THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

Managing resources (time or money) optimally in Conservation Biology

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Masters of Applied Science in Marine Biology

Bachelor of Science in Computer Engineering

A thesis submitted for the degree of Doctor of Philosophy at

The University of Queensland in 2013

School of Mathematics and Physics

Abstract

Currently, there are insufficient resources available across the world to secure all threatened species. In the past decade there has been increasing research in the field of resource allocation for conservation actions. Deciding how to allocate resources optimally poses a challenging problem that is difficult to solve due to a multitude of complexities associated with each action. This requires us to solve the problem using a multidisciplinary framework.

The research in this thesis is about addressing resource allocation problems using a decision theory framework. Specifically, we answer the general question about how much resource (time and money) we should allocate among multiple interacting management actions.

In chapter 2, we address the question of how social, technological and habitat limitations affect the allocation of money among multiple management actions to mitigate multiple threats. We examine this question using an example of the koala inhabiting the Koala Coast that is limited by constraints: the unwillingness of owners to enclose their dogs a night (social limitations), the effectiveness of road crossing structures (technological limitations) and the amount of suitable koala habitat available for restoration (habitat limitations). Using numerical optimisation, we found the best management option for any budget but we also found that that these limitations significantly reduce the effectiveness of management. Thus, it reduces our ability to achieve a stable population growth rate. The only plausible alternative is to find ways to alleviate these limitations.

In chapter 3, we addressed the question of how several key ecological variables influences the amount of resources (time and money) we spend on monitoring a population that we could be managing. Using a simulation model we examined how several demographic parameters influence the optimal monitoring strategy. We found that the amount of time one should spend on monitoring before translocating a population should increase as the unmanaged population growth rate or the initial population size increases. The optimal amount of money to invest in annual monitoring increases as the uncertainty associated with the wild or captive population growth rate, or the initial population size, increases.

In chapter 4, we considered the question of whether or not we should abandon our current population management strategy with reliable outcomes, or if we try a new and uncertain strategy, for how long should we pursue that new strategy before reverting to the old strategy. To do this, we uncovered an analytical solution to help us decide when to cease a new action before reverting back to an existing action. We applied this theory to the conservation management of the Christmas

Island Pipistrelle, where existing actions appear to have failed and a new strategy, captive breeding, might have secured the species. Our model revealed the time at which we should stop captive breeding before releasing animals back into the wild. We found that the optimal switching time depends on the growth rate of the population under different management actions, the management time frame and the management goal.

Chapter 5 and 6 are extensions of Chapter 4. Although Chapter 5 is an extension of chapter 4, it answers a different question. It address the question of finding the optimal time to stop an existing action that has an outcome that is known (certain) and replace it with a new action that is uncertain. We found that it is possible to integrate invasive and threatened species management issues under the same general framework. We illustrated the approach for the conservation of the malleefowl (*Leipoa ocellata*) where fox baiting has been ongoing and fire management is the new action being considered and for the invasive fire ant (*Solenopsis invicta*) where nothing was done initially before eradication was considered as the new management action. Even though the optimal time to change an action from the existing to the new management action was affected by similar variables compared to Chapter 4, the analytical solution is different.

In Chapter 6, we used stochastic dynamic programming (SDP) to find the exact solution for whether to trial a new action that is uncertain, or continue with an existing action that is certain under an active adaptive management framework. Chapter 6 differs from Chapter 4 and 5 because it uses a stochastic model. We compared the performance of the analytical solutions (Chapter 4 and 5) to the SDP. We found that the best management action depends on the population growth rate of the old, relative to the new management action.

Overall, my thesis shows how to allocate resources (money or time) in a wide variety of situations, solved using different mathematical techniques, within a decision theory framework. This thesis provide tools for conservation managers in an uncertain world.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted **to qualify for** the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications during candidature

Rhodes, J.R., Ng, C.F., de Villiers, D.L., Preece, H.J., McAlpine, C.A., Possingham, H.P. (2011). Using integrated population modelling to quantify the implications of multiple threatening processes for a rapidly declining population. *Biological Conservation.* 144, 1081-1088.

Ng, C.F., Possingham, H.P., McAlpine, C.A., Villiers, D.L.d., Preece, H.J., Rhodes, J.R. (2014).

Impediments to the success of management actions for species recovery. PLoS ONE 9, e92430.

Ng, C.F., Possingham, H.P., Wilson, H., Rhodes, J.R., Martin, T.G. (In review). Informing translocation decisions through optimal monitoring Journal of Applied Ecology.

Ng, C.F., McCarthy, M. A.,Martin, T.G., Possingham, H.P.(2014). Determining when to change course in management actions. Conservation Biology 28, 1617-1625.

Publications included in this thesis

Ng, C.F., Possingham, H.P., McAlpine, C.A., Villiers, D.L.d., Preece, H.J., Rhodes, J.R. (2014). Impediments to the success of management actions for species recovery. PLoS ONE 9, e92430 – incorporated as Chapter 2.

Contributor	Statement of contribution
Chooi Fei Ng (Candidate)	Formulated the model (50%) Wrote and edited the paper (60%) Data analysis and optimisation (100%)
Hugh P. Possingham	Wrote and edited paper (15%)
Clive A. McAlpine	Wrote and edited paper (5%)
Diedre de Villers	Contributed data (50%)
Harriet J. Preece	Contributed data (50%)
Jonathan R. Rhodes	Formulated the model (50%) Wrote and edited paper (20%)

Ng, C.F., Possingham, H., Wilson, H., Rhodes, J., Martin, T. (In review). Informing translocation decisions through optimal monitoring. Journal of Applied Ecology – incorporated as Chapter 3.

Contributor	Statement of contribution
Chooi Fei Ng (Candidate)	Formulated the model (60%) Wrote and edited the paper (50%) Coding of simulation (100%) Interpretation of results (60%)
Hugh P. Possingham	Formulated the model (20%) Wrote and edited paper (5%)
Howard Wilson	Wrote and edited paper (10%) Interpretation of results (20%)
Jonathan R. Rhodes	Formulated the model (10%) Wrote and edited paper (5%)
Tara G. Martin	Formulated the model (10%) Wrote and edited paper (30%) Interpretation of results (20%)

Ng, C.F., McCarthy, M. A.,Martin, T.G., Possingham, H.P.(2014). Determining when to change course in management actions. Conservation Biology 28, 1617-1625.

Contributor	Statement of contribution
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Michael. A. McCarthy	Formulated the model (30%) Wrote and edited paper (10%) Solved the problem (50%) Interpretation of results (10%)
Tara G. Martin	Wrote and edited paper (10%) Interpretation of results (10%)

Hugh P. Possingham	Formulated the model (20%) Wrote and edited paper (10%) Interpretation of results (10%)

Contributions by others to the thesis

The chapters in this thesis were written in close collaboration with scientist from The University of Queensland and The University of Melbourne. For each chapter in the thesis, I have conducted most of the design, analyses and writing. My primary supervisor, Hugh Possingham (HP) was involved in each chapter and provided additional research guidance and advice from the design of the model to the writing. I have written the introduction (Chapter 1), and conclusion (Chapter 7), with Hugh Possingham providing additional advice.

Chapter 2 examines how social, technological and habitat limitations influences our allocation of resources among multiple threats for a species that is in decline. The model was designed based on ecological data including radio tracking and abundance data of the koalas in the Koala Coast, South East Queensland. These data were obtained by working with Deidré L. de Villiers and Harriet J. Preece from Queensland Department of Environment and Heritage Protection. The data were combined together using Bayesian analysis using Markov Chain Monte Carlo Simulation from a paper written by me and Rhodes et al. (2011) that was not part of the PhD thesis. Under the supervision of Jonathan R. Rhodes, I have designed the model and the mathematics with some suggestions about decision theory from Hugh P. Possingham. The simulation model was written by me and the analysis was conducted under the supervision of Jonathan R. Rhodes. The chapter was written by me with editorial advice from Jonathan R. Rhodes, Clive A. McAlpine and Hugh P. Possingham.

Chapter 3 examines the influence of various ecological variables on the optimal monitoring strategy (yearly investment in monitoring and the number of years spent monitoring), before translocating this species into a captive breeding program. The idea for this model came from Hugh P. Possingham and I. The design and the mathematics came mainly from me under the supervision of Hugh P. Possingham and Tara G. Martin. The simulation model was written by me and the analysis of the results were conducted with help from Howard Wilson and Tara G. Martin. This chapter was written by me with editorial advice from Tara G. Martin, Jonathan Rhodes, Howard Wilson and Hugh P. Possingham.

Chapter 4 finds the optimal time to spend monitoring a new management action before reverting to an existing management action. The idea came from me where I combined Chapter 3 of this thesis and the model from Gerber et al. (2005). Under the supervision of Hugh P. Possingham, the design and mathematics was developed by me and Michael A. McCarthy. The analysis of this model was mainly conducted by me under the supervision of Michael A. McCarthy and Hugh P. Possingham. This chapter was written by me with editorial advice from Hugh P. Possingham, Michael A. McCarthy and Tara G. Martin.

Chapter 5 is an extension to the model in chapter 4 where we are trying to find an optimal stopping point to answer the question about how long, if ever we need to continue an existing action before starting a new management action that is uncertain. The idea came from me, where we use Chapter 4, as a basis for placing threatened species and invasive species management under the same general framework. The design and mathematics of this model was developed by me under the supervision of Michael A. McCarthy. The analysis of the result was done by me. This chapter was written by me with editorial advice from Hugh P. Possingham and Tara G. Martin.

Chapter 6 converts the model in chapter 4 and 5 to a stochastic dynamic programming model. The idea was conceived by Hugh P. Possingham and I where we use Chapter 4 and 5 as a rule of thumbs for active adaptive management. The design and mathematics of this model was developed by me under the supervision of Michael A. McCarthy and Cindy E. Hauser. The analysis of the result was done by me with help from Tracy M. Rout and Cindy E. Hauser. This chapter was written by me with editorial advice from Tracy M. Rout, Cindy E. Hauser, Hugh P. Possingham and Michael A. McCarthy.

Statement of parts of the thesis submitted to qualify for the award of another degree

None

Acknowledgements

I would like to thank my dear beloved partner Song Ling Tan for being supportive and encouraging throughout the entire PhD candidature. Without her patience, encouragement and financial support at times of need, it would be impossible to complete this PhD in time.

I am forever grateful to my supervisory team including Hugh Possingham, Michael A. McCarthy, Tara G. Martin and Jonathan R. Rhodes. Without their support, encouragement and academic insights, this PhD would not be successful.

I would like to thank of Christine A. Hoskings for providing emotional support throughout the entire PhD candidature. Without her providing good support and laughter at the right time, this PhD would not be the same.

I am grateful for the CSIRO top-up scholarship that provides extra financial support on top of the APA scholarship that I have received during the PhD.

Keywords

adaptive management, changing actions, decision theory, monitoring, multiple threats, resource allocation, time.

Australian and New Zealand Standard Research Classifications (ANZSRC)

ANZSRC code: 010202, Biological mathematics, 25%

ANZSRC code: 010206, Operations Research, 50%

ANZSRC code: 050205, Environmental Management, 25%

Fields of Research (FoR) Classification

FoR code: 0102, Applied Mathematics, 40%

FoR code: 0103, Numerical and Computational Mathematics, 30%

FoR code: 0502, Environmental Science and Management, 30%

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List of Abbreviations used in the thesis

SDP	Stochastic Dynamic Programming
AIC	Akaike Information Criteria
AAM	Active Adaptive Management

Chapter one – Introduction: Resource allocation

The world's biodiversity is in crisis, and the rate of biodiversity loss is much higher than background rates (Pimm et al. 1995). For instance, the Living Planet Index which is an indicator on the health of our global biodiversity, shows that from 1970 to 2008 the index, which is calculated using population time series data from more than 2600 vertebrate species, declined by 28% (WWF 2012). Similarly, the IUCN Red List Index, which measures the extinction risk of mammals, birds, amphibians and corals, reports a 6.1% decline from 1986 to 2008 (Butchart et al. 2010). All species are considered extinct if the Red List Index value drops from 1 to 0 (IUCN 2012). At least one-fifth of the 5487 mammals species assessed are at risk of extinction in the wild (Hoffmann et al. 2011; IUCN 2012). According to the Convention of Biological Diversity (CBD) 2010, we have failed to meet the goal of reducing the rate of biodiversity loss (Nicholson et al. 2012). This means that it is crucial to use what limited resources that we have prudently (Bottrill et al. 2008).

Deciding where to invest our resources is essential as there are never sufficient funds to manage everything. It would be ideal if we have sufficient resources to secure all species and habitats but recent estimates suggest that this is far from true (James et al. 2001; McCarthy et al. 2012). Despite years of conservation investments, the impact of humanity on biodiversity remains 100-1000 times the natural rates of extinction (Bottrill et al. 2008; Pimm et al. 1995). The amount of conservation spending remains well below what is needed to conserve biodiversity worldwide (James et al. 2001). Hence, we must develop strategies to prioritise what to save (Naidoo et al. 2006).

To make efficient conservation decisions and maximise the benefits of resource allocation to conservation actions, we need to know three key things – the costs of actions, the benefits of actions and the likelihood that those actions will succeed. The costs of actions are the amount of money necessary to implement an action, or the foregone profit from an action, that includes social costs, acquisition costs, management costs or transaction costs (Naidoo et al. 2006). The benefit of an action is the amount gained from an action in terms of the management objective, for example, reducing the probability of species extinction or maximising the area set aside for reserves (Bottrill et al. 2008). The likelihood that an action will succeed is a factor that helps us to determine whether an action should be implemented (Bottrill et al. 2008). In conservation priority setting, higher priority is given to an action that has low cost, high benefit and high likelihood of success (Bottrill et al. 2008). By understanding costs, benefits and the likelihood of success of an action, we can trade-off one action against another and set priorities as to how to allocate scarce conservation resources cost-effectively (Bottrill et al. 2009). Another reason for including costs and benefits is that it can change the outcome of what we are trying to conserve (Naidoo et al. 2006). For example, when managing protected areas, the number of species conserved when we include spatially varying costs is about two-three times the number of species conserved when we exclude these costs considerations for a given budget (Balmford et al. 2003; Naidoo et al. 2006). However, it is difficult to incorporate costs and benefits into an ecological problem as there can be multiple conflicting costs and benefits (Bottrill et al. 2008). To solve a resource allocation problem, it is not enough just to know the cost, benefit and likelihood of success of an action; we also need to have well defined management objectives in order to successfully attain the management goal. We also need constraints to understand the limitations surrounding the problem. Decision science is a technique that we can use to place all these issues into a systematic framework.

Decision science

Deciding how to allocate resources (time and money) optimally is a problem common to many fields of applied science: medicine, economics, natural disasters, sociology and, national security, agriculture and environmental management, to name but a few (Fiedrich et al. 2000; Ravindran 2008). Even though the mathematics behind this can be traced to earlier origins, the majority of the key advances originated during World War II, where the field of operation research arose to help strategic and tactical planning for limited military resources (Kittel 1947). Operation research is a discipline where the use of advanced analytical methods is applied to help make better decisions (Ravindran 2008). Since World War II, operation research has been known as a decision making science that provides great value towards management problems in the government and in the private sector (Gass and Assad 2004). Despite a long history of success in many fields, decision science has only been recently used in nature conservation in the past two decades.

To solve a problem in conservation requires skills and knowledge in ecology, socio-economics, mathematics and statistics. Ecology provides information about the relationships between actions and outcomes, socio-economics informs the values for various conservation outcomes and mathematics and statistics, especially in the field of operation research, give us tools to solve complex conservation problems (Balmford and Cowling 2006; Knight et al. 2006; Knight et al. 2011b; Saunders et al. 2006). By bringing together these multiple disciplines, decision theory provides a systematic way for solving conservation problems (Possingham and Shea 1999; Possingham et al. 2001). Possingham et al. (2001) describe seven steps for applying decision science to a conservation problem:

1. Define a management goal or outcomes that we wish to maximise or minimise. An example would be to maximise the expected number of individuals in a population at the end of 50 years.
2. List different types of management actions. Actions could include habitat restoration or eradicating invasive species.
3. Define state variables. For example, the abundance of a population is often a crucial state variable in conservation.
4. Devise a model that describes that dynamics of the system. This model will link the actions to the state variables and ultimately outcomes that we value.
5. Determine if there is a constraint such as amount of time or budget that limits what actions we can take.
6. Consider uncertainties such as uncertainty in the structure of the system model or uncertainty in parameters in any part of the problem.
7. Find one or more good solutions to the problem, either analytically, numerically or via computer simulations.

This description of the seven steps, however, ignores the monitoring and evaluation component that we will discuss later under adaptive management.

Decision science can be used to solve a variety of problems in pest management, forestry, conservation and fisheries management (Hoffman and Bevers 2002; Shea et al. 2000). In pest management, it is used to determine where to apply pesticide, the timing of application and the cost of applying pesticides to reduce the pest to some level that is acceptable (Higley and Pedigo 1996; Norton and Mumford 1993; Shea and Management 1998; Shea et al. 2000). In forestry management, it is used to decide on the maximum amount of logging allowable to have a sustainable forest and/or to maximise profits (Barth and Stahl 2012; Kangas et al. 2008). In fisheries science, it is often used to set the harvest quota to maximise the maximum sustainable yield – although the diversity of objectives are increasing as fisheries science evolves (Beverton and Holt 2004; Clark 1990; Lane and Stephenson 1998; Schaefer 1991). When decision science is incorporated into pest management, forestry and fisheries management, it considers uncertainty in the decision making process and allows us to evaluate the risk associated with making certain decisions (Norton and Mumford 1993).

Risk and uncertainty arise due to biological, technical and economic factors as well as imperfect knowledge about these factors in a given year (Norton and Mumford 1993).

In the field of conservation, decision science has been used to solve hundreds of problems ranging from optimal harvesting of animals (Getz and Haight 1989; Hauser et al. 2006; Hauser et al. 2007), translocation of animals in the event of climate change (Haight et al. 2000; McDonald-Madden et al. 2011; Rout et al. 2007; Rout et al. 2009b; Tenhumberg et al. 2004), managing two different subpopulations (McDonald-Madden et al. 2008; Nicol and Possingham 2010), managing populations threatened by multiple processes (Maguire et al. 1987), fire management in national parks (McCarthy et al. 2001; Richards et al. 1999), reserve design (Haight and Travis 2008), detection and eradication of invasive species (Epanchin-Niell et al. 2012; Mehta et al. 2007; Regan et al. 2006; Taylor and Hastings 2004) or how much time or money to spend on monitoring (Field et al. 2004; Field et al. 2007). A decision science framework can change how we allocate resources among management actions to achieve the management goal beyond existing practice. For instance, it can change the spatial allocation of resources for different areas (Brooks et al. 2006; Hoffman and Haight 2007; Wilson et al. 2006) or how we allocate funds to the secure and/or recover threatened species (Joseph et al. 2009).

Decision science finds its application in traditional methods such as population viability analysis (PVA) and scenario modelling. The traditional application of PVA is used to determine the viability of a population (Shaffer 1981). Decision science can be incorporated into PVA to form a management strategy evaluation framework that uses simulation to test multiple management actions to determine whether it meets the management objective for a range of uncertainties (Milner-Gulland et al. 2010; Milner-Gulland 2011; Possingham et al. 2002).

In this thesis, we explore how to allocate resources among different management actions using decision theory. First, we determine how to allocate resources among multiple threats. Second, we examine how to allocate money or time for monitoring. Third, we explore how to allocate resources between two mutually exclusive actions where monitoring is conducted concurrently with one of the actions in the context of active adaptive management.

Managing multiple threats

Many species are affected by multiple threats. Deciding how to invest our resources to mitigate multiple threats is a difficult issue because the majority of the species are threatened by multiple threats. These threats can include habitat loss or fragmentation, invasive species, introduced predators and pollution (Venter et al. 2006; Wilcove et al. 1998). In addition, climate change and changes to flooding and fire regimes are emerging as significant threats to these species (Rosenzweig et al. 2008; Thomas et al. 2004). For example, mountaintop or polar species have shown severe range contraction (Parmesan 2006). Coupled with this is human population growth and economic growth - that causes habitat loss and fragmentation (Forester and Machlist 1996; Sisk et al. 1994). Thus, we need to decide how to allocate our resources cost-effectively among multiple actions to mitigate multiple threats in order to save species from extinction.

Identifying how to allocate resources among multiple threats is critical as species are rarely impacted by a single threat (Lawler et al. 2002). For instance, 85% of the endangered and threatened species in the United States face at least four types of different threats, with the most prevalent being habitat loss and fragmentation followed by threats by invasive species (Lawler et al. 2002). Moreover, synergies that arise from multiple threats acting simultaneously can push a population below its minimum viable population size, increasing the extinction risk of a population (Brook et al. 2008). Research on multiple threats focuses on what actions to invest to recover a population (Maguire et al. 1987) or spatially to preserve biodiversity (Wilson et al. 2007). Yet, few studies consider simultaneous investment in multiple actions to mitigate multiple threats (Joseph et al. 2009; Wilson et al. 2006). Management approaches that consider multiple threats simultaneously can be more cost-effective as they provide a higher biodiversity benefit than actions that consider single threats independently (Evans et al. 2011).

Knowing what management action to conduct on paper does not guarantee its success in real life. Before successful implementation can happen, we need to consider an inconvenient reality: impediments. Impediments are a limiting rule or circumstances (Oxford University Press 2012), its influence on the chosen action ranges from making it less effective to completely infeasible to implement. For example, local social values prevent us from purchasing some parts of a region for conservation purposes when some land owners are unwilling to sell their land (Guerrero et al. 2010; Knight and Cowling 2007). Recent studies have examined these impediments mainly in the context of spatial prioritisation in order to preserve biodiversity in the design of protected areas (Guerrero et al. 2010; Knight et al. 2011a; Knight et al. 2011b). However, these impediments were seldom considered when deciding on an action to mitigate multiple threats (Knight et al. 2006; Prugh et al. 2010). In Chapter 2, we address the issue of how these impediments affect the optimal allocation of resources among multiple threats.

Optimal monitoring

Monitoring is to check the progress of something over time (Oxford University Press 2012). In conservation, it is used by ecologists to collect information to learn about the particular properties of a population, ecosystem, ecological community or threat (Gardner et al. 2008; Grantham et al. 2009). Monitoring is important because it documents environmental change (Gibbs et al. 1998). Monitoring can also be considered a management action. Its costs can be quantified but its benefits are hard to quantify as it has an indirect effect on management actions.

Optimal monitoring is the process of deciding how much to invest in monitoring, and what sort of monitoring to invest in, to achieve the best outcome. Traditional approaches to optimal monitoring involve obtaining sufficient statistical power to detect a real decline in a population (Barnes 2002; Forcada 2000; Peterman 1990b; Taylor and Gerrodette 1993; Taylor et al. 2000). Classical power analysis typically adheres to the five-eighty convention that sets significance and power at 0.05 and 0.80 respectively (Di Stefano 2003; Field et al. 2004; Walsh et al. 1999). When this convention is used, there is a probability of making Type I error (accepting a false null hypothesis) of 5% and Type II error (failing to reject a false null hypothesis) of 20% (Di Stefano 2003; Johnson 1999, 2002). This is known as statistical burden of proof, where the costs of making Type I error is four times more than Type II error (Di Stefano 2003). This is problematic and would likely have a negative impact on the environment (Dayton 1998; Di Stefano 2003; Mapstone 1995; Peterman 1990b; Taylor and Gerrodette 1993). This is because if we make a Type II error, there is a failure to detect an environmental effect, resulting in nothing done to mitigate threats to the environment. This can cause serious harm to the environment that is irreversible such as the extinction of a threatened species (Taylor and Gerrodette 1993), pollution to waterways (Di Stefano 2003; Mapstone 1995) or collapse of fishery stocks (Dayton 1998). This is an expensive mistake that can be avoided by a conservation manager. Whereas, making a Type I error (accepting an environmental effect when there is none), would result in a waste of resources as management actions would be conducted to turn the decline of a population around when there is no decline (Maxwell and Jennings 2005; Strayer 1999; Taylor and Gerrodette 1993). To avoid these errors, conservation managers can adjust the statistical Type I and Type II error based on cost and benefit of management using a decision theory framework (Field et al. 2004; Field et al. 2007; Mapstone 1995). Another possibility is to avoid null hypothesis testing by considering model selection techniques that use Akaike’s Information Criteria (AIC) or Bayesian inferences to find the best model that fits the data (Anderson et al. 2000a; Burnham and Anderson 2002).

Monitoring can be used to trigger another suite of management actions. Management actions can include doing nothing, monitoring, habitat restoration, land purchase, setting up a reserve system or eradicating an invasive species. To allocate resources efficiently among these management actions, we need to understand how to trade-off between these actions, including monitoring. It is necessary as time or money spent on one action, reduces the resources available for another. Examples of this include deciding when to translocate under climate change (McDonald-Madden et al. 2011), deciding how much time to spend on monitoring or management actions or how to value the information available in adaptive management models (Hilborn 1987; Moore and McCarthy 2010; Runge et al. 2011).

In the past decade, there has been a growing interest in using decision theory to decide how much to invest in monitoring (Nichols and Williams 2006; Possingham et al. 2001). Yokomizo (2003, 2004) was the first to find the optimal monitoring effort for a population in a stochastic environment. He found that the optimal effort depends on the population survival rate, the cost of management, the effectiveness of monitoring and the management timeframe. Since then, numerous researchers have worked on the topic of optimal monitoring. Examples of optimal monitoring include deciding when to stop monitoring in order to determine a reserve size (Gerber et al. 2005), to start an eradication program for an invasive species (Baxter and Possingham 2011), to protect critical habitat (Grantham et al. 2009; Martin et al. 2009) or to translocate a species (McDonald-Madden et al. 2011; Rout et al. 2009b). Others examine when to cease all monitoring and management efforts for cryptic (Chades et al. 2008) or invasive species (Regan et al. 2006; Rout et al. 2009a); determine the optimal survey or management investment or strategies for different sites (Hauser and McCarthy 2009) or across a network (Chadès et al. 2011); or determining whether to monitor every year or less frequently (Hauser et al. 2006). However, little is known about how several ecological variables influence the decision about when to stop monitoring before translocating a species into captive breeding. In Chapter 3, I examine how several key ecological parameters influence the yearly investment in monitoring or the average amount of money to spend on monitoring before translocation (Chapter 3).

Past studies on optimal monitoring tend to be situation specific, dealing with only one type of management action, with some providing a complex dynamic solution to the problem (Baxter and Possingham 2011; Chades et al. 2008). It is necessary to find a general theoretical solution that can be applied to a wide variety of situations. Recently, there are several studies that have started work on a general theoretical solution to decide on how to allocate resources optimally among different management actions in order to save a species from extinction (Chadès et al. 2011;

McDonald-Madden et al. 2010a). This includes deciding on how to allocate resources among different actions (McCarthy et al. 2010), deciding about how to design nature reserves (McCarthy et al. 2005) in terms of having several small or single large reserve system (McCarthy et al. 2011) or determining the level of investment required to conserve a species (McCarthy et al. 2008). However, the general question of when to cease a new management action, given that we already have a tried and tested existing action remains unanswered. In Chapter 4, we have obtained a general analytical solution that is applicable to a range of situations about how long we should trial a new management action that has unknown effectiveness before reverting back to an existing action with known effectiveness. Furthermore, we have expanded the general solution in Chapter 5 about how long we should conduct an existing action with known effectiveness in favour of a new action that has unknown effectiveness such that it is applicable to invasive and threatened species management.

Adaptive management

Adaptive management is seen as a cure towards managing a species in an uncertain environment (McDonald-Madden et al. 2010b; McLain and Lee 1996; Walters and Hilborn 1978; Williams 2011). It is an iterative process where we make decisions in the face of uncertainty, with the aim of reducing uncertainty over time using monitoring. (Halbert 1993; McCarthy and Possingham 2007; Nichols and Williams 2006; Parma 1998; Walters and Hilborn 1978). Decisions are made to meet the management objectives and to obtain information in order to improve future management actions (Hilborn 1987; Parma 1998; Walters and Hilborn 1978). It is a framework that allows us to learn about the system to improve long term management outcomes (Holling 1978). It is a powerful tool as managers often have to manage a species in an uncertain environment. If we fail to take into account of uncertainties, it can easily lead to poor management decisions.

There are two types of adaptive management, passive and active. The difference involves the different types of learning. Passive adaptive management is when anticipated future learning through monitoring occurs serendipitously and does not play a role in helping us decide the choice of our present actions (Halbert 1993; Williams 2011). Under active adaptive management, our action is placed under an experimental trial while we conduct monitoring (Halbert 1993; McLain and Lee 1996; Walters and Hilborn 1978). Active adaptive management actively learns about the system, further improving the management outcome in the future.

There has been a great deal of research on active adaptive management in fisheries, forestry and pest control (Rist et al. 2013). Even though its origin is old, it experienced a resurgence in the

1970s and 1980s (Parma 1998). In fisheries and waterfowl management, active adaptive management has been used to decide on the optimal harvest strategy through time as we learn about how well a population is performing (Halbert 1993; Walters 2007; Williams 1982). In forestry, it is used to determine how to allocate forest land or the optimal timber harvest strategy (Bormann et al. 2007) in the event of climate change (Ogden and Innes 2009). For pest control, active adaptive management has been used to study about when and where to release bio-control agents or pesticides as we learn about how well bio-control agents or pesticide is at controlling the pest population (Melzer et al. 2009; Shea et al. 2002). Even though active adaptive management has been well studied in the literature, it is seldom applied in actual management.

Recent studies on active adaptive management in conservation includes; choosing the optimal harvest strategy to manage a kangaroo population for a range of management timeframes (Hauser and Possingham 2008), deciding on the optimal harvest strategy for waterfowl management (Dorazio and Johnson 2003; Johnson and Case 2000; Johnson 2011; Nichols et al. 2007; Williams and Johnson 1995), deciding how many animals to translocate from a captive population to two sites (Rout et al. 2009b), deciding how to allocate resources between two management actions in order to maximise the success of revegetation projects (McCarthy and Possingham 2007), understand how to allocate resources for the Tasmanian devil that is affected by disease (McDonald-Madden et al. 2010b) and deciding whether we should continue surveying, manage or give up the management of the Sumatran tiger which is a cryptic species (Chades et al. 2008). However, the question of whether to trial a new action with unknown effectiveness or continues an existing action with known effectiveness every year remains unanswered (Chapter 6). This is an important question as conservation managers often have to decide how to trade-off between two different types of management actions: a management action that has uncertain effectiveness and a management action with known effectiveness.

Thesis overview

The main purpose of this thesis is to examine how to allocate resources between multiple actions that can include monitoring in a decision theory framework (Fig. 1.1). In this chapter, I provide an introduction to the entire thesis and lay out the decision theory framework. Next, I investigate the question about what influences the optimal allocation of resources (time or money) among multiple actions that include monitoring (Chapter 2 and 3). Then, I made an attempt to answer the question about how much to allocate resources (time) among multiple actions including monitoring (Chapter 4, 5 and 6). Specifically, chapter 2 examine the impact of social, technological and habitat impediments on how we allocate resources among multiple actions. In chapter 3, I identify the key parameters that influence how we allocate resources between two actions (monitoring and translocation). In contrast, the next two chapters deal with how much time to allocate between two mutually exclusive actions (Chapter 4 and 5) that are applicable to both invasive and threatened species management (Chapter 5). Finally, the last chapter deals with whether to continue an existing action or trial a new action in an active adaptive management framework (Chapter 6). Concluding statements about how to allocate resources optimally in conservation biology and future directions related to this thesis are presented in Chapter 7.

