# The Value of Using Feasibility Models in Systematic Conservation Planning to Predict Landholder Management Uptake

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**Running head:** Predicting landholder management uptake

**Keywords:** conservation opportunity, species distribution model, willingness-to-engage, 1080 fox baiting, invasive species, critical weight range mammals

Type of article: Contributed Paper, Conservation Biology
Number of words in abstract: 299
Number of words in main text: 6618
Number of references: 44
Number of figures: 3
Number of tables: 4

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## Abstract

Understanding the human and social dimensions of conservation opportunity is crucial for conservation planning in multiple-use landscapes. However, factors that influence the feasibility of implementing conservation actions such as the history of landscape management and landholders' willingness to engage are difficult or time-consuming to quantify, and are rarely incorporated into planning. We examine how conservation agencies could reduce costs of acquiring such data, by developing predictive models of management feasibility. Our models are parameterized with social and biophysical factors likely to influence landholders' decisions to engage in management, with the best-supported model including property size, number of neighbors, distance from conservation reserves, and recorded biodiversity surveys on the property. To test the utility of our best-supported model, we develop four alternative investment scenarios based on different input data for conservation planning: social data only, biological data only, potential conservation opportunity using modeled feasibility that incurs no social data collection costs, and existing conservation opportunity using feasibility data that incurred collection costs. We consider a case study in south-west Australia, an internationally recognized biodiversity hotspot managed for agriculture and conservation. Using spatially explicit information on biodiversity values, feasibility and management costs, we prioritize areas to control an invasive predator that is detrimental to both agricultural and biodiversity values: the red fox (*Vulpes vulpes*). We find the most cost-effective investment scenario is to use a predictive model of feasibility when social data collection costs are moderate to high, but combining actual feasibility data with biological data is more-cost-effective for prioritizing management when social data collection costs are low (<4% of the total budget). Calls for more data to inform conservation planning should take into account the costs and benefits of collecting and using such data, to ensure that limited funding for conservation is spent in the most cost-efficient and effective manner.

## Introduction

An understanding of the history of human use of a landscape, and associated opportunities for implementing conservation actions, is useful to effectively identify priority areas for management (Knight et al. 2010). Many regions of high conservation value are contained within private land (Curtis & Mendham 2011), and uncertainty in the opportunities for conservation in these areas means that information on the ease of management implementation can avoid misplaced effort in areas with low likelihood of landholder engagement, or that conflict with human resource use (Ban et al. 2013). Management feasibility, a component of conservation opportunity (Moon et al. this issue), predicts the likelihood of successfully implementing an action. Data reflecting feasibility are increasingly collected and included in conservation priority-setting exercises, including information on landholder willingness-to-sell (e.g. Guerrero et al. 2010) and social or cultural values of the landscape (Whitehead et al. in press). Because funding for conservation is limited, cost-effectiveness analysis is often used to solve problems of deciding where to do conservation actions, by choosing the strategy with the highest rate of conservation return relative to management costs (e.g. Joseph et al. 2009; Carwardine et al. 2012). These prioritization decisions usually account only for the costs of actions (Hughey et al. 2003), and rarely include the costs of investing in data (Baxter & Possingham 2011). No studies have examined how sensitive decisions are to the costs of data collected to inform the feasibility of management implementation (but see Grantham et al. 2008).

For any uncertain action constrained by time or funding, conservation agencies must trade-off the decision to collect additional biological, social or economic data against the urgency of the problem, and the resources allocated to action instead of planning (Grantham et al. 2008). Data on human characteristics used to assess and map feasibility are traditionally collected at a local-scale through social surveys or interviews, which can be costly, time consuming and riddled with uncertainty (Lechner et al., this issue). For example, Knight et al. (2010) undertook 48 interviews lasting an average of 3 hours each to understand opportunities and constraints over a 1466 km$^2$ region that represented a quarter of the local municipality area. The data collected therefore represented only a small fraction of the population. Scaling-up the surveys to encompass the remainder of the 4400 km$^2$ local municipality could have required four times the survey costs. Although more resources spent collecting data means fewer resources for action, an insufficient understanding of the planning region due to too few data can result in lost efficiencies and poorly-located management (Grantham et al. 2008).

Models of management feasibility could decrease the costs of obtaining social data by predicting likelihood of implementation (e.g. Guerrero et al. 2010), however there have been few attempts to create such models as human behavior is difficult to predict. Economic, social and environmental factors influence the willingness of a landholder to participate in a particular management action (Pannell et al. 2006; Raymond & Brown 2011). Important factors shown to influence management feasibility include budget constraints and profit expectations (e.g. Cary et al. 2001), property size and land use (e.g. Abadi Ghadim et al. 2005), existence and strength of landholders' social networks and local organizations (Sobels et al. 2001), membership of organizations such as catchment groups (Kington & Pannell 2003), the conservation values and education of the individual landholder (Burton 2014), and perceived environmental advantage (Cary 1993). Models of feasibility would require fewer resources if they could be developed from biophysical characteristics reflecting human values and land use. For example, the history of vegetation management by landholders in an agricultural landscape can be mapped using aerial photos or remote sensing to represent the production value of a property, or census data could be used to represent socio-economic factors such as organization memberships (Guerrero et al. 2010). Conservationists already apply sophisticated models based on biophysical characteristics to predict species occurrences and identify areas for prioritizing conservation efforts on the basis of highly uncertain biodiversity data (Guisan et al. 2013). Yet few studies have used biophysical characteristics to predict management feasibility (but see Guerrero et al. 2010; Mills et al. 2012), and none have compared the cost-effectiveness of using modelled behavior instead of actual landholder characteristics for informing conservation planning decisions.

Planning in multiple-use landscapes requires additional considerations related to the suitability and effectiveness of proposed management in any given landscape. Many resource management actions are beneficial for both farmers and biodiversity, and maximizing benefits to biodiversity may require only small modifications to existing practice at little additional cost to the conservation organization or the landholder. While most conservation planning studies assume a net negative impact of humans on biodiversity and plan to minimize interaction between resource use and biodiversity (Klein et al. 2008), land management practices can also have positive impacts. These might be intentional conservation benefits through landscape modification (e.g. restoring habitat, erosion control, fencing off remnant vegetation to protect from grazing) and private land conservation policies such as covenants or easements, or unintentional benefits to conservation through actions to improve economic yield of their land use (e.g. killing weed species to improve crop yield, or fighting wildfire) (Raymond et al. 2013). Consideration of such practices in conservation prioritization is essential, as the degree to which actions benefit the landholder can influence whether a landholders is interested in participating in conservation actions (Pannell et al. 2006).

In this study we ask: 1) Can we use the geographic locations of past management actions implemented by private landholders to predict the future distribution of management effort? 2) Is it possible to predict where management is most likely to be feasible based on landscape characteristics? 3) Assuming that future landholder engagement is spatially predictable, how would the priorities for conservation change when predictions of conservation opportunity are used in planning, compared with if no social data were used to prioritize actions? 4) In what circumstances is it more cost-effective to build a model of management feasibility, compared to collecting social data, to prioritize conservation management within an existing incentive scheme? Our case study is managing the invasive red fox in the south-west Australian biodiversity hotspot, where foxes predate on both livestock and native fauna. We utilize both ecological data on the distribution of six native fauna species threatened by fox predation and social data on the history of landholder engagement in fox baiting. Our objective is to minimize the cost of investing in management in a typical multiple-use landscape where conservation resources are limited.

