Choosing optimal trigger points for *ex situ, in toto* conservation of single population threatened species

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Abstract

Many endangered species exist in only a single population, and almost all species that go extinct will do so from their last remaining population. Understanding how to best conserve these single population threatened species (SPTS) is therefore a distinct and important task for threatened species conservation science. As a last resort, managers of SPTS may consider taking the entire population into captivity—*ex situ, in toto* conservation. In the past, this choice has been taken to the great benefit of the SPTS, but it has also lead to catastrophe. Here, we develop a decision-support tool for planning when to trigger this difficult action. Our method considers the uncertain and ongoing decline of the SPTS, the possibility that drastic *ex situ* action will fail, and the opportunities offered by delaying the decision. Specifically, these benefits are additional time for ongoing *in situ* actions to succeed, and opportunities for the managers to learn about the system. To illustrate its utility, we apply the decision tool to four retrospective case-studies of declining SPTS. As well as offering support to this particular decision, our tool illustrates why trigger points for difficult conservation decisions should be formulated in advance, but must also be adaptive. A trigger-point for the *ex situ, in toto* conservation of a SPTS, for example, will not take the form of a simple threshold abundance.

Introduction

The Earth’s most threatened species are often only found in a single location. Some were originally range-restricted endemics, while others have suffered catastrophic range and abundance declines. Well-known examples of “single population threatened species” (hereafter, SPTS) include the last remaining Javan rhinoceroses *Rhinoceros sondaicus*, which are restricted to a single Indonesian national park, Ujung Kulon [1]. Similarly, the Annobón scops owl *Otus feae* is found only on the island of Annobón in Equatorial Guinea [2], and the distribution of the Hainan gibbon *Nomascus hainanus* has shrunk to a single nature reserve in China [3]. The Alabama cavefish *Speoplatyrhinus poulsoni* only exists in a single cave in the Key Cave National Wildlife Refuge [4], while the global distribution of the Fitzroy Falls crayfish *Euastacus dhara-walus* in Australia has dwindled to less than a square kilometer of habitat [5].
SPTS face a particularly high risk of extinction because even local threats can cause global extinctions. It is a central and foundational tenet of conservation biology that species with multiple populations have much greater insurance against global extinctions \[6, 7\]. Remaining in a single population is so threatening—and so common—that the IUCN Red List automatically categorises SPTS as Critically Endangered, its highest category of risk. Natural population dynamics can push populations to low abundance, where they become vulnerable to Allee effects, genetic bottlenecks, or stochastic fluctuations. Even SPTS with high abundance and genetic diversity can still be threatened by environmental catastrophes. The Javan rhino, for example, could be pushed to extinction by tsunamis generated in nearby Anak Krakatoa \[8\].

SPTS are particularly vulnerable to human activities, even when protected by legislation. Australia’s stocky galaxias *Galaxias tantangara* (a listed species) are only found in the headwaters of Tantangara creek, and the approved development of hydroelectric infrastructure may increase the chances of highly competitive species migrating into the creek from adjacent catchments, endangering *G. tantangara* \[9\]. Although not all SPTS are currently in decline, most will experience periods of decline at some stage. Without conservation interventions, some SPTS will become extinct.

Management actions for SPTS can be broadly classified as either *in situ* or *ex situ* \[10\]. *In situ* conservation actions attempt to improve population viability within a species’ natural environment. *Ex situ* actions remove the species from its natural habitat (and therefore from the threatening process), generally into a captive breeding program. While both strategies may be undertaken simultaneously, for SPTS this choice is often exclusive. Moreover, when declines are rapid and abundances are low, it may be necessary to take the entirety of the remaining population into captivity. This extreme form of *ex situ* management—*ex situ, in toto*—is controversial because the species immediately becomes extinct in the wild. For this reason, it is only implemented as a last resort \[11\].

*Ex situ, in toto* conservation decisions are a genuine conservation dilemma. The action often appears essential, given a small, shrinking population. However, it is a drastic step, with a mixed record of success. In some cases, *ex situ, in toto* actions were able to pull SPTS back from the precipice of extinction. The California condor *Gymnogyps californianus* is perhaps the most famous example: in 1987, after decades of dwindling numbers, the remaining population of 27 individuals were taken into a captive breeding program. Their abundance recovered and the species was successfully re-released into the wild, where it now numbers 312 individuals (with 176 additional condors in captivity) \[12\]. Other examples of successful *ex situ, in toto* actions followed by successful reintroduction include red wolves *Canis rufus* (also *C. lycaon rufus* or *C. lupus rufus*, depending on the authority); the Guam kingfisher *Todiramphus cinnamominus* and Guam Rail *Hypotaenidia owstoni*; and black-footed ferrets *Mustela nigripes*.