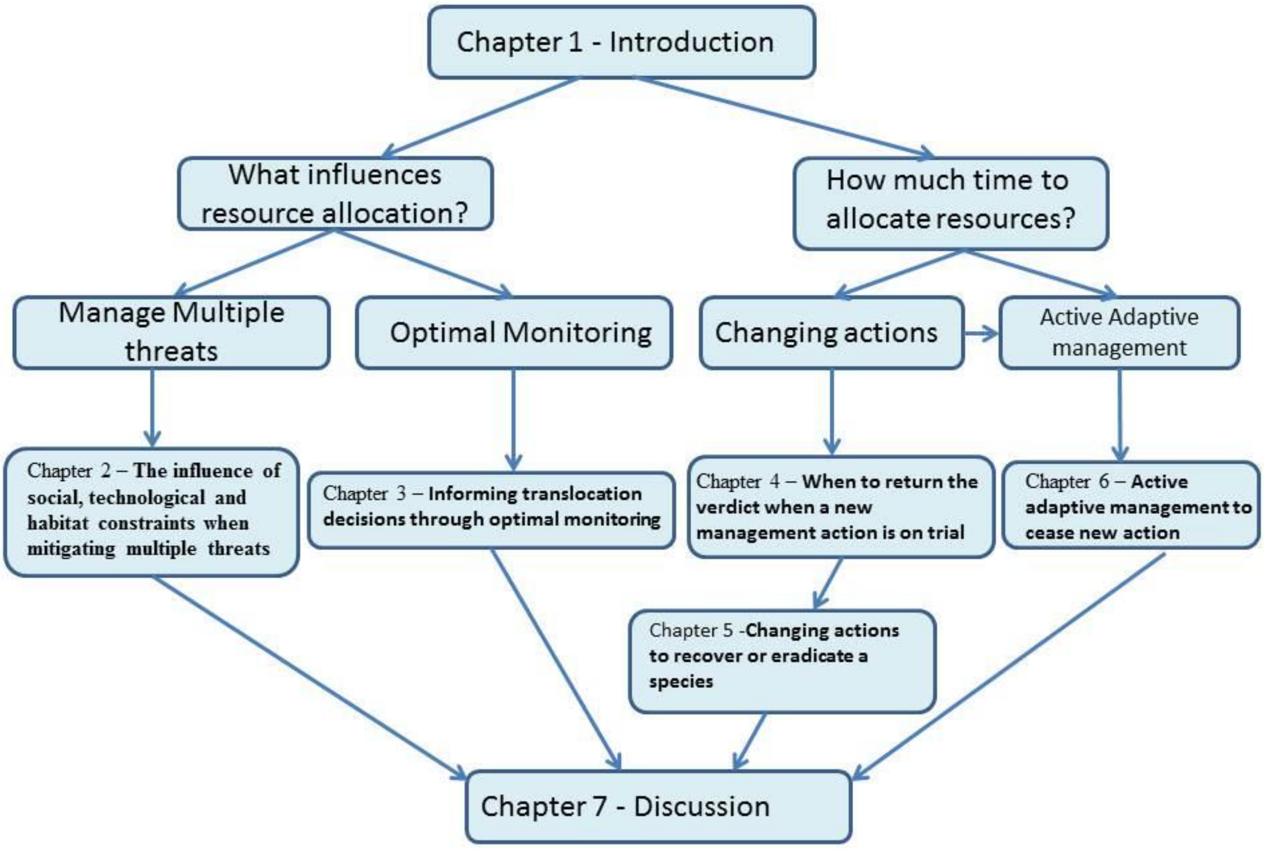


Figure 1.1. Flow diagram showing the linkages between chapters of thesis

In the **second chapter**, I use decision theory to examine how impediments can affect the way we allocate resources in order to mitigate multiple threats. Using the koalas as a case study, I examine how social, technological and habitat constraint affects the way we allocate our limited resources among multiple threats. Specifically, I examine the impact of the unwillingness of dog owners to secure their dogs at night (social impediments), the effectiveness of overpasses, underpasses and fencing of roadside in reducing vehicle collision on the koalas (technological impediments) and the land that was unavailable for habitat restoration (habitat impediments). While these impediments are well known, its impact on how we allocate resources among multiple threats has never been explored.

Using sensitivity analysis, **Chapter 3** explore how several key ecological variables affect our optimal monitoring strategy for a species that is declining rapidly before translocating it into captivity. It is important to identify which parameters are important because any extra parameter adds complexity to the model (Ginzburg and Colyvan 2004; Ginzburg and Jensen 2004). A complex model would complicate the result, thus, increasing the difficulty in analysing the results. This is problematic as some parameters might not contribute towards the optimal monitoring strategy. Thus, it is important to conduct sensitivity analysis to identify which parameters are important. If the optimal monitoring strategy is insensitive to the variation in the parameter of interest, we can discard the parameter from the model as it does not contribute towards the optimal solution. Using the Christmas Island Pipistrelle as a case study, I explore how the population growth rate, stochasticity in population growth rate and initial population size influences the optimal monitoring strategy.

In **chapter 4**, I develop a general solution to help us decide whether we should trial a new management action that is uncertain, and if so, how long we should trial the new action before reverting to an existing action with known effectiveness. There are relatively few general solutions that are applicable to a variety of situations. Previous research that formulates a theory about how to allocate resources optimally for different actions (McCarthy et al. 2005) includes deciding how to design a nature reserve (McCarthy et al. 2011) and deciding the level of investment needed to conserve a species (McCarthy et al. 2008). Yet, the general question about how long we should trial a new management action, given that we have an existing action remains unanswered. The reason to trial a new management is when an existing action is becoming ineffective or it has ceased working. After a certain amount of time trialling the new action, we swap back to an existing action if the new action is not performing as well as the existing action.

Chapter 5 is an extension of **chapter 4** where I ask a slightly different question. The question is to find when we should stop an existing management action with known effectiveness before continuing a new management action that is uncertain. In addition, I was able to apply the general analytical solution to invasive species management. Even though, few studies have attempted to place invasive species and threatened species management under the same framework

(Chadès et al. 2011; Thompson et al. 2012), there was never an attempt to find an optimal stopping time to decide how long we should manage an action. I find that a unique general analytical solution exists, which is applicable to both invasive and threatened species management.

In **chapter 6** of this thesis, I develop an active adaptive management framework to determine whether to trial a new management action that is uncertain or continue with an existing action with known effectiveness that is dynamic through time. We explored the influence of a range of parameters on the best management action. In **chapter 4** and **5**, we assumed a deterministic system where there is no stochasticity associated with the population growth rate, whereas in **chapter 6**, we have included environmental stochasticity into the population growth rate and use stochastic dynamic programming to find the optimal strategy. Then, we compared the analytical solutions developed in **chapter 4** and **5** and the active adaptive management approach in **chapter 6** to determine whether the general analytical solutions outperform results in active adaptive management.

Chapter two – Impediments to the success of management actions for species recovery

Introduction

Most of the world's species and ecosystems are at risk due to multiple threats (Burgman et al. 2007; Crain et al. 2009; IUCN 2001; Lawler et al. 2002; Tockner et al. 2010). These include habitat loss and fragmentation, invasive species, introduced predators and disease (Evans et al. 2011; Venter et al. 2006; Wilcove et al. 1998). In addition, climate change is an emerging threat for many species (Rosenzweig et al. 2008; Thomas et al. 2004). Given the limited resources for conservation and the large number of threatened species, recovery plans must consider how to allocate resources efficiently among actions to mitigate multiple threats.

Allocating resources efficiently requires an understanding of the costs and benefits associated with conservation actions (Chomitz et al. 2005; Naidoo et al. 2006). This requires us to identify the highest return-on-investment for our conservation efforts (Murdoch et al. 2007). Researchers have attempted to incorporate economic considerations when prioritising actions to mitigate multiple threats (Baxter et al. 2006; Wilson et al. 2007). For example, including costs and benefit into models that determine the number of species found within an area when managing multiple species increases our ability to decide in which actions to invest for a specific amount of habitat (Evans et al. 2010; Wilson et al. 2007). When dealing with a single species, incorporating cost and benefits into a population model can help identify how to allocate funds to mitigate threats (Baxter et al. 2006). However, there has been little attempt to incorporate the costs and benefits for mitigating multiple threats into population models to identify optimal investment in recovery actions. While it is important to consider the benefits and costs of mitigating multiple threats simultaneously, it is also crucial to examine other impediments that influence the outcome of our actions.

Whether an action can be successfully implemented in real life depends on a range of social, economic, technological, and habitat impediments (Balmford and Cowling 2006; Curran et al. 2012; Knight et al. 2006; Knight et al. 2011b; Knight et al. 2011a; Polasky 2008). For instance, local social values can limit how much land we can purchase in a region for conservation if some owners are unwilling to sell (Guerrero et al. 2010; Knight and Cowling 2007). Recent studies have examined these impediments mainly from the angle of spatial prioritization to preserve biodiversity when designing protected areas (Guerrero et al. 2010; Knight et al. 2011a; Knight et al. 2011b). However, these impediments were seldom considered when faced with the problem of choosing an appropriate action to mitigate multiple threats (Knight et al. 2006; Prugh et al. 2010).This is important as a failure to invest in an action that can be successfully implemented can result in a failure to recover a species.

In this paper, we address the question of, "How do social, technological and habitat impediments affect the optimal allocation of resources among multiple actions for species recovery?" The hypothesis in this chapter is that impediments affect the optimal allocation of funds to recover a population. To test this hypothesis, we develop a decision framework to allocate resources optimally among multiple threats to achieve a specific management objective. We apply this to a declining koala (*Phascolarctos cinereus*) population in eastern Australia, threatened by vehicle collisions, dog attacks and habitat loss. For the koala population, we examine how the allocation of resource among management actions are affected by social, technological and habitat impediments that include: the unwillingness of dog owners to restrain their dogs at night (social impediments), the effectiveness of wildlife crossings in reducing vehicle collisions (technological impediments) and the unavailability of areas for restoration (habitat impediments). The koala model in this chapter was built upon the koala model from Rhodes et al. (2011) that has mortality estimates for the koala population in Koala Coast. This chapter extends the matrix population model from Rhodes et al. (2011) by adding decision theory to it in order to find the optimal allocation of resources that will mitigate multiple threats in the face of impediments. This approach provides conservation managers with valuable insights into how social, technological and habitat impediments affect the allocation of resources among multiple threats.

Methods

In this section, we begin by describing the study species. Then, we outline the decision framework and management objective, followed by a description of the population model. Finally, we illustrate how we embed the social, technological and habitat impediments into the decision problem and outline how we evaluated the consequences of these impediments on the study species. The koala population model and the parameter estimates (equation 2.2 to 2.7) were obtained from Rhodes et al. (2011). The management objective (equation 2.1) and the return on investment curves (2.8 and 2.9) are new to this study.

Study species

The koala is an iconic species in Australia. One of the largest koala populations in the wild occurs in the Koala Coast, located 20 km southeast of Brisbane, Australia (area 375 km^2, human population size 2 million). Rapid urbanization has resulted in habitat loss and fragmentation, thereby, increasing koala mortality rates due to vehicle collisions, dog attacks and disease (Dique et al. 2003; Melzer et al. 2000; Rhodes et al. 2011). As a result, the koala population has declined by 64% over the past 10 years (DERM 2009). Identifying priorities for the recovery of this population is therefore urgently required.

Decision framework

To identify priorities for the recovery of this population, we applied a decision theoretic framework to allocate resources among various actions to mitigate multiple threats. This framework includes: (1) a management objective, (2) a list of management actions and the costs of implementing these actions, (3) a model of how these actions affect the population dynamics, and (4) an algorithm to find the optimal management strategy (Possingham et al. 2001).

Let x_m be the amount of money spent on action *m*; such that $\boldsymbol{x}$ is a control vector that represents the money invested in a group of actions (where x_m are the elements of $\boldsymbol{x}$); λ is the population growth rate; *n* is the maximum number of actions and *R* is the population growth rate that we want to achieve (which we subsequently refer to as the target growth rate). Our management objective is to find the optimal investment strategy that attains the target growth rate for minimum cost,

$$min\left(\sum_{m=1}^{n} x_m\right),\ subject\ to\ \lambda(\mathbf{x}) \geq R, \tag{2.1}$$

where $\lambda(\boldsymbol{x})$ describes how investment in a group of actions affects the population growth rate. We considered management goals with target growth rates, *R*, between 0.935 and 1.03. The lower bound for the target growth rates considered was the current expected growth rate for the koala population, and the upper bound was the maximum possible growth rate (Rhodes et al. 2011).

For the koala population, the management actions we considered include: dog control to reduce dog attacks, methods to reduce vehicle collision mortality and habitat restoration. Dog control involves restraining dogs at night in residential areas. To calculate the cost of this action, we estimated the cost of providing residents with dog enclosures (see Appendix A). If we want to reduce the koala mortality rates due to vehicle collisions, we need to provide them with wildlife crossing structures. This includes building underpasses and overpasses across roads with fencing of roadsides (van der Ree et al. 2008). We estimated the cost of building these structures based on Caneris and Jones (2004) (see Appendix A). Investment in habitat restoration involves setting land aside for conservation and active restoration of habitat. The cost of setting aside land for conservation was estimated from unimproved land values and the cost of restoration was taken from Schirmer and Field (2000).

Population dynamics

The population growth rate, λ, was obtained by calculating the dominant eigenvalue from an age-structured matrix model (Caswell 2001). We defined four age classes as: juveniles (0-1 year olds), sub-adults 1 (1-2 year olds), sub-adults 2 (2-3 year olds) and adults (3+ year olds) (Thompson 2006). Thus, the projection matrix is,

$$\begin{bmatrix} 0 & F_1S_1 & F_2S_2 & F_3S_3 \\ S_0 & 0 & 0 & 0 \\ 0 & S_1 & 0 & 0 \\ 0 & 0 & S_2 & S_3 \end{bmatrix}, \tag{2.2}$$

where S_i is the probability of individuals surviving in age class i and F_i is the probability of individuals giving birth in age class i. We considered females only as they are the ones who have the chance of mating regardless of the number of males. We assumed a discrete breeding season as koalas have a discrete annual breeding cycle from October to February each year (Thompson 2006). We multiplied the probability of individuals giving birth, F_i, with the probability of individuals surviving of the mother, S_i, in the first row of the projection matrix because the death of a mother results in the death of any dependent young (Handasyde et al. 1990). We assumed that the birth sex ratio is 1:1.

The probability of individuals surviving is define as,

$$S_i = 1 - \sum_{k=1}^{4} M_{i,k} \ , \tag{2.3}$$

where $M_{i,k}$ is the mortality probability for age class i and due to cause k. We assumed that the main causes of death were natural causes (k=1), vehicle collision (k=2), dog attack (k=3) and disease (k=4).

Using the law of conditional probabilities, the mortality probability due to cause k and age class i is then,

$$M_{i,k} = C_{i,k} M_i \, , \tag{2.4}$$

where $C_{i,k}$ is the mortality probability due to cause k, conditional upon the mortality probability in age class i and M_i is the mortality probability in age class i.

The mortality probability due to cause k, conditional upon the mortality probability in *age* class i is related to the forest cover as follows,

$$C_{i,k}=\begin{cases}1 & ,if\ i=0\ and\ k=1,\\ 0 & ,if\ i=0\ and\ k=2,3\ or\ 4,\\ \dfrac{e^{(\delta_k+\eta_k FOR)}}{\sum_{l=1}^{4}e^{(\delta_l+\eta_l FOR)}} & ,otherwise,\end{cases}\tag{2.5}$$

where δ_k is an intercept for cause *k*; *FOR* is the amount of forest cover surrounding the location of interest; and η_k is the coefficient that describes the influence of forest cover on $C_{i,k}$. δ_k and η_k are to be estimated from data. Juvenile koalas (age class 0) were assumed to only die of natural causes only. This equation is a standard logit transformation for parameters of a multinomial distribution.

The mortality probability in age class *i* were also assumed to depend on the amount of forest cover surrounding the location of interest, as follows,

$$\sum_{k=1}^{4}M_i=1-S_i=\begin{cases}1-\dfrac{e^{\mu_i}}{1+e^{\mu_i}} & ,if\ i=0,\\ 1-\left[\dfrac{e^{(\mu_i+\varphi FOR)}}{1+e^{(\mu_i+\varphi FOR)}}\right]^{365} & ,if\ i=1,2,3,\end{cases}\tag{2.6}$$

where μ_i is an intercept for the survival rate for age class *i* and φ is the coefficient that describes the influence of forest cover on survival probability. Here, adult survival is represented as a daily rate and then annualised, while juvenile survival is modelled directly as an annual rate because we only had data on the annual survival for juveniles.

Substituting equations 2.5 and 2.6 into equation 2.4 gives the mortality probability due to cause *k* and for age class *i*, such that

$$M_{i,k}=\begin{cases}\dfrac{1}{1+e^{\mu_i}} & ,if\ i=0\ and\ k=1,\\ 0 & ,if\ i=0\ and\ k=2,3\ or\ 4,\\ \left(1-\left[\dfrac{e^{(\mu_i+\varphi FOR)}}{1+e^{(\mu_i+\varphi FOR)}}\right]^{365}\right)\dfrac{e^{(\delta_k+\eta_k FOR)}}{\sum_{l=1}^{4}e^{(\delta_l+\eta_l FOR)}} & ,otherwise.\end{cases}\tag{2.7}$$

We assumed that the amount of forest cover has little influence on the birth rates (Rhodes et al. 2011). As such, the population growth rate depends upon the level of mortality from each cause and the amount of forest cover.

We obtained parameter estimates (in the form of posterior distributions) for the population model from Rhodes et al. (2011) that uses radio-tracking and population density data to approximate the posterior distributions by sampling from the joint posterior distribution of the parameters 9,900 times using Markov Chain Monte Carlo methods (MCMC) in WinBUGS Version 1.4.3 (http://www.mrc-bsu.cam.ac.uk/bugs/). This provided credible intervals for the mortality probability due to cause *k* for age class *i* (based on equation 2.7 and current amounts of forest cover in the Koala Coast (see Rhodes et al. 2011)) for the Koala Coast population.

Return-on-investment curves

To calculate the return-on-investment curves, we need to link the type of management actions required to the threats. To quantify how investment in each action affects the population growth rate (λ(**x**)), we need to define relationships between investment in each action and the survival rates. Investment in each action reduces mortality rates arising from a specific cause, such that

$$S_i\left(x_i\right)=1-\sum_{k=1}^{4} M_{i,k} f_{i,k}(x_m), \tag{2.8}$$

where $f_{i,k}(x_m)$ is a function that describes how investment in action *m* reduces the probability of koalas dying due to cause *k* for age class *i* (a value of one indicates there has been no reduction in mortality and a value of zero indicates that mortality from that cause has been completely eliminated). For these return-on-investment curves, we assumed diminishing marginal returns with increasing level of investment in each action (Murdoch et al. 2007). In the absence of prior information to motivate a more complex relationship, the functions $f_{i,k,m}(x_m)$ were described by a negative exponential function, such that

$$f_{i,k}\left(x_m\right)=\alpha_{i,k}+\left(1-\alpha_{i,k}\right)e^{-x_m/\beta_{i,k}}, \tag{2.9}$$

where $\alpha_{i,k}$ is an asymptote between 0 and 1 that describes the minimum value for $f_{i,k}(x_m)$; and $1/\beta_{i,k}$ represents the rate of decline in $f_{i,k}(x_m)$ as we invest in action *m* (i.e., the cost efficiency of action *m*).

Parameterising return-on-investment curves with and without impediments to success

We first parameterised the return-on-investment curves (equation 2.9) for each of the three actions (dog control, reducing vehicle collisions, and habitat restoration) assuming there are no impediments to success using empirical data on the costs of each action obtained for the Koala Coast (see Appendix A). In this case, we assumed that $\alpha_{i,k,m} = 0$ for the dog control and vehicle collision reduction actions (assuming they can reduce dog and vehicle collision mortalities to zero with sufficient investment), but estimated $\alpha_{i,k,m}$ from simulations for habitat restoration (where we assume that the replacement of habitat reduces natural and disease mortality (Possingham et al. 2001). We then modified each of the return-on-investment curves to account for impediments to success associated with each action. We achieved this by modifying the value for $\alpha_{i,k,m}$ to reflect the impact of each impediment on the maximum possible reduction in mortality. For each of the actions, the impediments that limit the success of the action are different and we explicitly accounted for these differences within our framework.

For dog control, there exist human social impediment that arise due to the unwillingness of some dog owners to enclose their dogs at night. Using data from Clark (2006), we incorporated the influence of this impediment into the return-on-investment curves. Clark (2006) show that 56% of dog owners who currently keep their dogs outside at night are unwilling to adopt enclosures under any circumstances. We therefore assumed that, due to this social impediment, we can only ever reduce the mortality rate due to dog attacks by up to a maximum of 44%. Consequently, under this impediment for the dog control action, we fixed $\alpha_{i,3,dog} = 0.44$ in equation 2.9 and then re-estimated the other parameters (see Appendix A).

Existing technology for preventing mortalities on roads that involves the building of wildlife crossings and fencing is generally not capable of eliminating road mortalities entirely (Glista et al.

2009). This is partly because we are uncertain about which technologies are best for which species (Glista et al. 2009; Lesbarrères and Fahrig 2012). But, it is also because existing technologies are usually not completely effective in stopping movement across the road surface, for example, due to the permeability of fencing (McCollister and Van Manen 2010). In the absence of data from the Koala Coast on the effectiveness of road crossings, we used data on koala mortalities from the Bonville upgrade of the Pacific Highway, New South Wales, Australia (Semeniuk et al. 2011) to characterize the implications of these technological impediments. Semeniuk et al. (Semeniuk et al. 2011) show that the overpasses and fencing in this location reduced koala road mortalities by 77%. Therefore, we assumed that the vehicle collision mitigation measures could only reduce road mortalities by a maximum of 77% and so fixed $\alpha_{i,2,car} = 0.23$ in equation 2.9 and then re-estimated the other parameters (see Appendix A).

For habitat restoration, urban and other intensive land-uses will impede implementation because they are unlikely to be available for restoration, or to allow successful restoration because they are highly modified. We accounted for these land-use impediments by re-estimating the parameters of equation 2.9, assuming that urban and other intensive land-uses are unavailable for restoration (see Appendix A).

Solving the decision problem

We found the optimal allocation of resources for target growth rates, R, between 0.935 (the current estimated growth rate) and 1.03 (the estimated maximum achievable growth rate), for both with and without the impediments to success. To find the optimal allocation of resources, we used an active set algorithm available via the ‘fmincon’ nonlinear constrained optimization function in Matlab Version R2010a (Mathworks 1984-2010). The active set algorithm uses Lagrange multipliers to calculate the optimal investment in each action that satisfies the management objective (see Appendix B). To prevent the function ‘fmincon’ in Matlab from leading into a local minima, we repeat the optimization process by repeatedly call the function ‘fmincon’ with different initial values until a general minima was found. We calculated the optimal strategy for each target growth rate based on the posterior mean of the population model parameters and then calculated the 95% credible interval for the growth rate for each target based on the joint posterior distributions that was obtained using Markov Chain Monte Carlo methods (MCMC) from Rhodes et al. (2011) (equation 2.9). The uncertainties that was related to the return-on-investment curves were not included in the estimates of the credible interval. Finally, we compared the optimal strategy and growth rate achieved when impediments to success are ignored, with when impediments to success are accounted for.

Results

When social, technological and habitat impediments were included, the effectiveness of our management actions were substantially reduced, although the extent to which this was true varied among actions (Fig. 2.1). Among the management actions, introducing the impediments had the largest impact on the effectiveness of dog control (54% reduction in effectiveness), followed by habitat restoration (50% reduction in effectiveness), and the smallest impact was on mitigating vehicle collisions (23% reduction in effectiveness). Investing in habitat restoration has qualitatively similar trends between the different age classes in reducing natural and disease mortalities (Fig. 2.1c & 2.1d).

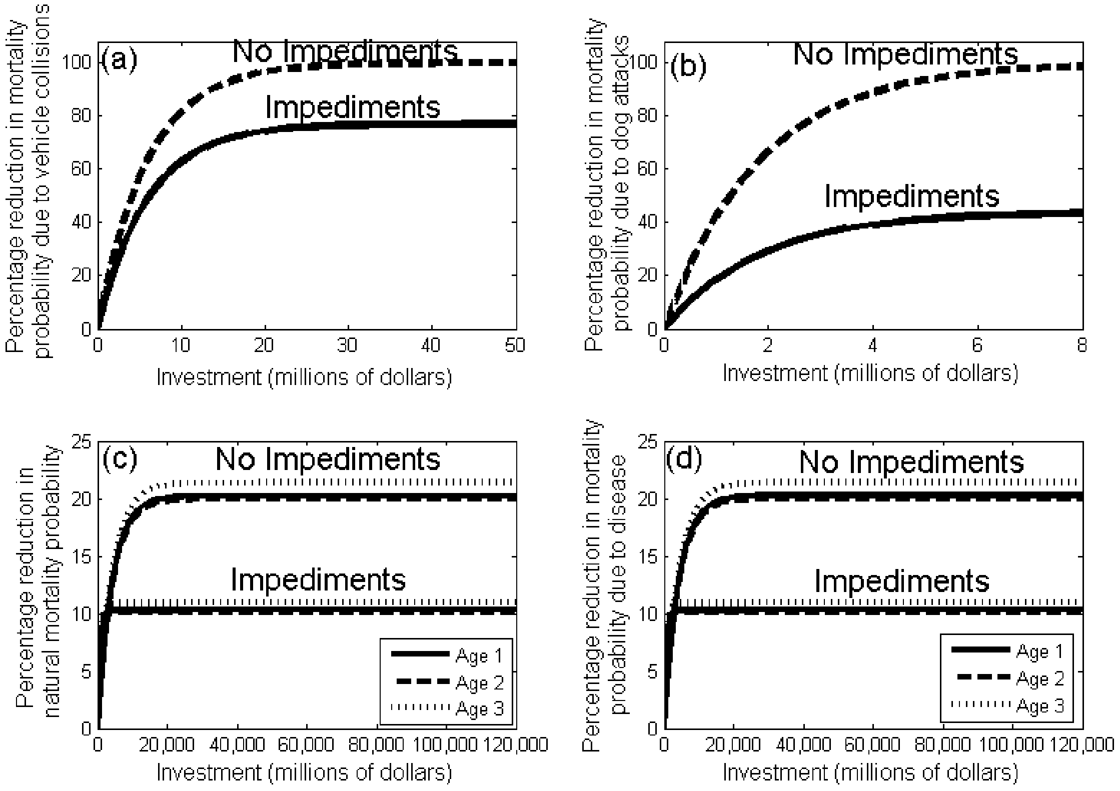


Figure 2.1. Percentage reduction in the mortality probability due to (a) vehicle collisions with and without technological impediments; (b) dog attacks with and without social impediments; (c) natural and (d) disease with and without habitat impediments, when we invest in various management actions. For (a) and (b) the relationship was the same for all age classes, except juveniles, and in (c) and (d) the dashed line applies to 1-2 year olds, the solid line applies to 2-3 year olds and the dotted line applies to 3+ year olds (Percentage reduction in mortality probability was calculated as $(1-f_{i,k}(x_m))*100\%$ *(from equation 2.9)).*

The optimal strategy for resource allocation among the management actions depended on the target population growth rate (Fig. 2.2). To achieve a low population growth rate, the optimal strategy was to invest predominantly in vehicle collision mitigation and dog control measures. However, to achieve a higher population growth rate, the optimal strategy shifts mainly to habitat restoration. This is true with and without the impediments, although with impediments, the optimal investment in mitigating vehicle collisions is slightly higher. As we aspire for higher population growth rates, the optimal investment strategy shifts towards habitat restoration. However, with the impediments, this shift occurs at a much lower growth rate (0.97) than without the impediments

(0.99). In addition, the maximum possible population growth rate that could be obtained was considerably lower in the presence of these impediments than in their absence (0.99 versus 1.03).

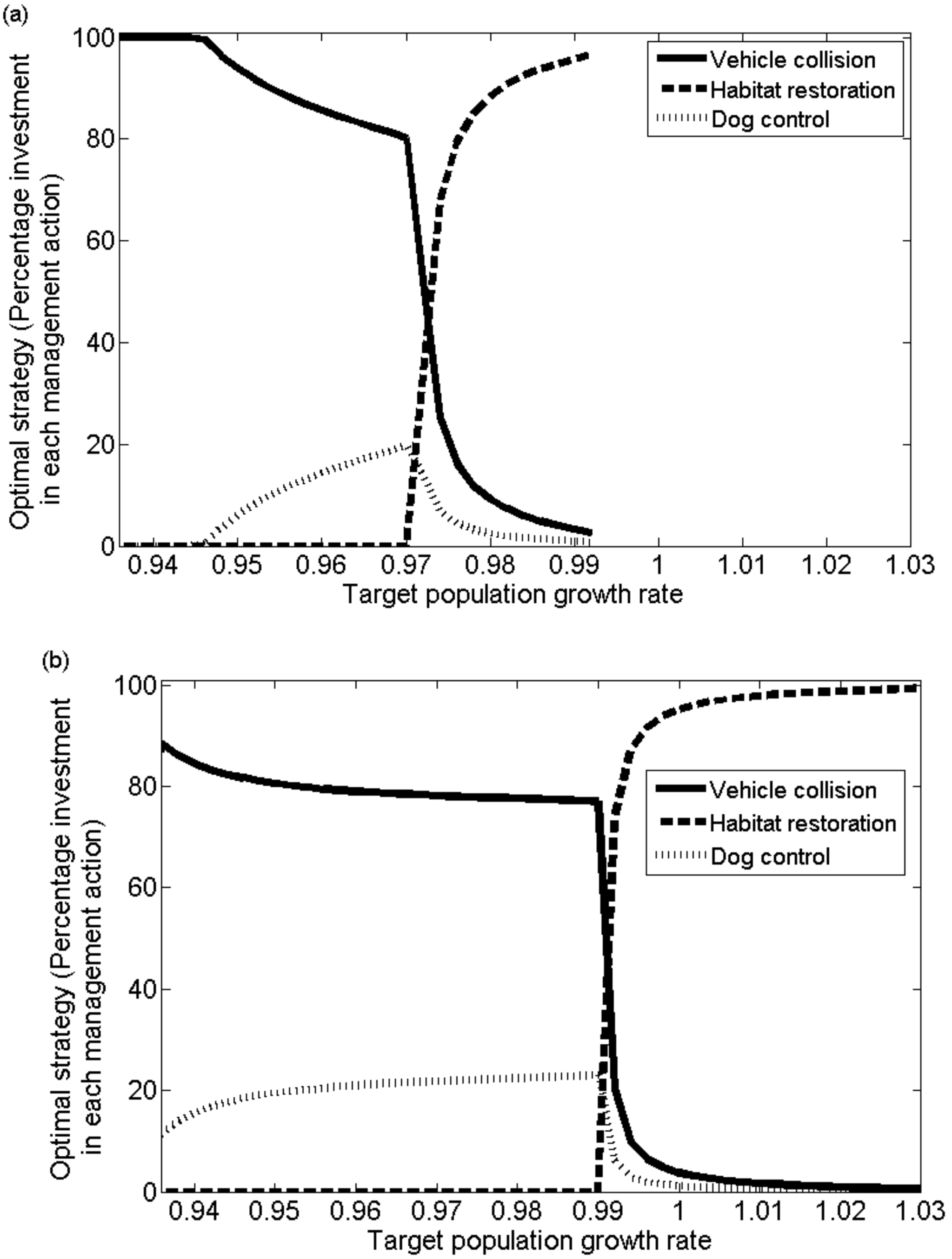


Figure. 2.2. The optimal management strategy (percentage investment in each management action) to attain the target population growth rate when we (a) include and (b) exclude social, technological and habitat impediments (the solid line is to invest in reducing vehicle collisions, the dashed line is to invest in habitat restoration and the dotted line is to invest in increasing dog control measures. The optimal management strategy was calculated by dividing the optimal investment in each action with the total investment for all actions, multiplied by 100).

As we increased the target growth rate, the total investment required increases (Fig. 2.3 and 2.4). This increase in investment was rapid when the optimal strategy shifts toward habitat restoration (at a growth rate of around 0.97 when social, technological and habitat impediments are incorporated and a growth rate of 0.99 when they are excluded) (Fig. 2.3 and 2.4). However, the actual investment required to attain these growth rates is uncertain (Figure 2.4). A low growth rate can be achieved relatively cheaply, but achieving growth rates closer to one is considerably more expensive. However, for a given target growth rate, the level of investment required was also considerably higher when we incorporated social, technological and habitat impediments than when we did not (Fig. 2.3). For instance, a population growth rate of 0.97 can be obtained for an investment of AU$25 million when we include social, technological and habitat impediments and AU$9 million when they are excluded (Fig. 2.4). When we take into account of uncertainty in parameter estimates, the estimated costs of investment both with and without impediments for a population growth rate of 0.97 range from below AU$10 million to about AU$1 billion. However, it is necessary to increase our investment substantially (to AU$1.8 billion when we include social, technological and habitat impediments and AU$98 million when they are excluded) to attain a slightly higher population growth rate of 0.992.

