# Evaluating the Costs and Benefits of Alternative Weed Management Strategies for Three Montana Landscapes

Prepared by

David Hanna, Nathan Korb, Brad Bauer, and Brian Martin The Nature Conservancy of Montana 32 South Ewing Helena, MT 59601

#### Leonardo Frid and Katy Bryan ESSA Technologies Ltd. 1765 West 8<sup>th</sup> Avenue, Suite 300 Vancouver, BC V6J 5C6

#### Brett Holzer

3206 Warbler Way #13, Bozeman MT 59718

February 2011

Citation: Frid, L., D. Hanna, N. Korb, B. Bauer, K. Bryan, B. Martin, and B. Holzer. 2011. Evaluating the Costs and Benefits of Alternative Weed Management Strategies for Three Montana Landscapes. Prepared by The Nature Conservancy of Montana, Helena, MT and ESSA Technologies Ltd., Vancouver, B.C., 56 pp. + appendices.

#### © 2011 The Nature Conservancy in Montana

No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording, or otherwise, without prior written permission from The Nature Conservancy.

# Acknowledgements

Lisa Bay, Steve Becker, Noelle Brigham, Amber Burch, Stan Buresh, Dan Clark, Clay Crawford, Jack Eddie, Joe Fidel, Vanessa Fields, Lindy Garner, Bryan Gartland, Randy Gazda, Lowell Hassler, Ron Hecker, Steve Henry, Greg Kelsey, Mara Johnson, Becky Kington, Mark Korte, Jim Lange, Erik Lehnhoff, Tom and Kelly Leo, Chuck Maddox, Marco Manukean, Allen and Yvonne Martinell, Bruce Maxwell, Craig McClure, Sue McNeal, Shilo Messerly, Mike Mooney, Monica Pokorny, Linda Poole, John Rappold, Lisa Rew, Alan Rollo, Tim Seipel, Jim Spinder, Scott Steinmaus, Adele Stenson, Kevin Suzuki, Rich Utt, Dale Veseth, and Paul Wick provided input at our expert workshops or in person. Many of these individuals and numerous private landowners provided mapping data. Amy Pearson helped manage our spatial data and create maps. Liz Martell helped with the preparation of figures, and Diana Abraham helped with document production. Funding was provided by The Nature Conservancy's Priscilla Bullitt Collins Trust.

# **Table of Contents**

l. Introduction	1
2. Study Area	3
3. Methods	5
3.1 Modeling Alternative Management Strategies	5
3.1.1 Model	
3.1.2 Alternative Actions	
3.1.3 Spatial Data Inputs	
3.1.4 Performance Measures	
3.2 Economic Analysis Framework	
3.3 Uncertainties of Weed Spread	
3.4 Model Calibration Analysis	
3.4.1 Calibration Runs	
3.4.2 Model Adjustments	22
1. Results	24
4.1 Model Calibration Analysis	24
4.2 Landscape Simulations	27
4.2.1 Montana Glaciated Plains	
4.2.2 Centennial Valley	
4.2.3 Rocky Mountain Front	38
5. Discussion	47
5.1 Model Calibration Analysis	47
5.2 Landscape Simulations	47
5.3 Model Assumptions and Uncertainties	49
5.4 Future Model Applications	51
5.5 Recommendations and Conclusions	51
References	53
Appendix 1: Example Transition Models	
Appendix 2: Maps	78

# List of Tables

Table 1:	E. esula biocontrol establishment rates by vegetation type.	8
Table 2:	States and transitions for our model of <i>C. maculosa</i> and <i>E. esula</i> at the scale of a 1 ha cell. Invasion is stochastic and its probability is influenced by proximity to existing infestations, dispersal vectors such as roads, and vegetation community. Control, Setback, and Failure represent the possible outcomes of treatment efforts. Age represents the time since initial weed infestation. Negative adjustments in age result in a reduction in weed density. The full detail of the state and transition model is shown in Appendix 1.	9
Table 3:	Spatial spread parameters for the three landscapes. Note that biocontrol was not simulated in the Centennial Valley. Multiple values specify alternative hypotheses for uncertain parameters.	12
Table 4:	Summary of parameters used for simulations.	13
Table 5:	Initial area infested by <i>C. maculosa</i> and <i>E. esula</i> for the three study landscapes	
Table 6:	Rules used to assign state (seed-bank, initial 1 (I1) & 2 (I2), and established (E)) and invasion age (years) to mapped weed infestation data.	15
Table 7:	Relative susceptibilities of vegetation communities to invasion by C. maculosa and E. esula	16
Table 8:	Relative probability of invasion by <i>C. maculosa</i> or <i>E. esula</i> in relation to landscape features that influence the dispersal of invasive weeds into the landscape. We used data from Pine Butte Swamp Preserve to develop probabilities for high and low use roads, probabilities for other features were set relative to roads based on input from expert workshops	17
Table 9:	Parameters used in economic calculations. Carrying Capacity was based on the estimates averaged across each landscape (USDA Soil Conservation Service 1987)	20
Table 10:	Final post-calibration Pine Butte model parameters.	24
Table 11:	Area invaded and cumulative area treated (ha) after year 40 in the MGP landscape. Results are shown by strategy, spread, and control rates. Existing area invaded at the beginning of the simulations was 7 ha.	27
Table 12:	Economic benefits, Net Present Value (NPV), and Benefit-cost Ratio (BCR), of unlimited management of <i>C. maculosa</i> and <i>E. esula</i> in the MGP under different assumptions for the spread rate of the weeds.	28
Table 13:	Area invaded and treated (ha) by <i>C. maculosa</i> and <i>E. esula</i> after 40 years in the CV as a function of spread rate and management strategy. Results are averaged across five Monte Carlo simulations. Existing area invaded at the beginning of the simulations was 10 ha	28
Table 14:	Area invaded and treated (ha) by <i>C. maculosa</i> and <i>E. esula</i> after 40 years in the RMF as a function of spread rate and management strategy. Existing area invaded at the beginning of the simulations was 1,859 ha.	38

# List of Figures

Figure 1:	The state of Montana showing study area locations for: (A) the Rocky Mountain Front (367,000 ha), (B) the Centennial Valley (147,000 ha), and (C) the Montana Glaciated Plains (822,000 ha)
Figure 2:	State and transition model representing the state and transition dynamics of noxious weeds. Invasion is a stochastic process influenced by proximity to neighboring infestations and vectors such as roads, vegetation community, and the proportion of the landscape invaded. Escape from initial to established infestations occurs after six years of inaction. Control efforts either setback population densities and prevent the onset of establishment, kill all weeds and cause a transition to seed-bank, or fail to have an effect. Extinction of the seed- bank occurs after 10 years. Resurgence of the seed-bank is a stochastic process
Figure 3:	Inverse cumulative spread probabilities for <i>C. maculosa</i> under two hypotheses: high spread ( $r = 0.04$ , top row) and slow spread ( $r = 0.08$ , bottom row). Different lines represent hypothesized spread distance distributions for three of the vegetation communities in the CV. Graphs represent spread distance distributions (meters) when the source polygon is in the initial state (left) or in the established state (right). Curves were calibrated with a retrospective analysis of <i>C. maculosa</i> and <i>E. esula</i> spread over 30 years at the Conservancy's Pine Butte Swamp Preserve in the RMF.
Figure 4:	Flowchart depicting simulation model to evaluate the consequences of alternative management strategies and budgets
Figure 5:	Weed density for a polygon as a function of time since Invasion. Bars represent % cover by modeled state (Initial 1, Initial 2, and Established). The line shows discrete logistic growth from an initial size of $1m^2$ with a carrying capacity of 75% of a polygon and an intrinsic growth rate of 1.6
Figure 6:	Depiction of how benefits are calculated for each management strategy. In our analysis, damages represent the loss of grazing fees associated with weed cover replacing forage species
Figure 7:	Results comparing the actual area invaded by <i>C. maculosa</i> and <i>E. esula</i> (blue) versus the modeled area invaded at two checkpoints under the high (maroon) and low (beige) spread scenarios.
Figure 8:	Actual area invaded by <i>E. esula</i> in 2008 (top) and predicted invaded area by the Pine Butte calibration simulation for the high spread 70% control effectiveness scenario (bottom). Initial invasions (less than 6 years) are shown in black. Established invasions (6 or more years) are shown in red. Areas where biocontrol is present are shown in green
Figure 9:	Actual area invaded by <i>C. maculosa</i> in 2008 (top) and predicted invaded area by the Pine Butte calibration simulation for the high spread 70% control effectiveness scenario (bottom). Initial invasions (less than 6 years) are shown in black. Established invasions (6 or more years) are shown in red
Figure 10:	Mean area treated per year in the CV (mean ± SE for 5 Monte Carlo simulations) for the unlimited management scenario at high and low spread rates
Figure 11:	Mean area treated per year in the CV as a function of polygon area treatment ceiling and spread rate (mean of 5 Monte Carlo simulations for each ceiling/spread rate combination)29
Figure 12:	Mean percent of the CV landscape treated annually (mean of 5 Monte Carlo simulations $\pm$ SE) as a function of the polygon treatment ceiling (ha) applied in the model for simulations with high- and low-spread rates (0.010% of landscape = 15 ha)
Figure 13:	Percentage (mean of Monte Carlo simulations $\pm$ SE) of the CV landscape invaded at year 40 as a function of the mean percentage of the landscape treated annually at two spread rates (0.010% of landscape = 15 ha)

Figure 14:	The Net Present Value (NPV) and Benefit-cost Ratio (BCR) (mean of 5 Monte Carlo simulations ±SE) as a function of the mean percent of the CV landscape treated annually at two spread rates.	.32
Figure 15:	Alternative strategy analysis results showing how the percent of the landscape treated annually in the CV varies as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 125 ha per year. Bars are sorted in ascending order for each spread rate	.33
Figure 16:	Alternative strategy analysis showing how the percent of the CV landscape invaded at year 40 (mean of 5 Monte Carlo simulations $\pm$ SE) varies as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 125 ha per year.	.34
Figure 17:	Alternative strategy analysis showing how the Net Present Value (mean of 5 Monte Carlo simulations $\pm$ SE) varies as a function of weed spread rate and management strategy in the CV. All runs shown here had a polygon area treatment ceiling of 125 ha per year. Bars are sorted in descending order for each spread rate	.35
Figure 18:	Simulation results showing how the percent of the CV landscape invaded at year 40 (±SEM) varies as a function of delay in the start of treatment and the spread rate of weeds. All simulation runs shown here had a polygon area treatment ceiling of 125 ha per year and the default management strategy.	.36
Figure 19:	Simulation results showing how the NPV and BCR of management with respect to retained grazing fees (mean across 5 Monte Carlo simulations $\pm$ SE) vary as a function of delay in the start of treatment and spread rate in the CV. Simulation runs shown here had a polygon area treatment ceiling of 125 ha per year and the default management strategy	.37
Figure 20:	Area treated per year in the RMF as a function of polygon area treatment ceiling and spread rate. Top graph shows results for high spread rates and the lower figure shows results for low spread rates.	.39
Figure 21:	Percent of the landscape treated annually in the RMF as a function of the polygon treatment ceiling (ha) applied in the model for two spread rates	.40
Figure 22:	The percentage of the RMF landscape invaded at year 40 as a function of the percentage of the landscape treated annually at two spread rates.	.41
Figure 23:	The Net Present Value (NPV) and Benefit-cost Ratio (BCR) as a function of the percent of the RMF landscape treated annually at two spread rates.	.42
Figure 24:	Alternative strategy simulation results showing how the percent of the landscape treated annually in the RMF varies as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 2300 ha per year. Bars are sorted in ascending order for each spread rate	.43
Figure 25:	Alternative strategy simulation results showing how the percent of the RMF landscape invaded at year 40 vary as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 2300 ha per year. Bars are sorted in ascending order for each spread rate.	.43
Figure 26:	Alternative strategy simulation results for the RMF showing how the Net Present Value varies as a function of weed spread rate and management strategy. All runs shown here had a polygon area treatment ceiling of 2300 ha per year. Bars are sorted in descending order for each spread rate.	.44
Figure 27:	Simulation results showing how the percent of the RMF landscape invaded at year 40 varies as a function of delay in the start of treatment and the spread rate of weeds. All runs shown here had a polygon area treatment ceiling of 2300 ha per year and the default management strategy.	
Figure 28:	Simulation results showing how the NPV and BCR of management with respect to retained grazing fees for the RMF landscape vary as a function of delay in the start of treatment and spread rate. All runs shown here had a polygon area treatment ceiling of 2300 ha per year and the default management strategy.	

# 1. Introduction

The ecological impact of invasive non-indigenous species has been variously described for terrestrial and aquatic systems around the world. In Montana, noxious weeds infest about 8 million acres, or roughly 9% of the state (Montana Department of Agriculture 2008). Spotted knapweed (*Centaurea maculosa*) and leafy spurge (*Euphorbia esula*) are among the most widespread of these weeds, each infesting more than 1 million acres in the western United States (DiTomaso 2000). To address the spread of invasive weeds, Montana and other western states have established various state laws to combat the spread of weeds. Additionally, Cooperative Weed Management Areas have been created to implement coordinated management among state, federal, and private landowners. Despite regulatory and organizational efforts, noxious weeds continue to spread at a rate of approximately 8-20% per year in the West (DiTomaso 2000, Svejcar 2003). The estimated cost of forage lost to grazing in pastures in the United States is one billion dollars annually; this is in addition to the associated cost of controlling invasive plants in pastures and rangelands which has been estimated at five billion dollars annually (Pimentel et al. 2005).

We believe that invasive plant species continue to spread across the West for two primary reasons. First, research and demonstration control efforts presented to land managers and land owners have focused on the refinement of control techniques at fine scales (e.g. small patches of weeds or experimental plots). As a result, management approaches across landscapes are often ad-hoc, rather than developed and tested strategic approaches to abate or manage infestations at broad scales. Ad-hoc strategies derived from finescale experience or arbitrary decisions ("rules of thumb") may provide adverse results at broad scales. For example, Wadsworth et al. (2000) found that the often recommended strategy of targeting small new populations of invasive species (Moody and Mack 1988) were ineffective in control of two species that spread by long-distance dispersal. Second, despite education efforts, implementation of control treatments tends to be uneven and inconsistent across landscapes. Non-management of a given species over portions of landscapes due to inadequate or changing budgets, lack of human action, or site limitations (e.g. topography or proximity to water) may result in robust source populations with profound consequences to landscape-level invasive plant distribution and abundance. Inability to predict the impact of unmanaged invasive species or the effects of varied management across large areas inhibits the design and implementation of strategies that will effectively conserve intact native plant communities.

Models of effective management of invasive species are relatively few, but they almost always exhibit a high level of organization and education among stakeholders, involve a plant with a vulnerable life history trait, and are supported by sufficient resources over the long-term (Mack et al. 2000, Anderson et al. 2003). Another critical factor in successful management is the ability to adapt rapidly in the face of tremendous uncertainty by using proper planning, experimenting, monitoring, and then adapting based on improved understanding of the system being managed (Shea et al. 2002, Eiswerth and van Kooten 2002, Chornesky et al. 2005).

Effective management of invasive species will require comparisons of weed management strategies at appropriate spatial and temporal scales. Comparisons must consider the feasibility of each goal within the context of sustaining viable conservation targets (e.g., desired plant communities). Due to the large spatial and temporal scales involved and the uncertainty surrounding our understanding of invasive species spread dynamics, empirical evidence alone is inadequate for evaluating management strategies at the landscape scale. GIS-based models have been used to predict the potential of strategies to abate invasive species (Frid and Wilmshurst 2009, Higgins et al. 2000 and Wadsworth et al. 2000), as well as appraise resource costs to implement the strategies (Leung et al. 2005). The most effective models consider susceptibility of habitats to invasion and predict the rates and patterns of invasive plant spread in the context of succession dynamics (Sheley and Krueger-Mangold 2003); however, a high degree of

uncertainty is associated with parameter estimates and formulations of GIS models for invasive species spread (Neubert and Caswell 2000, Bergelson et al. 1993, With 2002, Higgins et al. 2003).

Here we present an analysis for evaluating alternative weed management strategies in three Montana landscapes. Our alternative management strategies assign different levels of priorities and budgets to detecting and eradicating small, new infestations versus controlling large, known, existing infestations. The uncertainties we address include the rates at which invasive plants spread across landscapes and the effectiveness of management efforts at controlling local infestations. Our measures for success include the area infested, the management effort and costs accrued, and the costs of lost grazing over the 40-year period we model. We consider the economic outcomes of management strategies in terms of the Net Present Value (NPV) and Benefit-cost Ratio (BCR) of benefits in the form of retained grazing fees and costs of spraying. Using this decision analysis tool, we examine a variety of management scenarios to inform current management decisions and increase opportunities for long-term success.

# 2. Study Area

We modeled spread and management of invasive species for three landscapes in Montana: the Rocky Mountain Front (RMF), Centennial Valley (CV), and Montana Glaciated Plains (MGP) (Figure 1). These landscapes range in size from 150,000 to 800,000 ha, and each was identified through ecoregional assessments by The Nature Conservancy (the Conservancy) as a priority area for conservation action.<sup>1</sup> Each have expansive areas of grassland and/or shrub and grassland associations. They each contain riparian vegetation, as well as coniferous forest or woodland communities, although these associations were of reduced extent in the percent of geographic scope in the MGP. The dominant land use in all three landscapes is agricultural production, primarily ranching, although annual crop production is widespread in portions of the RMF and MGP.

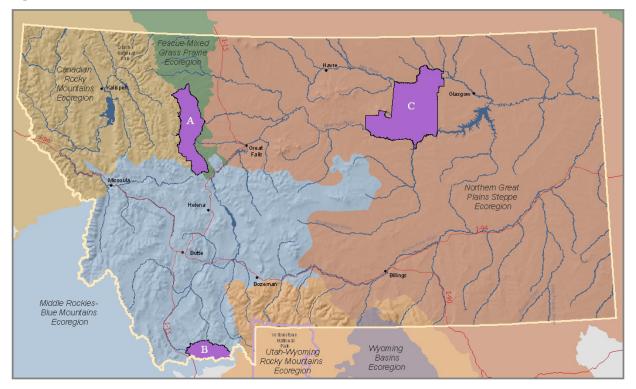


Figure 1: The state of Montana showing study area locations for: (A) the Rocky Mountain Front (367,000 ha), (B) the Centennial Valley (147,000 ha), and (C) the Montana Glaciated Plains (822,000 ha).

Each of these landscapes differ by the current relative extent of noxious weed invasion, with the MGP being relatively free of noxious weeds, the CV having many small, isolated infestations, and the RMF having a variety of early and established weed populations and the most widespread infestations. We selected spotted knapweed (*Centaurea maculosa*) and leafy spurge (*Euphorbia esula*) as the primary noxious weed species to model for all three areas. Though there are other invasive species in these landscapes, these two plant species were selected because: 1) an overwhelming majority of weed management resources are dedicated to their control, 2) both are capable of invading a wide variety of

<sup>&</sup>lt;sup>1</sup> See <u>conserveonline.org/docs/2002/05/ERP</u> with <u>appendices.pdf</u> for the Middle Rockies Ecoregion and <u>conserveonline.org/docs/2000/11/NGPS.pdf</u> for the Northern Great Plains Steppe Ecoregion.

priority native habitats, 3) their impacts on native plant communities tend to be severe, and 4) the most data suitable for model development was available for these species, both from our landscapes and in scientific literature.

The different life histories of *C. maculosa* and *E. esula* also can serve as surrogates for other noxious weeds with similar ecology. *C. maculosa* is a tap-rooted biennial or short-lived perennial that spreads rapidly through prolific seed production and dispersal, while *E. esula* has an extensive rhizomatous root system and so spreads both vegetatively and by seed dispersal. These are two common evolutionary strategies of successful invasive plant species in the West.

# 3. Methods

We used a spatially explicit simulation model to model the spread of *C. maculosa* and *E. esula* across heterogeneous landscapes and the effects of management actions over a period of 40 years. We compared several management strategies under a variety of budget constraints to evaluate the long-term advantages of different approaches, to identify appropriate resource allocation levels, and to assess costs and benefits of strategies within an economic analysis framework. A model calibration analysis of *C. maculosa* and *E. esula* spread within an area of known spatial weed history was also conducted to evaluate the adequacy of our simulation model at predicting future invasion conditions.

# 3.1 Modeling Alternative Management Strategies

### 3.1.1 Model

We developed a spatially explicit simulation model to compare different landscape level control strategies and examined the sensitivity of these strategies to uncertainties in the spread dynamics of invasive weeds. The model consists of two main components: 1) a state and transition sub-model that considers the sitespecific dynamics of weed succession and control at the scale of a 1 hectare polygon, and 2) a spatially explicit spread model that considers how weeds spread across a heterogeneous landscape.

