Incorporating Investment Uncertainty Into the Prioritisation of Conservation Resource Allocation

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EXTENDED ABSTRACT

Limited funds mean that conservation organisations must prioritise between regions in order to preserve as much biodiversity as possible. Biodiversity hotspots are one of the key strategies used to identify such priorities; however, they do not reveal how resources should be distributed. Identifying optimal returns for conservation investment requires the resource allocation problem to be properly formulated within a sound mathematical framework. A range of techniques can then be used in order to find an optimal solution.

A number of important factors must be incorporated into the resource allocation problem if we are to accurately model the process of making of conservation investments; including the biodiversity values of a region, threats to the biodiversity in that region, investment costs, the current state (amount of area reserved and lost) of the regions of interest, future uncertainty, and the likelihood of investment success. The probability of a successful investment in particular, can be severely affected by various political and economic factors, but has not been accounted for in previous work. Explicitly incorporating the possibility that conservation efforts may fail allows the effects of such uncertainty on the behaviour of the optimal investment strategy to be evaluated. This knowledge can then be used to inform future investments.

Each region is considered as being made up of a number of homogenous land parcels, each of which can be reserved, available for reservation, or lost to development. We use number of endemic species as a measure of regional biodiversity value, which avoids the need to consider species overlap between regions. The number of endemics protected with increasing investment in a region is modelled using the species area curve. We use the binomial distribution to model the probabilities of parcel loss due to development and investment uncertainty factors.

We treat conservation resource allocation as a dynamic and ongoing process. The method of stochastic dynamic programming (SDP) is used to determine how to optimally allocate conservation resources between biodiversity hotspots. The resultant solution is used to evaluate the performance of a number of simple heuristics: with and without consideration given to the likelihood of investment success.

We performed a sensitivity analysis on the outcomes of each of the SDP and heuristic approaches in order to properly assess the effects of including investment uncertainty over a range of parameter values. Investment uncertainty was varied against each of the two main factors of interest in the resource allocation problem: regional biodiversity value and threat level. The cost of investing in a region is also important but was not explicitly examined in the analysis.

Our results show that the optimal solution responds to the likelihood of investment success, with the outcome a complicated trade-off between the likely relative benefits of investing in different regions and the corresponding relative risks of investing in those regions. Due to the complex nature of this problem, the heuristic methods are unable to approximate the behaviour of the optimal solution, but can still provide a reasonable outcome. Heuristics accounting for investment uncertainty generally outperformed those that didn't, which suggests that future conservation action should take into account the likelihood of investment success when prioritising the allocation of conservation resources between regions.

1. INTRODUCTION

Conservation efforts have become a race against time, as conservation agencies struggle to protect what they can in the face of escalating biodiversity loss (Mittermeier *et al.*, 1998, Pimm *et al.*, 1995). The limited resources available necessitate that conservation resources be efficiently targeted in order to ensure the preservation of as much biodiversity as possible (Moore *et al.*, 2004). Much planning for conservation is focused at a regional or local level, but the increasing presence of international conservation organisations is driving the need for more globally-orientated allocation of resources (Meir *et al.*, 2004). Working at such a broad scale allows for global patterns in biodiversity to be examined, though at the cost of fine-scale and more spatially explicit data.

To date a considerable number of strategies to address the problem of global allocation of conservation resources have been proposed (eg. Myers et al., 2000, Olson & Dinerstein, 1998, Stattersfield et al., 1998), with most targeting areas rich in some form of biodiversity, or 'biodiversity hotspots'. Proposed by Myers in 1988, the hotspots concept encapsulates the notion that a large portion of terrestrial biodiversity can be protected within a relatively small region of land due to the uneven and often highly clustered distribution of species around the globe (Rodrigues *et al.*, 2004).

