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RESEARCH ARTICLE

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Statistical design and analysis for plant cover studies with multiple sources of observation errors

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Abstract

1. Effective wildlife habitat management and conservation requires understanding the factors influencing distribution and abundance of plant species. Field studies, however, have documented observation errors in visually estimated plant cover including measurements which differ from the true value (measurement error) and not observing a species that is present within a plot (detection error). Unlike the rapid expansion of occupancy and N-mixture models for analysing wildlife surveys, development of statistical models accounting for observation error in plants has not progressed quickly. Our work informs development of a monitoring protocol for managed wetlands within the National Wildlife Refuge System.
2. Zero-augmented beta (ZAB) regression is the most suitable method for analysing areal plant cover recorded as a continuous proportion but assumes no observation errors. We present a model extension that explicitly includes the observation process thereby accounting for both measurement and detection errors. Using simulations, we compare our approach to a ZAB regression that ignores observation errors (naïve model) and an "ad hoc" approach using a composite of multiple observations per plot within the naïve model. We explore how sample size and within-season revisit design affect the ability to detect a change in mean plant cover between 2 years using our model.
3. Explicitly modelling the observation process within our framework produced unbiased estimates and nominal coverage of model parameters. The naïve and "ad hoc" approaches resulted in underestimation of occurrence and overestimation of mean cover. The degree of bias was primarily driven by imperfect detection and its relationship with cover within a plot. Conversely, measurement error had minimal impacts on inferences. We found >30 plots with at least three within-season revisits achieved reasonable posterior probabilities for assessing change in mean plant cover.
4. For rapid adoption and application, code for Bayesian estimation of our single-species ZAB with errors model is included. Practitioners utilizing our R-based simulation code can explore trade-offs among different survey efforts and parameter values, as we did, but tuned to their own investigation. Less abundant plant species of high ecological interest may warrant the additional cost of gathering multiple independent observations in order to guard against erroneous conclusions.

KEYWORDS
beta regression, imperfect detection, measurement error, monitoring, observer errors, occupancy models, plant cover, trend detection

1 | INTRODUCTION

Effective wildlife habitat management and conservation requires understanding the factors influencing distribution and abundance of plant species. Recent studies, however, have raised concerns about ubiquitous observation errors in plant survey data (for a review, see Morrison, 2016). A common proxy for plant abundance, visually estimated areal cover within a plot (e.g., 1 m × 1 m quadrat), is known to exhibit both errors in measurement (recorded values differ from truth; e.g. Gorrod, Bedward, Keith, & Ellis, 2013; Helm & Mead, 2004; Killourhy, Crane, & Stehman, 2016) and detection (species is not observed even though present; e.g. Chen, Kéry, Plattner, Ma, & Gardner, 2013; Chen, Kéry, Zhang, & Ma, 2009; Clarke, Lewis, Brandle, & Ostendorf, 2012; Vittoz et al., 2010). Despite this, there are few applications that explicitly model the observation process for plant cover. Conversely, there has been a rapid expansion in models for wildlife count or detection/non-detection data that directly account for imperfect detection (e.g., occupancy or N-mixture models; Kéry & Royle, 2016). These approaches typically use multiple observations at each site and explicitly include the observation process within a hierarchical model to obtain unbiased estimates of the ecological state parameters of interest (Kéry & Royle, 2016). While some authors have advocated utilizing occupancy models when analysing plant data to account for imperfect detection (Bornand, Kéry, Bueche, & Fischer, 2014; Garrard, Bekessy, McCarthy, & Wintle, 2015), models that also account for plant cover measurement errors have not, to the best of our knowledge, been explored.

Proposed recommendations to minimize observation errors in visually estimated plant cover data include properly training observers (Burg, Rixen, Stöckli, & Wipf, 2015; Killourhy et al., 2016; Vittoz et al., 2010), having observers approximate their uncertainty about estimates for qualitative incorporation into decision-making (Gorrod & Keith, 2009), or using measurements averaged over multiple observers as the response (Gorrod & Keith, 2009; Helm & Mead, 2004; Milberg, Bergstedt, Fridman, Odell, & Westerberg, 2008; Vittoz et al., 2010). While thorough training and proper field methods are important to reduce observer errors, it is unrealistic to assume that any study protocol could completely prevent them. To date, few have focused on whether these observer errors effect statistical-based conclusions (but see Milberg et al., 2008 and Vittoz et al., 2010). Here we explore realistic scenarios to assess whether unaccounted for detection and measurement errors of single-species plant cover can result in misleading inferences drawn from statistical models.

Zero-augmented beta (ZAB) regression models have been advocated for analysing plant cover (Damgaard, 2009, 2013). Within the ZAB model framework, the proportional area of a plot covered by a single species is a beta distributed random variable. The beta distribution is used because it is ideal for continuous, proportion-type response variables and its flexible shape (U-shaped, L-shaped, etc.) is well-suited for describing distributions of cover values for plant species (Chen, Shiyomi, Yamamura, & Hori, 2006; Chen et al., 2008; Damgaard, 2009; Irvine & Rodhouse, 2010). The models zero-augmented component allows cover values of zero at plots where the species is not present. In other words, this model component describes the probability of plot-level species presence as in occupancy models. Here, we introduce a hierarchical model that extends ZAB regression to account for both measurement error and imperfect detection. This model could be applied to any continuous proportion-type response subject to measurement errors or false zeros.

