Ecological Applications, 26(2), 2016, pp. 475–483

Using counterfactuals to evaluate the cost-effectiveness of controlling biological invasions

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Abstract. Prioritizing limited conservation funds for controlling biological invasions requires accurate estimates of the effectiveness of interventions to remove invasive species and their cost-effectiveness (cost per unit area or individual). Despite billions of dollars spent controlling biological invasions worldwide, it is unclear whether those efforts are effective, and cost-effective. The paucity of evidence results from the difficulty in measuring the effect of invasive species removal: a researcher must estimate the difference in outcomes (e.g. invasive species cover) between where the removal program intervened and what might have been observed if the program had not intervened. In the program evaluation literature, this is called a counterfactual analysis, which formally compares what actually happened and what would have happened in the absence of an intervention When program implementation is not randomized, estimating counterfactual outcomes is especially difficult. We show how a thorough understanding of program implementation, combined with a matching empirical design can improve the way counterfactual outcomes are estimated in nonexperimental contexts. As a practical demonstration, we estimated the cost-effectiveness of South Africa's Working for Water program, arguably the world's most ambitious invasive species control program, in removing invasive alien trees from different land use types, across a large area in the Cape Floristic Region. We estimated that the proportion of the treatment area covered by invasive trees would have been 49% higher (5.5% instead of 2.7% of the grid cells occupied) had the program not intervened. Our estimates of cost per hectare to remove invasive species, however, are three to five times higher than the predictions made when the program was initiated. Had there been no control (counterfactual), invasive trees would have spread on untransformed land, but not on land parcels containing plantations or land transformed by agriculture or human settlements. This implies that the program might have prevented a larger area from being invaded if it had focused all of its clearing effort on untransformed land. Our results show that, with appropriate empirical designs, it is possible to better evaluate the impacts of invasive species removal and therefore to learn from past experiences.

Key words: adaptive management; biological invasions; Cape Floristic Region; evidence-based; impact evaluation; nonnative species; restoration; tree invasions; watershed; Working for Water program.

Introduction

Biological invasions pose a growing threat to biodiversity and ecosystem functioning worldwide (Gilbert and Levine 2013). It is widely accepted that multifaceted strategies are needed to reduce the likelihood of new invasions, eradicate early-stage invaders where feasible, and to reduce the density, extent, and impact of widespread invaders (Simberloff et al. 2005). Because there is far less funding available than is needed to control all biological invasions, conservation managers have to practice triage by prioritizing where they intervene, based on predictions of the effectiveness of interventions and, their costs and benefits (i.e. avoided damages; Gren 2008).

Despite a number of advances in approaches and tools for assigning priority to and within different phases of invasive species management (Panetta 2009, Epanchin-Niell and Hastings 2010), the practical usefulness of these approaches depend on the accuracy of the information on which they are based. Although billions of dollars have been spent controlling invasive species, there is a lack of evidence about the effectiveness and cost-effectiveness of controlling them (Kettenring and Adams 2011). Without

Manuscript received 24 February 2015; revised 14 July 2015; accepted 16 July 2015. Corresponding Editor: R. A. Hufbauer.
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such information, decision-makers risk not maximizing return on their limited budgets (Naidoo et al. 2006) and not learning from past successes and failures (Hobbs 2009, Roura-Pascual et al. 2010).

The paucity of evidence results from the difficulty in measuring the effect of invasive species removal. Researchers must estimate the difference between the outcome (e.g. percent cover) where the removal program intervened (Fig. 1C) and what would have been observed had there been no intervention (Fig. 1B; Ferraro and Pattanayak 2006). In the program evaluation literature, this is called a counterfactual analysis, which formally compares what actually happened and what would have happened in the absence of an intervention. Because the counterfactual is unobservable, researchers must use the outcome from an area that was not treated (Fig. 1E) or before the intervention happened (Fig. 1A) or as a surrogate for the counterfactual outcome (see the formal description in *Methods*).

