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Investigating detection success: lessons from trials using decoy rare plants

J. M. Dennett · **A. J. Gould** · **S. E. Macdonald** · **S. E. Nielsen**

Abstract Imperfect detection leads to underestimates of species presence and decreases the reliability of survey data. Imperfect detection has not been examined in detail for boreal forest understory plants, despite widespread use of surveys for rare plants prior to development. We addressed this issue using detectability trials conducted in Alberta, Canada with decoy vascular plants. Volunteer observers searched in survey plots for species while unaware of their true presence or abundance. Our findings indicate that the detection of cryptic species is very low when abundance is low (0–35%) and plot size is large (< 50% in ≥ 100 m²). Plant density (individuals per unit area) was the most important determinant of detection probability, where more abundant species were detected more often and with less survey effort. When abundance was held constant, diffusely arranged species were twice as likely to be detected compared to those in clumps. Detection of cryptic species can be low even when individuals are flowering, and even morphologically distinct species can go unnoticed in small plots. We suggest that future decoy trials investigate search strategies that could improve detection and that field surveys for vascular plants address imperfect detection through careful consideration of plot size, characteristics of the target species, and survey effort, both in terms of time expenditure within an area and the number of observers employed.

Keywords Detection trial · Detectability · Understory vascular plant · Rare plant · Plant survey · Plant monitoring

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J. M. Dennett (✉) · S. E. Macdonald · S. E. Nielsen
Department of Renewable Resources, University of Alberta, 751 General Services Building, Edmonton, AB T6G 2H1, Canada
e-mail: dennett@ualberta.ca

A. J. Gould
Parks Division, Alberta Environment and Parks, 9820 106 St, Edmonton, AB T5K 2J6, Canada

Introduction

Surveys conducted by ecologists generate data used in ecological applications. Observations made at the species level provide data used in conservation and management decisions, taxonomic studies, predictive modeling, and other areas of scientific interest; thus, accurate assessment of presence or absence is essential. Biased survey data, i.e., where detection errors are non-random, can severely undermine our ability to conserve, predict, and understand biodiversity on our

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landscapes (MacKenzie et al. 2002; Chen et al. 2013; Garrard et al. 2014; Lahoz-Monfort et al. 2014). Widely accepted sampling methodologies and statistical approaches reflect the reality of imperfect detection in faunal survey data (MacKenzie et al. 2002; Royle et al. 2005; Lele et al. 2012). Failing to detect a species when it is present (i.e., recording a false absence) is likely equally pervasive in studies of plants (Chen et al. 2013; Morrison 2016), though plant ecologists are among the least likely to consider imperfect detection in statistical analysis (Kellner and Swihart 2014).

Inaccurate or biased plant survey data affects our knowledge of species richness, distribution, demography, rarity, and conservation status (Kéry and Gregg 2003; MacKenzie et al. 2005; Royle et al. 2005; Archaux et al. 2009; Alexander et al. 2012). Bias can arise when observers consistently record false absences for species occurring at low local abundance or with cryptic morphology (Alexander et al. 2009; McCarthy et al. 2013). This can result in survey data that only accurately represent abundant, large, or distinct species, causing underestimates of species richness and abundance. Poor monitoring and conservation outcomes may result when detection is not considered in estimating population size and demography from counts of individuals (i.e., life-stage detection bias) (Kéry and Gregg 2003; Alexander et al. 2009). Kéry and Gregg (2003) demonstrated how reduced detection of less obvious individuals in a stable population could result in an erroneous estimated decline of 8%. Costly efforts to eradicate invasive orange hawkweed (*Hieracium aurantiacum* L., [Asteraceae]) could be undermined when small patches of non-flowering basal rosettes of the species are overlooked (Moore et al. 2011). Large-scale disturbance from resource extraction highlights another potential adverse outcome of false absences, the loss of opportunity for mitigation or conservation and adverse consequences for regional plant species diversity (Garrard et al. 2014). Consideration of imperfect detection in survey planning can be improved by understanding which factors most relate to successful detection across species and environments.

Local abundance is likely the major determinant of the successful detection of plant species (Moore et al. 2011; Alexander et al. 2012; McCarthy et al. 2013). This is logical as the rate of encounter between observers and plants will scale with abundance. Other factors related to imperfect detection include phenology or life-state, morphology, habitat attributes, survey conditions, and the observer (Kéry and Gregg 2003; Chen et al. 2009; Moore et al. 2011; Alexander et al. 2012; Garrard et al. 2013; McCarthy et al. 2013; Ng and Driscoll 2014). Observer effects are well documented in plant surveys (Ahrends et al. 2011; Morrison 2016). Most studies that focused on imperfect detection, or pseudo-turnover, demonstrated an observer effect; results for the effect of previous experience were variable (positive: Ng and Driscoll 2014; Garrard et al. 2014 (negative: Moore et al. 2011; Burg et al. 2013; Morrison and Young 2016)) and others did not consider experience as an explanatory variable (Archaux et al. 2007; Zhang et al. 2014; Bornand et al. 2014). Two studies did not demonstrate an observer effect (Kéry and Gregg 2003; Chen et al. 2009). Despite these variable results, expert botanists are still believed to be advantageous in reducing the risk of false-absences, and experience is often a condition of employment, particularly in surveys for species of concern (i.e., listed or tracked species at national or sub-national levels). Understanding how species traits, survey attributes, and the observer interact to increase or reduce detectability for plants can help inform design and analysis of survey data and improve plant species conservation.

