Incorporating detectability into environmental impact assessment for threatened species

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Abstract

Environmental impact assessment is a key mechanism for protecting threatened plant and animal species. Many species are not perfectly detectable and, even when present, may remain undetected during environmental impact assessment surveys, increasing the risk of site-level loss or extinction of the species. Numerous methods now exist for estimating detectability of plants and animals. Despite this, regulations concerning survey protocol and effort during environmental impact assessments fail to adequately address issues of detectability. Probability of detection is intrinsically linked to survey effort and thus minimum survey effort requirements are a useful way to address the risks of false absences in environmental impact assessments. We describe two methods for determining appropriate survey effort requirements during environmental impact assessment surveys and demonstrate their application for *Pimelea spinscens* subsp. *spinescens,* a critically endangered grassland plant species in Melbourne, Australia. We demonstrate how minimum survey effort requirements change with suboptimal survey conditions and shifting burden of proof (ie. from determining presence to demonstrating absence of the species). In our study, *P. spinescens* was detected in only half of the surveys undertaken at sites where it was known to exist. Modelled estimates of the survey effort required to detect the species or demonstrate its absence with any confidence are much higher than the effort traditionally invested in environmental impact assessment surveys for this species. We argue that minimum survey requirements be established for all species listed under threatened species legislation and hope that the work presented here will provide extra impetus for collecting, compiling and synthesizing quantitative detectability estimates for a broad range of plant and animal species.

Keywords: biological surveys, false absence, environmental impact assessment, *Pimelea spinescens*, time-to-detection

Introduction

Around the world, governments are responsible for managing and protecting threatened plant and animal species. In many countries, threatened species legislation is amongst the most important mechanisms for meeting national and international conservation commitments (McLean et al. 1999). Assessing environmental impacts of human activities on listed species is a key feature of such legislation. For example, Australia's *Environment Protection and Biodiversity Conservation Act* (EPBC Act) requires assessment and approval for any action that is likely to have a significant impact on a listed threatened species. Similarly, under Section 7 of the US *Endangered Species Act* (ESA), Federal agencies must gain approval from the Fish and Wildlife Service or National Marine Fisheries Service for any activity that may affect a listed species.

Assessing potential impacts requires that the presence or absence of listed species at impacted sites be ascertained. A large body of evidence now demonstrates that many species are not perfectly detectable; there is a non-negligible probability that the target species will remain undetected during a survey, even when it occupies the site (Kery 2002; MacKenzie et al. 2002; Bailey et al. 2004; de Solla et al. 2005; Wintle et al. 2005; Garrard et al. 2008; Chen et al. 2009). The consequences of false absences during an impact assessment may be especially severe as a poor decision can lead to the site-level extinction of the species. For many threatened species, a site-level loss would constitute a significant impact. Threatened species legislation should therefore address the issue of imperfect detectability and specify measures for avoiding inappropriately high false absence rates during impact assessments for threatened species. One way to do this is to specify requirements for biological surveys undertaken during environmental impact assessments for these species (Wintle et al. 2005).

Regulators can make qualitative recommendations about survey protocol by specifying the appropriate season and conditions for surveys, or a minimum experience level of the observer (See, for example, Department of the Environment, Water, Heritage and the Arts (DEWHA) 2009a)). Others specify the survey effort required (DEWHA 2009b; US Fish and Wildlife Service 2009) and a few go as far as to link survey effort requirements to achieving a minimum probability of detection (US Fish and Wildlife Service 1997). The latter remain the exception rather than the rule. For plants, quantitative survey effort requirements are noticeably absent (Doub 2012).

We describe methods for determining minimum survey effort requirements for threatened species during environmental impact assessment surveys. We discuss multiple models for estimating detectability, and two methods for determining survey effort requirements based on these estimates. We demonstrate the application of these methods for a critically endangered Australian grassland plant species, using a time-to-detection model to estimate detectability. We identify the variables that influence detection of the species and calculate the survey effort required to achieve: 1) a 0.95 probability of detection given presence; and 2) a 0.95 probability that the species is truly absent from the site. We conclude with a discussion about factors that influence detectability and the implementation of minimum survey effort requirements in environmental impact assessment regulations.