The most credible way of assessing this difference would be to randomly assign which areas get treated and which areas do not (i.e. the outcome of areas randomized to the untreated group provide an estimate of the counterfactual). A researcher would have to simply compare the difference in mean outcomes between treated and untreated groups (Holland 1986). Unfortunately, randomized-experimental studies have been restricted to very small temporal and spatial scales because most experiments are constrained by limited budgets and time-frames and do not form part of operational program interventions (Kettenring and Adams 2011,] but see Lindenmayer et al. 2015,] as an exception). The results of these small-scale experiments have limited use in estimating the cost-effectiveness of controlling invasive species in real-world operational contexts where decisions are made at the scale of landscapes and larger political units.

Another option would be to measure the cost-effectiveness of nonexperimental landscape-scale operations. In the absence of experimental manipulation, however, researchers cannot simply compare outcomes on treated (Fig. 1C) and untreated (Fig. 1E) units. If treatment selection bias exists which is also correlated with the outcome (e.g., sites that are selected for treatment have a lower baseline invasive plant presence than untreated areas, Fig. 1A vs. D), then naïve treated–untreated comparisons will be confounded by such factors (Pearl 2009). For these reasons, unbiased comparisons rely on the retrospective identification of, and adjustment for, confounding factors which requires a thorough understanding of the reasons for implementation of a program (Ferraro and Hanauer 2014).

Over the past two decades, the program-evaluation field has developed a number of innovative statistical techniques for improving the credibility of how counterfactual estimates are made in nonexperimental contexts (Imbens and Wooldridge 2009). As a practical demonstration we show how one of these approaches, a statistical matching technique, can be used to measure the cost-effectiveness of reducing invasive alien tree presence by selected operations within South Africa's Working for Water program. The operations took place in a large mountainous area in

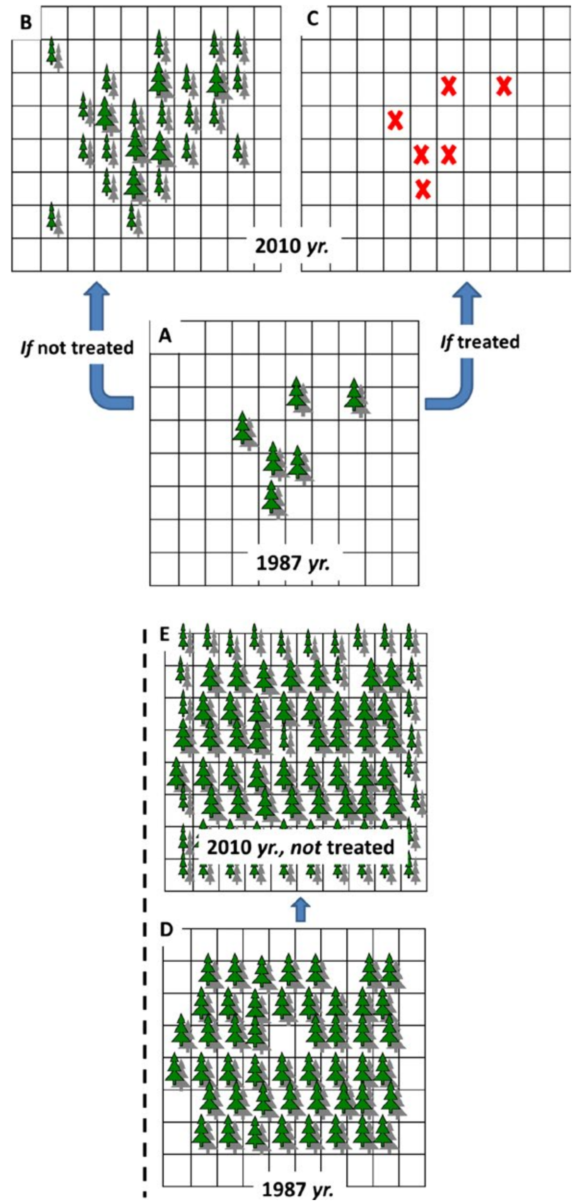

Fig. 1. Illustration of why measuring the effectiveness of removing invasive species requires accurate estimates of an unobservable counterfactual. (A) A starting point will result in different potential outcomes, depending on if it was (B) not treated or (C) treated. If (A) were treated, its true treatment effect would be the difference in the number of cells occupied by invasive trees between (C) and (B). The problem is that only (C) would be observable if (A) were treated; (B) is an unobservable counterfactual outcome. Without being able to observe the counterfactual a researcher has to use the outcome from an area that was not treated, for example (E), as a surrogate for the counterfactual (B). In this case, however, the treatment effect (difference in cells occupied between (C) and €) would be confounded because (C) was less invaded than (E) before it was treated (D).

