Designing Species Translocation Strategies When Population Growth and Future Funding Are Uncertain

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Abstract: *When translocating individuals to found new populations, managers must allocate limited funds among release and monitoring activities that differ in method, cost, and probable result. In addition, managers are increasingly expected to justify the funding decisions they have made. Within the framework of decision analysis, we used robust optimization to formulate and solve different translocation problems in which both population growth and future funding were uncertain. Performance criteria included maximizing mean population size and minimizing the risk of undesirable population-size outcomes. Robust optimization provided several insights into the design of translocation strategies: (1) risk reduction is obtained at the expense of mean population size; (2) as survival of released animals becomes more important, funds should be allocated to release methods with lower risks of failure, regardless of costs; (3) the performance gain from monitoring drops as the proportion of a fixed budget required to pay for monitoring increases; and (4) as the likelihood of obtaining future funding increases, more of the existing budget should be spent on building release capacity rather than saved for future operating costs. These relationships highlight the importance of performance criteria and economic costs in determining optimal release and monitoring strategies.*

Diseño de Estrategias de Traslado de Especies Cuando el Crecimiento Poblacional y el Financiamiento a Futuro son Inciertos

Resumen: *Cuando se trasladan individuos para fundar nuevas poblaciones los manejadores deben destinar financiamientos limitados para aquellas actividades de liberación y monitoreo que difieren en metodología, costo y posibles resultados. Además de esto, se espera cada vez más que los manejadores justifiquen el financiamiento de las decisiones que lleven a cabo. Dentro del marco de trabajo del análisis de decisiones, utilizamos optimizaciones robustas para formular y resolver diferentes problemas de traslado en los cuales tanto el crecimiento poblacional, como el financiamiento a futuro son inciertos. Los criterios de rendimiento incluyeron la maximización del tamaño de la media poblacional y la minimización del riesgo de obtener tamaños poblacionales no deseados. La optimización robusta aportó varias ideas para el diseño de estrategias de traslado: (1) la reducción del riesgo se obtiene a costa del tamaño poblacional promedio; (2) como la sobrevivencia de los animales liberados se hace más importante, los recursos se deben ubicar en aquellos métodos de liberación con el menor riesgo de fallar, independientemente del costo; (3) la ganancia en rendimiento debida al monitoreo baja en tanto que la proporción de un financiamiento fijo requerido para pagar el monitoreo se incrementa; y (4) cuando la posibilidad de obtener financiamiento a futuro se incrementa, una parte mayor del presupuesto deberá ser empleado en incrementar la capacidad de liberación y no en salvar los costos de operación futuros. Estas relaciones subrayan la importancia de los criterios de rendimiento y los costos económicos en la determinación de liberaciones óptimas y estrategias de monitoreo.*

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Introduction

Translocation is often used to establish or augment populations of animals (Griffith et al. 1989; Olney et al. 1994; Serena 1995) or plants (Pavlik et al. 1993; Allen 1994; Primack 1996). Managers may translocate wild individuals to new areas or reintroduce captive-bred individuals into unoccupied parts of their historical range. Managers planning a translocation must decide on the number of individuals to introduce, the number and timing of introductions, the method of introduction, how closely to monitor the results of the translocation, and the allocation of a limited budget among these activities. Furthermore, cheaper translocation strategies may be riskier than others, so a manager must decide on an appropriate degree of risk. For example, managers working with an endangered species are likely to minimize risk, whereas those working with common species may be able to tolerate a greater degree of risk.

To assist managers in making these decisions, models have been developed that use simulation and optimization methods to evaluate the probable effects of alternative translocation strategies (e.g., Maguire 1986; Maguire & Servheen 1992; Beier 1993; Haig et al. 1993; McCallum 1995; Lubow 1996; Bevers et al. 1997). None of those models, however, have explicitly incorporated economic costs, although financial considerations often influence managerial decisions because of limited budgets and uncertainty about future funding.

We looked at the problem of designing translocation strategies with an emphasis on cost control. Our framework also allowed exploration of the probable effects of avoiding or accepting risk. The problem was to decide how to allocate a limited budget among translocation activities to meet or come close to meeting different goals for the population when both population growth and future funding are uncertain.

We used methods of decision analysis, which prescribe how a decision maker who is faced with choices under uncertainty should go about choosing a course of action (Raiffa 1968). Decision analysis involves listing chronologically the decision points and possible actions, listing the events that may affect the outcomes of actions along with their probabilities of occurrence, and listing the decision maker's preferences for the outcomes. This information is synthesized in an optimization model for finding the best sequence of actions from the feasible set. *Best* is defined in terms of consistency with the decision maker's preferences and probabilities.

We used an analysis framework called *robust optimization* (Mulvey et al. 1995) to prescribe the optimal sequence of management activities. Its strength is that problems with large numbers of activities, constraints, and scenarios can be formulated as nonlinear optimization models and solved with commercial mathematical programing software for personal computers. Furthermore, the framework facilitates analysis of the multiple objectives and tradeoffs that are often involved when conservation decisions are made (e.g., Ralls & Starfield 1995). Thus, robust optimization is a pragmatic alternative to decision trees (e.g., Maguire 1986; Maguire & Servheen 1992) and stochastic dynamic programing (e.g., Lubow 1996), which are difficult to use to solve problems with multiple objectives and numerous state and decision variables.