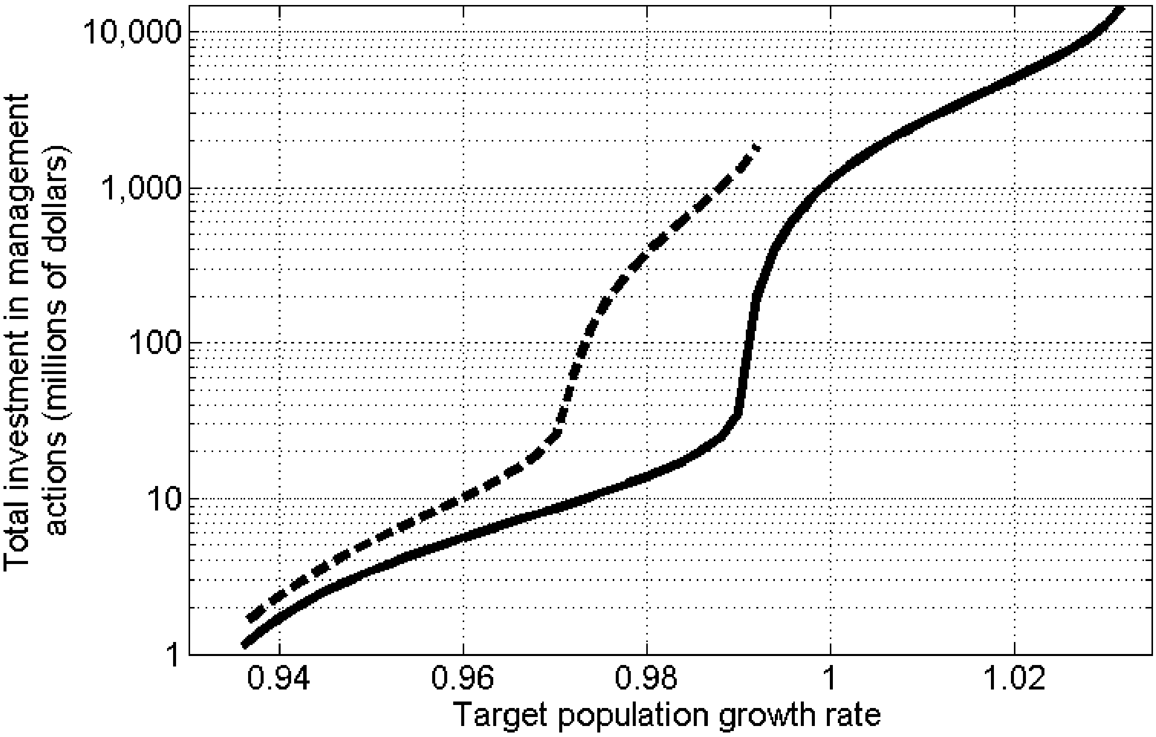


Figure 2.3. The total investment required to attain the target growth rate when we include (dashed line) and exclude (solid line) social, technological and habitat impediments.

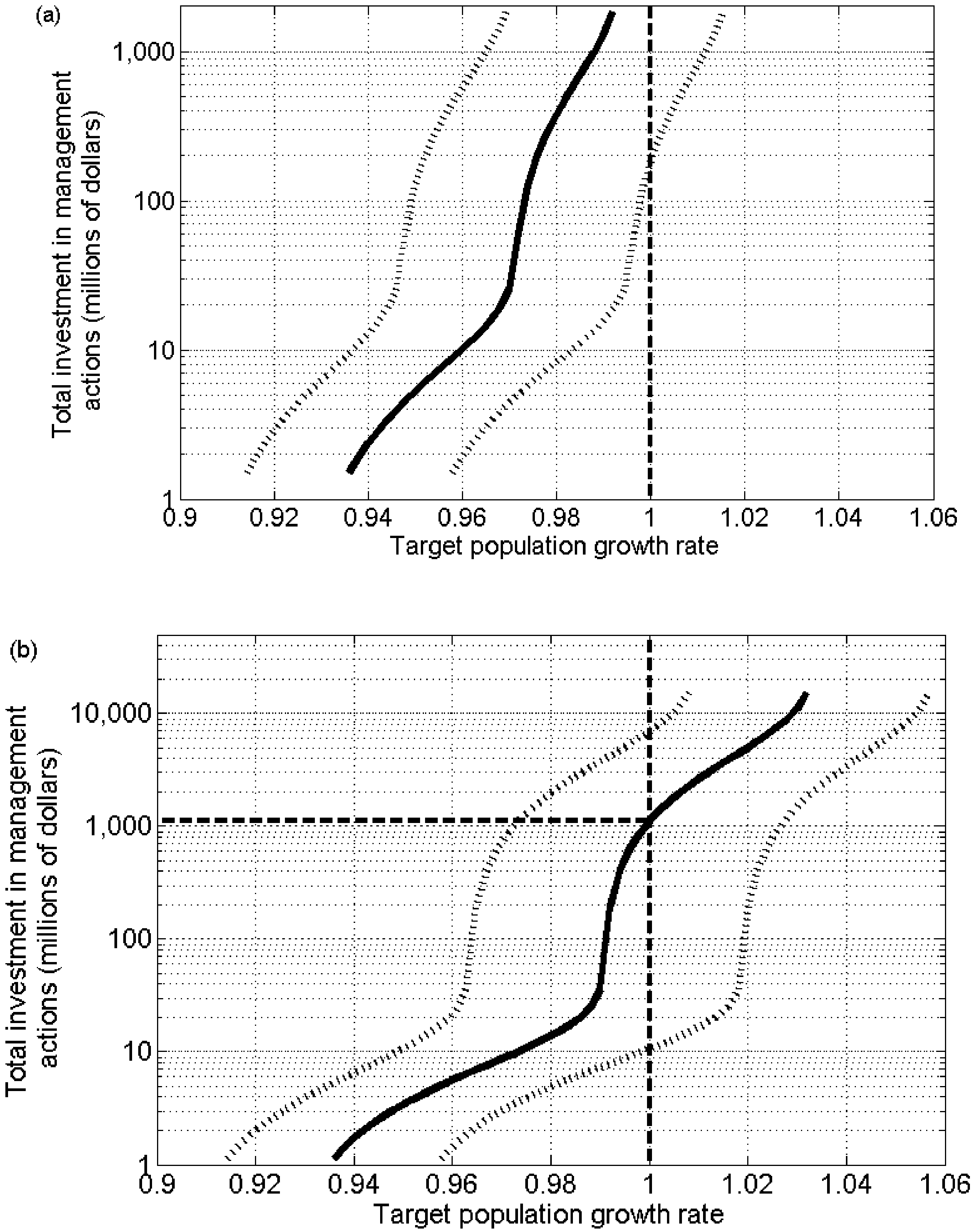


Figure 2.4. The total investment in management actions required with 95% credible intervals to achieve the target population growth rate when we (a)include and (b) exclude social, technological and habitat impediments (the dotted line indicates the point-wise 95% credible intervals and the

horizontal dashed line indicates the total amount of investment required to achieve a stable population size).

Discussion

We presented a framework for finding the optimal strategy to invest in actions that mitigate multiple threats simultaneously, while taking into account of a range of social, technological and habitat impediments. This is a significant advance because multiple threatening processes with social, technological and habitat impediments are rarely explicitly considered in approaches to conservation decision making (Evans et al. 2011; Knight et al. 2006). We found that social, technological and habitat impediments affect our ability to achieve species recovery, as we might never reach a population growth rate that enables the population to increase. The optimal investment in each management action depends on whether social, technological and habitat impediments are present or not. In general, given that actions to achieve species recovery are subject to a wide range of different impediments, it is critical we fully characterize and quantify these for each possible management action or threat.

Identifying how to allocate scarce resources among multiple threats for species recovery is a critical problem in applied ecology and biodiversity conservation because species are rarely impacted by single threats (Lawler et al. 2002). In this context, Maguire *et al.* (1987) show that it is critical to take into account the costs and benefit of each management action to reduce the probability of extinction of the Sumatran rhinoceros (*Dicerorhinus sumatrensis*). Further, Wilson *et al.* (2007) demonstrate that it is important to target management actions that address specific threats to maximise biodiversity outcomes in Mediterranean regions. However, these studies did not consider simultaneous investment in more than one action in any given area or population. Our study extends these works by demonstrating that successful species recovery depends on the simultaneous implementation of multiple actions and that the optimal investment in each action is dependent on the relative costs, benefits and impediments associated with each action. An integrated management approach that considers multiple threats simultaneously is likely to be more cost-effective and provide a higher biodiversity benefit than conservation actions that consider single threats independently (Evans et al. 2011).

Social, technological and habitat impediments can reduce our ability to achieve our management objectives in a wide range of circumstances. For instance, socio-economic impediments, such as the willingness of land owner’s to sell their land can reduce the ability to achieve conservation targets as we expand a reserve area network (Guerrero et al. 2010; Knight et al. 2011a). Including these impediments can increase the difficulty of finding an optimal solution when allocating resources spatially (Guerrero et al. 2010; Knight et al. 2011a). Similarly, in our koala case study, it was impossible to achieve a positive population growth rate when we included social, technological and habitat impediments. This could result in a failure to recover a declining population, resulting in species extinction. In such situations, if the impediments cannot be alleviated, it is necessary to consider shifting resources elsewhere, rather than wasting scarce resources (Bottrill et al. 2008; Schneider et al. 2010).

One possible management alternative is to develop strategies to remove the impediments that reduce the effectiveness of management actions. For example, reducing social impediments can increase the success of recovery actions (Knight et al. 2006). For our koala case study, a possible solution is to promote responsible dog ownership to reduce the social impediments that reduces the effectiveness of dog control measures. This could be achieved by educating the community about the importance of enclosing dogs at night to protect wildlife (DERM 2006). There are other actions available in the future, that will improve the effectiveness of approaches for mitigating vehicle collisions. However, the cost and feasibility of actions to remove impediments would need to be considered to identify whether they are cost-effective.

Our analysis demands information that will always be uncertain. By incorporating quantitative data into our study, we were able to quantify the consequences of uncertainty in our population model for achieving the target growth rate. However, we estimated the return-on-investment curves using a combination of published and unpublished data, some of which we were unable to estimate levels of uncertainty. Although the absolute return-on investment-curves are uncertain, we believe that the relative cost-effectiveness of each action is likely to be robust because the difference in cost between the three main actions to mitigate threats (reducing vehicle collisions, reducing dog attacks and habitat restoration) were in the orders of tens to hundreds of million dollars (Figure 2.1). However, dealing with such uncertainty in economic costs remain an important area for future research, as costs play a significant role in driving the optimal allocation of resources (Bode et al. 2009). To incorporate uncertainty in estimates of cost, where we often do not have good estimates of the level uncertainty, future studies could use approaches such as info-gap decision theory (Ben-Haim 2006; McCarthy and Lindenmayer 2007; Regan et al. 2005; Runge et al. 2011).

We formulated this study as a static non-spatial problem to ensure that we had a tractable problem. It would be possible to reformulate this problem within a spatially explicit and dynamic framework using stochastic dynamic programming (Hauser and McCarthy 2009). Yet, several simplifying assumptions are needed for the population model that links management actions to conservation outcomes. Nevertheless, extending the optimal allocation of resources for species recovery to include a dynamic decision process and spatial considerations remains an important area of future research.

An alternative to setting the management goal as the target population growth rate would be to estimate extinction risk using population viability analysis (PVA). The benefit of the PVA approach would be that we would be able to assess which investment would maintain the population and which did not. However, there is insufficient data to estimate extinction risk for the various investment scenarios.

An important issue that we did not consider is the presence of time lags between conducting restoration activities and the benefit to the population. For example, restored habitat might not be usable for koalas for 10 - 15 years after conducting habitat restoration (Vesk et al. 2008). Baxter *et al.* (2006) found that incorporating a lag in the benefit of restoration activities, density dependence and other spatial processes for the helmeted honeyeater (*Lichenostomus melanops cassidix*) did not change the preferred management strategy compared to a simpler projection matrix approach. However, understanding the consequences of these types of dynamic processes and time lags for the optimal allocation of resources among multiple recovery actions requires further research.

Resources are always a limiting factor in achieving species recovery. Therefore, it is necessary to identify cost efficient strategies to recover species, often in the face of multiple threats. Failure to account for social, technological and habitat impediments when we allocate resources can lead to a failure to achieve the stated management objective. If a management objective is unachievable then a consideration of alternative strategies to reduce these impediments might be an essential component of recovery planning.

Chapter three – Influence of ecological parameters on optimal monitoring

Introduction

Translocation is advocated as a last resort management action once all other means of saving a species from extinction in situ, have been exhausted (Griffith et al. 1989; Griffiths and Pavajeau 2008; Seddon et al. 2007). As rates of endangerment climb, conservation managers are increasingly turning to translocation to manage threats posed by predation, disease, habitat loss (Fischer and Lindenmayer 2000; Griffith et al. 1989), and more recently impacts of climate change (Carroll et al. 2009; Hoegh-Guldberg et al. 2008; Thomas 2011). Documented translocations of plant and animals now number in the hundreds with examples of both success and failure (Fischer and Lindenmayer 2000; Griffith et al. 1989; McLean and Armstrong 1995; Miller et al. 1999; Seddon et al. 2007; Short 2009). Despite the increasing use of translocation as a management tool, there remains much uncertainty around how to best monitor to inform translocation decisions.

Knowing when to best translocate a species is critical to the persistence of many species threatened by global change (Martin et al. 2012; McDonald-Madden et al. 2011). If translocation is conducted too late extinction will result, whereas, if translocation is conducted too early, we risk moving a species which may have recovered *in situ*. In the case of translocating a species into a captive breeding program, translocation is often conducted late when all other avenues for conservation have been exhausted; typically after the population has already declined drastically. This is because the risk of captive breeding failure is high and the cost of captive breeding is expensive (Snyder et al. 1996). Captive breeding can fail due to genetic inbreeding, loss of animal fitness in captivity, disease and other catastrophic events such as fire (Fraser 2008; Griffiths and Pavajeau 2008; Seddon et al. 2007). Thus, we need to be certain that we have detected a genuine, irreversible decline before conducting captive breeding.

Increasing the probability of detecting a population decline typically requires improving statistical power by increasing the amount of time spent monitoring (Barnes 2002; Forcada 2000; Legg and Nagy 2006; Peterman 1990a; Taylor and Gerrodette 1993; Taylor et al. 2000). Yet, for a species that is declining rapidly, there is often inadequate time to obtain sufficient statistical power (Maxwell and Jennings 2005; Taylor et al. 2000). An alternative way to enhance statistical power is to reduce the variability associated with monitoring. This can be achieved by increasing the monitoring effort per year (Dauwalter et al. 2009; Gibbs and Melvin 1997; Gibbs et al. 1998;

Wilson et al. 2011a). Researchers have been tackling optimal monitoring problems from the context of informing the management of conservation reserves (Gerber et al. 2005), setting animal harvest quotas (Hauser et al. 2006), and surveying to manage pests, diseases and endangered species (Chadès et al. 2011; Regan et al. 2006). On the issue of translocation, researchers have provided guidance on how many animals to move with optimal monitoring (Rout et al. 2009b) or when to translocate a species under climate change when the degree of threat to the species is uncertain (McDonald-Madden et al. 2011). The pressing question now is, how much investment in monitoring is required to inform the decision of when to move an endangered species into captivity, when resources for monitoring are scarce?

Decisions about how much to monitor to inform translocation decisions depends on what is being monitored. When building models to decide on the optimal monitoring strategy, it is important to understand how certain parameters influence this strategy (Colyvan and Ginzburg 2003; Ginzburg and Jensen 2004). Some of these parameters will be influential, others may not. Recent models about optimal monitoring consider the impact of a range of parameters, from growth rates of a population and their stochasticity, to the cost of management actions (Hauser and Possingham 2008; McDonald-Madden et al. 2010b; Rout et al. 2009b). Yet we do not really know which of these parameters are more important nor do we understand how these parameters influence the timing of translocation of a species into a captive breeding program or the optimal investment in monitoring.

The hypothesis in this chapter is that several key demographic parameters would influence the optimal monitoring and timing of translocation. Therefore, the first aim of this chapter is to understand the influence of several key demographic parameters (growth rates before and after translocation, uncertainty in these growth rates and the initial population size) on the optimal investment in monitoring every year and the number of years needed to monitor before translocating an animal into captivity. The second aim is to determine whether changing the translocation threshold (the rate of population decline falls below a particular level based on the International Union for the Conservation of Nature, IUCN- endangered versus critically endangered state) influences the relationship between the key demographic parameters and the optimal monitoring strategy. To do this, we constructed a simple stochastic population model and used simulations to find the annual optimal investment in monitoring to inform when to cease monitoring and instead translocate a species into a captive breeding program. Subsequently, we explored the relationship between the key demographic parameters, the translocation threshold and the optimal monitoring strategy using sensitivity analysis. Implementing the best monitoring strategy to inform translocation decisions will go a long way towards avoiding monitoring species to extinction (Martin et al. 2012).

Methods

We developed a general model to represent an ecological scenario where monitoring was undertaken to detect the best time to translocate a species, whose population is in decline (Fig. 3.1). When the rate of the population decline falls below a certain level (translocation threshold), we translocate these animals from the wild into captivity. We used the IUCN (1987, 2012) criteria of endangered and critically endangered to set the translocation threshold. The endangered and critically endangered state are defined as a rate of population decline of 50% and 80% or greater respectively over the longer of 10 years or 3 generations. We did not consider translocation of a species under other IUCN criteria (such as Vulnerable) as we assumed that there is sufficient time to consider alternative management actions.

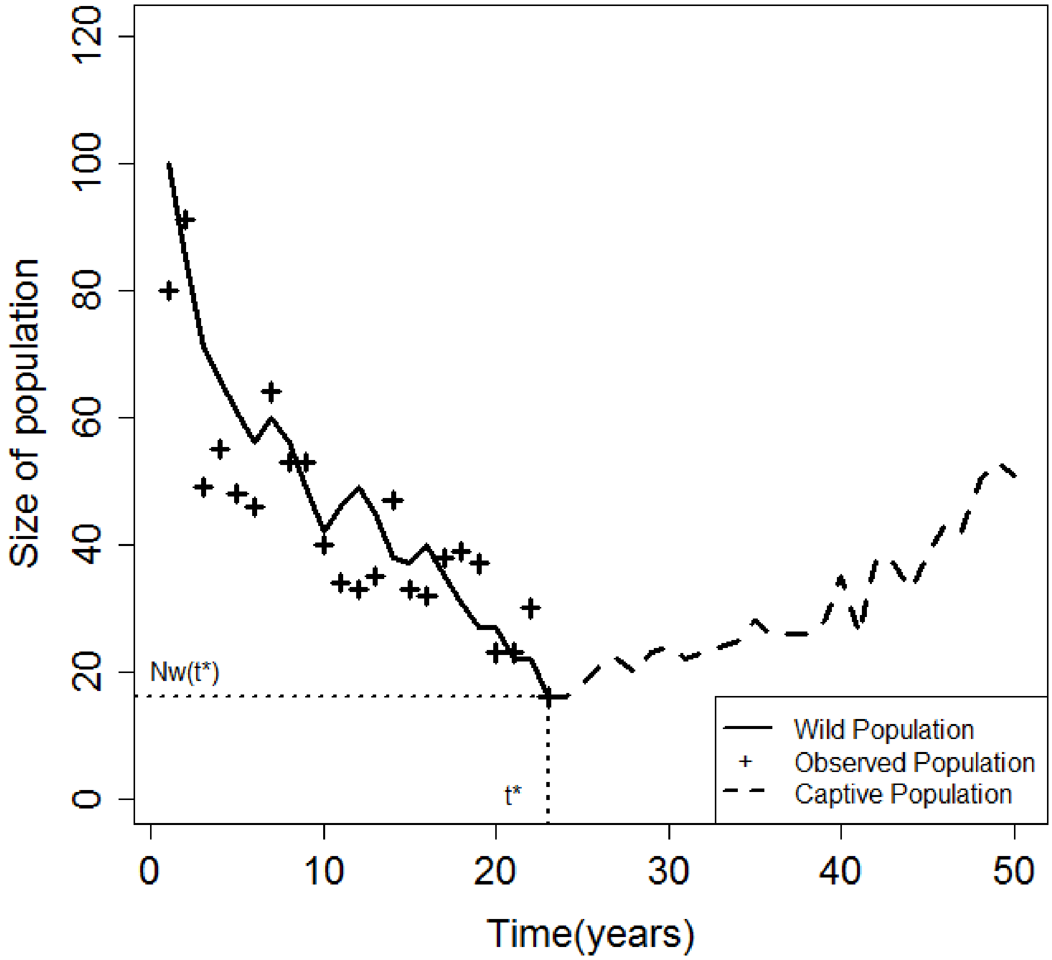


Figure 3.1. Conceptual diagram illustrating the optimal investment in monitoring of a wild population (denoted by solid line) to inform a translocation decision, where N(t*) is the population size at the average translocation time (t^*).

Using the now extinct Christmas Island pipistrelle *(Pipistrelle murrayi*) bat as a retrospective case study, we explored the model using sensitivity analysis to determine how key ecological parameters influence how much to invest in monitoring every year to inform when to translocate a species. We explored this relationship for both IUCN criteria, endangered and critically endangered (IUCN 2012). The Pipistrelle bat has a short generation time, thus, based on the IUCN criteria, we assumed a minimum 10 year timeframe to detect the translocation threshold.

We also explored the trade-off between the investment in monitoring each year and the likelihood of missing the translocation threshold (type II error) or moving a species that has not reached the translocation threshold (type I error). Missing the translocation threshold could result in the extinction of the species, as has recently occurred with Australia’s Christmas Island Pipistrelle bat (Martin et al. 2012).

Management Objective

To formulate this problem, we need to define our management goal. The management objective is to find the optimal amount of money to spend on monitoring yearly, C_m, that maximises the total value of the system, V_T, within the management timeframe of $T = 50$ years. We did not perform sensitivity analysis on the management time frame because preliminary simulation indicated that the management timeframe has little influence towards the optimal monitoring strategy. We define the value of the system using cost effectiveness analysis (Ravindran 2008), where we divide the probability of species survival, P_s by the total cost of various management actions over time C_T. The management objective is therefore to maximise:

$$V_T = P_s / C_T. \tag{3.1}$$

The total cost of various management actions was obtained by calculating the total cost of monitoring and translocation, $C_T = C_a + C_b$, where C_a is total cost of monitoring and C_b is the total cost of translocation. Thus the total cost of management action is

$$C_T = \sum_{t=1}^{t^*} C_m + C_\alpha + \sum_{t=t^*}^{T} C_\beta, \tag{3.2}$$

where C_m is the yearly investment in monitoring, C_α is the cost for establishing a captive breeding facility in year *t*, C_β is the cost of maintaining the captive breeding facility per year and t^* is the average amount of time spent monitoring before translocation.

A discount factor of 0.02 was applied to calculate the current value according to the consumer price index of 2%, that leads to,

$$C_T = \sum_{t=1}^{t^*} \frac{C_m}{(1+d)^t} + \frac{C_\alpha}{(1+d)^{t^*}} + \sum_{t=t^*}^{T} \frac{C_\beta}{(1+d)^t}, \tag{3.3}$$

where d is the discount factor, t* is when the stopping condition is met and a species is translocated, and T is the terminal time. We did not show the results for the sensitivity analysis of C_α and C_β because preliminary simulations showed that changes in C_α and C_β did not impact the optimal amount of time or money spent on monitoring.

The probability of the population surviving, P_s is the number of times the simulated population did not go extinct divided by the total number of simulations. We assumed that the species is extinct at the terminal time if the captive population size, N_c or the wild population size, N_w falls below 5 or less individuals. Below 5 individuals, we assumed environmental stochasticity and inbreeding depression would lead to extinction (Caro and Laurenson 1994; Ilik Saccheri and Hanski 1998).

Population Dynamics

We assumed that the wild population size, $N_w(t)$ in year *t* declines discretely with a randomly varying growth rate, R_w,

$$N_w(t+1) = R_w(t) N_w(t). \tag{3.4}$$

For this population model, we assumed that there is no density dependence. The growth rate is assumed to be lognormally distributed with mean μ_w and variance of the log transformed wild population growth rate σ_w^2,

$$R_w(t) = lognormal(log(\mu_w) - \frac{\sigma_w^2}{2}, \sigma_w^2). \tag{3.5}$$

Monitoring

Monitoring of the wild population was conducted to obtain information about when to translocate a species. The observed number of animals, $\widehat{N}$ differs from the true wild population size due to observation error that was assumed to be drawn randomly from a lognormal distribution,

$$\hat{N}(t) = \text{lognormal}(\log(\text{N}_\text{w}(\text{t})) - \frac{\hat{\sigma}^2}{2}, \hat{\sigma}^2). \tag{3.6}$$

where $\hat{\sigma}$ is the standard deviation of the observation error.

Using the law of diminishing marginal returns (Baumol and Blinder 2009), we assumed that the standard deviation of the observed population $\hat{\sigma}$ declines exponentially as the yearly investment in monitoring, C_m increases,

$$\hat{\sigma} = (\sigma_h - \sigma_l)e^{-\alpha C_m} + \sigma_l, \tag{3.7}$$

where α is the slope of the exponential function that describes the effectiveness of monitoring, and

σ_h and σ_l are the highest and lowest observation error respectively. We assumed a σ_h of 1 and a σ_l of 0.1 (Gibbs et al. 1998).Given that α is unknown for the pipistrelle, we assumed α has a starting value of $1e^{-4}$. We did not show the results of the sensitivity analysis for α because preliminary simulation showed that α did not impact the optimal amount of time or money spent on monitoring.

About when to translocate

Based on the information gained from monitoring, the manager must decide whether to continue or to stop monitoring and start translocation. We used linear or exponential regression fitted to the observed number of animals over time to determine whether the population had met the IUCN criteria of being critically endangered or endangered. We assumed that a population can be changing linearly or exponentially (or not changing at all). We therefore fitted the following three models:

$$\textit{Constant model: } \hat{N}(t) = N_0, \tag{3.8}$$

$$\textit{Linear model: } \hat{N}(t) = mt + N_0, \tag{3.9}$$

$$\textit{Exponential decline model: } \hat{N}(t) = N_0 e^{-mt}, \tag{3.10}$$

where N_0 is the initial size of the population, *m* is the slope of the curve. Equation 3.10 was fitted using log-transformed linear regression.

After fitting these three models, Akaike's information criterion (AIC) was used to determine which model was the best fit for the data (Akaike 1974; Anderson et al. 2000b). The best model was used to determine when we would have sufficient data to stop monitoring and implement translocation. As the model fit increases, we can predict declines with greater accuracy. In turn, this leads to better decisions about when, if ever, to translocate a species. We used sequential analysis to decide when to cease monitoring and start translocation based on the best model. Also known as sequential hypothesis testing, sequential analysis allows us to analyse the monitoring data as it is collected, until a predefined stopping rule, as defined by our IUCN criteria, is reached.

When the stopping criterion had been met, we assumed all the animals were captured from the wild and moved into a captive breeding facility at the translocation time $t = t^*$.We assumed that only half of the animals captured survived translocation and initial containment due to the risk associated with translocation (Chipman et al. 2008; Cunningham 1996). If the number of animals that survived translocation is higher, it would increase the probability of species persistence. On the other hand, if the number of animals that survived translocation is lower, there is a higher likelihood of species extinction.

The number of animals in captivity, N_c was determined after the animals were translocated. The number of captive animals follows similar dynamics as the wild population but with a different growth rate, R_c,

$$N_c(t+1) = R_c(t) N_c(t). \tag{3.11}$$

The growth rate of the captive breeding population was a random variable that was lognormally distributed with a mean, μ_c and variance of the the log transformed captive population growth rate σ_c^2,

$$R_c(t) = lognormal(log(\mu_c) - \frac{\sigma_c^2}{2}, \sigma_c^2). \tag{3.12}$$

The justification behind equations 3.11 and 3.12 were similar to equations 3.4 and 3.5 respectively. Each year, the size of the wild population, observed population and captive breeding population were calculated and rounded to the nearest integer value.

Case Study

The Christmas Island Pipistrelle bat was the only insectivorous bat endemic to Christmas Island, an external Australian territory. From discovery through to 1984, the species was considered common and widespread across the island (Tidemann 1985). However, from 1994 onwards consistent monitoring revealed the bat was in rapid decline (Lumsden et al. 2007). By 2005, 80% of the 1994 population had disappeared and by 2008, 99% had disappeared (Beeton et al. 2010; Lumsden et al. 2007). The exact cause of the decline remains unknown but was likely the result of a complex cascade of negative impacts due to the colonisation of the bat’s habitat by a suite of invasive species (Lumsden et al. 2007). By January 2009, fewer than 20 individuals were estimated to remain (Lumsden 2009; Martin et al. 2012). From 2006 onwards scientists and professional bodies urged the Federal Environment Minister to undertake a captive breeding program (Martin et al. 2012).

In July 2009, the Australian government initiated an emergency response plan to capture the last remaining bats in order to start a captive breeding program (Beeton et al. 2010). However, this rescue attempt failed. Only a single pipistrelle was detected in August 2009, and it could not be caught (Garrett 2009). The extinction of the Christmas Island Pipistrelle, suggests the timing of translocation came too late (Martin et al. 2012). This represents an excellent case study to identify whether we should have done something different in terms of monitoring effort.

Using published papers and government reports, we estimated the demographic and economic parameters for the Christmas Island Pipistrelle bats (Table 3.1). Then, we identified the optimal investment on monitoring each year that maximises V_T in 1000 simulations (eqn. 3.1). The optimal investment in monitoring, C_m was fixed, then the population simulated and this is iterated over C_m until V_T was maximised. The investment in monitoring that we examined ranged from $0-50,000 per year (Table 3.1). Using the IUCN thresholds, we found the average time to stop monitoring and translocate from over 1000 simulations. Next, we performed a sensitivity analysis by varying key parameters (growth rates, variance surrounding the growth rates and the initial population size) to assess their influence on the optimal investment in monitoring every year and the average time to stop monitoring before translocation (Table 3.1). The values explored for sensitivity analysis were based upon the uncertainty surrounding the parameters from published literature mainly from Lumsden et al. (2007) and Beeton et al. (2010). Given that the Pipistrelle bat was declining severely, the average time to stop monitoring has a lower bound of approximately 10 years due to the IUCN criteria of specifying the decline over the longer of 10 years or 3 generation.

Parameters	**Descriptions**	**Christmas Island Pipistrelle baseline values**	**Values explored for sensitivity analysis**
u_W	Mean of the wild population growth rate	0.78	0.7 – 1
σ_w	Environmental stochasticity of the wild population	0.20	0 – 0.95
u_c	Mean of the captive population growth rate	1.39	1-1.5
σ_c	Environmental stochasticity of the captive population	0.12	0-0.95
N_0	Size of population initially at $t = 0$	100	50-1000

C_α	Initial setup cost of captive breeding facility	\$1.55 million	\$5e^5-1e^8
C_β	Cost maintaining captive breeding facility per year	\$438000	\$1e^5-1e^6
T	Management timeframe	100	10 – 200 years
α	Slope of the exponential function describing the effectiveness of monitoring	1e-4	1e^-6 – 1e^-2
C_m	Cost of monitoring per year	-	\$0-50,000

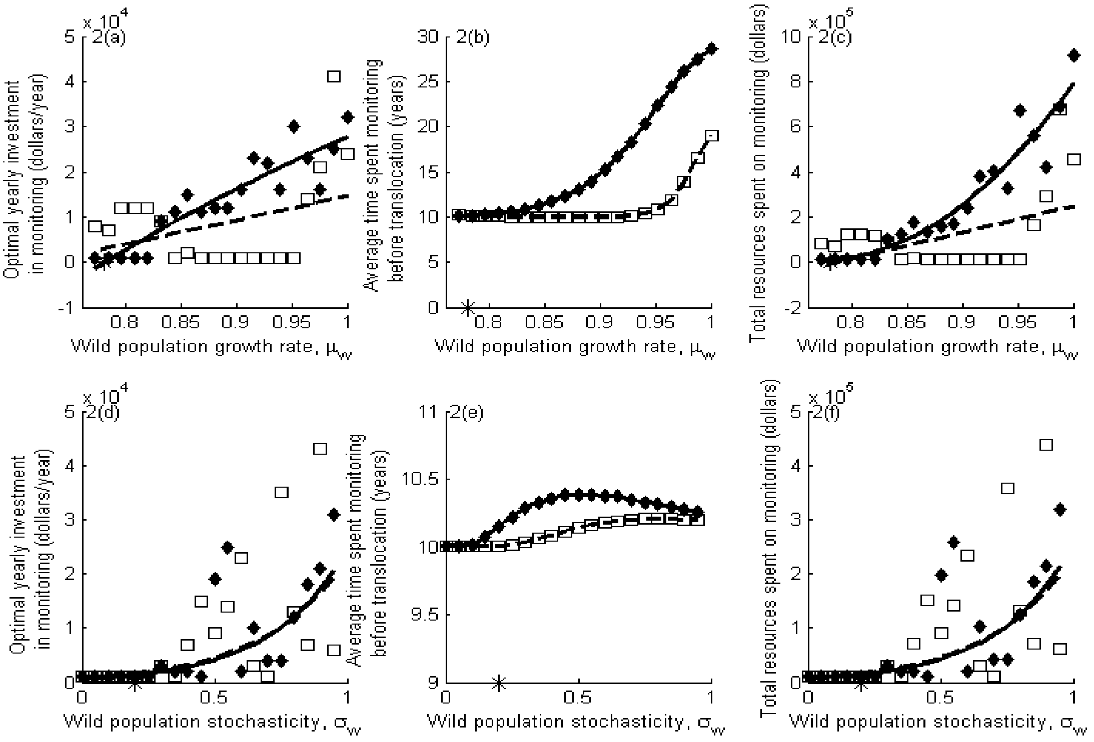
Table 3.1. Description of the ecological, management or economic parameters and the values considered when performing the analysis. Baseline values for the Christmas Island pipistrelle and the parameter values explored for sensitivity analysis were derived from Lumsden et al. (2007) and Beeton et al. (2010).