Methods

Estimating detectability

Numerous methods exist for estimating detectability. These methods vary in their data requirements, assumptions and outputs. Some models focus on the probability of detecting an individual within a population (i.e., Mark-recapture (Pollock et al. 2002; Kéry & Gregg 2003) and N-mixture models (Royle 2004; Joseph et al. 2009)). These models can be used to adjust for bias in abundance estimates and are most often used in demographic studies. Other models estimate the probability that a species will be detected at a site, given it is present (zero-inflated binomial (ZIB) and occupancy models (MacKenzie et al. 2002; Tyre et al. 2003; Wintle et al. 2005; Garrard et al. 2008)). These models are useful for accounting for false absences when estimating occupancy, making them particularly relevant for environmental impact assessment surveys. Detectability estimates are measured in units related to survey effort. Survey effort may be discrete (e.g., number of visits (Wintle et al. 2005)) or continuous (e.g., time spent searching (Garrard et al. 2008)).

Discrete measures are useful for assessing survey effort for species where multiple visits are appropriate. This is includes animals that roam or hide from the observer, and orchids and other cryptic plant species that undergo periods of above-ground dormancy. Multiple visits are necessary to maximize the probability of a survey occurring at a time when the species is visible (and therefore possible to detect) at the site. For these species, ZIB models can be used to estimate the single-visit detection probability and survey effort requirements. However, for many plant species, repeat visits offer little advantage: if the species occupies the site, it is possible to detect it. In this case, it makes sense to spend more time searching in a single visit than to return at a different time and incur the additional travel and other costs associated with locating survey sites.

Time-to-detection models can be used to estimate the average time required to detect a species in a biological survey (Garrard *et al.* 2008). Assuming that detection times are distributed exponentially and the species is detected at a constant rate, λ, the average time to detection, $\bar{t}$, is modelled as a function of observer and environmental variables:

$$\bar{t} = \frac{1}{\lambda} = e^{\alpha + \beta_1 x_1 + \cdots + \beta_n x_n}, \tag{1}$$

where α is the intercept of the linear function and $\beta_1, \ldots, \beta_n$ are the coefficients for the *n* explanatory variables, $x_1, \ldots, x_n$.

Under an exponential time-to-detection model, the probability of detecting the target species at time *t* is $\lambda \exp^{-\lambda t}$ (Cox & Oakes 1984). This model framework can also account for censored observations, which occur when the species is not detected in a survey of duration t_{cen}. The probability of the target species being detected by time t_{cen} (as opposed to *at* time *t*) is $1 - \exp(-\lambda t_{cen})$ and the probability of it being detected after time t_{cen} is therefore $\exp(-\lambda t_{cen})$. If Ψ is the probability of occupancy of the species and *S* is the duration of the survey, when the species is detected, the likelihood of a given detection time (t), given estimated parameters Ψ and λ is:

$$l(t|\Psi, \lambda) = \Psi \cdot \lambda exp^{-\lambda t} \qquad 0 < t < S, \qquad (2)$$

The likelihood of a censored observation (non-detection) given estimated parameters is equal to the probability that the species is present and the detection time is greater than the duration of the survey (Ψ.exp(–λS)) plus the probability that the species was absent from the site (1 – Ψ):

$$l(t_{\text{cen}}|\Psi, \lambda) = \Psi \cdot exp^{-\lambda S} + (1 - \Psi) \qquad t_{cen} = S, \qquad (3)$$

Determining survey effort requirements

We present two methods to determine appropriate survey effort requirements. The first method estimates D, the probability that a species that is present at a site will be detected in a survey of pre-specified effort. As survey effort increases, the probability of detecting the species when it is present also increases. Because the probability of recording a false absence is 1 – D, this allows regulators to assess whether the survey effort is adequate to ensure a sufficiently low risk of false absence records.

Where survey effort is measured in discrete units, such as repeat visits:

$$D = 1 - (1 - p)^n , \qquad (4)$$

where p is the single-visit detection probability of the species given presence and n is the number of repeat visits (Wintle et al. 2005).

When survey effort is measured in continuous units, such as time spent searching (t):

$$D = 1 - exp^{-\lambda t} , \qquad (5)$$

when the detection rate, λ, is constant (Garrard et al. 2008).

The second method estimates the probability that the species is present at the site given that a survey of given effort has failed to detect the species (Wintle et al. 2012). This formulation of the problem allows the regulator to place the burden on the proponent to demonstrate with sufficient probability that the species is absent from the site. The basic concept of this method is that, as more effort is expended searching for the species without a detection, the searcher/regulator becomes increasingly confident that the species is absent. For a given survey effort, there are two factors that affect the confidence with which absence is declared: (i) the detectability of the species (a species with low detectability is likely to remain undetected when present compared with a more detectable species); and (ii) the prior belief or confidence that the species is present. At a site where the species is likely to be present (for example, at sites where the species has previously been recorded), more survey effort is required to be confident that the species is absent than at a site where the species is believed unlikely to occur.

