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ORIGINAL PAPER

Clearing of invasive alien plants under different budget scenarios: using a simulation model to test efficiency

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Abstract Clearing of invasive alien plants (IAPs) is a necessary but expensive exercise. Typically, insufficient resources are available to clear all areas simultaneously. Consequently areas need to be prioritized for clearing. The financial resources available determine the extent of the area which can be cleared, while the prioritization identifies the location of the areas to be cleared. We investigate the following questions: (1) How does a change in the budget impact on the efficiency of the clearing operations over time? (2) How does this differ for different sites? (3) Can we identify pattern which make it possible for managers to determine if their budget is sufficient to achieve a management goal (e.g. clearing 95% of the area of IAPs) in a given time? (4) Can we draw general rules about how the time needed of achieving a management goal is changing when increasing the budget? We use a spatio-temporal explicit simulation model (SpreadSim) to simulate the spread of major woody IAPs over time, using a random prioritization strategy as a null model. This strategy requires no understanding or assumptions about the factors influencing spread; it is thus a reasonable baseline prioritization strategy. Our results confirm that a reduction of the budget increases the time needed to reach a management goal of 95% non-invaded areas and simultaneously increases the overall budget needed to achieve this goal. In addition, for each site, we can identify three values. Firstly, a "lower critical limit" of the budget, below which the IAP spread is only slowed down and management does not result in a reduction of the area invaded by IAPs, which is independent of the management goal. Secondly, the "critical budget", at which we have a chance of more than 50% of achieving our management goal in a given time. Thirdly, an "upper critical limit" for the budget, above which no substantial change in the time needed to reach the management goal can be observed. For all our three sites, the "upper critical limit" is located at approximately 1.7 times the "critical budget". The variability of the temporal trajectories of the area covered by IAPs for different simulations for the same input parameter and highly non-linear change in IAP cover over time indicate that an identification of the "critical budget" based on few years of IAP management is nearly impossible and that the use of simulation models is imperative. Nevertheless, the general pattern observed can be generalized to other prioritization strategies and provide important guidance for budget allocations.

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Introduction

Invasive alien plants (IAPs) have substantial ecological and socio-economic impacts in many parts of the world. They reduce the diversity of indigenous species, thereby increasing the risk of extinction (Gaertner et al. 2009), alter the functioning of ecosystems and disrupt their capacity to deliver a range of services. The economic impacts of IAPs on ecological systems and society justify the allocation of substantial resources towards reducing the density and extent of IAPs in many ecosystems (Higgins et al. 1997; Pyšek and Richardson 2010). Since resources are always limiting in management operations, tools for assigning priorities are urgently needed (MacDonald 2004).

Several studies have addressed the question of how to clear IAPs most efficiently and cost effectively, taking species, location of the IAPs and other factors into account. A crucial operational problem confronting managers is that resources are seldom, if ever, adequate to allow for the completion of all operations required to eradicate the IAPs. Consequently, the problem is reduced to a consideration of how best to spend available funds to make the greatest possible contribution to reducing the extent of IAPs. Annual budget (referred to as simply "budget" in the rest of the paper, in contrast to "cumulative budget", which refers to the total budget over all previous years, assuming a discount rate of 0%) thus plays an important role in determining the success of a clearing strategy. Despite its clear importance, this topic has received little attention. Several obvious statements have been made about the opportunities for IAPs management, e.g. no clearing can be done when the budget is zero or relatively low; IAPs can be cleared in 1 year if the budget is adequate; there is a "critical budget" above which we have a chance larger than 0.5 of eradicating IAPs in the area; etc. But how do we know if we are above or below the "critical budget" after a few years of IAP management? As we can expect that the "critical budget" is dependent on the site to be managed, how does the "critical budget per area", or "critical budget per area invaded", differ between different sites? Can we draw general rules about how the time needed of achieving a management goal (e.g. clearing 95% of the area of IAPs) is changing between the "critical budget" and the budget required to reach this management goal in one year?

Answers to these questions are required to provide motivation and justification for the substantial funding required to support the effective clearing of IAPs. To assess the effect of different budgets on the impact of alien clearing projects one needs to consider the effect of different budgets over time, and include recolonization of cleared areas in the assessment. Seen in this context, the impact of clearing is not as simple as one may initially assume: factors like properties of the invasive species, their initial distribution and densities, topography of the site and disturbance regimes (natural and anthropogenic) can have a profound impact on the effectiveness of the clearing program over time. Also, different strategies to prioritize areas for alien clearing impact on the success of clearing activities. Many different prioritization strategies are conceivable (Nel et al. 2004; van Wilgen et al. 2007). For the purposes of this paper, where our main aim is to investigate the impact of different annual budgets on the success of the IAP clearing, we decided to address a type of null-model for prioritization, i.e. a random prioritization, in which weights are randomly assigned to the different cells. We suggest that the random prioritization strategy can be considered representative of prioritization schemes which are typically based on highly unreliable data and criteria that change over time. This subjective and data-deficient prioritization results in decisions which change over time and which are not consistently related to conditions on the ground, except that only areas that are invaded by aliens will be targeted for clearing. The same criteria are met by the random prioritization as implemented in the model: only areas which are invaded by aliens will be cleared, but the selection of the areas for clearing is random and changes over time. It is important to note that this is only true in the context of this simulation and the question to be addressed. Although this prioritization scheme may appear unrealistic, we used the random scheme for the purpose of simplifying the exercise. In discussions with managers and planners in the Working for Water program, it was agreed that this was a rational null model to follow for exploring broad principles.

