

Report Cover Page

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Title

Determining necessary survey effort to detect invasive weeds in native vegetation communities.

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Summary

This report is submitted as the FINAL Report for ACERA Project 0906, *Determining necessary survey* effort to detect invasive weeds in native vegetation communities.

In Australia and internationally, the impact of invasive weeds on native ecosystems and agricultural productivity is undeniably significant. It is now accepted that early detection of invasive weeds is essential for their effective management. Designing monitoring and survey processes aimed at detecting new incursions of invasive weeds requires an understanding of the detectability of the targeted weed species. To date, weed detectability has been investigated mainly in the context of determining the interval between surveys. Here, we discuss weed detection in the context of designing optimal surveillance strategies.

This project aims to develop a collaboration between the Australian Centre of Excellence in Risk Analysis, Applied Environmental Decision Analysis and Northern Australian Quarantine Strategy practitioners aimed at incorporating new developments in optimal surveillance into NAQS activities and investigating options for addressing the uncertainty attributed to imperfect detectability where it exists. This report represents the first stage in the development of optimal survey methods under NAQS. Here we provide a brief review of issues associated with the design of optimal survey strategies, focussing on the problem of imperfect detectability. We review methods for data collection and estimation of detectability rates and provide two case studies that detail data collection and state-of-the-art modelling of detection rates for grassland species. Models of detection time are presented for two highly invasive *Nassella* species, as is a new trait-based model of plant detection model exists. We provide recommendations for the design of an optimal surveillance strategy under the NAQS and conclude with some general comments about surveillance and imperfect detection in Australian Government biosecurity programs.

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Determining Necessary Survey Effort to Detect Invasive Weeds in Native Vegetation Communities; ACERA Project No. 0906

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Disclaimer

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1. Executive Summary

- **1.1** Invasive weed species have a large and negative impact on native ecosystems and agricultural production, in Australia and internationally.
- **1.2** Early detection of new incursions of invasive weeds is essential for the effective management of those species and many plants are difficult to detect with field surveys.
- **1.3** Decision theory provides a useful framework for prioritizing surveillance activities and estimates of detection probability are key to determining optimal surveillance investment.
- **1.4** A number of methods exist for estimating the probability that a single species will be detected during a survey of a site at which it is present.
- **1.5** New modelling techniques, based on survival analysis, allow estimation of the average detection time of a plant species during a flora survey. In this report, the average detection times of two Weeds of National Significance, *Nassella neesiana* and *Nassella trichotoma*, are estimated based on environmental and observer variables. Detectability estimates can be used to determine the survey duration necessary to be reasonably certain of detecting the target species if it is present. Detectability curves reveal that even under the favourable survey conditions, the duration necessary to be 80% certain that a survey of a site will return a detection if the species is present at that site is 55 minutes/ha for *N. trichotoma* and 35 minutes/ha for *N. neesiana*.
- 1.6 Methods for modelling species' detectability are data-intensive and the construction of detection time models is unlikely to occur for many invasive species. We introduce a general model of detectability for plants of Western (Basalt) Plains Grassland, where the average detection time of a species is modelled as a function of plant traits. Such models may represent an efficient way to determine detectability estimates for a range of invasive weeds.
- 1.7 Determining optimal surveillance investment for a single species on Australia's border requires estimates of detection probability and probability of occupancy. It also requires estimates of the costs associated with surveillance and management of an undetected incursion. By collating such information, either through data collection or expert opinion, the Australian Government can improve its weed surveillance strategies.
- **1.8** The Northern Australian Quarantine Strategy is responsible for conducting surveys for early signs of new pests along Australia's northern coastline, but do not explicitly account for the uncertainty associate with imperfect detection of invasive species in their surveillance activities.

2. Introduction

There is no denying the scale of the impact of exotic species on native ecosystems. Worldwide biodiversity losses attributed to invasive exotic species are second only to the losses associated with land clearing and habitat destruction (Groves et al., 2001), and may soon surpass these to become the main cause of global ecological destruction (Clout and Veitch, 2002). Invasive weed species pose a serious threat to native ecosystems (Hobbs and Humphries, 1995). They out-compete native plant species and alter the structure and function of native vegetation communities. In Australia, invasive weeds constitute one of the most serious threats to the natural environment and primary production and considerable budgets are allocated to weed management projects every year (Australian Government, 2007).

The most effective method of weed management is to prevent the introduction and establishment of exotic species. Where this is not possible, early detection and eradication of the species is critical (Australian Government, 2007). By detecting weed species early, the chances of successful eradication are increased and the potential impacts on native systems and costs of management are reduced (Timmins and Braithwaite, 2002). It is therefore important that those responsible for managing invasive weeds understand the factors influencing detection rates during surveys of native vegetation communities.

There is a growing recognition that plants may not always be detected during a flora survey (Alexander *et al.*, 1997; Shefferson *et al.*, 2001; Kery and Gregg, 2003; Slade *et al.*, 2003; Brown *et al.*, 2004). In order to design effective weed management strategies for known invasive weeds, it is necessary to have estimates of species' detectability that can inform the development of survey effort protocols. Aside from a few notable exceptions (See Brown *et al.* (2004); Cacho *et al.* (2006)), plant detectability studies have, to date, focussed on native species in natural environments, and reference to weed detectability has largely been made in relation to the interval between repeat surveys (Brown *et al.*, 2004). Here, using a method developed in temperate lowland grasslands of southern Australia (see Garrard *et al.* (2008)), we estimate the detectability of invasive grassland weed species, *Nassella neesiana* and *Nassella trichotoma*, and make recommendations for the survey effort required to detect those species if they are present at a site. We also show how a general model of detection time, based on plant traits, can be developed to provide estimates of detectability where no species-specific detection model exists.

Estimates of detection probability are necessary for the development of optimal surveillance strategies for invasive species. The Northern Australia Quarantine Strategy (NAQS) is responsible, among other things, for conducting surveys for early signs of new pests along Australia's northern coastline (Australian Government, 2008). This project aims to develop a collaboration between ACERA, AEDA and NAQS practitioners aimed at incorporating new developments in optimal surveillance into NAQS activities and investigating options for addressing the uncertainty attributed to imperfect detectability where it exists. This report represents the first stage in the development of optimal survey methods under NAQS. Here we provide a brief review of issues associated with the design of optimal survey strategies, focussing on the problem of imperfect detectability. We review methods for data collection and estimation of detectability rates and provide two case studies that detail data collection and state-of-the-art modelling of detection rates for grassland species. We provide recommendations for the design of an optimal surveillance strategy under the NAQS and conclude with some general comments about surveillance, imperfect detection in other Australian Government bio-security programs.

3. Review of Strategies to Optimize Surveillance Investment

As with many ecological problems, uncertainty is inherent in weed surveillance and management. Uncertainty exists, for example, in determining the likelihood of establishment of a weed species in a particular location, the impact of the weed on native and agricultural systems, the point at which a species can be declared eradicated from an area and the probability that the species will be detected at a site at which it is present (Cacho *et al.*, 2006; Regan *et al.*, 2006; Mehta *et al.*, 2007; Hauser and McCarthy, 2008; Rout *et al.*, 2009). Because they offer a framework for explicitly incorporating uncertainty into the decision-making process, decision-theoretic methods are becoming prevalent in the ecological management literature (Possingham, 2001; Regan *et al.*, 2005; Regan *et al.*, 2006; Rout *et al.*, 2006; Rout *et al.*, 2009).

3.1 Optimization frameworks and decision theory

Recent applications of decision theory to invasive weed problems have demonstrated methods for determining optimal surveillance investment (Regan *et al.*, 2006; Hauser and McCarthy, 2008; Rout *et al.*, 2009) This is the process of identifying the most efficient allocation of resources by choosing the surveillance strategy (portfolio) that minimises the expected cost of a strategy for which there are clearly defined objectives. For example, optimal surveillance investment methods can be used to determine the survey effort required to assume eradication of a species at a site that minimizes the net cost of the strategy (Regan *et al.*, 2006). A key component in determining the optimal investment in surveillance is the detection probability of the target species, and thus optimal surveillance investment methods can provide a relatively simple framework for demonstrating how the uncertainty associated with imperfect detection may be incorporated into NAQS activities.

Figures 1 and 2 demonstrate the basic theory behind determining the optimal investment in surveillance for an invasive species. For any given survey strategy, or effort, there are associated surveillance and escape costs (Figure 1). The cost of escape refers to any known agricultural costs, ecological costs and the cost of controlling undetected incursions (this may be mandated in the case of listed species), and the costs of survey are the costs associated with conducting surveillance activities, include personnel costs, travel costs, equipment and removal of any detected incursions. The total cost of a strategy is the sum of the cost of surveillance and the cost of escape of undetected incursions, and the optimal surveillance strategy is the one that minimises the total cost (Figure 2).







Survey Effort

Figure 2. The total cost of an invasive species surveillance strategy (black, dotted line) is the sum of the cost of surveillance (blue line) and the costs associated with the escape of the species (red line). The optimal investment in surveillance may be determined as the survey effort that minimises the total cost (star).

3.2 Imperfect detection and its implications for survey design

In any survey, there is a possibility that the observer will fail to detect a species that is present at a particular survey location. Such observations are known as false absences (or false negatives). The probability that a false absence will arise in a single survey is defined as:

$$Pr(FA) = p(1-d),$$

where p is the probability that the species is present at the site and d is the probability that the species will be detected in a survey of that site.

An understanding of the detection probability of a particular species is essential for the determination of the optimal surveillance strategy of that species. Where the detection probability of a species under a given survey strategy is low, the likelihood of escape of that species is high, and, depending on the impacts of that escape, the costs associated with escape may be high. Regan *et al.* (2006) demonstrated that as the probability of recording a false absence increases, the number of consecutive absent surveys necessary to confidently declare eradication of an invasive species at a site also increases.

3.3 Estimating detectability

There are now a number of studies demonstrating methods for estimating the probability that a species will be detected during a survey of a site at which it is present. Mark-recapture (or capture-recapture) and N-mixture models have been used to estimate the probability of detecting an individual of a species. These methods have been demonstrated for both animals and cryptic plant species and

require the collection of count data over multiple surveys (Boulinier *et al.*, 1998; Kery and Gregg, 2003; Royle, 2004).

A number of studies have shown that it is possible to estimate species detection probabilities from presence-absence data using zero-inflated binomial (ZIB) models (Hall, 2000). For example, Tyre *et al* (2003) found that estimates of single-visit detection probabilities for woodland bird species in the Mount Lofty Ranges, South Australia ranged from 0.3 to 0.9. Similarly, Wintle *et al.* (2005) used ZIB models to estimate the detectability of owls and arboreal mammals in the Eden region of south-eastern New South Wales. In this study, single-visit detection probability estimates ranged from 0.14 for the powerful owl to 0.55 for the sugar glider. More recently, Garrard *et al.* (2008) presented a method for determining the average detection time of plant species during a flora survey, based on survival analysis techniques. This method requires information on the elapsed time at which a species is detected for the first time during a survey.

The methods described here enable the estimation of detectability for individual species or, in the case of N-mixture models, individuals within a population of a single species. There are, however, a number reasons why it is unreasonable to expect that detection time models can be constructed for all or even many invasive species: data collection is onerous, as is, to a lesser extent, the modelling process itself, and it is unlikely that data collection could keep pace with the rate of new incursions of invasive species previously unknown in a native community. To date, no methods exist for developing a model that could be used to estimate detection probabilities for multiple species. In the following sections, we use the detection time model introduced by Garrard *et al.* (2008) to estimate the survey effort necessary to detect two highly invasive grassland weed species, and show how a general model of plant detectability can be used to estimate detection times for multiple species based on plant traits.