Our work is motivated by surveys for submerged aquatic vegetation (SAV) on National Wildlife Refuges across the western United States. The National Wildlife Refuge System provides important wetland habitat in the Intermountain West for wetland-dependent migratory birds. An important consideration is whether wetland management actions, such as water-level manipulations, increase desired SAV species that provide high-quality forage for birds during breeding, migration, and/or winter periods. In a simulation study, we compare statistical inferences regarding a focal plant species' distribution and abundance based on three modelling options: ZAB model that ignores observation errors, an "ad hoc" approach that uses the ZAB model to analyse a composite response (based on information from multiple independent observations from the same plot), and our hierarchical ZAB with observation errors model (hereafter, ZABE). Specifically, we investigate whether imperfect detection and measurement error increase bias and reduce coverage of ecological parameters (species occupancy and mean plant cover) when using these approaches. Furthermore, to aid in developing a long-term monitoring protocol for SAV, we explore the effects of number of plots and number of observations per plot on the posterior probability of detecting a change in mean cover between two time periods using our ZABE model. Our simulation framework, analogous to a frequentist power analysis, is provided for others to use when designing their own plant surveys, thereby facilitating collection of datasets that allow employing our model for statistical inferences.

2 | MATERIALS AND METHODS

2.1 | Models

2.1.1 | Zero-augmented beta regression (ZAB) model

A continuous, proportion-type response variable (bounded between 0 and 1) that also includes true zeros, such as visually estimated percent canopy cover within a predefined areal plot, is appropriately analysed using ZAB regression (Ospina & Ferrari, 2010). This model is a hurdle-at-zero model where we assume the ecological mechanism for generating an absence of a species within a plot is independent of the ecological process leading to non-zero cover values for a species (see Irvine, Rodhouse, & Keren, 2016 for more discussion of hurdle-at-zero models for plant cover). Assuming no observation errors and a single observation per plot, a ZAB model for plots $i = 1, \ldots, n$ is as follows,

$$[Z_i] \sim \text{Bernoulli}(\psi), \tag{1}$$

and

$$[Y_i \mid Z_i = 1] \sim \text{Beta}(\alpha, \beta), \tag{2}$$

where Z_i represents an indicator for whether the focal species is present (1) or absent (0) in plot i and Y_i describes the proportional

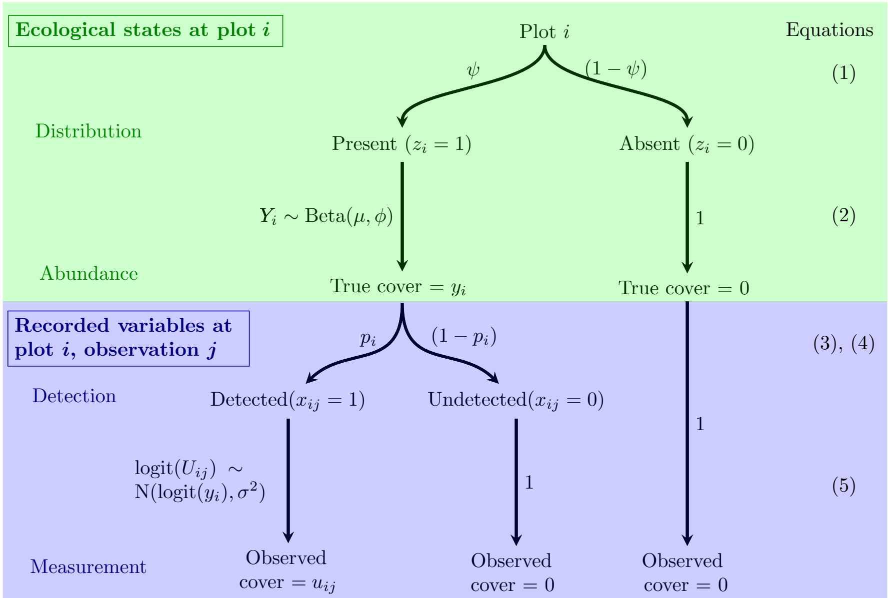

FIGURE 1 Diagram illustrating the data generating process for recorded plant cover at plot *i* and observation *j* under the zero-augmented beta with observation errors (ZABE) model. The ecological processes (green) of distribution (*Z*) and abundance (*Y*) are separated from the observation processes (blue) of detection (*X*) and measurement (*U*). Arrows and associated labels indicate the probability distributions for each node, conditional on the previous variable states. The model allows species to go undetected at occupied plots ($x_{ij} = 0|z_i = 1$) and for variability in observed cover values around the true cover ($u_{ij} \neq y_i$). At plots where the species is absent ($z_i = 0$), true and observed cover are equal to zero with probability 1. More details on the model are presented in Equations 1–5

coverage of a plot by that species given it is present. Here, ψ is the probability the species is present within a plot. As commonly done for beta regression (Ferrari & Cribari-Neta, 2004), we reparameterized the beta distribution for Y_i in terms of the mean, $\mu = \alpha/(\alpha + \beta)$, and precision parameter $\phi = \alpha + \beta$. This parameterization allows for inclusion of explanatory variables (**X**) to account for heterogeneity in occupancy and mean cover by way of $\text{logit}(\psi_i) = \mathbf{X}_i\boldsymbol{\beta}$ and $\text{logit}(\mu_i) = \mathbf{X}_i\boldsymbol{\lambda}$ where $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are parameter vectors. Under this approach, each Z_i and Y_i are directly observable, underscoring the ZAB model is only appropriate when presence and cover are observed without error at visited plots. For a fully Bayesian implementation of this model, we specify priors $\psi \sim \text{Uniform}(0, 1)$, $\mu \sim \text{Uniform}(0, 1)$, and $\phi \sim \text{half-Cauchy}(0, 10)$. The ZAB model can be fit using available software packages for implementing Bayesian analyses via Markov chain Monte Carlo (MCMC) methods such as JAGS (Plummer, 2003) or Stan (Carpenter et al., 2017).

