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Reports

# Improving occupancy estimation when two types of observational error occur: non-detection and species misidentification

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*Abstract*. Efforts to draw inferences about species occurrence frequently account for false negatives, the common situation when individuals of a species are not detected even when a site is occupied. However, recent studies suggest the need to also deal with false positives, which occur when species are misidentified so that a species is recorded as detected when a site is unoccupied. Bias in estimators of occupancy, colonization, and extinction can be severe when false positives occur. Accordingly, we propose models that simultaneously account for both types of error. Our approach can be used to improve estimates of occupancy for study designs where a subset of detections is of a type or method for which false positives can be assumed to not occur. We illustrate properties of the estimators with simulations and data for three species of frogs. We show that models that account for possible misidentification have greater support (lower AIC for two species) and can yield substantially different occupancy estimates than those that do not. When the potential for misidentification exists, researchers should consider analytical techniques that can account for this source of error, such as those presented here.

*Key words: anuran censuses; call surveys; false positive detection;* Lithobates *spp.; misclassification; misidentification; multiple states; presence–absence; proportion area occupied; site occupancy; species occurrence.*

## Introduction

Accurately determining patterns of species occurrence requires that detection errors are properly accounted for (MacKenzie et al. 2002, 2003). Methodological advances that address imperfect detection have motivated numerous recent ecological studies of site occupancy and local extinction and colonization dynamics. Occupancy estimation is now part of the standard tool kit for modeling species dynamics, monitoring trends, and informing management (MacKenzie et al. 2002, 2003, Mazerolle et al. 2007). Methods have largely focused on false negative detections, which occur when individuals are not detected at occupied sites. Less attention has been given to false positive detections, which occur when a species is recorded at a site that is unoccupied by that species. These errors typically arise when organisms are detected but the species is misidentified, but can also occur when detections are recorded at sites where no species are present. Controlled studies of electronically broadcast avian and anuran calls show that even highly trained observers can misclassify species as present when they are actually absent (Simons et al. 2007, Alldredge et al. 2008, McClintock et al. 2010*a*). False positive detections have negative consequences when estimating occupancy if not accounted for, leading to overestimation of occupancy probability (Royle and Link 2006) and biasing estimators for both extinction and colonization probabilities (McClintock et al. 2010*b*, *c*).

Royle and Link (2006) developed the existing approach to account for false positive detections when estimating occupancy (hereafter Royle-Link model). Numbers of observed detections for each site are treated as a simple binomial mixture, the result of false positive detections occurring at unoccupied sites and true positive detections at occupied sites. Unfortunately, limitations of the model have impeded its successful implementation (e.g., Fitzpatrick et al. 2009, McClintock et al. 2010*b*). These include correlation among parameters in the model and inability to distinguish heterogeneity in true positive detection probabilities among sites from heterogeneity due to false positive detections. This affects identifiability of model parameters and can result in unrealistic parameter estimates (Royle and Link 2006, Fitzpatrick et al. 2009, McClintock et al. 2010*b*). Estimators that incorporate additional information about the detection process, e.g., degree of certainty in a detection and multiple survey methods, may overcome these difficulties (McClintock et al. 2010*b*).

We present new methods for estimating occupancy, which incorporate additional information about the false positive detection process. We deal first with the

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case where a single detection method is utilized and detections are classified into multiple states according to the degree of certainty that the detection is correct. Then we address cases where multiple detection methods are utilized, and each method differs in the degree of certainty that any given detection is correct. For each of these models, we present the likelihood and examine the properties of maximum likelihood estimates using Monte Carlo simulations. We then demonstrate our methods using surveys of American bullfrogs (*Lithobates catesbeianus*), green frogs (*L. clamitans*), and pickerel frogs (*L. palustris*) conducted at 124 sites in and around the Maryland side of the Chesapeake and Ohio Canal National Historic Park (CHOH), USA, during March–July 2005. We also provide results from an experimental study that used observations of electronically broadcast calls of the southern leopard frog (*L. sphenocephalus*) to simulate surveys of sites with known occupancy states.

