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Source: Invasive Plant Science and Management, 6(1):36-47. 2013.
Published By: Weed Science Society of America
DOI: http://dx.doi.org/10.1614/IPSM-D-11-00065.1
URL: http://www.bioone.org/doi/full/10.1614/IPSM-D-11-00065.1

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Buffelgrass, a highly competitive and flammable African bunchgrass, is spreading rapidly across both urban and natural areas in the Sonoran Desert of southern and central Arizona. Damages include increased fire risk, losses in biodiversity, and diminished revenues and quality of life. Feasibility of sustained and successful mitigation will depend heavily on rates of spread, treatment capacity, and cost–benefit analysis. We created a decision support model for the wildland–urban interface north of Tucson, AZ, using a spatial state-and-transition simulation modeling framework, the Tool for Exploratory Landscape Scenario Analyses. We addressed the issues of undetected invasions, identifying potentially suitable habitat and calibrating spread rates, while answering questions about how to allocate resources among inventory, treatment, and maintenance. Inputs to the model include a state-and-transition simulation model to describe the succession and control of buffelgrass, a habitat suitability model, management planning zones, spread vectors, estimated dispersal kernels for buffelgrass, and maps of current distribution. Our spatial simulations showed that without treatment, buffelgrass infestations that started with as little as 80 ha (198 ac) could grow to more than 6,000 ha by the year 2060. In contrast, applying unlimited management resources could limit 2060 infestation levels to approximately 50 ha. The application of sufficient resources toward inventory is important because undetected patches of buffelgrass will tend to grow exponentially. In our simulations, areas affected by buffelgrass may increase substantially over the next 50 yr, but a large, upfront investment in buffelgrass control could reduce the infested area and overall management costs.

**Nomenclature:** Buffelgrass, *Pennisetum ciliare* (L.) Link.

**Key words:** Buffelgrass, Southern Arizona Buffelgrass Coordination Center, SABCC, decision support tools, Tool for Exploratory Landscape Scenario Analyses (TELSA), maxent, inventory, EDRR.

In a process analogous to triage, land managers need guidance on how best to allocate limited resources in managing invasive plants across species, space, and time (Eiswerth and van Kooten 2002; Leung et al. 2002). These kinds of decisions often need to be made with limited information about the location and degree of infestations, their spread rate, and the cost and effectiveness of alternative management actions (Frid and Wilmshurst 2009). Collecting information to reduce these uncertainties can improve the effectiveness of management; however, there is a cost associated with gathering this information. This tradeoff between allocating resources toward the treatment of established infestations vs. gathering information is not always taken into consideration.

An example of the tradeoff between allocating resources toward management actions vs. gathering information is the implementation of early detection and rapid response strategies (EDRR) (Maxwell et al. 2009). By definition, EDRR requires that land managers allocate time and resources to gather information by conducting inventory

DOI: 10.1614/IPSM-D-11-00065.1

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## Management Implications

Knowledge of where invasive species occur is often slim to nonexistent. In the face of this imperfect knowledge, land managers are still required to determine where to allocate their limited resources. Using a decision support model such as TELSA allows land managers to make a more informed decision on where to allocate funding. We addressed this imperfect knowledge in three ways. First, we acknowledged that there were many undetected buffelgrass plants on the landscape by stochastically adding and growing patches across the landscape throughout a 50-yr simulation. This is a way to see how populations that are not detected grow over time. We also developed a map of potentially suitable habitat to predict the future spread of buffelgrass patches. Finally, we calibrated spread rates by comparing past and current aerial photographs with simulation outputs. We found that areas invaded by buffelgrass may increase substantially over the next 50 yr, but that a large, upfront investment in buffelgrass control could reduce that area and overall management costs. The application of sufficient resources toward inventory is important because patches that remain undetected will tend to grow exponentially and, when eventually detected, will require substantially higher treatment efforts to control.

surveys to detect new infestations. In doing so, they forego the opportunity to allocate these resources toward treatment of detected infestations. There is consensus that detecting and treating nascent foci is usually most effective (Moody and Mack 1998). However, land managers often are inclined to focus resources on well-established infestations because performance measures are based on acres treated, and inventory surveys that fail to detect new infestations are often considered failures. Land managers require tools to evaluate the allocation of limited monetary and vocational resources between direct management actions and the gathering of information. These tools must demonstrate the value, if any, of investments made in gathering information.

Simulation models are a useful tool to explore alternative ways to allocate resources between management actions and information gathering. Various models exist that consider resource allocation strategies for invasive plant management (Frid and Wilmshurst 2009; Higgins et al. 2000; Provencher et al. 2007; Wadsworth et al. 2000). Some of these models consider the cost of gathering information on the occurrence and location of infestations (Regan et al. 2006), but few do so in a spatially explicit context (Maxwell et al. 2009). State-and-transition simulation models (STSMs), sometimes referred to as Markov process models, have been widely used to evaluate alternative land management scenarios (Forbis et al. 2006; Frid and Wilmshurst 2009; Hemstrom et al. 2007; Strand et al. 2009). These models are relatively simple and can be applied to different ecosystems and management questions. At their most basic, STSMs require that possible vegetation states for locations of interest be defined along with the transitions that can move that location from one state to another (Westoby et al. 1989). Transitions can occur either probabilistically each time step or deterministically with the passage of a specified time period. STSMs can either be nonspatial or spatially explicit.

One of the challenges of modeling the spread and control of invasive plants using STSMs is that there is often "imperfect detection" of the invader on the landscape. Searching for undetected infestations is costly and managers rarely are able to survey every location on the landscape to determine where an invader occurs. Even for locations that are surveyed, these efforts may fail to detect the invader when it is present at low densities. Regan et al. (2011) developed a nonspatial Markov process model that explicitly takes into account "imperfect detection" regarding the occurrence of an invasive plant at a specific location. This model is useful for making decisions about the allocation of management resources on a location-specific basis but, because of its nonspatial nature, it can not be applied to decision making at the landscape scale. A similar approach could be taken using a spatially explicit STSM to inform decisions about the allocation of management resources between treatments and information gathering at the landscape scale. With this type of model, land managers could address such questions as (1) what proportion of the overall budget for the landscape should be spent on surveying vs. treatment and (2) where the highest priority areas for these activities are located on the landscape.