This paper forms part of a series of studies that are examining the approaches used by managers for clearing IAPs in South Africa's Cape Floristic Region (CFR). The overall aim of this research is to identify the key processes that are relevant for effective management of IAPs at regional scales, the factors that influence the prioritization of areas for clearing (Roura-Pascual et al. 2009) and to provide a detailed analysis of the resulting spatial prioritizations and their sensitivity to changes in the values of the weights (Roura-Pascual et al. 2010). This paper builds on these initiatives, and analyzes the impact of different budget scenarios on the effectivity of one selected prioritization strategy on three different sites to provide practical guidelines for use in fiscal and policy decisions to improve the efficiency of IAP management.

Methods

Study sites

The analysis was conducted at three sites within South Africa's Cape Floristic Region: Agulhas Plain, Cape Peninsula and Outeniqua (see Fig. 1; Table 1 for details). All three sites have large areas that are formally protected. Whereas the Cape Peninsula and Outeniqua region have large areas of natural or semi-natural vegetation, the Agulhas Plain consists of a mosaic of agricultural landscapes and conservation areas. All sites are invaded by IAPs, albeit by different species and to different degrees. The most important IAP groups in the study sites and in the CFR overall are major woody plants, particularly species of *Acacia*, *Hakea* and *Pinus* (Richardson and Brown 1986; Richardson et al. 1992, 1994; van Wilgen et al. 1994; Richardson and Kluge 2008). In addition, the three sites differ in terms of fire patterns, e.g. with respect to the average area burned per year and the average number of fires per year (see Table D.2 in Electronic Supplementary Material).

Prioritization strategy

We use a random prioritization strategy, in which each cell invaded by IAPs gets a random priority assigned, ranging from 0 (lowest priority) to 1 (highest priority). The priority values are not unique, i.e. more than one cell can have (and very likely has) the same priority value and they are not standardized to sum up to a specific value. We do not suggest that the random selection of areas for clearing should be used as a prioritization strategy in management.

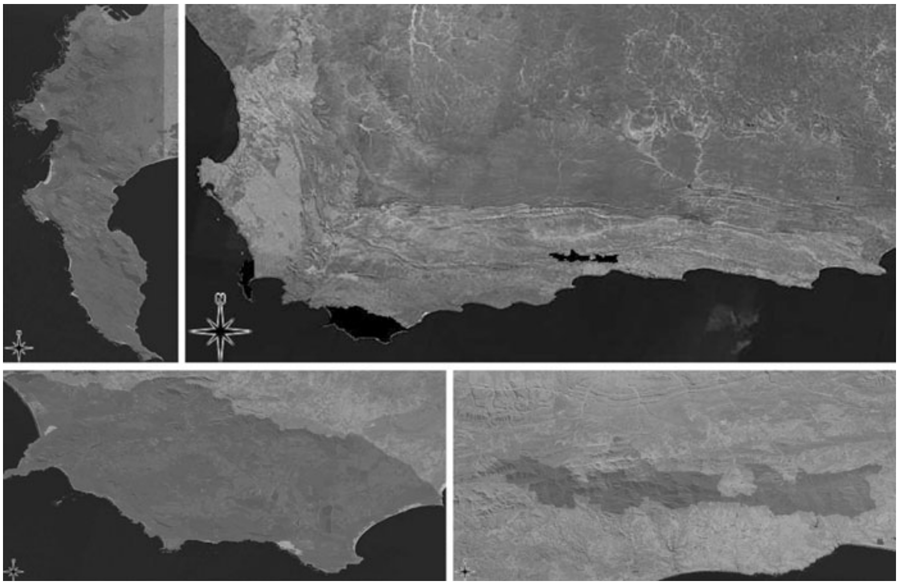

Fig. 1 Location of the three study sites in the Western Cape Province, South Africa. *Left*: Cape Peninsula; *Bottom left*: Agulhas Plain; *Bottom right*: Outeniqua. The *dark-gray* masks indicate the sites used for the case studies, the *light-gray* the Cape Floristic Region. See Electronic Supplementary Material for the color figure

Table 1 Details of the case study sites. b^{PC} is the budget per cell per year, b^{PC}inv is the budget per invaded cell per year (one cell = 1 ha)

	Area	Area invaded		Budget 2007/2008 (R)		
	ha	ha	%	Overall	b^{PC}	b^{PC}_{INV}
Agulhas Plain	215,982	142,672	66.1	3,691,728	17.09	25.88
Cape Peninsula	49,179	19,226	39.1	6,675.539	135.74	347.21
Outeniqua	57,697	57,454	99.6	1,937.220	33.58	33.72

Present selection of areas for clearing is based on the experience of managers making the results highly dependent on site and personnel (Roura-Pascual et al. 2009). As this approach cannot be formalized in a model because decisions are highly context specific (influenced by the site and the personnel involved), we consider that the selection can be approximated by using a random prioritization.

Model description

To assess the effectiveness of different IAP clearing budget scenarios on reducing the spread of IAPs over time, we used a grid based spatio-temporal explicit simulation model, called SpreadSim, with a random clearing strategy.

SpreadSim combines aspects of individual-based and grid-based modelling. It is written in R (R Development Core Team 2008) (with additional packages by Pebesma and Bivand 2005; Petzoldt and Rinke 2007; Bivand 2009; James 2009; Keitt et al. 2009; Lewin-Koh et al. 2009; Urbanek 2009) and uses GRASS (GRASS Development Team 2007) for the storage of the spatial results and spatial calculations.

