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SHOULD MANAGED POPULATIONS BE MONITORED EVERY YEAR?

Cindy E. Hauser,[1,4] Anthony R. Pople,[2,3] and Hugh P. Possingham[1,2]

[1]*Department of Mathematics, University of Queensland, St. Lucia, Queensland 4072 Australia*
[2]*The Ecology Centre, School of Integrative Biology, University of Queensland, St. Lucia, Queensland 4072 Australia*
[3]*Department of Natural Resources and Mines, GPO Box 2454, Brisbane, Queensland 4001 Australia*

Abstract. We often need to estimate the size of wild populations to determine the appropriate management action, for example, to set a harvest quota. Monitoring is usually planned under the assumption that it must be carried out at fixed intervals in time, typically annually, before the harvest quota is set. However, monitoring can be very expensive, and we should weigh the cost of monitoring against the improvement that it makes in decision making. A less costly alternative to monitoring annually is to predict the population size using a population model and information from previous surveys. In this paper, the problem of monitoring frequency is posed within a decision-theory framework. We discover that a monitoring regime that varies according to the state of the system can outperform fixed-interval monitoring. This idea is illustrated using data for a red kangaroo (*Macropus rufus*) population in South Australia. Whether or not one should monitor in a given year is dependent on the estimated population density in the previous year, the uncertainty in that population estimate, and past rainfall. We discover that monitoring is important when a model-based prediction of population density is very uncertain. This may occur if monitoring has not taken place for several years, or if rainfall has been above average. Monitoring is also important when prior information suggests that the population is near a critical threshold in population abundance. However, monitoring is less important when the optimal management action would not be altered by new information.

Key words: decision theory; harvest; Macropus rufus; *managed populations; monitoring regime; optimization; population model; red kangaroo; South Australia.*

Introduction

Wildlife management requires periodic monitoring to ensure informed decision making (Walters 1986, Possingham et al. 2001). Monitoring wildlife populations for management has two functions (Yoccoz et al. 2001). First, it is essential for circumstances in which decisions are determined by the estimated size (and more generally state) of the population: state-dependent decision making (Pollock et al. 2002). Second, it provides an understanding of system dynamics, which can be used in future decision making (Walters and Hilborn 1978).

Previous authors concerned with how we should monitor have focused on trend detection (e.g., Kendall et al. 1992, Eggeman et al. 1997, Forcada 2000, Tyre et al. 2003), recognizing the relationships among power, significance, effect size, and sample size in space and time. Some studies have devised monitoring procedures that maximize power to detect trends (Taylor and Gerrodette 1993, Hayward et al. 2002, Pollock et al. 2002). However, to determine the optimal monitoring strategy, we need to know what power or accuracy is necessary for decision making and an acceptable outcome. Di Stefano (2003) argues that acceptable Type I and Type II errors should be set by considering their relative costs. Yet it is only recently that authors (Yokomizo et al. 2003*b*, Field et al. 2004, Gerber et al. 2005) have explicitly considered the costs and outcomes of monitoring as part of management. Although decision theory tools are often used in the fields of harvesting, conservation, and control (Shea et al. 1998), there has been little optimization of monitoring by using decision theory.

Yokomizo et al. (2003*a*, 2004) were the first authors to combine monitoring and management within a single decision-theory framework. For a declining population, they identified the monitoring and conservation effort that minimized the total cost of monitoring, conservation effort, and extinction risk. They found that if prior information is highly uncertain or indicates that the population is small, then more effort should be spent on monitoring. The optimal conservation effort was large when the population estimate after monitoring was small, but effort was relatively independent of the uncertainty around the estimate. Results were more complex over a time horizon of more than one period.

When management is framed within decision theory, the traditional approach is to use the same monitoring effort before each management decision is made. Yokomizo et al. (2003*a*, 2004) challenged this practice by integrating the costs of monitoring in the optimization. If we are confident about our understanding of system dynamics, then we might be able to use our

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[4] E-mail: c.hauser@uq.edu.au

system model and previous data to make a reasonable prediction of the system state before monitoring even takes place. If monitoring is a costly procedure, then we must determine whether the extra information that it provides outweighs this expense. How much better is the state-dependent decision we make when we compare our observed state to our model-based prediction?

In this paper, we investigate the optimal monitoring of a harvested population. We integrate the costs and likely outcomes of monitoring within the framework of decision theory. Our focus is the management of commercially harvested red kangaroo (*Macropus rufus*) populations in South Australia, but there are broader applications to all wildlife populations. In our model, population fluctuations are caused by variable rainfall and its effect on food availability (Caughley 1987). Although quotas are currently set using a population estimate derived from an expensive survey, it may be preferable in some circumstances to use freely available rainfall data and a model-based prediction of population size to set the harvest quota. We weigh the reduced cost of using a modeled prediction for the harvest decision against the increased risk of making a bad harvest decision.

Problem Definition

Here we will provide some background information on management of the red kangaroo in Australia, with a particular emphasis on devising an integrated measure of the "value" of different kangaroo densities to society. We also will describe the components of the problem formulation, including the population model.

Background to case study

In South Australia, aerial surveys of the pastoral zone (~240 000 km^2) are conducted annually by the state government conservation agency to estimate the abundance of three kangaroo species. In this paper, we use density, harvest, and rainfall data for just one of the species, the red kangaroo, for the Northeast Pastoral Kangaroo Management Region (~31 000 km^2) from 1978 to 2002 (Grigg et al. 1999, Jonzén et al. 2005). Similar surveys are conducted in other Australian states. Vast areas are surveyed, incurring considerable costs. In South Australia, population estimates are used by the conservation agency to set regional quotas for commercial harvest throughout the state in the following year. In the last decade, annual harvest in the region has ranged between 12% and 22% of the estimated population in the previous survey.

Various stakeholders have different interests in kangaroo management. There is a desire for commercially viable harvests, control of kangaroo density to reduce grazing pressure, and maintenance of populations at levels consistent with social and cultural values (Pople and McLeod 2000, Grigg and Pople 2001). Kangaroos historically have been harvested for their skins, which produce fine-grade, valuable leather. More recently, their value has increased with an expansion of markets for kangaroo meat for human consumption in addition to lower value pet meat. Kangaroos also compete with domestic livestock, particularly sheep, damage crops, and hamper the rehabilitation of degraded vegetation communities. Finally, kangaroos are an iconic group of species in Australia and conservation concerns are frequently raised, forcing management agencies to demonstrate population viability. To integrate these stakeholder values, we pose a utility function that expresses the relative desirability of a range of kangaroo densities.

