CHAPTER

51

# Species Commonness and the Accuracy of Habitat-relationship Models

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Two types of error are possible when assessing the accuracy of models predicting species presence or absence: omission error (failure to predict species occurrence in an occupied area) and commission error (prediction of species occurrence in unoccupied areas)(see Fielding, Chapter 21). Of these two, omission errors are relatively easy to measure (Krohn 1996; Karl et al. 2000) because observation of a species in an unpredicted area necessitates an omission error. Conversely, failure to observe a species in a predicted area, while necessary to the definition, is not sufficient to classify it as a commission error (Krohn 1996; Boone and Krohn 1999; Karl et al. 2000). This can be due to inefficient or inappropriate sampling, species life history characteristics (e.g., avoids humans, cryptic nature, episodic), or temporal and spatial variation in species distributions (Karl et al. 2000; Fielding, Chapter 21; Schaefer and Krohn, Chapter 36). Thus, field measures of commission error contain both true error and apparent error (Karl et al. 2000; Schaefer and Krohn, Chapter 36).

Attributes of species biology can affect our estimates of model accuracy, but the effect of rarity on model accuracy is not well defined. It has been proposed that the presence of "species with high spatial and temporal evenness" (Krohn 1996) (e.g., common species) would be easier to predict with habitat-relationship models (e.g., gap analysis models) than species with low evenness (Boone and Krohn 1999) for most modeling applications. Karl et al. (2000) reported a significant decline in commission error accompanied with a slight increase in omission error with number of species detections on two study areas in north Idaho. As such, apparent error decreased with increased sample size. However, it was unclear whether high error rates at low numbers of detections were a result of differences in model accuracy between rare and common species or an artifact of sample size used to estimate model performance.

A rarity effect would exist if the models for species less-frequently encountered were less accurate than those for common species. Lower model accuracy for rare species in one situation could be caused by incomplete knowledge of the species' range or habitat associations, or the species responding to habitat features that cannot be measured (or mapped). Alternatively, because large numbers of rare species detections often take a large investment of time and money, model accuracy is assessed with few data points (if done at all). Depending on the statistics used, accuracy assessment with small sample sizes could lead to erroneous measures.

We investigated whether the pattern described by Karl et al. (2000) was due to a rarity effect or to an artifact of sample size. We simulated small sample sizes by randomly subsampling our data set for the most common species and using the subset of observations to test model accuracy. By doing this, we held the biological attributes of species constant, varying only the sample size. If models developed for rare species (i.e., those with few detections) have poorer prediction accuracy than common ones (rarity effect), then the slope of regression lines from a plot of error rates against number of detections for field data set should be steeper than that obtained by simulation. Although this approach did not consider reasons for rarity and may not appropriately approximate distribution of rare species, it was adequate for examining the effects of sample size on model accuracy.

## Study Area

Our study area encompassed most of the Idaho portion of U.S. Forest Service (USFS) Northern Region (the Idaho Panhandle, Clearwater, and Nez Perce National Forests) as well as land owned by the Potlatch Corporation (Fig. 51.1). This area (2.75 million hectares) begins just north of the Clearwater River, extending northward to the tip of the Idaho panhandle, but excluding the dry grasslands of the Snake River Valley and the Palouse agriculture lands. Most of this area is dominated by mixed coniferous forests in various stages of timber management.

## Methods

Breeding birds were surveyed on the U.S. Forest Service Northern Region in 1994 to 1996 (R. L. Hutto and U.S. Forest Service unpublished data; P. J. Heglund, Potlatch Corporation unpublished data) using a variable-radius circular plot technique (Ralph et al. 1995a). Each of 1,628 survey points was surveyed one time per year for up to three years following the methods described by Hutto and Hoffland (1996).

We eliminated from the data set all birds that were flying when detected, except for those birds whose detections are mostly restricted to aerial foraging (i.e., swallows, swifts, hawks). We further truncated the data set to only those observations occurring within 50 meters of the survey point for two reasons. First, the ability to accurately judge the distance of an observation and the cover type in which it occurred decreases with distance from the survey point (Hutto and Hoffland 1996; see also Scott et al. 1981). Second, limiting the area of analysis around the survey point reduces the potential for variation in the values of the geographic information system (GIS) data layers around the survey point.

