USING CLIMATE VARIABLES AND SATELLITE AND AIRBORNE LIDAR DERIVED VEGETATION PROPERTIES FOR ACCESSING THE HABITAT OF BREEDING BIRDS: A CASE STUDY IN MINNESOTA

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We certify that we have read this thesis and that, in our opinion, it is satisfactory in scope and quality as a thesis for the degree of Bachelor of Science in Global Environmental Science.

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ABSTRACT

Understanding the relationship between environment and the spatial distribution of species has always been important for environmental protections and ecological conservations. Remote sensing technologies provide opportunities for acquiring information on climate and vegetation more easily and faster, and have been applied in many fields such as geography, biology, ecology, etc. Recent advance remote sensing technologies such as airborne LiDAR provides useful information about canopy structure in three-dimensional space. In this study, airborne LiDAR data in the Northeast Minnesota were combined with conventional habitat variables to build models for predicting bird species abundance. Correlations were examined between different groups of variables and bird abundance. Results were discussed on the ecological factors on bird species abundance and future potential developments. It was found that airborne LiDAR derived canopy structure variables were important for predicting bird abundance. This study could improve our understanding of the relationship of bird species with vegetation and climate, which can help ecologists to estimate the bird biomass and biodiversity using these environmental variables.

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CHAPTER 1. INTRODUCTION

The ecosystems worldwide have been changed dramatically in the recent centuries. It is crucial to study the species biomass and biodiversity to present a global view of ecosystem circumstances and also its variations (Jacob, Wilson, & Lewis, 2014; McGill, 2015; Newbold et al., 2015). These biomass and biodiversity studies can help governments adjust their policies so that humans can simultaneously protect the ecosystem and maximize the economic profit both locally and globally (Chapin et al., 2011; McGill, 2015).

Avian species is one of the most sensitive class of vertebrates for ecosystem studies. Most birds can migrate over a large range and their reproduction abilities are highly impacted by their environment compared to other vertebrates (Podulka et al., 2004). Avian distributions are important indicators for ecologists to understand both the local and global health of different ecosystems.

Moreover, bird species richness and abundance can be influenced by forest attributes such as development stage, productivity, tree species diversity, and disturbance (Gil-Tena et al., 2007), which, in turn, impact forest morphological characteristics. Thus, the avian biomass and biodiversity, which can be calculated from avian distributions, are highly correlated canopy structure parameters. Previous studies have found that it is possible to estimate the bird abundance and diversity using the canopy structure parameters (Clawges et al., 2008; Lesak et al., 2011; Scott et al., 2014; Swatantran et al., 2012; Wallis et al., 2016).

Nevertheless, forest structure parameters are hard to quantify and measure over large spatial scales. In the recent two decades, LiDAR (Light Detection and Ranging) provides a novel method to study forest structures and makes it possible to accurately quantify forest structure and attributes. LiDAR uses a laser transmitter and receiver to record the intensity and interval between transmitting a laser at a target and receiving the reflection (Maltamo, Naesset, & Vauhkonen, 2014). By deploying LiDAR on aircraft, LiDAR can provide points cloud data of forests in high resolution and large scale (Chen, 2007a, 2007b; Chen et al., 2007). These data can be used to extract high quality forest structure data such as tree height, tree amount, and crown density, allowing for quantification of forest structure (Chen, 2007a, 2007b; Chen et al., 2007).Recently, many states in the United States have started LiDAR program and several states, such as Minnesota, have made their LiDAR data publically available. These data offer an unprecedented opportunity for avian habitat studying. In this study, we aim to quantify and analyze the relationships between avian biodiversity and LiDAR-derived forest structure and other environmental variables.

CHAPTER 2. METHODS

Physical environmental variables, satellite based vegetation properties variables and airborne LiDAR derived canopy structure variables were assessed for predicting our response variable: bird species abundance. For every predictor variable, we explored the strength of Person correlation coefficient. Stepwise regression (Cutler et al., 2007; Vilà et al., 2013) was used to test the correlation between bird species abundance and environmental variables. SVM (Supported Vector Machines) regression was used to build the prediction models.

2.1 Data

2.1.1Bird surveys

Breeding Bird Survey (BBS) data was derived from Northern American Breeding Bird Survey website https://www.pwrc.usgs.gov/bbs/ (Goetz et al., 2014). This survey has been conducted since 1966, there are 5267 survey routes throughout Northern America by 2010, among which 3140 routes were surveyed in 2010 (Figure 1). Each route is 4 km long and contains 50 stops, each of which is 0.5 mi (800 m) apart. Observers make a 3-minute count of heard and seen birds within 0.25mi (400 m) radius from the stop and observations are made at each stop in sequence along each route. Surveys start half hour before sunrise during the peak of each year's avian breeding season, and take about 5 hours to complete (Sauer et al., 2013).

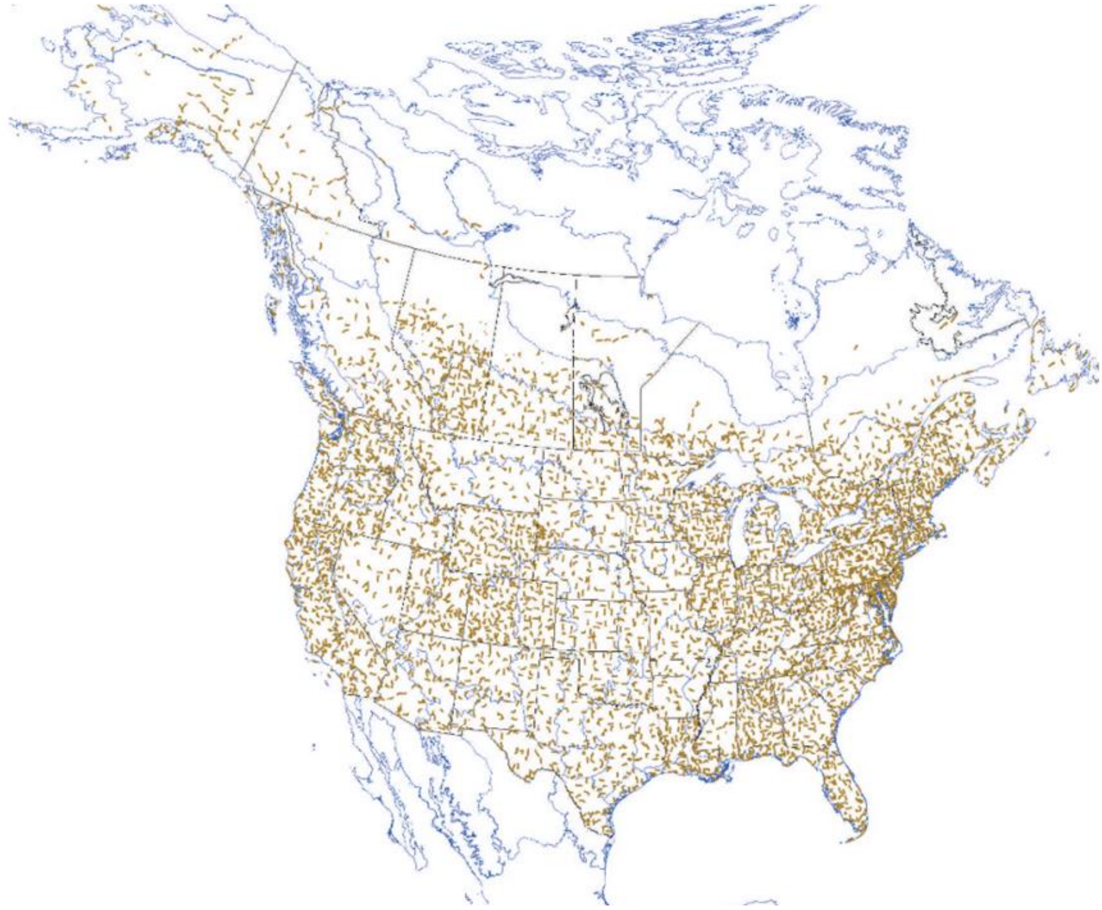


Figure 1. BBS route distribution in North America (Sauer et al., 2013).

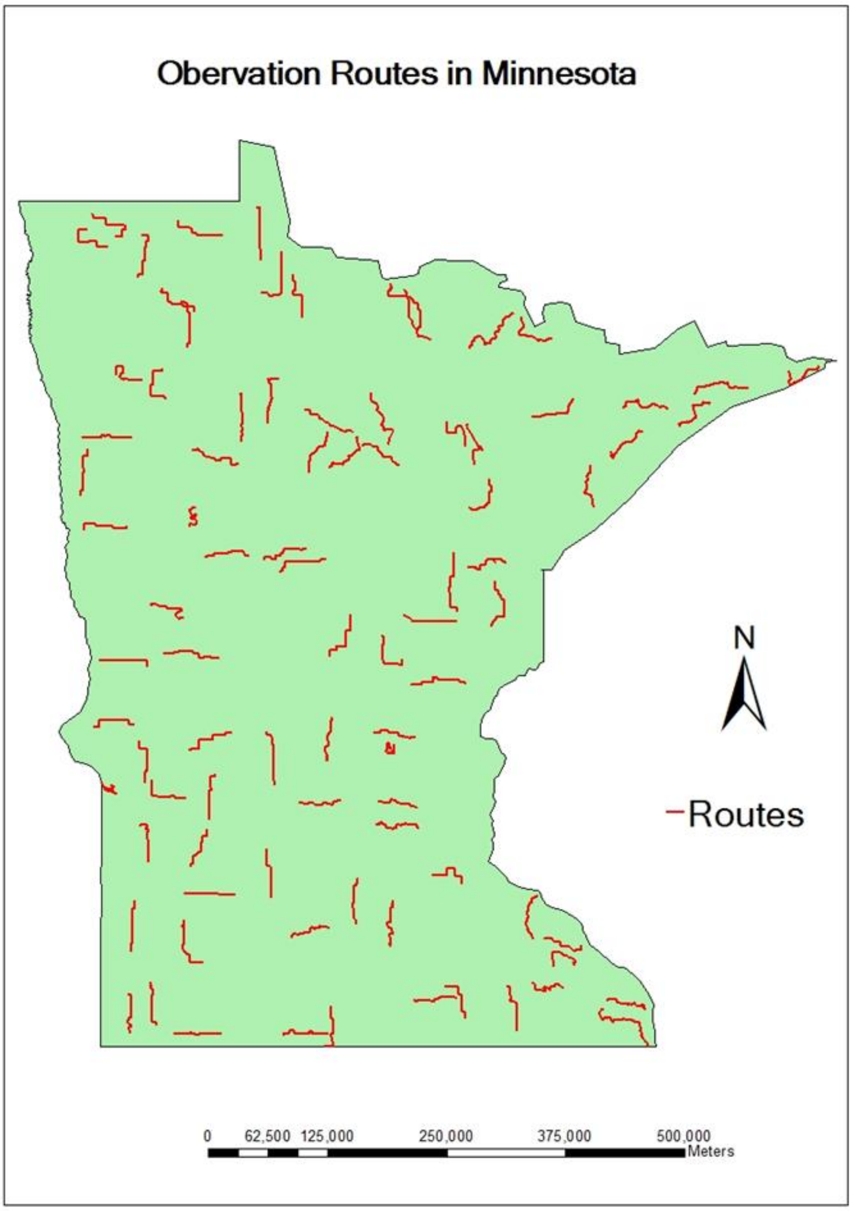


Figure 2. Principle BBS observation routes in Minnesota.