This method uses Bayes' Theorem to estimate the probability that the species is present, given that survey(s) have been undertaken and the species was not detected (ψ, the *posterior* probability of presence (Wintle et al. 2012)):

$$\psi = \psi' (1 - D) / (\psi' (1 - D) + (1 - \psi')) , \quad (6)$$

where ψ' is the *prior* probability of presence, D is the probability of detecting the species if it is present during a survey of given effort, and $(1 - D)$ is the probability that a species that is present is not detected. Under the exponential time-to-detection model, the probability of not detecting a species that is present in a survey of duration t is $exp^{-\lambda t}$, and the posterior probability of presence is therefore:

$$\psi(t) = (\psi' \, exp^{-\lambda t}) / (\psi' \, exp^{-\lambda t} + (1 - \psi')). \quad (7)$$

The posterior probability that the species is absent from the site after a survey of duration t is then $1 - \psi(t)$.

Case Study – Detectability and survey effort for a threatened grassland plant

The spiny rice-flower, *Pimelea spinescens* Rye, Fl. Australia 18:324 (1990) subsp. *spinescens* (hereafter *P. spinescens*), is an EPBC-listed critically endangered plant species. It is a small shrub (5 – 30 cm in height), endemic to grasslands of the volcanic plains of Victoria, Australia. The decline of this species is a direct result of habitat loss and fragmentation, as well as pressure and competition from exotic species (Carter & Walsh 2006; Department of Sustainability and Environment 2006). The proximity of remnant habitat to the urban fringe of Melbourne, a rapidly expanding city, means that threats posed to this species by habitat loss and weed encroachment are persistent and ongoing.

The presence of *P. spinescens* at a site may trigger a more thorough impact assessment process under the EPBC Act than would otherwise be required by local or state legislation. The pressure for urban development means that a false absence observation during impact assessment surveys is likely to result in site-level extirpation of the species. It is therefore important that impact assessment surveys are of sufficient rigour to achieve a reasonable probability of detecting the species.

Estimating time-to-detection

We estimated the average time to detection for *P. spinescens* using time-to-detection data collected from a multi-site, multi-observer field study in native grasslands in the urban fringe region of Melbourne. Surveys of 90 minutes were conducted in one-hectare plots at 16 sites in Spring, 2006 and 2007. Each plot was surveyed between 8 and 12 times by separate observers; partly in order to explore observer effects on detectability (Garrard 2008). A total of 157 90-minute surveys were conducted, in which observers were instructed to cover as much of the plot as possible. Within each 1-ha plot, observers were required to record the time of the initial detection of each species, including *P. spinescens*. Where *P. spinescens* was not detected by a particular observer at a particular site, it was treated in one of two ways. Where the species had been detected by another observer at the site, it was a known false absence (occurring with probability $\Psi.\exp(-\lambda S)$). Where the species was not detected by any observer at the site, it was considered a censored observation. The full likelihood for the observation of a detection time, *t*, by observer *j* at site *i* is:

$$l\left(t_{ij}\middle|\Psi_i,\lambda\right) = \Psi_i \prod_{\mathrm{j}}(\lambda e^{-\lambda t_{ij}})^{\delta_{ij}}\,(e^{-\lambda S})^{1-\delta_{ij}} \qquad \sum_j \delta_{ij} \geq 1 \qquad (8)$$

$$l\left(t_{ij}\middle|\Psi_i,\lambda\right) = \Psi_i \prod_{\mathrm{j}}(e^{-\lambda S})^{1-\delta_{ij}} \;+\; (1-\Psi_i) \qquad \sum_j \delta_{ij} = 0, \qquad (9)$$

where δ_{ij} is an indicator for detection of the species by observer *j* at site *i*: $\delta_{ij} = 1$ if detected, $\delta_{ij} = 0$ if not detected.