We formulated three optimization models for managers with different kinds of translocation problems. The first problem involved the allocation of funds among release activities that differed in method, cost, and population-size outcomes, assuming that population growth was uncertain. In the second problem, we estimated how much funding could be allocated efficiently to population monitoring. The third problem involved the allocation of funds between the capital costs of building translocation capacity (e.g., infrastructure required to capture, transport, house, and care for animals) and the operating costs of releasing and monitoring animals, assuming that future funding was uncertain.

Our models lack the details that would be a part of a real management problem. Nonetheless, our general formulation was designed to demonstrate that robust optimization is potentially useful and to deduce some simple relationships governing the design of translocation strategies when population growth and future funding are uncertain. Relevant details can always be added to the analysis in a real-life application.

In our hypothetical problems, we assumed that uncertainty about population growth and funding stemmed from incomplete knowledge of these processes. This kind of uncertainty arises when the evidence base is small; for example, when factors affecting the survival of released animals are poorly understood or when decision makers have little or no experience in estimating how an administration will fund species recovery programs. Consistent with methods of decision analysis, we used intuition and professional judgement to estimate probabilities of occurrence of different scenarios. Furthermore, we assumed that it was admissible to use subjective probabilities in the absence of empirical estimates derived from sampling or some objective experimental setting. The admission of subjective probabilities made our problem formulations consistent with a Bayesian approach to decision making (Raiffa 1968).

Model 1: Allocating Funding between Two Release Methods

Suppose a manager is considering the reintroduction of animals to start a new population and needs to determine how much of a limited budget to spend on different release activities that vary in per capita cost and likelihood of success. For example, activities that acclimate animals to their new environment before release may increase the probability that they remain in the release area (e.g., Ralls *et al.* 1992). Although the survival and reproduction rates of animals released under each method are uncertain, the manager can hypothesize the range of alternative population-growth scenarios and can assign probabilities to them. The manager has two performance criteria: maximizing mean population size at the end of a fixed time horizon and minimizing the risk of undesirable population-size outcomes. The manager is interested in the tradeoffs between these two performance criteria and optimal budget allocations under different criteria weights.

Model Formulation

We formulated a two-period model to evaluate budget allocations under different management objectives. We assumed J available release methods, and we wanted to determine x_j and y_j, the numbers of animals to release using method j, where $j = 1,\ldots,J$ in time periods 1 and 2, respectively. We assumed that release decisions in period 2 were made without knowledge of population growth during period 1.

The per capita periodic growth rate of animals released under each method was not known with certainty and was expressed as a range of possible growth rates and their likelihoods of occurrence. For example, suppose there were two release methods. Soft release had a relatively narrow range of possible periodic growth rates (0.90, $p = 0.50$; 1.10, $p = 0.50$) because more time and effort was expended to acclimate animals to their new environment. On the other hand, hard release had a wider range of growth rates (0.50, $p = 0.50$, 1.00, $p = 0.50$) because animals were released immediately without acclimation.

From this information, we constructed S growth-rate scenarios. Each scenario s was a vector of elements r_{sj} representing per capita periodic growth rates of animals released under methods $j = 1,\ldots,J$. Further, each scenario had probability of occurrence p_s, where $\Sigma_{s=1}^{S} p_s = 1$. For example, assuming that the growth rate outcomes for soft and hard release methods were independent, we constructed four growth-rate scenarios with equal probabilities of occurrence (Table 1).

The per capita periodic growth rates in each scenario were used to predict population size. Assuming growth rates were constant across time, population size at the end of period 2 under scenario s was

$$n_s = \sum_{j=1}^{J} x_j r_{sj}^2 + \sum_{j=1}^{J} y_j r_{sj}. \qquad (1)$$

Table 1. Per capita periodic growth rates (r) and probabilities of occurrence.

		Per capita growth rate	
Scenario	*Probability*	*soft release*	*hard release*
1	0.25	0.90	0.50
2	0.25	0.90	1.00
3	0.25	1.10	0.50
4	0.25	1.10	1.00

The first term represents the growth of animals released at the beginning of the first time period over the subsequent two time periods. The second term represents the growth of animals released at the beginning of the second time period over one more time period.

The release methods differed not only in their range of possible growth rates but also in their cost. For simplicity, we assumed that total cost increased linearly with number of animals released. This represented a situation in which the set-up costs of translocation had already been paid and the per capita operating cost of releasing animals was constant.

We also assumed that total cost must be less than an upper bound on expenditure. If we let c_j be the unit cost of release using method j and b_1 and b_2 be the upper bounds on budgets in periods 1 and 2, then the cost constraints were

$$\sum_{j=1}^{J} c_j x_j \leq b_1 \qquad (2)$$

and

$$\sum_{j=1}^{J} c_j y_j \leq b_2. \qquad (3)$$

Because soft release required more time and effort to acclimate animals, its unit cost (1.75) was larger than the unit cost of hard release (1.00). The upper bound on the budget in each period was 100 units.

