

MODELING THE RELATIONSHIP BETWEEN ESTIMATES OF LOCAL
OCCUPANCY AND LOCAL ABUNDANCE IN AVIAN SPECIES

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OCCUPANCY AND LOCAL ABUNDANCE IN AVIAN SPECIES

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ABSTRACT

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Occupancy, the percentage of an area occupied by one or more individuals of a species, and abundance, the number of animals in a population, are population variables often used to make management decisions. Because occupancy does not precisely estimate abundance for many wildlife species, it is not considered as vital to an informed management program. However, estimating occupancy usually requires less effort than abundance. If occupancy is strongly related to abundance then occupancy may be useful

to managers as a surrogate of abundance. Describing a linear relationship between occupancy and abundance would make estimating abundance more straightforward by allowing abundance to be calibrated to occupancy. Therefore, one objective was determining whether a linear relationship existed between occupancy and abundance. I also examined whether the relationship varies due to life history traits such as habitat use (specialist or generalist) and movement (year round resident or migrant). To address these objectives I conducted two seasons of avian point counts on Camp Swift in Bastrop County, TX during the fall of 2007 and winter of 2008. I sampled 100 detection stations located 200 meters apart and conducted four point count surveys of the detection stations for both seasons. I estimated occupancy using modified mark-recapture models and abundance using binomial mixture models. The findings indicated a linear relationship between occupancy and abundance. Moreover, slopes of the regressions for migrants and residents were significantly different. My research shows that occupancy-abundance relationships estimated at the local scale have the potential to be used to estimate abundance from occupancy. This has significant management implications for the use of occupancy models in lieu of the traditional, but more laborious, abundance estimators.

CHAPTER I

INTRODUCTION

Occupancy, the percentage of an area occupied by one or more individuals of a species, is a population variable that is not estimated as often as population abundance. Because occupancy does not precisely estimate abundance for many wildlife species, it is not considered as vital to an informed management program. However, estimating occupancy usually requires less effort than abundance, the number of animals in a population. If occupancy is strongly related to abundance then occupancy may be useful to managers as a surrogate of abundance; because the financial and logistical burdens of estimating occupancy can be less.

Measuring abundance precisely and in an unbiased manner is challenging; most studies resort to using raw count data collected from sampling points as an index of abundance (Rosenstock et al. 2002). This is problematic because the index assumes that the detection probability is binary, either a species is not present and not detected, or it is present and detected; count data does not take into account the possibility of animals of a species being present but not detected (imperfect detection). There are many factors that can affect detection probabilities, such as the abilities of the observer to detect the species (Sauer et al. 1994, Conway et al. 2004, Tracy et al. 2005, Alldredge et al. 2006), the physical and behavioral attributes of the species being counted (Chen et al. 2009), habitat

(Mancke and Gavin 2000, Bailey et al. 2004, Gu and Swihart 2004), and the survey methods (Conway and Simon 2003). The most commonly used techniques that account for imperfect detection are mark-recapture and distance sampling techniques, both of which can have high financial costs and logistical commitments (Bibby et al. 2000). Mark-recapture techniques can provide reliable estimates of the probability of detection, but the equipment needed to capture and mark the animals can be expensive, and a large time commitment is needed from observers for extensive training. Distance sampling also requires extensive training to ensure accurate measurements of direction and distance of observations, which can be difficult to obtain (Alldredge et al. 2007).

Occupancy may be a useful surrogate for abundance because occupancy is related to the size of a population (Blackburn et al. 1997, Gaston et al. 2000, Zuckerberg et al. 2009). Occupancy is typically estimated in bird populations using point counts where the presence or absence (more correctly non-detection) of a species is recorded (Pollock et al. 2002). Previous methods using this type of data assumed that if an animal was not detected, it was not present. Mackenzie et al. (2002) developed occupancy models by modifying mark-recapture models. Occupancy is estimated using repeated detection/non-detection data collected from spatially referenced sampling units that account for imperfect detection. Consequently, it is possible to estimate occupancy accurately. Occupancy models are appealing because they can be applied to many species that differ in life history and habitats used (Ball et al. 2005, Eraud et al. 2007). The point count sampling technique used in conjunction with occupancy estimation requires less personnel training and fewer logistical burdens than mark-recapture or distance sampling methods (Bibby et al. 2000). If occupancy reliably estimates abundance it may be a

useful surrogate of abundance, because estimating occupancy is more cost effective and has fewer logistical burdens than estimating abundance.

Many studies have examined the relationship between abundance and occupancy (Brown 1995, Gaston et al. 1999, Gaston et al. 2000, Blackburn et al. 2006, Zuckerberg et al. 2009). The idea that species of low local abundance occupy a smaller percentage of a region compared to species of high local abundance is known as the abundance-occupancy rule (Gaston et al. 2000). A region is usually defined as the size of the breeding (or wintering) range of the entire species, while local is a smaller area of less than 10 square kilometers (Zuckerburg et al. 2009). Abundance-occupancy relationships have two types: intra- and interspecific. Intraspecific relationships concern the changes in local abundance in relation to regional occupancy for one species over time (Blackburn et al. 1998, Gaston et al. 1999, Webb et al. 2007), and interspecific relationships concern the abundance and occupancy of many species at one point in time (Gaston 1996, Cade and Woods 1997, Blackburn et al. 1998, Gaston et al. 1999). Although some studies examining the abundance-occupancy rule for intra- and interspecific relationships found no relationship or a negative relationship (Blackburn et al. 2006, Symonds and Johnson 2006), usually a positive relationship is detected (Blackburn et al. 2006, Zuckerberg et al. 2009).

Studies examining the abundance-occupancy rule were focused on local abundance driving regional occupancy (Holt and Gaston 2003). No studies have examined how local occupancy relates to local abundance. Examining the relationship at the local scale has a practical implication; using occupancy to estimate abundance may spare managers the financial and logistical burdens of directly estimating abundance.

Estimating occupancy and abundance relationships from point count data, a commonly used bird survey technique, should be possible using the occupancy estimators developed by Mackenzie et al. (2002) and the binomial mixture models developed by Royle and Nichols (2003). Both of these estimation approaches account for imperfect detection. At the local scale spatial distribution of animals should enlarge as density increases, thus occupancy should also increase. If occupancy is positively related to abundance, it should be possible to estimate the abundance of a population using presence-non-presence data (Zhou and Griffiths 2007).

The form of the abundance-occupancy relationship may be influenced by life-history characteristics of the species being studied, specifically their migration status and habitat use patterns. Since migrant species may not have the familiarity with a given area that resident species have, the result should be a difference in the form of the abundance-occupancy relationship between migratory and resident species. Similarly, species that use a specific habitat should have a different abundance-occupancy relationship than species that are habitat generalists. It has been shown that life-history traits affect abundance (Blackburn et al. 1996), but whether the form of abundance-occupancy relationships differs as a function of life history attributes has not been examined (Blackburn et al. 1997, Zuckerberg et al. 2009).

I estimated occupancy and abundance for local populations of song bird species to address two questions about interspecific relationships of local occupancy and local abundance. One, is there a positive linear relationship and, two, does the relationship vary due to migration status and habitat use patterns. Describing the linear relationship (as opposed to a non-linear relationship) between occupancy and abundance would make

estimating abundance more straightforward by allowing abundance to be calibrated to occupancy.

CHAPTER II

SITE DESCRIPTION

Camp Swift, located in Bastrop County, Texas, is owned by the Army Corps of Engineers, and is licensed to the Texas National Guard for use as a training site. It is 4,718 ha in size, with 1% of the installation covered by buildings, 2% by firing ranges, and the remaining 97% is primarily unimproved grounds.

Camp Swift is in the southern Post Oak Savannah ecoregion of Texas. Topography varies from flat to gently rolling hills with elevations ranging from 90 to 148 m above sea level. The dominant vegetative communities are post oak (*Quercus stellata*)-blackjack oak (*Quercus marilandica*)-eastern red cedar (*Juniperus virginiana*) forest (74%), little bluestem (*Schizachyrium scoparium*)-indiangrass (*Sorghastrum nutan*) grassland(15%), green ash (*Fraxinus pennsylvanica*)-american elm (*Ulmus americana*) riparian forest (4%), and loblolly pine (*Pinus taeda*) forest (1%). Temperatures range from a low of -5° C in January to 39° C in June, with an annual precipitation of 49.61 cm (NOAA 2008). The area surrounding Camp Swift is mostly rural, undeveloped woodlands or agricultural land, mostly used for grazing cattle.

