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Chapter 13

State-and-Transition Models: Conceptual Versus Simulation Perspectives, Usefulness and Breadth of Use, and Land Management Applications

Louis Provencher, Leonardo Frid, Christina Czembor,
and Jeffrey T. Morisette

Abstract State-and-Transition Simulation Modeling (STSM) is a quantitative analysis method that can consolidate a wide array of resource management issues under a “what-if” scenario exercise. STSM can be seen as an ensemble of models, such as climate models, ecological models, and economic models that incorporate human dimensions and management options. This chapter presents STSM as a tool to help synthesize information on social–ecological systems and to investigate some of the management issues associated with exotic annual *Bromus* species, which have been described elsewhere in this book. Definitions, terminology, and perspectives on conceptual and computer-simulated stochastic state-and-transition models are given first, followed by a brief review of past STSM studies relevant to the management of *Bromus* species. A detailed case study illustrates the usefulness of STSM for land management. As a whole, this chapter is intended to demonstrate how STSM can help both managers and scientists: (a) determine efficient resource allocation for monitoring nonnative grasses; (b) evaluate sources of uncertainty in model simulation results involving expert opinion, and their consequences for

L. Provencher (✉)
The Nature Conservancy, Reno, NV 89501, USA
e-mail: lprovencher@tnc.org

L. Frid
Apex Resource Management Solutions Ltd., Bowen Island, BC, Canada
e-mail: leonardo.frid@apexrms.com

C. Czembor
Knight Piésold Ltd., Vancouver, BC, Canada
e-mail: c.czembor@gmail.com

J.T. Morisette
US Geological Survey, North Central Climate Science Center, Fort Collins, CO 80526, USA
e-mail: morisettej@usgs.gov

management decisions; and (c) provide insight into the consequences of predicted local climate change effects on ecological systems invaded by exotic annual *Bromus* species.

Keywords State-and-transition • Conceptual model • Simulation • Uncertainty • Climate change

13.1 Introduction

Land managers dealing with impacts of exotic brome invasions are challenged with understanding how local, site-level actions across heterogeneous landscapes and time periods will ultimately scale up to the region where outcomes are measured against desired conditions. State-and-Transition Simulation Modeling (STSM) provides a quantitative framework to combine these various facets at both regional and local scales. Spatial or nonspatial analyses are used to investigate “what-if” scenarios that incorporate management options and evaluate sensitivity of systems to specific parameterizations or assumptions.

This chapter is written for those who want to understand how STSMs can integrate ecological and economic understanding into a simulation environment to provide insight into invasive species and vegetation management at landscape and regional scales. The focus is on using STSMs for management of vegetation, and particularly invasion by exotic annual *Bromus* (*Bromus* hereafter). We begin by offering background definitions, terminology, and perspectives. We then highlight the utility of STSMs through two published examples where STSMs have been used in other systems to determine efficient resource allocation for monitoring exotic grasses and to evaluate sources of uncertainty in STSMs involving expert opinion. We conclude with a new case study application of STSMs to provide insight into the consequences of predicted local climate change effects on ecological systems invaded by *Bromus*. For further reading, several publications offer excellent descriptions or reviews of STSM concepts (Czembor and Vesk 2009; Rumpff et al. 2011; Knapp et al. 2011a, b; Daniel and Frid 2012).

13.2 Definition of State-and-Transition Models

Conceptual state-and-transition models are presented as discrete, box-and-arrow representations of the continuous variation in vegetation composition and structure of an ecological system (Westoby et al. 1989; NRCS 2003; Stringham et al. 2003; Bestelmeyer et al. 2004). The classification of an ecological system is important for framing each state-and-transition model. One example of a classification is the

USDA Natural Resources Conservation Service's (NRCS) "ecological site description" (ESDs) system. Each ecological site represents "a distinctive kind of land with specific physical characteristics that differs from other kinds of land in its ability to produce a distinctive kind and amount of vegetation," and can have a unique conceptual state-and-transition model (STM) associated with it (NRCS 1998). STMs represent a method to organize and communicate complex information about the relationships among vegetation, soil, animals, hydrology, disturbances, and management actions on an ecological site (Caudle et al. 2013). They are comprised of states and transitions.

13.2.1 States

Within STMs, boxes represent the possible vegetation conditions of a parcel of land within an ecological system and include different (a) plant community *states* or (b) *phases* within a state (Fig. 13.1). A *state* is formally defined in the rangeland literature as a "recognizable, relatively resistant and resilient complex with attributes that include a characteristic climate, the soil resource including the soil biota, and the associated aboveground plant communities" (NRCS 2003; Caudle et al. 2013). The associated plant communities are phases of the same state that can be represented in a diagram with two or more boxes. Relatively reversible changes caused by disturbance or stress (e.g., fire, flooding, drought, insect outbreaks, herbivory, and others) and succession operate on phases within a state. *Phases* are most often recognizable steps of succession, which is a naturally continuous process. Phases can also occur among uncharacteristic vegetation classes as a result of succession. Different states are separated by at least one threshold. A transition across a threshold is often caused by an anthropogenic disturbance or species invasion. *Thresholds* are defined by conditions sufficient to modify ecosystem structure and function beyond the limits of ecological resilience, resulting in the formation of alternative states (Briske et al. 2008). Crossing of thresholds usually indicates that substantial management effort is required to restore ecosystem structure and function to another state. The reference state represents the dynamic vegetation phases resulting from a natural disturbance regime, including disturbances caused by indigenous populations, where vegetation returns to the pre-disturbance conditions via succession. A threshold often implies the creation of uncharacteristic vegetation classes, which often exist because of European post-settlement disturbance regimes, changes in climate, or species invasions. Moreover, thresholds can occur between different uncharacteristic states, usually signaling increasing degradation of the ecological system. A monoculture of *Bromus tectorum* L. (cheatgrass or downy brome) in a sagebrush shrubland is an example of an uncharacteristic vegetation class, which could be a phase or a state depending on model structure. Uncharacteristic vegetation classes can be formed of entirely native species (native uncharacteristic) or contain nonnative plant species (exotic uncharacteristic), such as *Bromus* (Rollins 2009).

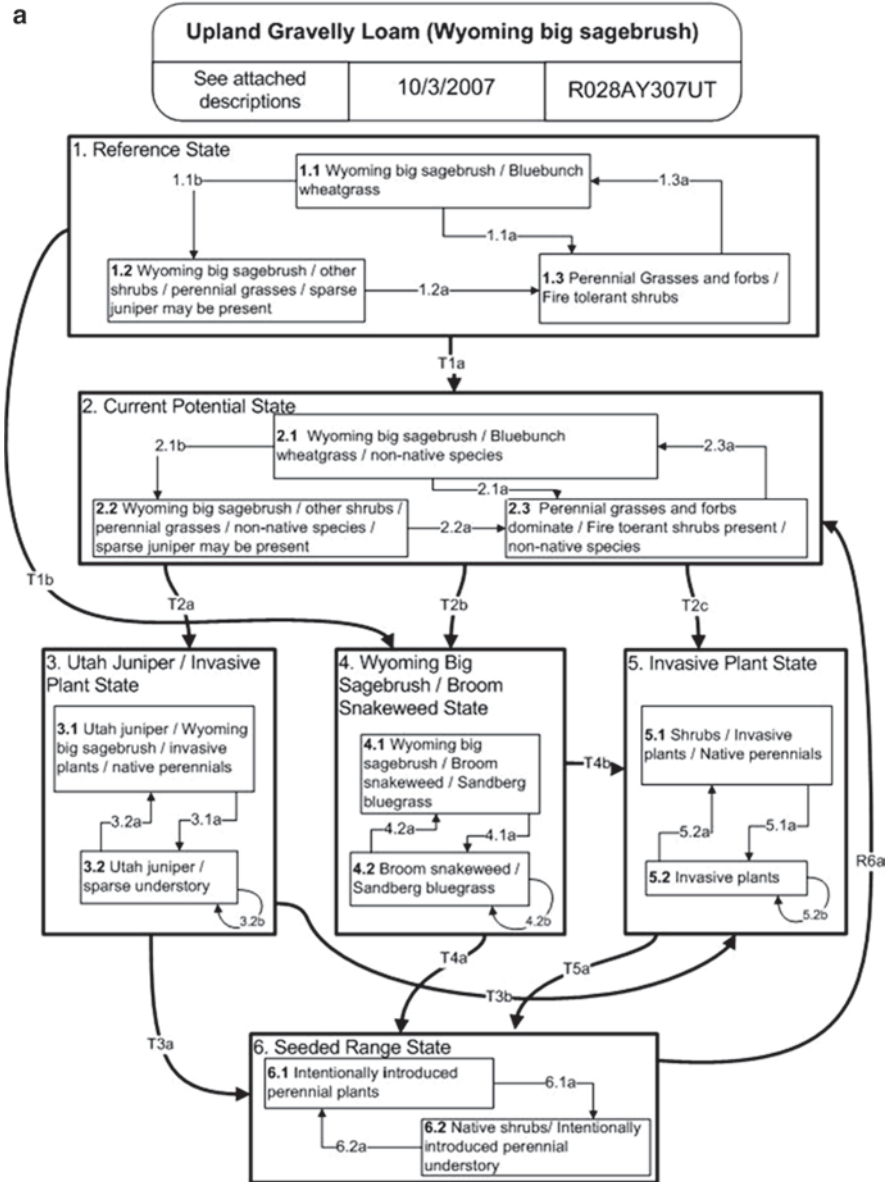


Fig. 13.1 (a) Conceptual state-and-transition model for NRCS ecological site R028AY307UT *A. tridentata* spp. *wyomingensis* growing on upland gravelly loam soils in Utah (Thacker et al. 2008). The larger bold boxes represent vegetation states with the top (#1) being the reference state and immediately below it (#2) the current potential state, which is similar to the reference with a non-dominant presence of nonnative plants. States #3–5 represent undesirable states that are invaded with *J. osteosperma*, *Gutierrezia sarothrae* (Pursh) Britton & Rusby (broom snakeweed), and invasive annual grasses or forbs, respectively. The final (#6) state represents a nonnative but more desirable vegetation community such as *Agropyron cristatum* (L.) Gaertn. (crested wheatgrass).