One of the key challenges to developing a model to support management decisions is obtaining the data necessary to parameterize the model. STSMs often rely on expert opinion for parameterization (Czembor and Vesk 2009) and this can lead to greater uncertainty in predictions when compared to models that rely on empirical data alone (Czembor et al. 2011). Two key inputs often used to parameterize STSMs are the rates of spread of invasive plants across the landscape and the habitat suitability of different locations on the landscape for the invasive plant being examined (Frid and Wilmshurst 2009). Ideally, a spatial time series depicting the extent of invasion at different points in time is required to accurately parameterize spread rates. Recent methodologies developed using remote sensing and aerial photography provide tools to obtain this type of information (Browning et al. 2009; Franklin et al. 2006; Huang and Asner 2009; Lonsdale 1993). Recent developments in the field of envelope modeling (Evangelista et al. 2008; Hijmans and Graham 2006; Hirzel and Arlettaz 2003; Jarnevich and Reynolds 2010) also provide opportunities to integrate such modeling techniques with STSMs, thereby reducing the need to rely on expert opinion to define a map of habitat suitability (see Frid and Wilmshurst 2009).

In this study we developed a STSM for buffelgrass [*Pennisetum ciliare* (L.) Link, synonymous with *Cenchrus ciliaris*], a bunchgrass native to subtropical and tropical

Africa and western Asia and invasive in Australia and the Americas (Marshall et al. 2011). Buffelgrass poses a problem in the warm, summer-wet deserts of North America by growing in dense stands and introducing a novel wildfire risk in vegetation not adapted to fire. Such invasions have introduced fine fuels and fire to desert shrublands that did not experience frequent or extensive wildfires until recently (Brooks 2008; Brooks et al. 2004; Schmid and Rogers 1988). Buffelgrass can also crowd out native plants (Morales-Romero and Molina-Freaner 2008; Stevens and Fehmi 2009), reduce primary productivity (Franklin et al. 2006), and negatively affect habitats of iconic native species, including giant columnar cacti such as saguaro (*Carnegiea gigantea* (Engelm.) Britton & Rose) (Esque et al. 2004) and the desert tortoise (*Gopherus agassizii* Cooper) (Esque et al. 2002). Following the classic grass fire cycle (Brooks et al. 2004; D'Antonio and Vitousek 1992), fires in buffelgrass stands will likely allow for even more vigorous growth of subsequent buffelgrass; native plants are killed by the heat of the fire, whereas buffelgrass resprouts quickly or rapidly colonizes by seed newly disturbed habitat (Miller et al. 2010). Even without fire, buffelgrass can eliminate native species through competition for space, water, and nutrients (Olsson et al. 2012b). Given the urgency of the situation, land managers need to make fast decisions about how to best allocate funds and effort to prevent further buffelgrass spread. This is a difficult process when there is a paucity of information about the rate of spread and distribution of buffelgrass across different habitats and jurisdictions, as well as about the effectiveness of management actions.

We used the Tool for Exploratory Landscape Scenario Analyses (TELSA, Version 3.6, ESSA Technologies Ltd. 2008) to simulate a spatially explicit STSM of buffelgrass spread and control on the south slope of the Santa Catalina Mountains on the outskirts of Tucson, AZ, a growing metropolis of nearly one million people. TELSA is a framework for developing spatially explicit STSMs. TELSA has been used to simulate the spread and control of other invasive plant species including cheatgrass (*Bromus tectorum* L.) in the Great Basin (Provencher et al. 2007), knapweed (*Centaurea stoebe* L.) and leafy spurge (*Euphorbia esula* L.) in Montana (Frid et al. 2013) and crested wheatgrass [*Agropyron cristatum* (L.) Gaertn.] in Grasslands National Park of Canada (Frid and Wilmshurst 2009). The algorithms that simulate invasive plant dynamics on the landscape are described in detail in the above publications. The spatial domain encompasses undeveloped natural areas owned and managed by Coronado National Forest (CNF) and adjacent subdivisions and resorts. Our model explicitly accounts for resource allocation tradeoffs between treatment of established patches and information gathering about the location of previously undetected infestations.

We calibrated the spatial spread of our invader with historical reconstruction of buffelgrass spread based on aerial photographs (Olsson et al. 2012a). Aerial photography is frequently used to map invasive species and reconstruct historical distributions of species (Browning et al. 2009; Franklin et al. 2006; Huang and Asner 2009; Lonsdale 1993), although discrimination among individual species is dependent on image quality, phenology, and physical characteristics of the species that may distinguish infested from uninvaded areas. Lonsdale (1993), for example, utilized historical photography of different spatial extents and resolutions to reconstruct *Mimosa pigra* L. spread in Australia during the 1980s. Browning et al. (2009) compared digitized canopy cover of *Prosopis glandulosa* Torr. in 1936 aerial photographs (digitized at 1-m spatial resolution) with field-based measurements from 1932 and found that *P. glandulosa* canopies $< 2.9$ m$^2$ (31.2 ft$^2$) were not consistently identified in aerial photographs. Huang and Asner (2009) point out that timing of image acquisition may also have a profound effect on the ability to distinguish between invasive and other cover.

Our objectives for this study were to (1) develop a STSM that explicitly considers "imperfect detection" when information about the occurrence of invasive plants on the landscape is incomplete, (2) develop a methodology that uses detailed aerial photography to calibrate the spread of invasive plants in a STSM, (3) integrate the quantitative envelope-based habitat suitability models to define habitat suitability and its influence on the spread probability for invasive plants in a STSM, and (4) apply the STSM developed through objectives 1 through 3 to evaluate alternative management scenarios for buffelgrass in the Santa Catalina Mountains.