It can be separated into five different modules, namely clearing, fire, seedProduction, seedDispersal and germEst (see Fig. 2). These modules consider the

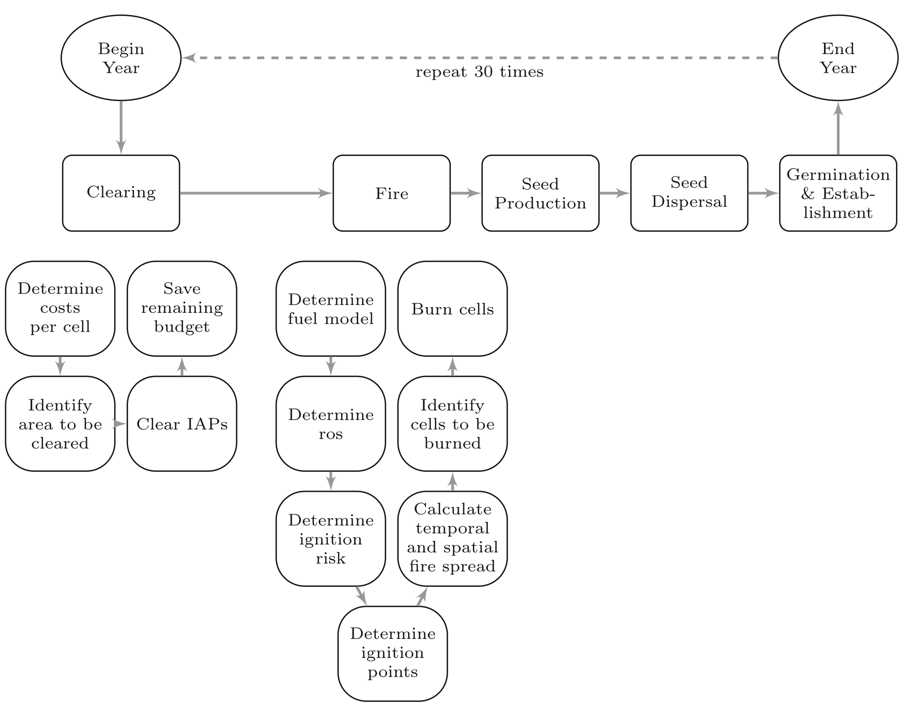

Fig. 2 Overview of the main steps and processes in SpreadSim. Processes are represented by *boxes* with *slightly rounded corners*. Details of the processes are represented by the *boxes* with *rounded corners*. More detailed flowcharts can be found in Appendix C in Electronic Supplementary Material

main processes and parameters influencing the management of IAPs (see Appendix D.4 in Electronic Supplementary Material for details), and together simulate the spread of major IAPs of the genera *Acacia*, *Hakea* and *Pinus*. These species groups have different parameters for most of the modules (see Appendix D.4 in Electronic Supplementary Material for details) and also use different algorithms in SEEDDISPERSAL based on their different dispersal syndromes. The different modules and differences between the species groups are discussed later.

The purpose of this model is to simulate the spread of three major IAPs groups, incorporating:

1. fire dynamics;
2. prioritization of areas for IAPs clearing based on the random prioritization strategy; and
3. clearing of IAPs based on the prioritization, the costs per ha for clearing (based on the Working for Water (WfW) cost guidelines, pers. com. Andrew Wannenburgh) and the given annual budget (based on the 2007–2008 budget (pers. com. Andrew Wannenberg) of the study sites

with the aim of assessing the effectiveness of different budget scenarios over a period of 30 years. Due to the stochasticity of the model, the different budgetary scenarios were repeated five times.

The state of the model, i.e. the combined states of the variables changing over time, is characterized by the following spatial variables (grids):

1. density class of each IAP group as defined by Working for Water Programme (2003): none, rare, occasional, very scattered, scattered, medium, dense and closed;
2. age class of each IAP group as defined by Working for Water Programme (2003): seedling, sapling and adult;
3. year of last fire;
4. clearing state as defined by Working for Water Programme (2003): initial clearing, follow-ups and maintenance; and
5. budget remaining after last year's clearing actions.

The simulated site was represented by a raster of 100 m × 100 m resolution and ranged from 49,179 (Cape Peninsula) to 215,982 ha (Agulhas Plain) (Fig. 1; Table 1).

The time step of the simulation was 1 year and we simulated 30 years.

The initial state of the model was determined by the spatial distribution of the IAPs age and density classes, clearing history of the site, fire history (number of fires and year of the last fire) and budget scenario used. The data were provided by the relevant nature conservation agencies and Working for Water (Roura-Pascual et al. 2009, 2010) and is based on field surveys and management records (clearing history). In addition to these dynamic data, static input variables (topography, natural vegetation type) were also included. Data were not always available for the same time period and we thus had to use data from different years. For example, data for the Cape Peninsula on the distribution of IAPs is from field surveys conducted in 1985 whereas fire data are from 2007. Although this would be problematic for using the model to plan real management operations, this discrepancy is not a problem for the purposes of our analysis.

Model modules

The modules described below are components of the SPREADSIM model. They interact via temporal spatial grids, which contain the results of the actions performed in the modules. At the end of the year, the final grids representing the state of the model are calculated.

Clearing

This module selects cells for clearing and performs the actual clearing of those selected cells. The main steps are (see Fig. 2):

1. prioritizing cells for clearing;
2. calculating the costs per cell;
3. identifying the cells to be cleared based on the budget available, the priority of the cells and their cost for clearing;
4. clearing of the IAPs in the identified cells and
5. calculating the budget left which will be carried over to the next year.

As a null model for prioritizing areas for clearing, we assume a random prioritization with no memory (referred to as "random clearing"), i.e. the selection of cells for clearing is completely random and not influenced by previous selections. The only constraint in the random prioritization is that only areas containing

IAPs can be cleared. This is accomplished by assigning a random priority $0 \leq P < 1$ to each cell invaded.