With these cost and growth parameters, population-size outcomes under different budget allocations were easily computed. For example, if all of the budget in each period was spent on soft release, 57 animals would be released per period; population-size outcomes would range from 98 to 132, with a mean of 115 (Table 2). If all of the budget in each period was spent on hard release, 100 animals would be released per period; population-size outcomes would range from 75 to 200, with a mean of 137 (Table 2).

Two criteria were used to measure the performance of different budget allocations. The first was the expected population size at the end of period 2:

Table 2. Population size after two time periods under different growth-rate scenarios assuming that all of the budget in both periods is assigned to either soft or hard release methods.

	Soft release	*Hard release*
Scenario	*57 animals/period*	*100 animals/period*
1	98	75
2	98	200
3	132	75
4	132	200
Mean	115	137

$$\mu = \sum_{s=1}^{S} p_s n_s. \tag{4}$$

The second criterion was a measure of risk. Suppose the decision maker set a population size target, N, representing the desired population size at the end of two time periods. In our application, we used a population target of 100 animals. We measured risk as the quadratic mean of the negative deviations from the population target. Letting z_s be the deviation from the target population size associated with scenario s, where

$$z_s = \begin{cases} N - n_s & \text{if } n_s < N \\ 0 & \text{if } n_s \geq N \end{cases} \tag{5}$$

risk was computed as

$$\sigma = \sqrt{\sum_{s=1}^{S} p_s z_s^2}. \tag{6}$$

Each deviation z_s was squared to represent increasing risk associated with outcomes farther from the target. Each deviation was also weighted by its probability of occurrence, p_s.

A formulation incorporating both performance criteria involved maximizing mean population size subject to an upper bound on risk:

$$\max_{\{x_j, y_j, j = 1,\ldots,J\}} \mu, \tag{7}$$

subject to $\sigma \leq D$, where upper bound D represented how far population-size outcomes were allowed to be below the target population size. We used this formulation to explore the trade-offs between the two performance criteria by incrementally increasing D from 0 to 20 animals and solving the optimization problem. If D was specified by the manager to be close to zero, then concern for risk was great because population-size outcomes were required to be close to or greater than the target. If D was set close to 20, then the manager's concern for risk was small because population-size outcomes could vary widely from the target. Mean population size was maximized for a given D, subject to growth dynamics (equation 1) and cost constraints (equations 2 & 3). The solution set $\{x_j, y_j, j = 1,\ldots,J\}$ was the number of animals released under each method in each period.

Results

The optimal number of animals released under each method depended on D, the upper bound on allowable risk. When D was >17.5 animals, mean population size was maximized without concern for risk. In this case, the budget was completely allocated to hard release in both periods, allowing the release of 100 animals per period (Fig. 1). Hard release was superior because it produced the greatest expected population growth per unit cost. When D was 1.4 animals, risk was minimized and the project stayed within budget. In this case, the budget was completely allocated to soft release in both periods, allowing the release of 57 animals per period (Fig. 1). Soft release was superior because its outcomes either exceeded or were very close to exceeding the population size target of 100 animals (Table 2). In the worst-

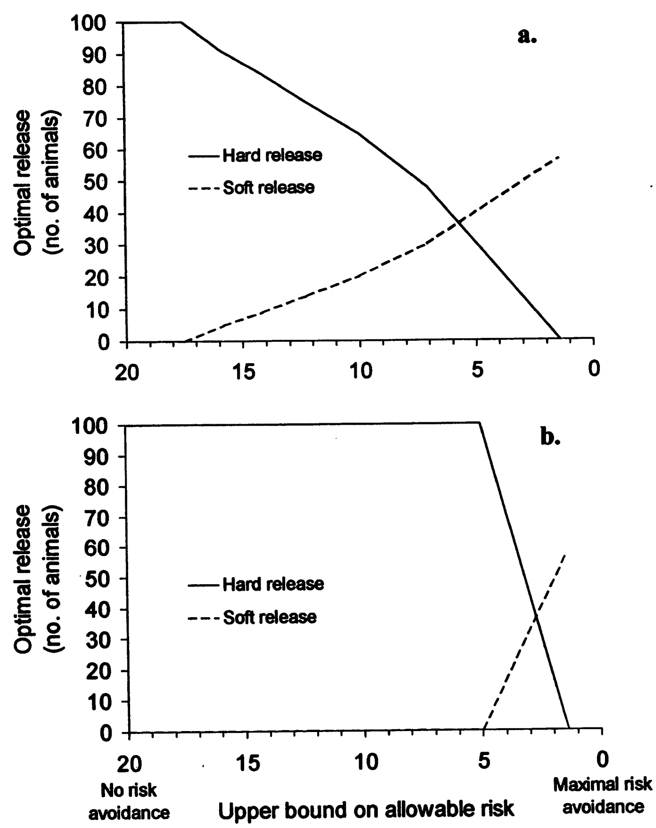

Figure 1. Optimal numbers of animals released in (a) period 1 and (b) period 2 based on hard and soft release methods as a function of the upper bound on allowable risk (D) measured by the number of animals below the population-size target of 100 animals.

case scenario, spending all of the budget on soft release in both periods produced 98 animals. In contrast, spending all of the budget on hard release produced only 75 animals.