To address questions of imperfect detection in forested environments, we conducted two decoy field trials in the manner of Moore et al. (2011). Populations of species of interest (decoys) that were not currently growing in the area were planted prior to surveys, permitting manipulation of survey attributes and thus determination of their influence on detection. Controlled trials where the true abundance and location of targets is known have been used in other search-related research, such as spotlight searches for wooden mammal decoys (Sunde and Jessen 2013) and trials using translocated lizards fitted with transmitters (Henke 1998). Detection trials such as these are potentially limited by creating search environments that may not mimic field conditions; however, they permit the manipulation of variables of interest in ways that are unfeasible in uncontrolled surveys and provide excellent learning opportunities.

We employed two trials to examine detection success as a function of plot size, observer experience, abundance and arrangement (clumped or diffuse) of

target species, species characteristics, and observer movement paths. Two decoy species were used in each trial, one of which had a more distinct appearance. We hypothesized that observer experience would be positively correlated with detection success; plot area would be negatively correlated with detection when target species abundance was held constant but detection rate in small plots (< 100 m^2) would be relatively similar. We expected abundance and arrangement would both affect detection, as clumps are more likely to be readily detected than single individuals, particularly in cryptic species, but potential encounters increase when individuals are diffuse.

Our research aims and hypothesized outcomes have important implications for survey guidelines and best practices in our area of Alberta, Canada. While ensuring high detection of plants may often require > 1 survey (Moore et al. 2014), logistical constraints in our region often limit effort to a single survey within a growing season. In the case of environmental impact assessments targeting rare species, available resources and short timelines often result in surveys conducted by one or more botanists over a narrow timeframe. In our jurisdiction, guidelines are limited and do not advise on suggested survey effort (Alberta Native Plant Council 2012). Therefore, maximizing detection within a single survey could make the highest impact and greatest contribution to the development and refinement of best practices for surveys, such as setting minimum survey effort requirements (Garrard et al. 2008). We believe that imperfect detection is pervasive in plant surveys and that management of species of concern will be made more effective by incorporating imperfect detection into study design and analysis.

Methods

Study site and decoy planting methods

Our experimental trials took place at the University of Alberta's Woodbend Forest, 20 km west of Edmonton, Alberta, Canada (53.3°, − 113.7°). The climate is continental with warm summers (average temperature of ∼ 15 °C in the summer months) and average summer precipitation of ∼ 300 mm. Upland forest across this 64 hectare property is predominantly dry to mesic mixed-wood with an overstory of spruce (*Picea*

A. Dietr.), aspen or poplar (*Populus* L.), and pine (*Pinus* L.) with moderate shrub cover, mainly *Corylus cornuta* Marsh. (Betulaceae). While plots differed slightly in tree and shrub density, we considered them to have been effectively similar in structure. We ran trials in the latter half of August in 2015 and 2016.

In both trials, we established square survey plots using wooden stakes and rope to deter observers from leaving the plots. Decoy plants were planted at randomly determined locations within the plots, where effort was made to reduce disruption during planting. We watered and checked individuals regularly over both trials and replaced any damaged specimens. We used two target species in each year, *Symphyotrichum lanceolatum* Willdenow (Asteraceae) and *Viola pedatifida* G. Don (Violaceae) (Trial One), and *Allium cernuum* Roth (Alliaceae) and *Petunia* sp. Juss. 'Red Velour' (Solanaceae) (Trial Two) (Appendix 1, Figure A1 in Supplementary Material). All species were short-statured (< 50 cm in height). In our first trial, we selected two species with different vegetative appearances; no individuals were in flower at the time of the survey. We considered *V. pedatifida* as visually distinct among species at the site given its deeply palmatifid, glaucous leaves. In contrast, individuals of *S. lanceolatum* looked very similar to other *Symphyotrichum* species and *Galium boreale* L. (Rubiaceae), blending well with the surrounding vegetation (cryptic). In Trial Two, we selected flowering or fruiting individuals of two distinctly different species. Individuals of *Petunia* sp. were in full bloom with showy, deep red flowers on otherwise short, sprawling plants. This species was selected to represent an extreme in flower showiness. *Allium cernuum* bears a pale, persistent umbel on a long slender scape, although this inflorescence is relatively large in comparison to small-flowered boreal plants, it tends to blend with the environment (cryptic). All individuals of *A. cernuum* had set seed in the characteristic umbel at the time of the trial.

Volunteer observers were recruited through email and word of mouth. In Trial One, we targeted individuals with varying seasons of vascular plant survey experience and who had or had not completed field surveys for plants in the summer months preceding the trials. In northern climates, a survey field season is considered approximately 40–60 days. In Trial Two, we recruited individuals who had experience conducting field surveys, but did not

require that these observers be experienced with vascular plants (e.g., we accepted individuals with experience surveying amphibians or bryophytes). Immediately prior to beginning their surveys, all observers were shown example specimens of the two decoy species and were able to revisit those specimens throughout the day. We told observers that neither, one, or both species might be present within plots and asked them to record the presence and time of detection, but not abundance, of any target species they encountered. We instructed all observers to survey plots until they felt they had adequately surveyed the area, starting from a fixed corner and using a meandering search pattern. Observers were not asked to make full species inventories, thus upon finding one target species they continued to look for the other, and in the event they encountered both species within a plot, they would terminate the survey. In this sense, the searches mimicked field scenarios where observers search for the presence of a short list of target species, such as rare or invasive taxa.

Effects of observer experience and plot size (Trial One)

In Trial One, we focused on manipulating plot size and determining the influence of observer experience. We maintained species abundance in all plots at one individual/species/plot across the following five square plot sizes: 1, 10, 100, 1000, and 2500 m^2 with three replicate plots per size ($n = 15$). We estimated horizontal cover around each plant using a 2-m range pole, where the number of 10-cm increments $> 25\%$ obscured by vegetation was recorded (Griffith and Youtie 1988). We recruited 16 observers and categorized them as follows: (1) Expert with > 5 seasons of plant survey experience ($n = 4$), (2) Intermediate with 2–3 seasons of general plant survey experience and had completed surveys within the preceding 4 months ($n = 8$), and (3) Intermediate with > 2 seasons of experience who had not completed a survey within the last 4 months (i.e., that field season) ($n = 4$). Group 2 (intermediate botanist) aligns with provincial recommendations for taxonomic experience for individuals completing rare plant surveys (Alberta Native Plant Council 2012).

