CSIRO PUBLISHING
www.publish.csiro.au/journals/wr *Wildlife Research*, 2005, **32**, 253–258

Improving the efficiency of wildlife monitoring by estimating detectability: a case study of foxes (*Vulpes vulpes*) on the Eyre Peninsula, South Australia

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Abstract. Demonstrating the existence of trends in monitoring data is of increasing practical importance to conservation managers wishing to preserve threatened species or reduce the impact of pest species. However, the ability to do so can be compromised if the species in question has low detectability and the true occupancy level or abundance of the species is thus obscured. Zero-inflated models that explicitly model detectability improve the ability to make sound ecological inference in such situations. In this paper we apply an occupancy model including detectability to data from the initial stages of a fox-monitoring program on the Eyre Peninsula, South Australia. We find that detectability is extremely low (<18%) and varies according to season and the presence or absence of roadside vegetation. We show that simple methods of using monitoring data to inform management, such as plotting the raw data or performing logistic regression, fail to accurately diagnose either the status of the fox population or its trajectory over time. We use the results of the detectability model to consider how future monitoring could be redesigned to achieve efficiency gains. A wide range of monitoring programs could benefit from similar analyses, as part of an active adaptive approach to improving monitoring and management.

Introduction

Demonstrating the existence of trends in monitoring data is of increasing practical importance to conservation managers wishing to preserve threatened species or reduce the impact of pest species (Dixon *et al*. 1998; Pollock *et al*. 2002; Bart *et al*. 2004). In Australia, for example, national programs that are aimed at ecosystem protection and restoration are now being developed within a framework requiring evaluation of progress against specific conservation objectives and targets (Australian Natural Resource Management Ministerial Council 2002). The increased emphasis on evaluating program impact is a response to accountability requirements for increased levels of funding (Australian National Audit Office 2001), as well as the uptake of active adaptive management approaches (Shea *et al*. 2002) based on monitoring of outcomes. To address the needs of managers and investors, monitoring programs need to be continuously evaluated against specific program objectives, and redesigned where opportunities for improvement are apparent.

Rigorous evaluation is difficult to achieve, however, in the face of multiple sources of observation and process error in ecological data that make identifying temporal patterns a challenging task. Applying methods that help overcome such barriers to inference are therefore particularly useful. One such method is zero-inflated modelling, which addresses the pervasive problem of 'excess zeroes' in ecological datasets caused by low detectability of the organism being surveyed (MacKenzie *et al*. 2002; Tyre *et al*. 2003). There has been a recent surge of interest in applying these methods, which can explicitly account for false absences (where the organism is present but not detected) and thus improve the chances of correctly concluding whether a population is declining or not (Field *et al*. 2001, 2005; MacKenzie and Kendall 2002; MacKenzie *et al*. 2002, 2003, 2005; Tyre *et al*. 2003; Wintle *et al*. 2004, 2005; MacKenzie 2005; MacKenzie and Royle 2005). Wider application of zero-inflated modelling could thus lead to significant improvements in the ability of managers to rigorously evaluate management programs.

In this paper, we demonstrate how this can be achieved by analysing data from the initial years of a predator-control program on the Eyre Peninsula, South Australia. Our aim was to look for initial evidence of a temporal pattern in fox numbers, to identify the factors that influence detectability and thereby explore how survey effort might be reallocated to improve the chance of demonstrating positive management outcomes. Using the first three years of data, we estimate detectability and identify the most plausible set of models for predicting fox occupancy across the study area.

 10.1071/WR05010 1035-3712/05/030253

We show that simple methods often used by managers for evaluating monitoring data, such as plotting the raw data or estimating occupancy using logistic regression, fail to accurately diagnose either the status of the fox population or its trajectory over time. Our analysis emphasises the importance of accounting for detectability when designing a survey regime capable of verifying that the objectives of a management program are indeed being met.