CHAPTER III

MATERIALS AND METHODS

Detection stations (stations) consisted of 100 points located 200 m apart (Figure 1). I created 100 points to have adequate sample sizes for estimating parameters of occupancy and abundance and to cover a reasonable proportion of the study area (MacKenzie et al. 2006). I placed stations 200 m apart to reduce the probability of a single individual being detected at multiple stations. For 80 of the 100 points I used ArcGIS 9.2 (ESRI, Redlands, CA) to create a random starting point on an unimproved road on Camp Swift. The stations were located 30 m (to the left or to the right, chosen randomly) from the road. I did this to reduce the influence of edge effects and disturbance from vehicle traffic on the road. The remaining 20 points were arranged in two U-shaped routes starting and ending at the road. The points on these routes sequentially increased in distance from the road and were designed to examine whether edge effect from the road influenced the avian surveys. I classified three kinds of habitats at Camp Swift; forest, grassland, and riparian. There are two types of non-riparian forest present at Camp Swift: post oak-blackjack oak-eastern red cedar forest and loblolly pine forest; since the loblolly pine forest comprises just 1% of the total area I combined the two in my classification. Of my points, 50% were classified as grassland, 37% were forest, and 13% were riparian. I conducted two surveys, one in November - December 2007 (fall survey), and the other in February – March 2008 (winter survey). I conducted

at least three sets of counts at each station for both surveys to ensure that survey effort was adequate to estimate parameters (Mackenzie and Royle 2005, Mackenzie et al. 2006). One of the assumptions of the model I used is that surveys took place when populations were closed, meaning no immigration, emigration, natality or mortality occurred (Mackenzie et al. 2002). The fall and winter surveys each were completed within a month and a half of their respective starts. There were four observers for each survey; all observers had previous experience conducting avian point-counts. Only one of the observers was used for both seasons. A single observer conducted counts at up to 25 stations per day. It took two to three days to complete all 100 stations. Each count was completed in less than a week and there were at least two days separating counts. Each day of counts started around local sunrise and ended by noon and was conducted under weather conditions considered adequate for avian surveys. I defined adequate weather as wind conditions less than or equal to four on the Beaufort scale (Robbins et al. 1986) and precipitation no heavier than a light drizzle. To minimize the effect of time of day and observer on counts, I randomized the observer and order in which the points were visited.

Count procedure

A single observer spent seven minutes at each station. The first two minutes were a settling period (Bibby et al. 2000). The following five minutes were spent recording every species detected by sight or sound and counting the number of individuals of species. The five minute observation period was chosen because this allowed me to maximize the number of stations surveyed per day while allowing sufficient time to identify the birds present at the station (Dettmers et al. 1999).

Life History Classification

I classified species by their winter habitat use and migratory status. I used the *Birds of North America Online* (Pool 2005) to classify avian species as either specialists or generalists in their habitat use in the non-breeding season. I considered a species to be a specialist if it was found primarily in a specific type of habitat (for example, the Tufted tit-mouse (*Baeolophus bicolor*) prefers dense-canopy forests). I considered a species to be a generalist if its habitat use was varied (for example the American kestrel (*Falco sparverius*) can inhabit a variety of open to semi-open habitats). I used Breeding Bird Survey classifications to identify species as migrants or residents, except in a few cases where a species was a short distance migrant over most of its range, but was a resident in the part of its range that included the study area (Freeman 2003, Pool 2005, Saur et al. 2008).

Data Analysis

To insure an adequate sample size for parameter estimation I only considered species that were observed ten or more times throughout a given season for occupancy analysis. For occupancy analysis I coded my count data -- the number of individuals observed for each species -- as either a 0 for no birds observed, or a 1 for one or more birds observed. I developed eight candidate models (Table 1) to assess the potential influence of habitat, count, time of day, and observer on detection and occupancy. I treated habitat, observer, and survey as categorical variables. I coded time of day that stations were surveyed in minutes after sunrise. Time of day, a continuous variable, was z

transformed (mean = zero, unit standard deviation) to improve reliability of parameter estimates (MacKenzie et al. 2003). I used program PRESENCE (version 2.3) to estimate parameters and standard errors (SE) (MacKenzie et al. 2006). The assumptions of Occupancy estimators are that species detections are independent, the population is closed, and that species are not falsely detected; however animals of a species can remain undetected if present (Mackenzie et al. 2003).

I selected models using the Akaike Information Criterion (AIC) corrected for small data sets (AICc). A model which summarizes the data well relative to the number of parameters estimated and has a small AICc value relative to the other models in the analysis. Models in the analysis that had AICc values within four units of the model with the lowest AICc were considered competing models (Anderson and Burnham 2002). I took all models from an analysis and calculated their Akaike weights, then used the models to estimate detection probability and occupancy for the set. When there were competing models I averaged parameter estimates according to their Akaike weights (Stanley and Burnham 1998).

To assess whether having most of my points along the road influenced occupancy, I created a categorical covariate wherein a detection station was either on one of the two U-shaped routes or it was not. Then I created a model where occupancy was allowed to vary by this covariate and detection was kept constant; I then applied this model to Fall occupancy data and calculated its AIC_c value compared to that of the chosen models from the same species.

I developed 6 candidate models (Table 2) to assess the potential influence of habitat, time of day, and observer on abundance. The parameter I estimated was λ , the

estimated abundance per point. I was unable to test for the influence of count on detection because binomial mixture models do not estimate survey-specific detection probability (Royle and Nichols 2003). I conducted the abundance analysis using the Repeated Count Data (Royle Biometrics) analysis in the program PRESENCE (v. 2.3), which uses a Poisson distribution to estimate abundance and a binomial distribution to estimate detection. The assumptions of this model are that animal detections are independent, the population is closed, and that the detection probability of a single animal is constant across time; these assumptions should apply to a wide variety of species (Royle and Nichols 2003). The procedure for model selection was the same as with the occupancy models.

To model the relationship between occupancy and abundance I used only the species which had reasonable estimates of abundance. Some of the estimates of abundance were unrealistic, such as 40 black vultures (*Coragyps atratus*) per point in the winter season when the most seen at one survey was 13, with most observations being one or two at a point. Because the number of species with reasonable estimates of abundance was low I combined the results from the two seasons. There were two species that had reasonable abundance estimates in both seasons, and for them I averaged their estimates. Regressions were estimated using bisector regressions because both x and y variables were measured with error and ordinary least square regressions assumes x is measured without error (Isobe et al. 1990, Sokal and Rohlf 1995). I grouped species by their life-history traits, estimated regressions, and assessed fit using r^2 , I tested whether slopes of life-history specific regressions differed using the t-test (Kleinbaum et al. 1998).

CHAPTER IV

RESULTS

I conducted the fall survey, consisting of four full counts, between 24 October and 19 December, 2007. Surveyors observed 60 species, but of those only 23 were observed enough times to be included in occupancy and abundance analyses. The point counts took place between 20 and 450 minutes after sunrise, and the average number of individual birds observed in a single point count was 8.4 (minimum = 0, maximum = 54). The average number of species observed at a single point was 5.0 (minimum = 0, maximum = 14).

I conducted the winter survey between 21 January and 2 March, 2008. I conducted four full counts; however, difficulties with one observer resulted in a loss of about 12 percent of the data. Despite this problem each point was surveyed at least three times over the course of the four counts, which was adequate for data analysis. A total of 66 species were observed during the winter season, but only 20 had enough observations for occupancy and abundance analysis. Points were surveyed 21 to 401 minutes after sunrise. The average number of birds observed in an individual point count was 10.3 (minimum = 0, maximum = 116). The high maximum counts were from several occasions on which huge flocks of either Cedar Waxwings (*Bombycilla cedrorum*) or American Robins (*Turdus migratorius*) were present. The average number of species observed was 5.0 (minimum = 0, maximum = 12).

Occupancy Estimates

I analyzed the data for 30 species, of which 23 species were from the fall season and 21 were from the winter season (Table 3). For some species the selected model had problems where the variance-covariance matrix was not estimated. Other models had a convergence of < 2 (parameters estimated to the nearest tenth) that resulted in program PRESENCE not being able to estimate parameters. In these cases I used the model with the next lowest AIC value as the selected model. Models including the observer as a variable (Table 1; models 3 and 7) were considered competing models more often than any other model. Model 3 was considered competing in an average of 60% of species analyzed over both seasons and model 7 was considered competing in 64% of them. Models that included habitat as a variable (Table 1; models 5 through 8) were chosen about as often as those that did not (Table 1; models 1 through 4). Estimated occupancies ranged from 0.12 to 1.0 of the points being occupied by a given species (Appendices 1 and 2). Detection probabilities ranged from 0.025 for the orange-crowned warbler (*Vermivora celata*) in fall to 0.77 for the northern cardinal (*Cardinalis cardinalis*) in winter. Some models that would have otherwise been competing models had either a variance-covariance problem or a convergence of < 2.0 and were not included in model averaging (Appendices 1 and 2).

The White-eyed vireo was the only species whose road effect model was considered a competing model (with a $\Delta AICc$ value of less than 4). The rest of the models had $\Delta AICc$ values of between 5.8 and 68.1 (Table 4).

Abundance Estimates

The model selection process for abundance estimates was similar to that for occupancy (Appendices 3 and 4). Models that included observer as a variable (Table 2; models 3 and 6) were considered competing models more often than any other model. Model 3 was considered competing in an average of 64% of species analyzed over both seasons and model 6 was considered competing in 82% of them. Models that included habitat as a variable (Table 2; models 4 through 6) were chosen about as often as those that did not (Table 2; models 1 through 3). Estimated abundances ranged from a minimum of 0.22 to greater than 40 individuals per point. The excessively high estimates of abundance were usually from species that had very low detection probabilities (less than 0.002). For example, the Carolina chickadee (*Poecile carolinensis*) had an abundance estimate of 40.0 with a detection probability estimate of 0.01 in the fall season. Estimates of detection probabilities for abundance ranged from 0.1% for the northern flicker (*Colaptes auratus*) in the fall to 0.287 for the pileated woodpecker (*Dryocopus pileatus*) in the fall. Most estimated detection probabilities were less than 0.05 (Appendices 3 and 4).