For other species, an *ex situ, in toto* actions hastened or caused their extinction. In South Australia in 1924, government scientists attempted to take the last known individuals of the toolache wallaby *Macropus greyi* into captivity. During the translocation, 10 of the 14 remaining individuals were accidentally killed and the remaining 4 re-released. The depleted population went extinct by 1939. For a final set of SPTS, the opportunity to undertake *ex situ, in toto* action passed before managers could make the difficult decision. This situation—monitoring a species to extinction \[13\]—is depressingly common in conservation. The Christmas Island Pipistrelle *Pipistrellus murrayi*, for example, was common until 1984, but thereafter began to decline for unknown reasons. Captive breeding was proposed as early as 2006, but was delayed for additional research until July 2009. By this point, no individuals could be found in the wild.

Retrospective analyses of the Pipistrelle extinction \[14\], and that of other threatened species extinctions \[13, 15\], suggest that many conservation failures—including some of the examples above—are partly attributable to inadequate preparatory planning. In particular, these analyses...
recommended that managers need to anticipate extinctions, and should identify thresholds ("trigger points") for when important actions should be implemented. Trigger points offer two significant benefits. First, they use the best information to calculate when to act, weighing the relevant costs, benefits, and uncertainties before the decision is made [15]. Second, they make it harder for factors such as political pressure, or shifting-baselines, to subliminally dissuade managers from making difficult choices [16].

While there are urgent calls for managers to set explicit trigger-points for drastic action when threatened species are in decline [13, 14], there is limited theoretical guidance available to support this decision for SPTS. Previous optimisation analyses of translocations between captive and wild populations offer useful insights and decision-support, but they primarily consider translocations between wild and captive populations to be continual and/or reversible [17, 18]. Tenhumberg et al. [17] find that ex situ, in toto emerges as an optimal solution to the question of captive breeding, but their analyses assume that the dynamics of both the captive and wild populations are known with certainty (i.e., that there is no parameter uncertainty), and again assume that animals can be shuttled continually between captive and wild populations. In contrast, the decision to initiate ex situ, in toto actions is fundamentally high-stakes, and high-uncertainty. It is critical that managers make the correct choice, but the irreversible and uncertain nature of the action makes it a very difficult decision. Our goal in this paper is to design a simple and robust decision-support tool that can help managers set a trigger point for ex situ, in toto action for a SPTS.

Methods

Trigger points for ex situ, in toto conservation of SPTS should incorporate three essential decision factors. The first and overriding concern is with uncertainty. Conservation decisions always involve uncertainty, and this is particularly true for the choice to initiate ex situ, in toto conservation. Uncertainty enters the decision at multiple points. There is uncertainty about the rate of population decline, which can be difficult to measure accurately. There is also uncertainty about whether ongoing in situ conservation actions will be able to halt the decline [19]. Finally, there is uncertainty about whether a captive breeding program—if attempted—will successfully establish an ex situ population [20–22].

The second complexity is the time-dependent nature of the decision. While a decision to delay action risks further population decline, it also gives ongoing in situ actions another opportunity to succeed. Decisive ex situ actions reduce future flexibility, and this cost must be incorporated in the decision. The third complexity involves learning (i.e., the reduction of uncertainty): until ex situ, in toto actions are triggered, managers can observe and learn about both the speed of population decline, and also the probability that in situ actions will be successful. Both pieces of information mean that longer periods of in situ management will be associated with better decisions. Setting trigger points is thus also a choice about how much learning will be allowed [19, 23, 24].

We therefore formulate the trigger point decision as a Bayesian optimal stopping problem, based on Markov chain model of the system dynamics [25, 26]. This formulation allows us to incorporate uncertainty, dynamical decisions, and learning, and to solve for the optimal solution using stochastic dynamic programming (SDP) [27, 28].

We assume that the abundance $N_t$ of a SPTS has been observed for $t_0$ years, during which time it appears to have declined at a linear rate (Fig 1 shows a hypothetical example; Fig 2 shows historical case-studies). Fitting this data with a regression line yields a probability distribution $p(r)$ for the decline rate, which allows us to construct a probability distribution for the expected time to extinction $p(t_E)$ in the absence of successful in situ or ex situ, in toto actions.
While this distribution may not be bounded (e.g., if we assume that the observation error is Gaussian), in practice we will choose an upper limit $\tau$ (e.g., the upper 99th percentile), beyond which we assume extinction is effectively guaranteed (a finite time horizon is needed to implement SDP). Note that we are assuming that variation in its observed decline trajectory is due to environmental and demographic stochasticity, not sampling error.