## Model Descriptions

### *Multiple detection state model*

We first developed the model for cases where a single detection method is used. Consider a general model where $R$ sites are each visited $T$ times. The true occupancy state of the $i$th site, $z_i$, is assumed to come from one of $K$ occupancy states. Observations of the $i$th site on the $t$th visit, $y_{it}$, are classified into one of $L$ observation states that differ in the probability of being a false positive detection. We define the probability of recording an observation $l$ conditional on the true occupancy as

$$\pi_{lk} = P(y_{it} = l \mid z_i = k). \quad (1)$$

The probability that the true occupancy state is $k$ (i.e., $z_i = k$) is denoted by $\psi_k$, where $\sum_k \psi_k = 1$. The likelihood can then be expressed as

$$\mathcal{L}(\pi, \psi \mid y) \propto \prod_{i=1}^{R}\left(\sum_{k=0}^{K-1}\left[\left\{\prod_{t=1}^{T}\pi_{y_{it}k}\right\}\psi_{ik}\right]\right). \quad (2)$$

We demonstrate use of the likelihood when two types of detections occur, where the first type may include false positive detections ("uncertain detections"), but the second does not ("certain detections"). For example, when sampling a site to determine whether it is occupied by a species, one might consider an indirect observation based on sign to be uncertain (e.g., scat or tracks) and a direct observation to be certain (e.g., visual encounter). Let $z_i$ be 1 if the $i$th site is occupied and 0 if it is unoccupied. An observation $y_{it}$ from the $i$th site on the $t$th visit is either 2, for a certain detection; 1, for an uncertain detection; or 0, for no detection.

We can then parameterize the model using three parameters: The probability of (incorrectly) detecting the species at a site given the site is unoccupied ($p_{10}$), the probability of detecting the species at a site given the site is occupied ($p_{11}$), and the probability that a detection is classified as certain given that the site is occupied and the species was detected ($b$). The reparameterized detection probabilities for Eq. 1 are given in Table 1, which maintains a necessary constraint that each row sums to 1. We illustrate how Eqs. 1–2 and Table 1 are used to calculate the probability of observing example detection histories for individual sites in Appendix A. A generalized linear model can be used to specify the relationship of each of the parameters to covariates (e.g., logit$[p_{11}] = \beta X$). Rather than the conditional binomial parameterization, one could also estimate the probabilities of each of the $L$ observation states, which come from a multinomial distribution, using a multinomial-logit function. We demonstrate how the likelihood can be applied to another sampling design where $K = 4$ occupancy states and $L = 4$ observation states occur in Appendix B. Other potential generalizations are considered in the *Discussion*.

Table 1. Parameterization for the expected probability of recording the observation state $y$ given the true state of the site $z$ ($P[y \mid z]$) for the multiple detection state model with only certain and uncertain detections.

| True state | $P(y = 0 \mid z)$ | $P(y = 1 \mid z)$ | $P(y = 2 \mid z)$ |
|---|---|---|---|
| $z = 0$; unoccupied | $1 - p_{10}$ | $p_{10}$ | 0 |
| $z = 1$; occupied | $1 - p_{11}$ | $(1 - b) \times p_{11}$ | $b \times p_{11}$ |

*Notes:* Possible observations were not detected (0), had uncertain detection (1), or had certain detection (2). Definitions: $p_{10}$, the probability of (incorrectly) detecting the species at a site given the site is unoccupied; $p_{11}$, the probability of detecting the species at a site given the site is occupied; and $b$, the probability that a detection is classified as certain given that the site is occupied and the species was detected.