## Materials and Methods

**Study Area.** The 46,000-ha (113,666 ac) study area (32.32°N, 110.75°W), is located on the lower southern slopes of the Santa Catalina Mountains in southern Arizona, just north of the city of Tucson (Figure 1). The dominant habitat is typical of the Arizona Upland (Turner and Brown 1994). The sparse (25 to 35%) canopy cover is dominated by palo verde (*Parkinsonia microphylla* Torr.), brittlebush (*Encelia farinosa* Torr. & A. Gray), the iconic saguaro cactus [*Carnegiea gigantea* (Engelm.) Britton & Rose], and numerous other trees, shrubs, cacti, grasses, and forbs (Turner and Brown 1994). This south slope of the Santa Catalina Mountains was selected for a number of reasons. First, this sector is one of the most visible and valued natural landscapes in southern Arizona, and buffelgrass invasion here poses novel fire risks to adjacent forest lands and subdivisions. Second, buffelgrass invasion has accelerated in this sector since the mid-1980s, but

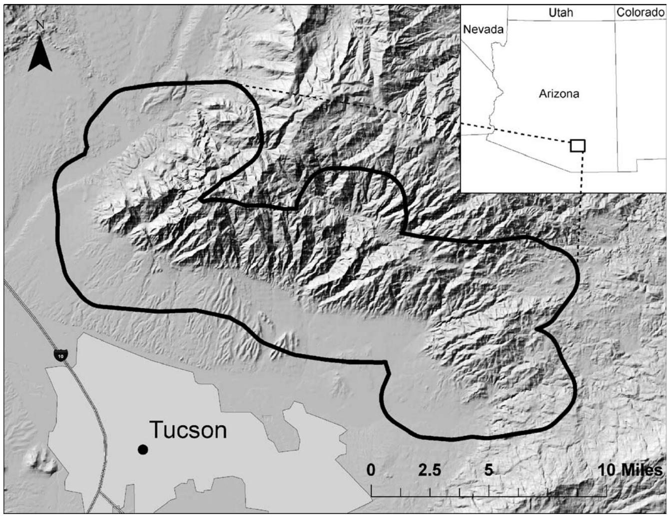


Figure 1. A map showing the study area boundary for the Santa Catalina Mountains north of Tucson.

efforts to control the spread on CNF only started in the past 2 yr and thus can still be heavily influenced by decision support models. Third, a rich data set was available for the region, comprising remotely sensed and field surveys (Olsson et al. 2012a). This readily available information helped with the process of initializing and calibrating the simulation model.

**Adding States to Account for Imperfect Detection.** Following previous work with TELSA (Frid and Wilmshurst 2009), the dynamics of buffelgrass spread, inventory, and management within any given polygon are represented with an STSM. To account for imperfect detections in this study, we used a similar approach to Regan (2011), in which modeled states represent both the state of the vegetation at a location and the accuracy of the information available to managers about that location. The STSM categorizes each polygon dynamically over time based on both the presence and abundance of buffelgrass and on whether the buffelgrass has been detected. The STSM has a total of eight possible states represented by five possible cover classes (absent, seedbank only, $< 5\%$, 5 to 50%, $> 50\%$) and by whether the presence of live plants has been detected by managers (Figure 2). These cover classes were defined based on discussions with buffelgrass managers and the rationale for these breakpoints was based on changes in the success of inventory and treatments. In areas of moderately suitable habitat (defined below) we exclude the $> 50\%$ cover classes and, in areas with low-suitability habitat, we exclude cover classes with $> 5\%$ buffelgrass cover.

**The Use of Historic Air Photos to Calibrate the Spread Rate Used in the Simulation Modeling.** Olsson et al. (2012a) reconstructed buffelgrass spread at 11 sites in the Santa Catalinas using historical aerial photographs with a spatial resolution varying between 0.25 and 1 m (3.28 ft) and found populations doubling approximately every 2.66 to 7.04 yr. We identified the three sites with the longest and most complete time series of data to calibrate our spatially explicit spread model. Each of the three sites had photos from at least eight dates dating back to 1988, 1994, and 1980, respectively, and represented the 5th, 6th, and 11th largest populations of the 11 sites. These sites range in infestation area from 0.39 to 2.46 ha for the 2006 survey year, up from their initial infestation areas of 0.02 to 0.13 ha. Additionally, reconstructed spread indicates these three populations have been doubling approximately every 3.04, 4.23, and 6.01 yr. We simulated spread using TELSA at each of the three sites for the equivalent time period of record (e.g., 1988 to 2006 for site 1, 1994 to 2008 for site 2, and 1980 to 2008 for site 3) and the area invaded was compared with the reconstructed area at three benchmark years.

We selected a probability distribution of spread distances (Weibull, scale 0.2, shape 0.5) for which the modeled spread of buffelgrass closely matches the aerial photography for the study area. Figure 3 depicts a spatial comparison of simulated and actual buffelgrass spread for these sites; each row in the figure represents a calibration site. Figure 4 shows the actual area invaded by buffelgrass pooled across the three sites and compared against the simulated area in the calibration. Calibration simulations were run using TELSA, which carves the landscape into tessellated polygons. In this study, the landscape was divided into 70,073 tessellated polygons ranging in size from 3 $m^2$ to 20,502 $m^2$ (2 ha) with a mean of 6,577 $m^2$ (0.66 ha) and standard deviation of 3,842 $m^2$. To calculate the area invaded by buffelgrass in the simulations, we assume that on average, polygons in the 0 to 5% cover class have 2.5% of their area invaded, polygons in the 5 to 50% cover class have 25% of their area invaded, and polygons in the $> 50\%$ cover class have 75% of their area invaded.