When the upper boundary on allowable risk was between 17.5 and 1.4 animals, avoiding risk was given intermediate importance. In these cases, optimal solutions involved releasing animals by both methods. As risk became more important (decreasing D), the first-period budget was incrementally reallocated from hard release to soft release (Fig. 1a). The second-period budget allocation switched from hard release to soft release only when the upper bound on allowable risk was <5 animals (Fig. 1b).

Risk reduction was obtained by reallocating the budget from hard to soft release. The cost of reducing risk was a reduction of the mean of the final population size (Fig. 2); in this example, however, the cost was small. Without regard for risk, the optimal budget allocation produced a mean population size of 137 animals and a mean negative deviation of 17.5 animals. Deviation from the population target was reduced to almost zero by reallocating the budget from hard to soft release, but this produced only an 11% reduction in mean population size.

In addition to mean population size, decision makers might want to know how the range of population-size outcomes change under optimal release strategies determined with different degrees of risk avoidance (Fig. 2). The distance between population sizes under best- and worst-case scenarios decreased as the importance given to risk avoidance increased.

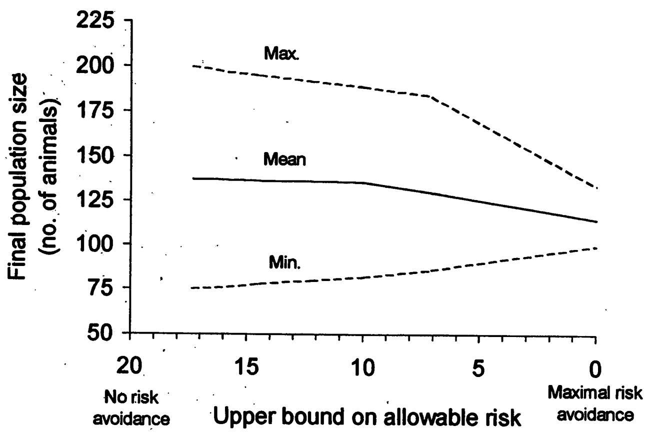

Figure 2. Tradeoffs between mean population size at the end of period 2 and upper bound on allowable risk (D) measured by the number of animals below the population-size target of 100 animals. Minimum and maximum population sizes are shown for comparison.

Model 2: Determining the Proportion of the Budget to Allocate to Population Monitoring

When growth rates of released animals are uncertain, a risk-averse manager would monitor their fate and use the information to design subsequent translocations. A manager working with a species that has never been reintroduced before, for example, would probably want to monitor the results of the first attempt to establish a new population, especially if the species is endangered. When funding is limited, the manager may be required to reallocate funds from release to monitoring activities. If the benefits of monitoring offset the costs of reduced funding for release, monitoring activities are efficient. We developed procedures to estimate the benefits of monitoring and the proportion of a fixed budget that could be allocated efficiently to monitoring.

Model Formulation

Our procedure for estimating the benefits of monitoring involved the comparison of results from models with and without monitoring. In the model without monitoring, decisions about the numbers of animals to release per period were made only with estimates of the probability distributions of growth rates of animals released by different methods (specified in Table 1). In the model with monitoring, the first-period decision was again made with estimates of the probability distributions of growth rates in Table 1, and the second-period decision was made assuming that the growth rates of animals released under each method were known with certainty in period 2. In the notation of the previous section, the second-period decision variables for the model with monitoring were y_{sj}, representing the numbers of animals released by method j under scenario s, where $j = 1,\ldots,J$ and $s = 1,\ldots,S$. In both models, the objective was to maximize mean population size subject to an upper bound on allowable risk (equation 7). The upper bound D on the mean number of animals allowed below the population-size target of 100 animals was 5, indicating a manager with low risk tolerance because population-size outcomes had to be close to or greater than the population-size target. The difference between the mean population sizes obtained from models with and without monitoring was an estimate of the gain from monitoring for a given level of risk.

The magnitude of the gain from monitoring was an index of the value of monitoring. If the gain was positive, a portion of the first-period budget could be allocated efficiently to monitoring. If the gain was negative, monitoring was not efficient. To estimate the proportion of the first-period budget that could be spent efficiently on monitoring, we used incrementally smaller budgets for first-period release to solve the model with monitoring.

Each reduction in the budget for release represented an increase in the expenditure required for monitoring. A plot of resulting mean population sizes estimated the effect of increasing monitoring cost. A break-even point was identified at which the mean population size obtained from the model with monitoring equaled the mean population size obtained from the optimization model without monitoring and with no reduction in the first-period budget. This break-even point represented the maximum proportion of the first-period budget that could be efficiently taken away from release and allocated to monitoring.