The Relationship between Occupancy and Abundance

There were 8 species in the fall and 9 species in the winter that had reasonable estimates of abundance, as determined by what fit our observations in the field (Tables 5 and 6). To increase sample sizes, I combined results from the two seasons, averaging estimates from the two species present in both seasons (Table 7).

The data indicate a significant linear relationship between occupancy and abundance ($\lambda = -0.69 + 6.39*\psi$, $p = 0.0002$, $r^2 = 0.629$). Moreover, significant linear relationships were detected for migrants ($\lambda = -0.19 + 4.94*\psi$, $p = 0.026$, $r^2 = 0.440$), and residents ($\lambda = -0.93 + 7.41*\psi$, $p = 0.004$, $r^2 = 0.856$) and a t-test shows that the slopes of the regressions for migrants and residents are significantly different ($t = 2.64$, $df = 13$, $p = 0.010$). There was no significant linear relationship for habitat generalists ($\lambda = -1.18 + 7.89*\psi$, $p = 0.072$, $r^2 = 0.451$), but there was one for habitat specialists ($\lambda = -0.54 + 5.84*\psi$, $p = 0.001$, $r^2 = 0.754$), the slopes were also not significantly different ($t = 1.12$, $df = 13$, $p = 0.141$) (Figures 2 and 3).

CHAPTER V

DISCUSSION

My data show a significant linear relationship between occupancy and abundance. Previous research has shown that local abundance influences regional occupancy, but occupancy influencing abundance has not been examined to the same extent. Also, previous investigations examined the relationship at different geographic scales (Brown 1995; Gaston et al. 1999, Gaston et al. 2000, Blackburn et al. 2006, Zuckerberg, Porter, Corwin 2009); while the data I collected were local for both occupancy and abundance. In addition, my data indicate that species life history influences the shape of the relationship between occupancy and abundance. By taking life history into account it may be possible to more accurately predict abundance from occupancy for a given species of bird.

Part of what makes the models that I used to estimate occupancy and abundance compelling is that they allow detection probabilities of less than one (Mackenzie et al. 2002); using model selection I was able to examine what factors may influence detection probability. Before these models were developed, the way to estimate occupancy was to assume either perfect, or at least constant, detection probability, and estimating abundance was the same, or if there was an attempt to estimate detection probability it was using costly and time consuming methods such as distance sampling or mark-recapture studies (Bibby et al. 2000). Possible influences I examined were observer,

time of observation, and survey. Models that included the observer as a variable were chosen much more often than any other model. That the abilities of observers to detect birds depends on factors such as experience, training, and hearing ability has been discussed at length in previous work (Kepler and Scott, 1981, Saur et al. 1994). This would be especially notable in a study like mine where observers must identify multiple species that could be encountered.

Models which included time of day and date were chosen for some species, but not at a noticeably higher rate than other models. Time of day has been indicated as an influence on detection probability (Skirven 1981), but it may have not been as important in my study simply because observers had greater impact on detection probabilities. It is also possible that time of day did not affect detection as much as expected because of the time of year of my study; most point counts are done during the breeding season, which is a season with hot day time temperatures. Birds are most active at dawn and then are quiet during the hottest part of the day. In the fall and winter, my survey period, there was not as great a change in temperature, and not as great a change in bird activity (Rollfinke and Yahner 1990).

The only variable I examined which could influence occupancy or abundance was habitat type. Habitat has been shown to influence both occupancy and abundance (Mancke and Gavin 2000, Bailey et al. 2004, Gu and Swihart 2004). Some bird species are normally associated with certain habitats and should be present there; however, my data did not show this to be the case. Forest birds such as the Carolina chickadee should have higher densities in forest habitats and grassland birds such as the Eastern meadowlark should have higher abundance in grassland habitats. There was no noticeable

difference between the number of competing models that included habitat as a factor and those that did not. It is possible that the habitat types present on Camp Swift are too fragmented for habitat to be a factor. Most of my points were close to multiple habitat types, so a point in grassland habitat could be within hearing distance of closed canopy forest habitat. Of the 100 points I surveyed, 80 were set 30 m off of the road and 200 m apart. The remaining 20 points were set in 2 U-shaped patterns of 10 points each with all points greater than 30 m from the road. The assumption in setting the points as I did was that distance from the road would be relevant to the fragmentation of the surrounding habitat; however the habitat around the points in the U-shaped routes was just as fragmented as the habitat around the road points, and models considering whether or not points were on the U-shaped routes were not considered competing models. I therefore think that the relative proximity of the 80 points to the service road was irrelevant to whether or not habitat influenced occupancy or abundance in my findings.

Despite my statistically significant results, I think that the many unrealistic estimates I obtained using binomial mixture models cannot be ignored, thus calling into question the usefulness of the estimators. Out of 60 species observed during the point counts, only about 10 per season had estimates of abundance that were reasonable. This brings into question how reliable the remaining estimates are as well as why the unreasonable estimates exist in the first place. It may have been because of low detection probabilities for abundance. With occupancy I was only estimating the probability of observing at least one member of a given species; when working with abundance estimates the important factor was the probability of observing a number of individuals.

This results in much lower detection probabilities and therefore estimating abundance is much more challenging.

Another possible reason for the estimates that did not fit reasonable expectations is that there may have been violations of model assumptions. Assumptions of the models include closed populations and random distribution of individuals. Because we were conducting these studies in the non-breeding season there may have been more movement of individuals than during the breeding season (Logan 1987). Also, animals may not have been randomly distributed; during the non-breeding season birds will join mixed-species flocks and may not stay in a set territory (Farley et al. 2008).

Most other work on this subject examined the ways in which local abundance affects regional occupancy (Holt and Gaston 2003). My work examined the occupancy variable at the local rather than regional scale. It also reversed the dependent and independent variables; as the above-referenced work treated abundance as the independent variable, I treated occupancy as the independent variable; this allowed me to look at how local occupancy affects local abundance. At the local scale spatial distribution of animals should enlarge as density increases, thus occupancy should also increase. There is a potential for a practical application to this work; presence - non-presence data may be used to estimate abundance, thus saving managers time and money. Additional work, however, is required to obtain occupancy and abundance estimates from a larger set of species than estimated herein. The inability of binomial mixture models to estimate abundance for a number of species with sufficient data preclude me from conducting a rigorous evaluation of whether abundance can be estimated from estimates of occurrence at the local scale.

Table 1. A list of the models used for estimating occupancy (ψ) and the probability of detection (p). Models 1-4 keep occupancy constant (.) while models 5-8 allow occupancy to vary with habitat. Detection probability is held constant (.), or allowed to vary by minutes from sunrise (time), between observers (observer), or between surveys (survey).

Model number	Model
1	$\psi(\cdot), p(\cdot)$
2	$\psi(\cdot), p(\text{time})$
3	$\psi(\cdot), p(\text{observer})$
4	$\psi(\cdot), p(\text{survey})$
5	$\psi(\text{habitat}), p(\cdot)$
6	$\psi(\text{habitat}), p(\text{time})$
7	$\psi(\text{habitat}), p(\text{observer})$
8	$\psi(\text{habitat}), p(\text{survey})$

Table 2. A list of the models used for estimating abundance (λ) and the probability of detection (p). Models 1-3 keep abundance constant (.) while models 4-6 allow abundance to vary with habitat. Detection probability is held constant (.), or allowed to vary by minutes from sunrise (time), or between observers (observer).

Model number	Model
1	$\lambda(\cdot), p(\cdot)$
2	$\lambda(\cdot), p(\text{time})$
3	$\lambda(\cdot), p(\text{observer})$
4	$\lambda(\text{hab}), p(\cdot)$
5	$\lambda(\text{hab}), p(\text{time})$
6	$\lambda(\text{hab}), p(\text{observer})$

Table 3. A list of the species included in this study with their 4-letter code, common name and scientific name.

4-Letter Code	Common Name	Scientific Name
AMCR	American Crow	<i>Corvus brachyrhynchos</i>
AMGO	American Goldfinch	<i>Carduelis tristis</i>
AMKE	American Kestrel	<i>Falco sparverius</i>
AMRO	American Robin	<i>Turdus migratorius</i>
BLJA	Blue Jay	<i>Cyanocitta cristata</i>
BLVU	Black Vulture	<i>Coragyps atratus</i>
CACH	Carolina Chickadee	<i>Poecile carolinensis</i>
CARW	Carolina Wren	<i>Thryothorus ludovicianus</i>
CEDW	Cedar Waxwing	<i>Bombycilla cedrorum</i>
CHSP	Chipping Sparrow	<i>Spizella passerina</i>
EABL	Eastern Bluebird	<i>Sialia sialis</i>
EAPH	Eastern Phoebe	<i>Sayornis phoebe</i>
EATO	Eastern Towhee	<i>Pipilo erythrophthalmus</i>
HETH	Hermit Thrush	<i>Catharus guttatus</i>
HOWR	House Wren	<i>Troglodytes aedon</i>
LISP	Lincoln's Sparrow	<i>Melospiza lincolnii</i>
NOCA	Northern Cardinal	<i>Cardinalis cardinalis</i>
NOFL	Northern Flicker	<i>Colaptes auratus</i>
NOMO	Northern Mockingbird	<i>Mimus polyglottos</i>
OCWA	Orange-crowned Warbler	<i>Vermivora celata</i>
PIWO	Pileated Woodpecker	<i>Dryocopus pileatus</i>
RBWO	Red-bellied Woodpecker	<i>Melanerpes carolinus</i>

Table 3. Continued.