4. Case Study 1: Estimating detectability of invasive grass species, *Nassella neesiana* and *Nassella trichotoma*, in Western (Basalt) Plains Grassland

Chilean needle-grass (*Nassella neesiana*) and serrated tussock (*Nassella trichotoma*) are considered to be two of the worst invasive weeds in Australia because of their invasiveness, potential to spread and economical and environmental impacts (CRC for Australian Weed Management, 2003; CRC for Australian Weed Management, 2003). Both are listed as Weeds of National Significance (Weeds Australia, 2008). Weed invasion by exotic perennial grasses, including *Nassella* species, is regarded as a significant threat to the surviving remnants of Western (Basalt) Plains Grassland (Department of Sustainability and Environment, 2003).

4.1 Field Methods & Data Collection

The data used in this analysis were collected during a multi-site, multi-observer field study undertaken in Western (Basalt) Plains Grassland during consecutive Spring seasons in 2006 and 2007. In this study, multiple observers conducted flora surveys in 16 one-hectare plots in grasslands to the west and north of Melbourne. Surveys were 90 minutes in duration¹, during which time observers were asked to record the time at which they first saw each new species. Observers searched each site in one of two ways: *systematic* searches were those where the observer followed some sort of repeated pattern when covering the full hectare, while observers conducting an *unsystematic* search were able to roam within the site as they pleased, using prior knowledge and intuition to determine search direction. In both cases, observers were instructed to cover as much of the site as possible during the 90 minutes allocated for the survey. Starting points for each observer were randomised around the perimeter of the site to avoid biases towards plants in specific locations, and the number of observers surveying each site at any one time minimised to avoid "copy cat" detections.

In addition to the detection times themselves, a number of other variables that may affect detection times were recorded at the time of survey: *observer experience* is a binary variable, indicating whether or not the observer had experience in grassland surveys; *time of day* is a categorical variable representing survey start times in the morning, midday or afternoon; *weather* conditions were recorded as either sunny, sunny with cloudy periods, overcast or raining; and *cover* describes the percentage cover of *Themeda triandra* at each site. Other variables recorded later include days since October 1st (*date*) and years since the site was last burnt (*burn*).

4.2 Modelling Techniques

Detection times for *N. neesiana* and *N. trichotoma* were modelled using the technique introduced by Garrard *et al.* (2008). Using this method, based on survival modelling techniques (Cox and Oakes, 1984; Parmar and Machin, 1995; Harrell, 2000), detection times are assumed to be exponentially distributed and the rate of detection, λ , is constant. The average detection time, \bar{t} , is modelled as a function of observer and environmental variables, x_n :

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

)

¹ Appropriate survey duration was determined following discussions with grassland survey experts. The 90 minutes allowed in these surveys was considered to be well above what was necessary to survey a 1 ha site.

The traditional likelihood for exponential survival analysis is:

$$l(t|\lambda) = \lambda^{\delta} e^{-\lambda t} \tag{2}$$

where λ is the constant hazard rate, *t* is the observed 'failure' time and δ is an indicator of the censorship (or lack thereof) of the observation: $\delta = 0$ when the observation is censored and $\delta = 1$ when the observation is not censored.

These likelihoods can be expressed individually as:

$$l(t|\lambda) = \lambda e^{-\lambda t} \qquad 0 < t < D \qquad (3)$$
$$= Pr(T = t),$$
$$l(t|\lambda) = e^{-\lambda t} \qquad t > 0, t > D \qquad (4)$$
$$= Pr(T > D),$$

where D is the duration of the study and T is the true failure time.

In order to account for the fact that the species may not eventually be detected at every site, these likelihoods have been modified to account for the probability that the species may be truly absent from a single observation at site, *i*, such that:

$$l(t|p_i, \lambda) = p_i \cdot \lambda e^{-\lambda t} \qquad 0 < t < D,$$
(5)

$$l(t|p_i, \lambda) = p_i \cdot e^{-\lambda t} + (1 - p_i) \qquad t > 0, t > D$$
(6)

where p is the probability of occupancy of the species at site i. To accommodate multiple observations at a site, the likelihoods become:

$$l(t_{ik}|p_i,\lambda) = p_i \prod \lambda^{\delta_{ik}} e^{-\lambda t_{ik}} \qquad \sum_k \delta_{ik} \ge 1$$
(7)

$$l(t_{ik}|p_i,\lambda) = p_i \prod e^{-\lambda t_{ik}} + 1 - p_i \qquad \sum_k \delta_{ik} = 0 = 0$$
(8)

 $\delta_{ik} = 1$ when the species is detected by observer *k* at site *i* and $\delta_{ik} = 0$ when not detected. Observations for which no detection was recorded are considered to be *censored*. All observations at sites where no detections were recorded will be censored (Eq. 8), as will those for which no time is recorded at sites where the species was detected by another observer (Eq. 7: $\delta_{ik} = 0$).

In this study, the probability of occupancy, p, is assumed to be constant across sites and was modelled as such. Under this modelling scenario, p is equivalent to the proportion of sites at which the species occurs. It is also possible to model p as a function of site-level variables z using the logit link (Eq. 4: Agresti, 1996), however this method requires a relatively large number of sites and an in-depth knowledge of the factors that might affect occupancy and was not used in this study.

$$logit(p_i) = k_i + \varphi z_i \tag{9}$$

Candidate explanatory variables are shown in Table 1. As the length of time since a site has been burnt increases, there is likely to be a build up in the cover of *Themeda* in the absence of other biomass management regimes. Table 2 reveals a positive correlation between these two variables and, as such, candidate models will not include both *cover* and *burn*. The influence of interactions between *Themeda* cover and variables that may affect sunlight (*weath* and *timeday*) was tested, as the effect of sunlight reflecting off dense *Themeda* can affect perception. An interaction between observer experience and search method was also investigated.

Models were run in the statistical freeware program, WinBUGS. The WinBUGS code for these models is shown in Appendix A. In the absence of prior information about parameter estimates, uninformative Bayesian prior distributions were specified for α , β_i and p_i , such that:

 $\alpha \sim dnorm(0, 0.0001)$ $\beta_j \sim dnorm(0, 0.0001)$ $p_i \sim dunif(0, 1)$

Competing models were assessed using Deviance Information Criterion (DIC: Spiegelhalter *et al.*, 2002), and other evaluation methods commonly used when running models in WinBUGS (Best *et al.*, 1995). DIC is a measure of model complexity and fit designed to allow comparison of hierarchical models (Spiegelhalter *et al.*, 2002). The internal consistency of the single-species exponential detection time model has been confirmed in a simulation study (Garrard *et al.*, 2008).

Estimates of the detection rate, λ , can be used construct a detectability curve for each species, which plots the probability of detecting the species, *D*, at a site where it is present against the time spent surveying the site, *t*:

$$D = 1 - e^{-\lambda t} \tag{10}$$

Sampling Hierarchy and Random Effects

As with all ecological studies, there are some issues associated with the hierarchy of replication in this study (Hurlbert, 1984). In the detection time models presented here, observations are assumed to be independent replicates, irrespective of site or observer, but it is possible that both site and observer may influence detection rates. Survey design necessarily involves trade-offs between rigour, sampling effort and cost and resource constraints (Keith, 2000), and replication limitations are common in ecological studies (Oksanen, 2001). If unaccounted for, replication issues can introduce bias in ecological models and reduce confidence in inference and prediction. However, replication hierarchy can be addressed through the addition of random effect terms to fixed effects models (Buckley *et al.*, 2003; Gillies *et al.*, 2006). Random effect terms have the advantage that they do not use up as many degrees of freedom as fixed effects with many levels (Buckley *et al.*, 2003). Nonetheless, they do add to the number of parameters that must be estimated by the model, which may be a limiting factor where data is restricted.

In order to investigate the influence of site and observer on detection times in this study, random effect terms for both variables were added to the nominal best 5 models for each species. The influence of random effects was assessed qualitatively by monitoring the rank order of models and the significance of predictor variables. If the addition of a random effect changes the rank order of models or the rank order of significance of the predictor variables, then the inference made from that model will be qualitatively different, and the random effect is assumed to be influential.

Variable Name	Description	Rationale
cover	Continuous variable indicating the percentage cover of the dominant grass species, Themeda triandra.	Species are naturally harder to detect where the surrounding vegetation density is high (Brown et al., 2004). Ecologically plausible response shape is linear and positive.
burn	Continuous variable indicating the time elapsed since the site was last burnt.	Fire is important in reducing dominant grass cover and maintaining species diversity in Western (Basalt) Plains Grassland (Morgan, 1998; Department of Sustainability and Environment, 2003). Plant detection rates can be different in years following burning (Slade et al., 2003). Ecologically plausible response shape is linear and positive.
date	Continuous variable indicating the date on which the survey was undertaken. Date measured as the number of days after October 1 st .	Species detectability may be affected by intra-season temporal variation. More complex response shapes are ecologically plausible. date modelled as linear and quadratic variable.
exper	Binary variable indicating level of experience of each observer. Intermediate observers have experience in botanical surveys but do not possess thorough knowledge of grassland species; experienced observers are experienced in grassland surveys.	<i>Observer experience is shown to affect the detection probability of plant species (Kery and Gregg, 2003).</i>
search	Binary variable for the search route used to cover the site. Systematic or unrestricted.	It is a common assumption that systematic surveys are the most effective search route (eg. Brown et al., 2004) however this doesn't allow observers to prioritise favourable locations.
timeday	Categorical variable indicating time at which each survey started. Morning (09:00-11;59), Midday (12:00-14:59), Afternoon (15:00- 17:59).	Observers may show a preference for certain times of day. The angle and intensity of the sun varies over the course of the day, and may affect visibility.
weath	Categorical variable indicating the weather conditions at the time of survey. Categories are sunny, sunny with clouds, overcast and raining.	Weather conditions may affect lighting and visibility of species. Adverse conditions may affect enthusiasm and concentration of the observer.
year	Binary variable indicating whether observation is from the 2006 or 2007 survey season.	Visibility and detection of plants can vary between years (Slade et al., 2003).

Table 2. Correlation matrix for Nassella detection time candidate explanatory variables

Variables	cover	date	exper	search	timeday	weath	year	burn
cover	1							
date	-0.13	1						
exper	-0.056	-0.056	1					
search	0.0021	-0.088	-0.19	1				
timeday	-0.0059	0.00022	0.050	-0.027	1			
weath	0.081	-0.085	0.048	-0.0018	-0.33	1		
year	-0.34	-0.049	0.078	-0.052	0.0097	0.14	1	
burn	0.41	-0.066	-0.035	0.044	-0.054	0.11	-0.28	1

4.3 Results

Serrated Tussock, Nassella trichotoma

Modelling was undertaken with the probability of occupancy, p, assumed to be constant across sites. The best model is one that models the average detection time as a function of the experience of the observer (*exper*), the search method (*search*), days from October 1^{st} (*days*) and the year in which the survey was undertaken (*yr*) (See Table 3). There is also substantial support for models that include an interaction between *burn* and the time of day, *burn* and the search method, and *Themeda* and the time of day, as well as the model that does not include the year in which the survey was undertaken. Each of these models is within 2 DIC units of the best model.