the Cape Floristic Region (CFR), a globally renowned biodiversity hotspot where invasive plants are one of the main problems facing conservation managers (Rouget et al. 2003, van Wilgen 2013). The Working for Water program has been described as the world's most ambitious invasive plant control program (Koenig 2009) and Africa's largest conservation project (van Wilgen 2009). However, mirroring the global situation, almost nothing is known about the cost-effectiveness of this intervention (McConnachie et al. 2012). To identify where the program was most cost-effective, we also measured its impact within different land use and ownership types.

Methods

Study area and program background

Our study area was located in the Hawequas Mountain Fynbos complex (Cowling and Heijnis 2001), covering an area of 1451 km^2 in the southwestern part of South Africa's Western Cape Province. Most of the study area was untransformed mountainous land, located within protected areas (Table 1). Within the study area, alien pine trees (*Pinus pinaster* and *P. radiata*) were grown in plantations for commercial forestry, and other alien trees (mostly Australian *Acacia* and *Eucalyptus* species) were grown in woodlots or as windbreaks. These alien tree species have invaded areas outside of where they were planted. Most of the plantations in the study area were state-run until the 1990s, after which they were either leased to private forestry companies or scheduled for "exit" from use for timber production (Louw 2004). Consequently, a portion of clearing effort has been devoted to abandoned plantations, as part of the "exit strategy" for commercial forestry in the region.

Mountain fynbos, the dominant vegetation type in the study area, is a fire-prone shrubland that is susceptible to invasion by fire-adapted invasive alien trees, even in the absence of human disturbance (Richardson and Cowling 1992, van Wilgen 2013). Fynbos areas covered by dense stands of invasive trees use more water than non-invaded fynbos, reducing the delivery of water from catchments (Le Maitre et al. 1996). This was the main justification for the establishment of the Working for Water program in 1995, along with the opportunities it offered to provide employment in impoverished rural areas (McConnachie et al. 2013). Studies predict that the region will become significantly dryer over the next 40 yr, which increases the urgency of dealing with water-reducing plant invasions (Stager et al. 2012).

The long-term cost-effectiveness of invasive-tree-clearing in the region depends importantly on the efficiency of clearing post-treatment regrowth (Holmes et al. 2008). For example, in our study area, regrowth can result from coppicing of felled *Acacia* and *Eucalyptus* trees, and from seed for all tree species, especially after fires. Treatment of regrowth requires either hand-pulling, mechanical cutting, or the application of herbicides or burning before the plants produce seed. If left for too long, these methods become ineffective, and full-scale felling would be required to re-clear the area, often at greater cost than the initial treatment (McConnachie et al. 2012). Depending on the size of the seed bank, multiple follow-up treatments are usually required, sometimes spanning decades (van Wilgen et al. 1992).

Data

We mapped invasive tree presence using aerial photographs taken in 1987 and 2010. We obtained the images from the Department of Rural Development and Land Reform (Chief Directorate: National Geo-spatial Information, Mowbray, South Africa). The scale of the 1987 and 2010 images was 1:30000 and 1:10000, respectively. The high resolution of the photographs, coupled with the contrast between fynbos and taller invasive trees, made it possible to identify individual adult trees. We first drew polygons around areas of solid invasive tree cover and added points for scattered

Table 1. Descriptive statistics of the different land use types and land ownership types in the study area.