We developed our state and transition models using The Vegetation Dynamics Development Tool (VDDT). VDDT is a software tool for creating and simulating semi-Markovian state and transition models (ESSA Technologies 2007). VDDT has been used to simulate various ecosystems including the dynamics and restoration of sagebrush steppe communities (Forbis et al. 2006), historic fire regimes across the Continental US for the LANDFIRE project (http://www.landfire.gov/NationalProductDescriptions24.php) and others (Merzenich and Frid 2005, Merzenich et al. 2003, Hemstrom et al. 2001, and Arbaugh et al. 2000).<sup>2</sup>

Models developed in VDDT outline the possible vegetation states on the landscape as well as transitions between states. These transitions are either deterministic and occur after the passage of time, or stochastic, having a given probability of occurring each time step. VDDT models are simulated numerically and track both the state of the landscape over time as well as the occurrence of transitions.

The model we developed for noxious weeds consists of six possible states: un-invaded, initial 1, initial 2, established, biocontrol and seed-bank (Figure 2). The state relates to the overall cover of weeds, the potential for and rate of spread, and the response of the patch to treatment. Box A represents the un-invaded state. The risk of invasion in the un-invaded state varies depending on the vegetation community and proximity to dispersal vectors and exiting patches of the invasive plant. Boxes B and C represent the initial infestation stage. During initial infestation, weeds are present at lower densities and spread less than established infestations, due to lower seed production and limited vegetative spread by rhizomatous species (e.g. *E. esula*). In the absence of any treatments, six annual time steps after a polygon first transitions from un-invaded to an initial infestation during its first three years (Box B: I1), three transitions are possible: (1) the infestation will be controlled and the polygon will transition to the seed-bank state, (2) the age and density of the infestation will be set back by two years, which will consequently reduce its ability to infect other polygons, or (3) the control efforts will fail and have no effect on the infestation age

<sup>&</sup>lt;sup>2</sup> VDDT is available for download at <u>http://www.essa.com/tools/vddt/download.html</u>

or density. If an initial infestation is more than three years old (Box C: I2), two transitions are possible when treatment is applied: (1) invasive plant density will be reduced by two years as noted above or (2) the treatment will have no effect. The setback transitions can reduce the "age" of a polygon such that control leading to the seed-bank state becomes possible again. Setback transition times were based on monitoring effects of treatments in our landscapes and the experience of experts at model development workshops. Experts also estimated control effectiveness, or treatment success (Control + Setback), to be somewhere between 70 and 95%. We explored this range of treatment success in earlier iterations of model development (Martin et al. 2007). Based on calibration simulations conducted at Pine Butte, the 70% success rates appeared most realistic (see section 3.4). For the model simulations we used the conservative end of this range and applied weed control measures at a 70% success rate. To test the effect of increasing success rates to 95% we conducted simulations at this level for a mid-level budget ceiling.

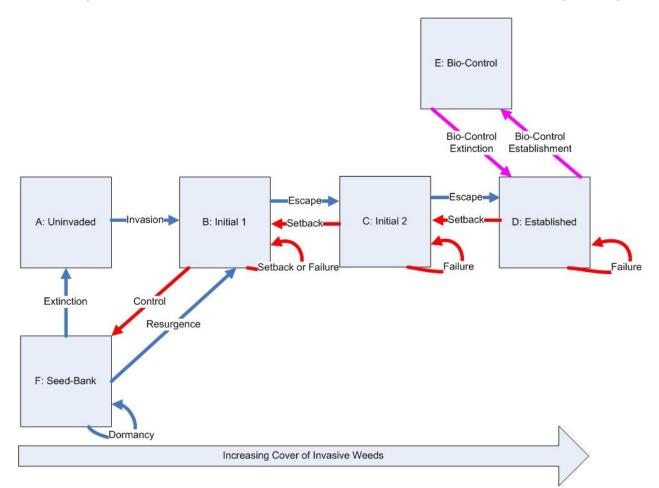


Figure 2: State and transition model representing the state and transition dynamics of noxious weeds. Invasion is a stochastic process influenced by proximity to neighboring infestations and vectors such as roads, vegetation community, and the proportion of the landscape invaded. Escape from initial to established infestations occurs after six years of inaction. Control efforts either setback population densities and prevent the onset of establishment, kill all weeds and cause a transition to seed-bank, or fail to have an effect. Extinction of the seed-bank occurs after 10 years. Resurgence of the seed-bank is a stochastic process.

Box D in Figure 2 represents an established infestation that has an age of six years or more, and has longer spread distances than the initial state (Figure 3). The infestation may have reached this age due to

lack of treatment, treatment failure, or lack of consistent treatment over time to keep the "age" under six years. When conventional treatment is applied to this state, either it fails to have an effect or it sets the age of the polygon back to the initial infestation state for one (*E. esula*) or two years (*C. maculosa*). If a biological control agent is introduced to an established leafy spurge state, its successful establishment is dependent on vegetation type. Biocontrol establishment success has been estimated between 50 and 90% (Table 1). The remaining 10-50% of biocontrol establishment success parameter was used in the model to determine the relative probability that new biocontrol populations become established in the different vegetation communities.

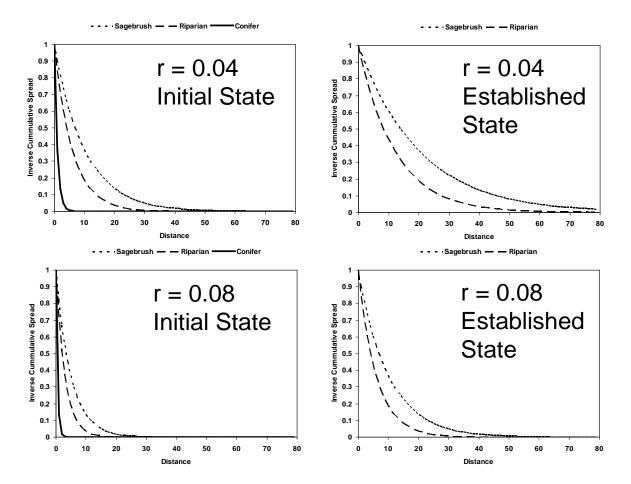


Figure 3: Inverse cumulative spread probabilities for *C. maculosa* under two hypotheses: high spread (r = 0.04, top row) and slow spread (r = 0.08, bottom row). Different lines represent hypothesized spread distance distributions for three of the vegetation communities in the CV. Graphs represent spread distance distributions (meters) when the source polygon is in the initial state (left) or in the established state (right). Curves were calibrated with a retrospective analysis of *C. maculosa* and *E. esula* spread over 30 years at the Conservancy's Pine Butte Swamp Preserve in the RMF.

		Bio-Control
Landscape	Vegetation Community	Establishment Rate
Rocky Mountain Front	Gravel Riparian	0.5
	Limber Pine	0.75
	Tamegrass	0.9
	Fescue	0.9
	Mixed Grass	0.9
	Riparian	0.5
Glaciated Plains	CRP	0.9
	Mixed Grass	0.9
	Shrubland	0.9
	Riparian	0.5

Box E of Figure 2 represents a weed infestation with robust biological control agents which significantly reduce weed density and seed production. Extinction or population crash of the biological control agent results in a transition back to the established infestation state. In this study we only simulated biological control for *E. esula* because biological control has resulted in consistent, effective control of *E. esula* at multiple sites in Montana (Lesica and Hanna 2004, Lajeunesse at al. 1999, Swaidon et al. 1998), while successful biocontrol of *C. maculosa* in similar ecological settings has not yet been demonstrated. Biocontrol was also not simulated in the CV because there have been no successful demonstrations of biocontrol for *E. esula* in similar locations of Montana, generally attributed to the lower temperatures of this high-elevation valley.

Box F in Figure 2 represents a polygon where weeds have been successfully managed and, while no plants can be found, seeds may remain dormant with the potential of germinating and transitioning back to an initial infestation. For each time step there is a 10% chance that this state will transition back to an initial infestation. After ten annual time steps, this state transitions to the un-invaded state and the weeds are considered fully eradicated.

Because *C. maculosa* and *E. esula* can often coexist at the same site, we combined the state and transition models for both species into a single model. To do this we had to divide the initial infestation state into two separate states: I1, representing a level of infestation where consistent control can lead to eradication or the seed-bank state, and I2, representing the state where eradication is only possible after first being setback to I1. *C. maculosa* has five possible states: un-invaded, initial-1, initial-2, established, and seedbank. *E. esula* has the same five states as well as the biological control state. The total possible number of combinations for the two species is 30. For this model we assumed that there was no competition or facilitation between the two species, so the rate of succession for each species remains the same and is independent of whether only one or both species are present at a site. However, we assume that any control efforts in polygons with both species present could affect both species. State and transition model parameters are documented in Table 2.

Table 2: States and transitions for our model of *C. maculosa* and *E. esula* at the scale of a 1 ha cell. Invasion is stochastic and its probability is influenced by proximity to existing infestations, dispersal vectors such as roads, and vegetation community. Control, Setback, and Failure represent the possible outcomes of treatment efforts. Age represents the time since initial weed infestation. Negative adjustments in age result in a reduction in weed density. The full detail of the state and transition model is shown in Appendix 1.

		Transition	Insition Destination State	
		Invasion	Initial	Set to 0
Initial	1 to 3	Control	Seedbank	Reset to 0
	1 to 6	Setback	Initial	-2
	1 to 6	Failure	Initial	0
	6	Escape	Established	0
Established	Any	Setback	Initial	-2 or -1
	Any	Failure	Established	0
	Any	Bio-Control Establishment	Bio-Control	0
	Any	Bio-Control Extinction	Established	0
Bio-Control	Any	Bio-Control Setback	Bio-Control	-2
	Any	Bio-Control Extinction	Established	0
Seed-Bank	< 10	Dormancy	Seedbank	Reset to 0
	< 10	Resurgence	Initial	Reset to 0
	10	Extinction	Uninvaded	Reset to 0

The state and transition model described above is not spatially explicit and describes the dynamics of weeds only within each 1 ha cell. We simulated the spread of weeds among polygons in our three landscapes using the Tool for Exploratory Landscape Scenario Analyses (TELSA). TELSA was developed to simulate landscape-level terrestrial ecosystem dynamics over time to assist land managers in assessing the consequences of various management strategies (Beukema et al. 2003, Kurz et al. 2000, ESSA Technologies 2008)<sup>3</sup>. Recently, TELSA has been used to model alternative strategies for restoration of grasslands invaded by crested wheatgrass (Frid and Wilmshurst 2009).

For this study, the inputs for our TELSA simulations in each landscape include:

- 1. State and transition models for the different vegetation communities on the landscape (see Figure 2, above).
- 2. Spatial, GIS data layers representing vegetation types, current weed distribution of the landscape, spatial restrictions on management actions, and features influencing the probability of new invasions.
- 3. Parameters governing the spatial spread and control of invasive species and biological control agents. These parameters include the distribution of neighbor-to-neighbor spread distances for each annual time step and the average number (Poisson) of new infestations from outside the landscape for each time step.

Input polygons defining vegetation communities, existing large weed infestations, and landscape features influencing spread of the landscape were subdivided into simulation polygons through a process called 'tessellation'. Unlike the use of a grid, this process divides original polygons into smaller units for simulation without losing any of the original spatial information. While computationally more demanding, the resolution of features that are important for weed spread, such as riparian corridors, is

<sup>&</sup>lt;sup>3</sup> TELSA is available for download at: <u>www.essa.com/downloads/telsa/download.htm</u>.

maintained. For our simulation polygons, we used an average polygon size of 1 ha. Data for small weed infestations and biocontrol agents was incorporated after tessellation as explained in sections 3.1.3.1 and 3.1.3.2 below.

Algorithms for simulation follow the sequence of events outlined in Figure 4. After initializing the landscape at year zero, the following events occur in this order for each time step: 1) treatment of infestations, 2) output of treatment results and polygons infested, 3) aging, 4) age dependent succession, 5) new infestations, and 6) expansion of existing infestations.

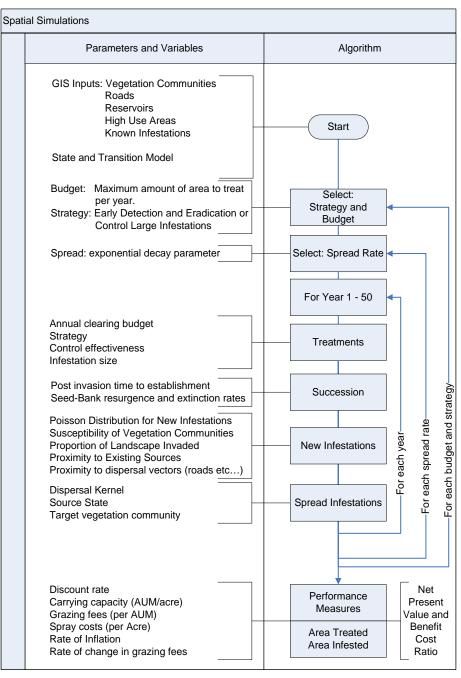


Figure 4: Flowchart depicting simulation model to evaluate the consequences of alternative management strategies and budgets.

The first step in the simulation process is the simulation of management actions and transitions. There are two distinct types of management transitions: 1) the use of conventional management techniques on all types of weeds and 2) the introduction of biological control agents for *E. esula*. Conventional management techniques may include both chemical and mechanical methods.

For conventional management, the model loops over all infestations in order of size. Depending on the scenario, we prioritized either the largest or smallest infestations for management. For each infestation, the model applies treatment to the polygons on the infestation edge first and then moves toward the infestation centers. The model continues to manage infected polygons in this order until either a management area ceiling for the time-step is reached or all infested polygons have been managed. Each time a management transition is applied, multiple outcomes are possible including control, setback, or failure (Figure 2). Conventional management was subject to certain restrictions in the model. For example, while conventional management was permitted in the riparian vegetation community for the initial state, once a weed reaches the established state management was prohibited. This recognizes that in the established state, the levels of pesticide required to treat weeds is generally unacceptable in these areas. In the RMF, the gravel-riparian vegetation community was also completely closed to management (at any infestation state) to reflect that, both historically and to date, minimal weed control efforts have been applied to these frequently disturbed areas.

Aging is the process of tracking the effective time since invasion for each noxious weed on every polygon where that weed is present. After aging, the model determines, for each polygon, whether an age dependent transition should take place (e.g. from the initial to the established state). The "age" is not the actual time since invasion, but rather a finer temporal unit within each state that can increase or decrease with model progression and management. The progression is based on time required to move from a new infestation to an established infestation with high densities of weeds, which significantly impact the local plant community. Conventional management sets back the "age" of the infestation one or two years based on effects of herbicide and mechanical treatments, as documented by monitoring field treatments and expert experience in our landscapes.

The simulations run at a temporal resolution of one-year time-steps. For every tenth time-step the state of every polygon is written to the database. This output was used to generate maps of the modeled state of the landscape. Any time a transition (management, biocontrol, invasion, or succession) occurs to a polygon, output is written to the database. These outputs were used to summarize the area affected by various transitions as well as to generate maps.

The next step in the simulation is the creation of new infestations. This process begins by determining the target number of new infestations from outside of the landscape based on a Poisson distribution (Table 3). The model then loops over potential polygons in a random sequence. Potential polygons consist of all polygons that are not invaded by the particular species for which new infestations are being created. Until the number of new infestations reaches the target number of new infestations, the model determines, based on a random draw, if target polygons will be invaded or not. The relative probability of invasion for a polygon is based on its vegetation community, as well as its location relative to high-use features such as roads and agricultural fields.

 Table 3:
 Spatial spread parameters for the three landscapes. Note that biocontrol was not simulated in the Centennial Valley. Multiple values specify alternative hypotheses for uncertain parameters.

Bio-Control Dispersal Kernel <sup>1</sup>	NA	-0.04	-0.04
		0.04	-0.04
Mean Number of Bio-Control Introductions per Year <sup>2</sup>	NA	9	40
Knapweed Dispersal Kernel <sup>1</sup>	-0.04 or -0.08	-0.04 or -0.08	-0.04 or -0.08
Mean Number of Knapweed Introductions per Year <sup>2</sup>	8	12	25
Spurge Dispersal Kernel <sup>1</sup>	-0.03 or -0.06	-0.03 or -0.06	-0.03 or -0.06
Mean Number of Spurge Introductions per Year <sup>2</sup>	1	21	5

Once the target number of infestations from outside of the landscape has been reached for a time step, the model simulates long-distance spread within the landscape (i.e. non-neighbor spread) by drawing a random source polygon for each potentially invaded polygon. If the source polygon contains weeds, the model draws a random spread distance from the negative exponential spread distance distribution for the weed. If this spread distance is greater than the polygon-to-polygon distance, then the model checks the relative invasion probability and determines whether a new infestation will occur at the polygon. This process continues until all potential target polygons have been examined, thus making non-neighbor, long-distance dispersal within the landscape a consequence of the proportion of the landscape currently infested with noxious weeds. This process of long-distance dispersal within the landscape is similar to the neighbor-to-neighbor spread described below.

After the simulation of new infestations, the model simulates the expansion of existing infestations (i.e. neighbor-to-neighbor spread). For each invasive species and each contagious (i.e. infested) polygon, the model loops over each neighboring polygon (i.e. polygons adjacent to the contagious polygon). For each source to neighbor pair, the model determines the potential spread distance and compares that to the centroid-to-centroid distance for the pair. The potential distance is determined by taking a random draw from the spread distance distribution for the species for each time step during which the source has been contagious. A draw is taken for each time step to capture the gradual spread of propagules along the centroid-to-centroid polygon vector. The sum of these distances is then multiplied by the source strength variable, which is dependent on the state of the source (Initial=0.5, Established=1.0, Biocontrol=0.25), and by the relative vulnerability of the target polygon vegetation community. Spread distances from established polygons are greater than those from initial and biocontrol polygons due to large differences in seed production. Spread distances into the most vulnerable vegetation communities are greater than spread distances into the least vulnerable communities (Figure 3). These rules are based on the probability of a seed transporting and establishing from a single infestation to a new location and the probability increases with the number of seeds produced and the relative vulnerability of the new location to the particular weed species. If the spread distance is greater than the centroid-to-centroid distance between source and target polygons, the target polygon is invaded and transitions to an initial infestation.

Biological control is simulated in a way that is similar to the spread of the weeds themselves. Every timestep there is a Poisson distributed number of new biological control introductions (Table 3). These introductions can only take place in the established state of *E. esula*. Once biocontrol is introduced the polygon transitions to the biological control state during the same time step. As with the weeds, established biological control agents can spread to neighboring polygons.

Because of the large size of the RMF and MGP landscapes, only a single simulation per scenario was conducted for these study areas. For the CV, we conducted five Monte Carlo simulations per scenario.

### 3.1.2 Alternative Actions

Treatment strategies differed between landscapes based on the distribution of the selected noxious weeds and current management programs (Table 4). For the MGP, we tested no management (zero budget) to unlimited management (unlimited budget) as management alternatives. The extremely limited extent of existing infestations presents a smaller decision space for managers.

Table 4: Summary	y of parameters us	sed for simulation	ns.		
Simulation	Treatment Priority	Treatment Ceiling	Control Success	I1 Aware	Landscape
No Management	No treatment	_	_	_	MGP, CV, RMF
Unlimited	Small Patch	Unlimited	70%	_	MGP, CV, RMF
Default	Small Patch	Multiple	70%	_	CV, RMF
High Control Success	Small Patch	Mid-level	<b>9</b> 5%	_	CV, RMF
Large Patch Edges	Large Patch Edges	Mid-level	70%	_	CV, RMF
I1 Aware	Small Patch	Mid-level	70%	On	CV, RMF
Roaming Treatment	Small Patch	Mid-level	70%	_	RMF
Delay before Treatment Starts	Small Patch	Mid-level	70%	-	CV, RMF

For the RMF and CV, we considered numerous management scenarios. First, we conducted a sensitivity analysis on the annual budget allocated to invasive weed treatment. Our alternative budgets were expressed in terms of the ceiling applied to the annual area that could be treated. Ceiling areas were defined at the resolution of model polygons (approximately 1ha). The budget alternatives (Treatment Ceiling) that we tested for the sensitivity analysis ranged from no management (zero budget) to unlimited management (unlimited budget). For the CV we explored two additional budget ceilings and for the RMF we explored four additional ceiling levels. These simulations used our default management strategy that prioritized treatment of small patches over large patches, which an earlier iteration of this model showed to be the most effective (Martin et al. 2007).

To further compare the effect of alternative management strategies for the CV and the RMF, we ran simulations at the mid-level budget ceiling with four alternative management scenarios:

- 1. We considered the effect of being able to increase control success, applying 95% management success instead of the default 70% (High Control Success).
- 2. We considered the tradeoffs between containing large, known infestations versus small, new infestations. This scenario (Large Patch Edges) prioritized the edges of large patches for treatment instead of the default prioritization of small patches.
- 3. We explored the assumption that immediate detection of newly infested weed patches would significantly reduce the area invaded in the landscape, though this may be difficult under real-world field monitoring conditions. In this alternative scenario (I1 Aware), the model allowed treatment of new infestations immediately. In the default scenario, treatment is not allowed until an infestation is at least 4 years old, to simulate a delay in detection of new patches until patches have grown to a noticeable size.

4. For the RMF, we conducted a roaming treatments scenario that focused all treatment resources on one third of the landscape every third year, alternating treatments between north, central and southern portions of the landscape (Roaming Treatment).

Finally, we explored the effect of delaying management (Delay before Treatment Starts) by conducting simulations at the mid-level budget ceiling and default management strategy in which we delayed the onset of management for 10, 20, and 30 years (CV) and 5, 10, and 15 years (RMF).

