Positive Analysis of Invasive Species Control as a Dynamic Spatial Process

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Abstract

This paper models control of invasive buffelgrass (*Pennisetum ciliare*), a fire-prone African bunchgrass spreading rapidly across the southern Arizona desert as a spatial dynamic process. Buffelgrass spreads over a gridded landscape. Weed carrying capacity, treatment costs, and damages vary over grid cells. Damage from buffelgrass depends on its spatial distribution in relation to valued resources. We conduct positive analysis of recommended heuristic strategies for buffelgrass control, evaluating their ability to prevent weed establishment and to reduce damage indices over time. The high dimensionality of the problem makes full dynamic optimization intractable. However, two heuristic strategies – potential damage weighting and consecutive year treatment – perform well in terms of percent damage reduction relative to no treatment and to static optimization. Results also suggest specific recommendations for deployment of rapid rapid-response teams to prevent invasions in new areas. The long-run population size and spatial distribution of buffelgrass is sensitive to priority weights for protection of different resources. Land managers with different priorities may pursue quite different control strategies, which may pose a challenge for coordinating control across jurisdictions.

Keywords: invasive species, integer programming
JEL codes: Q57, Q58

Introduction

This study examines the spread and management of invasive weeds as a spatial-dynamic problem (Wilen, 2007; Smith et al. 2009;). Wilen (2007) defines this as, "some (generally biophysical) process that generates potentially predictable patterns that evolve over space and time (p. 1134)." Here, underlying dynamics of biophysical (and economic) systems have important spatial manifestations. The spatial dynamic framework is applied to answer questions about management of buffelgrass (*Pennisetum ciliare*), an invasive fire-prone African bunchgrass that is spreading rapidly across the desert landscapes of southern Arizona. Buffelgrass forms dense stands, crowding out native species, reducing species diversity, and increasing wildfire risk.

While studies of invasive species account for spatial aspects of population growth, they usually abstract from other important aspects of spatial heterogeneity. For example, they may treat control costs as independent of the terrain where invasive weeds are found or model damage as a function of the total invasive weed population, but not the location of that population. New work has begun to formally model critical spatial-dynamic relationships in the study of biological invasions. For example, Epanchin-Niell and Wilen (2009) consider how optimal control of invasive weeds is affected by landscape size, landscape shape, and where an initial invasion occurs.

We begin by introducing a general dynamic spatial model of weed invasion with multiple sources of spatial heterogeneity. Buffelgrass spreads across a gridded landscape. Each cell in the grid represents one acre of land. The potential for an invasive weed to become established, the weed's carrying capacity (maximum achievable population density), the costs of its control, and the damages it causes all can vary across the landscape. Previous work has focused on a sub-set of these features, usually treating damage as a function of total weed population. Here, we emphasize that damages caused by invasive species depend on their location relative to resources of value. Damage caused by buffelgrass in a given cell depends on the buffelgrass population density in the cell and whether valued, threatened resources are in or near that cell. A land manager's problem is to minimize damage over time, subject to budget and labor constraints. A damage index is specified as a weighted sum of damages to different resources, with weights reflecting management priorities. Buffelgrass can be treated at most once per period. So, given constraints, the manager must choose exactly which cells to treat at each time period. A numerical simulation model is developed and calibrated to replicate historical spread behavior.

Because of the high dimensionality of the problem, a full, dynamic optimal solution to the general model is not tractable. Nevertheless, the model proves useful as an organizing framework and as a way to conceptualize invasive weed control. We simplify problems to address specific questions concerning buffelgrass management.

First, we use the model to estimate labor requirements to prevent buffelgrass from becoming established in a recently invaded area. Costs of delay are evaluated in terms of growing labor requirements needed to eradicate new infestations. The National Invasive Species Council (NISC) was established by Executive Order 13112 in 1999 to improve coordination of invasive species control programs. The Council's Management Plan stresses the importance of rapid response to invasive species and calls for the used of "rapid-response teams" to control new invasions before they spread (NISC, 2001). Model results have direct implications for the staffing and deployment of rapid response teams to prevent buffelgrass establishment. They suggest (a) how large these teams should be, (b) what size of infestation they should target, and (c) the number of years follow-up treatments should continue.

Second, we conduct positive analysis of treatment recommendations from the Southern Arizona Buffelgrass Strategic Plan (Rogstad, 2008). The Strategic Plan recommended using potential-damage weighting and consecutive-year treatment rules to prioritize which areas to treat. These recommendations are specified as heuristic treatment rules and applied as integer programming problems in the spatial-dynamic framework. These heuristic rules do not represent full dynamic optimization. They do, however, optimize objective functions that account for certain dynamic relationships. These heuristic rules are evaluated in terms of their effectiveness at (a) preventing buffelgrass from becoming established in a newly invaded area and (b) reducing damage over time. Rules are evaluated in terms of damage reduction compared to no treatment and to static optimization.

Our approach is in the tradition of research comparing specific strategies for invasive species management. For example, Moody and Mack (1988) and Martin et al. (2007) compare the efficiency of targeting new, small invasive weed populations over larger, established populations. Wadsworth et al. (2000) compare random treatment with alternative strategies based on proximity to human settlements and weed population size, age, and spatial distribution. Jetter et al. (2003) estimate the benefits and costs of biological control programs and subsidies for private rangeland restoration to control Yellow Starthistle. Cacho et al. (2004) compare the net benefits of immediate eradication versus containment and no-control strategies, examining under what conditions each of the three alternatives dominate.

A limitation of our approach is that while we can identify conditions where a particular decision rule will dominate other rules, we do not identify the dynamically optimal treatment regime. That is, we identify the strategy that is best among a set of selected strategies but do not attempt to find optimal solutions. However, many optimal control or dynamic programing models of invasives species management often fail to provide specific, useful recommendations. Often, robust results are so general that they could be derived from first principles. As Wilen (2007) points out, "the more important questions seem to be where to spray, when, and at what intensity in a landscape setting (p. 1139)." The heuristic rules introduced here have the advantage of telling land managers, "treat these acres now."

One distinct advantage of our approach, is its applicability. We are able to use Excel to (a) manage data layers, (b) use cell formulae to maintain spatial and dynamic relationships, and (c) use the chart function to produce maps of costs, damages, weed population, and treatment recommendations. The ILOG CPLEX software package, a powerful tool for solving linear integer (binary) programs interfaces with Excel programs so that model solutions can be readily converted to treatment priority (and other) maps.

