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ARTICLE *in* ECOLOGICAL INDICATORS · SEPTEMBER 2011

Impact Factor: 3.44 · DOI: 10.1016/j.ecolind.2011.03.003

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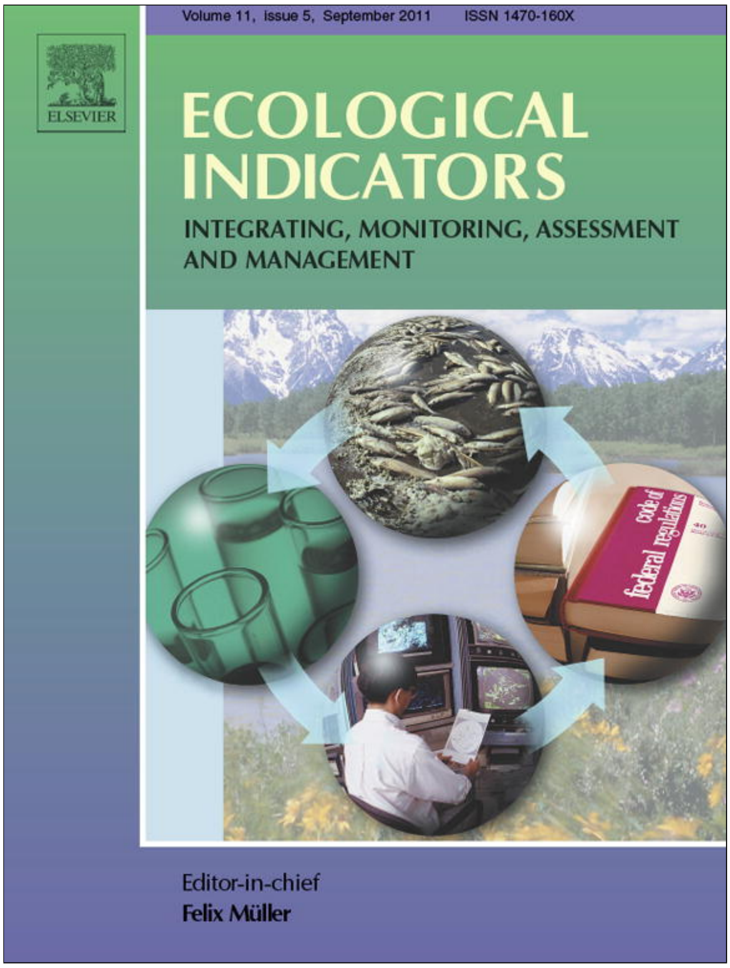
Volume 11, Issue 5, September 2011 ISSN 1470-160X
ELSEVIER
ECOLOGICAL INDICATORS
INTEGRATING, MONITORING, ASSESSMENT AND MANAGEMENT
code of federal regulations
Editor-in-chief
Felix Müller

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

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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

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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 preseason 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**

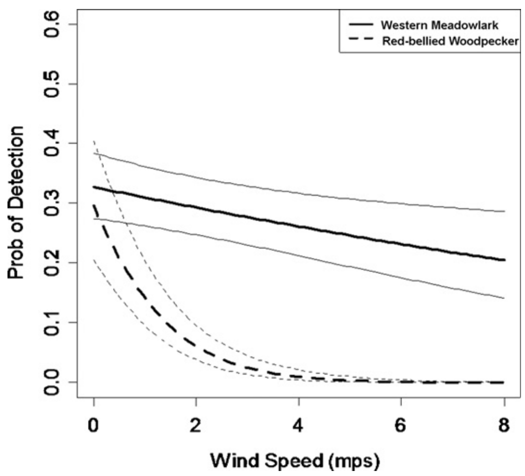

Fig. 1. Estimated variation in detection probability and 95% confidence interval due to change in wind speed.

model covariates. The greater number of covariates affecting detection probability of the Northern Bobwhite suggests this species may not be as suitable.