The data for each route for the year 2012 was chosen match the time when other variables especially the airborne LiDAR data were acquired. There were 91 survey routes in Minnesota and 70 of them were surveyed in 2012. There are 87 bird species were recorded through all the routes in Minnesota in 2012. A total of 52963 individuals were observed. The distributions of bird species and abundance of the active routes in Minnesota in 2012 were shown in Figure 3 and Figure 4.

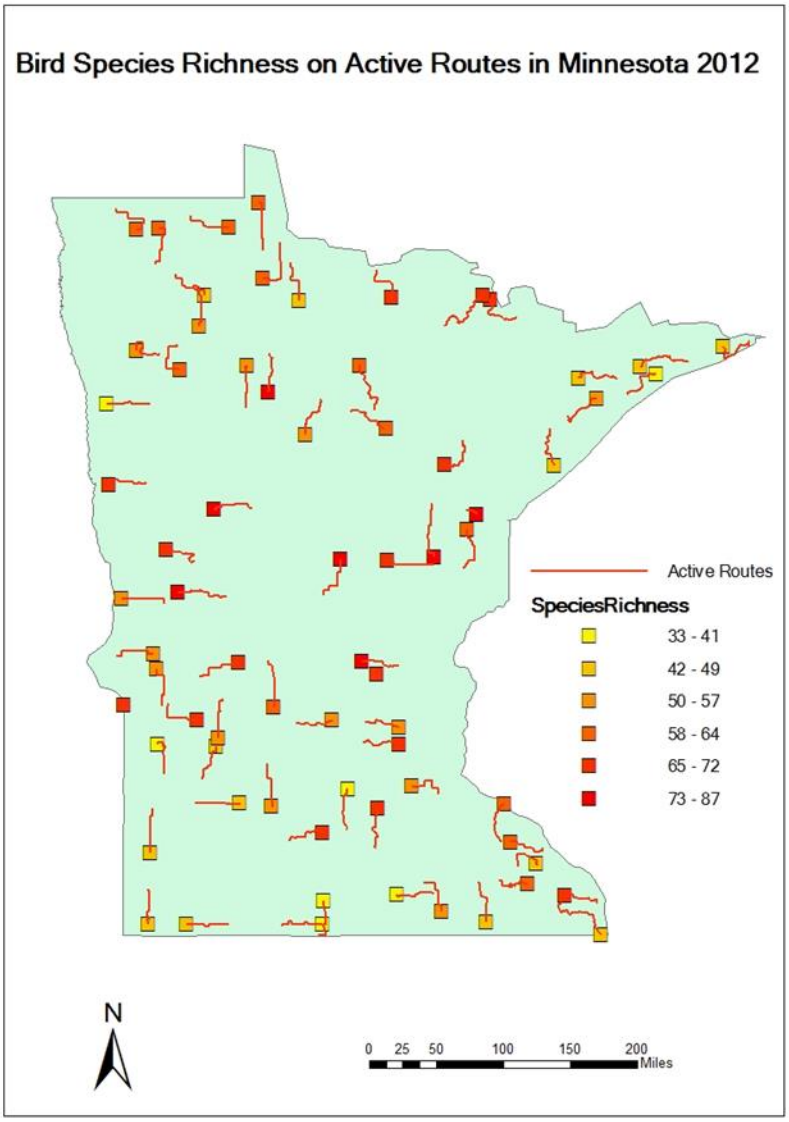


Figure 3. Bird species richness observed on the 70 active routes in 2012 in Minnesota. The colored square showed the amount of bird species observed on each route.

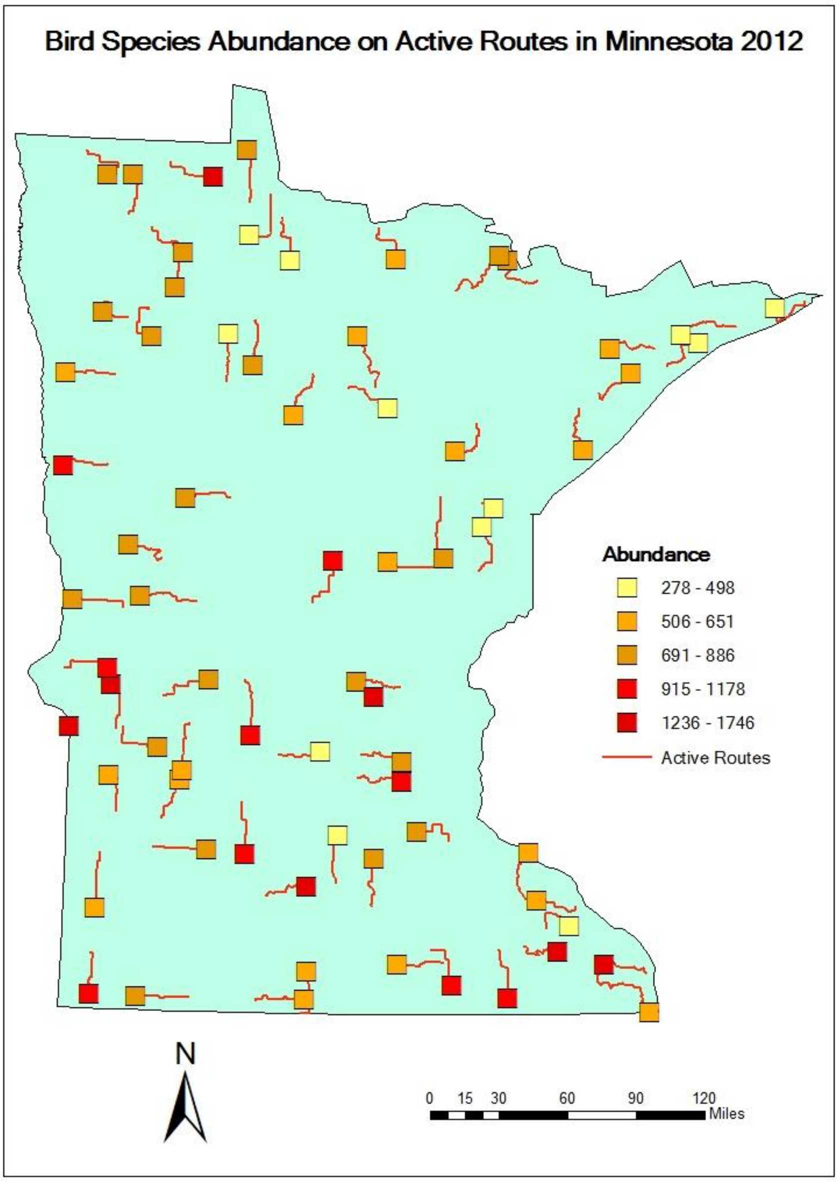


Figure 4. Bird abundance observed on the 70 active routes in Minnesota in 2012. The colored square showed the amount of bird individuals on each route.

2.1.2 Physical environment

Climate variables from temperature and precipitation, were derived from the WorldClim data set, which can be downloaded from http://www.worldclim.org/. The dataset is comprised of world climate map layers at 1 km spatial resolution. Climate conditions are represented from the year 1950 to 2000 (Hijmans et al., 2005).A total of 19 bioclimatic variables were studied (Table 1).

Shuttle Radar Topography Mission (SRTM) was used to derive elevation information. This publicly available (CIAT-CSI SRTM website: http://srtm.csi.cgiar.org/) elevation dataset is derived from interferometric radar imaging which covers approximately 80% of the world' land surface (Reuter et al., 2007). SRTM has a 30 meters spatial resolution in the United States.

Variable name	**Description**	**Source**
bio 1	Annual mean temperature	WorldClim
bio 2	Mean diurnal range (mean of monthly values)	WorldClim
bio 3	Isothermality	WorldClim
bio 4	Temperature seasonality	WorldClim
bio 5	Max temperature of warmest month	WorldClim
bio 6	Min temperature of coldest month	WorldClim
bio 7	Temperature annual range	WorldClim
bio 8	Mean temperature of wettest quarter	WorldClim
bio 9	Mean temperature of driest quarter	WorldClim
bio 10	Mean temperature of warmest quarter	WorldClim
bio 11	Mean temperature of coldest quarter	WorldClim
bio 12	Annual precipitation	WorldClim
bio 13	Precipitation of wettest month	WorldClim
bio 14	Precipitation of driest month	WorldClim
bio 15	Precipitation seasonality	WorldClim
bio 16	Precipitation of wettest quarter	WorldClim
bio 17	Precipitation of driest quarter	WorldClim

bio 18	Precipitation of warmest quarter	WorldClim
bio 19	Precipitation of coldest quarter	WorldClim
SRTM	Elevation(m)	SRTM

Table 1. Physical environmental variables. Descriptions and sources were shown.

2.1.3 Satellite-based vegetation properties

NLCD 2011(National Land Cover Database 2011) was used to derive vegetation cover information (Homer et al., 2015). This product reflects land cover of the United States at 30 m spatial resolution; and all classes are properly defined based on plant functional type mixtures and land cover types. All the 16 classes were categorized into 8 classes: LcWater (Land cover: water .etc.), LcShrubland, LcBarren, LcDeveloped, LcForest, LcWetlands, LcCultivated and LcHerbaceous. Within the class of Forests, 3 subclasses were created based on the longevity of leaves, they are LcDeciduous, LcEvergreen and LcMixed (Table 2). The proportional amounts of each cover variable was calculated and categorized as a particular vegetation function within the 500 m buffer of each BBS route.

MODIS (Moderate Resolution Imaging Spectroradiometer) products were used to derive the other vegetation property variables including: NPP (Net Primary Production), EVI (Enhanced Vegetation Index) area, and VCF (Vegetation Continuous Fields) (Table 2). These data sets were retrieved from https://lpdaac.usgs.gov.

Annual NPP information was provided by the MOD17A3H Version 6 product, which has a 500 m spatial resolution (Running et al., 2015). Data of the year 2012 was chosen.

MOD44B V006: the Terra MODIS Vegetation Continuous Fields (VCF) product was used for representing the surface vegetation cover annually and globally with a 500 m resolution (DiMiceli et al., 2017).

NBAR_EVI_Area is the integration of daily EVI in growing season, which was derived from MODIS Vegetation Dynamics product (MCD12Q2) V005, which uses MODIS EVI that computed from the MODIS Nadir Bidirectional Reflectance Distribution Function (BRDF)-Adjusted Reflectance (NBAR) product (Huete et al., 2002). This data sets are in a spatial resolution of 500 m on a global scale.