4-Letter Code	Common Name	Scientific Name
RCKI	Ruby-crowned Kinglet	<i>Regulus calendula</i>
RSHA	Red-shouldered Hawk	<i>Buteo lineatus</i>
SOSP	Song Sparrow	<i>Melospiza melodia</i>
SPTO	Spotted Towhee	<i>Pipilo maculatus</i>
TUTI	Tufted Titmouse	<i>Baeolophus bicolor</i>
TUVU	Turkey Vulture	<i>Cathartes aura</i>
WEVI	White-eyed Vireo	<i>Vireo griseus</i>
YRWA	Yellow-rumped Warbler	<i>Dendroica coronate</i>

Table 4. Summary of AICc values for the model $\psi(\text{road effect})$, $p(\cdot)$ and their ΔAICc and AICc weights when compared to the other models for that species. Species tested were those selected for inclusion in the final analysis from the fall season (Appendix 1). Only one of the road effect models was a competing model (with a ΔAICc value of less than 4).

Species	AICc	Δ AICc	AICc wgt
AMKE	126.04	8.852	0.006
EABL	126.70	19.712	0.000
LISP	249.06	16.693	0.000
NOMO	292.68	25.613	0.000
RBWO	158.10	5.412	0.025
TUVU	343.56	20.272	0.000
WEVI	102.44	2.352	0.309
YRWA	304.53	67.342	0.000

Table 5. Averaged occupancy (ψ) and abundance (λ) estimates and their detection probabilities (p) of selected species from the fall season. Estimates from competing models (Appendices 1-2) were averaged using model averaging.

	Occupancy				λ	Abundance		
	ψ	st.err	p	st.err		st.err	p	st.err
AMKE	0.548	0.044	0.064	0.017	2.264	8.009	0.015	0.054
EABL	0.283	0.186	0.130	21.498	1.163	1.356	0.048	7.523
LISP	0.078	0.065	0.266	0.074	1.538	0.540	0.134	0.048
NOMO	0.423	0.146	0.175	5.285	3.653	3.103	0.046	8.996
RBWO	0.219	0.074	0.253	0.103	0.270	0.103	0.270	0.104
TUVU	0.716	0.112	0.243	0.061	5.498	6.786	0.062	0.077
WEVI	0.157	0.088	0.195	4.593	0.178	0.085	0.242	7.651
YRWA	0.969	35.577	0.126	0.027	4.233	3.399	0.052	0.043

Table 6. Averaged occupancy (ψ) and abundance (λ) estimates and their detection probabilities (p) of selected species from the winter season. Estimates from competing models (Appendices 2-4) were averaged using model averaging.

Bird	Occupancy				avg. λ	Abundance		
	avg. ψ	st.err.	avg. p	st.err		st.err	avg. p	st.err
AMGO	0.697	0.295	0.115	0.052	3.447	2.072	0.056	2.386
AMRO	0.480	0.221	0.150	0.086	4.525	3.928	0.041	0.432
BLJA	0.126	0.052	0.339	0.141	0.228	0.110	0.199	0.068
EAPH	0.721	0.145	0.199	0.060	1.889	1.084	0.096	0.057
NOMO	0.234	0.108	0.198	0.106	0.342	0.215	0.149	0.098
RBWO	0.443	0.193	0.146	5.454	1.849	2.198	0.044	0.049
RSHA	0.854	0.155	0.227	0.066	3.723	3.236	0.060	0.052
SPTO	0.486	0.141	0.142	0.075	0.886	0.504	0.121	0.072
TUTI	0.962	0.045	0.439	0.062	6.504	2.950	0.107	0.049

Table 7. Combined occupancy (ψ) and abundance (λ) estimates of species from the fall and winter seasons and their guild classification. Estimates from species that occurred in both seasons were averaged. The specialist classification was applied to the species classified as Woodland Breeding or Successional or Scrub Breeding by the Breeding Bird Survey (BBS). The generalist classification was applied to species classified as Urban Breeding or that were unclassified by the BBS and were characterized as non-specialist breeders in the Birds of North America Online (Sauer *et al.* 2008, Pool 2005). Migratory status classification was either migrant or permanent resident. BBS classifications were used, except in the cases of some short-distance migrants, which are residents in parts of their range, including Bastrop County, TX (Pool 2005, Saur *et al.* 2008, TPWD PIF).

Bird	avg. ψ	avg. λ	migrant	habitat use
AMGO	0.697	3.447	migrant	specialist
AMKE	0.548	2.264	migrant	generalist
AMRO	0.480	4.525	migrant	generalist
BLJA	0.126	0.228	resident	generalist
EABL	0.283	1.163	migrant	generalist
EAPH	0.721	1.889	migrant	generalist
LISP	0.078	1.538	migrant	specialist
NOMO	0.328	1.997	resident	specialist
RBWO	0.331	1.059	resident	specialist
RSHA	0.854	3.723	resident	specialist
SPTO	0.486	0.886	migrant	specialist
TUTI	0.962	6.504	resident	specialist
TUVU	0.716	5.498	resident	generalist
WEVI	0.157	0.178	migrant	specialist
YRWA	0.969	4.233	migrant	specialist

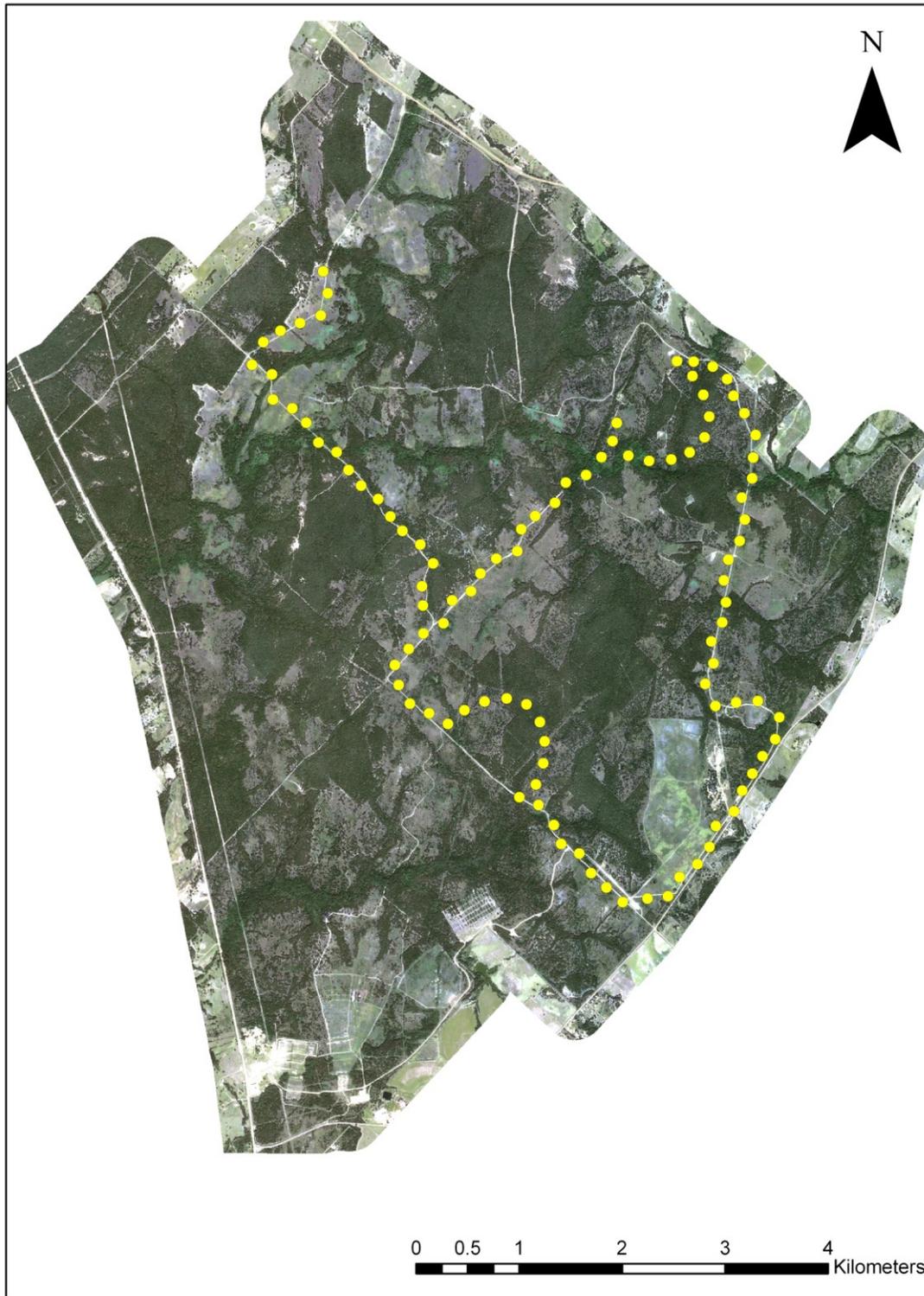


Figure 1. Avian Point Count locations (yellow dots) surveyed during October-December 2007 (Fall Survey) and January-March 2008 (Winter Survey) on Camp Swift Texas Army National Guard training site in Bastrop County, TX. Darker areas are forested and lighter areas are open habitat.

