00	2.154
6	7	\$143.00	2.154

Table J9. Normalized utilities data from [Figure H4](#).

Rank	Cost	Normalized Utility
1	\$0.00	1
2	\$50.00	0.65034965
3	\$65.00	0.545454545
4	\$78.00	0.454545455
5	\$93.00	0.34965035
6	\$115.00	0.195804196
7	\$143.00	0

Table J10. Example swing-weighting exercise data from [Figure H5](#).

Scenarios	Resultant		Cost	Rank	Score	Weight
	Vegetation State					
1. Benchmark	Exotic Annual Woodland	\$115.00	3	0	0.00	
2. Vegetation state	High Quality Prairie	\$115.00	1	100	0.91	
3. Cost	Exotic Annual Woodland	\$0.00	2	10	0.09	
Total						1.00

The Department of the Interior protects and manages the nation's natural resources and cultural heritage; provides scientific and other information about those resources; and honors its special responsibilities to American Indians, Alaska Natives, and affiliated Island Communities.

NPS 920/180388, May 2022

National Park Service
U.S. Department of the Interior



[Natural Resource Stewardship and Science](#)

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