**Using Quantitative Methods to Produce Habitat Suitability Maps.** A key input required in our simulation is a map of buffelgrass habitat suitability for the study area. We developed this habitat suitability map using maximum entropy modeling (Maxent, Princeton University, Department of Computer Science, Princeton NJ, v. 3.3.1) (Phillips et al. 2006). Maximum entropy modeling is a presence-only machine learning method. This algorithm estimates potential habitat distribution by finding the distribution of maximum entropy, or that farthest from random (Phillips et al. 2006). Maxent uses background data, or the environmental layers as model inputs (Hijmans and Graham 2006). The background layers used were gathered from the National Elevation Dataset (Gesch 2007; Gesch et al. 2002). We used elevation at approximately 30 $m^2$

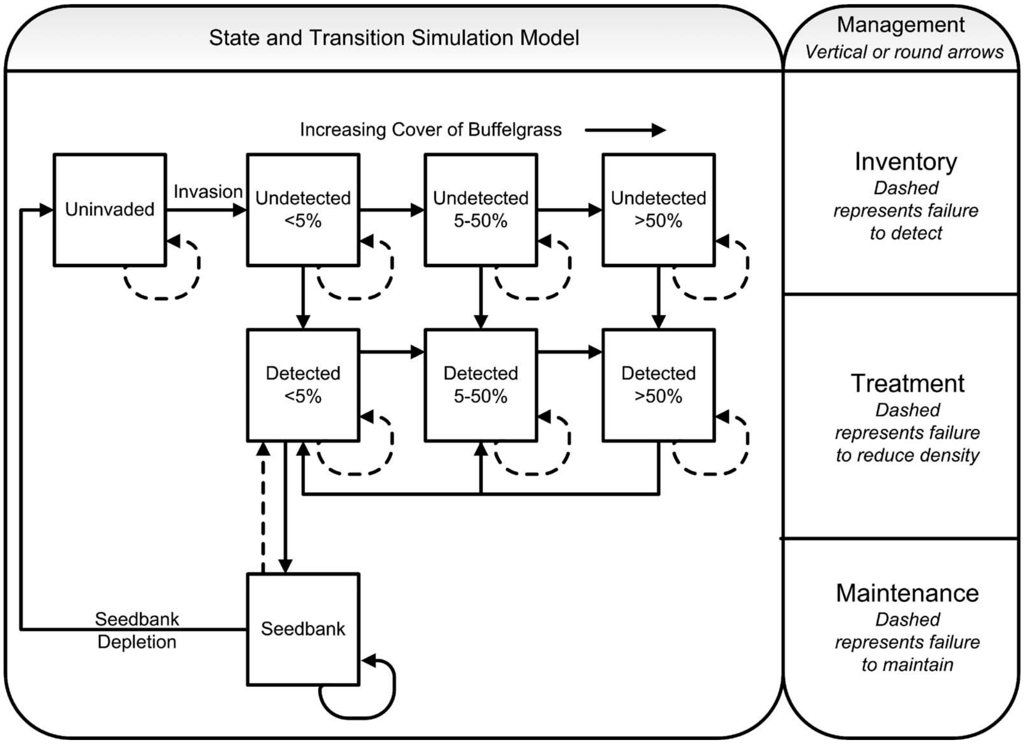


Figure 2. State-and-transition simulation model for buffelgrass succession, detection, treatment, and maintenance dynamics following initial dispersal to a simulation polygon.

spatial resolution and derived slope and absolute aspect from the elevation layer in ArcGIS (ArcMap 9.3, ESRI, Redlands, CA). Buffelgrass presence data used to develop the model were compiled by Olsson et al. (2012a). Duplicate points were removed within each cell, which left a total of 1,174 data points. The model was trained on 70% of the data with 30% reserved for testing the model. Maxent was run 25 times with the average of these runs used as the final model. The model's overall performance was assessed using the area under the receiver operating characteristic curve (AUC). This is a threshold-independent indication of model performance (Phillips et al. 2006). The AUC of the model is 0.783. Swets (1988) reports that AUC values greater than 0.7 are acceptable. The contributions of the variables are elevation, 65.1%; slope, 28.2%; and absolute aspect, 6.7%.

**Spatial Simulation Algorithms.** The algorithms that simulate invasive plant dynamics on the landscape are described in detail in the TELSA model description (ESSA Technologies Ltd. 2008:26–50). Here we give a brief overview of the algorithm with specific references to the settings used for modeling buffelgrass in the Santa Catalina Mountains. TELSA operates by carving the landscape into tessellated polygons. Within each tessellated polygon, transitions between states are driven by natural and anthropogenic processes that include the following: dispersal of buffelgrass seeds from neighboring and distant polygons; buffelgrass cover increase within the polygon over time; inventory; mechanical or chemical treatment; and posttreatment maintenance. Spread of buffelgrass from polygons where it is present to neighboring polygons is simulated with a probability distribution of annual spread distances or dispersal kernel. TELSA has the following dispersal kernels available: exponential, log-normal, Weibull, and Pareto. We chose a Weibull distribution to represent the dispersal kernel because it has a very flexible shape that may represent a variety of dispersal kernels (Morales and Carlo 2006) and out of the ones available in TELSA it seemed most appropriate based on visual examination of dispersal data from Olsson et al. (2012a). We used scale and shape parameters of 0.2 and 0.5, respectively, for the annual dispersal kernel (based on the spread rate calibration described above). The dispersal algorithm takes into account propagule pressure and habitat suitability by modifying dispersal distances selected from the kernel with multipliers for the source polygon state and for the target polygon habitat suitability. Distance multipliers for the source state were 0.05 for states with $<$ 5% cover, 0.5 for states with 5 to 50% cover and 1 for states with $>$ 50% cover. Distance multipliers for the habitat suitability of the target polygon were 0.05 for low suitability, 0.5 for moderate suitability, and 1 for high suitability.