We received GIS coordinates for the survey points from the U.S. Forest Service Northern Region's Landbird Monitoring Program. These coordinates were digitized from geo-registered aerial photographs of the study area. We then converted the vector point coverages from each study area to raster grids with a 0.09-hectare cell size.

We used models developed by Scott et al. (unpublished data) for the Idaho Gap Analysis Project to predict the presence/absence of the species detected in the breeding bird surveys. These models were built using methods proposed by Scott et al. (1993) (see also Butterfield et al. 1994; Csuti 1996; Smith and Catanzaro 1996) consisting of four major steps: (1) establishing a species list, (2) defining species range limits, (3) collecting species habitat information and determining habitat relationships, and (4) modeling the species habitat in a GIS using the information gathered.

To assess model accuracy, we compared the model predictions with survey data for each species detected. We tallied the number of omission errors (observed, not predicted) and commission errors (predicted, not observed) and calculated percent omission (number of omissions divided by the total number of observations) and commission error (number of commissions divided by the total number of survey points), respectively. All species measures were combined into one data set. We plotted omission and commission error by the number of species detections for all species. An inverse relationship existed between omission and commission errors (Karl et al. 2000); but, this relationship was not easily quantifiable. For this reason, we treated omission and commission error separately. We separately regressed omission and commission error rates against number of detections to achieve a regression coefficient and standard error describing the relationship between model error and number of detections.

We selected the seven species with more than five hundred detections and subjected their accuracy assessment to a simulation designed to approximate