All models converged within 10,000 iterations and model statistics were calculated after a further 100,000 iterations. Examination of model evaluation tools in WinBUGS revealed smooth densities and acceptably low autocorrelation. The model statistics show that the 95% credible intervals for each node exclude zero, and that the days from October 1st, experienced observers, unsystematic searches and year 2 all have a negative effect on average detection times (Table 4). Node statistics for candidate models within 2 DIC units of the best model are presented in Appendix A.

Table 3. Differences in Deviance Information Criterion (Δ DIC) between the best detection time model for *N*. *trichotoma* and other candidate models. Models with Δ DIC values greater than 10 are not shown as there is little support for models with DIC values more than 10 units greater than the best model (McCarthy, 2007).

	Model	⊿DIC
1	$\overline{t} \sim \exp(\alpha + exper + search + date + yr)$	0
2	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + cover)$	1.08
3	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + burn)$	1.36
4	$\overline{t} \sim \exp(\alpha + exper + search + date)$	1.68
5	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + weather)$	2.35
6	$\overline{t} \sim \exp(\alpha + search + date + yr)$	2.99
7	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + cover + cover*timeday)$	3.26
8	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + timeday)$	3.33
9	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + exper^{*}search)$	3.41
10	$\overline{t} \sim \exp(\alpha + exper + date + yr)$	4.00
11	$\overline{t} \sim \exp(\alpha + exper + search + date + yr + cover + cover*weather)$	4.26
12	$\overline{t} \sim \exp(\alpha + exper + search + yr)$	7.74

Table 4. Node statistics for the best model detection time model for *N. trichotoma* (Model 1, Table 3) after 100,000 iterations.

Node	Mean	2.50%	97.50%
α	5.53	4.72	6.35
days	-0.034	-0.055	-0.013
exper[2]*	-0.49	-0.91	-0.059
p	0.89	0.71	0.99
search[2]**	-0.54	-0.98	-0.11
year[2]***	0.41	0.0057	0.80

* *exper*[2] is coefficient for experienced observers; exper[1] = 0

***search*[2] is coefficient for systematic surveys; *search*[1] = 0

****year*[2] is coefficient for 2007; *year*[1] = 0

Figure 3 shows the average estimated detection times for *N. trichotoma* across dates ranging from 10 days past October 1^{st} (October 11^{th}) to 60 days past October 1^{st} (November 30^{th}). These dates are representative of the range of dates in which surveys were undertaken. It should be noted here that these results cannot be extrapolated to dates outside those in which surveys were conducted as part of this study. It is unreasonable to assume that detection times will continue to decrease indefinitely as the days since October 1^{st} increase.

Figure 3. Average estimated detection times for *N. trichotoma* across a range of days for best (a) and worst (b) conditions. Best conditions for the species are when surveys are undertaken by an experienced observer using a systematic search method in 2006. Worst conditions (intermediate observer, non-systematic survey in 2007) also correspond to the most commonly experienced conditions. Note scale on y-axes.



Detectability curves for *N. trichotoma* are shown in Figure 4. These curves allow the user to determine the survey effort necessary under best and worst conditions on the 31st of October. For example, to achieve a level of certainty of 80% that you will detect *N. trichotoma* if it is present in a site in Melbourne's native grasslands under best conditions, you would need survey for approximately 53 minutes per hectare. To achieve the same level of certainly under the worst conditions would require an increase in survey effort of more than four times to 224 minutes per hectare.

Figure 4. Detectability curves for *N. trichotoma* under best (blue) and worst (red) conditions on October 31st (30 days after the first of October). Mean estimated values are shown in solid dots, while the open dots show the 95% credible intervals.



Chilean Needle-grass, Nassella neesiana

As with *N. trichotoma* modelling was undertaken with the probability of occupancy, p, assumed to be constant across sites. The best model (See Table 5) is one where the average detection time is modelled as a function of observer experience, weather conditions at the time of survey and the year in which the survey was undertaken:

$$\overline{t} \sim \exp(\alpha + exper + weather + yr)$$

Table 5. Differences in Deviance Information Criterion (Δ DIC) between the best detection time model for *N*. *neesiana* and other candidate models. Models with Δ DIC values greater than 10 are not shown as there is little support for models with DIC values more than 10 units greater than the best model (McCarthy, 2007).

	Model	∆DIC
1	$\overline{t} \sim \exp(\alpha + exper + weather + yr)$	0
2	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn)$	0.082
3	$\overline{t} \sim \exp(\alpha + exper + weather + yr + cover)$	1.58
4	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + search)$	2.01
5	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + date)$	2.18
6	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + weather*cover)$	2.58
7	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + timeday*cover)$	3.23
8	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + exper*search)$	3.33
9	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + timeday)$	4.02
10	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + timeday + days)$	7.40
11	$\overline{t} \sim \exp(\alpha + exper + weather + yr + burn + timeday + days + search)$	9.38

The estimated values of the variable coefficients are shown in Table 6. Like *N. trichotoma*, detection times are lower when the survey is undertaken by a more experienced observer. Weather has a varying effect, however the most favourable weather conditions are overcast days (*weather*[3]). It is clear that the estimates for rainy days (*weather*[4]) are highly variable. This weather category had the lowest representation, and it is likely that further analysis is needed to confirm this relationship. There is also considerable support for the models that include the time since the site was last burnt and the cover of *Themeda triandra*. The difference in estimated average detection times for the best models for both *Nassella* species modelled here are presented in Table 7.

Table 6.	Node statistics for the best model detection time model for N. neesiana	(Model 1,	Table 5) after	100,00
iterations				

Node	Mean	2.50%	97.50%
а	4.87	4.43	5.36
exper[2]*	-1.15	-1.65	-0.65
p	0.83	0.64	0.96
weather[2]**	0.020	-0.40	0.83
weather[3]**	-0.45	-1.08	0.17
weather[4]**	80.55	5.41	223.0
year[2]***	0.94	0.41	1.47

* *exper*[2] is coefficient for experienced observers; *exper*[1] = 0

**weather[2] is coefficient for sunny weather with clouds; weather[3] is coefficient for overcast weather;

weather[4] is coefficient for rain; weather[1] = 0

***year[2] is coefficient for 2007; year[1] = 0

The average estimated detection times for *N. neesiana* for experienced and intermediate observers under otherwise favourable survey conditions (overcast day in 2006) are shown in Figure 5. It can be seen that average detection times increase from around 25 minutes per hectare for experienced observers to over 80 minutes per hectare for their less experienced counterparts. The detectability curves for *N. neesiana* under favourable (experienced observer, overcast day 2006) and average (intermediate observer, sunny day, 2007) are presented in Figure 6. To achieve a probability of detection of 0.80 requires around 44 minutes per hectare under favourable survey conditions. However, this figure increases significantly to over 500 minutes per hectare under the average conditions experienced at the time of survey.





Figure 5. Average estimated detection times (•) and 95% credible intervals (-) for *N. neesiana* for experienced and intermediate observers under otherwise favourable (overcast day in 2006) survey conditions.



Figure 6. Detectability curves for *N. neesiana* under favourable (grey) and average (black) survey conditions. For a given level of survey effort (mins/ha), dots show the average probability of detecting the species if it is present at a site and dashes show the 95% credible intervals.

Site and Observer Influence

The best 5 models for each species have DIC values within 2.5 units of each other, indicating that each model is essentially as good as the others (Tables 5.2 and 5.5). The influence of site and observer were tested by adding random effects for both variables separately and together to the nominal best 5 models for each species. As expected, the addition of random effects resulted in a widening of the credibility intervals around estimates for individual predictors and average detection times. With the exception of the 5^{th} best model for *N. trichotoma*, the addition of random effects did not affect the rank order of significance of individual predictors included in the models and, for N. neesiana, there was no real change in the rank order of the models according to DIC (See Appendix A). There was, however, a clear change in the rank ordering of models when observer (and, to a lesser extent, site) was added as a random effect to N. trichotoma models (Appendix A), indicating that observer is potentially having a strong influence on detection rates for this species. Having said this, the addition of random effects significantly increased the number of parameters that must be estimated by the model (from 8.6 to 19.9 in this case). There are less than 160 detection time observations available for each species - too few to support the estimation of almost 20 parameters – and a decision was made to proceed with the presentation of results without the inclusion of random effects. This is likely to have some implications for model inference in that the overall variance of the model may be underestimated, leading to an overestimation of the significance of individual predictor variables (Rodriguez and Goldman, 1995; Okamura et al., 2008). However, such trade-offs are common and necessary in ecological studies (Oksanen, 2001). This issue may be avoided in future studies by increasing the ratio of detection time observations to the number of sites and/or observers.

Table 7. Comparison of estimates from models within 2 DIC units of the 'best' models for *N. neesiana* and *N. trichotoma* (See Tables 5.4 and 5.7). The average time to detection for each species is presented under good and average survey conditions, along with the associated survey effort (minutes/hectare) required to achieve a probability of detection of 0.80 and 0.95 given the species' presence. 95% credible intervals are shown in brackets. For *N. neesiana*, good conditions are experienced observer, overcast day, 2006, and average conditions are intermediate observer, sunny day, 2007. For *N. trichotoma*, good conditions are experienced observer, unrestricted search route, 31^{st} October, 2006 and average conditions are intermediate observer is included, estimates are based on 35% cover. Where the time since last burn is included, estimates are based on 2 years since the site was last burnt.

	Time to Detection (mins/ha)		Required Effort (mins/ha) Pr(detect) = 0.80		Required Effort (mins/ha) Pr(detect) = 0.95	
Model	Good cond'ns	Ave. cond'ns	Good cond'ns	Ave. cond'ns	Good cond'ns	Ave. cond'ns
N. neesiana						
Model 1	27.62 (14.24, 49.72)	347.9 (191.0, 612.4)	44.46 (22.91, 80.02)	559.9 (307.4, 985.7)	82.75 (42.65, 148.9)	1042.0 (572.2, 1835.0)
Model 2	23.44 (11.69, 43.40)	404.4 (210.3, 737.0)	37.72 (18.82, 69.85)	650.9 (338.5, 1186)	70.21 (35.03, 130.0)	1212.0 (630.1, 2208.0)
Model 3	26.58 (13.48, 48.50)	370.9 (197.0, 666.8)	42.79 (21.70, 78.07)	596.9 (317.1, 1073)	79.64 (40.38, 145.3)	1111 (590.3 <i>,</i> 1998.0)
N. trichotoma						
Model 1	33.21 (20.76, 51.71)	139.2 (87.70, 214.3)	53.46 (33.42, 83.23)	224.0 (141.1, 344.9)	99.50 (62.21, 154.9)	417.0 (262.7, 641.9)
Model 2	32.35 (20.08, 50.54)	143.2 (90.08, 220.1)	52.06 (32.32, 81.35)	230.5 (145.0, 354.3)	96.91 (60.15, 151.4)	429.1 (269.9, 659.5)
Model 3	32.67 (20.35, 50.67)	141.9 (89.80, 218.9)	52.58 (32.75, 81.56)	228.3 (144.5, 352.2)	97.87 (60.96, 151.8)	425.0 (269.0, 655.6)
Model 4	41.63 (27.64, 61.35)	114.2 (72.4, 168.2)	67.00 (44.48, 98.74)	183.9 (124.6, 270.7)	124.7 (82.79, 183.8)	342.3 (231.9, 503.9)

4.4 Discussion of factors that affect Nassella detectability

The results suggest that there are a number of factors that affect the detectability of *Nassella* species in native grassland communities around Melbourne. The experience of the observer had a significant impact on detection times of both species: observers with experience in grassland surveys had much lower detection times than those without. The year in which the survey was undertaken was also important for both species, indicating that there may be a significant amount of inter-annual variation in detectability of *Nassella* species. A precautionary approach may be necessary to account for such variation until the exact causes are understood.