Variable	**Source**	**Spatial resolution**
LcWater	NLCD	30 m
LcDeveloped	NLCD	30 m
LcBarren	NLCD	30 m
LcForest	NLCD	30 m
LcShrubland	NLCD	30 m
LcHerbaceous	NLCD	30 m
LcCultivated	NLCD	30 m
LcWetlands	NLCD	30 m
LcDeciduous	NLCD	30 m
LcEvergreen	NLCD	30 m
LcMixed	NLCD	30 m
NPP	MOD17A3H V006	500 m
EVIarea	MCD12Q2) V005	500 m
VCF	MOD44B V006	500 m

Table 2. Satellite based vegetation properties variables and their spatial resolutions

2.1.4 Airborne LiDAR derived canopy structure

Airborne LiDAR data from airborne laser scanning (ALS) were used to derive canopy structure metrics (Chen, 2007a, 2007b; McRoberts et al., 2016). Acquired in 2012 in Minnesota (Figure 5), the wall-to-wall ALS data were with a nominal pulse density of 0.67 pulses / m^2. After being classified by the provider, the ground returns were then used to construct a digital terrain model via interpolation by using the Tiffs (Toolbox for Lidar Data Filtering and Forest Studies) software, which is dedicated to filtering point cloud and extracting individual tree structural information (Chen, 2007a). Metrics such as the mean, standard deviation, skewness, kurtosis, quadratic mean height of the distributions of heights for all echoes were included for each cell and plot (Lefsky et al., 1999; Chen et al., 2012). Additionally, canopy densities were calculated as the proportions of echoes with heights that are 0%, 10%,⋯, 90% of the range from 1.3 m above ground to the 95th height percentile, the corresponding heights to the 10th, 20th, …, 100th percentiles of the distributions were also calculated (Gobakken and Næsset, 2008).

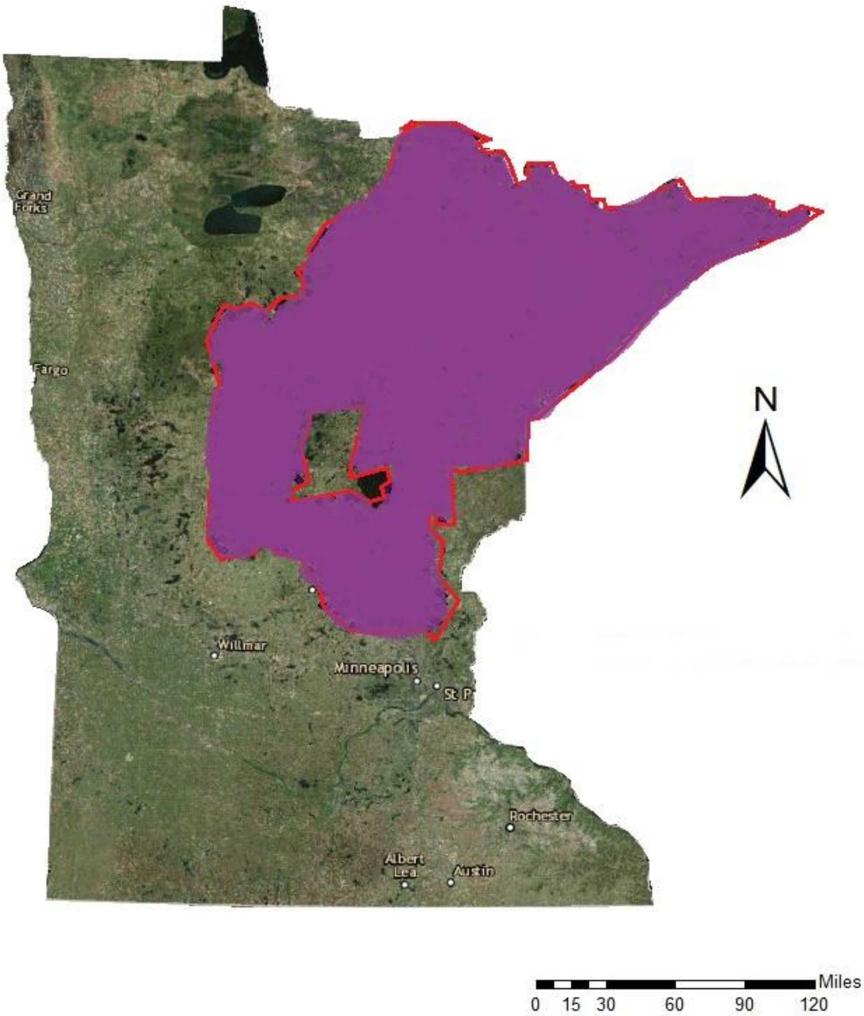


Figure 5. Study area (in purple) with airborne LiDAR coverage in Minnesota

2.2 Geospatial processing

The geospatial processing was performed in ArcMap 10.3. Each predictor variable data set was spatially intersected with the BBS routes. A 500 m buffer was created around each BBS route (Figure 6.) in order to corporate with the spatial resolutions of all variables, so that the average conditions for each BBS route can be extracted properly. After overlapping the 70 active routes with the airborne LiDAR coverage area, 18 routes were qualified for next step analysis. Figure 7 shows an example of one of the predictor variables bio1 (Annual Mean Temperature) intersects with the areas that within the 500 m buffer of each route.

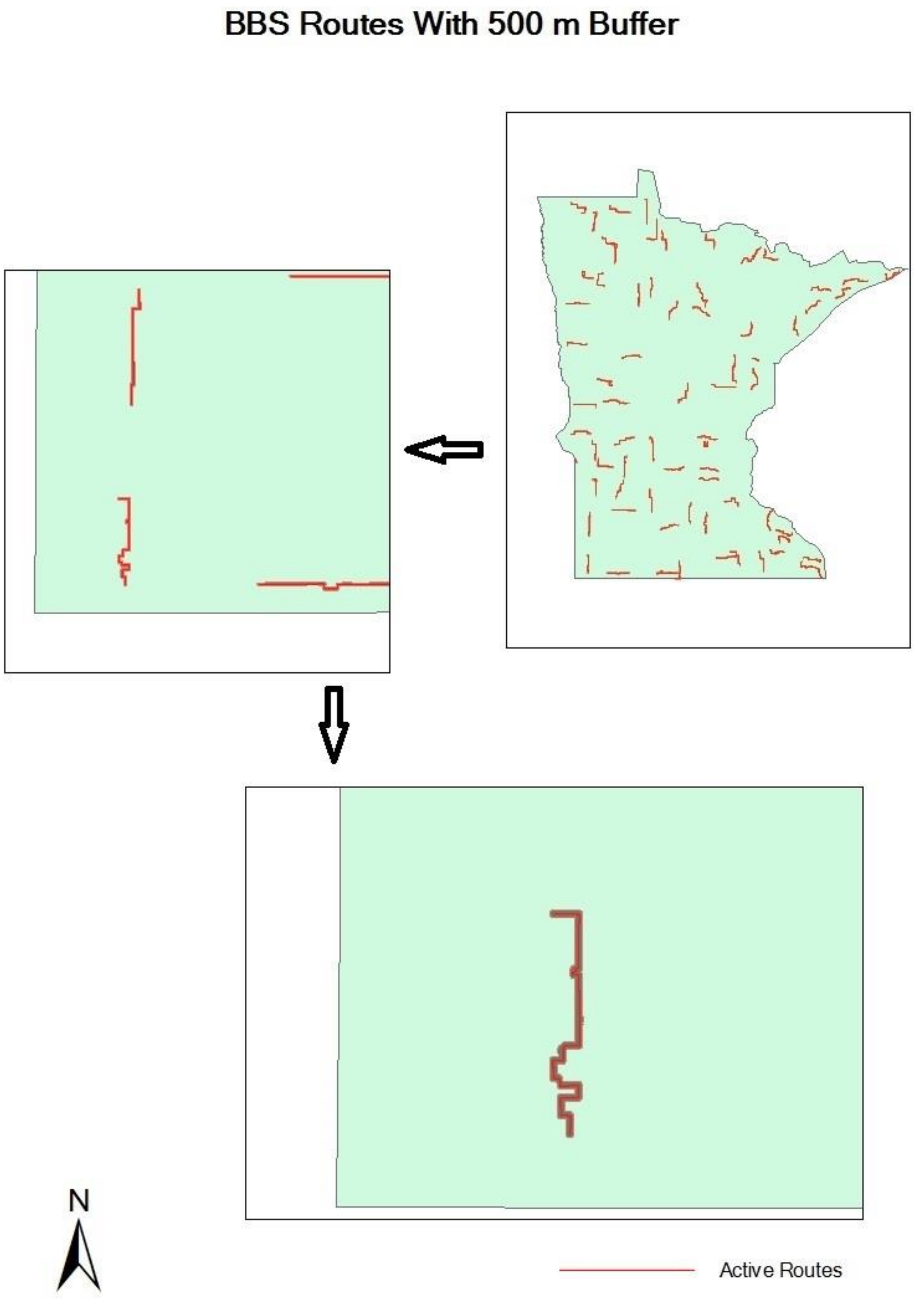


Figure 6. 500 m buffer was created for each of the 70 BBS routes in Minnesota.

