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Detectability of species of *Carex* varies with abundance, morphology, and site complexity

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Abstract

Questions: Are graminoids more poorly detected than other life forms of vascular plants in surveys? How well do observer-, species-, and site-specific variables explain variation in detection of *Carex* species across forests of different structure?

Location: Northeastern Alberta, Canada.

Methods: Species inventories were assessed within 50 belt transects, each 100 m in length and 2 m in width. Pseudoturnover was estimated for four life forms and all encountered species. Site-specific factors were then compared with pseudoturnover of all vascular plants and graminoids using generalized linear regression. *Carex* detection probabilities were compared based on morphological groups. Detection success at a site and delays in detection within a site were assessed using logistic regression with AIC used to rank a-priori hypotheses and standardized variables used to determine effect sizes of parameters related to plant detectability.

Results: Pseudoturnover for graminoids was similar to that for other life forms and best related to ground layer cover. Morphological groups related to differences in detection, with short, small-inflorescence *Carex* most poorly detected. Detection failure was best explained by species abundance and morphology, but delays were more tied to a site's vegetation structure and species abundance than to species morphology.

Conclusions: Surveys targeting graminoids, including species of *Carex*, can achieve high detection rates with high survey effort over small areas, but should consider species- and site-specific biases in detection success. Abundance is likely the most influential factor in determining detection success, and this must be accounted for when searching for low-density species. We recommend that increased effort (time, repeat observations) be applied when searching for morphologically small graminoids.

KEYWORDS
boreal forest, *Carex*, detectability, graminoid, imperfect detection, logistic regression, morphology, pseudoturnover, rare species, sedge, survey effort, vascular plant

1 | INTRODUCTION

Understanding the world around us requires observation and collection of data, yet we know observers to be imperfect in detecting events or patterns where they occur. Issues related to observer bias are common across a number of disciplines including medicine, manufacturing, and ecology (Bruno, Walker, & Abujudeh, 2015; Lavers, Oppel, & Bond, 2016; Poulton, 1973). In ecological applications,

understanding species' occurrence, abundance, and population dynamics requires that species are consistently detected in surveys (MacKenzie et al., 2006), yet imperfect detection exists and must be accounted for. In practice, those who study static events or species with low mobility (e.g., ground-dwelling arthropods and plants) rarely account for imperfect detection in analyses (Kellner & Swihart, 2014). Despite the fact that plants are static once established, previous studies make clear that the assumption of plants being perfectly detectable is often invalid (Chen, Kéry, Plattner, Ma, & Gardner, 2013).

Research on imperfect detection in vascular plants has regularly estimated detection probabilities <0.5 and as low as 0.09, suggesting that imperfect detection must be considered in survey planning and data analysis (Chen, Kéry, Zhang, & Ma, 2009; Clarke, Lewis, Brandle, & Ostendorf, 2012; Moore, Hauser, Bear, Williams, & McCarthy, 2011; Ng & Driscoll, 2014). Species that are locally abundant or are conspicuous, such as when flowering, have higher detection rates, with abundance generally considered as the greatest determinant of detection success (McCarthy et al., 2013; Royle & Nichols, 2003; Vittoz & Guisan, 2007). However, most species are rare (Kunin & Gaston, 1997; Whittaker, 1965), and species at low abundance in their environment are less likely to be detected in surveys with large plot sizes (Dennett, Gould, Macdonald, & Nielsen, 2018; Moore et al., 2011).

Imperfect detection can generally be categorized as resulting from observer-specific differences (experience, identity, etc.; Alexander, Slade, Kettle, Pittman, & Reed, 2009; Bornand, Kéry, Bueche, & Fischer, 2014; Morrison, 2016), species-specific differences such as morphology, abundance, flowering state, and size of individuals (Clarke et al., 2012; Garrard, McCarthy, Williams, Bekessy, & Wintle, 2013; Kéry & Gregg, 2003; Scott & Hallam, 2002), and site-specific differences (survey protocol, density of vegetation, management history, etc.; Alexander et al., 2009; Burg, Rixen, Stöckli, & Wipf, 2015; Clarke et al., 2012; Garrard, Bekessy, McCarthy, & Wintle, 2008). When detection probability scales with any one of these characteristics or combinations thereof, observed data become biased, limiting their usefulness. Therefore, the extent to which species- and site-specific attributes act to exacerbate observer errors is of increasing interest (MacKenzie et al., 2006).

