Ecological Indicators 11 (2011) 1413–1418

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Application of detectability in the use of indicator species: A case study with birds

John E. Quinn[a,*], James R. Brandle[a], Ron J. Johnson[b], Andrew J. Tyre[a]

[a] University of Nebraska-Lincoln, School of Natural Resources, 3310 Holdrege, Lincoln, NE 68583, USA
[b] Clemson University, Department of Forestry & Natural Resources, Clemson, SC 29634, USA

ARTICLE INFO

Article history:
Received 10 December 2010
Received in revised form 7 March 2011
Accepted 8 March 2011

Keywords:
Bioindication
Monitoring
Observer effect
Species inventory

ABSTRACT

The use of indicator species is popular in ecological monitoring and management. In recent years, new methods to improve the quality and application of indicator data have been proposed and developed. Here we propose the use of detection probability in the selection and application of indicator species. We evaluated environmental and observer factors believed to affect detection of potential species. Observer effects were the most evident factor and may necessitate the greatest consideration in the use of indicator species. Our results call attention to the fact that raw counts are far from accurate and that the use of detection probability can and should be incorporated into sampling protocols, species selection, and the allocation of effort for projects that use indicator species as part of monitoring and management programs.

1. Introduction

Indicator species are used by conservation practitioners as an efficient means of collecting and communicating information that reflects population trends or the health of communities and ecosystems (Canterbury et al., 2000; Chase et al., 2000; Browder et al., 2002; Fleishman et al., 2005). As the use of indicator species has grown, a list of proposed criteria has developed that includes scale, ease of use, cost, and sensitivity to change or stress (Landres et al., 1988; Noss, 1990; Dale and Beyeler, 2001; Bani et al., 2006; Gregory et al., 2008; Mandelik et al., 2010). One measure not adequately addressed is detectability, a measure of the likelihood of observing an individual of a species (Kéry, 2010).

Ideally, probability of detection would vary little and observed counts would reflect only the ecological condition the species is expected to indicate. However, in reality, observed changes in occupancy or abundance may reflect other factors in addition to deterministic stressors (MacKenzie et al., 2006). Factors that may influence detectability include weather condition, observation distance, and observer skill. These variables may play a greater or lesser role depending on the species and associated behaviors or habitats. For example, a bird species with a faint song may be a less reliable indicator in a region prone to high winds whereas a bird species with a complex or indistinct call may be subject to more frequent identification error. Moreover, species that vocalize or are active earlier in the morning might have greater detectability in counts near sunrise and the detectability of a species' color pattern against background vegetation may vary with cloud cover and amount of available sunlight.

Explicitly including detectability in the selection and application of indicator species would result in outputs that are more reliable and increase the value of data collected. To reduce the uncertainty of conclusions drawn from the use of indicator species, we consider the application of detectability in use of birds as indicator species, specifically how detectability can be incorporated into species selection, allocation of effort, and sampling protocols.

We present the evaluation of avian indicator species proposed as part of a farmland biodiversity assessment program designed for the Great Plains of North America (Quinn et al., 2009). Birds are frequent indicator species due to perceived ease of detection, sensitivity to environmental change, and broad presence in the environment (Jarvinen and Vaisanen, 1979; O'Connell et al., 2000; Browder et al., 2002). The described methods, however, would apply to other organisms deemed suitable for a research or monitoring program.

2. Material and methods

Birds were sampled at 335 points across twenty-two farms in the central Great Plains of the United States in 2007, 2008, and 2009. Surveys were conducted May 15–July 15 in all 3 years. Birds were surveyed at each point during the first 4 h after sunrise on two consecutive mornings. Each point was sampled twice each morning during separate time periods. Counts were 5 min in duration and all birds heard or seen were recorded by species. The order and time of day of counts were varied randomly. Twelve locally-breeding species (Table A.1), out of 104 detected at least once, were identified as possible indicators of habitat quality and ecosystem health of

* Corresponding author. Tel.: +1 402 472 8544; fax: +1 402 472 2946.
E-mail address: jquinn2@unl.edu (J.E. Quinn).

1470-160X/$ – see front matter
doi:10.1016/j.ecolind.2011.03.003

Table 1
Summary statistics for detection covariates.

	Mean (Median) ± SD	Min.	1st Qt	3rd Qt	Max.
Average wind speed (meters per second)	1.3 (1.0) ± 1.2	0.0	0.4	1.9	8.4
Percent cloud cover	37 (20) ± 37	0	0	70	100
Time (minutes since midnight)	475 (473) ± 64	349	421	525	640

Table 2
Null, model average, and model average range probability of detection.

Species	Null	Mod. avg.	Mod. avg. range
Bell's Vireo	0.28	0.25	0.31
Brown-headed Cowbird	0.11	0.18	0.14
Brown Thrasher	0.12	0.14	0.26
Dickcissel	0.41	0.43	0.30
Eastern Kingbird	0.08	0.10	0.13
Field Sparrow	0.27	0.27	0.38
Horned Lark	0.11	0.11	0.12
Killdeer	0.12	0.15	0.20
Northern Bobwhite	0.20	0.22	0.43
Red-bellied Woodpecker	0.17	0.16	0.63
Red-winged Blackbird	0.21	0.25	0.23
Western Meadowlark	0.30	0.34	0.47

working farmland. Selection was based on the individual species representation of habitat type and perceived sensitivity to land use change (Poole, 2005).