The costs for IAP clearing are measured in person-days (i.e. the number of days one person would need to clear the area, equivalent to R154 (pers. comm. Andrew Wannenburgh) as specified by Working for Water (Wise and Coetzee 2001). In a first step, the number of person-days required to clear a specific cell is calculated based on the growth form (represented by the species group), the age class and the density class of the IAP in the cell. In a second step, cells for clearing are identified based on their priority P and the budget available: cells are selected from the highest priority P downwards. If not all cells with the same priority $\hat{p}$ can be cleared because the budget is not sufficient, cells with this priority $\hat{p}$ are chosen randomly until the remaining budget is spent.

When a cell has been identified for clearing, the density of IAPs is reduced to a level dependent on the species group and density class (see Appendix D.4 in Electronic Supplementary Material for details) and the age class is set to "seedling". The soil seed bank (if it exists) is not affected, but seeds on the plant are removed. Finally, the budget not spent in the current year ("residual budget") will be carried over to next year's budget as done in real control operations. Residual budgets occur if a higher budget than necessary to clear all invaded cells is available or if, after already clearing higher priority cells, the remaining budget is not high enough to clear a single cell.

Fire

The fire module (see Fig. 2) determines the area which will be burned each year, based on fuel type classes as described by Anderson (1982). Each natural vegetation type was assigned a specific fuel model, as were areas invaded by invasive species. Based on these fuel models, the rate of spread of the fire was determined using the command *r.ros* in GRASS (GRASS Development Team 2007). This module determines the direction of the maximum rate of spread, the relating maximum rate of spread and the rate of spread perpendicular to the maximum rate of spread. The area burned annually and the number of fires is based on Forsyth (2007), who analyzed historical fire data in the Western Cape Province of South Africa. The number of fires (i.e. ignition points) follows a Poisson distribution with a given λ, while we assumed, to avoid additional complexity, the area which is burnt is constant for each year. λ and the area burnt per year is site specific (see Table D2 in the Electronic Supplementary Material for the values). The ignition points are selected using the maximum rate of spread in each cell as a proxy for flammability: the higher the maximum rate of spread, the higher the probability for an ignition point. The area burnt is determined through *r.spread* (also in GRASS (GRASS Development Team 2007)) until the overall area burned is equal to the area specified in the parameter set (see Appendix D2 in Electronic Supplementary Material).

Seed production

This module determines the number of seeds produced each year based on species group-specific parameters (Appendix D.4 in Electronic Supplementary Material).

Seed dispersal

This module simulates the dispersion of seeds from cells occupied by adult IAPs. The type of seed dispersal depends on the species group: *Acacia* seeds are dispersed by water, animals and locally (in the cell itself and neighboring cells) throughout the year; *Hakea* is highly serotinous, with seed release and dispersal by wind only after fire; and *Pinus* is also serotinous, but a small proportion of seeds are released and dispersed annually without fire (1%) (Richardson et al. 1992). Wind dispersal is modeled using a Weibull kernel (as used by Le Maitre et al. (2008) for *Hakea sericea*) with a given maximum distance, water-dispersal follows flow paths from the cell of origin, bird-dispersed seeds are distributed randomly over the whole simulated site and locally dispersed seeds are randomly distributed in the cell and its direct neighbors (for details see Appendix D.4 in the Electronic Supplementary Material).

GermEst

This module determines the number of seeds per cell that will germinate each year. The seeds germinate with species group-specific probabilities (Appendix D.4 in Electronic Supplementary Material) and dependent on the environmental conditions as quantified in suitability maps. The suitability maps were extracted from Rouget et al. (2004), and downscaled to the resolution needed (100 m × 100 m) using GDAL (2009) (see Appendix B in Electronic Supplementary Material). After germination, the seedlings are, in a first step, exposed to interspecific competition among the seedlings of all three species groups. In a second step, the seedlings are merged into the existing layer of the species and exposed to interspecific competition among all individuals of all age classes. The process of incorporating seedlings into a mixed age stand is done by calculating the cumulative density class and the weighted mean of the age class of each species, weighted by the density class, resulting in a combined age and density class for each cell.

Budget scenarios

The budget for IAP clearing for the financial year 2007/2008 from each study sites were used as baseline budgets (Table 1). To create additional budget scenarios, we multiplied the baseline budgets with factors, ranging from 0 to 7.0. For Cape Peninsula and Outeniqua we used 15 factors (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.3, 1.5, 1.7, 2.0), and for Agulhas Plain 16 (0, 0.5, 1.5, 1.7, 2.0, 2.2, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0). To compare different budgetary scenarios across sites (which are of different sizes), we calculated for each site the annual budget per cell (b^{PC})

$$b^{PC} = \frac{\text{budget per year}}{\text{number of cells}}$$

and, for the initial year, the annual budget per invaded cell ($b^{PC}inv$)

$$b^{PC}_{INV} = \frac{\text{budget in initial year}}{\text{number of invaded cells in initial year}}.$$

We included an annual increase of 10% of the budget as well as a 10% increase in clearing costs in the model.

All monetary values in this paper are provided in Rand (ZAR, South African Rand 1 R = €0.09 = 0.13US$, December 2009).

Analysis

The variables used to evaluate the efficiency of the clearing operations under different budgetary scenarios were: area covered by IAPs per year, IAP clearing budget per year, and area cleared of IAPs per year. The proportion of the site covered by aliens in year t, i.e. all cells for which the density class of aliens is higher than “rare”, is called cov(t). cov(t) = 0 indicates no alien infestation and cov(t) = 1 indicates complete cover of IAPs.

We set our “management goal” arbitrarily at clearing 95% (and for some scenarios 90%) of the area of IAPs. This “management goal” represents the threshold cover, below which the management is considered as being successful. An eradication of all IAPs would be ideal, but would require much higher resources.