Methods

Study area and survey methods

The fox-monitoring surveys were conducted as part of the West Coast Integrated Pest Management Program, which covers an area of ~30 000 km^2 on central and western Eyre Peninsula, South Australia. The area is predominantly grain-cropping and sheep-grazing land, with large tracts of remnant open mallee woodland (dominated in different areas by *Eucalyptus incrassata*, *E. diversifolia* and *E. porosa*), and also includes over 400 km of coastline. Average annual rainfall varies from 250 mm to 450 mm.

A large-scale 1080 baiting program to control fox numbers was established in 1999 to support reintroductions of brush-tailed bettongs (*Bettongia penicillata*) and greater bilbies (*Macrotis lagotis*) to Venus Bay Conservation Park. Initially, fox baits were offered to landholders in the immediate vicinity of the park to create a buffer zone to the reintroduction site. Because of community motivation to protect biodiversity and livestock in the region, the program expanded significantly in 2002 and at this time additional monitoring measures were instigated. By June 2004, there were 400 participating landholders, with properties totalling over 15 000 km^2, or ~50% of the district.

Fox surveys were carried out along seven transects ranging from 74 to 100 km in length, located in different parts of the program area near the following townships: Ceduna, Elliston, Lock, Port Kenny, Streaky Bay, Venus Bay and Wudinna. Routes followed minor roads, the majority of which are unsealed and pass through crop land, grazing land and, in some cases, remnant vegetation. Surveys were conducted every two months between July 2002 and July 2004 (with the exception of Ceduna, Streaky Bay and Wudinna: Table 1), commencing at least 1 h after sunset and taking 3–4 h to complete at a speed of ~30 km h^{-1}. All seven transects were surveyed within one day of each other. Observations were made from inside a 4WD-vehicle using a 100-W spotlight mounted on a roof-rack and operated with a swivel handle. Fauna were identified by eyeshine and/or appearance and all fauna sighted on either side of the road recorded (including the feral cat (*Felis catus*), European rabbit (*Oryctolagus cuniculus*), kangaroos and euros (*Macropus* spp.), and southern hairy-nosed wombat (*Lasiorhinus latifrons*)). Data were recorded in 1-km segments along the transect and comprised (1) numbers of each species in that segment, (2) the status of roadside vegetation (present or absent), and (3) adjacent land use (open paddock or remnant vegetation).

Modelling fox occupancy and detectability

As fox sightings were usually of single animals (average 1.22 per sighting), we modelled the fox population trajectory using a binomial model that estimated the occupancy level (Ψ) of foxes along a particular transect. Occupancy was defined as the proportion of 1-km segments on a particular transect that contained one or more foxes. Recent work has shown that estimates of Ψ can be significantly biased if detectability, p, is less than 1.0 (MacKenzie *et al*. 2002; Tyre *et al*. 2003), as this will introduce false absences and cause the dataset to be 'zero-inflated'. This can be remedied by fitting a zero-inflated binomial model (Hall 2000; MacKenzie *et al*. 2002; Tyre *et al*. 2003), in which the detectability is explicitly accounted for and the estimate of Ψ adjusted accordingly. In this case, as we allow detectability to vary in our models, they are somewhat more general than the zero-inflated binomial model in its original form and henceforth we refer to them simply as 'detectability models'. In the current context, occupancy, Ψ, refers to the probability of successfully recording a fox in a particular 1-km transect segment, given that its home range included that segment at the time. We fitted the model using the 'obserr' package in *R*, ver. 1.8 (Venables *et al*. 1999–2001). Note that here we have adopted the notation of MacKenzie *et al*. (2002) for occupancy (Ψ) and detectability (p), which have been variously denoted in other studies as p and q (Field *et al*. 2001, 2004, 2005; Tyre *et al*. 2003), p and d (Wintle *et al*. 2005) and P and p (Wintle *et al*. 2004).

