Optimal Translocation Strategies for Threatened Species

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EXTENDED ABSTRACT

Translocation—the deliberate, human-mediated movement of organisms—is a useful conservation tool most often employed in attempts to increase persistence of threatened or depleted species. Translocation projects involve difficult management decisions regarding the allocation of animals between sites. This research provides a rational scientific basis for these decisions. We use a stochastic population model and Stochastic Dynamic Programming to determine optimal translocation strategies for theoretical populations, and apply this framework to a case study on the Bridled Nailtail Wallaby (*Onychogalea fraenata*).

The translocation problem is defined as follows: in each time step of the translocation program, a set number of individuals are sourced from a captive population and translocated to two sites. Management decisions involve the allocation of these individuals between the two sites, over time. We use a first-order Markov chain stochastic population model to simulate each translocated population. This model follows females only, and does not consider age structure. Translocated populations *A* and *B* are limited by carrying capacities K_A and K_B, with population dynamics governed by Markov chain transition matrices $\mathbf{A}_A$ and $\mathbf{A}_B$. In the time step of their translocation, translocated individuals are governed by a separate transition matrix $\mathbf{A}_T$ with a higher mortality rate and no reproduction.

The Stochastic Dynamic Program (SDP) has three states: the number of individuals in the first site ($n_A = 0,\ldots,K_A$), the number of individuals in the second site ($n_B = 0,\ldots,K_B$), and the time period of the translocation project ($t = 0,\ldots,T$). Populations can change state by natural processes—as captured in the transition matrices—or by receiving translocated individuals. With *X* individuals available in each time step, Population *A* receives *d* individuals and Population *B* receives *X-d* individuals. The SDP steps backwards from the terminal time *T* where the final reward, given by an objective function, is received. For each time step all possible decisions—represented by the variable *d*—are evaluated for every combination of possible population sizes. The optimal decision is the one that produces the highest score, determined by the dynamic programming equation.

We compare the results given for two different objective functions. The first is a long-term persistence objective function, which maximises the persistence of translocated populations ε time steps after the end of the translocation program. The second is a total population size objective function, which maximises the number of animals present at the end of the translocation program. The SDP is applied to the Bridled Nailtail Wallaby by making each time step equal to four months, and by using realistic population parameters derived from relevant literature. The translocation program is assumed to run for four years (twelve time steps), with two individuals available in each time step. The carrying capacity of each site is set at 50. Population *A* has an approximate (per capita) growth rate of 1.305, while Population *B* has a growth rate of 0.87.

When using the long-term persistence objective function (with ε = 128), the optimal decision for most states is to translocate both available animals to Population *B*. These results satisfy the objective function, but are not sensible for a real-life translocation program, as population *B* has a declining growth rate. This indicates that the long-term persistence objective function considered here does not adequately express the goals of a translocation program. The results for the total population size objective function are more practically applicable. In these results the optimal decisions in each time step are dependent on the number of animals in Population *A*. The large difference in results between the two objective functions demonstrates the importance of careful consideration when specifying the goals of a project. This applies not only to translocation programs, but any project where clear decision-making is needed.

1. INTRODUCTION

Translocation is the deliberate, human-mediated movement of living organisms from one area to another (World Conservation Union (IUCN) 1987, Tenhumberg, et al. 2004). This movement can be between wild and captive populations, or between two or more wild populations (Tenhumberg, et al. 2004). As a conservation tool, translocation can be used to increase the range of a species through reintroduction to an area from which it has been extirpated, or to increase numbers in a critical population by adding individuals from a wild or captive population. It is one of the main management options for restoration and conservation of threatened animal species (Fischer and Lindenmayer 2000). Translocation projects involve difficult management decisions, which need a rational and transparent scientific basis. This research provides that basis by framing and solving the translocation problem within a decision theory context. We use a stochastic population model and Stochastic Dynamic Programming to determine the optimal state-dependent translocation strategies. We apply this framework to a case study on the Bridled Nailtail Wallaby (*Onychogalea fraenata*). Specifically, we ask the question: if we have a set number of wallabies to translocate in each time period and two translocation sites, how many animals should we put at each site given the state of each population?