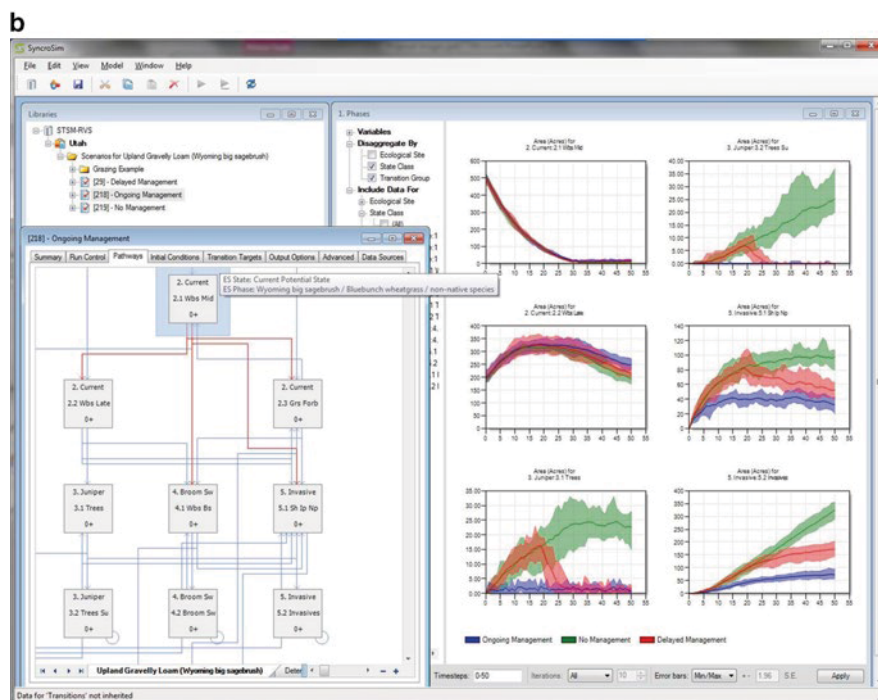


Fig. 13.1 (continued) Boxes within each state represent vegetation phases. *Arrows* represent either transitions between phases or states (i.e., 1.2a is a replacement event from late successional shrubs to grass forbs, while T2c represents invasion by annual grasses or invasive forbs). This conceptual state-and-transition diagram is accompanied by a detailed description of each state, phase, and transition in the NRCS source documentation. **(b)** Screen capture of STSM software showing a model developed for the same ecological site. The *box-and-arrow* “pathway diagram” shows phases for the current potential state (#2), and the three undesirable states (#3–5). *Arrows* in the diagram represent probabilistic or deterministic transitions driven by different process such as fire, grazing, or succession. The graphs on the *right* show model outputs for three different example management scenarios representing the amount of land in modeled states or phases. *Blue* represents ongoing management, *green* is no management, and *red* is delayed management. *Lines* represent the mean across multiple iterations and shaded areas represent model uncertainty

13.2.2 Transitions

The other fundamental component of a conceptual STM are *transitions* representing either succession between phases or disturbances that alter the structure or composition of phases and, eventually, states. Transitions can be natural (e.g., fire, flooding) or managed (e.g., prescribed burning). Furthermore, natural disturbances can represent pre-settlement (e.g., surface fire) and European post-settlement (e.g., *Bromus* invasion) events. Most transitions are reversible given succession, natural disturbances, or management actions; however, some transitions can result in crossing of biotic or abiotic thresholds that irreversibly change either the diagnostic species

composition of an ecological system (e.g., loss of aspen clones caused by prolonged fire exclusion or excessive herbivory) or the potential of a soil to support the ecological system due, primarily, to soil loss. *Bromus* invasion and community dominance is an example of a transition that may or may not be reversible (Bagchi et al. 2013; Knapp 1996) and hence both conceptual STM and corresponding STSMs are well suited to exploring related management questions.

Conceptual STMs are familiar to many students of natural resources because graphical, quantitative, and written models can all be represented by boxes and arrows or a written description. Graphical representation of states and transitions for different ecological systems is common not only in rangelands, but also in other systems such as reclaimed mine sites (Grant 2006). These conceptual models provide a flexible approach for describing and documenting the vegetation dynamics associated with a particular ecosystem (Daniel and Frid 2012).

13.2.3 A National Context in the United States

The US NRCS has been nationally revising their ecological site descriptions to include conceptual STMs (NRCS 2003). This revision is ongoing and many regions of the United States still do not have published ESDs or STMs. These models can be graphical (box-and-arrow models with larger boxes for states and smaller nested boxes for phases), written descriptions of reference and uncharacteristic states, plus disturbances causing transitions between thresholds or a combination of both. The initial state depicted in NRCS models is the historic plant community (i.e., reference state [Rumpff et al. 2011]) from which all other states are derived through natural and managed transitions. The reference state is based on the natural range of conditions associated with natural disturbance regimes and often includes several plant communities (phases) that differ in dominant plant species relative to type and time since disturbance (Caudle et al. 2013).

NRCS ecological site descriptions are frequently used by US Department of Interior and Department of Agriculture staff for restoration project prescriptions (e.g., native seed mix) and US National Environmental Protection Act documentation. Conceptual STMs generate non-quantitative, general predictions about desirable and undesirable processes causing transitions between states at a site-specific level. A recent criticism of purely conceptual STMs developed for ecological sites is that they lack the ability to project state transitions that will be important in the future and to link these to levels of conservation funding for management and restoration actions (Twidwell et al. 2013). Consequently, there are currently efforts under way to digitize conceptual STMs from ESDs and convert them into STSMs that can be used to generate testable hypotheses. For example, quantitative models developed by Evers et al. (2013) explicitly consider how warmer, drier sites function differently from cooler, moister sites.

13.2.4 *State-and-Transition Simulation Models*

STSMs begin with conceptual models, such as the ones described above. Before the models are applied, the landscape being simulated is subdivided into simulation cells, which can be nonspatial or spatially represented using a map. These models can be quantified with the following additional information: (1) an inventory, either spatial or nonspatial, of the vegetation conditions of the landscape at the start of the simulation, which describes the ecological system, and state class (state and phase) of each simulation cell in the landscape and (2) a rate associated with each possible transition between state classes. Then, these transition rates can be further quantified using three general approaches: (2.1) probabilistic, with a specified probability at any point in time; (2.2) deterministic, occurring after a specified period of time in a state class has elapsed; or (2.3) with target areas assigned to occur on the landscape over time. The first two approaches are typically used to emulate natural processes such as disturbances and succession, whereas the last is typically applied for management actions such as herbicide application. Computer software then uses the inventory of starting vegetation conditions and rates associated with each transition to project future vegetation conditions of the landscape (Fig. 13.1b), as well as occurrence of transitions over time. The overall approach to applying STSM is described in detail in Daniel and Frid (2012).

In recent years there has been a proliferation of quantitative STSM applications to a diverse set of natural resource management problems (see Daniel and Frid 2012 for examples). This development has been driven in part by the model development training and awareness created by the Landscape Fire and Resource Management Planning Tools Project (LANDFIRE) in the United States (Rollins 2009; Blankenship et al. 2012) and the need for new management decision support tools. The popularity of this approach has been facilitated by the availability of flexible software tools, beginning with the Vegetation Dynamics Development Tool (VDDT) in the early 1990s for the Interior Columbia Basin Ecosystem Management Project (Barrett 2001; Hann and Bunnell 2001). The most recent of these tools, ST-Sim (www.syn-crosim.com), has both nonspatial and spatially explicit capabilities. Note that while there are other modeling approaches and software packages for simulating landscape change, some of these are specifically tailored to forests (i.e., Landis II, Scheller et al. 2007) and many others are not documented or supported to the level available with ST-Sim (Keane et al. 2004). Prior to the availability of software, quantitative STMs have been either analytical (Horn 1975) or simulated with project-specific computer programs (Hardesty et al. 2000). Analytical STMs are rare because even the simplest models incorporate nonlinear step functions (i.e., age and time since past transitions) that render analysis difficult to intractable.

Many of the initial STSMs were created by US Forest Service ecologists and contractors (Merzenich et al. 1999; Barrett 2001; Hann and Bunnell 2001; Hemstrom et al. 2004) and ecologists of The Nature Conservancy (TNC; Hardesty et al. 2000; Forbis et al. 2006; Provencher et al. 2007) who were just starting to incorporate the conceptual developments and terminology proposed by rangeland ecologists

Table 13.1 Comparison of state-and-transition modeling terminology differentially used by rangeland ecologists, quantitative modelers, and simulation software

Rangeland ecologists	Quantitative modelers	Software
Ecological site	Ecological site(s) (TNC) Ecological system (NatureServe ^a and TNC) Potential natural vegetation type (US Forest Service) Biophysical setting (LANDFIRE and TNC)	Cover type (VDDT) Stratum (PATH ^b , ST-Sim)
State	≥1 vegetation class	Cover type × Structural stage (VDDT & Path) State Class (ST-Sim)
Phase	Vegetation class (reference or uncharacteristic) Existing vegetation class (US Forest Service)	Cover type × Structural stage (VDDT & Path) State Class (ST-Sim)
Reversible transition	Transition (specified as natural, uncharacteristic, or managed)	Transition (specified as probabilistic or deterministic)
Irreversible transition	Transition (uncharacteristic or managed)	Transition (probabilistic or deterministic)
Threshold	Transition (uncharacteristic or managed)	Transition (probabilistic or deterministic)

^a<http://www.natureserve.org/library/usEcologicalsystems.pdf>

^bPath is the landscape simulation freeware platform that replaced VDDT: www.pathmodel.com. Currently, the ST-Sim simulator in the SyncroSim state-and-transition platform (www.syncrosim.com) is the latest nonspatial and spatial generation of software development started with VDDT

(Westoby et al. 1989) and NRCS (2003). Despite these nearly independent paths, both groups approached state-and-transition modeling concepts in a remarkably similar manner with differences mostly in jargon (Table 13.1). Fortunately, specific jargon and definitions matter little for actual STSMs because simulation software is flexible and can accommodate different terminology.

13.2.5 *Nonspatial and Spatial Model Approaches*

Many STSMs are nonspatial with the fate of each simulation cell being independent of the fate of any other cell, because they are simpler and faster to create and run, and require less data and fewer assumptions than spatially explicit models. Spatially explicit STSMs require at a minimum a polygon- or raster-based vegetation layer(s), size frequency distributions for each transition process (the frequency of very small to very large events, such as fire), and spatial constraint layers defining management zones (e.g., ownership polygons) or priority areas (e.g., no fire tolerated to large fire size allowed; Kurz et al. 2000; Provencher et al. 2007). These data can be difficult and expensive to obtain. Given the additional data and computational requirements

of spatially explicit modeling, a compelling question or objective justifying the need to do spatially explicit modeling should be a prerequisite to developing a spatial STSM. That said, good cases for spatially explicit STSMs can usually be made for wildlife management, nonnative plant species control and monitoring (Frid and Wilmshurst 2009; Frid et al. 2013a, b), and wildland fire (Miller 2007). In these cases, the position and size of natural and managed transitions can critically affect project-specific metrics that track the condition of ecological systems studied. Extreme weather events and climate projection do vary across the landscape. Thus, studies looking to consider these issues ought to include a spatial component. There are a number of nonspatial (Evers et al. 2011, 2013; Provencher et al. 2013; Low et al. 2010; Forbis et al. 2006; Creutzburg et al. 2012) and spatially explicit (Provencher et al. 2007) STSM applications with a *Bromus* component.

13.2.6 Uses and Benefits of State-and-Transition Simulation Modeling

While conceptual STMs are useful tools for describing vegetation dynamics and identifying possible management prescriptions at the site-specific scale, they can fall short of providing prognostic information for landscape scale vegetation management efforts. Land managers are frequently faced with limited resources and competing objectives and an interest in knowing how their actions will play out on the landscape. For example, should restoration resources be applied toward areas affected by woody species encroachment or toward areas affected by annual species invasions? In addition to competing objectives such as these, land managers are often faced with uncertainties and incomplete information of the vegetation dynamics for the landscape of concern. Despite these challenges, land managers must frequently make decisions about the allocation of limited vegetation management resources. At landscape scales, STSMs are valuable tools for identifying robust management strategies, important trade-offs, and critical uncertainties for decision making.