Results

We discovered that the translocation threshold does not influence the relationship between the key ecological variables and the optimal yearly investment in monitoring or average time spent monitoring before translocation (Table 3.2). The yearly optimal amount of money to invest in monitoring depended on all of the key ecological parameters: the wild and captive population growth rates, the environmental stochasticity associated with the wild and captive populations and the initial population size (Table 3.2, Fig. 3.2). However, the average number of years it took to determine when to translocate an animal was affected by the translocation threshold (IUCN stopping rule). This was represented by the average time spent monitoring before translocation having a lower bound of 10 years or staying approximately 10 years, as we increased the key ecological variables (Figs 3.2b, 3.2e, 3.2h, 3.2k & 3.2n).

Parameters	Mean of wild population growth rate, u_w	Mean of captive population growth rate, u_c	Environmental stochasticity of the wild population, σ_w	Environmental stochasticity of the captive population, σ_c	Size of population initially at t=0, N_0
Optimal yearly investment in monitoring, C*	↑	↓	↑	↑	↑
Average time to change from monitoring to translocation, t*	↑	–	–	–	↑
Total resources (time x money) spent monitoring	↑	↓	↑	↑	↑

Table 3.2. The change in optimal investment in monitoring, C* and average time spent monitoring before translocation, t* as we increase the key ecological parameters (↑ is increase, ↓ is decrease and − is no pattern or constant) when species is translocated at either the critically endangered (CR) or endangered (EN) threshold.



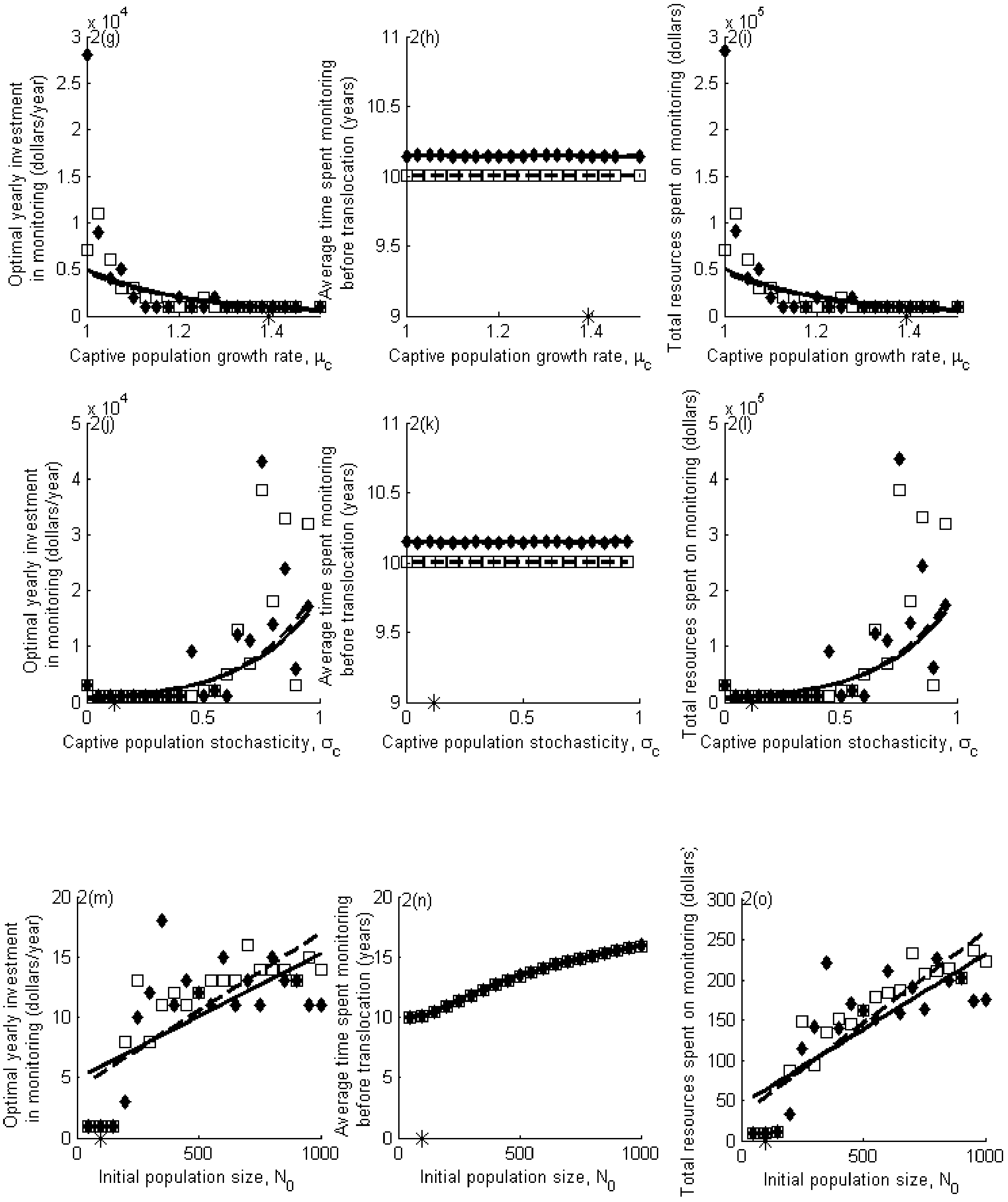


Figure 3.2. The influence of key ecological parameters on the optimal yearly investment in monitoring (money per year only), the average time spent monitoring before translocation (time only) and the total resources spent on monitoring (money x time) for two translocation thresholds: endangered (trend - dashed line, result - square) or critically endangered (trend - solid line, result – diamond). Asterisk is the baseline values for the Pipistrelle bats.

The total resources (time and money) spent on monitoring increased as the wild population growth rate, environmental stochasticity for the captive and wild populations and the initial population size increased (Figs 3.2c, 3.2f, 3.2l & 3.2o). The wild population growth rate and the initial population size, have a substantial impact on both the optimal yearly investment in monitoring (money per year) and the average time spent monitoring before translocation (time) (Figs 3.2a, 3.2b, 3.2m & 3.2n). In particular, the optimal yearly investment in monitoring or the average time spend monitoring before translocation increases linearly as we increase the wild population growth rate or initial population size (Figs 3.2a, 3.2b, 3.2m & 3.2n). In contrast, as the environmental stochasticity of the wild or captive population increased, the total resources spent (time and money) on monitoring were mainly driven by the optimal yearly investment in monitoring whereas the average time spent monitoring before translocation had a negligible impact (Figs 3.2d, 3.2e, 3.2j & 3.2k). For instance, the optimal yearly investment in monitoring only increases as the environmental stochasticity of the wild and captive population goes beyond a particular level (Figs 3.2d & 3.2j).

The only instance where the total resources, (time and money) spent on monitoring decreased exponentially was when the captive population growth rate increased (Fig. 3.2i). This decrease was mainly driven by the relationship between the captive population growth rate and the yearly investment in monitoring whereas the captive population growth rate did not influence the average time to switch from monitoring to translocation (Figs 3.2g & 3.2h).

Discussion

Knowing how much money and time to invest in monitoring is a pressing issue when we make decisions in conservation, especially when resources are limited. The majority of monitoring programs have been designed with the goal of increasing the power to detect a decline of a species. To achieve this goal, we can either increase the yearly sampling effort or the number of years spent monitoring (Barnes 2002; Dauwalter et al. 2009; Gibbs and Melvin 1997; Gibbs et al. 1998; Peterman 1990a; Taylor and Gerrodette 1993). If we spend money monitoring a species, fewer resources are available for management actions such as translocation that may prevent species extinction (McDonald-Madden et al. 2010a; McDonald-Madden et al. 2011). Thus, it is necessary to find the right balance between the resources spent on monitoring and translocation. To do this, we need to incorporate cost and benefits into our management actions including monitoring (Field et al. 2004; Field et al. 2007). Yet, management decisions associated with monitoring can be difficult as they can be situation- or species- specific, that depends on several key ecological variables (Maxwell and Jennings 2005; Woinarski et al. 2004). In this paper, we have conducted a sensitivity analysis to explore how these ecological variables affect our monitoring strategy (yearly monetary investment and the number of years spent monitoring) for a rapidly declining species before translocating it into captivity. By exploring these ecological variables, we can understand which ecological variable is important in our monitoring strategy. This will hopefully guide conservation managers to act in a timely manner to prevent species extinction.

One of the common ecological variables of interest is the wild population growth rate. The wild population growth rate has a substantial impact on the number of years spent monitoring and the yearly investment in monitoring. This result corroborates with studies about when to translocate a species from one location to another in the event of climate change (McDonald-Madden et al. 2011) and how much time to spend on monitoring to determine the amount of area to set aside for a Marine Protected Area (Gerber et al. 2005). As we increase the wild population growth rate, the population undergoes a slower decline. Since the population is declining slowly, there is an increase in the time of arrival at the translocation threshold; thereby prolonging the number of years spent monitoring before translocation. If a species is declining drastically (a growth rate below 0.8) (Fig. 3.2b), the timing of translocation has a lower bound of 10 years, restricted by the IUCN stopping rule. As we increase the wild population growth rate, it is harder to detect a population decline as the decline is mild. When this happens, there is a higher chance of a Type II error where we believe that there is no decline, when in fact there is one. Thus, we have to increase the optimal yearly investment in monitoring to combat the measurement error that causes Type II errors.

If the captive population growth rate is high, the population is less likely to go extinct. Thus, the yearly investment in monitoring decreases because there is less need to monitor the wild population accurately. Moreover, being late in starting translocation is less likely to have adverse consequences.

When there is high environmental stochasticity, there is a greater likelihood of conducting Type I (believing a decline is happening, when there is none) or Type II errors (believing that a decline is not happening, when there is a decline) (Jonzén et al. 2005; Strayer 1999; Woinarski et al. 2004). Even though environmental stochasticity can never be reduced, it is possible to reduce these errors by increasing the number of years spent on monitoring (time) or the yearly investment in monitoring (money) (Seavy and Reynolds 2007; Strayer 1999; Woinarski et al. 2004). Yet, we found that the number of years spent monitoring before translocation remains at approximately 10 years as we increase the environmental stochasticity of the captive and wild population. Again, this is driven by the IUCN rule. As we increase environmental stochasticity on the captive and wild population, there is an increase in Type II errors. To reduce Type II errors, we need to increase the optimal yearly investment in monitoring such that the measurement error in the data is minimised (Dauwalter et al. 2009).

The size of a population plays an important role in helping us decide about the amount of time or money to spend on monitoring. Usually, when we have a large population size, we spend less resource on monitoring due to an increase in our ability to detect the decline in a population (Barnes 2002; Forcada 2000; Taylor and Gerrodette 1993). Contrary to this, we found that as we increase the initial population size (larger population size), the total amount of resources (time and money) spent on monitoring increases. This was driven both by an increase in the average number of years spent monitoring before translocation and the yearly investment in monitoring. A large population size would naturally increase the probability of species survival in a captive breeding program as more animals are translocated when it reaches the translocation threshold. This allows us to delay the average translocation timing as species are less likely to go extinct when the population size is large. In contrast, losing a few animals when the population size is small would be sufficient to stop monitoring and trigger the emergency response of translocation as there is a higher chance of going extinct due to genetic inbreeding, disease, loss of fitness and others (Cunningham 1996; Fraser 2008). Statistically, it seems impossible that a huge population size requires a higher effort (an increase in yearly investment) in monitoring. However, according to Gerrodette (1987), as the size of population increases, the rate of decline will decrease, reducing the power to detect a population decline. The power relationship between the variance and abundance increases the amount of investment in monitoring to detect a population decline (Gerrodette 1987). Our study extends this by examining the influence of other parameters including population growth rates and uncertainty in these growth rates on the optimal investment in monitoring and the timing of translocation. Another reason is that the result is probably an artefact of the model assumption where observation error is lognormally distributed. Therefore, the variance will increase strongly with the mean, causing the declines harder to quantify as the population size increases, thus, requiring larger investment in monitoring to detect a population decline. It is possible in future studies to change this observation error into poisson distribution to reduce the effect of the mean-variance scaling.

LIMITATIONS AND FUTURE WORK

We assumed that there was little interaction between the ecological variables when we conducted a sensitivity analysis. Although not the focus of this study, some preliminary simulations showed that the interaction between the ecological variables can have a substantial impact on the optimal monitoring strategy (either yearly investment or time spent monitoring before translocation). For example, we can increase the wild and captive population growth rates simultaneously and explore its impact on the optimal monitoring strategy. It is well known that interactions between ecological variables can affect the optimal solution of a problem (Walters and Hilborn 1978). However, the complexity of this model prevents us from characterising these interactions fully. Yet, it remains an important extension of the current study to explore potential interactions between various ecological variables and the optimal monitoring strategy. Future studies could simplify the current model and explore the interactions between the key ecological variables identified in this study or the interactions between the optimal monitoring strategies (compare the relative size of optimal yearly investment in monitoring and the average time to spend monitoring before translocation).

We assumed that the observation error is lognormal distributed. Thus, the variance will increase with mean, causing the population declines harder to quantify as we increase the population size. An alternative to this is to use a Poisson distribution for the observation error, which has a weaker mean-variance scaling.

CONSERVATION IMPLICATIONS AND MANGEMENT RECOMMENDATIONS

Stochasticity often drives monitoring effort (Jonzén et al. 2005; Woinarski et al. 2004). A lot of time and money are spent on monitoring to obtain more samples or reduce the variability of a sample, especially in a highly stochastic environment, in order to obtain sufficient power to detect a decline (Woinarski et al. 2004). However, increasing the power to detect a decline is costly (Taylor and Gerrodette 1993). For a species that is declining drastically, time is of critical importance. The cost of implementing a translocation strategy too late has already resulted in the first mammal extinction in 50 years in Australia, the Christmas Island Pipistrelle. Thus, it is important for conservation managers to weigh the cost and risk associated with translocation against the cost of species extinction (Fraser 2008) when making translocation decisions.

Translocation of a species is often conducted when the species of concern has already reached a critically endangered state. Interestingly, we have discovered that even when we change the translocation threshold to endangered, it does not change the average timing to cease monitoring and conduct translocation. This is because of the IUCN rule of listing a species as endangered or critically endangered for the longer of the 10 years or three generations. If a species is declining drastically, e.g. the Christmas Island Pipistrelle bat, it can take less than 10 years to observe a decline of 50% (EN) or 80% (CR). Thus, it remains an important issue for future research to explore the optimal timing to stop monitoring before translocation for different IUCN categories. This is critical as any substantial delay in translocation can easily result in species extinction.

CONCLUSION

Deciding what type of ecological variables influence our monitoring effort is an important area of research. Without exploring this using sensitivity analysis, we will never know why certain ecological variables influence our optimal monitoring strategy. This study helps ecologists understand how certain ecological variables affect our optimal monitoring strategy. We have shown that it is important to weigh the benefit of monitoring through an increase in monitoring effort (time or money), against the cost of monitoring (that is species extinction) when making decisions about translocation. This may have implications especially when we are dealing with a species that is declining drastically, where time is of critical importance, because a slight delay can lead to the disappearance of a species.

Chapter four – Determining when to change course in management actions

Introduction

Time is a valuable resource in a world where every moment counts, and nothing, not even money, can buy time. In conservation biology, acting in a timely fashion plays a vital role in ensuring the success of recovery programs. If we lose time managing a threatened species, it can easily result in its extinction (Chades et al. 2008; Martin et al. 2012). For instance, we can lose a species if we miss the timing of translocation from the wild into captive breeding (Martin et al. 2012). Protecting particular habitat at a critical time can secure the recovery of a species (Grantham et al. 2009). Timely management is also important for the management of invasive species. Given limited resources, it is important to know when different management actions are required to maximise their success. (Baxter and Possingham 2011; Chadès et al. 2011; Regan et al. 2006). When dealing with species that are difficult to detect (cryptic species), it is also important to decide how to allocate time between managing, surveying and taking no action (Chadès et al. 2011).

Changing management actions at a suitable time is vital, especially when the current management action is insufficient to arrest the decline of a species. Time spent on the current action could be allocated to another action, and there is a growing interest in determining how to make this trade-off (Chades et al. 2008; McDonald-Madden et al. 2011; Wilson et al. 2007). Determining this trade-off requires placing the problem in a decision theory framework to account for the costs and benefits associated with different actions (Caughlan and Oakley 2001; Field et al. 2004; Peterman 2004; Possingham and Shea 1999; Possingham et al. 2001). This includes deciding what action to take for every time step (Baxter and Possingham 2011; McDonald-Madden et al. 2010b; Rout et al. 2007), deciding how much time to allocate to each management action and finally, to monitor the effectiveness of the management actions (Moore and McCarthy 2010; Runge et al. 2011). In the past, finding this optimal time has been management action or situation specific, with some providing a complex dynamic solution to the problem (Chades et al. 2008; McDonald-Madden et al. 2011). Yet, general solutions that are applicable to a wide variety of situations are scarce.

A good theoretical model is simple with few parameters but general enough that it is applicable to a wide variety of situations (Ginzburg and Jensen 2004). When a model has few parameters, it can be solved relatively easily where we can obtain a closed form analytical solution. For instance, the Lotka-Voltera Predator and Prey model has an analytical solution with relatively few parameters; yet, it is useful in a range of ecological situations where there are strong interactions between predator and prey (Ginzburg and Colyvan 2004). Whereas, a complex model that has a lot of parameters is often too complicated to be solved analytically, thus, we can only obtain numerical solutions and infer what is happening ecologically through the use of simulation. Moreover, simple models can sometimes provide a robust predication of an ecological phenomena with results that can be analysed easily, compared to complex models with results that cannot be easily understood (Scheffer and Beets 1994). Recently, several researchers have started to work on a general theoretical model about how to allocate resources optimally among different management actions to save a species (Chadès et al. 2011; McDonald-Madden et al. 2010a). This includes how to allocate resources among different actions (McCarthy et al. 2010), deciding how to design nature reserves (McCarthy et al. 2005) in terms of having several small or single large reserve system (McCarthy et al. 2011) or determining the level of investment required to conserve a species (McCarthy et al. 2008). However, the general question of when to cease a new management action, given that we already have a tried and tested existing action remains unanswered. The motivation to trial a new action is because our existing action is not performing well and may not achieve our goal. If we conduct a new action without the option of stopping, we run the risk of wasting valuable resources conducting an action that may not be working. On the other hand, if we stop too early, we may not obtain sufficient information via monitoring to understand whether the new action is working.

We developed a general theory to decide when to trial a new management action, and when to cease the trial. We assumed that a species is declining due to a threat that might be eased by one or more management strategies. We focused on answering the question about whether we should abandon our current management strategy and try something new, and if so for how long. We illustrate the approach for the recently extinct Christmas Island pipistrelle bat (*Pipistrelle murrayi*) where captive breeding was the recommended new management action prior to its extinction. This approach provides conservation managers with a valuable tool to make decisions about how long they should trial an untried management strategy when the existing action is unsuccessful.

Problem definition

In this section, we outline the broad assumptions of our problem, before giving details of the population model and the management objective. Then, we describe how to reduce the uncertainty about the population growth rate through monitoring as we conduct new management action. We explain how to find the optimal time to cease a new management action and revert to an existing management action. Finally, we discuss the results obtained and apply the approach to the Christmas Island pipistrelle.

In this hypothetical scenario, a manager is concerned with the persistence of a threatened species and they can perform two mutually exclusive actions: an existing action that we know how well it works and a new action when we do not know its influence on a population (Figure 4.1). Management actions could include do nothing, monitor and actions such as controlling a predator, parasite or competitor, translocating a species, restoring habitat, reducing the effect of climate change, or a combination of these actions.

Assume that we have been managing the population for several years using a tried and tested management strategy (existing action), which delivers a fixed population growth rate (Figure 4.1). The population growth rate under the new management strategy is uncertain, so it may not be better than the existing strategy. Our task is to decide whether we should try a new management action, and if so, for how long, given the goal is to maximise the chance of the population reaching a target population size, *A*. The question for our study is, when should the new strategy be trialled, and if trialled, when should it be abandoned if it is not performing as hoped.

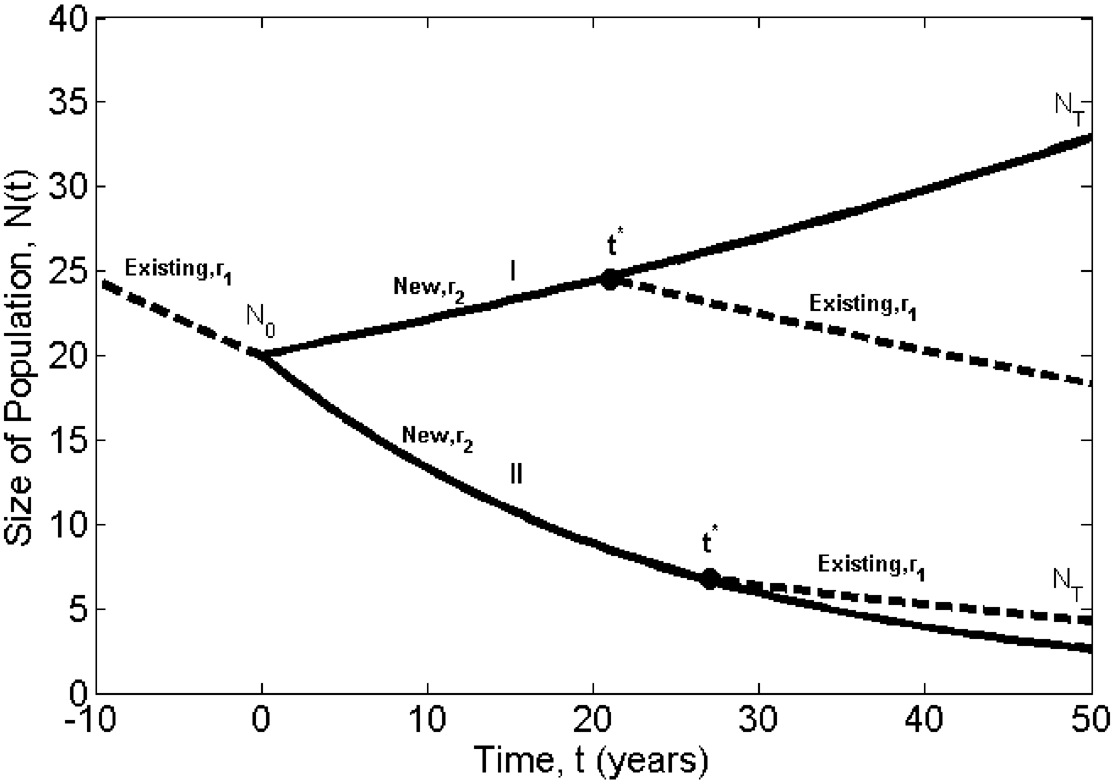


Figure 4.1. **Conceptual model for changing management actions for a population that is I) increasing or II) declining when conducting new management actions for species recovery.** The size of a population when new management action is conducted is shown using a solid line; the size of the population when an existing management action is conducted is shown using a dash line and the optimal switching time is shown using a dotted symbol (N_0 is the initial population size, N_T is the population size at the end of management timeframe and t^* is the optimal switching time).

Population Model

Depending on which management strategy we are using, we assumed an exponential growth rate at a constant rate of r_1 or r_2. The population declines if the population growth rate is less than zero and increases if it is greater than zero. When we are trialling the new management action, the population grows at an unknown exponential growth rate of r_2. Thus, the number of animals, N_s when the new management ceases at time, *t* is,

$$N_S = N_0 e^{r_2 t}, \qquad (4.1)$$

where N_0 is the current population size when we may choose to change from the existing to the new management action. In practice, there is never a perfect estimate of the population growth rate, r_2 when we are trialling the new management action (Gerber et al. 2005). Thus, r_2 is an uncertain estimate of the true growth rate, u_2.

There are limited resources (time or money) available to manage a population for *T* years, thus, the time available when we revert to the existing management action is *T*-*t*. We assume that we can pick a time, *t*, at which there is an immediate switch from the new to the existing management action with little time delay or loss of individuals. Once we have decided to revert to the existing management action and stop the new management action, the population can either grow at a stable population growth rate or increase at an exponential rate, r_1, which is known, so that the population size at the final time, *T* is,

$$N_T = N_0 e^{r_2 t} e^{r_1 (T-t)}. \qquad (4.2)$$

If the population growth rate (r_1 or r_2) is positive, the population is growing, otherwise, it is declining.

Benefit of monitoring

When dealing with species recovery, monitoring improves the estimate of the abundance or trend of a population , which can lead to better management outcomes (Gerber et al. 2005). Assume that we obtain a sample of the growth rate each year of the new management action, r_2 that is drawn from a normal distribution with a mean of μ_2 and a standard deviation of σ. We assumed a deterministic population dynamic, with an uncertain growth rate. In our case, we are uncertain about the impact of the new management action on the population growth rate, but as we monitor, the increase in knowledge produces better estimates of r_2, reflected in a smaller standard deviation (Halpern et al. 2006). This is represented as a reduction in the standard deviation of each annual sample of r_2 that we monitor, such that $\sigma = s/\sqrt{t}$, where s is the initial standard deviation of the growth rate (Figure 4.2). Thus, the probability of obtaining a growth rate r_2 as we trial the new action for t years is,

$$p(r_2 \mid t) = \frac{1}{t\sqrt{2\pi s^2}} e^{\frac{-(r_2-\mu_2)^2}{2s^2/t}} . \qquad (4.3)$$

In normal circumstances, r_2 is a true growth rate. However, in practice there is never a perfect estimate of the population growth rate, r_2 when we are trialling the new management action (Gerber et al. 2005). Thus, r_2 is the uncertain estimate of the true growth rate, u_2 when we trial the new management action.

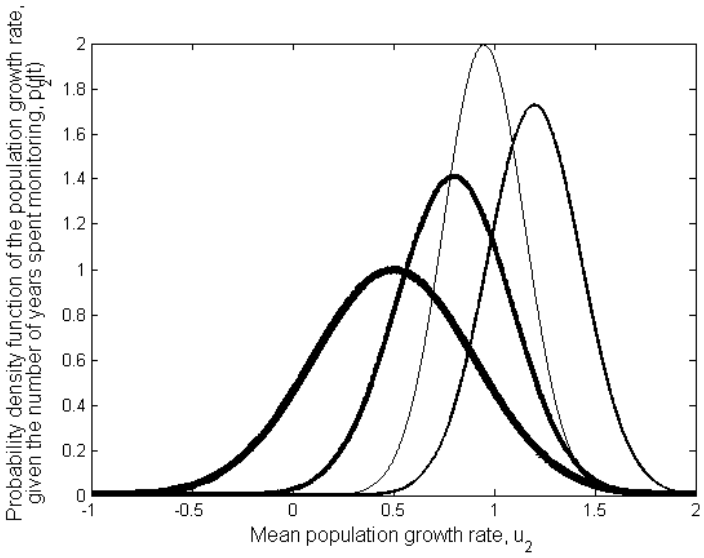


Figure 4.2. Probability density function of the estimated population growth rate, r_2 given the number of years spent monitoring, $p(r_2|t^*)$ for various true population growth rate, μ_2 (darkest to lightest: decrease in standard error, σ as the amount of time spent in monitoring increases)

Management Objective

The mathematical problem definition is to find the optimal switching time, t^* that maximises the chance that the population size is greater than or equal to a target amount, A,

$$\begin{aligned} &\text{maximise } Pr(N_T \geq A) \\ &\text{where } t \in \{0, T\}, \\ &\text{subject to } N_T = N_0 e^{r_2 t} e^{r_1 (T-t)}. \end{aligned} \tag{4.4}$$

Finding the optimal switching time

Next, we solved our problem of finding the best time to stop or whether to even start a new management action, by accounting for uncertainties associated with the population growth rate of the new action, r_2 (Fig. 4.2). To do this, we linearised eqn 4.2 by taking logs, leading to $logN_T = logN_0 + r_2 t + r_1(T-t)$. We satisfied the management goal by rearranging the previous equation to obtain the chance of r_2 being greater or equal to a critical threshold, r_c for a particular switching time,

$$\begin{aligned} \max Pr(N_T \geq A) &= \Pr(\log(N_0) + r_2 t + r_1(T-t) \geq \log A) \\ &= \Pr(r_2 \geq r_c) = Pr\left(r_2 \geq \frac{\log(A/N_0) - r_1(T-t)}{t} \right). \end{aligned} \tag{4.5}$$

Given the uncertainty defined by the probability density function $p(r_2 \mid t)$ (eqn 4.3), we find the chance of $r_2 \geq r_c$ by obtaining the integral of $p(r_2 \mid t)$ between r_2 and infinity; that is equal to,

$$Y = Pr\left(r_2 \geq r_c\right) = \frac{1}{2}\left(Erfc\left[\frac{log\left(A/N_0\right) + r_1(t-T) - t\mu_2}{\sqrt{2}\sigma\sqrt{t}} \right]\right), \tag{4.6}$$

where Erfc[x] is the complementary error function.

The optimal switching time, t^*, that maximises the chance of the population reaching A is obtained by taking the derivative of Y, setting it to zero, $dY/dt = 0$ and solving for t^*. This is the internal optima, so we must also look at the values of Y at the boundaries at t=0 and $t=T$. We find that the optimal switching time is (Fig. 4.1),

$$t^* = \begin{cases} \dfrac{\log\left(A/N_0\right) - r_1 T}{r_1 - \mu_2} & ,\text{if } r_1 > \mu_2 \text{ and } N_0 e^{r_1 T} < A, \\ T & ,\text{if } r_1 \le \mu_2 \text{ and } N_0 e^{r_1 T} < A, \\ 0 & ,\text{if } N_0 e^{r_1 T} \ge A. \end{cases} \tag{4.7}$$

Our result has a reasonably straightforward interpretation. When $N_0 e^{r_1 T} > A$, we are 100% certain that we will reach our goal of achieving A without changing the management strategy. In this instance, $t^*=0$ and we should continue our existing action and never attempt to start the new management action. The problem is more interesting if we do not expect to meet the goal from conducting the existing management action, where $N_0 e^{r_1 T} < A$. If we cannot meet the management goal and the population growth rate when we conduct our existing action (certain) is greater than the observed population growth rate when we trial our new action (uncertain) where $r_1 > \mu_2$, we continue monitoring the new management action, hoping that the estimate of the population growth rate would increase (increase u_2), such that we can obtain the goal of achieving A. If we set a higher management goal (increase A), the amount of time that we spend on the new action before reverting to an existing action increased because we spend more time monitoring, hoping that our new action that is uncertain can deliver a better outcome than expected (Fig. 4.3a). Even when we are clear that it can deliver a better outcome, we continue with the new action and monitor to check whether the outcome is sustained. The optimal amount of time to spend monitoring the new action is independent of the standard deviation of the growth rate as we trial the new action but depends on the management goal, the population growth rate as we conduct new or existing action and the management timeframe. If the difference between the population growth rates as we conduct an existing or new action increased ($r_1 - \mu_2$ increased), we would cease trialling our new action earlier and revert to the existing action (Fig. 4.3b). Yet, if $r_1 < \mu_2$, we continue with our new action beyond the final management timeframe such that $t^*=T$ as we know that the existing action with a known r_1 can never reach our goal.