## Methods

### Case Study: Invasive red fox management in Australia

The control or eradication of invasive pests is receiving increasing attention worldwide. In Australia, the invasive red fox (*Vulpes vulpes*) is implicated in the decline and possible extinction of native vertebrates, loss of agricultural production due to livestock predation, and disease transmission (Saunders et al. 2010). In 2004, foxes were estimated to cost Australian agricultural industries at least AUD$227 million annually (McLeod 2004), topping the list of costs incurred by vertebrate pests. In response to this ongoing threat, fox management programs have been implemented on public and private lands across Australia, typically using poison baits containing sodium 2-fluoroacetate ('1080'), with over AUD$16 million spent on this annually (Saunders et al. 2010). Our study region is the area of the Fitz-Stirling (17,000 km$^2$) in the south-west Australian biodiversity hotspot, characterized by high species endemism and high threat due to the coincidence of agricultural production and biodiverse areas (Myers et al. 2000; for additional information see Supporting Information). Until recently, most fox management was carried out in an ad hoc manner, with little cooperation or coordination between managers. However, recent work indicates that due to the high mobility and recolonization potential of foxes, increasing the frequency and spatial coverage of fox control with participatory stakeholder management increases survival of lambs (McLeod et al. 2010) and native animals (Western Australian (WA) Government Western Shield Program, unpub. data). Failure to strategically target areas of agricultural and conservation value risks severe economic losses to the agricultural industry as well as local extinctions of biodiversity.

Our scale of management is the property-level, with each privately-owned land parcel representing an area that can be managed. We divided the study area into planning units on the basis of cadastral boundaries. Properties were considered an appropriate management unit because the decision to conduct fox baiting is made by the individual landholder at the scale of the property. All properties less than 1 km$^2$ were merged with the neighboring unit that shared the longest boundary, resulting in 1337 planning parcels (area mean ± SE = 9.83 ± 0.24 km$^2$; see Supporting Information).

**Species distribution data**

We selected seven species for prioritization of invasive fox management based on results of a previous study (Tulloch et al. 2013a; Table 1). These species have suffered range and population declines over the past century (Burbidge et al. 2008), and are predicted to have greater than 50% chance of increasing under invasive predator management. One of these species, the dibbler (*Parantechinus apicalis*), occurs only in national parks, so this species was excluded from further analyses as we were interested in prioritizing conservation investment on private land. We modeled the distribution of the six remaining species in the software Maxent v. 3.2.1 using existing species distribution data and environmental variables (Phillips et al. 2006; for additional information see Supporting Information).

## Predicting management feasibility on private land

To inform management feasibility, data on landholder engagement in fox management (through poison baiting) were obtained from the WA Department of Agriculture and Food (DAFWA), from a dataset recording all baiting applications through a community engagement program ‘Red Card for Rabbits and Foxes’ that incentivized fox baiting between 2003 and 2010 (Table S1).

### *i. Feasibility model 1: Predicting future distribution of baiting effort from past effort*

Our first aim was to determine if landholders that have baited previously are likely to bait again, by exploring whether the spatial distribution of past landholder engagement in fox baiting can predict the distribution of future baiting. We split the dataset in two periods, early years and late years, and related the spatial distribution of management effort (number of baiting events per property parcel) from the 2007–2010 DAFWA data collection period (response variable) to the distribution in the first half of the data collection period (2003–2006; explanatory variable). We used generalized linear modeling (GLM1) with a Poisson distribution to test for the significance of the relationship and thus the ability of the distribution of past management effort to predict future locations of effort (Tulloch et al. 2013b).

### *ii. Feasibility model 2: Predicting future distribution of baiting effort from landscape characteristics*

Our second aim was to identify factors that motivate landholders to participate in an incentive scheme that has dual benefits for production and conservation, and explore whether characteristics of the landscape can be used to predict management feasibility, i.e. the distribution of landholder engagement. We set up hypotheses for factors that motivate landholders to conduct fox baiting across the landscape, and tested them using generalized linear modeling (Elith & Leathwick 2009; Table S2). Human behavior is complex, and to fully understand the reasons for landholders to bait an area, we would ideally run questionnaires on the incentives for fox baiting engagement, but this can be costly. To test whether feasibility could be predicted using landscape characteristics only, we used coarse-scale landscape surrogates representing factors that motivate landholders to bait for foxes (Table S3). Our hypotheses describing potential drivers for landholder engagement in fox baiting reflected economic, social and conservation motivations outlined in recent literature, resulting in 17 models (see Supplementary Information). Hypotheses were compared in an information-theoretic framework using AIC model selection (e.g. Burnham & Anderson 2002), and the best-supported model was used to predict management feasibility for every parcel in the region.

**Using management feasibility to prioritize investment in conservation action**

Our third aim was to develop plausible scenarios of investment prioritization of on-ground conservation management in a production landscape, to explore how the priorities for conservation might change when different types of datasets are used to inform decision-making. Systematic conservation planning is increasingly used to inform decisions about where to prioritize funding, and requires information on the costs and benefits of selecting a given parcel for management. We set up four scenarios of investment prioritization by a conservation agency to fund private land management:

(1) Social-only: The agency uses only social data on management feasibility based on which landholders have carried out management in the past (Feasibility model 1) to direct funding, with no biodiversity values considered. All properties with a known history of management are invested in.
(2) Biodiversity-only: The agency prioritizes investment based on biodiversity values and costs of parcels, with no social data considered.
(3) Conservation opportunity using current feasibility: The agency prioritizes investment based on biodiversity values, costs, and existing management feasibility based on which landholders have carried out management in the past (Feasibility model 1**)**.
(4) Conservation opportunity using modeled feasibility: The agency prioritizes investment based on biodiversity values, costs, and management feasibility predicted by landscape characteristics (Feasibility model 2***)***.

To calculate the total investment required for the social-only scenario, we allocated funding to every parcel with a previous history of fox management. To calculate the investment required under the remaining scenarios (2 to 4), we used an extension of the conservation planning decision-support software Marxan (Ball & Possingham 2000), Marxan with Zones, which uses a simulated annealing algorithm to identify near-optimal zoning configurations that minimize the sum of planning parcel and zone boundary costs whilst meeting a suite of conservation targets (Watts et al. 2009). Marxan with Zones improves our ability to accommodate multiple socio-economic and biodiversity considerations in conservation planning, through the addition of user-defined zones and ability to specify costs and targets for each zone. We planned for three management zones: (1) no fox management, (2) low intensity management (two baiting events per year), and (3) high intensity management (4 baiting events per year). The low intensity management zone represents current landholder baiting practices, which are typically once or twice a year and provide limited benefits to biodiversity but satisfy needs to protect sheep during key breeding seasons. The high intensity management zone reflects the management practices of the State conservation agency that bait statewide every three months in national parks (Armstrong 2004), where the primary objective is to provide conservation benefits to threatened species.