We asked participants to complete surveys in one replicate of each plot size (a requested minimum of 5 plots) and to complete additional plots if they were so inclined. Our observers completed 4–8 (most often 5) surveys each for a total of 83 surveys; in each of these the observers searched for both target species. The order in which plot sizes were completed and which replicate plot of a given size was surveyed was randomized for each individual, although complete randomization was forgone at the end of the trial to ensure all plots had been surveyed by at least one observer from each experience category. We recorded the order in which surveys were completed by an individual as a continuous variable to account for improved or reduced detection of plants over the day (e.g., improved search image increasing success or observer fatigue reducing success).

Effects of abundance and arrangement (Trial Two)

In our second trial, we maintained a constant plot size of 1000 m^2 (the 4th largest size from our 2015 trial, 33 × 33 m) and recruited 13 observers who had a background in field surveys for target species. We did not require that individuals had previously surveyed for vascular plants specifically, but recorded the number of seasons of vascular plant survey each individual had (i.e., an observer with experience surveying for bryophytes scored a "0"). We manipulated abundance within plots (1, 5, and 10 individuals) and arrangement (clumped or diffuse) of two target species (A. cernuum and Petunia sp.) across 15 plots using the design illustrated in Fig. 1. To achieve the desired well-spaced arrangement of individuals for the "diffuse" arrangement, we chose random locations with the restriction that individuals would be planted at least 2 m apart. Individuals were planted together at each randomized location to form the clumped arrangement (of 5 and 10); for A. cernuum this resulted in an area of ∼ 10 × 10 cm, for Petunia sp. the clumps covered an area of ∼ 50 × 50 cm. The 13 observers surveyed 3–5 plots each, resulting in 53 surveys where observers searched for both target species. We again recorded the order in which observers completed plot surveys to account for improvement or reduction in detection with increasing surveys completed by an individual. In addition, we asked participants to wear Columbus V990 GPS data loggers (Victory Technology Co., Ltd.) during surveys to generate location data suitable for analyzing observer movements, i.e., proportion of plot searched, speed, and tortuosity.

Fig. 1 Example configuration of decoy plants within square experimental survey plots in Trial Two. Closed circles indicate *Petunia* sp., open circles *Allium cernuum*. This design was replicated 3 times for a total of 15 experimental plots
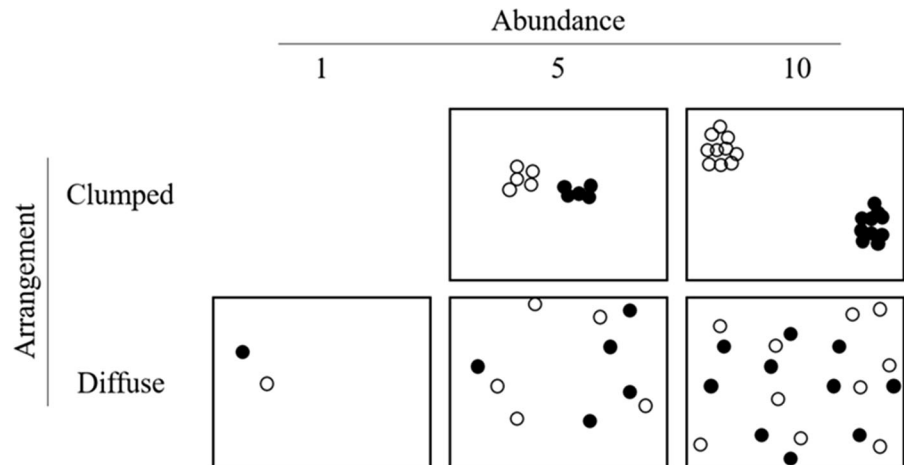
Statistical approach

Time-to-event (survival) analysis considers the time at which an event (detection) occurs, as well as censored observations, i.e., timed surveys that did not result in detection (right-censored). In traditional survival analysis, the influence of covariates upon the likelihood of an event occurring over time can be determined using Cox models (Cox and Oakes 1984). The Cox model framework assumes that a given event will inevitably occur at some time, censored observations therefore represent observation periods that were shorter than the time necessary for the event to occur. This assumption fails in most ecological applications, as the organism of interest may not be present; therefore, Cox models have been weighted by modeled occupancy (Bischof et al. 2014), or more complex Bayesian models have been applied to account for detection, given occupancy (Garrard et al. 2008). In our trials, occupancy is known and thus we meet the assumption that all target individuals would be detected at some survey time.

We first visualized the relationship between detection and plot size (Trial One) and abundance-arrangement levels (Trial Two) using Kaplan–Meier curves, which estimate the cumulative probability of events (Kaplan and Meier 1958). Next, we determined the influence of explanatory variables on the probability of detection over survey time using mixed effect Cox models. We built a single full model for each trial using all explanatory variables and two random effects to account for repeated measures by observers on replicate plots (plot id) and on observers across plots

(observer id). We first applied this approach using all observations (species identity was included as an explanatory variable), and for each species within a trial separately if species was determined to be an important predictor variable. All analyses were completed in R (Version 3.4.3) (R Core Team 2017) using the packages 'survival' (Therneau 2015a) and 'coxme' (Therneau 2015b).

