Does land-use affect bird abundance?

by

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ABSTRACT

Over the last 50 years many species have seen negative population trends and scientists have identified habitat loss, change, and fragmentation as possible causes. I investigated the ability of random forest and boosted trees models to predict bird abundances based on land-use throughout the United States. Bird abundance data was acquired from the North American Breed Bird Survey (BBS) and land-use data was gathered by the Multi-Resolution Land Characteristics (MRLC) consortium. The models had a mixed transferability between the training and test data with 14 of 21 models better fit the training data. The models were mixed in their ability to accurately predict abundances based on land-use compared to the mean; 14 of 21 models more accuracy predict abundance compared to the mean suggesting an effect of land-use on abundance. Six models were classified as “good,” 11 as “cautious,” and 4 as “poor.”

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Finally, I would like to thank the people who have provided invaluable support throughout this process - my family, my friends, both my parents and my grandparents.

STATEMENT OF RESEARCH CONTRIBUTION

I began researching and reading literature on bird abundance model and machine learning during the summer of 2018. In August I was given my dataset and shortly after I began building models and testing in September 2018 and continued until January of 2019. I completed the testing for all 21 species in February and submitted the final draft in March 2019.

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List of Nomenclature or Abbreviations

BBS: North American Breeding Bird Survey

DDT: Dichlorodiphenyltrichloroethane

MRLC: Multi-Resolution Land Cover Characteristics

PE: prediction error

RMSEP: root mean square error in prediction

U.S./U.S.A.: United States of America

Introduction

Negative trends in bird populations have been seen over the last 50 years (Askins, 1993; Robbins, Sauer, Greenberg, & Droege, 1989). One study performed found that 71% of species investigated had negative trends in abundance between 1978-1987 with 20 of the 44 species having a significant negative trend ($p < 0.05$) (Robbins et al., 1989). The studies that found negative trends in bird abundance associated this decrease with changes in habitat, habitat loss and/or habitat fragmentation (Askins, 1993; Robbins et al., 1989). With increasing urbanization development throughout the United States, there are growing concerns about increased habitat loss and declining bird abundance (Andrade, Bateman, Franklin, & Allen, 2018; Askins, 1993; Robbins et al., 1989).

Land-use types are usually defined by broad vegetation types but may also incorporate human-land-uses. Thus, land cover descriptions may include natural characteristics such as evergreen, deciduous, or mixed forest, or characteristics created by human activities such as low to high urban development or pastures and harvestable crops. Over the last 50 years in North America, native habitats have been converted at a higher rate than ever before, which is in part due to growing human populations requiring increased agriculture and developed urban landscapes (Andrade et al., 2018; Houghton, 1994).

Birds are a diverse and widely distributed group and they play a variety of functional roles in ecosystems. These roles include acting as seed vectors or pollinators, transporting nutrients from one location to another, and contributing provisioning and regulating services (Rosenberg, Kennedy, Dettmers, Ford, & Reynolds, 2016; Sekercioglu, 2006). Provisioning services are categorized as environmental benefits that directly impact harvestable crops or livestock (Rosenberg et al., 2016; Sekercioglu, 2006). Regulating services, on the other hand, include carbon sequestration and waste management (Rosenberg et al., 2016; Sekercioglu, 2006). Loss of these functional roles from ecosystems would result in millions of dollars of economic loss to the United States alone (Sekercioglu, 2006).

Factors affecting species abundance

Changes in land-use can have effects on the abundance of birds (Arévalo & Newhard, 2011; Blair, 1996; Verhulst, Báldi, & Kleijn, 2004). Increased fragmentation can result in smaller and more isolated populations, which can lead to decreased gene exchange and population mixing (Askins, 1993). Movement among fragments increases mortality rates due to increased risk of predation and the rate of collisions with vehicles, homes, and buildings (Arévalo & Newhard, 2011). Martensen et al. found that as available habitats with 50% forest cover increase from 20 to 50 hectares, species abundance increase from 60 to over 120 individuals in Atlantic Forest habitat in Brazil (Martensen, Ribeiro, Banks-Leite, Prado, & Metzger, 2012). Thus, the relationship between land-use and abundance may be a useful tool in predicting abundance (Barnagaud, Papaïx, Gimenez, & Svenning, 2015).

Habitat is not the only factor that can affect bird abundance (Evans, 2003; Molles, 2015). Population abundance are impacted by four major processes: immigration and births (both increase the populations) and emigration and death (decrease population size) (Molles, 2015). Predication is a major factor that affects species distribution and abundance in many communities (Evans, 2003; Molles, 2015). Additionally, other density-dependent processes such as disease, resource limitations (carrying capacity), and intra- and interspecies competition all impact species abundance (Evans, 2003; Molles, 2015). This can make predicting abundance complex due to all possible factors.

The habitat requirements for many bird species are reasonably well-known. For example, *Agelaius phoeniceus,* red-winged blackbird, is a generalist songbird with the ability to live in many different habitat types found throughout North America such as cultivated crops, forest and different levels of developed densities (Özesmi & Mitsch, 1997; Vierling, 2000). The red-winged blackbird can be found in many different habitat sizes ranging from wetlands spanning tens of meters to large urban landscapes exciding thousands of meters (Özesmi & Mitsch, 1997; Vierling, 2000). In comparison, *Setophaga kirtlandii,* Kirtland's Warbler, is an endangered songbird of similar size but has a requirement for jack pine forests, which are only found in a few Northern states (eBird, 2017). However, like many species, little is known about the spatial scale of habitat required for the Kirtland's Warbler.

North American Breeding Bird Survey

One organization looking to monitor changes in bird abundance throughout the US is the North American Breeding Bird Survey (BBS). The BBS is a large-scale, international avian monitoring program started in 1966 designed to track changes in bird abundances across North America (Downes, Hudson, Smith, & Francis, 2016; Hudson et al., 2017). It was intended to address growing concerns about the negative impacts of synthetic chemicals such as DDT but has shifted to address questions related to the impacts of changing habitat, loss of habitat, and habitat fragmentation more recently (Hudson et al., 2017).

Study objectives

The objectives of this study are to (1) model the relationship between bird abundance and land-use for 21 species, (2) determine the critical spatial scales that best predicts bird abundance for each species and (3) examine the relationship between a model's fit to both the training and test data and its predictive ability. The two forms of machine learning I used within this study are random forests and boosted regression trees.

Methods

BBS data collection

Skilled amateur and professional ornithologists survey bird populations every year on the 4100 BBS routes throughout the U.S., Canada, and Mexico (Figure 1) (Downes et al., 2016). Birds are counted during peak breeding season (i.e. May or June) (Downes et al., 2016). Each route consists of approximately 39.5 km (24.5 miles) section of roads with stops every 0.8 km (0.5 miles) (Downes et al., 2016). At each stop, a 3-minute point count is conducted where all birds seen or heard within a 400-meter radius are recorded (Downes et al., 2016). Surveys begin half-an-hour prior to local sunrise and take about 5 hours to complete (Downes et al., 2016). Routes used within this study where restricted to the U.S. between 2003-2009 and are between latitudes of 25.00 and 49.97 and longitudes of -124.32 and -67.80.

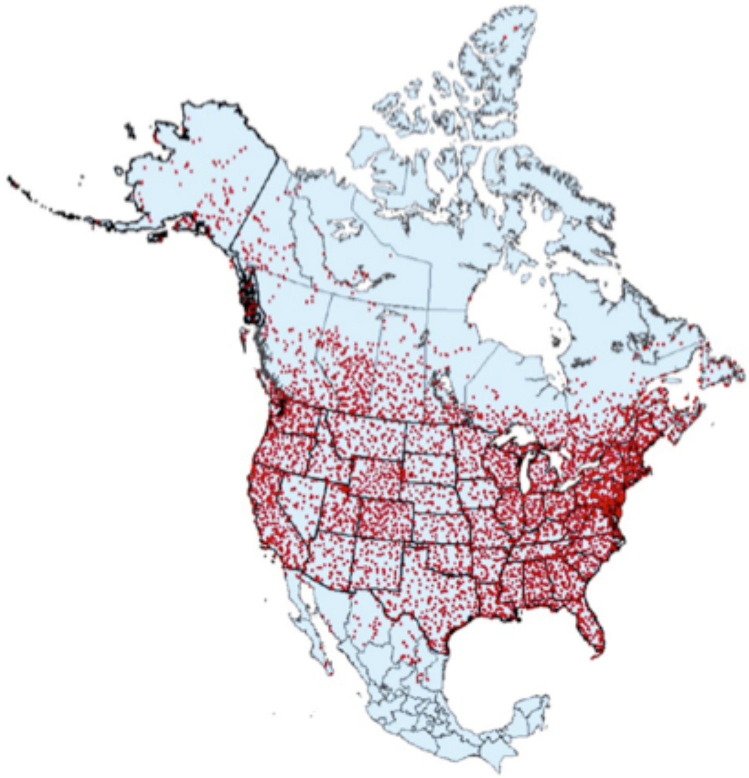

Figure 1: Map indicating all Breeding Birds Survey (BBS) routes in Canada, U.S., and Mexico, indicated by the red dots (Downes et al 2016). Not all routes were used within this study.