We considered our six threatened mammal species as the biodiversity values for each scenario, and set targets of 17% of their distributions to be managed. We assumed a species was present in a planning parcel if the maximum probability of occurrence in any remnant patch within the parcel was greater than 60%. The contribution of different land uses to the conservation of species varies depending on the relative sensitivity of species to threats and their management. We therefore developed a contribution matrix (the likely contribution of each zone to achieve targets) based on a previous study (Tulloch et al. 2013a): this was 90% for high intensity management, 50% for low intensity management, and zero for no conservation management (Table S5).

The costs of each parcel were calculated in two ways. For the 'social-only' and 'biodiversity-only' scenarios, we created a baseline management cost layer that identified three possible costs per parcel: no, low or high intensity management (zero, two or four baiting events per year respectively). The cost of high intensity management of parcel $i$, $c_i$, was calculated as the parcel area multiplied by the annual cost of baiting per km$^2$ of private land, estimated at \$100/km$^2$, reflecting the conservation agencies' average management expenditure in the region. The cost per parcel was halved for low intensity management, and was zero for no management.

For both conservation opportunity scenarios, we calculated the cost of baiting for foxes in each parcel (at a frequency that would benefit threatened species) by adjusting the costs of management to account for the predicted management feasibility in each parcel:

$$h_{iz} = c_{iz} (1 - \alpha),$$

where $h_{iz}$ is the adjusted cost of baiting parcel *i* under zone *z*, $c_{iz}$ is the baseline cost of baiting the parcel under zone *z* (accounting for area and baiting rate), and $\alpha$ is an adjustment factor applied to each parcel based on the value of management feasibility (a value from 0 to 1). If $\alpha$ = 0, there is no adjustment applied to the parcel (no existing management), and the cost is equal to the baseline cost. If the modeled management feasibility ($\alpha$) is equal to 1, this means that the landholder is already baiting to a frequency that would benefit threatened species (four times a year), and so no additional funding is required to manage this parcel for conservation.

In the conservation opportunity using current feasibility scenario, $\alpha$ was parameterized using the response curve of GLM1 (see section "Feasibility model 1"). Costs of managing each parcel were therefore reduced by the existing management feasibility values predicted using the DAFWA dataset on the history of past landholder management. In the conservation opportunity using modeled feasibility scenario, $\alpha$ was parameterized using the response curve from the best-supported GLM2 (see section "Feasibility model 2"). Costs of managing each parcel were reduced by the management feasibility values that had been predicted using landscape-level surrogates.

**Calculating cost-effectiveness of data and management**

Our fourth and final aim was to compare the cost-effectiveness of the different investment scenarios in relation to the costs and benefits of the data used to parameterize the decision solutions.

Using the best solutions of our prioritizations, we first calculated the benefit *M* of managing the *n* selected parcels in each zone, which is the summed managed area of all species distributions:

$$M = \sum_{i=1}^{n} x_{iz} \, . \, b_{iz} . \, e_z, \qquad (1)$$

where *x* is a control variable for parcel *i* that takes the values 0 (not selected) or 1 (selected for management) for zone *z*, $b_{iz}$ is the summed area of all species distributions that fall inside planning parcel *i* for zone *z*, and $e_z$ is the contribution of that zone's level of management to the conservation of species (in our study, 0.9 for high intensity management, 0.5 for low intensity management, and 0 for no conservation management). The parameter *e* is equivalent to the probability that, if implemented successfully, the action would be successful in managing the threat. This has been termed 'output success' in previous cost-effectiveness studies, and is likely to depend on ecological factors influencing outcomes (Tulloch et al. 2013a).

We then adjusted the benefit for each parcel by the probability of that parcel having been managed in the past, to give us a total expected benefit value *B* that accounted for feasibility in each parcel:

$$B = \sum_{i=1}^{n} x_{iz} \, . \, b_{iz} . e_z . p_i, \qquad (2)$$

where $p_i$ is the probability that the action could be undertaken successfully, ranging from 0.05 (no information on implementation opportunity, adjusted from a value of 0 to account for uncertainty) to 1 (100% probability of implementation – in our study, baited every year between 2003 and 2010). The parameter *p* was parameterized from the response curve on existing management feasibility, previously calculated from GLM1, and has been termed ‘input success’ in previous cost-effectiveness studies (Tulloch et al. 2013a).

The total investment allocated in the investment scenario, *C*, was calculated by summing the baseline (rather than adjusted) costs of each parcel selected for management in the best solution from each scenario:

$$C = \sum_{i=1}^{n} x_{iz} \, . \, c_{iz}, \qquad (3)$$

We then derived from experts the likely investment, given the size of the study area, required to obtain two different types of data, biological and social (A. Guerrero and V. Adams, pers. comm.). Biological data costs were set at a flat rate of AUD$3,000, the standard cost of purchasing biological atlas data in Australia. Social data costs were averaged across a range of different types of surveys (face-to-face, online and mail-out), and estimated at AUD$50,000 based on the area of the study region, and the number of interviews/surveys required to collect social data across that area. We recalculated the total scenario cost as the cost of management, *C*, plus the cost of data, *D*. The social-only scenario included only social data costs, the biodiversity-only scenario and conservation opportunity with modeled feasibility scenario included only biological data costs, and the conservation opportunity with current feasibility scenario included both biological and social data costs.

The total scenario cost-effectiveness (*CE*) was the overall benefit divided by the sum of the investment in data collection and management:

$$CE = \frac{B}{(C+D)}. \quad (4)$$

For each of our scenarios, we explored the results of changing the costs of social data collection, to explore whether there were thresholds at which the most cost-effective strategy changed.

## Results

### Predicting future distribution of baiting from past effort

Using GLM1 we confirmed that the spatial distribution of historical data on landholder engagement was able to predict future distributions of effort (Figure 1). The distribution of the number of baiting events per property parcel during 2007–2010 (response variable) was positively associated with the number of baiting events recorded during the previous time period of 2003–2006 (explanatory variable; deviance explained 34.5%, $\beta = 0.26$, SE = 0.02; Table S4).

### Predicting future distribution of baiting from landscape characteristics

The best-supported model for management feasibility in 2003 – 2010 was the hypothesis for social-economic and environmental motivation (Hypothesis 8), with an AIC weight of 1 ranking it conclusively above others (Table 2; see Tables S1 and S2 for description of explanatory variables). This model accounted for 15.46% of the deviance. Management feasibility increased with the number of neighbors that a property parcel had and the total property area (Table 3). The mean number of neighbors per parcel was 5.64 ± 0.06, and the mean property area was 21.29 ± 0.49 (range = 1.00 – 173.26 $km^2$). Management feasibility was higher in parcels further away from State protected areas ("distance(PAs)"; Table 3), with baiting landholders almost three times (2.97) more likely to be located further away from protected areas than non-baiting landholders. One surrogate for environmental motivations, the record of a bird survey on the property, was a significant predictor in our best-supported model, with baiting landholders 1.66 times more likely to have a bird survey record on their property compared with non-baiting landholders.

Hypotheses based on purely environmental (e.g. proportion of parcel covered in remnant vegetation, record of a bird survey) or social motivations predicted poorly (Hypotheses 2 and 4, Table 2), describing less than 6% of the deviance. Models using grazing potential (based on agricultural suitability) predicted poorly (Hypothesis 3), with the total property area appearing to be a better surrogate for production benefits of fox management.