On the basis of our knowledge of the system, we specified a model that allowed Ψ to vary according to transect and year and p to vary according to cropping season and the amount of roadside vegetation present (all as categorical covariates). Given the short ecological time series, we considered it premature to fit an explicit trend model for Ψ. Although it is possible that p may also vary systematically with year (MacKenzie *et al*. 2005; Olson *et al*. 2005), we considered this less likely than variation in Ψ. Initial models with interannual variation in both p and Ψ also showed poor convergence, so we restricted the year effects to Ψ. Crops were tall enough to provide cover for foxes from approximately August to November, so we treated cropping season as a binary covariate, with the January, March, May and July surveys having a value of 0 and the September and November surveys a value of 1. Assuming that detectability remains constant within seasons, this meant that there were potentially four repeat surveys per year available to estimate p when crops were absent, and two when crops were present. Note that such repeat surveys are essential if one is to estimate detectability (MacKenzie *et al*. 2002; Royle and Nichols 2003; Tyre *et al*. 2003). Thus the data for each year consisted of a number between 0 and 4 for each 1-km transect segment in the non-cropping season, and between 0 and 2 in the cropping season. Roadside vegetation was also treated as binary, as virtually any degree of cover seriously impacted spotlighting visibility, and vegetation, if present, was almost always (92% of cases) present on both sides of the road. We assumed that fox home ranges were stable across seasons and not affected by the level of crop cover.

As we identified no biologically plausible interaction terms *a priori*, we considered only additive models. Thus the total of four covariates produced 16 candidate models in total, whose relative explanatory power and parsimony we assessed using information-theoretic criteria (Burnham and Anderson 2002). For each model we calculated the Akaike information criterion (AIC), which is:

$$AIC = -2\ln(\lambda(\theta \mid data)) + 2k$$

where $\lambda(\theta \mid data)$ = the likelihood of the model (θ) given the data; and k = number of model parameters.

A low AIC value indicates that the candidate model has both a high likelihood (low negative likelihood) and relatively few parameters and

Table 1. Survey effort by year, season and transect
NC = non-cropping season; C = cropping season

Transect	2002	2003		2004	Total
	C	NC	C	NC	
Ceduna	0	1	2	4	6
Elliston	2	4	2	4	11
Lock	2	4	2	4	11
Pt Kenny	2	4	2	4	11
Streaky Bay	0	3	2	4	8
Venus Bay	2	4	2	4	11
Wudinna	0	2	2	4	7
Total	8	22	14	28	72

is thus a parsimonious explanation of the data. However, as other models may have AIC values very close to that of the best model, it is necessary to assess model-selection uncertainty by evaluating the difference between model AIC and the minimum AIC:

$$\Delta_i = AIC_i - \min AIC$$

Models having $\Delta_i < 2$ can be considered as having substantial support (Anderson *et al*. 2000; Burnham and Anderson 2001, 2002). Finally, Akaike weights can be calculated for each model:

$$w_i = \frac{\exp\left[\frac{-\Delta_i}{2}\right]}{\sum_{r=i}^{R} \exp\left[\frac{-\Delta_r}{2}\right]}$$

These weights sum to 1.0 and can be interpreted as the probability that model *i* is the best model in the set being considered (Anderson *et al*. 2000; Burnham and Anderson 2001, 2002).

Once a set of plausible models was identified, predictions were made using model averaging, which weights the predicted values from the candidate models by their Akaike weights (Burnham and Anderson 2002), as follows:

$$\hat{\theta} = \sum_{i=1}^{R} w_i \, \theta_i$$

where $\hat{\theta}$ = the model-averaged prediction, θ_i is the predicton from model *I*, and *R* is the number of candidate models being considered.

Finally, to highlight the advantages of using the detectability model over methods typically used by managers in this situation, we first plotted the raw data, and second ran the equivalent model but without a correction for detectability, i.e., a standard logistic regression model to estimate Ψ, with transect and year as covariates. To run this model, data from the repeat surveys within a year were combined such that if a fox was seen on any of the repeat surveys (up to six) during a year, it was recorded as present, and otherwise absent. Models were fit using the 'glm' function in *R*, ver. 1.8, and candidate models evaluated using AIC as above.