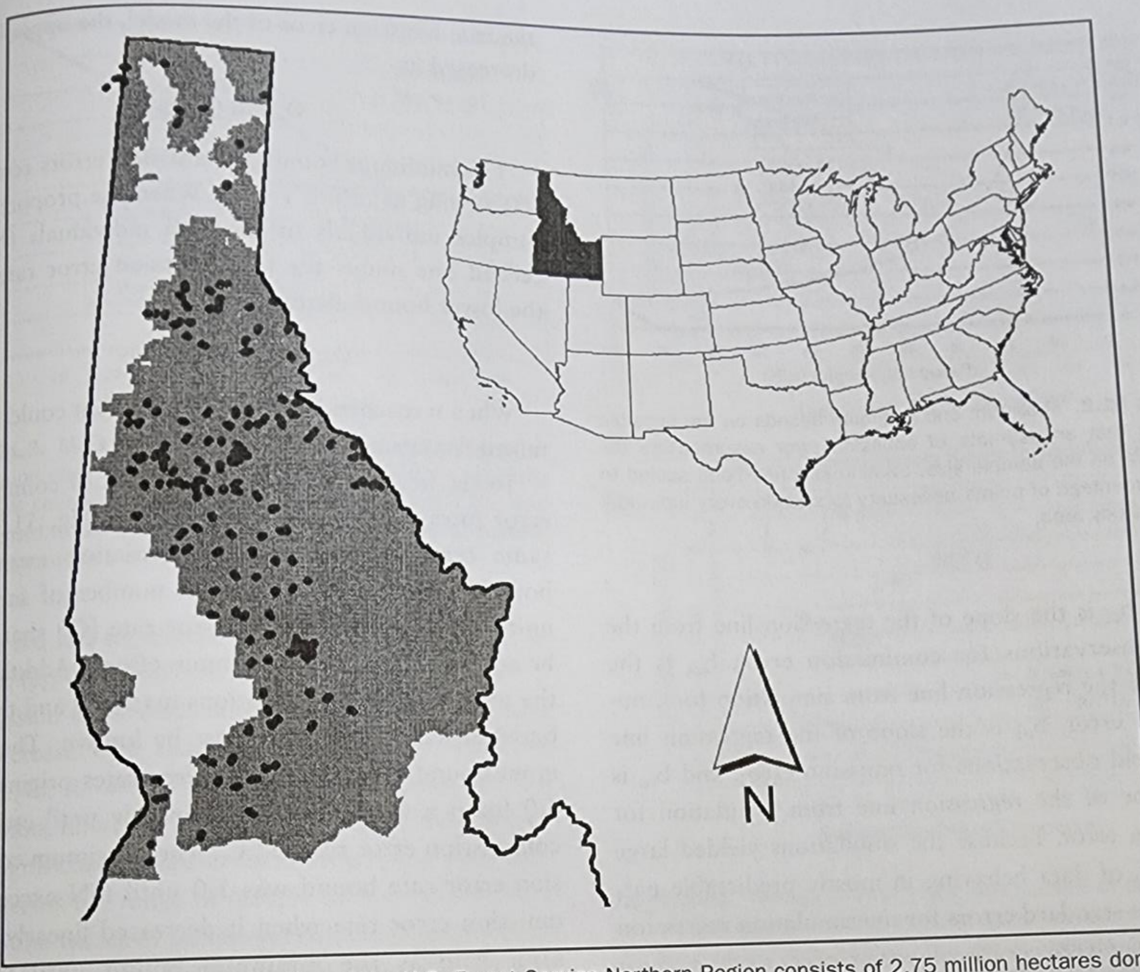

**Figure 51.1.** The Idaho portion of the U.S. Forest Service Northern Region consists of 2.75 million hectares dominated by coniferous forest land cover types, interspersed with dry grasslands and shrublands.

rarity. Exploratory data analysis indicated variability of omission error estimates was small for species with more than five hundred detections. Additionally, the seven species selected shared similar life history attributes (i.e., broadly distributed, similar habitat associations). For each species, we randomly selected a subset of its observations and estimated accuracy with this subset. Subset size was varied from five to the full number of observations for that species by increments of five (e.g., 5, 10, 15, . . . ). We repeated this procedure for each of the seven species. Simulation data for all seven species were combined into one data set. Once the simulations were run, we plotted the simulated accuracy data against the number of observations included in each subset. We separately regressed omission and commission error rates against number of detections to achieve a regression coefficient and standard error describing the relationship between model error types and number of detections.

If the observed pattern of change in error rates with number of species detections is an artifact of sample size, the slope of a linear regression line for the field data should be the same as that obtained by simulation. However, if there is a rarity effect, causing the models of less-common species to have lower accuracy than more common ones, then the slope of the field data regression line should be greater. To test for this, we used a student's t-test with the following null hypotheses:

$$H0: \beta_{cf} = \beta_{cs}$$ (51.1

$$H0: \beta_{of} = \beta_{os}$$ (51.2

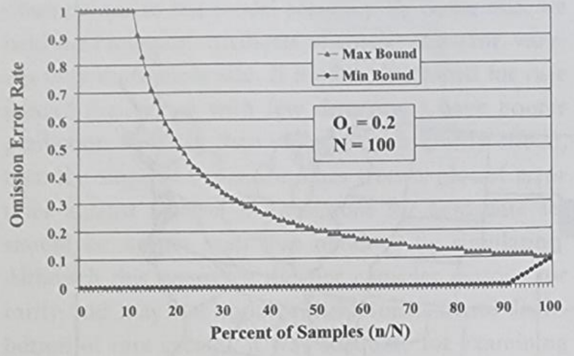

**Figure 51.2.** Maximum and minimum bounds on the possible values that an estimate of omission error assumes are dependent on the sample size. Sample size has been scaled to the percentage of points necessary to sample every individual in the study area.

where $b_{cf}$ is the slope of the regression line from the field observations for commission error, $b_{cs}$ is the slope of the regression line from simulation for commission error, $b_{of}$ is the slope of the regression line from field observations for omission error, and $b_{os}$ is the slope of the regression line from simulation for omission error. Because the simulations yielded large amounts of data behaving in mostly predictable patterns, the standard errors for the simulation regression coefficients were very small with respect to the parameter estimates. Thus, for the purpose of comparison, we constructed our statistical tests treating the simulation results as constants (Ramsey and Schafer 1997).

