Incorporating detectability of threatened species into environmental impact assessment

Running title: Species detectability in environmental impact assessment

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Keywords: biological surveys, false absence, *Pimelea spinescens*, time to detection

Word count (including Abstract, Main Text & References): 6,032

Tables: 2

Figures: 2

Supplementary Information: Yes, attached.

Abstract

Environmental impact assessment (EIA) 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 EIA surveys, increasing the risk of site-level loss or extinction of species. Numerous methods now exist for estimating detectability of plants and animals. Despite this, regulations concerning survey protocol and effort during EIAs fail to adequately address issues of detectability. Probability of detection is intrinsically linked to survey effort; thus, minimum survey effort requirements are a useful way to address the risks of false absences. We utilised two methods for determining appropriate survey effort requirements during EIA surveys. One method determined the survey effort required to achieve a probability of detection of 0.95 when the species is present. The second method estimated the survey effort required to either detect the species or reduce the probability of presence to 0.05. We applied these methods to *Pimelea spinscens* subsp. *spinescens,* a critically endangered grassland plant species in Melbourne, Australia. We detected *P. spinescens* in only half of the surveys undertaken at sites where it was known to exist. Estimates of the survey effort required to detect the species or demonstrate its absence with any confidence were much higher than the effort traditionally invested in EIA surveys for this species. We argue that minimum survey requirements be established for all species listed under threatened species legislation and hope that our findings will provide an impetus for collecting, compiling, and synthesizing quantitative detectability estimates for a broad range of plant and animal species.

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 substantial impact on a listed threatened species. Similarly, under Section 7 of the U.S. 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 information on the presence or absence of listed species at affected sites. 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 (e.g., Kéry 2002; Wintle *et al*. 2005; Garrard *et al*. 2008). The consequences of false absences during an impact assessment may be especially severe as a poor decision can lead to site-level extirpation of the species. For many threatened species, a site-level loss would constitute a signficant 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 (EIAs) for these species (Wintle *et al.* 2012).

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 (e..g, 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 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 aimed to demonstrate methods for determining minimum survey effort requirements for threatened species during EIA surveys. We considered multiple models for estimating detectability and two methods for determining survey effort requirements. We illustrated these methods for a critically endangered grassland plant species. We identified the variables that influence detection of the species and calculated the survey effort required to achieve a 0.95 probability of detection given presence and a 0.95 probability that the species is truly absent from the site. We also considered the factors that influence detectability and the implementation of minimum survey effort requirements in EIA regulations.

Methods

Estimating detectability

Numerous methods, varying in their data requirements, assumptions, and outputs, exist for estimating detectability. Some 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]) and adjust for bias 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*. 2004]), to account for false absences when estimating occupancy; these models are particularly relevant for EIA surveys. Detectability depends on survey effort, which 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 of survey effort are useful when multiple visits are appropriate, such as for animals that roam or hide from the observer and orchids and other cryptic plant species that undergo periods of aboveground 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 can be detected when it occupies the site. In this case, it makes sense to spend more time searching in a single visit than to incur the additional travel and other costs associated with multiple visits.

Time-to-detection models estimate the average time required to detect a species in a biological survey (Garrard *et al.* 2008). Recent results suggest these models provide cost-effective estimates of detection probabilities (Bornand *et al*. 2014). Assuming detection times are distributed exponentially and the species is detected at a constant rate, λ, the average time to detection, $\bar{t}$, may be modeled as a function of observer and environmental variables:

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

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

observer or survey conditions that may influence the ease with which the species is detected. The exponential function is a standard transformation in time-to-event modeling that ensures the mean time to the event is positive, even when values of covariates are equal to or less than zero. This function implies that for each unit increase in a covariate, the mean time to detection changes by a constant proportion.