At some point in the past, conservation managers began to apply in situ conservation actions. These might be a single consistent action, a sequence of different actions, or a suite of actions all at once. We assume that these in situ actions will result in successfully reverse or halt the observed ongoing decline with an unknown (but constant) probability $q$. Moreover, we assume that if in situ actions successfully halt or reverse the decline, the managers will become aware of this fact within a year (i.e., one timestep). The probability $q$ is not known with certainty, and may be zero. Our estimate of $q$ will improve through time, as managers observe the failure or success of the action. Repeated failures will make the managers increasingly pessimistic about the value of $q$, and therefore the likelihood that the action will eventually work (Fig 1 inset). In particular, if we assume that the SPTS response to the conservation action is a Bernoulli trial, then standard results from adaptive management [18] allow us to calculate the posterior belief about the value of $q$. If in situ management actions have been unsuccessful for $n_u$ years, then the probability that the next year’s attempt will be successful is the beta distribution $f(x|\alpha = 1, \beta = n_u+1)$, since the beta distribution is a conjugate distribution of the binomial distribution. The expected value of $q$ is $E[q(n_u)] = 1 - \frac{1}{n_u+2}$.

Managers also have the option of applying a single ex situ, in toto action, which has probability of success $p_x$. This parameter is clearly critical to the decision, but there will rarely be data available to estimate its value. Moreover, since we are considering a small SPTS, we assume that there is no opportunity to learn about $p_x$ over time. Canessa and colleagues [29] suggest that expert elicitation be used to estimate its value. Alternatively, Dolman and colleagues [30] used a stochastic, individual-based population model.
We can formulate the dynamics of this decision problem as a discrete time Markov chain model, with system states defined by three factors. First, the number of years $n_u$ that the in situ action has been attempted unsuccessfully (a number between 0 and $\tau$); second, whether an ex situ, in toto action has been taken (a binary variable $a_e$); third, whether the in situ action has been successful (a binary variable $a_s$). Thus the system is initially in state \{ $n_u$, $a_e$, $a_s$ \} = \{0,0,0\}, if the managers have not previously attempted the in situ management action, and therefore have no information about its probability of success. If the state were \{3, 0, 1\}, then four years have elapsed since in situ management began, ex situ, in toto actions were not taken, and in the fourth year the in situ management succeeded in reversing the population decline. Note that, because we assume that in situ and ex situ, in toto actions cannot both be undertaken in the same year, the number of years that have elapsed in the project is the sum of the values in the state vector. We uniquely enumerate state $S_i = \{n_u, a_e, a_s\}$ with the index $i = a_s + 2a_e + 4n_u + 1$, and there are a total of $R = 4(\tau + 1)$ states.

The system dynamics are expressed by two probabilistic transition matrices: $T^{(s)}$ and $T^{(e)}$. The former matrix describes the state dynamics that occur when the managers undertake in situ actions, and the latter describes the dynamics when managers decide to implement the

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**Fig 2. Results of applying the optimal decision method to four declining case-study populations.** In each case, the red arrow shows the point in time at which the method recommended ex situ, in toto action be undertaken, based on the range of linear declines shown in red. Closed markers show observations preceding the decision, open circles show observations after the decision would have been recommended.

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drastic ex situ, in toto action. We can define the elements of the in situ matrix as:

\[
T^{(i)}_{ij} = \begin{cases} 
E[q(n_s)], & \text{if } S_i = \{n_u, 0, 0\} \land S_j = \{n_u, 0, 1\}; \\
1 - E[q(n_s)], & \text{if } S_i = \{n_u, 0, 0\} \land S_j = \{n_u + 1, 0, 0\}; \\
1, & \text{if } (a_e = 1 \lor a_s = 1) \land (S_i = S_j); \\
0, & \text{otherwise}, 
\end{cases}
\]

Eq 1

where V denotes the union and \( \land \) denotes the intersection. The first case describes the state dynamics associated with a successful in situ action, the second with an unsuccessful in situ attempt. Note that these transition probabilities are state-dependent (specifically, on \( n_u \), the number of years that in situ management has been unsuccessful), and that managers are therefore able to anticipate future learning. The third case reflects the fact that once either ex situ, in toto action has been taken, or an in situ action was successful, the system no longer undergoes transitions (i.e., it has reached an absorbing state). Finally, we assert for completeness that the transition from state \( S_i = \{r, 0, 0\} \) to itself occurs with probability 1.