# 3.1.3 Spatial Data Inputs

We incorporated a variety of spatial data layers in a GIS environment as parameters that contributed to operation of the model, including: location and abundance of selected invasive plants, coarse-scale vegetation maps, and features that influence the probability of invasion such as roads, trailheads, and gravel pits.

### 3.1.3.1 Invasive Plants

In each landscape, spatial weed data were collected from existing sources, primarily land management agencies including the Bureau of Land Management and the Forest Service (BLM, USFS). Additionally, Conservancy staff conducted extensive inventories to map weed locations in the CV and MGP and collaborated with watershed-based weed management projects to map noxious weeds on private lands in the RMF. The data we used conformed to Montana Noxious Weed Survey and Mapping System standards (Roberts et al. 1999). In the MGP, a section-based weed mapping database (Montana Invaders database) was used to develop a map of additional *E. esula* source populations along the northern boundary of the study area. We used expert opinion to crosswalk existing attribute data for infestations to parameters used in the model. Given the size of the landscapes, our maps of existing weed locations are undoubtedly incomplete. This is particularly true for the RMF, where data were not available for some portions of the landscape which likely contain weed infestations. Our maps for the CV are the most complete, since the landscape is smaller and our surveys more comprehensive. The MGP represents our coarsest scale data, but given the paucity of existing infestations, relatively few infestations are likely to be unknown. We used the weed infestations data compiled through 2008 as the initial condition for all model simulations (Table 5).

Landscape	Total Area (ha)	Infested Area (ha)	Percent of Landscape Infested
Rocky Mountain Front	367,000 ha	1,860	0.51
Centennial Valley	147,000 ha	1.4	0.0009
Montana Glaciated Plains	822,000 ha	7.3	0.0009

 Table 5: Initial area infested by C. maculosa and E. esula for the three study landscapes.

We assigned model states and ages to tessellated polygons based on the patch size, shape, and weed cover class from mapped weed infestation data (Table 6). Tessellated polygons that intersected smaller infestations mapped as points (<1.2 ha) or small polygons ( $\leq$ 1ha) were assigned an age and state based on the patch size and weed cover class. The extent of large infestations field mapped as large polygons (>1ha) were maintained during tessellation and assigned an age and state based on weed cover class. Ages for large polygons in the established state were assigned based on distance from the edge of the polygon. Using a negative buffer on a large weed polygon, the outermost 100 meters were assigned to the established state with an infestation age of 6. The next 100 meters towards the center of the polygon were assigned to the established state with an infestation age of 10. Any area remaining at the center of the polygon was assigned to the established state with an infestation age of 15.

Table 6:Rules used to assign state (seed-bank, initial 1 (I1) & 2 (I2), and established (E)) and invasion<br/>age (years) to mapped weed infestation data.

	Weed Cover Classes				
Map Shape and Size (ha)	None present (past treatment)	Trace	Low	Medium	High
Point 0.02ha	Seed-bank	I1 - 2 years	I1 - 3 years	I2-4 years	I2-4 years
Point 0.2ha	Seed-bank	I1 – 3 years	I2 - 4 years	I2-5 years	I2 – 5years
Point 1.2ha	Seed-bank	I1 – 3 years	I2 – 5years	E – 6 years	E – 6 years
Polygons ≤1ha	Seed-bank	I1 – 3 years	I2-5 years	E – 6 years	E – 6 years
Polygons >1ha	Seed-bank	I1 – 2 years	I2 – 4 years	E - 6-15 years	E – 6-15 years

#### 3.1.3.2 Biological Control

For the RMF and MGP, we compiled release point data for *E. esula* biological control agents from various agencies and watershed-based weed management projects. *E. esula* infestations intersecting biocontrol releases greater than 3 years old were assigned to the biocontrol state. This state assignment was done after tessellation, and so applied to polygons averaging 1 ha in size.

#### 3.1.3.3 Natural Vegetation

Within each landscape we identified potential vegetation communities, each comprised of similar natural community associations that were relatively easy to delineate and identify (Table 7). These vegetation communities represent functionally different vegetation types relative to probability of weed occurrence and susceptibility to invasion (Rew et al. 2005). Different methods were used to map vegetation communities within each landscape in response to available data.

In the MGP, NRCS digitized soils maps served as the foundation for vegetation mapping. Each soil mapping unit was assigned to one of five potential vegetation types. A draft map was created and a field reconnaissance conducted in 2005 to test the map results. Corrections were made for either entire soil mapping units or individually mapped polygons of a soil mapping unit. We then tested the results and made corrections by conducting photo interpretation. Additionally, we mapped cropland and lands enrolled in the Conservation Reserve Program (CRP) as distinct vegetation communities. To delineate CRP areas and cropland, we used photo interpretation, mapping the approximate boundary of fields based on a 16 ha grid.

In the CV, the Montana Natural Heritage Program (Heritage Program) refined an existing SILC3 vegetation map developed by the University of Montana Wildlife Spatial Analysis Lab for southwest Montana and based on LANDSAT TM data. The Heritage Program conducted field sampling of vegetation types to improve accuracy of the original classification for the CV. The detailed classes were then grouped into six general potential vegetation types. Narrow riparian zones were not captured by the 30 m resolution LANDSAT data, but we considered them sufficiently important in modeling weed spread to amend the map and include these communities (Stohlgren et al. 1998). Narrow riparian zones were generated by buffering 10 m to either side of perennial streams.

For the RMF, vegetation types were mapped using aerial photo interpretation of 1995 imagery. Classification was coarse, using only the general vegetation types used in the model. Accuracy was improved using field sampling data as well as vegetation maps developed for a portion of the area by the Heritage Program (Kudray and Cooper 2006).

Landscape	Vegetation Community	C. maculosa	E. esula
Rocky Mountain Front	Road	1	1
-	Gravel Riparian	1	1
	Limber Pine	0.4	0.4
	Tamegrass	0.4	0.6
	Fescue	0.2	0.2
	Mixed Grass	0.2	0.2
	Riparian	0.15	0.75
	Aspen	0.1	0.15
	Conifer	0.05	0.05
Centennial Valley	Road	1	1
-	Sagebrush	0.4	0.4
	Sandhill	0.3	0.3
	Riparian	0.35	0.6
	Meadow	0.25	0.6
	Aspen	0.2	0.5
	Conifer	0.05	0.05
Iontana Glaciated Plains	Road	1	1
	Riparian	0.5	0.75
	CRP	0.4	0.4
	Mixed Grass	0.2	0.25
	Shrubland	0.3	0.25
	Badlands	0.1	0.1
	Ponderosa Pine	0.01	0.01

Table 7: Relative susceptibilities of vegetation communities to invasion by C. maculosa and E. esula

For each vegetation community, we assigned a susceptibility to invasion rating for each weed species (Table 7). Ratings were based on expert opinion, available literature, unpublished studies in similar environments, and the current extent of existing infestations. Ratings were then refined during numerous calibration simulations and field studies. A value of one was assigned to the most susceptible state; values less than one reduce the probability of invasion (e.g. limber pine is 40% as susceptible to invasion as gravel riparian in the RMF). The Montana State University Weed Ecology Lab randomly sampled the distribution of invasives across the RMF and areas close to the CV to evaluate probability of occurrence for *C. maculosa* and *E. esula* (Lehnhoff et.al. 2009, Dougher et. al. 2009). Even on the RMF, the most infested landscape we modeled, these invasive species were too rare to quantify accurately probability of occurrence using random sampling. Additionally, within the RMF and CV, the density and spread of individual populations of *C. maculosa* were monitored for several vegetation communities to inform susceptibility ratings. Cover types immune from invasion such as rock, water, wetland, and actively cultivated cover types such as annual cropland were excluded from the simulations.

Table 8 shows how landscape features influenced the susceptibility of each of the vegetation communities. Roads and subdivisions create large areas of disturbed habitat in which invasion is facilitated by lack of plant competition, altered nutrient cycling, and the increased proliferation of seeds associated with human corridors (Christen and Matlack 2006, Gelbard and Belnap 2003, Tyser and Worley 1992, Maestas et al. 2003). Although grazing and fire can influence invasions by non-indigenous plants (Parker et al. 2006, Keeley 2006), the spatio-temporal variability of these disturbance regimes was too complex to model over these large landscapes and examining their effects was beyond the scope of this project.

Table 8:	Relative probability of invasion by C. maculosa or E. esula in relation to landscape features that influence the dispersal of
	invasive weeds into the landscape. We used data from Pine Butte Swamp Preserve to develop probabilities for high and low
	use roads, probabilities for other features were set relative to roads based on input from expert workshops.

Feature	Relative Probability	Explanation
Public access point	1	High use sites with high probability of invasion and establishment.
Gravel pit	1	Highly disturbed sites with high probability of invasion and establishment.
Reservoir edge	0.5	Disturbed sites connected to source populations by major ditches with elevated risk of invasion and establishment. Only used reservoirs filled from main streams with significant infestations. Buffered 25m out from reservoir edge.
Irrigation ditch	0.5	Disturbed sites connected to source populations with elevated risk of invasion and establishment. Only used larger ditches connected to streams or reservoirs with known significant infestations. Buffered to 15m width since most ditches in layer are larger ditches coming from main streams or reservoirs
Crop edges	0.5	Disturbed sites with elevated risk of invasion and establishment. Buffered 15m out from crop PVT edge.
Small parcels	0.5	Represents residential developments and other lands with intensive use resulting in a elevated risk of invasion and establishment. Used parcels <40 acres from cadastral data.
High use road	0.5	County roads or other roads with significant or public use resulting in elevated risk of invasion and establishment. Buffered to total width of 30m.
Low use road	0.25	Private roads and two-tracks with low to moderate use levels. Invasion and establishment potential similar to high use road, but less. Buffered to total width of 15m.
Trails	0.125	Like low use road but even less potential for invasion and establishment. Buffered to total width of 5m.
None	0.005	Any other polygon is much less likely to be the source of new infestations.

#### 3.1.4 Performance Measures

The performance measures we used to evaluate each strategy were: (1) the cumulative area treated over a 40-year period as an indicator of the total level of investment of each treatment strategy, and (2) the final state of the landscape (area invaded) after that period, as an indicator of the on-the-ground outcome of each management strategy. Model results are reported in terms of polygon areas treated over the entire simulation period and polygon areas invaded over the course of the simulations. These results were converted to more realistic values for area actually invaded by multiplying polygon areas against the average percent cover of weeds for the state of the polygon. We assumed that the average percent cover was 1% for the first three years following invasion, 20% for years 4 to 6 post invasion, 75% if weeds were present for more than 6 years, and 25% if biocontrol was successfully established. For the biocontrol state, we assumed this 67% reduction in the cover of the established state based on reported reductions in *E. esula* due to biocontrol at Pine Butte Swamp Preserve (RMF) and elsewhere (Lesica and Hanna 2004, Mico and Shay 2002). Our estimates of percent cover for the 11, 12, and E state were based on an assumption of discrete logistic growth with a carrying capacity of 75% of a polygon, an initial patch size of  $1m^2$ , and an intrinsic growth rate of 1.6 (Figure 5).

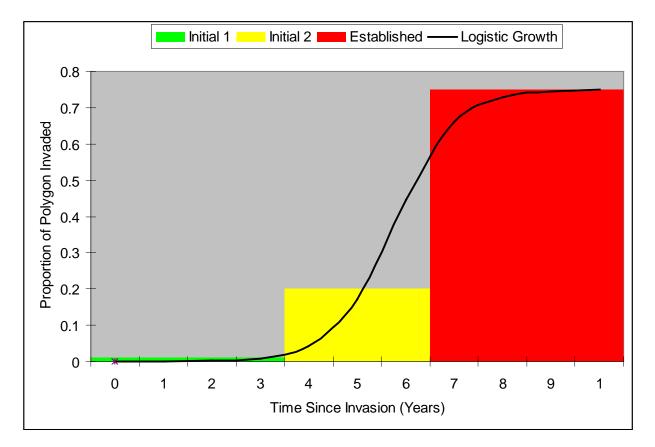


Figure 5: Weed density for a polygon as a function of time since Invasion. Bars represent % cover by modeled state (Initial 1, Initial 2, and Established). The line shows discrete logistic growth from an initial size of  $1m^2$  with a carrying capacity of 75% of a polygon and an intrinsic growth rate of 1.6.

# 3.2 Economic Analysis Framework

We used economic analysis for post-processing model outputs and evaluating the costs and benefits of alternative management strategies. This analysis takes into account both the damages caused over time by the presence of weed infestations and the costs associated with implementing the alternative management strategies. Damages caused by the presence of weeds on the landscape can be broken down into three different categories: (1) direct use such as loss of grazing lease fees or crop productivity, (2) indirect use such as the loss of ecosystem services like soil stabilization or water quality, and (3) non-use such as the loss of rare and endangered species that may not provide any direct or indirect use values: loss of grazing fees. Grazing represents the dominant land use in all three landscapes and provided a simple metric for evaluating long-term benefits of weed management expenditures. We did not attempt to quantify other direct uses, indirect uses, or non-use values, despite their potential significance to local economies and ecosystems. Our estimates of the economic benefits gained from management actions must be seen as conservative, since they only account for one portion of the potential benefits.

To consider the benefits of management with respect to retained grazing fees, we compare the area invaded over time under each management strategy with the area invaded under a strategy of no management. We then assume that the difference in area invaded represents the area for which grazing fees would be retained because of the management. We multiply this area by the carrying capacity for grazing (AUM/ha) and by the value of grazing fees per AUM. This value represents the retained grazing fees resulting from the management action. Grazing fees were assumed to be \$18.10 per AUM (USDA National Agricultural Statistics Service 2009). We did not model inflation in grazing fees or in costs of treatment and therefore present our results in terms of 2008 dollars. The method of calculating benefits is depicted in Figure 6.

We calculated the net present value of benefits and costs over the 40 years of the simulation period using a discount rate of 2.7%. The discount rate is the rate, per year, at which future values are diminished to make them comparable to values in the present. The appropriate discount rate to use for environmental protection projects is often debated. The office of Management and Budget recommends using a real discount rate of 2.7% on a 30 year horizon (US Office of Management and Budget 2009). However, others have argued that when impacts can affect future generations in catastrophic ways, lower discount rates should be used. For example Stern (2007) evaluates the future impacts of climate change using a discount rate of 0.1%.

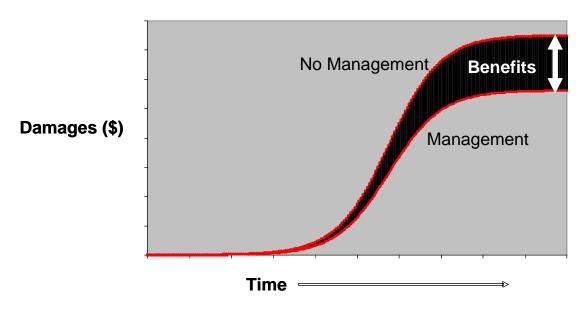


Figure 6: Depiction of how benefits are calculated for each management strategy. In our analysis, damages represent the loss of grazing fees associated with weed cover replacing forage species.

To estimate the costs associated with each management strategy, we used the model output in terms of total area treated over time (corrected for actual acreage rather than polygon area) and multiplied it by per unit area cost of treatment. Treatment costs are highly variable depending on the size and location of the infestation and the associated differences in overhead, travel, and labor costs. We obtained treatment cost data based on patch size from professional weed managers in the RMF and CV, from which we estimated treatment costs to be \$40/acre for the established state, \$85/acre for the I2 state, and \$225/acre for the I1 state. The cost of treating low-density initial patches reflects the intensive labor required to find and manage individual plants compared to the less costly method of broadcast control of established patches that are already known and require labor only for application of herbicide. We only include variable, per acre costs of management in our calculation of costs and assume that any fixed costs associated with land management would be incurred regardless of whether management of weeds is applied or not. Parameters used for economic analyses are shown in Table 9.

Table 9: Parameters used in economic calculations. Carryin	
averaged across each landscape (USDA Soil Conserva	tion Service 1987).
RMF per Acre Carrying Capacity (AUM)	0.26
CV per Acre Carrying Capacity (AUM)	0.28
MGP per Acre Carrying Capacity (AUM)	0.21
Discount Rate	2.7%
Per Acre Treatment Cost (2008 \$)	
Established State	40
Initial 2 state	85
Initial 1 state	225
Grazing Fees (2008 \$)	18.10

# 3.3 Uncertainties of Weed Spread

We focused our analysis of uncertainty on what is perceived to be a key uncertainty in invasive weed dynamics, both in the literature and among the experts and stakeholders that participated in our model development workshops. This key uncertainty is the rate at which invasive weeds spread across the landscape over time.

The spread of an exotic species through native vegetation is a highly complex ecological process (With 2002, Bergelson et al. 1993). Despite considerable research, there remain few models whose utility extends beyond the theoretical to predict spread of individual weed species across actual landscapes. One reason for this is the lack of mid-scale time-series of invasions (i.e. spread across 500-1000 square mile areas over periods of 20-50 years). County-level presence-absence data, which depict the spread of species across the nation, is too coarse to have meaningful applications for modeling spread within a landscape. Substantial research has measured the physical distances and mechanisms by which individual plants spread via roots, shoots, and seed dispersal, but these studies fail to capture the actual spread of patches, or groups of plants. Patches produce several orders of magnitude more seeds, thereby increasing the probability of any given seed being transported long distances by wind, water, animals, vehicles, or other vectors. Long-distance dispersal can have a dramatic effect on the distribution of annual spread distances (Clark et al. 1998, Neubert and Caswell 2000, Hastings et al. 2005), but is difficult to quantify due to relatively rare occurrences and inability to confirm the seed source of new infestations (Higgins et al. 2003).

We used a negative exponential distribution of annual spread distances for modeling short and intermediate spread distances (i.e. 1-100 meters). Most weed seeds disperse within a short distance of a source patch, but a small proportion of the annual seeds produced may be transported considerable distances. Although these long-distance dispersal events may be rare, they can have a greater effect on the actual spread of infestations than the frequent, short-distance dispersals (Neubert and Caswell 2000). Spread distributions for *E. esula* and *C. maculosa* were developed from existing spread and seed dispersal studies and were calibrated with time-series data from mapping efforts at Pine Butte<sup>4</sup> since 1995. We coupled those data with expert-based historic information from the mid-1970s to complete 30-year time series.

Our model considered two alternative hypotheses for spread rates by varying the shape parameter for the exponential distribution between the values of 0.08 and 0.04 for *C. maculosa* and 0.06 and 0.03 for *E. esula*. These values represent the minimum and maximum rates of spread expected in these landscapes based on expert opinion of preliminary simulations and the time-series analysis at Pine Butte. Spread distributions were reduced for initial infestations and *E. esula* patches with biological control. Seed production and successful establishment of each species vary with the vegetation type (e.g. conifer forest or sagebrush grasslands), therefore spread distributions were also modified to reflect the relative competitiveness and success of the weeds across habitat classes. To illustrate our approach, Figure 3 shows inverse cumulative *C. maculosa* dispersal kernels for our alternative spread rate hypotheses and for different source and destination vectors among vegetation types.

### 3.4 Model Calibration Analysis

In order to evaluate the adequacy of our alternative spread rate hypotheses we conducted a model calibration analysis of *C. maculosa* and *E. esula* spread at Pine Butte where we have a detailed spatial time series for these two weeds. Our analysis involved running simulations beginning with 1975

<sup>&</sup>lt;sup>4</sup> The Nature Conservancy's Pine Butte Swamp Preserve is ca. 6,000 ha on the Rocky Mountain Front.

conditions using our hypothesized fast and slow spread rates for both weeds. To reflect past conditions we ran simulations with no treatments from 1975 to 1990 and with effective control applied to all infested polygons from 1991 to 2008. We then compared both area infested and maps of predictions to our data for 2008.

# 3.4.1 Calibration Runs

A spatial time-series of area invaded by *C. maculosa* and *E. esula* in 1990 and 2008, collected by the Conservancy, was used for calibration. Areas within an initial, established, or biocontrol state were considered invaded. For simulation purposes, we buffered the preserve boundary out by 1km to eliminate artificial boundaries to spread created by the discontinuous nature of the preserve.

Post-processing of simulation results took place to allow for comparison against the 1990 calibration data target values. We accounted for the boundary difference by only considering invaded areas of tessellated polygons that intersected the 1990 study area. While some invaded areas would straddle the 1990 study area boundary, the portion of these polygons that actually fell outside the 1990 study area was considered negligible and remained included in the total invaded area for the simulation.

# 3.4.2 Model Adjustments

A series of over thirty calibration simulations explored various spread rate hypotheses, control effectiveness assumptions, the number of new infestations originating from outside of the calibration landscape, and assumptions concerning where and when invasive weeds could undergo treatment. Exploring this range of uncertainties during the calibration simulation phase led to the selection of the key uncertainty (spread rate) to explore at the full landscape level and across all landscapes.