2.1.2 | Bayesian Hierarchical zero-augmented beta with observation errors (ZABE) model

We propose a hierarchical extension to the ZAB model that specifies the observation process directly, accounting for both imperfect detection and measurement error, while making inferences about the ecological processes of plant distribution and abundance (Figure 1). We assume multiple observations *j* are available per plot *i* arising from multiple independent observers or multiple independent revisits to the same plot. Additionally, occupancy status and true plant cover are assumed constant across all observations of the same plot. The model specifies that if present ($Z_i = 1$), a species is detected at plot *i* and observation *j* ($X_{ij} = 1$) with probability p_i, that is,

$$[X_{ij} \mid Z_i = 1, Y_i = y_i] \sim \text{Bernoulli}(p_i), \tag{3}$$

where

$$\text{logit}(p_i) = \gamma_0 + \gamma_1 y_i. \tag{4}$$

The probability of detection is explicitly linked to areal cover within a plot (y_i) in Equation 4. Additional covariates or individual observer effects could be included to explain heterogeneity in detection probabilities among observations by extending Equation 4. Under this formulation, no detections are possible at plots where the species is absent ($Z_i = 0$) reflecting the assumption of no false positives or species misidentifications.

Given a species is detected ($X_{ij} = 1$), measurement errors are accounted for by assuming observed plant cover value from plot *i* and observation *j* (U_{ij}) is normally distributed with mean $\text{logit}(y_i)$ and variance σ^2 after being transformed to the logit scale ($\text{logit}(U_{ij})$), as follows:

$$[\text{logit}(U_{ij}) \mid X_{ij} = 1, Y_i = y_i] \sim \text{Normal}(\text{logit}(y_i), \sigma^2). \tag{5}$$

This approach assumes observed cover is unbiased on the logit scale. Although not explored here, a particular observer's tendency to consistently over or underestimate cover could be incorporated into the model by expanding Equation 5 to include individual observer effects in the mean, for instance, $\text{logit}(y_i) + \alpha\text{Observer}_j$.

With both types of observation errors, neither Z_i nor Y_i are directly observable and instead are latent variables in our hierarchical specification. This separates the ecological states of interest from the observation process where errors are made (green and blue respectively, Figure 1). The result is that even when present ($z_i = 1$), the species may still go undetected ($x_{ij} = 0$) for an observation and we assume a species with low cover within a plot is more likely to be missed. Additionally, even when detected, visually estimated cover (u_{ij}) values are not equal to true cover (y_i) within a plot. In this way, the ZABE model aims to estimate and adjust ecological inferences for detection and measurement errors.

The ZABE model (Equations 1–5) is motivated by empirically described characteristics of plant observation errors. Field studies have documented that detection probabilities increase as areal cover increases within a plot (Burg et al., 2015; Milberg et al., 2008; Vittoz et al., 2010) which is perhaps unsurprising given the abundance-detectability relationship observed in wildlife occupancy studies (Royle & Nichols, 2003). The logistic regression on p_i (Equation 4) accounts for this pattern by specifying detection is related to true cover within a plot. While we assume a linear relationship on the logit-transformed scale, increasing the slope coefficient (γ_1) effectively means detection can approach one as cover increases. Different link functions (e.g., probit) or functional forms for this relationship could be used instead but the flexibility and convenience of logistic regression make it useful in this application.

For measurement errors, the main consideration is that observed cover values are bounded between zero and one. The logit-transformation avoids this constraint and allows for normally distributed errors to be assumed. Alternative error distributions could be used on the untransformed scale, such as a truncated normal or beta, but we feel these options are computationally inconvenient or more difficult to interpret. For instance, an additional benefit of our approach is that assuming measurement errors have a constant variance (Equation 5, σ^2) on the logit-transformed scale ($\text{logit}(U_{ij})$), means on the proportion scale there is more variation at moderate values ($y_i \approx 0.5$) than at true cover values closer to zero or one. This pattern is consistent with empirical studies (Gorrod et al., 2013; Hahn & Scheuring, 2003; Killourhy et al., 2016; Vittoz et al., 2010). We also used simulations to show how observations generated under our proposed measurement error model (Equation 5) are aligned with those reported by field-based studies and explored other statistical properties of this parameterization (Appendix S1).

For a fully Bayesian model, we specify priors $\gamma_0 \sim \text{Cauchy}(0, 10)$, $\gamma_1 \sim \text{half-Cauchy}(0, 5)$, and $\sigma \sim \text{half-Cauchy}(0, 5)$ in addition to priors listed above for the other parameters. These are meant to provide little prior information while still incorporating the mathematical restrictions of the model. We restrict values for γ_1 to be positive with the half-Cauchy distribution to align with empirical studies (Burg et al., 2015; Milberg et al., 2008; Vittoz et al., 2010). We relaxed this assumption in the survey design simulations (described below in "Survey Design Requirement Investigation") and used a Cauchy(0, 5) prior for γ_1 instead.

2.2 | Simulation-based comparison of statistical models for plant cover datasets

A simulation study evaluated potential impacts of not accounting for multiple sources of observation error on statistical inferences. Datasets were simulated according to the hierarchical ZABE model (Equations 1–5) and we investigated eight different scenarios based on every combination of the parameter values $\mu = \{0.25, 0.75\}$, $\gamma_1 = \{2, 4\}$, and $\sigma = \{0.5, 1.0\}$. For all eight scenarios, we simulated datasets with 200 plots ($i = 1, \ldots, 200$) and three independent observations ($j = 1, 2, 3$) with $\psi = 0.5$, $\phi = 3$, and $\gamma_0 = -1.5$. Parameter values were guided by our aquatic vegetation pilot data (Appendix S2). We simulated 1,000 datasets for the first two scenarios, but only 500 datasets for subsequent scenarios in order to reduce computation time and because the additional datasets did not change summaries for the initial scenarios we examined.