We can define the elements of the ex situ, in toto matrix as:

\[
T^{(e)}_{ij} = \begin{cases} 
p_e, & \text{if } S_i = \{n_u, 0, 0\} \land S_j = \{n_u, 1, 0\}; \\
1 - p_e, & \text{if } S_i = \{n_u, 0, 0\} \land j = R; \\
1, & \text{if } (a_e = 1 \lor a_s = 1) \land S_i = S_j; \\
0, & \text{otherwise}. 
\end{cases}
\]

Eq 2

In this matrix, the first case describes the state dynamics associated with a successful ex situ, in toto action. In the second case, an unsuccessful ex situ, in toto intervention resulted in the species becoming entirely extinct, which we model as a transition to the last state of the model \( S_R = \{r, 1, 1\} \). This is a convenience that we can apply without altering the state dynamics, since this state cannot be reached from the initial state. The third case once again reflects the two categories of absorbing state.

It can be helpful to calculate the expected abundance of the SPTS in each of the system states. While this value is not included explicitly in the system state, it can be estimated on the basis of the observed (uncertain) population decline and the last observed abundance \( N(t_0) \):

\[
E[N(S_i = \{n_u, a_e, a_s\})] = \int_{r=-\infty}^{\infty} (N(t_0) + r(n_u + a_e + a_s)) \cdot p(r) \cdot dr,
\]

Eq 3

where \( r \) denotes the linear decline rate of the population. This equation relies on the fact that the total time elapsed is the sum of the number of unsuccessful attempts at in situ actions, and the success state of in situ and ex situ, in toto actions. Because the successful states are absorbing (see Eqs 2 and 3), the summation \( (n_u + a_e + a_s) \) captures the time until success.

Our conservation objective for a SPTS is to ensure its persistence. To apply SDP, we first need to define the relative value of being in each system state at the terminal time \( r \). By this time, the final state of the SPTS will be definitely known: either persisting in situ; persisting ex situ and extinct in the wild; or completely extinct. This value function should be defined for each particular threatened species. Here, we construct a general version of this function that reflects two factors. First, the value should be positively related to the abundance of the SPTS at the time that the in situ, or the ex situ, in toto action succeeds. Smaller population sizes are more exposed to extinction, and have less genetic variation, even as they begin to recover.
While managers always prefer larger populations, they are not twice as happy with a population that is twice as large. We use a parameter $w_1$ to control the rate at which larger populations deliver diminishing marginal benefits. Second, the value of a state should depend on whether the SPTS is in situ, or ex situ, in toto (with the former being preferable). We use a parameter $w_2$ to define their lower preference for the latter. We therefore define the value function as:

$$V(S_i, t) = w_2 \int_{-\infty}^{\infty} 1 - \exp \left[ -w_1(N(t_o) + r(n_s + a_s + a_e)) \right] \cdot p(r) \cdot dr.$$  \hspace{1cm} \text{Eq 4}

Equipped with the transition matrices and value function, stochastic dynamic programming can be applied via backward iteration, to determine the optimal action to take, in every state and year. The expected value for each system state, at intermediate times, can be calculated using the stochastic Bellman equation:

$$V(S_i, t) = \max_a \left[ \sum_{i=1}^{N_a} T_i^a \cdot V(S_j, t+1) \right].$$  \hspace{1cm} \text{Eq 5}

Following Bellman’s principle of optimality, we identify the best management policy by repeatedly iterating this equation and recording each state- and time-dependent optimal action $a^* (S_i, t)$, determined by the value function. We implement this procedure using MATLAB (ver. R2019b), however, the process is suitable to be adapted to alternate programming languages.