Results

The detectability model yielded quite different results to either the raw number of fox sightings or the logistic regression model. A plot of the raw figures yielded almost no information of use for management purposes (Fig. 1*a*). Occupancies across the seven transects ranged from 3% to 10%, with very little discernible variation among years (Fig. 1*a*). Of the logistic regression models considered, the only one with strong support was that in which Ψ varied among years and transects (Table 2) and this proved more informative than the raw data. Occupancy estimates from this model showed more variation than the raw figures, with occupancy varying across transects from 3% to 40% (Fig. 1*b*). Elliston, Lock and Venus Bay had the highest occupancies, and most transects showed a distinct rise in occupancy in 2003, followed by a slight fall in 2004 (Fig. 1*b*).

The analysis using the correction for detectability, however, revealed a different picture. There was strong support for only two of the 16 candidate models: the full model with transect and year effects on Ψ and season and roadside vegetation effects on *p*; and the same model with

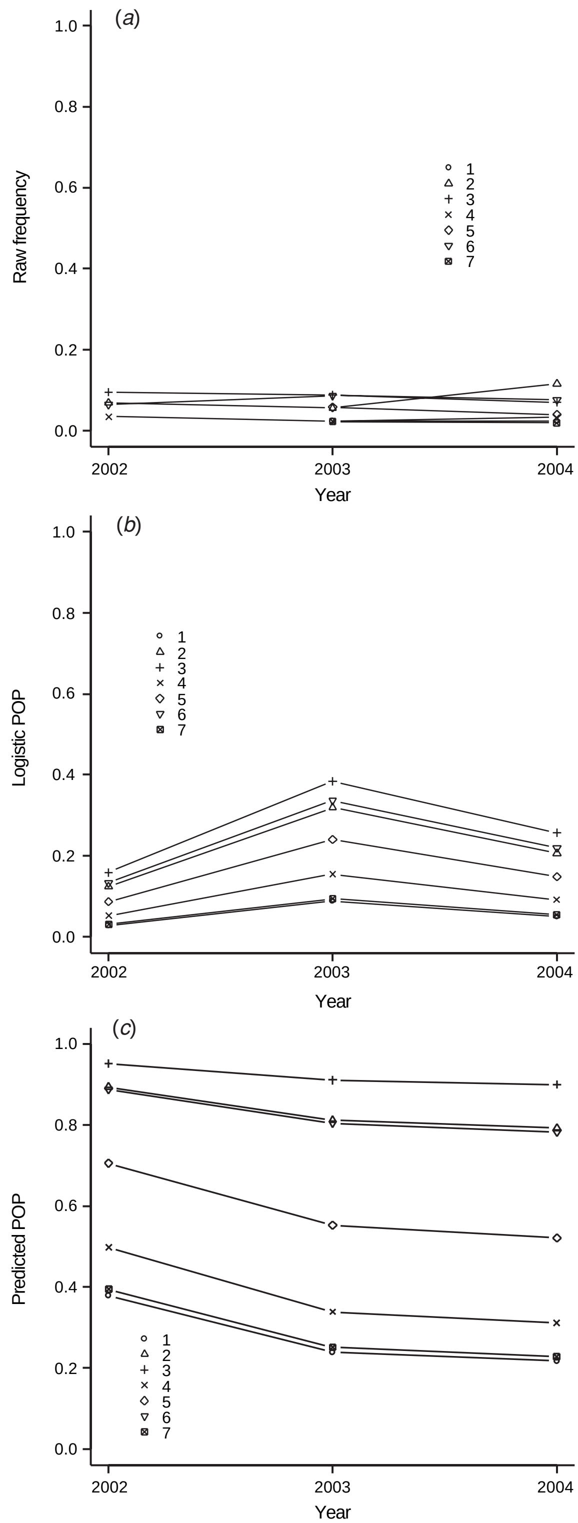

Fig. 1. Fox occupancy levels in different transects: (*a*) raw data (number of observations / total number of kilometres); (*b*) predicted occupancy from a standard logistic regression model with the same structure as the detectability model; (*c*) model-averaged predicted occupancy from the two detectability models shown in Table 3. Transects are numbered as follows: 1, Ceduna; 2, Elliston; 3, Lock; 4, Port Kenny; 5, Streaky Bay; 6, Venus Bay; 7, Wudinna.