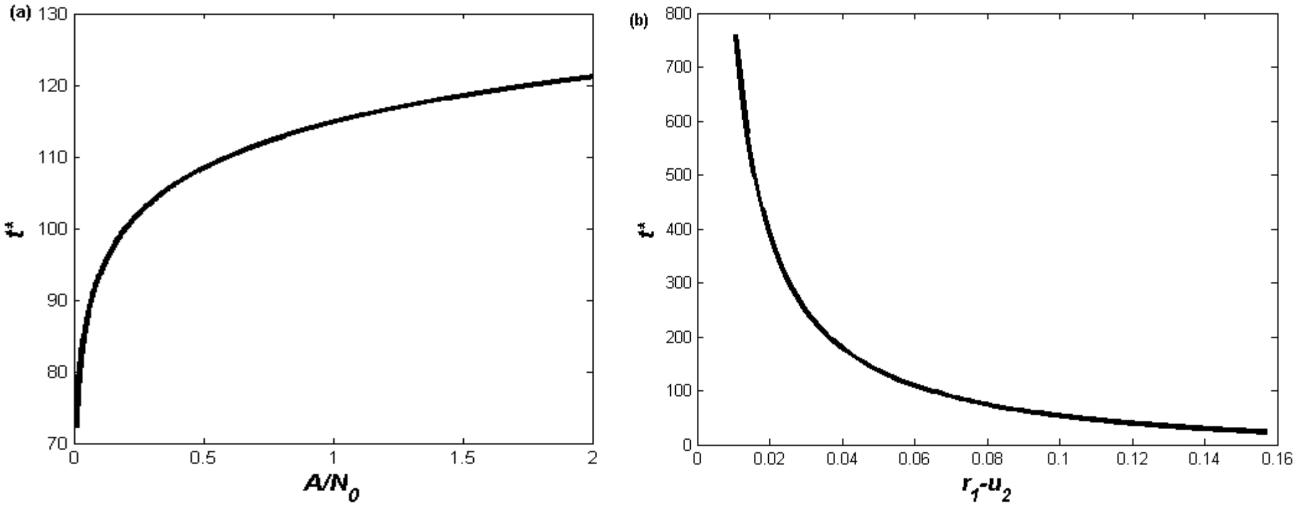


Figure 4.3. Optimal time spent on new management action before reverting to existing management action as a function of the (a) the management goal, given the initial population size, A/N_0 and (b) difference between the population growth rates of existing versus new management actions (r_1-μ_2) using the parameters in the pipistrelle bat as a baseline.

Case study

Christmas Island pipistrelle bat

As discussed in the previous chapter, the Christmas Island pipistrelle bat (*Pipistrelle murrayi*) was the only insectivorous bat endemic to Christmas Island, an external territory of Australia. Once common throughout the entire island, consistent monitoring from 1994 onwards has revealed that the bat was in rapid decline (Lumsden et al. 2007; Tidemann 1985). By 2005, 80% of the 1994 population had disappeared and 99% by 2008 (Beeton et al. 2010; Lumsden et al. 2007). The exact reason behind this decline remains unknown but was probably a result of complex interacting cascade of threats including the invasion of bats habitat by yellow crazy ants' (Anoplolepis gracilipe) (Lumsden et al. 2007; Martin et al. 2012). Since the detection of the decline, several threat mitigating actions were conducted such as installing bat boxes in core roosting areas and baiting to eradicate the invasive yellow crazy ants (Lumsden et al. 2007). By January 2009, fewer than 20 individuals remained (Lumsden 2009).

In 2006, several scientists and professional bodies advocated for a captive breeding program. Yet, it was only in July 2009 that the Australian government initiated an emergency response plan to capture the last of these bats to start a captive breeding program (Beeton et al. 2010). This rescue attempt failed and only one single pipistrelle was detected on the bat flyway and none was caught (Garrett 2009).

Leading experts agreed that raising the pipistrelle bats in captivity was feasible (Beeton et al. 2010), and a captive breeding program might have avoided the bat's extinction (Martin et al. 2012). Translocation stress and genetic inbreeding would impact how well the pipistrelle bat coped in a captive breeding environment (Fraser 2008; Teixeira et al. 2007). . If we could retrace our steps to year 2006, the approach presented in this paper might determine whether we should have conducted captive breeding and if so, for how long, given that the final aspiration is to have a viable population in the wild (Figure 4.4). The aspiration is that releasing the bats back into the wild following captive breeding, and elimination of the threats in the wild would result in a self-sustaining population. Another reason for releasing the bats back into the wild is when captive breeding is not successful enough to lead to a sufficient increase in the population growth rate or when the cost of maintaining a captive breeding facility is prohibitive (millions of dollars) in the long run (Beeton et al. 2010). Since we are uncertain about how well the Pipistrelle copes in a captive breeding environment, we conduct monitoring to understand the effectiveness of the captive breeding program or to ascertain when to stop captive breeding.

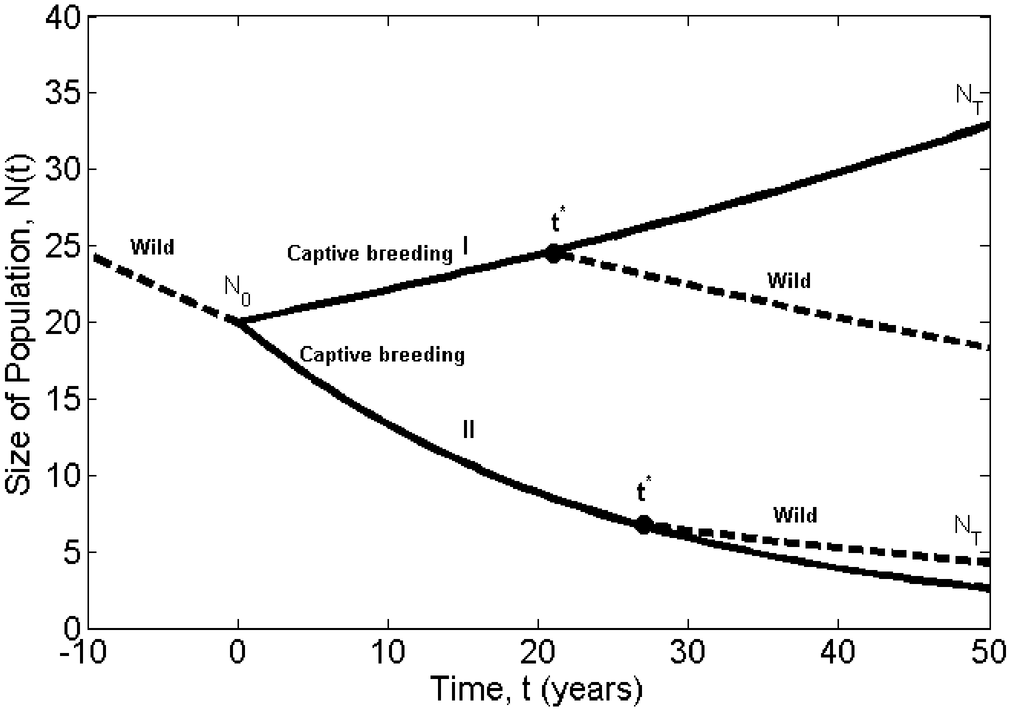


Figure 4.4 Conceptual model illustrating the change of management actions for the Christmas Island pipistrelle bat. Due to uncertainty, the new captive breeding program can cause the population to either I) increase or II) decline before releasing the population back into the wild where it is known that it will decline. The size of a population when captive breeding is conducted is shown using a solid line; the size of population when we release the species back into the wild is

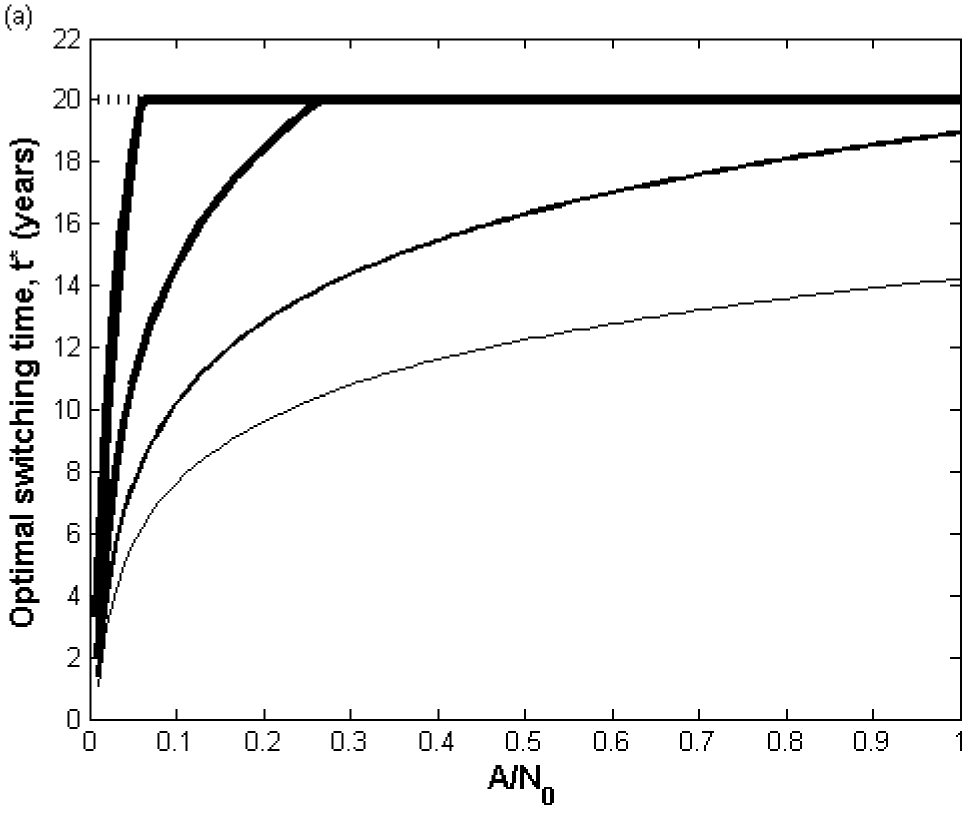
shown using a dash line and the optimal switching time is shown using a dotted symbol (N_0 is the initial population size, N_T is the population size at the end of management timeframe and t^* is the optimal switching time).

We estimated the parameters for the captive breeding and retaining a wild population of the Christmas Island pipistrelle bats from the literature (Table 4.1). Using these parameters as a baseline, we perform sensitivity analysis to ascertain the influence of these parameters on the optimal time to stop the new captive breeding program and revert to managing the species in the wild.

Parameter	**Symbol**	**Values**	**References**
Mean population growth rate (captive breeding)	μ_2	Log(1.39)=0.33	(Beeton et al. 2010)
Population growth rate (releasing into wild)	r_1	Log(0.78)= -0.25	(Lumsden et al. 2007)
Initial Population size	N_0	20% of 1994 population	(Lumsden et al. 2007)
Management timeframe	T	20 years	-

Table 4.1 Parameters for managing the pipistrelle bat that is subjected to captive breeding.

In the case of the pipistrelle bat, captive breeding was always desirable and we may trial this new management action for the full management timeframe of 20 years as long as the goal was to achieve a population size greater than 2 animals (Figure 4.5). If captive breeding was less effective (with μ_2 less than -0.25 such that the existing action growth rate is greater than the new action growth rate, $r_1 > \mu_2$) in achieving the management goal, it is better to release the bats back into the wild (existing management action) after spending a few years in captivity (Figure 4.5a). For example, a management goal of $A/N_0 = 0.2$ and a population growth rate of log(0.65) when the species is in captivity would require the bats to spend 13 years in captivity before releasing the bats back into the wild for the remaining 7 years (Figure 4.5a). Another reason to release the pipistrelle back into the wild after spending a few years in captivity is would occur if the conditions in the wild improved such that the wild population growth rate increases beyond $r_1 > 0.33$ or if the management goal is greater than 1000 of the initial population size (Figure 4.5b).


(a)
Optimal switching time, t* (years)
0
2
4
6
8
10
12
14
16
18
20
22
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
A/N_0

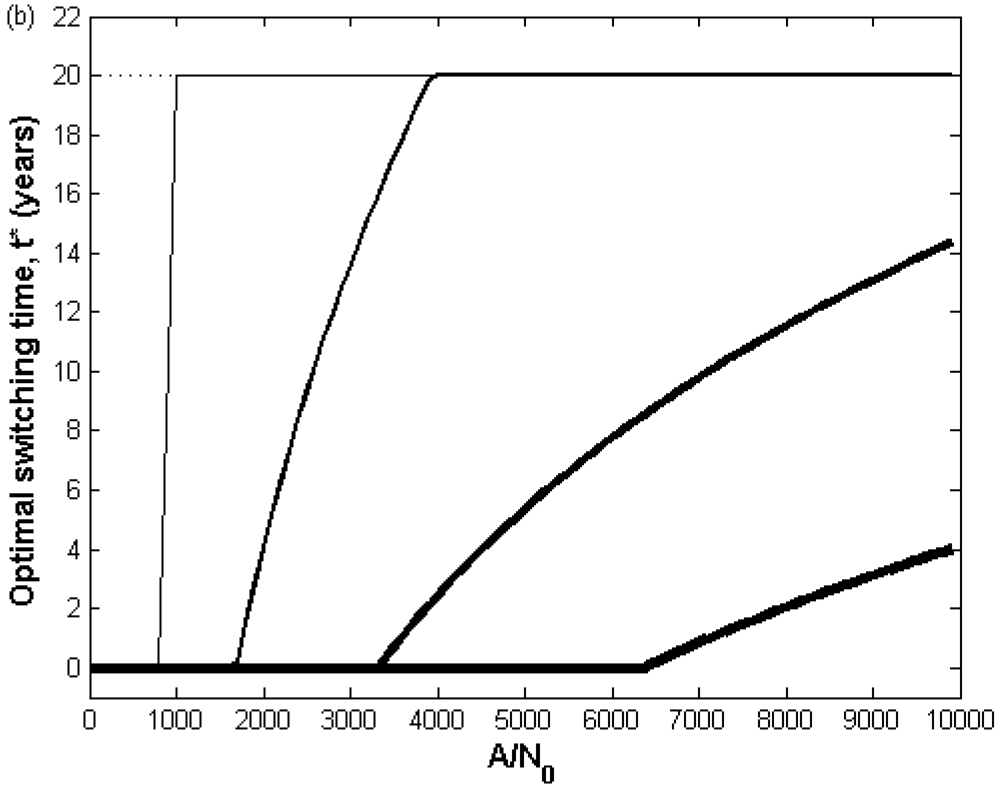

(b)
Optimal switching time, t* (years)
0
2
4
6
8
10
12
14
16
18
20
22
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
A/N_0

Figure 4.5. The optimal switching time from captive breeding to releasing a species back into the wild as the ratio A/N_0 increases and as we change the population growth rate when (a) the species is in captivity (u_2 changes from lightest to darkest line: log(0.55), log(0.6), log(0.65), log(0.7), log(1.39)); (b) when we release it back to the wild (r_1 changes from lightest to darkest line: log(0.78), log(1.4), log(1.45), log(1.5),log(1.55)) **.** Dashed line indicates the baseline parameters of the Christmas Island pipistrelle bat.

Discussion

Deciding when to cease a new management action is central to the survival of a species, especially when resources are limited (Martin et al. 2012; Possingham and Shea 1999; Possingham et al. 2012). Several researchers have attempted to obtain a numerical solution to the problem of how to allocate resources among actions resulting in complex solutions that require knowledge of the state of the system and the cost of each management action (Baxter and Possingham 2011; McDonald-Madden et al. 2011; Rout et al. 2009b). Yet, a general solution about how long we should trial and monitor a new management action, when we are certain about the impact of the existing management action, remains unanswered. We have derived an analytical solution to help conservation managers decide when to stop a new management action that requires monitoring before reverting to an existing and well-known action. The main benefit of obtaining an analytical solution compared to a numerical one is the exact form of the solution can be obtained and interpreted.

A meaningful and successful management program hinges on its ability to achieve the management goal (Legg and Nagy 2006; McCarthy and Possingham 2007; McDonald-Madden et al. 2010a; Nichols and Williams 2006; Yoccoz et al. 2001). Yet, it remains unclear how long we should conduct and monitor our new actions as our management goal changes. Our study shows that if we had a high target population size (high A), we should trial the new actions for several years before reverting to an existing action. The main problem was we are uncertain about how well our new management action is performing. Therefore, we spend time conducting and monitoring our new action, hoping that the new action can achieve our goal. However, even if the new action is ineffective in reaching our goal, by conventional wisdom we still continue our new action until we realise that our new action may never reach our goal that we change to a different action (revert to an existing action). For the Pipistrelle bat, abandoning the existing management action of managing the bats in the wild in favour of a captive breeding program was already fraught with political and economic considerations due to potential high economic cost of the captive breeding program and the potential embarrassment of losing an Australian mammal species (Garrett 2009; Martin et al. 2012). We can imagine the difficulty in deciding whether to cease a new captive breeding program that is no longer working especially when millions of dollars were already spent. There are many examples in conservation, where we have prolonged a management action beyond a reasonable timeframe such as monitoring that has little impact in saving biodiversity (Knight et al. 2006; Knight et al. 2010). This is evidenced by a recent call from Baillie et al. (2008) to increase our monitoring effort for global biodiversity without managing threats.

The growth rates of a population while conducting new (μ_2) or existing management action (r_1) plays a significant role in deciding when to change management actions. Similarly, studies have found that the growth rates of a population can influence the optimal timing of when to translocate a species from one location to another in the face of climate change (McDonald-Madden et al. 2011) or the extent of monitoring needed to determine the optimal reserve size on a Marine Protected Area (Gerber et al. 2005). Our study extends these results by showing how these growth rates interact with the management goal of achieving a certain target population size, A. For the pipistrelle bat, since captive breeding was highly effective ($u_2>r_1$) in achieving the management goal, it would have been desirable to place the species in captivity regardless of the management goal. Yet, placing this species in captivity forever can be expensive as it might have cost approximately half a million dollars per year to maintain the pipistrelle bats in captivity (Beeton et al. 2010). In the long run, captive breeding may not contribute towards preserving biodiversity as the genetic diversity and fitness of a population can decrease dramatically as we prolong captive breeding of a species (Griffiths and Pavajeau 2008; Snyder et al. 1996). For the Christmas Island pipistrelle, for the captive breeding program to be effective in ensuring an eventual sustainable wild population, the situation in the wild would need to be diagnosed and improved. This may have been impossible for the pipistrelle as the exact nature of the threats remains unknown and thus not readily managed. The situation becomes more interesting when captive breeding is highly ineffective such that $u_2 < r_1$. In this instance, the management goal plays an important role in deciding how long the pipistrelle bat should spend in captivity. A high target population size would prolong the timing of its release back into the wild, whereas a low target population size would shorten this timing. It is surprising that we should even consider spending any time in conducting an ineffective captive breeding program. This is because of our false belief that monitoring an ineffective captive breeding program is a better management alternative compared to releasing the bats back into the wild.

Normally, when we increase the amount of time spent monitoring, the measurement error would decrease. In turn, this would help us estimate the abundance or trend of a population accurately (Campbell et al. 2004; Marques et al. 2001; Rönnegård et al. 2008). Interestingly, we found that this measurement error does not influence the optimal timing of when we change our actions from the new action to an existing action. In our model, the measurement error, σ, drops out of the equation when we solve for the optimal time to spend monitoring the new action (eqn 4.9).

Several areas of improvement can be made to our model in the future. Density dependence occurs as a result of resource constraints, limiting the growth rate of a population (Turchin 2001). When managing for the recovery of the species in our model, we assume that density dependence has little influence on the population. In certain instances, density dependence has negligible impact on a population that is declining due to catastrophe or environmental influence, such as pollution (Edwards 2011). Additionally, some management action such as translocation can temporarily increase the amount of resources, for instance the availability of food or habitat, can reduce the effect of density dependence (Lawler and Olden 2011). Yet, density dependence can play a vital role especially in this resource dependent world where there is a lack of time, money and space available. This is especially prevalent in situations where habitat loss or fragmentation or competition with invasive species limits the ability of a population to grow incessantly (Sibly and Hone 2002). Therefore, incorporating density dependence is an important extension to this study especially when habitat loss and defragmentation is considered a major threat for species that are facing extinction (Lawler et al. 2002).

In this model, we assume that there is little uncertainty associated with our baseline existing management actions, thus assuming r_1 is known. Yet, the impact of implementing existing management actions can be somewhat uncertain due to a range of social, economic or political constraints that affect the successful implementation of management actions (Knight et al. 2006). However, there exist certain situations where these uncertainties are negligible. For instance, large scale restorations have such a huge impact that there is a high probability that the size of a population increases and the uncertainty associated with such management actions are negligible (Young 2000). Another possibility is when intense monitoring of an existing action has reduced the uncertainty associated with such an action such that it becomes negligible. Nevertheless, there remains a range of management actions whereby the consequences of such actions are uncertain, and this is an important extension in future studies. For instance, the implication of conservation actions such as translocation from one place to another is relatively uncertain in a changing climate (Hoegh-Guldberg et al. 2008; McDonald-Madden et al. 2011).

The performance measurement used in this model, $Pr\ (N_T>A)$ can be modified. For instance, instead of using the population size as an indicator of achieving the management objective, it is possible to use the probability of species survival or extinction. In fact, the probability of species extinction can be estimated using the mean time to extinction using diffusion theory (Grimm and Wissel 2004). Another alternative to estimate the probability of extinction is to use expected minimum population size (McCarthy and Thompson 2001). However, estimating this is far from simple as it is common to measure the abundance of a population when monitoring a population.

Conservation managers are already overstretched with the number of species at risk of extinction (Butchart et al. 2010; Chapin Iii et al. 2000; Dirzo and Raven 2003; Pereira et al. 2010; Possingham and Wilson 2005). In addition, they may not be equipped with the resources or skills necessary for undertaking complex mathematical algorithms such as Stochastic Dynamic Programming (SDP) so simple rules of thumb such as the solution provided in this study could be a good approximation to solutions found using SDP (Regan et al. 2006). Moreover, the curse of dimensionality when analysing data in high-dimensional spaces prevent us from obtaining a solution that is tractable as the states or actions get larger (Bellman and Dreyfus 1962). We have devised a general rule of thumb to assist conservation managers in their decision on when to stop a new management action regardless of the type of management action. This is important, especially when there are already limited resources in the world and there is a need for a simple tool that facilitates implementation.

The target population size, the management timeframe and the growth rates when conducting new or existing management actions all contribute to the decision of when to stop new management action before reverting to an existing management action. We have provided a simple general rule of thumb on when to stop a new management action to help conservation manager act in a timely manner. This is valuable in a world where we are slowly running out of time to save a wide range of species that are spiralling towards extinction.

Chapter five – Deciding when to abandon existing for new actions

Introduction

Uncertainty is common in population management, as managers struggle with a variety of unknowns when managing a threatened or invasive species (Regan et al. 2002). Some of these uncertainties such as natural variation cannot be reduced, while others such as measurement error can be reduced through monitoring. Thus, methods that help determine the best way to allocate resources to conserve biodiversity in the face of measurement error are required (McCarthy et al. 2010; Salomon et al. 2001).

Management resources must be allocated effectively, regardless of whether the goal is to eliminate an invasive species or save a species from extinction. Invasive species and endangered species management both involve deciding which species to manage (Joseph et al. 2009) and what resources to spend on different management actions (McCarthy et al. 2008; Regan et al. 2006; Rout et al. 2009a) . While conservation managers often have to manage invasive and threatened species concurrently, few studies have attempted to find a general solution for the management of both. Exceptions include deciding how much to invest in monitoring and management across a spatial network (Chadès et al. 2011) and deciding how much effort to spend on monitoring alone (Thompson et al. 2012). Given limited resources worldwide, it is prudent that resource allocation among invasive and threatened species management can be assessed within the same framework.

Time is a valuable resource. Knowing how much time to spend on an action is an important question in the field of conservation. Failure to instigate new actions in a timely manner can spell the difference between species persistence and extinction (Black et al. 2011; Martin et al. 2012). Time spent on a particular action could be spent on a different action or elsewhere to save another species (Bottrill et al. 2008, 2009). Examples of when to change action include deciding on when to translocate a species in the event of climate change (McDonald-Madden et al. 2011), deciding when to stop monitoring an invasive species (Regan et al. 2006), or determining how much time to spend on monitoring and management efforts for cryptic species (Chades et al. 2008). Yet, most of these studies are only applicable to a particular situation. In chapter 4, we developed a general analytical solution to help decide when to cease trialling a new action before reverting back to an existing action to recover a threatened species. Yet, the question of when to stop an existing action especially when there is uncertainty about the impact of new management actions remains unclear.

We integrate threatened and invasive species in the same general framework to develop a theory on when to cease an existing action that is performing poorly in favour of a new management action whose effectiveness is unknown. We illustrate the approach for two case studies: first, the malleefowl (*Leipoa ocellata*) in Australia, where fox baiting has been ongoing and fire management is the new action that could deliver better outcomes, and second for the eradication of invasive fire ants (*Solenopsis invicta*) in the United States, where nothing was done initially before eradication was considered as a new management action. The development of a general framework for deciding when to trial a new management action will assist conservation managers to act in a timely manner to preserve biodiversity.

Problem definition

We outline the broad assumptions of our problem and then describe the general population model. Next, we illustrate how to incorporate uncertainty into the model when we do not know the impact of the new management action in the future. We define the management objective and explain how to find the optimal time to stop an existing action before switching to a new but uncertain action. Finally, we discuss the results obtained and then illustrate our framework using the malleefowl and the invasive fire ants as case studies.

We considered two types of management scenario, a manager that is concerned with the persistence of a threatened species and a manager that is concerned with the eradication of an invasive species. There are two mutually exclusive management actions that they can perform: an existing management action and a new management action. Typical, actions could include: do nothing, monitor, translocate, eradicate, reserve habitat, restore habitat, actions to mitigate or adapt to climate change or any combination of these actions.

We assumed that the population growth rate under the existing management action is known. However, the existing management is insufficient to stop the decline of a population when managing a threatened species or stop the increase in population when managing an invasive species (Figure 5.1). The management goal for threatened species is to increase the chance of obtaining a population size above a target (Figure 5.1a). When managing an invasive species, the management goal is to decrease the population size below a particular level that is deemed acceptable, which might be extinction (Figure 5.1b). The question for our study is whether managers should continue an existing action, and if so for how long before switching to a new, but uncertain action.

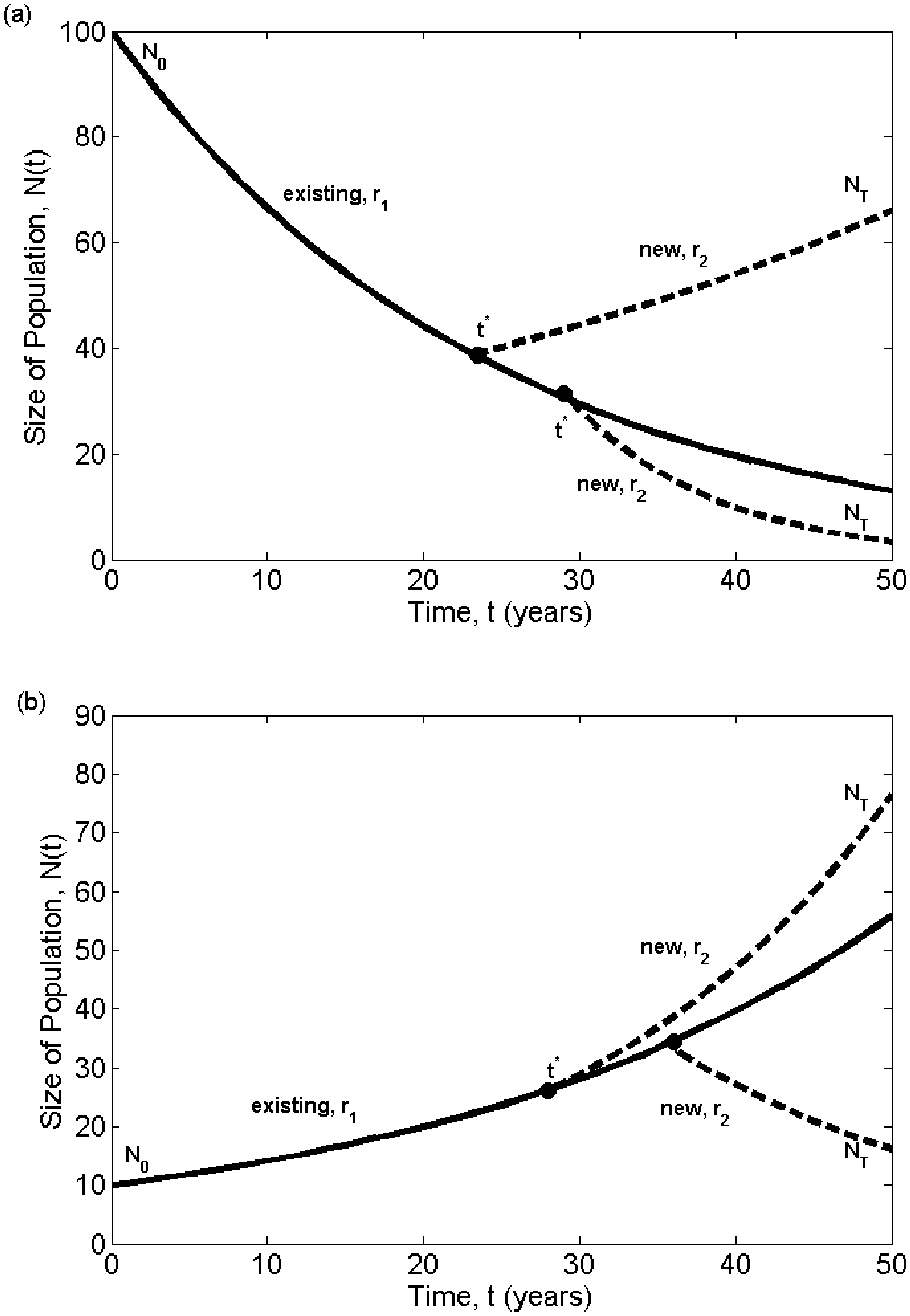


Figure 5.1. **A schematic of a system model to decide when to change conservation actions when the management scenario is to (a) recover or (b) eradicate a species.** The size of the population

before and after the change in conservation actions are shown using a solid line and the optimal point is shown using dotted lines (N_0 is the initial population size, N_T is the population size at the end of management timeframe, t^* is the optimal time and N^* is the optimal population size to switch between conservation actions).

Population Dynamics

We assumed the population grows exponentially, with the growth rate dependent on the management action. The known population growth rate for the existing action is denoted as r_1, and that of the new action. is r_2. The population declines if the population growth rate is less than zero and increases if it is greater than zero. Thus, the number of animals, N_t when an existing conservation action stops at time t is,

$$N_t = N_0 e^{r_1 t}, \tag{5.1}$$

where N_0 is the initial population size.

There are limited resources available to manage a population for T years. Hence, the time available to manage the population after switching to the new action is $T-t$, assuming little time delay or change in population size on switching. Having changed to the new action, the population can either grow or decrease at an exponential rate of r_2, which is uncertain. Thus, the population size at the terminal time, N_T is,

$$N_T = N_0 e^{r_1 t} e^{r_2 (T-t)}. \tag{5.2}$$

Uncertainty in the possible new action

We assume deterministic population dynamics under the new management action, but the growth rate r_2 is uncertain. We assume that while we are implementing the existing action, the estimate of the growth rate of the new action, r_2 becomes more precise. The improvement in precision might, for example, arise from research being conducted on the species. The question is, what parameter estimate for r_2 would justify switching strategies to the new action, recognising that r_2 will always remain somewhat uncertain. To model this, we assume that uncertainty in r_2 is described by a normal distribution with mean μ_2.