STMs are popular among range and forest managers because they are easy to communicate and typically require less data to parameterize than more complex process-based models under different applications. However, STSMs can include information from process-based models and analysis (Halofsky et al. 2013). These models are management oriented and simulations can be useful to solve complex management questions. STSMs have the major benefits of being flexible and fostering stakeholder engagement and buy-in (Price et al. 2012; Nixon et al. 2014). Simulations have the ability to predict changes in vegetation under different scenarios considering alternative management actions and hypotheses about the response of natural systems to them. The variety of scenarios that can be explored—from climate change to single management actions (e.g., prescribed burning)—is very large and feasible. The social benefit of model building is that it allows land managers and scientists to explicitly document their understanding and assumptions about ecological processes, management actions, and the interactions between the two. Such a

framework can help build support for proposed actions or provide useful direction for future experiments (Low et al. 2010; Price et al. 2012; Nixon et al. 2014).

13.2.7 Examples of STSM Applications from Non-Bromus Systems

Here we present two examples of STSM applications to non-*Bromus* systems that could similarly be applied to *Bromus*. Many challenges in conservation science can be (1) traced to altered disturbance regimes, (2) caused by legacies of vegetation classes or phases that differ from reference conditions, and (3) effectively resolved with alternative management scenarios. Because the issues of exotic annual *Bromus* control involve a wide array of ecological processes as well as economics (Chambers 2008; Knapp 1996) and land management options (Monsen et al. 2004), it is useful to have a framework to integrate our current understanding, assumptions, and potential scenarios in a tractable and repeatable form. In the different applications of STSM presented in these examples, we hope to illustrate how STSM can integrate a wide breadth of ecological processes and management options. Specifically, these examples were chosen to illustrate two different management-oriented uses of STSM: (1) identification of the most cost-effective approach to control nonnative grasses using spatial STSMs designed to consider trade-offs between monitoring and treatment; and (2) quantification of model uncertainty when expert knowledge is used to parameterize an STSM.

13.2.7.1 State-and-Transition Simulation Models as a Tool for Guiding Invasive Plant Monitoring and Treatments

Despite the high economic impacts of exotic plant invasions (Pimentel et al. 2005), including those of *Bromus* (Knapp 1996), control and restoration resources available for *Bromus* management on any one landscape are often limited and intermittently available. These limited resources must be allocated to multiple activities including treatment of detected infestations, monitoring treatment success, and monitoring to discover previously undetected infestations. Cost-efficiency of control measures is greatly increased by discovering and treating new infestations (“nascent foci”), before propagule banks are established at or beyond the invasion site (Moody and Mack 1988; Maxwell et al. 2009; Frid et al. 2013a). However, (1) land management programs are often evaluated based on numbers of acres treated, which creates an incentive to focus all resources toward already detected infestations; (2) allocating resources toward monitoring and failing to detect any new infestations is often viewed as a waste of resources; and (3) most land managers lack tools to detect nascent foci or determine how much of their budget should be allocated to monitoring versus treatment.

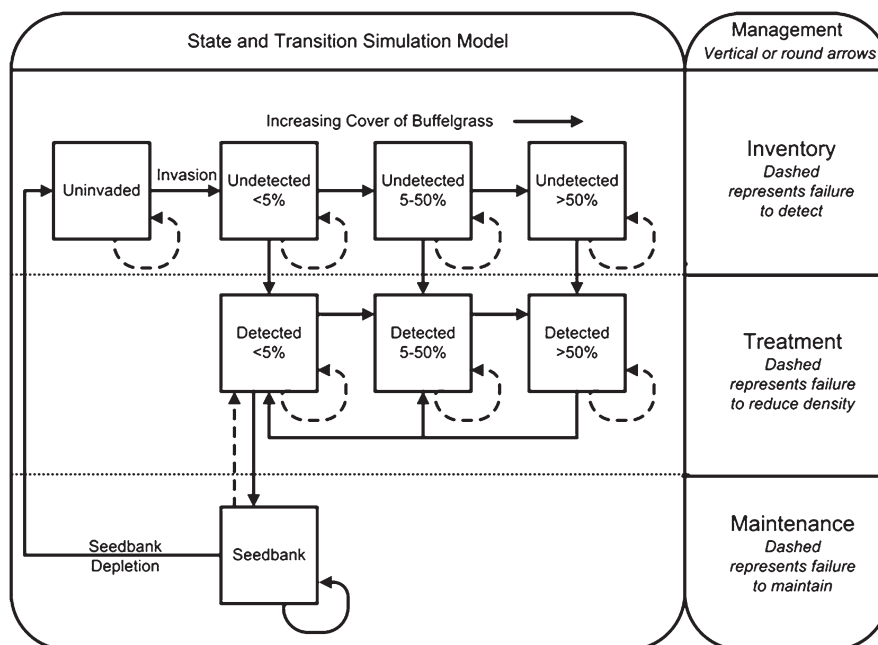


Fig. 13.2 State-and-transition model used by Frid et al. (2013b) to simulate alternative management strategies for *P. ciliare* in southern Arizona. The STSM categorizes each spatially explicit polygon dynamically over time based on both the presence and abundance of *P. ciliare* and on its detection status. The STSM has a total of eight possible states represented by five possible cover classes (absent, seedbank only, cover <5 %, cover 5–50 %, cover >50 %) and by whether the presence of live plants has been detected by managers

STSMs can help land managers determine appropriate strategies for resource allocation, including selection of management activities and locations. For this example, we draw upon a recent study of a non-*Bromus* invasive grass, *Pennisetum ciliare* (L.) Link (buffelgrass; synonymous with *Cenchrus ciliaris*), by Frid et al. (2013b) in the Sonoran Basin and Range, which demonstrates an application that could be applied in future work to *Bromus*. In this model, the phases distinguish between *P. ciliare* abundances (<5 %, 5–50 % and >50 % cover) and whether they are detected or not (Fig. 13.2).

This model was a spatially explicit STSM, developed using TELSA (Kurz et al. 2000), which included input and output maps of the *P. ciliare* over time, and distinguished between detected (and treatable) and undetected patches that would require resources to be detected. The model simulated dispersal of short- (i.e., neighbor-to-neighbor) and long-distance dispersal of *P. ciliare* to other locations on the landscape based on time series of spread determined from aerial photography (Olsson et al. 2012). A map of the current known distribution of *P. ciliare* was derived from the same aerial photographs. A habitat suitability model based on slope, aspect, and elevation was used to estimate where *P. ciliare* could grow, and at what densities.

Table 13.2 Simulated area invaded and cumulative area undergoing inventory treatment and maintenance for five scenarios showing area (ha) invaded by *P. ciliare* and cumulative area undergoing inventory, treatment, and maintenance at years 2030 and 2060

Scenario	Year	Hectares invaded	Cumulative area (ha)		
			Inventory	Treatment	Maintenance
Initial conditions	2010	82	0	0	0
No management	2030	1795	0	0	0
	2060	6263	0	0	0
Intermediate management: worst case	2030	997	82,281	682	9494
	2060	4952	236,142	3157	29,059
Intermediate management: best case	2030	603	104,520	971	18,244
	2060	3081	258,212	3364	46,843
Unlimited management: worst case	2030	864	81,897	837	10,060
	2060	637	358,643	11,543	99,986
Unlimited management: best case	2030	159	146,054	1460	27,851
	2060	54	392,803	3752	75,380

“Worst case” represents the low range and “best case” the high range of management efficiency as described in results of a survey conducted with *P. ciliare* managers. The total size of the landscape simulated was 46,000 ha

Treatment and monitoring effectiveness rates were derived from a survey of *P. ciliare* management practitioners.

Five alternative management options that varied in both the budget allocated toward monitoring and treatment and their effectiveness were evaluated in a binary fashion (high/low; Table 13.2). Budgets for treatments and monitoring were either unlimited, as a benchmark of what could be accomplished, or limited to half of what the unlimited scenario utilized. The model predicts that in the absence of management, the area infested with *P. ciliare* would grow exponentially until the ecological limit is reached within a 50-year period (Fig. 13.3).

Some of the key conclusions from these simulations were:

1. In the long term (2010–2060), unlimited budget scenarios used similar amounts of resources to those with a limited budget, yet resulted in less than an order of magnitude the amount of area infested per area treated because management was able to act when desirable plant community transitions required a lower energy input. In the short term (2010–2030), unlimited budgets used more resources than scenarios with a limited budget.
2. Monitoring for new infestations is a key component of the management strategy. When the monitoring budget or effectiveness was reduced, initial treatment costs were reduced because fewer detected patches of *P. ciliare* were treated. However, long-term treatment costs were much higher because plant community states that are difficult to transition from had been reached, requiring substantially greater investment. Reducing either the resources allocated to or the effectiveness of monitoring efforts results in larger, more distributed patches of *P. ciliare* on the landscape.

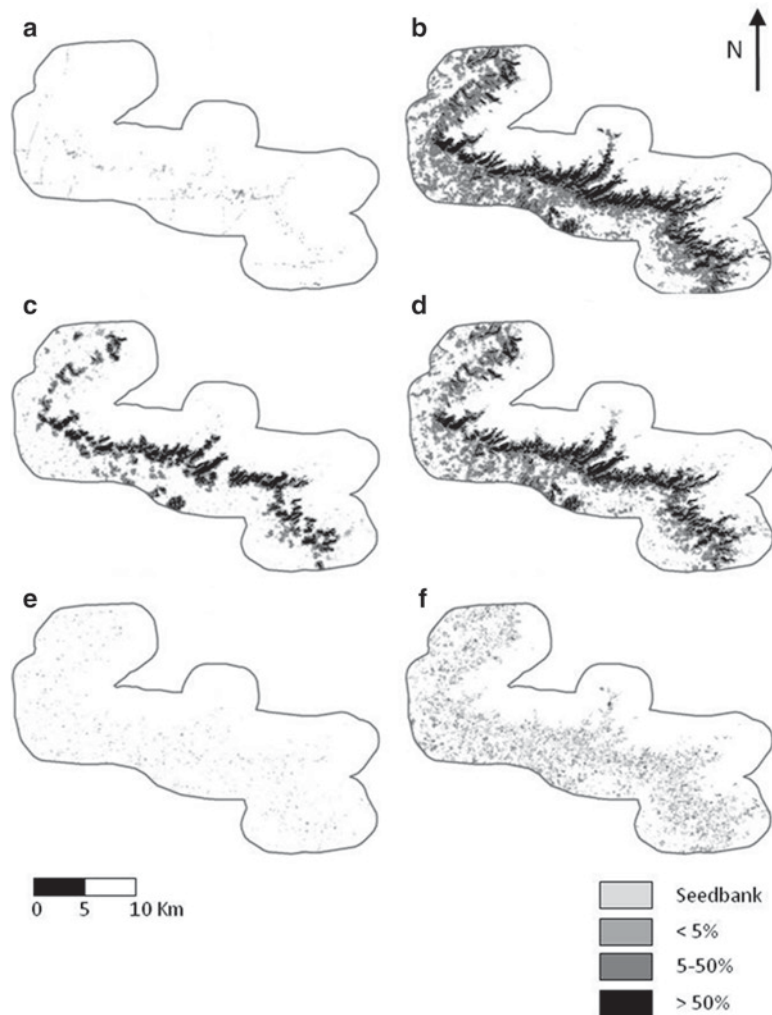


Fig. 13.3 Maps of the Santa Catalina Mountain Study area showing (a) mapped *P. ciliare* in 2010 and simulated *P. ciliare* invasion at year 2060 for five simulation scenarios: (b) no management, (c) intermediate management best case, (d) intermediate management worst case, (e) unlimited management best case, and (f) unlimited management worst case (From Frid et al. 2013b)