Buffelgrass invasion risks in southern Arizona

Buffelgrass (*Pennisetum ciliare*) is African bunchgrass originally brought to the United States for forage. It was selected for its drought hardiness, high establishment rates, and grazing tolerance (Stevens and Falk, 2009). Introduced in the 1940s, it has become invasive in southern Arizona. This region represents the northern stretches of the Sonoran Desert, home of unique species such as the giant saguaro cactus (*Carnegiea gigantean*). The Sonoran Desert ecosystem has sparse vegetation and is not fire adapted (Burquez-Montijo et al., 2002; Rogstad et al., 2009; Stevens and Falk, 2009). Buffelgrass, however, forms dense stands that crowd out native species and carry wildfire (Bowers, et al. 2006;). Evidence from Australia suggests that invasive buffelgrass can reduces biological diversity (Clarke et al., 2005; Jackson, 2005). The saguaro cactus, an iconic symbol in southern Arizona is particularly vulnerable to fire (Esque et al., 2004). Betancourt (2007) has warned that buffelgrass and other invasive perennial grasses are "rapidly transforming fireproof desert into flammable grassland." Wildfire not only threatens native species, but also poses risks to commercial and residential property bordering the desert.

A spatial dynamic model of buffelgrass management

Buffelgrass spread equations

Let $t \in \{0,\ldots,T\}$ be any year T is the entire time horizon. Define an index on the x-axis $i \in X=\{1,\ldots,I\}$ and an index on the y-axis $j \in Y=\{1,\ldots,J\}$ giving the coordinates of cell (i,j). At any time t, the pre-treatment population density of buffelgrass in a cell depends on the population density in that cell and in surrounding cells in the previous year.

(1) $N_{i,j,t} - N_{i,j,t\text{-}1} = g(N_{i,j,t\text{-}1}\ , \boldsymbol{N}_{\sim i\sim ,j,t\text{-}1}\ , K(\boldsymbol{s})_{i,j}\ )$

$N_{i,j,t}$ = pre-treatment buffelgrass population density in cell (i, j) in year t

$\boldsymbol{N}_{\sim i\sim ,j,t}$ = pre-treatment buffelgrass population density in the eight cells surrounding cell (i, j) in year t

$K(\boldsymbol{s})_{i,j}$ = carrying capacity (maximum buffelgrass population density) possible in cell (i, j)

$\boldsymbol{s}$ = vector of attributes affecting carrying capacity such as soils, altitude, climate, slope, aspect, and past land disturbance.

A cell receives propagules from plants within the cell and from neighboring cells. The rate at which a cell receives propagules from neighboring cells is governed by an exponential decay function. The function *g*() has a logistic growth form, where population grows at an increasing rate at first, then at a decreasing rate as the population approaches the carrying capacity in the cell. Growth slows as the cell becomes saturated with buffelgrass.

A numerical, biological spread model was calibrated using historical data (aerial photography, and population monitoring data) from the University of Arizona Desert Laboratory and environs laid out on a 40 x 50 acre grid. The Desert Lab on Tumamoc Hill is a 914-acre reserve west of downtown Tucson, where ecological research has been conducted for more than 100 years. The 2,000-acre study area includes the Desert Lab lands, Sentinel Peak (‘A’ Mountain) a city-managed park, other open space, and some homes. More homes, commercial real estate, and schools surround the area. Buffelgrass populations have been monitored regularly around the Desert Lab since 1983 (Bowers et al., 2006). Parameters of the numerical buffelgrass spread model were calibrated to replicate actual, historic spread behavior.

Buffelgrass treatment

The most effective means of controlling buffelgrass is treatment with the herbicide glyphosate. Buffelgrass can be manually removed using pry bars, but this method is highly labor intensive. Moreover, many sites in Arizona (including the Desert Lab) have Native American cultural resources lying below ground, limiting the extent too which removal via digging is permitted.

The decision whether to treat a cell is a discrete choice such that a cell is either treated (sprayed) or not. The treatment choice variable $x_{i,j}$ is binary, equal to 1 if cell (i,j) is treated, and 0 otherwise. The post-treatment buffelgrass population density in a cell, $n_{i,j,t}$, is

(2) $$n_{i,j,t} = N_{i,j,t} (1 - k)$$

where

k = kill rate of herbicide treatment; $k = 0.9$ if $N_{i,j,t} > \underline{N}_{i,j,t}$; $k = 1.0$ if $N_{i,j,t} \leq \underline{N}_{i,j,t}$

$\underline{N}_{i,j,t}$ = critical population, below which, it is possible to eradicate buffelgrass from a cell.

Treatment reduces the buffelgrass population by 90% in each year of treatment. Because herbicide treatment is only effective for a short time following (rare) rainfall events, we assume that cells are treated once a year, at most. Successive treatments reduce the population by 90%, based on recent data for treatment effectiveness on Tumamoc Hill. If the population falls below the minimum threshold $\underline{N}_{i,j,t}$, however, we allow for the possibility that an additional treatment can drive the population to zero in a cell.

The costs of treating a cell (i,j), $C_{i,j}$ are linearly increasing in pre-treatment buffelgrass population, average cell slope, and distance of the cell from the closest road.

(3) $$C_{i,j} = c_1 + c_2\, N_{i,j,t} + c_3\, slope_{i,j,} + c_4\, distance_{i,j,}$$

Treatment costs can vary for each cell, but the cost of treating an *individual* cell in a *given* year is constant. The cost of treating an individual cell can change, however, as pre-treatment buffelgrass population, $N_{i,j,t}$, changes. Without treatments to reduce the buffelgrass population, the cost of treating a landscape will increase over time. Treatments costs increase until they reach a maximum, where the buffelgrass population is at its carrying capacity in each cell. Cost parameters were estimated based on recent records of treatments in and around the Desert Lab.

Resource constraints

The land manager faces a budget constraint in treating buffelgrass

(4) $\sum_{i \in X} \sum_{j \in Y} C_{i,j,t}\, x_{i,j,t} \leq B_t$

where B_t is the annual control budget in time t. In reality, land managers are likely to face both a monetary budget constraint and a labor availability constraint. Volunteer labor conducts a significant amount of buffelgrass treatment. Moreover, chemical treatment is only effective at certain times of the year (not too long after rainfall) so time constraints can be as important as monetary ones.

Buffelgrass damage functions

Post-treatment damage caused by buffelgrass in a cell (i,j) depends on its density in the cell, whether there are resources that it threatens in that cell, and whether there are resources threatened in neighboring cells.

(5) $D_{i,j,t} = D_{i,j,t}\,(n_{i,j,t}\ ,\ R_{i,j,t}\ ,\ \boldsymbol{R}_{\sim i \sim ,j,t}\ )$

$D_{i,j,t}$ = damage caused by buffelgrass in cell (i,j)

$n_{i,j,t}$ = post-treatment buffelgrass population

$R_{i,j,t}$ = resource at risk in cell (i,j)

$\boldsymbol{R}_{\sim i \sim ,j,t}$ = resource at risk in cells surrounding cell (i,j)

Damage from buffelgrass follows an exponential decay pattern. Buffelgrass in the same cell as a threatened resource contributes most to damage. As a resource at risk is farther away from the buffelgrass, the buffelgrass causes less damage. Distance is measured from centroids of cells. We assume damage depends on resources in cell (i ,j) and the eight cells adjacent to it. The relevant risk factors for cell (i, j) are

$R_{i-1,j+1}$	$R_{i+1,j+1}$	$R_{i+1,j+1}$
$R_{i-1,j}$	$R_{i,j}$	$R_{i+1,j}$
$R_{i-1,j-1}$	$R_{i+1,j-1}$	$R_{i+1,j-1}$

Damage from buffelgrass depends not only on the total population of the invasive species, but also on the distribution of the species relative to resources of value throughout the landscape. There can be more than one resource at risk, so that there is a different damage function for each resource. In this paper, we focus on risks to buildings, to saguaro cactus, and to (ephemeral) riparian vegetation. Saguaros and vegetation may be threatened by crowing out from dense buffelgrass stands. Buildings, saguaros, and vegetation may all be at increased risk from wildfires.