The uncertainty in r_2 is defined by the standard deviation of the normal distribution, which is assumed to be $\sigma = s / \sqrt{t}$, where t is the amount of time spent investigating the new management action while the existing management action is applied to the population (Figure 5.2). This expression for the standard deviation is derived from the formula for a standard error, assuming that the same amount of data about r_2 is generated each year, and the standard deviation of that is s annually. Thus, the probability density function of r_2, which defines the uncertainty in the estimate, is a function of the time spent researching it prior to implementation:

$$p\left(r_2 \mid t\right) = \frac{1}{t\sqrt{2\pi s^2}} e^{\frac{-\left(r_2-\mu_2\right)^2}{2s^2/t}} . \tag{5.3}$$

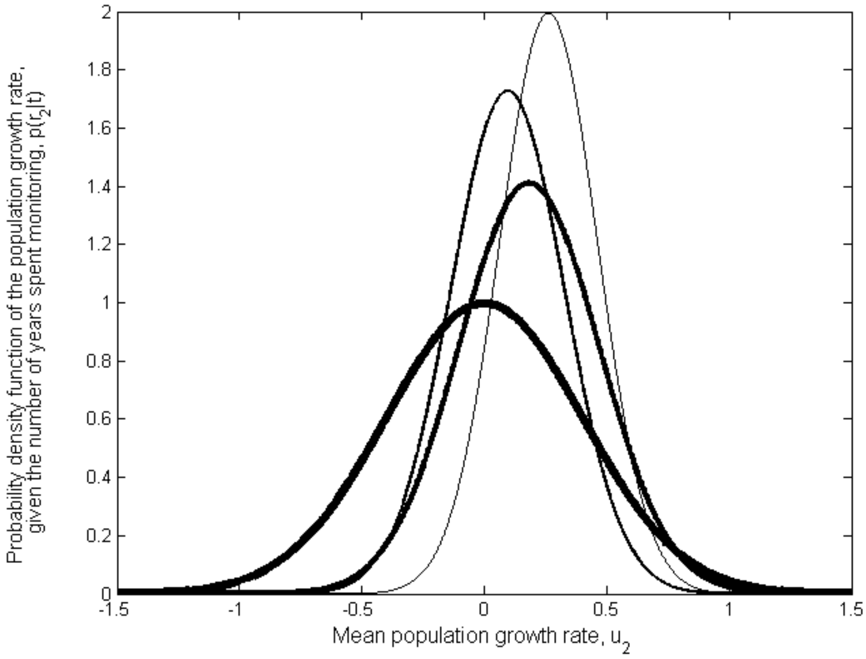


Figure 5.2. Probability density function of the population growth rate, r_2 with mean μ_2 and standard deviation, σ that decreases through time. (darkest to lightest: decrease in standard error, σ as the amount of time spent in monitoring increases).

Management objective

For threatened species management, the management objective is to find the optimal switching time, t^* that maximises the chance that the population size is greater than or equal to a target population, A,

$$\begin{aligned} &\max Pr\left(N_T \geq A\right) \\ &\text{subject to } N_T = N_0 e^{r_1 t} e^{r_2 (T-t)}, \\ &\text{where } t \in \left\{0, T\right\}. \end{aligned} \tag{5.4}$$

Solving for the optimal time

We solved the problem to find the best time to stop an existing action before changing to the new action, by accounting for uncertainties associated with the population growth rate of the new action, r_2 (Fig. 5.2). Taking logs of equation 5.2 leads to $logN_T = logN_0 + r_1 t + r_2(T-t)$. To satisfy the management objective $N_T \geq A$, rearranging the expression for $\log N_T$ means that r_2 must be greater than or equal to a critical threshold, r_c. Thus,

$$
\begin{aligned}
Pr\left(N_T \geq A\right) &= Pr\left(\log\left(N_0\right) + r_1 t + r_2\left(T-t\right) \geq \log\left(A\right)\right) \\
&= Pr\left(r_2 \geq r_c\right) = Pr\left(r_2 \geq \frac{\log\left({}^{A}\!/\!_{N_0} \right) - r_1 t}{\left(T-t\right)} \right).
\end{aligned}
\tag{5.5}
$$

Given the uncertainty defined by the probability density function $p(r_2 \mid t)$ (equation 5.3), we find the chance of r_2 being bigger than the critical growth rate, r_c by obtaining the integral of $p(r_2 \mid t)$ between r_2 and infinity; which is equal to,

$$
Y = Pr\left(r_2 > r_c\right) = \frac{1}{2}\left(1 + Erf\left[\frac{r_1 t + \left(T-t\right)\mu_2 - log\left({}^{A}\!/\!_{N_0} \right)}{\sqrt{2}\sigma\sqrt{\left(T-t\right)}} \right]\right), \tag{5.6}
$$

where $Erf[x]$ is the error function.

The optimal switching time, t^* that maximises the chance of the population reaching A is obtained by taking the derivative of Y, setting it to zero ($dY/dt = 0$) and solving for t. We are searching for the internal optimum in the interval $[0, T]$, so we must also look at the values of Y at the boundaries at t=0 and t=T. For threatened species, we find that the optimal switching time is (Fig. 5.1a),

$$
t^* = \begin{cases}
\dfrac{\log\left({}^{A}\!/\!_{N_0} \right) + \left(\mu_2 - 2r_1\right)T}{\mu_2 - r_1} & \text{,if } \mu_2 > r_1 \textit{ and } N_0 e^{(\mu_2 - 2r_1)T} < A, \\
T & \text{,if } \mu_2 \leq r_1 \textit{ and } N_0 e^{(\mu_2 - 2r_1)T} < A,. \\
0 & \text{,if } N_0 e^{(\mu_2 - 2r_1)T} \geq A.
\end{cases}
\tag{5.7}
$$

When dealing with an invasive species, the management scenario is opposite to the recovery of a threatened species. The management objective is to minimise the chance that the population size is greater than or equal to a target population, *A*,

$$
\begin{aligned}
&\min Pr\left(N_T \geq A\right) \\
&\text{subject to } N_T = N_0 e^{r_1 t} e^{r_2 (T-t)}, \\
&\text{where } t \in \left\{0, T\right\}.
\end{aligned}
\tag{5.8}
$$

When we solve for the above equation, the optimal time to switch to a new action when managing an invasive species is,

$$
t^* = \begin{cases}
\dfrac{\left(2r_1 - \mu_2\right)T - \log\left(A \big/ N_0 \right)}{r_1 - \mu_2} & \text{, if } \mu_2 < r_1 \text{ and } N_0 e^{(2r_1 - \mu_2)T} > A, \\
T & \text{, if } \mu_2 \geq r_1 \text{ and } N_0 e^{(2r_1 - \mu_2)T} > A, \\
0 & \text{, if } N_0 e^{(\mu_2 - 2r_1)T} \leq A.
\end{cases}
\tag{5.9}
$$

The scenarios for managing threatened and invasive species management are mirror images of one another (Figure 5.1). Similarly, the interpretations of the results for these two scenarios are also mirror images (Figure 5.3). For instance, when the new action is expected to be highly effective compared to the existing action in reaching the management goal of obtaining the target population for endangered species or the target management area for invasive species, *A* within the limited amount of time *T*, (when $\mu_2 > log(A/N_0)/\mathrm{T} + 2r_1$ as we managed threatened species or $\mu_2 < log(A/N_0)/\mathrm{T} + 2r_1$ as we managed for an invasive species), we stop our existing action in favour of the new action immediately (in this instance, $t^*=0$).

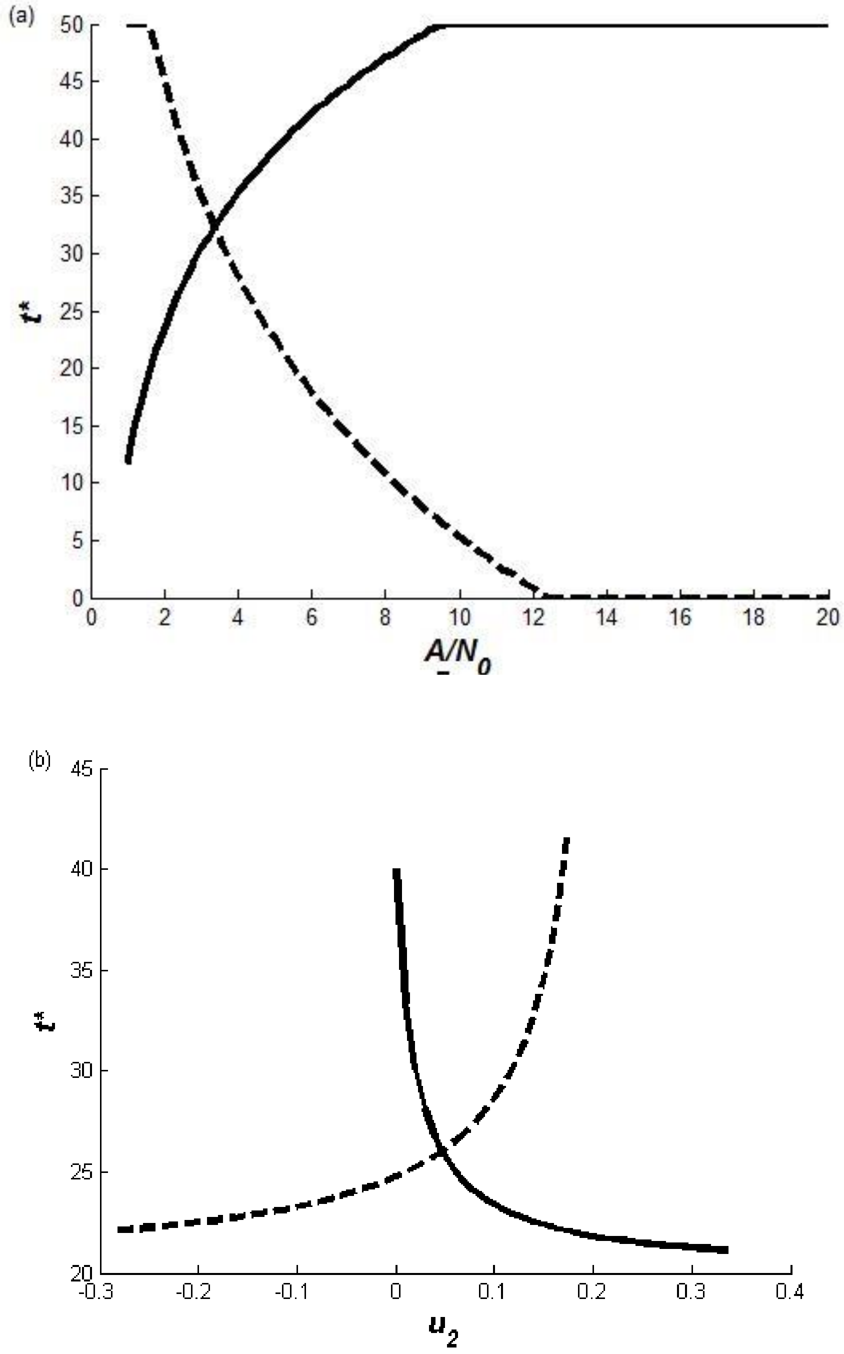


Figure 5.3. Optimal time to spend on the existing action before changing to the new management action as a function of the (a) relative benefit of achieving management objective, A/N_0, and (b) increase effectiveness of new action, u_2 (solid line is when the management purpose is to increase the population size, e.g. recovery of a species in decline; dashed line is when management purpose is to decrease the population size, e.g. eradication of invasive species). Note on the x-axis, for the endangered species case, a value of 20 indicates the greatest benefit, whereas for the invasive species case, a value of 1 indicates the greatest benefit.

If the we can never reach our goal of obtaining A within the limited amount of time T ($N_0e^{(u_2-2r_1)T}<A$ when we managed for threatened species or $N_0e^{(2r_1-u_2)T}>A$ when we managed for invasive species) and the new action is expected to be better at achieving A than our existing actions ($\mu_2 > r_1$ for threatened species management or $\mu_2 < r_1$ for invasive species management); the new action is chosen after continuing the existing action for several years; assuming that μ_2 remains the same. In this situation, the new action is assessed (via monitoring) as the existing management continues. Then, the new uncertain action is chosen, hoping that the growth rate will be sufficient (increase μ_2 for threatened species, decrease μ_2 for invasive species) to achieve the management goal A. Surprisingly, this optimal switching time was independent of the uncertainty in the new action (the standard deviation of the estimate of the growth rate of new action), but hinges on the growth rate of the existing action, r_1, the expected growth rate of the new action, μ_2, the management goal, A, and the management timeframe, T. As the management goal increases (A/N_0 increases), we wait longer before changing to the new action when we manage for species recovery, but the optimal switching time decreased exponentially when we manage an invasive species (Figure 3a). As u_2 increased, the optimal switching time decreased exponentially when managing for species recovery but increased when managing an invasive species (Figure 5.3b). Yet, if $\mu_2 \leq r_1$ for threatened species management or $\mu_2 > r_1$ for invasive species management, we continued the existing action forever, never swapping to a new action; because as we monitor the new action while implementing the existing action, we find that the existing action is performing better than the new action.

Case study

We demonstrated the applicability of this problem using the endangered malleefowl and the invasive fire ants as case studies.

Saving the malleefowl

The malleefowl (*Leipoa ocellata*) is a ground dwelling bird that builds a large mound from sand and leaf litter to incubate its eggs (Frith 1959). It is endemic to Australia, residing mainly in semi-arid and arid mallee habitat (Benshemesh 2007). Once common, it has declined over the last century due to multiple threats including habitat loss and fragmentation, predation by introduced foxes, grazing and wildfires (Benshemesh 2007). It is listed as Vulnerable according to the IUCN Red list (IUCN 2012).

Monitoring of the malleefowl has been conducted since the late 1980s and the 1990s in southern Australia (Benshemesh et al. 2007). The species has declined by approximately 2-3% per year across these monitoring sites (Table 1; Benshemesh et al. 2007). Past and current threat mitigation measures have focused on protection of critical habitat, captive breeding and fox baiting (Garnett and Crowley 2000). Despite millions of dollars being spent on these threat mitigation measures over the past two decades, the malleefowl remains a vulnerable species that is still declining (Garnett and Crowley 2000). This is because past clearing has fragmented most of the malleefowl habitat, with the remaining isolated populations located in suboptimal habitats (Garnett and Crowley 2000). Moreover, fox baiting does not appear to have a statistically significant positive impact on the malleefowl population growth rates (Walsh et al. 2012).

Since past mitigation measures were unsuccessful in recovering the malleefowl population, it is important to consider new management actions. One such management action that has been used recently is fire mitigation (Benshemesh 2007). However, substantial uncertainty surrounds the effectiveness of this action, which prevents implementation. Failure to switch to a more effective management action before a critical time may increase the risk of species extinction as a result of low population size and associated genetic and stochastic factors (Ilik Saccheri and Hanski 1998).

Since it was unknown how effective fire control measures are at recovering the malleefowl population, we examined a range of population growth rates associated with fire mitigation (Table 5.1). As the initial population size remains unknown even when monitoring was conducted, we assumed a population size of 100. We assumed a target population size similar to the initial population size, N_0 as a common management objective is to recover a species to its former range or distribution. The management timeframe is assumed to be 50 years.

We estimated the parameters for the poison baiting of foxes for the malleefowl from the literature (Table 5.1). Using these parameters as a baseline, we performed sensitivity analysis to determine the influence of these parameters on the optimal time to stop baiting of the foxes and change to fire mitigation measures.

Parameter	**Symbol**	**Values**	**References**
Population growth rate for poison baiting of foxes	r_1	log(0.97–0.98) = -0.13 – -0.009	(Benshemesh et al. 2007)
Mean population growth rate for fire mitigation	μ_2	log(1–1.5) = 0 – 0.18	-
Initial Population size	N_0	100	-
Target Population size	A	N_0	-
Management timeframe	T	50	-

Table 5.1. Parameters for managing the malleefowl with values used in case study.

When fire mitigation is expected to be more effective than fox baiting in achieving the target population for the malleefowl (*i.e.*, as μ_2 increases), the optimal time to spend on fox baiting decreased before changing to fire mitigation (Figure 5.4). This optimal time to spend on fox baiting increased as the management goal increased (Figure 5.4).

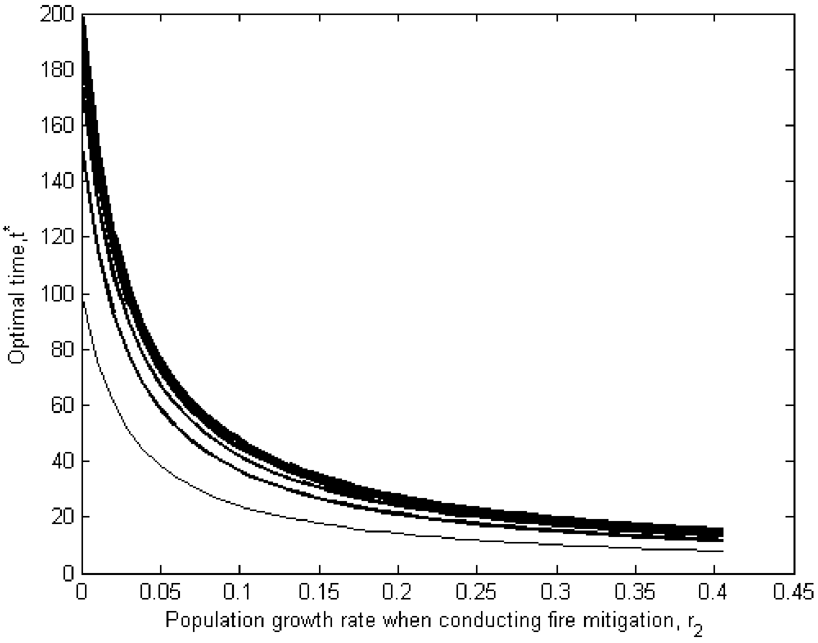


Figure 5.4. The optimal time to change actions as we increase the effectiveness of fire mitigation methods (increase the population growth rate while conducting fire mitigation) for the Malleefowl (light to darkest line: increase in target population growth rate from N_0, $5*N_0$, $10*N_0$, $15*N_0$ to $20*N_0$).

Eradication of the invasive fire ants

The red fire ant (*Solenopsis invicta*) is an invasive species that is considered a major economic, social and ecological pest worldwide (Ascunce et al. 2011; Morrison et al. 2004). Native to South America, it has the potential for rapid colonisation (Morrison et al. 2004; Porter et al. 1997). First detected in the United States of America near Mobile, Alabama in 1918, it spread rapidly to 8 states with a range of 25 million ha by 1958. More recently it occupies greater than 128 million ha in 13 states and Puerto Rico (Callcott and Collins 1996; Morrison et al. 2004).

Even though it was detected early in the 1920s', nothing was done until 1957 when the United States government agencies and states attempted to control the fire ants using a range of methods, such as quarantine, poison baiting, and biological control agents (Callcott and Collins 1996; Callcott et al. 2011). Millions of dollars have been spent, but the red fire ants were already established and spreading rapidly (Jemal and Hugh-Jones 1993).

By 2001, the red fire ant had been detected in Brisbane, Australia and then New Zealand (Moloney and Vanderwoude 2002). Due to rapid detection, eradication and containment in Australia and New Zealand, the red fire ant was declared contained within Brisbane and completely eradicated in New Zealand (Scanlan and Vanderwoude 2006). The successful quarantine and eradication measures in these two countries indicate that successful eradication hinges on a rapid response. If we retrace our steps back to 1918 in the United States, the question is whether eradication should have been attempted.

Little information exists regarding the population size or the growth rates of the fire ants, so we used data on the area infested by fire ants and the rate of infestation (Table 5.2) as surrogates for population size and population growth rates. Since we did not know the rate of infestation when quarantine or eradication is conducted, we explored a range of values associated with quarantine and eradication. The initial infestation of fire ants reported in 1918 was 0.4 ha. We assumed a management timeframe of 50 years, as any timeframe greater than this means that the fire ants are too widespread to be contained.

Parameter	**Symbol**	**Values**	**References**
Rate of infestation when nothing was done	r_1	Log(1.26) = 0.23	(Callcott and Collins 1996)
Rate of infestation when quarantine and eradication was conducted	μ_2	Log(0.6 – 1) = -0.22 – 0	-
Initial area infested by fire ants	N_0	0.4 hectares	(Callcott and Collins 1996)
Target area	A	N_0	-
Management timeframe	T	50	-

Table 5.2 Parameters for managing the invasive fire ants with values used in the case study.

We discovered that as the rate of infestation decreased, it is better to spend a time (approximately 20 years) doing nothing before starting an eradication or quarantine program (Figure 5.5). This optimal time spent doing nothing increased as the rate of infestation decreased (Figure 5.5). However, as the target area of infestation increased, the optimal time spent doing nothing decreased (Figure 5.5).

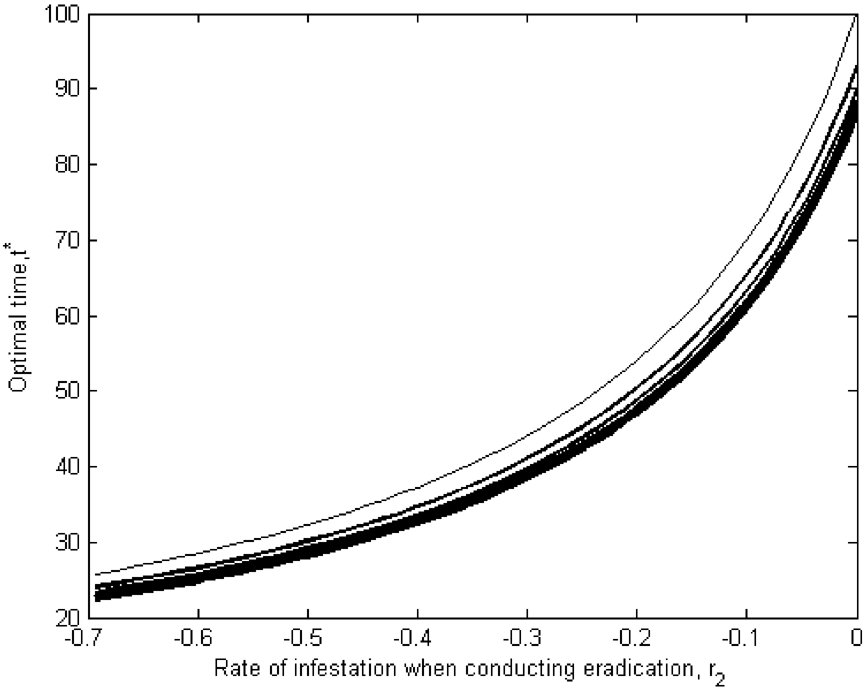


Figure 5.5. The optimal time to change actions as we increase the effectiveness of fire ant eradication (increase the rate of infestation while conducting eradication) (light to darkest line: increase in target area of infestation from N_0, $5*N_0$, $10*N_0$, $15*N_0$ to $20*N_0$).

Discussion

Deciding when to switch from a current management action with known but poor performance to a new management action with unknown effectiveness is a key question underpinning the survival of a species, especially when there are limited management resources (Martin et al. 2012; Possingham and Shea 1999; Possingham et al. 2012). Ng et al. (In press) find a general analytical solution to determine when to stop trialling a new action before reverting back to an existing action. However, the question of when to stop an existing action in favour of a new management action remained. We have presented an analytical solution to help conservation managers decide when to stop an existing action in favour of a new action that requires monitoring. We applied this to the recovery of the threatened malleefowl and the eradication of invasive fire ants. We found that the optimal timing of when to switch to a new action depends on the target population size, *A*, the growth rate while conducting existing or new actions and the management timeframe.

Traditionally, invasive species management and threatened species recovery are managed separately. Few have attempted to place these under the same general framework (Chadès et al.

2011; Thompson et al. 2012). Our study demonstrates that a general analytical solution exists for both invasive species management and endangered species recovery. This analytical solution is a local maximum for threatened species recovery and a local minimum for invasive species eradication. Interestingly, the relationship between these parameters and the optimal switching time were exactly opposite of each other when the management scenario changes from species recovery to invasive species eradication.

The optimal time to change from an existing to a new action hinges on the management goal A (Chapter 4). For instance, to recover the malleefowl, the management goal was to increase the population size beyond A, whereas for invasive species management, the goal was to decrease the number of hectares that contain the red fire ant below A. If the management goal was set close to N_0 (low for threatened species management and high for invasive species management) such that we were certain we can achieve N_0, we performed the new action immediately for both management scenarios, even though we were uncertain the new action can achieve N_0. On the contrary, if the management goal was set far from N_0 (high for threatened species management and low for invasive species management), the optimal time to change actions depended on the relationship between the population growth rates while conducting existing, r_1 or new action, u_2.

The population growth rates influence when to change the management action. Ng et al. (Ng et al. In press) found that this growth rate interacts with the management goal of achieving a particular target population size. Our study extended this by exploring how uncertainty in a new management action and invasive species management influences the optimal time to change management action. If the growth rate under a new action is uncertain, but expected to perform better than the existing action, ($\mu_2 > r_1$ for threatened species management or $\mu_2 < r_1$ for invasive species management), then any switch to the new action is delayed because we were uncertain the new action will be able to achieve A, unless the difference is sufficiently large (when $\mu_2 > log(A/N_0)+2r_1T$ as we managed threatened species or $\mu_2 < log(A/N_0)+2r_1T$), in which case immediate switch to the new action was recommended. In the case of the malleefowl, we found that as the impact of fire mitigation on the population growth rate increased (new action becomes more effective), we spend less time on existing action because we know that the new action has a greater chance of achieving A. In contrast, as the rate of infestation of the fire ants while conducting eradication increased (new action becomes less effective), we spend more time on existing action because we know the new action has less chance of achieving A. If the existing action was performing worse than our new action, we continue performing our existing action forever, never swapping to the new action because as we monitor the new action while performing the existing action, we will find that the new action can never achieve our management goal.

As the relative benefit A/N_0 of achieving the management objective increases under the existing action, it takes longer to switch to the new management action when the purpose was to recover a species because we are unsure whether the new action can outperform the existing action (Figure 5.3a). Therefore, we choose to prolong our existing action as we monitor the new action. On the other hand, when eradicating an invasive species, as the management objective increases, or in other words, the benefit of the existing management action declines, we choose to shorten our existing action to allow more time for the new action to eradicate the invasive species (Figure 5.3a). As the new action becomes more effective at recovering a species, the amount of time to spend on the existing action decreases because we spend more time trialling the new action that is more effective than the existing action (Figure 5.3b). On the other hand, as the new action becomes more effective at eradicating an invasive species, the amount of time to spend on the existing action increases because we are unsure that the new action can eradicate the invasive species (Figure 5.3b).

Various types of uncertainties drive conservation decision making (Regan et al. 2002). In this study, we explicity consider the uncertainty associated with trialling a new action. We did not consider different sources of uncertainty such as environmental or demographic stochasticity. These types of uncertainties can be considered by building a state based model that is stochastic using stochastic dynamic programming (SDP). Other types of uncertainties that could be included in future studies include the risk of climate change or natural disasters, two factors becoming increasingly important in conservation decision making (Kujala et al. 2012).

We assumed a simple utility function that is defined by the Heaviside function where we maximise or minimise the probability of achieving A. Yet, it is possible to model different utility functions based on the risk preferences of a decision maker (Holt and Laury 2002). For example, risk neutral behaviour would be reflected as a linear function of the population size, whereas risk-averse and risk-loving behaviour would be a concave and convex function respectively (DeGroot 2005; McDonald-Madden et al. 2011). Understanding different risk attitudes remains an important extension to this study. By modifying the management objective to different utility functions, this study can be expanded easily to reflect the different risk attitudes of decision makers.

We assumed that the monetary costs of implementing an existing or new action were equal or immaterial. In reality, this may not be the case. For example, the cost of captive breeding can be enormous, hundreds of times more expensive than the cost of releasing the species back into the wild. The difference in these costs can influence which action is implemented (Chades et al. 2008; McDonald-Madden et al. 2010b), thus affecting the timing of when to change management actions. For example, if faced with choosing between two actions whose effectiveness is unknown, it more likely that the action which is less expensive will be trialled first. Yet, it remains an important extension in future work to explore the optimal investment in each action within a given budget.

We have demonstrated that we can apply the same general solution of finding the optimal time of when to change management actions for both threatened and invasive species management. This approach allows us to manage threatened and invasive species under the same general framework, saving us precious time and money. In a world where the rates of extinction are now orders of magnitude greater than background rates, this is important as conservation managers are running out time to safeguard biodiversity.

Chapter six – Choosing new or existing actions in adaptive management

Introduction

Uncertainty is prevalent in conservation, as conservation managers struggle with a variety of unknowns when deciding how to manage a threatened species (Regan et al. 2002). These may include uncertainties about the type of model we choose for our management scenarios, the parameters estimates we use and intrinsic environmental variability (McCarthy et al. 2011; McDonald-Madden et al. 2010b). If we fail to take into account these uncertainties, it can easily lead to bad management decisions. Some of these uncertainties, such as intrinsic environmental variability, can never be reduced. Other uncertainties such as measurement error can be reduced through active adaptive management.

Adaptive management is a potential cure for the problem of managing a species in an uncertain environment (Halbert 1993; McDonald-Madden et al. 2010b; McLain and Lee 1996; Walters and Hilborn 1978). To manage adaptively, the task of managing and learning is performed in a continuous cycle (Parma 1998). Uncertainty is reduced as we use learning as a basis for improving our management action (McCarthy and Possingham 2007; Nichols and Williams 2006). In the context of conservation, this implies that we have to monitor in order to make informed management decisions about a species and manage to learn about a species through monitoring. When management of a species and monitoring is used concurrently in this way, it becomes a powerful tool as our management strategy changes as we learn about a species (Bellman and Dreyfus 1962; Williams 2011).

There are two types of adaptive management: passive and active (Probert et al. 2011; Williams 2011). Passive adaptive management is when anticipated future learning does not contribute towards the choice of our management actions in the present (Halbert 1993; Williams 2011). Our research focuses instead on active adaptive management, where we take into account how learning reduces measurement error and contributes towards choosing our future actions (Halbert 1993; McLain and Lee 1996; Walters and Hilborn 1978). Recent research on using active adaptive management in conservation provides guidelines for determining the best harvest strategy (Nichols et al. 2007) for varying management timeframes (Hauser and Possingham 2008), for deciding on how many animals to allocate between two sites (Rout et al. 2009b), for investigating what actions to take for managing a species that is threatened by disease (McDonald-Madden et al. 2010b), for deciding on how to allocate resources between two actions for a given budget

(McCarthy and Possingham 2007), and for determining whether to continue surveying, managing or to give up on the management of cryptic species (Chades et al. 2008). Yet, it remains unclear as to whether we should place a new action on trial or continue with an existing action, since adaptive management is all about treating management actions as an experiment. When managing a threatened species, it is advantageous to experiment with a new untested action when we do not know whether the new action has an impact on the species of concerned and we should continue with the existing action when the new action is unlikely to improve the condition of a species.

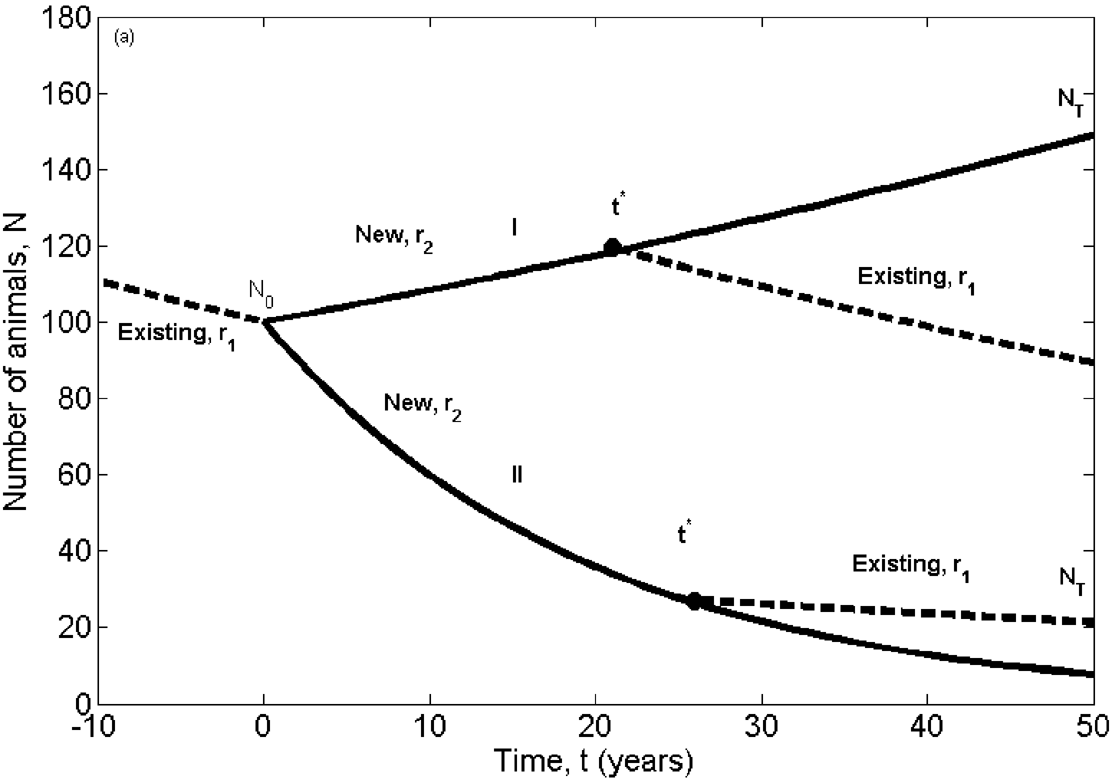
The aim of this study is to determine whether to continue with an existing action with known growth rate or trial a new action with unknown growth rates. To address this problem, we develop an active adaptive management framework to assist a manager in deciding whether to trial a new action or to continue an existing action, before changing to another suite of management actions. We used a range of parameters to explore their influence on the optimal management action. In our adaptive management framework, we use stochastic dynamic programming (SDP) to find the exact optimal solution. We also compare the active adaptive management approach to two analytic solutions developed previously about when to change management actions from new to existing actions(chapter 4) and existing to new actions (chapter 5). It will be of interest to conservation managers whether a simple analytical solution can be relied on to make an informed decision. Using the now extinct Christmas Island pipistrelle bats (*Pipistrelle murrayi*) as a case study, we are trying to decide between two management actions: either trialling the new management action of captive breeding or continuing with an existing management action of managing this species in the wild. We answer the question: should we continue an existing action or trial something new?