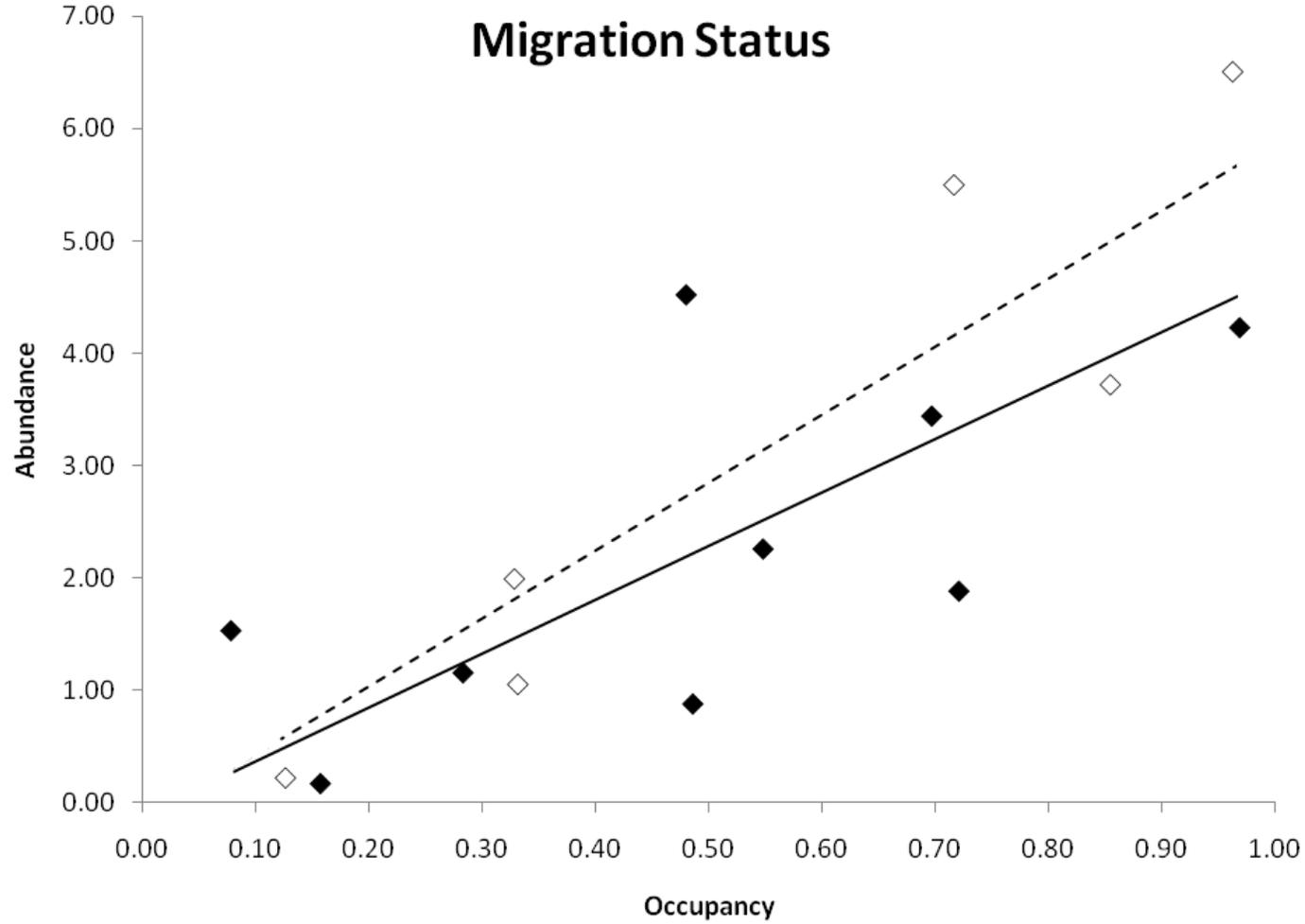


Figure 2. Scatterplot of occupancy vs. abundance using the combined points from the Fall and Winter surveys. Solid diamonds are migrant species ($\lambda = -0.11 + 4.77 * \psi$, $p = 0.026$, $r^2 = 0.440$) and hollow diamonds are resident species ($\lambda = -0.18 + 6.06 * \psi$, $p = 0.004$, $r^2 = 0.856$).

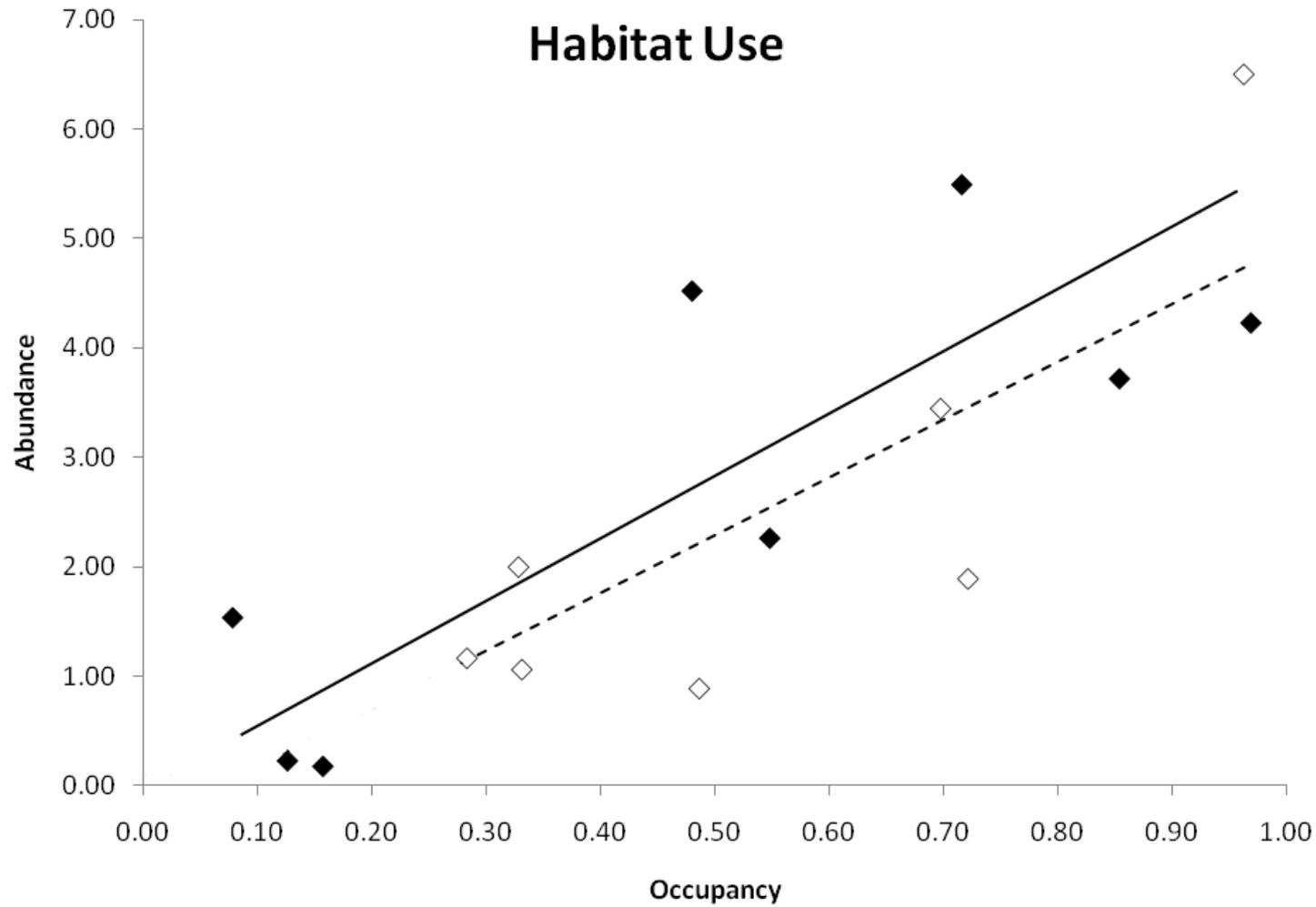


Figure 3. Scatterplot of occupancy vs. abundance using the combined points from the Fall and Winter surveys. Solid diamonds are generalist species ($\lambda = -0.029 + 5.71 * \psi$, $p = 0.008$, $r^2 = 0.647$), hollow diamonds are specialist species ($\lambda = -0.36 + 5.30 * \psi$, $p = 0.009$, $r^2 = 0.700$).