Results

The influence of observer experience and plot size on detectability (Trial One)

Detection of both species declined rapidly with increasing plot size, falling from 94% in 1 m^2 plots to less than 50% in plots > 100 m^2 (10 × 10 m). Effort, expressed as plot size divided by total survey time (m^2/min), where larger numbers indicate lower effort, declined with increasing plot size, as did detection success (Table 1). Kaplan–Meier curves are shown in Fig. 2, where *V. pedatifida* had higher overall success and faster detection in small plots; less than half the time was required to achieve the same detection in plots of 1 and 10 m^2 for *V. pedatifida* than for *S. lanceolatum* but the accumulation of detection events for both species was similar in larger plots. Censored observations occurred across a range of survey times in plots larger than 100 m^2; differences in survey times were as great as 2 h (Fig. 2).

For both trials, we considered models of each species separately because species was a significant

Table 1 Effort expenditure and average detection time and success across plot sizes for both target species, *Symphyotrichum lanceolatum* and *Viola pedatifida*, used in Trial One, $n = 83$

Plot area	Species	Av. time to detection (min)	No. of detections	No. of surveys	% detected	Median effort (m²/min)	± SE	Range
1	*S. lanceolatum*	1.1	15	17	88	0.7	± 0.03	0.3–1
	V. pedatifida	0.7	17	17	100			
10	*S. lanceolatum*	2.4	10	17	59	3.3	± 0.33	1.3–10
	V. pedatifida	1.1	14	17	82			
100	*S. lanceolatum*	5.8	7	17	41	8.2	± 1.09	1.8–25
	V. pedatifida	6.9	8	17	47			
1000	*S. lanceolatum*	30.9	4	17	24	20	± 2.11	8.8–51.8
	V. pedatifida	28.0	6	17	35			
2500	*S. lanceolatum*	60.5	3	15	20	33.5	± 2.67	13.4–71.1
	V. pedatifida	56.4	2	15	13			

explanatory variable in a full model built with all observations (Appendix 1, Tables A1 and A4 in Supplementary Material). Effect sizes for parameters considered for each species in each trial are visualized in Figs. 3 and 4; see Appendix 1, Tables A2, A3 and A5, A6 in Supplementary Material for parameter estimates and *p* values. In Trial One, plot size was the most important variable explaining the detection probability of both *V. pedatifida* and *S. lanceolatum*, and was the only significant predictor ($p \leq 0.001$) for detection of *S. lanceolatum* (Fig. 3a, Table A2 in Supplementary Material). For *S. lanceolatum*, a one unit increase in plot area decreased the detection rate by 0.06 times. There was weak evidence that plant height positively affected the detection of *S. lanceolatum*; the confidence interval for this parameter did not include zero but it was not a significant predictor (Fig. 3a). For detection of this species, random effect parameters indicate greater variation between individual observers than between replicate plots (SD = 1.25 and 0.02, respectively). Improved model fit over the null model was supported ($\chi^2 = 88.16$, $df = 9$, $p \leq 0.001$). For *V. pedatifida*, the confidence intervals of plot size, survey order (the order in which plots were surveyed by an observer), and experience category 2 did not include zero, though only survey order and plot size were significant predictors (Fig. 3b), model fit over null $\chi^2 = 91.59$, $df = 9$, $p \leq 0.001$. In particular, survey order (exp $\beta = 1.38$, SE = 0.11, $p \leq 0.01$) had a positive relationship with detection probability. There was support for an effect of observer experience for *V. pedatifida*; observers

belonging to category 2 (intermediate with recent experience) had a negative influence on detection probability as compared to those in category 1 (experts), but this did not extend to observers in category 3 (intermediate without recent experience). Standard deviation of both random effects was low, SD = 0.02 for both parameters.

The influence of abundance and arrangement on detection success (Trial Two)

Total detection success differed substantially between the showy *Petunia* sp. (94–100%) and cryptic *A. cernuum* (0–70%) in plots of 1000 m² (Table 2). *Petunia* sp. demonstrated near perfect detection with little variation among experimental treatments; it was missed on two occasions, both in plots containing only a single individual. Effort (m²/min) expended by observers was relatively consistent between plots, although detection was very rapid in one five-diffuse replicate for *A. cernuum* (Table 2). Observers always found *Petunia* prior to finding *A. cernuum*, thus total effort for the plot largely represents time spent searching for *A. cernuum* (Table 2). The accumulation of detection events for *Petunia* was notably faster than for *A. cernuum* in all abundance and arrangement combinations, and diffusely arranged *A. cernuum* plants were detected more frequently and rapidly than the same number arranged in clumps (Fig. 5).

For *Petunia* sp. the variables abundance, arrangement, and survey order were significant predictors ($p \leq 0.001$, 0.016, and 0.021, respectively) (Fig. 4a,