Under an exponential time-to-detection model, the probability density for detecting the target species (given it is present) 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 S. At sites where it is present, the probability of the target species being detected after time S is $\exp(-\lambda S)$. When the species is present at the site, the time to detection is drawn from an exponential distribution with rate λ. Thus, when the species is detected ($\delta = 1$), the likelihood of a given detection time (t) given parameters Ψ and λ is

$$L(\Psi, \lambda | T = t, \delta = 1) = \Psi \cdot \lambda e^{-\lambda t} \qquad 0 < t < S, \qquad (2)$$

where Ψ is the probability that the species occupies the site. Non-detection ($\delta = 0$) can occur because the species is absent from the site, which occurs with probability $1 - \Psi$ or because the species is present but detection times beyond the survey duration S remain unobserved. The likelihood of a non-detection is equal to the probability that the species is present and the detection time is greater than the duration of the survey ($\Psi.\exp(-\lambda S)$) plus the probability that the species was absent from the site ($1 - \Psi$):

$$L(\Psi, \lambda | S, \delta = 0) = \Psi \cdot e^{-\lambda S} + (1 - \Psi). \qquad (3)$$

This model can be expressed with a state-space formulation in which the true occurrence is partially observed and the data are the observations conditional on presence or absence. We used the likelihood functions for our analysis so that deviance could be calculated. We do not present a state-space formulation here, but it can be found in Bornand *et al*. (2014).

Determining survey effort requirements

We utilised 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. So, for example, the regulator can specify that survey effort must be sufficient to detect the species with probability (D) of 0.95 if it is present (probability of false absence = 0.05).

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

$$D = \Pr(\text{detected}|\text{present}) = 1 - (1 - p)^n , \qquad (4)$$

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). This equation assumes that surveys are independent and that p is constant. Similar expressions can be derived to account for non-independence and variable p.

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

$$D = 1 - e^{-\lambda t} . \qquad (5)$$

The second method uses estimates of D to determine 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 (e.g., survey effort must be sufficient to either detect the species or raise the probability of absence to 0.95 if it is not detected). The basic concept of this method is that as more effort is expended searching for the species without detection, the searcher or 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: detectability of the species (a species with low detectability is likely to remain undetected when present compared with a more detectable species) and prior belief or confidence that the species is present. At a site where the species is likely to be present (e.g., at sites where the species has previously been recorded or where known key habitat requirements are met within the range of the species), more survey effort may be required to be confident that the species is actually absent, rather than present but undetected. At sites in which the species is thought unlikely to occur, less evidence (in the form of non-detections) may be required to reach the conclusion that the species is almost certainly not present. This provides a coherent basis on which to allow variation in minimum survey effort requirements, depending on the perceived suitability of sites.

Bayes' rule provides the probability that the species is present, given that surveys have been undertaken and the species was not detected (ϕ, the posterior probability of presence [Wintle *et al*. 2012]):

$$\phi = \phi'(1 - D) / [\phi'(1 - D) + (1 - \phi')] . \qquad (6)$$

ϕ' is the prior probability of presence and D is the probability of detecting the species when present, so $(1 - D)$ is the probability of not detecting the species when present. Under the

exponential time-to-detection model with a survey of duration S, $1 - D = \exp(-\lambda S)$, so the posterior probability of presence given non-detection is

$$\phi(S) = (\phi' e^{-\lambda S}) / [\phi' e^{-\lambda S} + (1 - \phi')]. \quad (7)$$

The posterior probability that the species is absent from the site given non-detection during a survey of duration S is then $1 - \phi(S)$.

Detectability and survey effort for a threatened grassland plant

The spiny rice-flower (*Pimelea spinescens* subsp. *spinescens* [hereafter *P. spinescens*]) is an EPBC-listed critically endangered plant. It is a small shrub (5 – 30 cm in height) endemic to native grasslands of the volcanic plains of Victoria, Australia. The species has declined due to habitat loss and fragmentation and competition from non-native species (Carter & Walsh 2006; Department of Sustainability and Environment 2006). The proximity of its remnant habitat to the rapidly expanding city of Melbourne means habitat loss is a persistent and ongoing threat to the species..

The presence of *P. spinescens* at a site may trigger a more thorough impact assessment under the EPBC Act than would otherwise be required by local or state legislation. 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. Therefore, EIA surveys must achieve a reasonable probability of detecting the species.