However, the identification of biodiversity richness alone does not address the resource allocation problem, and instead offer a solution to a problem that has not been correctly formulated (Possingham *et al.*, 2000, Redford *et al.*, 2003). Hotspots address the problem of where species diversity is greatest; they do not identify the regions that should be priorities for investment in order to conserve the most biodiversity. Instead, organizations need to employ a more directed approach and set explicit, quantitative conservation targets which can then utilise systematic methods in order to optimise conservation outcomes (Margules & Pressey, 2000). Here we develop the conservation resource allocation problem using a mathematical framework, with the objective being to maximise the total species conserved in the long-term given financial constraints (i.e. a maximal coverage problem (Church *et al.*, 1996)). Conservation agencies typically receive funding on an annual basis, and to incorporate this we model resource allocation as an ongoing, dynamic process, where additional reserves may be acquired each year, and remaining unreserved land is subject to degradation, and subsequent species loss.

Current resource allocation methods in conservation planning assume all investments made will be completely successful in protecting the targeted biodiversity. In this paper we investigate the effects of incorporating uncertainty into the likelihood that once reserved, species remain protected. We refer to this uncertainty as 'investment uncertainty'. There are a wide range of factors that could potentially influence the likely success of conservation investments, including species or habitat viability, as well as various social and political-economic factors such as corruption, political instability, constitutional change, democracy, government effectiveness, and population pressures (Deacon & Murphy, 1997, Smith et al., 2003). Their effects on capital investments are well documented (Bohn & Deacon, 2000), but are only just beginning to be investigated in relation to allocating conservation resources.

There exists already a wide range of cases documenting the often deleterious impacts political-economy factors can have on conservation efforts (Brandon et al., 1998, Bruner et al., 2003, Smith et al., 2003). Indeed, Soule (1991) encourages the view of reserves as merely transient states, and emphasises the importance of structuring conservation action in response to such uncertainty, even suggesting the use of alternative measures in places where the risk of political instability and reserve loss is simply too high. Such factors are likely to be particularly relevant when operating at a global scale, as differences in investment certainty are subject to much wider variation across countries, and thus have the potential to significantly alter investment priorities.

2. FORMULATING THE GLOBAL CONSERVATION ALLOCATION PROBLEM

At a global scale, considering individually each of the potentially thousands of sites that could be reserved is impractical. Instead we treat each potential reserve within a defined region as simply one of many homogeneous 'parcels', with characteristics averaged over the entire region. Following allocation at the global level, further planning at a smaller, and more detailed resolution can follow. Thus, the problem reduces to how many 'parcels' to allocate funds to from each of the different regions in a given time step in order to ensure optimal species protection. For simplicity, just two regions are used here, in order to make computations easier, and results more transparent.

Each region and its component parcels are characterised by their total biodiversity value, threat level, cost per unit parcel, a measure of investment certainty due to political-economic factors and the current state of each of the parcels. Endemics are used to represent regional biodiversity levels in order to remove species overlap, and therefore the need to consider complementarity between regions. Parcels can be in one of three states: reserved, available for reservation or unsuitable for reservation due to development. Each currently available parcel has a probability of being converted to unsuitable during the next timestep, based on regional threat levels, and likewise, each currently reserved parcel has a probability of being converted to unsuitable, as determined by the level of investment uncertainty in the region.

For each successive parcel reserved, the resultant increase in biodiversity is dependant on the number of parcels already reserved within a region. This is because the number of distinct species within a region does not increase linearly with increasing area reserved. Instead the increase in number of species has been shown to follow a species-area relationship, with the number of species in a given reserve network equal to $\alpha A_R{}^z$, where A_R is the amount of area reserved, and α and z region-specific constants (Rosenzweig, 1995). For this analysis, a standard z value of 0.2 is used and α is calculated as the total number of species in a region divided by $A_T{}^z$**,** where A_T is the total area of the region of interest (MacArthur & Wilson, 1967).