Given that imperfect detection differs across species and sites, studies separating these effects are useful for understanding bias and addressing it in survey design (Alexander et al., 2009; Garrard et al., 2013; Kéry & Gregg, 2003). Comparisons of detectability by life stage, flower colour, or other characters help inform field surveys targeting species that share similar traits (Chen et al., 2013; Garrard et al., 2013; Kéry & Gregg, 2003). Understanding how detection of similar species may vary is important since many rare taxa share traits with their more common congeners, yet their accurate detection is of high conservation value (Garrard, Bekessy, McCarthy, & Wintle, 2015; Kunin & Gaston, 1997). Evidence suggests that graminoids, here referring to the Families Poaceae, Cyperaceae, and Juncaceae (colloquially grasses, sedges,

and rushes, respectively) may be more poorly detected than other vascular plants, yet these plants are an important source of diversity in many systems. Previous work found that graminoids were overlooked more often than other vascular plants, with moderately high mis-identification rates (Archaux et al., 2009). In a Swiss study, grasses had the lowest detection probability among trees, shrub, and forbs (Chen et al., 2013). Scott and Hallam (2002) reported pseudoturnover (the apparent change in species composition in an area due to differences in observers' species lists) values of 21, 22, and 16% for grasses, sedges, and rushes, respectively. In an analysis of pseudoturnover in alpine environments, Burg et al. (2015) reported 21% of the 62 species most often overlooked by observers were graminoids, although they also demonstrated high detectability of two abundant *Poa* L. (Poaceae) species. Collectively, this suggests that graminoids may be consistently under-detected, likely for reasons related to their morphology and taxonomy.

While these families include remarkable morphological diversity, differences typically occur at a small scale. Graminoids tend to be thin in profile, with low foliar cover and limited contrast between their vegetative and reproductive parts. To address detection of this challenging taxonomic group, we undertook a study of graminoid detection in Canada's boreal forest. First, we estimated the pseudoturnover of graminoids in comparison to other life forms to determine the extent to which these plants are subject to overlooking errors between observers. Next, we used the genus *Carex* L. (Cyperaceae) as a model group to examine variation in detection given species morphology and abundance. Our aim in selecting *Carex* was to take advantage of the broad variation in form and niche observed in this genus. Indeed, *Carex* are one of the most diverse angiosperm genera with ~2,000 species (Govaerts & Simpson, 2007) distributed globally across the earth's terrestrial surface, excluding the Antarctic (Ball & Reznicek, 2002). In our region of northeastern Alberta, Canada, *Carex* occur across the full range of nutrient and moisture conditions and vary significantly in size and form.

Working taxonomic knowledge of *Carex* is slow to accumulate, where some groups remain challenging to identify in the field even for relatively experienced botanists (e.g., section *Ovales*). The process of *Carex* identification for most beginner to intermediate botanists is likely best reflected by a combination of a natural method (grouping similar-appearing *Carex* into coherent search images) followed by the use of keys to confirm the species level identification (Ellis, 2011). Therefore, we considered *Carex* detection using morphological groups, and focused upon how morphology, abundance, and site attributes influence detection success. Specifically, we sought to answer three questions:

1. How large are overlooking errors for graminoids in contrast to other life forms in boreal forests, and what survey conditions minimize these errors?
2. To what extent do morphological traits make some groups of *Carex* more accurately detected?

3. Which species- and site-specific factors have the greatest influence on detection failures at sites and delays of detection within sites for *Carex*?

2 | METHODS

2.1 | Study area and inventory transects

Surveys took place in northeastern Alberta, Canada. Fifty belt transects 100 m in length and 2 m in width (200 m^2) were established in a region spanning from 45 km northeast of Fort McKay (57°32′23″ N, 111°14′48″ E) to Lac la Biche (54°59′9″ N, 112°0′6″ W), a north-south distance of ~300 km. The large geographic span of sites was intentional to reduce local improvement in detection rates due to familiarity with a single area. We selected sites by generating random points within 2 km of roads in ArcMap 10.2 (www.esri.com) and then used Google Earth (www.earth.google.com) imagery to stratify by landcover type, and used local knowledge to span the range of possible conditions. Specifically, transects were established in bog, graminoid-, shrub-, and treed-fens, as well as conifer and mixed-wood uplands. Deciduous-dominated upland forests were the only major landcover avoided due to low representation of *Carex*. Human disturbance was avoided, but natural disturbances, such as beaver activity and recent wildfires, were included as they represent important habitat for many boreal species. Transects were completed from 2 July to 13 August 2015. Two observers (JD and JT) generated a species inventory for each transect in 30-min independent surveys (effort of 0.15 m^2/min), recording the transect segment (1–10, 10 m × 2 m increments) where each species was first detected. Transects were established singly or in pairs <300 m apart, but always set in contrasting habitats when paired. No continuous habitat patch was surveyed twice (e.g., a large fen complex would contain only one transect).