If during the simulation the cover of IAPs was reduced below the “management goal”, we determined the year in which it occurred (tnf_{95}) and the cumulative costs per cell up to tnf_{95} ($B^{PC}{}_{95}$). Note that $B^{PC}{}_{95} \leq b^{PC}\cdot\text{tnf}_{95}$ as the whole budget might not be spent. The lowest budget at which more than 50% of all simulations resulted in a reduction of the alien cover to less than 5% within the time-frame of 30 years, was called the “critical budget” ($\hat{b}^{PC}$ relating to b^{PC} and $\hat{b}^{PC}_{INV}$ relating to b^{PC}_{INV}. Each budget scenario was simulated five times.

In addition, we calculated a budget index and a time index for each species separately. The budget index was calculated by dividing the actual budget b^{PC} by the critical budget $\hat{b}^{PC}$. Consequently, the budget index was one for the critical budget. The time index was calculated as follow:

$$\frac{\text{tnf}_{95}(\hat{b}^{PC}) - 1}{\text{mean}\left(\text{tnf}_{95}(\hat{b}^{PC}) - 1\right)}$$

By subtracting one from tnf_{95} we achieved that the lowest value of the index is zero, while 1 represents the average $\text{tnf}_{95}(\hat{b}^{PC})$.

Results

The annual budget per cell (b^{PC}) evaluated in the analysis ranged from 3.36 R/ha (Outeniqua) to 271.48 R/ha (Cape Peninsula), and per invaded cell ($\hat{b}^{PC}_{INV}$) from 3.37 R/ha (Outeniqua) to 694.43 R/ha (Cape Peninsula) (Fig. 3). The resulting critical budgets per cell ($\hat{b}^{PC}$, Fig. 3, top) and per invaded cells ($\hat{b}^{PC}_{INV}$, Fig. 3, bottom) were: Agulhas Plain $\hat{b}^{PC}$ = R85, $\hat{b}^{PC}_{INV}$ = R129; Cape Peninsula $\hat{b}^{PC}$ = R95, $\hat{b}^{PC}_{INV}$ = R243 and Outeniqua $\hat{b}^{PC}$ = R44, $\hat{b}^{PC}_{INV}$ = R44, differing by a factor of five.

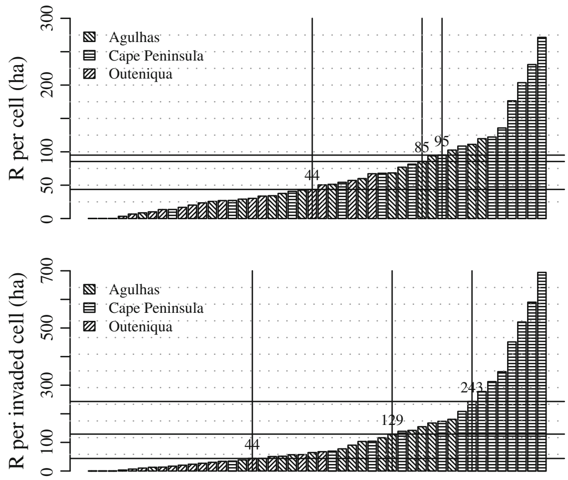

Fig. 3 Budgets in R per cell (i.e. hectares) used for the simulations. The *top graph* shows the budget per cell, the *lower* the budget per invaded cell. The *vertical lines* indicate the respective critical budgets for the different sites. See Electronic Supplementary Material for the color figure

For the Cape Peninsula, unexpected behavior was observed at the critical budget (Fig. 4) in all five simulations: the alien cover initially increased over the first 18 years and decreased rapidly thereafter. In Outeniqua, and to a lesser extent in the Agulhas Plain, the opposite was observed in some simulations: the alien cover dropped radically at the beginning and increased subsequently. Additionally, the variability for the different budgets increased, until reaching a maximum at the critical budget, and decreased thereafter again (Fig. 5).

The average proportion of the area under alien cover at each given year of all five simulations decreased with increasing budget (Fig. 5), but, the effect of the various budget scenarios on this proportion differed between sites. Looking at the five simulations separately, we see that the effectiveness does not necessarily increase over time, but can peak and decrease again (e.g. Outeniqua and Agulhas