### **3.4.2.1** Alternative spread rate hypotheses

The first set of calibration simulations was conducted assuming 70% control effectiveness, and used spread rate hypotheses that were based on a literature review. The initial spread rates we simulated used exponential decay parameters of 0.05 and 0.1 for *C. maculosa* high- and low-spread hypotheses, and 0.15 and 0.3 for *E. esula* high- and low-spread hypotheses (*C. maculosa* spreading faster than *E. esula*). Using these spread rates, simulation results for area invaded fell far short of the data on weed distribution. Subsequent simulations explored spread rates that ranged from 0.01 to 0.05 for *C. maculosa*, and 0.01 to 0.15 for *E. esula*. The spread rates, which reasonably achieved the calibration invaded area targets (0.02 for *C. maculosa* and 0.05 for *E. esula*, as a high-spread scenario), greatly exceeded a biologically reasonable range for *C. maculosa*. We therefore considered gaming with other parameters and model assumptions in combination with a biologically reasonable adjustment of spread rates.

### **3.4.2.2** Control restriction in the gravel-riparian

The amount of area invaded in the gravel-riparian zone was significantly lower in the simulations compared to the calibration data. Based on further consideration of the preserve history, we decided to turn off all control in the gravel-riparian. Because of its proximity to water and frequent disturbance from seasonal high water events, this area both historically and to date has seen little in terms of weed control efforts. Subsequent simulations of the entire RMF landscape also assumed that weed control activities are not conducted in the gravel riparian zone.

### 3.4.2.3 Varying new weed introductions

Examining the spatial distribution of weeds in the simulation results further revealed that not only was spread from existing weed patches lower in comparison to calibration data, but also that the occurrence of new weed patches was substantially lower. The initial numbers of new introductions from outside the landscape (two for *C. maculosa*, one for *E. esula*) were proposed based on the assumed vulnerability of

the entire RMF landscape to new invasions from adjacent areas (scaled down to the extent of the Pine Butte study area). These initial new introduction values were increased to as much as eight for *C*. *maculosa* and six for *E. esula*. This change was made since the Pine Butte area had higher vulnerability to invasion from adjacent areas than did the RMF landscape as a whole, because of the presence of significant large infestations immediately adjacent to the preserve.

#### 3.4.2.4 Creating an I2-Aware model

The last and most significant model adjustment applied during the calibration process was the application of an "I2-Aware" pathway model. Incorporating the previously discussed parameter and model adjustments, simulation results began achieving invaded areas within a reasonable range of the calibration data at the 1990 checkpoint. Invaded area remained too low, however, at the 2008 checkpoint. This pattern indicated that control effectiveness was too high in the simulation during the period between 1990 and 2008 when management began. Newly established weed infestations were being eradicated too quickly in the model. These results suggested that the detection of newly infested weed patches in their initial 3 years of growth (i.e. I1 state) is infrequent under actual field monitoring conditions. Simulation assumptions were adjusted to limit treatment to weed patches that had been invaded for at least 4 years. After 4 years of invasion, a polygon is classified as being in the I2 state and weeds are present at higher densities than in the II state. The higher density of weeds increases the likelihood of discovering the weed patch under actual field monitoring conditions. In the "I2-Aware" pathway model, once a weed patch achieves the I2 state, it is considered "discovered" or "known" and can continue to be treated even if it reverts to the I1 state. Note that weed patches mapped as I1 are treatable immediately since they are already included in the 2008 weed survey data. The "I2-Aware" model rules apply strictly to new infestations.

# 4. Results

# 4.1 Model Calibration Analysis

Factoring the parameter and model assumption adjustments described in Section 3 into the simulations, we achieved invaded area targets within a reasonable range of the calibration data (Figure 7). The final parameters applied are presented in Table 10. The spatial results are presented in Figure 8 and Figure 9.

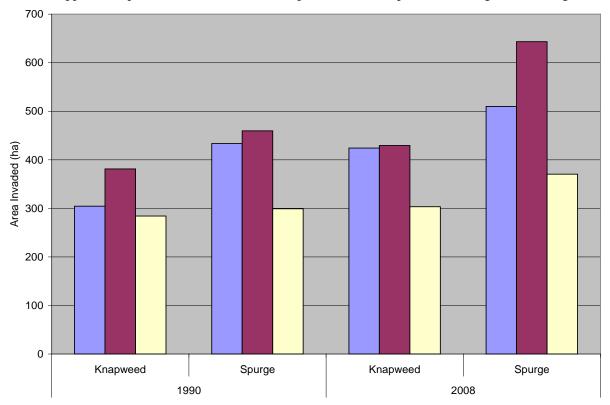


Figure 7: Results comparing the actual area invaded by *C. maculosa* and *E. esula* (blue) versus the modeled area invaded at two checkpoints under the high (maroon) and low (beige) spread scenarios.

Table 10: Final post-ca	libration F	ine Butte	model par	ameters.
	C. maculosa		E. esula	
	High	Low	High	Low
Spread rate	0.04	0.08	0.03	0.06
New introductions	6	6	6	6
BC spread rate		0.	04	
BC new introductions	4			
Pathway scenario	No control in Gravel-Riparian, I2 Aware			an, I2-
Control effectiveness		70	)%	

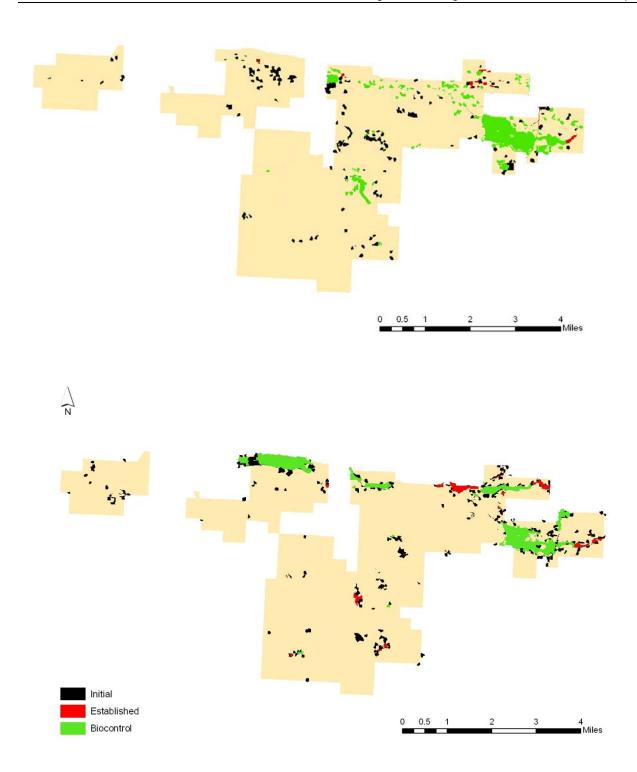


Figure 8: Actual area invaded by *E. esula* in 2008 (top) and predicted invaded area by the Pine Butte calibration simulation for the high spread 70% control effectiveness scenario (bottom). Initial invasions (less than 6 years) are shown in black. Established invasions (6 or more years) are shown in red. Areas where biocontrol is present are shown in green.

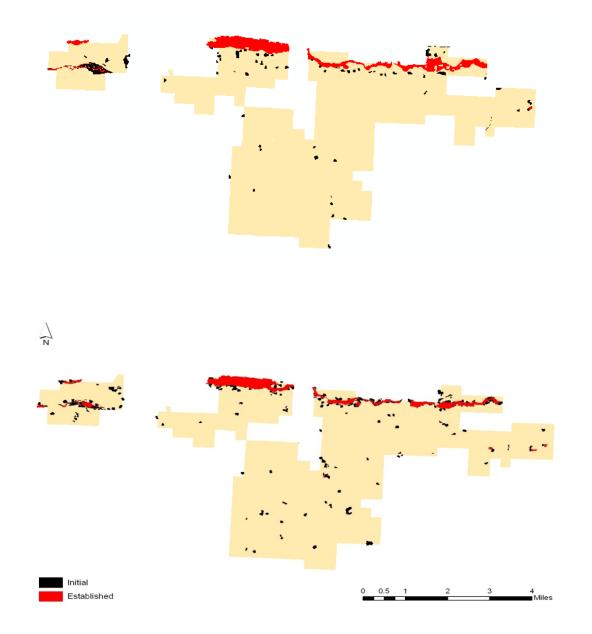


Figure 9: Actual area invaded by *C. maculosa* in 2008 (top) and predicted invaded area by the Pine Butte calibration simulation for the high spread 70% control effectiveness scenario (bottom). Initial invasions (less than 6 years) are shown in black. Established invasions (6 or more years) are shown in red.

# 4.2 Landscape Simulations

Regardless of landscape or invasive plant species modeled, simulations demonstrated that without treatment, noxious weeds substantially increase in area occupied. Depending on spread rate, *E. esula* and *C. maculosa* increased approximately 12 to 18 fold on the RMF after 40 years (from 1800 ha to between 21,314 and 33,185 ha infested at the end of the simulations). In the CV, increases were even more dramatic, ranging from approximately 260 to 590 fold after 40 years (from 10 ha to between 2,600 and 5,900 ha infested at the end of the simulations). Increases were most extreme in the MGP, ranging from approximately 450 to over 860 fold after 40 years (from 7 ha to between 3150 and 6050 ha infested at the end of the simulations). The dramatic nature of the increases in the CV and MGP is largely due to these landscapes being at the initial stages of the exponential increase phase of invasion.

Most management actions were effective at reducing the area infested in all three landscapes over the 40year period, though the areas treated and infested ranged widely among the various management scenarios. Economic analysis of treatment costs and grazing losses suggested that some strategies resulted in positive net present values over the 40-year period, while others were not economically viable. Maps of simulation results are shown in Appendix 2. Below we present quantitative and graphical results of simulations for each of the three study areas.

### 4.2.1 Montana Glaciated Plains

In the MGP, an unlimited management strategy kept total area of *C. maculosa* and *E. esula* to between 49 and 60 ha, or less than 0.01% of the landscape (Table 11). In terms of treatment cost, model results suggest that under this scenario 1,700 to 2,150 ha in the MGP will be treated cumulatively over a 40-year period. Mean treatment area per year was 48 ha, compared to approximately 10 ha treated the first year, suggesting that treatment area will need to increase over time as new infestations appear on the landscape. Taking into account the cost of treatment and the grazing fees lost due to the infestation, we estimate the economic benefits of management over a 40-year period to range from a gain of \$944 to a gain of approximately \$86,000 (Table 12). The benefit-cost ratio ranges from 1.00 to 1.51 for every dollar spent. Results appear to be particularly sensitive to spread rates. This is because *C. maculosa* and *E. esula* in the MGP are at the initial stages of invasion, and any significant benefits of management are experienced towards the end of the simulation, particularly if spread rates are low.

Strategy Spread Rate	Area Invaded (ha)		Area Treated (ha)		
	High	Low	High	Low	
No Management	6,050	3,150	0	0	
Unlimited Management	61	49	2,155	1,733	

Table 12: Economic benefits, Net Present Value (NPV), and Benefit-cost Ratio (BCR), of unlimited<br/>management of *C. maculosa* and *E. esula* in the MGP under different assumptions for the<br/>spread rate of the weedsSpread RateDiscount RateNPV (2008 \$)BCRHigh2.7%86,4241.51Low2.7%9441.00

### 4.2.2 Centennial Valley

In the CV, unlimited management scenarios maintained the total area infested by *C. maculosa* and *E. esula* between 11 ha and 21 ha, or less than 0.02% of the landscape (Table 13). In terms of treatment cost, model results suggest that 453 to 678 ha in the CV will be treated over a 40-year period. Mean treatment area per year was 14 ha, compared to approximately 1 ha treated the first year, suggesting that the actual treatment area will need to increase substantially over time to minimize infested area over the long term. Figure 10 shows how the area treated increases over time for the unlimited management scenario. Figure 11 shows the area treated over time for scenarios in which we imposed a budgetary ceiling on the total area that could be treated.

simulations. Existing area invaded at the beginning of the simulations was 10 ha.						
Strategy Spread Rate	Area Invaded (ha)		Area Treated (ha)			
	High	Low	High	Low		
No Management	5,960	2,600	0	0		
Unlimited	21	11	678	453		
125 Ha Ceiling	1,019	113	437	378		
63 Ha Ceiling	2,593	875	262	245		

28

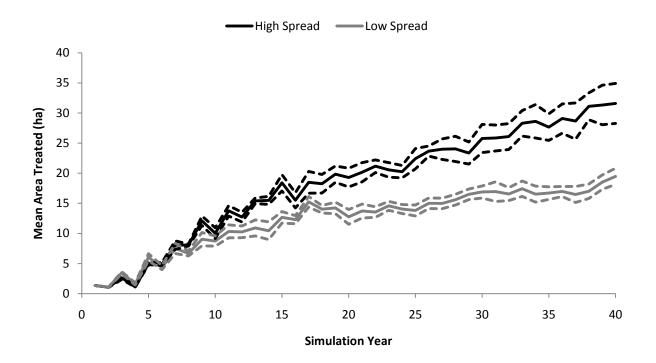


Figure 10: Mean area treated per year in the CV (mean  $\pm$  SE for 5 Monte Carlo simulations) for the unlimited management scenario at high and low spread rates.

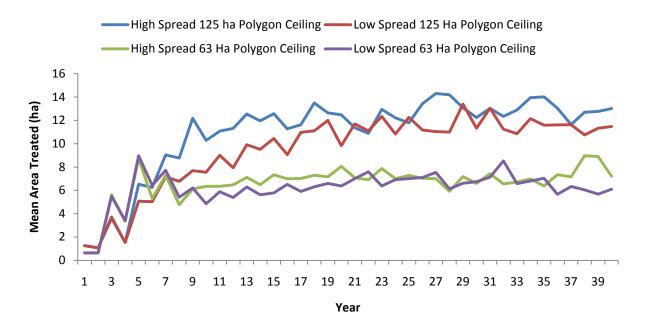
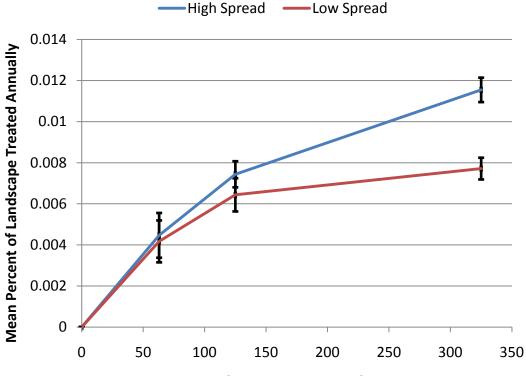


Figure 11: Mean area treated per year in the CV as a function of polygon area treatment ceiling and spread rate (mean of 5 Monte Carlo simulations for each ceiling/spread rate combination).

The actual area treated differs from the polygon area treatment ceiling applied in the model because the density of weeds depends on the state of infestation (I1, I2, and E). Treatment ceilings in the model, however, are applied at the resolution of the polygon independent of weed density. Figure 12 shows how the mean percent of the landscape treated annually varies as a function of the polygon area treatment ceiling. As the percentage of the landscape treated annually increases, the area invaded on the landscape after 40 years decreases in a near linear relationship (Figure 13). These were default simulations with small patch treatment priority, 70% success rate, and no immediate detection of new infestations (i.e. not I1-aware).



**Polygon Treatment Ceiling** 

Figure 12: Mean percent of the CV landscape treated annually (mean of 5 Monte Carlo simulations  $\pm$ SE) as a function of the polygon treatment ceiling (ha) applied in the model for simulations with high- and low-spread rates (0.010% of landscape = 15 ha).

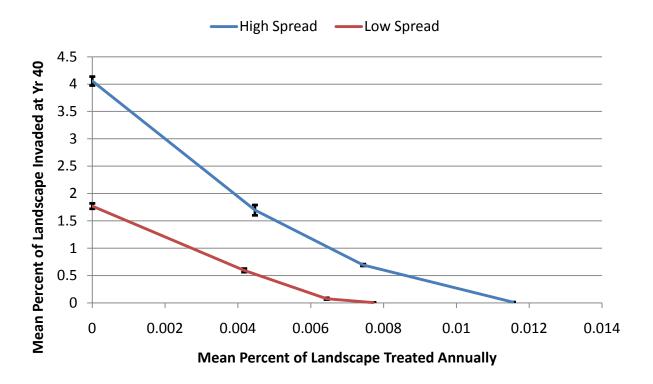


Figure 13: Percentage (mean of Monte Carlo simulations  $\pm$ SE) of the CV landscape invaded at year 40 as a function of the mean percentage of the landscape treated annually at two spread rates (0.010% of landscape = 15 ha).

Considering the polygon area ceiling for treatment, the cost of treatment, and the grazing fees lost due to weed infestation, we estimate the economic benefits of management over a 40-year period to range from a low of \$105,000 to a high of approximately \$335,000 (for 2.7% discount rates) based on our default simulations (Figure 14). The broad range is dependent on assumptions made about the spread rate of the weeds and the ceiling placed on the maximum area to be treated annually. Similarly, the benefit-cost ratios are all greater than one, ranging from a low of 4.01 to 8.55 (Figure 14).

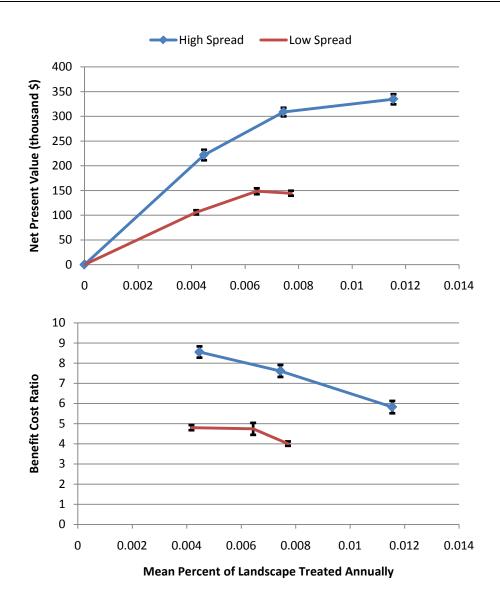


Figure 14: The Net Present Value (NPV) and Benefit-cost Ratio (BCR) (mean of 5 Monte Carlo simulations ±SE) as a function of the mean percent of the CV landscape treated annually at two spread rates.

Though management was always a viable financial investment in the CV, the value of management is significantly higher with higher spread rates. While increasing the percentage of the landscape treated annually always increases the NPV, at high spread rates the NPV is approximately double that at low spread rates. At high spread rates, the BCR is highest at the lowest treatment ceiling; whereas at low spread rates BCR is comparable between the lowest and middle treatment ceiling (Figure 14).

The alternative strategy analysis used a 125 ha treatment ceiling to evaluate management variables and produced wide ranges for area treated and area invaded (Figure 15 and Figure 16). Detecting and controlling new infestations as soon as they appear (I1 aware) is highly effective under both low and high spread rates. Prioritizing large patch edges is the least effective strategy both with respect to reducing the

total area treated and the total area invaded, especially under high spread rate scenarios. Spread rate was an important driver of total area invaded in all alternative scenarios.

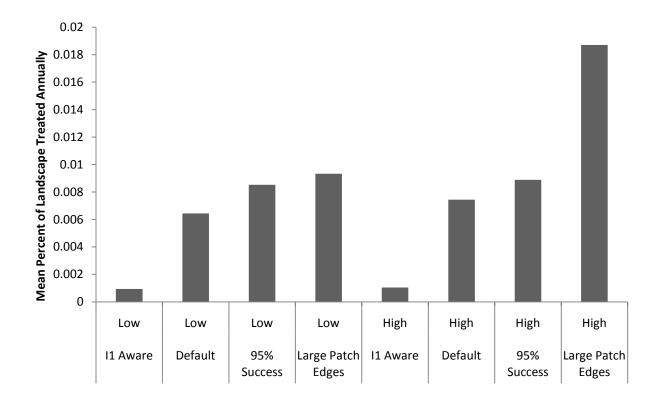


Figure 15: Alternative strategy analysis results showing how the percent of the landscape treated annually in the CV varies as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 125 ha per year. Bars are sorted in ascending order for each spread rate.

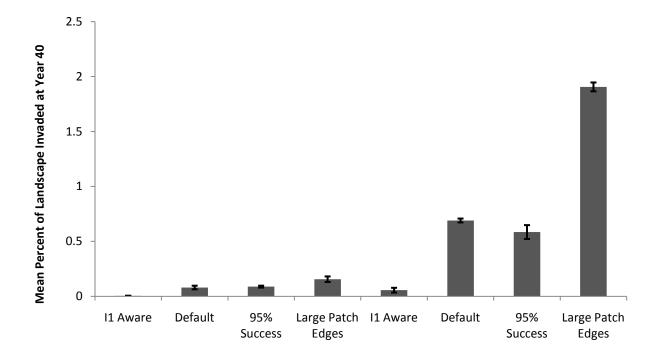


Figure 16: Alternative strategy analysis showing how the percent of the CV landscape invaded at year 40 (mean of 5 Monte Carlo simulations ±SE) varies as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 125 ha per year.

All alternative management scenarios across both spread rates yield positive NPV (Figure 17). NPV and BCR are significantly higher when managing a weed with higher spread rates. The differences among management strategies were greater for high spread than low spread scenarios. The II aware strategy has the highest value, and the strategy that focuses on large patch edges has the lowest value.

