Simulating the value of collaboration in multi-actor conservation planning

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Abstract

The loss of habitat and biodiversity worldwide has led to considerable resources being spent on conservation interventions. Prioritising these actions is challenging due to the complexity of the problem and because there can be multiple actors undertaking conservation actions, often with divergent or partially overlapping objectives. We explore this issue with a simulation study involving two agents sequentially purchasing land for the conservation of multiple species using three scenarios comprising either divergent or partially overlapping objectives between the agents. The first scenario investigates the situation where both agents are targeting different sets of threatened species. The second and third scenarios represent a case where a government agency attempts to implement a complementary conservation network representing 200 species, while a non-government organisation is focused on achieving additional protection for the ten rarest species. Simulated input data was generated using distributions taken from real data to model the cost of parcels, and the rarity and co-occurrence of species. We investigated three types of collaborative interactions between agents: *acting in isolation, sharing information* and *pooling resources* with the third option resulting in the agents combining their resources and effectively acting as a single entity. In each scenario we determine the cost savings when an agent moves from *acting in isolation* to either *sharing information* or *pooling resources* with the other agent. The model demonstrates how the value of collaboration can vary significantly in different situations. In most cases, collaborating would have associated costs and these costs need to be weighed against the potential benefits from collaboration. Our model demonstrates a method for determining the range of costs that would result in collaboration providing an efficient use of scarce conservation resources.

Keywords: *systematic conservation planning, reserve design, Marxan, multi-actor, conservation investment, game theory*

1. INTRODUCTION

The loss of habitat and biodiversity worldwide has led many governments and non-governmental organizations (NGOs) to expend considerable resources for conservation purposes. This is a challenging task, since determining the most effective conservation actions or policies involves balancing ecological, financial, and social constraints (Wu and Boggess, 1999). Additional difficulties result from the fact that multiple agencies with differing priorities and remits often undertake conservation actions within the same landscape (Bode et al., 2011).

A range of approaches have been developed to assist with allocating and managing conservation resources, and these approaches are collectively referred to as Systematic Conservation Planning (SCP) (Margules and Pressey, 2000). Initially this field focused on the efficient spatial allocation of conservation reserves for multiple biological features (Williams et al., 2005) but more recently it has evolved to provide decision support tools for a broader range of conservation interventions (Wilson et al., 2009). Despite the success of SCP, it is still common for conservation to be undertaken on the basis of community preference and local knowledge rather than using formal SCP techniques, simply because of the cost involved with collecting and analyzing biophysical data, and the need to acquire land as it becomes available. In addition, most conservation bodies continue to manage legacy suites of parcels, which were acquired without recourse to these more modern methods. To some extent, community knowledge is a surrogate for habitat and species information gathered in a more systematic way, and the resulting networks of parcels may achieve some measure of the ecological representation that could be achieved using SCP; however, experimental results imply that this ‘opportunistic’ approach ultimately fails to protect as many ecological features (Hansen et al., 2011).

To date, most applications of SCP implicitly assume that conservation actions are implemented by a single agent acting in isolation, even though this is often not the case (Bode et al., 2011). When multiple organisations are undertaking conservation actions in a landscape, they often vary in focus, resources and geographic extent, and can include diverse agents; e.g., governments, private individuals and NGOs such as land trusts and charities. As an example, three agencies operating in one region might focus on, respectively,

i) the conservation of breeding habitats generally used by migratory birds, ii) the acquisition of sites observed to support a specific threatened species, and iii) the development of sustainable forestry activities for local people. The ultimate goals of the three organisations may overlap substantially, in that the prospects of the threatened species may be improved by activities i) and ii). As the actions of one agency may contribute to (or may detrimentally affect) the aims of another (Gallo et al., 2009; Wiersma and Nudds, 2009) and strategic collaboration could increase the efficiency of planning efforts and actions for both agencies. This is particularly true where only a few organisations have the expertise and resources necessary for implementing an SCP approach (Prendergast et al., 1999), and others are constrained to act in an opportunistic manner (Ban et al., 2009). However, the metrics by which the organisations measure success are often very different. In some situations agencies compete for funding, volunteers and publicity, and the extent to which their conservation objectives overlap may differ (Haley and Clayton, 2003). However, collaboration is only worthwhile if the benefits outweigh the costs, and assessing the various costs of collaboration is rarely straighforward. Some factors, such as administrative burden or dilution of an agency's perceived achievement, may be relatively easily quantified. Others, such as mistrust and mission conflict, are more subjective (Endicott, 1993; Wondolleck and Yaffee, 2000; Macdonald, 2002).