The results also suggest that for *N. trichotoma*, the search method used to conduct the surveys and the date on which the surveys are undertaken can affect the probability of detecting the species. Observers who were unconstrained in their search method had lower detection times than those who were forced to follow a more systematic search route. In the past, studies investigating optimal weed surveillance strategies have assumed a systematic search pattern when estimating detection probabilities of target species (Brown et al., 2004; Cacho et al., 2006). The assumption is that this is most efficient method for searching a site, as random searches could result in some areas being covered multiple times and others not at all. However, the ability of a person to follow a truly random route without assistance from technology is doubtful. In reality, it is more likely that observers use intuition or previously accumulated knowledge when conducting a survey. For example, they may be attracted by different colours or appearance in the vegetation, or decide to walk towards an area of the site that is geographically different. Such decisions may explain why an unconstrained search pattern could lead to lower initial detection times. Where the aim of a study is to detect all individuals of a target species, systematic searches are appropriate, however the results of this study indicate that this is not necessarily the most efficient way to detect the presence of an invasive species in a native vegetation community and that, for some species, there is value in allowing observers some freedom in search route.

Average detection times for *N. trichotoma* were also lower on dates in late November than in early October. This may represent a change either in the appearance of the target species, or in the surrounding vegetation, or it may be explained by gradual improvement in each observer's ability to detect the species over time. Again, a precautionary approach may be needed until further research into the seasonal variation in detection times has been investigated.

For *N. neesiana*, detection times were lowest on overcast days, with rainy days showing highest detection times by orders of magnitude. The weather conditions at the time of survey may affect the visibility of species (for example, the confusing effect of sunlight on vegetation cover), or the ability of observers to operate at their most efficient. There is some evidence that detection times for this species increased with time since the site was last burnt (Model 2, Table 5). Burning is an accepted management technique in Western (Basalt) Plains Grasslands, considered necessary to prevent complete cover dominance by *Themeda triandra* and maintain species diversity (Morgan and Lunt, 1999). Burning may affect detection times by creating an opportunity for establishment of exotic species through the reduction in *T. triandra* canopy (Morgan, 1998) or increasing the ability of observers to see *N. neesiana* by reducing the aboveground biomass.

Tables 3 & 5 indicate that for each species there are a number of models within 2 DIC units of the 'best' model. As a general rule, such a small difference in DIC would indicate a significant level of support for these models (McCarthy, 2007) and it is therefore important to consider the results of those

models. In this study, these models are very similar to those recognised as the 'best' model for each species, and there is little difference in the average detection times estimated by different models (Table 7). Differences are attributable to the addition or removal of a single variable, most of which have been discussed above.

4.5 Estimating necessary survey effort

We have estimated the average time of detection for invasive *Nassella* species in native grasslands. The average detection times for *N. trichotoma* under best conditions decreased from 66.95 minutes per hectare at the start of the survey season (early October) to 21.88 minutes per hectare in late November, and for *N. neesiana*, the average time to detection under the most favourable survey conditions was 27.62 minutes. Even under the average conditions experienced during the survey period, the predicted average detection times increase by orders of magnitude (Table 7). These figures highlight the importance of considering the suitability of survey conditions for detecting target species in monitoring and impact assessment surveys.

Detectability curves allow the user to determine the survey effort required to detect a species with known detectability characteristics with a pre-specified level of confidence. These curves suggest that under the most favourable survey conditions, the survey duration required to achieve a probability of 0.80 that *N. neesiana* will be detected if it is present is 44.46 minutes per hectare. Estimates suggest that, for *N. trichotoma*, survey durations of at least 53 minutes per hectare are necessary to achieve the same level of confidence.

These figures are below the standard search effort assumed in some studies of weed eradication (1 hour 52 minutes to 7 hours per person per hectare: Panetta and Timmins, 2004), but well above that assumed as standard in surveys where the target species present in low numbers (12 minutes per person per hectare: Harris *et al.*, 2001). The important distinction of the methods presented in this paper is that the times recommended using the detection time model are those necessary to make the initial detection of the species at a site: any subsequent detections do are not modelled using this method. It is clear that during demographic and eradication surveys, where there may be many individuals, the search effort required will be much greater. The novel application of the methods demonstrated here is in determining appropriate survey effort when searching for new incursions of a target species in previously uninvaded sites or when monitoring for re-invasion in sites where some form of weed management action has taken place.

4.6 Model Assumptions

1. A key assumption of the exponential detection time models presented here is that detection times are distributed exponentially and that the rate of detection of a species is constant over the duration of the survey. While the exponential distribution has limited application in survival studies where 'aging' is an issue, these limitations do not apply here. For this assumption to be violated, the detection rate of the species would need to be dependent on the elapsed time of the survey. There is little reason to believe that the instantaneous potential for a species to be detected in the next timestep should change with time, particularly over the short duration (90 minutes) of the surveys undertaken in this study. However, simulations undertaken in a separate study suggest that the performance of the model is sensitive to violation of this assumption, and that where detection rates increase with time, estimates of mean detection time will be inflated (and vice versa) by the exponential detection time model.

2. All surveys undertaken at a site are considered to be replicate observations at that site, independent of year. As such, it is assumed that community composition at individual sites is closed to emigration or immigration, and that no species becomes extinct or colonises a site from one year to the next. Given the highly invasive nature of these species, it is possible that *Nassella* species were able to colonise uninvaded sites between surveys, especially where fire or other disturbance may have created an opportunity for establishment (Morgan, 1998; Colautti *et al.*, 2006; Catford *et al.*, 2009). At only 2 of the sites surveyed was there evidence that this may have occurred (*N. neesiana* was detected at two sites in 2007 where it was not seen in 2006: see Table 5.1). However, neither of these sites experienced disturbance between the two field seasons and, given the high rate of occupancy of this species, I believe it is more likely that the absence observations recorded in 2006 were false. Likewise, the management difficulties associated with the persistent seed bank of *Nassella* species (CRC for Australian Weed Management, 2003; CRC for Australian Weed Management, 2003) mean that it is unlikely to have been successfully eradicated from sites within a single year.

5. Case Study 2: A general (trait-based) model of detectability for Western (Basalt) Plains Grassland plants.

The estimation of species' detection times can be onerous and requires a relatively large dataset. It is unrealistic to assume that species-specific detection time models can be built for all potentially invasive weed species across a range of native vegetation communities. Further, invasive weed species may be unknown or new to an area, and it is unlikely that data collection would be able to keep pace with the rate of new invasions. As such, we aim to investigate the potential for a general model of plant detectability, whereby the average detection time is modelled across species as a function of plant traits. A successful general model could provide estimates of average detection time for plants with a specified set of traits in the event that no species-specific model exists.

5.1 Modelling Methods

In order to develop a general model of plant detectability for plants in Western (Basalt) Plains Grassland, it was necessary to modify the WinBUGS model such that the average time to detection, \bar{t}_{det} , is modelled across species and as a function of plant traits. This involved a simple modification of the likelihoods presented in Equation 2:

$$l(t_{nik}|p_{ni},\lambda) = p_{ni} \prod_{x=1}^{k} (\lambda \exp^{-\lambda t_{nik}})^{\delta_{nik}} (\exp^{-\lambda t_{nik}})^{1-\delta_{nik}}, \qquad \sum_{k} \delta_{nik} \ge 1$$
$$l(t_{nik}|p_{ni},\lambda) = p_{ni} \prod_{x=1}^{k} (\exp^{-\lambda t_{nik}}) + 1 - p_{ni}, \qquad \sum_{k} \delta_{nik} = 0 \qquad (11)$$

where p_{ni} is the probability of species *n* occurring at site *i*, λ is the detection rate, t_{nik} is the detection time for species *n* recorded by observer *k* at site *i*, and δ_{nik} is an indicator of whether the species was detected by observer *k* at site *i*: $\delta_{nik} = 1$ if detected and $\delta_{nik} = 0$ if not detected.

The rate of detection (λ) is modelled as a function of plant traits z_j :

$$\lambda = \frac{1}{\bar{t}_{det}} = exp^{(\alpha + \beta_1 z_1 + \dots + \beta_j z_j)} \tag{12}$$

As in previous sections, models were run in WinBUGS and candidate models were assessed using DIC. The WinBUGS code for the general exponential detection time model is presented in Appendix B.

The effects of site and observer were investigated by adding random effects to the nominal best model in this study. Site and observer random effects were included both individually and together. As described in the previous section, the influence of random effects was assessed qualitatively by monitoring the significance of predictor variables. If the addition of a random effect changed the rank order of significance of the predictor variables, then the inference made from that model will be qualitatively different, and the influence of the random effect cannot be overlooked.

5.2 Data

Detection time data for the general model of plant detectability were sourced from the 2006 survey data collected for the single species models. Because of the significant variation attributed to observer experience in detection time estimates for single species, the general model was built on a subset of this data that included only observations made by experienced observers. To further reduce the impact of unmodelled variation in the data, such as that caused by false positive observations, only those species that were detected on at least two occasions by experienced observers were included. Models were built on 81 species. A further 10 species were withheld from the model building process as test species. Candidate variables included traits that may influence the detectability of a plant (Table 8). Interactions between flower colour and flower size variables (*fl.sz* and *infl.sz*) were also tested.

5.3 Model Evaluation

Because of the explicit acknowledgement that the "truth" of censored observations in unknown, evaluation of time to event models is difficult (Hosmer Jnr. *et al.*, 1999). In the case of the general model of plant detection, it is possible to compare the observed proportion of detections of a species at any given time with the detectability curve for that species as estimated by the model. The proportion of detections (*PoD*) made by time, *t*, for species *n* is calculated by:

$$PoD_{nt} = \frac{\sum d_{it}}{\hat{p}_n},\tag{13}$$

where d_i is the proportion of detections made at each site by time *t*, and \hat{p}_n is probability of occupancy of species *n* predicted by the detection time model. Because \hat{p}_n is estimated as a constant across sites, it is equivalent to the proportion of sites occupied by species *n*. Where no estimate of \hat{p}_n is available (for example, for species withheld from the model selection process), the proportion of sites at which the species was detected is used.

5.4 Model Assumptions

As with the single species detection time models presented in the previous section, the general detection time model is subject to the assumptions that detection times are exponentially distributed and that sites are closed to species extinction or establishment over the survey period. The assumption of exponential detection times has been discussed in Section 4.6. The detection data used in this analysis is a combination of detection times for individual species and, as was discussed for single species detection time models, it is reasonable to assume that detection times are exponentially distributed. The detection time data used in the construction of the model were collected over the course of one month during the spring of 2006 and it was considered unlikely that species would appear or disappear from sites during this time.

Table 8.	Candidate plant trait variables used in the development of a general model of detection time for plant	ant
species i	in the Western (Basalt) Plains Grassland community.	