We made an optimistic assumption that the growth rate of animals released in period 1 was known with certainty in period 2 as a result of monitoring. It is unlikely that the growth rates of animals released in period 1 can be known with certainty in period 2 because of sampling error in monitoring and temporal variation in growth rates. Therefore, our estimates of the gain from monitoring and the maximum proportion of the first-period budget that could be spent efficiently on monitoring should be viewed as optimistic upper bounds.

Results

With an upper bound on allowable risk equal to 5 animals, the optimal solution without monitoring involved translocating 40 animals by soft release and 30 animals by hard release in the first period (Fig. 1a). In period 2, all the budget was used for hard release (Fig. 1b). With this strategy, population size outcomes ranged from 90 under scenario 1 to 178 under scenario 4, with a mean of 134 (Table 3).

With the same upper bound on allowable risk, the optimal solution with monitoring involved releasing 36 animals under each method in period 1. The optimal allocation of first-period funds was not identical to the optimal allocation without monitoring. With monitoring, more first-period funding was allocated to hard release, which produced the greatest expected population growth per unit cost, despite the higher risk of not reaching the population target. The higher risk assumed in period 1 was compensated for by making translocation decisions in period 2 dependent on the population-growth scenario observed in period 1. When the growth rate of hard-released animals was high (scenarios 2 and 4), hard release was funded in period 2. Conversely, when the growth rate of hard-released animals in period 1 was low (scenarios 1 and 3), soft release was funded in period 2. Population-size outcomes ranged from 90 to 180 animals, with a mean of 138 animals, a 3% gain in mean population size compared to the model without monitoring (Table 3).

Table 3. Population-size outcomes under different growth scenarios for optimal release strategies from models without and with monitoring.

	Model	
Scenario	*without monitoring*	*with monitoring*
1	90	90
2	162	166
3	106	116
4	178	180
Mean	134	138

The small gain in mean population size suggested that not much of the first-period budget could be efficiently spent on monitoring. For increasing proportions of the budget required for monitoring, we computed the increase in mean population size at the end of period 2 which resulted from monitoring during period 1 and used the information to adjust the number of animals released under each method in period 2 (Fig. 3). When none of the release budget was needed to pay for monitoring (e.g., an independent funding source paid for monitoring), an increase in mean population size of four animals was obtained. Whenever more than 5% of the first-period release budget was allocated to monitoring, the change in mean population size was negative, indicating that monitoring was not efficient.

The gain from monitoring obtained with our procedure was sensitive to the range of possible population-size outcomes and their probabilities. It was not difficult to find situations in which the gain from monitoring was greater than that obtained in our hypothetical problem.

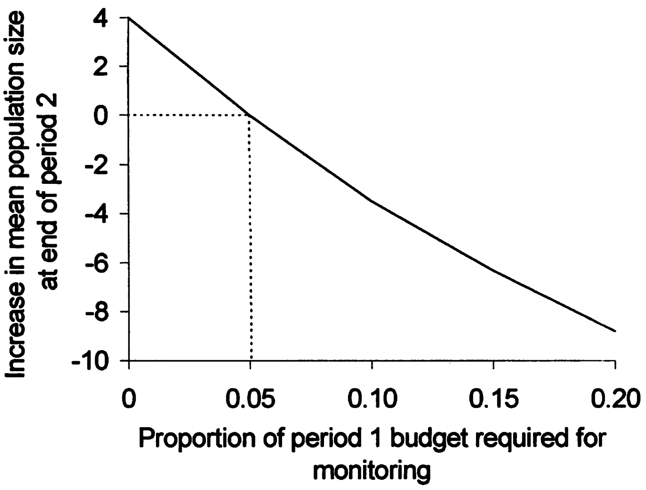

Figure 3. Increase in mean population size at the end of period 2 as a function of the proportion of the budget required to pay for monitoring during period 1. The information obtained from monitoring was used to adjust the number of animals released under each method in period 2. The dotted line identifies the break-even point where monitoring ceases to be efficient.

Therefore, one should not conclude that estimates of the gains from monitoring were small in all cases.

Model 3: Deciding How Much Translocation Capacity to Build When Future Funding Is Uncertain

Previously, we assumed that managers knew funding levels with certainty. In many cases, however, managers know their current funding but do not know with certainty if additional funding will be available next period. They must decide how much of the current funding to spend now and how much to save for later use. The degree of funding uncertainty may affect this allocation decision and the success of the translocation project.

We also assumed in the previous problems that cost per animal released was constant. In many cases, however, managers must first pay for equipment and personnel required to capture, transport, house, and care for animals that will subsequently be released. The money spent on prerelease activities determines the capacity of the release project—the maximum number of animals that can be released. When the costs of prerelease activities are included, the total cost of releasing the first animal is much greater than the per capita cost of subsequent releases.

