Comparing Naïve Occupancy Versus Modeled Occupancy to Monitor Declines in Rare Species

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Abstract: Monitoring changes in occupancy (i.e., probability a site has at least one individual of a species) across time is considered an inexpensive alternative to monitoring changes in abundance and can be used to monitor multiple species simultaneously across a watershed. Occupancy can be measured as the proportion of sites where a species is detected during surveys (i.e., naïve occupancy), but is more commonly modeled by surveying sites multiple times to estimate detection probability and address false-positive survey errors (sites that are occupied but with no survey detections of the species). This results in an unbiased estimate of occupancy, but at the expense of more effort. The purpose of this study was to determine management implications of using naïve occupancy versus using modeled occupancy. We generated simulated data to represent monitoring a population, then compared performance of using naïve occupancy vs. modeled occupancy for detecting changes. Different sampling scenarios were compared using different values of catchability (0.05 to 0.70) and various levels of known occupancy decline (35%, 55%, and 85%). Power to detect declines in both naïve occupancy and modeled occupancy increased with higher catchability and greater declines. Naïve occupancy and modeled occupancy performed similarly when catchability was high. Modeled occupancy performed slightly better than naïve occupancy at lower catchability; however, at a catchability of 0.05, neither occupancy approach was successful at correctly estimating the correct decline. Although modeled occupancy provides more accurate estimates of species occupancy, results of our study indicate that regulatory agencies concerned with personnel constraints could likely use a naïve occupancy approach to maximize geographical coverage without sacrificing their ability to correctly assign conservation status to imperiled species.

Keywords: catchability, detection, monitoring, presence-absence

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Monitoring of population trends is an important component of conserving imperiled species. Estimates of population trends provide vital information for determining population viability and conservation status (O'Grady et al. 2004) and are important components of most conservation status rubrics, including the ones used by the International Union for the Conservation of Nature (IUCN 2022) and NatureServe (Master et al. 2012). Species monitoring often involves comparing changes in abundance over time. However, determining abundance for numerous species is usually considered cost prohibitive (Noon et al. 2012), and a more cost-effective alternative is to monitor changes in species occupancy.

Determining occupancy (the number or proportion of sites where a species is found or predicted to occur) is typically less labor intensive than measuring abundance, thus more sites can be sampled for a given level of effort (Strayer 1999, Joseph et al. 2006, Pollock 2006, Noon et al. 2012). Monitoring changes in occupancy can be an effective means to detect changes in population status (Noon et al. 2012). A change in occupancy suggests that the proportion of occupied sites has changed but does not necessarily indicate that abundance differs (Strayer and Smith 2003, MacKenzie 2005), but occupancy and abundance are usually strongly correlated (Gaston et al. 2000, Joseph et al. 2006, Hui et al. 2012). Occupancy is also a state variable appropriate for large-scale monitoring by itself (MacKenzie et al. 2017).

Monitoring changes in occupancy is typically done in one of two ways. The first is monitoring changes where a species is detected or not detected after surveying a location with only one sampling event per season (e.g., Strayer and Fetterman 1999, Ewing and Gangloff 2015). The observed proportion of sites with detections is termed naïve occupancy (Wintle et al. 2004, MacKenzie 2005), which does not account for imperfect detection (i.e., detection probabilities < 1). The second method accounts for imperfect detection and potential false absences (sites that are occupied but in which the species was not detected during surveys) but requires repeated surveys of sites during each sampling period, usually by vising each site multiple times (e.g., Sewell et al. 2012, Barata et al. 2017).

Catchability (q), is the probability of capturing any individual of a particular species, given that it is present at a site (Bayley and Peterson 2001, Peterson and Bayley 2004, Smith 2006). It is considered a random variable conditional on factors such as observer

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experience, search time, sampling conditions, gear, and biological factors such as age and sex, and can be estimated using techniques such as mark/recapture or multiple pass depletion (Bayley and Peterson 2001, Peterson and Bayley 2004, Smith 2006). In the occupancy context, detectability, p, is the per-survey probability of detecting a species at a site where it is present (Bayley and Peterson 2001, MacKenzie et al. 2002, Peterson and Bayley 2004).