Land manager's problem

The land manager's problem is to minimize long-term damage by choosing which cells to treat. Cells are either treated or not. The land manager's objective function is a damage index DI, which is the sum of damages caused by buffelgrass in each cell over the time horizon, T. Formally, the land manager's objective is

(8) $\min DI = \sum_{i\in X}\sum_{j\in Y}\sum_{t\in T} D_{i,j,t}$ with respect to $x_{i,j,t} \in \{0\,;1\}$ for all i, j, t

subject to equations (1) – (5)

For completeness, optimization is also subject to initial conditions at $t = 0$. The problem can be generalized further to account for multiple types of damage.

(9) $\min DI = \sum_{i\in X}\sum_{j\in Y}\sum_{t\in T}\sum_{r\in R} \rho_r D_{i,j,t}$ with respect to $x_{i,j,t} \in \{0\,;1\}$ for all i, j, t

subject to equations (1) – (5)

where r denotes different resources the manager wants to protect and ρ_r represents the relative weight placed on protecting resource r in the overall objective function.

For a 40 x 50 acre grid, the problem involves 2,000 non-linear, interrelated state equations. Full, dynamic optimization of functions (8) or (9) is not tractable. We turn, therefore, to address two problems that are tractable. First, we consider the resource requirements necessary to prevent buffelgrass from becoming established in an area. Critical issues here are the costs of delay in response to new invasions and their implications for the design of invasive species rapid-response teams. Next, we consider alternative heuristic strategies to minimize buffelgrass damage under resource constraints. The strategies are compared in terms of their ability to reduce the path of the damage index, *DI* over time.

Preventing invasive species establishment

Our first simulations consider how much labor is required to prevent buffelgrass from becoming established after it first appears in an area. A related question is how much do delays in initiating a treatment regime increase these labor requirements. We focus on labor requirements because land managers in Arizona frequently face binding labor constraints for buffelgrass control.

It is assumed that buffelgrass is initially discovered on 48 cells of the 40 x 50 acre grid (about 2.4% of cells). In this initial year (Year 0), median, mean, and maximum buffelgrass densities on infested cells are 0.2, 0.5, and 2.6 plants per square meter. The maximum density possible is about 6 plants per square meter. Next, we consider a program of most rapid local eradication (MRLE). Under MRLE, each infested cell is treated each year until the population across the entire area is driven to zero, preventing buffelgrass establishment. Labor requirements can be measured in hours or in terms of 400-hour, team-weeks. Each team-week represents a 40-hour workweek of a 10-person team.

We consider labor required for MRLE given different start years for the local eradication program, Years 1, 3, 5, 9 and 13 (Figure 1). If the local eradication program is initiated in Year 1 or 3, labor requirements are modest. Fewer than three team-weeks would be required in any single year. It takes at least six years, however, to drive the population to zero. If treatment is delayed until Year 5, then five team-weeks are needed in Year 5, with declining labor requirements in subsequent years. If treatment is delayed to Year 9, however, 15 team-weeks are needed initially. By Year 13, requirements exceed 27 team-weeks in the initial year of treatment.

Treatment on a scale of 27 team-weeks or more is likely infeasible for two reasons. First, land management agencies face budget and labor time constraints. Second, backpack spraying with glyphosate is only effective when the plants have turned green after sufficient rainfall. In Arizona's arid climate, there may simply be too few weeks in a year when glyphosate treatment is viable. The need to deploy a large numbers of laborers during a short treatment window can create "peak-load" problems for land managers.

The cumulative discounted labor cost to prevent buffelgrass establishment is shown in Figure 2. The Buffelgrass Strategic Action Plan prices labor at $18.50 per hour based on trained applicator costs (Rogstad, 2008). Figure 2 presents cumulative labor costs of MRLE assuming that costs rise at the rate of inflation and using real discount rates of 2% and 4%. If treatment begins by Year 3, total discounted costs range from $70,000 to $78,000. The treatment regime requires about 8 years, so one can think of the annualized cost of $8,000-$10,000 per year over an 8-year period. If the treatment regime begins in Year 5, cumulative costs rise up to $119,000 (or up to $15,000 on an 8-year, annualized basis). After Year 5, however, cumulative labor costs rise substantially. By Year 17, costs range from $0.4-$0.6 million.

Our results have direct implications for the staffing and deployment of rapid response teams to prevent buffelgrass establishment. They suggest (a) how large these teams should be, (b) what size of infestation they should target, and (c) the number of years follow-up treatments should continue. Our results suggest that two, 10-person rapid response teams working 3 weeks per year would be sufficient to prevent buffelgrass from becoming established in a newly infested area if (a) they began treatment within 5 years of initial infestation and (b) they continued with follow-up treatments over 6-8 years. In most years, the two teams would not have to be deployed for the full three weeks (or alternatively, smaller teams could be assembled). While costs of delay between Years 1 and 3 are small, cost of delay grow quite large beyond Year 5. This suggests that beyond Year 5, land managers need to consider shifting strategies from local eradication in an area to longer-term management and damage containment.

Heuristic decision rules with binding resource constraints

We now consider the effectiveness of heuristic decision rules in reducing different types of damage. In southern Arizona, a Buffelgrass Working Group was established through a Memorandum of Understanding between federal, state and county agencies along with private organizations. In 2008, the Working Group published a Strategic Plan, which included recommendations for coordinating and implementing buffelgrass control across jurisdictions (Rogstad, 2008). One Working Group recommendation was to, "Set and implement control priorities based on actual and *potential* impacts (page vii) (emphasis added)." Another recommendation was for land managers to "institute a minimum three-year treatment and management program (Rogstad, 2008, p. 16, 32)" to control buffelgrass.

In this section we specify how these heuristic rules are incorporated as decision rules in our dynamic spatial model. While fully dynamic optimization is not tractable, we can obtain solutions following these heuristic rules. In subsequent sections, we examine how these rules perform in terms of their ability to prevent buffelgrass establishment and in terms of reducing the long-run path of damage indices.

Rule 1 – Static optimization.

We first establish static optimization as a baseline rule. Subsequent rules may be evaluated both in terms of their performance relative to no treatment and relative to this static rule. The static optimization decision rule is lexicographical. The objective is:

1. Reduce current damage as much as possible, subject to a labor constraint.
2. If all cells generating positive, current damage are treated and labor is remaining, then treat cells to minimize buffelgrass population, subject to remaining labor availability.