To our knowledge, the approach used by Frid et al. (2013b) using an STSM to simulate resource allocation to detection as well as treatment has not yet been applied to *Bromus*. Future work on *Bromus* species using this modeling approach could consider questions around resource allocation in space. For example, the model could consider trade-offs between monitoring and prioritizing treatment of more remote (and thus costly) areas versus accessible areas that require fewer resources to treat. In addition, the trade-off between monitoring and treatment could be explored further on a landscape and species-specific basis to determine which

management strategy might be most effective. While other non-STSM modeling approaches could also consider similar questions, this existing work provides an example STSM that in combination with conceptual state-and-transition models and STSMs for *Bromus* could be adapted to consider similar trade-offs for this species. In particular, the innovative use of states to distinguish between the information available to managers about an invasive species' presence or absence is ideally suited to STSMs. Since this study was conducted, there have been significant technological and design improvements to STSM software and conducting a similar expanded study for *Bromus* should be more feasible using the latest available tools (ST-Sim, see www.syncrosim.com).

13.2.7.2 Modeling with Uncertainty and Consequence for Conservation

STSMs can describe the current understanding of ecosystem dynamics and predict effects of invasive species and vegetation management, as seen in the example provided in Sect. 13.2.7.1 (see also Rumpff et al. 2011; Frid et al. 2013a). However, since models are simplified characterizations of complex natural systems, their predictions will deviate from reality; this deviation is hereafter called model uncertainty. It is important to estimate how well, or poorly, a model describes ecosystem dynamics because this knowledge provides managers with a level of confidence in predicted management outcomes. Ignoring model uncertainty can lead to ineffective or wasted management (e.g., Johnson and Gillingham 2004) and, given the high cost and limited resources often associated with invasive species and vegetation management, model uncertainty can have large consequences for management.

Model uncertainty in STSM can arise from many sources, such as estimated effects or rates of transitions, or the use of expert opinion (see Regan et al. 2002). Expert opinion is used when empirical data of reference conditions, states, or transitions are unavailable; or when transition rates are expected to deviate from historical values due to climate change (e.g., Sect. 13.3). A lack of data on transition rates in rangeland systems has necessitated a high reliance on expert opinion (e.g., Forbis et al. 2006; Vavra et al. 2007; Evers et al. 2011, 2013). While there are examples of STSM for *Bromus* management that investigate certain sources of uncertainty (e.g., Evers et al. 2013; Creutzburg et al. 2014), there are no examples of characterization of uncertainty due to expert opinion in an STSM for *Bromus* or other invasive annual grass. Below, we demonstrate how to characterize this uncertainty in STSM, drawing from a published example from *Eucalyptus* forests in Australia (Czembor and Vesik 2009; Czembor et al. 2011). This example describes consequences for management that have direct applications to *Bromus* STSM and is summarized here as a model approach that should be integrated into STSM for *Bromus* or other invaders in the semiarid western United States.

The example considered three sources of uncertainty: variation among experts, imperfect knowledge, and system stochasticity. To incorporate variation among experts, experts were provided with an STM and they specified how transitions would affect state change and the rate of each transition occurrence. In this way,

experts' own understanding of ecosystem dynamics was quantified and used to identify variation among experts.

Uncertainty due to imperfect knowledge occurs when an expert knows the approximate range for a model parameter, but is unsure of the exact, true value. Experts have provided single-value point estimates of transition rates in previous STSMs (e.g., Speirs-Bridge et al. 2010; McCarthy 2007) because, until recently, there was no option in STSM software to incorporate these bounds into models. However, using point estimates elicited from experts ignores imperfect knowledge and can lead to overconfidence in models and their predictions. Imperfect expert knowledge was addressed in the example by asking experts to estimate transition rates as a range of probable values, rather than as single-value point estimates. The ranges for each transition rate were converted to distributions; single points were sampled from distributions and compiled to create a set of replicate STSMs for each expert (Czembor et al. 2011).

Uncertainty due to system stochasticity arises because natural processes and disturbances occur randomly in space and time. It is independent of the uncertainty caused by using expert opinion and reflects the inherent variation in natural systems. The example incorporated system stochasticity using the VDDT software, which relies on Monte-Carlo random sampling methods where the occurrence of a transition to any one cell at a specific timestep is probabilistic and varies over multiple simulations (ESSA Technologies Ltd. 2007).

Once STSMs were constructed and simulations were complete, the example quantified which of the three sources of uncertainty contributed most to variance in model results (Quinn and Keough 2002). The authors conducted variance components analysis in R software using linear mixed-effects models in a maximum likelihood framework (Faraway 2006; Gelman and Hill 2007) to determine the contribution of each source of uncertainty to the variation in the proportion of cells in the desired vegetation state at the end of model simulations. Additional details regarding model parameterization and modeling can be found in Czembor et al. (2011).

All VDDT model results averaged together (i.e., with no consideration of uncertainty) indicated a slight increase in the desired vegetation state (low-density mature) over time, increasing from 6 % of the landscape to 15.6 % (Fig. 13.4). However, the model results for each expert separately are quite different from each other, with roughly 7.5–11.9 % of the landscape in the desired state for Experts 3–5, but up to 33.5 % predicted to occur in the desired state (Expert 2). Due to the similarity in results for Experts 1 and 2, it is interesting to note that these experts identified themselves as having expertise primarily in ecology, while Experts 3, 4, and 5 identified themselves as having expertise in natural resource and forest management. Variance due to imperfect knowledge (inner bars) was relatively constant over model simulations, while variance due to system stochasticity (outer bars) differed among experts' models and increased over time, particularly for Experts 1 and 5.

The results of the variance components analysis indicated that total variance in model results increased over time and reached equilibrium near the end of simulations (Fig. 13.5). The majority of total variance was due to the differences among

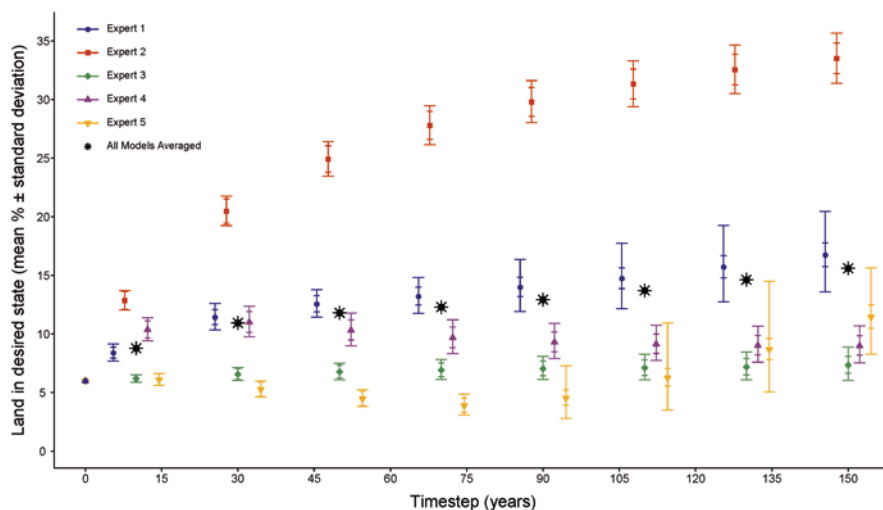


Fig. 13.4 The average percent of cells in the desired vegetation state (low-density mature) over time, for all models combined and for each expert. Error bars are stacked and represent the standard deviations for the variance due to imperfect knowledge (90 % confidence; inner bars) and system stochasticity (from end of inner bars to outer bars). Results adapted from Czembor et al. (2011)

experts (0.73), followed by system stochasticity (0.12), and then the imperfect knowledge component (0.01).

These results suggest that when a single or small group of similar experts provide the input to models, the results could deviate greatly from the true outcomes of vegetation management actions if the ecosystem dynamics are not well understood. However, even though the model results showed high variance, it is important to note that they are useful because they represent the current understanding of ecosystem dynamics and illustrate hypothetical depictions of landscape change. The large among-expert variance also makes selecting among management actions challenging because there is low confidence in model results. This variance could be reduced (i.e., masked) by subsampling similar individuals from available experts or aggregating opinions through consensus, both of which are very commonly done in rangeland management steering committees, at the risk of biasing results and to the detriment of management decisions. If experts are forced to form consensus, this uncertainty cannot be identified and management actions may be susceptible to unexpected results. Ascertaining which parameters are most variable among experts and collecting monitoring data to determine true rates and effects of transitions is therefore needed, and may be necessary for STSM applications to *Bromus* invaders.

There is no evidence provided in the example for the minimum number of experts needed to ensure adequate confidence in model predictions. Minimum expert sample sizes as high as 50 have been recommended, though typically less

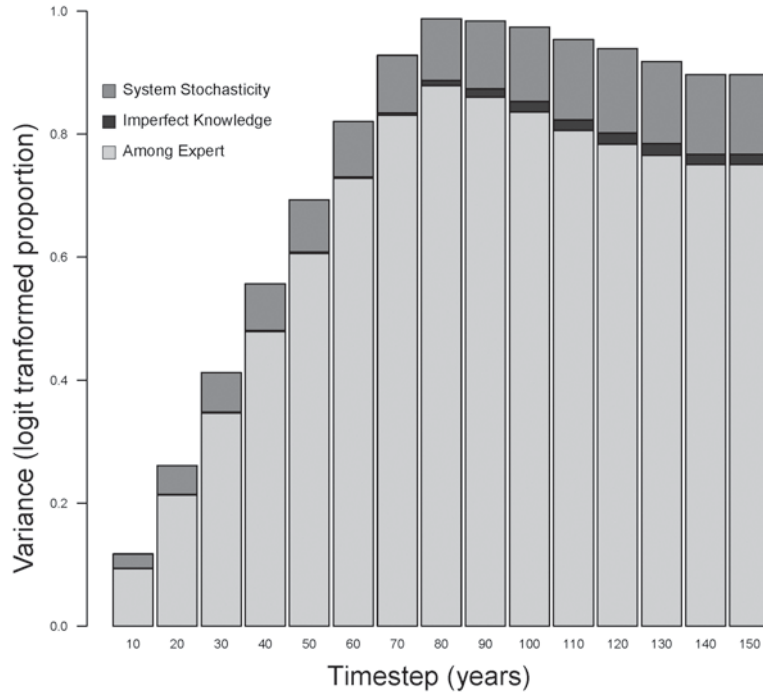


Fig. 13.5 Bar plots showing the variance due to among-expert uncertainty, imperfect knowledge, and system stochasticity every 10 years for 150 years. A 95 % Confidence Interval that corresponds to a logit transformed variance of 0.73 (the among-expert variance at timestep 150) would span 3–46 % of modeled cells in the desired vegetation state. Results adapted from Czembor et al. (2011)

than ten are sampled in practice because few appropriate experts are available (Czembor et al. 2011).