Candidate explanatory variables and model selection

Candidate detection time models for *P. spinescens* were of the general form expressed in Equation 1. Observer experience is known to influence detection rates in grassland species, as is the density of the dominant grass species, *Themeda triandra* (Garrard et al. 2008). Observers were classified as *experienced* (experience with botanical surveys in Victorian Volcanic Plains (VVP) grasslands) or *intermediate* (botanical survey experience, but limited familiarity with VVP species). The percentage cover of *T. triandra* was assessed in five one-m^2 quadrats in each one-ha plot (plots were located within homogenous patches of vegetation at each site). Observer experience and *T. triandra* cover (*%cover*) were included in all candidate models.

We also investigated the influence of date of survey, weather conditions and search strategy. Surveys were undertaken in late spring, as this is the most common period for surveys in this vegetation type. The two years in which surveys were undertaken were unseasonably dry and, as a result, many ephemeral species appeared, flowered and died back within a very short time. As such, it was thought that *P. spinescens*, a perennial, may become more easily detectable as the season progressed. The visibility of the species may be different under sunny or overcast conditions, and the over-riding weather condition at the time of each survey was recorded as *sunny, cloudy* or *overcast*. Observers were instructed to undertake surveys using one of two search methods: *systematic* or *random walk*. It was thought that the random walk would allow more scope for observers to use knowledge or intuition and may therefore lead to lower detection times.

Detection times might vary across sites and observers in ways not explained by variables tested here. We investigated mixed effect models with random effects for site and observer, but there was little evidence to support the inclusion of random effects (See

Appendix). The mixed effects models will not be discussed further here, but note that unmodelled variation in site and observer may contribute variability in future surveys beyond what is captured by the fixed effects in our models.

Models were run in OpenBUGS version 3.1.0, a freely available statistical software package for conducting Bayesian analyses using Markov chain Monte Carlo (MCMC) methods (Lunn et al. 2009). We used uninformative normal prior distributions for α and β_n (mean = 0, precision = 1000) to ensure that the posterior estimates were dominated by the data. The full model description and code can be found in the online supplementary material. To check for convergence, we sampled from two MCMC chains. The performance of candidate models was assessed using the Deviance Information Criterion (DIC: Spiegelhalter et al. 2002) which aims to identify the optimal trade-off between deviance reduction and model complexity.

Estimating survey effort

Using Equation 5, we estimated the probability of detecting *P. spinescens* where present under a range of survey conditions (experienced and intermediate observers and 10%, 35% and 70% *T. triandra* cover) across a range of survey durations. We also estimated the survey effort required to achieve a probability of detection of 0.95 for the species (probability of false absence = 0.05).

We used Equation 7 to estimate the posterior probability of presence for *P. spinescens* given non-detection under a range of survey durations and prior probabilities of occupancy. We also estimated the survey effort required to achieve a posterior probability of absence of 0.95.

Results

Naïve estimates of detection indicated that, even at sites where the species was known to be present, it was detected only 53% of the time. The detection time model with the lowest DIC was the one that included observer experience, cover of *T. triandra* and the date of survey (Table 1). There is little separating the two best models (ΔDIC = 0.7), and the 95% credible interval for the *date* coefficient includes zero (Table 1, Figure 1). As such, the model that included only observer experience and *T. triandra* cover was selected as the most general model for estimating detection probability. Under this model, average detection time decreases with observer experience and increases with cover of *T. triandra* (Table 1). Comparison of fitted detectability curves and observed detections indicates that this model is a good estimator of average detection times for *P. spinescens* (Appendix).

Predicted estimates of the average time to detection for experienced observers at sites with 10%, 35% and 70% *T. triandra* cover were 37.0 [95% CI: 22.1, 65.8], 66.9 [44.9, 105.4] and 152.1 [84.4, 307.9] minutes, respectively. Based on these estimates, the predicted probability of detection (given presence) in a 1-hour survey by an experienced observer is 0.79 [0.60, 0.93], 0.59 [0.43, 0.74] and 0.33 [0.18, 0.51] at 1-ha sites with 10%, 35% and 70% cover of *T. triandra*, respectively (Figure 2b). Conversely, the probability of recording a false absence after a one-hour survey is 0.21, 0.41 and 0.67, respectively. Note that average detection times are much longer and more uncertain under worse survey conditions. The increasing uncertainty can be attributed to the greater proportion of censored observations under these conditions.

At sites where the species is present, almost 2 hours of survey effort per hectare is required to achieve a probability of detection of 0.95, even under the most favourable conditions (Table 2). Again, this figure is significantly higher under more adverse conditions (Table 2, Figure 2a,b).