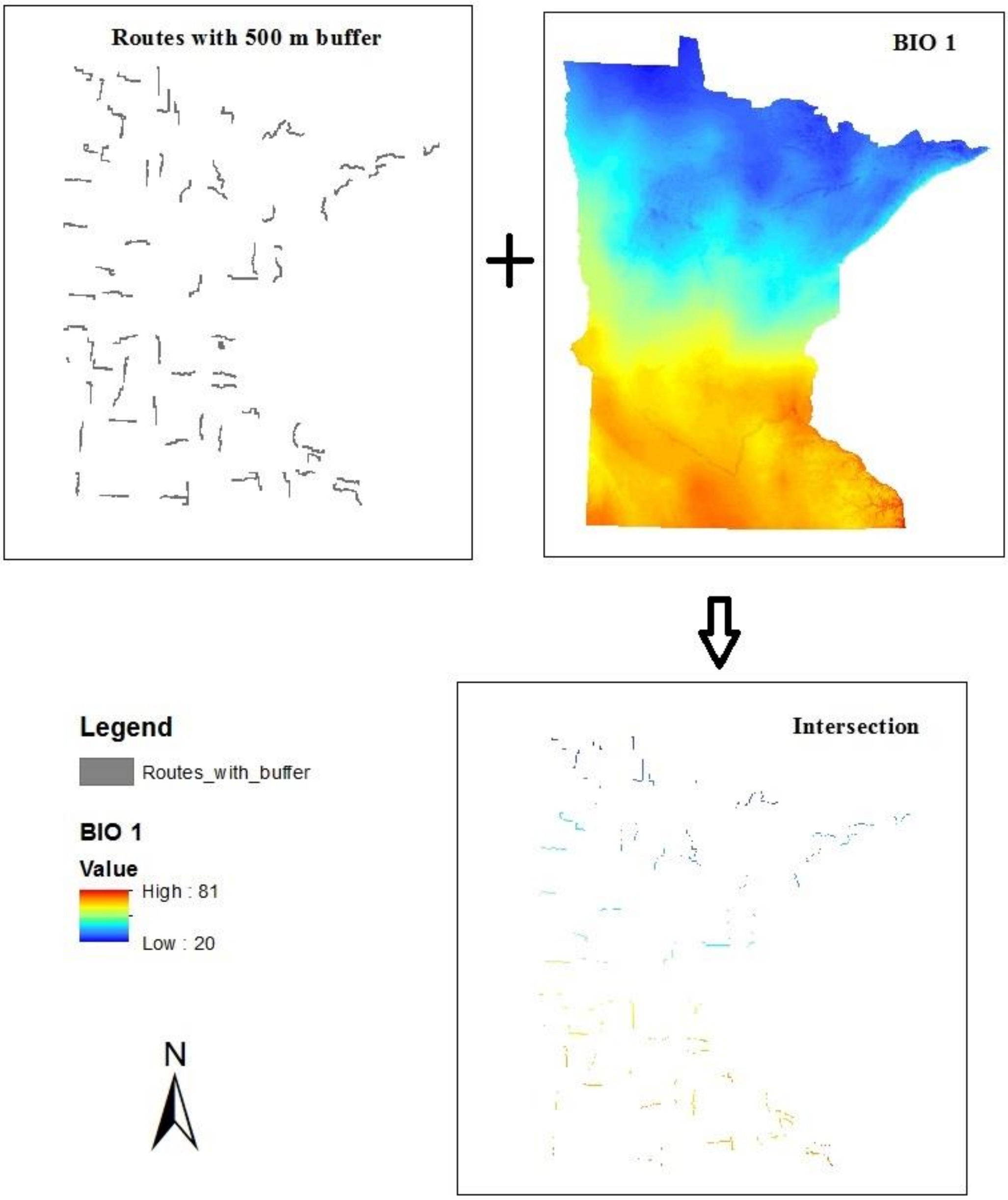


Figure 7. Intersection of bio1 (Annual Mean Temperature) and the BBS routes with 500 m buffer.

2.3 Statistical analysis

Statistical analysis was performed in Matlab2015b. Correlation coefficient between each predictor variable and bird abundance was obtained. Stepwise regression was used to interactively explore predictor variables' importance. Being simple and fast, stepwise regression is a process of building a model by adding or removing variables based on specified criterions (Hocking, 1976). Each predictor variable was assessed with the response variable (bird abundance) separately using the default criterion. In addition, all variables together were tested, so that the most significant variable could be obtained. Variables that fit the criterion were shown with corresponding P values. Prediction models were built for different variables by using SVM regression.

CHAPTER 3. RESULTS

3.1 Variable correlations

The correlation coefficient and the corresponding P value of each variable was shown in Table 3. Significance tests were done by applying stepwise regression for each group of variables. Among the physical environmental variables, BIO8 showed the strongest positive correlation with bird abundance (p=0.0057). Abundance increases as BIO8 increases. LcHerbaceous that within the vegetation property variables was most significant (p=4.3452e-06), showed positive correlation: as LcHerbaceous increasing, abundance also increasing. It's also the most significant variable of all assessed variables. A positive correlation was showed on Skewness, highest importance (p=0.0014) among these LiDAR derived metrics: when Skewness is increasing, bird abundance increases.

Variable	r	p
LcWater	-0.0649	0.7982
LcDeveloped	-0.2395	0.0338*
LcBarren	0.1017	0.6880
LcForest	-0.4712	0.0484*
LcShrubland	-0.0398	0.8753
LcHerbaceous	**0.8616**	**0.0000***
LcCultivated	0.4344	0.0716
LcWetlands	0.085	0.7375
LcDeciduous	0.4246	0.0790
LcEvergreen	-0.4086	0.0923
LcMixed	-0.2179	0.3850
NPP	-0.4039	0.0965
EVIarea	0.4603	0.0546
VCF	-0.5139	0.0291*
BIO1	0.5576	0.0162*
BIO2	0.1083	0.6687

BIO3	-0.3013	0.2244
BIO4	0.3596	0.1428
BIO5	0.5901	0.0099*
BIO6	0.1311	0.6041
BIO7	0.2969	0.2316
BIO8	**0.6236**	**0.0057***
BIO9	0.1184	0.6399
BIO10	0.6223	0.0058*
BIO11	0.1351	0.5931
BIO12	0.1699	0.5003
BIO13	0.6013	0.0083*
BIO14	0.0974	0.7006
BIO15	0.2118	0.3989
BIO16	0.4447	0.0644
BIO17	-0.1836	0.4657
BIO18	0.4435	0.0653
BIO19	-0.1837	0.4656
SRTM	-0.3971	0.1028
Mean	-0.6075	0.0075*
Std	-0.5377	0.0214*
Skewness	**0.6952**	**0.0014***
Kurtosis	0.2038	0.4174
CC	-0.6641	0.0027*
Pct10	NaN	NaN
Pct20	-0.4374	0.0695
Pct30	-0.479	0.0443*
Pct40	-0.4681	0.0501
Pct50	-0.4831	0.0423*
Pct60	-0.4795	0.0441*
Pct70	-0.5197	0.0271
Pct80	-0.6273	0.0053*
Pct90	-0.6861	0.0017*

Table 3. Correlation between predictor variable and bird abundance: r: correlation coefficient; p: p-value. Variable with “*” has p<0.05. Variables were bolded have the highest correlations among their variable group.

3.2 Prediction models

SVM regression was used to build prediction models. Each of the three categories of predictor variables were assessed with the response variable, in our case, bird abundance. Figures of the models between true response (observed bird abundance) and predicted response (predicted bird abundance) based on the three groups of predictor variables were listed below. The model based on airborne LiDAR derived canopy structure predictors and bird abundance had the lowest RMSE (134.89) and the highest R^2 (0.24) (Figure 9). The model based on physical environmental predictor variables and bird abundance had a RMSE of 140.45 and a R^2 of 0.18 (Figure 7).The prediction model based on vegetation properties and bird abundance had a RMSE of 140.25 and a R^2 of 0.18 (Figure 8).

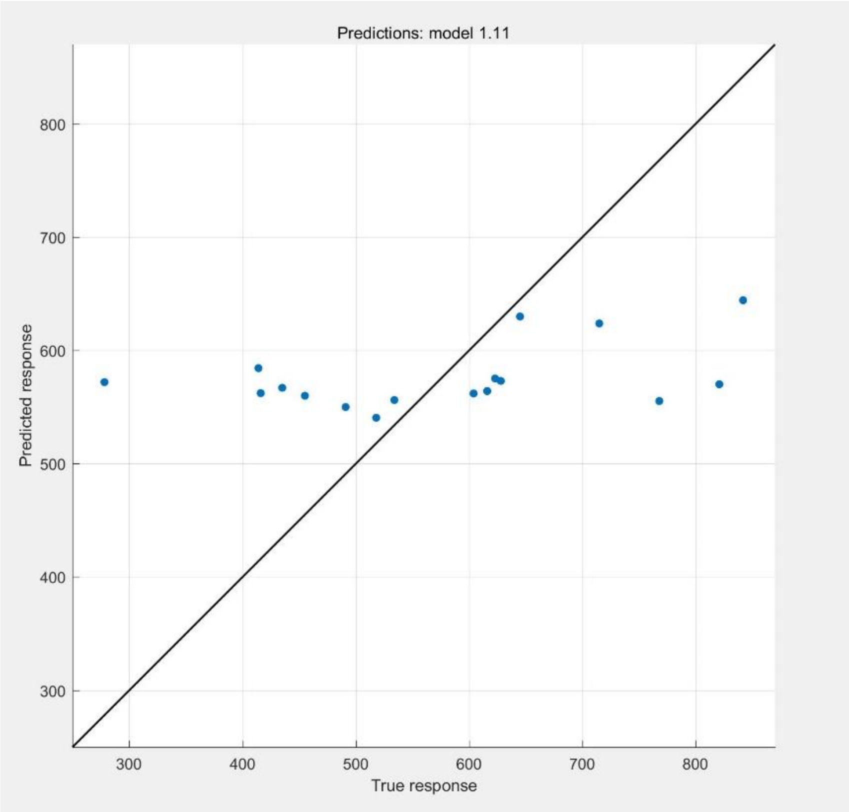


Figure 8. Predicted bird species abundance based on physical environmental variables vs. actual abundance (RMSE: 140.45, R^2: 0.18).

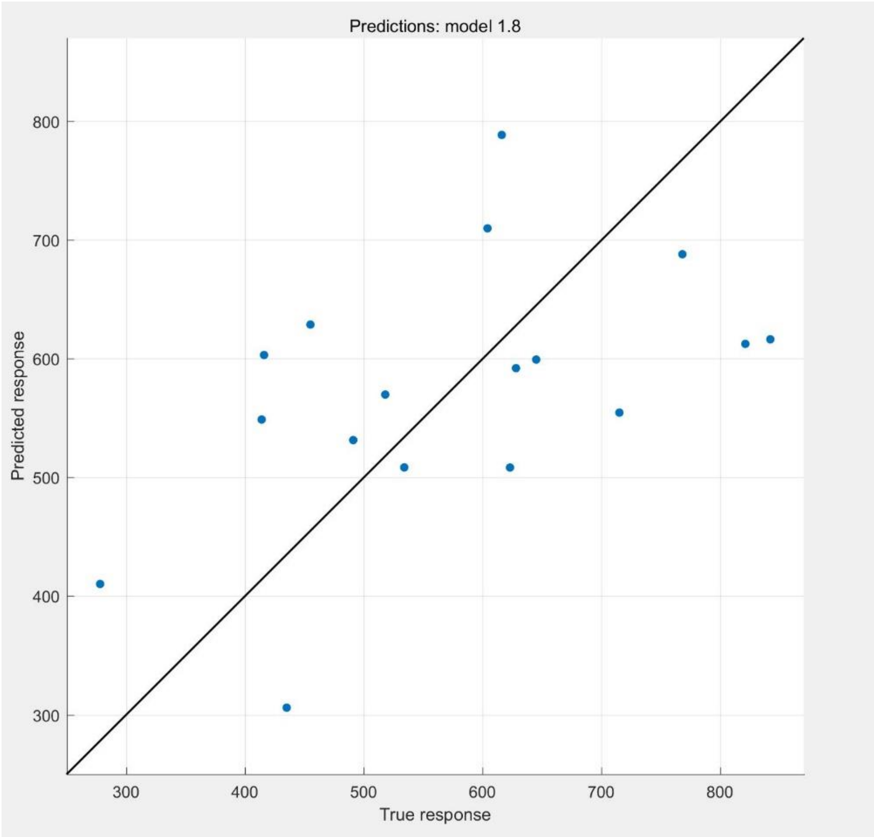


Figure 9. Predicted bird species abundance based on satellite-derived vegetation variables vs. actual abundance (RMSE: 140.25, R^2: 0.18).