Variables	Proportion of total study area	Proportion of treated area	Proportion of program expenditure	Proportion of total cells occupied by invasive trees		Mean proportion of cells occupied by invasive trees (standard deviation)	
				1987	2010	1987	2010
Land use type							
Untransformed	0.82	0.91	0.72	0.27	0.37	0.03 (0.17)	0.03 (0.17)
Transformed	0.13	0.04	0.10	0.30	0.28	0.19 (0.4)	0.15 (0.35)
Plantation	0.05	0.05	0.18	0.43	0.35	0.73 (0.44)	0.46 (0.5)
Land ownership type							
State protected area	0.42	0.53	0.34	0.12	0.19	0.02 (0.15)	0.03 (0.17)
Private protected area	0.33	0.29	0.25	0.19	0.18	0.05 (0.22)	0.04 (0.19)
Private unprotected area	0.21	0.10	0.20	0.45	0.41	0.18 (0.39)	0.13 (0.34)
Former state forestry	0.04	0.07	0.21	0.24	0.22	0.49 (0.5)	0.33 (0.47)

Notes: Records of Working for Water treatments began in 2001. Treatment management areas represented 31.9% of the total study area, which covers 1451 km^2. Total recorded costs were 34.8 million South African rand (ZAR); 1 US\$ ~10 ZAR.

trees. We then overlaid a 20 × 20 m grid and gave a presence–absence classification if cells intersected the polygons or points. The cells were our unit of analysis. Finally, we asked Working for Water managers to cross-check our mapping based on their knowledge of the area and other invasive tree spatial records that they had (e.g., Forsyth 2012).

We used Working for Water's spatial records, dating from 2000, to obtain the costs incurred in treating areas. The treatment areas, recorded as polygons (see blue areas in Fig. 2), were a group of management areas ranging in size from less than a hectare to several hundreds of hectares. For most polygons only a small fraction were invaded by trees and hence actually treated. We adjusted all costs to 2014 values to account for inflation. Costs excluded overhead costs, i.e., management and implementing agent fees. We therefore only included costs spent on clearing trees, excluding costs spent treating invasive shrubs. From anecdotal accounts we knew that the bulk of clearing took place after 2000 shortly when our treatment records began. However, there are accounts of clearing operations between 1987 (the date of our baseline estimate) and 2001 by agencies responsible for management at the time. These included the former Department of Forestry (1987–1990), CapeNature (1990–1995), and Working for Water (1996–2001).

We used several data sources for the covariate information. We used the South African Department of Land Affairs data sets for roads (excluding tracks and footpaths), altitude, and rivers. Riparian areas were defined by a 50-m buffer along rivers. We mapped the different land uses (listed in Table 1) using the 1987 aerial photographs and cross-checked this with the 2001 National Land Cover Layer. We classified areas where fynbos had been cleared for agriculture or settlements as transformed. For the land ownership types (listed in Table 1), we used the boundaries of protected areas in the 2011 National Biodiversity Assessment. Finally,

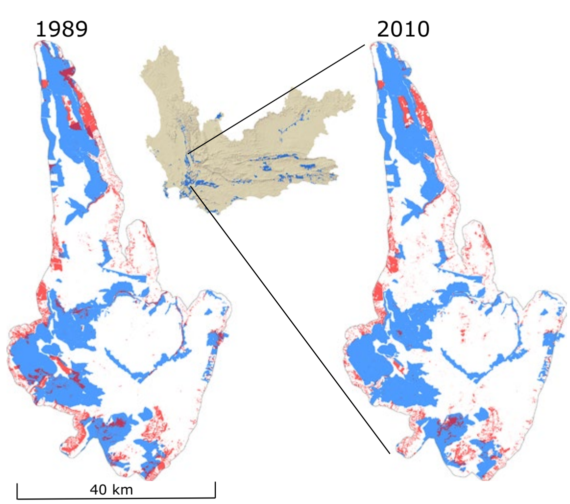

Fig. 2. Invasive tree presence marked in red, in 1987 and 2010, on the Hawequas study area within South Africa's Western Cape Province (see inset map) ~50 km east of Cape Town. Areas that Working for Water treated are marked blue.

for estimating the surrounding invasive tree presence, we used the ArcGIS 10.2 point density function to calculate for each cell the area of surrounding cells (within 100 m) occupied by invasive trees in 1987 (ArcGIS; ESRI, Redlands, California, USA). For the analysis we selected a sample of 15 000 cells. We did this to reduce potential interference between cells (i.e. the outcome on one cell is unaffected by the assignment of treatments on the other cell).