We defined the damage function such that buffelgrass only causes damage if a resource of value is either in that same cell or in an adjacent cell. This leaves open the possibility that buffelgrass would not be treated if it first appeared in a cell distant from resources of value, even though it could contribute considerably to future damage. Hence, the second rule prevents acres going untreated when the labor constraint is not binding.[1] This rule is myopic. It does not consider how current treatment affects future damage or subsequent treatment costs.

In a static setting, minimizing current damage is equivalent to maximizing the reduction in current damage. The reduction in damage from treating a cell is

$$DR_{i,j,t}\, x_{i,j,t} = x_{i,t}\, [D_{i,j,t}\,(N_{i,j,t}\ ,\ R_{i,j,t}\ ,\ \boldsymbol{R}_{\sim i\sim ,j,t}\,) - D_{i,j,t}\,(n_{i,j,t}\ ,\ R_{i,j,t}\ ,\ \boldsymbol{R}_{\sim i\sim ,j,t}\,)] \tag{10}$$

where $x_{i,j,t}$ denotes the binary decision of whether to treat the cell, the left term in brackets is damage at the pre-treatment population, and the right term in brackets is post-treatment damage.

[1] An alternative would be to reduce the decay rate of the damage function so that buffelgrass damage depends on more distant cells. This increases the computational complexity of the model, however.

The first part of Rule 1 is treated as a static integer linear programming (ILP) problem. The first objective is

(11) $\max DR_1 = \sum_{i \in X} \sum_{j \in Y} DR_{i,j,t}\, x_{i,j,t}$ with respect to $x_{i,j,t} \in \{0\,;1\}$ for all i, j, t

subject to constraints (2) – (5) from the dynamic spatial model, with an additional labor constraint

(12) $\sum_{i \in X} \sum_{j \in Y} L_{i,j,t}\, x_{i,j,t} \leq \underline{L}_t$

where $\underline{L}_t$ is a labor availability constraint. Labor requirements are assumed to be linearly increasing in pre-treatment buffelgrass population, cell average slope, and cell distance from the nearest road. We assume that the labor constraint becomes binding before the monetary budget constraint does, rendering the latter redundant. Throughout the rest of the paper we focus, therefore on labor constraints. The objective is the well-known, 0-1 knapsack problem formulation (Wolsey, 1998).

The second part of Rule 1 takes effect if the damage function is maximized and the labor constraint is not binding. In this case, *current* damage is reduced to zero. Buffelgrass may remain in the landscape that is *currently* distant from resources of value. It may not contribute to the current damage index, but can increase potential future damage. Let L^*_t represent the optimal amount of labor used to maximize (11). If $L^*_t < \underline{L}_t$ then the second part of Rule 1 implies the land manager will

(13) $\min \sum_{i \in X} \sum_{j \in Y} n_{i,j,t}$ with respect to $x_{i,j,t} \in \{0\,;1\}$ for all i, j, t

subject to constraints (2) – (5) as before with a labor constraint

(14) $\sum_{i \in X} \sum_{j \in Y} l_{i,j,t}\, x_{i,j,t} \leq \underline{L}_t - L^*_t$

where $n_{i,j,t}$ is the total post-treatment buffelgrass population, $\underline{L}_t - L^*_t$ is labor left over (if any) after current damage is reduced to zero, and $l_{i,j,t}$ is application of remaining labor to treatment.

Thus, our Rule 1 might be summarized as follows. First, minimize current buffelgrass damage. Second, if damage is reduced to zero, use any remaining labor to minimize the current buffelgrass population.

Rule 2 – Potential damage weighting

Under Rule 1, cells are prioritized for treatment based on their contribution to *current* damage. Rule 2 simulates the Buffelgrass Working Group's recommendation to prioritize areas to treat "based on actual and potential impacts." Rule 2 employs potential damage weighting as a way of simulating the Buffelgrass Working Group's recommendation. Cells are prioritized for treatment based not only on their contribution to current damage, but also on their potential contribution to future damage. The maximum potential damage buffelgrass can cause in cell $D^{+}_{i,j,t}$ depends on resources of value in proximity to that cell and the buffelgrass carrying capacity $K_{i,j}$, of the cell

(15) $D^{+}_{i,j,t} = D_{i,j,t}\,(K_{i,j}, R_{i,j,t}\ , \boldsymbol{R}_{\sim i\sim,j,t}\,)$

Rule 2 is

(16) Max $DR_2 = \sum_{i \in X} \sum_{j \in Y} (wDR_{i,j} + (1 - w)\, D^{+}_{i,j,t}\,)\, x_{i,j,t}$

subject to labor and other constraints (as under Rule 1). Again, this rule is lexicographical, where the first objective is to maximize DR_2, while the second is to minimize buffelgrass population with any labor remaining after maximizing DR_2. Rule 1 is simply the special case of Rule 2, where $w = 1$. In subsequent discussion, we focus on an equal weighting scheme where $w = 0.5$.

Rule 2 prioritizes cell treatment considering (a) how much current damage buffelgrass causes and (b) the potential damage that could be caused if the population were allowed to reach its carrying capacity. Thus, cells with higher carrying capacity will receive higher priority for treatment. This rule, thus accounts for factors such as soils, aspect, elevation, or climate that affect the suitability of an area to foster buffelgrass establishment and growth. Low populations in suitable areas may cause more *future* damage than higher populations in less suitable areas. While Rule 2 is not dynamic optimization, it is forward-looking in one sense. It considers potential future damage of leaving a cell untreated.

Rule 3. Treat 3 times

This rule simulates the Buffelgrass Working Group's recommendation to treat areas in at least three consecutive years. Because of buffelgrass' logistic growth, treating a cell with a population near its carrying capacity will push the population to the fast part of its growth path. Thus, if a high population cell is treated only once, there is great scope for it to rebound the following year. Repeated treatments can push populations down to the slow portions of their growth paths and may even reduce cell populations to zero. Rule 3 is lexicographical with the following priorities:

Rule 3. Treat three times consecutively; then follow Rule 1 (static optimization)

A. Treat a cell treated in the previous two years, but not the previous three
B. Treat a cell treated for the first time the previous year
C. Follow Rule 1 above
    a. Maximize current damage reduction
    b. Minimize buffelgrass population with any remaining labor.

In the initial year, the treatment strategy under Rules 1 and 3 are identical. After that, priorities shift to emphasize repeated treatments of cells, so that cells are treated in at least three consecutive years.

Rule 4. Treat 3 times with potential damage weighting

Rule 4 combines heuristics of previous rules:

Rule 4. Treat three times consecutively, and then follow Rule 2 (potential damage weighting)

A. Treat a cell treated in the previous two years, but not in the previous three years.

B. Treat a cell treated for the first time the previous year.

C. Follow Rule 2 above:

   a. Solve problem (16) with $w = 0.5$.

   b. Minimize buffelgrass population with any remaining labor.

