# Application of Stochastic Dynamic Programming to Optimal Fire Management of a Spatially Structured Threatened Species

Hugh Possingham: Department of Environmental Science, The University of Adelaide, Roseworthy Campus, Roseworthy SA 5371, AUSTRALIA & National Centre for Ecological Analysis and Synthesis, Suite 300, 735 State St, Santa Barbara, CA 93101-3351, USA & Geoff Tuck: CSIRO Marine Labs, Castray Esplanade, Hobart, Tasmania 7001, AUSTRALIA

Abstract Fire and other habitat disturbances are essential to the persistence of many species. Species that favour early and mid-successional habitats are often threatened with extinction because fire is too frequent, or not frequent enough. Here we consider a threatened species that inhabits two patches of habitat that may be burnt independently. Our problem is to choose the interval between fires for each patch that minimises the species extinction probability as a function of the state of the other patch and the state of the population in each patch. Because the dynamics of both populations are stochastic, we use Stochastic Dynamic Programming (SDP) to find the optimal state-dependent strategy. The optimal strategy depends strongly on whether the species can move from one patch to the other. When movement is possible the optimal strategy is relatively independent of the state of the population and the details of how habitat quality changes as a function of the time since the last fire. This means that the complex SDP results can be simplified to some fairly robust rules of thumb. There is an urgent need for the application of decision theory to problems in applied biology - this paper represents just one possibility for the application of such theory.

## 1 INTRODUCTION

A central question in nature conservation is: how should we manage habitat disturbances like fire? This is a question asked by park rangers and forest managers throughout the world as they must decide each year, whether to promote or suppress fire. Our goal is to provide these ecosystem managers with a theoretical framework for threatened species fire management.

Habitat disturbances like fire have both a direct and indirect effect on flora and fauna. They often cause a short term reduction in the size of populations (direct effect) and they usually change the quality of the habitat for a significant period of time, sometimes decades (indirect effect). For plants the recovery often occurs because of the release of space and nutrients that are in short supply in undisturbed habitat. For animals there are many species whose favoured habitat occurs a short time after fire.

Australia's forests, heaths and woodlands support many species that depend on fire. Some of these are threatened with extinction as a consequence of inappropriate fire regimes. The eastern bristlebird and ground parrot are two threatened heathland birds that prefer early successional heath [Pyke et al., 1995; Baker and Whelan, 1994]. Fire is a crucial component of their management. There is a huge variety of plants that need fire to persist [Gill, 1996]. Friend [1993] lists a large number of Australasian small vertebrates that prefer habitats that have been disturbed by fire.

Possingham and Tuck [1997] consider the problem of fire management for a threatened species. They provide

a framework for answering a specific question: How long after the last fire should we wait before imposing the next fire in a single patch of habitat? They use stochastic dynamic programming (SDP) to determine the best decision about when to burn a single patch given an estimate of the current size of a population. They conclude that:

- the habitat should be burnt well after the peak in habitat quality for a threatened species,
- a patch with a low population should be burnt later, if at all, and
- wildfires have relatively little impact on the optimal fire management strategy

These rules are applicable to the management of reserves where a single disturbance regime must be imposed across the entire reserve simultaneously. Often, however, reserves are large enough that we can disturb different parts at different times. The objective of this paper is to determine the optimal fire management strategy when a reserve is managed as two patches, each with different disturbance regimes. We use SDP to tackle this problem.

There are two parts to solving a management problem using SDP. First we need to model the stochastic dynamics of the system, in this case the population dynamics of the organism in each patch. Here we use a relatively simple stochastic population model where each population state is not the actual size of the population, but a rough measure of its abundance. Second there is the decision theory part, where the SDP equations need to be formulated, and rewards defined, for the outcome of management.

## 2 POPULATION MODEL

Assume that the threatened species of concern exists in two patches and let its population size in each of these patches be denoted  $x_1$  and  $x_2$  respectively. Given that abundance data on threatened species is often poor we will assume that the abundance of the species in each patch is in one of seven classes. Class zero represents local extinction and class six the maximum abundance of a patch (Figure 1). These abundance classes are not intended to represent a linear measure of real abundance, but some scaled measure of abundance such that the population only moves to adjacent classes with roughly equal probability (a natural log scale for example). First we describe a model for the dynamics of a population in a single patch, and then the way in which populations in the two patches interact.