We fit three different models to each simulated dataset. The "naïve" approach assumed no observation errors and fit the ZAB model using only the first observation ($j = 1$) from each plot. This approach reflects field surveys and subsequent analyses that ignore potential observation errors. Next, the "ad hoc" approach again fit the ZAB model but used information from all three observations. In this approach, a species was present ($Z_i = 1$) at plot i if any of the three observations had a detection and the average of non-zero plant cover values was used for the beta distributed response variable (Y_i). In other words, this approach excluded observations with a recorded zero at a plot when calculating the continuous portion of the composite response. The "full data" approach fit the data generating model (hierarchical ZABE) using every independent observation from each plot. The results from the full data approach explored how well the hierarchical ZABE model recovered true parameter values.

We used R (version 3.3.1; R Core Team, 2016) to conduct all simulations and provide the code as Supporting Information (Appendix S3). We fit the naïve ZAB and hierarchical ZABE models using a Bayesian approach with Stan (Carpenter et al., 2017) called from R using the `rstan` package (version 2.12.1; Stan Development Team, 2016). Posterior means and 95% posterior intervals (PIs) for all model parameters were saved for all model fits and simulated datasets. For each scenario and model, average 95% PIs (averages of 2.5% and 97.5% quantiles) and average posterior means were calculated across all simulated datasets as a summary. We also examined proportion of the 95% PIs that contained the corresponding parameter value used to generate the data (coverage). Model convergence was assessed with potential scale reduction factors ($\hat{R}$; Brooks & Gelman, 2012) and models that had any parameters with a $\hat{R}$ value larger than 1.1 were excluded from the summaries. Only results from state parameters in the model (ψ, μ, and ϕ) were reported because these are of interest ecologically and are common parameters across all the approaches.

2.3 | Survey design requirement investigation

This work was motivated by submerged aquatic vegetation surveys on National Wildlife Refuges in the western United States. One of the main questions of interest is whether a wetland management action (e.g., water-level manipulation) affects mean cover for targeted wetland plant species that are preferred food resources for migratory birds (Lyons, Runge, Laskowski, & Kendal, 2008; Sharp, Sojda, Greenwood, Rosenberry, & Warren, 2013). We conducted a simulation study to provide insights into recommended survey effort each year (number of plots and number of observations per plot) to estimate our hierarchical ZABE model. The available pilot data and current proposed sampling design were used to guide our assessment. Briefly, we assumed 1 m × 1 m plot locations within a wetland unit were randomly selected each year using a spatially balanced design.

Two years of data collection, pre- (denoted as T1) and post-management action (denoted as T2), were assumed where mean cover of a focal species changed as follows $\text{logit}(\mu_i) = \theta_0 + \theta_1 I(\text{time}_i = T2)$ with $\theta_0 = -1$ and $\theta_1 = 1$. This model results in a θ_1 difference on the logit-scale in mean plant cover between T1 and T2 for a given wetland unit. In the model, we assume that plot-level ecological states are independent among plots for both T1 and T2. The rest of the model remained consistent with our previous simulations. For the remaining parameters, we set $\psi = 0.5$, $\phi = 3$, $\sigma = 0.5$, $\gamma_0 = -1.5$, and $\gamma_1 = 2$ based on the available pilot datasets (Appendix S3). In order to compare different survey efforts, we simulated datasets based on all combinations of number of plots per year $N_1 = N_2 = \{30, 90, 120\}$, percentage of plots having independent observations {100%, 50%, 25%}, and number of independent observations per plot $J = \{3, 6\}$. Note that for each simulated dataset, the allocation of effort was the same for both years.

For each unique number of plots per year, we simulated a total of 250 datasets, each with a total of six observations for every plot. Then for the additional variants of within-season revisit designs (number of replicate observations and percentage of plots with multiple observations) the full dataset was subset accordingly. In other words, for the scenario with 50% of 30 plots surveyed three times, the first, second, and third of six simulated observations for 15 plots and the first of six observations for the remaining 15 plots was retained for fitting the ZABE model.

We focused on the ability to detect an increase in mean plant cover between 2 years using our hierarchical ZABE model under reasonable survey effort scenarios. For each simulated dataset, we considered evidence for a management effect the posterior probability that the θ_1 parameter was greater than zero. For each scenario, we used the posterior probabilities across all simulated datasets to approximate the distribution of this quantity. We compared the distributions of these posterior probabilities across the different scenarios to assess how the number of plots and within-season revisit structure impacted the ability to detect an increase in mean plant cover using our hierarchical ZABE model. This approach is similar to frequentist-based power analyses used to determine survey effort for a given set of parameter values informed by pilot data (e.g., Irvine & Rodhouse, 2010). Frequentist statistical power is the probability of rejecting the null hypothesis of no management effect when the alternative hypothesis is true (data are generated with a meaningful effect).

Again, models with any $\hat{R}$ values larger than 1.1 were excluded from our summaries. Some scenarios we examined resulted in additional computational difficulties due to a combination of a small number of plots and few replicate observations to each plot. In Stan the "divergent transitions" warning indicates the Hamiltonian Monte Carlo sampler is not reliably sampling from the desired posterior distribution. We also excluded model results which had more than 10 divergent transitions in our sampling design simulations. In practice, results should not be used when any divergent transitions occur, but we found that posterior summaries from model fits with few divergent transitions (≤10) were similar to those with none. We provide code to conduct these simulations or explore other parameter values (Appendix S3) but it should be noted that long computation times are required because models are fit using a Bayesian approach with MCMC.