Fig. 2 Kaplan–Meier
curves showing the
accumulation of detection
events over survey time in
Trial One for
*Symphyotrichum
lanceolatum* and *Viola
pedatifida*. Censored
observations are shown as
vertical ticks along the KM
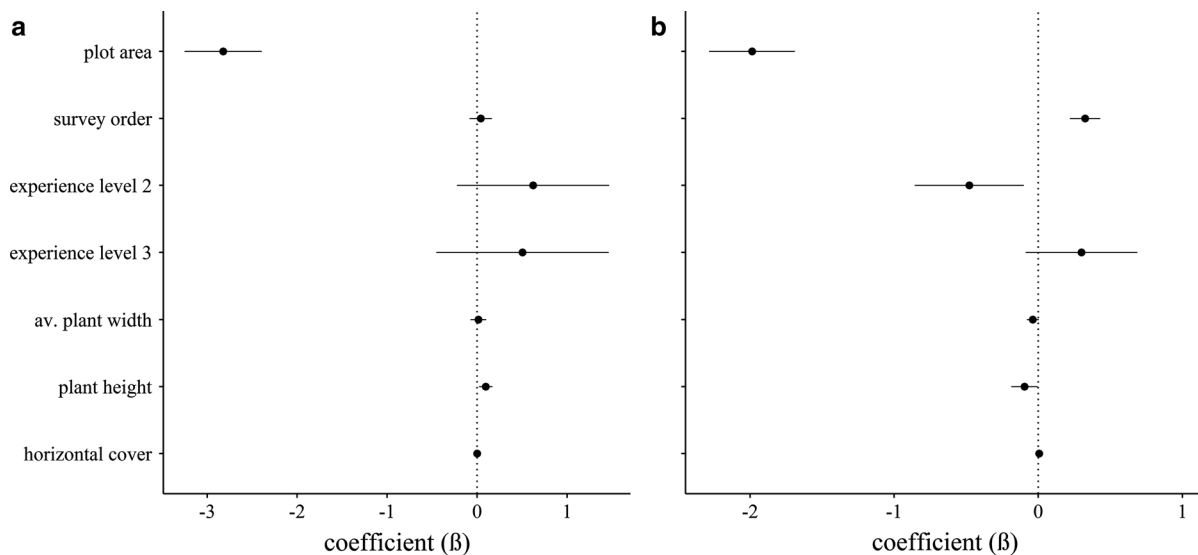curve; dotted lines show
95% confidence intervals,
$n = 83$
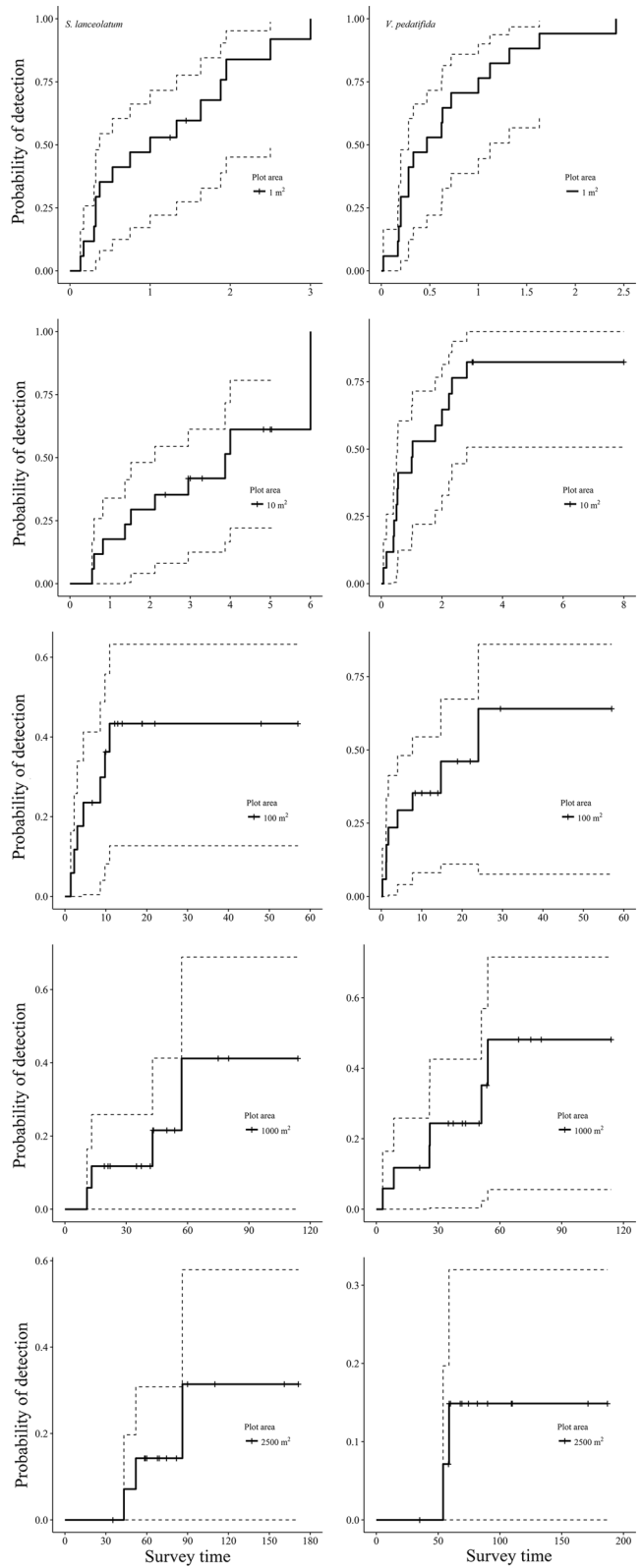
Fig. 3 Parameter estimates and associated confidence intervals for full models of **a** *Symphyotrichum lanceolatum* and **b** *Viola pedatifida*. A random effect of observer id and plot id were used in both models, see text for SD values. The variable plot area was log transformed in both models
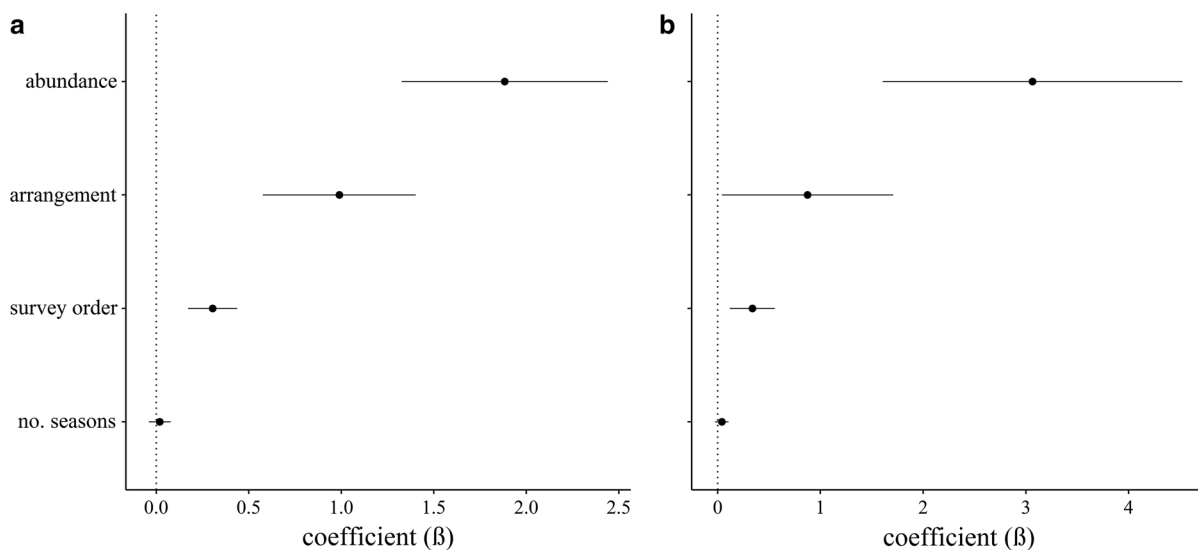