Land-use data

Land-use data for the U.S. was acquired from the Ecology metadata archive (Small, Veech, & Jensen, 2012). The data originated from the Multi-Resolution Land Characteristics (MRLC) consortium, a group of federal agencies that complies land-use data for the continental USA (Small et al., 2012). The MRLC compiled satellite imagery data in 2006 at a resolution of 30 x 30 meters (Small et al., 2012). This limited the study to only look at data between 2003-2009 to prevent large assumptions on changes in land-use from year to year or overtime. Small et al. then categorized the data into 17 different land-use classes for all BBS routes within US (Small et al., 2012). Fifteen of the land-use classes were used in this project (Table 1). Land-use classes, 'no data' and perennial ice/snow, were not used within the model because they are not useful (no-data) or not found within continental US (perineal ice/snow). Additionally, three measures of landscape configuration were found for each BBS route were calculated by Small et al. (patch density, largest patch index, and aggregation index) but were not used in the models (Small et al., 2012).

Table 1: Different land-use variables produced by the Small et al based on MRLC consortium (Small et al., 2012). Variables no data and perennial ice/snow were not used in the final models.

Woody Wetlands	Open Water	Emergent Herbaceous Wetlands	Developed, Open Space	Developed, Low Intensity
Developed Medium Intensity	Developed High Intensity	Barren Land (Rock/ Sand/ Clay)	Deciduous Forest	Evergreen Forest
Mixed Forest	Shrub/ Scrubs	Grassland/Herbaceous	Pastured/ Hay	Cultivated Crops

Critical scales

For all routes the land-use classes were compiled at 6 different spatial scales: 200 m, 400 m, 1000 m, 2000 m, 5000 m, and 10000 m. The different land-use were summed in hectares of total area per-type per route at each scale (Figure 2). For example, the 200-meter scale calculated the total land-uses of each type within a 200 m radius of each route. The sum and proportion of each land-use may vary between scales on the same route (Figure 2).

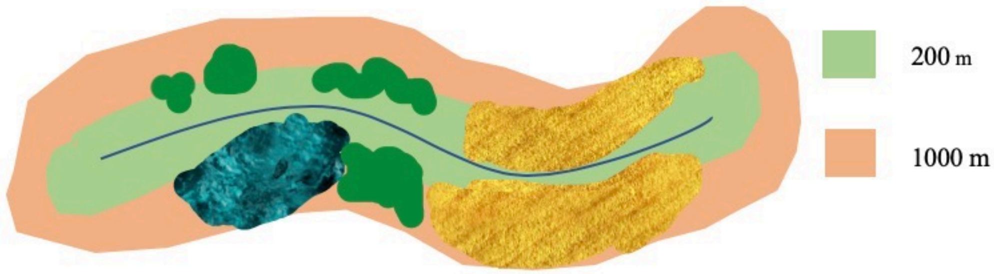

Figure 2: Visual description of critical scale calculation. The dark blue line represents a possible route used within this study. The golden colour represents pasture/ hay, dark green represents evergreen forest and blue represents open-water. This example only used 3 land-types while in reality the amounts for all land-use variables were calculated per route.

Species and route selection

Species were selected in two ways: most numerous species and species found within the most routes. In total, 21 species were used in this project, that were selected using a mixture of two methods (Table 2). Eleven species were selected by summing the total abundance of all species throughout all BBS routes in the US and taking the 11 most abundant. The remaining ten species were selected by counting the total number of routes that a species was found on and taking the 10 most abundant. Many species were found in the top 20 species of both methods.

Table 2: List of 21 species used within the study.

Rock Dove	Mourning Dove	Red-tailed Hawk	Broad-winged Hawk	Great Horned Owl	Blue Jay	Brown Head Cowbird
Red Winged Black Bird	Orchard Oriole	Baltimore Oriole	Common Grackle	Chipping Sparrow	Eastern Towhee	Cliff Swallow
Barn Swallow	Tree Swallow	N. Rough-winged Swallow	Gray Catbird	Sage Thrasher	Eurasian Collared-Dove	Killdeer

Separate training and test datasets were produced for each species based on their specific geographical range. The route selection protocol was a two-step process: (1) all routes that fell within a species geographical range in the U.S. and contained at least one individual between 2003-2009 was identified and (2) training and test datasets produced (Figure 3). The training dataset was built using 80% of routes in the outer portion of the geographic range (Figure 3). The test set contained the remaining 20% of routes found at the core of the species distribution (Figure 3).

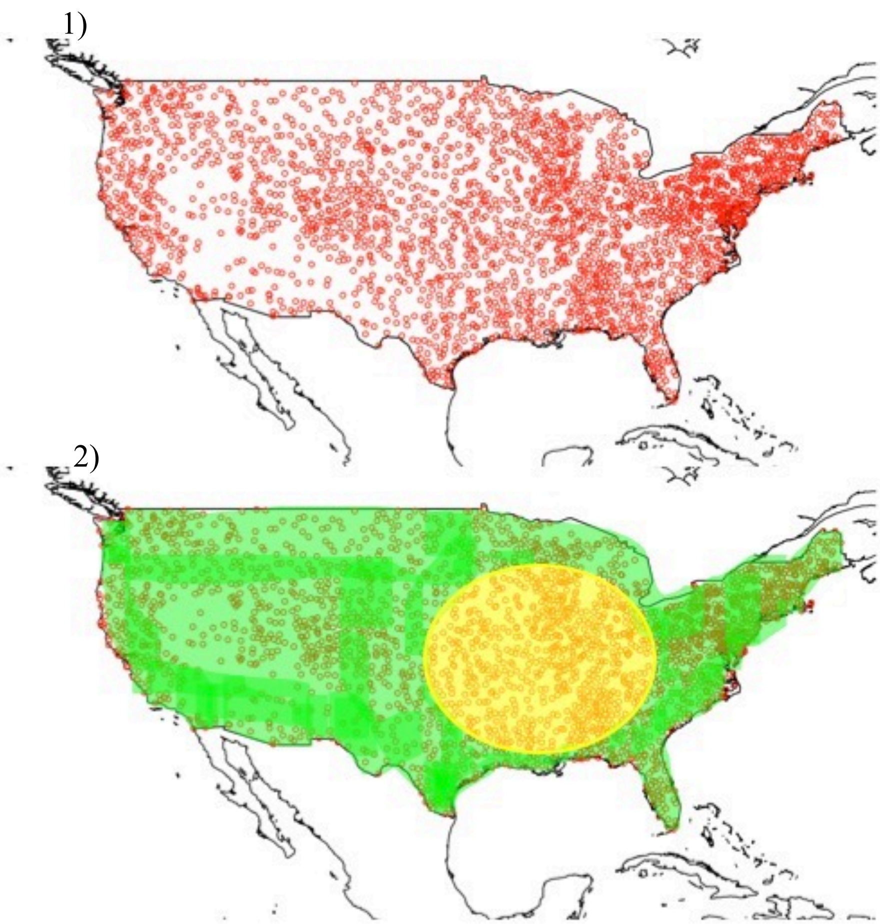

Figure 3: Illustration of the two-step route selection protocol. 1) represents all routes that the red winged black bird was found on between 2003-2009 and 2) represents the process in separating all routes into training and test sets. Highlighted green section represents 80% of route making the training datasets and yellow circle represents core 20% test set.