Once each transect was surveyed by both observers, it was then walked a third time for the collection of attribute data. We assigned each transect to a landcover class. Within each segment we assigned a Domin cover-abundance class (Mueller-Dombois & Ellenberg, 1974) for: (a) life forms (short tree [<2 m], tall shrub [>50 cm], short shrub [<50 cm], forb, non-*Carex* graminoid, all *Carex*, moss, and lichen), and (b) each *Carex* species found within that segment. We obtained horizontal cover estimates using a 2 m cover pole (Griffith & Youtie, 1988) with banded 10 cm increments at the midpoint of each transect segment. Finally, morphological characters were measured on three representative individuals of each *Carex* species at each transect. Measurements included plant height, leaf width, length and width of the inflorescence or peduncled spike, and the number of pistillate spikes. While collecting these data, observers had the opportunity to record any *Carex* missed by both individuals, and to communicate detections made by one observer but not the other. Observers also recorded detection delays (e.g., an observer first encountered a species in transect segment 8, but it was present in 2). Thus, this additional time (30–60 min) acted as a "third survey" focused on *Carex*. At approximately one-third of sites observers collected cover and site attribute data together, which had the benefit of allowing ongoing calibration of percent cover estimates. When these "third survey" data were collected independently, observers used radios to communicate the locations of encountered *Carex* species after both independent surveys had been completed. Both observers had similar field experience at the time of this study (multiple years of vascular plant surveys and previous *Carex*-specific training). Their familiarity with *Carex* was self-characterized as being at an intermediate level. Taxonomy of Carex follows Packer & Gould (2017).

2.2 | Analysis methods

2.2.1 | Pseudoturnover by growth form

We used pseudoturnover to estimate the magnitude of overlooking errors for all species encountered (total) and four broad growth forms; tree, shrub, forb, and graminoid. Percent pseudoturnover was calculated using the equation by Nilsson and Nilsson (1985), $[(S_a + S_b)/(S_{aa} + S_{bb})] × 100$ where S_a and S_b are the number of unique species detected by each observer not detected by the other, and S_{aa} and S_{bb} are the total number of species recorded by each observer respectively. To determine the influence of site-specific variables we related total and graminoid pseudoturnover to attributes of the search environment with generalized linear models (glm) using the package 'lme4' (Bates, Mächler, Bolker, & Walker, 2015) in R version 3.4.3 (https://www.r-project.org/). Predictor variables were reported to the transect level by summing species richness and averaging horizontal cover, total vegetative cover, and cover by growth form. Statistical models represented related, but distinct hypotheses of site conditions predicted to best explain variation in observer species lists and were evaluated using Akaike information criterion (AIC) model selection (Burnham & Anderson, 2002). All variables were standardized to their mean allowing for direct comparison of effect sizes between predictors.

2.2.2 | Morphological groups of *Carex*

We categorized all encountered *Carex* species into six groups based on their gross morphology, grouping by height and general appearance of the inflorescence. Broad groups based on morphology were expected to be informative in making inferences about differences in detection given the similarity in appearance (and therefore search image) of some species. To evaluate if our grouping scheme adequately represented apparent differences between groups of species, we used a Principal Components Analysis (PCA) with the package 'vegan' in R (version 2.4-4; https://cran.r-project.org/package=vegan). These groups were: aggregated (medium to tall species with spikes aggregated into a head), peduncled (medium height with pistillate spikes on peduncles), sessile (tall, robust aquatics with spikes mainly attached directly to the culm [lower pistillate spikes can be peduncled in some species]), sessile-remote (medium height with well-spaced sessile pistillate spikes), single-spike (short,

unispicate species), and small-aggregated (short to medium height with few, small spikes mostly clustered to a head).

To determine if two repeat surveys and additional site time were adequate to detect species within morphological groups (i.e., to determine if any group could be considered perfectly detected), we estimated detection probability for each group across all transects using data from all three survey periods, i.e., including 'third survey' observations, using a single-season occupancy-detection model in the program PRESENCE which did not include covariates (version 2.12.12; http://mbr-pwrc.usgs.gov/software/presence.html). For each group, if any species assigned to the group was missed by one or both observers, it was coded as an absence for that survey; thus, estimates of detection are likely under-estimates for some species.

2.2.3 | Detection success, failure, and delays

Studies of detection often aim to estimate occupancy, thus occupancy-detection models are commonly used (MacKenzie et al., 2006). We chose not to use occupancy-detection models because abundance, a major determinant of detection success and factor of interest, cannot be included as no abundance measure is available for species that were not detected along transects. This drawback also limits the applicability of traditional survival analysis (Cox & Oakes, 1984). Frameworks that allow for evaluation of occupancy-detection given measured abundance are limited to Bayesian approaches, which remain theoretical or challenging to implement (Garrard et al., 2008; McCarthy et al., 2013). Logistic regression provides a simple, accessible method to estimate detection probabilities, where instances of detection failure are known, while allowing for inclusion of abundance as a covariate (Chen et al., 2009; Delaney & Leung, 2010). We note that this approach may result in over-estimates of detection probabilities as we cannot account for sites that were occupied but a species was never detected.