Solution algorithm and data management

The above formulation for maximizing the reduction of the damage caused by buffelgrass invasion is a linear, binary integer program. Such programs are usually solved by linear programming based tree search, which guarantees that the solution obtained is optimal. In the literature these tree search based algorithms are called the branch and bound methods (Nemhauser and Wolsey, 1988). Modern software packages for solving linear integer (binary) programs are well developed and highly sophisticated. In our computations we used ILOG CPLEX (2010).

ILOG CPLEX has the additional advantage of having a straightforward interface with Excel spreadsheets. Data inputs and outputs can be managed and represented in Excel, while computations can be carried out efficiently using ILOG CPLEX. Data layers for buffelgrass population, treatment costs, resources at risk, and damages are maintained as Excel worksheets. Each cell in the worksheets corresponds to a specific acre of land. Three resources-at-risk layers are measured in terms of saguaro density, presence or absence of buildings/structures, and presence or absence of ephemeral riparian vegetation. In principle, money metrics for these risk layers could be developed and applied. The interface with Excel also makes it possible to use the surface function in Excel's chart command to generate maps. Thus, land managers following heuristic decision rules could print out maps indicating which acres to treat.

Heuristic rules and local eradication

We now compare the performance of the four decision rules in terms of their scope for preventing buffelgrass establishment (achieving local eradication) under binding labor constraints. Our previous analysis of most rapid local eradication (MRLE) assumed labor supplies were unconstrained. Using our 40 x 50 acre grid and initial infestation assumption as in the MRLE problem, we consider three different damage indices, risk to buildings and structures, risk to saguaro cacti, and risk to (ephemeral) riparian vegetation. The four decision rules are applied to maximizing damage reduction to the three different resources at risk separately. We are interested in whether, given binding labor constraints, these rules can achieve local eradication.

Most rapid local eradication (MRLE) of buffelgrass was possible using no more than 1,200 hours of labor in any single year, with treatment initiated by Year 3 in the model (Figure 1). If treatment did not begin until Year 5, nearly 2,000 hours were needed in the first year, while more than 1,600 hours were needed in Years 6 and 7 and more than 1,200 hours were needed in Year 8.

Local eradication is possible using less labor than under the MRLE rule, although it takes more years to accomplish (Table 1). Under Rules 3 and 4, which call for treating infested cells a minimum of three consecutive years, local eradication is possible using no more than 800 labor hours per year, if treatment is initiated in Year 1. Under Rules 1 and 2, however, buffelgrass is eradicated when the objective is to minimize risk to saguaros, but not when attempting to reduce the other risk factors. Ironically, because minimizing saguaro risk leads to local eradication, it performs better at reducing risk to buildings or risk to vegetation than rules directly targeting those risks. This is a peculiarity (and problem) of relying on rules of thumb instead of true constrained, dynamic optimization.

If treatment is delayed until Year 5 and labor is constrained to 1,200 hours, only following Rule 4 to minimize saguaro risk leads to local eradication. If the labor constraint is relaxed to 1,600 hours, then Rules 3 and 4 (requiring three treatments) lead to eradication, while the other two, again, only lead to eradication when targeting saguaro risk. The rules requiring three treatments lead to local eradication under more cases, when labor is constrained.

Heuristic rules and damage reduction

The decision rules may also be compared in terms of their effects on long-run damage paths. Damage indexes $DI_{,\mathrm{r,t}}$ for each resource, *r* (property, saguaros, riparian vegetation) are

(17) $$DI_{,\mathrm{r,t}} = \sum_{i\in \mathrm{X}}\sum_{j\in \mathrm{Y}} D_{r,i,j,t}$$

where (17) is just the single-year value of the objective function from the full dynamic programming problem (equation (8)). The indices for each resource are scaled so that, absent any treatment, each index approaches 1,000 after 30 years. We then evaluate the four decision rules in terms of how well they reduce the path of each damage index over time, given varying labor constraints.

We can examine how well the four decision rules reduce damage indexes when treatment begins in Year 9 and labor is constrained at 400 hours (Figures 3a-b) and at 2,000 hours (Figures 4a-b). In each case, Rule 4 (combining treating 3 times with potential damage weighting) reduces the path of the damage index the most. Without treatment, the damage indexes approach 1,000 by Year 29. Simple static optimization (Rule 1) consistently performs least well. Even under static optimization, however, the terminal value of the vegetation damage index is 20% lower than under no treatment if labor is constrained to 400 hours per year. If labor expands to 2,000 hours per year, then the terminal value of the vegetation damage index is reduced 40%. Following Rule 4, however, the terminal value of the vegetation damage index falls about 33%

(80%) with 400 (2,000) labor hours per year. Under Rule 1, the terminal value of the saguaro damage index is reduced 22% (75%) with 400 (2,000) labor hours per year. Under Rule 4, the index's terminal value falls 40% (98%) with 400 (2,000) labor hours per year. Treating at least 3 times (Rule 3) or applying potential damage weighting (Rule 2) are modest improvements over static optimization. Combining both approaches (Rule 4) provides the greatest damage reduction.

Figure 5 shows how the decision rules affect risk to buildings. This index is relatively easy to reduce because structures are primarily on the periphery of the grid, while initial infestations are not close to that periphery. Protecting building, then involves maintaining a "defensible space" in front of properties. With 800 hours of labor per year, each rule reduces the terminal value of damage below 120 on a 1,000-point scale (Figure 5). Again, Rule 4 outperforms the others.

The ordering of how well each rule performed was consistent across the three resources at risk and at labor levels between 400 and 1,200 (not reported here, but available upon request). Rule 1 always resulted in the highest damage trajectory, while Rule 4 always resulted in the lowest.

Figures 6a-c illustrate how labor constraints affect damage index trajectories. Trajectories are shown when Rule 4 is applied, labor is constrained at constant annual levels, and treatment commences in Year 13. For saguaros, treatment stabilizes damages at decreasing levels as more annual labor is applied. The damage trajectories have relatively little slope after Year 20. For building damage, the damage index is driven close to zero if 800 or more hours of labor are applied annually. While buffelgrass populations near structures are kept at low levels, they are continually re-infested from untreated cells that are farther away. Thus, creating a defensive space requires modest but continuous applications of labor if sources of buffelgrass are not removed. Riparian vegetation is the most difficult resource to protect. Terminal values of the damage index are highest for every quantity of annual labor. Moreover, the trajectory of damage increases after Year 18. Why does this occur? A likely possibility is that unlike saguaros that are in more concentrated stands and structures that are concentrated on the periphery of the grid, riparian vegetation is dispersed more widely across the grid. It is more difficult to establish defensible space around this dispersed vegetation.