Reserving each parcel entails a cost, and at each timestep total expenditure must be less then or equal to the total available funds. Any surplus funds are disregarded by the model and assumed to be utilised for other purposes. Regional costs, threat rates and investment certainty are taken to be constant throughout the entire allocation period.

As conversion is treated here as irreversible and reserved as well as unreserved land parcels are now subject to loss, all biodiversity must then eventually be lost from the system. This makes optimising for biodiversity gains at some final time irrelevant. Instead we optimise the number of 'biodiversity years' accumulated by the terminal time, with the points allocated each year reflecting the biodiversity currently protected by the reserved area. The terminal time is defined here as being when all biodiversity has been lost. Results obtained under this scoring system are then comparable to optimising for a terminal time when investment uncertainty is not taken into consideration.

For each possible system state $\mathbf{X}$, the value of the reserve system $V(t,\mathbf{X})$ at time t is determined by the total number of endemic species it protected that year, with the value function to be maximised as follows:

$$V(T,\mathbf{X}) = \sum_{t=0}^{T} \sum_{j=1}^{J} \alpha_j r_j(t)^z \tag{1}$$

where $\boldsymbol{T}$ is the terminal time and r_j (t), the number of parcels reserved at time t within region j, j=1…$\boldsymbol{J}$ for a total of $\boldsymbol{J}$ priority regions. This is subject to the budget constraint:

$$\sum_{j=1}^{J} c_j b_j \leq B \tag{2}$$

where c_j is the cost of acquiring any parcel from region j and B is the annual budget. At each time step, we must determine the number of new parcels, $s_j(t)$ to acquire from region j out of a total of a_j (t) possible parcels available for reservation, with vector $\boldsymbol{S}(t)$ representing our investment in all regions in year t. The available parcels a_j (t) are subject to a yearly loss rate d_j, and each of the currently reserved parcels $r_j(t)$, have a probability p_j of being lost due political-economic factors, with $p_j < d_j \; \forall \boldsymbol{J}$.

3. SOLVING THE RESOURCE ALLOCATION PROBLEM

The method of Stochastic Dynamic Programming (SDP) was used to find the optimal allocation solution $\boldsymbol{S}(t)$**.** SDP is a state-based, backwards iteration algorithm that determines for each possible system state, the optimal solution based on the current state and the expected return given the likely transition probabilities (Clark & Mangel, 2000). It has been used to solve a number of conservation planning problems, and has been applied to the dynamic reserve selection process for locally based cases involving small numbers of sites (Costello & Polasky, 2004, Meir et al., 2004).

Parcel loss was treated as a stochastic process and represented using the binomial distribution. The resultant value function for state $\mathbf{X}$ is then the sum of these transition probabilities weighted by the corresponding value of being in the new state $\mathbf{X'}$ at the next step, plus the score given for being in the current system state (Bellman, 1957).

$$\max_{S(t)}\left\{\sum_{m_j=0}^{a_j-s_j}\sum_{n_j=0}^{r_j+s_j}\left[\prod_{j=1}^{J}\binom{a_j-s_j}{m_j}d_j^{m_j}\left(1-d_j\right)^{a_j-s_j-m_j}\binom{r_j+s_j}{n_j}p_j^{n_j}\left(1-p\right)^{r_j+s_j-n_j}V(t+1,\mathbf{X}')\right]+\sum_{j=1}^{J}\alpha_j(r_j+s_j)^z\right\} \quad (3)$$

This equation is given by (3), with r_j and a_j defined by $\mathbf{X}$, m_j the number of parcels potentially lost due to development or other land use change pressures and n_j the number of parcels lost due to political-economic factors when accounting for the investment uncertainty, and subject to (2).

The SDP algorithm was run until the solution reached equilibrium, in order to remove time dependency, and then forward simulated using stochastic parcel loss probabilities to investigate the performance of the optimal solution (Clark & Mangel, 2000). Even when using much smaller state spaces, the SDP algorithm had trouble stabilising, and the forward simulation was also highly variable, requiring up to 100,000 simulations in order to produce consistent outputs.