Most existing studies on the value of coordinated conservation effort focus primarily on agencies operating at different geographic scales, and on strategic, hierarchical approaches to the conservation of assemblages and groups distributed between many administrative areas (Strange et al., 2006; Jantke and Schneider, 2010, Moilanen and Arponen, 2011). The context described here, in contrast, considers agencies operating in the same environment but with varying objectives. Given the importance of cost-balancing and knowledge, a useful approach to these multi-agency interactions may be to model them as 'games' (Colyvan et al., 2011) and the few studies which attempt to incorporate this issue into modelling conservation interventions do just this (Bode et al., 2010, Frank and Sarkar, 2010). Bode et al*.* (2011), for example, use a game-theoretic approach to examine conservation outcomes with two agencies conserving land containing two biological features. Based on a thorough review of real-world contexts where conservations agencies' efforts interfere, they simulate interactions between agencies which can be critical for the overall success of those efforts in a region, such as increases in land costs due to perceived demand. Albers et al. (2008) also took a game theoretic approach, modelling the effect of government actions on marginal benefits to private agents in the same landscape, and the resulting pattern of overall land conservation in a simple model containing 7 land parcels.

In this study we consider two agents, each applying SCP techniques to select land, and we specifically assess the utility of two different types of collaboration. Novel features of our analysis include varying land costs, agencies whose targets include multiple species, and realistic distributions of up to 200 species across 1600 parcels in the landscape. We also partly address the real-life problems of quantifying collaboration costs by instead quantifying the cost savings resulting from more efficient conservation actions under different collaboration regimes.

2. MATERIAL AND METHODS

We extended a computational framework described in Langford et al. (2009) to work with multiple agents, where each agent attempted to implement a conservation network of parcels that met its specified target for species representation at the minimum cost. In our simulations we examined three types of interactions between agents, which we label *acting in isolation, sharing information* and *pooling resources.* In each case we examined the utility of these interactions from the viewpoint of the combined conservation network resulting from both agents' actions, as well as from each agent's individual perspective. When the agents *act in isolation,* they are attempting to achieve their targets solely though their own actions and take no account of the benefits captured by the other agent's actions (Halpern et al., 2006). This could model the case where an agent wants to demonstrate gains as a direct result of their own actions, or is ignorant of what others have achieved (Albers and Ando, 2003). Under the *share information* assumption, each agent is aware of the species representation achieved within the other agent's conservation network and counts these gains towards their own targets, though they still act separately. For example, an NGO might consider the extent to which government reserves already protect their target species, and act to complement this by prioritising locations containing those species not yet covered. The *pool resources* assumption requires the greatest amount of interaction as agents combine their resources and undertake strategic conservation actions as a single entity with a shared objective (Kark et al., 2009). In our model the shared objective consisted of the sum of the two agents' individual objectives. Below we briefly describe the steps in our simulation.

2.1. Species distributions

We used a hypothetical landscape containing 1600 parcels and a scenario-specific number of species (see Section 2.3). Parcels were arranged in a rectangular lattice, but the spatial location of a parcel had no effect within our model. Habitat for each species was assigned as either *present* or *absent* from a parcel. The species habitat locations were determined by "rarity" and "richness" distributions. The "rarity distribution" describes the number of species that have habitat on a given number of parcels (e.g. 8 species have habitat on 3 parcels, 5 species have habitat on 6 parcels, etc.) while the "richness distribution" describes how the number of species that have habitat varies across parcels and represents the extent to which species tend to co-occur on the same parcels. The computational framework used allows users to generate synthetic conservation planning problems where species habitat is distributed to match both user-specified "richness" and "rarity" distributions simultaneously (Langford et al. 2009). We derived "Victorian" richness and rarity distributions from data gathered across the state of Victoria, Australia by the Victorian Government's Department of Sustainability and Environment. This data set consisted of 36,787 30×30m quadrats, scattered throughout Victoria, and contained information on the presence and absence of 4080 plant species. Fig. 1 shows examples of the "rarity" and "richness" values used in the simulations. These results were obtained using the "Victorian" rarity and richness distributions with 200 species and 1600 parcels.

2.2. Parcel costs

The cost for each parcel was determined by sampling from a lognormal distribution. The shape of the distribution was derived from a real data set comprising of a confidentialised extract of unit-record property sale valuations from agricultural land around Melbourne, Australia (2008 Victoria Valuer General Statewide Valuations Dataset). The best fit to the sale price distribution resulted in a lognormal distribution with mean of 0.37 AU$/m^2 and a standard deviation of 0.13.

2.3. Conservation actions

Each agent used the conservation planning tool Marxan (Ball and Possingham, 1999) to determine the set of parcels to purchase. Marxan uses a stochastic search algorithm (simulated annealing) to identify parcels that meet species representation targets for the least cost. We chose to use Marxan as it is the most widely used optimization tool for conservation planning and thus is likely to be used by real-world agents in situations similar to our modelled scenarios. Each agent used Marxan to find the set of unreserved parcels *(P)* which met its objective for the minimum cost:

$$\min_P \left[\sum_{i \in P} c_i \right], \text{ such that for each species, } j, \ \sum_{i \in P} r_{ij} \geq T_j \qquad (1)$$

where c_i is the cost of parcel *i*, r_{ij} is an element of the representation matrix $\boldsymbol{r}$ specifying whether species *i* is present on parcel *j*, and T_j is the *j*th entry in the target vector $\boldsymbol{T}$ which specifies the agent's representation target for each species *j*. We make the simplifying assumptions that i) each agent buys all its parcels at once, ii) each agent acts in turn, with agent 1 acting first, and iii) each agent only gets one turn. Even with these constraints, interesting dynamics emerge.