Plotting the possibilities that an estimate of omission or commission error could attain for a given sample size gave insight into the bounds within which error rates must be. To see how upper and lower bounds for omission error rates changed (Fig. 51.2), we assumed that a given model had a true omission error ($O_t$), that there were a definite number of individuals within the modeling area at a given time (N), and at some maximum amount of effort all individuals (N) were sampled and $O_t$ obtained. For all detections of n individuals (where n is less than or equal to N), omission error rates were bounded by 0.0 and 1.0 as long at n/N is less than or equal to $O_t$. When the proportion of sampled individuals (n) to the total number of individuals on the study area (N) exceeded the true omission error of the model, the upper bound decreased as

$$O_{max} = O_t N/n \tag{51.3}$$

The minimum bound for omission errors remained 0.0 as long as $n/N \leq 1 - O_t$. When the proportion of samples individuals (n) to total individuals (N) exceeded one minus the true omission error rate ($O_t$), the lower bound increased as

$$O_{min} = O_t - (N - n)/N \tag{51.4}$$

When n reached N, the only value that could be obtained for estimated omission error is $O_t$.

To see how upper and lower limits of commission error rates changed with sample size (Fig. 51.3), the same types assumptions for omission error rate bounds were made (i.e., actual number of sampling units and true commission error rate [$C_t$] that could be attained with some maximum effort). Additionally, the total number of predictions made (P) and the true omission error rate ($O_t$) must be known. The minimum bound for commission error rates originated at 1.0 for n = 0 and decreased linearly until estimated commission error reached $C_t$. The maximum commission error rate bound was 1.0 until n/N exceeds the omission error rate when it decreased linearly at the same rate as the minimum bound until $C_t$ was reached. The greatest difference between the maximum and minimum bounds for commission error rates was $O_t$.

## Results

The graph of commission error by number of detections (Fig. 51.4a) showed a strong negative trend as sample sizes increased across all species ($R^2 = 0.9861$: $P << 0.0001$) and behaved as predicted (Fig. 51.3). The regression line intercept was approximately equal to 1 (i.e., no observations necessitates total commission error). Commission error rates decreased 0.1 (or 10 percent) for every 167 observations. Five species had commission error rates less than predicted by the regression line (western meadowlark [see Appendix for scientific names and number of detections], spotted towhee, yellow warbler, song sparrow, warbling vireo). Omitting the seven species included in the sim-

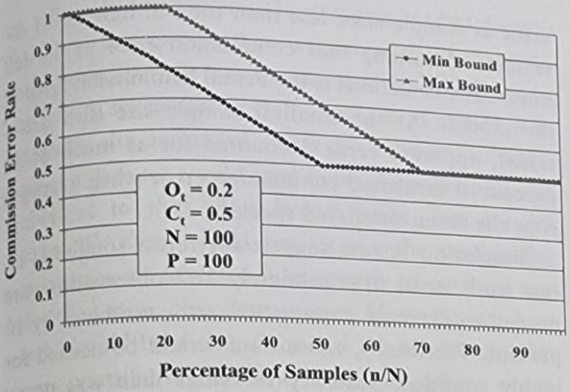

**Figure 51.3.** Maximum and minimum values that estimates of commission error assume are dependent on sample size and the actual omission error rate of the model. Sample size has been scaled to the percentage of points necessary to sample every individual in the study area.

ulation did not significantly change the regression coefficient ($\beta_{cf} = -0.0007$; $R^2 = 0.9577$; $P << 0.0001$)

Omission error rates showed a statistically significant decrease with changes in number of detections (Fig. 51.4b; $R^2 = 0.0716$; $P = 0.0051$). Given the low correlation, however, we did not consider this biologically significant because the change was less than 0.025 across the range of sample sizes 5 to 899. Variation in the values of omission error rates decreased as sample size increased. This was in line with our prediction (Fig. 51.2). Four species had significantly higher omission error rates than other species with similar numbers of detections (yellow warbler, song sparrow, black-capped chickadee, warbling vireo). Omitting the seven species included in the simulation significantly changed the regression coefficient ($\beta_{of} = -0.0009$; $R^2 = 0.0617$; $P = 0.0123$). We also did not consider this biologically significant.