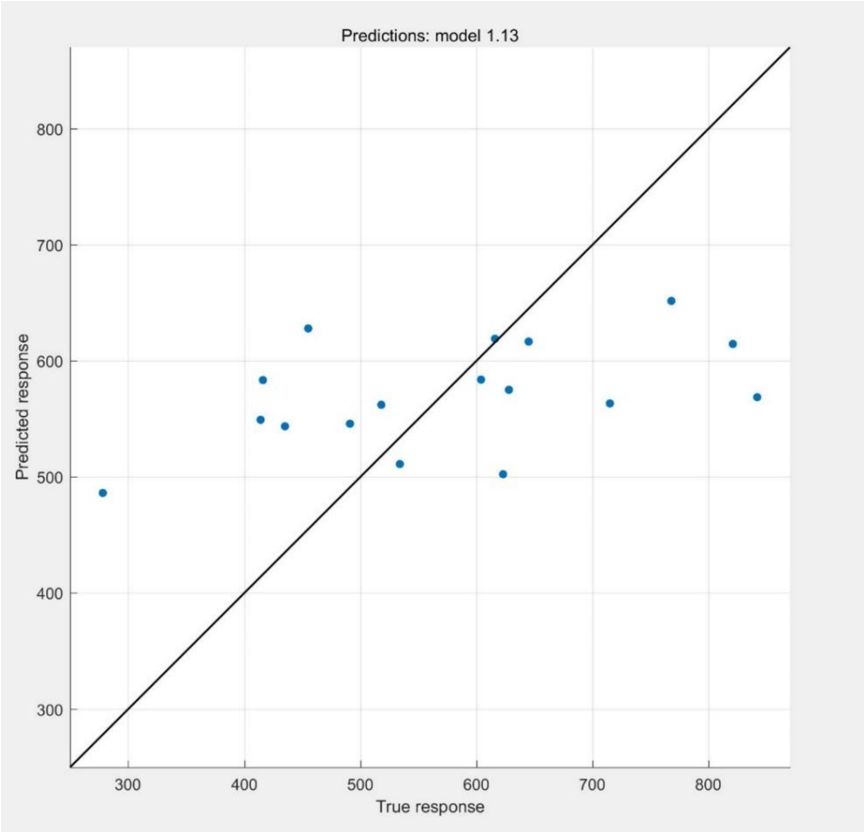


Figure 10. Predicted bird species abundance based on airborne LiDAR derived canopy structure variables vs. actual abundance (RMSE: 134.89, R^2: 0.24).

CHAPTER 4. DISCUSSION

The correlations between climate variables and bird abundance of our results were generally positive, while it was generally negative between canopy height and bird abundance. Correlations between vegetation properties and bird abundance varied, however, the importance was highest between LcHerbaceous and bird abundance (correlation coefficient = 0.742).

Temperature is an important factor on bird abundance from our results: BIO1, BIO5 and BIO8 all showed high positive correlations with bird abundance. Previous studies (Williams & Middleton, 2008; Zamora-Vilchis et al., 2012) all found that temperature is a significant climate variable on bird abundance. Annual mean temperature affects bird abundance could be related with breeding birds' laying dates. Annual mean laying date for breeding bird is strongly correlated with annual mean temperature, the earlier it gets warmer the earlier birds will bred (Møller et al., 2010). However, our results showed that bird abundance increases as mean temperature of wettest quarter increases, although few previous studied shown such direct relationship.

Airborne LiDAR derived metrics are correlated with bird abundance. Variables like Mean, Std, Skewness and CC, all have relative high correlations with bird abundance. Skewness showed the highest importance with bird species abundance among the group of variables of airborne LiDAR derived metrics. The overall negative relation between airborne LiDAR derived canopy structure height and bird abundance was observed: as the canopy heights increase, the bird abundance decrease, which was not as expected. However, the opposite relations between canopy characteristics such us canopy height and bird distribution was pointed out in other pervious works (Goetz et al., 2007; Lesak et al., 2011; Bradbury et al., 2005) that demonstrated bird habitat assessment with LiDAR data. Both bird species richness and abundance increase when canopy height increase in these studies, and therefore, forests could sometimes be crucial on avian community compositions, and so that forest managements could also be important on bird conservations. Theses possible causes of unexpected observations in this study were discussed below.

NLCD derived variable LcHerbaceous was the most significant variable with bird abundance. Herbaceous cover percentage was also found strong relationship with bird distribution in previous studies (Phillips et al., 2008). We anticipated that LcForest could be positively significant in our models, but it showed negative relation with bird abundance, which was not as expected. That might be because most of thirds observed were belong to the habitat guild of grassland, this could be future studied by tracing the observed birds' habitat types. However, that might also be related with the limitations of this study, such as the small sample size: even though the study area that covered with airborne LiDAR shots is relatively big, the available number of BBS routes within this area is only 18, despite with a 500 m buffer around each route, the total area of all created polygons is still small. Moreover, the buffer created around each BBS route was 500 m, which is bigger than the original observation radius (400 m). This could potentially lead to unexpected errors such as birds being less counted. Besides, the method of field data collection of breeding bird in BBS itself could have some uncertainties; observers' visions and hearings, distributions from environments, familiarities with bird morphology, observing time differences, etc., could all be the factors that might contribute to errors.

The overall R^2 of each prediction models were generally not strong, which may indicate that some predictor variables chosen in this study might not have more complex relations with bird abundance. Besides, low R squares might, again, caused by the small sample size in this study and other potential limitations mentioned above. However, the model with only airborne LiDAR derived canopy structure variables performed the best. As Lindberg et al. (2015) suggested that our availability to predict bird species abundance and distribution could be improved with considerations of ALS data.

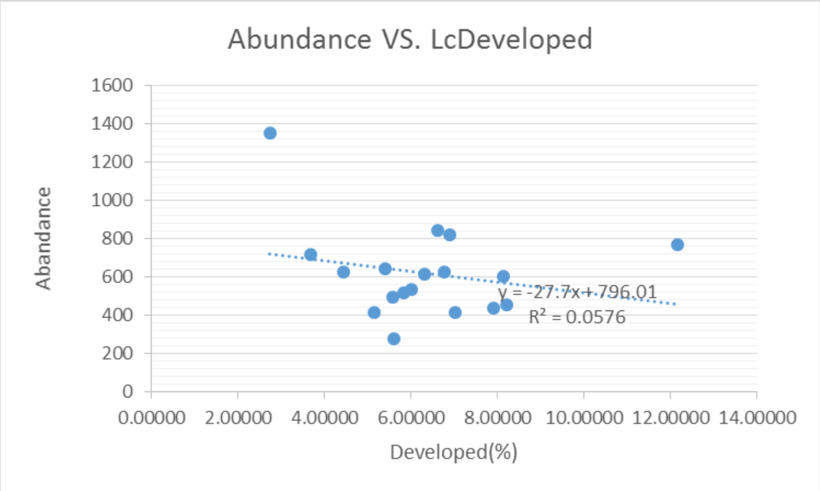
CHAPTER 5. CONCLUSION

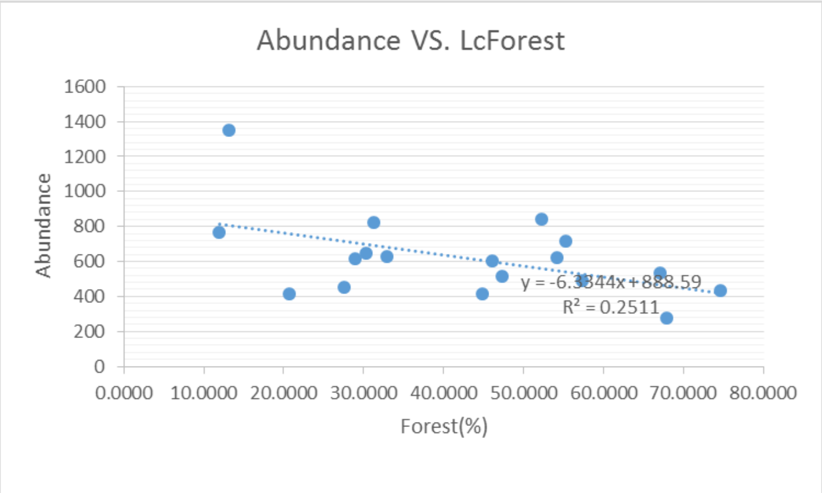
This study assessed bird species habitat using airborne LiDAR data, along with physical environmental data and satellite based vegetation properties data. A 3-D bird habitat structure was assessed for studying its distribution, which may help us get a better understanding of the relations between bird species and environmental variables. This relations could be useful for the future conservation and protection activities and research studies of biologists and environmentalists. However, besides the potential drivers mentioned in the study, other human induced factors could also affect bird distributions, such as the edge effect caused by forest clear cutting (Manolis et al., 2000), and the long term effect from global warming (Butler, 2003).

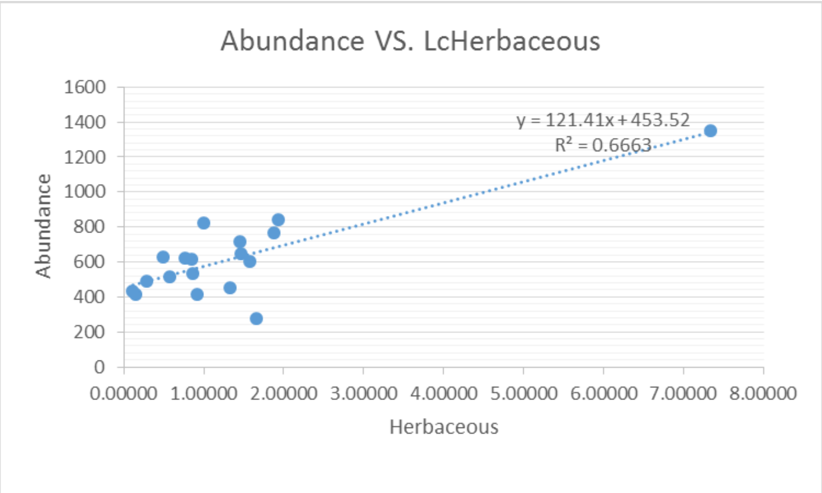
This study can be further developed to predict birds' population in a certain area with proper predictor variables data and high spatial resolution predicting maps could be produced; and when airborne LiDAR data is available, similar researches can also be done in other areas such as Hawai'i, of which bird species diversity is highly threatened.

