Longitudinal Trends of Bird Community Richness and Abundance over Fifteen Years in the Northern Reaches of the Sonoran Desert

by

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ABSTRACT

Although many studies have identified environmental factors as primary drivers of bird richness and abundance, there is still uncertainty about the extent to which climate, topography and vegetation influence richness and abundance patterns seen in local extents of the northern Sonoran Desert. I investigated how bird richness and abundance differed between years and seasons and which environmental variables most influenced the patterns of richness and abundance in the Greater Phoenix Metropolitan Area.

I compiled a geodatabase of climate, bioclimatic (interactions between precipitation and temperature), vegetation, soil, and topographical variables that are known to influence both richness and abundance and used 15 years of bird point count survey data from urban and nonurban sites established by Central Arizona–Phoenix Long-Term Ecological Research project to test that relationship. I built generalized linear models (GLM) to elucidate the influence of each environmental variable on richness and abundance values taken from 47 sites. I used principal component analysis (PCA) to reduce 43 environmental variables to 9 synthetic factors influenced by measures of vegetation, climate, topography, and energy. I also used the PCA to identify uncorrelated raw variables and modeled bird richness and abundance with these uncorrelated environmental variables (EV) with GLM.

I found that bird richness and abundance were significantly different between seasons, but that richness and winter abundance were not significantly different across years. Bird richness was most influenced by soil characteristics and vegetation while

abundance was most influenced by vegetation and climate. Models using EV as independent variables consistently outperformed those models using synthetically produced components from PCA. The results suggest that richness and abundance are both driven by climate and aspects of vegetation that may also be influenced by climate such as total annual precipitation and average temperature of the warmest quarter. Annual oscillations of bird richness and abundance throughout the urban Phoenix area seem to be strongly associated with climate and vegetation.

DEDICATION

I dedicate this work to my partner in life, Alecia, who continues to inspire me to achieve more than I believe I can.

ACKNOWLEDGMENTS

I must acknowledge my committee chair, Fabio Suzart de Albuquerque, and the countless hours of guidance and support that he has freely given me as I conducted this research. I could not have completed this work without the help of Chelsea Stratton in compiling a geodatabase of environmental variables. I also thank the many volunteers and surveyors who have ever conducted a bird point count survey as part of Central Arizona–Phoenix Long-Term Ecological Research (CAP LTER). This study would be nothing without their valuable, accurate data. I acknowledge CAP LTER for allowing me to use this data and for hosting the geodatabase of environmental variables for public use. Lastly, I recognize the United States Navy and their willingness to send a Naval officer back to school to study wildlife.

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CHAPTER 1

GEODATABASE OF CLIMATIC, BIOCLIMATIC, AND VEGETATION VARIABLES OF MARICOPA COUNTY

INTRODUCTION

Worldclim bioclimatic data (interactions between precipitation and temperature) have been used widely in ecology studies focusing especially on large regional and global scale species distribution models (Nix 1986; Waltari et al. 2014; Feilhauer 2012). Users can easily access bioclimatic variables for most portions of the globe and obtain bioclimatic variables that are based on past, future, and present climate conditions (Hijmans et al. 2005). Although these data are powerful and easily available, the user is limited to bioclimatic variables based on averaged interpolations of historical weather data from 1960 to 1990. Worldclim data is known to have inaccuracies especially in areas with few weather stations and large elevation differences (Bobrowski & Schickhoff 2017). Those studying these ecosystems may especially benefit from bioclimatic variables derived from climate data outside of Worldclim. Recently, researchers have developed Program R (R Core Team 2017) code to produce the same 19 bioclimatic variables that are available from Worldclim, by using climate data obtained from other sources (Hijmans 2017).

Bioclimatic variables are important predictors of species distributions and show how species distributions are driven by both climatic and non-climatic variables (O'Donnell & Ignizio 2012). Most species distribution studies look primarily at climate and topography, but several studies show the importance of including vegetation indices as part of distribution models (Wen et al. 2015; Buermann et al. 2008; Guisan & Zimmermann 2000). In each of these studies, the inclusion of vegetation indices consistently led to more robust models in varying ecological disciplines. The importance of vegetation in urban areas has also been documented (Zhao et al. 2016). Vegetation in urban areas reduces dust, reduces heat island effects, increases humidity, and social enjoyment (Susca et al. 2011).

Vegetation indices have been used to document vegetation structure, productivity, and overall health. Vegetation indices are often obtained by examining the near-infrared wavelengths compared to red spectrum wavelengths (Didan 2015). The moderate resolution imaging spectroradiometer (MODIS) sensor on the National Aeronautics and Space Administration (NASA) Terra satellite has been used for several decades to collect vegetation values throughout the world of the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI) (Didan 2015). MODIS captures one daily and one nightly image of every point on earth each month. Although raw index data has been shown useful in model development for researchers, there are no MODIS products generated for vegetation that show effects and seasonality of temperature on vegetation. Herein, I describe the development of a data repository including climate variables, bioclimatic variables, and vegetation indices for Maricopa County. This study provides a baseline for the interdisciplinary work of researchers associated with the Central Arizona–Phoenix Long-Term Ecological Research (CAP LTER) program.

Research Objectives

The purpose of this study was to document the compilation and creation of a geodatabase and the necessary bioclimatic variables, vegetation variables, and raw climatic variables comprised within the geodatabase for Maricopa County. My objectives were to:

1. Create 19 new bioclimatic variables using modeled data from NASA Earth Science Data and Information System Daily Surface Weather and Climatological Summaries (DAYMET) for 17 years (2000 – 2016) in the same methods as outlined by Worldclim and United States Geological Survey (Hijmans 2005; O'Donnell and Ignizio 2012).
2. Compile NDVI and EVI values and generate four new vegetation variables that reflect annual seasonality trends on vegetation index values for 17 years (2000 – 2016).
3. Compile and publish data into a publicly available data repository for the CAP LTER area of study.

METHODS

Raw Climatic Data

DAYMET data were produced by NASA using a model imposed onto daily outputs of ground weather stations throughout North America producing a continuous surface dataset (Thornton et al. 2018; Thornton et al. 1997). I downloaded monthly values of air temperature minimums, air temperature maximums, precipitation, and water vapor pressure from DAYMET. The monthly values for minimum and maximum air temperatures and water vapor pressure used in this geodatabase were generated by averaging the daily values for each month. Monthly precipitation totals were generated from summing the daily DAYMET precipitation output values for each month. The spatial resolution for all NASA DAYMET data was 1-km x 1-km.

I downloaded all data in Georeferenced Tagged Image File Format (GeoTIFF) for all North America directly from the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) which serves as a data center for the NASA Earth Observing System Data and Information System (EOSDIS). I downloaded data files in multispectral GeoTIFF raster format with 12 bands in each file (one band for each month). Each individual band contained monthly data for minimum temperature, maximum temperature, precipitation and water vapor pressure (Table 1.1). I conducted a batch download from ORNL DACC of 68 multispectral GeoTIFF rasters containing more than 3.5 GB of data. I separated all downloaded multispectral GeoTIFF rasters into single band rasters for each parameter and month for a total of 272 monthly single band rasters. I used a clip tool in ESRI ArcMap (ESRI 2011) to clip each single band raster to the Maricopa County extent.

Bioclimatic Variables

I used the single band rasters containing data for only Maricopa County to produce 19 bioclimatic variables for each year from 2000 - 2016. I generated bioclimatic variables using the biovars function of the dismo package on Program R version 3.5.1 (Hijmans 2017, R Core Team 2017). Bioclimatic variables containing quarters referred to any 3 months in consecutive order and November and December data were analyzed with January and February data of the following calendar year. Outputs of the biovars function were verified against bioclimatic variables that were calculated manually in ESRI ArcMap (ESRI 2011) to determine the integrity of the function. In total, 323 new datafiles composed of 19 new variables for all seventeen years were generated (Table 1.2, Nix 1986; Hijmans 2005; O'Donnell and Ignizio 2012).

1. Annual Mean Temperature (BIO 1) – Average monthly temperatures were calculated by summing each monthly temperature maximum and minimum and dividing by two. Using the average monthly temperatures for each year, the annual mean temperature was calculated by summing all average monthly temperatures and dividing by 12.
2. Annual Mean Diurnal Range (BIO 2) – Also described as the average monthly temperature ranges. This variable was generated by subtracting each monthly temperature minimum from each monthly temperature maximum and adding the difference for all 12 months; the total was divided by 12 to find the annual average temperature change.
3. Isothermality (BIO 3) – Isothermality is the comparison of the mean diurnal range (BIO2) to the annual temperature range (BIO7). It is calculated as a percentage and is important in showing the daily oscillations in temperature between day and night. Smaller values of isothermality signify that there are smaller fluctuations in temperature range in that area than the annual temperature range.
4. Temperature Seasonality (BIO 4) – Temperature seasonality indicates the temperature variation within a single year. It is calculated by taking the standard

deviation of all 12 average monthly temperatures for each year. This is then multiplied by 100; the larger the standard deviation the more variable the temperature is in that area.

5. Maximum Temperature of the Warmest Month (BIO 5) – Monthly maximum temperatures were compared for each year. Maximum temperature of the warmest month was generated by taking the maximum temperature value out of the 12 compared months. Max temperature of the warmest month is important in documenting events that are affected by warm weather.
6. Minimum Temperature of the Coldest Month (BIO 6) - Monthly minimum temperatures were compared for each year. Minimum temperature of the coldest month was generated by taking the minimum temperature value out of the 12 compared months. Minimum temperature of the coldest month is important in documenting events that are affected by cold weather.
7. Annual Temperature Range (BIO 7) – Annual temperature range shows the variation in temperature throughout the year. It differs from annual mean diurnal range in that it looks at temperature ranges of the warmest month compared to the coldest month instead of entire year periods. Annual temperature range is calculated by subtracting the minimum temperature of the coldest month (BIO 6) from the maximum temperature of the warmest month (BIO 5). Annual temperature range is important in documenting events that are affected by extreme temperature ranges.

8. Average Temperature of the Wettest Quarter (BIO 8) – Average temperature of the wettest quarter was calculated by summing the monthly total precipitation of 12 consecutive sets of three months. Average temperatures were then extracted for the set of three months with the highest total precipitation. Average temperatures for the three months were then summed and divided by three to obtain the average temperature of the wettest quarter.
9. Average Temperature of the Driest Quarter (BIO 9) – Average temperature of the driest quarter was calculated by summing the monthly total precipitation of 12 consecutive sets of three months. Average temperatures were then extracted for the set of three months with the lowest total precipitation. Average temperatures for the three months were then summed and divided by three to obtain the average temperature of the driest quarter.
10. Average Temperature of the Warmest Quarter (BIO 10) – Average temperature of the warmest quarter was calculated by summing the average monthly temperatures of 12 consecutive sets of three months. Once the warmest quarter of the year was identified, average temperatures were extracted for these months. Average temperatures for the three months were then summed and divided by three to obtain the average temperature of the warmest quarter.
11. Average Temperature of the Coldest Quarter (BIO 11) – Average temperature of the coldest quarter was calculated by summing the average monthly temperatures of 12 consecutive sets of three months. Once the coldest quarter of the year was identified, average temperatures were extracted for these months. Average

temperatures for the three months were then summed and divided by three to obtain the average temperature of the coldest quarter.

12. Annual Precipitation (BIO 12) – Annual precipitation was calculated by summing the total precipitation for 12 months in each year. Annual precipitation is important in understanding how events are affected by water availability.
13. Precipitation of the Wettest Month (BIO 13) – Precipitation of the wettest month is identified by comparing each monthly total precipitation value and selecting those values with the highest total precipitation between the 12 monthly datasets. Precipitation of the wettest month is important to show how extreme water availability affects events within a year.
14. Precipitation of the Driest Month (BIO 14) – Precipitation of the driest month is identified by comparing each monthly total precipitation value and selecting those values with the lowest total precipitation between the 12 monthly datasets. Precipitation of the driest month is important to show how extreme water availability affects events within a year.
15. Precipitation Seasonality (BIO 15) – Precipitation seasonality measures how much monthly precipitation varies over an entire year. Precipitation seasonality is calculated by finding the standard deviation of the total monthly precipitation values. The standard deviation of precipitation values is then divided by the sum of one and the quotient of annual precipitation (BIO 12) and 12. This quotient is then multiplied by 100 to give you the percent value of precipitation seasonality. As precipitation seasonality increases, there is more variance in total precipitation

in that area. Precipitation seasonality affects events that are dependent on precipitation stability.

16. Precipitation of the Wettest Quarter (BIO 16) – Precipitation of the wettest quarter was calculated by summing the monthly total precipitation of 12 consecutive sets of three months. Total monthly precipitation values were then extracted and summed for the set of three months with the highest total precipitation computing the precipitation of the wettest quarter. This variable is useful in identifying events that are affected by the amount of precipitation in the wettest season of the year.
17. Precipitation of the Driest Quarter (BIO 17) – Precipitation of the driest quarter was calculated by summing the monthly total precipitation of 12 consecutive sets of three months. Total monthly precipitation values were then extracted and summed for the set of three months with the lowest total precipitation computing the precipitation of the driest quarter. This variable is useful in identifying events that are affected by the amount of precipitation in the driest season of the year.
18. Precipitation of the Warmest Quarter (BIO 18) – Precipitation of the warmest quarter was calculated by summing the average monthly temperatures of 12 consecutive sets of three months. Once the warmest quarter of the year was identified, total precipitation values were extracted for these months. Precipitation totals for the three months were then summed to obtain the precipitation of the warmest quarter.

19. Precipitation of the Coldest Quarter (BIO 19) – Average temperature of the coldest quarter was calculated by summing the average monthly temperatures of 12 consecutive sets of three months. Once the coldest quarter of the year was identified, total precipitation values were extracted for these months. Precipitation totals for the three months were then summed to obtain the precipitation of the coldest quarter.

Vegetation Indices

MODIS vegetation data from NDVI and EVI monthly values used for this study were generated by taking the highest index value from each monthly batch of images (Didan 2015). All images were batch downloaded from NASA Earth Data Land Processes Distributed Active Archive Center. I downloaded multispectral GeoTIFF rasters comprised of calculated NDVI and EVI values. I conducted a batch download for a total of 204 multispectral GeoTIFF rasters. Multispectral GeoTIFF rasters were then separated into single band rasters for both NDVI and EVI by month. I used a clip tool in ESRI ArcMap 10.6 (ESRI 2011) to clip each single banned raster to the Maricopa County extent.

To better understand seasonality of NDVI and EVI index values, new vegetation variables were generated. New vegetation variables were created using the biovars function of the dismo package on Program R version 3.5.1 (Hijmans 2017, R Core Team 2017). Quarters referred to any three months in consecutive order and November and December data were analyzed with January and February data of the following calendar year in order to analyze three months. The new vegetation variables were generated for each calendar year from 2000 to 2016 (Table 1.3; based on Nix 1986; Hijmans 2004; O'Donnell and Ignizio 2012).

1. Average Vegetation Indices Values of the Quarter with Highest NDVI/EVI – Average vegetation indices values of the quarter with the highest NDVI/EVI values were calculated by summing the monthly NDVI/EVI values of 12 consecutive sets of three months. Average vegetation indices values were then extracted for the set of three months with the highest total NDVI/EVI. Average vegetation indices values for the three months were then summed and divided by three to obtain the average vegetation indices of the wettest quarter.
2. Average Vegetation Indices Values of the Quarter with the Lowest NDVI/EVI – Average vegetation indices values of the quarter with the lowest NDVI/EVI values were calculated by summing the monthly NDVI/EVI values of 12 consecutive sets of three months. Average vegetation indices values were then extracted for the set of three months with the lowest NDVI/EVI values. Average vegetation indices for the three months were then summed and divided by three to obtain the average vegetation indices values of the quarter with the lowest NDVI/EVI.
3. Average NDVI/EVI of the Warmest Quarter – NDVI/EVI of the warmest quarter was calculated by summing the average monthly temperatures of 12 consecutive sets of three months. Once the warmest quarter of the year was identified, NDVI/EVI values were extracted for these months. NDVI/EVI

totals for the three months were then summed and divided by three to obtain the average NDVI/EVI of the warmest quarter.

4. Average NDVI/EVI of the Coldest Quarter – NDVI/EVI of the coldest quarter was calculated by summing the average monthly temperatures of 12 consecutive sets of three months. Once the coldest quarter of the year was identified, NDVI/EVI values were extracted for these months. NDVI/EVI totals for the three months were then summed and divided by three to obtain the average NDVI/EVI of the coldest quarter.

RESULTS AND DISCUSSION

This is the first time that bioclimatic variables have been generated using NASA DAYMET climate data instead of relying on past interpolated data from Worldclim. Each of the 17 sets (one set/year) of 19 newly created bioclimatic variables were produced using climate data that were collected from the same year. Researchers have shown that Worldclim data is not always the most accurate in describing how bioclimatic variables affect events especially in areas with large elevation ranges and few weather stations (Bobrowski and Schickhoff 2017). Utilizing climate data generated from the same sample year reduces risks of error from past data interpolation. This is especially important as the rate of climate change increases, and recent past climate data becomes less reliable as a source for future climates (Bedia et al. 2015).