In our simulation studies, commission error rates decreased predictably as sample size increased (Fig. 51.5a; $R^2 = 0.9973$; $P << 0.0001$). The regression line intercept was equal to one. Omission error was generally low and showed no correlation with respect to sample size but was statistically significant due to the large sample size (Fig. 51.5b; $R^2 = 0.0283$; $P < 0.0001$). Given the low correlation, we did not consider it biologically significant. Variation in the simulated omission error rates tended to decrease as sample size increased.

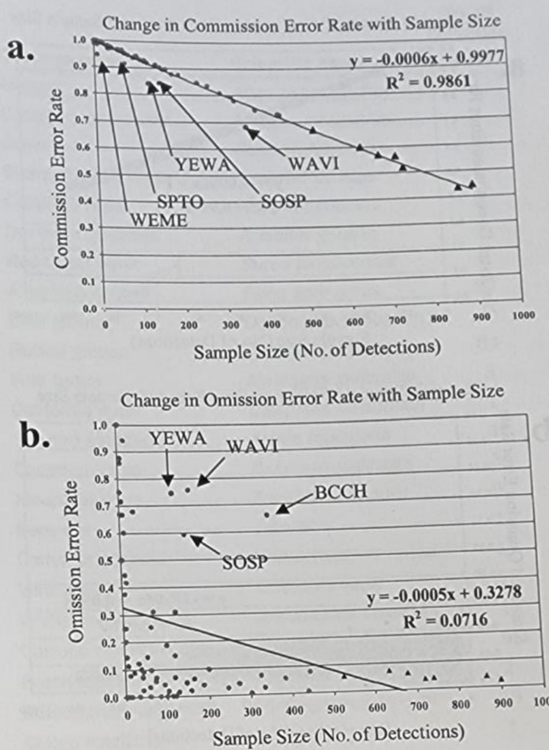

**Figure 51.4.** Change in error rates with number of detections for 108 bird species detected on the Idaho portion of U.S. Forest Service Northern Region. The seven species with more than five hundred detections (marked with dark triangles) were used in the simulation exercise. The dispersed nature of estimated commission (a) and omission (b) error rates obscured trends in the data due to sample sizes. Given that models with high commission error rates had low omission error and vice versa (indicating either over- or underprediction, correspondingly), we averaged commission and omission error rates for each model. Black triangles indicate the seven species included in the simulation. BCCH = black-capped chickadee (See Appendix for scientific names), WAVI = warbling vireo, YEWA = yellow warbler, SOSP = song sparrow, SPTO = spotted towhee, and WEME = western meadowlark.

### *Field and Simulation Comparison*

Field estimates of commission error change with number of detections were not significantly different from simulation estimates ($P = 0.1747$). The slope of the regression line for change in field estimates of omission error with number of detections was significantly less than that of simulation estimates ($P = 0.0065$). Given the variability in the omission error