Statistical analysis

I used random forest and gradient boosted regression trees, both of which are modifications of regression tree analysis. Regression trees are a form of machine learning that use observations to create dichotomous, called branches, that predict values of the dependent variable based on values of the independent variable(s) (Kuhn and Johnson 2013). Split points (i.e. branches) are selected, which minimizes the variability among data points in the node at the end of each branch (Kuhn and Johnson 2013). The lack of stability with regression tree models is the primary reason this method was not used in this study. Separate regression trees using the same data can vary depending on what data is used to build the tree. Additionally, small changes in the data can result is dramatic shifts in the trees morphology and the model.

Regression trees and gradient boosted trees were used over simple regression trees due to being more robust. Both strategies, random forest and gradient boost trees, are “averaged” over thousands of trees to build a robust final mode in addition to unique methods. The goals of this is to builds models that are more robust to variation within the data used to build them.

Random forest’s second method to build robust models is to select a random subset of variables at each split point to partition the data into groups that best minimize the overall error (Kuhn and Johnson 2013). Randomization subset of independent variables at each split point prevent the model was always picking the “best” independent variable locally which may not be the best option globally (Kuhn & Johnson, 2013). The random forest models used within my study use five independent land-use variables at each split point.

Boosted gradient trees use all independent variables at each split point but have the ability to gain information about the predictive ability after each iteration (i.e. each tree) (Kuhn and Johnson 2013). Boosted gradient trees adds weight to the data the it previously predict poorly and aims to improve it during the next interaction (Kuhn & Johnson, 2013). Random forest can be thought of as thousands of horizontally independent trees that are "averaged" out to become one final model, while gradient boosted regression are a series of dependent vertical trees with the last interaction becoming the final model.

For each of the 21 bird species, 12 different models were constructed to investigate the relationships between abundance and land cover. Each of the six different land-use scales (200 m, 400 m, 1000 m, 2000 m, 5000 m, 10000 m) were used for each of the two machine learning techniques (random forest and boosted trees). Models were evaluated based on (1) transferability of the models from the training to the test dataset (i.e. R^2 and prediction error (PE)) and (2) predictive ability on the test set (i.e. Observed - Predicted) compared to the mean of the training dataset. The mean of the training data was used to cross-validate the performance of models as a null model. If no information about a route in a new location was known the only method of estimate abundance was to take the mean abundance for all known routes. This indicated whether land-use affects the abundance of each species.

Model fit

R^2 values were used to identify the critical spatial scale for each of the different species. This was done by assessing changes in the model's fit among different scale (Findlay & Houlahan, 1997). Models with a high R^2 indicate that the model fits the data. If land-use beyond a certain critical scale has no impact on a certain species abundance, inclusion should not improve model fit (Findlay & Houlahan, 1997). The inclusion of information on land-use beyond the critical scale would add noise and variation, which would reduce the model's overall fit (Findlay & Houlahan, 1997). For example, if land-use within 400 m explained 20% of the variation within a certain species abundance, but land-use within 2000 m explained 45% of the variation (Findlay & Houlahan, 1997), this would strongly suggest that the land-use between 400 m and 2000 m has a strong impact on a species abundance (Findlay & Houlahan, 1997).

Prediction error (PE) was calculated for each model for the training and test dataset. Prediction error was calculated by subtracting the predicted bird abundance from the observed abundance for each route. The absolute value of the difference was then averaged between all the routes to produce the prediction error (Figure 4).

$$PE = mean(|observed\ abundance - predicted\ abundance|)$$

Figure 4: Equation for calculating prediction error (PE) of the models.

Predictability improvement compared to the mean was calculated by subtracting the PE of the model from the PE of the mean of the training dataset, then dividing by the PE of the mean observed (Figure 5).

$$Predictive\ improvement\ = \frac{PE\ mean\ of\ training - PE\ of\ the\ model}{PE\ mean\ of\ training}$$

Figure 5: Equation to calculate the predictive improvement of the model compared to the mean abundance of the training data.

Results

Important land-use and critical scale

The top four most important land-use for the species investigated were pasture/hay (n=11), evergreen forest (n=10), and grassland/herbaceous and open-water (both n=9) (Table 3). The majority of models used all, if not the most (n >12), of land-use variables within the model. All land-use types were identified as one of the top four most important land-use types expect mix forest (Table 3).

Table 3: Critical scale, top five important land-use classes and R^2 for the 21 species investigated.

AOU	Common Name	Critical Scale	1	2	3	4	R^2
2730	Killdeer	5000 m	Cultivated Crops	Pasture/ Hay	Emergent Herbaceous Wetland	Evergreen Forest	0.6252
3131	Rock Dove	5000 m	Grassland/ herbaceous	Open Water	Developed Highly Intensive	Pasture/ Hay	0.2938
3160	Mourning Dove	10000 m	Grassland/ Herbaceous	Cultivated Crops	Evergreen Forest	Woody Wetland	0.4496
3370	Red-tailed Hawk	5000 m	Open Water	Developed, Open Space	Developed, Low Intensity	Developed, Medium Intensity	0.2917
3430	Broad-winged Hawk	10000 m	Pasture/ Hay	Developed, Medium Intensity	Cultivated Crops	Deciduous Forest	0.2150
3750	Great Horned Owl	5000 m	Shrub/ scrub	Grassland/ herbaceous	Evergreen Forest	Deciduous Forest	0.1248
4770	Blue Jay	10000 m	Evergreen Forest	Shrub/ Scrub	Woody Wetland	Deciduous Forest	0.4279
4950	Brown Head Cowbird	10000 m	Grassland/ herbaceous	Shrub/ Scrub	Evergreen Forest	Cultivated Crops	0.5198
4980	Red Winged Black Bird	2000 m	Cultivated Crops	Pasture/ Hay	Barren Land	Grassland/ Herbaceous	0.3623
5060	Orchard Oriole	1000 m	Evergreen Forest	Emergent Herbaceous Wetland	Open Water	Shrub/ Scrub	0.3466
5070	Baltimore Oriole	10000 m	Grassland/ herbaceous	Shrub/ scrub	Pasture/ Hay	Developed, Medium intensity	0.3664
5110	Common Grackle	10000 m	Cultivated Crops	Developed, High Intensity	Grassland/ herbaceous	Evergreen Forest	0.4837
5600	Chipping Sparrow	1000m	Deciduous Forest	Grassland/ Herbaceous	Developed, Open Space	Evergreen Forest	0.4566
5870	Eastern Towhee	400 m	Woody Wetland	Evergreen Forest	Emergent Herbaceous Wetland	Barren land	0.3985
6120	Cliff Swallow	400 m	Open Water	Barren Land	Emergent Herbaceous Wetland	Pasture/ Hay	0.3082
6130	Barn Swallow	2000 m	Emergent Herbaceous Wetland	Open Water	Woody Wetlands	Pasture/ Hay	0.4004
6140	Tree Swallow	2000 m	Emergent Herbaceous Wetland	Deciduous Forest	Evergreen Forest	Open Water	0.2517
6170	N. Rough-winged Swallow	200 m	Open Water	Emergent Herbaceous Wetland	Woody Wetland	Pasture/ Hay	0.0703
7040	Gray Catbird	5000 m	Developed, Open Space	Developed, Medium Intensity	Grassland/ Herbaceous	Deciduous Forest	0.5147
7020	Sage Thrasher	10000 m	Cultivated Crops	Evergreen Forest	Shrub/ scrub	Pasture/ Hay	0.3294
22860	Eurasian Collared-Dove	2000 m	Emergent Herbaceous Wetland	Open Water	Developed, Low Intensity	Developed, Medium Intensity	0.3403

Critical scales of 2000 m, 5000 m and 10000 m were found to make up 77% (18 out of 21 species) of the most important critical scale (Figure 6). R^2 was found to vary within each species, which was associated with variation within land-use scales (Figure 6). Critical scale was found to vary for all species, but an emphasis on the larger scales were found (Figure 6). A table comparing the critical scales indenified by each method can be seen in the appendix (Table 6).