Vegetation indices are important tools used as surrogates for understanding plant productivity, habitat structure, health, and growth patterns (Zelleweger et al. 2016). The use of vegetation indices has spread from simple estimates of productivity to robust models of groundwater availability and carbon sequestration (Fu & Burgher 2015; Lagomasino et al. 2019). Several studies found that understanding vegetation patterns during temperature extremes increased understanding of overall vegetation impacts (Alcaraz-Segura et al. 2009; Mkhabela et al. 2011). This is the first time that seasonality effects of temperature have been applied to vegetation indices for all of Maricopa County (Figure 1.1).

Although bioclimatic variables have been used primarily to investigate species distributions and other similar ecological studies, researchers from all disciplines can gain nuanced understandings of climate interactions by using bioclimatic variables as opposed to simple temperature and precipitation values (Hijmans 2005). Researchers that are investigating the impacts of climate change will gain significant power by using bioclimatic variables generated from present data instead of historical trends. All users of this data repository will benefit from the ease of access to high-quality continuous data.

All raw climate data from NASA DAYMET as well as the 19 bioclimatic variables for Maricopa County have been made publicly available for all users for years 2000 – 2016 through CAP LTER. Vegetation variables of NDVI and EVI, as well as all newly created seasonal impacted vegetation variables will also be made publicly available through CAP LTER. To download data or obtain supplementary information for any of the datasets used in this study, visit the following URLs:

https://doi.org/10.6073/pasta/ded1548e4ee8611ba587d26432d5e269

https://doi.org/10.6073/pasta/88bde1cfeeb4c94774343a943cfe23e8

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Table 1.1. Raw climatic variables for Maricopa county obtained from National Aeronautics and Space Administration (NASA) daily surface weather and climatological summaries (DAYMET) (Thornton et al. 2018; Thornton et al. 1997).

Parameter	Units	Description
Precipitation	mm/month	The total accumulated precipitation over the monthly period of the daily total precipitation. Precipitation is the sum of all forms of precipitation converted to water equivalent
Maximum air temperature	degrees C	The average over the monthly period of high temperature for a 24-hour period
Minimum air temperature	degrees C	The average over the monthly period of minimum temperature for a 24-hour period
Water vapor pressure	Pa	The average over the monthly period of the daily average partial pressure of water vapor

Table 1.2. Explanation of 19 bioclimatic variables, their units of measurements, and calculations used to generate variables (Nix 1986; Hijmans et al. 2005; O'Donnell & Ignizio 2012).

Bioclimatic Predictor	Units	Calculation
Annual mean temperature	degrees C	Sum(monthly avg)/12; monthly avg = (max temp + min temp)/2
Annual mean diurnal range	degrees C	Sum(max temp - min temp)/12
Isothermality	%	(Annual Mean Diurnal Range/Annual Temperature Range) * 100
Temperature seasonality	%	Std_Dev(monthly avg temp)
Max temp. of warmest month	degrees C	Max Temperature all months
Min temp. of coldest month	degrees C	Min Temperature all months
Annual temperature range	degrees C	Max Temp of Warmest Month – Min Temp of Coldest Month
Mean temp. of wettest qrt.*	degrees C	Max precip 3 consecutive month sum; sum temp avg of max months/3
Mean temp of driest qrt.	degrees C	Min precip 3 consecutive month sum; sum temp avg of min months/3
Mean temp of warmest qrt.	degrees C	Max monthly avg temp 3 consecutive month sum; sum temp avg of max months/3
Mean temp of coldest qrt.	degrees C	Min monthly avg temp 3 consecutive month sum; sum temp avg of min months/3
Annual precipitation	mm	Sum total precipitation all 12 months
Precipitation of wettest month	mm	Max total precipitation between 12 months
Precipitation of driest month	mm	Min total precipitation between 12 months
Precipitation seasonality	%	((Std_Dev(total monthly precipitation))/(1+(Annual Precip/12)))*100
Precipitation of wettest qrt.	mm	Max precip of 3 consecutive month sum
Precipitation of driest qrt.	mm	Min precip of 3 consecutive month sum
Precipitation of warmest qrt.	mm	Max monthly avg temp 3 consecutive month sum; sum total precip of max months
Precipitation of coldest qrt.	mm	Min monthly avg temp 3 consecutive month sum; sum total precip of min months

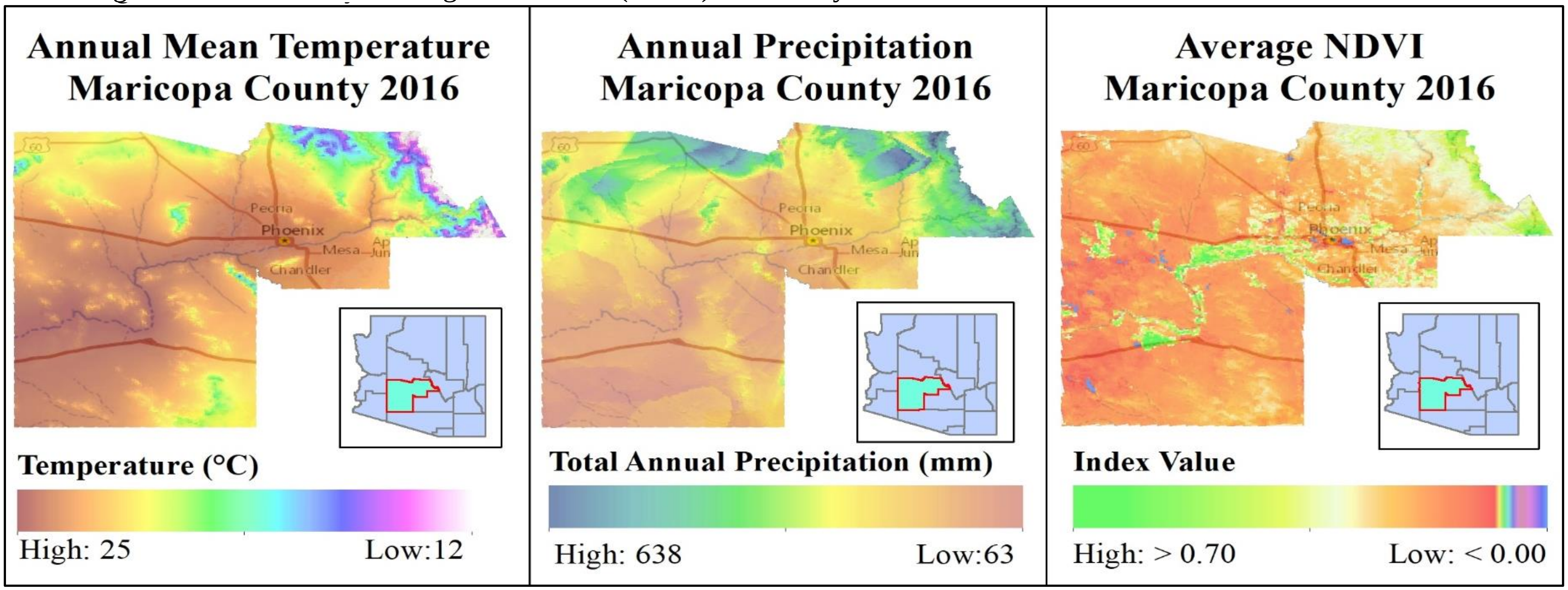
qrt*= Quarter

Table 1.3. Explanation of four new vegetation variables for both NDVI & EVI based on seasonality and extremes of temperature.

Bioclimatic Predictor	Calculation
Average vegetation indices values of qrt with highest NDVI/EVI	Max NDVI/EVI 3 consecutive month sum; sum NDVI/EVI values of max months/3
Average vegetation indices values of qrt with lowest NDVI/EVI	Min NDVI/EVI 3 consecutive month sum; sum NDVI/EVI values of min months/3
Average NDVI/EVI of the warmest qrt	Max monthly avg temp 3 consecutive month sum; sum total NDVI/EVI of max months/3
Average NDVI/EVI of the coldest qrt	Min monthly avg temp 3 consecutive month sum; sum total NDVI/EVI of min months/3

qrt = Quarter

Figure 1.1. Examples of three continuous variables generated for Maricopa County: Annual mean temperature, annual precipitation, and average normalized difference vegetation index (NDVI) value for year 2016.



CHAPTER 2

DRIVERS OF BIRD SPECIES RICHNESS IN THE NORTHERN SONORAN DESERT

INTRODUCTION

Desert birds show several attributes that potentially favor their resilience to seemingly inhospitable environments. Birds' overall water and energy needs are modest because of their reduced size, which allows them to tolerate thermal and hydric extremes (Wolf 2000). Birds are also highly mobile and can search for spatially localized resources over broad areas and can also increase their body temperature in response to heat or water stress. This physiological change allows birds to lose heat to the environment (heat flow) and thus help conserve valuable water resources (Wolf 2000). By analyzing the complex determinants of bird richness, this study provides a better insight into how to address the conservation problems derived from the impact of climate change on bird richness patterns and will help practitioners to design more inclusive strategies to conserve birds in the face of climate change.

The climate hypothesis states that the geographical patterns of species richness strongly correlate with climate variables, often related to ambient energy and water variables (Hawkins et al. 2003; Fine 2015). This idea emerged from the beginning of biogeography (Von Humboldt 2014) and has driven biogeographical studies in the last three decades. The water-energy dynamics theory proposes that the interaction between water and energy, either directly or indirectly, generates and maintains geographical patterns of species richness (Currie 1991; O'Brien 2000; Hawkins et al. 2003; Albuquerque & Beier 2015).

Besides measures of ambient energy and precipitation, another important factor for explaining animal and plant diversity is annual stability (seasonality). Stable areas, with less variability throughout the year, may permit specialization and therefore may accumulate more species (Klopfer 1959). The annual stability hypothesis postulates that regions with variation in temperature and precipitation have promoted species to coexist in the same amount of space as well as increased speciation and reduced extinction rates (Begon 1996; Fine 2015).

Species richness is also related to many environmental gradients such as area, evolutionary speed, soil, topography, biotic interactions and processes, human factors, and time (Fine 2015). Previous studies have shown how topography impacts bird species richness in areas of large elevation heterogeneity (Melo et al. 2009). Habitat heterogeneity is often calculated as the number of habitat types or as range in elevation (difference between the maximum and minimum elevation within an area, Davies et al. 2006). Urbanization can have broad effects on habitat heterogeneity.

Urban areas are the fastest growing ecosystems in the world with over half of the world's 7.7 billion people found living in municipalities, and the vast majority of all population increases are happening within urban ecosystems and will continue for the expected future (United States Population Fund 2007). Researchers have found on the global scale that bird diversity in urban ecosystems is lower compared to natural ecosystems, and that diversity is primarily driven by landcover and city age as opposed to climate and topography (Aronson et al. 2014). Urban areas convert natural landscapes and vegetation into structures and municipality infrastructure which increases impervious surfaces, municipal green space, and building density all of which have had negative effects on bird diversity (Silva et al. 2015).

Although studies have identified environmental factors as a primary driver of richness in natural habitats (Hawkins et al. 2003), there is still not enough evidence to reach a consensus regarding the primary factors influencing richness patterns especially at local extents in urban arid environments. Herein, I investigated how climate, topography, and vegetation affect bird geographical distribution in urban ecosystems of the northern Sonoran Desert, areas usually defined by climatic extremes, in both time and space.

The impacts of climate on plant and animal abundance and distributions have already been discussed in desert ecosystems (Albuquerque et al. 2018). Deserts warm and dry more quickly than other ecosystems (Iknayan & Beissinger 2018). Since studies reported measures of water and ambient energy as the primary drivers of species distribution (Naujokaitis-Lewis et al. 2018; Albuquerque et al. 2018; Iknayan and Beissinger 2018), the predicted changes in climate may result in a substantial contraction of the suitable habitat over the next century (Albuquerque et al. 2018). In addition, significant changes in environmental temperatures may produce a negative consequence for wildlife, including desert bird deaths (Albright et al. 2017).

Research Objectives

Several studies have reported the effects of urbanization on bird species richness and they have indicated that variables such as taxonomic group, extent of analysis, and intensity of urbanization produces no change, decrease or even increases richness in some cases (McKinney 2008). Herein, I determine how bird richness compares through time and seasons in the urban ecosystems of the northern reaches of the Sonoran Desert as well as document which environmental variables most influence bird richness in the same area. I did not consider urban related variables because accurate temporal detailed urban inventories are unavailable for the Phoenix area.

My objectives were to:

1) Test if bird species richness was different between seasons for all sites, as well as if bird species richness was significantly different between years.
2) Identify those environmental variables that most influence bird species richness in the ecosystems of the northern Sonoran Desert by season and year and compare how models perform longitudinally.

METHODS

Study area

The study area includes the northeast portion of the Sonoran Desert, which includes Maricopa County and the greater Phoenix metropolitan area (GPMA), one of the fastest growing regions in the United States (Appendix A). The Sonoran Desert includes more than 350 birds and more than 2,000 species. Maricopa County is the nation's 4th largest county by population as well as the fastest growing county in the United States (U.S. Census Bureau 2010). Regarding climate, there are two separate rainfall seasons, one from November through March, and another from July and August. The other months are generally dry. The Sonoran Desert is considered much lusher than the surrounding deserts due to this seasonal rainfall pattern and mild winters (Dimmitt 2015).

Bird data

I obtained data from the long-term monitoring of bird abundance and diversity from the Central Arizona–Phoenix Long-Term Ecological Research (CAP LTER). As seen in Appendix A, a total of 104 sites was visited on three separate days by three different observers in winter (Dec-15 Mar) and spring (15 Mar – May) from 2001 to 2016 excluding 2003 (surveys were not conducted in 2003). At each point count survey, observers would wait five minutes after arriving at a site and then record all birds seen or heard within a 40-meter radius from the observer for 15 minutes as suggested by Bibby et al. (1992). All surveys were conducted within four hours of dawn. No species were documented that were seen outside or above the 40-meter radius except for wide-ranging migrating or soaring species. All species were classified by alpha codes as prescribed by Ralph (1993).

The bird dataset includes survey locations in six general site groupings: (1) ESCA - a subset of the CAP LTER's Ecological Survey of Central Arizona (ESCA) long-term monitoring sites. ESCA sites include a diversity of habitats including urban, suburban, rural, commercial areas, parks, agricultural fields, and the native Sonoran Desert. (2) North Desert Village (NDV) - small neighborhoods which reflect dominant landscaping preferences employed throughout Phoenix. (3) Riparian habitats - sampling locations span a wide diversity of habitats throughout the -Phoenix area. (4) Salt River - Locations along the Salt River. (5) Desert Fertilization - Areas located at desert parks. (6) PASS - locations related to Phoenix Area Social Survey (PASS) neighborhoods.

To prepare a reliable presence dataset, I cleaned the data by (1) removing records with partial information (e.g. unidentified bird species); (2) deleting records that did not have longitudinal consistency among all survey years and (3) reducing spatial aggregation by ensuring a minimum distance of 1-km between consecutive locations (the same spatial resolution of environmental variables). Finally, I included a total of 47 locations from the ESCA and Riparian surveys consisting of sites throughout Maricopa County in the following habitat types and sites per habitat: commercial (4), residential (12), desert (13), agricultural (3), agricultural/residential (4), riparian (11) (Appendix B).

Environmental data

I used raw temperature, precipitation, and water vapor pressure data from NASA DAYMET remote sensing program as described in Chapter One (Raw Climatic Data, page 3).

Bioclimatic Variables

In order to view seasonality and nuanced climatic impacts on bird richness throughout Phoenix, I used 19 bioclimatic variables that were produced for each study year as described in Chapter One (Bioclimatic Variables, page 4).

Vegetation

Because researchers have seen positive correlations between bird richness and vegetation productivity (Seto et al. 2004), I used NDVI and EVI as surrogates of vegetation productivity and formatted vegetation datasets as described in Chapter One (Vegetation Indices, page 9). I produced and used four new annual vegetation variables based on NDVI and EVI values driven by seasonality and temperature as described in Chapter One (Vegetation Indices, page 9).

Soil/Geomorphology Data

I obtained soil data from the International Soil Reference and Information Centre (ISRIC) for Maricopa County for 2017. I conducted batch downloads of data directly from the ISRIC Soil Grid user interface (Hengl et al. 2014). I used the digital elevation model (30-m) for Maricopa County to generate 1-km resolution maps of elevation (mean elevation), elevation range (the difference between the maximum and minimum elevation values), aspect, and slope in ESRI ArcMap (ESRI 2011). I obtained all sunshine variables from Neteler (2005).

Environmental Variables and Richness

I divided analyses by season with data separated into winter and spring surveys. I used R (R Core Team 2017) version 3.5.1 to derive species richness for each site in each season and year using the aggregate function. For the seasonal data, I hypothesized that there was no difference among richness values across all years (Null hypothesis). To test this hypothesis, I first performed a Shapiro-Wilk normality test. Results from this test indicated that the data are not normally distributed. Therefore, I used the Kruskal-Wallis rank sum test to verify if richness values are the same across all years. I also performed a Wilcoxon rank sum test with continuity correction to verify if richness differs between the winter and spring seasons. The null hypothesis is that there is no difference between bird richness between seasons.