### *Multiple detection method model*

Our second approach allows multiple detection methods to be employed on unique sampling occasions for a site where the true occupancy state is static. We keep the same notation from the multiple detection state model for the first detection method. In addition, the $R$ sites are now visited $S$ additional times using the second detection method. Observations of the $i$th site on the $s$th visit, $w_{is}$, are classified into one of $M$ observation states. The probability of detecting a species, conditional on whether a site is occupied or not, for each of the methods is

$$\pi_{lk} = P(y_{it} = l \mid z_i = k)$$

and

$$\tau_{mk} = P(w_{is} = m \mid z_i = k). \quad (3)$$

The likelihood is

$$\mathcal{L}(\pi, \tau, \psi \mid y, w) \propto \prod_{i=1}^{R}\left(\sum_{k=0}^{K-1}\left[\left\{\prod_{t=1}^{T}\pi_{y_{it}k}\right\}\times\left\{\prod_{s=1}^{S}\tau_{w_{is}k}\right\}\psi_{ik}\right]\right). \quad (4)$$

Table 2. Parameterization for the expected probability of recording the observation state $y$ using an uncertain detection method, and of recording observation state $w$ using a certain detection method, given the true state of the site $z$ for the multiple detection method model with only certain and uncertain detections.

| | Uncertain detection method | | Certain detection method | |
|---|---|---|---|---|
| True state | $P(y = 0 \mid z)$ | $P(y = 1 \mid z)$ | $P(w = 0 \mid z)$ | $P(w = 1 \mid z)$ |
| $z = 0$; unoccupied | $1 - p_{10}$ | $p_{10}$ | 1 | 0 |
| $z = 1$; occupied | $1 - p_{11}$ | $p_{11}$ | $1 - r_{11}$ | $r_{11}$ |

*Notes:* Possible observations for each sampling method were not detected (0) or detected (1). Parameters include: $p_{10}$, the probability of a false positive detection using the first method; $p_{11}$, the probability of a true positive detection using the first method; and $r_{11,}$ the probability of a true positive detection using the second method.

Consider the case where two methods are used; the first may include false positive detections but the second does not. As an example, the first method could be auditory call surveys with some level of uncertainty and the second method direct handling under the assumption species can be identified with certainty. Data obtained from the first detection method are of the type envisioned by Royle and Link (2006). Data obtained from the second method follows the standard design of MacKenzie et al. (2002), where false positive detections are assumed not to occur.

We use $p$ to specify detection probabilities for the uncertain detection method and $r$ to specify detection probabilities for the certain method. The full detection probabilities for all state combinations are found in Table 2. Parameters include: $p_{10}$, the probability of a false positive detection using the first method; $p_{11}$, the probability of a true positive detection using the first method; and $r_{11}$, the probability of a true positive detection using the second method. In Appendix A we illustrate how Eqs. 3–4 and Table 2 are used to calculate the probability of observing a set of example detection histories. When only one visit can be conducted using the certain method, for all parameters to be identifiable, at least two visits must be conducted using the uncertain detection method and vice versa, so that $T + S \geq 3$. It is not necessary that both methods be employed at all sites. When sampling is incomplete one assumes that the sites where the second detection method was used are representative of both false positive and true positive detection probabilities for all sites in the study. The model is easily generalized to incorporate multiple occupancy and observation states. This involves specifying $\pi_{lk}$ and $\tau_{mk}$ to incorporate additional observation and occupancy states as is done in Table 1 and Appendix B. Although the number of observation states could differ between the two detection methods, the number of occupancy states must be the same for both methods. Similarly, more than two detection methods can be specified by expanding the likelihood in Eq. 4 to incorporate additional products specifying detection probabilities for the additional methods.

Example code for running both models using R (version 2.10.1; R Development Core Team 2009) is provided in Supplement 1. Models are also implemented in the latest version of Program Presence (version 3.1; Hines 2010). We found that the maximum likelihood estimator was well behaved for standard numerical optimization routines. However, it is always advisable to try multiple starting values for parameters when fitting models to double-check that results are not for a local maximum.