Assuming a manager had already chosen a release method and made a decision regarding monitoring, we formulated an optimization model for a reintroduction problem in which the manager needed to decide how much of an existing budget to spend on prerelease activities that determine release capacity and how much to save and use to pay operating costs of subsequent releases. Although the existing budget was known, additional future funding was uncertain. Furthermore, the survival and reproduction rates of the released animals were uncertain. The criterion to evaluate success of alternative budget allocations was risk minimization, in which, as before, risk was measured by the magnitude and probability of negative deviations from a population-size target. We used the model to estimate how the level of current funding and the likelihood of future funding affect the success of the translocation project.

Model Formulation

We formulated a two-period model to evaluate budget allocations. The first-period decision variable x was release capacity defined in terms of the maximum number of animals that could be released in period 2. In the second period, the decision variable y represented the number of animals released, which was less than the release capacity x. Only one release method was considered in this case. Both decision variables were constrained by available funding. If we let c_1 represent the per capita cost of prerelease activities and b be an upper bound on expenditure in period 1, the first-period budget equation was

$$c_1 x + v = b, \tag{8}$$

where v represented budget surplus carried over to period 2 to pay the operating costs of release. The budget surplus was important because there was a chance that additional funding in period 2 might not become available. We assumed that the per capita cost of prerelease activities was 10 units and the upper bound on the first period expenditure was 1000 units, so the maximum translocation capacity was 100 animals.

There were two sources of uncertainty affecting capacity and operating decisions: the per capita periodic growth rate of released animals and the funding level in period 2. Growth rates were 0.2 (p = 0.1), 0.5 (p = 0.4), 0.8 (p = 0.4), and 1.1 (p = 0.1) representing a wider range of possibilities than the models in the previous sections. There was a 20% chance of no additional funding in period 2 and an 80% chance of receiving 1000 units. With these growth-rate and budget possibilities, we constructed a set of S scenarios in which each scenario s included a per capita periodic population growth rate r_s and a second-period funding level f_s with associated probability of occurrence p_s (Table 4).

The scenarios were used in the second-period budget constraint. Associated with the decision variable y for the number of animals released in period 2 was per capita cost c_2, representing the operating cost of the release effort. We assumed that the operating cost was 5 units, recognizing that, once the translocation infrastructure was in place, the per capita release cost was relatively low. The amount of money expended in period 2 had to be less than the sum of the budget surplus carried over from period 1 (v) and the additional funding in period 2 (f_s):

$$c_2 y_s \leq v + f_s \qquad \text{for } s = 1, \ldots, S. \tag{9}$$

Table 4. Scenarios of per capita periodic population growth rates and second-period funding.

Scenario	*Probability*	*Growth rate*	*Funding*
1	0.05	0.2	0
2	0.20	0.5	0
3	0.20	0.8	0
4	0.05	1.1	0
5	0.05	0.2	1000
6	0.20	0.5	1000
7	0.20	0.8	1000
8	0.05	1.1	1000

The subscript s on decision variable y denotes that release numbers depended on the funding scenario. In addition, the number of animals released had to be less than release capacity:

$$y_s \leq x \qquad \text{for } s = 1,\ldots,S. \tag{10}$$

The scenarios were also used to define the population-size outcomes. Population size at the end of the second period was

$$n_s = y_s r_s \qquad \text{for } s = 1,\ldots,S. \tag{11}$$

The objective of the optimization model was to minimize risk as measured by the mean number of animals below a population-size target. Risk was defined by equations 5 and 6, and the population-size target was 50 animals. The problem was to determine translocation capacity x and the numbers of animals released under different population growth and funding scenarios y_s, where $s = 1,\ldots,S$, to minimize the mean number of animals below the population-size target subject to cost constraints (equations 8 & 9), capacity constraints (equation 10), and growth dynamics (equation 11).

Results

With first-period funding of 1000 units and second-period funding probability of 0.8, the optimal solution was to allocate 72% of the first-period funding to prerelease activities and save the remaining 28% for second-period release costs. This allocation built a release capacity of 72 animals in the first period and carried over enough money to release 56 animals in period 2 if no additional funding was obtained. With this budget allocation, the mean number of animals below the population-size target of 50 was 15 animals.

As the probability of obtaining second-period funding increased, the proportion of the first-period budget efficiently spent on prerelease activities increased (Fig. 4). For example, when additional second-period funding was assured, all of the first-period funding could be spent on prerelease activities to build the greatest possible release capacity. In this case, none of the first-period funding needed to be saved for use in period 2 because additional funding was assured. When the probability of second-period funding dropped below 60%, the proportion of the first-period budget spent on release capacity remained at 0.66. With this level of funding, the optimal release capacity was equilibrated with the number of animals that could be released with the first-period budget surplus.