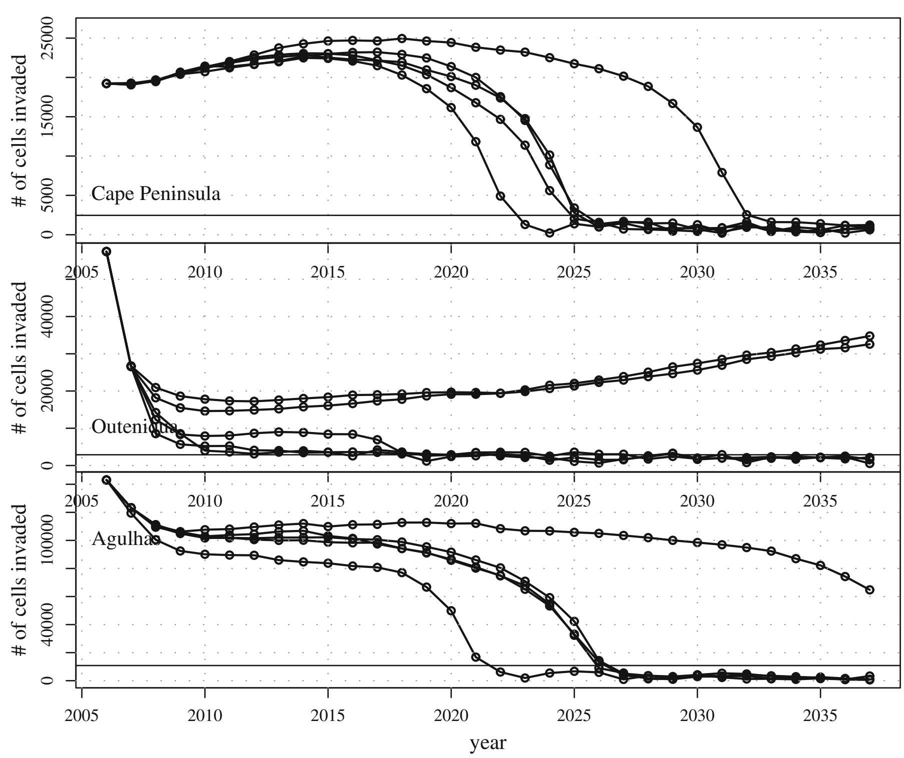

Fig. 4 Example of change of cover over time. The *top panel* shows Cape Peninsula, *middle panel* Outeniqua, *lowest panel* Agulhas Plain, all at the critical budget $\hat{b}^{PC}$. *Different lines* indicate different simulation runs. The *horizontal line* indicates the 95% management goal. See Electronic Supplementary Material for the color figure

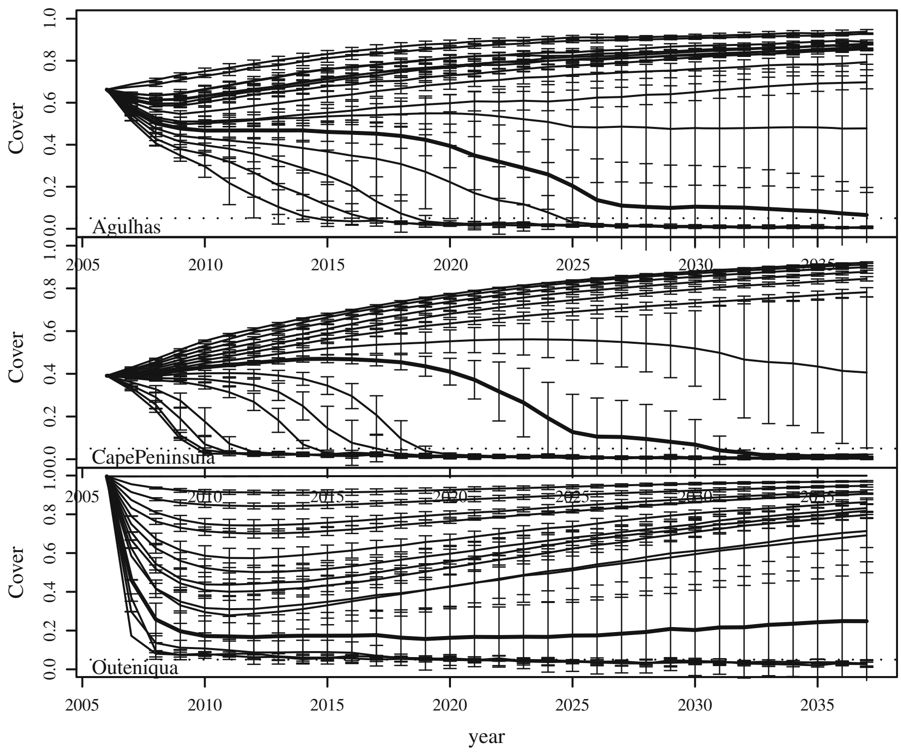

Fig. 5 Cover cov(t) of the different budget scenarios and for the different sites. *Lines* represent mean cover, *error bars* the standard deviation, based on the simulations, of the different budgets. *Top line* in each panel is based on no clearing, budget increasing towards the bottom. *Thick line* indicates critical budget. *Horizontal dotted* line marks the clearing target (95% of the area). See Electronic Supplementary Material for the color figure

Plain) or decrease and increase again (e.g. Cape Peninsula) (Fig. 4).

Examining the impact of different annual budgets (b^{PC}) on the years needed to reduce the area covered by IAPs below the management goal (tnf_{95}) and the respective cumulative costs (B_{95}^{PC}; Fig. 6 top panel), one can see clearly that for two of the three sites (Agulhas Plain and Cape Peninsula) an increase in the annual budget leads to a decrease of the cumulative costs and a decrease in the time needed to reach that goal. The decrease of both (tnf_{95} and B_{95}^{PC}) is not linear, but resembles an exponential decay, with a steep decline after reaching the critical budget $\hat{b}^{PC}$, and a slow decline later. This pattern is the same for a management goal of 0.95 and 0.9.

Outeniqua shows a different pattern, namely a high variability of b^{PC} and B_{95}^{PC} above the critical budget which does not change when increasing the budget. In contrast to Cape Peninsula and Agulhas, this pattern changes when the management goal is relaxed from achieving 95% clearance of IAPs to 90% removal: in the case of the 90% goal, the pattern becomes similar to the ones observed in the other two sites.

By plotting the time index against the budget index (Fig. 6, bottom graph), we can compare the actual rate of the decay of the three sites. Cape Peninsula and Agulhas Plain require about the same time and costs under all budget scenarios and both management goals. In the case of the management goal of 95% clearance, Outeniqua shows no clear pattern. This changes when considering a management goal of 90% clearance: here we can see the same pattern as in Agulhas and Cape Peninsula, namely the decay of the budget index with increasing time index. In addition, the values are in the same range as the ones for Agulhas and Cape Peninsula.