Candidate Variable		Description
Rarity	(rare)	Categorical variable assigning rarity according to Rabinowitz's (1981) classification of plant rarity.
Growth form	(GF)	Categorical variable assigning growth form, as described in (Cornelissen <i>et al.,</i> 2003).
Lifeform	(LF)	Categorical variable assigning lifeform, as described in (Cornelissen et al., 2003).
Plant height	(pl.ht)	Continuous variable; typical height of species in metres.
Exotic	(exotic)	Binary variable; indicates whether species is exotic or not.
Peak flowering	(pk.fl)	Continuous variable; number of months from peak flowering month at time of survey.
Flower colour	(fl.col)	Categorical variable assigning flower colour.
Flower size	(fl.sz)	Continuous variable for size of individual flowers in centimetres.
Inflorescence	(infl)	Binary variable; indicates presence of inflorescence or not.
Number of flowers	(no.fl)	Continuous variable indicating maximum number of flowers in inflorescence. <i>no.fl</i> = 1 if no inflorescence.
Inflorescence size	(infl.sz)	Continuous variable. <i>fl.sz</i> x <i>no.fl.</i>
Leaf colour	(lf.col)	Categorical variable assigning leaf colour.
Leaf length	(lf.len)	Continuous variable for length of leaves in centimetres.
Leaf width	(lf.wid)	Continuous variable for width of leaves in centimetres.
Leaf size	(lf.sz)	Continuous variable; <i>lf.len</i> x <i>no.fl.</i>
Leaf shape	(lf.shp)	Categorical variable assigning leaf shape according to Victoria's Flora Information System.
Number similar species	(no.sp)	Continuous variable indicating number of species in the same genus that occur in grasslands.
Spinescence	(spines)	Binary variable; indicates presence or spines or not.

Trait data was compiled from a range of sources, including Groves (1965), Rabinowitz (1981),Carr and Horsfall (1995), Cornelissen *et al.* (2003), Meers (2006), Flora of Melbourne (Australian Plants Society Maroondah Inc., 2001), Flora of Victoria (Walsh and Entwisle, 1994; Walsh and Entwisle, 1996; Walsh and Entwisle, 1999) and Victoria's Flora Information System.

5.5 Results

The model with the lowest DIC value is the one that models detection time as a function of rarity, lifeform, leaf colour, the number of similar species, the peak flowering month, whether or not the species is exotic, and an interaction between flower colour and inflorescence size (See Table 9). There is also significant support for the model that includes flower size instead of inflorescence size however investigation revealed very little difference between the predictions from the two models.

The influence of site and observer on detection times was tested by adding random effects to the best nominal model in this study. These random effects were found to have little qualitative effect on model inference and no significant effect on the average detection times predicted for 10 test grassland species (Appendix B) and, as such, results will be presented for the fixed effect model with no random effects for site or observer. As discussed in the previous section, this may some implications for model inference in that the overall variance of the model may be underestimated, leading to an overestimation of the significance of individual predictor variables (Rodriguez and Goldman, 1995; Okamura *et al.*, 2008)

Table 9. Differences in Deviance Information Criterion (Δ DIC) between the best general detection time model and other candidate models.

	Model	∆DIC
1	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz)$	0
2	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*fl.sz)$	0.8
3	$\overline{t} \sim \exp(\alpha + rare + LF + no.sp + pk.fl + exotic + fl.col*infl.sz)$	3.24
4	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*fl.sz + lf.shp)$	3.77
5	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + fl.col*infl.sz)$	9.61
6	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + exotic + fl.col*infl.sz)$	14.82
7	$\overline{t} \sim \exp(\alpha + rare + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz)$	20.22
8	$\bar{t} \sim \exp(\alpha + rare + LF + lf.col + pk.fl + exotic + fl.col*infl.sz)$	27.25
9	$\bar{t} \sim \exp(\alpha + LF + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz)$	27.94
10	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic)$	34.61

Node estimates for the best model are shown in Table 10. These results suggest that detection times are high for species that are similar to a large number of other grassland species, and for species whose peak flowering month is far from the time of survey. In addition, detection times tend to increase with increasing rarity of the plant, and are higher for native species than exotics. Geophytes, or those species that experience annual reduction of shoots to underground storage organs, are detected more quickly than other lifeforms if they are present at the site. This group of plants includes a number of the lily-like grassland species. The results also suggest that the colour of both the flowers and leaves can have an impact on detectability of grassland plant species. Plants with grey-green leaves appear to be easier to detect than those with blue-green, bright green or green leaves, species with brown or black flowers tend to have the lowest detection times. Node estimates for the 2nd best model are presented in Appendix B.

Predicted average detection times for the 10 test species are shown in Table 11, and detectability curves predicted by the best model are compared to observed proportions of detections in Figure 7.

Table 10. Node statistics for the best general model of detection time for Western (Basalt) Plains Grassland

 species after 40,000 iterations. Negative values result in a decrease in the estimated average time to detection.

Node	Mean	95% Credible Interval
Α	3.52	(2.39, 4.61)
Lifeform		
- phanerophytes	0	(0,0)
- chamaeophytes	-0.85	(-2.04, 0.34)
- hemicryptophytes	-0.67	(-1.72, 0.50)
- geophytes	-1.59	(-2.67, -0.42)
- therophytes	-0.69	(-1.82, 0.46)
Leaf colour		
- grey-green	0	(0,0)
- blue-green	-0.67	(-1.20, -0.15)
- dark green	-0.0085	(-0.58, 0.55)
 light/dull green 	-0.56	(-1.47, 0.35)
- bright green	-0.34	(-0.74, 0.014)
- green	-0.77	(-1.33, -0.25)
Number of species	0.060	(0.036, 0.083)
Peak flowering	0.34	(0.17, 0.51)
Exotic		
- exotic	0	(0,0)
- native	0.62	(0.29, 0.96)
Flower colour:		
inflorescence size		
- cream	0	(0,0)
- yellow	0.018	(-0.0095, 0.047)
- green	0.0059	(-0.018, 0.035)
 blue/purple 	-0.0089	(-0.030, 0.012)
- pink/red	0.031	(0.013, 0.049)
 brown/black 	-0.090	(-0.12, -0.062)
Rarity*		
-LWL	0	-
-LNL	0.21	(-0.24, 0.69)
-LWS	0.52	(0.24, 0.80)
-LNS	0.95	(0.51, 1.34)
-SNS	1.44	(0.39, 2.56)

*Rabinowitz rarity categories. LWL: large geographic range, wide habitat specificity, large local population; LNL: large geographic range, narrow habitat specificity, large local population; LWS: large geographic range, wide habitat specificity, small local population; LNS: large geographic range, narrow habitat specificity, small local population; SNS: small geographic range, narrow habitat specificity, small local population.

Table 11.	Estimates of average detection time for test species	. Also shown is the minimum survey effort
required to	detect the species if it is present at a site with 80%	and 95% certainty.

required to detect the species in it is present at a site with 60% and 25% certainty.							
Species	Average Detection Time	95%	Minimum Survey Effort Required to Detect Species if Present (mins/ha)				
	(mins/ha)	C.I.	80%	90%			
*Anagalis arvense	26.62	(19.77, 35.18)	42.84	79.75			
*Bromus hordaceous	66.53	(39.57, 105.6)	107.1	199.3			
Burchardia umbellata	12.61	(3.845, 30.92)	20.30	37.78			
Dianella amoena	476.9	(146.0, 1207.0)	767.5	1428.7			
Linum marginale	26.47	(15.8, 41.7)	42.60	79.30			
*Nassella neesiana	16.71	(6.106, 37.73)	26.89	50.06			
*Nassella trichotoma	12.53	(5.589, 24.68)	20.17	37.54			
Pimelea spinescens	1499.0	(353.9, 4823.0)	2412.5	4490.6			
Plantago guadichaudii	291.6	(172.2, 468.1)	469.31	873.6			
*Rosa rubiginosa	72.69	(18.25, 198.7)	117.0	217. 8			





Figure 7a. Comparison of detectability curves estimated by the best general detection time model and the observed proportion of detections for eight test species withheld from the model selection process. Blue curves show the mean (*) and 95% credible intervals (-) of the posterior distributions estimated by the model. Red dots represent the proportion of detections observed during field surveys after given survey durations (Eq. 13).





Figure 7b. Comparison of detectability curves estimated by the best general detection time model and the observed proportion of detections for eight species included in the model selection process. Blue curves show the mean (•) and 95% credible intervals (-) of the posterior distributions estimated by the model. Red dots represent the proportion of detections observed during field surveys after given survey durations (Eq. 13).

5.6 Discussion of the general model of detection time

The best general model of detectability for plants in Western (Basalt) Plains Grassland is the one that models detection time as a function of rarity, lifeform, leaf colour, the number of similar species, the peak flowering month, whether or not the species is exotic, and an interaction between flower colour and inflorescence size. There is also significant support for the model that includes flower size instead of inflorescence size (Table 9), however there is very little difference between the predictions from the two models.

Many of these relationships are clearly ecologically sensible. Species that are very abundant on a site will naturally be detected more quickly than those that are only present in small numbers. Using Rabinowitz's (1981) rarity categories, the general model predicts that those species with small, non-dominant local populations have higher detection times than those with larger local population sizes. Rabinowitz's (1981) categories provide a course way to classify species' abundance by considering the geographical distribution, habitat specificity and the local population size of each species. Actual abundance estimates from a subset of sites would further improve our understanding of the influence of abundance on detectability. The model also predicts that those species with many similar species will have longer detection times than those who are more unique within the grassland community. Identifying a species with certainty can be complicated if there are a number of very similar 'potential' species. In a situation where there are a number of similar species, an observer might wait to observe and compare particular characteristics before assigning a formal identification.

The general model predicts that exotic species will be easier to detect than indigenous species in a native grassland. This finding can be linked with the invasive species literature, where a number of theories are based around the idea that species that are functionally or phylogenetically novel or that possess traits previously unrepresented in an ecological community may be more likely to invade that community (Mack, 2003; Callaway and Ridenour, 2004; Catford *et al.*, 2009). A separate theory relating to propagule pressure suggests that the pool of species that become invasive is not a random sample; rather it is biased towards species that are selected for particular traits (Colautti *et al.*, 2006). It is possible that the features that make a species novel (eg. lifeform) or more likely to be introduced (eg. showy flowers) may also make it more detectable.

Optimal strategies for declaring eradication rely on estimates of cost-of-escape, eradication effort, and the probability of detection under a given survey effort. Our results suggest that as the local population size of an invasive species declines under an eradication program, that species will, on average, take longer to detect during a survey. This means that as an invasive species population is successfully managed, the survey effort required to detect any remaining individuals in further surveillance will increase. The difficulties associated with declaring an invasive species eradicated at a site have been extensively discussed within the eradication and surveillance literature (Panetta and Timmins, 2004; Regan *et al.*, 2006; Panetta, 2007; Rout *et al.*, 2009). By beginning to quantify the increase in survey effort necessary to detect smaller local population sizes, this research can aide those developing invasive species surveillance strategies.

Other factors that affect the visibility of a plant species were also recognised as important determinants of detection time. For example, plant with green or blue-green leaves tend to have lower detection times than those species with grey-green leaves and plants tend to be detected more quickly if surveys are undertaken at a time close to their peak flowering month. This indicates that the presence of flowers, buds or fruit may increase the detectability of a plant, which is ecologically

sensible. This concurs with the findings of Kery and Gregg (2003), and highlights the importance of seasonality in detectability studies (Burrows, 2004).

The relationship between flower colour and detection times is less sensible. This study found that species with red flowers have the longest detection times, while those with brown or black flowers are detected more quickly than other plants. This relationship is difficult to explain, as brightly coloured flowers would be considered to make a species more detectable. It is possible that this relationship may be driven by the local abundance of individual species: for example, *Themeda triandra*, a very common and abundant species, has brown/black flowers and many of the plant species with pink or red flowers are present at few sites in small populations. The collection of more detailed local abundance data in the future may help to clarify this.