Resource protection priorities and long-run invasive species populations

The resources a land manager chooses to protect can have important effects on the total number and spatial distribution of the invasive species. Reducing the damage indexes is not the same as reducing the buffelgrass population. Figures 7a-c show population densities of buffelgrass in year 29, assuming treatment commences in Year 9, Rule 4 is used to control buffelgrass, and 2000 hours of labor are used annually. The objectives are to minimize damage to saguaros (7a), buildings (7b), and riparian vegetation (7c). Compare figures 7a and 7b, recalling that buildings border the northern, eastern, and southern edges of the grid. When the objective is to minimize risk to buildings, the terminal population of buffelgrass is cleared from these borders. In contrast, when the objective is to protect saguaros, buffelgrass is allowed to grow along the southern edge of the grid. However, terminal buffelgrass populations are cleared from a patch in the south-central part of the grid, where there is a large stand of saguaros.

Figures 7a-c also illustrate that the long-run populations of invasive species can be quite sensitive to the choice of weights in a multi-attribute damage index. For policy makers, this means that the choice of weights is not an innocuous assumption. The approach used here can be used to develop maps illustrating the consequences of different weighting schemes. The figures also illustrate what could happen if different agents have different priorities in damage reduction. For example, private homeowners or the city government may care about protecting buildings and structures, while federal land agencies may have mandates to protect endangered species. Different land managers may treat acres quite differently. This may pose challenges for coordinating control across jurisdictions.

Conclusions

This paper developed a general spatial dynamic model of invasive weed spread and management and applied it to address questions about management of buffelgrass in southern Arizona. A numerical simulation model was developed and calibrated to match historic buffelgrass spread, treatment effectiveness, and treatment cost data. Although full dynamic optimization of the model proved intractable, we were nevertheless able to solve simplified problems to address policy relevant questions.

First, the National Invasive Species Council's Management Plan (NISC, 2001) calls for "rapid-response teams" to control new invasions before they spread. Our first simulations quantified labor requirements needed for such teams to prevent new buffelgrass establishment. The also illustrated how requirements increase with delay of program initiation. Results quantified how large response teams need to be (b) what size of infestation they should target, and (c) the number of years that follow-up treatments should continue in order for team efforts to be effective. The approach developed here is readily applicable to rapid response to other invasive species.

Next, we evaluated two control recommendations – potential-damage weighting and consecutive-year treatment rules – from the Southern Arizona Buffelgrass Strategic Plan (Rogstad, 2008). These recommendations were modeled as heuristic treatment rules solved as special-case integer programming problems in the spatial-dynamic framework. Applying these rules together increased scope for preventing buffelgrass establishment under resource constraints. They also, reduced paths of buffelgrass damage substantially, both relative to the no-treatment option and relative to static optimization.

Third, the long-run population size and spatial distribution of buffelgrass is sensitive to priority weights for protection of different resources. Land managers with different priorities may pursue quite different control strategies, which may pose a challenge for coordinating control across jurisdictions. A possible of extension of work presented here would be to consider problems of coordination between land managers with different priorities for buffelgrass control. Work by Grimsrud et al. (2008) suggests that such multi-agent problems can provide important insights concerning invasive species control.

While the simulations show heuristic rules can be a significant improvement over static optimization, static optimization is a lower bound of performance. The key question is, "how far are these heuristic rules from full, dynamic optimization?" Our ongoing research seeks to answer this important question. A weakness of many invasive species optimal control models is their failure to provide specific, useful recommendations. If these heuristic rules are good approximations of the dynamic optimum, this means easy-to-determine treatment strategies can be effective. If, however, these rules are not good approximations to the optimal solution, this is also important to know. If not, one could explore under what conditions they are or are not reasonable approximations. This could lead to other rules of thumb that are still easy to implement, but close to optimal.

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Table 1. Occurrence of eradication depending on labor constraints, treatment starting year, and decision rule followed

	Rule 1 Static Optimization	Rule 2 Potential Damage Weighting	Rule 3 Treat 3x	Rule 4 Treat 3x + Potential Damage Weighting
Labor = 800; Start Year = 1				
Vegetation Risk	no	no	yes	yes
Building Risk	no	no	yes	yes
Saguaro Risk	yes	yes	yes	yes
Labor = 1200; Start Year = 5				
Vegetation Risk	no	no	no	no
Building Risk	no	no	no	no
Saguaro Risk	no	no	no	yes
Labor = 1600; Start Year = 5				
Vegetation Risk	no	no	yes	yes
Building Risk	no	no	yes	yes
Saguaro Risk	yes	yes	yes	yes

Figure 1. Annual labor requirements (400-hr. work teams) to prevent buffelgrass establishment, by year of control initiation

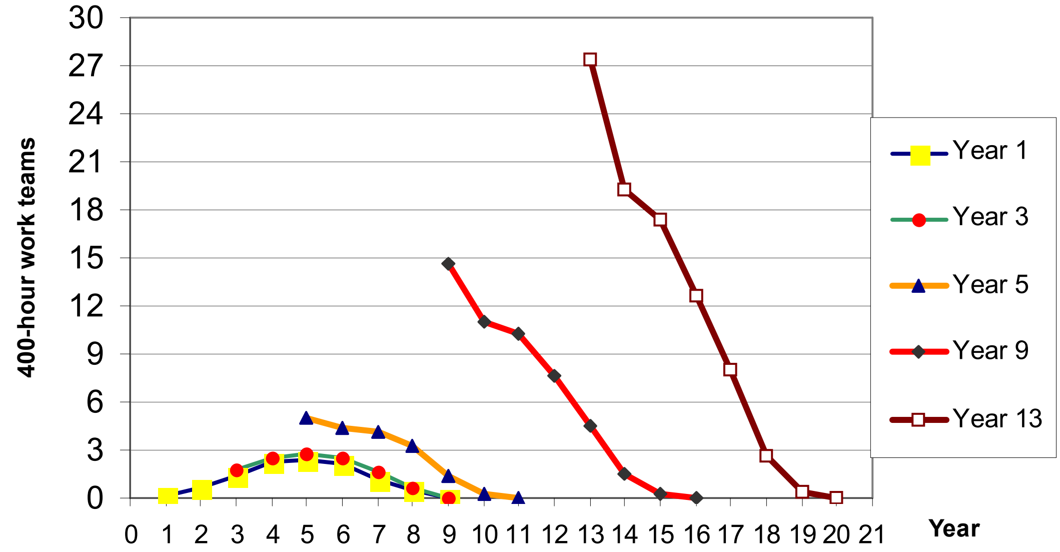
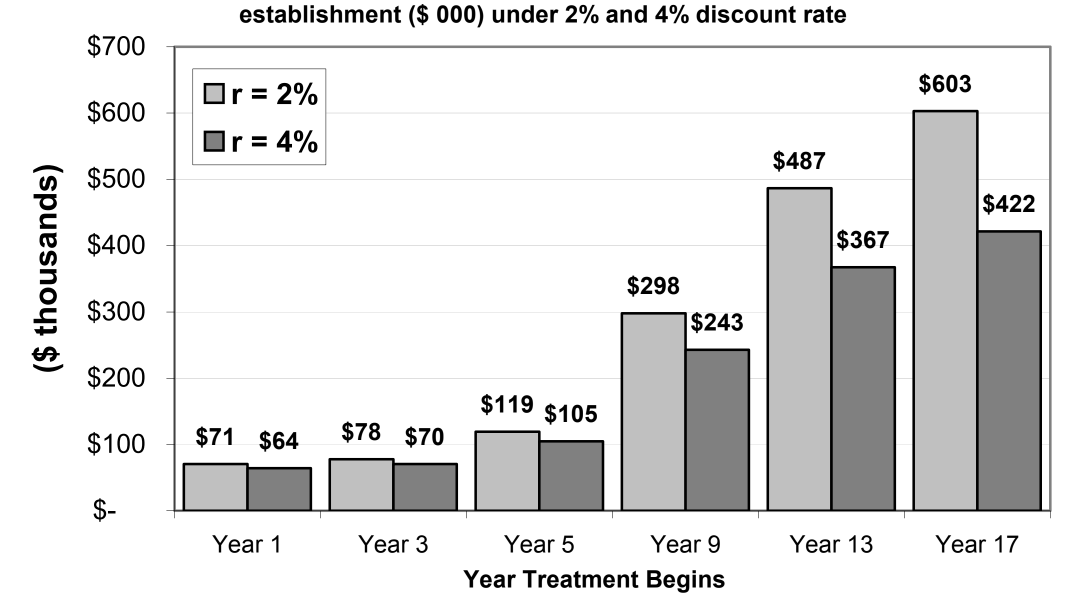