We solved the optimization problem with incrementally larger first-period funding to estimate the effect on translocation success. Not surprisingly, translocation success was sensitive to the size of the first-period budget: as funding increased, the mean number of animals below the population-size target decreased and approached zero

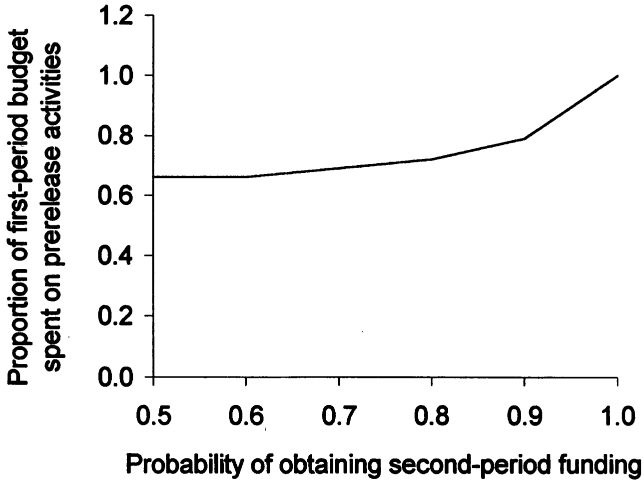

Figure 4. The effect of increasing the probability of obtaining second-period funding on the proportion of the first-period budget spent on prerelease activities.

(Fig. 5). Such risk-cost curves provide useful information about reductions in risk obtainable from increased funding. In this example, risk was greatly reduced by increasing the existing budget from 500 to 1000 units. For existing budgets greater than 1000 units, the slope of the risk-cost curves was flatter, indicating diminishing returns. When the initial budget was relatively high, greater risk reduction was obtained by increasing the probability of obtaining additional second-period funding.

Discussion

We addressed the problem of allocating limited funds among translocation activities to meet different goals for

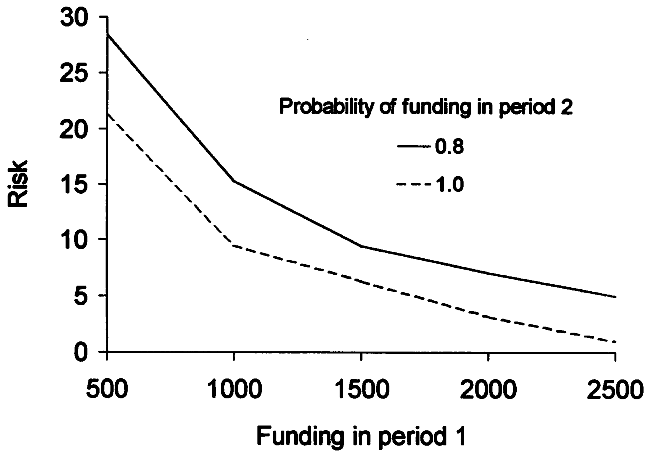

Figure 5. The effect of increasing first-period funding on the riskiness of the translocation project, where risk is defined by the number of animals below a population-size target of 50 in period 2.

a wildlife population. We used robust optimization to analyze translocation problems because it provided an easy framework in which to incorporate population growth and funding uncertainty and it conveyed easy-to-understand relationships for designing translocation strategies.

When population growth is uncertain, translocation strategies produce distributions of possible population-size outcomes, and the decision maker can choose different performance criteria, including maximizing mean population size or minimizing the likelihood of undesirable population-size outcomes. The choice of performance criteria depends on the translocation problem. For example, a manager trying to establish a population of game birds when many individuals are available for reintroduction and additional individuals can be produced at low cost might prefer to maximize mean population size. In contrast, a manager attempting to reintroduce an endangered species when only a few individuals are available for reintroduction and additional individuals are costly to produce would likely prefer to minimize risk. We demonstrated some simple ways to formulate these performance criteria and their tradeoffs in terms of optimal allocation of a fixed budget.

A key feature of our modeling approach was our handling of uncertainty using a range of different scenarios for population growth and funding. In many applications, scenario probabilities will be reasonable guesses. In these cases, sensitivity analysis can be used to determine changes in the optimal translocation and funding strategies in response to changes in the assigned scenario probabilities. If the optimal strategy stays fixed for a wide range of probabilities surrounding the best guess, then the decision maker need not be concerned about fine-tuning scenario probabilities and can focus attention on the effects of other model parameters such as the weights given to alternative management objectives. If the optimal strategy is sensitive to changes in scenario probabilities in the area of the best guess, then the decision maker must decide whether or not more information should be obtained. Procedures for scaling judgements about uncertain probabilities in light of additional sample information are described by Raiffa (1968).

Of course, additional details important in specific situations could be included in the formulation. For example, a manager might want to account for the effect of removing individuals from a wild source population in addition to modeling the growth of the new population (Lubow 1996). This effect could be modeled by placing an upper bound on the allowable risk to the source population, which depends on the number of individuals removed. A manager might also be concerned about the possible deleterious genetic effects of releasing a small number of individuals. In this case, a minimum bound could be set on the number of individuals to be released or plan multiple releases over time (Ralls & Ballou 1992).

Monitoring released animals can improve translocation success by providing information about population growth for use in future decisions. We estimated potential improvements in translocation success by comparing the results from models with and without monitoring. When funding is limited, increases in expected population size that result from monitoring must be compared with reductions in expected population size that result from reduced funding for translocation. Using results from models with monitoring and with incrementally smaller budgets for translocation, we estimated the maximum proportion of the budget that could be used efficiently for monitoring.