Variable Selection

In order to determine the most important environmental variables for the richness dataset, I generated an average dataset of each environmental variable across all years. I then used the function principal (R Core Team 2017) and the average environmental variables to perform a principal component analysis (PCA) in order to reduce the dimensionality of the data. The PCA allowed me to recognize discontinuous subsets and, most importantly, to identify sets of relatively uncorrelated environmental variables. I used the varimax rotation function to produce rotated component loadings which are easier to interpret. This function maximizes the sum of the variance of the squared loadings while producing a smaller number of important variables (Stevens 1992). Then, I used the Kaiser criterion to select the number of principal components, i.e. those factors with an eigenvalue greater that one (Appendix C; Kaiser 1964). For each principal component or factor, I selected the variable with the largest absolute factor loading value (correlation between the averaged environmental variables and the global richness PCA factors) as the component defining a variable for all further analysis. Alternatively, I produced factor scores - new variables, expressed as z-scores, derived from original variables (Appendix D).

Once I identified the set of relatively uncorrelated environmental variables (EV) from the PCA, I used generalized linear models (GLM) with a Poisson distribution by season and site for each year's species richness. Additionally, I also performed the same GLM with a Poisson distribution for each season and site with the PCA components as exploratory variables. I extracted R^2 values (Model Goodness of Fit) for each model. In addition, I used the beta function in R (R Core Team 2017), to calculate standardized beta coefficients to determine long-term trends in variable importance through time. For each season, a frequency was generated for the number of times each variable was the first or second most important driver in the yearly GLM compared to the rest of the independent variables.

RESULTS

Variable selection

PCA analysis with Varimax rotation identified 9 major components (Appendix C). Two of them corresponded to variables related to vegetation structure, as expressed by NDVI and EVI values. Three of them corresponded to precipitation and temperature (energy) values. Two factors corresponded to topographic variables and sunshine variables. One factor corresponded to water vapor pressure variables (Appendix D). I next selected the variable with the highest loadings, the remaining variables were used with the EV analysis: (1) mean diurnal range, (2) mean temperature of warmest quarter, (3) precipitation of driest quarter, (4) NDVI average, (5) NDVI standard deviation, (6) water vapor pressure standard deviation, (7) aspect, (8) sunshine hours and (9) sunshine hours minimum. Because soils variables were not strongly correlated with any PCA factors, I decided to add them as separate environmental variables to the EV analysis. The GLM with the environmental variables (EV) as predictors of richness included the most correlated variables (9 variables) plus bulk density, soil pH and soil diversity.

Variation in Richness Across Years

Bird species richness ranged from 4 to 43 and from 7 to 44 for the winter and spring seasons respectively (Figure 2.1 & 2.2). The Wilcoxon rank sum test with continuity correction revealed that richness values differed between seasons - spring and winter (W = 369260, p-value < 0.001), rejecting the null hypothesis that richness was equal across seasons.

The average richness values varied widely across years for both seasons. For the spring season, the highest richness value was observed in 2001 and 2016, whereas the lowest values were observed in 2004 and 2005 (Figure 2.1). For the winter, the highest richness value was observed in 2008 and the lowest value was observed in 2002 (Figure 2.2). In both cases, the Kruskal-Wallis rank sum test indicated that there was not significant difference in species richness among the years: Spring - Kruskal-Wallis chi-squared = 11.989, df = 14, p-value = 0.607 and Winter - Kruskal-Wallis chi-squared = 22.188, df = 14, p-value = 0.075 (Figure 2.3).

Predictors of bird richness

GLM models provided strong descriptions of bird species richness patterns across all habitats in the upper Sonoran Desert ecosystem. Over the years, models explained a similar percentage of patterns of species richness - 41% and 55%, on average, for the winter and spring seasons respectively (Figure 2.4; Appendix E). GLM models with environmental variables (EV) performed better than models with PCA factors as predictors. On average, EV models explained 50% and 55% of the variance of spring and winter bird species richness, respectively (Figure 2.4; Appendix E). PCA models explained on average 41% and 44% of the variance of spring and winter bird species richness, respectively. The minimum coefficient of determination value was observed in 2005 for both winter and spring seasons. The highest explanatory power was observed in

2001 (winter) and 2002 (spring) (Figure 2.4; Appendix E). In all cases, the explanatory power of EV and PCA models was low from 2008 to 2011 and was high from 2001 to 2004 and in 2014 and 2016. All coefficients of variation are given in Appendix E.

PCA models and their standardized coefficients indicated that vegetation structure, as expressed by NDVI variables, was the most important driver of bird species richness in all seasons (Figure 2.5). Vegetation, as expressed as EVI minimum and standard deviation, and sunshine variables were the second most important drivers of spring bird species richness, while precipitation, climate, topography and sunshine figured as secondary drivers of winter bird species richness (Figure 2.5).

EV models and their standardized coefficients indicated that soil variables, as expressed by pH and bulk density variables, were the most important drivers of bird species richness in all seasons (Figure 2.6). Vegetation structure, as expressed by NDVI values (mean and SD), was the secondary driver of bird species richness (Figure 2.6). All variance importance factors for PCA are given in Appendix F & G. All variance important factors for EV are given in Appendix H & I.

DISCUSSION

I describe the first graph of long-term variation in richness across multiple ecosystems in the upper Sonoran Desert. Banville et al. (2017) investigated the decadal declines in bird diversity in urban riparian zones of the northern Sonoran Desert area. They concluded that bird richness declined across riparian areas during their period of study. Different to Banville et al. (2017), my results indicate an oscillation, rather than a decline of bird richness. Results also suggest that richness values do not differ across years for either season, supporting the hypothesis that richness values are not significantly different. The uncovering of indirect, vegetation-structure effects of soil variables on bird species richness across urban areas of Phoenix, is the most novel result of my research.

For EV models, the soil variables, especially soil pH and bulk density, were the primary drivers of richness seen across all years. Since soil strongly affects vegetation structure and composition (Myers et al. 2015), our results indicate that that soil variables are acting as a surrogate for vegetation structure and thus influencing bird diversity. Previous species distribution studies have shown the importance of abiotic factors, such as topography, soil pH, and soil bulk density as key indicators of site vegetation diversity (Myers at al. 2015; Grime 1979; Kerr & Packer 1997; Pausas & Austin 2001; Rahbek & Graves 2001 as cited in Zellweger et al. 2016). Myers et al. (2015) investigated the effect of soil diversity and composition on birds and butterflies and observed that species richness was similar on different soil types, but species compositions varied among soil types and vegetation treatments. While my results demonstrate that soils variables are strong predictors of bird species richness, Zellweger at al. (2016) found that soil pH was less effective in predicting bird richness as it was in predicting plant diversity. The results of this study suggest that the degree to which soil variables affect bird diversity is a subject for future research.

For PCA models, vegetation structure was the primary driver followed by a combination of water and energy variables as the second and third most important variables. Results for bird species richness in the northern Sonoran Desert show a consistent, shared selection of major environmental variables, even though the primary drivers of richness changed with the method used (PCA and EV). These trends show that results obtained depend on what environmental variables are included in the study. Models with EV generally explained more variance than models including PCA scores as synthetic variables. This might be because the PCA analysis did not capture the full soil gradient.

Vegetation structure, as expressed by NDVI mean and standard deviation, was the next most common variable. The results support the hypothesis that vegetation productivity as expressed by vegetation indices is an important predictor of bird species richness at local scales (Seto et al. 2004). Other studies have also documented the direct relationship between bird richness and vegetation productivity in semi-arid ecosystems such as the Chauhan Desert and interior Australia (St. Louis et al. 2006; Pavey & Nano 2009). They found that vegetation productivity as measured from remote sensing sources had the largest impact to overall bird richness. Pavey and Nano (2009) found that desert birds were most influenced in distribution and diversity by fixed vegetation stands with diverse structure that offered food resources and nesting habitat. St. Louis et al. (2006) showed positive relationships between vegetation productivity and bird richness in multi-canopied woodland habitats. MacArthur and MacArthur (1961) found that bird diversity was not driven as much by vegetation diversity as by vegetation structure with vegetation composing an understory, mid-story, and canopy. Ecosystems with complex vegetation structure support higher species richness from increased niche space availability thus reducing competition as well as providing more availability to required resources.

Besides soils and vegetation, results indicated that climate was a key variable driving bird richness in the study area. Overall, climate accounted for only a small proportion of the explained variation of bird richness for all 15 years. Two possible reasons for this outcome may be that (1) the urban expansion of Phoenix is diverse enough to sustain bird richness across years and/or (2) that bird richness is more directly linked to vegetation and soil characteristics than general climate trends. The first option seems unlikely since several studies have documented that urban ecosystems tend to have higher abundance and lower richness of birds (Faeth et al. 2011). It is likely that the EV analysis does not find climate as impactful because of the addition of the soil variables. Climate directly impacts vegetation diversity and productivity as well as soil characteristics.

Results support the climate water-energy dynamics hypothesis (Hawkins et al. 2003). This hypothesis claims that the interaction of water-energy variables generates and maintain richness. Rodriguez et al. (2005) argued that annual actual evapotranspiration (AET), a joint measure of energy and water variables, and the global vegetation index, an estimate of plant biomass, constrain herptile richness at a global extent. Davies et al. (2007) investigated the global distribution of bird species richness and observed that topography and energy were the key drivers of bird species richness. This study demonstrates that both vegetation and climate contribute to total bird richness even at the local scale.

Also, since I reported evidence that bird species richness is strongly correlated with abiotic drivers, the results of this study support the tenet that bird richness can be modeled and predicted as a function of environmental variables at local scales in arid urban environments (Hawkins et al. 2003, Albuquerque & Beier 2015). The majority of these studies which investigated patterns of bird species were conducted at broadscale extents. However, I do acknowledge the lack of urban associated variables such as impervious surface and land use to compare importance between urban variables and climate driven variables.

Management Implications

The vegetation indices used in my study showed longitudinal consistency that the areas with highest NDVI/EVI values were along riparian corridors and suburban/agricultural portions at the periphery of the GPMA. Positive relationships between vegetation indices and species richness overall years suggest that riparian and agricultural habitats are a vital component of increasing and sustaining bird diversity in the urban ecosystems at the northern reaches of the Sonoran Desert. Bateman et al. (2015) found that bird richness along the Salt River of the GPMA was highest in riparian areas that had been actively restored. I recommend ecosystem managers continue to protect and restore critical riparian habitat to promote and maintain bird diversity. One way that managers can protect riparian corridors is by understanding how vegetation structure will change in riparian areas with changes in the climate.

Researchers found on Mt. Kilimanjaro that vegetation and food availability were indirectly affected by the prevailing climate (Ferger et al. 2006). Wildlife managers now have access to climate data that can capture the seasonality and extremes of both temperature and precipitation on an annual basis for all of Maricopa County (Boehme et al. 2019). These data along with the understanding that bird richness is driven primarily by vegetation and climate in the arid northern Sonoran Desert as seen in this study, provide a valuable baseline understanding of vegetation and climate changes through time.

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Table 2.1. Soil/Geomorphological variables from international soil reference and information center (ISRIC) soil grid and Neteler 2005

Soil Variable	Resolution	Description
Elevation	1km x 1km	Site elevation in m above sea-level
Elevation range	1km x 1km	Difference in elevation between min and max
Aspect	1km x 1km	Site gradient from 1° to 360°
Slope	1km x 1km	Site gradient from 0° to 90°
Bulk density	1km x 1km	Bulk density (fine earth) kg/m^3
Soil pH	1km x 1km	pH index measured in water solution
Soil diversity	1km x 1km	Differing soil series; number
Soil organic matter	1km x 1km	Soil organic carbon content permille
Sun hours avg	1km x 1km	Average sun hours
Sun hours max	1km x 1km	Maximum sun hours
Sun hours min	1km x 1km	Minimum sun hours
Sun hours Q1	1km x 1km	Sun hours of first quartile
Sun hours Q3	1km x 1km	Sun hours of third quartile
Sun hours range	1km x 1km	Range of sun hours

avg = Average

FIGURE 2.1. Spring bird richness for all sites combined. Mean and quartiles can be seen on the boxplot. Kruskal-Wallis chi squared showed that richness is not significantly different between any years.

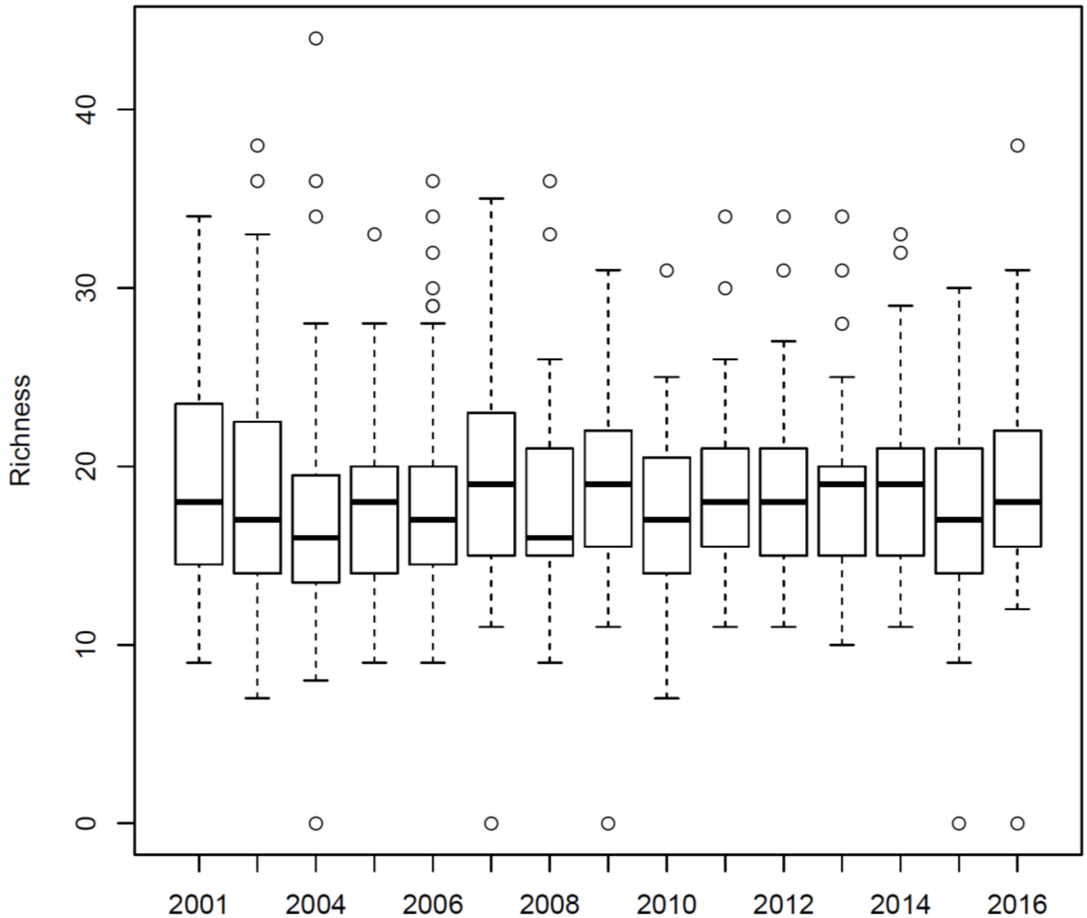


FIGURE 2.2. Winter bird richness for all sites combined. Mean and quartiles can be seen on the boxplot. Kruscal-Wallis chi squared showed that richness is not significantly different between any years

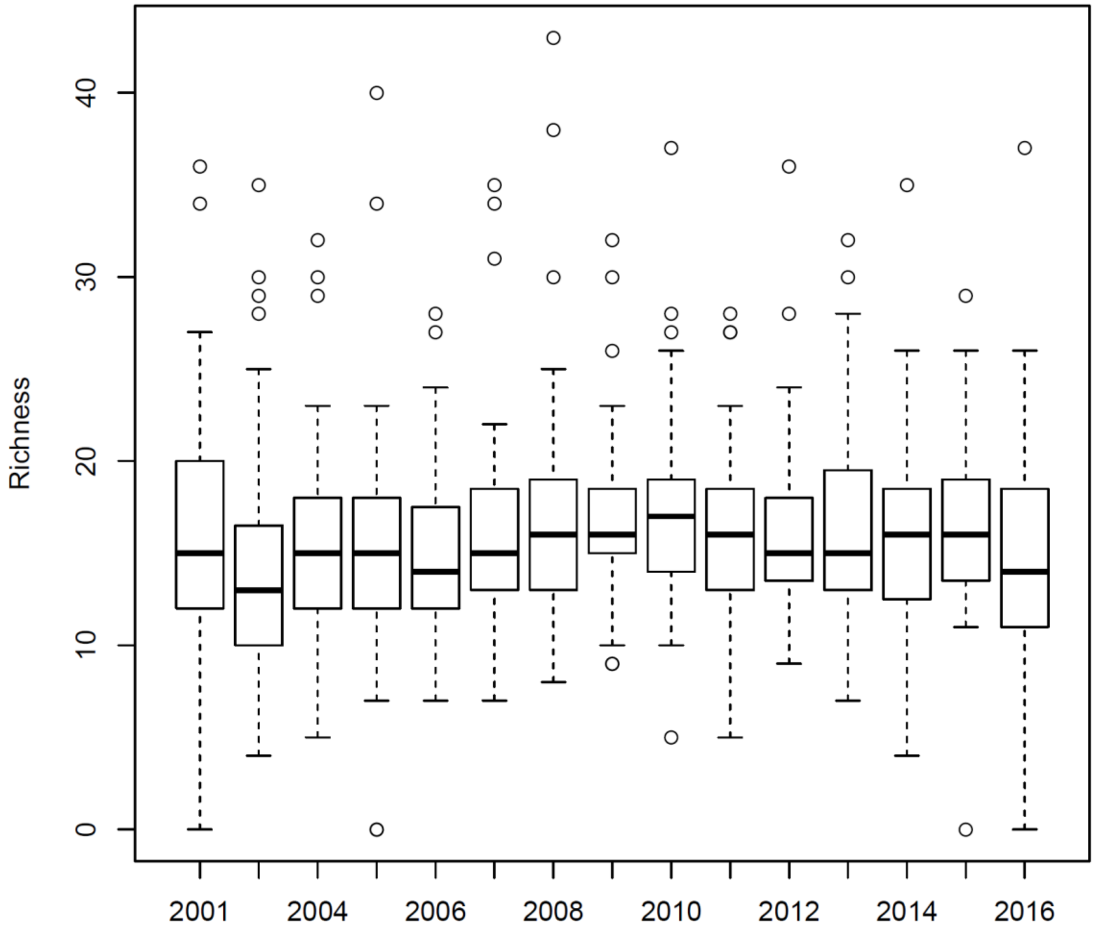


FIGURE 2.3. Mean richness values for the spring and winter seasons, across fifteen years with coordinating confidence intervals. Kruskal-Wallis rank sum test indicated that there was not significant difference in species richness among the years while Wilcoxon rank sum test with continuity correction revealed that richness differed between seasons.
Seasons - W = 369260, p-value < 0.001
Spring - Kruskal-Wallis chi-squared = 11.989, df = 14, p-value = 0.607
Winter - Kruskal-Wallis chi-squared = 22.188, df = 14, p-value = 0.075