Finally, the model predicts that geophytes –species whose aboveground parts annually die back to underground storage organs during non-growth periods – have lower detection times than species that do not die back. In Victoria, this classification of plants includes many of the orchid and lily-like species (Parsons, 2000). While no orchid species were detected in this study, other geophytes and species present in Western (Basalt) Plains Grassland include a number species with bold, noticeable flowers, which may explain the low predicted detection times. Further, because they die back during the off-season, geophytes must necessarily regrow all or most above ground parts during the growth season. It is possible that this fresh regrowth makes these species easier to detect during spring surveys than other species that may consist of a combination of old and new growth. In addition, they tend to invest resources into flowering quickly and, as such, when they are visible above ground, flowers or reproductive organs are often present. This finding highlights the importance of seasonality in detectability studies (Burrows, 2004). Surveys for this study were undertaken in spring, the peak season for geophytes in Western (Basalt) Plains Grassland. While geophytes have low detection times during this season, it is not likely that they will be so easy to detect during other seasons when they may be completely reduced to below-ground organs.

Because of the explicit recognition that the true status of censored observations is unknown, evaluation of these detection time models is difficult. High average detection times might indicate a species that has low rates of known false absence observations and is consistently difficult to detect, however a species with low observed detection times but a high rate of false absences will also have a high predicted average detection time. Conversely, low average detection times will be predicted for species with low false absence rates and short observed detection times. Therefore, without knowledge of the true false absence rate, it is impossible to evaluate the results of these models with any certainty. Aside from a notable exception (Pimelea spinescens) the average detection times predicted by the general model are within a range that would be considered reasonable (Table 11) and the comparison of estimated detectability curves with observed detections suggest that the general detection time model is estimating reasonably well (Figure 7). While the times predicted for Nassella species by the general model are optimistic, the 95% credible intervals include the values predicted by the species specific models under the most favourable conditions. Similarly, the estimated detection time for *Dianella amoena* is within the range predicted by a single-species model under average survey conditions (Garrard *et al.* unpublished manuscript). The predicted detection time for *P*. spinescens is clearly inflated, however a number of the trait values and classifications (lifeform, number of similar species, month of peak flowering and rarity) assigned to this species are extreme or poorly represented within the training dataset. Similarly, the comparison of observed and predicted detections presented in Figure 7 reveals that the model is predicting longer detection times for some species than is evident in the observed data (eg. A. echinata, C. citreus). As in any natural system,

there is considerable variation in the plant species found in the Western (Basalt) Plains Grassland community, and it is impossible to ensure that the features of all species are well represented in the model building and selection process. Estimates of detection rates for species that possess a set of traits that is poorly represented in the training dataset may therefore be imprecise and caution should be used these cases.

We have demonstrated a new method for modelling detection times across species within a native vegetation community, based on plant traits. Estimates of average detection time from a general model of plant detectability can be used to determine the survey effort required to detect invasive species with a pre-specified level of certainty in the absence of species-specific detection time models. Reasonable estimates of the survey effort required to achieve a probability of detection of 80% given species presence as predicted by the general model of plant detectability range from 20 minutes per hectare (*Nassella trichotoma*) to over 400 minutes (*Dianella amoena, Plantago guadichaudii*). Of the exotic species for which predictions were made, the highest recommended search effort to achieve this level of certainty was 117 minutes per hectare (Table 11). While the model developed in this study is specific to species occurring in Western (Basalt) Plains Grassland, the methods presented are generally applicable and could be used to develop models of detection time in other native vegetation communities. Data collection for future studies should place emphasis on the use of experienced observers to reduce variation associated with observer experience.

6. Detectability and the Northern Australian Quarantine Strategy

The Northern Australia Quarantine Strategy (NAQS) was developed in 1989 to address the quarantine risks unique to the northern Australian coastline. Implemented through the Australian Quarantine and Inspection Service (AQIS) and the Department of Agriculture, Forestry and Fisheries (DAFF), NAQS is responsible, among other things, for conducting surveys for early signs of new pests along Australia's northern coastline (Australian Government, 2008). NAQS weed surveillance activities are limited by resources, an extremely large surveillance area and the need to co-ordinate multidisciplinary survey teams with multiple objectives. There is a general awareness of detection issues within NAQS, however the uncertainty attributed to imperfect detection is not currently incorporated into surveillance activities in an explicit way. Decision thereotic and optimal surveillance investment methods present a useful framework for incorporating imperfect detectability into NAQS surveillance activities. Here, we discuss the application of optimal surveillance investment practice to NAQS activities, with reference to a single species recently discovered on a remote island of the Torres Strait.

6.1 The Problem

Blechum pyramidatum is a herb species native to Mexico and northern South America. It is known to occur outside its natural range in the United States of America (Florida, Hawaii, Guam), Pacific Islands (Fiji, Samoa), Micronesia and the Philippines, however it is not always invasive in regions where it has been introduced. The lack of literature on this species suggests that it does not have serious invasive potential (Waterhouse, 2009: Pers. Comm.), however it has recently been listed on the NAQS Target List for Weeds (Australian Quarantine and Inspection Service, 2008).

During routine NAQS surveillance on Saibai Island (Torres Strait) in 2008, a single patch of what was thought to be Browne's blechum was discovered in a private garden. Following positive identification of the species, NAQS officers returned to Saibai in early 2009 and removed the species from the site (Waterhouse, 2009: Pers. Comm.). NAQS officers are now interested in determining the appropriate level of effort to invest in continuing surveillance for this species on Saibai and across other Torres Strait islands. Focussing on this species provides a useful scope for investigating detectability and surveillance, however this scenario is not unique to this species and has more general relevance.

6.2 An optimal survey strategy and its components

The decision theory literature specifies number of steps for problem solving (Possingham, 2001). It is vital that the management objectives and options be specified from the outset, and that the state of the system be understood. Next, a conceptual model of the system should be constructed. This step will commonly involve the specification of equations to describe the relationships between variables in the system. It is important at this stage that any constraints or uncertainties surrounding variables be identified and incorporated into the model.

In the context of optimal surveillance investment for an invasive pest, the management objective is to minimise the total cost associated with monitoring and management of the species, and the management options include surveillance of individual sites, and taking action (or not) to control any detected invasions. For each series of actions there is a set of associated costs, for which values must be estimated (eg. Figure 8).



Figure 8. A conceptual model of the decision-making framework showing end costs for a range of scenarios. At a site where the species is absent, surveillance will reveal no detections and no control action will be taken. Under this scenario, surveillance costs are the only costs associated with the surveillance strategy. For sites where the species is present, surveillance may either result in detection of that species or no detection (false absence). The end costs of these scenarios may be quite different. (Adapted after Hauser (pers comm)).

Determining the likely outcome under a given surveillance strategy requires a probabilistic approach. In the example described in Figure 8, there are two possible outcomes for the site at which the species is present, each with its own set of costs. Crucial to determining which outcome is likely to occur is an understanding of D, the probability of detecting the species at site at which it is present under a given surveillance strategy, s. Under the simplest scenario, the probability of an escape, E, can be considered to be equal to the probability of observing a false absence (FA) during surveillance of a site at which the species is present. This probability is related to D as shown in Equation 14.

$$E_s = FA_{s},$$

$$FA_s = p(1 - D_s),$$
(14)

where p is the probability that the species is present at the site.

The probability of escape may also be modelled in a more complex equation based on an understanding of the potential for spread of the species:

$$E_s = FA_{s}.y.z , \qquad (15)$$

where y is the ability of the species to spread, and z is the probability that the species will establish in the receiving landscape.

The total cost (Ct) of any given survey strategy, *s* may be determined as the sum of the total cost of surveillance (Cs) and the total cost of escape (Ce) multiplied by the probability of escape (E):

$$Ct_s = Cs_s + Ce_s E_s \tag{16}$$

Identification of the optimal surveillance strategy for *B. pyramidatum* requires estimates of the cost of conducting surveillance activities, as well as any costs associated with the escape of the species if it is undetected during surveillance. The sites of potential invasion in this case are isolated and accessible only by light aircraft or boat. The costs associated with surveillance in this case are therefore likely to be quite high and survey effort restricted. A formal risk assessment is currently in preparation by the Queensland Government, however the potential threat posed by this species to agricultural production and native ecosystems is thought to be quite low (Waterhouse, 2009: Pers. Comm.). Estimation of the various costs associated with escape of an invasive species may pose a number of challenges. Firstly, there is often uncertainty surrounding the precise impact of the species on native and agricultural systems (Byers *et al.*, 2002); and secondly, there is difficulty in assigning measures of cost for different impacts in a single unit (Peterman and Anderson, 1999).

Even the simplest case, determining the probability of escape of the invasive species (E) requires an estimate of the probability of occupancy (p) and detection probability (D: Equation 9). Given how little is known about the species, it is unlikely that detailed probability of occupancy estimates are available. In this case, course estimates may be determined based on known travel routes between nearby islands or by an assessment of suitable habitat. There are currently no available estimates on detection rates or probabilities for Browne's blechum. A number of methods exist for estimating the value of D for individual species, one of which has been demonstrated in detail in Section 4 of this report (Garrard *et al.*, 2008). This method provides a way to estimate the probability that the species will be detected for a given survey effort where effort is measured in units of time. Other methods exist for estimating a species' detection probability in a single visit to a site (Slade *et al.*, 2003; Tyre *et al.*, 2003; Wintle *et al.*, 2005). Such estimates can be used to determine the probability of detection for a given number of visits to a site.

Methods for estimating detection probabilities are data intensive and can be statistically complex. However, we have shown in Section 5 of this report that it is possible to construct a general model of detectability where detection time is modelled across species according to plant traits. Models such as this may provide useful estimates of D for a given survey strategy where no species-specific model exists. Where models of detectability are absent or impossible to construct, expert opinion may be used to specify 'realistic' estimates of D (Martin *et al.*, 2005). Estimates of the spreading ability and likely establishment of the weed in receiving landscapes may also assist in determining the probability of escape of the species.

Finally, it is necessary to determine the range of possible survey strategies for which costs should be estimated. Currently, inhabited islands in the Torres Strait are surveyed annually for a period of between 2 and 6 hours each (Waterhouse, B. pers. comm.). Surveys are focussed on areas in an immediately surrounding communities and settlements. Options for varying surveillance effort include altering the frequency & duration of surveys on each island. The isolated nature of the of the islands mean that the increase in surveillance costs associated with increasing the frequency of surveys is likely to be greater than that associated with increasing duration.

6.3 Conclusions and Recommendations

Optimal surveillance investment methods provide a useful framework for incorporating concepts of detectability into the surveillance strategies of the NAQS. In this report, we have highlighted a number of variables that are necessary to determine the optimal surveillance strategy for detecting new incursions of invasive species in northern Australia, focussing specifically on Browne's blechum.

There is currently insufficient information to incorporate detectability into NAQS activities in a robust way. In order to develop optimal surveillance strategies, NAQS must compile information on the impact of the invasive species, cost of surveillance, likelihood of presence of the species and the probability that the species will be detected under a range of surveillance strategies. We have discussed a number of methods by which these variables might be estimated. Here, we make a number of specific recommendations relating to the information required to design optimal surveillance strategies in northern Australia. While Browne's blechum provided an opportunity to describe specific issues, the problems identified in this case study are not unique to this species and the recommendations made will be general in nature.