We estimated the average time to detection for *P. spinescens* with time-to-detection data collected from a multi-site, multi-observer field study in native grasslands north and west of Melbourne. Surveys of 90 minutes were conducted in 1-ha plots at 16 sites in Spring 2006 and 2007. Each plot was surveyed from 8 to 12 times by separate observers, partly to explore observer effects on detectability (Garrard *et al.* 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. If the species had been detected by another observer at the site, it was a known false absence (occurring with probability $\Psi.\exp(-\lambda S)$). If the species was not detected by any observer at the site, it was considered a censored observation with two possible explanations: that the species was present but not detected by any observer or that it was truly absent. The full likelihood for the observation of a detection time, t, by observer j at a site is

$$L((\Psi,\lambda|\{t_j\}) = \begin{cases} \Psi \prod_j (\lambda e^{-\lambda t_j})^{\delta_j} (e^{-\lambda S})^{1-\delta_j}, & \text{for } \sum_j \delta_j \geq 1 \\ \Psi \prod_j (e^{-\lambda S})^{1-\delta_j} + (1-\Psi), & \text{for } \sum_j \delta_j = 0, t_j = S \end{cases}, \qquad (8)$$

where δ_j indicates detection ($\delta_j = 1$) or non-detection ($\delta_j = 0$) of the species by observer j at the site.

Candidate detection time models for *P. spinescens* were of the general form expressed in Eq. 1. Observer experience affects detection rates in grassland species, as does 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 moderately experienced (botanical survey experience, but limited familiarity with VVP species). The percentage cover of *T. triandra* was assessed in 5 1-m^2 quadrats in each 1-ha plot (plots were in homogenous patches of vegetation at each site). Observer experience and *T. triandra* cover (%cover) were included in all candidate models. We investigated a square-root transformation of the continuous variable *T. triandra* cover, which models diminishing increases in mean time to detection as *T. triandra* cover increases. It did not improve model fit or substantially change model predictions. As such, we are confident that the exponential function adequately modeled the influence of *T. triandra* cover over the range of data (which encompassed the full range of possible values).

We also investigated the influence of date of survey, weather conditions, and search strategy. Surveys were undertaken in late spring because this is the most common period for surveys in this vegetation type. The 2 years in which surveys were undertaken were unseasonably dry, and flowering periods for ephemeral species were brief. Therefore, it was thought that *P. spinescens*, a perennial, might become more easily detectable as the season progressed. The visibility of the species may be different under sunny or overcast conditions, and the weather condition at the time of each survey was recorded as sunny, cloudy, or overcast. Observers were instructed to use one of two search methods: systematic or random walk. The random walk was thought to allow more scope for observers to use knowledge or intuition and may therefore lead to lower detection times.

Detection times may have varied 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 Supporting Information). The mixed effects models are not discussed further here, but

unmodeled variation in site and observer may contribute variability in future surveys beyond what was 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 (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. To check for convergence, we sampled from two Markov chain Monte Carlo chains. The performance of candidate models was assessed with the deviance information criterion (DIC) (Spiegelhalter et al. 2002), which aims to identify the optimal trade-off between deviance reduction and model complexity. We used the "ones trick" (McCarthy 2007) to implement the non-standard likelihood and obtain estimates of DIC. The full model code is in the Supporting Information.

Using Eq. 5, we estimated the probability of detecting *P. spinescens* where present for a range of survey conditions and durations. We also estimated the survey effort required to achieve a probability of detection of 0.95 for the species (probability of non-detection if present = 0.05).

We used Eq. 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 assuming a range of prior probabilities of presence.

Results

Naïve estimates of detection (which assume the species is truly absent at sites where it was not detected) indicated that even at sites where the species was known to be present it was detected only 53% of the time during 90-minute surveys of 1-ha sites. The detection time model with the lowest DIC included observer experience, cover of *T. triandra* , and the date of survey (Table 1). Little separated the two best models (ΔDIC = 0.7), and the 95% credible interval for the date coefficient included 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 decreased as observer experience increased and increased as cover of *T. triandra* increased (Table 1). Comparison of fitted detectability curves and observed detections indicated this model was a good estimator of average detection times for *P. spinescens* (Supporting Information).

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. The predicted probability of detection (given presence) in a 1-hour survey by an experienced observer was 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 1-hour survey was 0.21, 0.41, and 0.67, respectively. Average detection times were much longer and more uncertain under worse survey conditions. This was attributed to the greater proportion of censored observations under these conditions.

At sites where the species was present, an allocation of almost 2 hours of survey effort per hectare was required to achieve a probability of detection of 0.95, even under favorable

conditions (Table 2). Again, this figure was substantially higher under more adverse conditions (Table 2, Figure 2a,b).