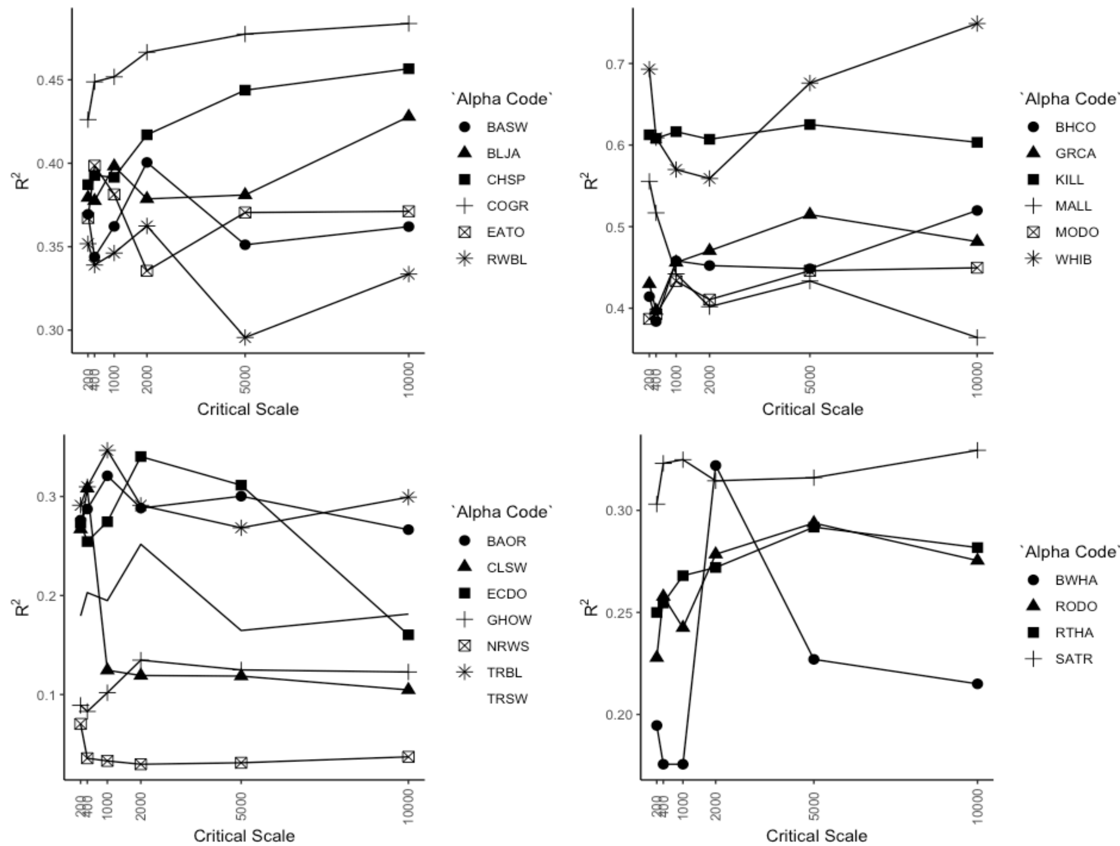

Figure 6: R^2 values for training data used to identify critical scale. Each point represents one of the critical scales (200 m, 400 m, 1000 m, 2000 m, 5000 m, 10000 m) with highest R^2 representing the critical land-scale for each species.

Model fit

The majority of models were transferable to new data (Figure 7). This was indicated by the models better fitting the training dataset for only 14 out of 21 species (Figure 7). Between species, R^2 for the test set was found to range from 0.07 to 0.749 with 81% of the models having a reasonably good fit with R^2 equal to or greater than 0.3 (17 out of 21; Table 3). Prediction error associated with the training data was found to range from 0.205 to 45.76 (Figure 7). A table comparing the PE and R^2 for each species can be found within the appendix (Table 6).

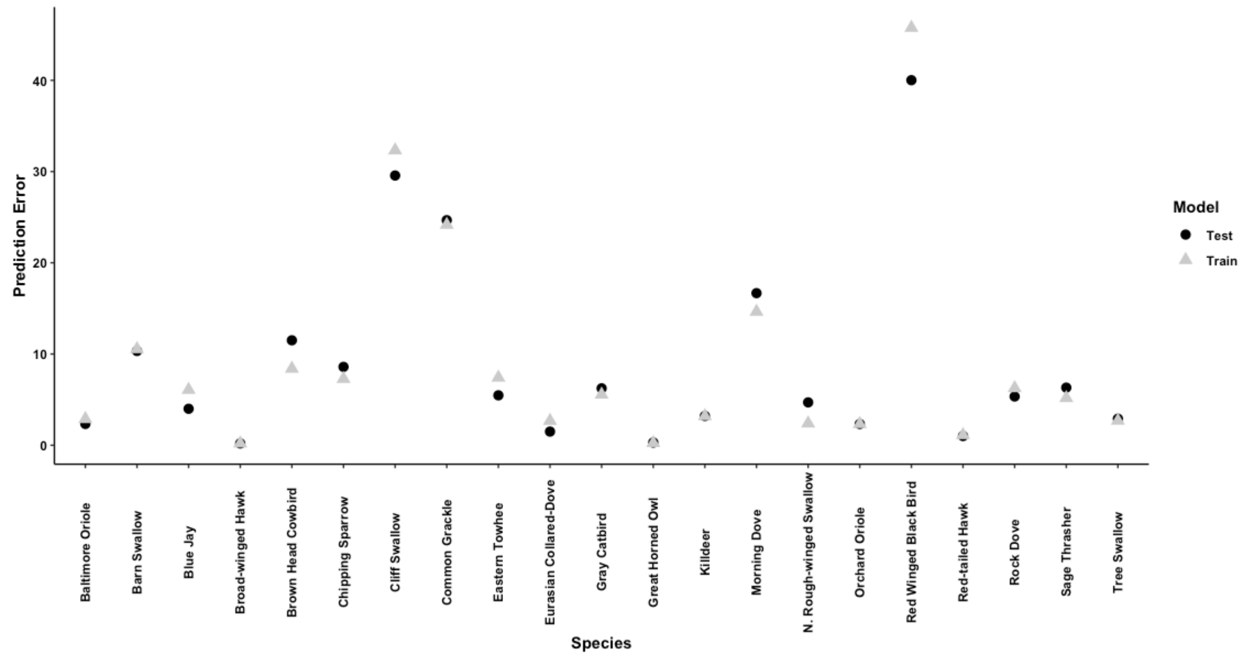

Figure 7: Prediction error values calculated for the training and test datasets on the critical scale for each species.

Models vs. Mean

The models were found to better predict bird abundance compared to the mean for 14 out of 21 species (Figure 8). The model's PE ranged from 0.1991 to 40.02 (Figure 8). No strong indicator of whether the model would better predict bird abundance compared to the mean could be seen based on the fit to the test data. The greatest improvement of a model compared to the mean was 31% increase in predictive improvement (model's PE = 3.203 and mean's PE=4.674 for *Charadrius vociferous* (killdeer)).

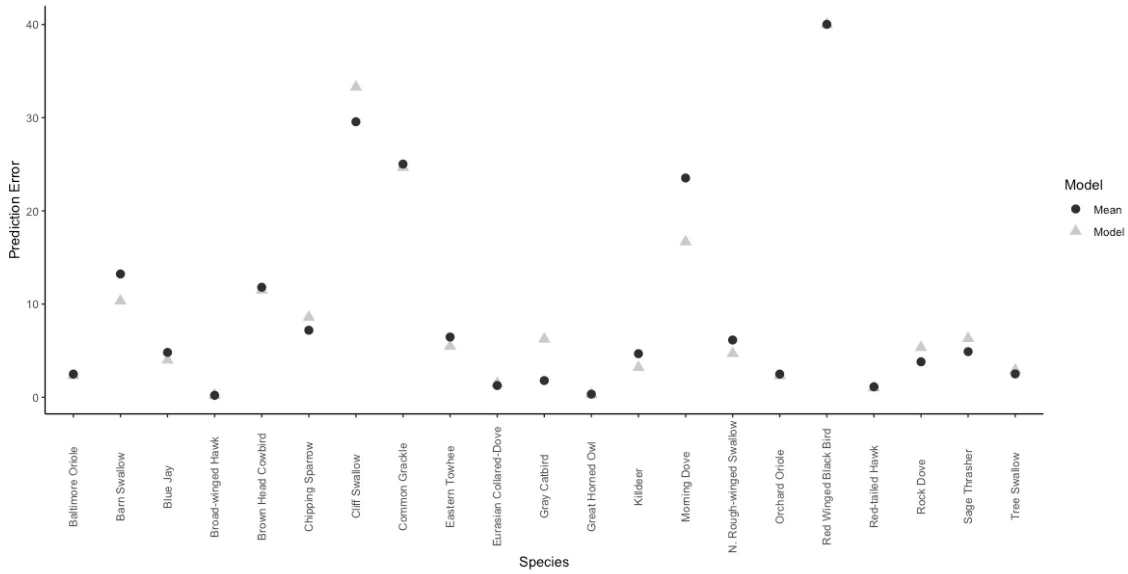

Figure 8: Prediction error calculated for the mean abundance of each bird (solid black circle) and models (gray solid triangles). Plotted model values for critical scales for each species.