**Case studies**

To illustrate the application of the method and its results, we use it to assess 4 historical datasets of declining vertebrate populations: the vaquita *Phocoena sinus*, the Christmas Island pipistrelle *Pipistrellus murrayi*, the northern hairy-nosed wombat *Lasorhinus krefftii*, and the North American wood turtle *Clemmys insculpta* (Fig 2). We choose these datasets because they are published examples of declining populations with well-studied abundance timeseries, and because they exhibit a range of behaviours and final outcomes, including extinction. The vaquita population, for example, has shown more than 25 years of ongoing decline, and currently numbers fewer than 50 individuals. During this period its abundance has not been observed to increase. In contrast, observations of northern hairy-nosed wombats have gone through periods of increase and decrease, even during longer-term declines. Some of the datasets are quite consistent in their declines (the vaquita and pipistrelle), while the others are much more variable (the turtle and wombat). The latter result in more uncertain predictions of future dynamics, and therefore less certainty about how much time is available to managers before extinction occurs. Two of the species eventually declined to extinction (the pipistrelle and turtle populations), while the wombat population recovered after a period of precipitous decline, after in situ management actions and environmental changes saved the species. See S1 File for more details on the data, and optimal solution to each of these case study populations.

For each case-study, we choose parameters for the value function that are arbitrary but plausible (for real SPTS, we expect that these parameters would be chosen by ecologists and stakeholders). First, we assume that managers’ preference for wild in situ populations over captive ex situ, in toto populations is $w_2 = 2/3$. Second, we assume that managers were relatively satisfied with the abundance of the in situ population before the onset of decline. Specifically, we assume that they were 95% satisfied, and therefore that $w_1 = \ln(20)/N(t_0)$. Finally, we assume that ex situ, in toto action is more likely than not to be successful ($p_x = 0.75$), but that there is still a substantial probability of failure. To evaluate the impact of varying our three
arbitrary parameter choices (for $w_1$, $w_2$, and $p_x$), we repeated the optimisation process for val-
ues that were higher and lower than our previous selections.

We apply our SDP optimal solution method to each dataset in turn, simulating the actions
of a decision-maker who begins to take in situ actions at in the first year of the population
decline. Our simulated optimal decision processes assume that the dataset is being gathered in
real time. After each new abundance data point is gathered, we re-estimate the decline rate,
update the posterior probability of in situ success, and calculate whether the decision-maker
should initiate ex situ, in toto conservation. We continue this process until either the SDP solu-
tion recommends that ex situ, in toto action should be taken, or extinction occurs. The code
and data required to apply the methods and generate these results is available online (at:
https://github.com/MikeBode/SinglePopulationThreatenedSpecies).

Results
The timeseries for each of the case-study populations is shown in Fig 2, and the SDP-defined
solution to the ex situ, in toto conservation problem has been superimposed on these observ-
tions. The circular markers denote the observed timeseries. The red arrows denote the point at
which the SDP solution recommended that ex situ, in toto conservation action be taken. The
red shaded region shows the 95% confidence intervals of the predicted future SPTS abundance
at that point. Uncertainty varied between the different case-studies, with the wood turtle and
wombat timeseries exhibiting the greatest abundance variation, and the vaquita and pipistrelle
timeseries both showing consistent and linear declines over more than a decade.

In implementing SDP, we first determine some upper time limit above which we assume
extinction is guaranteed and implement backwards iteration from this point in time. As the
linear regressions for the wood turtle and the northern hairy-nosed wombat have larger confi-
dence intervals, the upper limit for these cases is significantly larger than in the other cases,
resulting in a greater number of iterations. Since each iteration requires the calculation of an
expected population value based on a previous expected value, the uncertainty is compounded
resulting in greater uncertainty in the output.

In all four cases, the optimal solution triggers ex situ, in toto conservation action before the
population declines to extinction. In the case of the Christmas Island pipistrelle, ex situ, in toto
actions are recommended 6 years before the population declines to zero. For the vaquita, the
optimal solution recommends that dramatic ex situ actions should be taken in 2006, more
than 15 years ago. Ex situ, in toto actions are recommended for the wood turtle, but only in
1990, a mere two years before the population vanishes. Finally, for the northern hairy-nosed
wombat, the optimal solution recommends ex situ, in toto conservation of the SPTS in 1985,
the precise year that the population began to recover.

The three parameters $w_1$, $w_2$, and $p_x$ each affect the timing of the optimal decision in pre-
dictable ways. For higher values of $w_1$, declining populations lose their value more slowly at
first, allowing managers to wait longer before taking action (S1 Fig). Higher values of $w_2$, which indicate a weaker preference for in situ populations, result in earlier ex situ, in toto action because managers are less reluctant to accept ex situ populations (S2 Fig). Finally, higher values of $p_x$, which correspond to a higher likelihood of ex situ, in toto conservation success, encourage managers to attempt ex situ translocation earlier, since it carries less risk and is therefore a more attractive substitute for an in situ population (S3 Fig).