2. MODEL

2.1. Model Scenarios

In each scenario we assume there is a captive source population and two sites to which individuals can be translocated. The dynamics of the source population are not considered explicitly—it is assumed to produce a set number of 'excess' individuals available for translocation in each time step. Management decisions focus on the allocation of these individuals between the two translocation sites. We determine the optimal management decisions using Stochastic Dynamic Programming.

2.2. Stochastic Population Model

We use a first-order Markov chain stochastic population model to simulate each translocated population. These models follow only the number of females, consequently assuming that females always have the opportunity to mate regardless of male abundance. These models also ignore the age structure of the populations. We assume that the sex ratio is constant and that females can have a maximum of one newborn in each time step. We label the translocated populations A and B, which are limited to a maximum size of K_A and K_B, respectively. This population size limit can be interpreted as the carrying capacity of the translocation site. The Markov chain transition matrix for each population from time step (t) to time step ($t + 1$) is $\mathbf{A} = \mathbf{LS}$, the matrix product of the recruitment matrix $\mathbf{L}$ and the survival matrix $\mathbf{S}$. This assumes that within each time step survival occurs before reproduction—only surviving individuals can reproduce. The Markov chain matrices are constructed following Tenhumberg et al. (2004). The processes of immigration and emigration are not considered, as we believe that in cases of threatened species with isolated translocation sites and low population densities dispersing animals are unlikely to survive and reproduce.

2.3. Stochastic Dynamic Program

Stochastic Dynamic Programming is a mathematical optimisation method. It can be applied to any stochastic system that can be described as a finite set of states where a series of sequential decisions must be made (Lubow 1996). This Stochastic Dynamic Program (SDP) determines the exact optimal strategy for translocation, which is dependent on the management objective and the state of the system (i.e. the number of individuals in each population and the amount of decision-making time available).

The population model has three states: the number of individuals in the first site ($n_A = 0,\ldots,K_A$), the number of individuals in the second site ($n_B = 0,\ldots,K_B$), and the time period of the translocation project ($t = 0,\ldots,T$). Changes in the state of each population (i.e. number of individuals) through births and deaths governed by the Markov chain transition matrices $\mathbf{A}_A$ for Population A and $\mathbf{A}_B$ for Population B. Populations can also change state by receiving translocated individuals.

In each time period, X individuals from the source population are allocated between populations A and B. The decision variable d is an integer value between 0 and X. Population A receives d translocated individuals, while Population B receives $X-d$ individuals. Translocation is assumed to occur early in the time step, before the death and birth processes. Translocated individuals have a separate transition matrix $\mathbf{A}_T$—with a higher mortality rate and no reproduction—describing their dynamics in the time step of their translocation. It is not known whether animals would breed immediately after translocation, so the worst case scenario is assumed.

Stochastic Dynamic Programming works by stepping backwards from the terminal time T where the final reward, given by an objective function, is received. For each time step all possible decisions—represented by the variable d—are evaluated for every combination of possible population sizes. The optimal decision, assuming all future decisions are optimal, is the one that produces the highest score. This score is determined by the dynamic programming equation:

$$S(d) = \sum_{i=0}^{K_A} \sum_{j=0}^{K_B} \sum_{k=0}^{d} \sum_{l=0}^{X-d} V(t+1, i+k, j+l) a_{i,n_A}^A a_{j,n_B}^B a_{k,d}^T a_{l,X-d}^T$$

(1)

where V is the objective function, a_{i,n_A}^A is an element of the transition matrix $\mathbf{A_A}$, a_{i,n_B}^B is an element of the transition matrix $\mathbf{A_B}$, and $a_{k,d}^T$, $a_{l,X-d}^T$ are elements of the transition matrix $\mathbf{A_T}$.