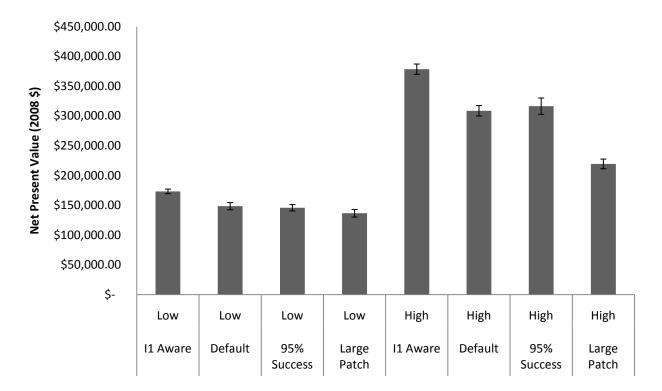


Figure 17: Alternative strategy analysis showing how the Net Present Value (mean of 5 Monte Carlo simulations ±SE) varies as a function of weed spread rate and management strategy in the CV. All runs shown here had a polygon area treatment ceiling of 125 ha per year. Bars are sorted in descending order for each spread rate.

Figure 18 shows how delay in the beginning of treatment can result in a large increase in the proportion of the landscape invaded after 40 years. Figure 19 shows how NPV and BCR vary as a function of delay in treatment, spread rate, and discount rate. The most significant decrease in both of these two variables occurs within the first ten years of delay.

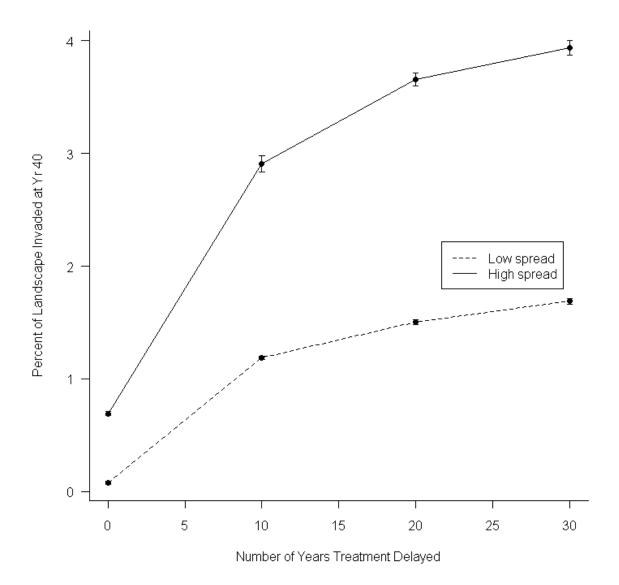


Figure 18: Simulation results showing how the percent of the CV landscape invaded at year 40 (±SEM) varies as a function of delay in the start of treatment and the spread rate of weeds. All simulation runs shown here had a polygon area treatment ceiling of 125 ha per year and the default management strategy.

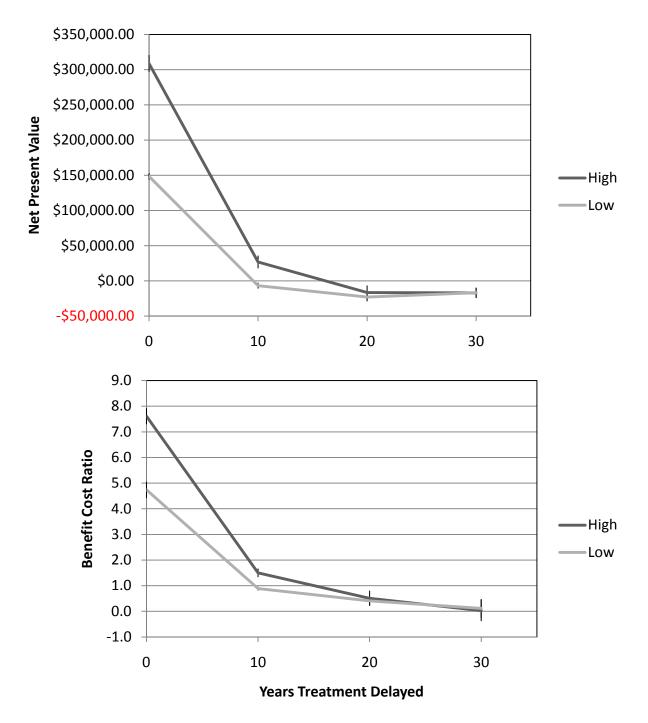


Figure 19: Simulation results showing how the NPV and BCR of management with respect to retained grazing fees (mean across 5 Monte Carlo simulations  $\pm$ SE) vary as a function of delay in the start of treatment and spread rate in the CV. Simulation runs shown here had a polygon area treatment ceiling of 125 ha per year and the default management strategy.

### 4.2.3 Rocky Mountain Front

In the RMF, an unlimited management scenario kept the total area of *C. maculosa* and *E. esula* between 2,630 and 2,750 ha, or less than 1% of the landscape (Table 14). In terms of treatment cost, model results estimate that 15,783 to 19,285 ha in the RMF will be treated over a 40-year period. Mean treatment area per year was 438 ha, compared to approximately 1000 ha treated the first year, suggesting that, in contrast to the MGP and CV, the actual treatment area will be reduced over time with the large initial effort of unlimited management. This is due to repeated treatment of infestations already on the landscape at the beginning of the simulations, which drives the infestations to earlier states and reduces their cover values. This pattern becomes less pronounced as treatment ceilings decline, since increasingly fewer pre-existing established infestations are treated in these simulations. Figure 20 shows how the area treated changes over time depending on treatment ceilings.

Strategy	Area Invadeo	l (ha)	Area Treat	ed (ha)
Spread Rate	High	Low	High	Low
No Management	33,185	21,315	0	0
Unlimited	2,750	2,630	19,285	15,783
2300 Ha Ceiling	11,053	5,947	10,938	13,412
1150 Ha Ceiling	17,130	10,204	5,353	5,405
575 Ha Ceiling	21,883	13,157	2,745	2,780
100 Ha Ceiling	27,567	16,435	479	494

As with the CV, the actual area treated differs from the polygon area treatment ceiling applied in the model because the density of weeds depends on the state of infestation (I1, I2, and E). Figure 21 shows how the mean percent of the landscape treated annually varies as a function of the polygon area treatment ceiling. As the percentage of the landscape treated annually increases, the area invaded on the landscape after 40 years decreases in a near linear relationship (Figure 22). These were default simulations with small patch treatment priority, 70% success rate, and no immediate detection of new infestations (i.e. not I1-aware).

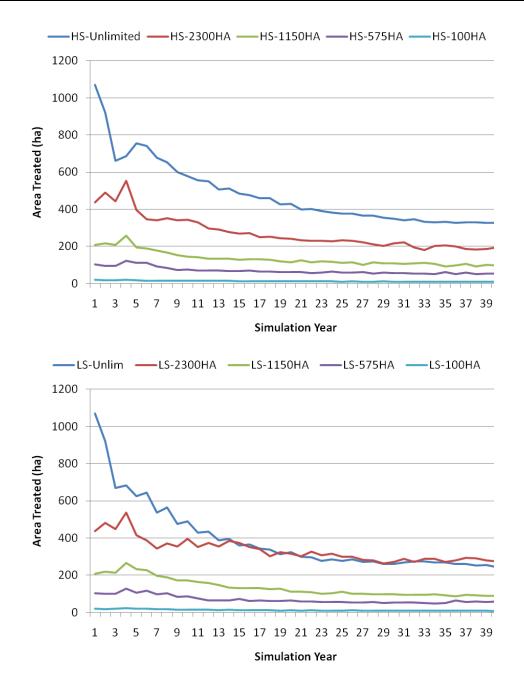


Figure 20: Area treated per year in the RMF as a function of polygon area treatment ceiling and spread rate. Top graph shows results for high spread rates and the lower figure shows results for low spread rates.

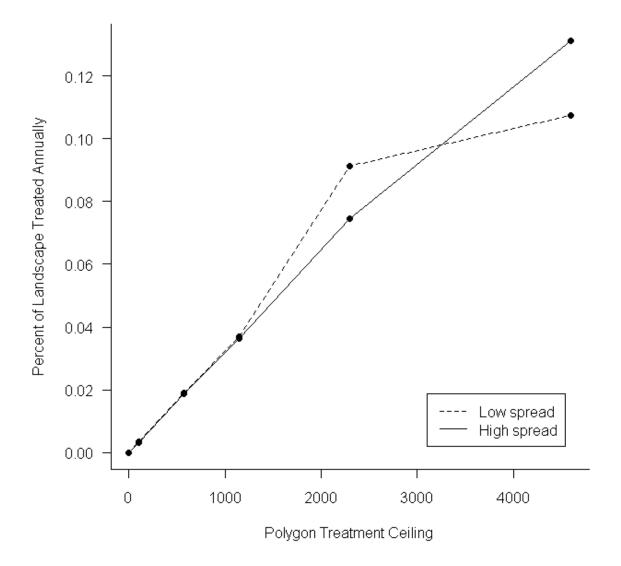


Figure 21: Percent of the landscape treated annually in the RMF as a function of the polygon treatment ceiling (ha) applied in the model for two spread rates.

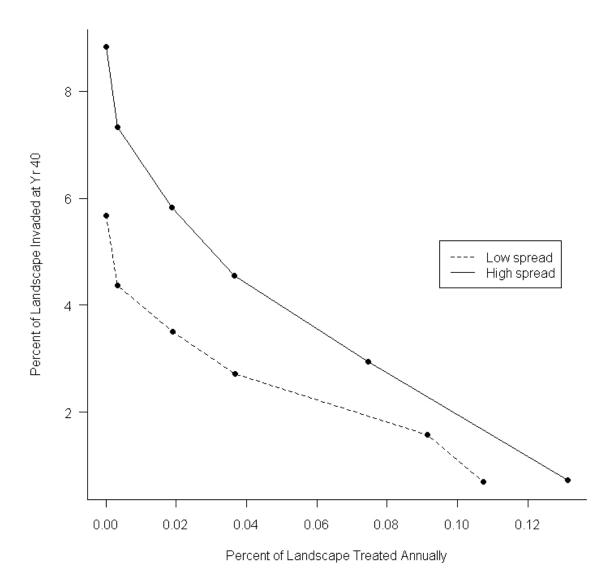


Figure 22: The percentage of the RMF landscape invaded at year 40 as a function of the percentage of the landscape treated annually at two spread rates.

For the RMF, taking into account maximum polygon area ceiling for treatment, the cost of treatment, and grazing fees lost due to weed infestations, we estimate the economic benefits of management over a 40-year period to range from approximately \$200,000 to \$860,000 in our default simulations (Figure 23). The benefit-cost ratio ranges from a low of 1.15 to a high of 8.04. The broad range is dependent on assumptions made about the spread rate of the weeds and the level of resources applied for treatment. To maximize NPV, it is most beneficial to treat the maximum area possible. From a BCR perspective, the highest values result from the lowest polygon area treatment ceilings, with the relationship appearing to be hyperbolic.

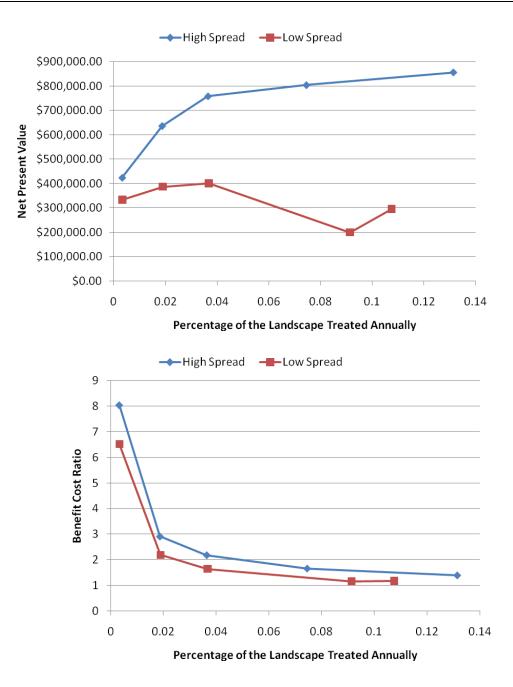


Figure 23: The Net Present Value (NPV) and Benefit-cost Ratio (BCR) as a function of the percent of the RMF landscape treated annually at two spread rates.

Alternative strategy simulations, in comparison to the default results with a 2300 ha ceiling, produced a range of results different from those in the CV in several ways (Figure 24 and Figure 25). The most effective strategy at reducing the total area treated and the amount of area invaded at year 40 is one that can maximize site specific treatment success (95% success simulations). This is in contrast to the CV where early detection (II aware) was more important than increasing site specific treatment success levels. Both roaming treatments and large patch edges were ineffective with respect to reducing the total area treated and the total area invaded.

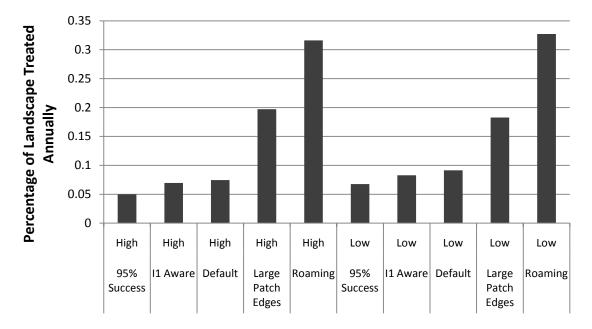


Figure 24: Alternative strategy simulation results showing how the percent of the landscape treated annually in the RMF varies as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 2300 ha per year. Bars are sorted in ascending order for each spread rate.

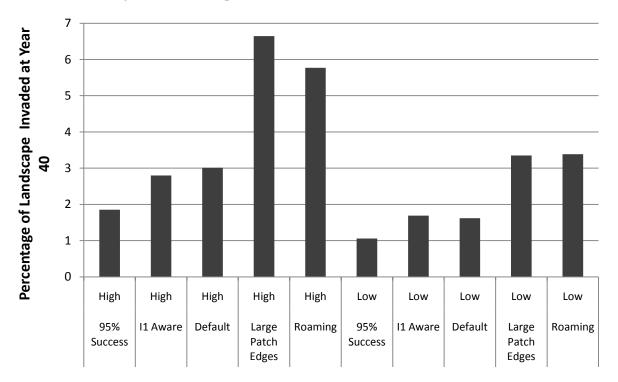


Figure 25: Alternative strategy simulation results showing how the percent of the RMF landscape invaded at year 40 vary as a function of management strategy and weed spread rate. All runs shown here had a polygon area treatment ceiling of 2300 ha per year. Bars are sorted in ascending order for each spread rate.

Figure 26 shows how the net present value with respect to retained grazing fees varies as a function of spread rate and management strategy. Again, the 95% success strategy has the highest value, while the large patch and roaming treatment strategies have negative values. Management is most valuable when spread rates are high.

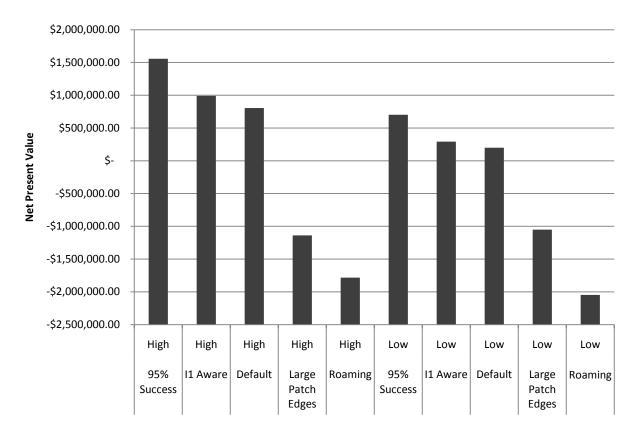


Figure 26: Alternative strategy simulation results for the RMF showing how the Net Present Value varies as a function of weed spread rate and management strategy. All runs shown here had a polygon area treatment ceiling of 2300 ha per year. Bars are sorted in descending order for each spread rate.

Figure 27 shows how delay in the beginning of treatment can result in a large increase in the proportion of the landscape invaded after 40 years. Figure 28 shows how NPV and BCR vary as a function of delay in treatment and spread rate. The most significant decrease in both of these variables occurs within the first five years of delay.

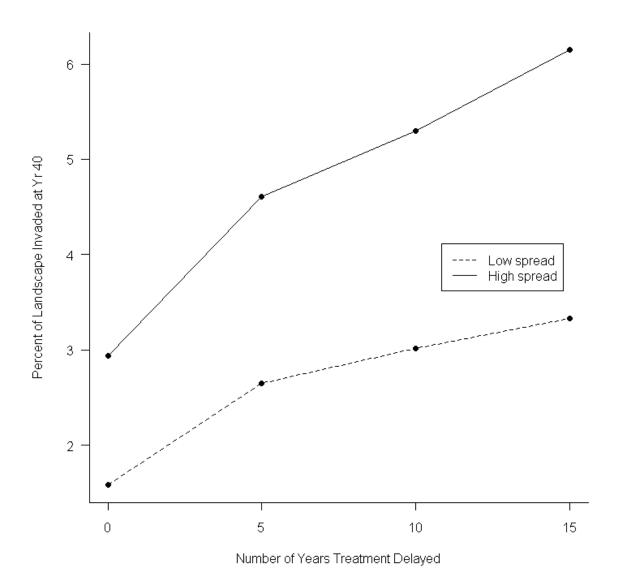


Figure 27: Simulation results showing how the percent of the RMF landscape invaded at year 40 varies as a function of delay in the start of treatment and the spread rate of weeds. All runs shown here had a polygon area treatment ceiling of 2300 ha per year and the default management strategy.

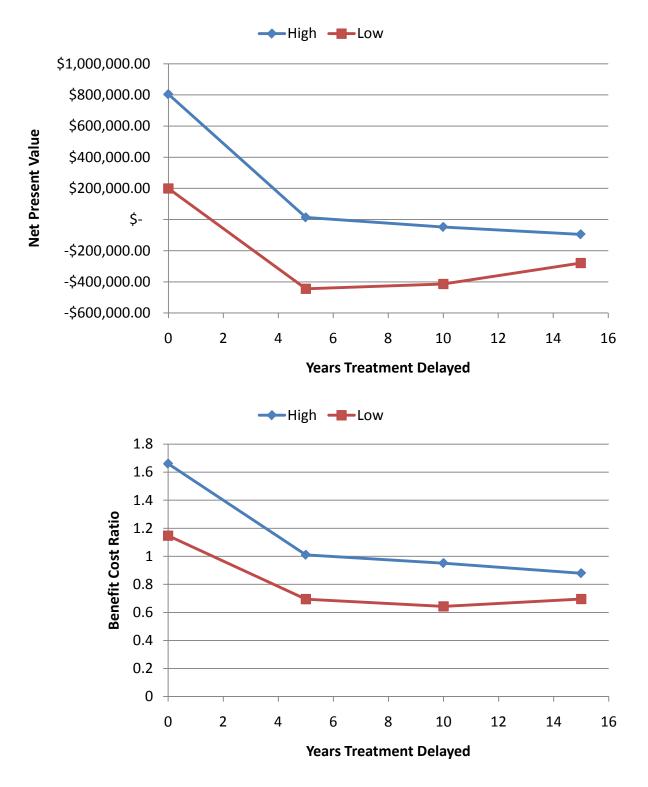


Figure 28: Simulation results showing how the NPV and BCR of management with respect to retained grazing fees for the RMF landscape vary as a function of delay in the start of treatment and spread rate. All runs shown here had a polygon area treatment ceiling of 2300 ha per year and the default management strategy.

# 5. Discussion

## 5.1 Model Calibration Analysis

The calibration analysis of our chosen spread rates for *C. maculosa* and *E. esula* at Pine Butte modeled a range of areas invaded that encompasses the actual area invaded. However, these results do not validate our model as 'true'. We may be getting the right results for the wrong reasons. However, they do increase our confidence about the range of spread parameters chosen for alternative hypotheses and provide a 'partial confirmation' of our model (Oreskes et al. 1994). While these spread rates are reasonable for the RMF, we are less confident in their application to other landscapes. Because of this, absolute areas of infestations are not directly comparable among our landscapes.

## 5.2 Landscape Simulations

Our performance measures (total area infested, cumulative area treated, net present value, and benefit-cost ratio) provide a valuable understanding of the relative ecological and economic efficacy of alternative strategies and budgets. The total area infested and the cumulative area treated represent meaningful metrics about landscape condition and management effort, while net present value and the benefit-cost ratio account for both the cost of treatment and grazing value lost due to infestation. We considered the strategies with robust performance in controlling spread at reasonable cost as having the greatest value for long-term management.

### Montana Glaciated Plains

In the MGP, the no management strategy results in significant increases in total area invaded by *C*. *maculosa* and *E. esula* after 40 years, while an unlimited management strategy kept total area invaded to very low levels, less than ca. 0.007% of the landscape. Total area treated in the unlimited scenario was relatively low, suggesting an unlimited management approach is feasible from a real world, management perspective. Regardless of the spread rate, the treatment strategy leads to a slight economic gain. While the economic benefits of management seem marginal for the MGP, this is only because significant economic benefits are not experienced until towards the end of the simulation due to limited initial invasion. Overall, the current low levels of infestation in the MGP make an unlimited management strategy appear ecologically effective as well as practically and economically attainable.