We recorded two types of imperfect detection, detection failures where one or both observers overlooked a species, and detection delays, where a species was detected after its first known location along the transect. Given that each case has implications for effective surveying, we considered these two types separately by examining success (detection at first opportunity) vs detection failures ($n = 374$), and success vs detection delays ($n = 417$). Specifically, the influence of species- (morphology and abundance) and site- (structure and cover of life forms) specific variables were examined for each question (set of data) using mixed-effect logistic regression with exploratory hypotheses ranked for model support using AIC evaluation with the package 'lme4' in R. In all cases we included information gained from one observer (e.g., species presence recorded by JT and not by JD), as well as observations collected during the "third survey". We note that as with detection failure, estimates of detection success over delays are likely overestimates. We did not encounter incidents of false presence (misidentification) in our surveys and therefore do not address misidentification in analysis.

3 | RESULTS

3.1 | Experimental detection transects and pseudoturnover

We recorded 260 vascular plant species across all 50 transects, 36 (13.8%) of which were species of *Carex*. Transect species richness of *Carex* ranged from 1 to 10 with a mean of 4.5 (standard error [*SE*] = 0.4), while total species richness ranged from 15 to 81 with a mean of 34.8 (*SE* = 2.2). Observed detection failures of *Carex* were low. Of 227 unique instances of *Carex* sp. presence across the study, JD missed 22 (9.7% detection failure), while JT missed only 15 (6.6%). In eight instances both individuals missed a *Carex* sp. during their individual survey, but it was detected during the 'third survey'. We note that occurrences missed during this time and by both observer surveys remain unknown. Although detection failures were low, delayed detections within a site (transect segments) were more common with JD recording 39 instances (17.2%) of detection delay, and JT recording 41 instances (18.1%).

Considering all species of vascular plants, the average pseudoturnover rate was 11.6% (range: 2.2–23.3, *SE* = 0.7) with no meaningful differences in pseudoturnover across life forms. Graminoids were the least overlooked group at 10.0% (range: 0–33.3, *SE* = 1.3), while forbs were highest at 12.7% (range: 0–38.5, *SE* = 1.4; Figure 1). Model ranking suggested weak support for site complexity (horizontal and total vegetation cover) in explaining total pseudoturnover, where horizontal cover was positively related to pseudoturnover and total vegetation cover was negatively associated. When considering only graminoids, pseudoturnover was best explained by a model with a positive relationship with forb and short shrub cover, representing ground layer visual obstructions, with forb cover having almost twice the effect of short shrub cover (Tables 1 and 2).
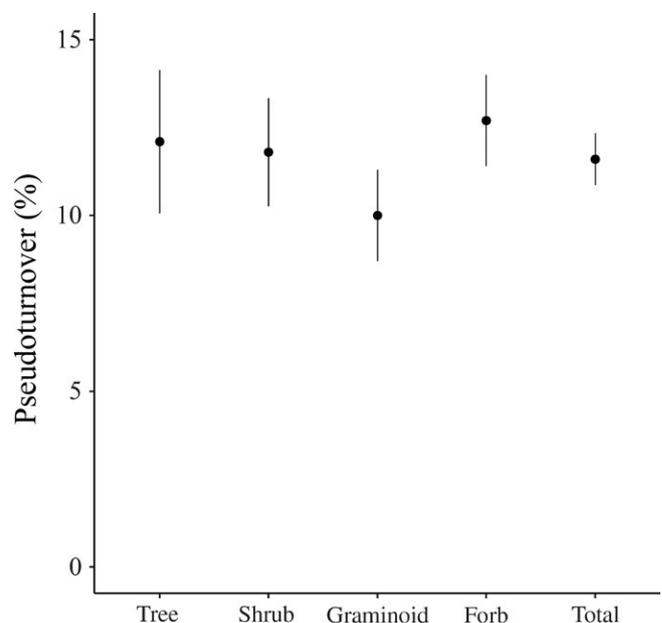

FIGURE 1 Average (and standard error) percent pseudoturnover by life form of all encountered species for 50 transects

TABLE 1 Generalized linear models relating pseudoturnover of all species (top) and graminoids (bottom) to site-specific variables representing different conditions of the search environment (*n* = 50)