Defining the treatment effect

We introduce notation to define the treatment effect that we estimated. Our outcome variable (Y) was equal to one ($Y = 1$) if a cell (20 × 20 m) was occupied by invasive trees in 2010, and equal to zero ($Y = 0$) otherwise. Like the outcome, the treatment variable (D) was also binary, with cells either treated ($D = 1$) or untreated ($D = 0$). Therefore, each cell had two potential outcomes regardless of whether it was treated or not: Y^1, the invasive tree occupation when the unit was treated (e.g. Fig. 1C), and Y^0, invasive tree occupation when the cell was untreated (e.g. Fig. 1B). We were interested in measuring, in statistical jargon what is called the "average treatment effect on the treated" cells (ATT): ATT = $E(Y^1 - Y^0 | D = 1)$; the average impact of treatment for a randomly chosen cell from the population of cells that were treated by the program. In other words, the ATT was the difference in invasive tree presence with the program and without the program for the cells actually exposed to the program. For these cells, we can observe outcomes with the program, and thus we can estimate $E(Y^1 \mid D = 1)$. However, we cannot observe the counterfactual outcomes of treated cells had they remained untreated, and thus we needed a way to estimate $E(Y^0 | D = 1)$ from what we could observe (e.g. untreated cells).

Identifying confounding factors through understanding program implementation

The first step in selecting a comparison group was to identify possible confounding factors: variables that jointly affect why cells were treated and the outcome. To identify confounders we drew on our experience of how the program is implemented (van Wilgen et al. 2012*a*, McConnachie et al. 2013) and discussions with program managers. The main potential confounders that we identified related to the type of land ownership and land use the program worked on, baseline invasive tree presence (the program tended to treat less invaded cells), site accessibility, and where invasive trees grow in the landscape (see Table 2 for details).

Selecting untreated cells for the counterfactual using matching

We used a matching technique to account for the confounding factors that we identified above (Ho et al. 2007). The goal of matching was to make the treated and selected

TABLE 2. A list of the types of confounding factors, the variables used to measure them, and a description of the mechanism through which the confounders jointly affect why certain areas were treated by Working for Water and the outcome (invasive tree presence).

		Mechanism through which it affects		
Type	Variables used	Treatment selection	Outcome	References
Land ownership	State protected area, private protected area, private unprotected or state forestry land	Program prefers to work on state owned land (protected areas and plantations) because program is state funded.	State protected land and state plantation land might be less or more invaded, respectively, than other land ownership types.	van Wilgen et al. 2012*b*,
Land use	Untransformed, transformed, and plantation land	Program prefers untransformed land compared to other land use types because of greater potential for recovery of native biodiversity.	Transformed and plantation land more invaded, older invasions, more disturbed	Rouget et al. 2003, Spear et al. 2013,
Pre-treatment invasive tree presence	Invasive tree presence and surrounding presence in 1987, mean annual precipitation, altitude	Presence and density of invasive trees could influence treatment location.	Sites more invaded prior to treatment more likely to be invaded after treatment	Holmes et al. 2008,
Access	Distance to nearest road, or transformed land and plantation, altitude	Accessibility of a site might affect if it gets treated.	More accessible sites (closer to roads and areas where humans live) tend to be more invaded.	Rouget et al. 2003, Spear et al. 2013,
Growth location	Riparian area	Program might target invaded riparian areas because invasive trees consume more water here.	Riparian areas more prone to disturbance, resulting in higher risk of being invaded.	Holmes et al. 2008

untreated comparison cells (counterfactual) as similar as possible to what would result from a randomized experiment. The matching algorithms worked by reweighting the untreated cells to select a comparison group that, on average, was observably similar to the treated cells in terms of the distributions of the confounding factors (called "balance"). To assess balance we used summaries of the difference in means as well as summaries of the empirical quantile–quantile plots (see Appendix S1: Tables S1–S4 for summaries of these measures for each confounding variable).

We selected a matching approach that gave the best balance: a genetic search optimization algorithm (Diamond and Sekhon 2006), using one-to-one matching with replacement. We used the package matching (Sekhon 2011) in R (R Development Core Team 2013). To calculate the precision of our estimates, we calculated heteroskedasticity robust estimates of the standard errors (Abadie and Imbens 2006).

Cost-effectiveness estimates

We calculated the cost-effectiveness estimates by dividing the total treatment costs by the area of previously invaded cells that had been cleared of invasive trees in 2010 as a result of control (estimated by the estimates of the ATT). Our cost-effectiveness estimates did not include allowances for future follow-up costs.