Figure 2. Discounted cumulative labor costs to prevent buffelgrass establishment ($ 000) under 2% and 4% discount rate



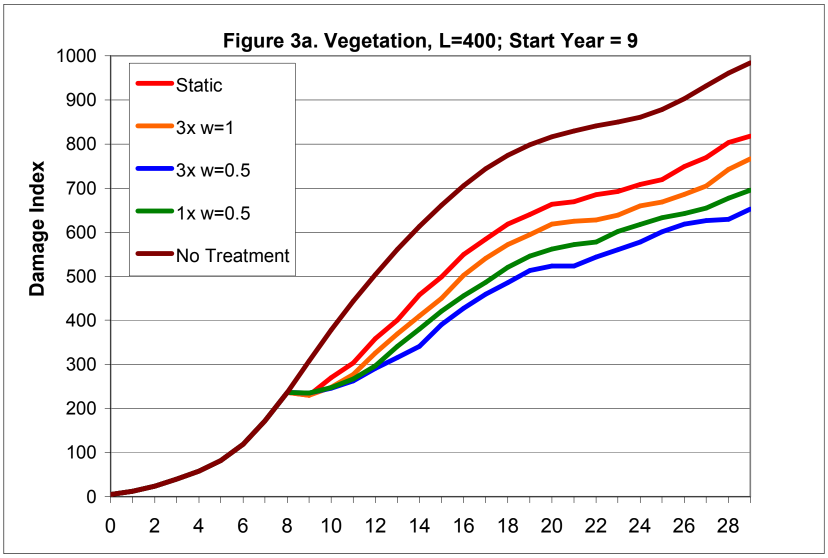


Figure 3a. Vegetation, L=400; Start Year = 9
Damage Index
Static
3x w=1
3x w=0.5
1x w=0.5
No Treatment
0
100
200
300
400
500
600
700
800
900
1000
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28

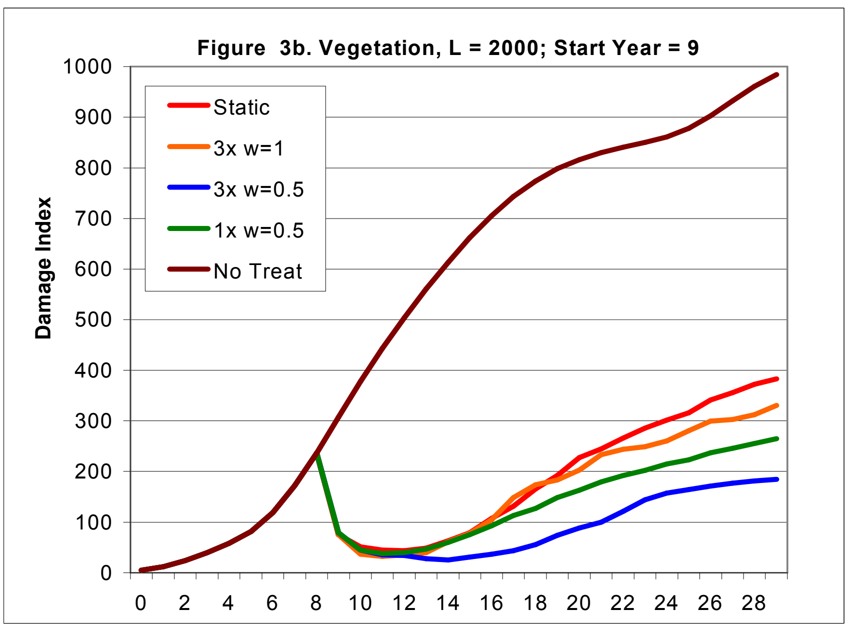


Figure 3b. Vegetation, L = 2000; Start Year = 9
Damage Index
Static
3x w=1
3x w=0.5
1x w=0.5
No Treat
0
100
200
300
400
500
600
700
800
900
1000
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28

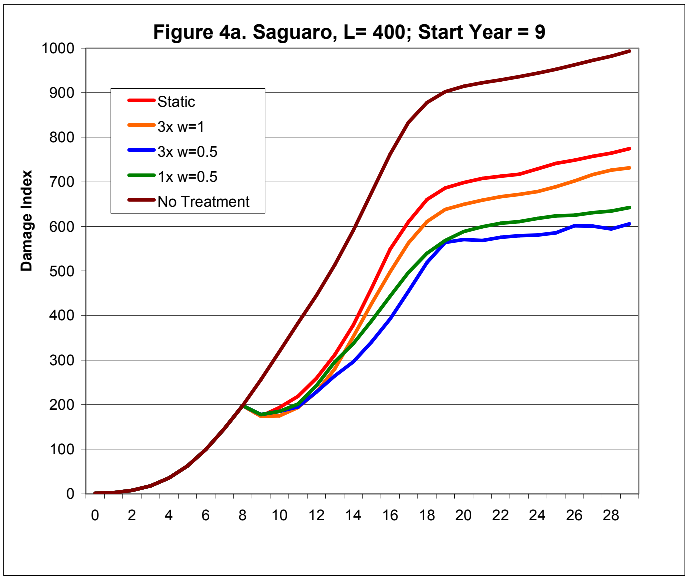


Figure 4a. Saguaro, L= 400; Start Year = 9
Damage Index
Static
3x w=1
3x w=0.5
1x w=0.5
No Treatment
1000
900
800
700
600
500
400
300
200
100
0
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28