Effective monitoring requires sound sampling design with sufficient power and ability to accurately detect changes of interest to avoid drawing incorrect conclusions about a population (Field et al. 2007). Accounting for imperfect detection is considered more statistically and biologically sound than basing inference on naïve occupancy when monitoring changes in occupancy (MacKenzie 2005, Kéry and Schmidt 2008). Trends derived from two or more naïve occupancy estimates will produce biased estimates unless the detectability is virtually equal across samples, as is often assumed (MacKenzie 2005, Kéry and Schmidt 2008). However, the assumption of equal detectability across samples is often incorrect (Kéry and Schmidt 2008). Nevertheless, several studies have shown that monitoring naïve occupancy could be effective at detecting declines in occupancy. Strayer (1999) and Pollock (2006) found that monitoring naïve occupancy has adequate power to detect a statistically significant decline in occupancy, especially if decline was high (Strayer 1999). Joseph et al. (2006) found that monitoring naïve occupancy can even be more effective than measuring declines in abundance for assigning the correct IUCN conservation status.

The IUCN assigns a threat category, Critically Endangered, Endangered, Vulnerable, or Least Concern, to taxa based on multiple quantitative criteria. Criterion A is a reduction in population size. A reduction in population can be measured by declines in abundance, area of occupancy, extent of occurrence, or some other index appropriate index. The thresholds for Critically Endangered are a reduction of ≥80%, ≥50% for Endangered, and ≥30% reduction for Vulnerable over a 10-yr or three-generation period (IUCN 2022). The IUCN protocol is used by many countries, states, and other entities to determine conservation status of a species. An advantage of the IUCN protocol and similar protocols is that they do not require highly accurate estimates of population decline, as they assign ranks based on specific ranges of population decline.

Changes in occupancy are often used to measure population declines (e.g., Strayer and Fetterman 1999, Joseph et al. 2006, Sewell et al 2012, Ewing and Gangloff 2016, Barata et al. 2017). Measuring changes in modeled occupancy is resource intensive in the sense that sites must be surveyed multiple times per time point (i.e. "season"; see below), generally at least three times and often more (MacKenzie and Royle 2005). Consequently, this limits the number of sites that can be surveyed on a given budget (Field et al. 2005). One appeal of using naïve occupancy over modeled occupancy is that typically many more sites could be sampled for a given amount of effort. Agency biologists are often tasked with managing hundreds of species across multiple watersheds. Because of this, biologists are often interested in sampling more sites because it gives them information about a greater portion of the landscape and a greater number of species. Therefore, biologists must balance the tradeoff of sampling more sites less intensively (i.e., fewer site visits) or fewer sites more intensively (i.e., more site visits). However, there have been few if any studies comparing the relative performance of modeled occupancy vs. naïve occupancy. The purpose of this study was to compare changes in modeled occupancy versus naïve occupancy in a monitoring scheme to determine what the practical ramifications are when accounting for detection when monitoring for changes in occupancy. Our objective was to determine the relative performance of using modeled occupancy vs naïve occupancy of determining the correct IUCN conservation classification.

Methods

We use a simulation approach to compare modeled occupancy and naïve occupancy in a monitoring context. First, we generated populations of known occupancy consisting of various numbers of individuals arranged among 500 sites. The populations followed a zero-inflated Poisson distribution (Wenger and Freeman 2008) with a mean abundance of 10 individuals per site and an initial occupancy of 20% (i.e., 20% of sites contain at least one individual). We then simulated sampling these sites with observation error, by first calculating detectability at each site. Detectability (p) was estimated as a function of catchability (q) and the number of individuals of a species present at a site (n) using the formula $p = 1 - (1 - q)^n$ (Bayley and Peterson 2001). This generated a per-survey probability of detecting the species if present at a given site (Bayley and Peterson 2001, Peterson and Bayley 2004). We then generated a uniformly distributed random number between 0 and 1. If the random number was less than or equal to the detection probability, then the species was considered detected at that site during the survey. If the random number was greater than the detection probability (Strayer 1999), then the species was recorded as not detected at that site. We used mean catchability (q) values ranging from 0.05 to 0.70, based on catchability ranges reported in the literature for nongame fishes (Bayley and Peterson 2001) and freshwater mussels (Meador et al. 2011). Catchability is usually dependent on sampling conditions and should be considered as a random variable (Peterson and Bayley 2004), so we modeled q as a beta distributed random variable with a standard deviation of one-tenth of the mean (Wintle et al. 2004).

Our model assumed we had the resources to conduct 210 surveys in each season. Here a season is defined as a time period where the occupancy state of a site is unlikely to change, that is the site is always occupied or unoccupied during the surveying period (MacKenzie et al. 2017). We simulated surveying 210 sites one time per season to estimate naïve occupancy and 70 sites three times per season as three sampling occasions is typically the minimum number recommended for estimating occupancy (Field et al. 2005, MacKenzie and Royle 2005). This allowed for comparing tradeoffs of sampling more sites once or a lesser number of sites more intensively. Naïve occupancy was calculated as the number of sites where the species was detected divided by the total number of sites sampled. Modeled occupancy was calculated using a single-species, single-season occupancy model with no covariates (MacKenzie et al. 2017).