Discussion

This study provides important insights on the efficiency of clearing efforts in reducing the area invaded

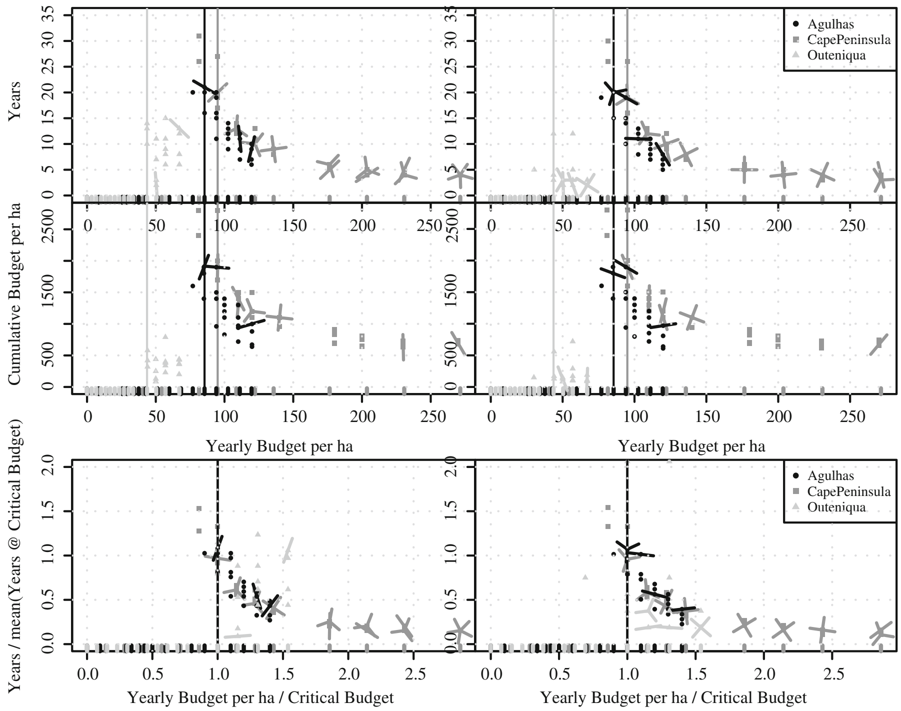

Fig. 6 Impact of different b^{PC} on tnf$_{95}$ (*upper graph top panel*) and B^{PC}_{95} (*bottom graph top panel*). Each point is based on one simulation, i.e. a maximum of five per each b^{PC}. Segments indicate number of points in case of overplotting, rugs on the bottom of each panel represents the b^{PC} simulated; vertical lines indicate the critical budget $\hat{b}^{PC}$. The bottom panel shows results from the top panel, with the critical budget $\hat{b}^{PC}$ and mean tnf$_{95}$ at $\hat{b}^{PC}$ standardized to one. The left graphs show the results based on a management goal of 95%, the right graphs on a management goal of 90%. See Electronic Supplementary Material for the color figure

by IAPs under for different sites different budget scenarios, and demonstrates the need to adjust investment to the particularities of each site and to ensure the long-term commitments in clearing programs. Other studies have also shown that economics plays an important role in clearing operations (Marais et al. 2004; Higgins et al. 1997). For example, Odom et al. (2005) showed that investment in managing the Scotch broom (*Cytisus scoparius*) is economically justified and that higher budgets yield higher value for the society. Cacho et al. (2008) used a decision model based on economic analysis to identify the most appropriate management goal (eradication, containment or no management). Both studies coincide in indicating that the major factor determining the management goal is the available budget, with higher budgets resulting in more eradication oriented goals. Likewise, Cacho et al. (2006, 2007) examined the impacts of the detectability of a target species on the resources (time and budget) needed for eradication of the species and found that eradication efforts also depend on the characteristics of the species and the environment. Overall, these studies coincide with our findings that investment needs to be adjusted to the particularities of each study site and maintained over time to maximize the efficiency of clearing programs.

Besides the similarities, our study is the only one we know of that has quantified the impact of different annual budgets (b^{PC}) on the time (tnf$_{95}$) and cumulative budget (B^{PC}_{95}) required to achieve a clearly stated management goal (proportion of the area free of IAPs, in this particular study case 95%). This information is crucial for managing IAPs efficiently at the local level, but also for optimizing the allocation of resources at the regional level. Nevertheless, we need to emphasize that the quantitative interpretation of the model simulations (i.e. the direct interpretation of the absolute values obtained from individual budget scenarios) is only valid if the input data reflects the current state of the environment and is of sufficient quality. If updated data at the appropriate resolution would be available, the model could be used to determine the critical budget (i.e. budget at which we have a 50% chance of achieving the management goal) and to quantify the influence of different budget scenarios on the outcome of management interventions. Unfortunately, the data available for this project did not fulfill these requirements, e.g. datasets for the same area were only available from different years, suitability maps had to be re-sampled, as they were at a coarse resolution, and IAP distribution data was incomplete. Therefore, a realistic quantitative interpretation of the results is not possible yet. Nevertheless, comparisons between different scenarios are possible and provide useful information.

Our results show that increasing the annual budget, apart from the expected decrease of the time required to achieve the management goal, resulted in a decrease of the cumulative budget needed to achieve this target. For two of the three sites (Agulhas Plain and Cape Peninsula), the trajectories followed by tnf_{95} and B_{95}^{PC} over time resemble an exponential decay. In Outeniqua, the situation is different: neither the time required to achieve the management goal nor the cumulative budget required does change over time. This is reflected in the time and budget indices. However, when loosening the management goal to 90%, the pattern observed in Agulhas Plain and Cape Peninsula at a goal of 95% appear in Outeniqua as well. When looking at the area covered by IAPs over time for the individual simulations at the critical budget in Outeniqua, one can observe that the IAP cover fluctuates around 95% even when the budget is increased. Consequently, the time when the cover of IAPs falls below 95% is more or less random. When loosening the management goal to 90%, the goal is reached before these fluctuations occur and consequently the same pattern as in Agulhas Plain and Cape Peninsula can be observed.