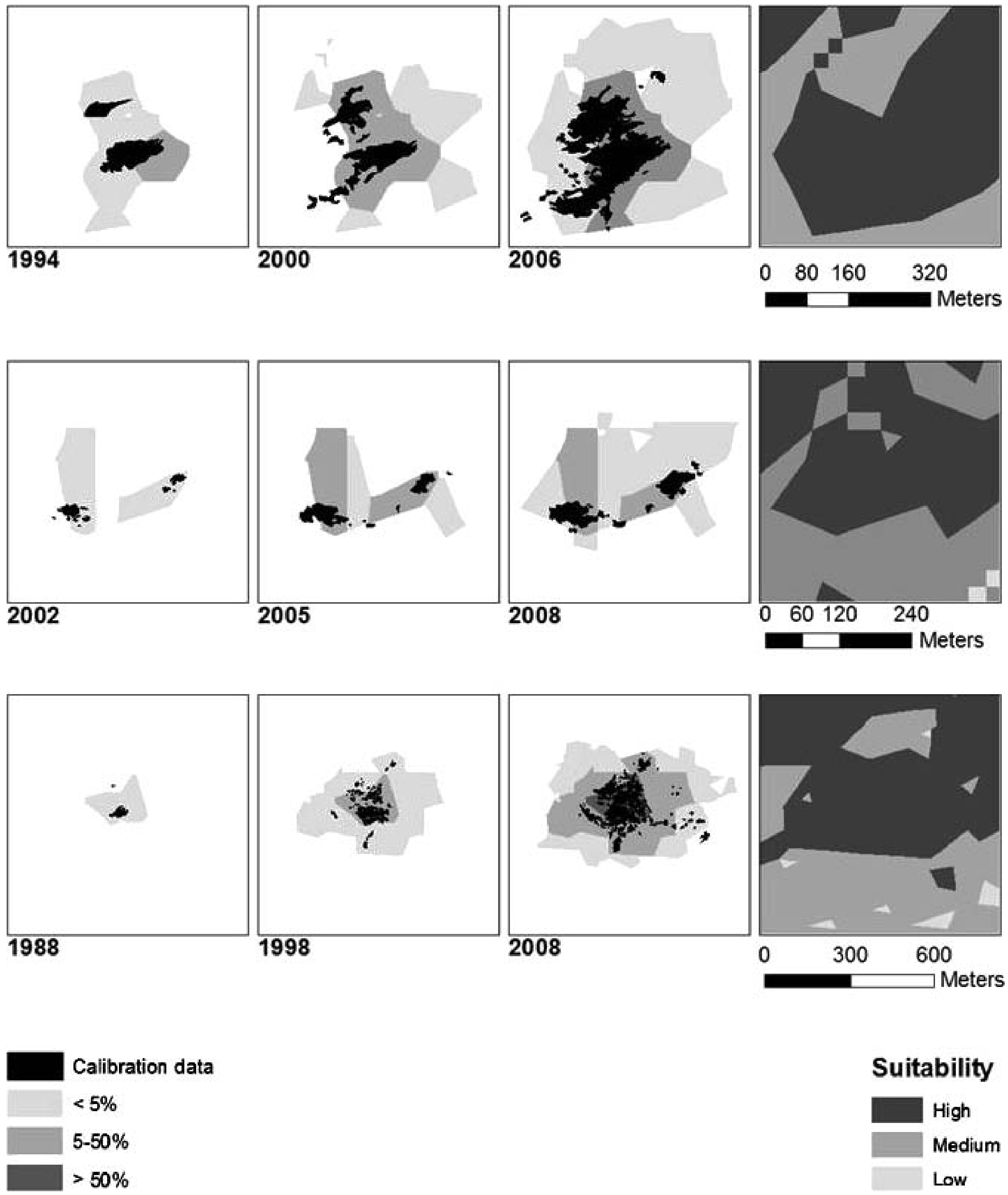


Figure 3. Map comparing buffelgrass distribution data against calibration results. Simulations were started in 1980 using known buffelgrass locations. Each row represents a different calibration site. The first three panels for each row show the time series of actual buffelgrass cover in black and the simulated extent of buffelgrass with shading representing percentage of cover of the simulation polygons. The final panel shows habitat suitability for the same area. The dispersal kernel used was a Weibull distribution with alpha equal to 0.2 and beta equal to 0.5.

Long-distance dispersal to polygons where buffelgrass is absent was modeled using a random, Poisson-distributed number of new buffelgrass introductions per year with an average value of six. High-habitat-suitability polygons were twice as likely to have new introductions compared to moderate-suitability polygons, and 20 times more likely than low-suitability polygons. Polygons adjacent to a road were also 20 times more likely to have new infestations than polygons not adjacent to roads. There are very few data available to inform long-distance dispersal rates and therefore the assumptions of six new introductions per year to the landscape and the relative likelihood of establishment according to habitat suitability was based on the best guess of buffelgrass managers attending a workshop held in Tucson in May 2010. We acknowledge that this is one aspect of our simulations that is uncertain and in the future

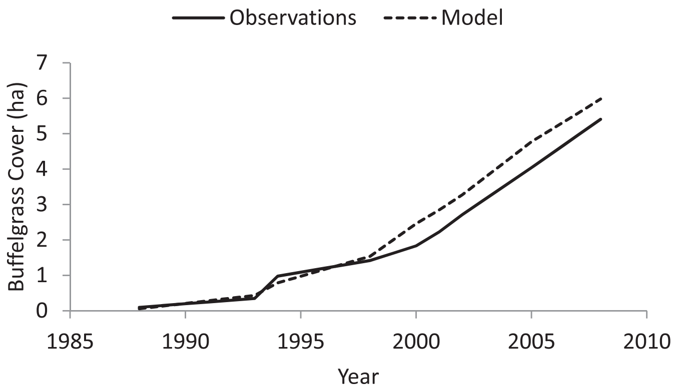


Figure 4. Area invaded by buffelgrass at three model calibration sites in the study area as observed in the data and in the calibration simulations.

would benefit from further sensitivity analyses such as those conducted on treatment and inventory effectiveness.

Buffelgrass cover increase in the absence of treatment within each tessellated polygon was modeled deterministically as a function of time since invasion. The time to transition to > 5% cover is 10 yr postinvasion; for > 50% cover it is 20 yr postinvasion. Inventory actions are broken down into two distinct categories: (1) inventory that occurs adjacent to polygons that have detected infestations of buffelgrass and (2) inventory that occurs randomly across the landscape. The first is modeled with a specified yearly budget that prioritizes areas adjacent to the smallest patches of detected buffelgrass. The second is applied randomly to 5% of the landscape that has no detected buffelgrass per year. Inventory can be applied to polygons where buffelgrass is absent or present. The probability of detection through inventory increases with increasing cover. Based on a survey of land managers, we defined best and worst case scenarios for inventory detection success as a function of cover class (Table 1). Failure to detect buffelgrass maintains the polygon in its current state whereas successful detection transitions a polygon to the detected state for the equivalent cover class where treatment can then take place.