System stochasticity was a moderate source of variance in the model results for the *Eucalyptus* example. In VDDT, this variance reflects the stochastic sequence of disturbances over repeated simulations (i.e., transitions occur at random times within simulations, but with the same average probability through time across simulations). While stochasticity in the rate of disturbances over time was not evaluated in the *Eucalyptus* example, this source of uncertainty can be incorporated into “temporal multipliers” (see Sect. 13.3). Temporal transition multipliers were used to parameterize uncertainty in a study of the effects of the exotic annual grasses, *B. tectorum*, *Taeniatherum caput-medusae* L (medusahead), and *Ventenata dubia* (Leers) Coss. (North Africa grass), on native plant species in sagebrush steppe ecosystems across years differing in wildfire occurrence (Creutzburg et al. 2014).

The variance in model results due to imperfect knowledge was the least important source of uncertainty in this case study. The example incorporated imperfect knowledge using replicate models that used ranges of values for transition rates, but

it is also possible to incorporate imperfect knowledge through sensitivity analyses. Evers et al. (2013) tested sensitivity of imperfect knowledge by adding, removing, or changing probabilities of disturbance (derived from expert opinion) to determine vulnerability of model outputs to succession and interactions with exotic annual grasses such as *B. tectorum* in big sagebrush steppe (*Artemisia tridentata* Nutt. subsp. *wyomingensis* Beetle & Young (Wyoming big sagebrush). In doing so, they could ascertain the degree of model sensitivity and the potential magnitude of error if the expert estimates were incorrect.

The example illustrates how uncertainty due to expert opinion can cause large variation in model predictions. This has consequences for models constructed using expert opinion, which is common in rangeland management. The example also provides a template for how expert uncertainty can, and should, be incorporated into STSM for *Bromus* management.

13.3 Case Study: Simulating Predicted Climate Change Effects on *B. tectorum*

13.3.1 Introduction

The US National Environmental Policy Act (NEPA 1969) requires federal agencies to integrate environmental values into their decision-making processes by considering the environmental impacts of their proposed actions and reasonable alternatives to those actions. Environmental values include climate change, although it was only recently added to lists of environmental concerns for the Bureau of Land Management (Manual 7300: Air Resource Management Program), US Forest Service (USFS, FSH 1909.12–Land Management Planning Handbook), and National Park Service (National Park Service: Climate Change Response Strategy). Rarely do federal planners have local data on climate change to make predictions; therefore, planners use more generic concepts to comment in NEPA documents. Climate change effects imply changing local trends and temporal variability for temperature, precipitation, evapotranspiration, and carbon dioxide. All of these variables can impact the growth and spread of invasive annual grasses, such as *B. tectorum* (Smith et al. 2000; Brown et al. 2004; Bradley 2009b), and native species, such as trees (Tausch and Nowak 1999) in the US arid Intermountain West.

The purpose of this case study is to propose a new methodology of incorporating readily available data on future CO₂ levels, precipitation, and temperature into the ecological processes of STSMs. To illustrate climate change effects on ecological systems and *B. tectorum*, we modeled *Artemisia tridentata* Nutt. spp. *vaseyana* (Rybd.) Beetle (mountain big sagebrush, 30–36 cm of average annual precipitation) sites within the boundary of Great Basin National Park in Nevada and adjacent *A. tridentata* spp. *wyomingensis* (25–30.4 cm of average annual precipitation) just

outside the boundary of the Park (Provencher et al. 2013). The *A. tridentata* spp. *vaseyana* system occurs at higher elevations on cooler and moister soils than the *A. tridentata* spp. *wyomingensis* system; therefore, this study assumed that *A. tridentata* spp. *wyomingensis* would respectively replace the lowest and middle elevations of *A. tridentata* spp. *vaseyana* in the Park with climate change, especially warming. Both ecological systems are readily invaded by *B. tectorum*, especially on relatively warmer and drier soils, as well as by trees such as *Pinus monophylla* Torr. & Frém. (singleleaf pinyon) and *Juniperus osteosperma* (Torr.) Little (Utah juniper). As a result, both *A. tridentata* spp. *vaseyana* and *A. tridentata* spp. *wyomingensis* systems needed to be modeled together to predict climate change effects on vegetation class abundances using the Path Landscape Model (Path) software (see footnote of Table 13.1 about Path). Using climate change data to affect ecological processes in STSMs is rather new (Halofsky et al. 2013); therefore, both the novelty of our approach and forecasted values of precipitation and temperature from global circulation models introduced uncertainty in our simulation results. Another source of uncertainty was expert opinion, which was required as the scientific literature for Great Basin rangelands is data poor for model parameterization. We addressed uncertainty by using Monte-Carlo replicates that deliberately introduce strong variability into ecological processes. Therefore, this case study focuses more on demonstrating a new methodology and less on the accuracy of ecological results.

13.3.2 Methods

13.3.2.1 State-and-Transition Models

The *A. tridentata* spp. *vaseyana* STM presented here is part of a group of 21 such models previously developed with Path for cost-effective management of Great Basin National Park's ecological communities (Provencher et al. 2013). The *A. tridentata* spp. *wyomingensis* STM was obtained from concurrent STSM efforts in nearby Hamlin Valley and Pine Valley Mountains of southwest Utah's Great Basin, respectively, on lands managed by the US Department of Interior Bureau of Land Management and US Forest Service. Both STSM models originated during 2005–2007 from LANDFIRE's STSM development effort for the Great Basin mapping zone (Rollins 2009). These models were subsequently modified by (1) improving representation of fire disturbances, (2) adding uncharacteristic vegetation classes representing states or phases (e.g., invasive annual grassland), (3) incorporation of new disturbances observed in the field, including adding uncharacteristic ones such as invasive species expansion, and their rates, (4) adding management actions and budgets to the list of disturbances that affect states and transitions, and (5) introducing external sources of temporal variability that would modify disturbance rates over time (e.g., replacement fire). Models and results were reviewed by federal and state agency specialists, contractors, and academics during the Park's project workshops and in workshops of previous projects (Low et al. 2010). Informal but extensive sensitivity analyses were part of the review process.

13.3.2.2 Range Shifts

The replacement of “cooler or wetter” ecological systems and their indicator species by “warmer or drier” systems and their indicator species during climate change is called range shift. Theoretical bioclimatic envelope modeling (Rehfeldt et al. 2006; Bradley 2009a) and one field study (Kelly and Goulden 2008) provided widely conflicting conclusions on the speed of range shifts. Thus, in this modeling example, the percentage of the area shifting from *A. tridentata* spp. *vaseyana* to *A. tridentata* spp. *wyomingensis* systems over 100 years was first set at 10 %. We iteratively determined that a rate (probability per year) of 0.0604 year^{-1} (i.e., 604 virtual pixels shifted per 10,000 pixels per year) matched the 10 % range shift over 100 years. We further set values of 87 % and 13 % for the total area of *A. tridentata* spp. *vaseyana* that would be replaced by *A. tridentata* spp. *wyomingensis* and *A. nova* A. Nelson (black sagebrush), respectively, based on current sagebrush community proportions as found by Provencher et al. (2013). For simplicity, we only tracked the range shift between *A. tridentata* spp. *vaseyana* and *A. tridentata* spp. *wyomingensis* for this chapter. Moreover, we gradually introduced the range shift by setting the initial value of range shift to zero under the assumption of no climate change at year zero, and then linearly increased temporal multipliers for range shifts to a value of two by year 75 of the simulation. Therefore, the average rate of range shift of 0.0604 year^{-1} had a value of one over the 75 years of the time series to maintain rate integrity. In comparison, a control simulation without climate change would have a range shift temporal multiplier series equal to zero for all time intervals.

13.3.2.3 Climate Variability Effects on Ecological Processes

Temporal multipliers act as forcing factors of ecological processes in the STSM and also reflect hypotheses about the effects of climate variability on ecological processes. One temporal multiplier is a non-dimensional number ≥ 0 in a yearly time series that multiplies a base disturbance rate in the STSM. For example, for a given year, a temporal multiplier of one implies no change in a disturbance rate, whereas a multiplier of zero is a complete suppression of the disturbance rate, and a multiplier of three triples the disturbance rate. A temporal multiplier can be obtained from time series data or theoretically derived. In the current case, multipliers vary for scenarios with or without climate change. Temporal multipliers are determined by dividing each yearly value of the time series (for example, area burned) by the temporal average of the time series, thus creating a non-dimensional time series with an average of one. Division by the time series' average would remove the hypothesis of altered levels of the ecological process being modeled under climate change scenarios; thus each raw value of the new time series (e.g., future area burned) with climate change must be divided by the average of the time series not experiencing climate change.

The dominant ecological processes of big sagebrush models, fire, drought, invasive annual grass expansion, and tree expansion, all required temporal multipliers without and with climate change forcing. Forcing factors were based on future trends in atmospheric CO₂, local temperature, and local precipitation and included:

1. Increased expansion of invasive species (annual grasses, forbs, and trees) into uninvaded areas caused by CO₂ fertilization effects during wetter than average years (Smith et al. 2000; Brown et al. 2004; Bradley 2009b);
2. Decreased expansion of invasive species (annual grasses, forbs, and trees) into uninvaded areas during drier than average years regardless of CO₂ concentrations (Smith et al. 2000; Brown et al. 2004; Bradley 2009b);
3. Longer fire return intervals in shrubland systems due to increased drought frequency preventing fine fuel buildup (Westerling and Bryant 2008, Westerling 2009; Abatzoglou and Kolden 2011; Littell et al. 2009); and
4. Increased expansion of *P. monophylla* and *J. osteosperma* trees in shrublands caused by CO₂ fertilization during wetter-than-average years (Tausch and Nowak 1999).

The temporal multiplier for elevated CO₂ was calculated from time series for future CO₂ levels using the A2 emission scenario from IPCC's (2013) report, simply as change in CO₂ from time=0 to the end of the simulation period (i.e., division of each yearly CO₂ level by the level of the first year of simulation).