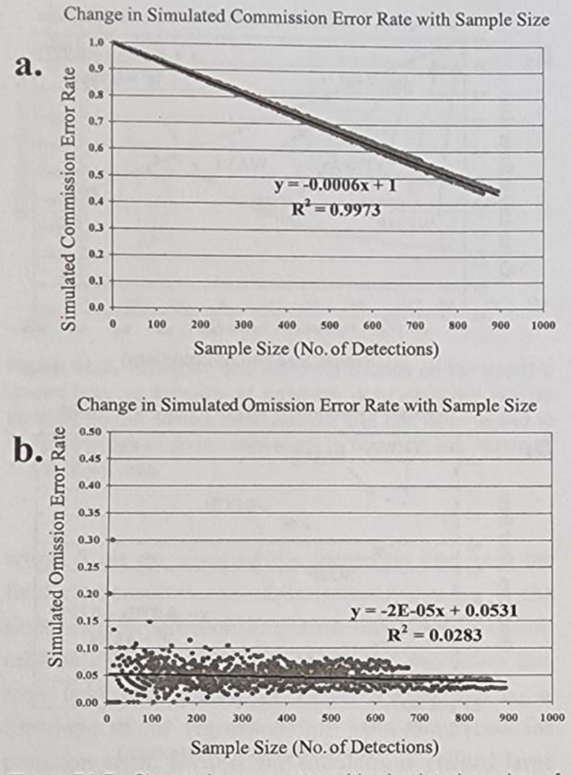

**Figure 51.5.** Change in error rates with simulated number of detections for the seven most common species detected on the U.S. Forest Service Northern Region. Because random subsets of observations were selected from the total observation set for each species, commission error decreased in a predictable manner (a). Omission error rates were low and exhibited more variability (b). Mean error rates for the simulations indicated similar patterns in error rate change with number of detections as the field observations.

data, we do not believe that this difference is biologically significant.

### *Error Rate Possibilities*

We found it was possible to account for the pattern in model error by changing the number of species detections. Error rates at small sample sizes were characterized by high estimates of commission error and high variability in omission error estimates. Commission error rates declined predictably with increasing number of observations. Variability in omission error estimates also decreased with increased observations. For predicting presence and absence of the seven simulated species, we can estimate the true versus apparent error at sample sizes less than the full number of detections (assuming that commission error at the full number of detections is the actual commission error of the model). At the smallest sample size (five detections), apparent error accounted for as much as 55 percent of measured commission error when averaged over the seven simulated species.

Simulation results suggest for forest songbirds on our study area, approximately 167 observations are needed to decrease commission error estimates by 10 percent. Potentially, more data would be needed for highly confident accuracy measures than was necessary for constructing the model. However, this is undoubtedly related to number of survey points versus area modeled. Still, this is a significant finding, as most accuracy assessments for wildlife-habitat models are either carried out with a very small number of field observations or not conducted at all (Salwasser and Krohn 1982; Morrison et al. 1998; Verbyla and Litvaitis 1989; T. C. Edwards personal communication). Project goals and the precision of results may need to be modified to fit within budgetary constraints. Thus, the additional expense in getting a test set of sufficient size may not always be possible to managers operating with small budgets.

Rabinowitz et al. (1986; see also Rabinowitz 1981) described rarity in terms of the interaction of geographic range, habitat specificity, and local density. Under this hypothesis, a species that occurred over a large region and in a variety of ecological conditions but had naturally low densities can be distinguished from a narrow endemic species that was strongly associated with localized habitat features but occurred in dense populations. This has important implications for assessing the accuracy of wildlife-habitat models. For habitat-general species that occurred in low densities over large regions, commission error rates at low sample sizes would contain a large apparent error component. However, for habitat-specific species occurring in high densities over small areas, true commission error may be much greater than apparent model error. Boone and Krohn (1999) attempted to quantify the attributes associated with rarity in Maine birds to predict whether wildlife-habitat models could be expected to have high apparent error components.

The intermountain northwest of the United States has relatively few endemic bird species (AOU 1998). Therefore, the species that we detected infrequently would most likely fit into the category of broad-range, low-density species (after Rabinowitz et al. 1986). Additionally, simulation of rarity by random subsampling of a data set would tend to produce distributions equivalent to that of a broad-range, low-density species. We then would not expect the models for most species we detected infrequently to perform any worse than more-abundant species. However, more research should be directed toward the effects of other factors contributing to rarity (i.e., geographic range, habitat specificity).

Given that the presence or absence of a species is related to habitat features that are easily mapped, it is plausible that the ability to correctly model species occurrence could be as much a function of how much is known about the species as it is a function of factors contributing to rarity. In the case of a species with a limited geographic range, incomplete knowledge as to the extent of its range could result in higher commission error. For widely distributed species occurring at low densities, apparent model error is likely very high given the difficulty in collecting sufficient observations. However, often more is known about the habitat associations and ranges of the rarest species than many common ones. Therefore, small sample sizes preclude reliable estimates of accuracy of habitat-relationship models for many rare species.