As with adjacent inventory, treatment (mechanical or chemical) is modeled with a fixed area budget per year, and small patches of detected buffelgrass are prioritized over large ones. We assigned worst and best case scenarios for detection error and treatment efficacy rates based on a survey of land managers (Table 1). Successful treatment transitions a polygon to a lower cover class; if the polygon is already in the lowest cover class (< 5%), it transitions to the seedbank state. Thus, for polygons that have > 5% cover, at least 2 yr of repeated successful treatment are required to achieve the seedbank state. If treatment is inconsistent over time (e.g., a year goes by without treatment), or the application of treatment fails to reduce cover, the polygon will transition to the next higher cover

Table 1. Success rates used in the simulations for inventory and treatment transitions based on management responses to a treatment-success questionnaire.

| Treatment intervention | Success rate: Worst case | Success rate: Best case |
|---|---|---|
| Inventory < 5% | 0.01 | 0.9 |
| Inventory 5–50% | 0.25 | 0.9 |
| Inventory > 50% | 0.5 | 1.0 |
| Treatment < 5% to seed | 0.5 | 0.9 |
| Treatment 5–50% to < 5% | 0.9 | 1.0 |
| Treatment > 50% to < 5% | 0.4 | 0.9 |
| Treatment > 50% to 5–50% | 0.5 | 0.1 |

class until it reaches the cover class at which treatment began. This is consistent with observations at Saguaro National Park showing that a single treatment is a waste of resources because an active seedbank is left in the soil and a polygon will rapidly return to its original state of infestation if it is not treated for several consecutive years in a row (D. Backer, personal communication). Once a polygon reaches the seedbank state and no live buffelgrass plants remain, managers must revisit the site at least once per year to remove any seedlings. Without this maintenance process the site quickly returns to an infested state. As we did for treatment, maintenance was modeled with a fixed area budget per year prioritizing small buffelgrass patches over large ones. After 3 yr of residence in the seedbank state, polygons transition to the uninvaded state at a rate of 10% per year.

In addition to the map of habitat suitability and the STSM model for within-polygon dynamics, the model requires an initial distribution of buffelgrass on the landscape. We obtained data on the current distribution of buffelgrass in the Santa Catalina Mountains from Olsson et al. (2012a). Because survey efforts for buffelgrass have been limited to aerial photography, only patches greater than 0.5 ha have been mapped. In contrast, at nearby Saguaro National Park, where surveys have been intensive, 90% of observed buffelgrass patches are < 0.5 ha in size. It is likely, therefore, that small unknown patches of buffelgrass existing in the study area need to be added to the current distribution data. To do this, we compared the cumulative size distribution for the Catalina Mountains to that for Saguaro National Park. We determined the number of small patches (< 0.5 ha) that, when added to the Santa Catalina Mountains, would minimize the sum of squared differences between the cumulative patch size distribution for both landscapes. The number of small patches we added to the Santa Catalina Mountains was 2,808. To set the location of these simulated undetected patches on the landscape we used the TELSA simulation algorithm for adding new patches to the landscape.

Table 2. Simulation results for area invaded by buffelgrass and cumulative area inventoried, treated, and maintained at years 2030 and 2060.

| Scenario | Year | Invaded | Cumulative Inventory | Cumulative Treatment | Cumulative Maintenance |
|---|---|---|---|---|---|
| | | ha | | | |
| Initial conditions | 2010 | 82 | 0 | 0 | 0 |
| No management | 2030 | 1,795 | 0 | 0 | 0 |
| | 2060 | 6,263 | 0 | 0 | 0 |
| Intermediate management worst case | 2030 | 997 | 82,281 | 682 | 9,494 |
| | 2060 | 4,952 | 236,142 | 3,157 | 29,059 |
| Intermediate management best case | 2030 | 603 | 104,520 | 971 | 18,244 |
| | 2060 | 3,081 | 258,212 | 3,364 | 46,843 |
| Unlimited management worst case | 2030 | 864 | 81,897 | 837 | 10,060 |
| | 2060 | 637 | 358,643 | 11,543 | 99,986 |
| Unlimited management best case | 2030 | 159 | 146,054 | 1,460 | 27,851 |
| | 2060 | 54 | 392,803 | 3,752 | 75,380 |

Once the model was calibrated through the retrospective analysis described above, we simulated forward in time from 2010 for 50 yr to 2060. We simulated a total of five scenarios, including no management and four possible combinations of management with and without a budget limitation and with high or low effectiveness. Each management scenario was simulated first with an unlimited budget in terms of area undergoing management interventions, and then with an annual limit for each management activity set at 50% of the maximum area managed in the unlimited scenario. For each scenario, we present the total area invaded by buffelgrass over time and the total area undergoing each type of management intervention.

## Results and Discussion

**Simulation Results for Buffelgrass in the Santa Catalina Mountains.** Our simulations predict that in the absence of any treatment, the area invaded by buffelgrass in the Santa Catalina Mountains will increase exponentially from 82 ha in 2010 to nearly 1,800 ha by 2030, and to more than 6,000 ha by the year 2060 (Table 2). This area amounts to almost 80% of all suitable habitats having buffelgrass at carrying capacity, which would amount to 7,700 ha invaded (Figure 5). The pattern of spread in the model is logistic, with exponential growth occurring over the first 30 yr followed by a slower rate of growth as buffelgrass approaches its ecological limit (Figure 5). If it proceeds