Fig. 4 Parameter estimates and associated confidence intervals for full models of **a** *Petunia* sp. and **b** *Allium cernuum*. Random effects of observer id and plot id were used in both models, see text for SD values. The variable abundance was log transformed in both models

Table A5 in Supplementary Material). Improved model fit over the null was supported ($\chi^2 = 20.86$, $df = 6$, $p = 0.002$). Abundance and survey order had a positive relationship with detection, where a unit increase in abundance increased the detection rate by 6.5 times. Diffusely arranged individuals resulted in a twofold increase in the detection rate as compared to clumps. The random effects of observer and replicate

id had standard deviations of 0.4 and 0.3, respectively. *Allium cernuum* model parameters indicated that a unit increase in abundance increases the detection rate by 21 times. Although not significant predictors, arrangement and survey order had confidence intervals that did not include zero (Fig. 4b). Diffusely arranged individuals of *A. cernuum* were twice as likely to be detected as those in clumps. Improved model fit was

Table 2 Effort expenditure and average detection time and success across plot sizes for both target species, *Petunia* sp. and *Allium cernuum*, used in Trial Two, $n = 53$

Abundance and arrangement	Species	Av. time to detection (min)	No. of detections	No. of surveys	% detected	Median effort (m^2/min)	$\pm$ SE	Range
1D	*Petunia* sp.	15.3	9	11	82	22.7	$\pm$ 3.4	6.1–43.5
	A. cernuum	–	0	11	0			
5C	*Petunia* sp.	13.7	11	11	100	22.2	$\pm$ 7.2	11.5–76.9
	A. cernuum	34.7	4	11	36			
5D	*Petunia* sp.	8.8	10	10	100	57.6	$\pm$ 51.1	13.7–500
	A. cernuum	10.8	7	10	70			
10C	*Petunia* sp.	14.6	10	10	100	28.2	$\pm$ 4.6	20–62.5
	A. cernuum	25.7	3	10	30			
10D	*Petunia* sp.	5.7	11	11	100	24.4	$\pm$ 14.2	13.2–142.9
	A. cernuum	23.8	6	11	55			

supported over the null ($\chi^2 = 14.45$, $df = 6$, $p = 0.025$). The random effect observer id had minimal variation (SD = 0.02), but variation between replicate plots was higher (SD = 1.12). Observers in this trial had quite variable backgrounds (plant surveys within Alberta, Canada, and internationally) and number of seasons of survey experience (range 0–14, median = 3), but again observer experience had no influence (Fig. 4).

Movement metrics (speed, tortuosity) generated from data loggers were not included in the main analysis due to instances of collection failure; descriptions and analysis using these metrics are given in Appendix 2 in Supplementary Material. We observed uniform speeds across individuals ($\bar{x} = 0.14$ m/s, SE = 0.001) and speed and tortuosity ($\bar{x} = 0.01$, SE = 0.00006) had no significant influence on detection using mixed-effect Cox models. We observed a trend of *A. cernuum* detections occurring most frequently when $< 30\%$ of the plot had been searched (Appendix 2 in Supplementary Material).

Discussion

These detection trials have clearly demonstrated that the probability of detecting cryptic understory species at low density (i.e., 1 individual/1000 m^2) is very low ($< 35\%$); this provides further evidence that imperfect detection in plants is pervasive and can be severe (Kéry and Gregg 2003; Chen et al. 2009; Alexander et al. 2012). We observed complete failure at detecting single individuals of *A. cernuum* in 1000 m^2 plots, as compared to 35% success for *V. pedatifida* and 23% for *S. lanceolatum*, this was despite the fact that the latter two species were in a vegetative condition at the time of survey. While phenology is important in detection (Kéry and Gregg 2003; Alexander et al. 2012), it is likely that most species would go undetected when rare within plots and when not bearing showy flowers. Detection of the showier species in both trials was often more rapid (requiring less survey effort) than for the cryptic species, although this trend diminished with increasing plot area in Trial One. In addition, our largest plot size (0.25 ha) is smaller than the area typically covered for environmental assessment surveys, suggesting that field surveys may be even less successful than our findings. The importance of survey conditions, observer effects, and plant abundance and plot area (density) varied among species in results of time-to-event analysis.