The predicted values for parcels at which baiting was conducted in 2003–2010 were, on average, higher than those for unbaited parcels (0.54 and 0.35 respectively), indicating a good discrimination capability of the best model. This was confirmed by a plot of the Receiver Operating Curve, with an AUC of 0.75. The refinement of the values predicted by the model was also good, with predictions ranging from 0.05 to 0.99.

**Spatial conservation priorities under different data investment scenarios**

There were considerable spatial differences in the selected priority management areas between the scenario using only socio-economic data for spatial prioritization, and the scenarios also incorporating biological information (Figure 2). There was no correlation between results of the social-only scenario and the other three scenarios based on biological or biological and social information (Pearson's product-moment coefficient < 0.65, Table S6), but good correlation between the scenarios incorporating biological information (Pearson's product-moment coefficient > 0.65, d.f. = 1335, $P < 0.0001$). Of the 431 parcels selected for management using social-data only, 40% were not selected for management in the best solutions for both conservation opportunity scenarios. The highest correlation between prioritization solutions was between the scenarios using conservation opportunity using modeled feasibility and conservation opportunity using current feasibility (Pearson's product-moment coefficient = 0.73, d.f. = 1335, $P < 0.0001$). Only 11% of the parcels selected as high priority for meeting conservation targets in the conservation opportunity using current feasibility scenario were not selected by the conservation opportunity using modeled feasibility scenario.

**Cost-effectiveness of investment scenarios**

The cost of the social-only scenario, investing in high intensity management for every landholder that had previously conducted baiting, was AUD$460,344, whereas the cost of prioritizing management using only biological-only scenario was 10% more than this (AUD$499,944). Incorporating both social and biological data into investment scenarios reduced the costs of the social-only scenario by 26% and 21% for the conservation opportunity with current and modeled feasibility scenarios respectively, and reduced the costs of the biological-only scenario by 20% and 13% for the conservation opportunity with current and modeled feasibility scenarios respectively (Table 4). Under conservation targets of 17% for each species, the conservation opportunity with current feasibility scenario had the highest expected program cost-effectiveness (Table 4). When the cost of data collection (social and biological surveys) was added to the program costs, the conservation opportunity with modeled feasibility scenario was the highest-ranked in terms of cost-effectiveness. Sensitivity analyses showed that this result was robust to changing costs of survey data collection except when social data costs were low (below $15,000, 4% of the total management budget), with the highest-ranked scenario in terms of cost-effectiveness for low survey costs being the conservation opportunity with current feasibility scenario (Figure 3). Prioritizations using social data alone generally performed the worst in terms of total program cost-effectiveness, except when the cost of social data was zero.

## Discussion

It is increasingly recognized that information on management feasibility is useful for finding efficient solutions to conservation planning problems (McCarthy & Possingham 2007; Carwardine et al. 2012). There is, however, an implicit assumption that collecting this information improves the overall cost-effectiveness of designing and implementing a conservation plan, but this has never been tested. We assessed the cost-effectiveness of incorporating management feasibility data into conservation planning by estimating the costs and benefits of collecting and using both social and biological data in conservation prioritizations. We found that high quality data on management feasibility, collected at a local landholder scale (our conservation opportunity with current feasibility scenario), improved decision-making compared with situations in which these data were not used. However, using these data comes at a cost (Figure 3). For managers with a limited budget for data collation (in this study, below $15,000), a conservation opportunity with modeled feasibility scenario provided the biggest improvement to conservation outcomes for the smallest cost. Our approach is applicable for agencies proposing investment in conservation in landscapes where management is undertaken for dual benefits of production and conservation.

In this study, we took the perspective of a typical conservation agency working in a multiple-use landscape, and considered different scenarios of possible investment to explore the value of using social data to identify investment priorities for conservation. Our social-data only scenario is typical of many real-life situations, where local conservation agencies distributing limited funds target the stakeholders that are most likely to participate in a particular program in order to minimize costs and risk (Green et al. 2009; Sutton & Armsworth this issue). The poor performance of the social-data scenarios is not surprising, since indiscriminately allocating funds to all landholders with existing baiting plans selects the most secure projects with the lowest risk of failure, but fails to consider where the conservation benefits could be most efficiently delivered across the landscape (Ando & Mallory 2012). Incorporating conservation opportunity using modeled feasibility was the most cost-effective scenario when the cost of data on feasibility was more than 4% of combined management and data acquisition costs (Figure 3, Table 4). High costs of social data are typical of large landscape-scale surveys requiring many one-on-one surveys, or surveys revisiting landholders at different points in time (e.g. Gordon et al. this issue). However, if the costs of social data are low, such as for online surveys or limited one-on-one questionnaires, our results indicate that it is more cost-effective to collect and use this data alongside ecological data to identify investment priorities. Our case study considered baiting for the invasive red fox, as there were available data on existing landholder engagement that allowed us to validate our feasibility models. However, our modeling approach could be used to inform investment in a range of other management actions with socio-economic uncertainty, such as ecological restoration, carbon plantings, fencing off remnants or creating covenants (Chen et al. 2009; Curran et al. 2012).

The models we developed in this study identify the key predictors of landholder participation, and were easy and cheap to construct due to the reliance on freely-available landscape data. We found that the most important predictor of baiting activity was the size of a landholder's property, which is not surprising as larger properties can stock more animals, with higher prospective economic loss driving greater incentive to control predators (Lubell et al. 2013). However, our results also showed that other variables such as the number of neighboring properties are important. This was a surrogate for social networks, which enable different actors to collaborate and coordinate management efforts (Guerrero et al. 2010; Lubell et al. 2013). The importance of previous bird surveys recorded on the property (a surrogate for interest in biodiversity) for predicting where resources could be most effectively allocated to management has implications for evaluating management effectiveness, as properties with a previous history of bird monitoring might also be more motivated to monitor management outcomes. The significance of the variable for proximity to protected areas suggests that rather than protected areas having a positive environmental influence on the landholders, protected areas may act as a disincentive to manage private land for invasive predators. The management of protected areas for foxes for over 15 years by the WA Department of Conservation appears to have resulted in many landholders adjacent to parks opting to not manage their lands, despite the potential additional benefits this may provide due to coordinated invasive species management (McLeod et al. 2010). Our findings suggest that a targeted campaign to landholders adjacent to national parks could yield improved conservation outcomes.

There are a number of additional challenges to using data on feasibility to prioritize allocation of funding for conservation in multiple-use landscapes. Social data are context- and time-specific, with people's willingness to act motivated by many extrinsic and intrinsic factors that change over time (Lechner et al. this issue). Our conservation opportunity scenarios incorporated information on historical landscape management, predicting future landholder participation in a single management action by assuming that the incentives for the existing management practices would remain in place. The likelihood of a landholder carrying out another management action (such as landscape restoration) would most likely be predicted by different factors, and it would be unwise to apply models built for one objective (here fox baiting) to alternative objectives without testing them (e.g. with a small sample of social surveys). We assumed that engaging property owners with a high feasibility of future baiting would be less costly than engaging property owners with no baiting history. Previous studies have also prioritized conservation investment according to the likely cost reductions afforded by more feasible management, for example reduced transaction costs due to predicted stakeholder collaboration (Levin et al. 2013). However, data on willingness to participate in an action do not always predict actual participation. Likewise, lack of action in the past does not rule out future participation. In this study, we set low feasibility values for properties (5% likelihood of success) that were not engaged in baiting, a pessimistic approach, but future studies could explore thresholds of uncertainty in this value.