# 2.1 One patch population dynamics

Let s be the state-independent probability of the population staying in its current state. By making s bigger we model a more stable population. Let  $r_F$  be the probability the population moves up one state, assuming it is not staying in its current state, if it has been F years since the last fire. When there is a fire assume that the population falls by one state (after any transitions for that year). The transition probabilities for a particular patch are sketched in Figure 1.

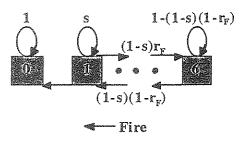


Figure 1: Population transition probabilities for a single patch.

The suitability of the habitat changes with the time since the last fire by changing  $r_F$ . We assume that  $r_F$  takes the form shown in Figure 2 with very low habitat quality immediately after a fire, followed by a rapid rise to a peak in habitat quality five years after a fire,  $(r_5 = 1.0)$ , then a decline to the habitat quality of mature habitat,  $(r_{10} = 0.5)$ . This habitat quality dynamic is typical for an early or mid-successional species.

# r, habitat quality

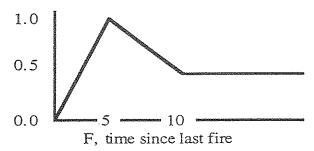


Figure 2: The relationship between the time since the last fire in a patch and its habitat quality.

Using these definitions of s and  $r_T$  and the state transition diagram in Figure 1 it is possible to define the probability of a population in a single patch moving from any state to any other state. Now we need to define how the populations in the two patches interact.

# 2.2 Two patch population dynamics

To model the dynamics of two patches simultaneously we need to make two sets of assumptions. First we need to decide how environmentally connected the two patches are - that is, if one patch experiences a bad year (and the population is likely to decline) does the other population experience the same bad year? Second we need to model the movement of the individuals between the two patches.

In the cases presented here we assume that the patches are environmentally correlated and a good year for one patch is a good year for the other. In terms of the population transition probabilities this means that if both patches are in the same successional state (the same time since the last fire) then when it is a good year for one it is a good year for the other. If the habitat quality in one patch is better than the habitat quality in the other, then if the worst patch has a good year the best patch has a good year, if the best patch has a bad year the worst patch has a bad year, but there is a chance that the patch in the better successional state will have a good year while the patch in the worst successional state has a bad year. Mathematically this can be written as (assuming without loss of generality that patch 1 is better habitat than patch 2 and ignoring boundary conditions, Figure 1)

$$P((x_1+1,x_2+1)/(x_1,x_2)) = (1-s)r_{F2}$$

$$P((x_1+1,x_2-1)/(x_1,x_2)) = (1-s)(r_{F1} - r_{F2})$$

$$P((x_1,x_2)/(x_1,x_2)) = s$$

$$P((x_1-1,x_2-1)/(x_1,x_2)) = (1-s)(1-r_{F1})$$

where  $P((x_1,x_2)/(y_1,y_2))$  is the probability that the population state moves from  $(y_1,y_2)$  to  $(x_1,x_2)$ .

We consider two extreme forms of population connection between the two habitat patches to illustrate the range of possible behaviours. In the no movement case we assume that individuals are unable to move between patches - the patches are disconnected (plants with poorly dispersed seed is a good example). In the movement case we assume that the populations are connected and some individuals are able to select the best patch in which to live (the ground parrot is a good example). There are many options for modelling a habitat selecting and mobile species such as this. We will assume that if patch one is the best patch  $(r_{\rm Fl} > r_{\rm F2},$  at a particular time and without loss of generality) then

$$x_1 = \max(x_1, x_2)$$
  
$$x_2 = \min(x_1, x_2).$$

We assume that movement of the population occurs before the population transitions each year. Now we have a full description of the dynamics of the stochastic state variables we need to determine the state-dependent strategy that minimises extinction probability.