The current management procedure involves monitoring with the same effort each year, providing an estimate with relatively constant precision and cost. A survey of the pastoral zone of South Australia costs about 50 000 Australian dollars, and the resulting population estimate for the Northeast Pastoral region has a coefficient of variation of ~20%.

We contrast the existing strategy of an annual survey with an alternative strategy in which we set the harvest quota using a prediction of density from a model and previous data. In this situation, the harvest decision will be made in the face of greater uncertainty, which increases the risk of setting an inappropriate harvest quota. For example, we might incorrectly predict that the population is of moderate density when it is actually low. The moderate quota that is set will cause overharvest, a lower average population density in the long term, and, hence, a potential negative impact on public perception and kangaroo industry profitability. If we incorrectly predict that the population is of moderate density when it is actually high, then too many kangaroos may survive after harvest, leading to overgrazing. Our task is to weigh the risk and consequence of making such mistakes against the cost of monitoring.

The population model

Previous models for population dynamics of kangaroos generally have included density dependence and an environmental variable. The environmental variable is most commonly rainfall, a surrogate for food supply, over some previous period (Bayliss 1985*a*, *b*, Cairns and Grigg 1993, McCarthy 1996) although pasture biomass has been modeled directly (Caughley 1987). Jonzén et al. (2005) use a time series model that includes the effect of harvest and sheep population size. We use a similar approach and assume that red kangaroo density changes from year to year according to a Ricker-type function with intrinsic growth rate a, effect of density dependence b, effect of rainfall c, and process error ε_t:

$$N_{t+1} = (N_t - C_t)\exp(a + bN_t + cR_t + \varepsilon_t) \qquad (1)$$

where N_t is the red kangaroo population density at the beginning of year t. The harvest removed from the population during year t is expressed as a density by the term C_t. All reproduction and natural mortality are assumed to occur after harvest, but the density-depend-

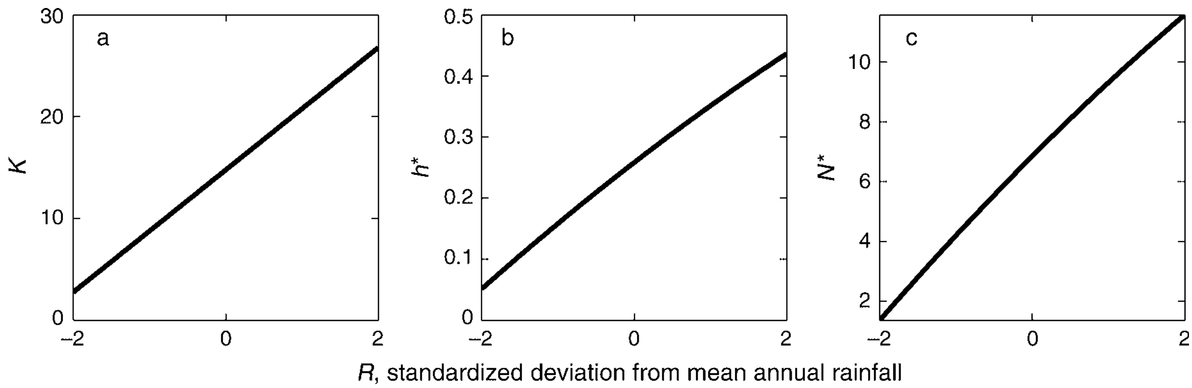

FIG. 1. Equilibrium results for the deterministic model as a function of rainfall: (a) carrying capacity K; (b) optimal harvest rate h^*; and (c) equilibrium density N^* under optimal harvest, in relation to the index R, the standardized deviation from the mean annual rainfall.

ent term acts on the population density before harvest. The process errors $\{\varepsilon_t, t = 0, 1, ...\}$ are independent, identically distributed normal random variables with mean zero and variance ν^2. The rainfall term R_t is the total rain falling during year $t - 1$.

To fit this model to available data for the Northeast Pastoral Kangaroo Management Region, we standardized annual rainfall using the mean and variance of the 102-year time series. Relevant rainfall data were matched to density estimates and harvest data for the region from 1978 to 2002. We used a log transformation of Eq. 1 and minimized the sum of the squares of the errors, assuming that there was no observation error in the data. In this way, we obtained parameter estimates $a = 0.5316$, $b = -0.0377$, $c = 0.2264$, and $\nu^2 = 0.0507$. It is possible to incorporate observation error in the fitting of such a population model to data (de Valpine and Hastings 2002, Calder et al. 2003). This is much more computationally intensive, and we wish to use these parameter estimates only for illustration. By ignoring observation error at this stage, we overestimate the ability of our population model to predict population density (see *Discussion*).

To help our understanding of the system dynamics, we consider the equilibrium behavior of this model (in a manner similar to that of Runge and Johnson [2002]) in Appendix A. Carrying capacity, maximum sustainable yield, and equilibrium population density are functions of rainfall. These are shown for our parameter values in Fig. 1. Under average rainfall, the unharvested population will tend toward a density of 14.8 individuals/km^2 (Fig. 1a). The harvest rate that maximizes annual harvest under average rainfall is 25.8% (Fig. 1b), which gives an equilibrium population density of 6.8 individuals/km^2 (Fig. 1c).

We assume that the harvest C_t taken in year t is exactly the quota that is set. However, the quota is based on an imperfect measure of population density. The annual harvest quota is set as a constant proportion of the point estimate for density at the beginning of the year, and we use the expected density, $E(N_t)$, for this point estimate. If harvest fraction h is used to set the quota, then the total harvest is $C_t = hE(N_t)$.

We use a fixed harvest fraction of $h = 20\%$. This is currently the maximum harvest fraction set for red kangaroos in South Australia (SADEH 2002). Our equilibrium analysis shows that this is close to the maximum sustainable yield for the deterministic model. Furthermore, in a deterministic world, a harvest rate of 20% would generate a stable equilibrium density of 5.3 individuals/km^2.

The measure of density in year t affects the harvest taken, which in turn affects future density through Eq. 1. The expected density, $E(N_t)$, and the uncertainty of this value as a point estimate, will depend on whether or not we conducted a survey before setting the harvest quota. Thus the survey decision, and the resulting level of uncertainty in population density, will determine the consequences of management.