Covariates thought to affect detection were recorded for each count (Table 1). Start time was recorded at the initiation of each count and later adjusted to minutes since midnight. Cloud cover was estimated at intervals of ten between 0 and 100%. Average wind speed was recorded for 10 s prior to each count using a Kestrel® 1000 Pocket Wind Meter (Boothwyn, PA). Four different observers with different levels of experience conducted all counts. All observers received the same core training that included pre-season listening sessions and identification quizzes.

We used negative binomial–binomial N-mixture models (Royle, 2004) and the unmarked package (Fiske et al., 2010) for the software package R V2.12.0 (R Development Core Team, 2010) to estimate detection probabilities of avian species in the central Great Plains of North America. N-mixture models use spatial and temporal replication to estimate detectability independent of abundance. Land use and land cover types can be included as covariates of abundance. However, for our analysis of detection probability, abundance covariates were not included in the model selection process.

For each species, we tested 16 a priori model combinations of start time, wind speed, cloud cover, and observer. Parametric bootstrapping was used to evaluate goodness of fit. We used the negative binomial–binomial mixture distribution due to observed overdispersion of the data. Models were tested using Akaike's information criterion (AIC) model selection (Burnham and Anderson, 2002). Models were ranked and compared by delta AIC. Competing models describing variation in detection probability of proposed indicator species were sorted according to their Akaike weight. The best models were averaged to estimate detection probabilities of the selected species. The top models in the 95% confidence set (95% of Akaike's weight) for each species were used to identify species with beneficial detection traits (Burnham and Anderson, 2002).

3. Results

All detection covariates considered were within the 95% confidence set of at least one species (Table A.1). Parametric bootstrapping suggested acceptable goodness of fit (Table A.2). Subsequent examination of model complexity in a confidence set provided one application of detection probability. Species with simple top models can be identified as more suitable for application as indicator species. Bell's Vireo (*Vireo bellii*) and Brown-headed Cowbird (*Molothrus ater*) had a single covariate in the top model, with the respective covariate nested within other top models in the confidence set (Table A.1). Because top models for the two species were the most parsimonious, it may be worthwhile to give these species greater consideration as candidates for use as indicators, though the top models did not carry sufficient Akaike weight to rule out competing models. In contrast, the top Northern Bobwhite (*Colinus virginianus*) model, with 68% of the Akaike weight, had three

Table 3
Parameter estimates (Est.) and standard error (SE) from N-mixture models. Estimates of detection probability are on the logit-scale. Species abbreviations are shown in Table A.1. Parameter estimates with 95% confidence intervals that do not include zero in bold.

	BEVI		BHCO		BRTH		DICK		EAKI		FISP	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Alpha	−0.19	1.08	6.56	18.34	**1.12**	**0.38**	**1.36**	**0.15**	**0.91**	**0.23**	−0.40	0.24
p(Int)	−0.72	0.51	**−1.26**	**0.17**	**−1.63**	**0.28**	0.25	0.24	**−2.08**	**0.30**	**−0.78**	**0.30**
p(ObsB)	0.00	0.01	**−1.02**	**0.08**	**−0.83**	**0.16**	**−0.52**	**0.07**	**−0.43**	**0.11**	−0.05	0.16
p(ObsC)	0.00	0.01	**−0.13**	**0.07**	**0.59**	**0.12**	**0.12**	**0.06**	**0.57**	**0.10**	**0.50**	**0.17**
p(ObsD)	0.00	0.01	**−0.33**	**0.08**	**0.26**	**0.13**	**−0.30**	**0.07**	**−0.72**	**0.15**	−0.08	0.20
p(Start)	0.00	0.00			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p(Wind)	**−0.39**	**0.15**	0.01	0.01	**−0.25**	**0.05**	**−0.09**	**0.02**	0.00	0.01	**−0.26**	**0.07**
p(Cloud Cov)	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	−0.01	0.01	0.00	0.01

	HOLA		KILL		NOBO		RBWO		RWBL		WEME	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Alpha	**−1.28**	**0.13**	−0.06	0.26	**0.76**	**0.32**	3.93	6.28	**0.23**	**0.10**	**0.43**	**0.15**
p(Int)	**−2.76**	**0.30**	**−1.89**	**0.32**	−0.41	0.44	0.37	0.61	**−1.03**	**0.13**	0.63	0.34
p(ObsB)	**−0.28**	**0.13**	**−0.63**	**0.18**	−0.26	0.14	−0.28	0.24	**−0.50**	**0.07**	**−0.94**	**0.10**
p(ObsC)	0.14	0.12	**0.46**	**0.15**	**0.87**	**0.14**	1.52	0.19	**0.46**	**0.07**	**0.52**	**0.09**
p(ObsD)	−0.15	0.12	−0.22	0.17	0.20	0.15	**0.95**	**0.25**	−0.03	0.09	**−0.47**	**0.12**
p(Start)	**0.00**	**0.00**	0.00	0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00
p(Wind)	−0.01	0.01	**0.08**	**0.04**	**−0.24**	**0.06**	**−0.84**	**0.11**	**−0.07**	**0.02**	−0.01	0.01
p(Cloud Cov)	**0.05**	**0.02**	0.00	0.01	0.00	0.00	−0.02	0.01	0.00	0.00	**−0.02**	**0.01**