Table 2. Akaike information criteria (AIC) and Akaike weights (*w*) for the two best logistic regression models and the best-candidate occupancy models with detectability (Det1 and Det2)
All other models had Akaike weights close to zero

Model	Structure	AIC	k	Δ	*w*
Logistic	Ψ (transect+year)	1611	9	0	1.00
Det1	Ψ (transect+year), *p* (season+roadside)	2036	12	0	0.70
Det2	Ψ (transect), *p* (season+roadside)	2038	10	2	0.30

the year effect on Ψ removed (Table 2). Importantly, detectability was extremely low, varying from a minimum of 6% in the cropping season when roadside vegetation was present, up to a maximum of 18% in the non-cropping season with roadside vegetation absent (estimates back-transformed from the parameter estimates of the full detectability model shown in Table 2). Although the model-averaged occupancy estimates from the two best models concurred with the logistic regression model in their relative rankings for the occupancy levels of the transects (again with Elliston, Lock and Venus Bay clearly higher in all years: Fig. 1*c*), they differed markedly in two respects. First, the correction for low detectability meant that the detectability model occupancy estimates were substantially higher (2- to 5-fold) than their logistic regression counterparts (Fig. 1*b*, *c*). Second, it suggested a downward trajectory in the fox population, although the uncertainty in model selection means that the evidence for this remains tentative (Fig. 1*c*).

Discussion

Our results demonstrate how detectability estimation can be useful both in the identification of trajectories in monitoring data and in guiding adaptive changes to monitoring design. Using a small amount of data from the beginning of a long-term fox-monitoring program, we have used zero-inflated modelling to assess the current status and likely trajectory of the fox population to estimate fox detectability and to identify some factors affecting it. As well as facilitating a preliminary evaluation of the baiting program, this analysis allows the allocation of survey effort to be reassessed with a view to improving the ability to detect trends in the future.

A key result from our analysis was that fox detectability using this survey method was extremely low, ranging from 6 to 18%, and consequently both the raw data and conventional logistic regression estimates provided a poor guide to the extent of the fox population and its trajectory over time. Both methods severely underestimated fox occupancy and although logistic regression was able to resolve which transects contained the most foxes, its inability to correct for seasonal fluctuations in detectability meant that it failed to identify the decrease in occupancy suggested by the detectability model. Owing to the ecologically short time series, some model uncertainty and the fact that we did not fit an explicit trend model, the conclusion of a downward trend in fox numbers should be treated with caution. Nevertheless, our results provide an example of how explicitly modelling detectability can enhance the ability of managers to acquire a more accurate picture of the state of the target population and thus assess whether management efforts are achieving the desired outcome.

The low levels of detectability also highlight the benefits of taking an adaptive approach to monitoring, in which analysis of past data is used to iteratively modify and improve survey design. The finding that detectability decreased in the cropping season and when roadside vegetation was present suggested modifications to the survey design that could

Table 3. Parameter estimates (logits) from the best-supported occupancy models with detectability (Det1 and Det2) and the best-supported logistic model
n.a., not available

Parameters		Det1		Det2		Logistic	
		Mean	s.e.	Mean	s.e.	Mean	s.e.
Occupancy	Ceduna	0.48	1.25	–1.28	0.34	–3.51	0.32
	Elliston	2.51	0.65	2.54	0.64	1.54	0.31
	Lock	2.89	0.78	3.93	1.98	1.89	0.30
	Port Kenny	0.35	0.43	0.62	0.41	0.60	0.33
	Streaky Bay	1.43	0.45	1.57	0.46	1.25	0.32
	Venus Bay	2.15	0.52	2.50	0.63	1.60	0.31
	Wudinna	0.14	0.45	0.19	0.45	0.14	0.37
	All 2003	–1.56	1.17	n.a.	n.a.	1.17	0.19
	All 2004	–1.96	1.21	n.a.	n.a.	0.79	0.19
Detectability	Intercept	–1.51	0.15	–1.57	0.17	–	–
	Season	–0.60	0.14	–0.64	0.13	–	–
	Roadside	–0.68	0.15	–0.49	0.13	–	–