Similarly, the amount of survey time with no detections required to achieve a posterior probability of absence of 0.95 increases with cover of *T. triandra* and observer inexperience. Required survey effort also increases with the prior probability of species presence (Table 2, Figure 2c, d). Under the most favourable conditions tested (experienced observer, 10% *T. triandra* cover), the survey effort required to achieve a posterior probability of absence of 0.95 is 58 minutes per hectare when the prior belief in presence is 0.2. This figure increases to 109 minutes when the prior probability is 0.5 and to 160 minutes when the prior probability is 0.8.

Discussion

Imperfect detectability and survey effort

We have demonstrated a method for determining survey effort requirements for threatened species during environmental impact assessments. We have used a threatened grassland plant species in our example, but the method is general and can be applied to most species. In addition, the findings of this case study raise some general issues that should be considered when determining survey effort for threatened species.

Even the most optimistic estimate of detectability for our critically endangered plant species was very low – a little over 0.50 for a survey of 90 minutes in a single hectare of grassland. Ours is one of many studies demonstrating imperfect detectability of listed threatened species (Slade et al. 2003; MacKenzie et al. 2005; Wenger & Freeman 2008; Guillera-Arroita et al. 2010). This serves to highlight the importance of our message; that addressing issues of detectability and survey effort in threatened species legislation is critical for the protection and conservation of threatened species.

The influence of observer experience is intuitive. That surveys be conducted by an experienced professional is a requirement for many species under the EPBC Act and ESA. Lists of approved observers are even specified for some species under the ESA (Doub 2012). However, the significance of observer experience may be species- or taxa-specific. A number of previous studies have failed to find any impact of observer on detectability of plant species (Kéry & Gregg 2003; Chen et al. 2009). This difference may be explained by the nature of the surveys. In the previously mentioned studies, observers were searching for a single species or a small number of species. In our study, observers were required to record every species they detected. This may be more representative of comprehensive flora surveys undertaken as part of environmental impact assessments; however, the effect of observer experience may be reduced in a targeted survey, where a less experienced observer can be trained relatively quickly to identify the target species.

The large effect of *T. triandra* cover on detectability in this case study highlights the importance of considering the historical context and management of the site during environmental impact assessments. *P. spinescens* occurs in grasslands in and close to the urban fringe of a rapidly developing city. Historical grazing and burning of these grasslands regularly reduced the biomass of *T. triandra*. More recently, changes to fire regimes and speculative acquisition of these sites for urban development have reduced regular biomass removal. Our research indicates that, where regular biomass removal has not occurred, the survey effort required to detect *P. spinescens* or declare its absence with any certainty may be much larger than otherwise. Fire, via its influence on biomass and flowering, also affects detectability of the threatened prairie plant species *Asclepias meadii* (Slade et al. 2003).

The qualitative findings of this study are reflected in the survey guidelines for impact assessment for *P. spinescens* under the EPBC Act, which specify that surveys should be undertaken by an experienced professional and that detectability may be highest following a low-intensity biomass reduction burn (DEWHA 2009a). Qualitative survey protocols and recommendations are now common for species listed under the EPBC Act and ESA. However, without quantitatively addressing the relationship between survey effort and detection probability, it is impossible to thoroughly assess the rigor of the biological survey or any potential impact on the target species. Our findings suggest that even under extremely favourable survey conditions, almost 2 hours per hectare is required to detect the species with probability 0.95. This is well above the survey effort historically invested in environmental impact assessments in this ecosystem (Garrard 2009). Furthermore, the survey effort required to detect the species with the same confidence increases dramatically under sub-optimal conditions. Quantitative survey effort guidelines will improve the rigor, transparency and enforcement of environmental impact assessments for threatened species.

An important issue related to survey effort recommendations relates to the time of year in which surveys are undertaken. Peak detectability may be associated with flowering in plants or breeding season in animals. Many species may be difficult or impossible to detect at other times of the year, particularly cryptic species such as orchids. Surveys for this study were undertaken in late spring to coincide with the flowering period of most species and the time at which ecological surveys are most commonly undertaken. The peak flowering period for *P. spinescens* is between April and August (Department of Sustainability and Environment 2005), although it remains visible in the non-flowering period. Average detection times and minimum survey effort requirements for this species might be shorter during the *P. spinescens* flowering months when ephemeral plants are not flower and therefore not creating distractions for observers. Note also that average detection times are likely to be shorter in a targeted survey than in a comprehensive survey of a site, because observers are not expending effort searching for and recording other species.