All simulations of temperature and precipitation effects were based on five replicate Global Circulation Models (GCM) forecasts available from the Downscaled Climate Projections Archive (of 37 GCMs available; http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html, version 1.2, 06-August-2011) using the mean values for the Park and surrounding area. Normally, average values of an "ensemble" of many randomly selected GCM model outputs are used for simulations such as ours, given computing and cost limitations. The five model outputs were selected based on their marked differences for projected precipitation which varied much more than temperature among the models (listed in Fig. 13.6's caption). One GCM selected forecasted increasing precipitation, albeit from initial low levels (first replicate), three forecasted no change in precipitation but had different average precipitation levels (second, third, and fourth replicates), and one forecasted less precipitation over a century (fifth replicate). All data were displayed by year and month and our time series were 75 years into the future.

Five future time series replicates without climate change were created by using observed historic temperature and precipitation data obtained from the same library and for the same area using the same spatial averaging methods. We assumed that past climate reflected future climate without climate change and that recent warming of the past decades had not significantly affected the slow growing Great Basin vegetation as shown by Kelly and Goulden (2008) in a Mojave Desert elevation gradient. However, there was only one observed time series from 1950 to 1999, but five future replicates without climate change were needed. To create five replicates

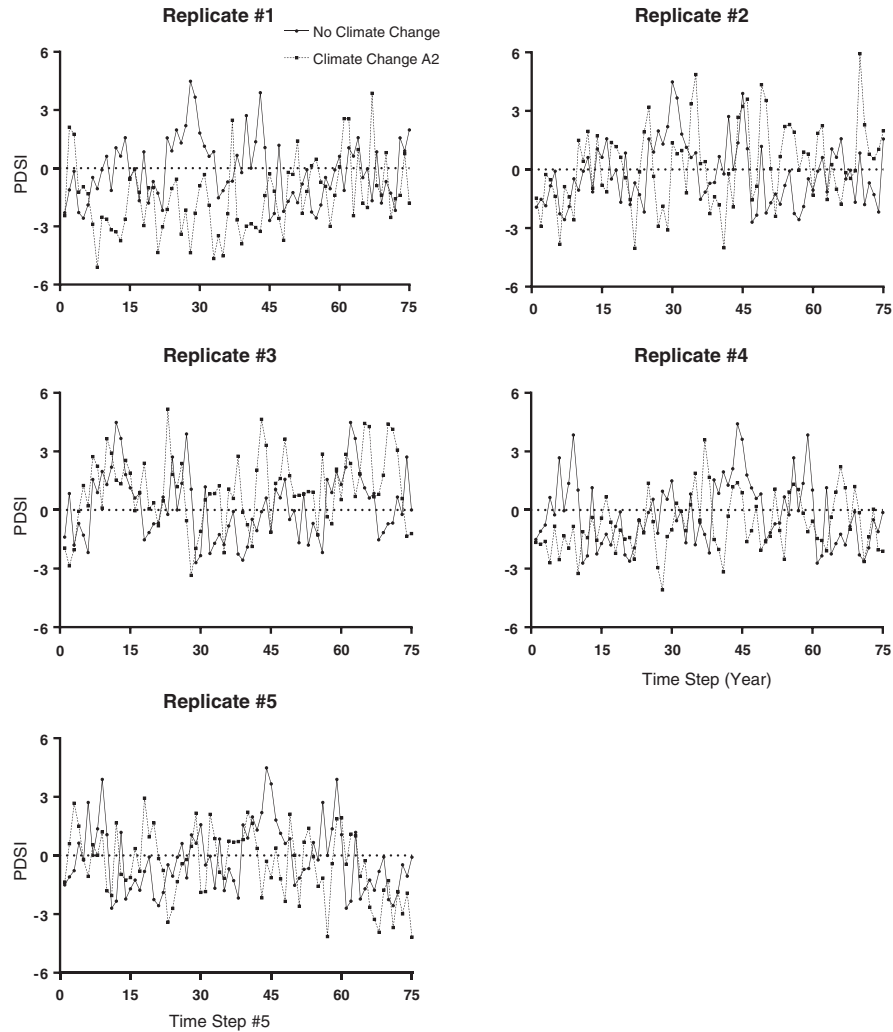


Fig. 13.6 Replicated and calculated PDSI time series using Eqs. (13.1) and (13.2) assuming no climate change (resampled historic precipitation and temperature time series) and assuming the A2 scenario from five Global Circulation Models as five 75-year replicates. Climate change legend: replicate #1=mri_cgcm2_3_2a.2.sresa2; replicate #2=ukmo_hadcm3.1.sresa2; replicate #3=ncar_pcm1.1.sresa2; replicate #4=ncar_ccsm3_0.1.sresa2; and replicate #5=ncar_ccsm3_0.2.sresa2

and preserve potential seasonal and multiyear climate patterns in the data, the 1950 to 1999 time series was wrapped around as a time loop (i.e., year 1950 followed year 1999) and was resampled by randomly selecting five start years (replicate #1=1956; replicate #2=1954; replicate #3=1972; replicate #4=1960; replicate #5=1990) until 75 years of data were accumulated. The next step was to use the historic and projected CO₂, temperature, and precipitation to create the final temporal multipliers.

All projections of temperature and precipitation were integrated into the Palmer Drought Severity Index (PDSI; Palmer 1965; Heddinhaus and Sabol 1991) from which temporal multipliers for replacement fire, drought, annual grass expansion, and tree expansion were obtained when combined with future projections of CO₂. Because the literature offered no guidance on this subject, heuristic relationships were created to translate the variability of the PDSI into the local variability of drought, replacement fire, invasive annual grass expansion, and tree expansion. Hopefully our heuristic approach will spur research to improve upon our effort. Calculations of future values of the PDSI are found in the Appendix (Eqs. 13.1 and 13.2).

Drought was assumed to kill woody species (for trees; Pennisi 2010), sometimes mediated by triggering insect and disease attacks on trees, whereas wetter conditions suppressed this disturbance. In the STSMs for *A. tridentata* spp. *vaseyana* and *A. tridentata* spp. *wyomingensis*, the drought disturbance operated both by partial thinning of the dominant upper-layer lifeform (i.e., shrubs or trees that characterize the vegetation class) within a vegetation class without causing a transition to another state or phase (about 90 % of probabilistic outcomes) and by killing most woody individuals of the dominant upper-layer lifeform and thus causing a transition to a younger succession class (10 % of probabilistic outcomes). As drier (PDSI < 0) or wetter (PDSI > 0) conditions, respectively, were observed in the GCM time series, the base rate for the drought disturbance in the STSMs was increased (>1) or decreased (<1) by the yearly value of the temporal multiplier (Eq. 13.3).

Invasive annual grass expansion and tree expansion into uninvaded areas did not include infilling by invasive annual grasses and native trees, although that could be done in a more complicated STM. Rates of invasive plant advance in the STSMs could vary by vegetation classes and ecological systems based on the natural resistance of established vegetation (Chambers et al. 2014). We used a single temperature multiplier to relate moisture (precipitation) to greater dispersal (more seeds) and, thus, invasion (Eq. 13.4). Fertilization with elevated CO₂ was predicted to enhance the effect of a wetter condition but was a weaker effect overall (Nowak et al. 2004). We assumed that tree expansion was a much slower process than invasive annual grass expansion and also less responsive to PDSI (Eq. 13.5).

Fire frequency and total area burned have a complicated relationship to the PDSI in shrublands—they are more likely to burn if they first experience consecutive wetter-than-average years leading to accumulation of fine fuels that will more likely burn in a dry year immediately following the wet year sequence (Westerling and Bryant 2008, Littell et al. 2009; Westerling 2009). Area burned was first estimated by applying equations using PDSI and by assuming that the maximum fire size achieved under any scenario represents 10 % of the area sum of all shrubland–woodland ecological systems for the shrubland–woodland temporal multiplier. We chose 10 % of the area because managers considered fires exceeding 10 % of Great Basin National Park’s area were very large and unusual according to the federal record. However, different managers may choose different percentages for different landscapes. The shrubland–woodland fire temporal multipliers considered the roles of 3 prior years of PDSI, more specifically that fine fuels will more likely burn in the current dry year immediately following 2 previous and consecutive wetter-than-average years during which fine fuels accumulated (Eq. 13.6).

13.3.3 Results

Three uncharacteristic states of the *A. tridentata* spp. *vaseyana* model (coded as MSu to represent Mountain Sagebrush upland) were invaded by *B. tectorum*: shrubland with mixed annual grass and perennial grass (MSu-SAP), tree-dominated shrubland with annual grass (MSu-TEA), and annual grassland (MSu-AG). Using remote sensing data to populate the initial conditions of the simulations (year=0; Provencher et al. 2013), the MSu-TEA state was the most abundant (~2700 ha), followed by MSu-SAP (~1000 ha), whereas MSu-AG was nearly absent (~10 ha; Fig. 13.7). As a result of the simulated ecological processes with and without climate change, the area occupied by the MSu-SAP state gradually decreased over time as a result of fire, drought mortality, and tree encroachment. In the model's transitions, the first two disturbances caused the increase in area of the MSu-AG state, which closely matched the decrease in area of the MSu-SAP state (Fig. 13.7). The small area of the MSu-TEA state primarily loss to fire after year 40 also contributed to the increase in area of the MSu-AG state. The area of the MSu-TEA state was relatively stable compared to the other states because the area that burned was offset by the new area of the MSu-SAP state that became encroached by trees.

The simulated effect of climate change was nearly undetectable for *A. tridentata* spp. *vaseyana* (Fig. 13.7). Because of the strong variability in drought cycles in the Great Basin, the trends in ecological processes caused by climate change indicated here are far smaller than their natural variability; therefore, the effects of climate change in STSMs must become strong to be detected, and this takes several decadal iterations. Although climate change differences between simulations were not clearly observable for *A. tridentata* spp. *vaseyana*, they still incrementally occurred because states from *A. tridentata* spp. *wyomingensis* replaced those of *A. tridentata* spp. *vaseyana* starting on the fifth year of simulations (Fig. 13.8). Only range shifts caused this replacement in our models. Furthermore, as a result of model design, these range shifts will first be observed in all early-succession phases and classes and will occur more rapidly in phases or states with shorter fire intervals because we assumed stand-replacing events remove the biomass of original indicator species and allow the new indicator species to colonize in the same phase or state (see also Halofsky et al. 2013; Creutzburg et al. 2014). Range shifts do not usually change the phase or state, they only change the potential for certain dominant indicator species (e.g., from MSu-AG to the annual grassland state of *A. tridentata* spp. *wyomingensis*).