#### 3 SDP METHOD

The objective of an SDP is to determine the state-dependent optimal decision for controlling a stochastic process [Intriligator, 1971]. To use the method we need to define "payoff" values for achieving a certain state for the system, describe the management options mathematically, and define the dynamic programming equation. In this example our payoff will be one if the population persists and zero otherwise. The optimal management strategy is found by back-stepping through time, choosing the optimal decision for each year assuming that later decisions are made optimally.

For our problem there are four possible decisions in the strategy set  $s \in S = \{0,1,2,3\}$ :

burn neither patch, s = 0, burn patch one, s = 1, burn patch two, s = 2, and burn both patches, s = 3.

To determine the best decision for every possible state of the system we start from the penultimate decision before some terminal time.

Let the terminal time at which our success is assessed be t=T. If the population is extinct at that time we gain no points, if it is extant we gain one point so

$$J_T(x_1,x_2,F_1,F_2) = 0$$
 if  $x_1 = x_2 = 0$   
= 1 otherwise.

where  $J_1(x_1,x_2,F_1,F_2)$  is the value of being in state  $(x_1,x_2,F_1,F_2)$  at time t. To find the best decision for the penultimate time, T-1, we express the value of being in state  $(x_1,x_2,F_1,F_2)$  as a function of the value of being in each state at the terminal time,  $J_T(x_1,x_2,F_1,F_2)$ ,

weighted by the probability of moving to each of these terminal states. These probabilities arise from our population model and depend on the current state of the system and the decision that is chosen from the strategy set. This generates the optimal strategy if we are only interested in one year ahead. To determine the best long-term strategy the back-stepping method is repeated until an equilibrium strategy is found. This is the best state dependent long-term strategy. Here we report the optimal decision, given a the size of the population in each patch and the time since the last fire in each patch, when we are 50 time steps from the terminal time. After this length of time we have reached a stable optimal long-term fire management minimises long-term that strategy probabilities. Any extinction probabilities mentioned represent the chance of extinction over that 50 year time frame.

## 4 RESULTS AND DISCUSSION

We do not explore all possible scenarios in this paper. We are primarily interested in how the optimal strategy changes when we move from the movement case - with connected patches and directional movement to the best habitat - to the no movement case where patches are isolated as far as the threatened species is concerned.

## 4.1 Baseline scenario

Our point of departure is a baseline scenario in which there is a 50% chance of a patch changing state, s = 0.5, and fire in a patch reduces the population size in a patch by one state. When there is movement between patches by a habitat selecting organism, the optimal decision for each possible combination of times since last fire (assuming  $x_1 = x_2 = 2$ ) is shown in Figure 3.

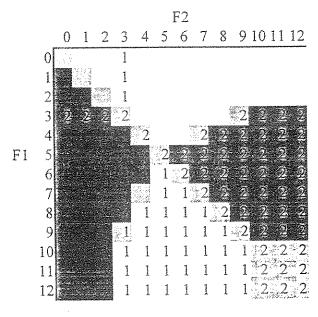


Figure 3: The optimal decision for each combination of times since last fire in the baseline scenario with movement. Dark shaded states are those for which

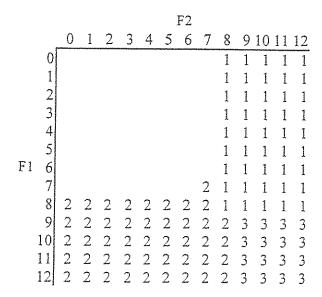


Figure 5: The optimal decision for each combination of times since the last fire with no movement and low old-growth habitat quality.

When there is movement between patches Figure 6 shows the optimal strategy. If you start from any state, the set of states through which the system cycles is very similar to the previous case:  $(F_1=4, F_2=8)$ ,  $(F_1=5, F_2=0)$ ,  $(F_1=9, F_2=4)$  and  $(F_1=0, F_2=5)$ . The fifty year probability of persistence is now more than 40% regardless of which state we start from, a large improvement over the no movement case. In contrast to the previous example, the no movement and movement optimal strategies are quite similar, both show that patches should be burnt eight or nine years after a fire. The big difference is that, with movement, the strategy forces an asynchronous cycling of patch states.