In both trials, we manipulated the density of the target species by maintaining plant abundance while increasing plot area (Trial One), or increasing plant abundance over plots of the same size (Trial Two). The positive relationship between density and detection is a product of increased encounter rate between the observer and a greater number of individuals and is well demonstrated in other work (Moore et al. 2011; Alexander et al. 2012; McCarthy et al. 2013). Manipulating species arrangement in Trial Two indicated that clumps of 5 and 10 individuals were more easily detected than single individuals of *A. cernuum*,
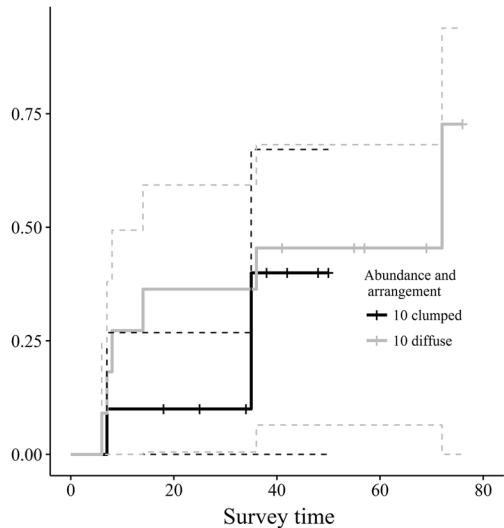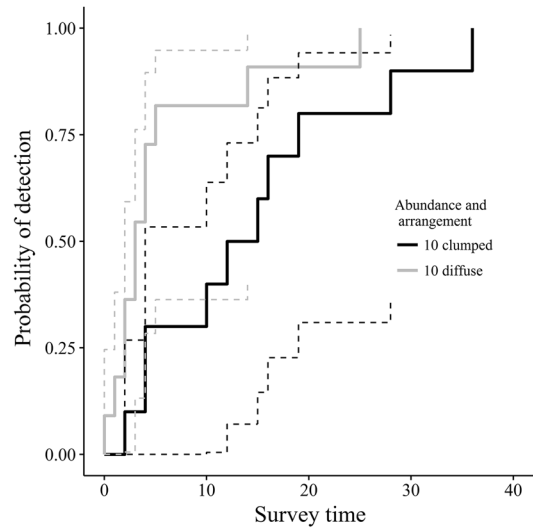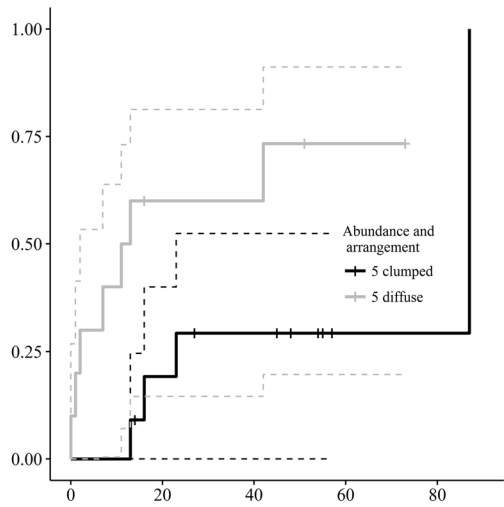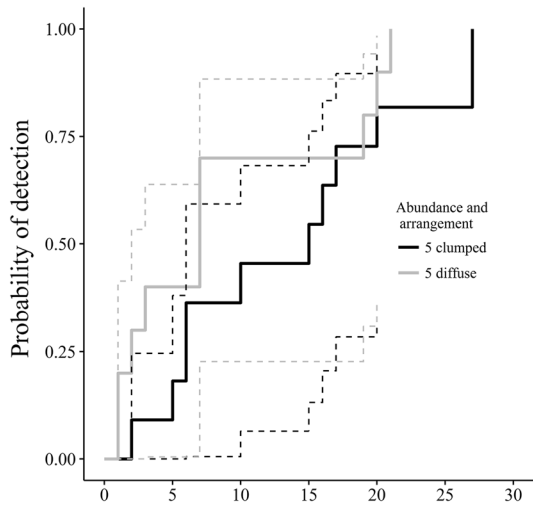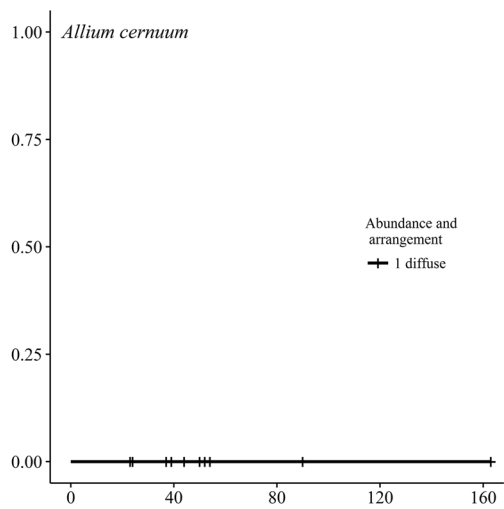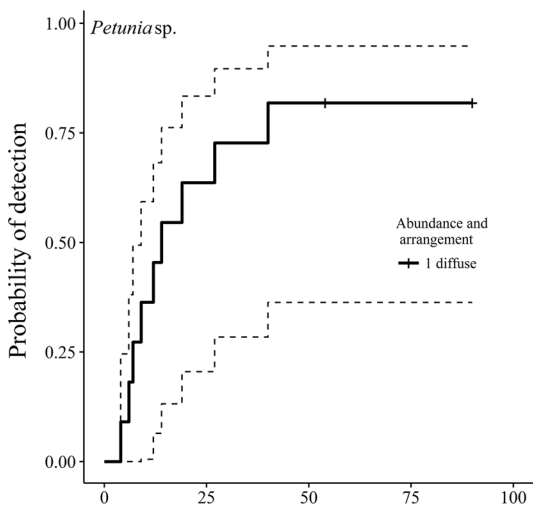
◄ **Fig. 5** Kaplan–Meier curves of detection events over time of *Petunia* sp. and *Allium cernuum* in Trial Two. Censored observations are shown as vertical ticks along the KM curve, dotted lines show 95% confidence intervals, $n = 53$

presumably due to increased visibility of clustered individuals. However, clumps of 5 and 10 had similar total detection success and rates for both species used in the trial, suggesting that this visual advantage may not scale with clump size. This is supported by the findings of Moore et al. (2011), where clumps of 3 and 5 individuals of their target species were detected at an equal rate. These results suggest that surveys targeting species that are known to occur at high local densities or in caespitose growth forms could be successful with less effort than those targeting species that consistently occur at low densities (e.g., some members of the *Orchidaceae*). Further, including measures of effort along with reported absences of cryptic species will improve the understanding of how species abundance and distribution influence detection, and aid in setting effort requirements for environmental impact assessment surveys (Garrard et al. 2008).