The amount of survey time without detection required to achieve a posterior probability of absence of 0.95 increased with cover of *T. triandra* and observer inexperience. Required survey effort also increased as the prior probability of species presence increased (Table 2, Figure 2c, d). Under the most favorable conditions tested (experienced observer, 10% *T. triandra* cover), the survey effort required to achieve a posterior probability of absence of 0.95 was 58 minutes/ha when the prior belief in presence was 0.2. This figure increased to 109 minutes when the prior probability was 0.5 and to 160 minutes when the prior probability was 0.8.

Discussion

Imperfect detectability and survey effort

We demonstrated a method for determining survey effort requirements for threatened species during EIAs. We applied the method to a threatened plant species, but the method is general and can be applied to most species. In addition, our case-study findings 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 0.5 for a 90-minute survey of a single hectare of grassland. Ours is one of many studies demonstrating imperfect detectability of listed threatened species (e.g., MacKenzie *et al*. 2005; Wenger & Freeman 2008; Guillera-Arroita *et al*. 2010). Therefore,

addressing issues of detectability and survey effort in threatened species legislation is critical for the protection and conservation of threatened species.

It is intuitively clear why observer experience should affect detection time. 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 EIAs; 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 our case study highlights the importance of considering the historical context and management of the site during EIAs. *P. spinescens* occurs in grasslands in and around the fringe of a rapidly expanding 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).

Our qualitative findings 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 favorable 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 EIAs 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 EIAs 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 from April to 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 flowering and therefore not creating distractions for observers.

We believe the assumption of a constant detection rate is reasonable under the conditions of our study, but it might be violated under some conditions. For example, detection rate may decrease over time if the observer becomes bored, disheartened, or tired. Where the observer is required to detect multiple individuals in the same survey (not just the first individual), detection rate may increase as the observer becomes familiar with the search image or decrease because the observer finds the more easily detected plants first. The assumption of constant detection rate may be relaxed by assuming a distribution for detection times in which the rate changes with time, such as the Weibull distribution, or by breaking the continuous survey period into discrete units of time and using a multiple-visit occupancy model to estimate detectability (e.g. MacKenzie *et al*. 2002).

Setting minimum survey effort requirements

We demonstrated two methods for determining minimum survey effort requirements for threatened species during EIA surveys: one specifies the minimum effort required to detect the species if it is present with a given probability and the other specifies the minimum effort required to either detect the species or demonstrate with some probability that the species is truly absent from the site. Each addresses issues of risk and burden of proof differently, but both require pre-specified thresholds of certainty. We arbitrarily set targets of 0.95 for Pr(detected|present) and Pr(absent|not detected). Ideally, these targets should 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 EIA reports.

The survey effort that minimizes total costs in invasive species management can be optimized (Hauser & McCarthy 2009). However, several obstacles hamper determining optimal survey effort for threatened species in EIAs. First, these optimization 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 does one put on the site-level loss of the species?

Second, optimal surveillance problems for invasive species minimize the total cost to a single party (usually government) responsible for both surveillance and eradication. Under the EPBC Act, the cost of EIA 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 public and future generations, who may be denied the opportunity to enjoy the species. Reconciling the different risks and costs borne by multiple parties is a policy challenge beyond the scope of this paper.

Concluding remarks

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 presented a protocol for establishing minimum survey effort.

While the importance of imperfect detectability is increasingly recognized, the number of species for which detection information is available remains small. Ideally, detection models should be constructed for each species under a range of survey conditions to allow investigation of the influence of explanatory variables such as those shown to be important here. However, 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 or may provide an informative prior on detectability when available data provide highly uncertain estimates (Garrard *et al*. 2012).

We hope the work presented here will provide impetus for collecting, compiling, and synthesizing quantitative detectability estimates, especially for species on threatened species lists. 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.

Acknowledgments

G.E.G. was supported by an Australian Postgraduate Award and an ARC Linkage Grant (LP0454979). B.A.W., M.A.M., and S.A.B. are supported by ARC Future Fellowships

FT100100819, FT100100923, and FT130101225. B.A.W., G.E.G., M.A.M., and S.A.B. were supported by funding from the National Environment Research Program Environmental Decisions Hub and the Australian Research Council Centre of Excellence for Environmental Decisions.

Supporting Information

The OpenBUGS model code (Appendix S1) and descriptions of the investigation of random effects (Appendix S2) and model calibration evaluation (Appendix S3) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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Table 1. Candidate detectability models for *P. spinescens* and Deviance Information Criterion (DIC) rankings.