While guaranteed to find the optimal solution, SDP is severely limited in the number of regions and parcels it can consider due to the 'curse of dimensionality', which limits its use to relatively small problems. In light of this, we formulate a number of heuristic algorithms and evaluate their performance relative to the optimal SDP solution over a range of scenarios. Previous work has applied a similar approach (Costello & Polasky, 2004, Drechsler, 2005, Meir et al., 2004) and a number of myopic and greedy algorithms have been investigated and found to be quite effective in approximating the optimal solution, with outputs differing by less then 5%.

Here we select two heuristics: 'maximising short term gain' and 'minimising short term loss', and compare them to the equivalent heuristics when the expected gain in total number of biodiversity years under investment uncertainty is used rather then the number of species. A myopic SDP solution is also considered. For the heuristic that maximises short-term gain, the value function to be maximised at each timestep is the number of additional species that are reserved and this is given by:

$$V(t,\mathbf{X})=\sum_{j=1}^{J}\alpha_j r_j(t)^z \quad (4)$$

subject to (2). For the heuristic that minimises short-term loss, the value function maximised is dependant not only on the species reserved but also on those present in unreserved parcels:

$$V(t,\mathbf{X})=\sum_{j=1}^{J}\alpha_j(r_j(t)+a_j(t))^z \quad (5)$$

subject to (2). In the heuristics accounting for investment uncertainty, α_j is replaced by α_j / p_j in (4) and (5) in order to evaluate the expected return on 'biodiversity years' when investing in a region.

4. RESULTS AND DISCUSSION

The optimal solution was investigated over a wide range of scenarios in order to assess its sensitivity to different parameter values, with forward simulations each repeated 100,000 times and the average score at each timestep recorded. A base level of 1% per year for investment uncertainty was chosen for the contour plot sensitivity analyses. Regions having lower levels of investment uncertainty were favoured; with the weighting given to this factor dependant on the relative difference between regions. Thus, a loss probability difference of 0.15 to 0.10 was not equivalent to 0.50 and 0.45, but instead more closely reflected the outcome of a 0.75 to 0.50 comparison.

However, when conflicting differences in parcel biodiversity value are incorporated, the results varied depending on the overall level of investment uncertainty, with higher uncertainty levels causing the more stable region to be increasingly favoured. This ultimately reflects the benefit each parcel is likely to provide, but represents a key flaw in the heuristics that account for investment certainty: they can only respond to differences between sites rather then to the absolute level of investment uncertainty.

This dependency on absolute uncertainty levels is only when weighed against regional biodiversity value and does not apply relative to parcel threat differences. Thus, for scenarios with no biodiversity value differences, the solution remains constant regardless of how high or low overall investment uncertainty levels are. This apparent inconsistency essentially just reflects how the threat and biodiversity value characteristics of a parcel are viewed: once acquired, a parcel's threat level is no longer relevant, but the certainty of investment and biodiversity value are and will together influence the number of biodiversity years gained. Investment uncertainty is more influential then regional threat levels in determining the optimal approach, with the SDP almost always choosing to act first in the region with the greatest investment certainty, even when the alternative region is highly threatened.

Overall, none of the heuristic methods were found to closely approximate the rather complex nature of the optimal solution. In particular, the myopic SDP, though able to respond to different levels of investment uncertainty, failed to provide a good approximation to the SDP solution (Figure 1). On average it fared no better than the heuristics not accounting for investment certainty and differed from the optimal solution by up to 12%. In scenarios without investment uncertainty, the myopic SDP solution closely approximated the optimal solution. These differences are likely to reflect the overall increased complexity of the problem, with a single look-ahead algorithm no longer able to capture the essence of the optimal solution.

Of the simple heuristics, the 'maximise gain' heuristic slightly outperformed the 'minimise loss' heuristic; with both being least effective when large differences in investment uncertainty were coupled with only small differences in the biodiversity value of parcels (Figure 2). These differences in performance are primarily because maximising gain early on provides an increased amount of time in which to accumulate 'biodiversity years'.