### Centennial Valley

In the CV, the no management strategy results in significant increases in total area invaded by *C*. *maculosa* and *E. esula* at year 40 (ca. 2-4% of the landscape area), while an unlimited management strategy kept total area invaded to very low levels, less than ca. 0.02% of the landscape. Across the range of treatment levels, the percentage of the CV invaded after 40 years decreases as the mean annual area treated increases. The levels of management necessary to maintain the current limited extent of weeds in the CV are greater than current management, suggesting an increase in management effort will be needed.

The results of the alternative strategy simulations suggest that the most effective strategy at reducing the total area treated and the amount of area invaded at year 40 is one that detects new infestations as soon as they appear (I1 aware) and prioritizes small patches for treatment. A treatment strategy targeting large patch edges was the least effective strategy based on total area treated and the total area invaded. Additionally, delaying treatment led to substantial increases in total area invaded at year 40.

Most of the management strategies modeled resulted in favorable economic measures. For the default management strategy, higher treatment levels resulted in the greatest economic benefits, although benefit-

cost ratios decline as treatment levels increase. A strategy that prioritizes small infestations and targets new infestations as soon as they appear provided the maximum economic benefits. Additionally, strategies that either targeted large patch edges or delayed management resulted in poor economic performance while providing only marginal improvement over no management in terms of area invaded.

As with the MGP, current low levels of infestation in the CV make long-term ecological success appear practically and economically attainable. With a moderate management effort, the percent of the CV invaded at year 40 can be kept very low, while yielding a positive net present value.

#### Rocky Mountain Front

For the RMF, the no management strategy again results in significant increases in total area invaded by *C. maculosa* and *E. esula* at year 40, while an unlimited management strategy kept total area invaded to less than ca. 0.7% of the landscape. For lower treatment levels, the percentage of the RMF invaded at year 40 decreases as the area treated annually increases. From the standpoint of total area invaded, increasing management always has value, and there are no clear thresholds beyond which additional treatment produces diminishing returns. The more advanced stage of invasion in the RMF landscape results in continued sources for spread at reduced treatment levels.

The results of the alternative strategy simulations suggest that the most effective strategy to reduce the total area treated and the amount of area invaded at year 40 is one that maximizes site specific treatment success (95% success simulations) and prioritizes small patches for treatment. Strategies that target large patches or focus management effort on 1/3 of the landscape each year were ineffective with respect to minimizing the total area treated and the total area invaded at year 40. Additionally, delaying treatment led to substantial increases in total area invaded at year 40.

Like the CV, most of the management strategies modeled resulted in favorable economic measures. For the default management strategies, higher treatment levels always resulted in the greater economic benefits at high spread rates, but with low spread rates lower treatment levels yielded greater benefits. Prioritizing small patches and ensuring high management success resulted in the maximum economic benefits. Additionally, strategies that targeted large patch edges, treated a location only every three years, or delayed management resulted in only marginal improvements over no management in terms of area invaded, while also incurring significant economic costs. These results demonstrate the importance of maintaining consistent weed management efforts on the RMF. Regularly managing only a portion of weed infestations or waiting until patches become a noticeable problem to initiate management may appear attractive options for dealing with numerous infestations, but these strategies prove more costly in the long-run and result in significantly higher levels of invasions in the future, which will be more difficult to manage.

Although weed invasions on the RMF are already established at a level that precludes widespread eradication, significant increases in area invaded can be prevented with strategic management and a long-term commitment. With a moderate management effort, the percent of RMF invaded after 40 years can be kept at reasonable values while resulting in a very strong net present value.

#### Across the Landscapes

Regardless of landscape or invasive plant species modeled, simulations demonstrated that without treatment, noxious weeds substantially increase in area occupied. For all of the landscapes, an unlimited treatment strategy was the best strategy at reducing the total area invaded at year 40. However, our model suggests that the optimum management strategy to balance the area invaded, area treated, cost of treatment, and retained grazing fees varied for each landscape and is sensitive to the initial proportion of the landscape infested, weed spread rate, and control effectiveness.

The MGP and the CV simulations show that for both large and small landscapes that are relatively uninvaded, management can successfully limit spread and maintain nearly all the landscape in an uninvaded state after 40 years. The reductions in area invaded for the MGP came with a small economic effect; while the reductions in area invaded for the CV produced very favorable economic measures. The favorable results for the CV are the result of a management strategy that targets small patches and early detection of new populations.

For large, already invaded landscapes like the RMF, it may be possible to maintain the area invaded at close to existing levels, but eradication is likely impossible. Even at the higher invasion levels on the RMF, management still provides positive economic results with a management strategy that prioritizes small patches and maximizes treatment success. The CV and the RMF simulations also show that focusing treatment on large patches or delaying management leads to a greater area invaded and poor economic performance by year 40. For all simulations, management was more valuable when weed spread rates were high. However, invasion levels and long-term control costs were lower at low spread rates, emphasizing the benefit of any management actions that reduce spread rates by limiting weed dispersal via vehicles and other vectors.

The importance of early detection of new infestations has been a central strategy of many weed management programs and the I1-aware scenario demonstrates the benefit of rapidly detecting new infestations. However, we did not estimate detection costs in our model since early detection relies on multiple approaches. Recent work suggests that probability of occurrence mapping can focus search efforts to manage the challenge of finding small infestations within large uninvaded areas (Rew et al. 2005, Chong et al. 2006). Another key component of early detection is education and effective communication among all persons who use the landscapes, including landowners, agricultural workers, recreationists, and agency staff.

## 5.3 Model Assumptions and Uncertainties

Our conclusions are only valid under conditions in which our underlying assumptions are true. These underlying assumptions include the parameter ranges chosen for alternative hypotheses of control effectiveness and spread rates. Control effectiveness depends on a variety of conditions including weather and human error that are not addressed by the model; but the results of control efforts should be monitored, both to improve model predictions and to improve the control efforts themselves. In our landscapes, severe infestations often receive more management action since they are easier to re-locate and treat than smaller or sparser infestations. High control effectiveness, especially in small, initial patches, often requires longer search time and multiple visits to individual patches during the growing season. While our model accounted for the higher costs associated with managing small versus large patches, we did not estimate costs of additional efforts to maximize control effectiveness. Our model also assumes a predictable response to invasion and successful control, but both invasion and control may result in alternative stable states completely different from initial uninvaded conditions (Pearson and Ortega 2009, Beisner et al. 2003)

Weed spread rates are extremely difficult to predict, and model results in all three landscapes were highly sensitive to weed spread. Clark et al. (1998) showed long-tailed distributions can have dramatically higher spread rates for plants than exponential distributions with the same mean dispersal distance. Even rare events of long-distance dispersal can overwhelm the effects of more common short-distance spread mechanisms for some plants (Neubert and Caswell 2000). Future research to better understand actual weed spread would be beneficial given the profound effect of weed spread rates on our results. This model can provide one approach to considering alternative distributions and calibrating real world observations with theoretical spread rate distributions.

Additionally, the relative susceptibility of each vegetation community to invasion, the effect of landscape features and topography that influence weed dispersal, and the biological control establishment rate by vegetation type were all assigned single values by vegetation type, whereas in reality each factor is dynamic within and across vegetation or landscape-feature types. Other researchers are examining these factors and their results will yield needed information for improving both the model parameters and the prioritization of resources on the ground (Rew et al. 2005, Chong et al. 2006).

In model development and analysis, relating the actual area invaded and treated to model polygon area invaded and treated proved challenging. Actual canopy cover and density of weeds changes with time and is influenced by the susceptibility and disturbance of local sites among other factors. For the model, single values were assigned to each infestation state (e.g. initial, established, etc.) based primarily on field experience in each landscape. These values have the potential to change the outputs significantly when they are translated from model polygon area to actual area, which is important for developing meaningful recommendations to specific landscapes. In field monitoring to support parameter development, there were not sufficient numbers of unmanaged initial patches in our landscapes to measure changes in cover and density or account for variability across vegetation types. Studies that measure cover and density across infestations of various ages and management histories could reduce uncertainty related to these parameters.

A major assumption made by our model is complete knowledge about the location of weeds on the landscape and prioritization of action based on this knowledge. In reality, this is never the case, and managers are much more likely to have information about large existing infestations than about the higher priority, small, new infestations. It may be valuable to test monitoring strategies to evaluate their effectiveness in relocating infestations and to examine tradeoffs between monitoring and treatment costs explicitly. Mapping infestations has long been a priority for many projects, but, in our experience, these data are often not used in the field to relocate hard-to-find infestations, especially new weed patches or patches where management has successfully reduced the size or density of weeds. Our model results indicate that treatment of these small patches is important to achieve positive ecological and economic measures. In the CV, we have observed that small, previously treated patches were often missed when management crews were not using global positioning units. This emphasizes the importance of not only mapping weeds, but also using those data each year to relocate patches for management. Ongoing use and improvement of weed mapping data can help maximize management efficiency and efficacy over time.

The economic analysis is also sensitive to assumptions. Broad ranges in NPV and BCR are dependent on assumptions made about the spread and discount rates. Higher rates of weed spread are associated with greater benefits under the same management strategy. Additionally, the cost of lost grazing fees was based on an Animal Unit Month (AUM) value that was averaged across an entire landscape. The loss of grazing fees and the cost of management were given static values, although in reality these values vary dynamically across the landscape. Our economic analysis was limited since we only considered how management benefited livestock grazing values, and did not quantify numerous other potential benefits. Results would be more robust if additional economic metrics could be included in the analysis, such as the effects of the reduction of livestock carrying capacity on the multiplier effect of dollars spent locally on ranching production inputs (Bangsund and Leistritz 1991) or the economic benefits of sporting industry revenues flowing into communities with healthy wildlife populations (Bangsund et al. 1997). Non-use values, such as preserving rare native species, represent the greatest challenge to quantify because they are largely value-driven and difficult to assign a market-based value. Since economic calculations are applied to the outputs of the spatial simulations, additional economic analysis can be conducted using our existing simulation outputs without the need for further spatial model runs.

## 5.4 Future Model Applications

Even considering the uncertainties discussed above, the model we developed provides a platform for further analysis to inform numerous other management decisions. For example, simulations for other weed species in other landscapes could be modeled with relevant parameter modifications to help develop long-term strategies, determine appropriate allocation of resources, and communicate decision-making effectively. Model simulations could compare the difference in economic and ecological results of current landscape management versus the "ideal" management strategy. The effect of disturbances such as development, fire, or grazing could be incorporated if disturbance regimes are adequately understood. Different expected and modeled effects of climate change on vegetation susceptibility and spread rates could also be modeled. The model would enable comparison of the relative economic and ecological contributions of biological control versus chemical control methods at different invasion levels. Numerous economic factors besides grazing values could also be incorporated depending on identified landscape values, ecosystem services, and data availability. Additional scenarios of interest for our landscapes include modeling the effects of changing land use on weed cover (Maestas et al. 2003), and periodic simulation runs to compare actual and modeled results of landscape weed management efforts.

The three landscapes we modeled represent areas where continued invasive plant management appears justified because the levels of infestations appear manageable over the long term. Many landscapes in the West have higher levels of invasion. Using the model to evaluate varying initial extents and patterns of weed infestations for a landscape may be one approach to determining thresholds, past which, management has no significant long-term effect on area infested. Some weed management efforts may use resources on infestations or areas where there is no hope for long-term success, and forecasting will further improve the ability to identify effective and ineffective priorities. Predicting spatially explicit economic and ecologic impacts of not only weeds but also management actions is necessary for planning and implementing appropriate landscape-scale invasive species programs (Pearson and Ortega 2009).

### 5.5 Recommendations and Conclusions

Our model provided a useful way to assess the relative performance of alternative management strategies and varying budget levels across broad spatial scales in terms of ultimate area invaded, long-term treatment requirements, landscape grazing values, and benefit-cost ratios. It is important for managers to pursue strategies that are both ecologically effective and economically justified, and that meet long-term goals for desired future condition of the landscape.

The early detection and small patch control strategies consistently outperformed the large patch strategies, as well as most other strategies. Targeting early detection and rapid response is consistent with the predictions made by others (Moody and Mack 1988, Rejmanek and Pitcairn 2002). Despite recommendations for early detection and rapid response programs, managers are often mandated to focus on large infestations where weeds are well established. Small infestations early in their invasion do not present an immediate loss of productivity and are often more remote and time-consuming to control; consequently, resources are directed toward locations where, based on these model results, treatment is less beneficial. Our model results support the reallocation of resources to an effective early detection and treatment strategy.

Our model results also indicate managers should avoid delaying management, or applying inconsistent treatment over time. In these cases, weed populations outpace management efforts or can reinvade previously treated areas (Robertson and Gemmel 2004), ultimately leading to a greater area invaded with greater economic costs. Preventative actions that reduce weed dispersal distances and spread rates will lower ultimate invasion levels and long-term management costs. For landscapes with relatively few

existing infestations of noxious weeds, managers should dedicate resources to detecting and controlling new infestations as early as possible to prevent the development of large or new source populations. For invaded landscapes where some large noxious weed infestations already exist and higher levels of treatment are required, early detection and control remains a foundational strategy and managers should also work to maximize treatment success. At the broadest scale, resources should be allocated to landscapes with lower infestation levels and thus greater potential for long-term management success, rather than primarily to highly invaded landscapes.

## References

- Anderson, G.L., C.W. Prosser, L.E. Wendel, E.S. Delfosse and R.M. Faust. 2003. The Ecological Areawide Management (TEAM) of leafy spurge purge program of the United States Department of Agriculture Agricultural Research Service. Pest Manag. Science 59: 609-613.
- Arbaugh, M.J., S. Schilling, J. Merzenich and J.W. van Wagtendon. 2000. <u>A test of the strategic fuels</u> <u>management model VDDT using historical data from Yosemite National Park</u>. *In:* L.F. Neuenschwander and K.C. Ryan (tech. eds.). Proc. Joint Fire Sci. Conf. and Workshop, Vol. II. Univ. Idaho and Int. Assoc. Wildland Fire. pp. 85-89.
- Bangsund, Dean A. and F. Larry Leistritz. 1991. Economic Impact of Leafy Spurge in Montana, South Dakota, and Wyoming. Agricultural Economics Report No. 275, Agricultural Experiment Station, North Dakota State University, Fargo (85 pages).
- Bangsund, D. A., F. L. Leistritz, and J. A. Leitch. 1997. Predicting future economic impacts of biological control of leafy spurge in the upper Midwest. AgriBusiness and applied economics report No. 382, Department of Agribusiness and Applied Economics, Fargo, ND: North Dakota State University. 54 p.
- **Beisner**, **B.E.**, **D.T. Haydon**, and **K. Cuddington**. 2003. Alternative stable states in ecology. Frontiers in Ecology and the Environment 1(7):376-382.
- Bergelson, J., J. Newman and E. Floresroux. 1993. Rates of weed spread in spatially heterogeneous environments. Ecology. 74(4): 999-1011.
- Beukema, S.J., W.A. Kurz, W. Klenner, J. Merzenich and M. Arbaugh. 2003. <u>Applying TELSA to</u> <u>assess alternative management scenarios</u>. *In:* G.J. Arthaud and T.M. Barrett (eds.). Systems Analysis in Forest Resources. Kluwer Academic Publishers. pp. 145-154.
- Christen, D. and G. Matlack. 2006. The Role of Roadsides in Plant Invasions: a Demographic Approach. Conservation Biology. 20(2): 385-391.
- **Chong, G.W., Y. Otsuki, T.J. Stohlgren, D. Guenther, P. Evangelista, C. Villa, and A. Waters.** 2006. Evaluating plant invasions from both habitat and species perspectives. Western North American Naturalist 66(1): 92–105.
- Chornesky, E.A., A.M. Bartuska, G.H. Aplet, K.O. Britton, J. Cummings-Carlson, F.W. Davis, J. Eskow, F.R. Gordon, K.W. Gottschalk, R.A. Haack, A.J. Hansen, R.N. Mack, F.J. Rahel, M.A. Shannon, L.A. Wainger, and T.B. Wigley. 2005. Science priorities for reducing the threat of invasive species to sustainable forestry. Bioscience 55(4):335-348.
- Clark, J.S., C. Fastie, G. Hurtt, S.T. Jackson, C. Johnson, G.A. King, M. Lewis, J. Lynch, S. Pacala, C. Prentice, E.W. Schupp, T. Webb and P. Wyckoff. 1998. Reid's paradox of rapid plant migration. Bioscience: 48:13.
- **DiTomaso, J.M.** 2000. Invasive weeds in rangelands: Species, impacts and management. Weed Science, 48: 255-265.
- Dougher, F., L. Rew, and B. Maxwell. 2009. Invasive plant species probability of occurrence Centennial Valley, southwestern Montana. Report to The Nature Conservancy, Helena, MT. 4pp.
- **Eiswerth, M. and G. Cornelis van Kooten.** 2002. Uncertainty, Economics, and the Spread of Invasive Plant Species. American Journal of Agricultural Economics. 84(5): 1317-322.

- **ESSA Technologies Ltd.** 2007. <u>Vegetation Dynamics Development Tool User Guide</u>, Version 6.0. Prepared by ESSA Technologies Ltd., Vancouver, BC. 196 pp.
- **ESSA Technologies Ltd.** 2008. TELSA Tool for Exploratory Landscape Scenario Analyses: User's Guide Version 3.6. Prepared by ESSA Technologies Ltd., Vancouver, BC. 235 pp.
- Forbis, T.A., L. Provencher, L. Frid, and G. Medlyn. 2006. Great Basin land management planning using ecological modeling. Environmental Management 38(1):62-83.
- Frid, L. and J. Wilmshurst. 2009. Decision Analysis to Evaluate Control Strategies for Crested Wheatgrass in Grasslands National Park of Canada. Invasive Plant Science and Management 2: 324-336.
- Gelbard, J. and J. Belnap. 2003. Roads as Conduits for Exotic Plant Invasions in a Semiarid Landscape. Conservation Biology. 17(2): 420-432.
- Hastings, A., K. Cuddington, K.F. Davies, C.J. Dugaw, S. Elmendorf, A. Freestone, S. Harrison, M. Holland, J. Lambrinos, U. Malvadkar, B.A. Melbourne, K. Moore, C. Taylor and D. Thomson. 2005. The spatial spread of invasions: new developments in theory and evidence. Ecology Letters 8: 91-101.
- Hemstrom, M.A., J.J. Korol and W.J. Hann. 2001. <u>Trends in terrestrial plant communities and landscape health indicate the effects of alternative management strategies in the interior Columbia River basin</u>. Forest Ecology and Management 153:105-125.
- Higgins, S., R. Nathan and M. Cain. 2003. Are long-distance dispersal events in plants usually caused by nonstandard means of dispersal? Ecology. 84(8): 1945-1956.
- **Higgins, S.I., D.M. Richardson, and R.M. Cowling.** 2000. A dynamic spatial model for managing alien plant invasions at the landscape extent. Ecological Applications 10:1833–1848.
- Keeley, J. 2006. Fire Management Impacts on Invasive Plants in the Western United States. Conservation Biology. 20(2): 375-384.
- **Kudray, G.M. and S.V. Cooper.** 2006. Montana's Rocky Mountain Front: vegetation map and type descriptions. Report to the United States Fish and Wildlife Service. Montana Natural Heritage Program, Helena, Montana. 26 pp. plus appendices.
- Kurz, W.A., S.J. Beukema, W. Klenner, J.A. Greenough, D.C.E. Robinson, A.D. Sharpe and T.M. Webb. 2000. <u>TELSA: the Tool for Exploratory Landscape Scenario Analyses</u>. Computers and Electronics in Agriculture 27: 227-242.
- Lajeunesse, S., R.L. Sheley, C. Duncan, and R. Lym. 1999. Leafy spurge. *In:* R.L. Sheley and J.K. Petroff (eds.). Biology and management of noxious rangeland weeds. Oregon State University Press, Corvallis. pp. 249-260.
- Lehnhoff, E., L. Rew, and M. Herstand. 2009. Invasive plant species probability of occurrence Rocky Mountain Front, Montana. Report to The Nature Conservancy, Helena, MT. 6 pp.
- Lesica, P. and D. Hanna. 2004. Indirect effects of biological control on plant diversity vary across sites in Montana grasslands. Conservation Biology 18:444-454.
- Leung, B., D. Finnoff, J. Shogren and D. Lodge. 2005. Managing Invasive Species: Rules of Thumb for Rapid Assessment. Ecological Economics. 55: 24-36.
- Mack, R.N., D. Simberloff, W.M. Lonsdale, H. Evans, M. Clout, and F.A. Bazzaz. 2000. Biotic invasions: Causes, epidemiology, global consequences, and control. Ecological Applications 10(3): 689-710.
- Maestas, J., R. Knight and W. Gilgert. 2003. Biodiversity across a rural land-use gradient. Conservation Biology. 17(5): 1425-1434.