Discussion
As we outlined in our introduction, extinction is an ever-present danger for any of the Earth’s
many SPTS. Experience teaches us that conservation can often fail to intervene effectively
when SPTS have declined, even in cases where conservation actions are sufficiently funded and supported by broader management objectives. A key driver of this inaction is a lack of effective planning. We have therefore formulated a straightforward, optimal stochastic management tool for a declining SPTS.

The *ex situ, in toto* management of a threatened species is an irreversible decision, and must therefore be approached with caution by conservation managers. This is particularly true when there is uncertainty about both the likely success of both *in situ* and *ex situ* actions. The optimisation methods most suitable for the SPTS problem—and for many trigger-point problems—are therefore “optimal stopping” methods [26], which delay a critical action while more information is gathered. Optimal stopping problems differ substantially from adaptive management methods, where actions and observations occur continuously in a reinforcement learning loop. The latter are more common in conservation biology [17, 23, 24].

In our optimal solutions (Fig 2), the decision about whether to take or delay *ex situ, in toto* action balanced several competing factors. The superiority of *in situ* populations over *ex situ* is a constant factor recommending against intervention. However, the relative belief in the probability of *in situ* success (\(q\), which declines through time) versus *ex situ* success (\(p_{ex}\), which remains constant) diminishes through time, until *ex situ* actions deliver superior expected outcomes. This process of learning, which will occur in all ongoing conservation management projects, means that trigger points must be more complicated than simple abundance thresholds (e.g., “"Ex situ action should be taken once the population falls below 100 individuals"”). In Fig 2A, for example, the optimal manager would have taken action once the population fell below 300 individuals. However, this trigger point is specific to a timeseries which began (along with unsuccessful *in situ* management) in 1991. If observations and actions had only been started in 2000, by contrast, the trigger point for *ex situ, in toto* actions would have been lower.

Our approach can be readily applied to any declining SPTS, to ensure that decision-makers have an *a priori* plan for when to initiate the drastic step of *ex situ, in toto* conservation actions. In its current incarnation, the tool is not based on a sophisticated population model, and we would be happy to see it superseded by a more complex description of decline (e.g., an exponential function), or better still, a species-specific population viability model. For these reasons, our optimal solutions (Fig 2) are not intended as recommendations for these particular species, nor to retrospectively second-guess the conservation actions that were (or were not) taken.

Several of our parameter assumptions and prior belief distributions could be improved for particular threatened species. For example, the two parameters in the value function (\(w_1\) and \(w_2\)) depend significantly on the value that stakeholders associate with *in situ* populations of different sizes, relative to the value placed on *ex situ* populations. These should be estimated from a range of stake-holders and rights-holders. As with the underlying population model, our model of *in situ* actions, and their expected probability of success, could be superseded by a bespoke, parameterised model or by expert opinion [29, 30]. The probability of *ex situ* actions being successful could be estimated for the particular species, based on experience with similar types of species (e.g., several species in the genus *pipistrellus* have been successfully bred in captivity). Such experience could be readily incorporated using an informative prior belief distribution. Finally, we modelled the likely future abundance of the SPTS as a simple extrapolation of the observed decline. More complicated models could yield better predictions (e.g., by considering measurement error as well as ecological stochasticity), but these can be readily incorporated into the optimisation framework through different formulations of Eqs 3 and 4.

Our choice of optimisation tools imposed limitations on our methods, which may limit its application, or reduce its optimality. For example, we assumed that, once the *in situ* actions are
successful, managers become immediately aware of the fact. However, declining timeseries can include interregnums of apparent increase (e.g., the northern hairy-nosed wombat during 1983–1984; Fig 2). As a consequence, the positive proof of in situ success may need to come from very strong increases, or alternative evidence (e.g., substantial new recruitment into the population, or the successful eradication of a primary threat). If managers had to wait for several years of increase before they could conclude that in situ actions had been successful, or if it was known that these actions would take some time to be effective (e.g., if the management action was habitat restoration, which has a substantial time-lag), then the problem would cease to be Markovian, and a technique like SDP would become unsuitable.

Despite these opportunities for improvement, for species that do not have such complex models, or for species where these models are still being constructed and parameterised, we believe that our tool offers a transparent and quantitative justification for taking (or not taking) a difficult and contentious conservation management action. Essentially, we believe that conservation management plans for every SPTS should contain a clear and defensible trigger-point for ex situ, in toto action, and we devised this tool to offer quantitative support for that decision.

Supporting information

S1 File. (DOCX)
S1 Fig. (TIF)
S2 Fig. (TIF)
S3 Fig. (TIF)

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