If the scoring scheme was modified so that points were given for every year a species existed, regardless of whether it was in or out of a reserve, then the performance of the minimise loss heuristic would likely be improved. Both heuristics can lead to suboptimal solutions under investment uncertainty (Figure 2), which is important to note, given that these are in line with the approaches currently recommended for efficient resource allocation.

Adjusting these two heuristics to account for expected long-term species gain significantly improved their performance; with subsequent final differences being significantly lowered (Figure 3). The heuristic that minimises expected short-term loss under investment uncertainty is closest to the optimal solution, giving percentage differences of less then 3%. However this heuristic tends to be less effective when there are high relative differences in both investment uncertainty and either biodiversity value or threat levels.

These results demonstrate that incorporating this relatively simple measure of investment uncertainty can lead to varying recommendations concerning resource allocation, and highlights the need for political-economic measures along with other sources of investment uncertainty, to be considered more explicitly in future planning frameworks.

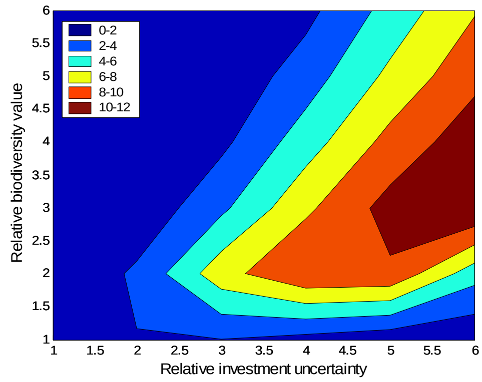
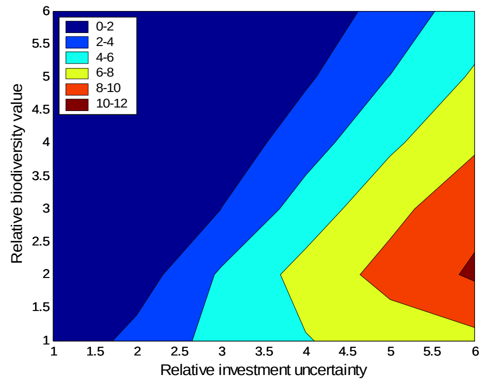
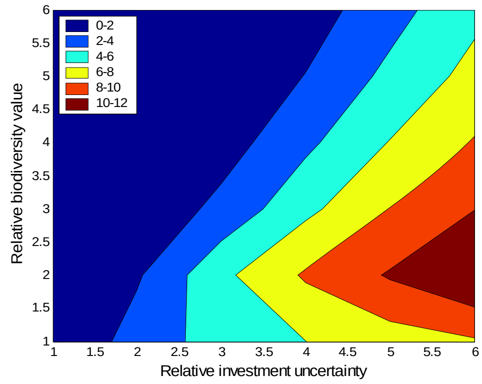


Figure 1. The percentage difference from the optimal solution of the myopic SDP solution over a range of biodiversity value and investment uncertainty levels. Results for varying threat levels were similar.



(a)



(b)

Figure 2. The percentage difference from the optimal SDP solution of (a) the 'maximising gain' heuristic and (b) the 'minimising loss' heuristic over a range of biodiversity value and investment uncertainty levels. Results for varying threat levels were within similar ranges for both (a) and (b).