Starting with no area of *A. tridentata* spp. *wyomingensis* within the Park, simulated range shifts replacing *A. tridentata* spp. *vaseyana* with *A. tridentata* spp. *wyomingensis* (coded as WS) first caused new increases in area of two classes of vegetation: early-succession (WS-A) and annual grassland (WS-AG; Fig. 13.8). The cumulative area converted to *A. tridentata* spp. *wyomingensis* represented a large fraction of the area initially in *A. tridentata* spp. *vaseyana* (about 10 %, as built into the STSM—see *Range Shifts*). Following STM transitions, the other three phases and state emerged, albeit with low areas, as the product of succession (from

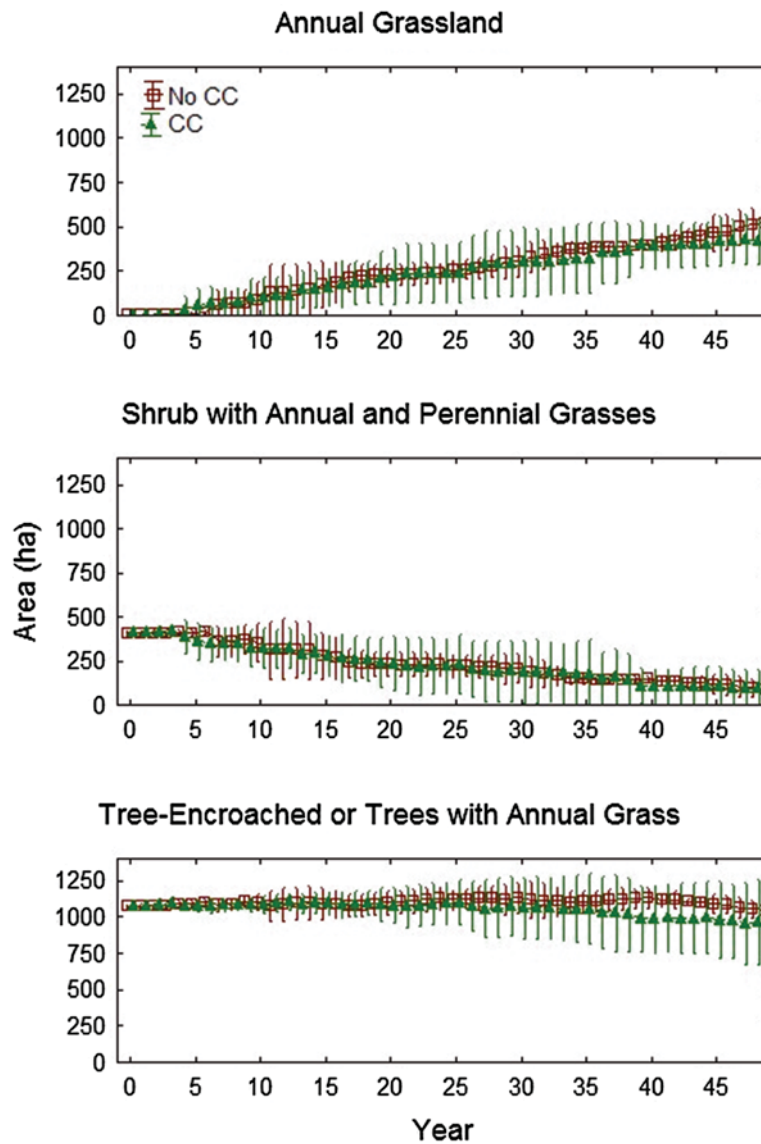


Fig. 13.7 The area of vegetation classes invaded by *B. tectorum* (ha) in the *A. tridentata* spp. *vaseyana* ecological system assuming no climate change (NoCC; based on resampled historic data) and assuming climate change for the A2 scenario (CC) from five Global Circulation Models (GCM). Legend: MSu-AG=annual grassland; MSu-SAP=shrubland with annual and perennial grasses; and MSu-TEA=tree encroached or wooded shrubland invaded by annual grass. Climate change GCMs replicates are mri_cgcm2_3_2a.2.sresa2, ukmo_hadcm3.1.sresa2, ncar_pcm1.1.sresa2, ncar_ccsm3_0.1.sresa2, and ncar_ccsm3_0.2.sresa2. Error bar represents the 95 % confidence interval for five replications

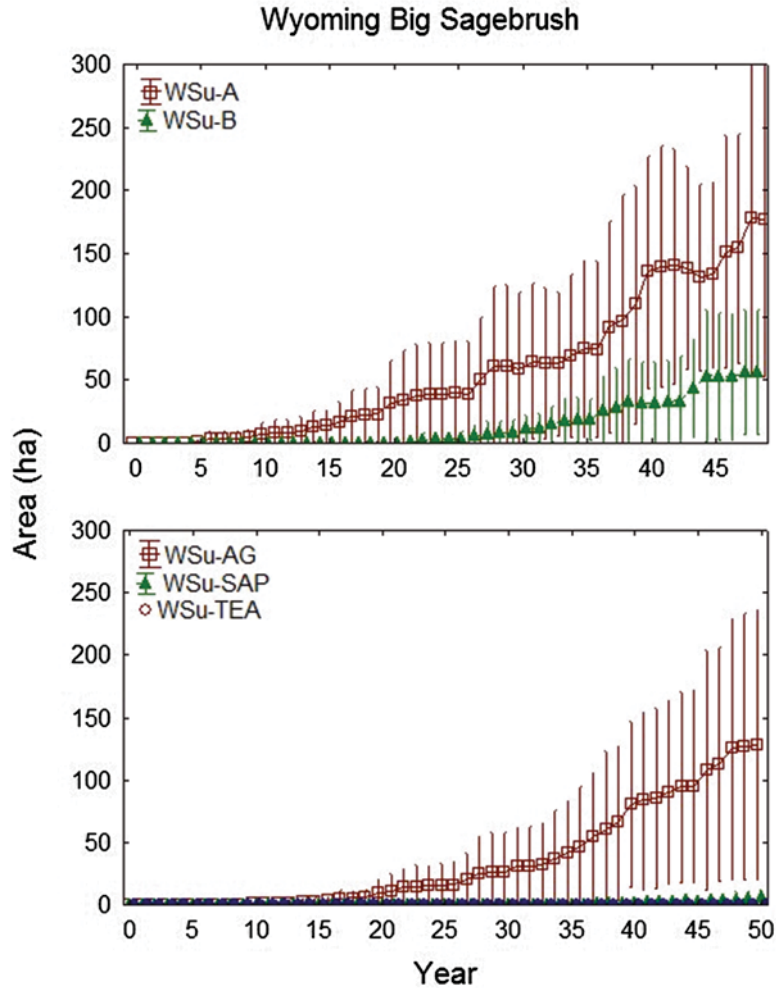


Fig. 13.8 The area of reference and *B. tectorum*-invaded vegetation classes (ha) in the *A. tridentata* spp. *wyomingensis* ecological system assuming climate change for the A2 scenario from five Global Circulation Models. Legend: WS-A=early-succession; WS-B=mid-succession; WS-AG=annual grassland; WS-SAP=shrubland with annual and perennial grasses; and WS-TEA=tree encroached or wooded shrubland invaded by annual grass. Climate change GCMs replicates are mri_cgcm2_3_2a.2.sresa2, ukmo_hadcm3.1.sresa2, ncar_pcm1.1.sresa2, ncar_ccsm3_0.1.sresa2, and ncar_ccsm3_0.2.sresa2. Error bar represents the 95 % confidence interval for five replications

WS-A to WS-B and from WS-SAP to WS-TEA) and invasion of uninvaded class by *B. tectorum* (from WS-B to WS-SAP; Fig. 13.8).

Three lessons learned from simulating *A. tridentata* spp. *vaseyana* and *A. tridentata* spp. *wyomingensis* community transitions were that (1) it may take

decades to detect climate change effects on the distribution of vegetation classes within an ecological system because in the models natural “background” drought variability appears stronger than the variability caused by climate change in the Great Basin region of the United States, (2) range shifts between ecological systems, but not between phases or states, were accelerated by the short fire return interval of the annual grassland state, and (3) climate change did not cause more *B. tectorum* expansion 50 years into the future landscapes (e.g., MSu-AG in Fig. 13.7) because the trends in temperature and precipitation from the GCMs decreased soil moisture (i.e., increased drought intensity) and, as a result, decreased *B. tectorum* expansion (and tree expansion) regardless of the level of CO₂ fertilization. Range shifts, therefore, are predicted to occur more readily in the areas having an annual grassland state, because we hypothesized that range shifts occur through stand-replacing events in long-lived and drought-resistant shrublands and woodlands. The presence or dominance of *B. tectorum* shortens fire return intervals in landscapes, which in turn increase the likelihood of stand-replacing events. We have not, however, simulated the process of invasion by a new invasive annual grass species adapted to warmer conditions, such as *Bromus rubens* L. (red brome), although that would be feasible with additional data (e.g., Bradley et al. 2015).

This case study integrated STSM to predict distribution of *A. tridentata* spp. *vaseyana* and *A. tridentata* spp. *wyomingensis* plant community phases and states over time with relationships between GCM outputs and their effects on the number of ecological disturbance occurrences per year in STMs. Finding ways to incorporate climate change variability into STSM processes was the most difficult and time-consuming part of the case study, and furthermore this step introduced uncertainty. An alternative approach linking STSM to climate change effects was pioneered by the Integrated Landscape Assessment Project (ILAP; Halofsky et al. 2013; Creutzburg et al. 2014), which linked vegetation change and wildfire trend data from the GCMs and the MC1 dynamic vegetation model with STMs to inform watershed-level prioritization of fuel treatments in Arizona, New Mexico, Oregon, and Washington. Whereas we used a bottom-up approach based on precipitation, temperature, and CO₂ concentrations output from GCMs affecting disturbances and range shifts, ILAP was a top-down process where GCMs and MC1 determined range shifts and the variability of fire. ILAP’s process required downscaling GCMs and MC1 subcontinental coarse resolution predictions of climate change to the project areas, and meshing processes from widely different spatial scales. This is major source of uncertainty because MC1 predicted (1) changes in general lifeforms groups (shrublands, grasslands, and forest), but not different ecological systems within a group, and (2) changes in general fire activity regardless of how drought affects differently forested and shrubland systems (Taylor and Beaty 2005; Westerling and Bryant 2008; Littell et al. 2009; Westerling 2009). Moreover, MC1 only generated predictions for fire (Creutzburg et al. 2014), whereas our bottom-up method also introduced climate variability for drought,

invasive upland and riparian species expansion, tree expansion, insect outbreak, flooding, subalpine spring freezing, snow deposition, and tree encroachment (different from tree expansion).

13.4 Management Implications

The examples and case study in this chapter have the following management implications.

1. STSM simulation outcomes presented in this chapter indicate that a program evaluating unlimited budgets for detection, monitoring, and treatments with a long-term scope is worth considering through STSM-based assessments. In landscapes where invasion by species such as *Bromus* is in its early stages allocating resources toward monitoring may increase treatment success. STSMs such as the one discussed for *P. ciliare* can help better understand the trade-off between treatment and monitoring, thereby supporting management investment decisions.
2. Uncertainty among experts over nonnative brome invasion rates and control/restoration success could waste already limited funding for natural resources management. How can diverse opinions be integrated into a robust management strategy for *Bromus* species? At a minimum, the research presented herein indicates that a simple sensitivity analysis of expert opinion on nonnative brome invasion rates and control success should be explored with STSM where experts are able to offer different opinions. In this way, those environmental or management parameters that are most uncertain (i.e., vary most between experts) can be identified for sensitivity analyses. Those uncertain parameters that matter most to management outcomes can then be used to focus efficient monitoring and data collection.
3. Several scenarios can be explored using STSMs. Local managers planning for the conservation of natural resources far into the future (e.g., 50–100 years) can implement programmatic changes in the next decade that might determine whether range shifts will happen sooner or later. For example, managers might have resources to only restore degraded annual grassland to a more resilient state of vegetation that would result in resistance to range shifts or to only control wildfires while maintaining the age diversity of phases in the reference state, thus resulting in plant communities more similar to the reference condition. These two scenarios could readily be explored with STSM.