APPENDIX

MODEL SELECTION

Appendix 1. Fall Occupancy model selection. The eight models used are listed in Table 2. Competing models (those with a $\Delta AICc$ of less than 4) are bolded for each species and their estimates of occupancy (ψ) and detection probability (p) are given. Models with variance-covariance problems or a convergence of < 2.0 were unusable and are marked with an asterisk (*). All data was collected from October 24 to December 17, 2007 on Camp Swift Texas Army National Guard training site in Bastrop County, TX.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err	
AMCR	1	454.9	0.000					
	2	402.3	0.838	0.994	0.010	0.295	0.062	
	3	432.5	0.000					
	4	442.2	0.000					
	5	458.2	0.000					
	6	405.5	0.162	*				
	7	436.0	0.000					
	8	445.6	0.000					
AMKE	1	125.6	0.006					
	2	124.7	0.010					
	3	128.9	0.001					
	4	131.0	0.000					
	5	117.2	0.409		0.548	0.044	0.064	0.017
	6	116.8	0.495	*				
	7	121.2	0.055	*				
	8	122.9	0.024					
AMRO	1	306.3	0.000					
	2	270.0	0.895	0.981	0.237	0.217	0.057	
	3	300.5	0.000					
	4	310.7	0.000					
	5	310.4	0.000					
	6	274.2	0.105	*				
	7	305.0	0.000					
	8	315.1	0.000					

Appendix 1. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
CACH	1	436.6	0.028				
	2	431.9	0.301	0.920	0.920	0.249	0.056
	3	436.6	0.027				
	4	441.0	0.003				
	5	435.7	0.043				
	6	430.6	0.552	*			
	7	435.8	0.041				
	8	440.5	0.004				
CARW	1	376.2	0.000				
	2	368.1	0.000				
	3	301.7	0.908	1.000	7.077	0.174	9.186
	4	375.4	0.000				
	5	380.5	0.000				
	6	372.4	0.000				
	7	306.3	0.092	1.000	10.200	0.174	8.991
	8	380.0	0.000				
CHSP	1	212.6	0.000				
	2	213.7	0.000				
	3	201.3	0.000				
	4	186.6	0.792	0.724	0.360	0.099	0.057
	5	215.0	0.000				
	6	215.9	0.000				
	7	203.9	0.000				
	8	189.3	0.207	0.724	0.418	0.099	0.060
EABL	1	125.6	0.000				
	2	125.8	0.000				
	3	106.6	0.709	0.282	0.176	0.130	22.017
	4	124.1	0.000				
	5	127.4	0.000				
	6	127.5	0.000				
	7	108.4	0.291	0.285	0.204	0.130	20.575
	8	126.2	0.000				

Appendix 1. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err	
EAPH	1	464.7	0.000					
	2	441.3	0.099					
	3	466.2	0.000					
	4	464.2	0.000					
	5	458.4	0.000					
	6	436.8	0.901		0.858	16.805	0.316	0.046
	7	459.9	0.000					
	8	458.1	0.000					
HOWR 1	516.2	0.000						
	2	510.6	0.002					
	3	500.6	0.224		0.924	0.059	0.361	0.053
	4	500.3	0.260		0.932	0.063	0.357	0.053
	5	516.4	0.000					
	6	511.4	0.001					
	7	500.2	0.276		0.912	17.942	0.366	0.050
	8	500.5	0.238	*				
LISP	1	261.7	0.000					
	2	258.6	0.000					
	3	253.6	0.000					
	4	257.8	0.000					
	5	240.1	0.011					
	6	236.2	0.076					
	7	231.4	0.847		0.078	0.065	0.266	0.074
	8	236.5	0.066					
NOMO 1	291.8	0.000						
	2	293.2	0.000					
	3	268.7	0.212		0.669	0.149	0.174	0.052
	4	286.5	0.000					
	5	288.5	0.000					
	6	289.9	0.000					
	7	266.1	0.787		0.374	0.145	0.175	6.320
	8	283.4	0.000		0.620	0.172	0.188	0.062

Appendix 1. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
NOCA	1	561.8	0.000				
	2	548.6	0.002				
	3	554.4	0.000				
	4	537.9	0.482	0.970	0.033	0.494	0.051
	5	562.2	0.000				
	6	547.9	0.003				
	7	554.7	0.000				
	8	537.8	0.512	*			
NOFL	1	138.7	0.001				
	2	137.2	0.001				
	3	125.8	0.377	1.000	0.000	0.040	0.016
	4	131.7	0.020				
	5	137.7	0.001				
	6	136.8	0.002				
	7	125.0	0.568	*			
	8	130.8	0.031				
OCWA 1	97.8	0.127	1.000	0.000		0.025	0.008
	2	98.9	0.076	1.000	0.000	0.027	0.018
	3	97.3	0.161	1.000	0.000	0.025	0.013
	4	95.3	0.439	*			
	5	100.5	0.033				
	6	101.5	0.020				
	7	100.1	0.040				
	8	98.2	0.104	*			
PIWO	1	180.4	0.002				
	2	172.5	0.111	1.000	38.968	0.084	0.029
	3	168.7	0.740	1.000	1.266	0.057	0.019
	4	179.8	0.003				
	5	183.8	0.000				
	6	176.3	0.016				
	7	172.3	0.126	0.671	0.344	0.063	0.094
	8	183.1	0.001				
RBWO	1	157.9	0.024				
	2	153.1	0.266	0.255	0.083	0.245	0.093
	3	152.3	0.393	0.204	0.060	0.262	0.109
	4	154.3	0.146	0.212	0.065	0.245	0.106
	5	161.1	0.005				
	6	156.1	0.061	0.258	0.119	0.246	0.092
	7	155.6	0.076	0.156	0.092	0.262	0.109
	8	157.5	0.030				

Appendix 1. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
RCKI	1	481.8	0.000				
	2	483.8	0.000				
	3	463.2	0.000				
	4	458.2	0.004	0.909	0.079	0.309	0.052
	5	472.2	0.000				
	6	474.2	0.000				
	7	453.8	0.037	*			
	8	447.3	0.959	*			
RSHA	1	312.4	0.000				
	2	298.2	0.095				
	3	311.7	0.000				
	4	313.4	0.000				
	5	306.3	0.002				
	6	293.7	0.900	0.748	0.097	0.199	0.046
	7	305.7	0.002				
	8	307.2	0.001				
SOSP	1	162.8	0.014				
	2	158.5	0.122	0.882	0.572	0.075	0.053
	3	159.7	0.068	0.675	0.414	0.074	0.054
	4	166.4	0.002				
	5	159.4	0.079	0.688	0.480	0.072	0.051
	6	156.1	0.403	0.708	0.096	0.084	0.034
	7	156.7	0.299	*			
	8	162.9	0.013				
TUTI	1	405.0	0.000				
	2	381.4	0.132				
	3	391.4	0.001				
	4	409.6	0.000				
	5	399.4	0.000				
	6	377.6	0.846	0.795	14.963	0.284	0.046
	7	385.0	0.021				
	8	404.2	0.000				
TUVU	1	342.5	0.000				
	2	328.3	0.036				
	3	331.5	0.007				
	4	338.9	0.000				
	5	334.8	0.001				
	6	322.9	0.518	0.700	0.154	0.285	0.077
	7	323.3	0.429	0.731	0.074	0.205	0.047
	8	331.3	0.008				

Appendix 1. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err	
WEVI	1	101.3	0.154		0.206	0.122	0.132	0.083
	2	103.5	0.053					
	3	99.7	0.341		0.139	0.066	0.221	8.402
	4	100.1	0.279	*				
	5	104.2	0.036					
	6	106.4	0.012					
	7	103.0	0.066		0.139	0.090	0.221	0.143
	8	103.3	0.057		0.181	0.130	0.151	0.106
YRWA 1	302.4	0.000						
	2	301.4	0.000					
	3	236.8	0.767		1.000	42.821	0.122	0.024
	4	288.7	0.000					
	5	304.7	0.000					
	6	304.3	0.000					
	7	239.2	0.233		0.891	17.421	0.136	0.033
	8	291.2	0.000					

Appendix 2. Winter Occupancy model selection. The eight models used are listed in Table 2. Competing models (those with a Δ AICc of less than 4) are bolded for each species and their estimates of occupancy (ψ) and detection probability (p) are given. Models with variance-covariance problems or a convergence of < 2.0 were unusable and are marked with an asterisk (*). All data was collected from January 21 to March 02, 2008 on Camp Swift Texas Army National Guard training site in Bastrop County, TX.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
AMCR	1	297.8	0.006				
	2	287.7	0.993	1.000	0.000	0.745	0.065
	3	302.1	0.001				
	4	303.2	0.000				
AMGO	1	198.5	0.001	0.697	0.295	0.115	0.052
	2	200.5	0.001				
	3	185.6	0.860	*			
	4	200.0	0.001				
	5	201.8	0.000				
	6	203.9	0.000				
	7	189.3	0.137	*			
	8	203.7	0.000				

Appendix 2. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
AMRO	1	178.1	0.034				
	2	177.3	0.053				
	3	176.6	0.072				
	4	172.4	0.584	0.481	0.212	0.150	0.087
	5	180.0	0.013				
	6	179.3	0.019				
	7	179.2	0.020				
	8	174.5	0.206	0.479	0.241	0.150	0.086
BLJA	1	101.0	0.048				
	2	103.0	0.018				
	3	98.5	0.168	0.136	0.049	0.432	0.075
	4	95.9	0.615	0.124	0.049	0.319	0.155
	5	104.2	0.010				
	6	106.1	0.004				
	7	102.0	0.029				
	8	99.4	0.108	0.124	0.071	0.318	0.156
BLVU	1	115.1	0.152	0.730	0.686	0.051	0.049
	2	117.0	0.061				
	3	112.5	0.555	0.636	0.582	0.030	11.808
	4	120.0	0.013				
	5	117.8	0.040				
	6	119.7	0.015				
	7	115.0	0.161	*			
	8	123.0	0.003				
CACH	1	425.7	0.167	1.000	9.314	0.292	0.024
	2	425.9	0.150	1.000	14.313	0.279	0.062
	3	424.1	0.370	*			
	4	428.4	0.045				
	5	428.0	0.054	*			
	6	428.1	0.051	0.967	0.666	0.288	0.064
	7	425.9	0.149	0.965	0.025	0.300	0.063
	8	430.6	0.015				
CARW	1	432.6	0.000				
	2	427.6	0.000				
	3	387.4	0.805	1.000	26.253	0.316	0.056
	4	417.8	0.000				
	5	436.5	0.000				
	6	431.5	0.000				
	7	390.3	0.195	*			
	8	421.7	0.000				