The objective and the utility function

The identification of an appropriate objective for a given management problem can be an enormous task in itself. It is a subjective decision that should be made by managers and other stakeholders under the guidance of social scientists. We will describe a simple relationship between overall utility, the expected value of which we attempt to maximize, and kangaroo density. Although it is important to define a utility function and, hence, an objective, that is not the central focus of this paper. Our choice is primarily to illustrate the method.

Some densities are considered more desirable than others. Low densities put the population at risk of local extinction, reduce yield and longer term viability for harvesters, and may lead to reduced visual amenity for tourists, whereas high densities cause overgrazing. Thus we have created a utility function that is very low as the population approaches local extinction, positive for densities of 5–20 individuals/km^2, and decreasing as density increases above 20 individuals/km^2. We use the

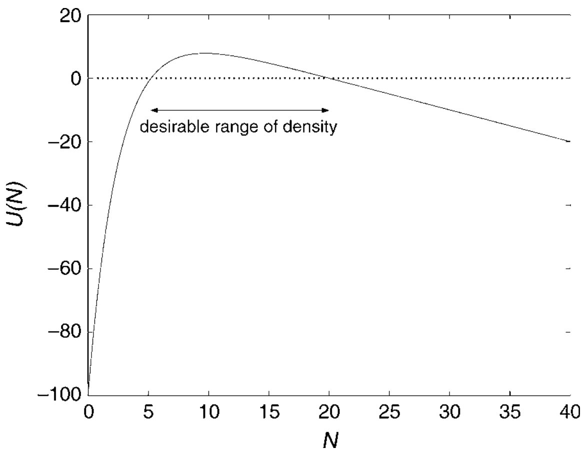

FIG. 2. The relative utility, $U(N)$, of density N, as in Eq. 2, with $\alpha = 120$, $\beta = 0.4$, $\gamma = 1$, and $\delta = 20$.

utility function

$$U(N) = -\alpha e^{-\beta N} - \gamma N + \delta \qquad N \geq 0 \qquad (2)$$

with $\alpha = 120$, $\beta = 0.4$, $\gamma = 1$, $\delta = 20$, where $U(N)$ is the "desirability" of kangaroo density N, and density N is measured in individuals per square kilometer. The utility does not need to be measured in monetary units; it simply reflects the relative integrated community desirability of different densities.

The utility function $U(N)$ is plotted in Fig. 2. Local extinction ($N = 0$) is considered very undesirable and the utility of low densities decays exponentially as population density increases (the first term in Eq. 2). As density increases, utility decreases linearly as a response to increasing damage and overgrazing caused by kangaroos (the second term in Eq. 2). The parameter values were chosen so that extinction was considered much more undesirable than any realistic level of property damage. Densities between 5 and 20 individuals/km^2 are most desirable. We note from our equilibrium analysis (Appendix A) that both the equilibrium population density without harvest and the equilibrium density with a harvest rate of 20% are within the desirable range of 5–20 individuals/km^2.

The process of data collection and decision making

Consider the decision that we must make at the beginning of year t. Regardless of whether or not we choose to conduct a survey, we must set a quota for the harvest to be taken during year t. This harvest will affect the population density at the beginning of year $t + 1$. Our utility function $U(N)$ will give the value of this population density. The objective is to maximize the combined utility of the population density at the beginning of year $t + 1$ and the survey decision at the beginning of year t. In making the survey decision, we use Eq. 1 and relevant previous data. We need total rainfall during year $t - 2$ and an estimate for density in year $t - 1$ to predict kangaroo density in year t in the absence of a survey. Then we need rainfall during year $t - 1$ to predict kangaroo density in year $t + 1$ and, hence, to calculate the expected utility.

We assume that rainfall data are obtained without cost or observation error. Each year we will estimate or predict the current population density with some uncertainty. A prediction generated using our model and previous survey data would be subject to greater uncertainty than an estimate derived from a survey conducted this year. We describe our measure of the population by a lognormal distribution with parameters μ and σ. Therefore the probability density function for population density N is

$$f_N(n) = \frac{1}{\sqrt{2\pi\ \sigma^2 n}} \exp\left[-\frac{(\ln n - \mu)^2}{2\sigma^2}\right].$$

The expected mean and variance of this probability density function are

$$\mathrm{E}(N) = \exp[\mu + \sigma^2/2]$$
$$\mathrm{var}(N) = \exp[2(\mu + \sigma^2)] - \exp(2\mu + \sigma^2).$$

We use distribution parameters μ_{t-1} and σ_{t-1}, and rainfall data R_{t-1} and R_t as state variables when making a state-dependent monitoring decision for the beginning of year t. Parameters μ_{t-1} and σ_{t-1} provide a distribution of plausible values for last year's density N_{t-1}. Rainfall data R_{t-1} and R_t can be combined with Eq. 1 to find plausible values for this year's density N_t, next year's density N_{t+1}, and ultimately the utility $U(N_{t+1})$. The complete process of data collection and decision making is shown in Fig. 3.

Assume that we have the required state variables μ_{t-1}, σ_{t-1}, $R_{\mathrm{t}-1}$, R_t to make the optimal monitoring decision. Let D be a Boolean variable that indicates the monitoring decision made, where $D = 1$ indicates that a survey is to be carried out and $D = 0$ indicates that a harvest quota is set using a model-based prediction. Then the value of the best decision $F(\mu_{t-1}, \sigma_{t-1}, R_{\mathrm{t}-1}, R_t)$ is

$$F(\mu_{t-1}, \sigma_{t-1}, R_{t-1}, R_t) = \max\{V_0, V_1\}$$

where

$$V_0 = \mathrm{E}[U(N_{t+1}) | D = 0] \qquad (3)$$

$$V_1 = \mathrm{E}[U(N_{t+1}) | D = 1] - S. \qquad (4)$$

The variable V_0 is the value of deciding not to conduct a survey. It is simply the expected utility of next year's population density if our quota is set using a model-based prediction of kangaroo density. The variable V_1 is the value of deciding to conduct a survey. It is the expected utility of the population density next year under the assumption that a survey is conducted, with a