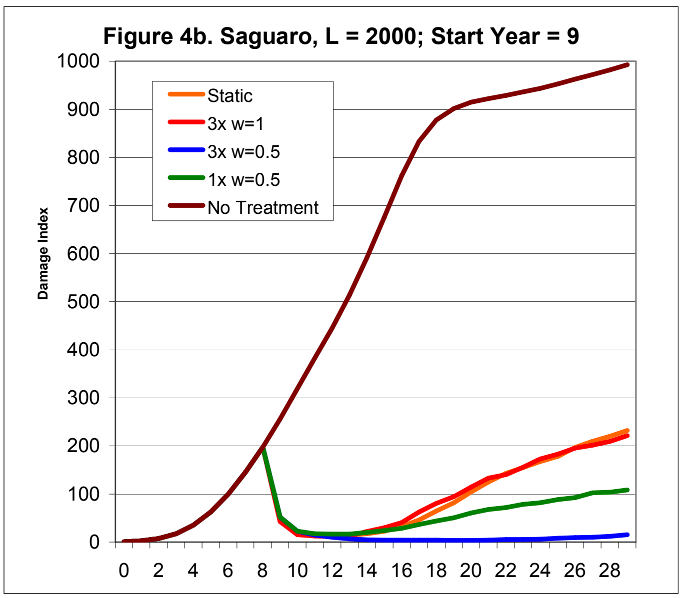


Figure 4b. Saguaro, L = 2000; Start Year = 9
Damage Index
Static
3x w=1
3x w=0.5
1x w=0.5
No Treatment
1000
900
800
700
600
500
400
300
200
100
0
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28

Figure 5. Buildings, L = 800, Start Year = 9

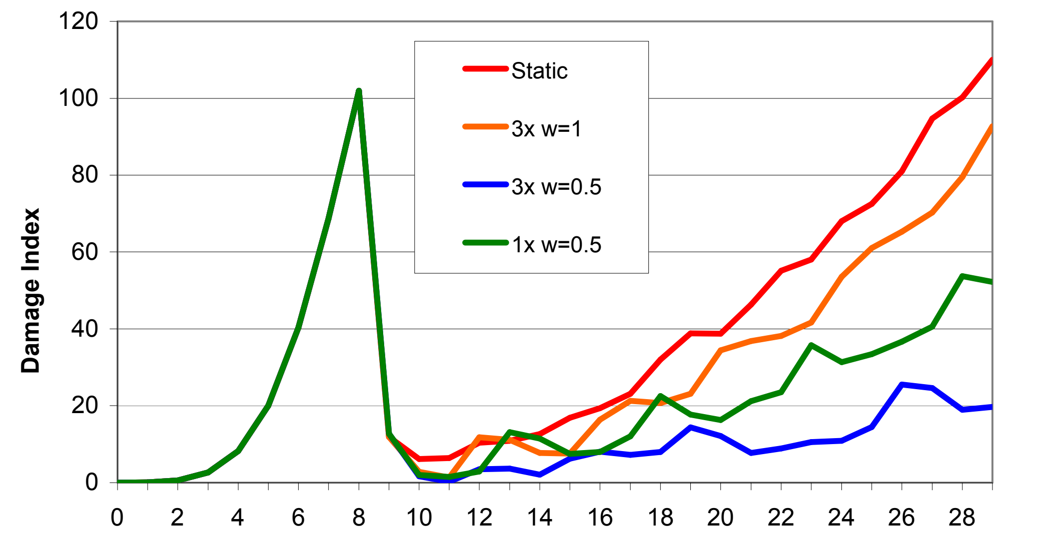
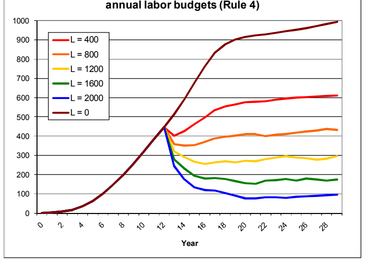


Figure 6a. Saguaro Damage Function with different annual labor budgets (Rule 4)



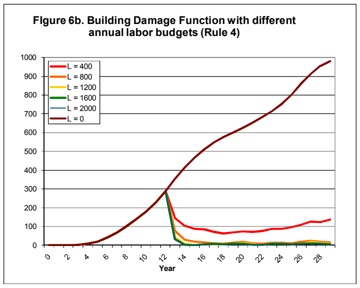


Figure 6b. Building Damage Function with different annual labor budgets (Rule 4)

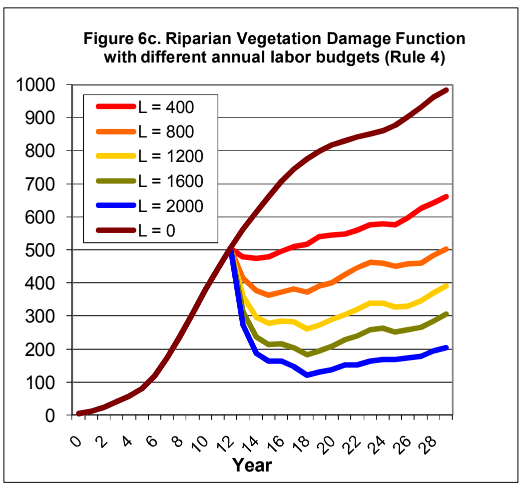


Figure 6c. Riparian Vegetation Damage Function with different annual labor budgets (Rule 4)

Figure 7a. Buffelgrass population in year 29 with objective to protect saguaro cacti

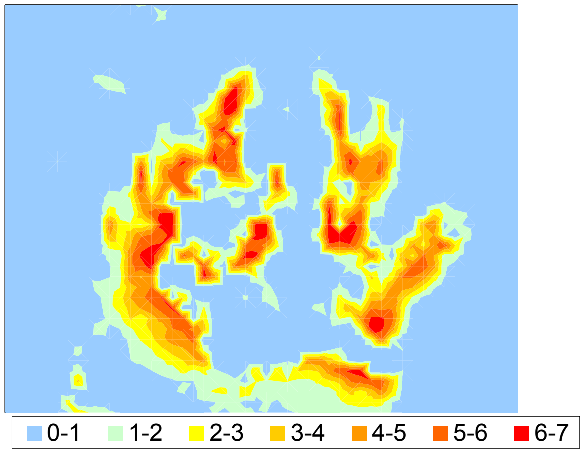


Figure 7b. Buffelgrass population in year 29 with objective to protect buildings

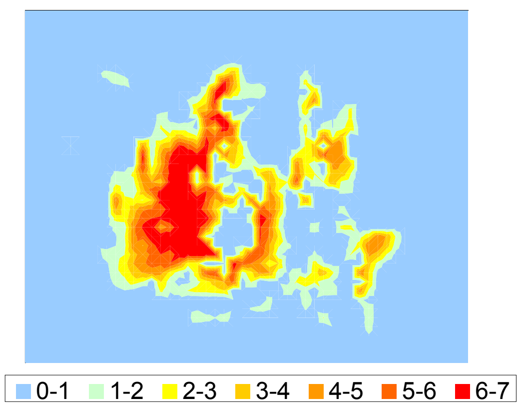


Figure 7c. Buffelgrass population in year 29 with objective to protect riparian vegetation