Appendix 2. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
CEDW	1	203.8	0.125	0.895	0.442	0.093	0.049
	2	200.6	0.619	0.984	0.493	0.098	0.059
	3	206.3	0.034				
	4	208.4	0.012				
	5	206.4	0.033				
	6	203.2	0.163	0.808	16.292	0.118	0.048
	7	208.9	0.010				
	8	211.0	0.003				
CHSP	1	108.0	0.005				
	2	109.9	0.002				
	3	108.6	0.004				
	4	107.2	0.008				
	5	99.9	0.313	*			
	6	101.6	0.140	0.526	10.289	0.081	0.100
	7	101.2	0.163	0.431	18.234	0.072	0.071
	8	99.6	0.364	0.499	10.981	0.074	0.075
EAPH	1	306.1	0.327	0.737	0.148	0.212	0.047
	2	307.9	0.130	0.740	0.148	0.206	0.081
	3	306.6	0.253	0.693	0.133	0.182	0.064
	4	310.1	0.045	0.732	0.145	0.218	0.066
	5	308.4	0.104	*			
	6	310.3	0.039				
	7	308.7	0.088	0.703	0.163	0.180	0.061
	8	312.3	0.015				
EATO	1	121.6	0.000				
	2	123.7	0.000				
	3	93.1	0.297	1.000	7.432	0.022	0.005
	4	119.0	0.000				
	5	117.9	0.000				
	6	120.0	0.000				
	7	91.4	0.703	0.611	0.098	0.033	0.009
	8	115.9	0.000				
HETH	1	172.9	0.013				
	2	170.9	0.036				
	3	168.0	0.149	0.572	0.267	0.103	0.073
	4	178.2	0.001				
	5	170.6	0.041				
	6	168.5	0.116	0.467	0.142	0.160	0.073
	7	165.1	0.641	0.445	0.131	0.132	0.073
	8	176.0	0.003				

Appendix 2. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
HOWR	1	168.3	0.025				
	2	169.9	0.012				
	3	161.3	0.825	1.000	35.724	0.054	0.026
	4	168.5	0.023				
	5	172.1	0.004				
	6	173.8	0.002				
	7	165.4	0.107	0.892	12.443	0.062	0.227
	8	172.8	0.003				
NOCA	1	311.5	0.000				
	2	300.1	0.114				
	3	296.0	0.847	1.000	0.000	0.770	0.056
	4	302.2	0.038				
NOMO	1	133.4	0.178	0.246	0.100	0.195	0.082
	2	135.6	0.061	0.246	0.100	0.197	0.147
	3	132.7	0.250	0.223	0.087	0.276	0.147
	4	138.0	0.018				
	5	133.0	0.217	0.249	0.129	0.194	0.081
	6	135.2	0.072	0.249	0.129	0.197	0.148
	7	133.3	0.187	0.221	0.113	0.126	0.077
	8	138.2	0.016				
RBWO	1	171.6	0.019				
	2	173.2	0.009				
	3	168.0	0.114	0.703	0.346	0.136	0.070
	4	164.5	0.654	0.410	0.165	0.147	8.228
	5	174.0	0.006				
	6	175.7	0.002				
	7	171.0	0.026				
	8	167.2	0.171	0.412	0.202	0.147	0.073
RSHA	1	345.1	0.018				
	2	347.2	0.007				
	3	338.5	0.485	0.872	0.149	0.229	0.069
	4	339.4	0.309	0.821	0.139	0.224	0.060
	5	348.3	0.004				
	6	350.3	0.001				
	7	341.5	0.109	0.882	0.192	0.228	0.069
	8	342.5	0.066	0.828	0.180	0.223	0.060

Appendix 2. Continued.

Species	model	AICc	AICc wt	ψ	st.err	p	st.err
SPTO	1	230.2	0.026				
	2	229.2	0.044				
	3	224.1	0.539	0.487	0.126	0.141	0.074
	4	230.8	0.019				
	5	230.9	0.018				
	6	229.9	0.030				
	7	225.2	0.314	0.485	0.160	0.144	0.076
	8	231.9	0.011				
TUTI	1	485.5	0.005				
	2	475.5	0.702	0.968	0.046	0.438	0.062
	3	489.9	0.001				
	4	486.6	0.003				
	5	487.5	0.002				
	6	477.2	0.287	0.952	0.043	0.443	0.061
	7	492.4	0.000				
	8	489.1	0.001				
TUVU	1	319.9	0.005				
	2	321.4	0.003				
	3	324.7	0.000				
	4	323.7	0.001				
	5	310.6	0.565	0.681	0.154	0.254	0.049
	6	311.7	0.323	0.685	0.155	0.281	0.100
	7	315.8	0.042				
	8	315.1	0.060				

Appendix 3. Fall Abundance model selection. The eight models used are listed in Table 2. Competing models (those with a Δ AICc of less than 4) are bolded for each species and their estimates of abundance (λ) and detection probability (p) are given. Models with variance-covariance problems or a convergence of < 2.0 were unusable and are marked with an asterisk (*). All data was collected from October 24 to December 17, 2007 on Camp Swift Texas Army National Guard training site in Bastrop County, TX.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
AMKE	1	126.1	0.010	2.264	8.009	0.015	0.054
	2	127.7	0.004				
	3	127.7	0.005				
	4	117.9	0.595	*			
	5	120.0	0.209	*			
	6	120.3	0.178	*			

Appendix 3. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
AMRO	1	1017.9	0.000				
	2	850.9	0.000	40.056	6.224	0.027	0.004
	3	971.6	0.000				
	4	1022.2	0.000				
	5	834.2	1.000	*			
	6	956.5	0.000				
CACH	1	763.2	0.000				
	2	752.0	0.029				
	3	746.0	0.599	40.001	6.059	0.010	0.002
	4	763.4	0.000				
	5	751.3	0.041				
	6	747.1	0.331	*			
CARW	1	538.5	0.000				
	2	520.4	0.000				
	3	434.8	0.801	45.919	1E+13	0.010	0.001
	4	539.7	0.000				
	5	523.0	0.000				
	6	437.5	0.199	*			
CHSP	1	436.2	0.000				
	2	438.5	0.000				
	3	397.4	0.461	*			
	4	434.8	0.000				
	5	437.5	0.000				
	6	397.0	0.539	41.662	5E+10	0.005	0.001
EABL	1	187.7	0.000				
	2	107.0	0.709	*			
	3	158.3	0.000	1.163	1.356	0.048	7.523
	4	190.1	0.000				
	5	108.8	0.291	*			
	6	160.3	0.000				
EAPH	1	617.0	0.000				
	2	585.6	0.022				
	3	614.2	0.000				
	4	605.7	0.000				
	5	578.0	0.978	14.750	41.224	0.026	0.073
	6	603.9	0.000				

Appendix 3. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err	
HETH	1	555.7	0.000					
	2	548.9	0.000					
	3	512.3	0.000					
	4	538.9	0.000					
	5	530.1	0.000					
	6	493.7	1.000		15.289	34.068	0.016	0.037
HOWR	1	790.5	0.000					
	2	775.2	0.000					
	3	765.4	0.029		5.142	2.047	0.098	0.041
	4	797.6	0.000					
	5	766.7	0.014					
	6	758.3	0.957	*				
LISP	1	474.9	0.000					
	2	473.4	0.000					
	3	455.6	0.000					
	4	420.8	0.000					
	5	419.2	0.000					
	6	401.9	1.000		1.538	0.540	0.134	0.048
NOCA	1	1,107.7	0.000					
	2	1,089.6	0.001					
	3	1,079.6	0.124		16.480	10.263	0.056	0.035
	4	1,112.0	0.000					
	5	1,081.8	0.040					
	6	1,075.7	0.835		21.910	19.353	0.042	0.037
NOFL	1	169.8	0.000					
	2	164.7	0.000					
	3	151.4	0.083		40.584	29.407	0.001	0.737
	4	159.8	0.001					
	5	165.3	0.000					
	6	146.5	0.916	*				
NOMO	1	412.9	0.000					
	2	412.1	0.000					
	3	378.4	0.561		3.692	3.213	0.046	9.380
	4	413.0	0.000					
	5	413.0	0.000					
	6	378.8	0.439		3.613	2.989	0.046	8.603