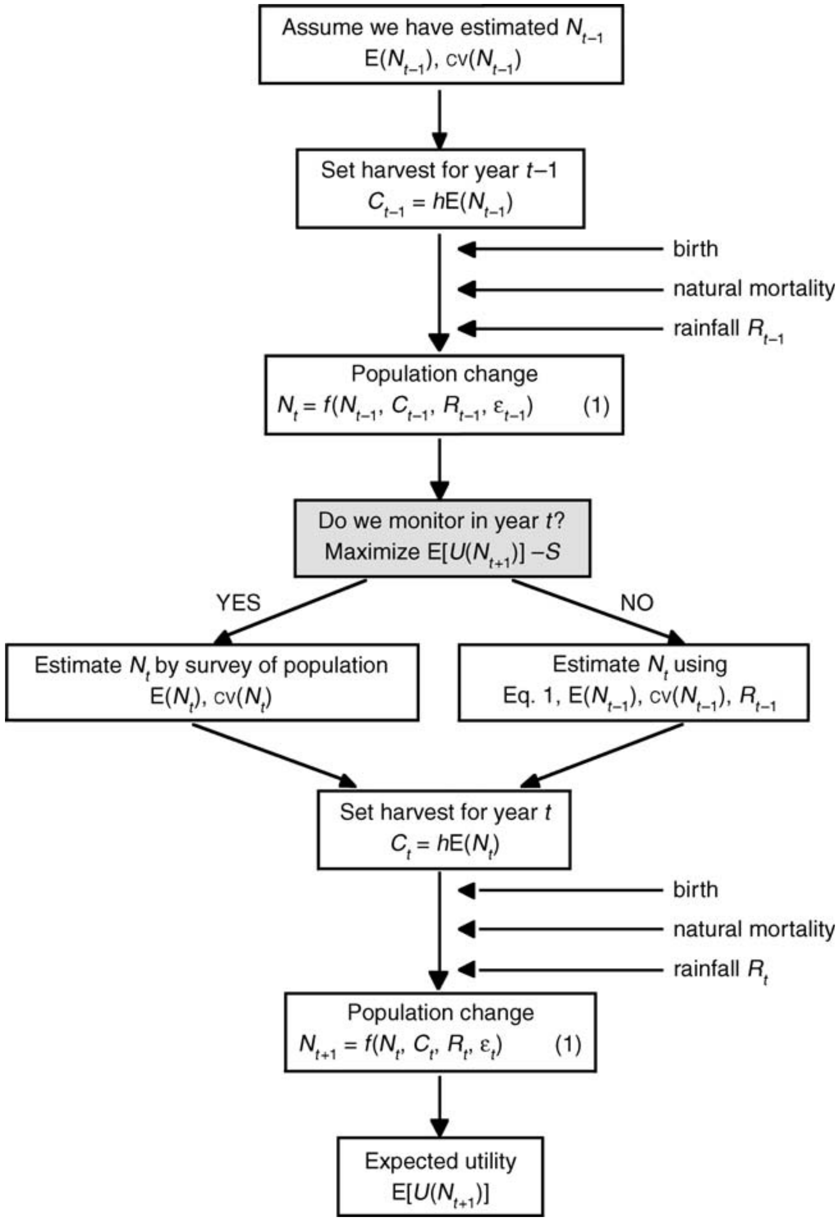

FIG. 3. The process of data collection and optimization to make a survey decision for the beginning of year t. Note that to describe the expected distribution of the population in year $t - 1$, we use the expected value $E(N_{t-1})$ and coefficient of variation $cv(N_{t-1})$, not the parameters μ_{t-1} and σ_{t-1}. Here, C_t is the harvest removed from the population during year t; h is the harvest fraction used to set the quota; R_t is the total rain falling during year $t - 1$; ε_t is process error; S is the cost of conducting a survey; and $U(N)$ is the utility of population density N.

cost, S, for the survey. This represents the expense associated with obtaining a precise population estimate, and should be expressed on the same scale as the utility function. To obtain the maximum value F, we choose the larger of V_0 and V_1.

Note that the expected utility of the population density at the beginning of year $t + 1$ depends on the monitoring decision made at the beginning of year t. Choosing not to conduct precise surveys makes our density prediction increasingly uncertain each year and, hence, affects the expected utility of the decision.

Expected value of not conducting a survey

Eq. 3 gives the value of deciding not to conduct a survey this year:

$$V_0 = E[U(N_{t+1})|D = 0].$$

That is, we wish to find the expected utility of next year's kangaroo density under the decision that we do not conduct a survey of kangaroos this year. If we have a probability distribution for population density next year under this decision $\Pr(N_{t+1} = n|D = 0)$, then

$$V_0 = \int_0^\infty U(n)\Pr(N_{t+1} = n|D = 0)dn.$$

We can use Eq. 1 and rainfall R_t to find a distribution for next year's kangaroo density conditional on current density $\Pr(N_{t+1} = n|N_t = m)$. This is useful if we have a probability distribution for current population density under the decision that a survey is not conducted $\Pr(N_t = m|D = 0)$. Then,

$$V_0 = \int_0^\infty U(n)\int_0^\infty \Pr(N_{t+1} = n|N_t = m) \times \Pr(N_t = m|D = 0)\, dm\, dn.$$

Because we know that last year's density comes from a lognormal(μ_{t-1}, σ_{t-1}) distribution, then we can use Eq. 1 and rainfall R_{t-1} to find the probability distribution for the current population density conditional on the population density last year $\Pr(N_t = m|N_{t-1} = l)$. Thus the expected utility next year if a survey is not carried out is

$$V_0 = \int_0^\infty U(n)\int_0^\infty \Pr(N_{t+1} = n|N_t = m) \times \int_0^\infty \Pr(N_t = m|N_{t-1} = l)\Pr(N_{t-1} = l)\, dl\, dm\, dn. \quad (5)$$

The probability distributions used in Eq. 5 are described in Appendix B.

The triple integral (Eq. 5) is efficiently approximated by simulation. For each combination of state variables μ_{t-1}, σ_{t-1}, R_{t-1}, and R_t, we first draw a large number M of lognormal(μ_{t-1}, σ_{t-1}) random variables to approximate our distribution for last year's density N_{t-1}. Then we draw M Normal(0, ν^2) random variables to represent process error ε_{t-1}. These are combined in Eq. 1 with rainfall R_{t-1} to approximate the distribution for current density N_t. The harvest over year $t-1$ is

$$C_{t-1} = h\mathrm{E}(N_{t-1}) = h\exp\left(\mu_{t-1} + \frac{1}{2}\sigma_{t-1}^2\right).$$

Similarly, we draw another M Normal(0, ν^2) random variables to represent ε_t and combine them with current density N_t and rainfall R_t to approximate a distribution for next year's density N_{t+1}. Harvest over year t is the fraction h of the mean of all M values for N_t. For each of the M random variables that we have for N_{t+1}, we find $U(N_{t+1})$. The mean of these utilities is an approximation for V_0.