R^2 and prediction error

The model fit to the training data (i.e. R^2) provided no evidence of its predictive ability to the test set (Figure 7, 8 and Table 4). When plotted, the relationship between R^2 and predictive improvement was found to be a weak negative trend ($R^2 = -0.00396$; Figure 9 and Table 4).

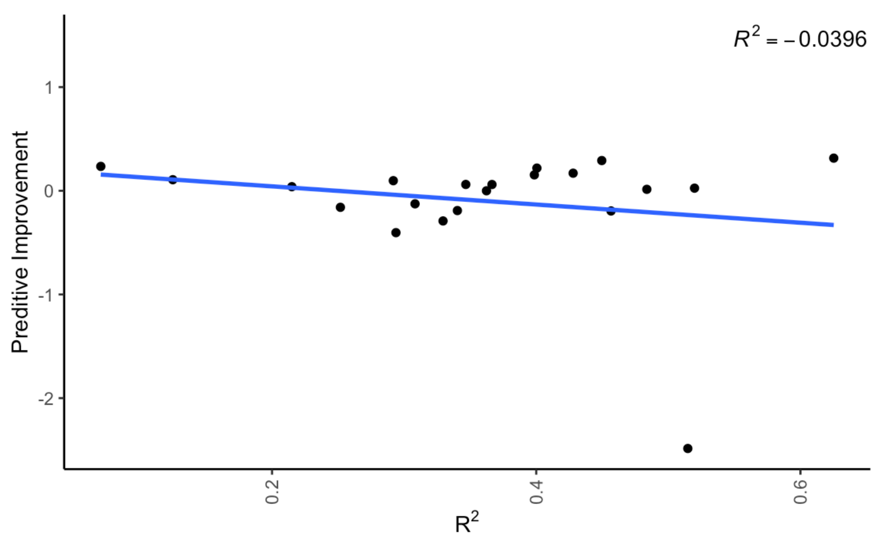

Figure 9: Relationship between R^2 on the training dataset and training dataset prediction error.

Table 4: Critical scale, R^2 value for the training data, and the model's predicative improvement over the mean for each species used.

AOU	Common Name	Critical Scale	R^2	Predictability Improvement
2730	Killdeer	5000 m	0.6252	31%
3131	Rock Dove	5000 m	0.2938	-40%
3160	Mourning Dove	10000 m	0.4496	29%
3370	Red-tailed Hawk	5000 m	0.2917	10%
3430	Broad-winged Hawk	10000 m	0.2150	4%
3750	Great Horned Owl	5000 m	0.1248	11%
4770	Blue Jay	10000 m	0.4279	17%
4950	Brown Head Cowbird	10000 m	0.5198	3%
4980	Red Winged Black Bird	2000 m	0.3623	0%
5060	Orchard Oriole	1000 m	0.3466	6%
5070	Baltimore Oriole	10000 m	0.3664	6%
5110	Common Grackle	10000 m	0.4837	1%
5600	Chipping Sparrow	1000m	0.4566	-19%
5870	Eastern Towhee	400 m	0.3985	15%
6120	Cliff Swallow	400 m	0.3082	-13%
6130	Barn Swallow	2000 m	0.4004	22%
6140	Tree Swallow	2000 m	0.2517	-16%
6170	N. Rough-winged Swallow	200 m	0.0703	24%
7040	Gray Catbird	5000 m	0.5147	-249%
7020	Sage Thrasher	10000 m	0.3294	-29%
22860	Eurasian Collared-Dove	2000 m	0.3403	-19%

Model classification

The models were classified into three groups: "good", "cautious," and "poor". Models classified as "good" (n=6; 29% of models; Table 4) were transferable to new data (equal or lower R^2 or PE on test data compared to training data) and these models better predicted abundance compared to the mean of the training data. "Poor" models (n=4; 19% of models; Table 5) were not transferable, and the mean better predicted abundance compared to the model. The remaining model were classified as "cautious" (n=11; 53% of models; Table 5) and only contained one of the two above characteristics. Results from models classified as "good" are more robust and likely represented the true relationship between abundance and land-use compared to "cautious" and "poor" models. Results from models classified as "poor" are likely due to models trying to fit data and likely do not represent real world results and interactions.

Table 5: Indicating whether the models better fit (i.e. lower PE) on either the training or test data and whether the model or mean better predicted abundance (PE). √ indicates that the statement at the top is true.

AOU	Common Name	Test > Train	Model > Mean
2730	Killdeer	X	√
3131	Rock Dove	√	X
3160	Mourning Dove	X	√
3370	Red-tailed Hawk	√	√
3430	Broad-winged Hawk	X	√
3750	Great Horned Owl	X	√
4770	Blue Jay	√	√
4950	Brown Head Cowbird	X	√
4980	Red Winged Black Bird	√	√
5060	Orchard Oriole	√	√
5070	Baltimore Oriole	√	√
5110	Common Grackle	X	√
5600	Chipping Sparrow	X	X
5870	Eastern Towhee	√	√
6120	Cliff Swallow	√	X
6130	Barn Swallow	X	√
6140	Tree Swallow	√	X
6170	N. Rough-winged Swallow	X	X
7040	Gray Catbird	X	X
7020	Sage Thrasher	X	X
22860	Eurasian Collared-Dove	√	X

Discussion

I found that (1) some of the machine learning models were spatially transferable to new data; (2) models using land-use were better at predicting abundance for a majority of the species, which indicates that the majority of species' abundance were affected by land-use (although 33% (n=7) had models classified as "cautious"); (3) the critical scale varied and was species-specific and (4) a model's fit to the data does not indicate transferability or predictability.

The ability of models to predict bird abundance is not unexpected as several other studies have also been able to predict bird abundances (Ahrestani, Saracco, Sauer, Pardieck, & Royle, 2017; Davis, 2004; Kéry, 2008). I was not able to find any other study that used machine learning to compare the ability of our models with. The second result also agrees which several other studies that conclude similar results (Ahrestani et al., 2017; Davis, 2004; Kéry, 2008; Lichstein, Simons, & Franzreb, 2002). Several studies concluded that for a majority of species, land-use did have an effect on bird abundance (Ahrestani et al., 2017; Davis, 2004; Kéry, 2008) but a few studies found that land-use had little impact on the model's ability to predict abundance (Lichstein et al., 2002). Although none of the studies looked at whether the models were transferable (Ahrestani et al., 2017; Davis, 2004; Kéry, 2008; Lichstein et al., 2002). When comparing different resources (eBird, 2017) and literature, my conclusion that critical scale varies and is species-specific is supported (Monkkonen & Reunanen, 1999). Several other studies also stated the importance of cross validation in understanding the strength of the model.

Land-use and critical scale

The majority of models used most, if not all (n >12) of land-use variables within the model. Pasture/hay land-use was the most important land-use found in half of all species investigated top-four most important land-use. Several other studies also concluded that pasture/hay land-use, under low grazing conditions, was found to be important to several bird species (Barnagaud et al., 2015; Hennings & Edge, 2003; Li et al., 2018; Willcox, Tanner, Giuliano, & McSorley, 2010). Evergreen forest (n=10), open water and grassland/herbaceous (n=9) land-use were found to be second, third, and fourth most important land-use variables, all of which were found in 41% or more of investigated species top four most important land-uses. All land-use types were found to be at least one species' top four land-uses expect mix forest (Table 2), although their results may not indicate the true habitat preference or requirements. Only 29% (n=6) of the species were classified as "good" with the remaining 71% (n=15) species had either "cautious" or "poor" models. The land-use categories of these models were not transferable to new data and/or did not better predict in comparison to using the mean abundance of the training data. This indicates that the identified land-use for these models could be the modeling trying to fit to the data.