### *Relationship to other occupancy models*

The standard occupancy model first proposed by MacKenzie et al. (2002; MacKenzie model) and the Royle-Link model are both special cases of the two models presented here. The MacKenzie model is a special case of the multiple detection state model when $p_{10} = 0$ and $b = 0$ and the multiple detection method model when $p_{10} = 0$ and $p_{11}$ is allowed to differ among survey occasions when each of the detection methods is used. The Royle-Link model is intermediate for both models, in that $p_{10}$ is estimated for all occasions and all detections are uncertain.

Similarly, there is a direct relationship between our multiple detection state model and the multi-state occupancy framework developed by others (e.g., Royle 2004, Royle and Link 2005, Nichols et al. 2007, MacKenzie et al. 2009). The multiple detection state model, where detections are classified as certain ($y = 2$) or uncertain ($y = 1$), is similar to other multistate models in that even when a species is detected, uncertainty can remain about the true state of the site. The parallel is fully realized in our example where occupied sites are classified into multiple occupancy states based on potential call intensity levels (Appendix B). In this case, our model is an extension of the model described by Royle and Link (2005), allowing for the possibility of false positive detections. The multiple detection method model also has parallels to the approach developed by Nichols et al. (2008) for multiple detection methods at the same site.

## Simulation Study

Using Monte Carlo simulations, we examined efficiency of our models for estimating occupancy probabilities. Complete descriptions of methods and results are included in Appendices C and D, respectively. We conducted 1000 simulations each for 324 parameter

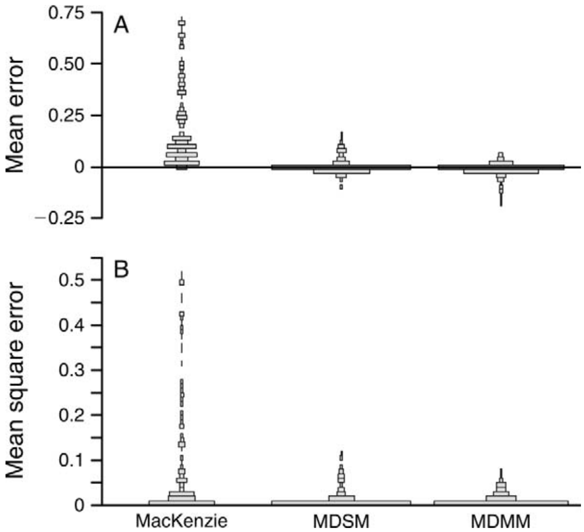


FIG. 1. We compared (A) mean error and (B) mean square error for occupancy estimates (proportion of sites in which the species occurs) for each of 324 simulated parameter combinations (see Appendix: Table C1 for values). Bar widths are relative to the number of simulated parameter combinations falling in an interval, and within each plot a given width represents the same number of combinations for each estimator. Results are given for the MacKenzie model, the multiple detection state model (MDSM), and the multiple detection method model (MDMM). For the MDSM and MDMM, the simulated probability of certain detections (certain state, $b$, or certain method, $r_{11}$) was set at 0.50.

combinations that included false positives. All analyses were done using R (version 2.10.1; R Development Core Team 2009). The Multiple Detection State and Multiple Detection Method estimators of occupancy had reduced bias and increased precision when false positive detections occurred compared to the MacKenzie model, which systematically overestimated occupancy (Fig. 1). Improvement using our models was greatest when occupancy was low, true positive detection probabilities were small, and the number of sampling occasions great (Fig. 2). In simulations where false positive detections were not included in data sets, model selection procedures ranked estimators that did not include a false positive detection probability over those that did >95% of the time. The multiple detection state model also performed better than the alternative of removing all uncertain detections from the data set and analyzing data using the MacKenzie model. Thus, uncertain detections contain information that can be used to improve occupancy estimates when false positive detections are accounted for in the estimation process.