Methods

In this section, we outline the broad ecological problem and its assumptions; follow by the population model. Next, we use an active adaptive management approach (AAM) and use stochastic dynamic programming (SDP) to find the optimal management strategy of whether to trial a new management action or continue with an existing action. Subsequently, we use the management of the Christmas Island pipistrelle as a case study to understand the influence of different parameters on the optimal management strategy. Finally, we compare the analytical solution developed previously (chapters 4 and 5) with the active adaptive management approach.

We consider a scenario where the manager of a threatened species must decide whether to continue implementing an action of known effectiveness, or trial a new action of unknown effectiveness. Thus, the choice of our actions, *a*(*t*)= (1,2) is to either (1) continue an existing action that was known, or (2) trial a new action that was unknown. Each action influences the population growth rate of the threatened species, in turn affecting the population size. The manager's ultimate goal is to maximise the chance of the population size reaching a critical threshold *A*. We chose this objective to enable comparison with the analytical solutions (Chapter 4 and 5). We assumed that the manager has a limited amount of resources available to manage a species over a timeframe of *T* years.

The analytical solutions were developed for two types of management scenario. The first scenario was for a manager using an existing management action, but would like to know how long to trial a new management action before reverting to an existing action (Fig. 6.1a). The second scenario was when a manager is already using an existing action, but would like to know long to continue this action before starting a new management action (Fig. 6.1b). Management actions could include actions such as doing nothing, monitoring, controlling a predator, parasite or competitor, translocating a species, restoring habitat, actions to reduce the effect of climate change such as massive tree planting, or instigating a combination of these actions.



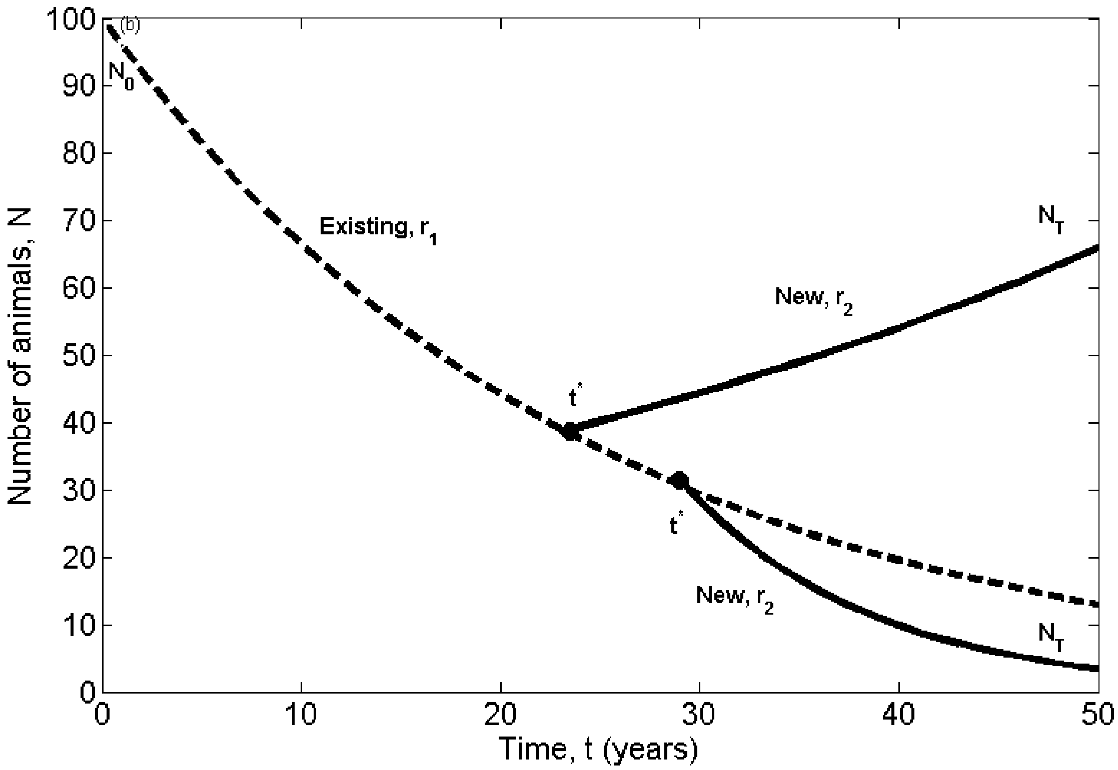


Figure 6.1.Conceptual model to describe the number of animals that changes through time depending on the management action that changes from (a) new action to an existing management action or (b) existing action to new action to recover a species. The number of animals when new management action is trialled is shown using a solid line and the number of animals when we continue an existing management action is shown using a dash line (N_0 is the initial population size, r_1 is the population growth rate while continuing existing action and r_2 is the population growth rate while trialling new action, N_T is the population size at the end of management timeframe and t^* is the optimal switching time).

Population dynamics

The population size next year, $N(t+1)$ depends on the population size in the previous year, $N(t)$,

$$N(t+1) = r_a N(t), \qquad (6.1)$$

where r_a is the population growth rate under action a. We assume that under the existing action, a = 1, demographic stochasticity arises from a Poisson distribution. The Poisson distribution is a discrete distribution that is made of positive integers (McCarthy 2007). It is particularly suitable in situations when we are dealing with the abundance of population where it is impossible to have negative population size. For a given growth rate, r_1 and a known population size, $N(t)$, the chance of the population next year being a certain size k is described by a Poisson distribution with probability density function

$$Pr\left(N\left(t+1\right)=k|r_1N\left(t\right)\right)=\frac{\left(r_1N\left(t\right)\right)^k e^{-r_1N(t)}}{k!}, for\ 0\leq k<M, \qquad (6.2)$$

where the mean and variance is given by $r_1N(t)$,and M is the maximum possible population size. For $k = M$, we subtract 1 from the sum of all Poisson distribution from 0 to $M-1$, such that the Poisson distribution adds up to 1,

$$Pr\left(N\left(t+1\right)=k|r_1N\left(t\right)\right)=1-\sum_0^{M-1}\frac{\left(r_1N\left(t\right)\right)^k e^{-r_1N(t)}}{k!}, for\ k=M. \qquad (6.3)$$

As we place the new management action under trial, we are uncertain about what the trend of the population will be under this new management action, r_2. We represent all possible values of r_2 between 0 and infinity for a given α and β using a gamma distribution that has a probability density function,

$$Pr\left(r_2|\alpha,\beta\right)=\frac{\beta^\alpha}{\Gamma\left(\alpha\right)}r_2^{\alpha-1}e^{-R_2\beta}, for\ \alpha>0\ and\ \beta>0, \qquad (6.4)$$

where α is the shape parameter, β is the rate parameter for the gamma distribution that describes the uncertainty of r_2 and $\Gamma\left(\alpha\right) = \int_0^\infty e^{-t}t^{\alpha-1}dt$ is the gamma function. The mean of this gamma distribution is α/β and the variance is α/β^2. This distribution takes a variety of shapes as we vary α and β, that represent the different states of belief regarding r_2. The manager can reduce their uncertainty about the effectiveness of the new action by monitoring its outcome. We used Bayesian updating to describe how monitoring improves the estimate of r_2, which we assumed to be constant and independent over time. In Bayesian updating, the prior distribution has to be specified, followed by a distribution that described the data that will generate a posterior distribution. We used the gamma distribution as it is the conjugate of the parameters in the Poisson distribution in Bayesian inference(McCarthy 2007).This means that the posterior and prior distribution is a gamma distribution, when we have data that is described by the Poisson distribution. It is a natural choice to represent the measurement error that reduces through time as we spent time monitoring. This is reflected in the posterior distribution where the variance reduces through time, as we update r_2.The posterior gamma distribution has updated parameters of $\alpha+N(t+1)$ and $\beta+N(t)$ (see Appendix C).This gives us a mean of $\frac{\alpha+N(t+1)}{\beta+N(t)}$ and a variance of $\frac{\alpha+N(t+1)}{(\beta+N(t))^2}$ for the posterior gamma distribution. The mean and variance gives us an updated mean and variance of r_2.

For a given r_2, the chance of obtaining a population size of k next year is described by the Poisson distribution (equation 6.2). Since r_2 is uncertain that varies according to the gamma distribution when we trial the new action, the chance of obtaining a population size of k next year population size for a given α, β and population size this year is given by the marginal distribution of the gamma and Poisson distribution. The marginal distribution is obtained when we integrate the Poisson-gamma mixture over all possible growth rates, r_2 from 0 to infinity, that leads to a negative binomial distribution,

$$
\begin{aligned}
Pr\left(N(t+1)\,|\,\mathrm{N}(t),\alpha,\beta\right) &= \int_0^\infty P\left(N(t+1)=k|r_2N(t)\right)P\left(r_2|\alpha,\beta\right)dr_2 \\
&= \int_0^\infty \frac{\left(r_2N(t)\right)^k e^{-r_2N(t)}}{k!}.\frac{\beta^\alpha}{\Gamma(\alpha)} r_2^{\alpha-1}e^{-\beta R_2}dr_2 \\
&= \frac{\Gamma(\alpha+k)}{k!\Gamma(\alpha)}\frac{N(t)^k\beta^\alpha}{\left(\beta+N(t)\right)^{\alpha+k}} \\
&= \frac{\Gamma(\alpha+k)}{k!\Gamma(\alpha)}\frac{\beta^\alpha}{\left(\beta+N(t)\right)^{\alpha}}\frac{N(t)^k}{\left(\beta+N(t)\right)^{k}} \\
&= \binom{\alpha+k-1}{k}\left(\frac{\beta}{\beta+N(t)}\right)^\alpha\left(\frac{N(t)}{\beta+N(t)}\right)^k.
\end{aligned}
\tag{6.5}
$$

with a mean of $\frac{\alpha N(t)}{\beta}$ and variance of $\frac{\alpha N(t)\left(\beta+N(t)\right)}{\beta^2}$. The negative binomial distribution is a prior predictive distribution that arises from a mixture between the parameters in the Poisson distribution and the gamma distribution.

Stochastic dynamic programming

Using Bellman's equation, stochastic dynamic programming iterates backward in time to find the optimal decision for every single state of a stochastic system (Bellman and Dreyfus 1962; Clark and Mangel 2000). To do this, we need to understand the value for being in a particular state (population size) at the terminal time. Then, we compare the values for having a specific population size when we trial a new action against an existing action backward in time. To calculate the values for having a particular population size when we implement an action, stochastic dynamic programming finds the expected value of all possible population size in the next time step because there is uncertainty about the future population size. For a given α and β, the expected value for an action is obtained by multiplying the probability of transitioning to a new state in the next time step, as defined by $N(t+1)$, α', β',by the value of being in that state. This value function for having a certain population size, for a given α and β and action, a is,

$$V\left(N\left(t\right),\alpha,\beta,t\right)=max_{a\in\{a_1,a_2\}}\sum_{k=0}^{M}Pr\left(N\left(t+1\right)=k\middle|\mathrm{N}\left(t\right),\alpha',\beta',a\left(t\right)\right)x \\ V\left(N\left(t+1\right)=k,\alpha',\beta',t+1|a\left(t\right)\right),for\ t<T. \tag{6.6}$$

where α' and β' describes the distribution for the population size in the next time step. The action that has the maximum value is the optimal decision that a manager should take when observing a population size of $N(t)$.

When we continue an existing action, $a(t) =1$,the chance of having population size of k next year for a given α and β is defined by the Poisson distribution in equation 6.3. Since uncertainty arises only from stochasticity, and we assumed that there was little uncertainty associated with the growth rate r_1, α and β would remain the same for every single time step. Thus, the Bellman equation for an existing action, $a(t) = 1$, becomes,

$$V\left(N\left(t\right),\alpha,\beta,t\right)=\sum_{k=0}^{M}\frac{\left(r_1N\left(t\right)\right)^k e^{-r_1N\left(t\right)}}{k!}x \\ V\left(N\left(t+1\right)=k,\alpha'=\alpha,\beta'=\beta,t+1|a\left(t\right)=1\right). \tag{6.7}$$

When we trial a new management action, $a(t) = 2$, we were uncertain about the population growth rate, r_2. Therefore, we monitor to improve our understanding, thereby, updating α' by $\alpha+N(t+1)$ and β' by $\beta+N(t)$ for every single time step. Thus, the Bellman equation when we trial a new action for $a(t) = 2$ and $0\leq k<M$, becomes,

$$\begin{aligned}
&V\left(N\left(t\right),\alpha,\beta,t\right)\\
&=\sum_{k=0}^{M} Pr\left(N\left(t+1\right)=k \middle| \mathrm{N}\left(t\right),\alpha,\beta,a\left(t\right)\right) x\\
&\quad V\left(N\left(t+1\right)=k,\alpha'=\alpha+N\left(t+1\right),\beta'=\beta+N\left(t\right),t+1 \,|\, a\left(t\right)=2\right),\\
&=\sum_{k=0}^{M-1} \frac{\Gamma\left(\alpha+k\right)}{k!\Gamma\left(\alpha\right)} \frac{\beta^{\alpha}}{\left(\beta+N\left(t\right)\right)^{\alpha}} \frac{N\left(t\right)^{k}}{\left(\beta+N\left(t\right)\right)^{k}} x\\
&\quad V\left(N\left(t+1\right)=k,\alpha'=\alpha+N\left(t+1\right),\beta'=\beta+N\left(t\right),t+1 \,|\, a\left(t\right)=2,k<M\right).
\end{aligned} \tag{6.8}$$

The chance of obtaining a population size of *k* next year given *α*, *β* and *N*(*t*) is the negative binomial in equation 6.4. For *k* = *M*, the sum of all negative binomial distribution from *0* to *M-1* is subtracted from 1, such that the negative binomial distribution adds up to 1. Thus, the Bellman equation for *k* = *M* is,

$$\begin{aligned}
&V\left(N\left(t\right),\alpha,\beta,t\right)\\
&=1-\sum_{k=0}^{M-1} \frac{\Gamma\left(\alpha+k\right)}{k!\Gamma\left(\alpha\right)} \frac{\beta^{\alpha}}{\left(\beta+N\left(t\right)\right)^{\alpha}} \frac{N\left(t\right)^{k}}{\left(\beta+N\left(t\right)\right)^{k}} x\\
&\quad V\left(N\left(t+1\right)=k,\alpha'=\alpha+N\left(t+1\right),\beta'=\beta+N\left(t\right),t+1 \,|\, a\left(t\right)=2,k=M\right).
\end{aligned} \tag{6.9}$$

Our main goal is to find the optimal stopping time that maximise the chance of the population reaching a target population size, *A* at the final time frame, *T*, such that,

$$V\left(N\left(t\right),T,\alpha,\beta\right)=\begin{cases} N(t) & \text{if } N\left(T\right)\geq A, \\ 0 & \text{if } N\left(T\right)<A. \end{cases} \tag{6.10}$$

where *V* is the value of implementing an action and *N(t)* is the state of the system that describes the number of animals at time *t*.

Case study : Christmas Island Pipistrelle bats

The Christmas Island Pipistrelle (*Pipistrelle murrayi*) is endemic to Christmas Island, that an external territory of Australia. Since 1994, monitoring showed that the bat had been declining rapidly (Lumsden et al. 2007; Tidemann 1985). Eighty per cent of the population had disappeared by 2005 and by 2008, 99% of them had disappeared (Beeton et al. 2010; Lumsden et al. 2007).The main reason behind this disappearance is unknown, but is probably due to multiple threats (Lumsden et al. 2007; Martin et al. 2012). By 2009, fewer than 20 individuals probably remained.

In 2006, several scientists and professional bodies advocated a captive breeding program to secure the species. However, nothing was done until July 2009, when the Australian government initiated an emergency plan to capture the last of individuals (Beeton et al. 2010). The rescue attempt failed and only a single bat was detected (Garrett 2009)**.**

A few experts believe that raising the species in captivity was feasible (Beeton et al. 2010**)** and it would have stopped its extinction (Martin et al. 2012)**.** If we could retrace our steps back to 2006, the approach presented in this paper could determine whether we should conduct captive breeding and if so, whether to release the bats back into the wild, given the final goal is to have a self-sustaining population in the wild. Since we are uncertain how well the pipistrelle copes in a captive breeding environment, we would need to monitor the population to understand the effectiveness of a captive breeding program. The existing action is to place the pipistrelle bats in the wild, whereas the new action is to start a new captive breeding program. We estimated the parameters for the pipistrelle from existing literature (Table 6.1).

Parameter	**Symbol**	**Values**	**References**
Population growth rate while trialling new action (captive breeding)	r2	1.39	(Beeton et al. 2010)
Population growth rate when continuing existing action (releasing into wild)	r1	0.78)	(Lumsden et al. 2007)
Initial Population size	N_0	20 (i.e.20% of 1994 population)	(Lumsden et al. 2007)
Management timeframe	T	20 years	-

Table 6.1 Parameters for managing the pipistrelle bat that is subjected to captive breeding.

Using the parameters for the pipistrelle as a baseline, we performed forward simulation to find the probability of the final population size that satisfied the management goal of achieving A, $Pr(N_T \geq A)$ for different states of the system. We forward simulated the active adaptive management (AAM) approach and the analytical solutions developed in chapter 4 and 5 of the thesis 10,000 times with different initial states of the system to calculate the $Pr(N_T \geq A)$. Then, we compare the AAM and the analytical solution results to determine whether AAM or the analytical solutions has better performance.

Results

Sensitivity analysis

The optimal management strategy for the Christmas Island pipistrelle was driven by the time frame, the management goal, the population growth rate while continuing an existing action (r_1), the expected population growth rate while trialling a new action (α/β) and the variance of the uncertain growth rate under the new action (α/β^2). In Fig 6.2 and 6.3, we compare optimal management strategies for different values for the mean and variance of the estimated growth rate under the new action. We examined how these change through time and for different values of the current population size $N(t)$ the growth rate under existing action, r_1, and the management goal at the end of management period, A.

If the current population size is small ($N(t)$=20) and the manager aims only to maintain this size by the end of the management period (A=20) or to increase this size by the end of management period ($A=40$), the best action is to continue an existing action initially, and delay trialling the new action because the manager is unsure whether the new action can achieve A (Fig. 6.2a and 6.3a). However, as time progresses (t increases), the manager starts trialling the new action and continues to do so because he is more confident that it will achieve the management goal as the uncertainty surrounding the new action decreases through time (Fig 6.2b, 6.2c, 6.2d, 6.3b,6.3c and 6.3d).

If the current population size is large ($N(t) = 40$) and the manager aims to reduce this size by the end of management period (A=20) or maintain this size by the end of management period ($A=40$), when the existing action is highly effective compared to the new action ($r_1>\alpha/\beta$), the manager can afford to be a bit more experimental at the initial time step because it is uncertain whether the new action can ever reach the management goal A (Fig. 6.2e and 6.3e). However, as time progresses (t increases), the manager is more certain that management action can achieve our goal. Hence, the best action is to continue trialling the new action even though it performs worse than the existing action (Figs. 6.2f, 6.2g, 6.2h, 6.3f, 6.3g and 6.3h). When the existing action is less effective compared to the new action ($r_1<\alpha/\beta$), if the current population size is small ($N(t)$=20) and the manager aims to reduce this size by the end of management period (A=20) or maintain this size by the end of management period, (A=40),the best action is to continue an existing action initially, even though the manager knows that the existing action can never achieve the management goal and delay trialling the new action because the manager is unsure whether the new action can achieve A. However, as time progresses (t increases), the manager start trialling the new action and continue to do so because he is more confident that it will achieve the management goal as the uncertainty surrounding the new action decreases through time (Figs. 6.2e, 6.2f, 6.2g, 6.2h, 6.3e, 6.3f, 6.3g and 6.3h).

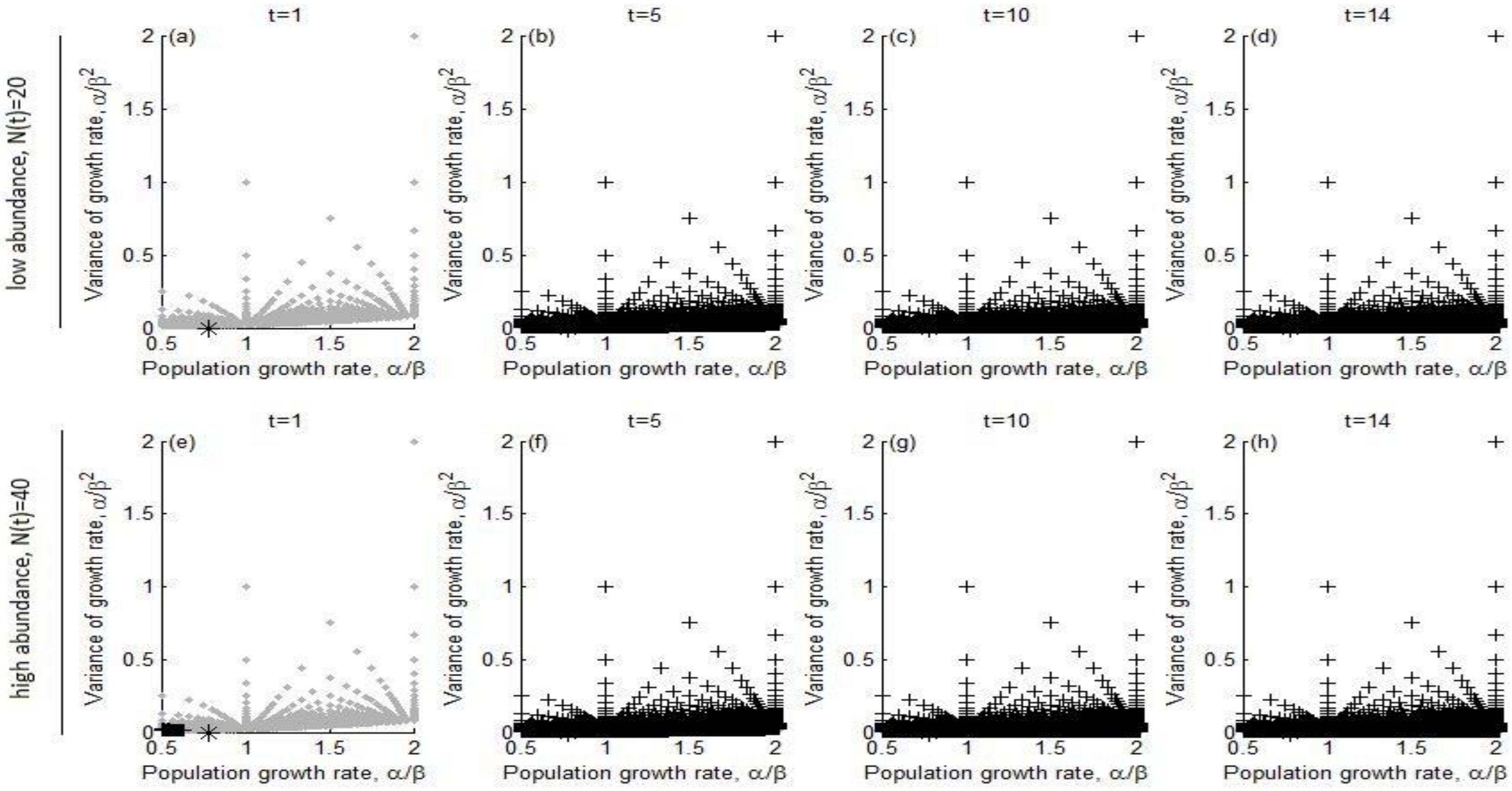


Figure 6.2. The optimal management strategy for various population growth rate and variance of the growth rate while trialling a the new action that changes through time for different current population size, N(t) and the manager aims to have a management goal of A = 20 by the end of management period. New action (black colour plus shape) and an existing action (grey colour diamond shape) at time t and r_1 = 0.78 (baseline parameter for Pipistrelle bats denoted by asterisk (*)). The time horizon changes from t = 1 to t =14.The current population size changes from N(t) = 20 to N(t) = 40. α/β describes the population growth rate and α/β^2 describes the variance of the population growth rate while trialling a new action.

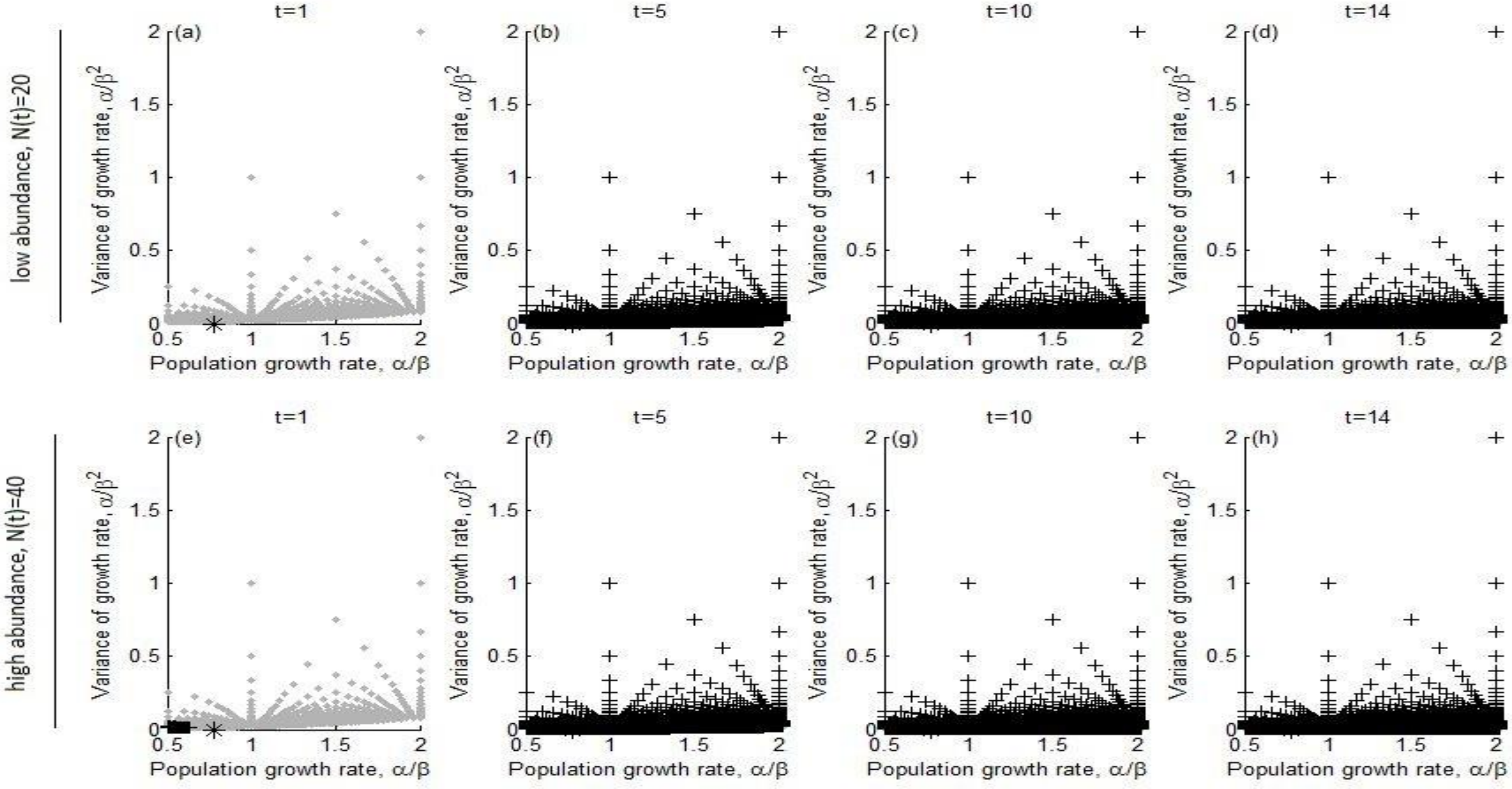


Figure 6.3. The optimal management strategy for various population growth rate and variance of the growth rate while trialling a the new action that changes through time for different current population size, N(t) and the manager aims to have a management goal of A = 40 by the end of management period. New action (black colour plus shape) and an existing action (grey colour diamond shape) at time t and r_1 = 0.78 (baseline parameter for Pipistrelle bats denoted by asterisk (*)). The time horizon changes from t = 1 to t =14.The current population size changes from N(t) = 20 to N(t) = 40. α/β describes the population growth rate and α/β^2 describes the variance of the population growth rate while trialling a new action.

Forward simulation

An example of the active adaptive management to either continue an existing or trial a new action is shown in Fig. 6.4. Initially, the population size is 20. The population growth rate when continuing an existing action is known to be 0.78 while the population growth rate when trialling a new action is uncertain with a gamma (1,1) prior distribution that has a mean of 1.39, with a possibility of an increase or decline of the population size (Fig. 6.4b). Surprisingly, AAM shows that there is a change of management more than once, swapping back and forth between new and existing action (Fig. 6.4a). In this example, AAM starts with an existing action initially, but switch to an uncertain new action every single time the population size is close to the management goal of achieving A = 20. This is because we know that the existing action with a growth rate of r_1 = 0.78 can never achieve the goal of achieving a population abundance of 20. Thus, we trial a new action that is uncertain such that the population size does not fall below A. However, if the population size is high, we safely continue existing action because we know that it is far from A. Initially, when we continue with an existing action, the variance surrounding the population growth rate remains wide (Fig. 6.4b). However, as we trial the new action, the variance surrounding the population growth rate reduces as we learn about the state of the system (Fig. 6.4b).

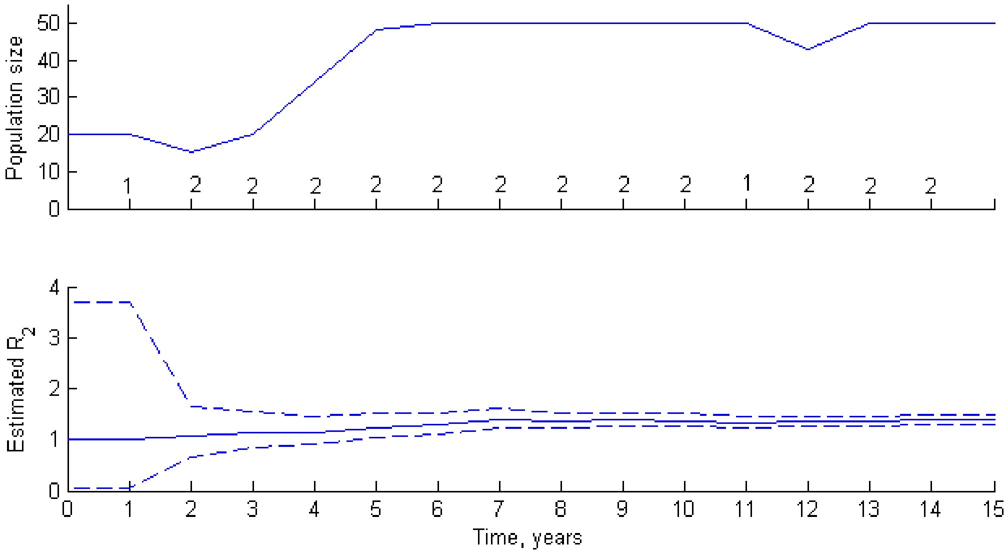


Figure 6.4. An example of active adaptive management for 15 years of simulation with an initial population size of 20 and a management goal of A = 20. (a) Number of animals while continuing an existing action (#1) or trialling a new action (#2), (b) estimated population growth rate denoted by the mean (solid line), with 2.5th and 97.5th percentiles on the gamma distribution (short -dashed lines). The true population growth rate for existing action, r_1 = 0.78 and new action, r_2 = 1.39.