We compare the optimal decisions for two different management objectives. The long-term persistence objective function maximises the expected number of persisting populations ε time steps after the end of the translocation project (time T). This is specified by the equation:

$$V_1(T, n_A, n_B) = (1 - a_{0,n_A}^{A'}) + (1 - a_{0,n_B}^{B'}) \quad (2)$$

where $a_{0,n_A}^{A'}$ is the element of the transition matrix $\mathbf{A}^A{}_\varepsilon$ containing the probability that n_A individuals at time T become 0 individuals at time $T + \varepsilon$, and $a_{0,n_B}^{B'}$ is the element of the transition matrix $\mathbf{A}^B{}_\varepsilon$ containing the probability that n_B individuals become 0 individuals.

The total population size objective function maximises the total number of individuals in the final time step of the translocation program. The equation describing this objective is:

$$V_2(T, n_A, n_B) = n_A + n_B \quad (3)$$

2.4. Case Study

To demonstrate the approach, we apply it to a case study of Bridled Nailtail Wallabies (*Onychogalea fraenata*). The Bridled Nailtail Wallaby was once distributed throughout the semi-arid inland of eastern Australia, from Charters Towers in the north to the Murray River in the south (Johnson 2003). Due to threats such as land clearing, predation, and competition with livestock it was reduced to a small population in Taunton National Park, near Dingo in Central Queensland (Lundie-

Jenkins 2001, Johnson 2003). It has recently been successfully reintroduced to Idalia National Park, near Blackall (Johnson 2003). The Bridled Nailtail Wallaby is currently listed as endangered and according to its 1997-2001 Recovery Plan needs to be re-established at two more sites to satisfy the conditions of recovery (Lundie-Jenkins 2001).

Bridled Nailtail Wallabies have one offspring at a time, but breed continuously in the wild and may raise up to three young per year (Lundie-Jenkins 2001). We incorporate this into the SDP by making each time step equal to four months, so at each four-month interval a female may or may not produce a female offspring. A literature review of articles on the demography of the species established realistic ranges for model parameters. The probability of a female giving birth in a four-month period ranges from 0.89 to 1 (Fisher, et al. 2000, Pople 2005). The probability of an individual dying in any four-month period ranges from 0.01 to 0.46 (Fisher 1998, Fisher, et al. 2000, Pople, et al. 2001). The ratio of female to male newborns is assumed to be constant at 0.5, a figure supported by some field data (Fisher, et al. 2000) and used previously in population models of the species (McCallum 1995, Pople 2005).

In both scenarios the translocation program is assumed to run for four years, or twelve time steps. Translocation occurs in the first eleven time steps ($t = 0...10$), with two individuals available each time. The final reward, given by the objective function, is received at $T=11$. The carrying capacity K of each site is set at 50 individuals. Population parameters are chosen from the established ranges to create an interesting management situation. The birth probability is set at 0.9 for each population, while the death probability is set at 0.1 for Population A and 0.4 for Population B. A higher death probability of 0.5 is given to translocated individuals (matrix $\mathbf{A_T}$). An approximation of the per capita growth rate r for each population can be calculated using the equation:

$$r = \sum_{i=1}^{K} i A_{i,1} \approx E\left(\frac{n_{t+1}}{n_t}\right) \quad (4)$$

where A is a Markov chain transition matrix. Given the above parameters, r is 1.305 for Population A and 0.87 for Population B. In cases where the long-term persistence objective function (2) is used, ε is set at 128 time steps, or 42 years 8 months. As in Tenhumberg et al. (2004), a power of 2 is used to simplify calculations by enabling the repeated squaring of a matrix.

3. RESULTS AND DISCUSSION

The use of a carrying capacity K in the SDP is mathematically convenient, but is not particularly realistic for the Bridled Nailtail Wallaby. For this reason the most relevant and applicable results of the SDP are those not affected by carrying capacity. The focus of analysis is therefore on those results for which both populations are small.