The observed decrease of the time required to achieve the management goal can be separated into two phases: at first the time drops considerably, and then changes slightly until asymptotically approaching 1. This point, which may be called the upper critical limit, is at approximately $1.7 \cdot \hat{b}^{PC}$ for the sites analyzed and represents the budget after which the time needed to reach the management goal does not change considerably anymore. When the annual budget b^{PC} is increased to a value above this upper critical limit, the effect of the increased budget on tnf_{95} is minimal and it would be more effective to reallocate the money to other sites with less budget allocated. In other words, spending more on an area helps, but only up to a certain budget.

On the other hand, when the budget is below the critical budget $\hat{b}^{PC}$, the chances of achieving our management goal are reduced and we only achieve a reduction of the final density of the IAPs after *n* years which is lower than the initial density. Reducing the budget even further, below a lower critical limit, slows the spread of IAPs and the resulting density after *n* years is as high or even higher than the initial area invaded.

Depending on the management goal, the critical budget and the upper critical limit change, but the lower budget limit will not change when another management goal is used. As the critical budget is the budget at which we have a 50% chance of achieving the management goal, it will change considerably with a changing management goal. Why the critical budget does not change in our simulations when changing the management goal from 95 to 90% can be contributed to the relatively large differences between the different budget scenarios. Simultaneously, the upper limit, which is the budget after which the time needed to reach the management goal does not change considerably anymore, will also change. In contrast, for the lower critical limit, which is the budget below which clearing will only slow the spread (spread > 0) but not reduce the area cleared, the management goal is irrelevant.

To sum up, the critical budget therefore identifies the lower limit of the budget required to achieve the management goal, whereas the upper critical limit identifies the maximum budget which should be invested at the site. In contrast to the upper critical limit and the critical budget, which depend on the management goal, the lower critical limit does not. Budgets between the critical budget and this lower critical limit reduce IAP cover, but not to the level of the management goal.

The critical budget, as well as the respective upper and lower limits, are influenced by the characteristics of IAPs (density-, spatial- and age distribution) and site (such as topography and environmental suitability). Topography affects the dispersal of water dispersed IAPs (e.g. *Acacia* spp.), while environmental suitability influences the establishment and growth of the seedlings. Fire also has an an important influence on the spread of IAPs (especially *Pinus* and *Hakea* spp.) because these species influence the fire regimes (by increasing total biomass and changing the spatial arrangement of fuels) (van Wilgen and Richardson 1985; Brooks et al. 2004).

The natural vegetation also influences the likelihood of fires and their extent. Consequently, fire regimes are not only determined by the site-specific input parameter of number of fires per year and area burned each year, but also by the natural vegetation and topography, which influences flammability. All these factors together play an important role in determining the critical budget and its respective limits, and no simple formula can calculate them.

Irrespective the limitations of the model as discussed above, the simulation program presented here allowed us to determine whether the current budget was above or below the critical budget ($\hat{b}^{PC}$). The highest critical budget is found in Cape Peninsula ($\hat{b}^{PC} = \text{R95}$), which has the lowest rate of infestation (33%) but a high density of IAPs, whereas the lowest critical budget was found in Outeniqua ($\hat{b}^{PC} = \text{R44}$), which has the highest rate of infestation (99%) but the lowest overall density of IAPs. This task is, however, difficult because the variability in the annual proportion of the area covered by aliens cov(t) increases towards $\hat{b}^{PC}$ and produces some unexpected patterns. In the Cape Peninsula, at $\hat{b}^{PC}$, the IAP cover increases at first (up to 125% from the initial cover) and only declines several years after the first clearing actions. A different pattern emerges in Outeniqua: out of the five simulations, three are successful in achieving the management goal within 30 years, whereas two actually show increasing IAP cover after decreasing for the first 6–7 years. In both simulations, the cover is reduced to 15,000 ha, and then increases again to nearly 30,000 ha. This variable behavior complicates the identification of $\hat{b}^{PC}$ based on a small number years of clearing and data collection. Considering the range of $\hat{b}^{PC}$ from the three sites analyzed (between R44 and R95), an extrapolation from one site to another will be extremely difficult, if not impossible.

This suggests an important aspect of alien clearing which can be highlighted from the results of this study: it is not possible to evaluate the success achieved with a given budget after only a few years. In three out of five simulations, the IAP cover actually increases initially substantially but then decreases until the management goal is reached. One must therefore conclude that long term commitment is crucial for IAP management and that short-term clearing operations are very unlikely to achieve management goals, unless they have unlimited resources available to conduct the clearing.

Conclusions

All these observed patterns are based on the random prioritization strategy. It can, however, be reasoned that the same general pattern will hold true for other prioritization strategies. In contrast to the random prioritization, which ignores information on actual IAP distributions and site factors, specific prioritisations (as discussed by Roura-Pascual et al. 2009) do include factors which are considered to be important for the spread of the species. These prioritization strategies can either be more specific in selecting areas critical for the spread of the IAP (i.e. giving areas which are driving the spread of the IAPs a higher priority) or less specific (i.e. giving areas which are driving the spread of the IAPs a lower priority). In contrast to the random prioritization strategy, these will be consistently more or less specific. This results, in comparison with the random prioritization, in a reduced tnf_{95} when the strategy is more specific and an increased tnf_{95} when the strategy is less specific. Less specificity in the selection can therefore be expected to cause the same pattern to emerge later, where more specificity can be expected to cause these pattern to be manifested earlier (and faster) in time, although those can be more or less pronounced. Impacts on the budget scale are not straightforward to predict. Nevertheless, the arguments used for the random prioritization can be expected to hold true for other prioritization strategies as well, using the same reasoning as for the tnf_{95} above. Further research to evaluate these predictions for different prioritization strategies to be able to obtain a more detailed understanding of their impact on the budget requirements is currently being conducted.

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