Our results support previous studies suggesting that assessing conservation opportunity improves the cost-effectiveness and efficiency of conservation decisions, due to the ability to prioritize areas for management with higher feasibility (Whitehead et al. in press). However, we show that it is not always cost-effective to collect social data. If the costs of collecting social data are high and incorporated into the total program budget, using social data can lead to lower cost-effectiveness of the decision. If low-cost social data can be obtained, they enable targeting of management to cheaper areas with a history of engagement, which avoids missed opportunities and minimizes costs of conservation decisions. Our study has implications for conservationists and policy-makers planning private land conservation incentives, as we demonstrate a way to reward highly engaged landholders whilst identifying implementation gaps across the landscape.

**Acknowledgements**

We would like to thank Chris Raymond, Hugh Possingham and Kerrie Wilson for discussions and comments on earlier versions of this manuscript.

## References


Abadi Ghadim, A. K., D. J. Pannell, and M. P. Burton. 2005. Risk, uncertainty, and learning in adoption of a crop innovation. Agricultural Economics **33**:1-9.

Ando, A. W., and M. L. Mallory. 2012. Optimal portfolio design to reduce climate-related conservation uncertainty in the Prairie Pothole Region. Proceedings of the National Academy of Sciences of the United States of America **109**:6484-6489.

Armstrong, R. 2004. Baiting operations: Western Shield review - February 2003. Conservation Science Western Australia **5**:31-50.

Ball, I. R., and H. P. Possingham. 2000. Marxan (v. 1.8.6): Marine Reserve Design Using Spatially Explicit Annealing. User Manual: http://www.uq.edu.au/marxan.

Ban, N. C., M. Mills, J. Tam, C. C. Hicks, S. Klain, N. Stoeckl, M. C. Bottrill, J. Levine, R. L. Pressey, T. Satterfield, and K. M. A. Chan. 2013. A social–ecological approach to conservation planning: embedding social considerations. Frontiers in Ecology and the Environment **11**:194-202.

Baxter, P. W. J., and H. P. Possingham. 2011. Optimizing search strategies for invasive pests: learn before you leap. Journal of Applied Ecology **48**:86-95.

Burbidge, A. A., N. L. McKenzie, K. E. C. Brennan, J. C. Z. Woinarski, C. R. Dickman, A. Baynes, G. Gordon, P. W. Menkhorst, and A. C. Robinson. 2008. Conservation status and biogeography of Australia's terrestrial mammals. Australian Journal of Zoology **56**:411-422.

Burnham, K. P., and D. R. Anderson 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. Springer-Verlag, New York.

Burton, R. J. F. 2014. The influence of farmer demographic characteristics on environmental behaviour: A review. Journal of Environmental Management **135**:19-26.

Carwardine, J., T. O'Connor, S. Legge, B. Mackey, H. P. Possingham, and T. G. Martin. 2012. Prioritizing threat management for biodiversity conservation. Conservation Letters **5**:196-204.

Cary, J., T. Webb, and N. Barr 2001. The adoption of sustainable practices: some new insights. An analysis of drivers and constraints for the adoption of sustainable practices derived from research. Bureau of Rural Sciences, Canberra.

Cary, J. W. 1993. The nature of symbolic beliefs and environmental behaviour in a rural setting. Environment and Behavior **25**:555-576.

Chen, X., F. Lupi, G. He, and J. Liu. 2009. Linking social norms to efficient conservation investment in payments for ecosystem services. Proceedings of the National Academy of Sciences **106**:11812-11817.

Curran, P., D. Smedley, P. Thompson, and A. T. Knight. 2012. Mapping Restoration Opportunity for Collaborating with Land Managers in a Carbon Credit-Funded Restoration Program in the Makana Municipality, Eastern Cape, South Africa. Restoration Ecology **20**:56-64.

Curtis, A., and E. Mendham. 2011. Bridging the gap between policy and management of natural resources. Pages 153-176 in D. Pannell, and F. Vanclay, editors. Changing land management: Adoption of new practices by rural landholders. CSIRO publishing, Collingwood.

Elith, J., and J. R. Leathwick. 2009. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. Annual Review of Ecology Evolution and Systematics **40**:677-697.

Grantham, H., A. Moilanen, K. A. Wilson, R. L. Pressey, T. Rebelo, and H. P. Possingham. 2008. Diminishing return on investment for biodiversity data in conservation planning. Conservation Letters **1**:190-198.

Green, A., S. E. Smith, G. Lipsett-Moore, C. Groves, N. Peterson, S. Sheppard, P. Lokani, R. Hamilton, J. Almany, J. Aitsi, and L. Bualia. 2009. Designing a resilient network of marine protected areas for Kimbe Bay, Papua New Guinea. Oryx **43**:488-498.

Guerrero, A. M., A. T. Knight, H. S. Grantham, R. M. Cowling, and K. A. Wilson. 2010. Predicting willingness-to-sell and its utility for assessing conservation opportunity for expanding protected area networks. Conservation Letters **3**:332-339.

Guisan, A., R. Tingley, J. B. Baumgartner, I. Naujokaitis-Lewis, P. R. Sutcliffe, A. I. T. Tulloch, T. J. Regan, L. Brotons, E. McDonald-Madden, C. Mantyka-Pringle, T. G. Martin, J. R. Rhodes, R. Maggini, S. A. Setterfield, J. Elith, M. W. Schwartz, B. A. Wintle, O. Broennimann, M.

Austin, S. Ferrier, M. R. Kearney, H. P. Possingham, and Y. M. Buckley. 2013. Predicting species distributions for conservation decisions. Ecology Letters **16**:1424-1435.

Hughey, K. F. D., R. Cullen, and E. Moran. 2003. Integrating economics into priority setting and evaluation in conservation management. Conservation Biology **17**:93-103.

Joseph, L. N., R. F. Maloney, and H. P. Possingham. 2009. Optimal Allocation of Resources among Threatened Species: a Project Prioritization Protocol. Conservation Biology **23**:328-338.

Kington, E. A., and D. J. Pannell. 2003. Dryland salinity in the Upper Kent River catchment of Western Australia: farmer perceptions and practices. Australian Journal of Experimental Agriculture **43**:19-28.

Klein, C. J., A. Chan, L. Kircher, A. J. Cundiff, N. Gardner, Y. Hrovat, A. Scholz, B. E. Kendall, and S. AiramÉ. 2008. Striking a Balance between Biodiversity Conservation and Socioeconomic Viability in the Design of Marine Protected Areas. Conservation Biology **22**:691-700.

Knight, A. T., R. M. Cowling, M. Difford, and B. M. Campbell. 2010. Mapping Human and Social Dimensions of Conservation Opportunity for the Scheduling of Conservation Action on Private Land. Conservation Biology **24**:1348-1358.