Hypothesis	Model	K	ΔAIC
Total pseudoturnover			
Site complexity	Horizontal cover + mean transect cover	2	0
Null	Null	0	2.02
Richness	Transect species richness	1	2.12
Visual obstruction (low cover)	Mean forb cover + mean short shrub cover	2	4.37
Physical obstruction (high cover)	Mean tall shrub cover + mean short tree cover	2	5.17
Habitat	Habitat class	1	11.20
Graminoid pseudoturnover			
Visual obstruction (low cover)	Mean forb cover + mean short shrub cover	2	0
Graminoid prevalence	Mean graminoid cover	1	2.58
Null	Null	0	3.69
Graminoid richness	Graminoid richness	1	5.62
Habitat	Habitat class	1	4.10
Physical obstruction (high cover)	Mean tall shrub cover + mean short tree cover	2	6.86
Site complexity	Horizontal cover + mean transect cover	2	7.01

All variables were standardized to their mean prior to their inclusion in candidate models so that their values can be compared among each other for effect size.

3.2 | Morphological groups of *Carex*

Morphological groups had meaningful differences across field-measured traits when evaluated with a PCA (Figure 2; see Appendix S1 for summarized measurement data), with obvious separation across the axes representing plant height and leaf width. Naïve detection probabilities demonstrated that the survey effort used here

TABLE 2 Parameters of the best supported generalized linear models relating pseudoturnover of all species (top) and graminoids (bottom) (*n* = 50)

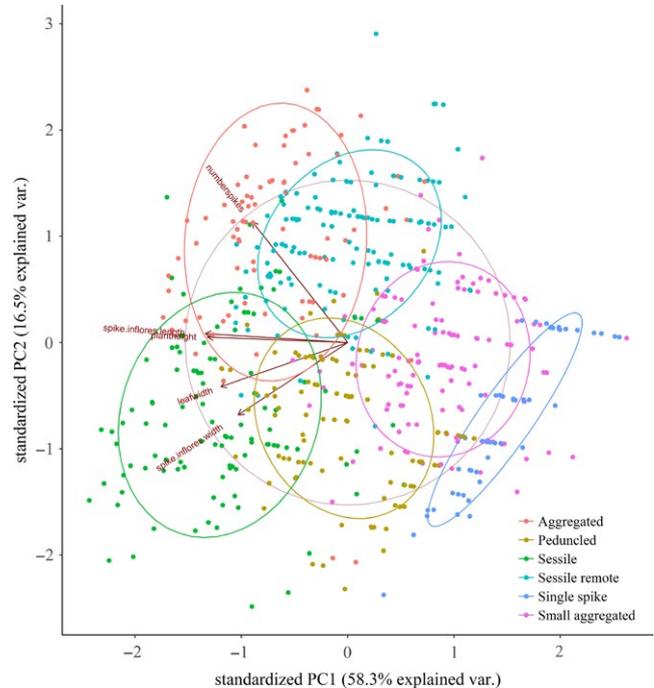|	*β*	SE
Total pseudoturnover		
Horizontal cover	1.25	0.81
Total mean transect cover	−1.89	0.79
Graminoid pseudoturnover		
Forb cover	3.10	1.24
Short shrub cover	1.52	1.24

FIGURE 2 Principal Components Analysis (PCA) of six morphological groupings of *Carex*. Each point represents an individual plant measured in the field (*n* = 593). Measurements used in the PCA include plant height, leaf width, spike/inflorescence length, width, and number of spikes. Axis 1 is related most to plant height, while Axis 2 is related most to leaf width [Colour figure can be viewed at wileyonlinelibrary.com]

was not adequate to achieve a census of *Carex* on transects, and probabilities varied across morphological groups. Sessile and aggregated *Carex* were the most reliably detected, while unispicate and small-aggregated *Carex* were most poorly detected. Even three survey periods were not sufficient to achieve >95% detectability for half of morphological groups (Table 3).

3.3 | Detection success, failure, and delay

Nine candidate models explaining variation in success vs detection failure (*n* = 374) and vs delays (*n* = 417) were compared based on

TABLE 3 Detection probabilities estimated using both repeat surveys (30 mins each) and additional 'third survey' time (30 to 60 mins) in the program PRESENCE across six morphological groups of *Carex* (*n* = 417)

Morphological group	Detection probability ± SE
Sessile	0.99 ± 0.01
Aggregated	0.99 ± 0.01
Sessile-remote	0.98 ± 0.02
Peduncled	0.91 ± 0.03
Single-spike	0.87 ± 0.05
Small-aggregated	0.82 ± 0.04

TABLE 4 Mixed-effect logistic regression models relating detection success vs failure (*n* = 374) (top) or delay (*n* = 417) (bottom) to species- and site-specific variables