3 | RESULTS

3.1 | Comparison of statistical models for plant cover with observation errors

Only our hierarchical ZABE model showed minimally biased estimates and near 95% coverage for occupancy (ψ) across all scenarios we investigated (squares Figure 2). The average 95% PIs for ψ using the naïve model substantially underestimated true occupancy and displayed coverage much lower than 95% (circles Figure 2). Improving the average detectability by increasing mean cover (μ from 0.25 to 0.75) and increasing γ_1 (from 2 to 4) resulted in minimal bias and nominal coverage rates for the "ad hoc" approach (triangles Figure 2). With the "ad hoc" approach and $\gamma_1 = 4$ and $\mu = 0.75$, the chances of having at least one of three observations with a detection is nearly one (perfect detection), reducing that source of observation error substantially. Also, increasing average detectability increased the precision of the average 95% PIs based on our hierarchical ZABE model. Our results also illustrate that increasing the variance of the distribution for observed values (σ from 0.5 to 1) did not noticeably impact the posterior distributions for ψ using any of the models (Figure 2 comparing left to right panels).

For the naïve and "ad hoc" approaches, μ estimates were positively biased when $\mu = 0.25$ but were less biased when $\mu = 0.75$ (Figure 3). This makes sense intuitively because, again, an increase in mean cover increases detectability on average (since $\gamma_1 > 0$ in Equation 4). Additionally, the positive bias for μ is due to more non-detections at plots with smaller plant cover values. In other words, imperfect detection results in fewer plots used for estimating μ, and those plots are biased toward the higher cover values. For all of the scenarios, the average posterior means for μ from our hierarchical ZABE model were near the true values and the 95% PIs showed coverage rates close to nominal (Figure 3). For the misspecified models (naïve and "ad hoc"), increasing the variance of observed values (σ from 0.5 to 1, left to right columns) and improving detection (γ_1 from 2 to 4, within panel comparison) shifted the average posterior means away from the true value when $\mu = 0.25$. These changes, however, were not as consistent when $\mu = 0.75$ potentially because measurement error partially counteracts the bias due to imperfect detection when mean cover is larger than 0.5 (see Appendix S1 for more details). Increasing

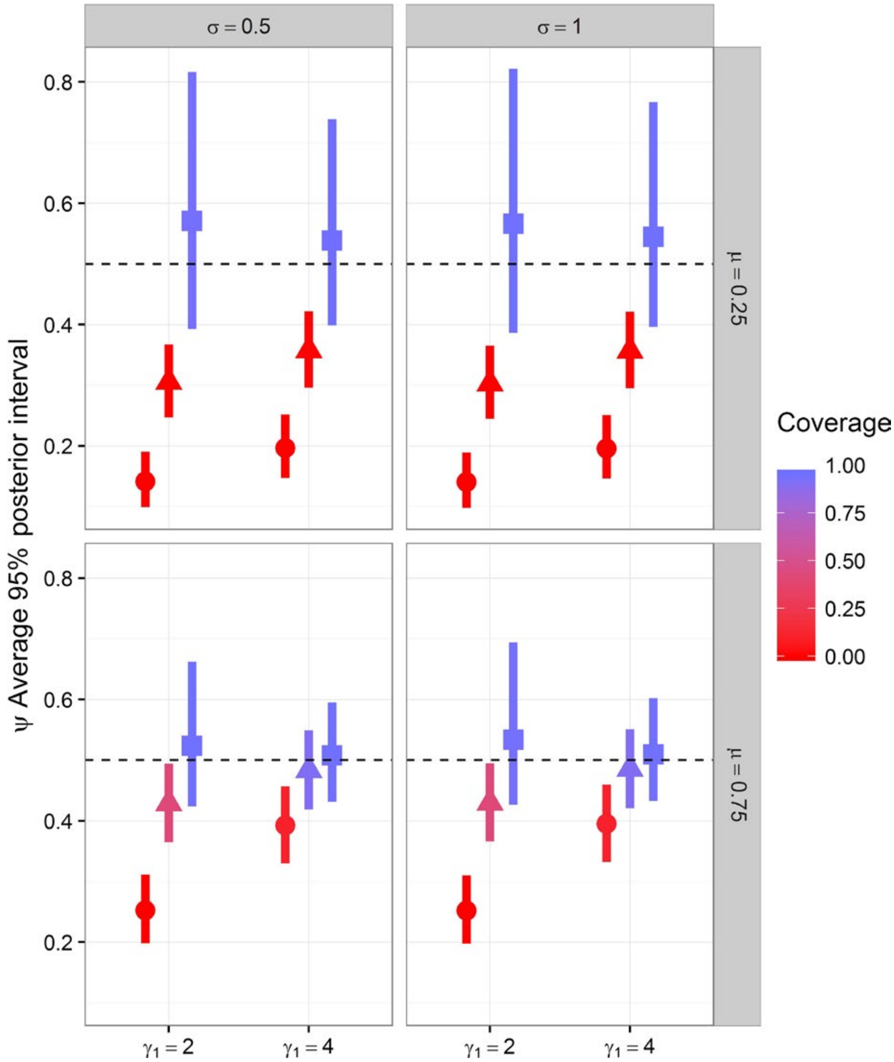

FIGURE 2 Average 95% posterior intervals for probability of occupancy, ψ, for different parameter combinations investigated and data generated with both detection and measurement errors. Plotting characters denote the different models fit with circles showing the naïve model with a single observer (ZAB), triangles showing the "ad hoc" approach of using a synthesis of three observations as the response in ZAB, and squares showing the hierarchical zero-augmented beta regression model (ZABE). The colour of each average PI indicates coverage rate of the 95% PIs based on 500 simulated datasets. Dashed lines indicate the true value of ψ = 0.5. For each scenario, an average 95% posterior interval was found by averaging the 2.5% quantile, 97.5% quantile, and posterior means across all simulated datasets

the strength of the relationship between cover and detection (γ_1 from 2 to 4) had a larger impact on the average posterior intervals for μ than increased variability (σ from 0.5 to 1) in the measurement error model (Figure 3).

Imperfect detection and measurement error did not impact inferences as strongly for the precision of the cover distribution, ϕ, using the naïve and "ad hoc" models (circles and triangles, Figure 4). Again, the hierarchical ZABE model consistently had nominal coverage rates for ϕ across all scenarios we investigated (Figure 4). The naïve and "ad hoc" models' underestimation for precision when $\sigma = 1$ demonstrates the potential gain by fitting the ZABE model and accounting for variation among observations related to measurement errors.