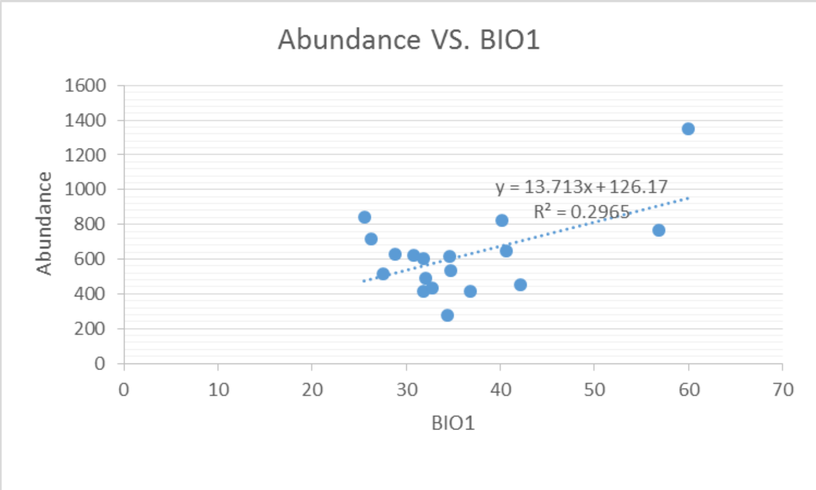
APPENDIX

Scatter plots of predictor variables and bird abundance, only with $p<0.05$ were shown.

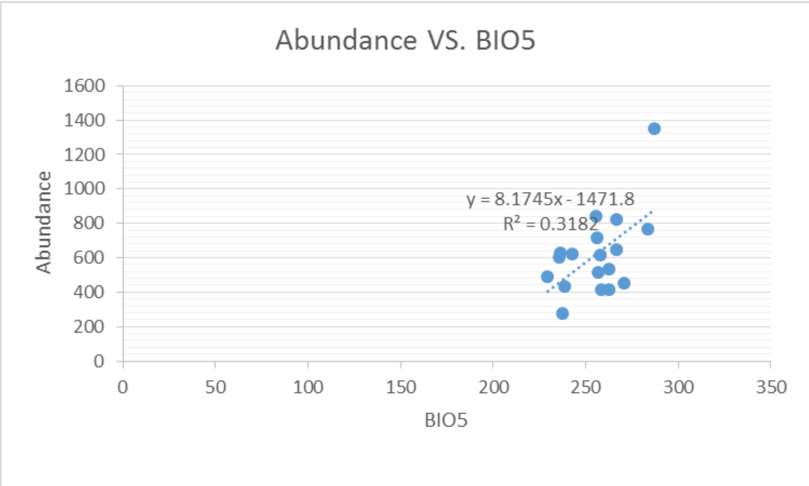




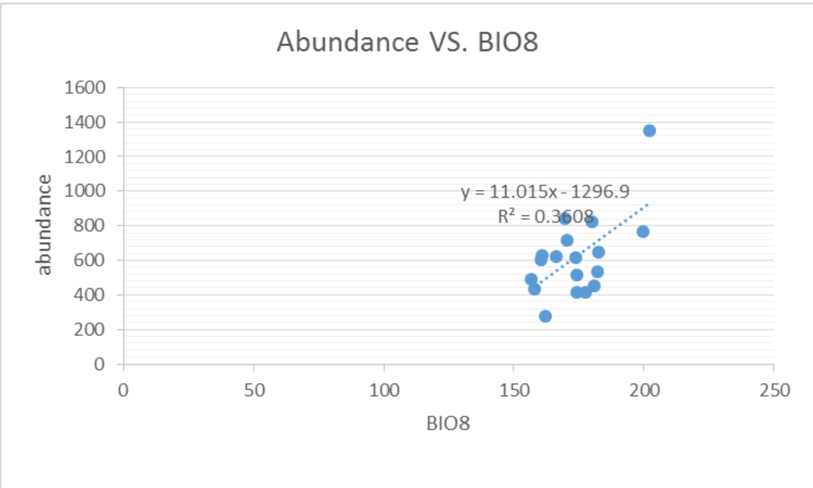




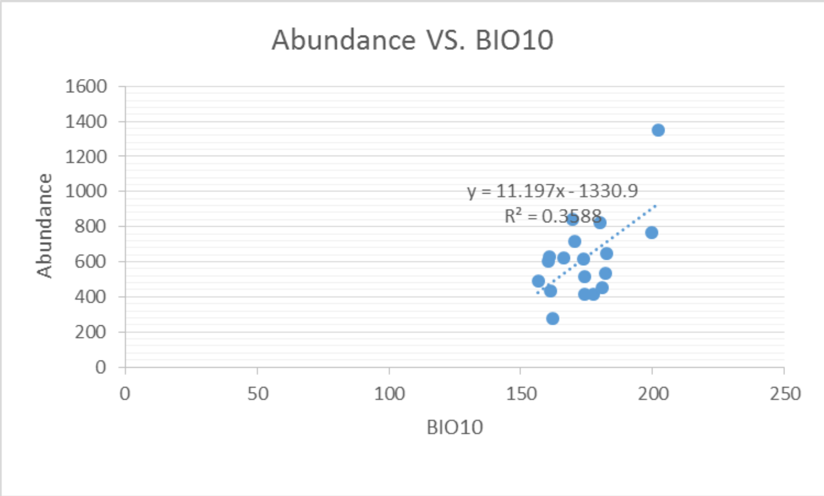
Abundance VS. BIO1
y = 13.713x + 126.17
R² = 0.2965
Abundance
BIO1

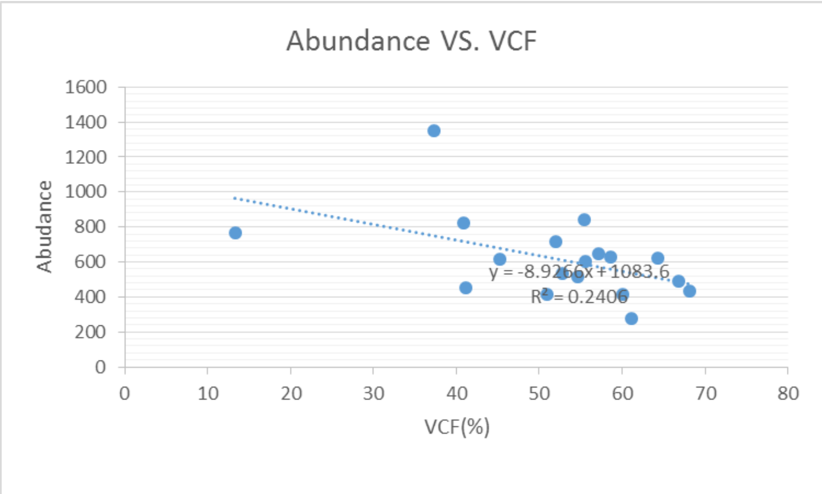


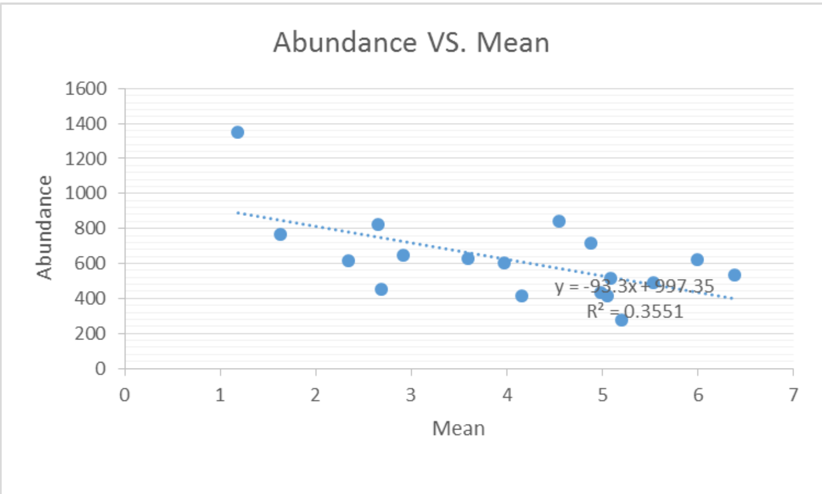
Abundance VS. BIO5
y = 8.1745x - 1471.8
R² = 0.3182
Abundance
BIO5

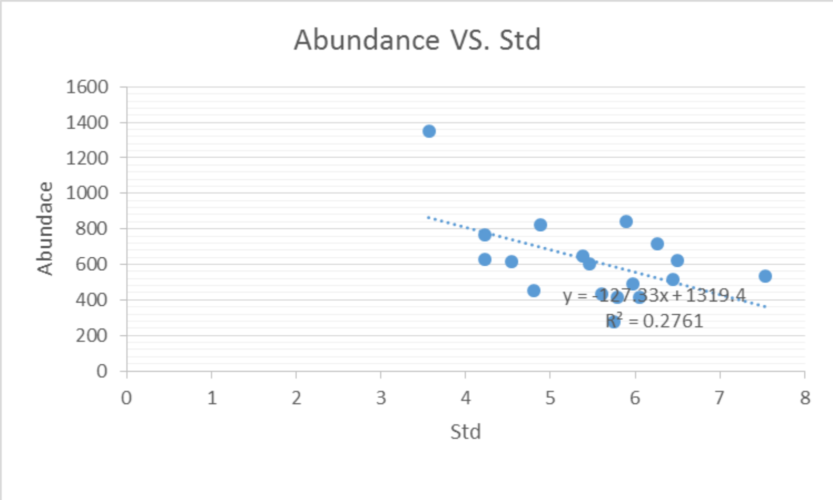


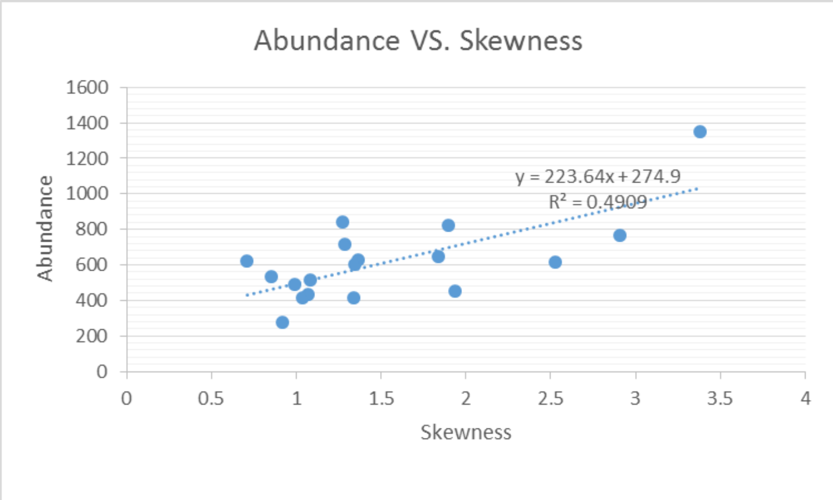
Abundance VS. BIO8
y = 11.015x - 1296.9
R² = 0.3608
abundance
BIO8