Hypothesis	Models	K	ΔAIC
Detection failure			
Morphological group	Morphological group + species segment cover	3	0
Visual obstruction (low cover)	Short shrub segment cover + forb segment cover + species segment cover	4	7.34
Richness	Transect species richness + species segment cover	3	13.34
Physical obstruction (high cover)	Short tree segment cover + tall shrub segment cover + species segment cover	4	14.32
Species cover	Species segment cover	2	15.20
Site complexity	Total segment cover + horizontal cover + species segment cover	4	15.48
Observer	Observer identity + species segment cover	3	15.60
Carex prevalence	Total *Carex segment* cover + species segment cover	3	16.14
Null	1 + transect random effect	1	55.84
Detection delay			
Physical obstruction (high cover)	Short tree segment cover + tall shrub segment cover + species segment cover	4	0
Site complexity	Total segment cover + horizontal cover + species segment cover	4	0.20
Species cover	Species segment cover	2	7.54
Carex prevalence	Total *Carex segment* cover + species segment cover	3	8.00
Richness	Transect species richness + species segment cover	3	8.73
Observer	Observer identity + species segment cover	3	9.53
Visual obstruction (low cover)	Short shrub segment cover + forb segment cover + species segment cover	4	11.38
Morphological group	Morphological group + species segment cover	3	14.25
Null	1 + transect random effect	1	22.22

All variables were standardized to their mean prior to inclusion in candidate models. A random effect of transect was used in all candidate models. The morphological group 'sessile' was withheld as the reference for the variable "morphological group".

species- and site-specific predictors (Table 4). All models included abundance (mid-point of Domin cover class). Detection success over failure was best explained by the morphological group of the missed species, and the segment cover (abundance) of that species (Table 4, Figure 3). Specifically, *Carex* species cover had the greatest, positive influence on detection success (β = 12.8, *SE* = 3.39). The morphological groups aggregated and sessile-remote were most similar to sessile *Carex*, while single-spike, peduncled, and small-aggregated had reduced detection in comparison to this group (Table 5). *Carex* morphology was not supported in explaining detection success over delays (Table 4). The best supported model instead contained variables representing physical obstructions at sites (Table 5). Short tree cover was positively associated with detection success over delays (but note the large *SE*s), and tall shrub cover was inversely

related to success. Increasing cover of each *Carex* species in the block where they were first present was again the most important parameter in explaining immediate detection (β = 1.28, *SE* = 0.43; Figure 4), although this parameter was not as influential as in models explaining detection success over failure (Table 5).

4 | DISCUSSION

High detection of some *Carex* (>95%) can be achieved in field surveys using narrow (2 m wide) belt transects with abundance, morphology, and site structure affecting detection success. Overlooking errors between two similar, well-trained observers were low relative to published estimates (Lepš & Hadincová, 1992; Morrison, 2016; Scott
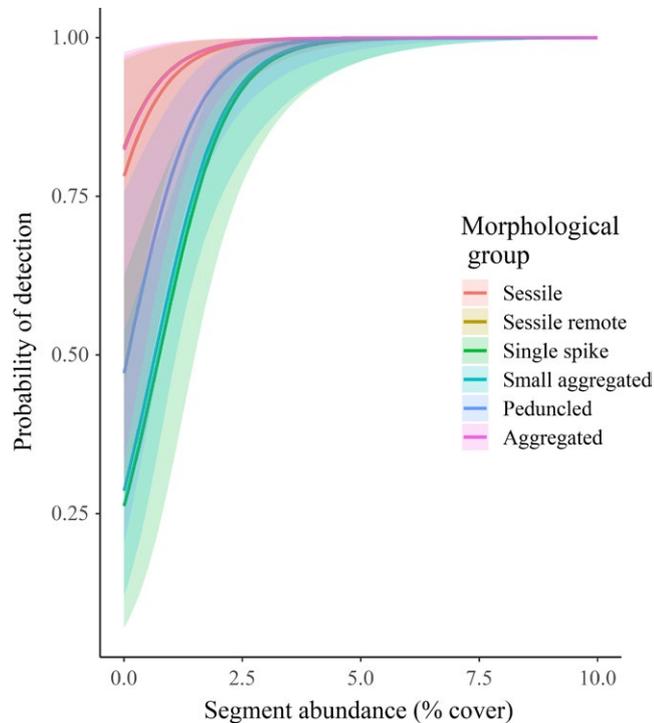
FIGURE 3 Predicted detection probabilities given *Carex* species abundance (% cover) within transect segments (20 m²) as per the best supported logistic regression model of detection success over failure shown in Table 4. The effect of transect identity (included in the model as a random effect) has been averaged. Lines indicate predicted detection probabilities, shaded bands indicate 95% confidence intervals. Species segment abundance is truncated at 10% for ease of viewing, as all groups had predicted detection probabilities ~1 past this value. Note that detection probabilities are poorly estimated at 0% cover [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Parameters of the most supported mixed-effect logistic regression models of detection success vs failure (*n* = 374) (top) or delay (*n* = 417)