We then simulated declines in occupancy in our population of 35%, 55%, and 85%. We chose these percentage declines because they are just slightly larger than the thresholds established by the IUCN (2022) for different conservation status levels. Population reductions were achieved by reducing abundances at randomly selected sites to zero until the desired percent reduction in occupancy was attained (Strayer 1999). Since natural populations tend to fluctuate in abundances and occupancy over time, abundances at each site were multiplied by a random uniform number between 0.5 and 1.5 which simulated anywhere from a 50% decline to a 50% increase in abundance. These populations were then sampled as before, with the same sites being sampled. Naïve occupancy and modeled occupancy were again calculated, and percent reduction in occupancy was calculated based on the differences between the occupancy prior to the reduction and afterwards.

This process was repeated 1000 times for each catchability value. To evaluate relative performance of the two different methods, we calculated proportions of the 1000 simulations that the model correctly predicted the correct IUCN classification based on the decline in occupancy. We then assessed whether simulations were able to assign population decline to the correct IUCN category at least 80% of the time, comparable to the frequently used threshold for power analyses in ecological studies (Field et al. 2007). All analyses were done in R version 4.2.3 (R Core Team 2023). We used the R package unmarked version 1.2.5 (Fiske and Chandler 2011) for occupancy modeling. Artificial populations of known occupancy were generated using the R package VGAM version 1.1-8 (Yee 2010).

Results

Naïve occupancy and modeled occupancy performed similarly when catchability was high but modeled occupancy performed slightly better than naïve occupancy at lower catchability. Under a 35% decline scenario, modeled occupancy reached the 80% correct categorization threshold at a catchability of approximately 0.15, whereas, naïve occupancy did not reach this threshold until catchability reached 0.3 (Figure 1). At a 55% decline the two