Setting minimum survey effort requirements

We have demonstrated two methods for determining minimum survey effort requirements for threatened species during environmental impact assessment surveys. Each addresses issues of risk and burden of proof differently, but both require pre-specified thresholds of certainty. We have arbitrarily set targets of 0.95 for *Pr*(detected|present) and *Pr*(absent|not detected). Ideally, these targets would be sufficiently high that they are effectively equal to 1, particularly when a critically endangered species is involved. However, increasing survey effort produces diminishing returns in certainty (Figure 2). In reality, minimum survey effort requirements involve a trade-off between minimizing the risks and costs of a false absence and the increasing cost of surveys. In the absence of a formal decision framework that places a monetary value (cost) on failing to detect an endangered species where it is present, this trade-off remains a political decision taken on behalf of society, usually by agency officials who are charged with approving or rejecting impact assessment reports.

Optimisation methods have been used to determine the survey effort that minimizes total costs in invasive species management (Hauser & McCarthy 2009). However, there are a number of obstacles to determining optimal survey effort for threatened species in environmental impact assessments. First, these methods require the costs of survey effort and false absences to be measured in the same units. This is relatively straightforward for invasive species because the monetary costs of eradication and loss of agricultural productivity can be directly traded against the costs of surveillance. The costs of failing to detect a threatened species are more difficult to quantify. What price do we put on the site-level loss of the species?

Second, optimal surveillance problems for invasive species are formulated in a way that minimises the total cost to a single party (usually government), who is responsible for both surveillance and eradication. Under the EPBC Act, the cost of environmental impact assessment surveys is borne by the proponent, but the costs of false absences will be borne by government (in the form of increased costs of protecting the species in the long term), or by the environment. Policies and techniques such as offsetting and restoration may help estimate costs of false absences in threatened species surveys, but identifying optimal survey effort when the costs are borne by multiple parties is more problematic.

Conclusions

Given the importance of detectability in determining the effectiveness of biological surveys, we argue that minimum survey requirements be established for all species listed under threatened species legislation. We present a protocol for establishing minimum survey effort.

While the importance of imperfect detectability is increasingly recognised, the number of species for which detection information is available remains small. For many threatened species, little or no information on detectability is available. Trait-based models of detectability may offer some potential for informing survey effort requirements for these species while data are being collected to inform detectability estimates for those species, or as an informative prior on detectability when available data provide highly uncertain estimates (Garrard et al. 2012).

We hope that the work presented here will provide extra impetus for collecting, compiling and synthesizing quantitative detectability estimates, especially for species on threatened species lists that are likely to be the subject of future impact assessments. Requiring consultants to collect impact assessment data in a way that can be useful for computing detectability estimates would be a positive step, as would investing in better approaches for centralized storage and syntheses of existing, relevant data.

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Table 1. Candidate detectability models for *P. spinescens* and DIC rankings. *exper* is experienced observers, *%cover* is the percentage cover of *Themeda triandra*, *date* refers to the number of days since October 1, *search* refers to random survey search strategy, and *sunny, cloudy* and *overcast* indicate prevailing weather conditions at the time of survey.

Model	DIC (pD)
$\bar{t}$ = 1/λ = exp(4.49[3.84,5.20] – 1.11[-1.80, -0.45]*exper* + 0.024[0.011, 0.038]*%cover*)	443.6 (3.9)
$\bar{t}$ = 1/λ = exp(5.30[4.11,6.52] – 1.16[-1.84, -0.50]*exper* + 0.022[0.009, 0.036]*%cover* - 0.023[-0.052, 0.006]*date*)	442.9 (4.8)
$\bar{t}$ = 1/λ = exp(4.49[3.69, 5.34] – 1.13[-1.83, -0.42]*exper* + 0.024[0.011, 0.038]*%cover* + 0.018[-0.671, 0.704]*search*)	445.6 (4.8)
$\bar{t}$ = 1/λ = exp(4.49[3.81, 5.24] – 1.07[-1.76, -0.39]*exper* + 0.024[0.011, 0.038]*%cover* + 0**sunny* - 0.25[-1.05, 0.61]*cloudy* + 0.20[-0.59, 1.07]*overcast*)	446.6 (5.8)

Table 2. Average time to detection given presence and survey effort requirements for *Pimelea spinescens* for a range of observer experienceand *T. triandra* cover values. Survey effort requirements are those necessary to achieve a 0.95 probability of detection given presence and posterior probability of absence given no detections. Estimates for the latter are shown for prior probabilities of presence of 0.2, 0.5 and 0.8. All estimates are calculated using the time-to-detection model with observer experience (*exper*) and *T. triandra* cover (*%cover*) as explanatory variables. Estimates shown are the median values of the Bayesian posterior distributions, with 95% credible intervals in brackets.