	β	SE
Detection failure		
Species segment cover	12.84	3.39
Morphological group		
Aggregated	0.26	1.47
Peduncled	−1.39	1.13
Sessile-remote	0.29	1.28
Single-spike	−2.31	1.19
Small-aggregated	−2.19	1.09
Detection delay		
Species segment cover	1.27	0.43
Short tree segment cover	0.26	0.23
Tall shrub segment cover	−0.55	0.21

A random effect of transect was used in all candidate models. The morphological group "sessile" (large, robust aquatics) was withheld as the reference for the variable "morphological group".
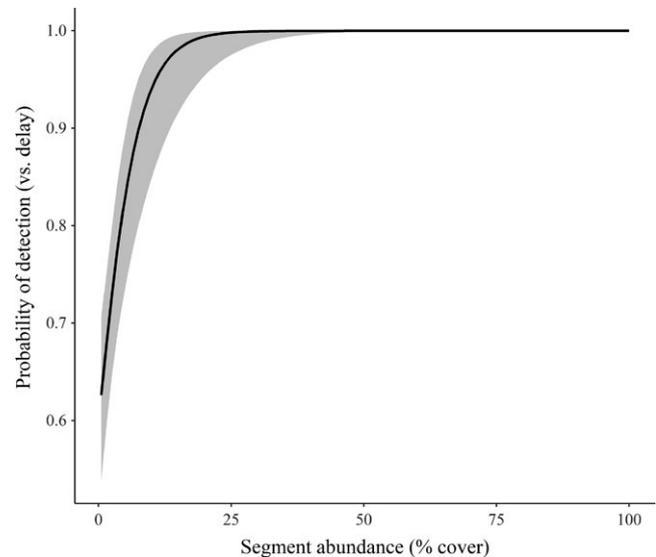

FIGURE 4 Predicted detection probabilities given *Carex* species abundance (% cover) within transect segments (20 m²) as per the best supported logistic regression model of detection success over delays shown in Table 4. The effect of transect identity (included in the model as a random effect) has been averaged, and short tree and tall shrub cover held to their mean. The black line indicates predicted detection probability, the shaded band indicates a 95% confidence interval. Note that detection probability is poorly estimated at 0% cover

& Hallam, 2002) with graminoids having the lowest pseudoturnover among four major life forms. Variation in total pseudoturnover was weakly predicted by site complexity, while graminoid pseudoturnover was best explained by ground layer visual obstruction. Here, two repeat surveys and additional site time focused on *Carex* was still not sufficient to achieve detection probabilities of >95% for half of the morphological groups considered, suggesting that surveys that employ less effort than used here (0.15 min/m²) are even less likely to meet this threshold. Species- and site-specific factors differ in their effect on an observer's detection ability in a plot vs delaying detection within a plot along segmented belt transects. Abundance and morphology best explain detection failures in general, while abundance and site structure best explain delays in detection within a plot. These results speak to the importance of considering species- and site-specific attributes in survey planning and data collection.

Low rates of pseudoturnover in boreal forest surveys are encouraging. While forbs were more often overlooked, there was little meaningful variation among groups, suggesting no bias in detectability among life forms. Our results differed from previous examples that compared site-specific factors to pseudoturnover. Burg et al. (2015) found support of observer-specific variables over vegetation density and other site-factors in explaining pseudoturnover among an 11-person team working in alpine habitats. In our study total pseudoturnover was higher at sites with more structurally complex vegetation, and reduced at sites with greater total vascular plant cover. This may reflect observers being more cautious in detecting species when vegetation cover was high. The positive relationship

with horizontal cover likely reflects increased distractions at sites with a more complex understory. However, these results were only marginally more supported than a null model of constant detectability. Increased graminoid pseudoturnover at sites with higher forb and short-shrub cover likely reflects the larger foliage of forbs obscuring the narrow leaves of graminoids. Finally, our pseudoturnover rates align with low-end published estimates, where it is uncommon to observe rates below 10%, this being potentially related to species abundance where observers are unlikely to encounter species which are scarce in the search environment (Burg et al., 2015; Lepš & Hadincová, 1992; Morrison, 2016; Scott & Hallam, 2002; Vittoz & Guisan, 2007).