3.1. Comparison of Objective Functions

For the SDP with the long-term persistence objective function (2), the optimal decision for most system states is to translocate both available animals to Population B—the population with the lower growth rate. In the first time step (Figure 1), it is optimal to put both individuals into Population A if Population B is greater than 40 individuals and Population A is less than around 35 individuals. This is an effect of the imposed carrying capacities. When both populations are small, it is optimal to put both individuals into Population A only if Population A is zero. This changes only slightly over the time period, as can be seen at t=10 (Figure 2). In this time step it is optimal to put at least one animal into Population A if that population has less than three individuals.
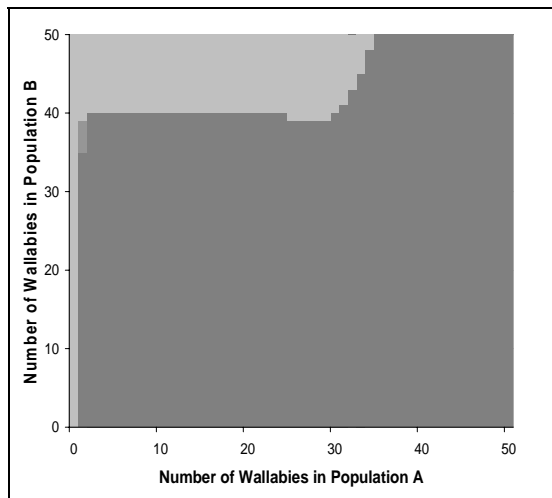

Figure 1: Optimal Decisions for t=0, using the long-term persistence objective function
Legend: Light grey – Two to Population A,
Medium grey – One to each population,
Dark grey – Two to Population B

On initial inspection these results seem counter-intuitive—how can we maximise long-term persistence by translocating animals into a declining population? However, these results are driven by the long-term persistence objective function. If Population A contains one individual at the terminal time, the probability of the population persisting 128 time steps into the future is

approximately 0.75. If Population A has two individuals, this probability increases to 0.94, and if it has three individuals it increases to 0.99. So with an estimated growth rate of 1.305, Population A is almost guaranteed to persist if it contains three or more individuals. This explains the results seen in Figures 1 and 2. If Population A has three or more individuals, the benefit of translocating animals into the population is very low, as the population is already extinction resistant. A greater increase in the probability of persistence results if the translocated individuals are added to Population B. This is therefore almost always the optimal decision. Furthermore, Population A only needs three individuals at time T to have a high probability of persisting to time $T + \varepsilon$. It is not important to ensure Population A's viability in the time steps prior to this, as it is known that by adding two individuals as a result of the final decision, a persistence probability of at least 0.94 can be achieved. This explains the slight change in optimal decisions through time from t=0 to t=10.
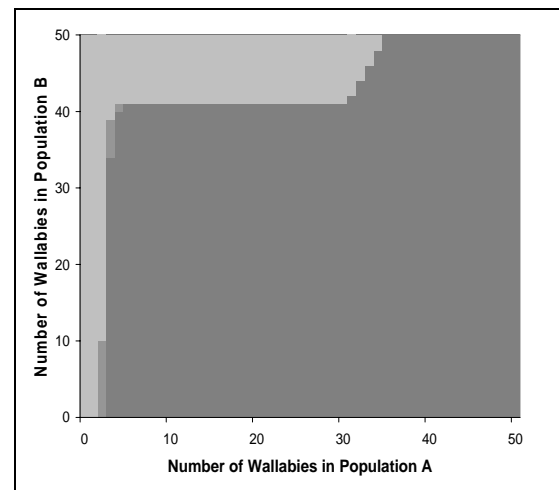

Figure 2: Optimal Decisions for t=10, using the long-term persistence objective function
Legend: as for Figure 1

Although these results make sense mathematically, they do not seem practically applicable—it is doubtful whether the advice: 'Don't worry about the good site, put them all in the bad site' would be well-received by a translocation manager. However, the optimal decisions satisfy the objective function, suggesting that this objective function does not accurately describe the goal of the translocation program.