We examine three scenarios where a pair of agents interact, which we label *NGO-NGO*, *Gov-NGO*, *NGO-Gov*. In the first scenario there are 40 species in the landscape, which all have the same rarity (occurring on 5% of parcels) and co-occurrence is determined by the Victorian species richness distribution. In this scenario both agents are interested in a mutually exclusive set of species. Agent 1's objective consists of obtaining two representations of the first twenty species, and has a target vector $T_1 = \{2_1, 2_2, ..., 2_{20}, 0_{21}, ..., 0_{40}\}$, where each element of the vector represents the target number of parcels for the species labeled in the subscript. Agent 2 has the mutually exclusive objective consisting of the target vector $T_2 = \{0_1, 0_2, ..., 0_{20}, 2_{21}, ..., 2_{40}\}$. This could represent the situation where two NGOs are operating in the same landscape but both are targeting different sets of threatened species (e.g. plants and amphibians). We label this scenario as *NGO-NGO*, and because the representation targets are symmetrical with resect to the species distributions, it doesn't matter which agent acts first.

In the *NGO-Gov* and *Gov-NGO* scenarios, 200 species are distributed on parcels such that they match both the Victorian richness and rarity distributions (Langford et al., 2009). One agent (*Gov)* attempts to select parcels such that all species are represented and has a target vector $T_{Gov} = \{2_1, 2_2, ..., 2_{200}\}$. The other agent (*NGO)* focuses only on the 10 rarest species with a target vector $T_{NGO} = \{2_1, 2_2, ..., 2_{10}, 0_{11}, ..., 0_{200}\}$ (assuming species are ordered by decreasing rarity). This could represent the case where a government agent attempts to implement a complementary conservation network representing all species, while an NGO is focused on achieving additional protection for the rarest and/or most endangered species. In these scenarios the two agents' objectives overlap, and therefore the order in which agents act is important. Thus in the *NGO-Gov* scenario, the *NGO* agent acts first and the order is reversed in the *Gov-NGO* scenario.

Finally, when collaborating as a single agent via the *pool resources* interaction, the representation target of the single agent is the sum of the two individual agents' representation targets. Thus for the *NGO-NGO* scenario this would consist of a target vector $T_{NGO,NGO} = \{2_1, 2_2, \ldots, 2_{40}\}$ and for the *Gov-NGO* and *NGO-Gov* scenarios the target vector is $T_{NGO,Gov} = \{4_1, 4_2, \ldots, 4_{10}, 2_{11}, \ldots, 2_{200}\}$.

2.4 Running simulations

There were three sources of stochasticity in our model, resulted from: i) the algorithm for distributing species amongst the parcels (Section 2.1), ii) the process of assignment of costs to each parcel (Section 2.2) and iii) Marxan's simulated annealing algorithm, which may result in different sets of parcels being selected for multiple model realisations (Section 2.3). Each scenario was run 20 times to incorporate the effects of model stochasticity, and the figures presented show the median values resulting from the 20 runs. Some figures also show the variance from the multiple runs.

3. RESULTS

The costs for each agent to achieve their objectives varied depending on the order in which the agents acted, the type of interaction between agents, and the extent to which the agent's goals overlapped. These costs are shown in Fig. 2 as boxplots to summarise the stochastic variation in multiple model runs. All costs were normalised with respect to the median value of the total cost to achieve both agents' objectives under the *pool resources* scenario. In all cases when the two agents were either *acting in isolation* or *sharing information,* the combined cost of both agents was greater than when the agents acted as a single entity in the *pool resources* scenario (Fig. 2 (a)-(f)). This cost increase was greatest where the agents acted in isolation and could result in almost a 50% increase (Fig. 2(b)).

In the *NGO-NGO* scenario the agent acting second (agent 2) tended to spend less than the agent acting first if they *shared information* (Fig. 2(a)). This is because agent 2 knew which species were represented in the first agent's conservation network and could select additional complementary parcels until they reached their objective. When *acting in isolation*, agent 2 had no knowledge of the species represented by agent 1 and needed to implement a whole new conservation network that met their objectives. This resulted in agent 2 tending to spend slightly more than agent 1 (Fig. 2 (b)).

This situation was reversed in the *NGO-Gov* scenario when the agents *share information* (Fig. 2 (c)). In this case the *NGO* targeted a small subset of the species compared to *Gov* and thus when it acted first, it spent significantly less than *Gov*. In this case *Gov* spent approximately 90% of what both agents would spend if they *pooled resources*. There was little difference when the agents acted in isolation except that *Gov*, as second agent, tended to spend slightly more compared to what it spent in the *share information* scenario.