To the manager using habitat-relationship models to aid decision-making, this means that reported accuracies could be misleading. We do not advocate that effort should not be spent toward assessing model accuracy. Assessment with even the smallest sample size can give some information about model performance. However, the results of such calculations should be viewed with extreme caution since actual error rates could by above or below what is estimated.

## Appendix

Common and scientific names for species detected on U.S. Forest Service's Northern Region (Region 1), and the number of sites at which each species was detected.

| Common name | Scientific name | No. of detection sites |
|---|---|---|
| Mallard | *Anas platyrhynchos* | 2 |
| Common merganser | *Mergus merganser* | 2 |
| Osprey | *Pandion haliaetus* | 2 |
| Sharp-shinned hawk | *Accipiter striatus* | 4 |
| Cooper's hawk | *Accipiter cooperii* | 1 |
| Northern goshawk | *Accipiter gentilis* | 5 |
| Red-tailed hawk | *Buteo jamaicensis* | 8 |
| American kestrel | *Falco sparverius* | 12 |
| Blue grouse | *Dendragapus obscurus* | 2 |
| Ruffed grouse | *Bonasa umbellus* | 84 |
| Wild turkey | *Meleagris gallopavo* | 3 |
| California quail | *Callipepla californica* | 1 |
| Spotted sandpiper | *Actitis macularia* | 1 |
| Common snipe | *Gallinago gallinago* | 3 |
| Mourning dove | *Zenaida macroura* | 9 |
| Barn owl | *Tyto alba* | 1 |
| Common poorwill | *Phalaenoptilus nuttallii* | 1 |
| Vaux's swift | *Chaetura vauxi* | 2 |
| White-throated swift | *Aeronautes saxatalis* | 1 |
| Calliope hummingbird | *Stellula calliope* | 9 |
| Broad-tailed hummingbird | *Selasphorus platycercus* | 2 |
| Rufous hummingbird | *Selasphorus rufus* | 59 |
| Belted kingfisher | *Ceryle alcyon* | 7 |
| Lewis's woodpecker | *Melanerpes lewis* | 4 |
| Williamson's sapsucker | *Sphyrapicus thyroideus* | 8 |
| Red-naped sapsucker | *Sphyrapicus nuchalis* | 122 |
| Downy woodpecker | *Picoides pubescens* | 7 |
| Hairy woodpecker | *Picoides villosus* | 63 |
| Three-toed woodpecker | *Picoides tridactylus* | 8 |
| Black-backed woodpecker | *Picoides arcticus* | 1 |
| Northern flicker | *Colaptes auratus* | 112 |
| Pileated woodpecker | *Dryocopus pileatus* | 42 |
| Olive-sided flycatcher | *Contopus cooperi* | 56 |
| Western wood-pewee | *Contopus sordidulus* | 11 |
| Willow flycatcher | *Empidonax traillii* | 34 |
| Hammond's flycatcher | *Empidonax hammondii* | 302 |
| Dusky flycatcher | *Empidonax oberholseri* | 247 |
| Cordilleran flycatcher | *Empidonax occidentalis* | 23 |
| Violet-green swallow | *Tachycineta thalassina* | 1 |
| Barn swallow | *Hirundo rustica* | 1 |
| Gray jay | *Perisoreus canadensis* | 94 |
| Steller's jay | *Cyanocitta stelleri* | 67 |
| Clark's nutcracker | *Nucifraga columbiana* | 5 |
| American crow | *Corvus brachyrhynchos* | 1 |
| Common raven | *Corvus corax* | 15 |
| Black-capped chickadee | *Poecile atricapilla* | 171 |

(continues)