Levin, N., A. I. T. Tulloch, A. Gordon, T. Mazor, N. Bunnefeld, and S. Kark. 2013. Incorporating Socioeconomic and Political Drivers of International Collaboration into Marine Conservation Planning. BioScience **63**:547-563.

Lubell, M. N., B. B. Cutts, L. M. Roche, M. Hamilton, J. D. Derner, E. Kachergis, and K. W. Tate. 2013. Conservation Program Participation and Adaptive Rangeland Decision-Making. Rangeland Ecology & Management **66**:609-620.

McCarthy, M. A., and H. P. Possingham. 2007. Active adaptive management for conservation. Conservation Biology **21**:956-963.

McLeod, L. J., G. R. Saunders, S. R. McLeod, M. Dawson, and R. van de Ven. 2010. The potential for participatory landscape management to reduce the impact of the red fox (*Vulpes vulpes*) on lamb production. Wildlife Research **37**:715-721.

McLeod, R. 2004. Counting the Cost: Impact of Invasive Animals in Australia 2004. Cooperative Research Centre for Pest Animal Control, Canberra.

Mills, M., V. M. Adams, R. L. Pressey, N. C. Ban, and S. D. Jupiter. 2012. Where do national and local conservation actions meet? Simulating the expansion of ad hoc and systematic approaches to conservation into the future in Fiji. Conservation Letters **5**:387-398.

Moon, K., V. Adams, S. Januchowski-Hartley, M. Mills, M. Polyakov, A. Knight, D. Biggs, and E. Game. this issue. Towards a theory of conservation opportunity.

Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent. 2000. Biodiversity hotspots for conservation priorities. Nature **403**:853-858.

Pannell, D. J., G. R. Marshall, N. Barr, A. Curtis, F. Vanclay, and R. Wilkinson. 2006. Understanding and promoting adoption of conservation practices by rural landholders. Australian Journal of Experimental Agriculture **46**:1407-1424.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling **190**:231-259.

Raymond, C. M., and G. Brown. 2011. Assessing conservation opportunity on private land: Socio-economic, behavioral, and spatial dimensions. Journal of Environmental Management **92**:2513-2523.

Raymond, C. M., G. G. Singh, K. Benessaiah, J. R. Bernhardt, J. Levine, H. Nelson, N. J. Turner, B. Norton, J. Tam, and K. M. A. Chan. 2013. Ecosystem Services and Beyond: Using Multiple Metaphors to Understand Human-Environment Relationships. BioScience **63**:536-546.

Saunders, G. R., M. N. Gentle, and C. R. Dickman. 2010. The impacts and management of foxes Vulpes vulpes in Australia. Mammal Review **40**:181-211.

Sobels, J., A. Curtis, and S. Lockie. 2001. The role of Landcare group networks in rural Australia: exploring the contribution of social capital. Journal of Rural Studies **17**:265-276.

Sutton, N. J., and P. R. Armsworth. this issue. Spatial grain of acquisition cost and biodiversity benefit data determines the apparent effectiveness of an opportunistic conservation strategy.

Tulloch, A. I. T., I. Chadès, and H. P. Possingham. 2013a. Accounting for Complementarity to Maximize Monitoring Power for Species Management. Conservation Biology **27**:988-999.

Tulloch, A. I. T., K. Mustin, H. P. Possingham, J. K. Szabo, and K. A. Wilson. 2013b. To boldly go where no volunteer has gone before: predicting volunteer activity to prioritise surveys at the landscape scale. Diversity and Distributions **19**:465-480.
Watts, M. E., I. R. Ball, R. S. Stewart, C. J. Klein, K. Wilson, C. Steinback, R. Lourival, L. Kircher, and H. P. Possingham. 2009. Marxan with Zones: Software for optimal conservation based land- and sea-use zoning. Environmental Modelling & Software:1-9.
Whitehead, A. L., H. Kujala, C. D. Ives, A. Gordon, P. E. Lentini, B. A. Wintle, E. Nicholson, and C. M. Raymond. in press. Integrating biological and social values when prioritising places for biodiversity conservation. Conservation Letters.

**Table 1.** Study species and expected response to fox management (from Tulloch et al. 2013)

| Species no. | Species name | Probability of positive growth rate under fox management | Number of records |
|---|---|---|---|
| 1 | Tammar wallaby<br>*Macropus eugenii* | **0.99** | **42** |
| 2 | Western brush wallaby<br>*Macropus irma* | **1.00** | **269** |
| 3 | Western quoll<br>*Dasyurus geoffroii* | **1.00** | **12** |
| 4 | Dibbler<br>*Parantechinus apicalis* | 0.85 | 16 |
| 5 | Red-tailed phascogale<br>*Phascogale calura* | 0.57 | 10 |
| 6 | Southern brown bandicoot<br>*Isoodon obesulus* | 0.99 | 40 |
| 7 | Western brushtail possum<br>*Trichosurus vulpecula* | 1.00 | 16 |

**Table 2.** Multi-model inference table for the multivariate analysis of probability of fox baiting in 1337 land parcels of south-west Australia (GLM2), showing number of model parameters *K*, deviance explained, corrected AIC (AICc), AIC differences (ΔAIC) and AIC weight *w*.

| Model | Rank | K | Deviance explained (%) | AICc | ΔAICc | *w* |
|---|---|---|---|---|---|---|
| Socio-economic-environment | 1 | 5 | 15.46 | 1271.86 | 0 | 1 |
| Economic-environment 2 | 2 | 5 | 14.55 | 1285.44 | 13.58 | 0 |
| Economic-environment 1 | 3 | 5 | 14.42 | 1287.32 | 15.46 | 0 |
| Social-economic | 4 | 4 | 10.72 | 1340.68 | 68.82 | 0 |
| Production + bait store access | 5 | 4 | 10.62 | 1342.13 | 70.27 | 0 |
| Production benefits 2 | 6 | 3 | 10.48 | 1342.19 | 70.33 | 0 |
| Production benefits 1 | 7 | 3 | 10.34 | 1344.21 | 72.35 | 0 |
| Social-environment | 8 | 4 | 7.03 | 1395.72 | 123.87 | 0 |
| Global environmental | 9 | 5 | 5.55 | 1419.75 | 147.9 | 0 |
| Conservation concern | 10 | 3 | 5.13 | 1422.05 | 150.2 | 0 |
| Biodiversity restoration | 11 | 3 | 4.88 | 1425.72 | 153.87 | 0 |
| Global social effects | 12 | 3 | 2.74 | 1457.67 | 185.82 | 0 |
| Neighbor effects | 13 | 2 | 1.62 | 1472.38 | 200.53 | 0 |
| Social group effects | 14 | 2 | 1.07 | 1480.73 | 208.87 | 0 |
| Biodiversity interest | 15 | 3 | 0.69 | 1488.29 | 216.43 | 0 |
| Regional incentives | 16 | 4 | 0.69 | 1490.36 | 218.50 | 0 |
| Local incentives | 17 | 4 | 0.50 | 1493.1 | 221.24 | 0 |
| Null model | 18 | 1 | 0 | 1494.61 | 222.75 | 0 |