Surveillance costs, impact and suitable habitat for potentially invasive species

The impact of invasive species and the suitable habitat for that species are likely to be identified in during the risk assessment process. Estimation of these parameters, including the estimated cost of escape of the species, should become standard requirements in risk assessments undertaken by NAQS, DAFF or other government bodies if they are not already. Similarly, NAQS will have good information on the cost of surveillance within the regions for which they are responsible. It is important that the limitations to surveillance are recognised and that the full range of possible surveillance strategies, including the area/sites to be surveyed and the frequency and duration of surveys, is clearly identified.

Detectability of invasive species

We have demonstrated two novel methods for estimating the probability that a plant species will be detected for a given amount of survey effort. Single species models can be used to identify the survey conditions that are most (or least) desirable when conducting surveillance for a particular species. However, these models require the collection of detection time information for the species in question and are therefore only applicable to species that are established in Australia. The scenarios most commonly faced by NAQS are the detection of new incursions of known and unknown invasive species. Estimating the detectability of an unknown species is not possible; however a general model of detection time could be used to determine the survey effort required to detect a species with a known set of traits in a range of habitats. We recommend that DAFF and NAQS consider building general models of detection time for plant species in habitats that are of particular interest or importance. Construction of these models requires:

- 1. Detection time data for species within *each habitat type*
 - This data can be collected in a multi-site, multi-observer study as in this report. Observers should record the time at which they first see each species within a designated area. Attention should be paid to the duration of the surveys undertaken in the data collection process: allowing too short a time will result in a high proportion of censored observations and imprecise estimates.
 - It is important that the starting point of each observer is randomly located to avoid bias towards species located close to a common starting point.
 - Observers should be of the same experience level as those who will be conducting surveillance activities.
- 2. Plant trait information on species within each habitat type

- Traits of interest are those that might influence the probability that the species is detected during the survey, including attributes relating to the appearance or abundance of the species.
- 3. Modelling programs and statistical code
 - The WinBUGS code for the general model of plant detection time is provided in Appendix B. As with any statistical modelling software, it is important that the limitations and assumptions of the program and the model itself are understood by the user.

Estimates of detection time from the general, trait-based, models introduced in this study can only be made within the vegetation community from which the model was constructed. Ultimately, such models may be constructed for all vegetation communities, however NAQS/DAFF may wish to prioritise ecosystems according to the likelihood of incursion (ie. gardens), potential for early detection (ie. frontier ecosystems) or threat (ie. agricultural systems). Although these models of detectability cannot be used to estimate the survey time necessary to detect unknown invasive species, they can provide some useful information relating to the detection of unknown species incursions. By estimating the average detection times for each species within the community, these models can provide information on the *range* of survey efforts required to detect species within that community with reasonable certainty. Such estimates may be used to inform a minimum survey effort requirement within a specified vegetation community.

7. Conclusions and Recommendations

It is now widely accepted that a species may not be detected during a survey of a site at which it is present. Failure to detect an invasive weed species in a native ecosystem may incur serious environmental and financial costs, and it is therefore important that the detectability of invasive species in native ecosystems is understood. In this study we have demonstrated a novel method for determining the average survey time needed to detect weed species and have constructed detection time models for two Weeds of National Significance in native grasslands. We have also identified the survey conditions which maximise the probability of detecting these species. In addition, we have demonstrated how detectability curves can be used to estimate the minimum survey effort necessary to detect these invasive weeds if they are present at a site. Such information could easily be included as recommended survey practices in management strategies and policy. We recommend that detection time models be constructed for other invasive species of great concern.

The development of single species models of detection time is data-intensive and it is unlikely that they will be built for many invasive species. In this report, we have demonstrated that general models can be used to generate estimates of average detection time and required survey effort for invasive species where no species-specific model exists. Such models have the potential to be of great use to government agencies responsible for managing invasive species and, if proven to be robust across a range of vegetation types, represent an efficient way to determine detectability estimates for a range of invasive weeds. The general models introduced in this study are specific to individual native vegetation communities and future effort should be invested in constructing general models of detection times for a range of native vegetation types.

The uncertainty associated with imperfect detection is not explicitly addressed in the design of surveillance activities of the Northern Australian Quarantine Strategy. Decision theoretic approaches provide a way for land-managers to incorporate imperfect species detectability, the *a priori* probability that the species is present, the cost of surveillance, and the cost of escape and management of the species into the design of an optimal surveillance strategy. Estimation of these costs and probabilities may not always be straight-forward, and expert opinion or prior estimates from similar scenarios should be used in the absence of relevant data. In this report, we have demonstrated methods for estimating the detectability of invasive weeds at the individual level and more generally across species within a vegetation community. We recommend that DAFF/NAQS construct general models of plant detection time in vegetation communities of particular interest or importance. Future collaborative research might focus on more detailed investigation of plant detection times for priority weed species.

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9. Appendices

9.1 Appendix A: WinBUGS code and node estimates for competing Nassella models

WinBUGS Code

1

```
mode
{
for (i in 1:16)
                                                     # number of sites
                                                     # probability of occupancy is constant across sites
  procc[i] <- p
for(i in 1:16)
   for(k in offset[i]:(offset[i+1] -1)) {
    dd[k] <- step(50-tcen[k])
  d[i] <- step(sum(dd[offset[i]:(offset[i+1] -1)]) - 0.5)
                                                               # d[i] indicates whether species was seen at site i
 for(i in 1:16){
  for(k in offset[i]:(offset[i+1] -1)) {
                                                     #k is number of observations across all sites
                                                     #offset notation allows handling of uneven datasets - see WinBUGS User
                                                     #Manual (Spiegelhalter et al., 2003)>Section "Tricks: Advanced Use of the
                                                     #BUGS Language> Handling unbalanced datasets
   pp1[k] <- lambda[k]*exp(-lambda[k]*ft[k])
                                                     # likelihood if seen at the site (by anyone) and by the observer
  pp2[k] <- exp(-lambda[k]*tcen[k])
                                                     # likelihood if seen at the site (by anyone), but not by the observer - censored
  pp[k] <- dd[k]*pp1[k] + (1-dd[k])*pp2[k]
                                                     # likelihood if not seen (by anyone)
   pn[k] <- exp(-lambda[k]*tcen[k])
   lambda[k] <- 1/mu[k]
                                                     # lambda is detection rate
  # average detection time (mu) modelled as function of explanatory variables
  mu[k] <- exp(alpha + exper[obsr[k]] + yr[year[k]] +weather[weath[k]] + burn*fire[k])
  psite[i] <- d[i] * procc[i] * prod(pp[offset[i]:(offset[i+1] -1)]) + (1-d[i]) * (procc[i]*prod(pn[offset[i]:(offset[i+1] -1)]) + 1 - procc[i]) # likelihood at the site level
   Y[i] <- 1
                                                     # ones trick
   Y[i] ~ dbern(psite[i])
 1
# Estimating average detection time under favourable conditions
predmu[1] <- exp(alpha + exper[2] + yr[1] +weather[3] + burn*2)
# Specify prior distributions
                                # uninformative uniform distribution
p \sim dunif(0, 1)
exper[1] <- 0
exper[2] ~ dnorm(0, 0.0001) # uninformative normal distribution
alpha ~ dnorm(0.0, 0.0001)
yr[1] <- 0
yr[2] ~ dnorm(0.0, 0.0001)
weather[1] <- 0
weather[2] ~ dnorm(0.0, 0.0001)
weather[3] ~ dnorm(0.0, 0.0001)
weather[4] ~ dnorm(0.0, 0.0001)
burn ~ dnorm(0.0, 0.0001)
}
# Specify initial values
Inits
list(alpha = 0, yr = c(NA,0), p = 0.5, weather = c(NA,0,0,0), burn = 0, exper = c(NA,0))
```

Enter data: detection time (ft[]), censored time (tcen[]), explanatory variables (year[], weath[], fire[], obsr[]), offset[]) Data

ft[] 9999 28 9999 9999 84 9999 61 13 22 9 9999 25 9999 25 9999 52 0 9999 52 0 9999 52 0 9999 14 9999 21 9999 21 9999 9999 999 999 999 9	tcen[] 90 0 90 90 90 0 90 0 0 90 0 90 0 90 0	year[] 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2	<pre>weath[] 1 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 1 1 1 3 3 3 4 4 4 weath[k]</pre>	fire[] 2.5 2.5 2.5 0.5 0.5 0.5 0.5 2.5 2.5 2.5 3.5 3.5 3.5 3.5 3.5 3.5 3.5 3	obsr[] 1 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2	#observation level variables [k]
offset[] 1 9	# offset v	ariable mu	ist be leng	th <i>i</i> +1		

Effect of Adding Site and Observer Random Effects to the Best Models for each Nassella species.

Table A1. The rank order (according to DIC), difference in DIC (Δ DIC) and effective number of estimated parameters (pD) for the 5 best models for each species with no random effects, site effect, observer effect and site and observer effects. The influence of site and observer is assessed qualitatively by comparing the rank order of models with and without random effects. Where there is a clear change in the rank order of models, the random effect is influential. The difference in DIC between the top model and all other models (Δ DIC) can be used to assess whether the change in rank order of models is clear. For example, while there are minor changes in the rank order of models for *N. neesiana* under different random effects modelling scenarios, there is very little alteration in Δ DIC, and so no clear influence of site or observer can be concluded. For *N. trichotoma*, observer and, to a lesser degree, site are influencing detection times, however this is accompanied by a significant increase in estimated parameters compared to the models run without random effects.

	No Random		S	Site Effect		Observer Effect		Observer
Species/	Effects		Ef					Effect
Best 5 Models ¹	Rank	ΔDIC ² / pD	Rank	ΔDIC ² / pD	Rank	ΔDIC ² / pD	Rank	ΔDIC ² / pD
Nassella neesiana								
Model 1	1	0.00/5.7	1	0.00/14.6	1	0.00/8.2	1	0.00/18.3
Model 2	2	0.08/6.6	3	1.85/15.4	2	0.40/9.8	3	1.19/19.7
Model 3	3	1.58/6.7	2	1.23/15.7	3	1.40/9.2	2	0.51/20.2
Model 4	4	2.01/7.6	5	3.32/16.1	4	2.03/10.8	5	2.93/20.7
Model 5	5	2.18/7.6	4	2.89/16.3	5	2.65/10.9	4	2.03/20.6
Nassella								
trichotoma								
Model 1	1	0.00/5.7	4	3.43/15.8	2	7.68/15.7	4	2.93/26.7
Model 2	2	1.08/6.5	2	0.16/16.7	4	9.68/16.7	2	0.48/27.4
Model 3	3	1.36/6.5	1	0.00/16.7	3	8.59/16.9	3	0.53/27.5
Model 4	4	1.68/4.6	3	2.36/15.0	5	13.27/14.9	5	6.15/25.9
Model 5	5	2.35/8.6	5	7.63/18.5	1	0.00/19.9	1	0.00/30.2

¹ As presented in Tables 5.2 and 5.5

 2 ΔDIC is measured as the difference in DIC of that model relative to the number 1 ranked model for a given random effect column.