In addition to the total number of detection covariates, average detection probability and range of detection probability (Table 2) can identify species more suitable for use as indicator species. Average estimated detection probability can be used to identify species with a greater probability of detection that would require the least amount of sampling effort when using replicated counts over time (Field et al., 2002) or calculate the number of visits needed to obtain a predetermined acceptable probability of detection for an individual of a species accurately. This step decreases the likelihood of false negatives that reduce value of the data (Fleishman and Murphy, 2009). Species with a narrow range of detection probability (e.g., Eastern Kingbird (*Tyrannus tyrannus*) or Horned Lark (*Eremophila alpestris*)) may serve as better indicator species because their probability of detection is relatively constant, allowing greater confidence in the allocation of sampling effort. However, if a species has a low detection probability, whether due to home range size or elusiveness, availability may be a factor, and increasing allocation of effort through more frequent sampling may be necessary to be confident in estimates of abundance.

Consideration of species' detection probability in respect to cloud cover, start time, wind, and observer provided a means to identify potential indicator species that demonstrate minimal variation in response to detection covariates of concern in individual monitoring efforts. It is well known that probability of detection decreases for most bird species as the morning passes (Ralph et al., 1995). However, perhaps because counts were limited to within 4 h of sunrise, observed variation in detection was minimal (Table 3). This may rule out start time as a criterion when counts are constrained to early mornings. Additionally, no trends emerged for cloud cover, though limited variation was evident for a small number of species (Table 3).

Detection probability declined with increased wind speed for ten of twelve species (Table 3). Strong variability in detection probability with respect to wind speed (e.g., Red-bellied Woodpecker (*Melanerpes carolinus*), Fig. 1) could limit a species' value as an indicator in a windy region like the Great Plains. Consistent detectability in relation to wind speed, as demonstrated by the Eastern Kingbird, may suggest a species is more suitable indicator in windy regions. A moderate detection probability in response to wind (e.g., Western Meadowlark (*Sturnella neglecta*), Fig. 1) may not rule a species out, but would require the collection of detection covariates as part of monitoring efforts.

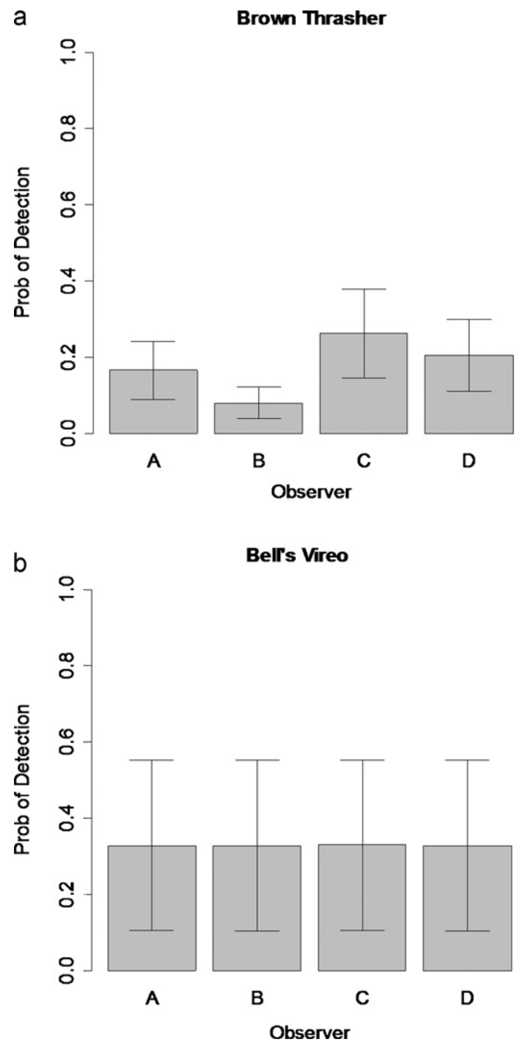

Fig. 2. Estimated variation in detection probability and 95% confidence interval due to observer.

Despite core training undertaken by all observers before each research season, detection probability of individual species varied among observers (e.g., Brown Thrasher (*Toxostoma rufum*), Fig. 2a) with one exception, the Bell's Vireo (Fig. 2b). If a monitoring program has a revolving set of observers, unaccounted for variation because of observer error could bias results. Therefore, if citizen scientists are undertaking the primary data collection, a species with a constant probability of detection among observers is highly desirable. Given, however, that only one species demonstrated minimal variation, accounting for observer variation will likely need to occur in the analysis stage of a monitoring program. Ultimately, given relative ease of adjusting sampling effort for environmental covariates of detection (e.g., not counting during periods of high wind), accounting for observer effects may be the greatest challenge, but provide for the greatest return when selecting and using indicator species.