**Table 3.** Model parameters for the best-supported model predicting probability of fox baiting in 1337 land parcels of south-west Australia from landscape characteristics (GLM2), describing economic (area(prop)), social (neighbors) and environmental (distance(PAs)) + birdsurveys) factors.

| Covariates | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| intercept | -0.46 | 0.08 | -5.59 | <0.0001 |
| neighbors (standardized) | 0.23 | 0.15 | 1.52 | 0.1300 |
| sqrt(area(prop)) (standardized) | 1.69 | 0.16 | 10.44 | <0.0001 |
| sqrt(distance(PAs)) (standardized) | 1.09 | 0.14 | 7.60 | <0.0001 |
| birdsurveys | 0.51 | 0.15 | 3.33 | 0.0009 |

**Table 4.** Comparing the costs and benefits of data types for conservation planning, and the resulting cost-effectiveness of the conservation prioritization strategies when data costs are incorporated (most cost-effective scenario highlighted).

| Input data type | Quality of data or model for predicting conservation opportunity | Benefit of zone 1 (eq. 1) *M* | Benefit of zone 2 (eq. 1) *M* | Expected benefits adjusted for feasibility (eq. 2): *B* | Investment in data ($AUS) *D* | Investment in management ($AUS) (eq. 3) *C* | Expected program cost-effectiveness (eq. 4) $CE = B/(C+D)$ |
|---|---|---|---|---|---|---|---|
| Social data only - High intensity | High | 2027 | 0 | 408 | 50,000 [A] | 460,344 | 0.080 |
| Social data only - Low intensity | High | 0 | 1126 | 226 | 50,000 [A] | 230,172 | 0.081 |
| Biodiversity only | Zero | 3773 | 987 | 488 | 3,000 [B] | 499,944 | 0.097 |
| Conservation opportunity using current feasibility | High | 3609 | 602 | 451 | 53,000 [A,B] | 369,030 | 0.106 |
| Conservation opportunity using modeled feasibility | Low | 3757 | 642 | 468 | 3,000 [B] | 397,428 | **0.117** |

[A] Social data costs based on expert elicitation of survey costs averaged across different types of surveys (face-to-face, online and mail-out)

[B] Biodiversity costs based on standard cost of acquiring atlas data for threatened species from State Government and NGOs, all conservation opportunity model data freely available

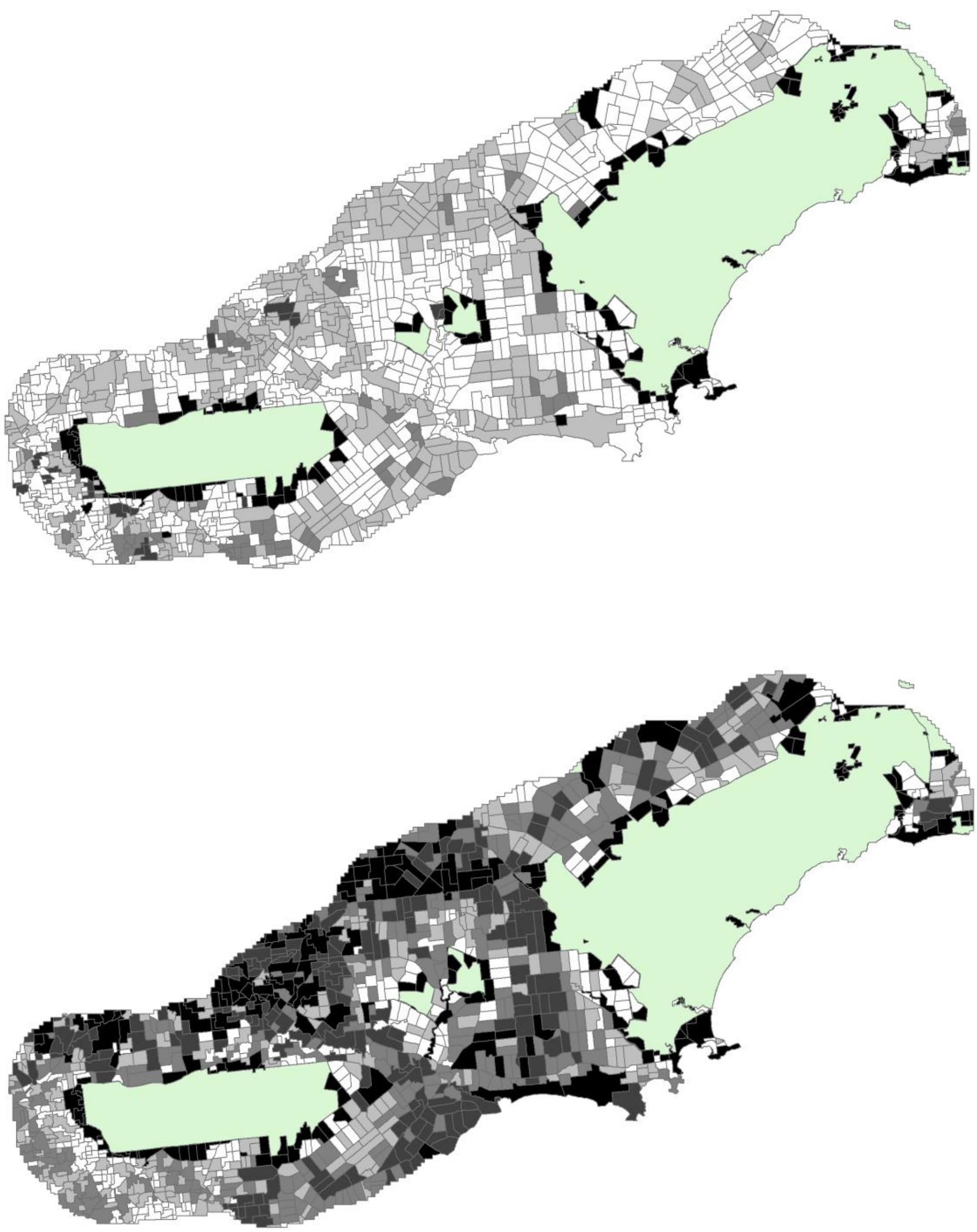

**Figure 1.** Comparison of results of models for (a) feasibility model 1 (GLM1) reflecting actual baiting frequency and (b) feasibility model 2 (GLM2) representing modeled conservation opportunity predicted from biophysical characteristics. Hashed areas are managed by the WA Department of Conservation. Darker areas have higher conservation opportunity.