Observer success in recognizing graminoids, and *Carex* specifically, is more closely tied to taxonomic knowledge than for more easily identified vascular plants. In cases where this knowledge is lacking, there may be significant impediments to estimating graminoid detectability. For example, Garrard et al. (2013) did not include grasses in their detection analysis due to high uncertainty in species identification, pointing to serious gaps in taxonomic expertise. We suggest using morphological groups as an approach to understanding detectability for difficult taxa provided there is confidence in species-level detections. Gross morphological groupings may more closely mimic the recognition process for *Carex*, whereby some species are easily recognized (e.g., *C. aquatilis* in our region), but others are more readily assigned to groups of similar-appearing species (e.g., *C. concinna*, *C. deflexa* and *C. peckii*). Here, robust, large species of *Carex* were 1.3-times more likely to be detected than those with a short, small inflorescence. Searches must therefore compensate for this detection bias against short, small inflorescence species with additional survey effort or number of observers. Morphological groupings may be relevant in adjusting for detectability in post-hoc analyses, for example, correcting for detection probability given morphology when estimates are not available from survey data for species of interest (e.g., single visit data) (Lele, Moreno, & Bayne, 2012; Sólymos, Lele, & Bayne, 2012).

Working with morphological groups is also useful to characterize the effect of morphology on detection failures and delays. As anticipated, abundance was the most important determinant of success over failure, with a negative influence of species morphology that differs from large, robust *Carex*. In contrast, abundance and site structure, but not morphology, affected the probability of delayed observations within a site, where abundance had a more moderate effect than for detection failures. Considering the relationship between abundance and detection, our data suggest that failure to detect species is most likely to occur where species cover is <5% in transect segments of 20 m^2, but delays in detection may occur up to 25% cover. Given that we demonstrate a large influence of abundance on these two types of imperfect detection, it is important that future work incorporates this variable where possible, as quantifying the detection–abundance relationship allows for determining appropriate survey effort (McCarthy et al., 2013; Moore et al., 2011). Finally, physical obstructions, specifically tall shrubs, on transects were inversely related to detection success over delays. This is likely due to tall shrubs acting as physical impediments and causing a lapse in surveying focus while navigating through dense sites, which again should be compensated for by using greater search effort or number of observers at shrub-dominated sites.

Our naïve detection probabilities are high relative to other work, even among more showy species than the challenging *Carex* considered here. For example, four species considered to be highly recognizable had detection probabilities <0.6 in an Australian rangeland over eight years of surveying (Clarke et al., 2012). However, it is important to consider survey effort in interpreting our results. We used a standard survey effort of 0.15 min/m^2 across all transects, which is high relative to published examples of effort in previous detection studies (Dennett et al., 2018; Garrard et al., 2008; Moore et al., 2011; Zhang et al., 2014), over a small search area (200 m^2), where both have been shown to improve detection success (Dennett et al., 2018; Moore et al., 2011). The effort used in this study exceeds that of surveys typically used for environmental impact assessments, but helps establish benchmarks of when high detection is achievable. Although our detection probabilities are likely over-estimates given that truth in species presence was unknown, we did not achieve probabilities of 95% for half of the morphological groups considered, and detection of small-aggregated *Carex* was much poorer than other morphological groups at 0.82. This suggests that some *Carex* will go unnoticed despite high search effort, and this is likely exacerbated in field surveys for these plants. Finally, we expect that using well-trained observers with knowledge of *Carex* was advantageous, and we found no support for an effect of observer in our analysis, although such effects have been important in previous work, even in teams as small as two individuals (Bornand et al., 2014).

Inferring species occupancy and trend from survey data requires accurate detection, yet variability in detection is the norm. We encourage future work focused on detecting graminoids or other challenging taxa (e.g., Asteraceae or Ophioglossaceae). A clear benefit in using *Carex* as a model genus is that many species can occupy a single site, allowing for direct comparison of the effects of morphology and abundance of similar plants under the same site conditions. One consideration lacking in this study was consideration of cespitose and rhizomatous growth forms. This may influence the detection of *Carex* and other graminoids, but varies within some species given environmental conditions and should be assessed on a per-site basis, and we encourage future work to consider this trait. This study of graminoid detection in boreal environments found no bias in detection among life-forms, the potential suitability of using morphological groupings for difficult taxa, and the importance of biases associated with abundance of target species. We hope that our example encourages future work in forested systems using this and other focal taxa.

other vascular plant species. Two anonymous referees provided suggestions and discussion which greatly improved the quality of the manuscript.

DATA ACCESSIBILITY

Calculated pseudoturnover values and mean transect variables, detection histories for *Carex* groups per transect, transect segment-level *Carex* detection data, and basic R script for linear and logistic regression models described in the text are provided in Appendices S2, S3, S4, and S5.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1 Summarized measurement data for 36 *Carex* sp. found within the study

Appendix S2 Pseudoturnover values and summarized transect attribute data

Appendix S3 Detection histories for morphological groups per transect

Appendix S4 Observations of *Carex* sp. within the study and associated transect segment data

Appendix S5 Basic R code for linear and logistic regression models for pseudoturnover and detection delays and failures