## EXAMPLE APPLICATIONS

We used two data sets to illustrate the application of our methods. The first example utilized both for an experimental study where true occupancy state was known and false positive detections were known to occur (complete descriptions of analysis and results are included in Appendix E). For these data, the MacKenzie model overestimated true occupancy by nearly 80%. However, when a small portion of true detections was classified as certain, estimated occupancy probabilities using both models were highly accurate.

Our second example used data for three frog species: American bullfrogs (*Lithobates catesbiana*), green frogs (*L. clamitans*), and pickerel frogs (*L. palustris*). All sites were sampled via anuran call surveys where sites were classified to observation state based on calling intensity.

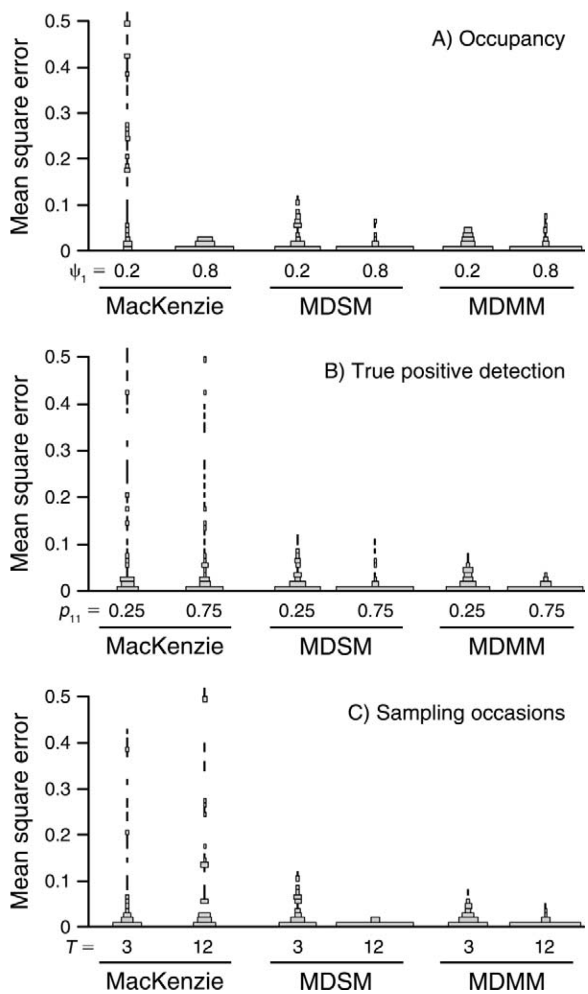


FIG. 2. Mean square error for occupancy estimates (proportion of sites in which the species occurs) for each of 324 simulated parameter combinations (see Appendix: Table C1 for values). Bar widths are relative to the number of simulated parameter combinations falling in an interval, and within each plot a given width represents the same number of combinations for each estimator. Results are given for the MacKenzie model, the multiple detection state model (MDSM), and the multiple detection method model (MDMM). For the MDSM and MDMM, the simulated probability of certain detections (certain state, $b$, or certain method, $r_{11}$) was set at 0.50. Results are presented for the lowest and highest simulated values of (A) occupancy ($\psi_1$), (B) true positive detection probability ($p_{11}$), and (C) number of sampling occasions ($T$).

Reports

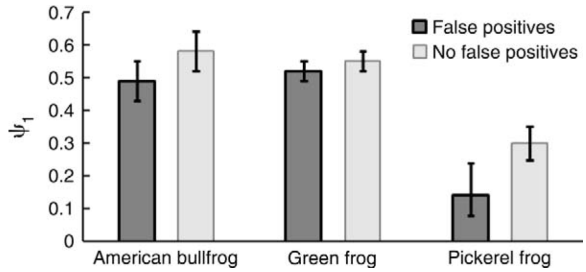


FIG. 3. Estimates of occupancy (proportion of sites in which the species occurs) for three species of frogs at sites in and around the Maryland side of the Chesapeake and Ohio Canal National Historic Park, USA. These estimates were systematically lower when the possibility of false positive detections was included in models than when it was not.