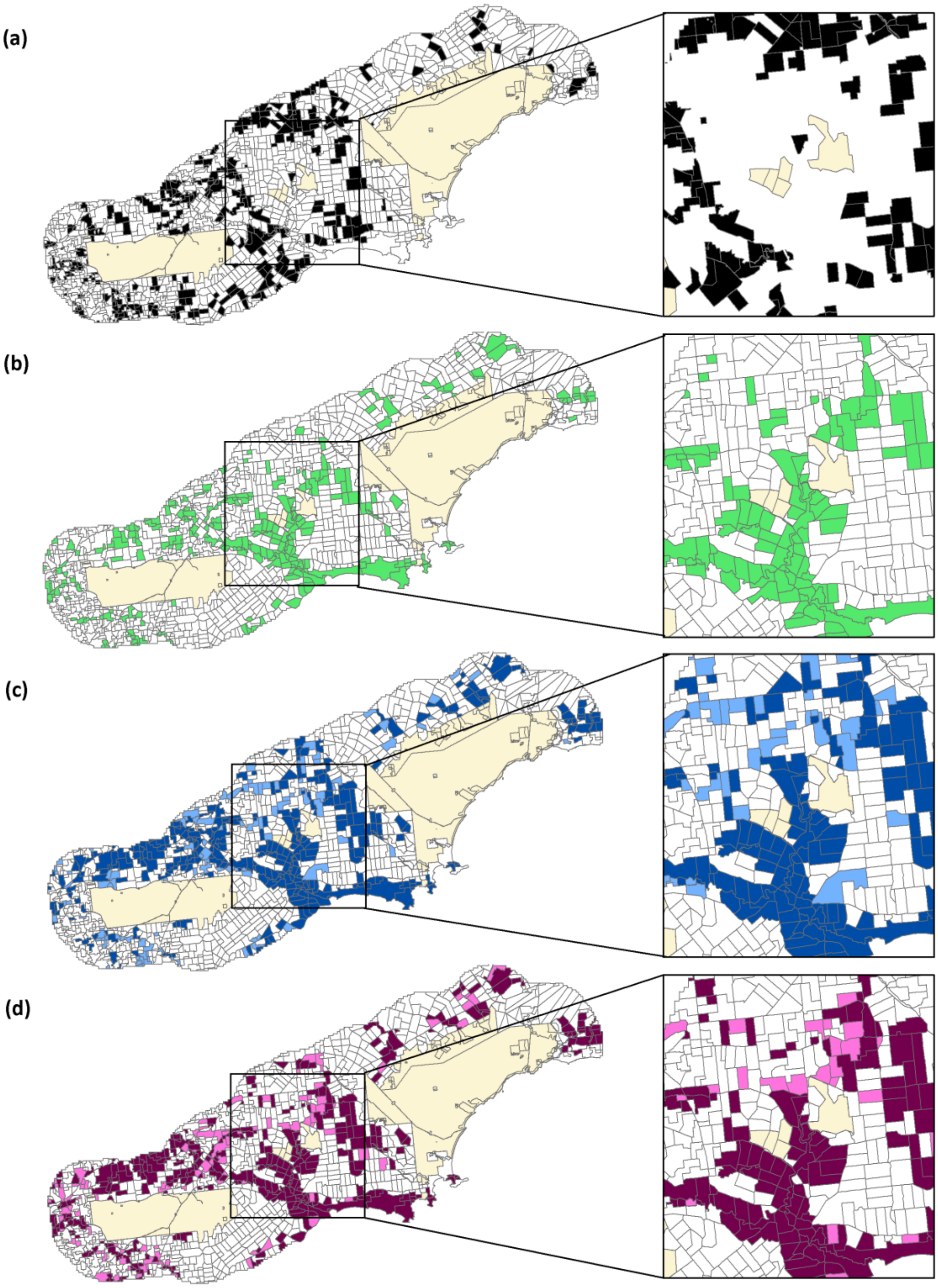


**Figure 2.** Comparison of results of prioritization of spending on fox baiting informed by (a) social data only, (b) biodiversity data only, (c) conservation opportunity with modeled feasibility and (d) conservation opportunity with existing feasibility (darker colors are high focus baiting, lighter are low focus).

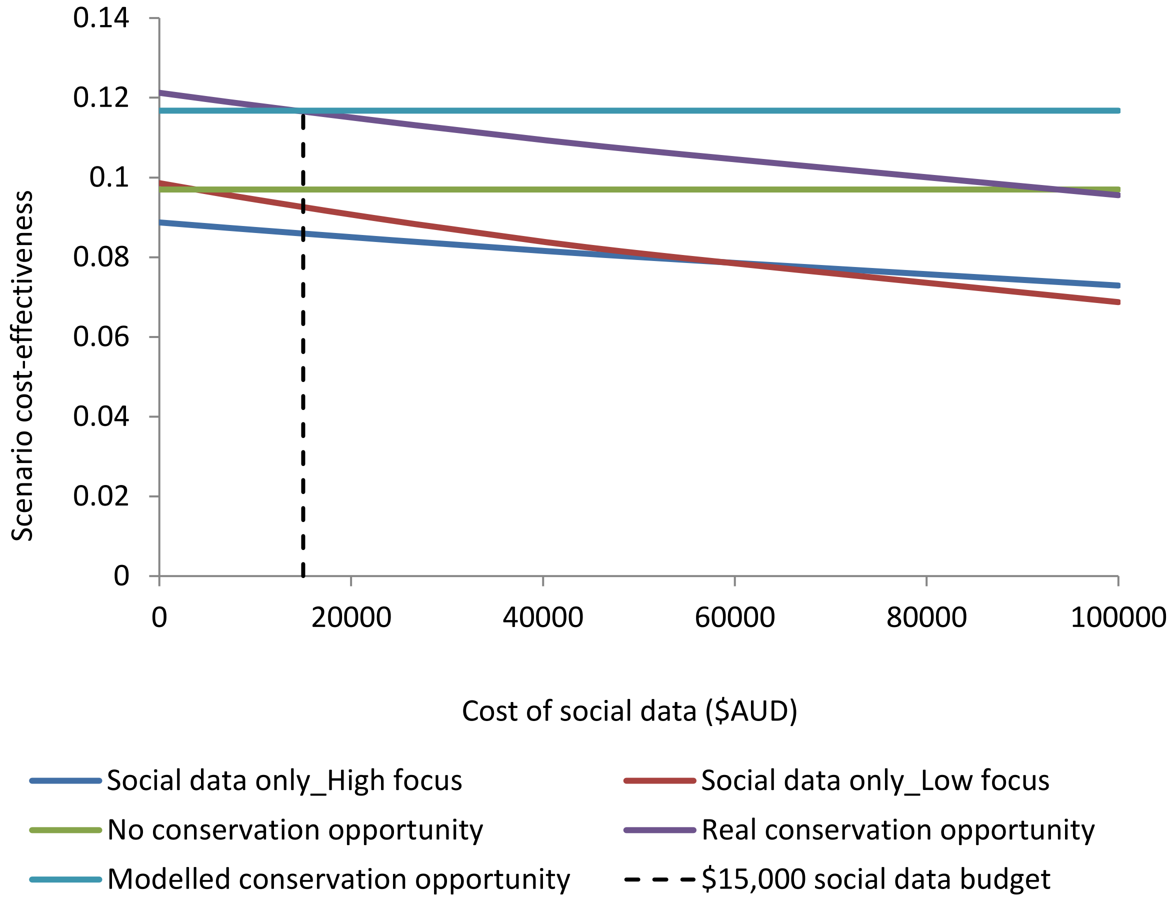


**Fig. 3.** Expected program cost-effectiveness for each of our four scenarios and different levels of investment in social data. The $15,000 social data budget is highlighted, below which modeled data on feasibility becomes less cost-effective than the use of actual data on feasibility.