We defined the benefits of monitoring in a narrow sense as the gain in final average population size when the results of releasing animals in the first period were monitored. Of course, monitoring has other potential benefits. For example, monitoring might reveal correctible causes of mortality of the released animals, and there are always long-term benefits from monitoring when it feeds into an adaptive management framework. Monitoring decisions should be made based on a full accounting of the potential benefits and costs of monitoring. Weights assigned to short-term benefits and costs, such as those described in our monitoring analysis, depend on the preferences of the decision maker.

When future funding is uncertain, the decision maker must allocate existing funds between time periods to meet the goals of the translocation project. To demonstrate the effects of funding uncertainty, we formulated a two-period problem in which the manager first paid for prerelease activities that determined the capacity of the release project and then paid for operating costs of release. As the likelihood of obtaining future funding increased, more of the existing budget was spent on prerelease activities and less was saved for operating expenses. Solving the optimization problem with incrementally larger funding levels produced curves showing the probable effects of increased funding on the success of the translocation project. These cost curves quantify the benefits from incremental increases in spending and could be useful to managers who must justify their requests for increased funding. In many government agencies in the United States, funding allocated in a given year must be spent that year and cannot be saved for future use. Our model could easily be modified to reflect this situation.

Using decision-analysis models to address funding allocation problems helps the decision maker find management activities that are consistent with stated preferences and beliefs. The analysis also helps the decision maker determine how robust decisions are to changes in preferences and beliefs. Uncertainty in data and outcomes is often viewed as a reason to avoid systematic analysis of a problem, but an analysis that explicitly deals with uncertainty often produces useful insights. These insights are important to managers who require an explicit, well-documented justification for funding decisions. Of course, the results of modeling should be only one of many factors considered when conservation decisions are made (Dale & Van Winkle 1998).

Literature Cited

Allen, W. H. 1994. Reintroduction of endangered plants. Bioscience 44:65-68.

Beier, P. 1993. Determining minimum habitat areas and habitat corridors for cougars. Conservation Biology 7:94-108.

Bevers, M., J. Hof, D. W. Uresk, and G. L. Schenbeck. 1997. Spatial optimization of prairie dog colonies for black-footed ferret recovery. Operations Research 45:495-507.

Dale, V. H., and W. Van Winkle. 1998. Models provide understanding not belief. Bulletin of the Ecological Society of America **April**:169-170.

Griffith, B., J. M. Scott, J. W. Carpenter, and C. Reed. 1989. Translocation as a species conservation tool: status and strategy. Science 245:477-480.

Haig, S. M., J. R. Belthoff, and D. H. Allen. 1993. Population viability analysis for a small population of Red-cockaded Woodpeckers and an evaluation of enhancement strategies. Conservation Biology 7:289-301.

Lubow, B. C. 1996. Optimal translocation strategies for enhancing stochastic metapopulation viability. Ecological Applications 6:1268-1280.

Maguire, L. A. 1986. Using decision analysis to manage endangered species populations. Journal of Environmental Management 22: 345-360.

Maguire, L. A., and C. Servheen. 1992. Integrating biological and sociological concerns in endangered species management: augmentation of grizzly bear populations. Conservation Biology 6:426-434.

McCallum, H. 1995. Modeling translocation strategies for the bridled nailtail wallaby *Onychogalea fraenata* Gould, 1840. Pages 7-14 in M. Serena, editor. Reintroduction biology of Australian and New Zealand fauna. Surrey, Beatty, and Sons, Chipping Norton, New South Wales, Australia.

Mulvey, J. M., R. J. Vanderbei, and S. A. Zenios. 1995. Robust optimization of large-scale systems. Operations Research 43:264-281.

Olney, P. J. S., G. M. Mace, and A. G. C. Feistner. 1994. Creative conservation: interactive management of wild and captive populations. Chapman and Hall, London.

Pavlik, B. M., D. L. Nickrent, and A. M. Howald. 1993. The recovery of an endangered plant. I. Creating a new population of *Amsinckia grandiflora*. Conservation Biology 7:510-526.

Primack, R. B. 1996. Lessons from ecological theory: dispersal, establishment and population structure. Pages 209-233 in D. A. Falk, C. Millar, and P. Olwell, editors. Strategies for reintroduction of endangered plants. Island Press, Washington, D.C.

Raiffa, H. 1968. Decision analysis: introductory lectures on choices under uncertainty. Addison-Wesley, Reading, Massachusetts.

Ralls, K., and J. D. Ballou. 1992. Managing genetic diversity in captive breeding and reintroduction programs. Transactions of the North American Wildlife and Natural Resources Conference. 57:263-282.

Ralls, K., and A. M. Starfield. 1995. Choosing a management strategy: two structured decision-making methods for evaluating the predictions of stochastic simulation models. Conservation Biology 9:175-181.

Ralls, K., D. B. Siniff, A. Doroff, and A. Mercure. 1992. Movements of sea otters relocated along the California coast. Marine Mammal Science 8:178-184.

Serena, M., editor. 1995. Reintroduction biology of Australian and New Zealand fauna. Surrey, Beatty, and Sons, Chipping Norton, New South Wales, Australia.