- Martin, B., D. Hanna, N. Korb and L. Frid. 2007. Decision analysis of alternative invasive weed management strategies for three Montana landscapes. The Nature Conservancy, Helena, MT. 33 pp.
- Merzenich, J. and L. Frid. 2005. Projecting Landscape Conditions in Southern Utah Using VDDT. In: M. Bevers and T.M. Barrett (comps.). 2005. Systems Analysis in Forest Resources: Proceedings of the 2003 Symposium; October 7-9, Stevenson, WA. General Technical Report PNW-GTR-656. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. pp. 157-163.
- Merzenich, J., W.A. Kurz, S. Beukema, M. Arbaugh and S. Schilling. 2003. Determining forest fuel treatments for the Bitterroot front using VDDT. *In:* G.J. Arthaud and T.M. Barrett (eds.). Systems Analysis in Forest Resources. Kluwer Academic Publishers. pp. 47-59.
- Mico, M and J.M. Shay. 2002. Effect of flea beetles (*Aphthona nigriscutis*) on prairie invaded by leafy spurge (*Euphorbia esula*) in Manitoba. Great Plains Research 12: 167-184.
- Montana Department of Agriculture. 2008. The Montana Weed Management Plan. Montana Noxious Weed Summit Advisory Council and Weed Management Task Force 100 pp.
- Moody, M.E. and R.N. Mack. 1988. Controlling the spread of plant invasions: the importance of nascent foci. The Journal of Applied Ecology 25:1009-1021.
- Neubert, M. and H. Caswell. 2000. Demography and Dispersal: Calculation and Sensitivity Analysis of Invasion Speed for Structured Populations. Ecology. 81(6): 1613-1628.
- **Oreskes, N., K. Shrader-Frechette and K. Belitz.** 1994. Verification, validation, and confirmation of numerical models in the earth sciences. Science 263: 641-647.
- Parker, J., D. Burkpile and M. Hay. 2006. Opposing Effects of Native and Exotic Herbivores on Plant Invasions. Science. 311: 1459-1461.
- Pearson D. and Y. Ortega. 2009. Managing invasive species in natural areas: moving beyond weed control. *In* Rudolph V. Kingely (editor). Weeds: Management, Economic Impacts and Biology. Nova Publishing. 195pp.
- **Pimentel, D., R. Zuniga, and D. Morrison.** 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. Ecological Economics 52: 273-288.
- **Rew L.J, B.D. Maxwell, R. Aspinall.** 2005. Predicting the occurrence of nonindigenous species using environmental and remotely sensed data. Weed Science 53:2 236-241.
- **Rejmanek, M., and M. J. Pitcairn.** 2002. When is eradication of exotic plants a realistic goal? Pages 249–253 in C. R. Veitch and M. N. Clout, editors. Turning the tide: the eradication of invasive species. IUCN SSC Invasive Species Specialist Group, IUCN [World Conservation Union], Gland Switzerland, and Cambridge, UK.
- Roberts, E., D. Cooksey and R. Sheley. 1999. Montana Noxious Weed Survey and Mapping System Weed Mapping Handbook. Bozeman, MT, Montana State University
- **Robertson, B.C. and N.J. Gemmell.** 2004. Defining eradication units to control invasive pests. J. Appl. Ecol. 41: 1042–1048.
- Shea, K., H.P. Possingham, W.W. Murdoch, and R. Roush. 2002. Active Adaptive Management in insect pest and weed control: intervention with a plan for learning. Ecological Applications. 12(3): 927-936.
- Sheley, R.L. and J. Kruger-Mangold. 2003. Principles for restoring invasive plant infested rangeland. Weed Science 51(2): 260-265.
- Stern, N. 2007. The Economics of Climate Change: The Stern Review. Cambridge University Press.

- Stohlgren T.J., K.A. Bull, Y. Otsuki, C.A. Villa, and M. Lee. 1998. Riparian areas as havens for exotic plant species in the central grasslands. Plant Ecology 138(1): 113-125.
- Svejcar, T. 2003. Applying ecological principles to wildland weed management. Weed Science 51:266-270.
- Swaidon, L., T. Drlik, and I. Woo. 1998. Integrated control of leafy spurge. IPM Practitioner 20(7):1-11.
- Tyser, R. and C. Worley. 1992. Alien Flora in Grasslands Adjacent to Road and Trail Corridors in Glacier National Park, Montana (U.S.A.). Conservation Biology. 6(2): 253-262.
- USDA National Agricultural Statistics Service. 2009. Private grazing fee rates: average rates by method of payment, Montana, USA. US Department of Agriculture, online at <a href="http://www.nass.usda.gov/Statistics\_by\_State/Montana/Publications/economic/prices/grazefee.ht">http://www.nass.usda.gov/Statistics\_by\_State/Montana/Publications/economic/prices/grazefee.ht</a> <a href="million\_m">m</a>
- **USDA Soil Conservation Service.** 1987. 1987 National Resources Inventory Montana. Unpublished survey information. Bozeman, MT.
- **US Office of Management and Budget.** 2009. Circular No. A-94: Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs. Revised December 2009. Washington, DC. Online at http://www.whitehouse.gov/omb/assets/a94/a094.pdf
- Wadsworth, R.A., Y.C. Collingham, S.G. Willis, B. Huntley, and P.E. Hulme. 2000. Simulating the spread and management of alien riparian weeds: are they out of control? Journal of Applied Ecology 37:28-38.
- With, K.A. 2002. The landscape ecology of invasive spread. Cons. Biology 16(5):1192-1203.

## Appendix 1: Example Transition Models

#### What is included in this appendix?

This appendix contains 3 example transition models representing each of the following: Transitions for base models (applied to all yellow-highlighted PVTs). Transitions for riparian models (applied to all blue-highlighted PVTs). Transitions for forested models (applied to all orange-highlighted PVTs).

Differences between these example transition models and those that will be applied to each PVT (vegetation community) are documented herein.

#### Differences between the Sample-Base model (RMF Mixed-Grass) and other base PVTs

The RMF Mixed-Grass PVT is used as the base transition model.

All other yellow highlighted PVTs use the same transitions as the 'Sample-Base' transitions with the following exceptions:

Invasion probabilities (K-Invasion, S-Invasion) were set individually by PVT and region according to the values in the

- **1** Invasion Probabilities tables below.
- 2 Biocontrol establishment probabilities were set according to the Biocontrol Establishment Probabilities table below.
- **3** Biocontrol transitions were turned off in the CV PVT transitions.
- 4 Tamegrass time to spurge escape is 6 years, not 8 years.

### Differences among the Sample-Base model, Sample-Riparian model, and Sample-Forested model

The Sample-Riparian model is the same as the Sample-Base model with the following exceptions:

- 1 Established control transitions are included in the riparian models but they were turned off (probability set to zero).
- 2 Time to spurge escape is 6 years.

The Sample-Forested model is the same as the Sample-Base model with the following exceptions:

1 Forested models have no established or biocontrol states.

<b>RMF</b> Invasion	Probabiliti	es
PVT	Spurge	Knapweed
Gravel- Riparian	0.01	0.01
Limber-Pine	0.004	0.004
Tame-Grass	0.006	0.004
Fescue	0.002	0.002
Mixed-Grass	0.002	0.002
Riparian	0.0075	0.0015
Aspen	0.0015	0.001
Roads	0.01	0.01
Conifer	0.0005	0.0005

<b>CV</b> Invasion	Probabilit	ies	MGP Invasion Pro	obabilities	
PVT	Spurge	Knapweed	PVT	Spurge	
Sagebrush	0.004	0.004	Riparian	0.0075	
Sandhill	0.003	0.003	CRP	0.004	
Riparian	0.006	0.0035	Mixed-Grass	0.0025	
Meadow	0.006	0.0025	Shrubland	0.0025	
Aspen	0.005	0.002	Badlands	0.001	
Roads	0.01	0.01	Roads	0.01	
Conifer	0.0005	0.0005	Ponderosa Pine	0.001	

Spurge Knapweed

0.005

0.004

0.002

0.003

0.001 0.01

0.001

Control Probabi	ilities	
	70%	95%
С	0.25	0.25
S1	0.45	0.7
F1	0.3	0.05
S2	0.7	0.95
F2	0.3	0.05

Biocontrol est probabilities	ablishment
RMF Limber-Pine	0.0075
RMF Riparian	0.005
RMF Gravel-Riparian	0.005
MGP Riparian	0.005
All other regions/PVTs	0.009

## Sample Base Transitions (RMF Mixed Grass)

Transition Pulo Scopario	PVT	Erom	То	Disturbanco	Probability	סוקס	Min	Max	TSD	Max	Koon	Dolton	Voorelo	A 90
TransitionRuleScenario		From StateClass	To StateClass	Disturbance Type	Probability	PZID	Min Age	Max Age	150	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Mixed-Grass	BE	BE	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BE	BI2	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BE	EE	BC-Extinction	0.01	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BE	BE	BC-Setback	0.2	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI1	BS	_C	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI1	BI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI1	BI1	_S1	0.45	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI1	EI1	BC-Extinction	0.01	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI1	BI1	BC-Setback	0.2	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI1	BI2	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI2	BI2	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI2	BI1	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI2	EI2	BC-Extinction	0.01	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI2	BI2	BC-Setback	0.2	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BI2	BE	K-Escape	1	2	2	999	6	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BS	BS	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BS	BI1	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BS	BU	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BS	ES	BC-Extinction	0.01	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BS	BS	BC-Setback	0.2	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BS	BI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BU	EU	BC-Extinction	0.01	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BU	BU	BC-Setback	0.2	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	BU	BI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EE	BE	BC-Establishment	0.009	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EE	EE	F2F2	0.09	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EE	El2	F2S2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EE	I2E	S2F2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EE	1212	S2S2	0.49	2	0	999	0	9999	FALSE	-2	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	BI1	BC-Establishment	0.009	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	ES	F2C	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	El1	F2F1	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	El1	F2S1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	El2	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	12S	S2C	0.175	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	1211	S2F1	0.21	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EI1	1211	S2S1	0.315	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	El2	BI2	BC-Establishment	0.009	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	El2	EI2	F2F2	0.09	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	El2	El1	F2S2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	El2	EE	K-Escape	1	2	2	999	6	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	El2	1212	S2F2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	El2	1211	S2S2	0.49	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	ES	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	EI1	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	EU	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	BS	BC-Establishment	0.009	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	ES	F2_	0.3	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	EI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	ES	I2S	S2_	0.7	2	0	999	0	9999	FALSE	-1	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EU	BU	BC-Establishment	0.009	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EU	EU	F2_	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EU	El1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	EU	I2U	S2_	0.7	2	0	999	0	9999	FALSE	-1	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	SE	CF2	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	SI2	CS2	0.175	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	I1E	F1F2	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	1112	F1S2	0.21	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	I1E	S1F2	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	1112	S1S2	0.315	2	0	999	0	100	FALSE	-2	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1E	I2E	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	SS	CC	0.0625	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1 1	SI1	CF1	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	SI1	CS1	0.1125	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	I1S	F1C	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	1111	F1F1	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	1111	F1S1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	1112	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	I1S	S1C	0.1125	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	1111	S1F1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	1111	S1S1	0.2025	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1111	1211	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	SI2	CF2	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	SI1	CS2	0.175	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	1112	F1F2	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	1111	F1S2	0.21	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	I1E	K-Escape	1	2	2	999	6	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	1112	S1F2	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	1111	S1S2	0.315	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1112	1212	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	I1S	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	1111	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	I1U	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	SS	C_	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	I1S	F1_	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	1111	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	I1S	S1_	0.45	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1S	I2S	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1U	SU	C_	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1U	I1U	F1_	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1U	1111	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	RelTSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1U	11U	S1_	0.45	2	0	999	0	100	FALSE	-2		FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I1U	12U	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2E	I2E	F2F2	0.09	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2E	1212	F2S2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2E	I1E	S2F2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2E	1112	S2S2	0.49	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2E	EE	S-Escape	1	2	1	999	8	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	12S	F2C	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	1211	F2F1	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	1211	F2S1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	1212	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	I1S	S2C	0.175	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	1111	S2F1	0.21	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	1111	S2S1	0.315	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1211	El1	S-Escape	1	2	1	999	8	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1212	1212	F1F2	0.09	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1212	1211	F2S2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1212	I2E	K-Escape	1	2	2	999	6	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1212	1112	S2F2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1212	1111	S2S2	0.49	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	1212	El2	S-Escape	1	2	1	999	8	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2S	12S	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2S	1211	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	12S	12U	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2S	12S	F2_	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2S	1211	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2S	I1S	S2_	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2S	ES	S-Escape	1	2	1	999	8	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2U	12U	F2_	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2U	1211	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2U	I1U	S2_	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Mixed-Grass	I2U	EU	S-Escape	1	2	1	999	8	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SE	SE	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SE	SI2	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SE	SE	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SE	I1E	R_	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SE	I1E	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SE	UE	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	SU	_C	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	SI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	SI1	_S1	0.45	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	SI1	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	SI2	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	1111	R_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	1111	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI1	UI1	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	SI2	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	SI1	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	SI2	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	SE	K-Escape	1	2	2	999	6	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	1112	R_	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	1112	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SI2	UI2	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	SU	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	SS	DD	0.81	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	SI1	DR	0.09	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	SI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	I1S	RD	0.09	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	1111	RR	0.01	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	I1S	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SS	US	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SU	SU	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZID		Max Age	TSD	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Mixed-Grass	SU	SI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SU	I1U	R_	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SU	I1U	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	SU	UU	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UE	UE	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-12-Aware-70	Mixed-Grass	UE	UI2	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UE	I1E	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI1	US	_C	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI1	UI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI1	UI1	_S1	0.45	2	0	999	0	100	FALSE	-2	-999	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI1	UI2	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI1	1111	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI2	UI2	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI2	UI1	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI2	UE	K-Escape	1	2	2	999	6	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UI2	1112	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	US	US	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	US	UI1	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	US	UU	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	US	UI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	US	I1S	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UU	UI1	K-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Mixed-Grass	UU	I1U	S-Invasion	0.002	2	0	999	0	9999	FALSE	-9999	0	FALSE

## Sample Riparian Transitions (RMF Riparian)

		From	То				Min	Ма			Keep		YearsIn	
TransitionRuleScenario	PVT	StateClas s	StateClas s	Disturbance Type	Probabilit v	PZI D	Ag e	x Age	TS D	Max TSD	RelAg e	ReITS D	ClassAd i	Age Reset
GR-Control-Off-I2-Aware-70	Riparia	BE	BE	, <u>, , , , , , , , , , , , , , , , , , </u>		2		999	0	999	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	n Riparia	BE	BE	_F2	0	2	0	999	0	9 999	FALSE	0	0	E FALS
GR-Control-Off-I2-Aware-70	n	BE	BI2	_S2	0	2	0	999	0	9	FALSE	-2	0	E
GR-Control-Off-I2-Aware-70	Riparia n	BE	EE	BC-Extinction	0.01	2	0	999	0	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BE	BE	BC-Setback	0.2	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI1	BS	_C	0.25	2	0	999	0	100	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI1	BI1	F1	0.3	2	0	999	0	100	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI1	BI1		0.45	2	0	999	0	100	FALSE	-2	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI1	El1	BC-Extinction	0.01	2	0	999	0	999 9	FALSE	-9999	0	FALS E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n Riparia	BI1	BI1	BC-Setback	0.2	2	0	999	0	9 999	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	n	BI1	BI2	K-Succession	1	2	0	999	4	9	FALSE	-9999	0	Е
GR-Control-Off-I2-Aware-70	Riparia n	BI2	BI2	_F2	0.3	2	0	999	0	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI2	BI1	_S2	0.7	2	0	999	0	999 9	FALSE	-2	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI2	El2	BC-Extinction	0.01	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI2	BI2	BC-Setback	0.2	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BI2	BE	K-Escape	1	2	2	999	6	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BS	BS	_D	0.9	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BS	BI1		0.1	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BS	BU	X	1	2	0	999	10	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BS	ES	BC-Extinction	0.01	2	0	999	0	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	BS	BS	BC-Setback	0.2	2	0	999	0	999 9	FALSE	-9999	0	FALS E

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	y	D	e	Âge	D	TSD	e	D	j	Reset
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n Dia ani a	BS	BI1	K-Invasion	0.0015	2	0	999	0	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	BU	EU	BC-Extinction	0.01	2	0	999	0	999 9	FALSE	-9999	0	FALS E
	Riparia	20	20	DO EXINOION	0.01	-	0	000	0	999	TALOL	0000	0	FALS
GR-Control-Off-I2-Aware-70	n	BU	BU	BC-Setback	0.2	2	0	999	0	9	FALSE	-9999	0	E
	Riparia						_			999				FALS
GR-Control-Off-I2-Aware-70	n Dimenie	BU	BI1	K-Invasion BC-	0.0015	2	0	999	0	9	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	Riparia n	EE	BE	Establishment	0.005	2	0	999	0	999 9	FALSE	-9999	0	FALS
	Riparia		DL	Establishintent	0.000		0	555	0	999	TALOL	-0000	0	FALS
GR-Control-Off-I2-Aware-70	n	EE	EE	F2F2	0	2	0	999	0	9	FALSE	0	0	Е
	Riparia				_		_			999		_		FALS
GR-Control-Off-I2-Aware-70	n Dia ani a	EE	El2	F2S2	0	2	0	999	0	9	FALSE	-2	0	E
GR-Control-Off-I2-Aware-70	Riparia n	EE	I2E	S2F2	0	2	0	999	0	999 9	FALSE	-2	0	FALS E
	Riparia			0212	0		0	555	0	999	TALOL		0	FALS
GR-Control-Off-I2-Aware-70	n	EE	1212	S2S2	0	2	0	999	0	9	FALSE	-2	0	E
	Riparia			BC-		_	_		_	999				FALS
GR-Control-Off-I2-Aware-70	n Dimenie	EI1	BI1	Establishment	0.005	2	0	999	0	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	EI1	ES	F2C	0	2	0	999	0	100	FALSE	-9999	0	FALS E
	Riparia		20	120	0		0	555	0	100	TALOL	-0000	0	FALS
GR-Control-Off-I2-Aware-70	n	EI1	EI1	F2F1	0	2	0	999	0	100	FALSE	0	0	E
	Riparia													FALS
GR-Control-Off-I2-Aware-70	n Dia ani a	EI1	EI1	F2S1	0	2	0	999	0	100	FALSE	-2	0	E
GR-Control-Off-I2-Aware-70	Riparia n	EI1	El2	K-Succession	1	2	0	999	4	999 9	FALSE	-9999	0	FALS E
	Riparia			T Ouccession	I	2	0	555		5	TALOL	-0000	0	FALS
GR-Control-Off-I2-Aware-70	n	EI1	I2S	S2C	0	2	0	999	0	100	FALSE	-9999	0	E
	Riparia													FALS
GR-Control-Off-I2-Aware-70	n	EI1	1211	S2F1	0	2	0	999	0	100	FALSE	-2	0	E
GR-Control-Off-I2-Aware-70	Riparia n	EI1	1211	S2S1	0	2	0	999	0	100	FALSE	-2	0	FALS E
	Riparia		1211	BC-	0	2	0	333	0	999	TALOL	-2	0	FALS
GR-Control-Off-I2-Aware-70	n	El2	BI2	Establishment	0.005	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n Dia aria	El2	El2	F2F2	0	2	0	999	0	9	FALSE	0	0	E
GR-Control-Off-I2-Aware-70	Riparia n	EI2	EI1	F2S2	0	2	0	999	0	999 9	FALSE	-2	0	FALS E
	Riparia			1 202	0	2	0	333	0	999	TALOL	-2	0	FALS
GR-Control-Off-I2-Aware-70	n	EI2	EE	K-Escape	1	2	2	999	6	9	FALSE	0	0	E