3.2 | Survey design requirement investigation

For the survey effort scenarios we investigated, the distributions of posterior probabilities that $\theta_1 > 0$ became more concentrated towards 1 as the proportion of plots receiving revisits increased (across panels, Figure 5), the number of plots in each year increased (within panels, Figure 5), or the total number of observations within a plot increased (red vs. blue boxplots, Figure 5). Of these factors, increasing the sample size from 30 to 90 had the most meaningful impact on the distributions of posterior probabilities. Overall, with at least 90 total plots, any of the revisit scenarios we explored showed distributions of posterior probabilities that $\theta_1 > 0$ strongly concentrated at one. This can be interpreted as a high probability that a change in mean plant cover would be detected using the specified level of effort and our ZABE model. We also found that sparser datasets (30 plots with 3 observations per plot) tended to have more realizations with convergence issues.

4 | DISCUSSION

While imperfect detection and measurement errors in vegetation surveys have been widely reported (Morrison, 2016), these errors are still underappreciated when analysing and interpreting plant cover data. Our hierarchical ZABE model directly accounts for these observation errors and expands the available approaches for modelling occupancy and abundance (cover) for plants. Simulations showed our proposed ZABE model consistently produced unbiased

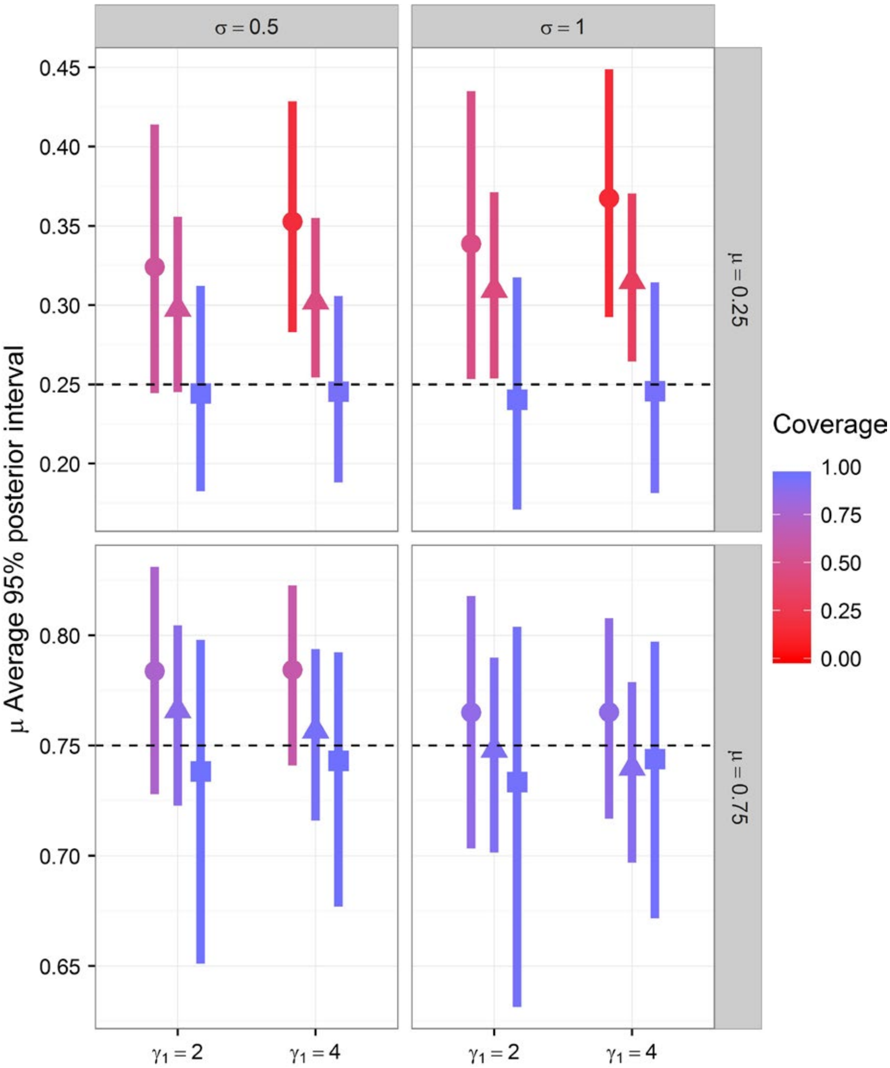

FIGURE 3 Average 95% posterior intervals for the average cover proportion, μ, for the different parameter combinations investigated and data generated with both detection and measurement errors. Plotting characters denote the different models fit with circles showing the naïve model with a single observer (ZAB), triangles showing the " hoc" pproach of using a synthesis of three observations as the response in ZAB, and squares showing the hierarchical zero-augmented beta regression model (ZABE). The colour of each average PI indicates coverage rate of the 95% PIs from simulations. Dashed lines show the true values of μ = 0.25 and μ = 0.75. For each scenario, an average 95% posterior interval was found by averaging the 2.5% quantile, 97.5% quantile, and posterior means across all simulated datasets

estimates and nominal coverage of ecological parameters (occupancy and mean cover) when observation errors were present. On the other hand, when measurement errors and imperfect detection were ignored, inferences for the ecological parameters using the naïve or "ad hoc" approaches could be severely misleading, resulting in erroneous conclusions. The only exception was when detection was nearly perfect, analysing a composite response from multiple observations (presence indicated by at least one detection and the average non-zero cover values) with the ZAB model might be reasonable.