As STSMs inform agency land management decisions and become more visible as a planning tool to other users, future applications will become more complicated

and address increasingly larger landscapes. Future applications will require investments in software enhancements to accelerate processing and to accomplish new processes. Given that the most commonly used STSM platforms are freeware, these investments must come from users, which implies that agency and private users should budget for software enhancements. In addition, while there are various examples of STSMs being used by public land management agencies (Forbis et al. 2006; Provencher et al. 2007, 2013; Low et al. 2010), in most of these applications funding for training and technical support in applying the models has been a key requirement for the success of the initiative. Land management agencies often lack the technical expertise required to be able to apply STSMs without such support (Blankenship et al. 2013).

13.5 Ecological Research Needs

The following are some concepts that need additional consideration in order to move forward with applying STSMs to *Bromus* management.

1. Evaluate how effective alternative inventory approaches are at detecting *Bromus* invasion at different stages. How costly are these different approaches? What is the most effective allocation of resources between management activities including preventive restoration, inventory, treatment, and posttreatment maintenance? A combination of field experiments and STSM development is required to answer these questions at the landscape scale.
2. Explore the reasons for divergence among experts, to refine expert estimates via discussion and comparison to new monitoring data, and to weight expert opinion using established datasets.
3. Determine the rate and fate of range shifts of ecological systems potentially invaded by *Bromus* using field studies coupled with modeling approaches that do not assume infinite species dispersal rates and no resistance to drought.
4. Empirically demonstrate that wildfires primarily fueled by *Bromus* will accelerate range shifts (e.g., from *A. tridentata* spp. *vaseyana* to *A. tridentata* spp. *wyomingensis* and *A. nova*) compared to unburned vegetation
5. Standardize the methodology and science for creating multiple and potentially correlated temporal multipliers in STSMs that reflect different hypotheses between environmental variability and model disturbance rates.
6. Determine to what extent we are uncertain about the rate of spread of invasive *Bromus* species across different ecological systems and about invasive *Bromus* species control success. What field data are already available to reduce uncertainty in estimates for *Bromus* invasion rates (probability of spread and successful establishment of new areas per year)? How might these sources of uncertainty affect vegetation management decisions?

With the existing data available to land managers and the STSM framework as a tool to investigate alternative scenarios and management actions, the above research needs can be addressed. With time, it is hoped that these modeling strategies will assist management decisions and result in desired outcomes with higher efficiency and reduced resources.

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Appendix

Calculating the Palmer Drought Severity Index

The Palmer Drought Severity Index (PDSI) time series was used to calculate the temporal multipliers for replacement fire, drought, annual grass invasion, and tree invasion. Drought is a major influence for these disturbances. PDSI measures long-term soil drought and is updated monthly (Palmer 1965; Heddingtonhaus and Sabol 1991). Positive values indicate above average soil moisture (>3 is very wet), whereas negative values represent droughty soil (<-3 is very dry). A PDSI of zero is average soil moisture. The formula for PDSI at time t (month) is as follows:

$$\text{PDSI}_t = 0.897 \times \text{PDSI}_{t-1} + (k_t / 3) \times (P_t - \underline{P}_t) \quad (13.1)$$

where P_t is precipitation during month t , \underline{P}_t is average (historic) precipitation for month t , and k is a monthly climatic coefficient that weighs the local importance of $(P_t - \underline{P}_t)$ (Palmer 1965). For example, k might imply that $(P_t - \underline{P}_t)$ in January does not contribute as much to PDSI as the same deviation in precipitation observed in August (Palmer 1965). Although we downloaded monthly precipitation values and obtained monthly \underline{P}_t from historic precipitation data (respectively, month, precipitation [mm/day]: January, 0.8004; February, 0.8368; March, 1.0234; April, 0.9310; May, 0.9612; June, 0.6130; July, 0.6356; August, 0.7394; September, 0.6876; October, 0.7502; November, 0.7476; December, 0.6858), the value of k_t is unknown and requires complicated field estimation based, among others, on evapotranspiration (Palmer 1965). (To remove this complication and need for a heuristic equation, future projects will use the Standard Precipitation Index [Hayes et al. 1999]). Therefore, we made several arbitrary assumptions to imitate k using the month's temperature differential. Specifically,

$$k_t / 3 = 1.5 \times (1 - e^{-0.15 \times (\text{Max}T - T_t)}) \quad (13.2)$$

where $\text{Max}T = 31$ (°C) is the maximum temperature observed, and T_t is the average temperature during month t . In this heuristic equation, higher temperatures cause smaller values to multiply $(P_t - \underline{P}_t)$ when monthly precipitation is higher and thus

PDSI becomes smaller (more evapotranspiration). The coefficients 1.5 and -0.15 are fitting constants we iteratively selected that allow the PDSI to vary within the observed range and be responsive to changes in precipitation, primarily, and secondarily to temperature. Using the latest observed monthly PDSI from March 2012 as the first $PDSI_{t-1}$, we estimated future monthly PSDIs per replicate for 75 years using Eqs. (13.1) and (13.2) for both without and with climate change. Compared to the PDSI replicates without climate change, it is noticeable that three temporal replicates of PDSI estimated for climate change effects were drier during certain decades only (replicates #1, 4, and 5), whereas the third replicate was wetter and the second replicate neutral (Fig. 13.6).

Because PDSI can be negative and the STSM software requires positive values, heuristic functions (arbitrary coefficients) were developed for drought, replacement fire, invasive annual grass expansion, and tree expansion that transformed negative values into positive values while maintaining the role of PDSI on the intensity of the disturbance. Not many flexible functions allow the conversion of negative values into positive ones while also accepting positive values; therefore, these curve fitting requirements led us to adopt functions with exponential components that could be easily calibrated. These functions do not calculate the rate of the disturbance, which is found in the STSM, but the temporal variability of the disturbance. All equations generated non-dimensional values and the final temporal multipliers were also non-dimensional.

Drought Disturbance

Because PDSI can be negative, therefore incompatible with PATH's format for temporal multipliers, we chose a negative exponential function for drought to create positive values that increased exponentially with more negative (drier) PDSI values:

$$\text{Yearly drought variability factor} = 0.6 \times e^{-0.6 \times \text{PDSI}} \quad (13.3)$$

The parameters of this function (0.6 and -0.6) were chosen such that PDSI values close to -3 (very dry) were slightly greater than 3 (actually, 3.63) and that very severe droughts with PDSI of -5 (extreme drought) translated into slightly more than doubling of the function (12). Another consideration for curve fitting was that a mild drought characterized by a PDSI of -1 would be about equal to a neutral value of 1. Equation 13.3 is not the final temporal multiplier, however, because it is not divided by its average. In the absence of climate change effects, yearly values of Eq. (13.1) were divided by their temporal average over 75 years, whereas each yearly value of Eq. (13.3) with climate change was divided by the no-climate change average to reflect the hypothesis of altered levels.

Annual Grass Invasion and Tree Invasion Disturbances

The temporal multipliers for invasive annual grass expansion and tree expansion were calculated from two heuristic Gompertz equations (not including the CO₂ fertilization). The Gompertz equation is highly flexible for curve fitting and a special case of it is the negative exponential:

$$\begin{aligned} \text{Yearly annual grass expansion variability factor} = \\ 4.5 \times e^{-2 \times \exp(-0.75 \times (\text{PDSI}+1))} \times \text{TMCO}_2 \end{aligned} \quad (13.4)$$

$$\begin{aligned} \text{Yearly tree expansion variability factor} = \\ 2.5 \times e^{-2 \times \exp(-0.75 \times (\text{PDSI}+1))} \times (\text{TMCO}_2)^{0.5} \end{aligned} \quad (13.5)$$

where TMCO₂ is the temporal multiplier for CO₂ levels, which is <2 for any yearly value with climate change and equal to one without climate change. In accordance with our hypothesized relationship between species expansion and soil moisture and CO₂ levels, the effect of CO₂ levels as expressed by its temporal multiplier (between 0 and 1) on variability is proportional, whereas the effect of PDSI is exponential (i.e., greater). We arbitrarily dampened the effect of CO₂ fertilization on trees by taking the square root of the CO₂ temporal multiplier. The Gompertz equations allow for some expansion during even dry years (PDSI < 0), average expansion (temporal multiplier close to 1) during average moisture years, and a rapid rise of expansion (multiplier increasing to 4.5 and 2.5), respectively, for invasive annual grass expansion and tree expansion during very wet years. The parameters 4.5 and 2.5 were chosen to match values from the initial Park's study by Provencher et al. (2013). Equations 13.4 and 13.5 are not temporal multipliers, however, because they are not divided by their averages. In the absence of climate change effects, yearly values of Eqs. (13.4) and (13.5), respectively, were each divided by their temporal average over 75 years, whereas each yearly value of Eqs. (13.4) and (13.5) with climate change, respectively, was divided by the no-climate change average to reflect the hypothesis of altered levels.

Fire

The shrubland–woodland fire temporal multipliers considered the roles of 3 years of PDSI, more specifically that fine fuels will more likely burn in the current dry year immediately following two previous and consecutive wetter-than-average years where fine fuels accumulated. The equation to calculate the temporal multipliers from shrubland fire contained two Gompertz functions to account for 3 years of PDSI:

$$\begin{aligned} \text{Yearly shrubland–woodland area burned variability factor} \\ = \text{MaxFire} \times e^{-3 \times \exp(-0.7 \times \text{PDSI}_{t-1} + (1-0.7) \times \text{PDSI}_{t-2})} \times (1 - e^{-3 \times \exp(-2 \times \text{PDSI}_t)}) \end{aligned} \quad (13.6)$$

where MaxFire = 1547 hectares and is 10 % of the area sum of all shrubland–woodland ecological systems. Equation 13.6 combines two Gompertz functions to accommodate negative and positive values of PDSI. The first part of Eq. (13.6) after MaxFire, representing fine fuels production, is a classic Gompertz function where a weighted sum is applied to soil moisture during 2 previous years (70 % of PDSI in year $t-1$ and 30 % of PDSI in year $t-2$). Wetter years (PDSI > 0) increase the value of this function (fine fuels accumulation) to a maximum of one. The first part is multiplied by the second function representing the current year, which is one minus another Gompertz function bound between zero and one. Increasingly drier soil moisture (PDSI < 0) causes the second part of Eq. (13.6) to increase to a maximum of one (maximum ignition probability). The PDSI values from the scenarios without and with climate change were used to calculate future area burned. Equation 13.6 is not the final temporal multiplier, however, because it is not divided by its average. In the absence of climate change effects, yearly values of Eq. (13.6) were divided by their temporal average over 75 years, whereas each yearly value of Eq. (13.6) with climate change was divided by the no-climate change average to reflect the hypothesis of altered levels.

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