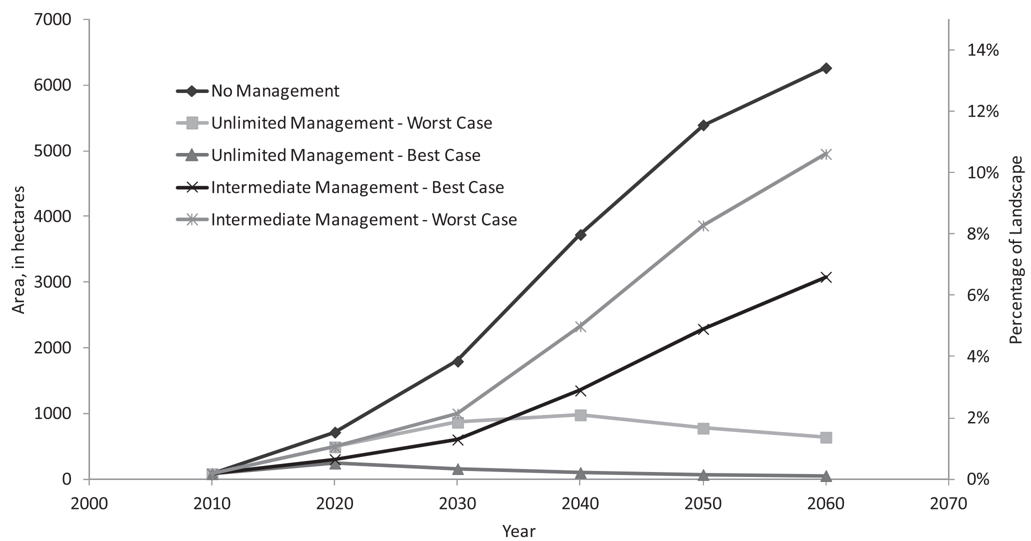


Figure 5. Results of five simulation scenarios showing the extent of buffelgrass invasion in the Santa Catalina Mountains over time. Areas were calculated by taking the sum product of polygon area and the percent cover multiplier for each polygon invaded by buffelgrass in the model. The percentage of cover multipliers used were: 0.025 for $<$ 5% cover, 0.25 for 5 to 50% cover, and 0.75 for $>$ 50% cover.

without intervention, the invasion will significantly impact the ecological integrity of the study area and increase the fuel loads and continuity in the wildland–urban interface (McDonald and McPherson 2011). Unchecked buffelgrass growth will result in increased wildfire risk for adjacent communities.

Management interventions can reduce both the rate and final extent of the invasion, depending on the resources allocated toward possible interventions and the effectiveness of the management actions. All management scenarios reduced the total area infested compared with no management, but in the short term (to 2030) scenarios assuming high effectiveness of management actions made a more significant reduction. In the long term (to 2060), scenarios assuming unlimited management resources made the most significant reduction in area invaded (Table 2; Figure 5). In terms of fuel continuity across large areas, all management scenarios reduced the size of contiguous high-density patches of buffelgrass up to 2030. However, only scenarios with unlimited management resources were able to maintain this up to the year 2060 (Figure 6).

Assuming that costs are directly proportional to area treated, the potential costs of management interventions over time can be quite variable and dependent on both the total resources allocated towards management and on the effectiveness of management actions. For example, for treatment alone, Table 2 shows that up to 2030, the unlimited best case scenario will be the most costly (at 1,460 ha) but that by 2060 the same scenario will be comparable in cumulative cost to the intermediate scenarios (3,752 ha and 3,364 ha, respectively) and significantly cheaper than the unlimited worst case scenario (11,543 ha). Our simplifying assumption about costs being proportional to area treated does not take into account factors such as the accessibility of the sites to be treated. Future simulation studies could explore the consequences of this assumption and explore strategies that focus on treatments and inventory of remote vs. accessible areas.

The implications of reductions in either the effectiveness or budget allocated to management on overall treatment costs are shown in Table 2. Reducing the effectiveness of management efforts when management resources are unlimited results in an initial reduction in costs (total area undergoing management interventions) because, with less effective inventory, there is less area being managed in the short term. In the long term, however, the unlimited worst case scenario results in substantially greater area undergoing management interventions as the unmanaged buffelgrass population expands substantially early in the simulation. Similarly, when resources for management are limited, as in the scenarios where budgets are cut by 50%, initial treatment costs are reduced. With a reduction in inventory budgets, less buffelgrass is initially detected and treated. However, by the end of the simulation the cumulative area undergoing treatment in scenarios with reduced budgets is comparable to the effective unlimited budget scenario.

Resources for the management of buffelgrass in the Santa Catalina Mountains are very limited so our scenario of "unlimited resources" is hypothetical, and the likelihood for increased resources for buffelgrass management within the CNF is low. CNF is managed under a multiple-use management paradigm and faces substantial internal and external demands for allocation of limited financial resources on a variety of fronts. Continuing federal budget reductions make long-term planning and consistent treatment problematic. However, the unlimited budget scenario provides a benchmark for what could be accomplished. In the case of unlimited management resources, the total area invaded by buffelgrass after 50 yr relative to a no-management scenario would be substantially reduced by one or two orders of magnitude depending on the effectiveness of management interventions. Though the costs of such a scenario may seem prohibitive, it should be noted that a large upfront investment can reduce the total management cost substantially over the long term. The cumulative area treated for the unlimited best case scenario was similar to that for the intermediate budget scenarios even though the ecological outcome was significantly improved.

In the short term, the intermediate best case scenario performed better than the unlimited worst case scenario. Although this result needs more probing through sensitivity analyses on the costs associated with increasing effectiveness, it does suggest that if there is a tradeoff between allocating resources to treat more area or to increase the efficiency of treatment for a smaller area, the latter may be better. This is particularly true for inventory that is ultimately limiting for the other management activities that occur downstream. If buffelgrass patches can be effectively discovered early on in the invasion process, the total area to be treated and maintained could be substantially reduced. Conversely, ineffective or insufficient inventory could lead to complacency and a belief that there is little buffelgrass present in the landscape. In this situation, by the time that buffelgrass is discovered, the area invaded could be so large as to overwhelm any possible management effort. Future scenarios that explore shifting more resources from treatment towards inventory should be conducted to explore this question further.