**Appendix. (Continued)**

| Common name | Scientific name | No. of detection sites |
|---|---|---|
| Mountain chickadee | *Poecile gambeli* | 165 |
| Boreal chickadee | *Poecile hudsonica* | 1 |
| Chestnut-backed chickadee | *Poecile rufescens* | 385 |
| Red-breasted nuthatch | *Sitta canadensis* | 635 |
| White-breasted nuthatch | *Sitta carolinensis* | 40 |
| Pygmy nuthatch | *Sitta pygmaea* | 4 |
| Brown creeper | *Certhia americana* | 74 |
| Rock wren | *Salpinctes obsoletus* | 1 |
| Canyon wren | *Catherpes mexicanus* | 1 |
| House wren | *Troglodytes aedon* | 102 |
| Winter wren | *Troglodytes troglodytes* | 335 |
| American dipper | *Cinclus mexicanus* | 14 |
| Golden-crowned kinglet | *Regulus satrapa* | 740 |
| Ruby-crowned kinglet | *Regulus calendula* | 120 |
| Western bluebird | *Sialia mexicana* | 1 |
| Mountain bluebird | *Sialia currucoides* | 13 |
| Townsend's solitaire | *Myadestes townsendi* | 75 |
| Veery | *Catharus fuscescens* | 1 |
| Swainson's thrush | *Catharus ustulatus* | 524 |
| Hermit thrush | *Catharus guttatus* | 33 |
| American robin | *Turdus migratorius* | 439 |
| Varied thrush | *Ixoreus naevius* | 187 |
| Gray catbird | *Dumetella carolinensis* | 4 |
| Cedar waxwing | *Bombycilla cedrorum* | 34 |
| European starling | *Sturnus vulgaris* | 1 |
| Plumbeous vireo | *Vireo cassinii* | 327 |
| Warbling vireo | *Vireo gilvus* | 361 |
| Red-eyed vireo | *Vireo olivaceus* | 17 |
| Orange-crowned warbler | *Vermivora celata* | 127 |
| Nashville warbler | *Vermivora ruficapilla* | 100 |
| Yellow warbler | *Dendroica petechia* | 129 |
| Yellow-rumped warbler | *Dendroica coronata* | 678 |
| Townsend's warbler | *Dendroica townsendi* | 865 |
| American redstart | *Setophaga ruticilla* | 10 |
| Northern waterthrush | *Seiurus noveboracensis* | 7 |
| MacGillivray's warbler | *Oporornis tolmiei* | 719 |
| Common yellowthroat | *Geothlypis trichas* | 8 |
| Wilson's warbler | *Wilsonia pusilla* | 158 |
| Western tanager | *Piranga ludoviciana* | 444 |
| Black-headed grosbeak | *Pheucticus melanocephalus* | 128 |
| Lazuli bunting | *Passerina amoena* | 104 |
| Spotted towhee | *Pipilo maculatus* | 74 |
| Chipping sparrow | *Spizella passerina* | 273 |
| Savannah sparrow | *Passerculus sandwichensis* | 3 |
| Fox sparrow | *Passerella iliaca* | 147 |
| Song sparrow | *Melospiza melodia* | 156 |
| Lincoln's sparrow | *Melospiza lincolnii* | 7 |
| White-crowned sparrow | *Zonotrichia leucophrys* | 8 |
| Dark-eyed junco | *Junco hyemalis* | 899 |
| Red-winged blackbird | *Agelaius phoeniceus* | 1 |
| Western meadowlark | *Sturnella neglecta* | 9 |
| Brewer's blackbird | *Euphagus cyanocephalus* | 2 |
| Brown-headed cowbird | *Molothrus ater* | 120 |
| Bullock's oriole | *Icterus bullockii* | 1 |
| Pine grosbeak | *Pinicola enucleator* | 5 |
| Cassin's finch | *Carpodacus cassinii* | 43 |
| Red crossbill | *Loxia curvirostra* | 45 |
| White-winged crossbill | *Loxia leucoptera* | 4 |
| Pine siskin | *Carduelis pinus* | 202 |
| American goldfinch | *Carduelis tristis* | 4 |
| Evening grosbeak | *Coccothraustes vespertinus* | 59 |
| House sparrow | *Passer domesticus* | 2 |