Expected value of conducting a survey

Eq. 4 gives the expected value of conducting a survey this year:

$$V_1 = \mathrm{E}[U(N_{t+1})|D = 1] - S.$$

We can use the same argument as in the previous section to show that

$$V_1 = \int_0^\infty U(n)\int_0^\infty \Pr(N_{t+1} = n|\hat{N}_t = \hat{m}) \times \int_0^\infty \Pr(\hat{N}_t = \hat{m}|D = 1)\, d\hat{m}\, dn - S$$

where we have added hats to the distribution for current density N_t. These indicate that the distributions are derived from observation of the actual system, not from a predictive model.

Now we find plausible current densities from the survey. We do not yet know the outcome of the survey, but we can say something about its precision. We assume that all surveys have a coefficient of variation of 20%, which is comparable to the precision of surveys conducted from 1978 to 2002 (Grigg et al. 1999, Jonzén et al. 2005). That is,

$$\mathrm{CV}(N_t) = [\mathrm{SD}(N_t)]/[\mathrm{E}(N_t)] = 0.2$$

where CV denotes coefficient of variation, SD denotes standard deviation, and E denotes expected value. Because we describe likely values for N_t by a lognormal probability distribution with parameters μ_t and σ_t, then this equation can be solved in terms of these parameters to find that $\sigma_t^2 = \ln(1.04)$.

However, we still do not know the outcome of μ_t for the survey. If we assume that we know the true current density N_t, then the mean density $\hat{N}_t$ that we observe will come from a lognormal distribution with $\mathrm{E}(\hat{N}_t) = N_t$ and $\mathrm{CV}(\hat{N}_t) = 0.2$. Hence, the probability of getting an estimated density of $\hat{m}$ individuals/km^2 given that we carry out a survey is

$$\Pr(\hat{N}_t = \hat{m}|D = 1) = \int_0^\infty \Pr(\hat{N}_t = \hat{m}|N_t = m)\Pr(N_t = m)\, dm.$$

As in the previous section, we can find a distribution for likely current density through modeling using

$$\Pr(N_t = m) = \int_0^\infty \Pr(N_t = m|N_{t-1} = l)\Pr(N_{t-1} = l)\, dl.$$

The actual probability distributions are included in Appendix B.

We again use simulation to approximate this integral. For each combination of state variables μ_{t-1}, σ_{t-1}, R_{t-1}, and R_t, we use the same method outlined for expected utility when a survey is not conducted to obtain M random variables that describe the distribution for current density. For each of these M random variables N_t, we draw a lognormal random variable with mean N_t and CV = 0.2. This gives us a distribution for likely survey estimates $\hat{N}_t$. Then we draw M Normal(0, ν^2) random variables to represent ε_t and combine them with

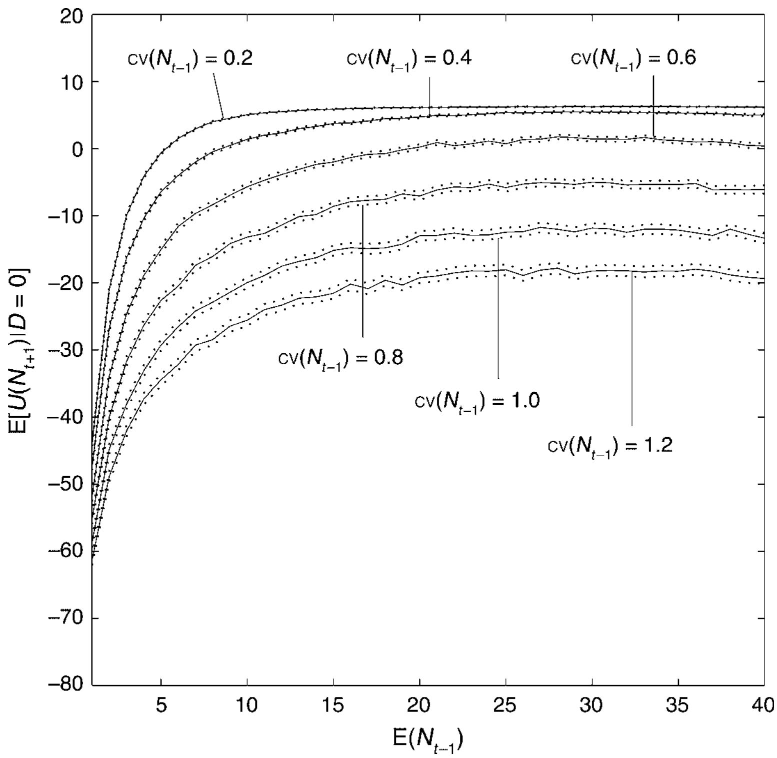

FIG. 4. Estimated expected utility without a survey, $E[U(N_{t+1}) \mid D = 0]$ (solid lines), as a function of last year's density estimate, $E(N_{t-1})$, with 95% confidence intervals on the estimations (dotted lines). Expected utilities are estimated using simulation (with the number of random variables, M, set at 10 000), and rainfall data are assumed to be $R_{t-1} = 0$, $R_t = 0$. Each solid line depicts different levels of uncertainty $\mathrm{cv}(N_{t-1})$ (labeled).

current estimate $\hat{N}_t$ and rainfall R_t to approximate a distribution for next year's density N_{t+1}. This sets the harvest $C_t = h\hat{N}_t$. For each of the M random variables we have for N_{t+1}, we find $U(N_{t+1})$. The mean of these utilities is an approximation for $E[U(N_{t+1}) \mid D = 1]$.

Results

Here we first investigate the expected utility of each decision approximated by simulation with $M = 10\ 000$. We assume that the last two years of rainfall have been average ($R_{t-1} = R_t = 0$) and calculate expected utility $E[U(N_{t+1}) \mid D = 0]$ or $E[U(N_{t+1}) \mid D = 1]$ over a variety of distributions for last year's density by varying μ_{t-1} and σ_{t-1}. The Central Limit Theorem is used to find the standard error of simulations. Then we compare the utility of these decisions in the optimization under a broader range of rainfall information.