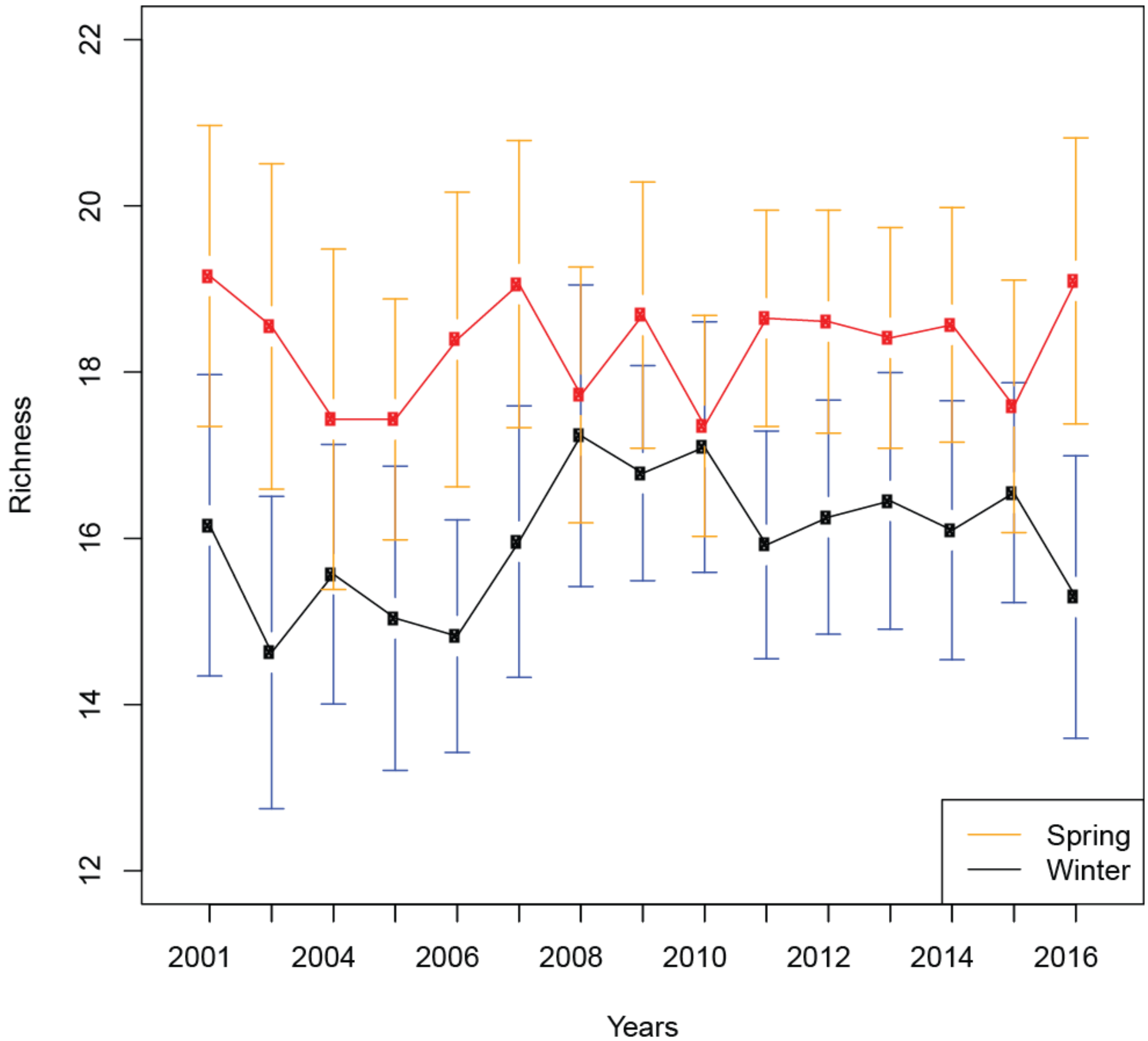


FIGURE 2.4. Explanatory power, expressed by the coefficient of determination, of generalized linear models of bird species richness for two seasons; winter and spring. Values are expressed per year, from 2001 to 2016. The year 2003 was excluded from the analysis because of lack of data.

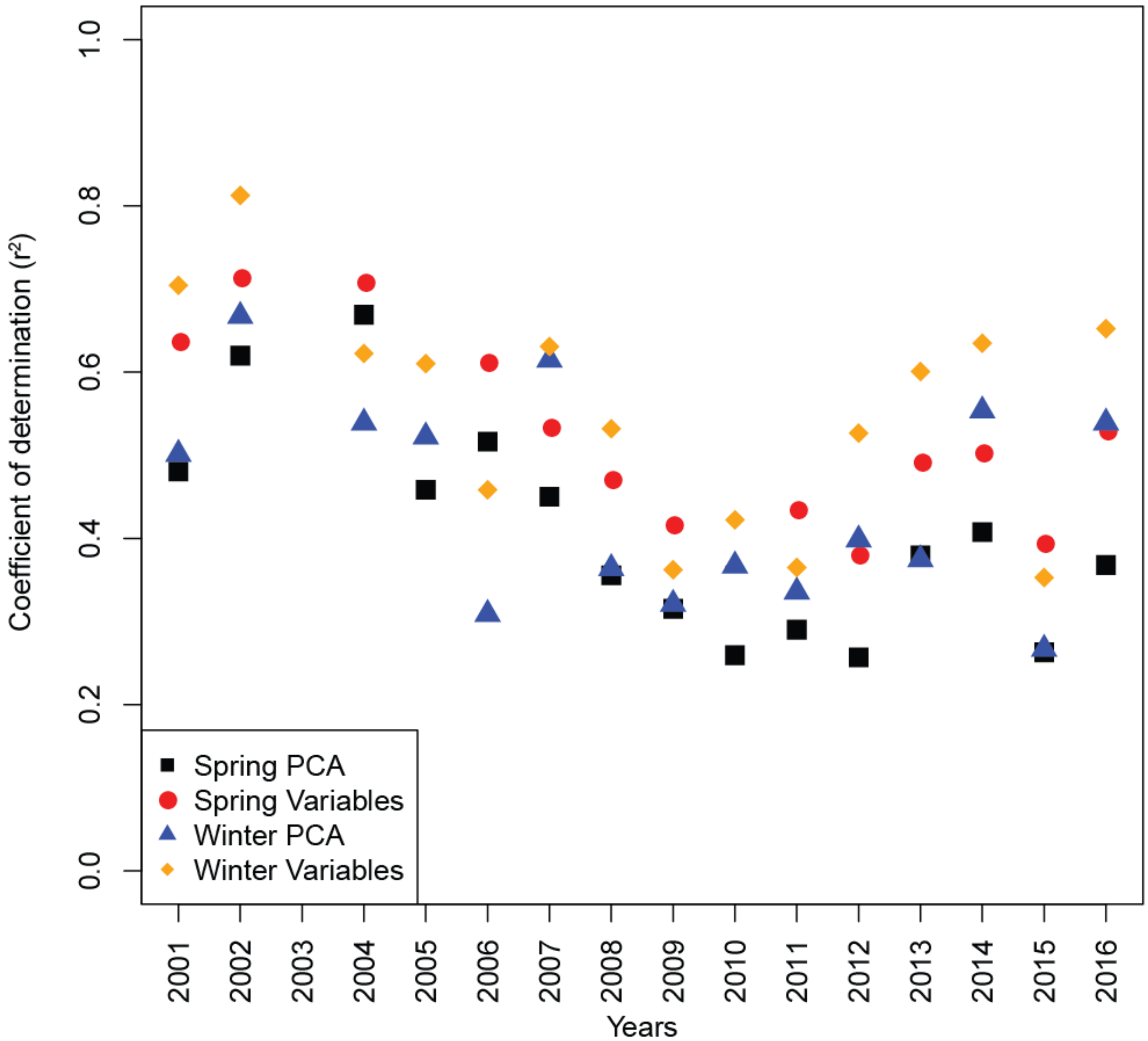


FIGURE 2.5. Frequency of most important drivers of spring and winter bird species richness in the northern Sonoran Desert. Values represent the number of times which a given PCA factor figured as primary or secondary drivers of species richness from 2001 to 2016. Relationships between variables and abundance shown by symbols (+/-).

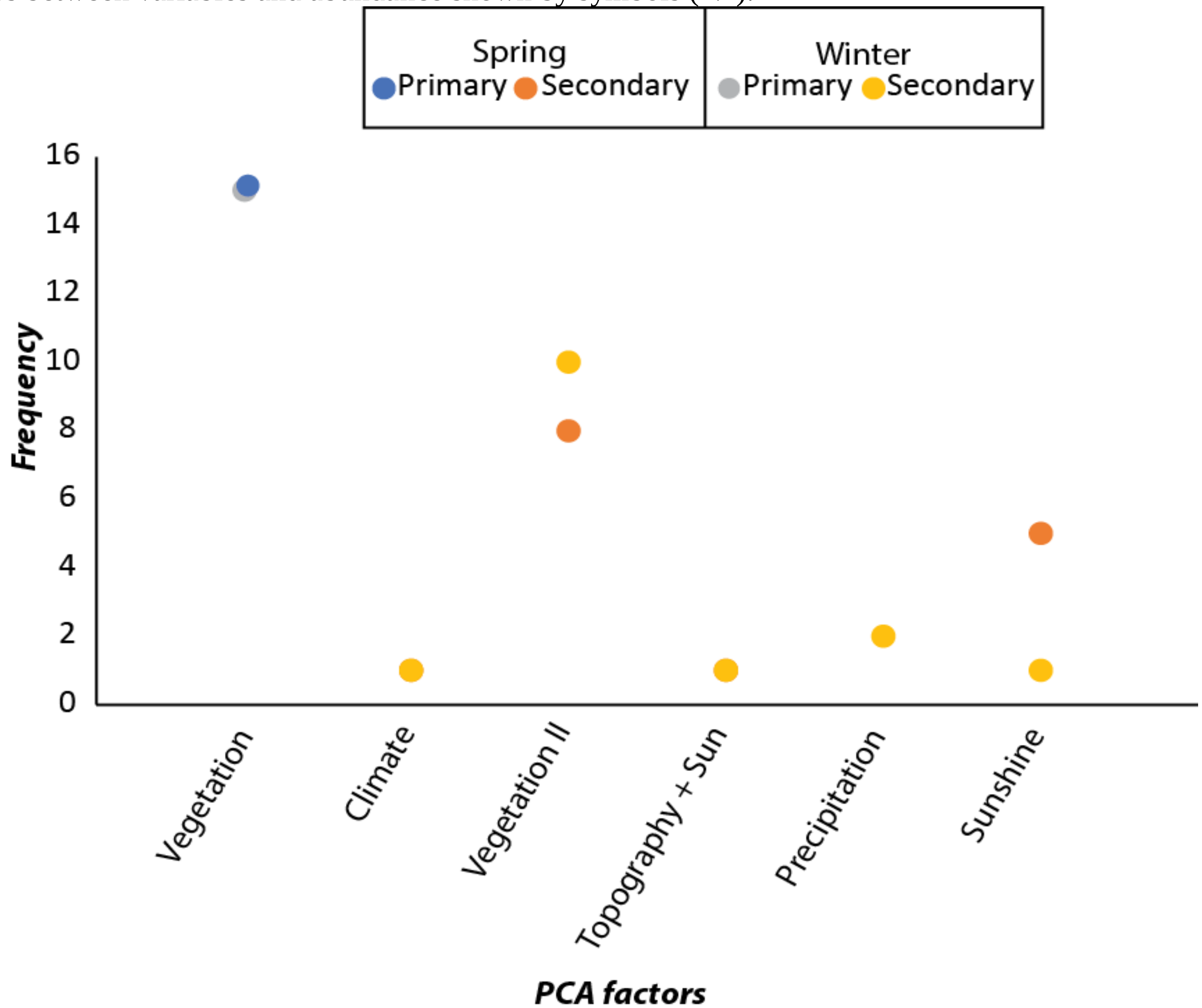
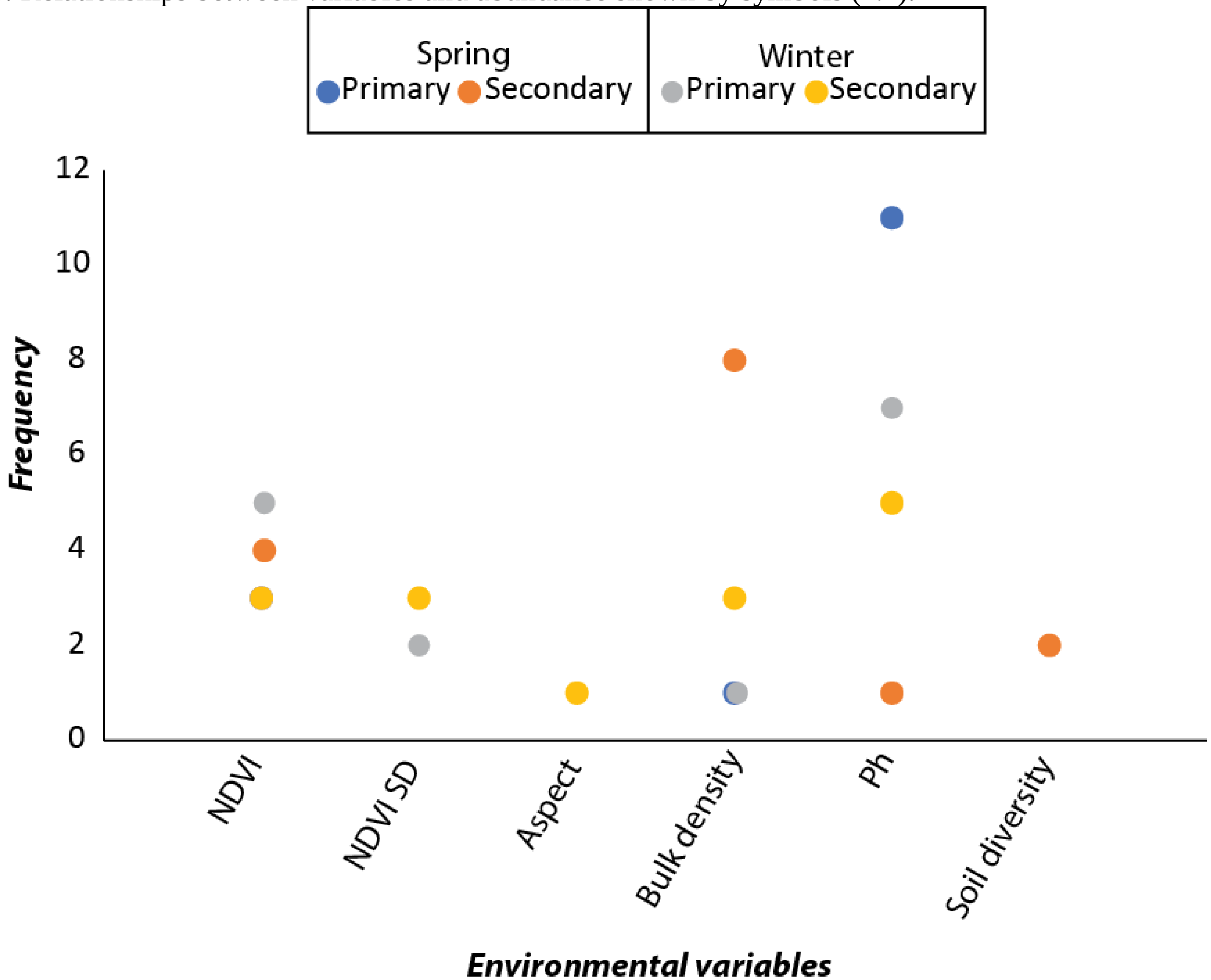


FIGURE 2.6. Frequency of most important drivers of spring and winter bird species richness in the northern Sonoran Desert. Values represent the number of times which a given environmental variable (EV) figured as primary or secondary drivers of species richness from 2001 to 2016. Relationships between variables and abundance shown by symbols (+/-).