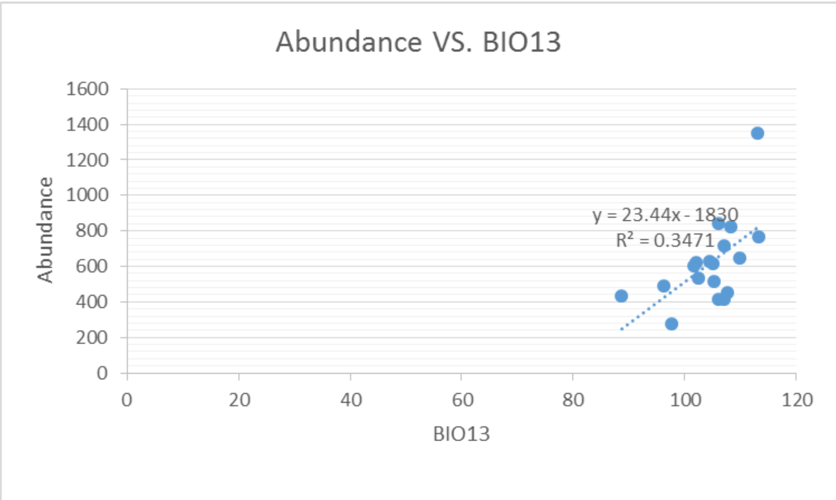

Abundance VS. BIO10
1600
1400
1200
1000
800
600
400
200
0
Abundance
y = 11.197x - 1330.9
R² = 0.3588
0
50
100
150
200
250
BIO10

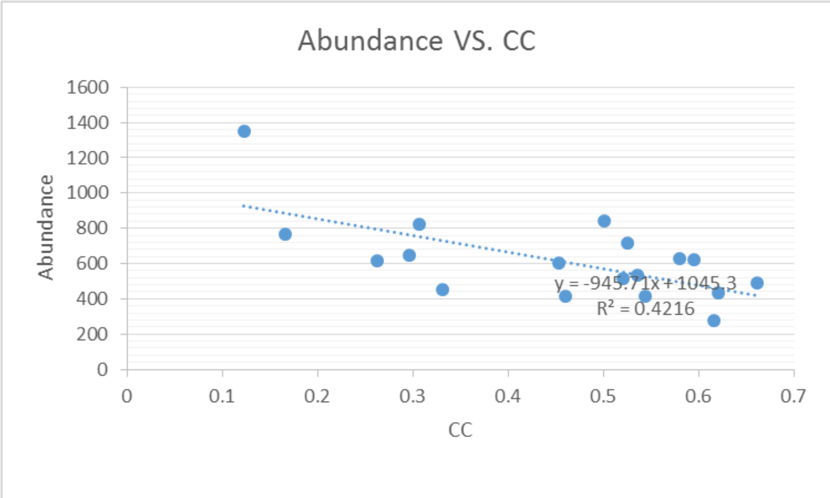

Abundance VS. VCF
1600
1400
1200
1000
800
600
400
200
0
Abudance
y = -8.9266x + 1083.6
R² = 0.2406
0
10
20
30
40
50
60
70
80
VCF(%)

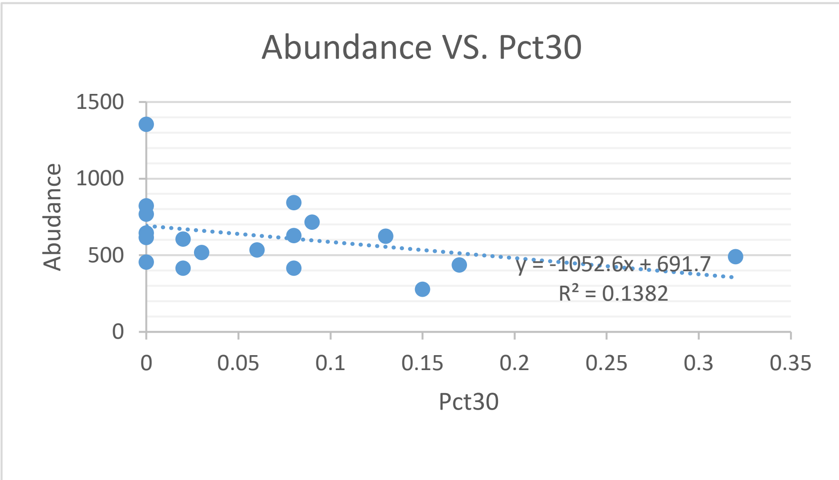

Abundance VS. Mean
1600
1400
1200
1000
800
600
400
200
0
Abundance
y = -93.3x + 997.35
R² = 0.3551
0
1
2
3
4
5
6
7
Mean

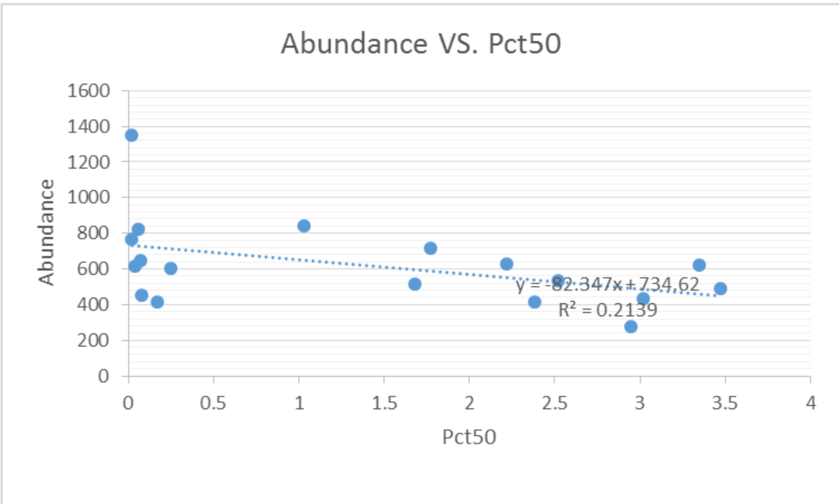

Abundance VS. Std
1600
1400
1200
1000
800
600
400
200
0
Abundace
y = -127.33x + 1319.4
R² = 0.2761
0
1
2
3
4
5
6
7
8
Std

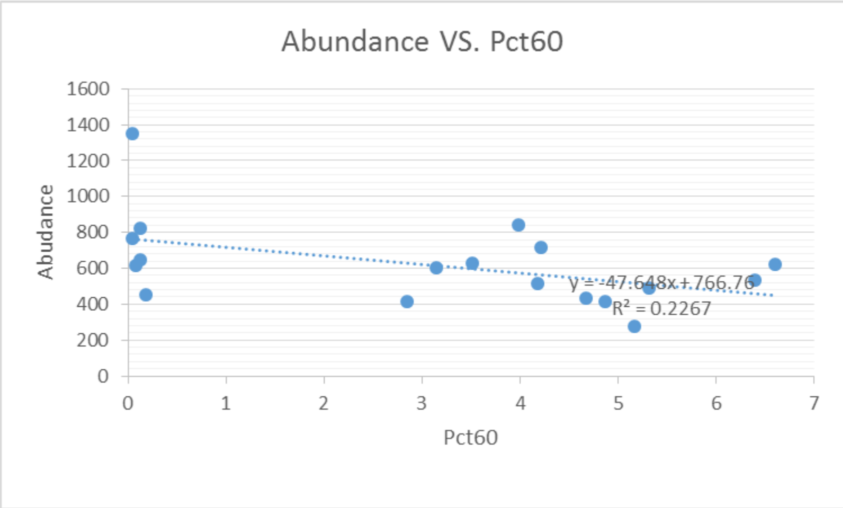

Abundance VS. Skewness
1600
1400
1200
1000
800
600
400
200
0
Abundance
y = 223.64x + 274.9
R² = 0.4909
0
0.5
1
1.5
2
2.5
3
3.5
4
Skewness

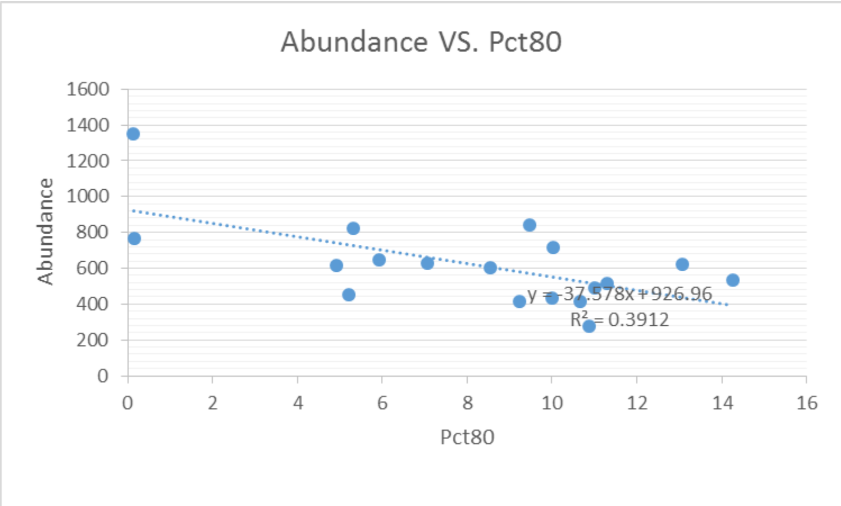

Abundance VS. BIO13
1600
1400
1200
1000
800
600
400
200
0
Abundance
y = 23.44x - 1830
R² = 0.3471
0
20
40
60
80
100
120
BIO13

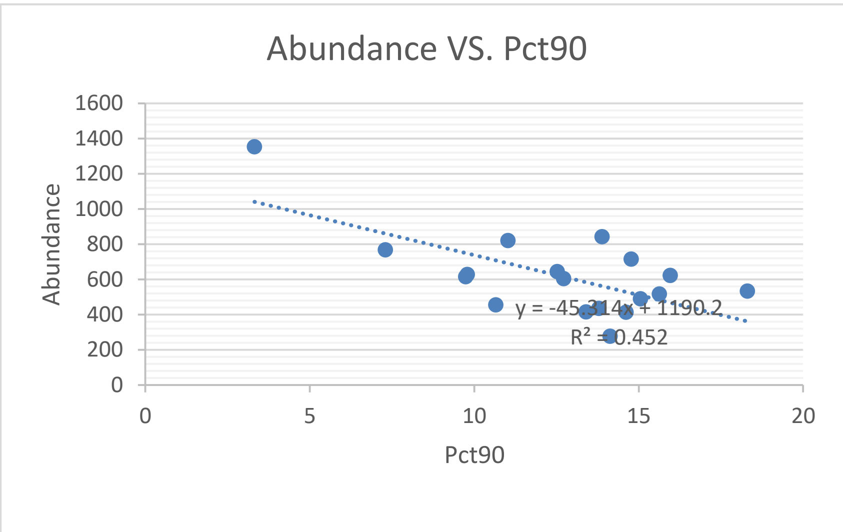

Abundance VS. CC
Abundance
1600
1400
1200
1000
800
600
400
200
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
CC
y = -945.71x + 1045.3
R² = 0.4216


Abundance VS. Pct30
Abudance
1500
1000
500
0
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
Pct30
y = -1052.6x + 691.7
R² = 0.1382


Abundance VS. Pct50
Abundance
1600
1400
1200
1000
800
600
400
200
0
0
0.5
1
1.5
2
2.5
3
3.5
4
Pct50
y = -82.347x + 734.62
R² = 0.2139


Abundance VS. Pct60
1600
1400
1200
1000
800
600
400
200
0
Abundance
0
1
2
3
4
5
6
7
Pct60
y = -47.648x + 766.76
R² = 0.2267


Abundance VS. Pct80
1600
1400
1200
1000
800
600
400
200
0
Abundance
0
2
4
6
8
10
12
14
16
Pct80
y = -37.578x + 926.96
R² = 0.3912


Abundance VS. Pct90
1600
1400
1200
1000
800
600
400
200
0
Abundance
0
5
10
15
20
Pct90
y = -45.314x + 1190.2
R² = 0.452

REFERENCES

Bradbury, R. B., Hill, R. A., Mason, D. C., Hinsley, S. A., Wilson, J. D., Balzter, H., ... & Bellamy, P. E. (2005). Modelling relationships between birds and vegetation structure using airborne LiDAR data: a review with case studies from agricultural and woodland environments. Ibis, 147(3), 443-452. DOI: 10.1111/j.1474-919x.2005.00438.x.