9.2 Appendix B. WinBUGS code and node estimates for competing general detection time models

WinBUGS code

```
*******
mode
{
for (n in 1:81)
                                                                                      #81 species
{
for (i in 1:14)
                                                                                      # 14 sites surveyed by expert observers
     procc[n,i] <- p[n]
                                                                                      # probability of occupancy is constant across sites but varies with species
}
for(i in 1:14){
     for(k in offset[i]:(offset[i+1] -1)) {
                                                                                                                                  # 'k' is observation level variable
        dd[n,k] <- step(50-tcen[n,k])
                                                                                                                                  # dd[k] = 0 if observation k censored
     d[n,i] <- step(sum(dd[n,offset[i]:(offset[i+1] -1)]) - 0.5
   for(i in 1:14){
     for(k in offset[i]:(offset[i+1] -1)) {
     pp1[n,k] <- lambda[n,k]*exp(-lambda[n,k]*ft[n,k])
                                                                                                                                     # likelihood if seen at the site (by anyone) and by the observer
     pp2[n,k] <- exp(-lambda[n,k]*tcen[n,k])
                                                                                                                                     # likelihood if seen at the site (by anyone), but not by the
                                                                                                                                     # observer - censored
     pp[n,k] \le dd[n,k]*pp1[n,k] + (1-dd[n,k])*pp2[n,k]
     pn[n,k] <- exp(-lambda[n,k]*tcen[n,k])
                                                                                                                                       # likelihood if not seen (by anyone)
     lambda[n,k] <- 1/mu[n,k]
     mu[n,k] <- exp(alpha + beta[exotic[n]] + gamma[LF[n]] + theta[1]*pk.fl[n] + theta[2]*no.spp[n] + leaf[ff.col[n]] +
     flower[fl.col[n]]*infl.sz[n] + rare[rarity[n]]) #+ group[clump[n]] + shape[lf.shp[n]]
                                                                                                                                                                                                  #average detection time, mu
     psite[n,i] < -d[n,i] * proc(n,i] * prod(pp[n,offset[i]:(offset[i+1] - 1)]) + (1 - d[n,i]) * (procc[n,i]*prod(pn[n,offset[i]:(offset[i+1] - 1)]) + 1) + (1 - d[n,i]) * (procc[n,i]*prod(pn[n,offset[i]:(offset[i+1] - 1)]) + 1) + (1 - d[n,i]) * (procc[n,i]*prod(pn[n,offset[i]:(offset[i+1] - 1)]) + 1) + (1 - d[n,i]) * (procc[n,i]*prod(pn[n,offset[i]:(offset[i+1] - 1)]) + (procc[n,i]*procc[n,i]*prod(pn[n,offset[i]:(offset[i+1] - 1)]) + (procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n,i]*procc[n
                                                                                                                                    # likelihood at the site level
 - procc[n,i])
      Y[n,i] <- 1
                                                                                                                                    # ones trick
      Y[n,i] ~ dbern(psite[n,i])
   1
# predicting to a new species
pred.them <- exp(alpha + beta[2] + gamma[3] + theta[1]*1 + theta[2]*1 + leaf[6] + flower[6]*20 + rare[1])
 # specify prior distributions
for(n in 1:81){
p[n]~ dunif(0, 1)
                                                                 # uninformative uniform distribution
alpha ~ dnorm(0.0, 0.0001) # uninformative normal distribution
beta[1] <- 0
beta[2] ~ dnorm(0.0,0.0001)
theta[1] ~ dnorm(0.0,0.0001)
theta[2] ~ dnorm(0.0,0.0001)
gamma[1] <- 0
gamma[2] ~dnorm(0.0, 0.0001)
gamma[3] ~dnorm(0.0, 0.0001)
gamma[4] ~dnorm(0.0, 0.0001)
gamma[5] ~dnorm(0.0, 0.0001)
leaf[1] <- 0
leaf[2] ~dnorm(0.0, 0.0001)
leaf[3] ~dnorm(0.0, 0.0001)
leaf[4] ~dnorm(0.0, 0.0001)
leaf[5] ~dnorm(0.0, 0.0001)
leaf[6] ~dnorm(0.0, 0.0001)
flower[1] <- 0
flower[2] ~dnorm(0.0, 0.0001)
flower[3] ~dnorm(0.0, 0.0001)
```

flower[4] ~dnorm(0.0, 0.0001) flower[5] ~dnorm(0.0, 0.0001) flower[6] ~dnorm(0.0, 0.0001) rare[1] <- 0 rare[2] ~dnorm(0.0, 0.0001) rare[3] ~dnorm(0.0, 0.0001) rare[4] ~dnorm(0.0, 0.0001) rare[5] ~dnorm(0.0, 0.0001)

}

specify initial values

Inits

list(beta = c(NA,0), flower = c(NA,0,0,0,0), rare = c(NA,0,0,0,0), leaf = c(NA,0,0,0,0), gamma = c(NA,0,0,0,0), theta = c(0,0), alpha = 0, p = 0, p

specify data Data

Data needs to contain explanatory variables ...[k], detect time: ft[k], censored time: tcen[k], and offset[i+1]

Testing the influence of site and observer via the addition of random effects to the general model of detection time

The addition of random effects to the nominal best model has a significant impact on the DIC value of the model (Table B1), however there is no qualitative change in the rank order of predictors included in the model (Table B2), and estimates of average detection time predicted by fixed and mixed effects models for the 10 test species are not statistically different (Table B3). Even without the inclusion of random effects, the general model of detection time is a large model with many parameters to be estimated. The addition of the random effects results in a complex model that is cumbersome to run and fitting mixed effects models for all combinations of predictor variables would not be a trivial task. Because the addition of random effects results in no qualitative change in model inference, model results and predictions will be discussed without the inclusion of random effects in this study.

Table B1. Differences in DIC (Δ DIC) between the best fixed effect general detection time model and mixed effects models with random effects included for site (*re_site*), observer (*re_obsr*) and both variables. The final column shows the effective number of parameters (pD) estimated by the model.

	Model	⊿DIC	pD
1	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz)$	0.00	76.04
2	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz + re_obsr)$	-40.18	80.90
3	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz + re_site)$	-56.69	87.30
4	$\overline{t} \sim \exp(\alpha + rare + LF + lf.col + no.sp + pk.fl + exotic + fl.col*infl.sz + re_obsr + re_site)$	-79.96	90.23

Table B2. Rank order of the significance of predictors included in the best general detection time model with and without site and observer random effects. Numbers in brackets indicate the model number as in Table 6.6. Predictors with a higher absolute value are assumed to have a greater influence over detection times. Where variables are categorical, rank is determined by the largest absolute value for a category coefficient. Asterisks indicate a small change in the rank order of categories within a single variable. See Appendix 6.2 for all node estimates for mixed effects models.

	Rank Order of Predictor						
Predictor Variable	Fixed	Observer Random	Site Random	Observer & Site			
	Effect (1)	Effect (2)	Effect (3)	Random Effects (4)			
Lifeform	1	1*	1	1			
Rarity	2	2	2	2			
Leaf colour	3	3	3*	3*			
Native/exotic	4	4	4	4			
Peak flowering	5	5	5	5			
Inflorescence size/colour	6	6	6	6			
Number similar species	7	7	7	7			

Table B3. Average detection times for the 10 test species as predicted by the best general detection time model without (1) and with (2-4) random effects for site and observer. Numbers in brackets indicate the model as described in Table 6.6. 95% credibility intervals are shown in brackets.

Creasion	Predicted Average Detection Time (mins/ha)						
Species	Fixed Effects (1)	Mixed Effects (2)	Mixed Effects (3)	Mixed Effects (4)			
*Anagalis arvense	26.62 (19.77, 35.18)	29.74 (15.71, 28.02)	21.16 (13.48, 31.2)	27.33 (12.89, 63.98)			
*Bromus hordaceous	66.53 (39.57, 105.6)	68.01 (31.34, 134.5)	58.23 (31.49, 99.51)	74.44 (30.52, 182.9)			
Burchardia umbellata	12.61 (3.85, 30.92)	13.07 (3.64, 34.49)	9.34 (2.70, 23.77)	9.89 (2.43, 29.08)			
Dianella amoena	476.9 (146.0, 1207.0)	493.7 (127.9, 1366.0)	548.0 (152.6, 1414.0)	725.6 (168.1, 2261.0)			
Linum marginale	26.47 (15.8, 41.7)	27.61 (12.99, 53.93)	20.33 (10.76, 34.49)	24.35 (9.91 <i>,</i> 60.37)			
*Nassella neesiana	16.71 (6.12 <i>,</i> 37.73)	21.08 (6.45, 52.89)	14.30 (4.64, 33.87)	19.53 (4.76 <i>,</i> 59.89)			
*Nassella trichotoma	12.53 (5.59 <i>,</i> 24.68)	14.73 (5.39, 32.98)	10.15 (4.02, 21.16)	13.27 (3.97, 37.57)			
Pimelea spinescens	1499.0 (353.9, 4823.0)	1819.0 (363.5, 5650.0)	1619.0 (337.1, 4804.0)	2347.0 (408.3, 8141.0)			
Plantago guadichaudii	291.6 (172.2, 468.1)	332.1 (147.0, 681.1)	250.3 (134.0, 428.9)	340.0 (138.6, 814.9)			
*Rosa rubiginosa	72.69 (18.25, 198.7)	122.4 (20.21, 359.1)	89.24 (18.35, 245.4)	173.3 (22.35, 772.5)			

Node estimates for competing candidate models within 2 DIC units of the best general detection time model

Table 9.4. Node statistics for the best general model of detection time for Western (Basalt) Plains Grassland species. Negative values result in a decrease in the estimated average time to detection.

Node	Mean	95% Credible Interval
Α	3.75	(2.60, 4.95)
Lifeform		
- phanerophytes	0	(0,0)
- chamaeophytes	-1.12	(-2.38, 0.11)
- hemicryptophytes	-0.87	(-2.01, 0.25)
- geophytes	-1.75	(-2.90, -0.61)
- therophytes	-0.89	(-2.06, 0.24)
Leaf colour		
- grey-green	0	(0,0)
- blue-green	-0.77	(-1.30, -0.23)
- dark green	-0.060	(-0.64, 0.52)
 light/dull green 	-0.64	(-1.55, 0.31)
- bright green	-0.39	(-0.78, 0.018)
- green	-0.83	(-1.39, -0.27)
Number of species	0.057	(0.034, 0.079)
Peak flowering	0.36	(0.17, 0.53)
Exotic		
- exotic	0	(0,0)
- native	0.65	(0.30, 0.98)
Flower colour:		
flower size		
- cream	0	(0,0)
- yellow	0.019	(-0.043, 0.082)
- green	0.0076	(-0.016, 0.037)
 blue/purple 	-0.0078	(-0.031, 0.016)
- pink/red	0.033	(0.013, 0.054)
 brown/black 	-0.090	(-0.12, -0.062)
Rarity*		
-LWL	0	-
-LNL	0.19	(-0.26 <i>,</i> 0.69)
-LWS	0.55	(0.27, 0.84)
-LNS	0.96	(0.59, 1.35)
-SNS	1.45	(0.35, 2.59)

*Rabinowitz rarity categories. LWL: large geographic range, wide habitat specificity, large local population; LNL: large geographic range, narrow habitat specificity, large local population; LWS: large geographic range, wide habitat specificity, small local population; LNS: large geographic range, narrow habitat specificity, small local population; SNS: small geographic range, narrow habitat specificity, small local population.

9.3 Appendix C. Selected relevant references - attached

- Garrard, G. E., Bekessy, S. A., McCarthy, M. A. & Wintle, B. A. (2008) When have we looked hard enough? A novel method for setting minimum survey effort protocols for flora surveys. *Austral Ecology*, 33(8), 986-998.
- Regan, T. J., McCarthy, M. A., Baxter, P. W. J., Panetta, F. D. & Possingham, H. P. (2006) Optimal eradication: when to stop looking for an invasive plant. *Ecology Letters*, 9759-766.
- Rout, T. M., Salomon, Y. & McCarthy, M. A. (2009) Using sighting records to declare eradication of an invasive species. *Journal of Applied Ecology*, 46(1), 110-117.