Observers also visited a subsample of wetlands near acoustic observation points and recorded species seen and handled, providing a second detection method. The auditory survey occurred on 11 routes each consisting of 10 sites on three occasions during March–June 2005 as part of the North American Amphibian Monitoring Program (NAAMP; Weir and Mossman 2005). All were within a 32 km radius of the Chesapeake and Ohio Canal National Historic Park (CHOH), USA. An additional route, consisting of 14 sites, was located within CHOH, and these sites were surveyed for calling anurans on 14–30 occasions. Detections from call surveys were classified based on NAAMP calling intensity categories: low (individuals can be counted; there is space between the calls), medium (calls of individuals can be distinguished, but there is some overlapping of calls), and high (full chorus, calls are constant, continuous, and overlapping). In addition, 34 randomly selected wetlands <250 m from CHOH call count locations were directly sampled eight times during the same time period (i.e., by two independent observers over four survey occasions). Observers recorded observations of individuals in all life history phases (adults, egg masses, and tadpoles) from visual encounter surveys and captures by dip net. Data for all ponds associated with a site were combined to yield certain detection data for each of the eight sampling occasions.

We combined multiple detection state and method models to analyze the data. We treated call surveys as our first detection method, where false positive detections were allowed, and the pond surveys as our second detection method, where species were identified in the hand and detections were assumed to be certain. Furthermore, for the first survey, we assumed medium and high intensity detections were certain ($y = 2$) and low intensity detections were uncertain ($y = 1$). The complete parameterization for both models is given by replacing the parameterization for the uncertain detection method in Table 2 with the one in Table 1 and maximizing the multiple detection method likelihood (Eq. 4).

We estimated separate occupancy probabilities for NAAMP and CHOH sites. Ambient air temperature has an important effect on calling frequency and intensity for amphibians (Mazerolle et al. 2007). Therefore, $p_{11}$ and $b$ were allowed to vary as a quadratic function of air temperature (temp) at the time of the survey, where $\text{logit}(p_{11}) = \alpha_0 + \alpha_1 \times \text{temp} + \alpha_2 \times \text{temp}^2$ and $\text{logit}(b) = \beta_0 + \beta_1 \times \text{temp} + \beta_2 \times \text{temp}^2$. To determine support for the presence of false positives in the data sets we compared the full parameterization to one where false positive detections were assumed not to occur by making the constraint that $p_{10} = 0$. We calculated the overall occupancy probability as a weighted mean, based on the relative proportions of NAAMP and CHOH sites.

The estimated false positive probability, $p_{10}$, was 0.030 for bullfrog, 0.008 for the green frog, and 0.027 for the pickerel frog. For the green and pickerel frogs the model where false positive were accounted for had lower AIC than the model where they were assumed not to occur ($\Delta$AIC = 3.2 and 0.3, respectively). The model where false positives did not occur had lower AIC for the bullfrog ($\Delta$AIC = 0.8). As expected, for all species the estimates of occupancy were lower for the model where false positive detections were accounted for (Fig. 3). The greatest difference occurred for the pickerel frog, where the occupancy estimate was less than half the estimate from the model assuming no false positive detections.

## DISCUSSION

By accounting for false positive detection probability researchers can significantly reduce bias and increase precision of estimators of occupancy when false positive detections occur. Our models offer a flexible approach to account for misclassification, applicable to a range of situations encountered in occupancy studies. Methods can take advantage of additional information that may exist in established protocols and can limit use of costly sampling methods such as direct handling to a subset of sites and sampling occasions. The results from our simulations and example applications reinforce previous findings that even small probabilities of misclassification can lead to significant biases in estimates of the proportion of occupied sites (Royle and Link 2006, McClintock et al. 2010*b*), making analytical methods that account for false positive detections necessary for many studies.