Model[a,b]	**DIC (pD[c])**
$\bar{t}$ = 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 - 0.25[-1.05, 0.61]cloudy + 0.20[-0.59, 1.07]overcast)	446.6 (5.8)

[a]Abbreviations: exper, experienced observers; %cover , percent cover of *Themeda triandra*; date, number of days since 1 October; search, random walk search strategy; sunny, cloudy, and overcast, prevailing weather conditions at the time of survey.

[b] 'moderately experienced observer', 'systematic search method' and 'sunny' represent the reference conditions for categorical variables describing observer experience, search method and prevailing weather conditions. These reference conditions are set to zero and not estimated by the model.

[c] Estimate of the number of parameters to be estimated.

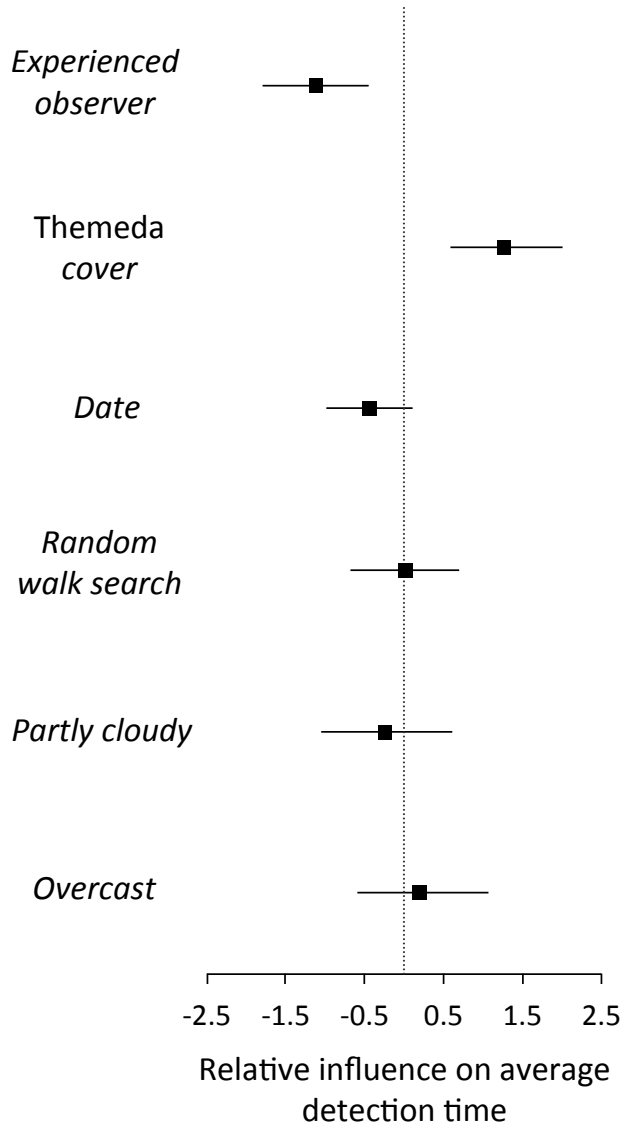
Table 2. Average time to detection given presence and survey effort requirements for *Pimelea spinescens* for a range of observer experience and cover of *T. triandra*.*

Observer experience	*T. triandra* cover (%)	Average 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]
Moderate	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]
Moderate	35	202.9 [126.1, 353.0]	607.7 [377.6, 1058]	316.1 [196.4, 550.1]	597.3 [371.2, 1039]	878.5 [545.9, 1529]
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]
Moderate	70	461.8 [235.9, 1026]	1384 [706.8, 3073]	719.6 [367.6, 1598]	1360 [694.6, 3020]	2000 [1022, 4442]

*Survey effort requirements are those necessary to achieve a 0.95 probability of detection given presence (Pr (detect|present) = 0.95) and posterior probability of absence given no detections (Pr(absent|not detected) = 0.95. 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 and *T. triandra* cover as explanatory variables. Estimates shown are the median values of the Bayesian posterior distributions, with 95% credible intervals in brackets.