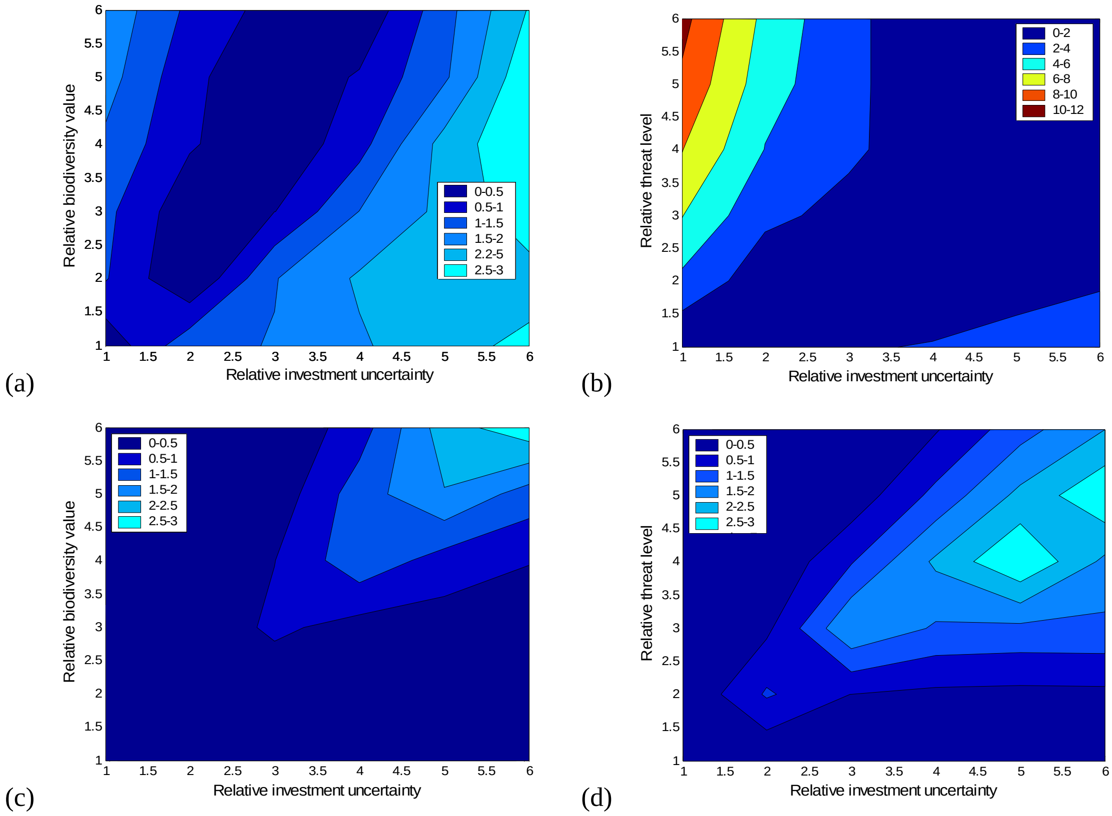


Figure 3. The percentage difference from the optimal SDP solution of the heuristic that maximises expected gain under investment uncertainty over a range of (a) biodiversity value and investment uncertainty levels, and (b) threat and investment uncertainty levels.

Percentage difference from the SDP solution of the heuristic that minimises expected loss under investment uncertainty over a range of (a) biodiversity value and investment uncertainty levels, and (b) threat and investment uncertainty levels.

5. CONCLUSION

This analysis investigated the effects of incorporating potential reserve loss as a measure of investment uncertainty into the conservation resource allocation problem. We found investment uncertainty to have a significant impact on how regions were prioritised. Those with high investment certainty were selected more readily, even when a parcel was otherwise less favourable, with the optimal approach determined by the degree and relative difference of the investment uncertainty. Of the heuristics investigated, none were able to closely approximate the optimal solution, although their performance improved when our objective was modified to concern the expected long-term gain of species.

Our results suggest that neglecting considerations of investment uncertainty could result in sub-optimal outcomes, but that this can be avoided if regional biodiversity value is scaled up relative to its expected return. However, planners could also consider alternative proactive approaches, such as policy changes or increased funding, that may prove more beneficial in the long-term then simply avoiding those areas with low investment certainty. Further development of this problem will include such approaches and examine the effects of alternative political-economic factors.

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