improve the ability to detect trends. By consolidating survey effort in the non-cropping season and in transect segments lacking roadside vegetation, surveyors could improve their ability to detect foxes when present. If subsequent surveys were to be explicitly designed to gather further information on the factors that influence detectability, it could allow survey effort to be consolidated in those times and places when and where detectability is highest. For example, future analyses could examine whether there are peaks and troughs of detectability within the non-cropping season and, if so, whether clustering repeat visits at such times would improve the ability to detect trends. Although there is little published information on fox ecology in Australia, dispersal studies from the Northern Hemisphere and local expert opinion suggest that autumn, when subadults disperse, is the most likely candidate time when a spike in detectability might occur (Saunders *et al*. 1995). This may have contributed to our result that detectability was higher in the period January–July. By exploring such temporal variations in detectability, it is possible that survey resources could be progressively consolidated in a more productive manner, leading to more cost-efficient monitoring, improved inference about population trajectories, and, ultimately, better management decisions. The possibility that detectability, as well as occupancy, also varied systematically among years could also be explored as a larger dataset is accumulated.

Finally, our analysis reinforces a point made in numerous recent papers (Field *et al*. 2001, 2005; MacKenzie and Kendall 2002; MacKenzie *et al*. 2002, 2003, 2005; Tyre *et al*. 2003; Wintle *et al*. 2004, 2005; MacKenzie 2005; MacKenzie and Royle 2005), namely that ecological inference can be seriously impaired if analyses fail to account for false absences induced by low detectability. This can be particularly critical in monitoring programs, where budgets are typically tight and it is imperative to make the best possible use of the limited data available when attempting to detect long-term ecological trends. We suggest that a wide range of monitoring studies, whether aimed at conserving threatened species or eliminating pest species, could benefit from the application of such methods.

In doing so, it is important to stress that such analysis requires that at least a subset of sample sites be visited multiple times (MacKenzie *et al*. 2002; Royle and Nichols 2003; Tyre *et al*. 2003). When budgets are small and fixed, this in turn forces a trade-off between the number of sites to be surveyed and the number of repeat visits made at each site. Recent work shows that, as a general rule, three surveys per site will approximate the optimum for minimising the variance of occupancy estimates (MacKenzie and Royle 2005) and 2–3 surveys per site will maximise the power to detect trends (Field *et al*. 2005). However, high occupancy levels and/or low detectabilities will both tend to increase the number of repeats required. For example, the combination of moderate to high occupancy and low detectability for foxes in this study suggests that at least five, and perhaps as many as nine, repeat visits would be optimal (Field *et al*. 2005: fig. 5; MacKenzie and Royle 2005: table 1). We encourage managers and consultants to consider these design issues before embarking on a new survey program, or when making adjustments to an existing one, so that adaptive improvements to survey design and associated cost-savings can be made as promptly as possible.

Acknowledgments

We thank Darryl Mackenzie and an anonymous reviewer for helpful comments on the manuscript, and David Peacock and Kirstin Long for helpful discussions. This work was supported by funding from the Australian Research Council, the West Coast Integrated Pest Management Program and the South Australian Department of Environment and Heritage, in partnership with the Elliston–Le Hunte Animal & Plant Control Board, the Western Animal & Plant Control Board, the Eyre Peninsula Natural Resource Management Group and the Natural Heritage Trust. This paper is a contribution of the University of Nebraska Agricultural Research Division, Lincoln, NE 68583, Journal Series No. 14833.

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Manuscript received 21 January 2005, accepted 3 May 2005