The results of the SDP using the total population size objective function (3) are very different to those found with the long-term persistence objective function. At t=0, it is optimal to put both individuals into Population A if the population is

smaller than six individuals (Figure 3). This threshold increases over the time period, and by $t=9$ it is optimal to put both individuals into Population A if it has less than 28 individuals (Figure 4). The results of the final decision at $t=10$ are not shown here, as they are not as indicative of general trends due to their proximity to the receipt of the final reward at $t=11$.
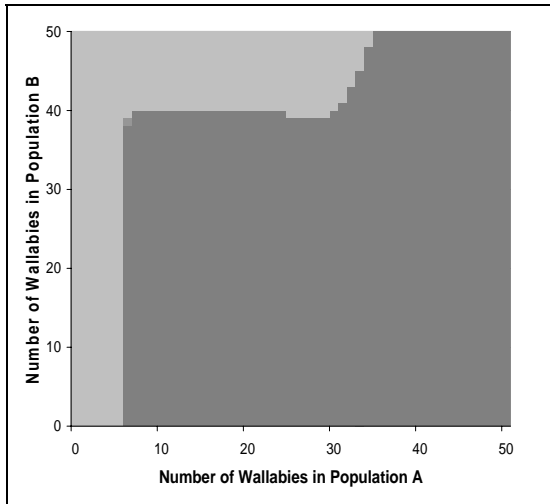

Figure 3: Optimal Decisions for $t=0$, using the total population size objective function
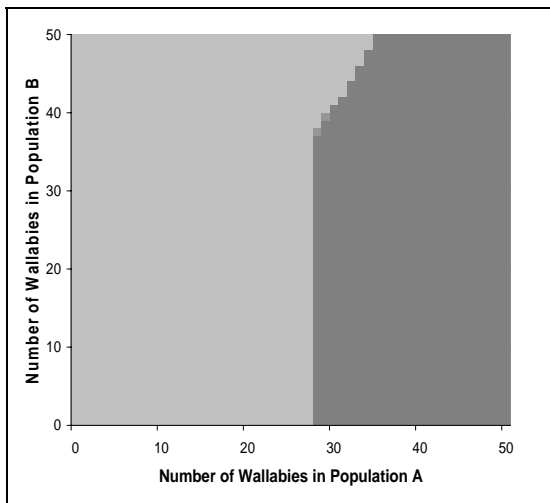Legend: as for Figure 1

Figure 4: Optimal Decisions for $t=9$, using the total population size objective function
Legend: as for Figure 1

This objective function produces optimal decisions that make practical, as well as mathematical, sense. By making the reward dependent on the state in the final time step instead of far into the future, decisions made earlier in the program become more important. Focusing on the number of animals rather than extinction/persistence probabilities is more suited to the goals of a

translocation program for threatened species, as we want to maximise growth rather than just prevent extinction. The optimal decisions according to this objective can also be easily condensed into rules of thumb for managers to follow, as they are dependent on the number of individuals in Population A. Although both objectives seem reasonable, the total population size objective function more accurately describes the goals of the translocation program, and produces results that are practically applicable.

3.2. Future Directions

This method provides a useful framework to generate rules of thumb for translocation managers when the specifics of translocated populations are known. However, a real-life situation in which we know all population parameters would be extremely unlikely. A more useful model would be one in which at least one of the parameters for one population is unknown. We could incorporate this into the current SDP by assuming a prior distribution for the unknown parameter, and updating this distribution in each time step according to information obtained about the population dynamics. This has not been done before in research into translocation strategies and would be a significant and useful extension.

4. CONCLUSIONS

This research shows the utility of Stochastic Dynamic Programming for developing rules of thumb for translocation managers. More importantly, it demonstrates the necessity of having a clear goal for decision-making. The two objectives used in this study, although superficially similar, produced very different results when used as part of a Stochastic Dynamic Program. One of these results was practically applicable, and the other was not. The choice of an appropriate and specific objective for a translocation program—or any venture where clear decision-making is essential—is the most important decision to be made.

5. ACKNOWLEDGEMENTS

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