The ZABE model provides a framework for plant cover analyses that can be adapted and adjusted depending on particular studies and questions of interest. Some straightforward adjustments, for example, would be to model systematic differences in both measurement error and detectability related to observers, time of year, or other factors. Additionally, environmental gradients of interest (e.g., hydrological factors) that may influence distribution and abundance of, in our case, submerged aquatic plants can be investigated. However, proper ecological interpretation of the site-level occupancy and mean cover parameters in the ZABE model depend on plot size (grain size or analysis unit used) and spatial domain of inference. Further, measurement error and detection probability estimates likely depend on plot size, morphology of the focal plant species and life stage (e.g., Chen et al., 2009; Kéry & Gregg, 2003). Future work could explore accounting for false positive detections that occur because of species misidentifications.

Another common method for monitoring plant species is visually assessing areal coverage within a plot and then recording an integer value based on a predefined cover class classification (e.g., cover class = 1 if percent cover >0% and <5%; Daubenmire, 1959). Without observation errors, these ordinal data can be analysed within the ZAB approach by treating continuous cover as a latent variable that is clipped or discretized into the observed categories (Herpigny & Gosselin, 2015; Irvine et al., 2016). Modelling ordinal category probabilities with a ZAB distribution can yield a more intuitive interpretation compared to cumulative logit models (Irvine et al., 2016). A useful next step is to extend our hierarchical ZABE model to allow for plant cover data recorded as ordinal categories while still accounting for measurement error and imperfect detection.

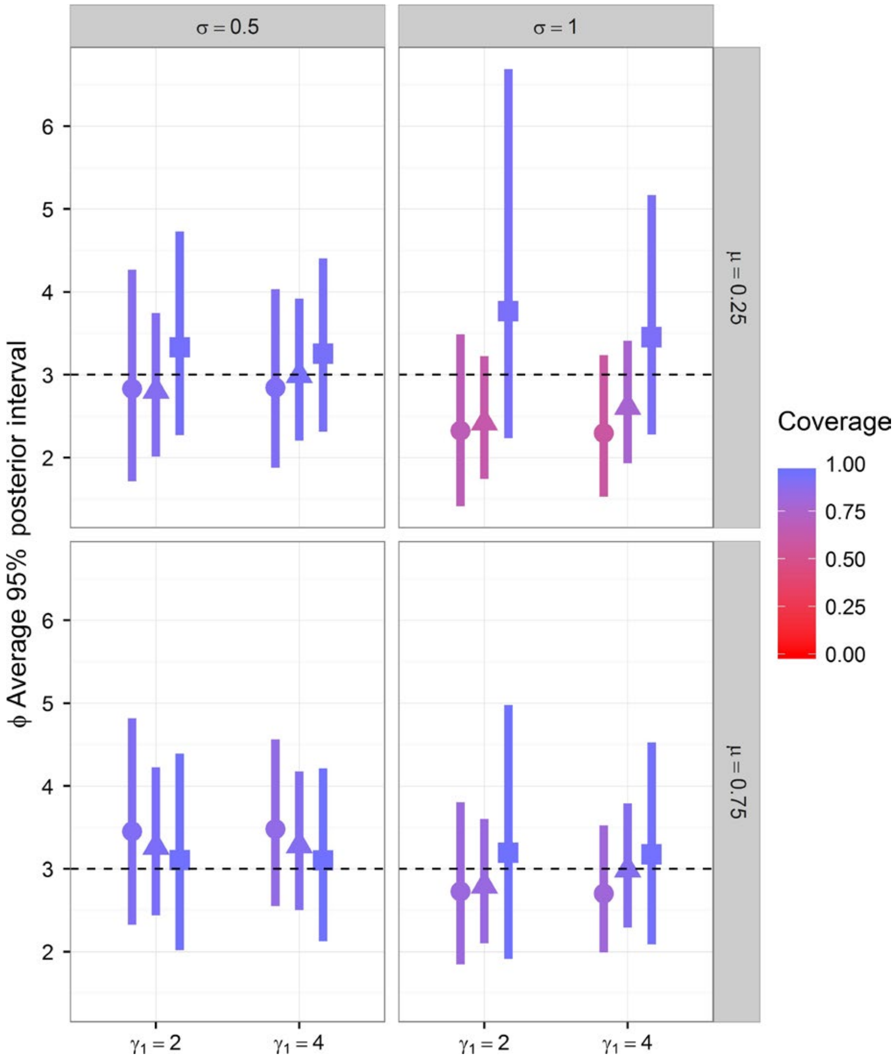

FIGURE 4 Average 95% posterior intervals for precision of the beta distribution for cover, ϕ, for different parameter combinations investigated and data generated with both detection and measurement errors. Plotting characters denote different models fit with circles showing the naïve model with a single observer (ZAB), triangles showing the "ad hoc" approach of using a synthesis of three observations as the response in ZAB, and squares showing the hierarchical zero-augmented beta regression model (ZABE). The colour of each average PI indicates coverage rate of the 95% PIs from simulations. Dashed lines indicate the true value of $\phi = 3$. For each scenario, the average 95% posterior interval was found by averaging the 2.5% quantile, 97.5% quantile, and posterior mean across all simulated datasets

Our results also highlighted that detection errors more negatively impacted ecological parameter estimates than measurement errors based on our scenarios. For occupancy, this result was not surprising given the large body of work on occupancy models for wildlife populations (Bailey, MacKenzie, & Nichols, 2014). However, imperfect detection also led to poor inferences about mean plant cover due to the positive relationship between detection and cover within a plot. Again, this connection was supported by field studies (Burg et al., 2015; Milberg et al., 2008; Vittoz et al., 2010) and is also similar to the relationship between infection intensity and detection in applications of occupancy models for epidemiological studies (Miller, Talley, Lips, Campbell Grant, 2012). The relationship between detection and cover emphasizes that an occupancy model alone, as some have proposed for vegetation studies, is not adequate because it does not account for this potentially important source of heterogeneity in detection probabilities. Our findings underscore that relative abundance of plant species can strongly influence statistical inferences when related to detectability.