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	У	D	е	Age	D	TSD	е	D	j	Reset
GR-Control-Off-I2-Aware-70	Riparia n	EI2	1212	S2F2	0	2	0	999	0	999 9	FALSE	-2	0	FALS E
GR-Control-On-12-Aware-70	Riparia		1212	521 2	0	2	0	999	0	999	TALSE	-2	0	FALS
GR-Control-Off-I2-Aware-70	n	EI2	1211	S2S2	0	2	0	999	0	9	FALSE	-2	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	ES	ES	_D	0.9	2	0	999	0	9	FALSE	-9999	0	E
	Riparia	50		-					•	999	<b>EAL OE</b>			FALS
GR-Control-Off-I2-Aware-70	n Riparia	ES	El1	_R	0.1	2	0	999	0	9 999	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	n	ES	EU	х	1	2	0	999	10	999	FALSE	-9999	0	FALS
	Riparia	20	20	BC-	I	۷	0	555	10	999	TALOL	- 5555	0	FALS
GR-Control-Off-I2-Aware-70	n	ES	BS	Establishment	0.005	2	0	999	0	9	FALSE	-9999	0	Ē
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	ES	ES	F2_	0	2	0	999	0	9	FALSE	-9999	0	E
CD Control Off 12 Amore 70	Riparia	50	EI1	K lauration	0.0045	2	~	999	0	999		0000	0	FALS
GR-Control-Off-I2-Aware-70	n Riparia	ES	EN	K-Invasion	0.0015	2	0	999	0	9 999	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	n	ES	I2S	S2_	0	2	0	999	0	999	FALSE	-1	0	E
	Riparia			BC-						999				FALS
GR-Control-Off-I2-Aware-70	n	EU	BU	Establishment	0.005	2	0	999	0	9	FALSE	-9999	0	Е
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	EU	EU	F2_	0	2	0	999	0	9	FALSE	0	0	E
GR-Control-Off-I2-Aware-70	Riparia n	EU	EI1	K-Invasion	0.0015	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-On-12-Aware-70	Riparia	LU		R-IIIvasion	0.0013	2	0	999	0	999	TALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	n	EU	I2U	S2	0	2	0	999	0	9	FALSE	-1	0	E
	Riparia		_											FALS
GR-Control-Off-I2-Aware-70	n	I1E	SE	CF2	0	2	0	999	0	100	FALSE	-9999	0	E
	Riparia		010	000				000		100	541.05	0000		FALS
GR-Control-Off-I2-Aware-70	n Piparia	I1E	SI2	CS2	0	2	0	999	0	100	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	Riparia n	I1E	I1E	F1F2	0	2	0	999	0	100	FALSE	0	0	FALS E
	Riparia				0	<u> </u>	0	000	0	100	THEOL	0	0	FALS
GR-Control-Off-I2-Aware-70	n	I1E	1112	F1S2	0	2	0	999	0	100	FALSE	-2	0	E
	Riparia													FALS
GR-Control-Off-I2-Aware-70	n	I1E	I1E	S1F2	0	2	0	999	0	100	FALSE	-2	0	E
CD Control Off 12 Autors 70	Riparia	I1E	1112	S1S2	0	2	0	000	0	100	FALSE	-	0	FALS
GR-Control-Off-I2-Aware-70	n Riparia	TIE	1112	5152	0	2	0	999	0	999	FALSE	-2	0	E FALS
GR-Control-Off-I2-Aware-70	n	I1E	I2E	S-Succession	1	2	0	999	4	999	FALSE	-9999	0	E
	Riparia						,			J			5	FALS
GR-Control-Off-I2-Aware-70	n	1111	SS	CC	0.0625	2	0	999	0	100	FALSE	-9999	0	Е

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	y	D	e	Age	D	TSD	e	D	j	Reset
GR-Control-Off-I2-Aware-70	Riparia n	1111	SI1	CF1	0.075	2	0	999	0	100	FALSE	-9999	0	FALS E
	Riparia		_											FALS
GR-Control-Off-I2-Aware-70	n Riparia	1111	SI1	CS1	0.1125	2	0	999	0	100	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	n	1111	I1S	F1C	0.075	2	0	999	0	100	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	1111	1111	F1F1	0.09	2	0	999	0	100	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1111	1111	F1S1	0.135	2	0	999	0	100	FALSE	-2	0	FALS E
	Riparia			1101	0.100		0	000	0	999	TALOL		0	FALS
GR-Control-Off-I2-Aware-70	n Di i	1111	1112	K-Succession	1	2	0	999	4	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	1111	I1S	S1C	0.1125	2	0	999	0	100	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1111	1111	S1F1	0.135	2	0	999	0	100	FALSE	-2	0	FALS E
	Riparia			_										FALS
GR-Control-Off-I2-Aware-70	n Riparia	1111	1111	S1S1	0.2025	2	0	999	0	100 999	FALSE	-2	0	E FALS
GR-Control-Off-I2-Aware-70	n'	1111	1211	S-Succession	1	2	0	999	4	999	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	1112	SI2	CF2	0.075	2	0	999	0	100	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1112	SI1	CS2	0.175	2	0	999	0	100	FALSE	-9999	0	FALS E
	Riparia	1112		002	0.170	2	0	000	0	100	TREOL	0000		FALS
GR-Control-Off-I2-Aware-70	n	1112	1112	F1F2	0.09	2	0	999	0	100	FALSE	0	0	E
GR-Control-Off-I2-Aware-70	Riparia n	1112	1111	F1S2	0.21	2	0	999	0	100	FALSE	-2	0	FALS E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n Riparia	1112	I1E	K-Escape	1	2	2	999	6	9	FALSE	0	0	E FALS
GR-Control-Off-I2-Aware-70	n	1112	1112	S1F2	0.135	2	0	999	0	100	FALSE	-2	0	Е
GR-Control-Off-I2-Aware-70	Riparia n	1112	1111	S1S2	0.315	2	0	999	0	100	FALSE	-2	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia	1112	1212	S-Succession	1	2	0	999	4	999 9	FALSE	-9999	0	FALS E
GR-CONTOF-OIF-IZ-Aware-70	n Riparia	1112	1212	3-Succession	1	2	0	999	4	999	PALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	n	I1S	I1S	_D	0.9	2	0	999	0	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	I1S	1111	_R	0.1	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	I1S	I1U	_X	1	2	0	999	10	999 9	FALSE	-9999	0	FALS E

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	У	D	e	Age	D	TSD	e	D	j	Reset
	Riparia													FALS
GR-Control-Off-I2-Aware-70	n Dinaria	I1S	SS	C	0.25	2	0	999	0	100	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	11S	I1S	F1_	0.3	2	0	999	0	100	FALSE	0	0	FALS E
	Riparia			· · _	0.0		Ū	000		999	TREEL			FALS
GR-Control-Off-I2-Aware-70	n	I1S	1111	K-Invasion	0.0015	2	0	999	0	9	FALSE	-9999	0	Е
	Riparia			a.		-	_							FALS
GR-Control-Off-I2-Aware-70	n Dinaria	I1S	I1S	S1_	0.45	2	0	999	0	100 999	FALSE	-2	0	E
GR-Control-Off-I2-Aware-70	Riparia n	11S	12S	S-Succession	1	2	0	999	4	999	FALSE	-9999	0	FALS E
	Riparia	110	120	Ouccession	I	۷	0	555		5	TALOL	-0000	0	FALS
GR-Control-Off-I2-Aware-70	n	I1U	SU	C_	0.25	2	0	999	0	100	FALSE	-9999	0	E
	Riparia													FALS
GR-Control-Off-I2-Aware-70	n Dia aria	I1U	I1U	F1_	0.3	2	0	999	0	100	FALSE	0	0	E
GR-Control-Off-I2-Aware-70	Riparia n	I1U	1111	K-Invasion	0.0015	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-Oll-12-Aware-70	Riparia	110		IX-IIIVa3i0II	0.0013	2	0	333	0	3	TALOL	-3333	0	FALS
GR-Control-Off-I2-Aware-70	n	I1U	I1U	S1_	0.45	2	0	999	0	100	FALSE	-2	-999	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	I1U	12U	S-Succession	1	2	0	999	4	9	FALSE	-9999	0	E
CD Control Off 12 Aurora 70	Riparia	I2E	I2E	F2F2	0	2	0	000	0	999		0	0	FALS
GR-Control-Off-I2-Aware-70	n Riparia	IZE	120	ΓΖΓΖ	0	2	0	999	0	9 999	FALSE	0	0	E FALS
GR-Control-Off-I2-Aware-70	n	I2E	1212	F2S2	0	2	0	999	0	9	FALSE	-2	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	I2E	I1E	S2F2	0	2	0	999	0	9	FALSE	-2	0	E
CD Constral Off 12 Aurora 70	Riparia	105	1410	0000	0	0	~	000	0	999		0	0	FALS
GR-Control-Off-I2-Aware-70	n Riparia	I2E	1112	S2S2	0	2	0	999	0	9 999	FALSE	-2	0	E FALS
GR-Control-Off-I2-Aware-70	n	I2E	EE	S-Escape	1	2	1	999	6	999	FALSE	0	0	E
	Riparia					_								FALS
GR-Control-Off-I2-Aware-70	n	1211	I2S	F2C	0.075	2	0	999	0	100	FALSE	-9999	0	E
CD Control Off 12 August 70	Riparia	1014	1014	5054	0.00	0	0	000	0	100		0	0	FALS
GR-Control-Off-I2-Aware-70	n Riparia	1211	1211	F2F1	0.09	2	0	999	0	100	FALSE	0	0	E FALS
GR-Control-Off-I2-Aware-70	n	1211	1211	F2S1	0.135	2	0	999	0	100	FALSE	-2	0	E
	Riparia				0.150		5		5	999		_		FALS
GR-Control-Off-I2-Aware-70	n	1211	1212	K-Succession	1	2	0	999	4	9	FALSE	-9999	0	E
	Riparia	1014	14.0	000	0.475	C	0	000	0	100		0000		FALS
GR-Control-Off-I2-Aware-70	n Riparia	1211	I1S	S2C	0.175	2	0	999	0	100	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	Riparia n	1211	1111	S2F1	0.21	2	0	999	0	100	FALSE	-2	0	FALS

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	У	D	e	Age	D	TSD	e	D	j	Reset
GR-Control-Off-I2-Aware-70	Riparia n	1211	1111	S2S1	0.315	2	0	999	0	100	FALSE	-2	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1211	El1	S-Escape	1	2	1	999	6	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1212	1212	F1F2	0.09	2	0	999	0	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1212	1211	F2S2	0.21	2	0	999	0	999 9	FALSE	-2	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1212	I2E	K-Escape	1	2	2	999	6	999 9	FALSE	0	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1212	1112	S2F2	0.21	2	0	999	0	999 9	FALSE	-2	0	FALS E
GR-Control-Off-I2-Aware-70	Riparia n	1212	1111	S2S2	0.49	2	0	999	0	999 9	FALSE	-2	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	1212	El2	S-Escape	1	2	1	999	6	999 9	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	125	12S	D	0.9	2	0	999	0	999 9	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	128	1211	R	0.1	2	0	999	0	999 9	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	128	12U	X	1	2	0	999	10	999 9	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	120	 F2	0.3	2	0	999	0	999 9	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	120	K-Invasion	0.0015	2	0	999	0	999 9	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	I1S	S2	0.0013	2	0	999	0	999 9	FALSE	-2	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	ES	S-Escape	1	2	1	999	6	999 9	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	12U	F2	0.3	2	0	999	0	999 9	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	120	K-Invasion	0.0015	2	0	999	0	999 9	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	110	S2	0.7	2	0	999	0	999 9	FALSE	-2	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	120	EU	S-Escape	1	2	1	999	6	999 9	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	SE	SE	F2	0	2	0	999	0	999 9	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	Riparia n	SE	SI2	_S2	0	2	0	999	0	999 9	FALSE	-2	0	FALS E

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	У	D	е	Age	D	TSD 999	е	D	j	Reset FALS
GR-Control-Off-I2-Aware-70	Riparia n	SE	SE	D	0.9	2	0	999	0	999	FALSE	-9999	0	FALS E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SE	I1E	R_	0.1	2	0	999	0	9	FALSE	-9999	0	E
	Riparia			<b>_</b>		_	_		_	999				FALS
GR-Control-Off-I2-Aware-70	n Dinaria	SE	I1E	S-Invasion	0.0075	2	0	999	0	9 999	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	Riparia n	SE	UE	x_	1	2	0	999	10	999	FALSE	-9999	0	FALS
	Riparia	02	02	<u></u>	•	-	U	000	10	0	TALOL	0000		FALS
GR-Control-Off-I2-Aware-70	n	SI1	SU	_C	0.25	2	0	999	0	100	FALSE	-9999	0	Е
	Riparia					_	_		_					FALS
GR-Control-Off-I2-Aware-70	n Dia sais	SI1	SI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	E
GR-Control-Off-I2-Aware-70	Riparia n	SI1	SI1	S1	0.45	2	0	999	0	100	FALSE	-2	0	FALS E
	Riparia		011	_01	0.43	2	0	555	0	999	TALOL	2	0	FALS
GR-Control-Off-I2-Aware-70	n	SI1	SI1	D_	0.9	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SI1	SI2	K-Succession	1	2	0	999	4	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia	SI1	1111	Р	0.9	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-On-12-Aware-70	n Riparia	511	1111	R_	0.9	2	0	999	0	999	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	n	SI1	1111	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SI1	UI1	X_	1	2	0	999	10	9	FALSE	-9999	0	E
	Riparia	010	010	50			•		•	999	541.05			FALS
GR-Control-Off-I2-Aware-70	n Riparia	SI2	SI2	_F2	0.3	2	0	999	0	9 999	FALSE	0	0	E FALS
GR-Control-Off-I2-Aware-70	n	SI2	SI1	_S2	0.7	2	0	999	0	999	FALSE	-2	0	E
	Riparia	0.2		_02	0.1		Ū	000		999	TREEL			FALS
GR-Control-Off-I2-Aware-70	n	SI2	SI2	D_	0.9	2	0	999	0	9	FALSE	-9999	0	E
	Riparia	010								999				FALS
GR-Control-Off-I2-Aware-70	n Dinaria	SI2	SE	K-Escape	1	2	2	999	6	9	FALSE	0	0	E FALS
GR-Control-Off-I2-Aware-70	Riparia n	SI2	1112	R_	0.1	2	0	999	0	999 9	FALSE	-9999	0	FALS
	Riparia		1112	· · _	0.1	2	0	555	0	999	TALOL	0000	0	FALS
GR-Control-Off-I2-Aware-70	n	SI2	1112	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SI2	UI2	X_	1	2	0	999	10	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia n	SS	SU	_x	1	2	0	999	10	999 9	FALSE	-9999	0	FALS E
GR-Control-On-12-Aware-70	Riparia	00	30	_^	1	2	0	999	10	999	TALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	n	SS	SS	DD	0.81	2	0	999	0	9	FALSE	-9999	0	E

		From StateClas	To StateClas	Disturbance	Probabilit	PZI	Min Ag	Ma x	TS	Max	Keep RelAg	ReITS	YearsIn ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	y	D	e	Age	D	TSD	e	D	j	Reset
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SS	SI1	DR	0.09	2	0	999	0	9	FALSE	-9999	0	E
	Riparia	00	014	K have a loss	0.0045	0	0	000	•	999	FALOF	0000	0	FALS
GR-Control-Off-I2-Aware-70	n Dinaria	SS	SI1	K-Invasion	0.0015	2	0	999	0	9 999	FALSE	-9999	0	E FALS
GR-Control-Off-I2-Aware-70	Riparia n	SS	11S	RD	0.09	2	0	999	0	999	FALSE	-9999	0	FALS
	Riparia	00	110		0.00	2	0	555	0	999	TALOL	-0000	U	FALS
GR-Control-Off-I2-Aware-70	n	SS	1111	RR	0.01	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SS	I1S	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia					_	_			999				FALS
GR-Control-Off-I2-Aware-70	n Dia aria	SS	US	X_	1	2	0	999	10	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia	SU	SU	D_	0.9	2	0	999	0	999 9	FALSE	-9999	0	FALS E
GR-Control-On-12-Aware-70	n Riparia	30	30	D_	0.9	2	0	999	0	999	FALSE	-9999	0	FALS
GR-Control-Off-I2-Aware-70	n	SU	SI1	K-Invasion	0.0015	2	0	999	0	9	FALSE	-9999	0	E
	Riparia				0.0010					999				FALS
GR-Control-Off-I2-Aware-70	n	SU	I1U	R_	0.1	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	SU	I1U	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia					_	_			999				FALS
GR-Control-Off-I2-Aware-70	n Dia aria	SU	UU	X_	1	2	0	999	10	9	FALSE	-9999	0	E
GR-Control-Off-I2-Aware-70	Riparia	UE	UE	F2	0	2	0	999	0	999 9	FALSE	0	0	FALS E
GR-Control-On-12-Aware-70	n Riparia	UE	UE		0	2	0	999	0	999	FALSE	0	0	FALS
GR-Control-Off-I2-Aware-70	n	UE	UI2	_S2	0	2	0	999	0	9	FALSE	-2	0	E
	Riparia	02	0.2	_02				000		999	TALOL		<b>U</b>	FALS
GR-Control-Off-I2-Aware-70	n	UE	I1E	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia													FALS
GR-Control-Off-I2-Aware-70	n	UI1	US	_C	0.25	2	0	999	0	100	FALSE	-9999	0	E
	Riparia			= 1			-		-		EAL 05	-		FALS
GR-Control-Off-I2-Aware-70	n Dia aria	UI1	UI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	E
GR-Control-Off-I2-Aware-70	Riparia n	UI1	UI1	S1	0.45	2	0	999	0	100	FALSE	-2	-999	FALS E
GIV-CONITOF-OII-12-Aware-70	Riparia	011	011	_31	0.40	2	0	999	0	999	TALSE	-2	-999	FALS
GR-Control-Off-I2-Aware-70	n	UI1	UI2	K-Succession	1	2	0	999	4	999	FALSE	-9999	0	E
	Riparia		0.2		•	_	5	000		999	THEOL	0000	0	FALS
GR-Control-Off-I2-Aware-70	n	UI1	1111	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	UI2	UI2	_F2	0.3	2	0	999	0	9	FALSE	0	0	E
	Riparia									999		_		FALS
GR-Control-Off-I2-Aware-70	n	UI2	UI1	_S2	0.7	2	0	999	0	9	FALSE	-2	0	E

		From	То				Min	Ма			Keep		YearsIn	
		StateClas	StateClas	Disturbance	Probabilit	PZI	Ag	х	TS	Max	RelAg	ReITS	ClassAd	Age
TransitionRuleScenario	PVT	S	S	Туре	У	D	е	Age	D	TSD	е	D	j	Reset
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	UI2	UE	K-Escape	1	2	2	999	6	9	FALSE	0	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	UI2	1112	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	US	US	_D	0.9	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	US	UI1	_R	0.1	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	US	UU	_X	1	2	0	999	10	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	US	UI1	K-Invasion	0.0015	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	US	I1S	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n <sup>.</sup>	UU	UI1	K-Invasion	0.0015	2	0	999	0	9	FALSE	-9999	0	E
	Riparia									999				FALS
GR-Control-Off-I2-Aware-70	n	UU	I1U	S-Invasion	0.0075	2	0	999	0	9	FALSE	-9999	0	E

## Sample Forested Transitions (RMF Aspen)

				1										
TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZ ID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	RelTSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Aspen	1111	SS	CC	0.0625	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	SI1	CF1	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	SI1	CS1	0.1125	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	I1S	F1C	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	1111	F1F1	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	1111	F1S1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	1112	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	I1S	S1C	0.1125	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	1111	S1F1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	1111	S1S1	0.2025	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1111	1211	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	SI2	CF2	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	SI1	CS2	0.175	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	1112	F1F2	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	1111	F1S2	0.21	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	1112	S1F2	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	1111	S1S2	0.315	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1112	1212	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	I1S	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	1111	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	I1U	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	SS	C_	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	I1S	F1_	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	1111	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	I1S	S1_	0.45	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1S	I2S	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1U	SU	C_	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1U	I1U	F1_	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1U	1111	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZ ID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	RelTSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Aspen	I1U	I1U	S1_	0.45	2	0	999	0	100	FALSE	-2	-999	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I1U	I2U	S-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	I2S	F2C	0.075	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	1211	F2F1	0.09	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	1211	F2S1	0.135	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	1212	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	I1S	S2C	0.175	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	1111	S2F1	0.21	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1211	1111	S2S1	0.315	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1212	1212	F1F2	0.09	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1212	1211	F2S2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1212	1112	S2F2	0.21	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	1212	1111	S2S2	0.49	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2S	I2S	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2S	1211	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2S	I2U	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2S	I2S	F2_	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2S	1211	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2S	I1S	S2_	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2U	I2U	F2_	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2U	1211	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	I2U	I1U	S2_	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	SU	_C	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	SI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	SI1	_S1	0.45	2	0	999	0	100	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	SI1	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	SI2	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	1111	R_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	1111	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI1	UI1	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZ ID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Aspen	SI2	SI2	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI2	SI1	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI2	SI2	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI2	1112	R_	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI2	1112	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SI2	UI2	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	SU	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	SS	DD	0.81	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	SI1	DR	0.09	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	SI1	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	I1S	RD	0.09	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	1111	RR	0.01	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	I1S	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SS	US	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SU	SU	D_	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SU	SI1	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SU	I1U	R_	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SU	I1U	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	SU	UU	X_	1	2	0	999	10	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI1	US	_C	0.25	2	0	999	0	100	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI1	UI1	_F1	0.3	2	0	999	0	100	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI1	UI1	_S1	0.45	2	0	999	0	100	FALSE	-2	-999	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI1	UI2	K-Succession	1	2	0	999	4	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI1	1111	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI2	UI2	_F2	0.3	2	0	999	0	9999	FALSE	0	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI2	UI1	_S2	0.7	2	0	999	0	9999	FALSE	-2	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UI2	1112	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	US	US	_D	0.9	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	US	UI1	_R	0.1	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	US	UU	_X	1	2	0	999	10	9999	FALSE	-9999	0	FALSE

TransitionRuleScenario	PVT	From StateClass	To StateClass	Disturbance Type	Probability	PZ ID	Min Age	Max Age	TSD	Max TSD	Keep RelAge	ReITSD	YearsIn ClassAdj	Age Reset
GR-Control-Off-I2-Aware-70	Aspen	US	UI1	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	US	I1S	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UU	UI1	K-Invasion	0.001	2	0	999	0	9999	FALSE	-9999	0	FALSE
GR-Control-Off-I2-Aware-70	Aspen	UU	I1U	S-Invasion	0.0015	2	0	999	0	9999	FALSE	-9999	0	FALSE

## Appendix 2: Maps