The majority of species favored large critical scales (2000 m, 5000 m and 10000 m making up 77% of species critical scale), but varied between species and methods used to identify the critical scale (Table 8 Appendix). The two forms of identifying the critical scale in this project (high R^2 and low PE) resulted in the majority of species having two different critical scales. While only the critical scale identified by the highest R^2 was stated in this paper, both methods can be seen within the appendix. The different critical scales between species is an expected result, but the variation within species between methods is unexpected and needs to be addressed in future studies surrounding critical scale (Findlay & Houlahan, 1997; Hennings & Edge, 2003). Uncertainly surrounding critical scale can lead to issues for conversation projects looking at special requirements and in data needed to make predictions.

Transferability

The majority of the models (14 out of 21) were transferable to new data, while the remaining 7 species may not able to be spatially transferable to new data. No model showed a large enough difference between PE for the training and test dataset that cannot be attributed to normal variation within the data. However, this difference is subjective and varies from person to person and what they would accept as transferability.

Traditionally, a model's transferability is not assessed, which can lead to poor model strength and misuse of data and results (Consonni, Ballabio, & Todeschini, 2010; Ellis, Smith, & Pitcher, 2012; Randin et al., 2006; Townsend Peterson, Papeş, & Eaton, 2007). In this study, I compared the PE of the model on test data to the known observed values of the routes. Other studies suggest different methods such as 1) comparing observed to predicted values based on area under plotted curves (Randin et al., 2006), 2) comparing goodness-of-fit between training and test data (Ellis et al., 2012) or 3) calculating root mean square error in prediction (Consonni et al., 2010). Level of complexity varies across the different methods, but all methods work to compare the observed value and the model's predictions (Consonni et al., 2010; Ellis et al., 2012; Randin et al., 2006; Townsend Peterson et al., 2007).

Models can either be transferable in time or space. In this project I looked into the ability of a model to be built using data from one geographical location in order to predict onto another location. It is important to note that although a model is not able to be transferred spatially it can still be transferrable in time. To test whether a model is transferable in time, a similar process of cross-validation and comparing observations to the model's predictions are needed.

A model's fit to either the training or test data does not directly translate into a model's predictability. My results show that several species dispute the model better fitting the test data

(Figure 4) performed worse compared to the mean of the training data (Figure 5). Lack of cross-validation can lead to poor predictions and inaccurate results (Consonni et al., 2010; Hawkins, Basak, & Mills, 2003).

The degree of the model's predictive ability compared to the mean ranged. A majority of the models using the test data were more accurate compared to the mean (n=13; 61%), but a wide range of variation in the success of models can be seen (0 to 6.68). A weak relationship was seen between R^2 and a model's predictive improvement; however, this needs to be investigated further and tested before any conclusions can be made. Despite the outcome of this, cross-validation is still a critical step in all model building that needs to be tested.

Models limitation

One of the biggest limitations of machine learning models is the amount of data required (Kuhn & Johnson, 2013). When the model is found to only slightly better than the mean, it can be useful to use the mean. The large amount of data required for the models may be expensive to collect on an annual or semi-annual basis; however, it may be useful information when collected on a less regular basis a rough estimate is needed. Therefore, it may be beneficial to collect his data on a less consecutive schedule (every 5 years instead of yearly) and then use the mean; however, when only using the mean as an estimate, information such as critical scale and information land-uses are not identified. Therefore, this is subjective and depends on either the individual or organization and whether they are willing to accept that it could be worse than the model.

Models that perform strong indicate a strong relationship between land-use and a species abundance. When the amount of land-use (i.e. the critical scale) allowed the model to accurately predict the abundance it can be inferred that it is important to abundance. For this reason, land-use that is indicated to be important for the model are important for the species abundance, however, the transferability of the model should be checked first. Other factors in addition to land-use would prevent the model from being predicted perfectly include predation, density-dependent process, and non-land-use factors.

Study limitations and direction for future studies

In my study, I used land-use data at six different scales for 15 different variables, but I did not use any information on land-use density, patch size, or interactions between different species. In future studies, I think it would be useful to investigate the effects of these different parameters. My model has room for improvement and the addition of these predictor variables may lower the PE. Additionally, including information on interactions between different species (i.e. predictor-prey) has shown promising results in other models (Etienne & Olff, 2005; Hurlbert & Jetz, 2007; Kéry, 2008; Willcox et al., 2010). While the interactions between species can be complex and thus make the models themselves complex, which would require more data, they may give more accurate predictions (Etienne & Olff, 2005; Kuhn & Johnson, 2013).

As mentioned previously, the biggest limitation of machine learning is the amount of data required (Kuhn & Johnson, 2013; Recknagel, 2001). In the future for machine learning models to be used on different species in they would need to be both abundant and found within enough routes that both large training and test datasets can be built. There is no baseline for what is enough data but more complex interactions and relationships require more data than more simple problems (Kuhn & Johnson, 2013). This limits this method to more abundant species and organizations with access to large amounts of data.

Future studies could investigate the ability of different models and areas of statistics in their population abundance potential. Karanth et al. showed success modeling tiger's abundance using patch density models of their prey, which may show promise for birds of prey and other predatory and omnivore species (Karanth, Nichols, Kumar, Link, & Hines, 2004). Another possible form of modeling may be hierarchical spatial count models, which have been shown to handle autocorrelated counts (delayed response to an action) in year to year observations (Thogmartin, Knutson, & Sauer, 2006). Thogmartin et al have already used hierachial spatial count models to predict bird abundance with success (Thogmartin et al., 2006). Bayesian, Markov Chain and Monte Carlo statistics may be methods to increase understanding between relationships, handle year-to-year variation, and cross-valid predictions (Etienne & Olff, 2005; Kuhn & Johnson, 2013; Thogmartin et al., 2006).

Conclusion

I conclude, the relationship between land-use and the abundance of different species is complex and challenging to predict. In conclusion (1) models containing land-use variables were transferable to new data for some species; (2) there is evidence that some species are responding to land-use; (3) several species abundance were not affected by land-use; (4) using different methods to calculate critical scale resulted different critical scales. Future research is need still to improve the prediction of models, more accurately identify critical scale and investigate model's transferability, and predictive power.

References

Ahrestani, F. S., Saracco, J. F., Sauer, J. R., Pardieck, K. L., & Royle, J. A. (2017). An integrated population model for bird monitoring in North America. *Ecological Applications*, *27*(3), 916–924. https://doi.org/10.1002/eap.1493

Andrade, R., Bateman, H. L., Franklin, J., & Allen, D. (2018). Waterbird community composition, abundance, and diversity along an urban gradient. *Landscape and Urban Planning*, *170*, 103–111. https://doi.org/10.1016/j.landurbplan.2017.11.003

Arévalo, J. E., & Newhard, K. (2011). Traffic noise affects forest bird species in a protected tropical forest. *Revista De Biologia Tropical*, *59*(2), 969–980.

Askins, R. A. (1993). Population Trends in Grassland, Shrubland, and Forest Birds in Eastern North America. In D. M. Power (Ed.), *Current Ornithology* (pp. 1–34). Boston, MA: Springer US. https://doi.org/10.1007/978-1-4757-9912-5_1

Barnagaud, J.-Y., Papaïx, J., Gimenez, O., & Svenning, J.-C. (2015). Dynamic spatial interactions between the native invader Brown-headed Cowbird and its hosts. *Diversity and Distributions*, *21*(5), 511–522. https://doi.org/10.1111/ddi.12275

Blair, R. B. (1996). Land Use and Avian Species Diversity Along an Urban Gradient. *Ecological Applications*, *6*(2), 506–519. https://doi.org/10.2307/2269387

Consonni, V., Ballabio, D., & Todeschini, R. (2010). Evaluation of model predictive ability by external validation techniques. *Journal of Chemometrics*, *24*(3–4), 194–201. https://doi.org/10.1002/cem.1290

Davis, S. K. (2004). AREA SENSITIVITY IN GRASSLAND PASSERINES: EFFECTS OF PATCH SIZE, PATCH SHAPE, AND VEGETATION STRUCTURE ON BIRD ABUNDANCE AND OCCURRENCE IN SOUTHERN SASKATCHEWAN. *The Auk*, *121*(4), 1130. https://doi.org/10.1642/0004-8038(2004)121[1130:ASIGPE]2.0.CO;2