Observer Experience	*T. triandra* cover	Ave. Detection Time, $\bar{t}$ (mins/ha)	Required Survey Effort Pr(detect|present) = 0.95	Required Survey Effort Pr(Absent|Not detected) = 0.95		
				Ψ' = 0.2	Ψ' = 0.5	Ψ' = 0.8
experienced	*10%*	37.0 [22.1, 65.8]	110.8 [66.3, 197.0]	57.6 [34.5, 102.5]	108.9 [65.2, 193.6]	160.2 [95.9, 284.8]
experienced	*35%*	66.9 [44.9, 105.4]	200.4 [134.6, 315.6]	104.2 [70.0, 164.2]	197.0 [132.3, 310.2]	289.7 [194.6, 456.3]
intermediate	*10%*	112.1 [64.2, 211.9]	335.9 [192.4, 634.9]	174.7 [100.1, 330.2]	330.2 [198.1, 624.0]	485.6 [278.2, 917.8]
intermediate	*35%*	202.9 [126.1, 353.0]	607.7 [377.6, 1058.0]	316.1 [196.4, 550.1]	597.3 [371.2, 1039.0]	878.5 [545.9, 1529.0]
experienced	*70%*	152.1 [84.4, 307.9]	455.8 [252.9, 922.4]	237.0 [131.5, 479.8]	448.0 [248.5, 906.6]	658.9 [365.6, 1333.0]

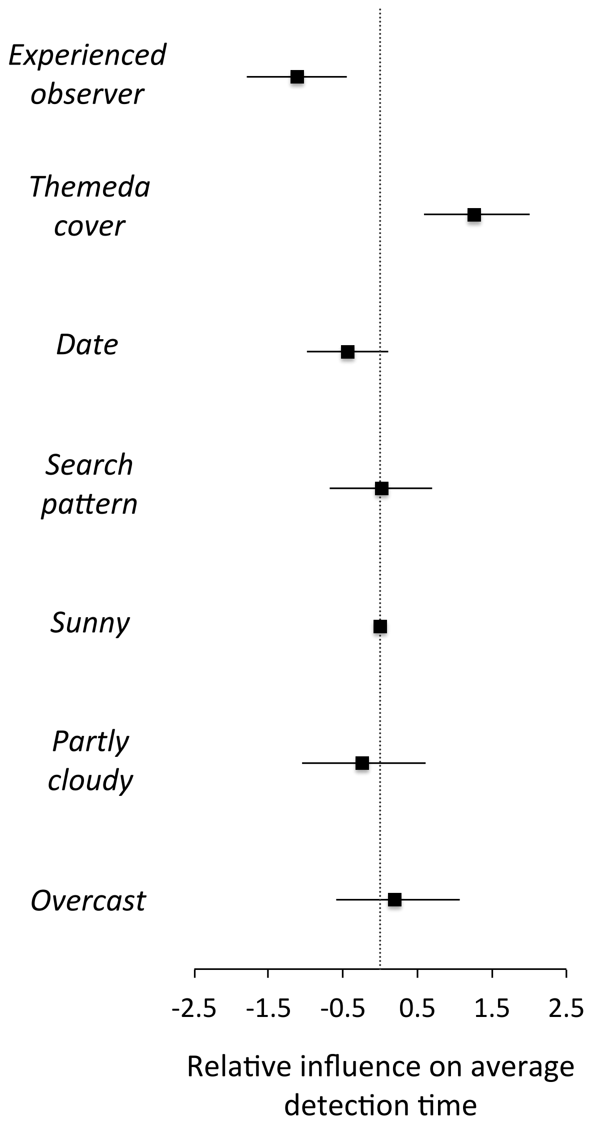

Figure 1. Relative size of the influence of candidate explanatory variables on average time to detection for *P. spinescens*.