Results presented here can be used to determine when our methods will be most useful, how to optimally implement sampling when using these models, and some general guidelines for analyses. False positive detections induced significant bias, and as misidentifications increased, bias also increased. Data collection methods where false positive errors are known to occur such as large-scale volunteer-based surveys (e.g., Weir and Mossman 2005), interviews with local experts (Karanth et al. 2010, Zeller et al. 2011), use of historical records (Boessenkool et al. 2010), call surveys (Simons et al. 2007, McClintock et al. 2010*a*), computer algorithms to detect species from recordings (Acevedo et al. 2009), and laboratory assays (McClintock et al. 2010*c*), should address this bias when analyzing occupancy data. In our simulation and data studies, the largest bias occurred when occupancy probability was low. Given the serious consequences for management of rare species when inaccurate estimates of status occur, accounting for this bias will be especially important (McKelvey et al. 2008). Interestingly, bias also increased as sampling occasions increased, and increasing true positive detection probabilities and the number of sampled sites did little to reduce bias. Thus, problems with false positive detections are not solved by simply increasing sampling effort.

Performance improved for both of our models as the proportion of certain detections increased. The multiple detection state model performed poorest when occupancy probability was low and the number of sampling occasions was few. The multiple detection method model performed poorest when occupancy probability was high and true positive detection probability low. We did not examine how the number of visits using the certain detection method affected estimates, but increasing occasions is likely to also improve performance.

For simulations and examples presented here we assumed that a subset of observations was certain, an assumption that may be relaxed. For example, observations could be assigned to "uncertain" and "less uncertain" categories. Allowing that $\pi_{20} > 0$ and $\tau_{10} > 0$ (Eqs. 1 and 3) and specifying the constraints that $\pi_{20} < \pi_{10}$ and $\tau_{10} < \pi_{10}$, would result in a model with multiple uncertain observation states. Similarly, the likelihoods easily accommodate additional true occupancy states ($K > 2$), observation states ($L > 3$), or more than two detection methods (e.g., see Appendix B).

For purposes of illustration, we used a model selection criterion in our example to discriminate between models that did and did not allow for false positive detections. When false positive detections are known to occur using a model where the false positive detection probability was 0 would not make sense. As shown by simulation, when detection probabilities are sufficient and false positive detections occur, our models consistently outperform the MacKenzie model across a wide range of scenarios. We saw some evidence that even when false positives occur, power may still be somewhat limited to discriminate between models where false positives are and are not accounted for in the model. Therefore, we suggest a safe approach is to use model averaging when estimates are obtained under models that both do and do not allow for false positives (Burnham and Anderson 2002).

Other extensions that account for false positives may further improve inference about occupancy. When misclassifications occur directly between two species (i.e., when one of the species is typically mistaken for the other) two-species occupancy models (MacKenzie et al. 2004) could be modified to allow for false positives for a species to only occur when a second species is present at the same site. As shown here, auxiliary covariate information (e.g., distance and temperature) is also useful to disentangle true positive and false positive detections. Spatial information regarding occupancy of nearby sites is another potential source of auxiliary information. Finally, our models can readily be extended to cases when occupancy changes across time using dynamic occupancy models (MacKenzie et al. 2003, 2009, McClintock et al. 2010*c*).

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## APPENDIX A

Calculating probabilities for example encounter histories for both multiple detection state model and the multiple detection method model (*Ecological Archives* E092-121-A1).

## APPENDIX B

Multiple detection state model with four occupancy states and four observation states (*Ecological Archives* E092-121-A2).

## APPENDIX C

Simulation methods (*Ecological Archives* E092-121-A3).

## APPENDIX D

Simulation results (*Ecological Archives* E092-121-A4).

## APPENDIX E

Additional example application for experimental data with known occupancy probability (*Ecological Archives* E092-121-A5).

## SUPPLEMENT

Examples of R code to fit models (*Ecological Archives* E092-121-S1).