Downes, C. M., Hudson, M.-A. R., Smith, A. C., & Francis, C. M. (2016). The Breeding Bird Survey at 50: scientists and birders working together for bird conservation. *Avian Conservation and Ecology*, *11*(1). https://doi.org/10.5751/ACE-00855-110108

eBird. (2017). *eBird: An online database of bird distribution and abundance*. New York: Cornell Lab of Ornithology. Retrieved from http://www.ebird.org

Ellis, N., Smith, S. J., & Pitcher, C. R. (2012). Gradient forests: calculating importance gradients on physical predictors. *Ecology*, *93*(1), 156–168. https://doi.org/10.1890/11-0252.1

Etienne, R. S., & Olff, H. (2005). Confronting different models of community structure to species-abundance data: a Bayesian model comparison: Bayesian analysis of species-abundance data. *Ecology Letters*, *8*(5), 493–504. https://doi.org/10.1111/j.1461-0248.2005.00745.x

Evans, K. L. (2003). The potential for interactions between predation and habitat change to cause population declines of farmland birds: Population declines and predation/habitat interactions. *Ibis*, *146*(1), 1–13. https://doi.org/10.1111/j.1474-919X.2004.00231.x

Findlay, C. S., & Houlahan, J. (1997). Anthropogenic Correlates of Species Richness in Southeastern Ontario Wetlands. Correlativos Antropogenicos de la Riqueza de Especies en Humedales del Sureste de Ontario. *Conservation Biology*, *11*(4), 1000–1009. https://doi.org/10.1046/j.1523-1739.1997.96144.x

Hawkins, D. M., Basak, S. C., & Mills, D. (2003). Assessing Model Fit by Cross-Validation. *Journal of Chemical Information and Computer Sciences*, *43*(2), 579–586. https://doi.org/10.1021/ci025626i

Hennings, L. A., & Edge, W. D. (2003). RIPARIAN BIRD COMMUNITY STRUCTURE IN PORTLAND, OREGON: HABITAT, URBANIZATION, AND SPATIAL SCALE PATTERNS. *The Condor*, *105*(2), 288. https://doi.org/10.1650/0010-5422(2003)105[0288:RBCSIP]2.0.CO;2

Houghton, R. A. (1994). The Worldwide Extent of Land-Use Change. *BioScience*, *44*(5), 305–313. https://doi.org/10.2307/1312380

Hudson, M.-A. R., Francis, C. M., Campbell, K. J., Downes, C. M., Smith, A. C., & Pardieck, K. L. (2017). The role of the North American Breeding Bird Survey in conservation. *The Condor*, *119*(3), 526–545. https://doi.org/10.1650/CONDOR-17-62.1

Hurlbert, A. H., & Jetz, W. (2007). Species richness, hotspots, and the scale dependence of range maps in ecology and conservation. *Proceedings of the National Academy of Sciences*, *104*(33), 13384–13389. https://doi.org/10.1073/pnas.0704469104

Karanth, K. U., Nichols, J. D., Kumar, N. S., Link, W. A., & Hines, J. E. (2004). Tigers and their prey: Predicting carnivore densities from prey abundance. *Proceedings of the National Academy of Sciences*, *101*(14), 4854–4858. https://doi.org/10.1073/pnas.0306210101

Kéry, M. (2008). ESTIMATING ABUNDANCE FROM BIRD COUNTS: BINOMIAL MIXTURE MODELS UNCOVER COMPLEX COVARIATE RELATIONSHIPS. *The Auk*, *125*(2), 336–345. https://doi.org/10.1525/auk.2008.06185

Kuhn, M., & Johnson, K. (2013). *Applied Predictive Modeling*. New York, NY: Springer New York. https://doi.org/10.1007/978-1-4614-6849-3

Li, L., Tietze, D. T., Fritz, A., Lü, Z., Bürgi, M., & Storch, I. (2018). Rewilding cultural landscape potentially puts both avian diversity and endemism at risk: A Tibetan Plateau case study. *Biological Conservation*, *224*, 75–86. https://doi.org/10.1016/j.biocon.2018.05.008

Lichstein, J. W., Simons, T. R., & Franzreb, K. E. (2002). LANDSCAPE EFFECTS ON BREEDING SONGBIRD ABUNDANCE IN MANAGED FORESTS. *Ecological Applications*, *12*(3), 836–857. https://doi.org/10.1890/1051-0761(2002)012[0836:LEOBSA]2.0.CO;2

Martensen, A. C., Ribeiro, M. C., Banks-Leite, C., Prado, P. I., & Metzger, J. P. (2012). Associations of Forest Cover, Fragment Area, and Connectivity with Neotropical Understory Bird Species Richness and Abundance: *Modulators of Avifaunal Composition*. *Conservation Biology*, *26*(6), 1100–1111. https://doi.org/10.1111/j.1523-1739.2012.01940.x

Molles, M. C. (2015). *Ecology: concepts and applications* (Seventh edition). New York, NY: McGraw-Hill Education.

Monkkonen, M., & Reunanen, P. (1999). On Critical Thresholds in Landscape Connectivity: A Management Perspective. *Oikos*, *84*(2), 302. https://doi.org/10.2307/3546725

Özesmi, U., & Mitsch, W. J. (1997). A spatial habitat model for the marsh-breeding red-winged blackbird (Agelaius phoeniceus L.) in coastal Lake Erie wetlands. *Ecological Modelling*, *101*(2–3), 139–152. https://doi.org/10.1016/S0304-3800(97)01983-2

Randin, C. F., Dirnböck, T., Dullinger, S., Zimmermann, N. E., Zappa, M., & Guisan, A. (2006). Are niche-based species distribution models transferable in space? *Journal of Biogeography*, *33*(10), 1689–1703. https://doi.org/10.1111/j.1365-2699.2006.01466.x

Recknagel, F. (2001). Applications of machine learning to ecological modelling. *Ecological Modelling*, *146*(1–3), 303–310. https://doi.org/10.1016/S0304-3800(01)00316-7

Robbins, C. S., Sauer, J. R., Greenberg, R. S., & Droege, S. (1989). Population declines in North American birds that migrate to the neotropics. *Proceedings of the National Academy of Sciences*, *86*(19), 7658–7662. https://doi.org/10.1073/pnas.86.19.7658

Rosenberg, A. C., Kennedy, J. A., Dettmers, R., Ford, R. P., & Reynolds, D. (2016). *Partners in Flight Landbird Conservation Plan: 2016 Revision for Canada and Continental United States*. Partners in Flight Science Committee.

Sekercioglu, C. (2006). Ecological Significance of Bird Populations (Vol. 11, pp. 15–51).

Small, M. F., Veech, J. A., & Jensen, J. L. R. (2012). Local landscape composition and configuration around North American Breeding Bird Survey routes: *Ecological Archives* E093-215. *Ecology*, *93*(10), 2298–2298. https://doi.org/10.1890/12-0724.1

Thogmartin, W. E., Knutson, M. G., & Sauer, J. R. (2006). Predicting Regional Abundance of Rare Grassland Birds with a Hierarchical Spatial Count Model. *The Condor*, *108*(1), 25. https://doi.org/10.1650/0010-5422(2006)108[0025:PRAORG]2.0.CO;2

Townsend Peterson, A., Papeş, M., & Eaton, M. (2007). Transferability and model evaluation in ecological niche modeling: a comparison of GARP and Maxent. *Ecography*, *30*(4), 550–560. https://doi.org/10.1111/j.0906-7590.2007.05102.x

Verhulst, J., Báldi, A., & Kleijn, D. (2004). Relationship between land-use intensity and species richness and abundance of birds in Hungary. *Agriculture, Ecosystems & Environment*, *104*(3), 465–473. https://doi.org/10.1016/j.agee.2004.01.043

Vierling, K. T. (2000). SOURCE AND SINK HABITATS OF RED-WINGED BLACKBIRDS IN A RURAL/SUBURBAN LANDSCAPE. *Ecological Applications*, *10*(4), 1211–1218. https://doi.org/10.1890/1051-0761(2000)010[1211:SASHOR]2.0.CO;2

Willcox, E. V., Tanner, G. W., Giuliano, W. M., & McSorley, R. (2010). Avian Community Response to Grazing Intensity on Monoculture and Mixed Florida Pastures. *Rangeland Ecology & Management*, *63*(2), 203–222. https://doi.org/10.2111/REM-D-09-00092.1

Appendix Title

Table 6: Critical scale for each bird species indicated when using the R^2 and lowest prediction error.