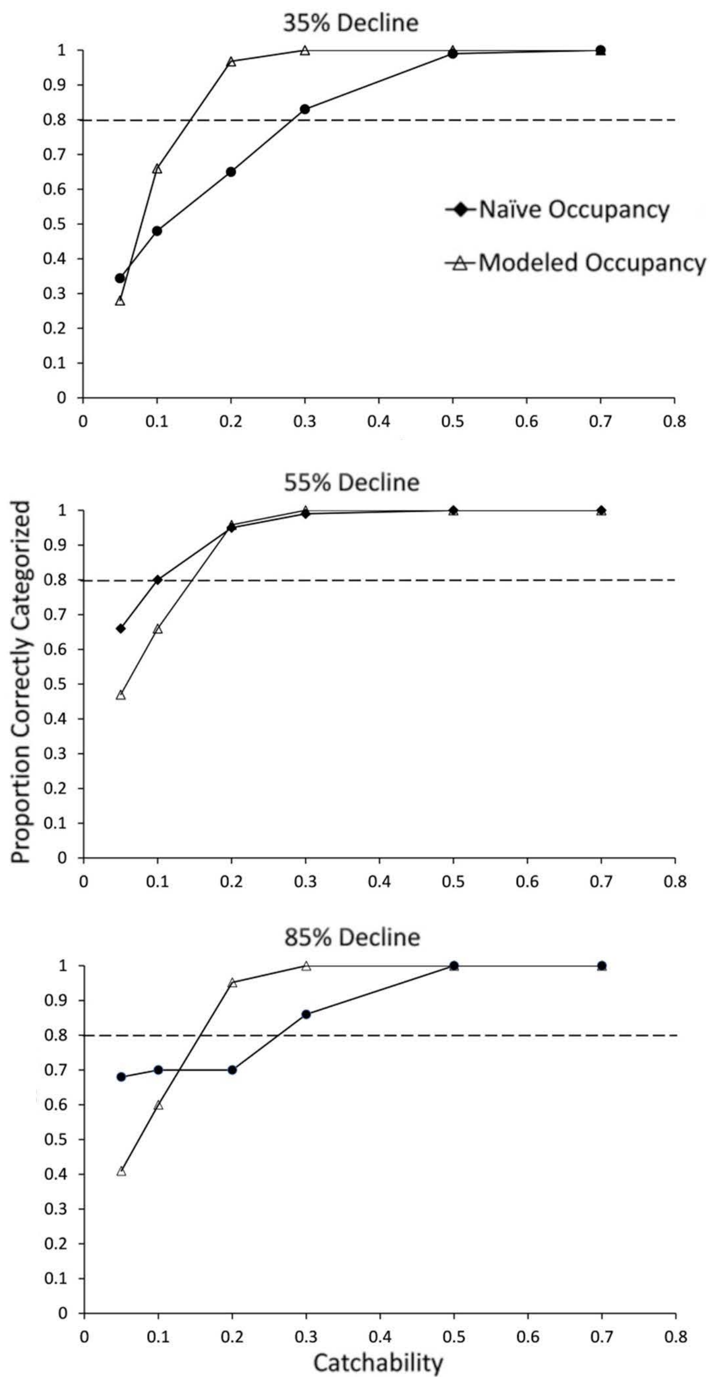

Figure 1. Proportion of 1000 model runs using modeled occupancy or naïve occupancy that correctly placed the estimated population decline in the correct IUCN category as a function of catchability (q). The dashed line represents where the proportion of correct model runs exceeds 0.8. Models were run over a range of catchabilities at three levels of population declines.

modeling approaches performed more closely; however, the naïve approach reached the 80% threshold when catchability was only 0.10 while the modeled approach did not reach this threshold until catchability exceeded 0.15 (Figure 1). At higher catchabilities, the two approaches performed virtually identically. At an 85% decline, the naïve approach outperformed the modeled approach at catchabilities <0.10 but thereafter the modeled approach performed better, reaching the 80% threshold at a catchability of approximately 0.15 (Figure 1). The naïve approach did not exceed the 80% threshold until catchability reached approximately 0.28. Changes in modeled occupancy were typically more precise and accurate than naïve occupancy. Modeled occupancy had narrower ranges and interquartile ranges and the medians of the model runs for modeled occupancy were usually closer to the true value of the decline than those for naïve occupancy (Figure 2).

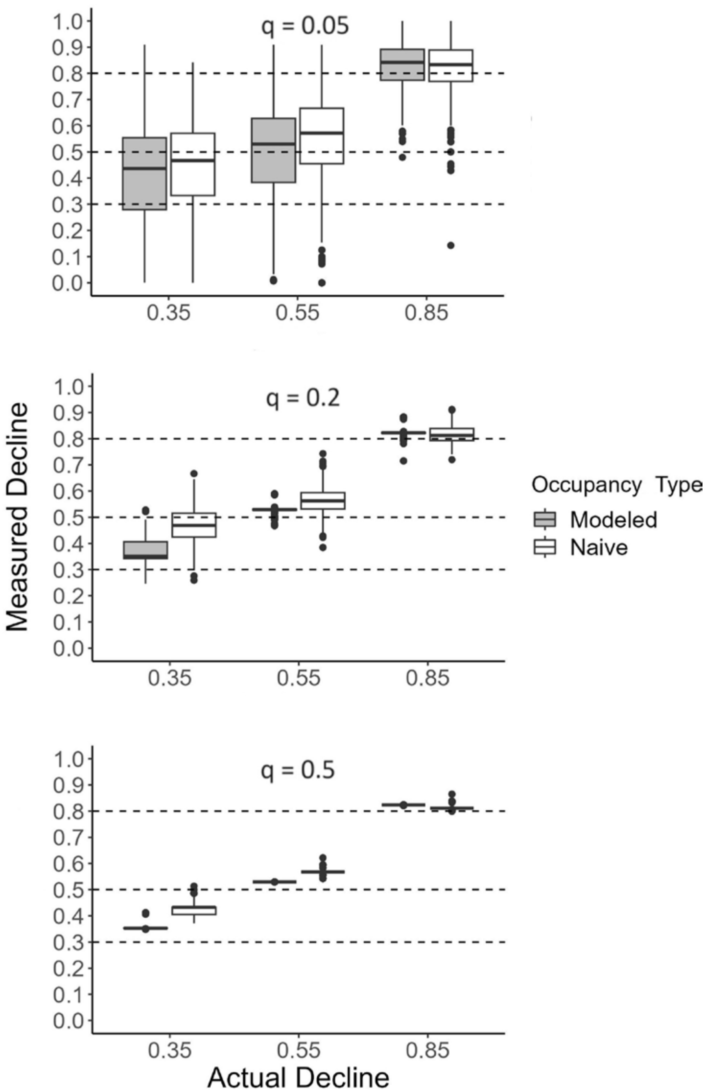

Figure 2. Box plots showing the distribution of estimated population decline based on 1000 model runs using modeled occupancy or naïve occupancy for three different catchability (q) values. Horizontal dashed lines represent the different threat categories based on the IUCN (2022) protocol (Vulnerable = 30–50% decline, Endangered = 50–80% decline, and Critically Endangered = >80% decline).