Most of the time, the analytical solution approximates the solution provided by true optimal AAM. However, when the new action resulted in a stable population growth rate, the solution that is provided by AAM significantly outperforms the analytical solution (Table 6.2). In such situations, it is better to use the solution provided by AAM.

r1(existing)	**r2(new)**	**N0**	**A**	**Pr(NT≥A)**		
				SDP	**Analytical solution1 (new to existing)**	**Analytical solution 2 (existing to new)**
0.78*	0.7	20	20	0	0	0
0.78*	1	20	20	0.72	0.70	0.56
0.78*	1.39*	20	20	1	1	1
0.78*	0.7	40	20	0	0	0
0.78*	1	40	20	0.86	0.81	0.
0.78*	1.39*	40	20	1	1	1
0.78*	0.7	20	40	0	0	0
0.78*	1	20	40	0.25	0.24	0.21
0.78*	1.39*	20	40	1	1	1
0.78*	0.7	40	40	0	0	0
0.78*	1	40	40	0.52	0.50	0.50
0.78*	1.39*	40	40	1	1	1

Table 6.2. Using Pr($N_T \geq A$) as a measurement to compare of SDP with the analytical solutions for different states of the system. Grey colour has the best performance. Asterisk (*) indicates baseline parameters used for the Pipistrelle bats.

Discussion

The world of conservation management is plagued with various types of uncertainty. To manage a species in this uncertain world, we used active adaptive management that iteratively updates the belief of the state of the system that is informed through monitoring. While there are several studies on active adaptive management in conservation that help us find the best management strategy among multiple actions (Hauser and Possingham 2008; McCarthy and Possingham 2007; Moore and McCarthy 2010; Rout et al. 2009b; Runge et al. 2011), we provided the first framework to determine whether we should implement an existing action or to trial a new action. We have presented three methods to answer the question of whether to change management actions for a threatened species: two analytical solutions and a stochastic process that is solved using SDP.

Rules of thumb can be a good approximation and at times perform almost as well as the exact solution provided by stochastic dynamic programming (SDP)(Regan et al. 2006; Rout et al.

2009a). Several studies have developed rules of thumb to approximate an SDP solution, ranging from when to stop looking for invasive plants (Regan et al. 2006; Rout et al. 2009a), how to allocate resource optimally between regions (Wilson et al. 2006) and how to allocate resources between two regions and deciding how many subpopulations to manage (McDonald-Madden et al. 2008). Even though our study answers a different question of finding the optimal stopping time to change management actions, our results agrees with these study where we illustrate that simple analytical solutions approximates the performance provided by SDP with SDP slightly outperforming the analytical solution. The analytical solutions that we have developed are deterministic process that has no stochasticity, and is a simplification of the SDP solution. Specifically we cover two analytical solutions that have different management scenarios where an existing action was implemented first before changing to a new action that is uncertain and the scenario where a new action is trialled before reverting to an existing management action. The optimal stopping time provided by these two management scenarios is different. The analytical solution was found by maximising the chance of obtaining a particular target population size over the management timeframe, whereas SDP considers all possible future states of the system for every single time step within the management time frame(McDonald-Madden et al. 2008).

The benefit of SDP is that it covers multiple management scenarios. Among the management scenarios, we have presented analytical solutions for two scenarios which involved finding one optimal time to change management actions. Other possible management scenarios involved having more than one optimal time to change management actions. For example, we have a new management action initially, and then switch to existing action. After some time, we switch back again to a new management action, and then to existing action. Another possibility is to start with an existing action, switch to a new action and then switch back to an existing action. In the case of the Pipistrelle bats, this would mean placing the pipistrelle in captivity and releasing the bats back into the wild every few years. It is possible for future studies to find the analytical solution for these optimal stopping times to switch actions using partial differentiation.

The solution provided by SDP is more realistic compared to the analytical solution as it covers every single possibility. Nonetheless, there is no single optimal stopping point for the SDP solution as there is more than one optimal stopping point, resulting in multiple optimal times to change management actions. SDP swaps back and forth between one action and another in the forward simulation. Thus, the analytical solution cannot be used to approximate the situations provided in SDP. However, we can compare the performance of the analytical solutions and the SDP solution. We found that the analytical solution approximates the performance the analytical solution, with SDP slightly outperforming the analytical solution when the new action resulted in a stable population growth rate. In such situation, it is better to use SDP compare to the analytical solution. The main reason SDP outperforms the analytical solution is because SDP considers every single possible situations and provides the optimal solution for these situations whereas the analytical solution considers only on single management scenario.

For the SDP, whether we spend time trialling and learning the new action or continue an existing action hinges on the known and estimated population growth rates as we continue an existing action or trialling a new action (relationship between r_1 and α/β). This is comparable to the results obtained through the analytical solutions, where the optimal decision of when to stop an action and change to another action depends on the population growth rate while implementing these actions. The difference is SDP provides extra information about the choice of our optimal management action: whether we should continue an existing action or trial a new action in the first place. Making decision about whether to continue an existing or trial a new action initially depends on a variety of factors including the management goal, the state space and the population growth rate while trialling a new action.

Learning is incorporated in this model while we trial the new action by updating the expected population growth rate which is a Poisson distribution in this model with a gamma distribution using Bayesian inference, resulting in a variance that reduces through time. We assume that there is no learning associated with the existing action. However, it is possible to incorporate learning into an existing action. To do this, we need to model the existing action similar to the new action using Bayesian updating with an updated gamma distribution. However, this would increase the state space of the model as there would be two extra parameters to reflect the updated α and β parameters for the existing action. This would be problematic as there would be a geometric increase in the computational time needed for the SDP. In addition, it would also increase the complexity of the results, making it harder to interpret.

We also assume that there is little influence of density dependence on the optimal strategy. In reality, density dependence can play an important role in deciding our optimal management strategy as in the case of deciding how many animals to translocate or when to translocate in the event of climate change (McDonald-Madden et al. 2011). It remains an important extension for future studies to explore the impact of density dependence on the optimal management strategy. However, incorporating density dependence in the new or existing actions would require two extra parameters that would increase the computational time needed and increase the complexity of the SDP results.

We assume a management goal with a cut off at A. It is possible to choose another type of management objective such as maximising population size for the SDP. The main reason we choose this was because we need to compare SDP with the analytical solution where the Heaviside function is its management objective. Solving for other management objective is not plausible with the analytical solution as it can result in an intractable solution. However, it would be an interesting extension for SDP to explore other management objectives.

Conservation managers already have difficulty managing with the limited amount of resources available. There is little time available to learn and implement complex calculations such as SDP even though it is more realistic. We have shown that simple analytical solution approximates the performance of SDP solutions, therefore, it would be easier to use these simple analytical solution compare to performing complex endeavours such as SDP.

The SDP results are surprising, as we cannot find the optimal stopping point because the management action swaps back and forth. However, we show that analytical solutions can approximate the performance obtained from SDP. This indicates the analytical solution can serve as a useful tool for conservation managers who are slowly running out of time to manage biodiversity.

Chapter seven - Discussion

In this thesis, I have explored how to allocate resources, namely money and time optimally between different management actions. In chapter 2 and 3, I have investigated what influences the optimal allocation of resources (time or money) among multiple actions, where one of the actions may include learning more through monitoring. Specifically in chapter 2, I examine the influence of social, technological and habitat constraints on how to allocate resources among multiple actions to mitigate multiple threats. In chapter 3, I have identified several key parameters that influence how to allocate resources between two actions (monitoring and translocation). The next three chapters of the thesis (chapter 4, 5 & 6), examined how much time to spend among multiple actions including monitoring. Specifically, in chapter 4 and 5, I determined how much time to allocate between two mutually exclusive actions, the results of which are applicable to both invasive and threatened species management (chapter 5). Finally, chapter 6 explored whether to continue an existing action or trial a new action in an active adaptive management framework.

Summary of key points and major contributions

Incorporating impediments

Incorporating impediments into how we allocate resources is one of our greatest challenges as researchers. Impediments are social, political, economic, habitat or technological factors that prevent an action from being 100% effective when implemented in real life (Balmford and Cowling 2006; Curran et al. 2012; Knight et al. 2006; Knight et al. 2011b; Knight et al. 2011a; Polasky 2008). When building a model, it is important to incorporate these impediments as it may affect how conservation managers allocate resources. Not doing so, may result in a misallocation of resources by investing in actions which have little likelihood of being successful. In order to allocate resources on actions that are successful in real life, I believe that researchers should move towards incorporating impediments into their model. In chapter 2, I have illustrated that social, technological and habitat impediments can change the allocation of resources among multiple threats. In addition, I have shown that by incorporating impediments into our model, it may prevent us from reaching our management objective. In general, conservation scientists are often unable to implement certain actions due to impediments. The benefit of incorporating impediments is it takes into account of the factors that directly affects the efficiency of the management action. This allows conservation managers to adjust their management strategy in order to compensate for the loss in efficiency of management actions or find an alternative strategy if the management goal cannot be reached. For instance, incorporating impediments can reduce our ability in achieving the management goal. In such instances, instead of allocating resources in actions to mitigate threats, conservation managers can allocate resources in removing the impediments.

Understanding key parameters

Improvement in our understanding about why a parameter is used when building a model contributes towards better model building and ultimately conservation outcomes. Decisions about how to allocate resources on monitoring to inform translocation decisions depends on what is being monitored. Thus, it is important to understand how a particular parameter influences the optimal monitoring strategy when building models to decide on the optimal strategy (Colyvan and Ginzburg 2003; Ginzburg and Jensen 2004). Some of the parameters will influence the outcome of the model, while some may not. Any extra parameters will require extra time spent analysing the model. In addition, if there is less parameters in a model, the model would be simpler to build and easier to understand. The problem with recent models about optimal monitoring is it covers a huge range of parameters, from growth rates of a population, their stochasticity to the cost of management actions (Hauser and Possingham 2008; McDonald-Madden et al. 2010b; Rout et al. 2009b). However, it is not known why certain parameters are important nor is there any understanding about how it influences the timing of translocation or the optimal investment in monitoring. In chapter 3, I have shown that out of 10 variables, only 6 variables (population growth rate of captive and wild population, environmental stochasticity related to the population growth rate of captive and wild population and initial population size) influences the optimal monitoring strategy (average time spend on monitoring before translocation and the yearly amount of money to spend on monitoring). Our research provides a unique contribution to the field by providing an understanding of how a variable influences the optimal monitoring strategy and why a particular parameter is important when building models that deals with monitoring and translocation of animals into a captive breeding program. By incorporating our findings, conservation managers can design a simpler and more efficient model on optimal monitoring by not incorporating unnecessary parameters that requires valuable resources and does not contribute towards achieving the management goal. In general, it is important to conduct sensitivity analysis to understand why a particular parameter is used when building a model.

When to change management actions

Time is of critical importance as a failure to change management actions in time could result in the extinction of a species. In the past, finding the optimal time to change management actions has been management action or situation specific, with some providing a complex dynamic solution to the problem (Chades et al. 2008; McDonald-Madden et al. 2011). In chapter 4 and 5, I have obtained analytical solutions to answer the question about when to change management actions between two mutually exclusive management actions: an uncertain new action and an existing action that is certain that is applicable to a wide variety of conservation actions. My result show that the optimal time to change management action depends on the management timeframe, the population growth rates under the different management action and the management goal. Unexpectedly, the measurement error associated with monitoring did not influence the optimal time to change action. My result shows that this measurement error drops out of the equation when I attempt to find the optimal solution. This implies that an imperfect monitoring program would seldom influence the optimal time to change management action which is a surprising result.

There is a belief that a complex solution is better as it is more realistic and accurate (Volker 1999). Most conservation models tend to strive for realism in the model and one common way of achieving this is by stochastic dynamic programming where the result covers every single situation that changes through time (Baxter and Possingham 2011; Drechsler and Wätzold 2007; Hauser et al. 2007; McCarthy et al. 2001; McCarthy and Possingham 2007; McDonald-Madden et al. 2008; Rout et al. 2007; Tenhumberg et al. 2004). This is problematic as it requires complex mathematical knowledge and programming skills to build and solve the problem. In addition, the results are complicated to understand. Given the limited skills and time a conservation managers has, it is better to provide them with simple solutions to a complex problem. This is where my study comes in where I have shown that a simple general analytical solution approximates the performance of complex solution provided by stochastic dynamic programming in answering the question of when to change management actions (Chapter 6). In a resource scarce world, a general solution is more appealing because it save time and money as it can be applied to a range of situations. The analytical solution is simple because of its unique solution that is an equation which a conservation manager can use by changing the parameters of the equations.

Conservation managers often have to manage invasive species and threatened species concurrently, but it is a challenge to combine these under the same general framework due to the opposite nature of managing these species where managing invasive species requires eradication and managing threatened species requires maximising the population size. Examples of attempts to combine invasive species and threatened species management under the same general framework include deciding how much to invest across a network for metapopulations (Chadès et al. 2011) and deciding how much effort to spend on monitoring (Thompson et al. 2012). However, the question of developing a general theory for when to change management action for both invasive species and threatened species management remains unanswered. I have answered this in Chapter 5 where I develop a general theory on when to cease an existing action when a possible new management action might be attempted in the future. It not only provides theoretical insights into when to change management actions, but is the first study that integrates threatened and invasive species management into a single general framework. Given the limitation of resources worldwide, it is only prudent that conservation manager save time and money managing threatened and invasive species by using a single general framework.

Chapter 6 is an expansion of chapter 4 and 5 where I include stochasticity in the model within an active adaptive management framework. Chapter 6 provides a unique contribution to the field whereby it answers a different question of whether to select an existing action that is certain or trial a new action that is uncertain, which has never been addressed. Chapter 6 also encompasses multiple management scenarios from a single optimal time to change action to having multiple optimal time to change management actions. For instance, there is a new management action initially, then switch to an existing action. After some time, there is a switch back again to a new management action, and then to an existing action. In addition, in chapter 6 I showed that the analytical solution approximates the performance provided by SDP, where the performance is measured by the probability of the population at terminal time achieving a target population size, A. The analytical solution provides conservation managers with a quick and simple rule of thumb to assess if there is any benefit in trialling a new action or to stay with the existing action.

<u>Tools for conservation managers</u>

Conservation managers have trouble deciding how to allocate resources (time or money) among management action. Resources are normally allocated randomly, without much guidance on how or where to allocate these resources. Researchers are able to tackle some of these resource allocation problems (Chades et al. 2008; Chadès et al. 2011; Joseph et al. 2009; McCarthy et al. 2008; McCarthy et al. 2010; McDonald-Madden et al. 2008; McDonald-Madden et al. 2010b; McDonald-Madden et al. 2011; Rout et al. 2010; Thompson et al. 2012; Wilson et al. 2011b). However, some questions such as how to allocate resource among multiple threats or when to change management actions remain unanswered. In this thesis, I have provided tools for conservation managers to solve these resource allocation problems. Specifically in chapter 2, I have provided guidance for conservation managers who need to decide on how to allocate money among multiple management actions to mitigate multiple threats with impediments. In chapter 4 and 5, I have provided rules of thumbs to help conservation managers decide on when to change from one management action to another, that approximates the performance of a realistic problem of deciding every year which action to take using stochastic dynamic programming in chapter 6. These tools will go a long way in helping conservation managers allocate resources wisely among management actions.

Limitations and future research directions

There is a need for models to be simple and as parsimonious as possible (Ginzburg and Jensen 2004; Ginzburg and Colyvan 2004). If we build a complex model in the first instance, it may not be working, wasting valuable resources in figuring how it works. Therefore, it is important to build simple models initially and add complexity to it once we understand how a simple model works. In the following sections, I discuss the complexity that we can add to the existing model since we already know how the simple model works.

Exploring how different types of uncertainty affects the allocation of resources can enhance our ability to make better decisions. In turn, this reduces the risk of making a wrong decision when developing conservation plans (Lawler *et al.* 2002; Regan *et al.* 2005; McDonald-Madden *et al.* 2008b). In chapter 2, I was able to quantify the consequences of uncertainty in the population model to achieve the target growth rate. However, I have not considered uncertainty in the return on investment curves. Dealing with uncertainty in economic costs is an important area for future research, as costs can drive the optimal allocation of resources (Bode et al. 2009; Drechsler and Wätzold 2007; Murdoch et al. 2007). One method of incorporating uncertainty in cost estimates would be to use info-gap decision theory (Ben-Haim 2006; McCarthy and Lindenmayer 2007; Regan et al. 2005; Runge et al. 2011). Other approaches would be to use expert opinion in a Bayesian framework to estimate the uncertainty in cost estimates.

In reality, most funds are allocated dynamically through time. In Chapter 2, I assumed that the allocation of funds were immediate to ensure that the problem was tractable. Future studies could incorporate dynamic allocation of funds for multiple threats using stochastic dynamic programming (SDP), which explores the optimal action to take for every single state (Bellman and Dreyfus 1962; Dreyfus and Law 1977; McCarthy et al. 2001). In addition, monitoring can be incorporated into the model to develop an active adaptive management approach to mitigate multiple threats (Johnson 2011; McCarthy and Possingham 2007; Rist et al. 2013). However, the population dynamics of the model would need to be simplified, such that there is a direct link between the investment in each action and the population growth rate.

Preliminary simulations in chapter 3 show that the economic value we assign to a species has an impact on the optimal monitoring strategy. In chapter 3, I only considered the value of a single species, the Pipistrelle bats. In reality we are often faced with a choice of investment amongst many species, and the allocation of resources amongst them is likely to be sensitive to the value assigned to each species. One way to measure the value of species, is to calculate how much we are willing to pay to preserve a species (Jakobsson and Dragun 2001; Martin-Lopez et al. 2007). However, this human preference does not take into account how valuable a species is towards the ecosystem. An interesting extension to the value of species for the Pipistrelle bat is to incorporate the value of the ecosystem services provided by the Pipistrelle such as pollination, and pest control services (Boyles et al. 2011; Kunz et al. 2011; Losey and Vaughan 2006; Wenny et al. 2011).

In chapter 3, I did not consider the interactions between the key ecological variables when conducting sensitivity analysis. Ecological variables are likely to interact with one another and the way in which they interact is likely to influence the optimal monitoring strategy. Some preliminary simulations showed that the interaction between the ecological variables influences the optimal monitoring strategy. An example would be to increase the wild and captive population growth rates simultaneously and explore its impact on the optimal monitoring strategy. It is known that interactions between ecological variables can affect the optimal solution to a problem (Walters and Hilborn 1978). However, the sheer amount of ecological variables examined in this study prevents us from characterising the interactions between these ecological variables fully. Yet, it is an important extension to the current study to explore potential interactions between the key ecological variables and examine its influence on the optimal monitoring strategy.

Density dependence occurs as a result of resource constraints, limiting the growth rate of a population (Turchin 2001). The models in this thesis assume that density dependence has little influence on the population. In some instances, such as when a population is declining due to environmental influences such as pollution or natural catastrophe, density dependence can have negligible impact on a population (Edwards 2011). In addition, some management actions such as translocation can temporarily increase the amount of resources available, reducing the effect of density dependence (Lawler and Olden 2011). However, density dependence can play a vital role in this resource dependent world, where there is a lack of time, money and space available. Including density dependence in chapter 4 and 5, would change the analytical solution such that density dependence will be influential when conservation managers decide to change management actions. Incorporating density dependence into chapter 2 will likely change how resources are allocated among multiple threats. Including density dependence into chapter 3 will have an impact over how the ecological variables affect the optimal monitoring strategy. Therefore, incorporating density dependence into this thesis remains an important area for future studies especially when habitat loss and fragmentation is considered a major threat for a species that are facing extinction (Lawler et al. 2002).

Deciding how to allocate resources optimally depends on what is being allocated. There are three things that need to be allocated optimally in conservation biology: money, space and time. In this thesis, I have concentrated on developing models to allocate money or time optimally among conservation actions. It is important in the future to explore how to allocate space optimally among different management actions. The ultimate goal would be to answer a fundamental question of when, where and how to allocate time, space and money among conservation actions. However, answering such a question would be beyond the scope of this study.

Even though we have assumed that the management actions were mutually exclusive in chapter 4 to 6, in the real world, few management actions are mutually exclusive. This assumption could be removed from the problem by reframing the problem using a different case study that shows that there is a change in management strategy. In this instance, the problem would be to find the optimal time when there is a change in management strategy that can include a bunch of action that does not have to be mutually exclusive, as long as the change in management strategy has an impact on the change in population growth rates. For example, we could use the Orange-bellied Parrot as a case study where captive breeding was an existing action was implemented in 1986 (Martin et al. 2012) and a change to a new management strategy would be to to release the bats back into the wild while maintaining the captive population size or capture more parrots from the wild to bolster the captive population.

The complexity of the SDP approach in chapter 6 makes it hard to implement. However, as long as we understand what state we are in (population size in the previous time step), and what type of management action was implemented previously, it would be possible to know the optimal management strategy to implement for the next time step that would result in achieving the final management objective of having a population size greater than A in the final time step.

Several chapters of this thesis focus on allocation of time between two mutually exclusive actions using analytical solution and stochastic dynamic programming. I have shown that heuristic analytical solution approximates the performance of stochastic solution provided through stochastic dynamic programming. This has far reaching implications as it is easier to use and understand the analytical solution compared to stochastic dynamic programming. In addition, I have examined several factors that affect the optimal allocation of resources including impediments and several ecological variables. By understanding how these factors affect resource allocation, conservation managers can make better informed decisions and reduce the risk of making wrong decisions.

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Appendix A: Constructing return-on-investment curves

Reducing Vehicle Collisions

Management strategies to reduce vehicle collisions include the building of overpasses and underpasses, installation of exclusion or guide fencing, cat eye reflectors, speed signage, high alert signage, and improvements in lighting and landscape modification. These strategies reduce the impact of roads on koalas and we considered them collectively as an action to mitigate vehicle collisions (e.g. Dique et al. 2003). We constructed a return-on-investment curve to illustrate how investment in management action reduces koala mortality rates due to vehicle collision.

Cost estimates were obtained for road upgrades to reduce vehicle collisions at nine locations within the Koala Coast from Caneris and Jones (2004) and indexed to 2008 using the Consumer Price Index (CPI). In addition, the mean mortality rates due to vehicle collision per year for each location as well as the entire Koala Coast from 1997 to 2004 was obtained from Preece (2007).

We assumed that investment in an action starts from the most cost-effective to the least at each location. An exponential curve was fitted to the data using the following equation,

$$p = \alpha_1 + (1 - \alpha_1) e^{-x_c / \gamma_1}, \qquad \text{A.1}$$

where *p* is the cumulative koala mortality rates due to vehicle collisions; x_c is the investment in methods to reduce koala mortality rates due to vehicle collisions; α_1 is the asymptote (i.e. the maximum annual mortality rates that could be mitigated); and $1/\gamma_1$ measures efficiency in investment. Both α_1 and γ_1 are estimated from the data using least squares. Next, we recalculate equation A.1 for the entire Koala Coast. Without data about technological constraint, the return-on-investment curve is,

$$p_v = e^{-x_1 / \beta_1}, \qquad \text{A.2}$$

where p_v is the koala mortality rates due to vehicle collision for the Koala Coast; x_1 is the investment required to reduce vehicle collisions mortality rates; and $\beta_1 = \gamma_1 M / \alpha_1$ that represents the scaling of equation A.1 for nine locations to the entire Koala coast. This equation was obtained by fitting the exponential curve (A.2) with data using least squares, where M = 268.88 koala mortality due to vehicle collision/year is the mean koala mortality rates due to vehicle collision per year across the entire Koala Coast between 1997 and 2004 (Preece 2007).

It is impossible to be 100% effective in reducing koala mortality rates due to vehicle collisions. This represents technological impediments. Although there is limited data on the effectiveness of road underpasses and overpasses for koalas, the Bonville upgrade of the Pacific Highway in New South Wales (Semeniuk et al. 2011) indicates that road underpasses or overpasses with exclusion fencing reduce mortality at a site by an estimated 77%. Even though this data is unpublished, it is sufficient to demonstrate the influence of technological impediments in this study. The actual effect of these impediments requires further research. Thus, the return-on-investment curve with technological impediments is,

$$p_V = 0.23 + 0.77e^{\left(-x_1 / \gamma_1\right)}. \qquad \text{A.3}$$

Reducing Dog Attacks

To reduce dog attacks on koalas, we need to reduce the contact between domestic dogs and koalas. We can use legislation, education, or incentives to encourage dog owners to exercise greater control over domestic dogs. Specifically, we considered the provision of enclosures for domestic dog owners to encourage the restraint of dogs at night. The Redland City Council (the local government area that covers the majority of the Koala Coast) currently considers this as a possible management alternative (Daniel Carter personal communication).

To construct the return-on-investment curve, we obtained data on the number of medium sized and large domestic dogs between 1997 and 2008 in each suburb in Redland City Council (Redland City Council unpublished data). We assumed that small dogs are not a threat to koalas. Then, we obtained costs of building outdoor enclosures for medium sized dogs (4' x 8' enclosure) and large dogs (10' x 10' enclosure), that are AU$1,326.05 and AU$1,784.42 respectively from Kennel Solutions (http://www.kennelsolutions.com.au/dog_kennel_kits/premier_kennel_kits.html). We calculated the total investment required to supply a dog owner of each suburb with an enclosure by summing the costs of enclosing medium dogs multiplied by the number of medium dogs with the costs enclosing large dogs multiplied by the number of large dog. Then, we relate the total investments required for each suburb with the mean dog-related koala mortality rates per year between 1997 and 2008 in each suburb (Department of Environment and Resource Management unpublished data), using the same approach as the vehicle collision return-on-investment curve in equation A.1.

We obtained the return-on-investment curve for the entire Koala Coast from Equation A.2 by setting *M* equal to the mean annual dog-related koala mortality rates for the entire Koala Coast. This provides us with the return-on-investment curves for dog control measures, without social constraint (Department of Environment and Resource Management unpublished data).

A study by Clark (2006) found that 36% of dog owners in Redland City Council currently keep their dogs outside at night, but 20% of dog owners indicate that nothing will convince them to constrain their dogs. Consequently, only 16% of dog owners are likely to adopt dog enclosures. Since 16 out of 36 dog owners who currently keep their dogs outside at night will adopt dog enclosures, this reduce dog attack related koala mortality rates by a maximum of 44%. Therefore, the return-on-investment curve for investment in dog-mitigation measures with a social impediments is,

$$p_d = 0.56 + 0.44e^{\left(-x_2/\beta_2\right)}. \tag{A.4}$$

where p_d is the dog related mortality rates for the Koala Coast; x_2 is the investment in dog control measures; $\beta_2 = \gamma_2 N / \alpha_2$ estimated by fitting the exponential curve with the data using least squares, where N = 55.08 koala mortality rates/year is the mean annual dog related mortality rates across the entire Koala Coast between 1997 and 2008 (Department of Environment and Resource Management, unpublished data), and β_1 is the scaling factor obtained when we scaled A.1 to reflect the dog attack mortality rates and the investment required to save these koalas for the entire Koala Coast.

Habitat Restoration

The cost of habitat restoration consists of the unimproved land value, plus the cost of the restoration activity itself. Unimproved land value was included as land is taken out of economic production for habitat restoration. This is an economic opportunity cost that should be accounted for in conservation planning (Naidoo et al. 2006). Land value is commonly used under the assumption that it provides an estimate of the economic benefit for productive land uses, whereas there is little economic benefit for conservation land usage (Chomitz et al. 2005). A return-on-investment curve for habitat restoration was developed by simulating the influence of habitat restoration on the natural and disease mortality rates.

We mapped the unimproved land value per hectare for the Koala Coast by indexing the 2006 data from the Queensland Valuation database using CPI to obtain values for 2008. Since reserves and protected areas are already used for conservation, we assumed that these land values are zero. We added the cost of restoration of eucalypt forest as AU$7,605 per hectare estimated from Schirmer and Field (2000). Then, we estimated the cost of habitat restoration by simulating the cost of restoration of all grid cells that are available for restoration within each suburb of the Koala Coast. Without habitat impediments, we assumed that all land in the Koala Coast is available for restoration (although in reality habitat restoration is still constrained by the area of land in the Koala Coast). Subsequently, we considered habitat impediments by assuming that urban areas and intensive land use zones are unavailable for restoration

We assumed that investment in habitat restoration starts from the most cost- effective suburb to the least cost-effective suburb based on how it influences the population growth rate (i.e., highest increase in growth rate per dollar spent first). We fitted an asymptotic curve to the cumulative change in natural and disease mortality and the cumulative costs of habitat restoration. The curves fitted for each mortality cause had the form,

$$p_h = \tau + (1-\tau) e^{\left(-x_3 / \gamma_3\right)}, \qquad \text{A.5}$$

where p_h is the decline in mortality rate; x_3 is the investment in habitat restoration; and τ and γ_3 are the asymptote and exponent, respectively, estimated by fitting the exponential curve with the data using least squares. We produced an investment curve with and without habitat impediments. A separate investment curve was estimated for each female sub-adult and adult age class, but juvenile mortality rates are assumed to be unaffected by habitat restoration.

Types of mortality rates for the koala	With or without constraints	Age class	α_i	γ_i
Vehicle collision	With constraints	All age classes	0.23	5.93
	Without constraints	All age classes	1	5.93
Dog attacks	With constraints	All age classes	0.56	1.81
	Without constraints	All age classes	1	1.81
Natural mortality	With constraints	1	0.90	677.81

	With constraints	2	0.90	674.63
	With constraints	3	0.89	679.74
	Without constraints	1	0.80	4197.44
	Without constraints	2	0.80	4225.62
	Without constraints	3	0.79	4194.29
Disease mortality	With constraints	1	0.90	676.55
	With constraints	2	0.90	676.21
	With constraints	3	0.89	679.95
	Without constraints	1	0.80	4203.33
	Without constraints	2	0.80	4234.81
	Without constraints	3	0.79	4194.48

Table A. The parameter estimates for different types of return on investment curves associated with various koala mortality rates with and without implementation constraints.

Appendix B: Nonlinear programming and optimization

Nonlinear programming is used to study a set of problems where it has to be minimised or maximized over a set of nonlinear constraints (Theodore 2008). The objective function (eqn 1) for the case study was considered a nonlinear programming problem because the relationship between the population growth rate λ (C_1, C_2,….C_n) and the total cost for each management action is nonlinear. An active set algorithm from nonlinear programming was selected to determine the optimal allocation of resources to each management action for the target population growth rate.

An active set algorithm starts with an active set which is any possible set of variables that we are trying to maximize or minimize (Mordecai 2003). In this problem, the active set is the investment in reducing vehicle collision, dog attacks and habitat restoration (C1,C2,C3). Then, it calculates the Lagrange multiplier of the active set and removes the constraints that are impossible, that have negative Lagrange multipliers (Mordecai 2003). Then, it moves on to another active set and repeats this again until it finds the minimum or maximum active set that satisfies the condition specified by the constraints (Mordecai 2003). By using the Lagrange multiplier, this algorithm has the added advantage of breaking a nonlinear problem that is unsolvable into small linear sub problems that can be solved (Mordecai 2003).

Appendix C: Bayesian inference

If we have data about λ, the chance of the population size next year being a certain size is given by the Poisson distribution (from equation 3). With a gamma prior distribution for the population size, the posterior distribution is,

$$Pr(r_2|N(t+1)=k, N(t), \alpha', \beta') = \frac{Pr(N(t+1)=k|r_2N(t))Pr(r_2|\alpha,\beta)}{\int_0^\infty Pr(N(t+1)=k|r_2N(t))Pr(r_2|\alpha,\beta)dr_2}$$

$$= \frac{\frac{(r_2N(t))^k e^{-r_2N(t)}}{k!}\frac{\beta^\alpha}{\Gamma(\alpha)}r_2^{\alpha-1}e^{-\beta r_2}}{\int_0^\infty \frac{(r_2N(t))^k e^{-r_2N(t)}}{k!}\frac{\beta^\alpha}{\Gamma(\alpha)}r_2^{\alpha-1}e^{-\beta r_2}dr_2} \tag{C.1}$$

$$= \frac{e^{-r_2(N(t)+\beta)}(r_2(N(t)+\beta))^{\alpha+k}}{r_2\Gamma(\alpha+k)}$$

$$= \frac{(\beta+N(t))^{\alpha+k}}{\Gamma(\alpha+k)}r_2^{\alpha+k-1}e^{-(\beta+N(t))r_2}$$

The posterior distribution is a gamma distribution that is updated with new parameters of α+k and β+N(t) where k = N(t+1).