Robustness tests

Spillovers

Our estimates might have been biased if the outcomes of untreated cells close to *Working for Water* treated cells were affected by the treatments (called spillover effects). This could happen, for example, if landowners adjacent to treatment areas were incentivized to clear their lands. We tested for spillover effects by comparing the difference in invasive tree presence between cells within 100 m of treated cells, with similar cells greater than this distance (i.e., the counterfactual). We selected the counterfactual cells using the same statistical matching technique used in the other analyses. We note that our local spillover analysis would not be able to pick up potentially more complex spillover scenarios (for example public awareness being raised about invasive species by Working for Water's presence in the study area).

Unobserved confounding factors

The major challenge of nonexperimental studies is that researchers have to retrospectively account for all possible confounding factors (i.e., no unobservable confounders exist, or are perfectly correlated with the observable confounders; Ferraro and Hanauer 2014). Although we believe we accounted for the most important possible confounding factors we might well have missed others. To address this issue we used Rosenbaum's (2002) sensitivity analysis, using the R package rbounds (Keele 2011), to determine how strongly a hidden confounder (or set of them) would have to be to result in us falsely rejecting a null hypothesis of no treatment effect (using the Wilcoxon test statistic). Intuitively, the test works by increasing the odds of comparison group cells being treated by a factor of gamma (Γ). The farther the gamma values are from one, the more robust the estimated effect is to potential hidden bias.

Results

Descriptive statistics

The percentage of all grid cells occupied by invasive trees in the study area declined from 8.6% (standard deviation: 28%) in 1987 to 6.6% (25%) in 2010. On treated cells the percentage presence declined from 8.2% (27%) to 2.8% (17%), whereas on untreated cells it declined from 8.7% (28%) to 8.3% (28%).

In terms of the land use sub-groups, plantation and transformed land made up a small percentage (5% and 13%, respectively) of the total study area (Table 1). However, most of the invasive trees were found on these land use types (63% of grid cells occupied in 2010; Table 1). Likewise, in terms of different land ownership types, the majority of invasive trees occupied unprotected private land and plantations formerly managed by the state.

Most the program's treatment management areas were located on untransformed land (91%) and protected area land (82%, state and privately owned combined), which was only sparsely invaded (Table 1). Transformed and plantation land only made up a small percentage of the total treatment area (4% and 5%, respectively), but because it was more densely invaded a sizable percentage (10% and 18%, respectively) of the program's budget was spent on these areas.

Effectiveness and cost-effectiveness estimates

The relatively sparse nature of tree invasions in the untransformed landscapes meant the treatment effects (in terms of reduced occupancy) were not large (Table 3). Clearing treatments on densely occupied transformed and plantation land, however, led to large reductions in occupancy. This meant that clearing dense areas appears more cost-effective over the time period.

Counterfactual rates of spread on treated cells

On treated untransformed land, had the treatments not happened, the percentage of cells occupied by invasive trees would have increased slightly over the treatment period (0.8%; Table 3). This was calculated by subtracting the counterfactual outcome values for treated cells in 2010 from the same treated cells in 1987. On the other land use types the invasive tree presence would have declined slightly even if there had been no intervention by Working for Water, because clearing by other agencies also took place.

Robustness tests

Our estimates were robust to potential hidden bias (Table 3). We detected no significant ($P = 0.46$) spillover effects from treatment areas to neighboring untreated areas. The proportion of cells occupied by alien trees within 100 m of treated areas was only 0.8% (standard error of 1.2%) lower than cells further away than this.

Discussion

Improving counterfactual estimates

We have demonstrated that accurately measuring the effectiveness of invasive species removal depends on accurately measuring counterfactual outcomes: in our case, the proportion of grid cells occupied by invasive trees without Working for Water treatments. For example, our estimates of impact would have been different if we had used the proportionate invasive tree occupancy on untreated

Table 3. Estimates of treatment effectiveness (change in proportion of sampled cells occupied by invasive trees resulting from the program intervention) and cost-effectiveness.