The influence of increased plot area likely affects detection beyond the change in target species density. In Trial One, increasing plot area in our forested site included greater cover of large plants (trees and shrubs), meaning greater physical and visual obstruction for observers, although horizontal cover was not an important predictor variable. In large plots, observers must employ more search techniques and maintain a spatial awareness that is different from surveying small plots. Several observers expressed feeling overwhelmed by the physical search area in large plots. We observed a wide range in expended search times in large plots, suggesting that observers differ in their motivations and decision-making for the 'stop time' when given the opportunity to survey for unlimited time. We hypothesize that the effect of search area includes, but extends beyond, the effect of reduced density of the target species to include factors such as observer fatigue, which has been shown to influence aerial detection of mammals (Habib et al. 2012; Ransom 2012). These results suggest that using time-unlimited surveys can only go so far in solving the issue of incomplete detection. Future experiments should consider the search techniques used by observers, perhaps through requesting the use of specific strategies such as dividing the total area into smaller, searchable sections (McCaffrey et al. 2014), or using different plot configurations (e.g., belts vs. large, square plots) to search equivalent area. Further, limiting plot area may be advantageous to ensure that effort (m^2/min) remains high, as we saw a rapid decrease in search effort with increasing plot area.

Considering all four target species and the two trials, the limited relationship between observer experience and detection was surprising, but supported by findings by Moore et al. (2011). While we recorded variation among observers, demonstrated by wide confidence intervals in Kaplan–Meier curves for all species, experience level was not an important explanatory variable; but see *V. pedatifida*. We speculate that the observed variation was instead due to inherent differences, i.e., personality traits or mental attitude. Studies suggest that observer experience or training should be related to detection success (Garrard et al. 2008, 2013; Morrison 2016), and surveys completed by expert botanists are often regarded as more reliable. It is possible that trial conditions negated the ability of experts to outperform less experienced surveyors. For example, many botanists use their knowledge of microsite associations when searching for target species with which they are familiar, but our study did not allow for such associations due to random planting locations. However, the surveyed area in Trial One was often small (3 of 5 plot sizes ≤ 100 m^2) and microsite associations can generally be considered irrelevant at this scale, but we did not observe an advantage of using expert botanists in small plots. Therefore, our results suggest that intermediate and expert observers can achieve similar results, particularly when they have the opportunity to examine live plants prior to initiating surveys. We found weak, but consistent, evidence of observer improvement over an increasing number of surveys, presumably due to improved search image after early successful detections. Our observers completed surveys over a single day; it is possible that observer improvement over a season could be an important consideration when planning surveys. Finally, we observed minimal trampling in survey plots over time and do not suspect trampling improved or reduced plant detection, but we note this can be an important consideration in decoy trials.

Although our most rapid and consistent detections occurred in plots of 1 and 10 m^2 in Trial One and in observations of *Petunia* sp. in Trial Two, in both years, the majority of plots had at least one successful observation when considering all surveys. It should be noted that *Petunia* sp. detection was exceptional in comparison to the other three species. This could be attributed to the fact that this decoy species is quite distinct in comparison to natural understory boreal species and was also generally familiar to observers; this highlights the importance of careful selection of decoy species traits in trials such as these. In Trial One, only one plot replicate of 2500 m^2 was perfectly undetected for each of *V. pedatifida* and *S. lanceolatum*. In Trial Two, excluding the complete failure in plots with only one individual, only one replicate went without a successful detection of *A. cernuum*. Thus, teams of 3–4 observers completing repeat observations in plots could compensate for low individual detection probabilities on a per-site basis and we encourage this survey approach where feasible, as has been suggested in other work (Alexander et al. 2012). We also note that data resulting from such repeat plant surveys, including those collected here, are suitable for estimating detectability using mark-recapture methods when the time of a detection event is either not collected or is not of interest (MacKenzie et al. 2005; Alexander et al. 2012).

In closing, we encourage future decoy trials such as those conducted here and by Moore et al. (2011) to examine relationships between species and survey variables against detection probability in a controlled field setting. As our understanding of the pervasiveness and severity of imperfect detection in vascular plants grows, our hope is that future work will more reliably incorporate techniques to address this issue (Kellner and Swihart 2014). We suggest that improvements to field surveys for low abundance species can be achieved through careful consideration of allocation of survey effort, for example, increasing the number of observers within plots and limiting plot size where accurate detection of single individuals is critical (e.g., monitoring applications). Although using small plots may require a trade-off in total area searched, our results suggest that false absences are more likely when species are in low abundance and the survey area is large. We suggest that future research in the field of imperfect detection in plants explore how survey techniques such as using a series of small plots

to search a large area in lieu of large plots could improve detection of cryptic species. Considering observer movement using GPS, as was done here, may reveal interesting trends in how observers search plots and when they are most likely to make successful detections (Appendix 2 in Supplementary Material). Recording survey effort through person hours and area covered will not only improve confidence in reported absences, but will add to our understanding of how required effort may fluctuate with species characters and phenological state. Collecting time-to-event data where possible to determine rates of imperfect detection and relevant covariates influencing success in different environments is encouraged.

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