CHAPTER 3

DRIVERS OF BIRD ABUNDANCE IN THE NORTHERN SONORAN DESERT

INTRODUCTION

Most of the research conducted on impacts of environmental variables on species abundance is relegated to modeling species distribution patterns (Ehrlen & Morris 2015). Further, most of the studies involving modeling species distributions never address abundance directly and rely on an indirect habitat-based model approach instead of an abundance or density-based model. Researches have documented the relationship that exists between resource selection functions and abundance in many species (Boyce & McDonald 1999), but resource selection function or habitat selection can vary even within species (Wagner et al. 2011).

Environmental variables influence species abundance both directly and indirectly (Aspinall & Matthews 1994; Masters et al. 1998; Menendez et al. 2007). Severe droughts have accelerated habitat biome shifts in all terrestrial ecosystems globally (Martínez-Vilalta & Lloret 2016). Increased temperatures have impacted food chains and introduced new interspecies interactions on every continent (Walther 2010). Temperature extremes have killed entire subpopulations in one species of flying fox in Australia (Welbergen et al. 2007). Extreme temperatures have also impacted many bird species through widespread nest failures that have lasting effects for several years (Stenseth et al. 2002). I acknowledge that species abundance is greatly affected by competition, resource availability, and land use, but each of these falls outside of the scope of this study. What environmental drivers have direct impacts on bird abundance?

Boyce and McDonald (1999) were able to show that there is a relationship between a resource selection function and species abundance. Therefore, species abundance may be indirectly impacted by climate through changes in vegetation structure and productivity. Riparian corridors often have higher bird diversity, vegetation index values, such as the normalized difference vegetation index (NDVI), and productivity than most surrounding areas; vegetation indices, therefore, may be an important variable in understanding bird abundance through time (Knopf et al. 1988). Although habitat modeling and resource selection functions are valuable in determining density and distribution, a more direct approach, such as modeling environmental variables directly to abundance can be useful in determining possible effects on abundance as climate shifts.

Research Objectives

The purpose of this study was to determine how bird abundance compares through time and seasons in the ecosystems of the northern Sonoran Desert as well as understand which environmental variables most influence bird abundance in the same area. My objectives were to:

1) Test if bird abundance was different between seasons for all sites, as well as if bird abundance was significantly different between years.
2) Identify environmental variables that most influence bird abundance in the ecosystems of the northern Sonoran Desert by season and year and compare how models perform longitudinally.

METHODS

Study area

The study area includes the northeast portion of the Sonoran Desert, which includes Maricopa County and the greater Phoenix metropolitan area (GPMA) as described in Chapter One (Study Area, page 24; Appendix A).

Bird Data

I obtained data from the long-term monitoring of bird abundance from the Central Arizona–Phoenix Long-Term Ecological Research (CAP LTER) as described in Chapter Two (Bird Data, page 25; Appendix B).

Environmental data

I used raw temperature, precipitation, and water vapor pressure data from NASA DAYMET remote sensing program as described in Chapter One (Raw Climatic Data, page 3).

Bioclimatic Variables

In order to view seasonality and nuanced climatic impacts on bird abundance throughout Phoenix, I used 19 bioclimatic variables that were produced for each study year as described in Chapter One (Bioclimatic Variables, page 4).

Vegetation

Researchers have seen positive correlations between bird abundance and vegetation type (Pavey & Nano 2009). I used NDVI and EVI to quantify vegetation productivity and formatted vegetation datasets as described in Chapter One (Vegetation Indices, page 9). I produced and used four new annual vegetation variables based on

NDVI and EVI values driven by the seasonality of temperature as described in Chapter One (Vegetation Indices, page 9).

Soil/Geomorphology Data

As described in Chapter Two (Soil/Geomorphology Data, page 27), I compiled several variables that helped described soil, geomorphology, and sunshine for all of the survey sites.

Environmental Variables and Abundance

I divided the abundance analysis by season with data separated into winter and spring surveys resembling the analysis for bird richness in Chapter Two (Environmental Variables and Richness, page 27). I used R (R Core Team 2017) version 3.5.1 to calculate bird abundance for each site in each season and year using the aggregate function. For the seasonal data, I hypothesized that there is no difference among abundance values across all years (null hypothesis). To test this hypothesis, I performed the same tests as described in richness analysis in Chapter Two (Environmental Variables and Abundance, page 27) namely: (1) Shapiro-Wilk normality test on spring and winter abundance data, (2) Kruskal-Wallis rank sum test on abundance values across all years per season (seasonal data results indicated that data are not normal), and (3) Wilcoxon rank sum test with continuity correction to compare winter and spring abundance by site.

Variable Selection

In order to reduce the dimensionality of data (43 variables), I conducted a principal component analysis (PCA) as described in Chapter Two (Variable Selection, page 27; Appendix C & D). I then used generalized linear models (GLM) with a Poisson distribution by season and site for each year's bird abundance as described in Chapter Two (Variable Selection, page 27). I extracted R^2 values (model goodness of fit) for each model. In addition, I used the beta function in R (R Core Team 2017), to calculate standardized beta coefficients to determine long-term trends in variable importance through time.

RESULTS

Variable selection

Since PCA analysis with Varimax rotation was conducted before the addition of dependent variable (bird richness or abundance), results were the same as those reported for bird richness in Chapter Two (Variable Selection, page 29; Appendix C & D).

Variation in Abundance Across Years

Bird abundance ranged from 8 to 3,463 and from 18 to 1,577 for the winter and spring seasons respectively (Figure 3.1 & 3.2). The Wilcoxon rank sum test with continuity correction revealed that abundance values differed between seasons - spring and winter ($W = 264101$, p-value < 0.001), rejecting the null hypothesis that abundance was equal across seasons. Winter had greater than 13,000 more individuals identified than spring over all 47 sites.

The average abundance values varied widely across years for both seasons and survey types. For the spring season, the highest abundance value was observed in 2012 and 2013, whereas the lowest values were observed in 2002 (Figure 3.3). For the winter, the highest richness value was observed in 2008 and the lowest value was observed in 2002 (Figure 3.3). The Kruskal-Wallis rank sum test indicated that there was not a significant difference in abundance among the years for winter; however, abundance values between spring years were significantly different: Spring - Kruskal-Wallis chi-squared = 30.613, df = 14, p-value = 0.006 and Winter - Kruskal-Wallis chi-squared = 20.24, df = 14, p-value = 0.123.

Predictors of Bird Abundance

Both the PCA and environmental variable (EV) GLM provided strong descriptions of bird abundance patterns in the northern Sonoran Desert ecosystem. Over the 15 years, individual models explained a similar percentage of patterns of bird abundance - 54% and 53%, on average, for the winter and spring seasons respectively (Figure 3.4). Overall, GLM models with environmental variables (EV) performed better than models with PCA factors as predictors. On average, EV models explained 56% and 60% of the variance of spring and winter bird abundance, respectively (Appendix J). PCA models explained on average 50% of the variance for both spring and winter bird abundance. The minimum coefficient of determination value was observed in 2002 (winter) and 2006 (spring). The highest explanatory power was observed in 2005 (winter) and 2012 (spring) (Figure 3.4). In all cases, the explanatory power of EV and PCA models was low in 2006. Winter explanatory power was much more volatile than spring with several back-to-back years of high and then low with drops of more than 30 percent. The explanatory power of spring abundance was low in 2009 and 2010 and then again in 2014 and 2015 (Figure 3.4). All coefficients of variation are given in Appendix J.

PCA models and their standardized beta coefficients indicated that vegetation and climate were the most important drivers of bird abundance in all seasons (Figure 3.5;

Appendix K & L). Topography, as expressed by aspect, and vegetation II (vegetation standard deviations) were the second most important drivers of winter bird abundance, while precipitation, climate, topography, and sunshine figured as secondary drivers of spring bird abundance (Figure 3.5; Appendix K & L).

EV models and their standardized coefficients indicated that climate and vegetation as expressed by mean temperature of the warmest quarter and NDVI were the most important drivers of spring bird abundance (Figure 3.6; Appendix M & N). The secondary drivers of spring abundance were expressed by average NDVI and standard deviation of NDVI as well as soil pH and soil diversity values. Primary drivers of winter abundance were climate and vegetation as expressed by mean temperature of the warmest quarter and average NDVI values. Secondary drivers of winter abundance were composed of climate, vegetation and soil variables to all small amounts (Figure 3.6). All EV variable importance values are given in Appendix M & N.

DISCUSSION

My study provides a comprehensive assessment of changes in urban bird abundance throughout 16 years. This study documents changes, mostly a decline, in abundance values that differed between seasons - spring and winter. Banville et al. (2017) studied the spring and winter abundances of birds in urban riparian areas of the Phoenix metropolitan area and also observed seasonal differences in riparian bird abundance and composition. They reported declining trends in both migratory and resident species and that urban riparian areas are key for supporting high levels of bird species diversity. In a recent global study about the impacts of urbanization on bird diversity, Aronson et al.

(2014) revealed that global urban bird diversity has decreased substantially. They also reported that urban areas support regional biodiversity, and that urbanization has had profound effects on biodiversity (Aronson et al. 2014).

A potential explanation for the decline observed herein is urban change (Kane et al. 2014). Callaghan et al. (2018) investigated the effect of local landscape attributes on bird diversity across 51 cities and observed that green areas were the most important predictor of bird biodiversity, highlighting the critical importance of vegetation structure as the primary factor explaining bird biodiversity and mitigating loss from urbanization. The urbanization in metropolitan areas is changing the vegetation cover patterns which directly affect bird abundance (Rodrigues et al. 2018). Since vegetation structure and cover are key drivers of species distribution, I believe that the vegetation cover in this area may play a key role in explaining the fluctuations in abundance. Like most of the major cities in the US, the Phoenix Metropolitan area is densely urbanized which directly affects current land cover patterns (Kane et al. 2014). This change often leads to substantial native vegetation suppression, which may negatively affect birds, especially specialist species (Rodrigues et al. 2018).

Besides urbanization, extrinsic factors such as climate are key to explain the fluctuation of bid abundance (Hawkins et al. 2003). Without the inclusion of climate data, McFarland et al. (2011) saw minimal success in using average NDVI to account for the variation seen in bird abundance on the San Pedro riparian area in southeast Arizona (R^2=0.30). In this study, I found that the lowest average coefficient of variation (R^2) was 0.50 when using PCA components and 0.56 when using environmental variables (EV).

This supports using a comprehensive multifaceted dataset to explore variations seen in bird abundance. Other studies have also found that explanatory power is increased with combinations of vegetation variables along with other variables of climate and/or topography (Seoane et al. 2004).

Regarding the modelling choices, I found that bird abundance was better explained by models that used raw environmental variables than the synthetically produced components from the PCA variable selection. I urge researchers conducting regression and generalized linear models to contrast analyses using PCA components against raw variables. I consistently found more explanatory power in EV models compared to those models that used synthetic components. To determine if soils were responsible for the increase of variation explained in the EV models compared to the PCA models, I conducted a post hoc analysis without any soil variables and found that the EV models dropped on average 10% in their ability to explain the variation seen in abundance in both spring and winter seasons. Soil characteristics, namely soil pH, bulk density, and soil diversity, drive bird abundance in this study area along with climate and vegetation and support the hypothesis that many different environmental variables should be used to produce the most powerful models of bird abundance (Seoane et al. 2004 & McFarland et al. 2011). Soil factors affect directly and indirectly the growth and distribution of landcover and vegetation structure, which ultimately affect bird abundance and distribution (Myers et al. 2015; Girma et al. 2017).

I acknowledge that the fluctuations of species abundance found in this study may be related to intrinsic factors such as migratory behavior, competition, and breeding

(Aynalem & Bekele 2008). Banville et al. (2017) supported that the decrease in bird diversity is mostly explained by changes in the occurrence of migratory birds and specialists. They reported that both species types were more common at earlier years, and that some of them have been lost or replaced by more abundant species (Banville et al. 2017).

In summary, consistent with previous analyses of bird diversity in urban areas, the abundance of bird species in the Phoenix Metropolitan area declined among the years and seasons. For the first time, results show that this pattern is largely associated with current climatic conditions and vegetation variables, with energy variables being one of the most relevant (according to Hawkins et al.'s conjecture 2003). The climate–vegetation models developed here show that mean temperature of the warmest quarter and NDVI were the most important drivers of spring bird abundance. My results support the tenet that the abundance of urban birds is strongly affected by the spatiotemporal distribution of environmental variables (McCain 2009).

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FIGURE 3.1. Spring bird abundance for all sites combined. Mean and quartiles can be seen on the boxplot. Kruscal-Wallis chi squared showed that abundance is significantly different between any years

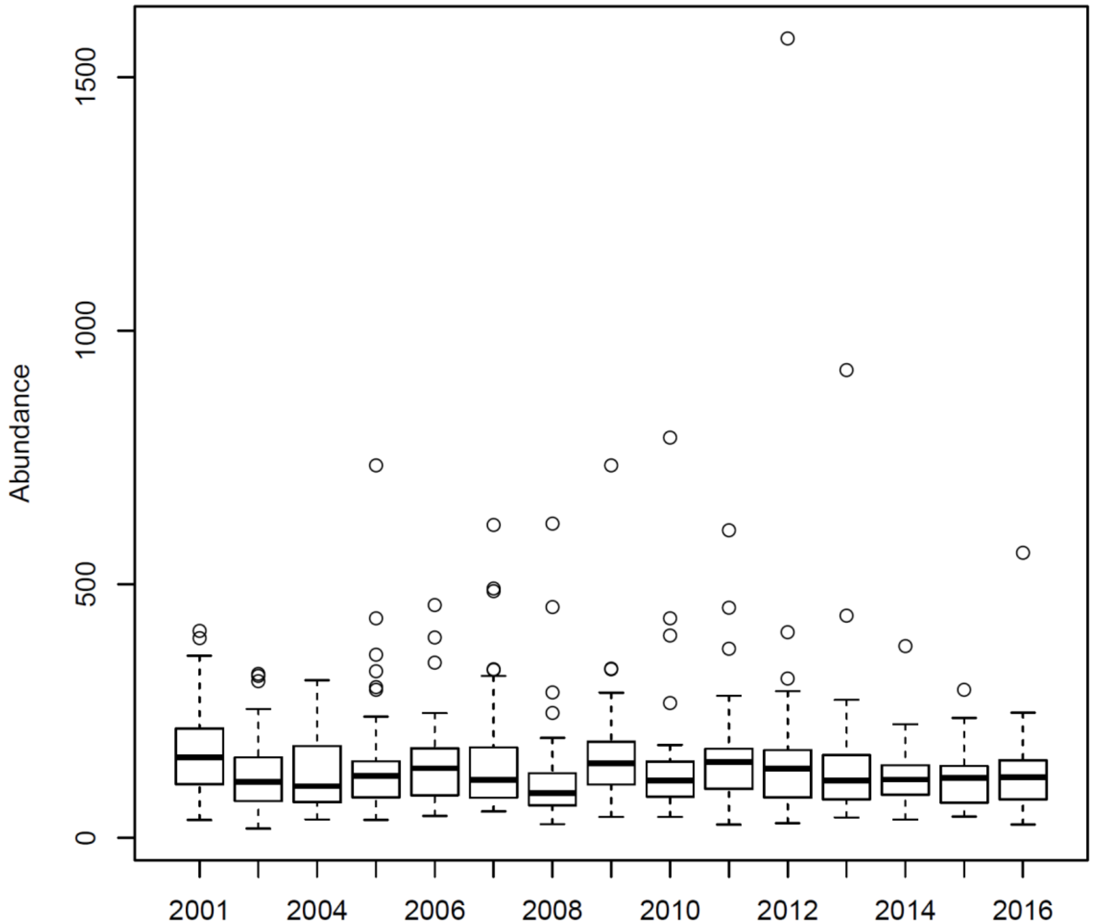
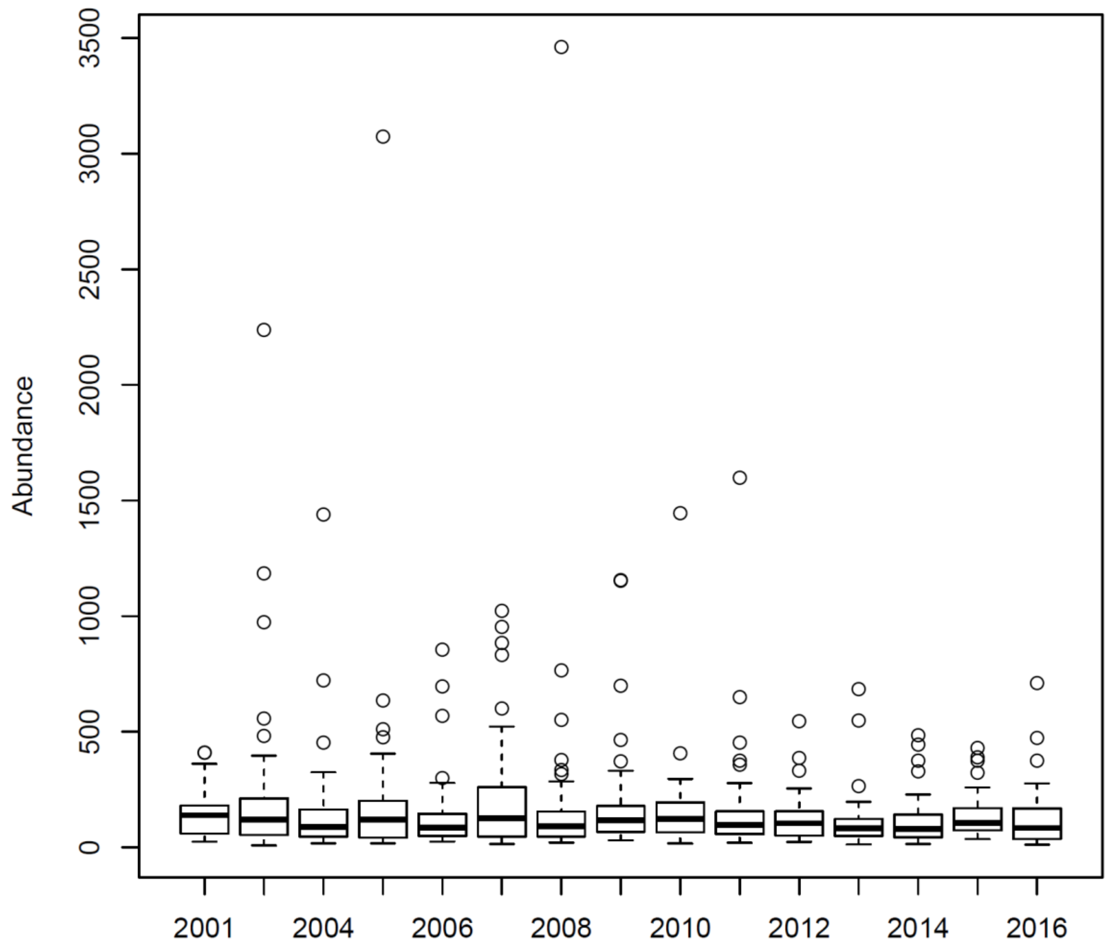