Expected utility without a survey

Without a survey, expected utility generally increases as the expected density last year increases, until expected density reaches 30 individuals/km^2 (Fig. 4). The most dramatic increase occurs as expected density increases from 0 to 5 individuals/km^2, and then expected utility is somewhat steady for expected densities above 10 individuals/km^2. Expected utility is improved as last year's estimate becomes more accurate (cv decreases).

Expected utility was explored under a variety of rainfall scenarios not shown here. Rainfall does not have a large effect on expected utility, although expected utility is slightly higher if rainfall is high. Each of the rainfall state variables R_{t-1} and R_t has the same effect.

Expected utility when a survey is conducted

With a survey, expected utility has a response to last year's density estimate similar to that when a survey is not conducted (Fig. 5). It increases markedly as expected density increases from 0 to 5 individuals/km^2, and then is somewhat steady for expected densities above 10 individuals/km^2. Expected utility is improved as last year's estimate becomes more accurate, but the effect is not as strong as for expected utility when a survey is not conducted.

Again, the two rainfall state variables R_{t-1} and R_t have similar effects (not shown). High rainfall produces higher expected utility. The effect of uncertainty in last year's estimate is reduced under high rainfall.

Optimal survey decision

In order to calculate V_1 and determine the optimal state-dependent survey decision, we have a cost, S, of carrying out a survey of the population at the beginning of year t. To accurately determine the trade-off between the cost of monitoring and expected utility, we would

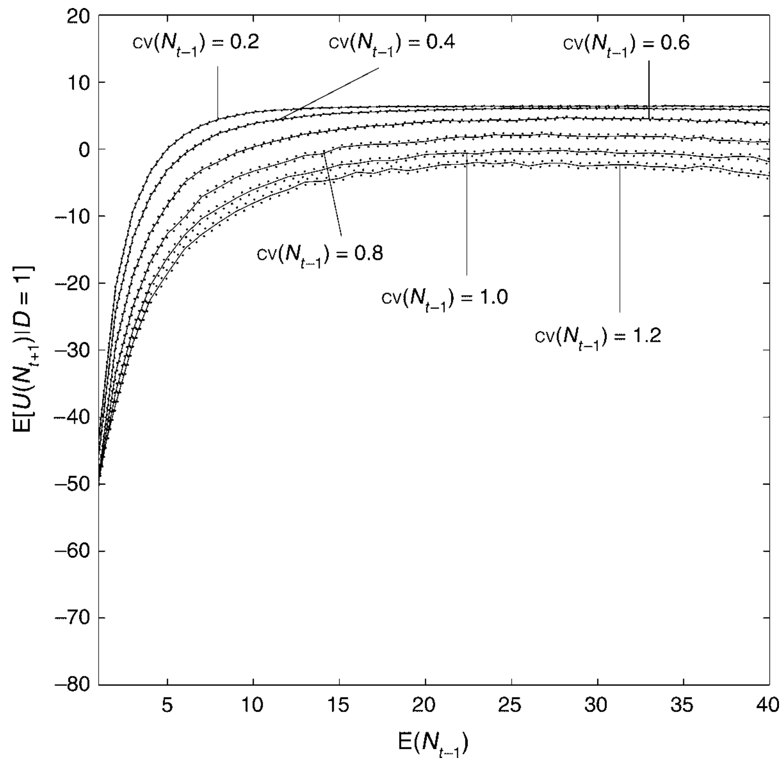

FIG. 5. Estimated expected utility when a survey is conducted, $E[U(N_{t+1}) \mid D = 1]$ (solid lines), as a function of last year's density estimate, $E(N_{t-1})$, with 95% confidence intervals on the estimations (dotted lines). Expected utilities are estimated using simulation with $M = 10\ 000$, and rainfall data are assumed to be $R_{t-1} = 0$, $R_t = 0$. Each solid line depicts different levels of uncertainty $\text{cv}(N_{t-1})$ (labeled).

have to transform the two into one single currency. Although we know the cost of a survey, it is very difficult to translate the utility of a particular kangaroo density into a monetary value. Consequently, we investigated the difference between the expected utilities under each decision, i.e., $E[U(N_{t+1}) \mid D = 1] - E[U(N_{t+1}) \mid D = 0]$. This indicates the improvement to management that conducting a survey will make over the use of a model-based prediction. It is the maximum utility cost, S, that we would be willing to pay to conduct a survey.

Figs. 6, 7, and 8 show the difference between expected utilities under three combinations of recent rainfall. Other combinations of rainfall information R_{t-1} and R_t were also considered, but are not shown here. It was found that higher rainfall increases the acceptable survey cost S, and that both rainfall state variables are equally important.

We found that the expected utility using modeling, $E[U(N_{t+1}) \mid D = 0]$, is always less than the expected utility when a survey is conducted, $E[U(N_{t+1}) \mid D = 1]$ (see Figs. 6–8, where the plot is always nonnegative). The difference between these expected utilities increases as uncertainty in last year's estimate increases. The difference is not so great if the population was thought to be at a low density in the previous year, especially when rainfall has been low. At higher rainfall levels, we are most likely to pay for a survey when the previous year's density estimate was $\sim$5 individuals/km^2.

We show a simulation of the decision-making process in Fig. 9. The actual population density is initially 10 individuals/km^2, and a survey is conducted with a penalty of $S = 2$. A harvest that is 20% of the population estimate is taken. In Fig. 9a, we see how the actual population density fluctuates from year to year as a function of rainfall. Fig. 9b shows how the optimal monitoring strategy tracks population density. A survey is conducted every 2–4 years, reducing uncertainty around the expected population density.

DISCUSSION

We have demonstrated that the costs and likely outcomes of monitoring can be integrated into the framework of decision theory for population management. In this way, we see that it may not be optimal to use the same monitoring effort before each decision. Rather, the level of monitoring effort to be used depends on the current state of the system.