When the agents acted in reverse order in the *Gov-NGO* scenario, the situation was more similar to the *NGO-NGO* scenario with the *share information* interaction (Figs. 2(e) and 2(f)). Compared to the *NGO-Gov* scenario, *NGO* now had increased costs while *Gov's* costs were reduced. As with the *NGO-Gov* scenario there was little difference between the agents *acting in isolation* and *sharing information*. By comparing Figs. 2(c) and 2(d) with Figs. 2(e) and 2(f), it is clear that there was an increase in cost in moving from acting first to acting second for *NGO* and *Gov* under both the *share information* and *act in isolation* interactions. This is in contrast to the *NGO-NGO* scenario where it was advantageous for an agent to act second in the *share information* scenario, but slightly disadvantages to act second in the *act in isolation* scenario.

3.1. Gains from sharing information

From the results shown in Fig. 2, the cost savings generated by moving from *acting in isolation* to interacting by *sharing information* can be calculated. This was only of consequence for the agent acting second, since in this simulation, the first agent was assumed not to anticipate the second agent's actions and thus acted in an identical way in both the *act in isolation* and *share information* scenarios. This cost saving is shown in Fig. 3 for each of the three scenarios. The largest savings occurred in the *NGO-NGO* scenario, with a median proportional cost saving of 0.27 but with a large variance. When acting second, the government achieves a significantly smaller cost saving in the *NGO-Gov* scenario and the NGO has the smallest saving when acting second in the *Gov-NGO* scenario.

3.2. Gains from pooling resources

It is also possible that additional cost savings could be made for each of the agents if they act as a single entity via the *pool resources* interaction. This situation is more complex because the two agents are implementing a reserve network that meets both of their objectives in a single step, and there are multiple ways that the total cost could be split between both agents. There is always some cost-sharing proportion that would result in one agent gaining financially, but a more interesting question is whether a cost split exists whereby *both* agents benefit. Fig. 4 shows the proportional cost saving for each agent when moving from *acting in isolation* or *sharing information* to *pooling resources* under all possible proportions for dividing the total cost between agents. As in Fig. 2, proportional cost for each agent is defined as the proportion of the cost of the *pool resources* scenario. Gains and losses are shown as a solid line for the first agent and as a dashed or dotted line for the second agent when *sharing information* or *acting in isolation*, respectively. Cost splits where both agents would receive financial benefit occur at *x*-axis values where the sloping lines for both the first and second agents have *y*-values greater than zero. The *x*-value where the two lines intersect represents the cost-sharing proportion where both agents gain the same amount. At points away from this intersection, either one agent gains more than the other, or one agent makes a gain and the other a loss. Thus the intersection point defines the location for a “fair” sharing of costs while satisfying the two agents' differing objectives. In multi-objective optimization terms, any sharing proportion represents a Pareto optimum and the lines in Fig. 4 represent Pareto frontiers. This means that at any sharing proportion, no improvement can be made for one agent that is not to the detriment of the other agent.

In the *NGO-NGO* scenario, when moving from *acting in isolation* to *pool resources* there was a wide range of cost-sharing proportions where both agents benefited (Fig. 4(a)). This occurred if the first agent paid anything between 32% and 67% of the total cost. The point that equalized the gains for both agents occurred when costs were split almost equally, such that the first agent paid 49% of the total cost. This small divergence from the expected 50-50 split can be attributed to model stochasticity (see Section 2.4). In this case both agents had a proportional cost saving of 0.18. The location of the equal-sharing proportion when moving from *share information* to *pool resources* occurred when the first agent paid 66% of the total cost. In this case, gains to each agent had reduced to a proportional cost saving of 0.05.

In the *NGO-Gov* scenario, the difference between the curves representing *acting in isolation* and *sharing information* was reduced (Fig. 4(b)) and in the *Gov-NGO* scenario these two curves were almost identical (Fig. 4(c)). This indicates little difference between these two interactions as shown in Fig. 3. The point where the curves representing each agent intersect was close to zero on the *y*-axis in both Fig. 4(b) and 4(c), meaning that the financial gains were small for the cost-sharing proportions where both agents could make savings.

4. DISCUSSION

We have presented a model that seeks to quantify the changes in cost efficiency for various types of interactions between two agents undertaking land purchases using a Systematic Conservation Planning approach in a two-step sequential process. This setup could also cover contexts where the second agent acts in an area where conservation reserves already exist, and must decide whether it is cost effective to spend resources gathering information about existing reserves before implementing a conservation plan.

The advantage of acting first varied between and within the scenarios. The *NGO-NGO* scenario showed a significant advantage for the agent acting second only if they *shared information*, while in the second and third scenarios, acting first was always advantageous, regardless of whether *information was shared*. Thus the second and third scenarios comprise a Stackelberg game (Albers et al., 2008) where it is advantageous to lead in a two-step sequential game. The Stackelberg game arises in the *NGO-Gov* and *Gov-NGO* scenarios, because one agent, *Gov*, has all 80 species in its representation target and thus needs to select a larger set of parcels in its conservation network than the *NGO* agent. When *Gov* acts first, this larger set of parcels places constraints on where *NGO* can act; when *Gov* acts second, the fact that it needs a larger number of parcels also makes its task more difficult after *NGO* has already made their parcel selection. As the representation targets of *Gov* and *NGO* overlap, the set of candidate parcels for the agent acting second will be constrained under *act in isolation* and *sharing information,* while under *sharing information* the agent acting second will also have their targets partially met (albeit in an inefficient way, from their perspective). In either case this usually results in greater costs for the second agent than those incurred if they could make an efficient selection of parcels without being constrained by the other agent's actions. The first scenario did not comprise a Stackelberg game, since both agents had mutually exclusive objectives and attempted to implement similarly-sized conservation networks to fulfill their objectives.