Butler, C. J. 2003. The disproportionate effect of global warming on the arrival dates of short-distance migratory birds in North America. Ibis 145: 484–495. doi;10.1046/j.1474-919X.2003.00193.x

Chapin, F. S., Chapin, C., Matson, P. A., & Vitousek, P. (2011). *Principles of Terrestrial Ecosystem Ecology*: Springer New York.

Chen, Q. (2007a). Airborne lidar data processing and information extraction. *Photogrammetric engineering and remote sensing, 73*(2), 109.

Chen, Q. (2007b). *Measuring vegetation structure and modeling ecological functions for a heterogeneous savanna ecosystem in California.* (3275368 Ph.D.), University of California, Berkeley, Ann Arbor. Retrieved from http://eres.library.manoa.hawaii.edu/login?url=http://search.proquest.com/docview/304900842?accountid=27140

Chen, Q., Gong, P., Baldocchi, D., & Xie, G. (2007). Filtering Airborne Laser Scanning Data with Morphological Methods. *Photogrammetric Engineering & Remote Sensing*, *73*(2), 175-185. doi:10.14358/PERS.73.2.175.

Chen, Q., Laurin, G. V., Battles, J. J., & Saah, D. (2012). Integration of airborne lidar and vegetation types derived from aerial photography for mapping aboveground live biomass. Remote Sensing of Environment, 121, 108-117. doi: http://dx.doi.org/10.1016/j.rse.2012.01.021

Clawges, R., Vierling, K., Vierling, L., & Rowell, E. (2008). The use of airborne lidar to assess avian species diversity, density, and occurrence in a pine/aspen forest. *Remote Sensing of Environment, 112*(5), 2064-2073. doi:http://dx.doi.org/10.1016/j.rse.2007.08.023

Cutler, D. R., Edwards, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). Random forests for classification in ecology. *Ecology, 88*(11), 2783-2792. doi:10.1890/07-0539.1.

DiMiceli, C., R. Sohlberg, M. C., Kim, D. H., Kelly, M. J., Townshend, R. G. (2017). MOD44B MODIS/Terra Vegetation Continuous Fields Yearly L3 Global 250m SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. doi:https://doi.org/10.5067/MODIS/MOD44B.006.

Gil-Tena, A., Saura, S., & Brotons, L. (2007). Effects of forest composition and structure on bird species richness in a Mediterranean context: implications for forest ecosystem management. *Forest ecology and Management*, *242*(2), 470-476.

Gobakken, T., & Næsset, E. (2008). Assessing effects of laser point density, ground sampling intensity, and field sample plot size on biophysical stand properties derived from airborne laser scanner data. *Canadian Journal of Forest Research*, *38*(5), 1095-1109. doi: 10.1139/X07-219.

Goetz, S. J., Sun, M., Zolkos, S., Hansen, A., & Dubayah, R. (2014). The relative importance of climate and vegetation properties on patterns of North American breeding bird species richness. Environmental Research Letters,9(3), 034013.

Goetz, S., Steinberg, D., Dubayah, R., & Blair, B. (2007). Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA. *Remote Sensing of Environment*, *108*(3), 254-263.

doi: http://doi.org/10.1016/j.rse.2006.11.016.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. International journal of climatology, 25(15), 1965-1978.

Hocking, R. R. (1976). A Biometrics invited paper. The analysis and selection of variables in linear regression. Biometrics, 32(1), 1-49.

Homer, C. G., Dewitz, J. A., Yang, L., Jin, S., Danielson, P., Xian, G., ... & Megown, K. (2015). Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. *Photogrammetric Engineering and Remote Sensing*, *81*(5), 345-354.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote sensing of environment*, *83*(1), 195-213. doi: http://dx.doi.org/10.1016/S0034-4257(02)00096-2.

Jacob, A. L., Wilson, S. J., & Lewis, S. L. (2014). Ecosystem services: Forests are more than sticks of carbon. *Nature, 507*(7492), 306-306. doi:10.1038/507306c.

Jung, M., Henkel, K., Herold, M., & Churkina, G. (2006). Exploiting synergies of global land cover products for carbon cycle modeling. Remote Sensing of Environment, 101(4), 534-553. doi: http://dx.doi.org/10.1016/j.rse.2006.01.020

Lefsky, M. A., Harding, D., Cohen, W. B., Parker, G., & Shugart, H. H. (1999). Surface lidar remote sensing of basal area and biomass in deciduous forests of eastern Maryland, USA. Remote Sensing of Environment, 67(1), 83-98. doi: http://dx.doi.org/10.1016/S0034-4257(98)00071-6

Lesak, A. A., Radeloff, V. C., Hawbaker, T. J., Pidgeon, A. M., Gobakken, T., & Contrucci, K. (2011). Modeling forest songbird species richness using LiDAR-derived measures of forest structure. *Remote Sensing of Environment, 115*(11), 2823-2835. doi:http://dx.doi.org/10.1016/j.rse.2011.01.025.

Lindberg, E., Roberge, J. M., Johansson, T., & Hjältén, J. (2015). Can Airborne Laser Scanning (ALS) and Forest Estimates Derived from Satellite Images Be Used to Predict Abundance and Species Richness of Birds and Beetles in Boreal Forest?. *Remote Sensing, 7*(4), 4233-4252. doi: 10.3390/rs70404233.

Maltamo, M., Naesset, E., & Vauhkonen, J. (2014). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies*: Springer Netherlands.

Manolis, J.C., Andersen, D.E., and Cuthbert, F.J. 2000. Patterns in Clearcut Edge and Fragmentation Effect Studies in Northern Hardwood-Conifer Landscapes: Retrospective Power Analysis and Minnesota Results. Wildlife Society Bulletin (1973-2006). Vol.28. No.4. pp. 1088-1101.

McGill, B. (2015). Biodiversity: Land use matters. *Nature, 520*(7545), 38-39. doi:10.1038/520038a.

McRoberts, R. E., Domke, G. M., Chen, Q., Næsset, E., & Gobakken, T. (2016). Using genetic algorithms to optimize k-Nearest Neighbors configurations for use with airborne laser scanning data. *Remote Sensing of Environment, 184*, 387-395. doi: http://dx.doi.org/10.1016/j.rse.2016.07.007

Møller, A. P., Fiedler, W., & Berthold, P. (2010). *Effects of climate change on birds*. Oxford University Press.

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., . . . Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature, 520*(7545), 45-50. doi:10.1038/nature14324

http://www.nature.com/nature/journal/v520/n7545/abs/nature14324.html#supplementary-information

Podulka, S., Rohrbaugh, R. W., Bonney, R., Ornithology, C. U. L. o., & Sounds, C. U. M. L. o. N. (2004). *Handbook of Bird Biology*: Cornell Lab of Ornithology.

Phillips, L. B., Hansen, A. J., & Flather, C. H. (2008). Evaluating the species energy relationship with the newest measures of ecosystem energy: NDVI versus MODIS primary production. Remote Sensing of Environment, 112(12), 4381-4392.

doi: http://doi.org/10.1016/j.rse.2008.08.002.

Reuter, H. I., Nelson, A., & Jarvis, A. (2007). An evaluation of void-filling interpolation methods for SRTM data. *International Journal of Geographical Information Science*, *21*(9), 983-1008.

doi: http://dx.doi.org/10.1080/13658810601169899.

Running, S. W., Mu, Q., & Zhao, M. (2015). MOD17A3H MODIS/Terra Net Primary Production Yearly L4 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC.

doi: 10.5067/MODIS/MOD17A3H.006.

Sauer, J. R., Link, W. A., Fallon, J. E., Pardieck, K. L., & Ziolkowski Jr, D. J. (2013). The North American breeding bird survey 1966-2011: summary analysis and species accounts. North American Fauna, 79(79), 1-32.

doi: http://dx.doi.org/10.3996/nafa.79.0001.

Scott, J. G., Mindy, S., Scott, Z., Andy, H., & Ralph, D. (2014). The relative importance of climate and vegetation properties on patterns of North American breeding bird species richness. *Environmental Research Letters*, *9*(3), 034013. Retrieved from http://stacks.iop.org/1748-9326/9/i=3/a=034013.

Swatantran, A., Dubayah, R., Goetz, S., Hofton, M., Betts, M. G., Sun, M., . . . Holmes, R. (2012). Mapping Migratory Bird Prevalence Using Remote Sensing Data Fusion. *PLoS ONE*, *7*(1), e28922. doi:10.1371/journal.pone.0028922.

Vilà, M., Carrillo-Gavilán, A., Vayreda, J., Bugmann, H., Fridman, J., Grodzki, W., ... & Trasobares, A. (2013). Disentangling biodiversity and climatic determinants of wood production. *PLoS One*, *8*(2), e53530.

doi: http://dx.doi.org/10.1371/journal.pone.0053530.

Wallis, C. I. B., Paulsch, D., Zeilinger, J., Silva, B., Curatola Fernández, G. F., Brandl, R., . . . Bendix, J. (2016). Contrasting performance of Lidar and optical texture models in predicting avian diversity in a tropical mountain forest. *Remote*

Sensing of Environment, *174*, 223-232.

doi:http://dx.doi.org/10.1016/j.rse.2015.12.019.

Williams, S. E., & Middleton, J. (2008). Climatic seasonality, resource bottlenecks, and abundance of rainforest birds: implications for global climate change. *Diversity and Distributions*, *14*(1), 69-77.

doi: 10.1111/j.1472-4642.2007.00418.x.

Zamora-Vilchis, I., Williams, S. E., & Johnson, C. N. (2012). Environmental Temperature Affects Prevalence of Blood Parasites of Birds on an Elevation Gradient.

doi: http://dx.doi.org/10.1371/journal.pone.0039208.