For the management of a red kangaroo population in South Australia, rainfall data and a past estimate of population density are used to determine the value of conducting a survey. Our results show that if there is no cost attached to conducting a survey, then it is always

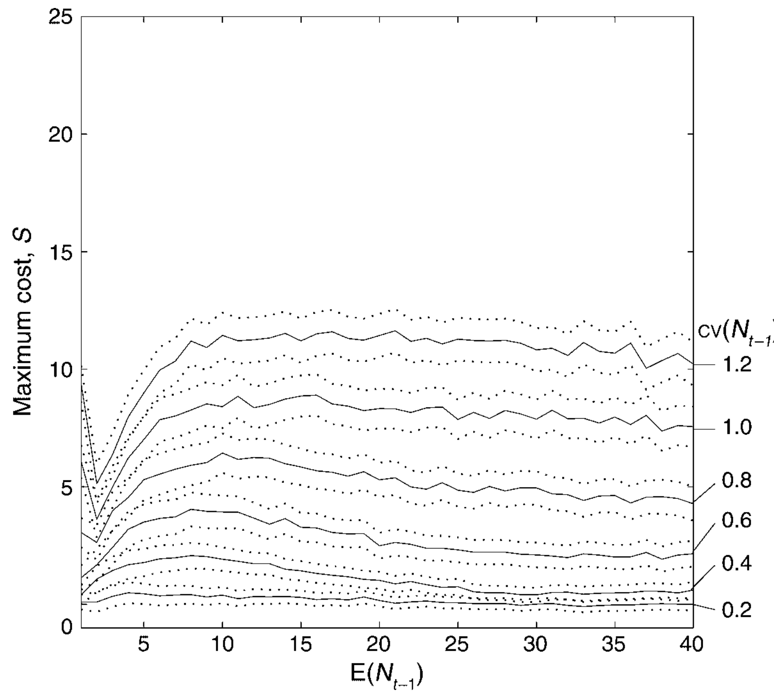

FIG. 6. The maximum cost S for which conducting a survey is the optimal decision (solid lines). Expected utilities are estimated using simulation with $M = 10\ 000$, and dotted lines indicate 95% confidence intervals on the estimation. Rainfall data are assumed to be $R_{t-1} = -2$, $R_t = -2$. Each solid line depicts different levels of cv(N_{t-1}) (labeled on right).

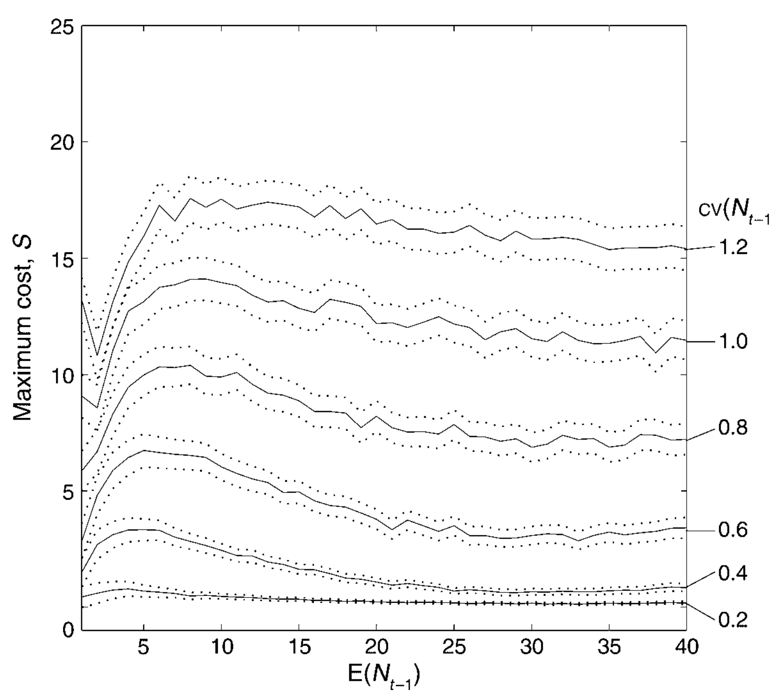

FIG. 7. The maximum cost S for which conducting a survey is the optimal decision (solid lines). Expected utilities are estimated using simulation with $M = 10\ 000$, and dotted lines indicate 95% confidence intervals on the estimation. Rainfall data are assumed to be $R_{t-1} = 0$, $R_t = 0$. Each solid line depicts different levels of cv(N_{t-1}) (labeled on right).

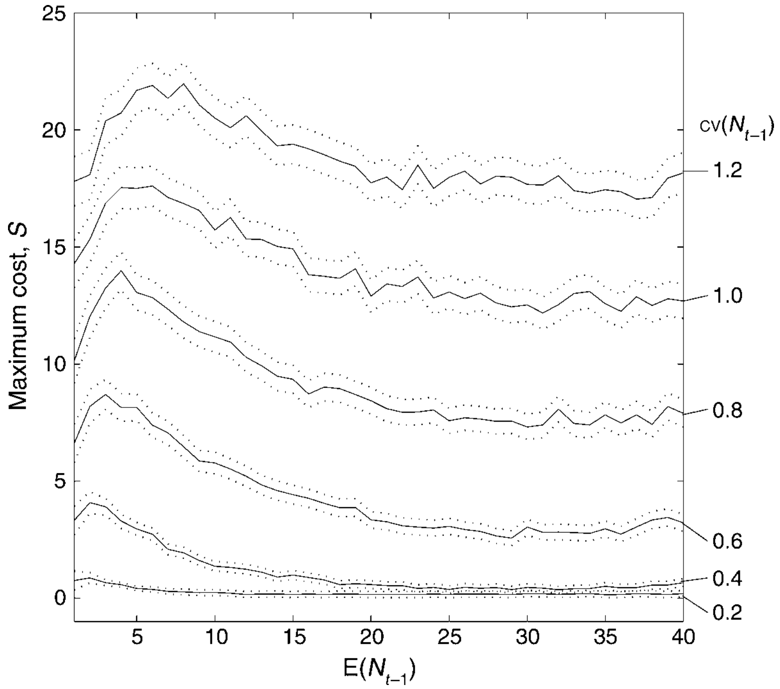

FIG. 8. The maximum cost S for which conducting a survey is the optimal decision (solid lines). Expected utilities are estimated using simulation with $M = 10\,000$, and dotted lines indicate 95% confidence intervals on the estimation. Rainfall data are assumed to be $R_{t-1} = 2$, $R_t = 2$. Each solid line depicts different levels of $\mathrm{cv}(N_{t-1})$ (labeled on right).