Only the NGO-NGO scenario showed significant value in both types of collaboration. Moving from *acting in isolation* to *sharing information* provided a median proportional cost saving of 0.27 (with considerable variation (Fig. 3)), while moving from *acting in isolation* to *pooling resources* provided varying losses or gains depending on the cost-sharing between the agents (Fig. 4(a)). With the fairest cost-sharing, a median proportional cost saving of 0.18 was possible. Although smaller, this gain applied to both agents, whereas moving from *acting in isolation* to collaborating by *sharing information* only benefited the agent acting second. If expenses involved in collaborating exceeded these cost savings then collaboration would not be an efficient use of funds. Thus these cost savings provide bounds to determine the range of costs associated with collaboration that would make it a worthwhile undertaking for either agent.

In the *NGO-Gov* and *Gov-NGO* scenarios, increased collaboration generated much smaller savings, with the largest gains from *sharing information* by the government agent in the *NGO-Gov* scenario (Fig. 3). There were no cost-sharing proportions where both agents could significantly gain from *pooling resources* (Fig. 4(b), (c)). In cases like this, there may still be situations where both agents are willing to *pool resources* using an unfair cost-sharing. The agent that makes a loss relative to *acting in isolation* is then providing an incentive or subsidy for the other agent due to their cost savings from collaborating. A real word example of this could be a government agency which wishes to provide incentives for NGOs to undertake conservation actions targeting specific species or locations. For example if *Gov* paid 90% of the *pool resources* cost in Fig.

4(c), *NGO* would have saved a proportional cost of 0.14 while *Gov* would have made a proportional cost loss of 0.11, relative to both agents *acting in isolation*.

While the model presented here shows a range of interesting behaviors, the results only apply to the specific species/landscape/cost and action scenarios described. One of the advantages of a simulation approach is that it is possible to vary the problem characteristics in a systematic way to explore the extent to which the conclusions are in fact general, rather than an artifact of the model structure, parameterisation and inputs. There are numerous ways we plan to extend this model to make the results more generalisable. These extensions include i) modeling a greater range of species, landscapes, and costs ii) allowing agents to anticipate each others' actions and to act sequentially or simultaneously for an arbitrary number of turns, and iii) modeling uncertainties in the information on which the agents base their decisions. This last extension provides many interesting opportunities as it includes both uncertainties in the species and cost information as well as uncertainties in an agent's predictions about what the other agent might do. Systematic conservation planning, as practiced in these examples, can be sensitive to common uncertainties, such as variations in predicted species distribution (Wilson et al., 2005; Langford et al., 2009). Using this approach there is considerable scope for exploring how these uncertainties impact outcomes, relative to uncertainties in predicting the behaviour of other agents undertaking conservation actions in multi-agent problems.

5. CONCLUSION

Although the model presented here has a range of simplifying assumptions, it demonstrates that the value of collaboration can vary significantly in different situations. In most cases, collaboration would have associated transaction costs and these costs need to be weighed against the potential benefits from collaboration. Our model demonstrates a method for quantifying the benefits of collaboration and thus determining the range of costs that would result in collaboration providing an efficient use of scarce conservation resources. This approach can be useful for the pragmatic allocation of resources in many real-world contexts where monetary costs of collaboration are not immediately obvious, but must be inferred indirectly from subjective factors such as changes to an agent's reputation or perceived effectiveness in addition to estimates of the transaction costs for collaboration. We believe that our approach (and its future extensions) may help encourage collaboration in situations where it will truly deliver improved conservation outcomes.

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Figure Captions

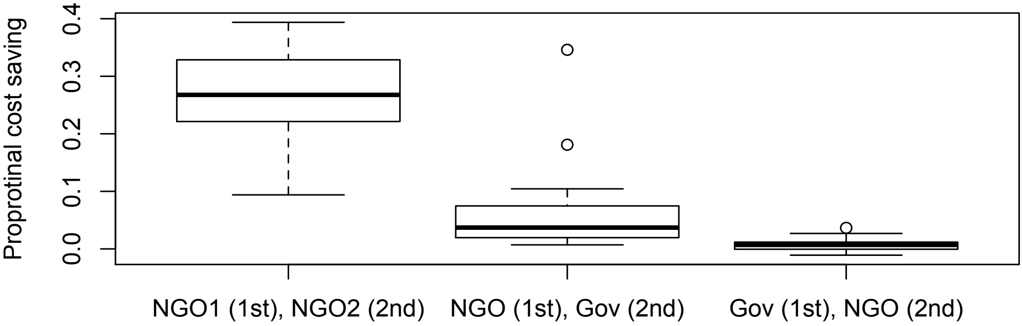
Fig. 1. Examples of the “rarity” and “richness” values used in simulations, derived from the “Victorian” dataset (see Section 2.1) using 200 species and 1600 parcels. (a) shows the rarity distribution, i.e., for each possible number of parcels that could contain habitat for a species (shown on the x-axis), the y-axis indicates the total number of species habitats in the sampled distribution that occupy the given number of parcels. (b) shows the number of species that have habitat on each parcel, sorted in decreasing order of number of species.