**Calibrating STSMs using Aerial Photography.** State-and-transition modeling is a powerful tool to examine many different management and budget scenarios. Often state-and-transition models rely heavily on surveys of land managers for calibration and validation (Czembor and Vesk 2009; Czembor et al. 2011). Alternatively, state-and-transition modeling can use available data to inform the modeling process. Although we conducted a survey of experts in the Tucson area to fill in gaps in our knowledge,

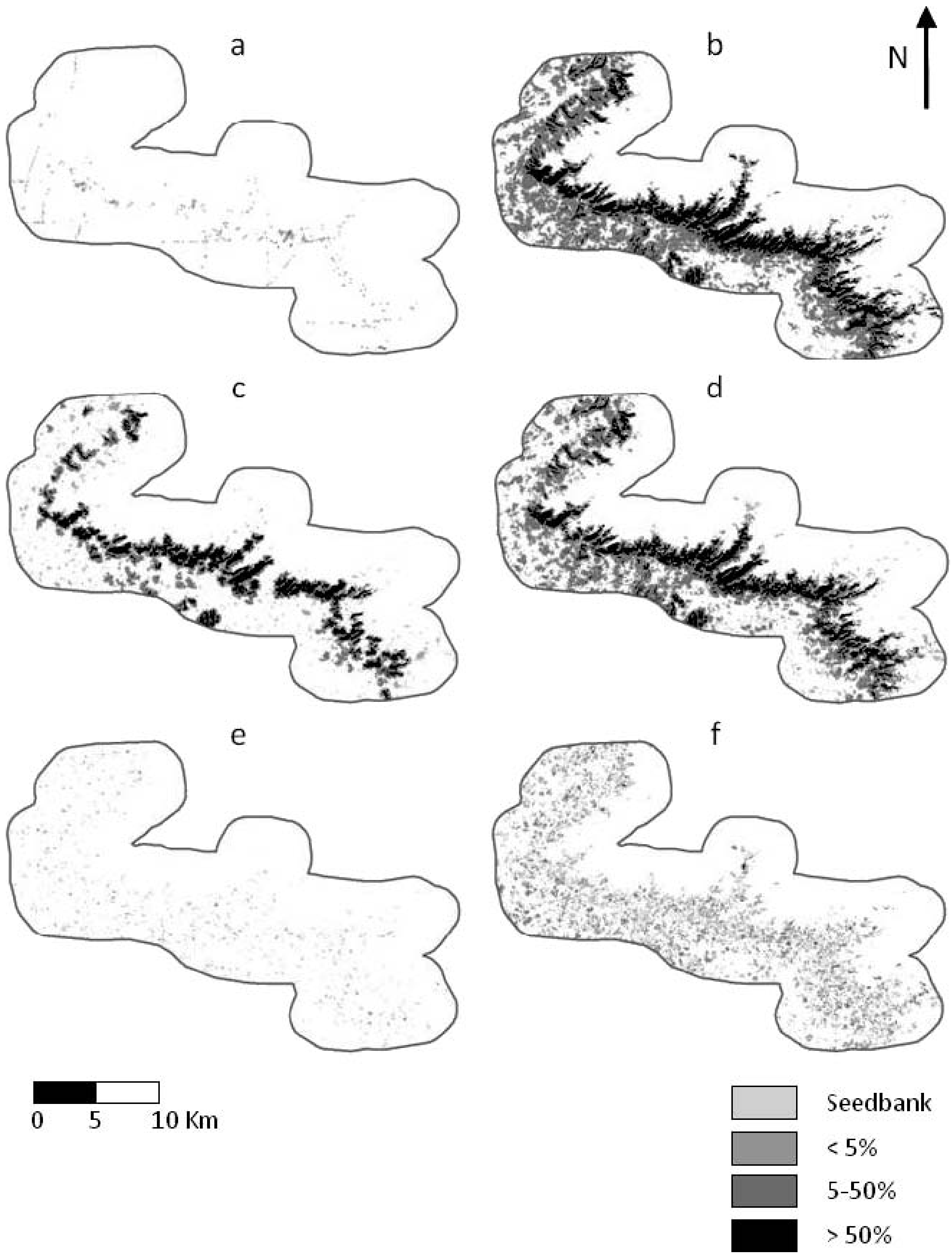


Figure 6. Maps of the Santa Catalina Mountain Study area showing (a) mapped buffelgrass in 2010 and simulated buffelgrass invasion at year 2060 for five simulation scenarios: (b) no management, (c) intermediate management best case, (d) intermediate management worst case, (e) unlimited management best case, and (f) unlimited management worst case.

we also populated many of the probabilities of the model, such as spread rate and state duration, with data from the photo interpretation done by Olsson et al. (2012a). This ability to inform various aspects of the model with empirical data helps us to form a stronger and more realistic model that can be augmented in the future when more data become available, thus creating an iterative modeling process that will be more predictive. The models created here can help inform the decisions managers make between allocating resources to control or inventory.

**Integrating STSMs with Quantitative Environmental Envelope Models.** This study also shows how different types of quantitative models can be integrated to better guide decisions for invasive plant management. Habitat suitability models are commonly used to predict the potential distribution of invasive plants (Bradley et al. 2009; Evangelista et al. 2008; Hirzel and Arlettaz 2003; Jarnevich and Reynolds 2010). However, these models do not incorporate dispersal rates and management actions. Integrating the habitat suitability model with the spatially explicit STSM allows us to account for both the biophysical determinants of potential buffelgrass distribution and for the dynamics of both buffelgrass spread and alternative management actions.

**Accounting for "Imperfect Detection" at the Landscape Scale.** Our model incorporated a quantitative method to explicitly include both detected and undetected buffelgrass populations in the study area. These populations then had the potential to remain undetected if no monitoring was done, or if monitoring efforts failed to detect buffelgrass when present at low densities. Invasive populations are not always detected, or detectable (Regan et al. 2011), yet managers need to determine how to allocate resources between gathering information about their distribution and treating infestations that have been detected. As with the work of Maxwell et al. (2009) our study highlights the critical importance of conducting inventory to detect new infestations. Land management agencies should therefore develop policies that encourage not only the treatment of detected infestations but also the search for nascent foci. Such policies could be guided by the use STSMs that account for ''imperfect detection'' and provide a flexible framework with which to examine landscape level alternative management scenarios for invasive plants such as buffelgrass.

## Acknowledgments

We would like to thank all of the participants of the Buffelgrass Science Workshop (May 2010), especially Perry Grissom, Marilyn Hanson, Dan Hatfield, B.J. Cordova, Darrel Tersey, Dana Backer, and Sue Rutman. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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*Received August 14, 2011, and approved September 10, 2012.*