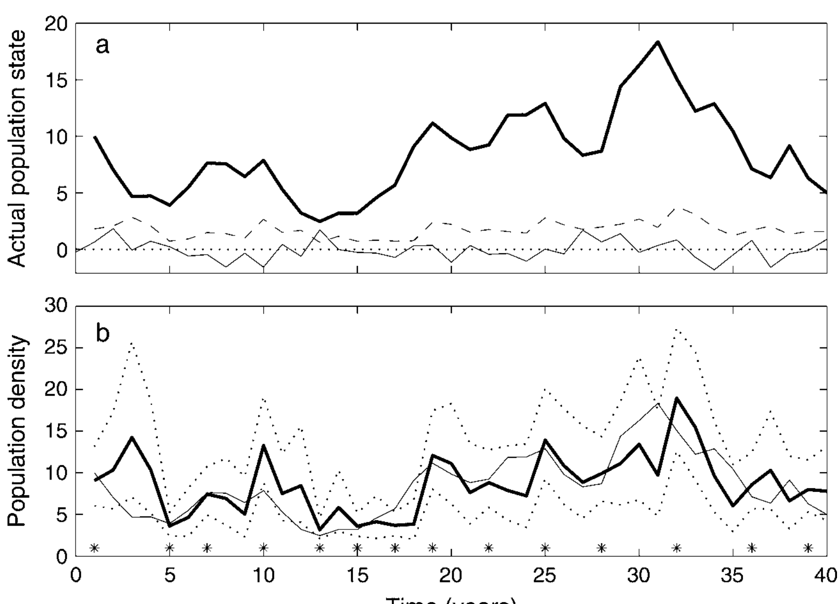

FIG. 9. A simulation of the management of a kangaroo population, with a survey conducted on an initial population of 10 individuals/km^2, at a cost of $S = 2$. Plot (a) shows the actual population state (thick solid line), the standardized deviation from mean annual rainfall (R; thin solid line) and annual harvest (dashed line) taken each year. Plot (b) shows the actual population density (thin solid line), the expected population density (thick solid line, derived from either prediction or a survey), and the 2.5th and 97.5th percentiles on population density (dotted lines, assuming a lognormal distribution). Asterisks indicate the years in which a survey was conducted based on our optimization method.

better than using modeling to set harvest quotas. This is a sensible result because we would expect that collecting further data and reducing uncertainty about population density would improve management decisions where the utility function is nonlinear.

Expected utility, whether or not a survey is conducted, decreases dramatically as the estimated density in the previous year decreases below 5 individuals/km^2 (Figs. 3 and 4). Even if monitoring does improve management somewhat, it is unlikely that the population will increase to a higher, more desirable, density next year, so the population will still be at a density with low utility. In contrast, utility does not decrease significantly when density in the previous year is estimated to be very high, suggesting that the population is likely to be in a state of high utility even if monitoring does not take place. This is a consequence of the density-dependent term in Eq. 1, which ensures that the population is likely to decrease if it is large. For example, consider a population with density of 40 individuals/km^2 under average rainfall and a 20% harvest rate. Using the deterministic model in Appendix A, the population density will decline to only 12.4 individuals/km^2 in the course of one year. This is an outcome with very high utility, indicating that although the current high density is of low utility, the consequences over one or more years are acceptable.

As we would expect, increasing uncertainty in last year's population density estimate increases the value of conducting a survey now. As the number of years between subsequent surveys increases, so does the uncertainty in population estimates obtained by modeling. This result indicates that eventually we must carry out a survey to reduce the uncertainty brought about by modeling year after year. This will reduce the chance of an inappropriate harvest quota.

If last year's density estimate is small (e.g., <3 individuals/km^2), then surveys are generally less valuable than if the estimate is large. This is particularly apparent when rainfall has been very low. We might expect that monitoring would be important when the population is in such an undesirable state, but, in fact, the optimal management decision is probably in no doubt. A small harvest quota should be set, regardless of the uncertainty surrounding our population estimate. Additional information provided by a survey is unlikely to alter the optimal harvest decision.

The value of conducting a survey is greater when rainfall has been high. We believe that this is a consequence of the structure of the population model in Eq. 1. The rainfall variable creates exponential growth and there is lognormal process error. In combination, these terms indicate that above-average rainfall creates a highly uncertain increase in population density. Thus, monitoring to reduce this uncertainty will improve management.

The most significant limitation of this study is that calculations are made under the assumption that Eq. 1 gives a true description of population dynamics. In this way, we assume that modeling (skipping surveys) will give the best possible density estimate, even though the process error in Eq. 1 will cause uncertainty to increase from year to year. Hence, our results may underestimate the value of conducting surveys. Some of the results are clearly influenced by the structure of the population model (in particular, the terms describing density dependence and the effect of rainfall). There may be a variety of functional forms that describe the available data equally well, yet prescribe very different optimal management strategies (Runge and Johnson 2002).

An important extension to this study would be to relax this assumption of model certainty by considering multiple models. Multiple hypotheses of population dynamics would allow full utilization of the second function of monitoring: understanding of system dynamics to improve future management. We expect that monitoring would become more valuable when the population is in a state at which the optimal actions prescribed by each hypothesis are very different. However, this would only occur when there is an incentive to resolve model uncertainty, as in the case of adaptive management (Walters 1986, Williams 2001). If the time horizon were extended beyond one year, then model discrimination might allow better management in the future. This could be achieved using a method such as stochastic dynamic programming (Williams 2001).

In this study, we used a fixed harvest strategy of taking 20% of the expected population density each year. For this red kangaroo population, a different harvest strategy might allow a population of low density to more rapidly recover to an acceptable level. For example, taking 20% of the expected population density only when the expected population density is >3 individuals/km^2 and allowing no harvest for population measures of <3 individuals/km^2 may improve utility over the long term. Ultimately, the optimization of harvest in conjunction with monitoring is required to maximize the impact of management. Under this scenario, it may be that monitoring is still of little value when population density is low, and we should take conservative management action regardless of what a survey could tell us (Field et al. 2004).

In summary, monitoring is more valuable when prior information (previous density estimates) indicates that the population is near a critical threshold. This threshold is where the utility function is changing rapidly. In this example, it is at a density of 5 individuals/km^2, when the population becomes undesirably small. However, monitoring is less valuable when the optimal management action is the same under all levels of uncertainty. This is the case for this kangaroo population as density declines below 3 individuals/km^2, and a small harvest quota must be set. The value of monitoring increases as the uncertainty around a previous population estimate increases. Environmental variables (such as rainfall, in this study) may indicate that the current state of the population is particularly uncertain, also increasing the value of monitoring. Further work on different species is needed to determine if these broader insights have general applicability.

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APPENDIX A

Equilibrium behavior of the deterministic equivalent of the population model. (*Ecological Archives* A016-032-A1).

APPENDIX B

Equations for V_0 and V_1, the value of each monitoring decision (*Ecological Archives* A016-032-A2).