Fig. 2. Boxplots representing the costs required for each agent to achieve their objectives, as a proportion of the total cost required when the two agents *pool resources* (depicted by the grey horizontal line). The left and right columns show the results when agents *share information* or *act in isolation*, respectively. Each plot shows three boxplots representing the distribution of costs for the agent acting first, the agent acting second, and the summed cost of both agents.

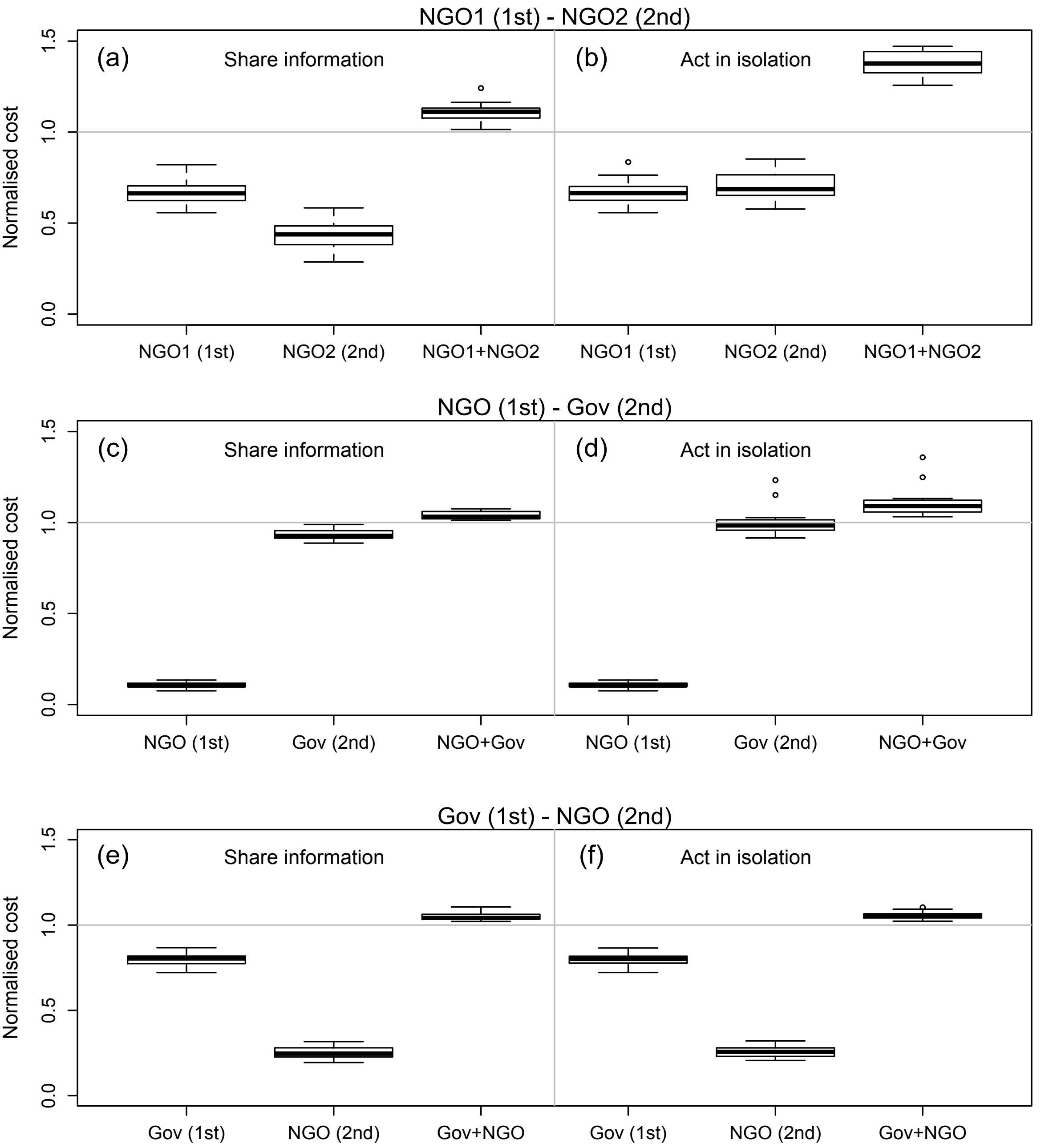
Fig. 3. Boxplots showing the cost savings for the agent acting second when moving from *acting in isolation* to interacting by *sharing information.*