FIGURE 3.2. Winter bird abundance for all sites combined. Mean and quartiles can be seen on the boxplot. Kruscal-Wallis chi squared showed that abundance is not significantly different between any years



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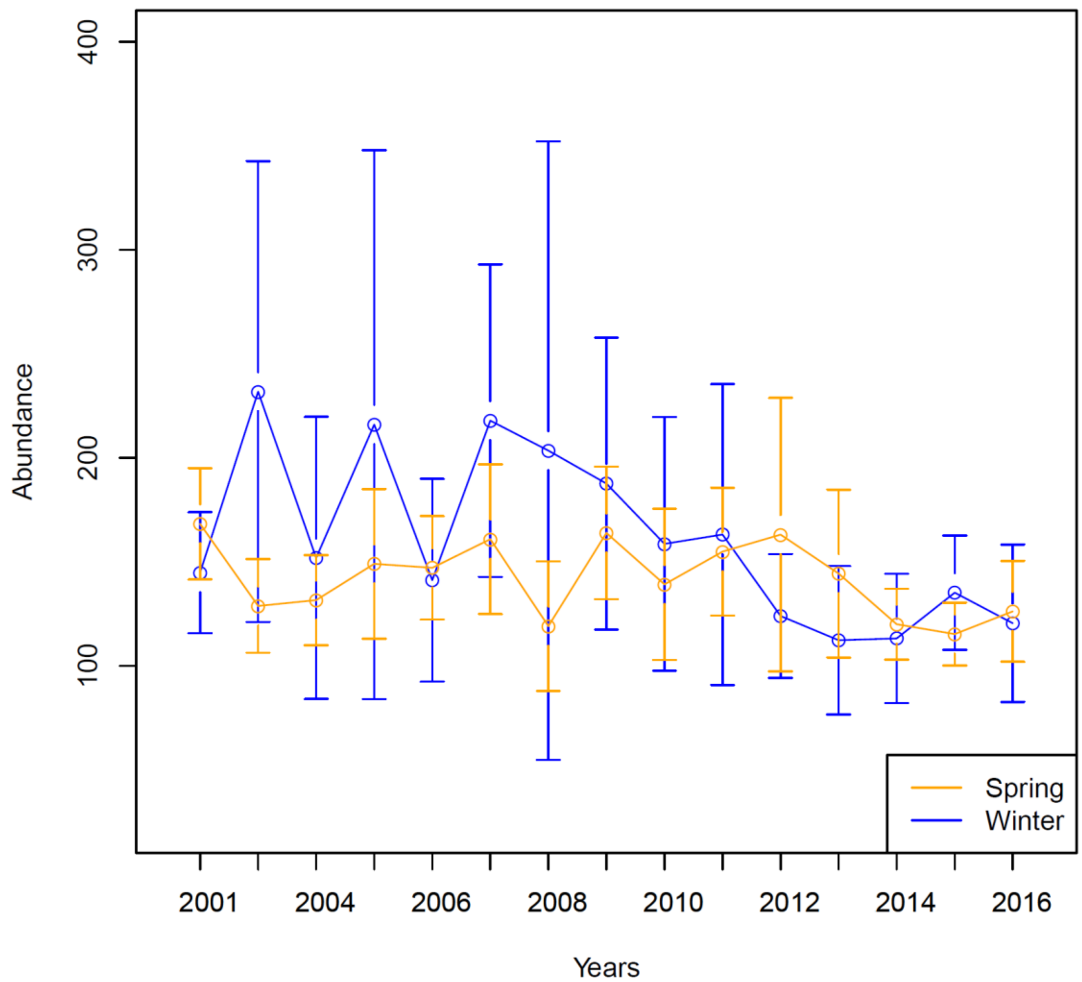

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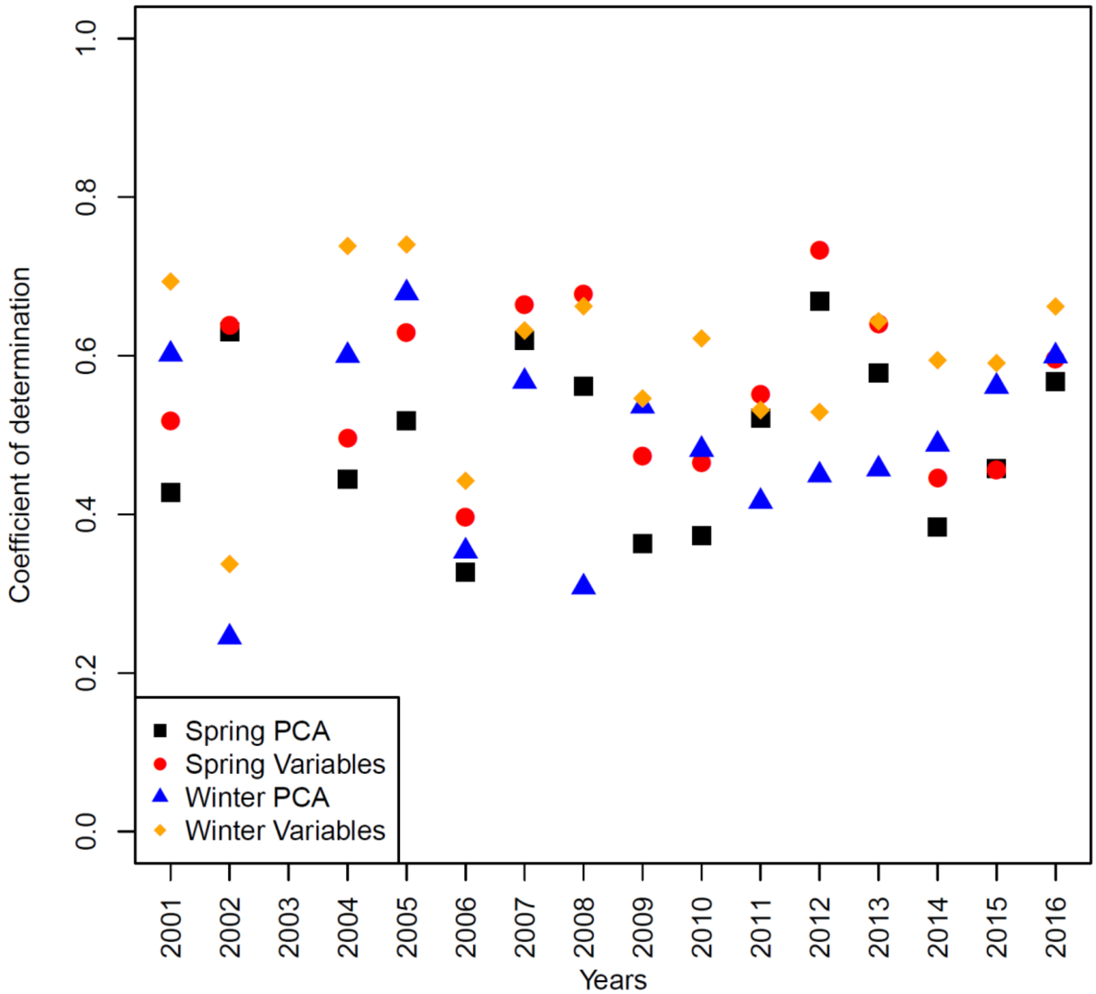

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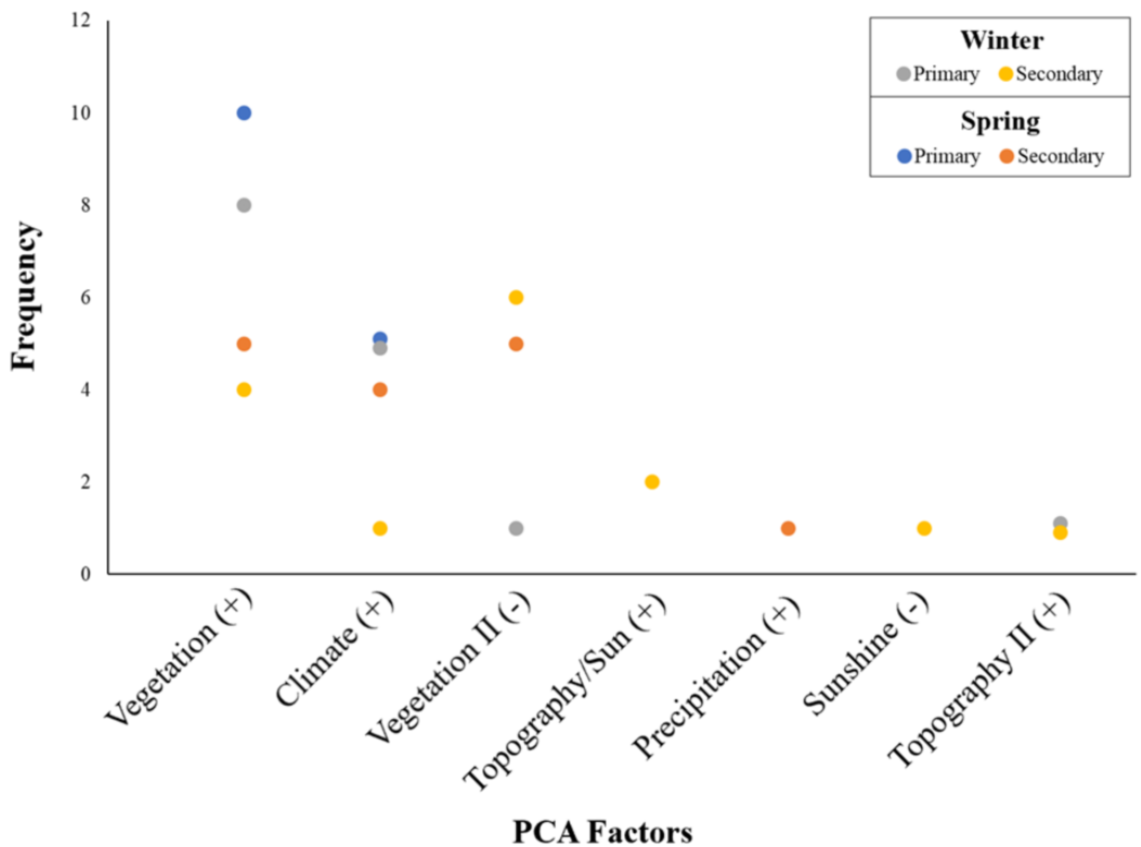

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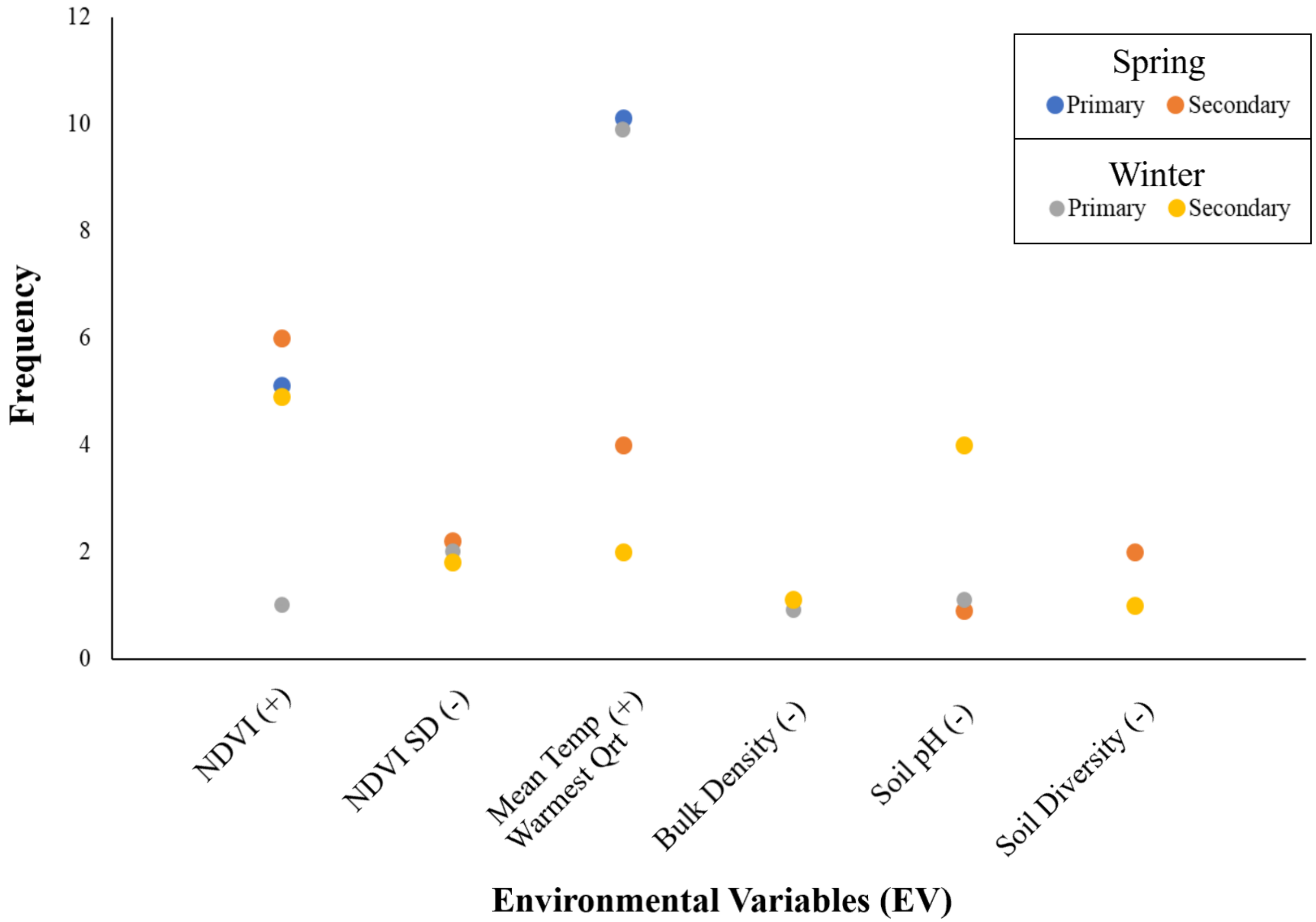