4. Discussion

Our results call attention to the fact that raw counts may not accurately represent true abundance patterns and that there is value in including detection covariates as a criterion in the selection and use of indicator species. Moreover, our results suggest that it is feasible to identify species more suitable for use as indicator species based on consideration of detectability and detection covariates.

Given that many environmental covariates can be controlled for, observer effects may necessitate the greatest consideration in the use of indicator species.

While we have focused on detection probability, an indicator species needs to remain sensitive to environmental change or disturbance (Dale and Beyeler, 2001). As such, it will be important to address the response of a species to ecological conditions of interest. For example, the Killdeer (*Charadrius vociferus*) has a moderately high detection probability, but as an indicator species is not representative of high quality agricultural habitat. Consequently, it is unlikely to be a suitable indicator of agroecosystem health. In contrast, a rare or reclusive species may provide more information about a population or ecosystem; however, it will likely require added costs of repeated visits and additional data collection. The added costs of time or funds required to make multiple visits to a site may be worth the price if greater knowledge of the reclusive species provides a more accurate measure of local conditions (Field et al., 2004, 2005). Ultimately, research participants, perceived costs, and/or project goals will dictate an appropriate balance. These decisions will need to be made on a case-by-case basis for different projects, species, and ecosystems.

We believe that when possible, given the moderate to low probability of detection for many of the observed species, repeated surveys followed by analysis with detection models (Royle, 2004) will improve the quality of data produced. This requires additional time, training, and data collection as part of any local monitoring program that incorporates indicator species. However, use of detectability covariates and repeated visits when gathering and analyzing data will greatly improve its value. Inclusion of detectability has become standard practice in studies of avian habitat use (Royle et al., 2005; MacKenzie et al., 2006) and monitoring (Barbraud and Thiebot, 2009) and should become the norm in the selection and use of indicator species.

5. Conclusion

Although detectability has been alluded to in the literature of indicator species (Bryce et al., 2002; Bani et al., 2006) and acknowledgement given that perceived absence of a species from a habitat is of less value than a confirmation of a species presence (Fleishman and Murphy, 2009), detectability is not explicitly stated as a criterion in the evaluationprocess. This omission may result in incorrect conclusions drawn from data sets that do not account for variation in detectability. Additionally, monitoring programs are presented with the challenge to collect data over extended periods, under varied conditions, and with revolving participants. Detectability will be an important point of consideration to include as use of monitoring and adaptive management increases.

Given the demonstrated variation in probability of detection, consideration and use of detectability parameters to reduce bias and improve precision will validate and increase the value of data generated from monitoring programs, better informing future management and policy decisions (Lindenmayer, 1999). As such, it is essential to address issues relating to detectability if indicator species are going to achieve the scientific rigor and reliability necessary to be defensible by decision-makers. Our work proposes a framework to assess detection probability in selecting indicator species suitable for ecological and environmental conditions of interest. Further, it demonstrates that it is possible to identify species more suitable for use as indicator species by considering and applying probability of detection.

Acknowledgements

The authors thank L. Powell, E. Blankenship, J. Loomis, and A. Larson for helpful comments on early drafts. We appreciate comments provided by F. Müller and two anonymous reviewers that improved the manuscript. Funding for this work was provided by USDA CSREES Integrated Organic Program Grant Number: 2005-51300-02374, USDA McIntire-Stennis program, and the UNL Center for Great Plains Studies.

Appendix A.

See Tables A.1 and A.2.

Table A.1
Model selection results for summed AIC weights > 0.95 (n = 572, Wind = Average wind speed, Start = Start time, Obs = Observer, Cloud = Percent cloud cover).