Appendix 3. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err	
OCWA	1	132.6	0.095	40.530	31.386	0.001	0.000	
	2	132.0	0.127	40.001	20.234	0.001	0.001	
	3	129.0	0.597	40.105	22.027	0.001	0.053	
	4	135.6	0.021					
	5	135.2	0.026					
	6	131.9	0.134	*				
PIWO	1	202.9	0.001					
	2	196.2	0.030					
	3	189.6	0.839	*				
	4	206.2	0.000					
	5	200.4	0.004					
	6	193.3	0.126		42.717	5E+11	0.002	0.001
RBWO	1	188.2	0.005					
	2	182.2	0.091	0.334	0.119	0.235	0.088	
	3	178.6	0.578	*				
	4	189.3	0.003					
	5	182.6	0.076					
	6	180.2	0.248		0.249	0.111	0.275	0.108
RCKI	1	647.9	0.000					
	2	650.3	0.000					
	3	628.4	0.008					
	4	639.1	0.000					
	5	641.7	0.000					
	6	618.7	0.992		12.647	19.138	0.029	0.044
RSHA	1	352.1	0.000					
	2	339.8	0.044					
	3	351.7	0.000					
	4	343.4	0.007					
	5	333.7	0.942		11.645	111.700	0.015	0.143
	6	343.7	0.006					
SOSP	1	242.8	0.000	*				
	2	230.6	0.030	*				
	3	243.9	0.000		9.2447	52.1974	0.008	0.047
	4	233.4	0.007	*				
	5	223.7	0.958	*				
	6	234.6	0.004	*				

Appendix 3. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
TUTI	1	575.8	0.000				
	2	546.3	0.039				
	3	555.5	0.000				
	4	567.9	0.000				
	5	540.1	0.881	28.311	8.047	0.013	0.003
	6	544.9	0.079				
TUVU	1	460.8	0.000				
	2	436.1	0.000				
	3	448.4	0.000				
	4	440.5	0.000				
	5	418.5	0.994	5.498	6.786	0.062	0.077
	6	428.9	0.005				
WEVI	1	131.2	0.013				
	2	133.6	0.004				
	3	123.6	0.603	0.175	0.069	0.247	5.580
	4	131.8	0.010				
	5	134.5	0.003				
	6	124.5	0.368	0.181	0.105	0.237	10.341
YRWA	1	513.8	0.000				
	2	506.8	0.000				
	3	411.9	0.809	4.189	3.321	0.052	0.043
	4	517.0	0.000				
	5	510.7	0.000				
	6	414.7	0.191	4.383	3.665	0.050	0.043

Appendix 4. Winter Abundance model selection. The eight models used are listed in Table 2. Competing models (those with a Δ AICc of less than 4) are bolded for each species and their estimates of abundance (λ) and detection probability (p) are given. Models with variance-covariance problems or a convergence of < 2.0 were unusable and are marked with an asterisk (*). All data was collected from January 21 to March 02, 2008 on Camp Swift Texas Army National Guard training site in Bastrop County, TX.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
AMCR	1	1,268.2	0.000				
	2	1,255.6	0.000				
	3	1,227.8	0.213	29.255	18.402	0.066	0.042
	4	1,262.7	0.000				
	5	1,251.4	0.000				
	6	1,225.1	0.787	34.363	8.633	0.056	0.014

Appendix 4. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
AMGO	1	463.4	0.000				
	2	462.9	0.000				
	3	445.9	0.644	3.548	2.167	0.054	2.359
	4	462.9	0.000				
	5	465.1	0.000				
	6	447.0	0.356	3.297	1.931	0.058	2.425
AMRO	1	458.0	0.000				
	2	440.4	0.001				
	3	429.4	0.152	5.461	5.476	0.035	3.093
	4	452.3	0.000				
	5	435.1	0.009				
	6	425.9	0.839	4.386	3.698	0.042	0.036
BLJA	1	133.4	0.006				
	2	135.9	0.002				
	3	123.7	0.777				*
	4	135.9	0.002				
	5	138.6	0.000				
	6	126.2	0.213	0.228	0.110	0.199	0.068
BLVU	1	244.3	0.000				
	2	229.3	0.013	40.074	13.675	0.008	0.004
	3	233.8	0.001				
	4	239.7	0.000				
	5	220.7	0.962				*
	6	228.1	0.024				*
CACH	1	659.1	0.045				
	2	656.9	0.134	40.061	6.237	0.011	0.002
	3	656.7	0.155	40.019	6.200	0.011	0.002
	4	658.7	0.055				
	5	656.8	0.143				*
	6	654.4	0.468	36.442	7.417	0.012	0.002
CARW	1	630.8	0.000				
	2	626.1	0.000				
	3	560.3	0.801	40.001	6.017	0.011	0.002
	4	633.0	0.000				
	5	629.5	0.000				
	6	563.0	0.199	32.578	8.933	0.013	0.004

Appendix 4. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
CEDW	1	1107.5	0.000				
	2	1057.7	0.724	1905.7	6E+13	0.019	0.003
	3	1062.9	0.056				
	4	1101.6	0.000				
	5	1062.3	0.073				
	6	1060.9	0.146	39.371	7E+11	0.018	0.003
CHSP	1	230.4	0.000				
	2	229.8	0.000	40.007	14.579	0.003	0.002
	3	210.2	0.000	*			
	4	203.5	0.000	*			
	5	201.1	0.001	*			
	6	187.2	0.999	*			
EAPH	1	353.2	0.264	2.153	1.334	0.083	0.052
	2	355.6	0.079	2.151	1.332	0.081	0.057
	3	352.3	0.429	1.702	0.883	0.106	0.060
	4	355.5	0.084	2.117	1.359	0.084	0.052
	5	358.2	0.022				
	6	354.7	0.124	1.684	0.930	0.107	0.060
EATO	1	153.2	0.000				
	2	155.2	0.000				
	3	116.2	0.099	*			
	4	145.0	0.000	19.186	17.562	0.003	0.001
	5	147.5	0.000				
	6	111.7	0.901	*			
HETH	1	219.4	0.000				
	2	217.6	0.000				
	3	210.3	0.001				
	4	207.8	0.004				
	5	206.7	0.006				
	6	196.5	0.989	11.813	6.355	0.008	0.003
HOWR	1	183.4	0.027				
	2	185.5	0.010				
	3	176.6	0.853	*			
	4	187.6	0.003				
	5	189.9	0.001				
	6	180.7	0.105	40.153	7E+11	0.002	6.072

Appendix 4. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
NOMO	1	142.8	0.214	0.339	0.186	0.150	0.083
	2	145.3	0.061	0.339	0.186	0.150	0.124
	3	143.6	0.149	0.308	0.161	0.164	0.106
	4	141.9	0.336	0.364	0.250	0.140	0.084
	5	144.7	0.083	0.364	0.250	0.142	0.124
	6	143.4	0.157	0.316	0.208	0.158	0.108
NOCA	1	1,297.1	0.000				
	2	1,254.1	0.009				
	3	1,246.6	0.411	16.776	6.137	0.135	0.050
	4	1,291.2	0.000				
	5	1,246.9	0.342	32.350	7.041	0.070	0.016
	6	1,247.6	0.238	*			
RBWO	1	184.6	0.051				
	2	185.7	0.029				
	3	179.9	0.557	1.390	1.318	0.049	0.049
	4	185.2	0.038				
	5	186.8	0.017				
	6	181.0	0.307	2.511	3.466	0.036	0.048
RCKI	1	423.5	0.145	10.837	38.194	0.022	0.077
	2	422.7	0.215	8.088	17.331	0.029	0.062
	3	427.0	0.026				
	4	422.5	0.240	25.404	9.929	0.009	0.003
	5	421.8	0.341	25.420	10.204	0.009	0.004
	6	426.4	0.034				
RSHA	1	409.8	0.120	3.400	2.557	0.066	0.050
	2	411.9	0.042				
	3	406.7	0.585	3.584	2.960	0.062	0.053
	4	412.7	0.028				
	5	415.0	0.009				
	6	408.6	0.217	4.159	4.120	0.054	0.054
SPTO	1	246.4	0.016				
	2	246.1	0.018				
	3	239.4	0.539	0.847	0.432	0.126	0.071
	4	246.7	0.014				
	5	246.8	0.013				
	6	239.9	0.401	0.930	0.584	0.115	0.073

Appendix 4. Continued.

Species	model	AICc	AICc wt	λ	st.err	p	st.err
TUTI	1	784.8	0.001				
	2	771.2	0.815	6.439	2.874	0.108	0.049
	3	790.6	0.000				
	4	787.4	0.000				
	5	774.2	0.184	6.715	3.196	0.104	0.049
	6	793.1	0.000				
TUVU	1	503.6	0.000				
	2	503.4	0.000				
	3	502.2	0.000				
	4	476.5	0.249	*			
	5	475.2	0.478	25.515	6.087	0.014	0.005
	6	476.3	0.273	25.714	5.788	0.010	0.002

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VITA

Amber Lee Jonker was born in Memphis, Tennessee on 9 February 1981; she uses this fact as a reason to slip into an inexcusable southern accent as often as possible. When she was two years old, her parents returned to the land of their ancestors: Holland, Michigan. Amber spent her formative years learning about the geological history of western Michigan and falling face first out of canoes, much to the delight and chagrin, respectively, of her parents. Prior to attending Michigan State University, where she attained her B.S. in zoology, she lettered in Dutch dancing at Holland High School. During her time as an undergraduate, Amber studied abroad in Spain, Australia, Cuba, and Ecuador, where she lost her toenails running down an active volcano which inexplicably had a store selling Coca-Cola near its summit. After her toenails returned and she graduated, Amber spent four years in such exotic locales as the central valley of California, Salt Lake City, Vass, North Carolina, and Killeen, Texas, working as a seasonal field biologist. She came to the important conclusion that she would prefer to live somewhere in which it is possible to obtain beer after five in the afternoon and began her Master's work at Texas State University-San Marcos (29.888, -97.947) in 2007. She is survived by her wife and three cats.

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