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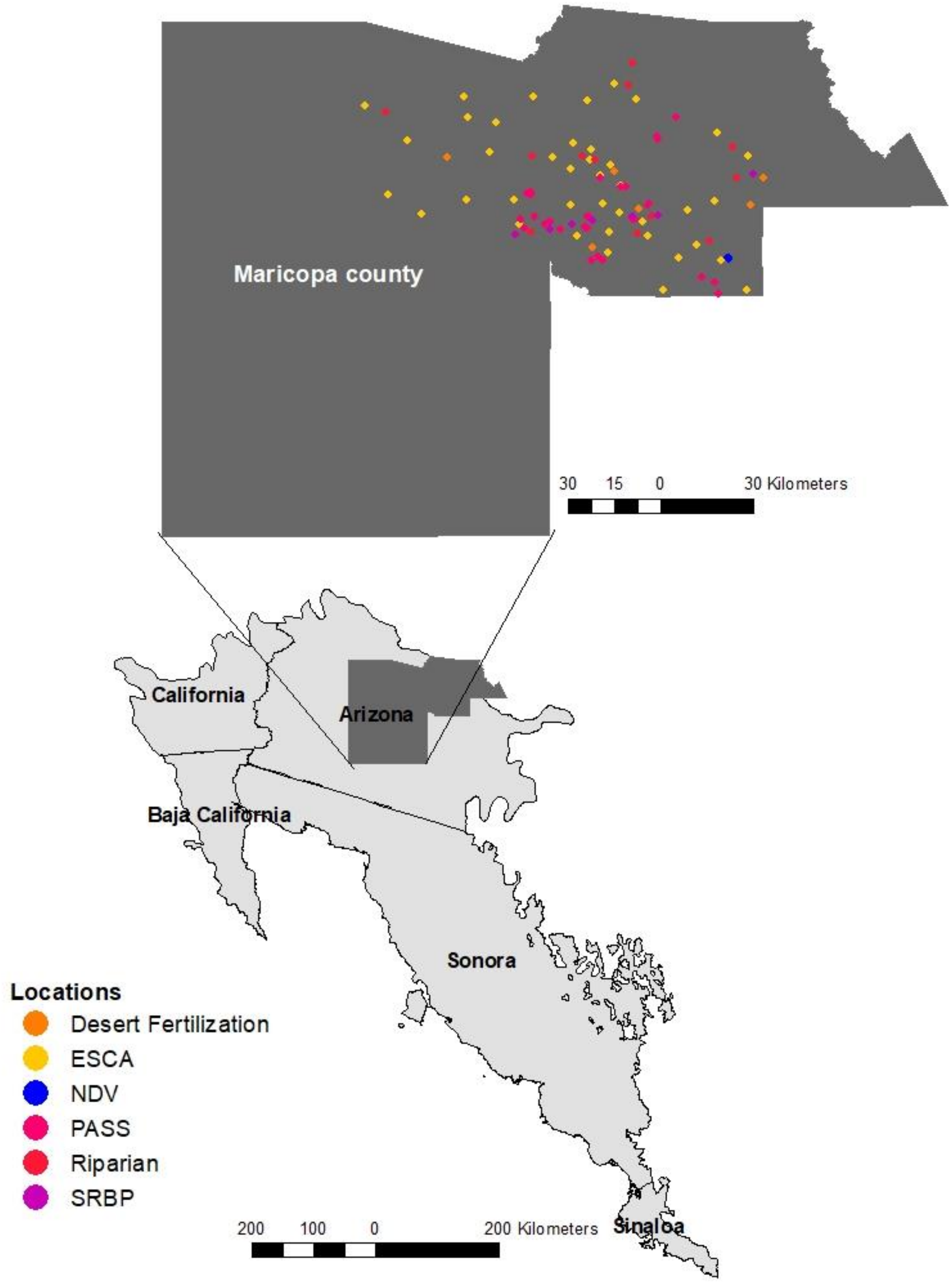
APPENDIX A

STUDY AREA MAP

APPENDIX A. Site map of Maricopa County in relation to the Sonoran Desert. Locations of Central Arizona–Phoenix Long-Term Ecological Research survey sites spread across the Maricopa County. I used 47 sites from the Riparian and Ecological Survey of Central Arizona (ESCA) surveys. No sites were used from North Desert Village (NDV) Phoenix Area Social Survey (PASS), or Salt River (SRBP) surveys.



APPENDIX B

POINT COUNT SURVEY LOCATIONS AND DESCRIPTION

APPENDIX B. Site identification, location and habitat of 47 sites used for this analysis. Riparian and Ecological Survey of Central Arizona (ESCA) surveys were the only two surveys used after filtering process was complete.

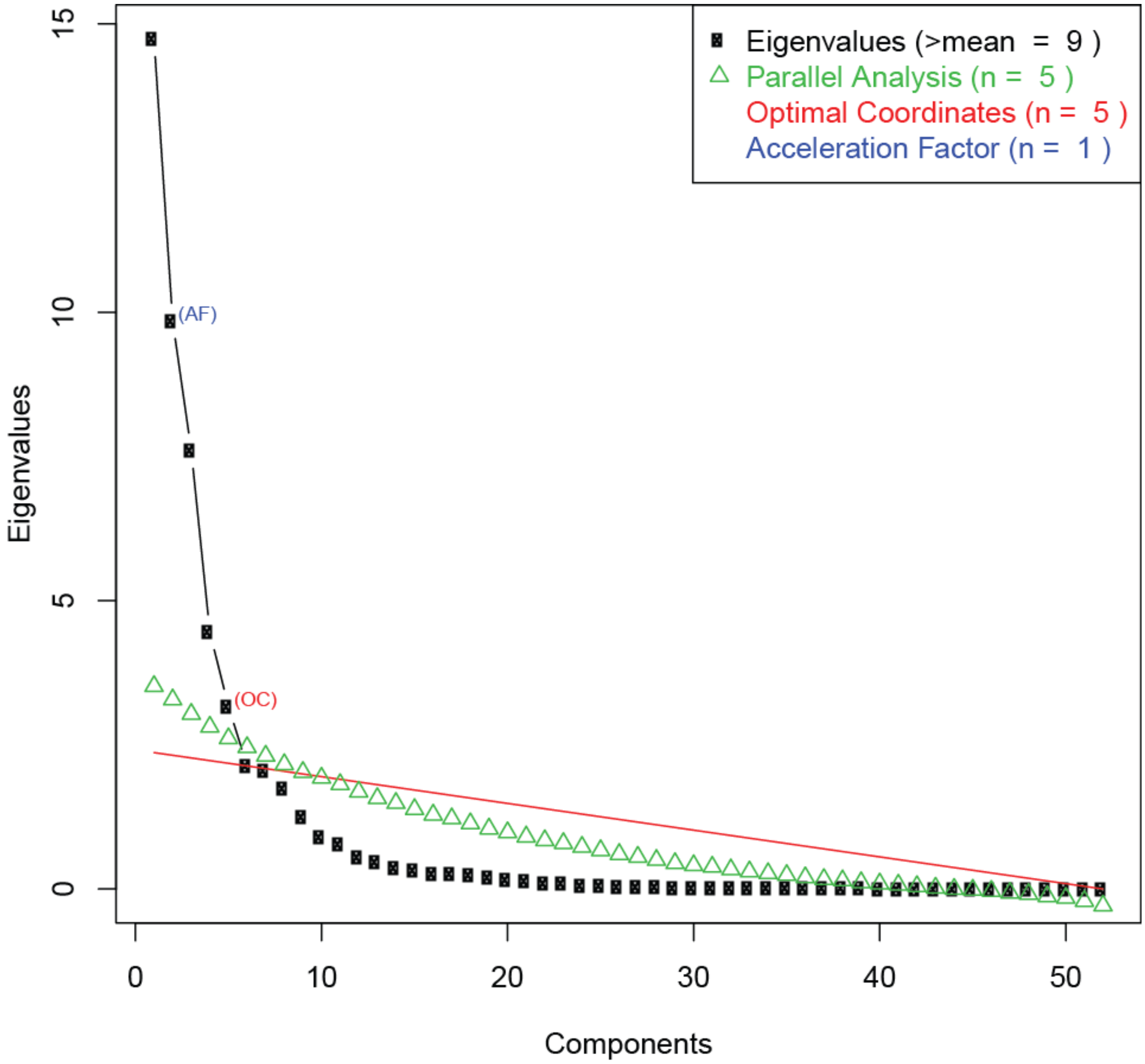
Site ID	Survey	lat	long	Habitat Classification
AA-17	ESCA	33.45215	-111.801	Commercial
AA-20	ESCA	33.31575	-111.824	Residential
AB-19	ESCA	33.35162	-111.774	Residential
AC-16	ESCA	33.47894	-111.719	Commercial
AD-10	ESCA	33.67689	-111.711	Desert park
AD-21	ESCA	33.30702	-111.703	Agricultural
AE-23	ESCA	33.2187	-111.626	Agricultural/Residential
AF-12	ESCA	33.61024	-111.622	Scrub flat desert
EE-15A	Riparian	33.38449	-111.947	Riparian, ephemeral-engineered
EE-6A	Riparian	33.61084	-112.251	Riparian, ephemeral-engineered
EE-7C	Riparian	33.60987	-112.108	Riparian, ephemeral-engineered
EN-4B	Riparian	33.73959	-112.681	Riparian, ephemeral-natural
EN-7B	Riparian	33.8162	-111.973	Riparian, ephemeral-natural
F-8	ESCA	33.75598	-112.742	Scrub flat desert
G-15	ESCA	33.49892	-112.674	Natural desert
I-11	ESCA	33.65442	-112.618	Natural desert
I-17	ESCA	33.44059	-112.577	Scrub flat desert
L-7	ESCA	33.7813	-112.452	Scrub flat desert
M-16	ESCA	33.48267	-112.444	Agricultural
N-12	ESCA	33.62206	-112.376	Agricultural/Residential
O-9	ESCA	33.70632	-112.357	Scrub flat desert
P-16	ESCA	33.4821	-112.304	Residential
P-18	ESCA	33.41178	-112.291	Agricultural
PE-10B	Riparian	33.3894	-112.257	Riparian, perennial-engineered
PE-11A	Riparian	33.36293	-111.735	Riparian, perennial-engineered
PE-13A	Riparian	33.5983	-112.069	Riparian, perennial-engineered
PE-1D	Riparian	33.43499	-111.904	Riparian, perennial-engineered
PN-1B	Riparian	33.54746	-111.657	Riparian, perennial-natural
PN-7A	Riparian	33.88142	-111.959	Riparian, perennial-natural
Q-7	ESCA	33.78404	-112.25	Natural desert
R-12	ESCA	33.60712	-112.194	Residential
S-16	ESCA	33.46672	-112.142	Residential
T-11	ESCA	33.64816	-112.133	Residential
T-13	ESCA	33.57299	-112.139	Residential
T-19	ESCA	33.37853	-112.121	Agricultural/Residential
U-12	ESCA	33.62722	-112.079	Residential
U-13	ESCA	33.59796	-112.083	Desert remnant
U-8	ESCA	33.7711	-112.092	Natural desert
V-13	ESCA	33.58346	-112.023	Residential
V-14	ESCA	33.55222	-112.055	Residential

V-20	ESCA	33.3282	-112.032	Natural desert
W-15	ESCA	33.52389	-111.992	Residential
W-17	ESCA	33.44464	-112	Commercial
W-6	ESCA	33.82083	-112.011	Natural desert
X-18	ESCA	33.41963	-111.929	Commercial
Y-19	ESCA	33.37724	-111.915	Residential
Z-23	ESCA	33.21929	-111.872	Agricultural/Residential

APPENDIX C

NON-GRAPHICAL SOLUTIONS TO SCREE PLOT

APPENDIX C. Non graphical solutions to scree plot. Using the Kaiser criterion, I selected components based on the number of components with eigenvalues greater than one.



APPENDIX D

PRINCIPAL COMPONENT ANALYSIS VALUES

APPENDIX D. Principal Component Analysis (PCA) used to reduce the dimensionality of the 43 total environmental variables before conducting further generalized linear models. PCA components have been renamed for those variables that contribute the highest loading for each.

Environmental variables	PC1 (Veg)	PC2 (Climate)	PC3 (Energy)	PC4 (Veg II)	PC5 (Topo+Sun)	PC6 (Precip)	PC7 (Sunshine)	PC8 (Water Vpr)	PC9 (Topo II)
Annual Mean Temp	0.17	**0.94**	-0.14	-0.09	0.07	0.1	-0.02	0.13	0.04
Mean Diurnal Range	0.07	0.19	**0.97**	0.05	-0.01	0.02	-0.08	0.06	0.02
Isothermality	0.08	-0.03	**0.97**	0.02	0	0.1	-0.07	0.05	0.02
Temp Seasonality	0.04	**0.75**	0.5	0.12	-0.05	-0.23	-0.07	0.1	0.04
Max Temp of Warmest Month	0.15	**0.87**	0.41	0.01	0.05	-0.03	-0.08	0.14	0.09
Min Temp of Coldest Month	0.07	0.39	**-0.89**	-0.12	0.08	0.06	0.05	0.05	0.06
Temp Annual Range	0.07	0.41	**0.89**	0.09	-0.02	-0.06	-0.09	0.07	0.03
Mean Temp of Wettest Qrt	0.27	**0.61**	-0.09	-0.11	-0.21	0.01	0.09	0.33	-0.38
Mean Temp of Driest Qrt	0.05	**0.52**	-0.39	0.06	-0.01	0.33	0.2	0.08	0.39
Mean Temp of Warmest Qrt	0.14	**0.97**	0	-0.04	0.06	-0.01	-0.03	0.14	0.05
Mean Temp of Coldest Qrt	0.17	**0.87**	-0.33	-0.13	0.12	0.14	0	0.13	0.04
Annual Precip.	-0.06	**-0.96**	-0.1	0	-0.07	0.08	-0.04	0.05	0.13
Precip. of Wettest Month	-0.11	**-0.89**	0.08	0.06	0.01	-0.27	-0.1	0.16	0.16
Precip. of Driest Month	0.05	0.23	-0.08	-0.08	-0.27	**0.67**	0.22	-0.06	0.39
Precip. Seasonality	-0.1	-0.29	0.2	0.12	0.23	**-0.8**	-0.06	0.2	0.17
Precip. of Wettest Qrt	-0.08	**-0.95**	-0.02	0.04	0	-0.16	-0.06	0.08	0.15
Precip. of Driest Qrt	0.07	-0.44	0.13	0.02	-0.15	**0.82**	-0.01	0.06	0.12
Precip. of Warmest Qrt	-0.15	**-0.73**	0.39	-0.1	-0.02	0.12	0.02	0.41	-0.15
Precip. of Coldest Qrt	-0.05	**-0.91**	-0.27	0.05	-0.05	0.13	-0.06	-0.07	0.16

EVI max	0.57	0.03	0.16	**0.77**	0.03	-0.07	-0.02	-0.06	0.01
EVI	**0.95**	0.2	0.08	0.18	0.05	0.02	-0.06	0	0
EVI min	**0.8**	0.01	-0.02	-0.38	0.08	-0.08	-0.07	-0.06	-0.03
EVI sd	0.45	0.03	0.17	**0.85**	0.04	-0.01	-0.01	0	0.05
EVI of Wettest Qrt	**0.95**	0.11	0.03	0.23	0.03	-0.02	-0.03	0	0.02
EVI of Driest Qrt	**0.93**	0.19	0.13	0.22	0.07	0.03	-0.09	-0.01	0.01
EVI of Warmest Qrt	**0.92**	0.28	0.11	0.09	0.07	0.06	-0.06	-0.03	-0.02
EVI of Coldest Qrt	**0.92**	0.06	0	0.3	0.01	-0.05	-0.05	0.04	0.02
NDVI max	0.48	-0.14	0.01	0.79	-0.05	-0.06	0.12	-0.05	0.04
NDVI	**0.98**	0.11	-0.03	0.14	-0.01	0.06	0.02	-0.01	0
NDVI min	**0.83**	0.05	-0.14	-0.46	-0.01	0.09	0	-0.07	-0.03
NDVI sd	0.32	-0.15	0.1	**0.9**	-0.03	-0.02	0.07	-0.01	0.07
NDVI of Wettest Qrt	**0.97**	0.04	-0.08	0.15	-0.03	0.05	0.04	0	0.03
NDVI of Driest Qrt	**0.96**	0.14	0.02	0.17	0.01	0.06	-0.01	-0.02	0
NDVI of Warmest Qrt	**0.94**	0.24	0.02	0.05	0.04	0.1	-0.01	-0.03	-0.03
NDVI of Coldest Qrt	**0.92**	-0.1	-0.11	0.29	-0.08	-0.01	0.07	0.01	0.03
Water vapor pressure max	-0.07	0.15	-0.27	0.04	0.15	-0.05	-0.01	**0.84**	0.14
Water vapor pressure	0.04	-0.28	**-0.83**	-0.14	-0.04	0.23	0.06	0.21	0.14
Water vapor pressure min	0.03	0.08	**-0.97**	-0.07	0.03	0	0.09	-0.01	-0.04
Water vapor pressure sd	-0.05	0.19	0.27	-0.1	0.01	-0.12	0.03	**0.86**	-0.21
Elevation	-0.15	**-0.91**	-0.24	0.03	-0.13	0.06	0.13	-0.16	-0.1
Slope	0.01	-0.25	-0.04	0.02	**-0.77**	0.05	0.13	-0.1	0.18
Aspect	-0.04	-0.1	-0.04	0.21	0.17	0.07	-0.1	-0.09	**0.55**
Sunshine hours	0.11	0.06	-0.05	-0.05	**0.93**	-0.13	0.02	0.02	0.16
Sunshine hours max	0.11	-0.05	-0.12	-0.04	**0.89**	-0.03	0.18	0.03	0.23
Sunshine hours min	0.12	0.03	0.18	-0.07	0.13	-0.1	**-0.93**	-0.01	0.06
Sunshine hours Q1	-0.13	0.02	-0.05	0.13	**0.54**	-0.04	-0.19	-0.12	-0.65
Sunshine hours Q3	0.03	0.27	0.03	0.01	**0.81**	-0.27	0.15	0.01	-0.17

Sunshine hours range	-0.05	-0.05	-0.21	0.04	0.33	0.07	**0.9**	0.02	0.06
Bulk density	0.38	0.5	-0.17	-0.28	0.13	-0.05	-0.19	-0.22	-0.04
Soil pH	-0.4	-0.03	0.38	0.24	0.37	-0.39	-0.14	0.22	0.2
Soil diversity	0.06	0.45	-0.16	-0.49	0.12	0.26	0.09	0.05	-0.38
Soil organic carbon	-0.02	**-0.69**	-0.2	0.02	-0.38	0.11	0.24	-0.09	-0.08
Loadings	11.78	11.60	6.80	4.10	4.00	2.59	2.16	2.14	1.80
Proportional variance	0.23	0.22	0.13	0.08	0.08	0.05	0.04	0.04	0.03
Cumulative variance	0.23	0.45	0.58	0.66	0.74	0.79	0.83	0.87	0.90

Veg = Vegetation; Qrt = Quarter; Precip = Precipitation; Topo = Topography; sd = Standard Deviation; Temp = Temperature

APPENDIX E

COEFFICIENT OF VARIATION (BIRD RICHNESS)

APPENDIX E. Coefficient of variation (R^2) or goodness of fit for each model to yearly bird abundance. Values closer to one have more explanatory power. All R^2 values extracted using Effron Pseudo R^2. All seasons shown for principal component analysis (PCA) and environment variable (EV) analysis for all years.