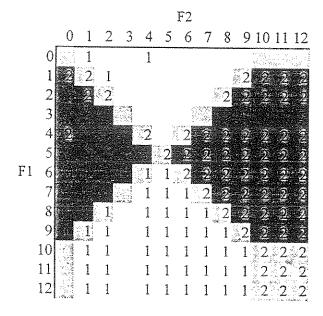


Figure 6: As for Figure 3 with poor old-growth habitat quality.

By examining a number of examples we find that when there is movement between patches:

- the extinction probability with optimal decision making is a lot lower compared to the case without movement, and
- the optimal strategy is quite robust to changes in the state of the population and the details of the habitat quality function (Figure 2).

## 5 Conclusion

We have derived some useful rules of thumb for fire management where threatened species are concerned. When there is more than one habitat patch and the species can move freely to the best patch we can speculate that there is a general strategy. This strategy involves burning a patch when the other patch is close to, or at, its peak in habitat quality. This shows that, while managers could not be expected to use SDP themselves, this state-dependent decision-making method can be used to derive useful rules of thumb. The rules developed here and in Possingham and Tuck [1997] are just a first step towards a general theory of fire management for biodiversity.

application of decision-making tools conservation biology is rare [Maguire. Possingham, 1996; Milner-Gulland, 1997]. Usually wildlife managers have been forced to use general nonprescriptive theory to make decisions. In the case of habitat disturbance and biodiversity the only general theory is the intermediate disturbance principle. This principle states that maximum species diversity at any one location is maximised when the disturbance frequency is intermediate. The theory is robust but provides little specific guidance for a manager faced with a particular ecosystem, species of concern, and kind of disturbance. More importantly, this theory, like all other ecological theory, is not couched within a decision-making framework. Managers must make decisions within the constraints of time and money, and where there are tradeoffs between actions - general ecological theory is of little guidance.

Applied theory for nature conservation is sorely lacking. This paper represents an attempt to fill part of that need and expose managers to the merits of state-dependent decision-making.

# Acknowledgments

We are grateful to the rest of the University of Adelaide theoretical ecology research group for valuable comments. We are also grateful for comments from the NCEAS Working Group on Population Management, particularly Priyanga Amarasekare. This work was supported by a Large ARC grant to H. P. Possingham and I. R. Noble.

#### References

- Baker, J., and Whelan, R.J., Ground parrots and fire at barren grounds, new south wales a long-term study and an assessment of management implications. *Emu* 94, 300-304, 1994.
- Friend, G. R., Impact of fire on small vertebrates in mallee woodlands and heathlands of temperate Australia: a review. *Biological Conservation* 65, 99-114, 1993.
- Gill, A. M., How fires affect biodiversity. Pp. 47-55 in Biodiversity and fire the effects and effectiveness of fire management. Department of Environment, Sports and territories, Canberra, 1996.
- Intriligator, M. D., Mathematical optimisation and economic theory. Prentice-Hall, Englewood Cliffs, NJ, 1971.
- Maguire, L. A., Using decision analysis to manage endangered species populations. *Journal of Environmental Management* 22, 345-360, 1986.
- Milner-Gulland, E.J., A stochastic dynamic programming model for the management of the saiga antelope. *Ecological Applications* 71, 130-142, 1997.
- Possingham, H. P., Decision theory and biodiversity management: how to manage a metapopulation. Pp. 391-398 in The Proceedings of the Nicholson Centenary Conference 1995, eds. R.B Floyd, A.W. Sheppard and P.J. De Barro. CSIRO Publishing, Canberra, Australia, 1996.
- Possingham, H. P. and Tuck, G. Fire management strategies that minimise the probability of population extinction for early and mid-successional species: an application of stochastic dynamic programming to state-dependent environmental decision-making. Pp. ?? in Statistics in Ecology and Environmental Monitoring, eds. D. Fletcher and B. Manly, Otago University Press, Dunedin, NZ, 1997.
- Pyke, G. H., Saillard, R. and Smith, J., Abundance of eastern bristlebirds in relation to habitat and fire history. *Emu* 95, 106-110, 1995.