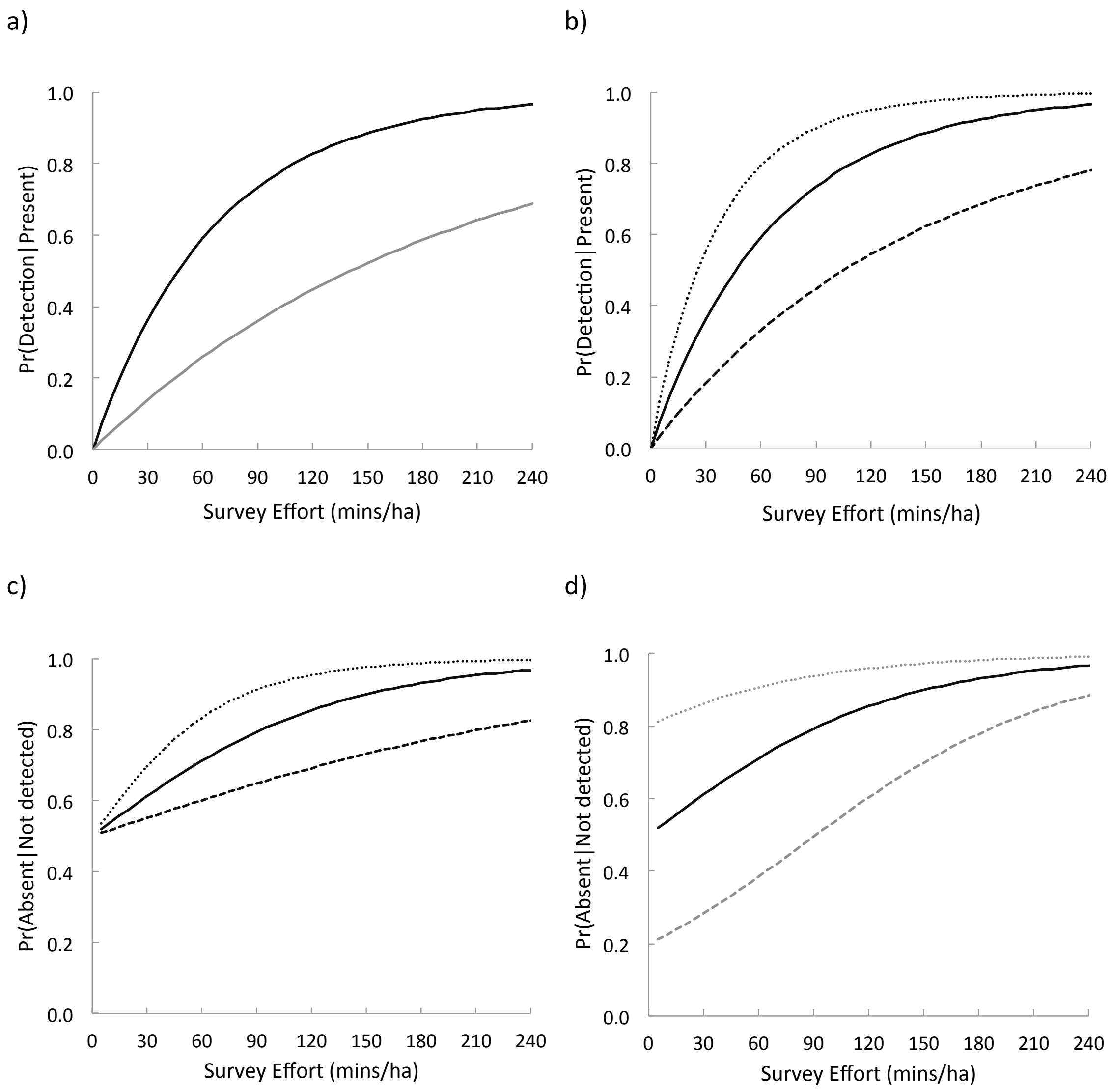

Figure 2. Relationship between survey effort and: probability of detection given presence (a & b); and probability of absence given no detections (c & d) for *P. spinescens*. a) Detectability curves for experienced (black line) and intermediate (grey line) observers at sites with 'average' cover of *T. triandra* (35%). b) Detectability curves for experienced observers at sites with 10% (dotted line), 35% (solid line) and 70% (dashed line) *T. triandra* cover. c) Relationship between survey effort and probability of absence where the prior probability of presence at the site is 0.5 and surveys are undertaken by experienced observers. Dotted, solid and dashed lines are for sites with 10%, 35% and 70% cover, respectively. d) Experienced observers undertaking surveys at sites with 35% *T. triandra* cover. Dotted, solid and dashed lines represent prior probabilities of occupancy of 0.2, 0.5 and 0.8, respectively.