	Model	*K*	Delta AIC	AIC weight
Bell's Vireo (BEVI)	Wind	4	0.00	0.47
Vireo bellii	Wind + Start	5	1.95	0.18
	Wind + Cloud	5	1.95	0.18
	Wind + Start + Cloud	6	3.90	0.07
	Null	3	4.78	0.04
	Wind + Obs	7	5.75	0.03
	Start	4	6.47	0.02
	Cloud	4	6.75	0.02
Brown-headed Cowbird (BHCO)	Obs	6	0.00	0.48
Molothrus ater	Wind + Obs	7	1.34	0.25
	Obs + Cloud	7	1.99	0.18
	Wind + Obs + Cloud	8	3.33	0.09
Brown Thrasher (BRTH)	Wind + Obs	7	0.00	0.42
Toxostoma rufum	Wind + Obs + Cloud	8	0.37	0.35
	Wind + Obs + Start	8	2.52	0.12
	Global	9	2.75	0.11
Dickcissel (DICK)	Wind + Obs + Start	8	0.00	0.87
Spiza americana	Global	9	3.76	0.13
Eastern Kingbird (EAKI)	Obs + Cloud	7	0.00	0.33
Tyrannus tyrannus	Obs	6	0.68	0.24
	Obs + Start + Cloud	8	1.49	0.16
	Wind + Obs + Cloud	8	1.92	0.13
	Wind + Obs	7	2.60	0.09
	Global	9	3.49	0.06
Field Sparrow (FISP)	Wind + Obs	7	0.00	0.52
Spizella pusilla	Wind + Obs + Cloud	8	2.00	0.19
	Wind + Obs + Start	8	2.08	0.18
	Global	9	4.06	0.07
	Wind	4	5.25	0.04
Horned Lark (HOLA)	Obs + Cloud	7	0.00	0.35
Eremophila alpestris	Obs + Start + Cloud	8	0.96	0.21
	Wind + Obs + Cloud	8	1.93	0.13
	Global	9	2.20	0.12
	Cloud	4	2.60	0.09
	Start + Cloud	5	3.36	0.06
	Wind + Cloud	5	4.59	0.03
Killdeer (KILL)	Wind + Obs	7	0.00	0.44
Charadrius vociferus	Wind + Obs + Cloud	8	1.76	0.18
	Obs	6	1.88	0.17
	Wind + Obs + Start	8	3.02	0.10
	Obs + Cloud	7	3.72	0.07
	Global	9	4.63	0.04
Northern Bobwhite (NOBO)	Wind + Obs + Start	8	0.00	0.68
Colinus virginianus	Global	9	1.91	0.26
	Wind + Obs	7	4.96	0.06
Red-bellied Woodpecker (RBWO)	Wind + Obs + Start	8	0.00	0.55
Melanerpes carolinus	Global	9	0.44	0.45
Red-winged Blackbird (RWBL)	Wind + Obs	7	0.00	0.58
Agelaius phoeniceus	Wind + Obs + Cloud	8	1.08	0.34
	Wind + Obs + Start	8	4.88	0.05
	Obs	6	5.94	0.03
Western Meadowlark (WEME)	Obs + Start + Cloud	8	0.00	0.62
Sturnella neglecta	Global	9	1.01	0.38

Table A.2
Summary of parametric bootstrapping (O = original statistic computed from data, V = vector of 1000 bootstrap samples).

Species	SSE.O	SSE.V Mean	SSE.V SD	SSE.V 0.025%	SSE.O 0.975%
BEVI	90.0	87.0	14.8	59.4	118.5
BHCO	2170.8	2261.1	98.5	2073.3	2467.9
BRTH	730.0	743.0	53.5	644.8	848.0
DICK	5952.0	6842.4	451.5	5990.2	7770.2
EAKI	1046.1	1070.2	71.6	933.5	1223.6
FISP	520.2	571.7	92.3	435.4	819.8
HOLA	875.4	923.4	157.0	661.6	1277.4
KILL	515.0	525.7	52.7	426.3	632.3
NOBO	746.7	782.8	64.5	667.9	914.9
RBWO	271.8	273.7	24.0	229.7	321.3
RWBL	4175.7	4582.9	414.2	3793.3	5421.9
WEME	2343.0	2593.7	225.9	2173.9	3060.5

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