Variables	1987 T	1987 U	2010 T	2010 U	2010 CF	Estimate Naive	Estimate Match	P	SE	Γ	CE (ZAR)	CF spread
Overall	0.056	0.061	0.027	0.065	0.055	−0.038	−0.028	0.001	0.008	2	27,838	−0.01
Land use type												
Untransformed	0.046	0.021	0.022	0.035	0.054	−0.013	−0.032	0.000	0.006	2.8	18,932	0.08
Transformed	0.298	0.185	0.092	0.148	0.221	−0.057	−0.130	0.000	0.021	2.9	14,394	−0.08
Plantation	0.648	0.761	0.068	0.621	0.439	−0.552	−0.371	0.000	0.027	11.7	8,069	−0.21

Notes: Treated (T) and untreated (U) columns for 1987 and 2010 show the mean proportion of sampled cells occupied by invasive trees for the respective treated and untreated cells. The counterfactual (CF) estimate shows counterfactual mean presence of invasive trees for treated cells in 2010. The naïve estimate is the difference between these treated cells and the untreated cells in 2010 without accounting for confounding factors. The matching estimate is the difference between the treated cells and the counterfactual cells. Γ measures a sensitivity test. Cost-effectiveness (CE) is shown as South African rand per ha reduced; 1$ US ~10 ZAR. The counterfactual spread for treated cells was calculated by subtracting the counterfactual outcome values for treated cells in 2010 from the same treated cells in 1987.

cells, or the occupancy before treated cells were treated, as a surrogate for the average counterfactual outcome (as used elsewhere, e.g. McConnachie et al. 2012, van Wilgen et al. 2012*b*). Likewise, our impact estimates would have been inaccurate if we had assumed that invasive trees would have spread at a constant rate across the different land use and land ownership types in the absence of the program. We estimated that invasive tree occupancy would have actually declined on transformed and plantation land, even had Working for Water not intervened, because of other clearing that took place. On untransformed land we estimated that invasive trees would have spread by only 0.8% per annum, compared to estimates of between 3.75% and 20.6% made by other studies (Richardson and Brown 1986, Higgins et al. 2000, Moeller 2010). By using the matching design we were able to select untreated cells that were as similar as possible to treated cells (in terms of observable confounding factors) and hence a make a more credible counterfactual estimate. The matching design that we demonstrated here is just one of many innovative empirical designs developed by the program evaluation field to evaluate the impact of public policy interventions in nonexperimental contexts (Imbens and Wooldridge 2009). These approaches offer many opportunities for improving the way conservation interventions are evaluated (Ferraro and Hanauer 2014).

Cost-effectiveness of clearing effort

Compared to previous evaluations of Working for Water's effectiveness (McConnachie et al. 2012, van Wilgen et al. 2012*b*), we found that within the study area the program has effectively reduced invasive plant occupancy on treated areas, and depending on the rate of future spread it could bring the tree invasion under control. For example, if the program were to focus its clearing effort on untransformed land, at the current rate of reduction (181 ha per annum on average during the treatment period) it would bring the invasion under control (i.e. reduce cover close to zero) within 20–63 yr (depending on if the future spread rate were 0% or 5% per annum, respectively).

Importantly though, the clearing operations in our study area are regarded as being among the more effective projects in the region, and our findings may therefore not be representative of the outcome of clearing operations when assessed at the scale of the CFR (e.g. van Wilgen et al. 2012*b*). The relatively high level of effectiveness of clearing in our study area could also arguably be attributed to management by a motivated implementing agent (in this case the provincial conservation agency Cape Nature, which has a mandate for biodiversity conservation, and is staffed by trained and motivated conservation managers). In our experience, the same levels of motivation are not always found in alternative implementing agents used by Working for Water, who may have other priorities. Further evaluations are urgently needed so that the drivers and determinants of efficiency can be better understood (van Wilgen et al. 2012*a*). There are major opportunities for transferring lessons from successful to less successful operations (Roura-Pascual et al. 2011).