AOU	Bird Species	Best R Scale	R^2	Model	Best Prediction Error	Prediction Value	Better Model	Mean
4980	Red Winged Black Bird	2 km	0.362343	BT	10 km	40.017	RF	40.017
1840	White Ibis	10 km	0.749	RF	1 km	10.886	RF	4.71
1320	Mallard	200 m	0.555	RF	400 m	2.9035	RF	1.511627
2730	Killdeer	5 km	0.6252	BT	1 km	3.203	BT	4.674
3131	Rock Dove	5 km	0.2938	BT	5 km	5.342	BT	3.805
3160	Mourning Dove	10 km	0.4496	BT	1 km	16.672	BT	23.53
3370	Red-tailed Hawk	5 km	0.29179	BT	5 km	1.01	RF	1.119
3430	Broad-winged Hawk	10 km	0.215	BT	10 km	0.19918667	BT	0.207345
3750	Great Horned Owl	5 km	0.12489	BT	5 km	0.2967768	RF	0.332207
4770	Blue Jay	10 km	0.42793	BT	400 m	3.997	BT	4.8134
4950	Brown Head Cowbird	10 km	0.51982	BT	400 m	11.50213	RF	11.80015
5060	Orchard Oriole	1 km	0.34667	BT	5 km	2.3306	RF	2.48203
5070	Baltimore Oriole	10 km	0.366487	BT	10 km	2.332163	RF	2.482038
5110	Common Grackle	10 km	0.483706	BT	200 m	24.6702	BT	25.02066
5600	Chipping Sparrow	10 km	0.456625	BT	5 km	8.589218	BT	7.188786
5870	Eastern Towhee	400 m	0.3985644	BT	200 m	5.469321	RF	6.459882
6120	Cliff Swallow	400 m	0.3082506	RF	400 m	33.28901	RF	29.5662
6130	Barn Swallow	2 km	0.40049	BT	5 km	10.33374	BT	13.22731
6140	Tree Swallow	2 km	0.2517566	BT	400 m	2.90258	BT	2.503429
6170	N. Rough-winged Swallow	200 m	0.0703732	RF	200 m	4.697047	BT	6.141078
7040	Gray Catbird	5 km	0.5147325	BT	10 km	6.240094	RF	1.790238
7020	Sage Thrasher	10 km	0.3294491	BT	400 m	6.315971	RF	4.891806
22860	Eurasian Collared-Dove	2 km	0.3403105	BT	400 m	1.498374	BT	1.258166

Table 7: Critical scale and prediction error for both the training and test dataset for all species.

AOU	Alpha Name	Bird Species	Critical Scale	Prediction Error	Model
4980	RWBL	Red Winged Black Bird	10 km	40.017	Test
4980	RWBL	Red Winged Black Bird	10 km	45.75706	Train
2730	KILL	Killdeer	1 km	3.203	Test
2730	KILL	Killdeer	1 km	3.192748	Train
3131	RODO	Rock Dove	5 km	5.342	Test
3131	RODO	Rock Dove	5 km	6.26149	Train
3160	MODO	Mourning Dove	1 km	16.672	Test
3169	MODO	Mourning Dove	1 km	14.63476	Train
3370	RTHA	Red-tailed Hawk	5 km	1.01	Test
3370	RTHA	Red-tailed Hawk	5 km	1.115916	Train
3430	BWHA	Broad-winged Hawk	10 km	0.19918667	Test
3430	BWHA	Broad-winged Hawk	10 km	0.2054026	Train
3750	GHOW	Great Horned Owl	5 km	0.2967768	Test
3750	GHOW	Great Horned Owl	5 km	0.2505676	Train
4770	BLJA	Blue Jay	400 m	3.997	Test
4770	BLJA	Blue Jay	400 m	6.077848	Train
4950	BHCO	Brown Head Cowbird	400 m	11.50213	Test
4950	BHCO	Brown Head Cowbird	400 m	8.392301	Train
5060	OROR	Orchard Oriole	5 km	2.3306	Test
5060	OROR	Orchard Oriole	5 km		Train
5070	BAOR	Baltimore Oriole	10 km	2.332163	Test
5070	BAOR	Baltimore Oriole	2 km	2.8728	Train
5110	COGR	Common Grackle	200 m	24.6702	Test
5110	COGR	Common Grackle	200 m	24.17321	Train
5600	CHSP	Chipping Sparrow	5 km	8.589218	Test
5600	CHSP	Chipping Sparrow	5 km	7.27538	Train
5870	EATO	Eastern Towhee	200 m	5.469321	Test

5870	EATO	Eastern Towhee	200 m	7.415198	Train
6120	CLSW	Cliff Swallow	400 m	29.5662	Test
6120	CLSW	Cliff Swallow	400 m	32.3358	Train
6130	BASW	Barn Swallow	5 km	10.33374	Test
6130	BASW	Barn Swallow	5 km		Train
6140	TRSW	Tree Swallow	400 m	2.90258	Test
6140	TRSW	Tree Swallow	400 m		Train
6170	NRWS	N. Rough-winged Swallow	200 m	4.697047	Test
6170	NRWS	N. Rough-winged Swallow	200 m	2.3994875	Train
7040	GRCA	Gray Catbird	10 km	6.240094	Test
7040	GRCA	Gray Catbird	10 km	5.560251	Train
7210	SATR	Sage Thrasher	400 m	6.315971	Test
7210	SATR	Sage Thrasher	400 m	5.177558	Train
22860	ECDO	Eurasian Collared-Dove	400 m	1.498374	Test
22860	ECDO	Eurasian Collared-Dove	400 m	2.676989	Train

Table 8: Critical scale for each species indemnified by both the highest R^2 and the lowest PE. Best method of machine learning model also identified (BT: boosted trees and RF: random forest).

AOU	Alpha Name	Bird Species	Best R^2 Scale	R	Model	Best Prediction Error Scale	Better Model
4980	RWBL	Red Winged Black Bird	2 km	0.362343	BT	10km	RF
1840	WHIB	White Ibis	10 km	0.749	RF	1km	RF
1320	MALL	Mallard	200 m	0.555	RF	400 m	RF
2730	KILL	Killdeer	5 km	0.6252	BT	1 km	BT
3131	RODO	Rock Dove	5 km	0.2938	BT	5 km	BT
3160	MODO	Mourning Dove	10 km	0.4496	BT	1 km	BT
3370	RTHA	Red-tailed Hawk	5 km	0.29179	BT	5 km	RF
3430	BWHA	Broad-winged Hawk	10 km	0.215	BT	10 km	BT
3750	GHOW	Great Horned Owl	5 km	0.12489	BT	5 km	RF
4770	BLJA	Blue Jay	10 km	0.42793	BT	400 m	BT
4950	BHCO	Brown Head Cowbird	10 km	0.51982	BT	400 m	RF
5060	OROR	Orchard Oriole	1 km	0.34667	BT	5 km	RF
5070	BAOR	Baltimore Oriole	10 km	0.366487	BT	10 km	RF
5110	COGR	Common Grackle	10 km	0.483706	BT	200 m	BT
5600	CHSP	Chipping Sparrow	10 km	0.456625	BT	5 km	BT
5870	EATO	Eastern Towhee	400 m	0.39856441	BT	200 m	RF
6120	CLSW	Cliff Swallow	400 m	0.3082506	RF	400 m	RF
6130	BASW	Barn Swallow	2 km	0.40049	BT	5 km	BT
6140	TRSW	Tree Swallow	2 km	0.2517566	BT	400 m	BT
6170	NRWS	N. Rough-winged Swallow	200 m	0.07037323	RF	200 m	BT
7040	GRCA	Gray Catbird	5 km	0.5147325	BT	10 km	RF
7020	SATH	Sage Thrasher	10 km	0.3294491	BT	400 m	RF
22860	ECDO	Eurasian Collared-Dove	2 km	0.34031053	BT	400 m	BT