Our simulation framework assessed the ability to detect a biologically meaningful change in mean cover using the ZABE model. For our situation, we found that more than 30 plots with at least three observations per year produced posterior probabilities consistently near 1 (Figure 5). To minimize field effort, not all the plots require multiple observations and it is possible to focus multiple-observer survey effort on a subset of the total sample size (25%) each year. However, these suggestions are conditional on our assumed sampling design, parameter values, and question of interest. In our example, SAV assemblages were surveyed within 1 m × 1 m plots that were randomly selected each year within a predefined geographic extent that corresponded to a managed wetland unit. The chosen areal extent of the sampling frame, plot size and shape, and sampling design should be considered when interpreting the needed level of effort to achieve the desired statistical inferences if our simulation code is directly adopted for other situations (Appendix S3).

For plant studies, as others have shown for wildlife surveys, it is important to account for imperfect detection when modelling species distribution and abundance. However, an underappreciated consideration is that plant cover is often a meaningful predictor for wildlife-related response variables (e.g., sage grouse nest-site selection and success; Moynahan, Lindberg, Rotella, &

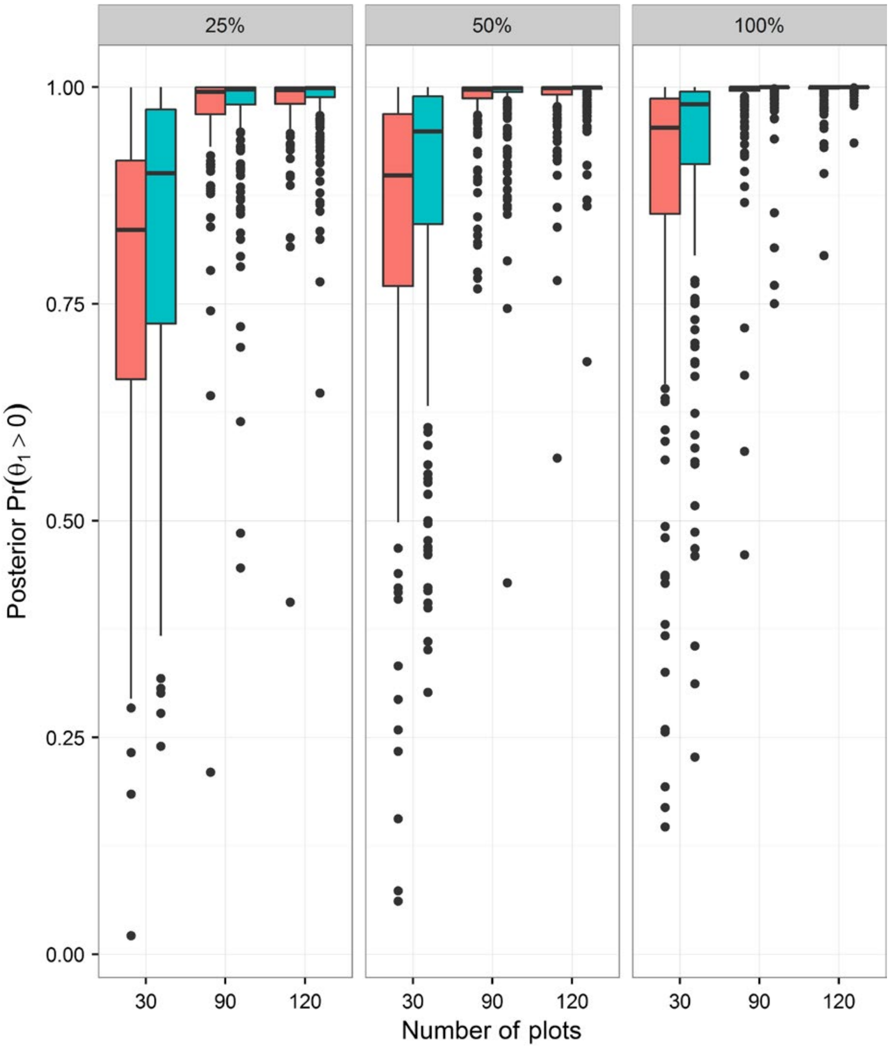

FIGURE 5 Boxplots showing the distribution of posterior probabilities of an increase in mean cover between 2 years or seasons ($\theta_1 > 0$) from fitting the hierarchical ZABE model to simulated datasets under different levels of survey effort and 3 years or seasons of data collection. Panels show percentage of plots receiving revisits {100%, 50%, 25%} with red and blue distinguishing between 3 and 6 independent, replicate observations per plot, respectively

Thomas, 2007). Observation error in plant cover could influence a researcher's ability to properly select among competing hypotheses regarding drivers of wildlife populations. These relationships may provide the basis for broadly-applied management recommendations (e.g., Connelly, Schroeder, Sands, & Braun, 2000) and if misidentified or poorly estimated could lead to unforeseen consequences at broad geographic extents. Future work should explore these potential downstream ramifications related to unaccounted for observation errors in plant percent cover and other habitat metrics. In any study, plant species with low average abundance and high ecological value may warrant the additional cost of gathering and analysing multiple independent observations per plot to guard against potentially serious underestimation of occupancy and overestimation of abundance.

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AUTHOR'S CONTRIBUTIONS

W.J.W. and K.M.I. conceived the approach and designed the methods; W.J.W. authored code, conducted simulations, and led writing of the manuscript; K.M.I. contributed critical revisions to the manuscript; J.M.W. and J.K.B. had substantial contribution to acquisition and interpretation of data and assisted with writing the manuscript. All authors gave final approval for publication.

DATA ACCESSIBILITY

All code and data are archived at https://doi.org/10.5066/F7MW2FMC.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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