Although we found that the treatments were more effective in reducing invasive tree occupancy than found in other study areas (van Wilgen et al. 2012*a*), our estimates of cost were between 2.7 and 4.9 times higher than those estimated elsewhere (Le Maitre et al. 2002, Marais and Wannenburgh 2008). We likely underestimated costs because we did not account for the costs of clearing future invasive tree regrowth on the sites. In addition, the area of grid cells where invasive trees were present might have been greater than the actual canopy cover of invasive trees. This has implications for what the program can achieve with its limited budget and how cost-effectively it can protect ecosystem services like the delivery of water from catchment areas. To date it has cost 35 million rand (US$3.5 million) to reduce invasive tree occupancy by 2.8% on treated areas. At this rate of clearing, it would cost a further 67 million rand (US$6.7 million) to remove invasive trees from untransformed areas in the study area, even if no further spread occurs. To put this cost into perspective, this is equivalent to 84% of an earlier estimate of the cost (112 million rand, US$ 11.2 million) to control all invasive plants (shrubs and trees) in the entire CFR (Frazee et al. 2003). This highlights the need to focus scarce resources on priority areas, so that available funds can be more effectively utilized. Currently, there is a lack of focus that leads to the dilution of funding, with the inevitable consequence that not enough projects are making adequate progress (van Wilgen et al. 2012*a*).

Why is our estimate of cost-effectiveness so much higher than the predictions of previous studies? Previous studies used estimates of cost-effectiveness that assumed that the trees would not reestablish after clearing, but in reality trees do regrow if not properly treated (McConnachie et al. 2013). These previous studies also assumed that only two follow-up treatments would be required when in reality many more treatments may be needed (some areas have been treated 10 times and still need further follow-up treatments).

We assessed one possible outcome from the program (invasive tree presence), future research is needed to assess the long-term impacts of the program on native species recovery and its impact on ecosystem services such as increases in water runoff. Future research is also needed to make more detailed species-level cost-effectiveness estimates.

How the counterfactual informs removal effort

Counterfactual estimates are important for informing where conservation effort should be targeted, depending on the goal, budget, and time-frame of the intervention. We found that if the goal is to reduce invasive tree occupancy as much as possible within the time of the treatment period (2002–2009), given its budget of 35 million rand during this period, Working for Water would have been able to reduce the highest amount of invasive tree occupancy on transformed and abandoned plantation areas because the treatments were most cost-effective there. However, over a longer time-frame, and given that invasive trees will likely continue to spread on untransformed areas, it would be more cost-effective to target untransformed areas (Higgins et al. 2000). If the goal of the program were to avoid new areas from becoming invaded (e.g. to minimize biodiversity loss), then the program would have been better off targeting untransformed areas exclusively. However, clearing effort would still be required to contain invasive trees spreading from plantation and transformed areas into untransformed areas (McConnachie et al. 2015).

The finding that it would be most effective to focus clearing efforts on sparse rather than densely invaded portions of an infestation is not new. Higgins et al. (2001), for example, concluded that clearing strategies that prioritize low-density sites dominated by juvenile alien plants proved to be the most cost effective. van Wilgen et al. (2000) also suggested that an approach that focused clearing operations on scattered, outlying populations would be the most cost effective in situations where the funds available for control are limited (as is almost always the case). Both of these studies support our finding that clearing would have been more effective had it focused on clearing surrounding sparsely invaded land as opposed to densely invaded areas.

Decisions regarding strategies for clearing invasive species over large areas will not be resolved until credible empirical evidence on the cost-effectiveness of controlling them is available. Even large programs like Working for Water currently do not evaluate the outcomes of their interventions (called impact evaluations). Instead, at best, they only evaluate whether or not interventions were implemented properly (called process evaluations; Mascia et al. 2014). Although process evaluations are important, they cannot elucidate differences that interventions are making.

Acknowledgements

We acknowledge support from the DST-NRF Centre of Excellence for Invasion Biology and the Working for Water program through their collaborative program on "Integrated management of invasive alien species in South Africa." We thank D. Rossouw, A. Moolow, and Stellenbosch University's Centre for Geographical Analysis for assistance. M. M. McConnachie received support from the National Research Foundation (NRF), South Africa, through an Innovation Fellowship and D. M. R acknowledges incentive funding from the NRF (grant 85417).

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Supporting Information

Additional supporting information may be found in the online version of this article at http://onlinelibrary.wiley.com/doi/10.1890/15-0351.1/suppinfo

Data Availability

Data associated with this paper have been deposited in the KNB repository: https://knb.ecoinformatics.org/#view/knb.792.1