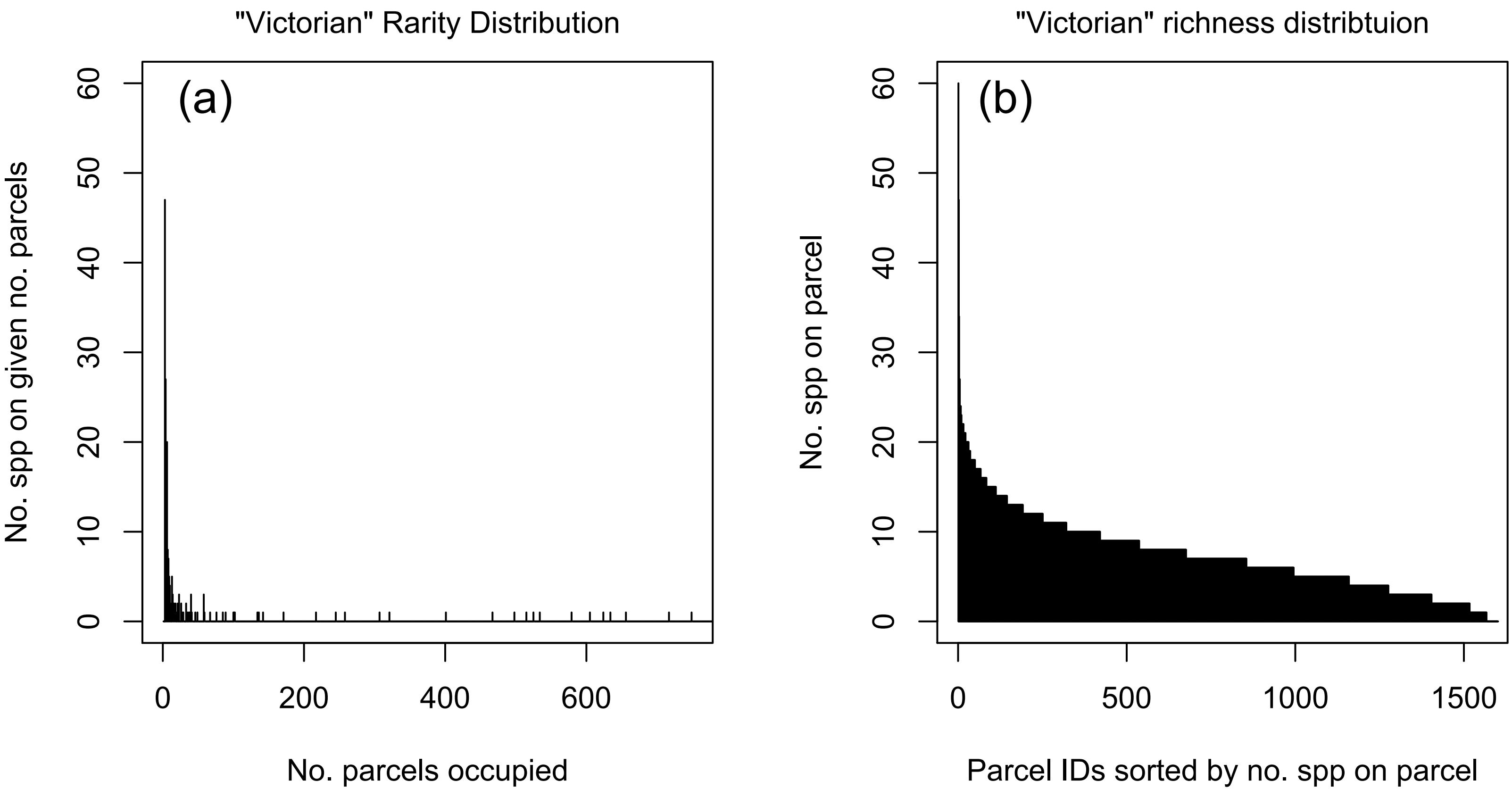
Fig. 4. The cost saving or increase for each agent when moving from *acting in isolation* or *sharing information* to *pooling resources* under all possible cost-sharing proportions. The cost proportion for the first agent is shown on the lower axis of (c) and the proportion for the second agent is shown on the upper axis in (a). Values on the *y*-axis greater than zero represent a proportional cost saving and negative values represent