Figure 1. Relative strength of the influence of candidate explanatory variables on average ti

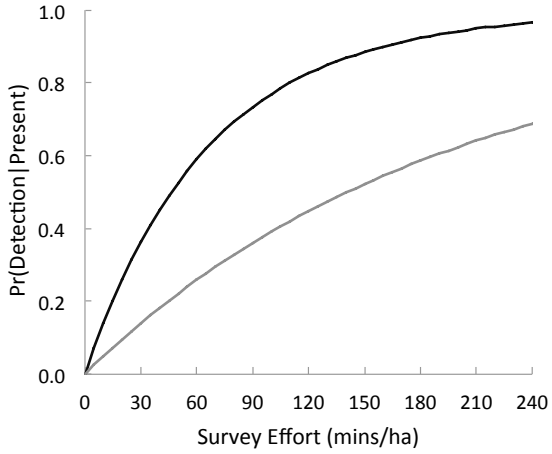
detection for *P. spinescens*



* Reference conditions 'moderately experienced observer', 'systematic search' and 'sunny' are set t
and not shown. The influence of the continuous variables (Themeda *cover* & *Date*) as been rescale
multiplying by 2 times the standard deviation of the estimate, so that it is comparable with that of bi
variables (Gelman and Hill 2007: p. 57).

Figure 2. Relationship between survey effort and (a, b) probability of detection given presence and (c, d) probability of absence given no detections for *P. spinescens*: (a) detectability curves for experienced (black line) and moderately experienced (grey line) observers at sites with average cover (35%) of *T. triandra*; (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); and (d) relationship between survey effort and probability of absence where the prior probability of presence at the site is 0.2 (dotted line), 0.5 (solid line), and 0.8 (dashed line) and surveys are undertaken by experienced observers at sites with 35% *T. triandra* cover.

a)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0.4
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Pr(Detection|Present)
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30
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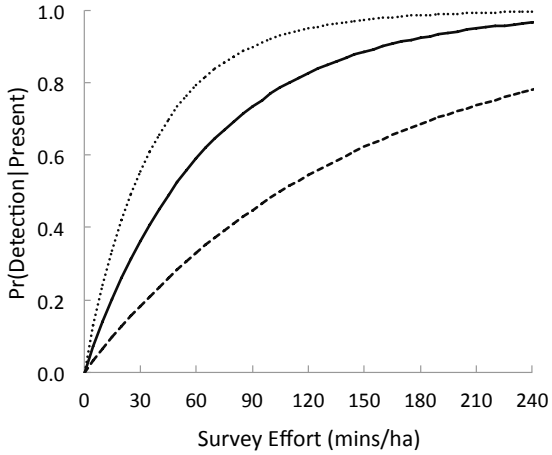
90
120
150
180
210
240
Survey Effort (mins/ha)

b)


1.0
0.8
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Pr(Detection|Present)
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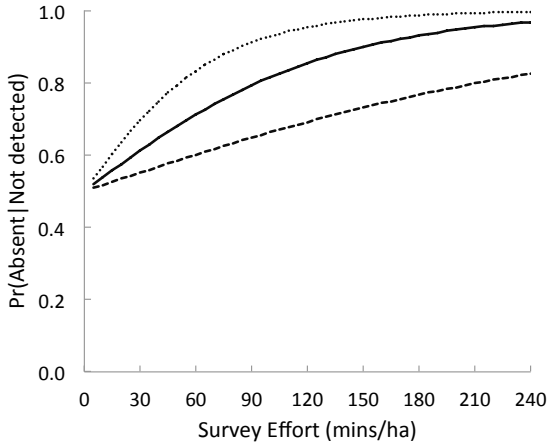
Survey Effort (mins/ha)

c)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Pr(Absent|Not detected)
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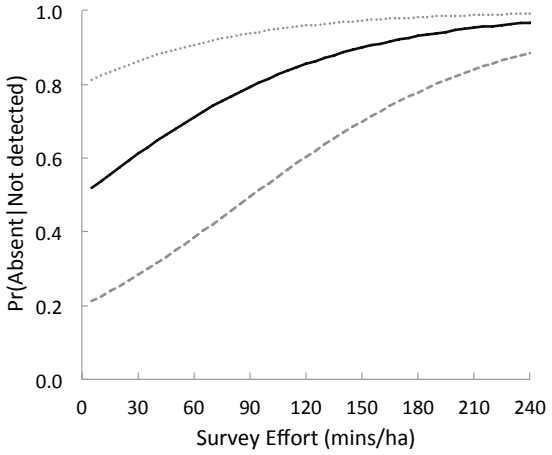
Survey Effort (mins/ha)

d)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Survey Effort (mins/ha)