Discussion

Modeled occupancy performed better than naïve occupancy for monitoring population declines. Modeled occupancy typically had a higher proportion of correctly allocating declines to the correct IUCN conservation status category, greater accuracy, and better precision than naïve occupancy. Our results are in line with those of previous authors that noted modeled occupancy is superior to using naïve occupancy (i.e. MacKenzie 2005, Kéry and Schmidt 2008). Neither method was effective at the lower end of catchability values used during this study (≤0.1). However, this changed for modeled occupancy as catchability approached 0.2 and for naïve occupancy as catchability approached 0.3 where both methods exceeded 80% correct allocation.

Despite not performing as well as modeled occupancy, naïve occupancy still appeared to be a useful method for monitoring populations under some circumstances. Even at the lowest level of decline (35%), naïve occupancy attained appropriate power once catchability reached 0.3 and approached 100% correct allocation at higher levels of catchability. These results are consistent with those of previous studies that found that using naïve occupancy can be effective for monitoring populations (Strayer 1999, Joseph et al. 2006, Pollock 2006). Perhaps the most useful role for naïve occupancy will be for monitoring large numbers of species across large landscapes such as entire watersheds. This method is especially useful when highly accurate or precise measures of population decline are not required, such as when using a protocol such as those of the IUCN (2022) or NatureServe (Master et al. 2012) where status is assigned based on measured declines falling within a specified range.

This study underscores the need to increase catchability as much as possible when conducting surveys. One way to increase catchability is to use experienced personnel when monitoring, especially for very rare, cryptic, or hard to sample species. For example, Rondel (2019) noted that catchability of a rare, federally listed mussel species increased as surveyor experience increased. Conducting sampling during appropriate conditions also increases catchability. For example, sampling during low flow and sunny conditions has been shown to increase catchability for many species of freshwater mussels (Smith 2006, Meador et al. 2011). Increasing search effort at a given location also increases catchability (Metcalfe-Smith et al. 2000, Smith 2006, Reid 2016). Lastly, using the correct gear is extremely important, as Bayley and Peterson (2001) noted extreme differences in catchability of stream fishes depending on the gear type used.

The results of this study are not intended to set guidelines when trying to establish a given level of power to detect a decline. There are more factors than catchability that determine the power to detect population declines using occupancy. Factors such as population abundance, initial occupancy of the population, magnitude of decline, and sample size are also extremely important in determining power to detect a population decline (Strayer 1999, Rhodes et al. 2006, Guillera-Arroita and Lahoz-Monfort 2012, Ewing and Gangloff 2015).

Monitoring changes in abundance is often expensive and requires extensive field surveys. This can make it infeasible to monitor abundance for numerous species across large landscapes such as entire watersheds as resource agencies are often tasked to do, often with limited budgets and personnel constraints. Estimating a species' occupancy typically requires much fewer resources than abundance thus lending itself to large-scale monitoring (Noon et al. 2012). It also can be effective at monitoring numerous species at once, especially those species that lend themselves to omnibus surveys where numerous species are monitored simultaneously (Manley et al. 2004, Noon et al. 2012). Monitoring changes in modeled occupancy is typically more statistically and biologically sound when monitoring occupancy than monitoring changes in naïve occupancy (MacKenzie 2005, Kéry and Schmidt 2008). However, this study has shown that using naïve occupancy can be effective, especially when catchability is high, plus it has the advantage over modeled occupancy of being able to survey more sites across thus providing better coverage across a landscape.

There are circumstances where using naïve occupancy is not adequate and should not be used. Strayer (1999) and Manley et al. (2004) found that naïve occupancy was not effective at monitoring very rare species or highly endemic species. In these cases, dedicated studies utilizing modeled occupancy should be used. Modeled occupancy also has the advantage of utilizing environmental covariates to make to make occupancy predictions stronger (MacKenzie et al. 2017) and so in practice, modeled occupancy might perform even better against the naïve model than this study suggests. Also, research studies designed to examine the effects of environmental factors or land uses on changes in occupancy, as well as those examining temporal changes where detectability may have changed significantly over time, should use modeled occupancy rather than naïve occupancy (MacKenzie et al. 2017). However, this study does show that agencies facing manpower shortages and concerned about monitoring changes in geographic extent could use naïve in lieu of modeling occupancy.

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