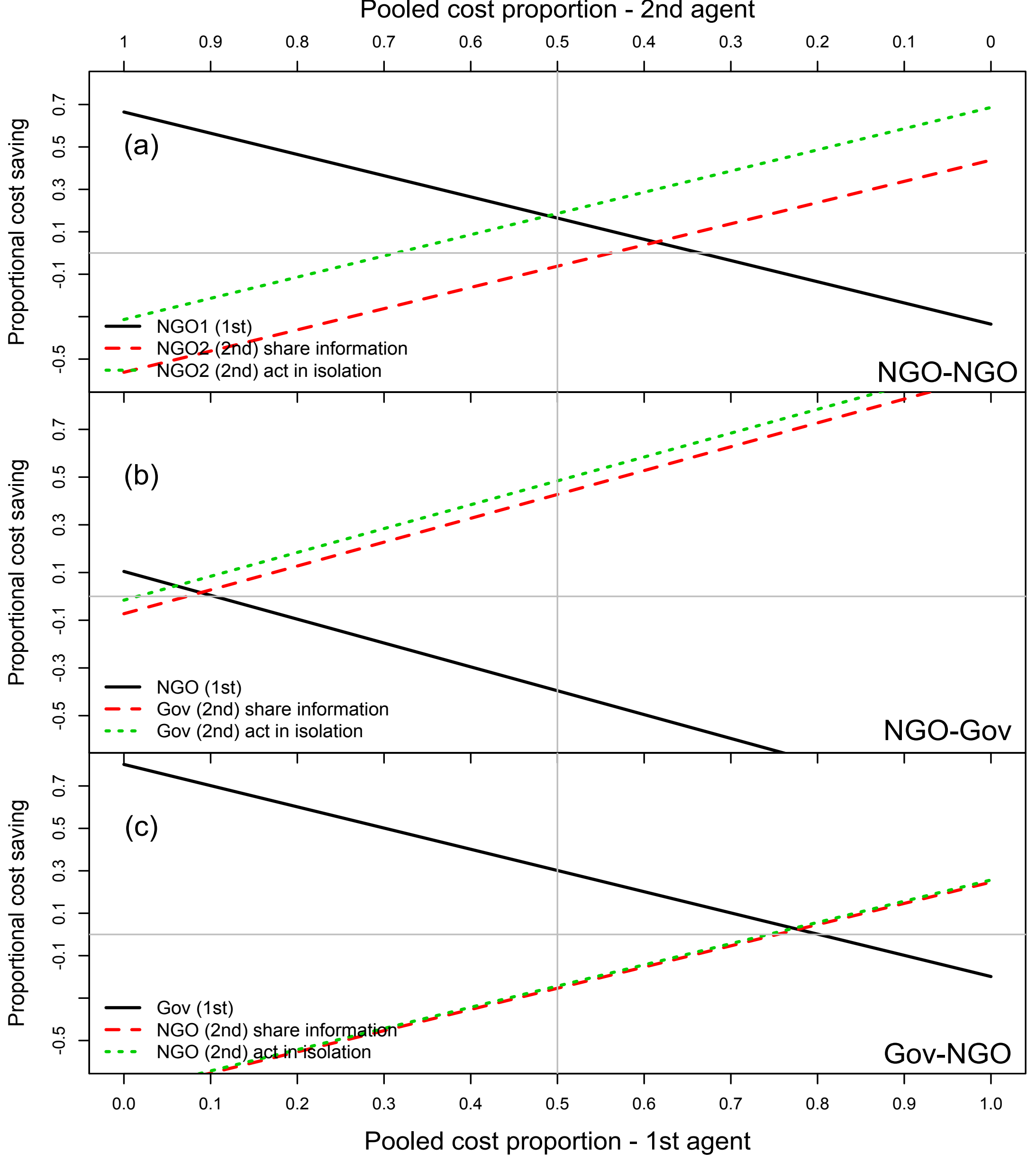
an increase in cost relative to the *acting in isolation* scenario. The lines represent the median values from Fig. 2.



Proprotinal cost saving
0.0
0.1
0.2
0.3
0.4
NGO1 (1st), NGO2 (2nd)
NGO (1st), Gov (2nd)
Gov (1st), NGO (2nd)


NGO1 (1st) - NGO2 (2nd)
(a)
Share information
(b)
Act in isolation
Normalised cost
0.0
0.5
1.0
1.5
NGO1 (1st)
NGO2 (2nd)
NGO1+NGO2
NGO1 (1st)
NGO2 (2nd)
NGO1+NGO2
NGO (1st) - Gov (2nd)
(c)
Share information
(d)
Act in isolation
Normalised cost
0.0
0.5
1.0
1.5
NGO (1st)
Gov (2nd)
NGO+Gov
NGO (1st)
Gov (2nd)
NGO+Gov
Gov (1st) - NGO (2nd)
(e)
Share information
(f)
Act in isolation
Normalised cost
0.0
0.5
1.0
1.5
Gov (1st)
NGO (2nd)
Gov+NGO
Gov (1st)
NGO (2nd)
Gov+NGO


"Victorian" Rarity Distribution
(a)
No. spp on given no. parcels
No. parcels occupied
0
10
20
30
40
50
60
0
200
400
600
"Victorian" richness distribtuion
(b)
No. spp on parcel
Parcel IDs sorted by no. spp on parcel
0
10
20
30
40
50
60
0
500
1000
1500



Pooled cost proportion - 2nd agent
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Proportional cost saving
0.7
0.5
0.3
0.1
-0.1
-0.5
(a)
NGO1 (1st)
NGO2 (2nd) share information
NGO2 (2nd) act in isolation
NGO-NGO
(b)
-0.3
NGO (1st)
Gov (2nd) share information
Gov (2nd) act in isolation
NGO-Gov
(c)
Gov (1st)
NGO (2nd) share information
NGO (2nd) act in isolation
Gov-NGO
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Pooled cost proportion - 1st agent