	PCA		EV	
	Spring	Winter	Spring	Winter
2001	0.48	0.50	0.62	0.70
2002	0.62	0.67	0.70	0.81
2004	0.67	0.54	0.69	0.62
2005	0.46	0.52	0.52	0.61
2006	0.52	0.31	0.59	0.46
2007	0.45	0.61	0.52	0.63
2008	0.36	0.36	0.45	0.53
2009	0.32	0.32	0.40	0.36
2010	0.26	0.37	0.37	0.42
2011	0.29	0.34	0.42	0.37
2012	0.26	0.40	0.36	0.53
2013	0.38	0.37	0.47	0.60
2014	0.41	0.55	0.49	0.63
2015	0.26	0.27	0.38	0.35
2016	0.37	0.54	0.51	0.65
Avg	0.41	0.44	0.50	0.55
Max	0.67	0.67	0.70	0.81
Min	0.26	0.27	0.36	0.35
Range	0.41	0.40	0.33	0.46

APPENDIX F

STANDARDIZED REGRESSION GLM COEFFICIENT (RICHNESS SPRING PCA)

APPENDIX F. Standardized regression GLM coefficients (β) for spring bird richness PCA models. Higher absolute values indicate more importance within model. Signs indicate relationship to richness. β values were used to generate spring portion of Figure 2.5.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Vegetation	0.14	0.26	0.29	0.20	0.24	0.21	0.16	0.14	0.19	0.21	0.14	0.22	0.24	0.19	0.18
Climate	-0.06	-0.06	-0.10	-0.07	-0.08	-0.08	-0.11	-0.05	-0.09	-0.03	0.01	-0.03	-0.09	-0.06	-0.06
Energy	-0.05	0.08	0.03	0.00	-0.01	0.01	-0.03	0.00	0.01	0.04	0.01	0.05	0.07	0.05	0.01
Vegetation II	0.00	-0.11	-0.15	-0.13	-0.08	-0.08	-0.03	-0.04	-0.13	-0.13	-0.05	-0.12	-0.17	-0.16	-0.09
Topography/Sun	-0.12	-0.11	-0.13	-0.11	-0.12	-0.06	0.01	-0.06	-0.07	-0.07	-0.02	-0.05	-0.06	-0.02	0.00
Precepitation	-0.06	-0.05	-0.10	-0.08	-0.12	-0.06	0.01	-0.01	-0.07	-0.12	-0.03	-0.02	-0.09	-0.13	-0.05
Sunshine	0.06	0.13	0.10	0.10	0.12	0.09	0.03	0.06	0.07	0.09	0.05	0.06	0.10	0.11	0.07
Water vapor	-0.01	-0.02	0.01	-0.04	0.00	-0.05	-0.03	-0.01	0.02	-0.05	-0.03	-0.02	-0.02	-0.06	-0.08
Topography II	0.01	0.04	0.11	0.03	0.01	0.03	0.02	0.03	0.01	0.04	0.05	0.03	0.09	0.05	0.04

APPENDIX G

STANDARDIZED REGRESSION GLM COEFFICIENT (RICHNESS WINTER PCA)

APPENDIX G. Standardized regression GLM coefficients (β) for winter bird richness PCA models. Higher absolute values indicate more importance within model. Signs indicate relationship to richness. β values were used to generate winter portion of Figure 2.5.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Vegetation	0.19	0.24	0.25	0.32	0.20	0.24	0.11	0.19	0.21	0.21	0.24	0.23	0.22	0.20	0.30
Climate	-0.02	-0.08	0.01	-0.10	-0.08	0.02	0.04	-0.09	0.01	-0.03	-0.02	-0.04	0.06	-0.01	-0.03
Energy	0.01	0.02	0.06	0.11	-0.02	0.01	0.04	0.01	0.05	0.02	0.09	0.07	0.06	0.07	0.04
Vegetation II	-0.03	-0.01	-0.10	-0.25	-0.08	-0.14	-0.03	-0.04	-0.11	-0.11	-0.15	-0.12	-0.18	-0.15	-0.24
Topography/Sun	-0.08	-0.01	-0.13	-0.08	-0.07	-0.06	0.01	-0.01	-0.05	-0.09	-0.03	-0.02	-0.05	-0.07	-0.01
Precepitation	0.02	0.10	-0.06	-0.11	-0.04	-0.01	0.07	-0.01	-0.03	-0.03	-0.02	-0.01	0.01	-0.13	-0.07
Sunshine	0.09	0.09	0.11	0.12	0.06	0.06	-0.01	-0.01	0.04	0.06	0.05	0.09	0.05	0.09	0.06
Water vapor	-0.04	-0.02	-0.03	-0.04	0.01	-0.05	-0.05	-0.05	-0.01	0.03	-0.03	0.01	-0.08	-0.04	-0.04
Topography II	0.00	0.01	0.03	0.11	0.02	0.10	0.04	-0.03	0.04	0.03	0.05	-0.01	0.04	0.08	0.09

APPENDIX H

STANDARDIZED REGRESSION GLM COEFFICIENT (RICHNESS SPRING EV)

APPENDIX H. Standardized regression generalized linear models (GLM) coefficients (β) for spring bird richness environmental variables (EV) models. Higher absolute values indicate more importance within model. Signs indicate relationship to richness. β values were used to generate spring portion of Figure 2.6.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean diurnal Range	0.00	0.08	0.03	0.02	0.03	0.01	-0.01	0.01	0.03	0.06	0.03	0.05	0.04	0.05	0.04
Mean temp Warmest qrt	0.02	0.02	-0.05	-0.03	-0.06	-0.03	-0.02	0.03	-0.01	0.00	0.08	0.04	0.00	-0.02	0.00
Precip driest qrt	-0.07	-0.05	-0.06	-0.05	-0.10	-0.02	0.00	-0.01	-0.05	-0.09	-0.01	0.00	-0.03	-0.10	-0.05
NDVI	0.08	0.18	0.22	0.12	0.14	0.17	0.10	0.08	0.06	0.11	0.07	0.13	0.16	0.10	0.10
NDVI sd	0.00	-0.08	-0.09	-0.11	-0.03	-0.09	-0.04	-0.03	-0.07	-0.08	-0.03	-0.09	-0.14	-0.09	-0.07
WVP sd	-0.04	-0.03	0.01	-0.03	0.03	-0.05	-0.02	-0.01	0.03	-0.03	-0.04	-0.02	-0.01	-0.06	-0.06
Sunshine hrs	0.02	0.01	-0.04	0.00	0.02	0.01	0.06	0.03	0.06	0.05	0.08	0.05	0.04	0.10	0.10
Sunshine hrs min	0.02	-0.04	-0.02	-0.05	-0.03	-0.05	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.03	-0.02	-0.01
Aspect	-0.02	0.03	0.12	0.02	0.05	0.01	0.03	0.03	-0.01	0.02	-0.01	-0.01	0.03	-0.02	0.03
Bulk density	-0.19	-0.18	-0.13	-0.10	-0.13	-0.06	-0.06	-0.11	-0.08	-0.12	-0.08	-0.05	-0.14	-0.14	-0.12
Soil pH	-0.21	-0.20	-0.12	-0.15	-0.19	-0.08	-0.13	-0.14	-0.19	-0.16	-0.15	-0.14	-0.12	-0.13	-0.17
Soil diversity	-0.08	-0.06	-0.03	-0.08	-0.03	-0.10	-0.08	-0.06	-0.10	-0.07	-0.08	-0.10	-0.10	-0.04	-0.06

qrt = Quarter; temp = Temperature; Precip = Precipitation; sd = Standard Deviation; WVP = Water Vapor Pressure; hrs = hours

APPENDIX I

STANDARDIZED REGRESSION GLM COEFFICIENT (RICHNESS WINTER EV)

APPENDIX I. Standardized regression generalized linear models (GLM) coefficients (β) for winter bird richness environmental variables (EV) models. Higher absolute values indicate more importance within model. Signs indicate relationship to richness. β values were used to generate winter portion of Figure 2.6.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean diurnal Range	0.07	0.03	0.06	0.07	0.01	-0.01	0.07	0.04	0.06	0.02	0.09	0.09	0.06	0.06	0.05
Mean temp Warmest qrt	0.06	0.06	0.08	-0.02	-0.01	0.11	0.07	-0.05	0.05	0.05	0.06	0.06	0.12	0.01	0.08
Precip driest qrt	-0.09	0.00	-0.02	-0.05	-0.07	0.04	0.00	-0.05	-0.03	0.00	-0.02	-0.07	0.01	-0.05	-0.04
NDVI	0.11	0.22	0.19	0.27	0.14	0.19	0.07	0.13	0.14	0.11	0.14	0.12	0.16	0.14	0.15
NDVI sd	-0.01	-0.05	-0.10	-0.23	-0.08	-0.13	-0.01	-0.03	-0.07	-0.06	-0.11	-0.08	-0.17	-0.14	-0.16
WVP sd	-0.06	-0.06	-0.03	-0.04	0.01	-0.05	-0.02	0.01	-0.01	0.02	-0.01	0.01	-0.08	-0.03	0.00
Sunshine hrs	0.05	0.08	-0.01	0.00	0.03	0.00	0.04	0.03	0.02	0.03	0.04	0.13	0.02	0.00	0.12
Sunshine hrs min	0.01	-0.02	-0.04	-0.06	0.00	-0.02	0.04	0.03	0.01	0.01	0.00	0.00	-0.01	-0.06	0.01
Aspect	0.03	0.06	0.04	0.05	0.07	0.05	0.10	0.01	0.03	-0.01	0.05	-0.02	0.01	0.02	0.04
Bulk density	-0.23	-0.26	-0.14	-0.15	-0.16	-0.10	-0.07	-0.04	-0.08	-0.09	-0.11	-0.19	-0.10	-0.04	-0.10
Soil pH	-0.29	-0.25	-0.16	-0.09	-0.17	-0.11	-0.17	-0.12	-0.11	-0.15	-0.17	-0.27	-0.16	-0.06	-0.21
Soil diversity	0.00	0.01	-0.08	-0.11	-0.03	-0.07	-0.01	-0.03	-0.05	-0.07	-0.06	-0.05	-0.06	-0.14	-0.08

qrt = Quarter; temp = Temperature; Precip = Precipitation; sd = Standard Deviation; WVP = Water Vapor Pressure; hrs = hours

APPENDIX J

COEFFICIENT OF VARIATION (BIRD ABUNDANCE)

APPENDIX J. Coefficient of variation (R^2) or goodness of fit of each model to yearly bird abundance. Values closer to one have more explanatory power. All R^2 values extracted using Effron Pseudo R^2. All seasons shown for principal component analysis (PCA) and environment variable (EV) analysis for all years.

	PCA		EV	
	Spring	Winter	Spring	Winter
2001	0.43	0.60	0.52	0.69
2002	0.63	0.25	0.64	0.34
2004	0.44	0.60	0.50	0.74
2005	0.52	0.68	0.63	0.74
2006	0.33	0.35	0.40	0.44
2007	0.62	0.57	0.66	0.63
2008	0.56	0.31	0.68	0.66
2009	0.36	0.54	0.47	0.55
2010	0.37	0.48	0.47	0.62
2011	0.52	0.42	0.55	0.53
2012	0.67	0.45	0.73	0.53
2013	0.58	0.46	0.64	0.64
2014	0.38	0.49	0.45	0.59
2015	0.46	0.56	0.46	0.59
2016	0.57	0.60	0.60	0.66
Avg	0.50	0.49	0.56	0.60
Max	0.67	0.68	0.73	0.74
Min	0.33	0.25	0.40	0.34
Range	0.34	0.43	0.34	0.40

APPENDIX K

STANDARDIZED REGRESSION GLM COEFFICIENT (ABUNDANCE SPRING PCA)

APPENDIX K. Standardized regression generalized linear models (GLM) coefficients (β) for spring bird abundance principal component analysis (PCA) models. Higher absolute values indicate more importance within model. Signs indicate relationship to abundance. β values were used to generate spring portion of Figure 3.5.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Vegetation	0.24	0.42	0.15	0.29	0.19	0.15	0.44	0.22	0.31	0.43	0.72	0.54	0.18	0.29	0.48
Climate	0.14	0.30	0.31	0.29	0.17	0.34	0.19	0.24	0.24	0.26	0.22	0.23	0.20	0.17	0.09
Energy	0.07	0.26	-0.02	-0.05	-0.13	0.04	0.01	-0.05	0.04	0.05	0.04	0.21	0.00	0.06	0.05
Vegetation II	-0.11	-0.32	-0.03	-0.02	0.04	0.15	-0.12	-0.10	-0.14	-0.25	-0.38	-0.31	-0.09	-0.23	-0.23
Topography/Sun	0.06	-0.03	0.05	0.05	-0.02	0.03	0.12	0.03	0.08	-0.07	0.12	0.10	0.07	0.06	0.04
Precepitation	0.20	-0.07	0.14	0.07	-0.05	0.12	-0.06	0.00	0.01	-0.16	-0.21	-0.08	0.05	-0.05	-0.09
Sunshine	-0.01	0.14	-0.08	-0.08	-0.01	-0.04	-0.01	-0.03	0.03	0.08	-0.05	0.09	-0.04	0.01	0.03
Water vapor	0.06	-0.18	-0.04	0.04	-0.02	-0.06	-0.10	-0.08	-0.22	-0.07	-0.01	-0.10	-0.08	-0.12	-0.10
Topography II	0.01	0.16	0.10	0.13	0.02	0.13	0.16	0.12	0.08	0.15	0.35	0.27	0.12	0.15	0.10

APPENDIX L

STANDARDIZED REGRESSION GLM COEFFICIENT
(ABUNDANCE WINTER PCA)

APPENDIX L. Standardized regression generalized linear models (GLM) coefficients (β) for winter bird abundance principal component analysis (PCA) models. Higher absolute values indicate more importance within model. Signs indicate relationship to abundance. β values were used to generate winter portion of Figure 3.5.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Vegetation	0.35	0.08	0.76	0.95	0.32	0.35	-0.41	0.57	0.56	0.58	0.33	0.46	0.50	0.52	0.44
Climate	0.36	0.07	0.50	0.41	0.46	0.76	0.83	0.21	0.26	0.43	0.28	0.29	0.23	0.18	0.47
Energy	0.16	-0.09	0.24	0.15	0.10	0.39	-0.05	0.06	-0.04	-0.04	0.11	0.21	0.09	0.14	-0.10
Vegetation II	-0.22	0.19	-0.58	-0.65	-0.16	-0.46	0.54	-0.20	-0.47	-0.36	-0.29	-0.49	-0.45	-0.39	-0.13
Topography/Sun	0.10	0.52	0.24	0.29	0.02	0.31	0.25	0.30	0.15	-0.02	0.19	0.17	0.19	0.07	0.05
Precepitation	0.10	0.12	-0.05	-0.19	-0.02	0.22	0.24	-0.01	-0.11	-0.31	0.08	0.05	0.07	-0.08	-0.04
Sunshine	0.13	-0.16	-0.09	-0.30	0.00	-0.09	-0.63	0.00	-0.10	0.08	-0.06	0.07	-0.06	0.06	-0.03
Water vapor	-0.14	0.16	0.00	0.14	-0.02	-0.41	0.08	-0.20	-0.21	-0.23	-0.22	-0.33	-0.21	-0.11	-0.24
Topography II	0.06	0.54	0.48	0.61	0.19	0.50	0.02	0.16	0.15	0.06	0.13	0.13	0.21	0.17	0.00

APPENDIX M

STANDARDIZED REGRESSION GLM COEFFICIENT (ABUNDANCE SPRING EV)

APPENDIX M. Standardized regression generalized linear models (GLM) coefficients (β) for spring bird abundance environmental variables (EV) models. Higher absolute values indicate more importance within model. Signs indicate relationship to abundance. β values were used to generate spring portion of Figure 3.6.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean diurnal Range	0.06	0.20	0.00	-0.02	-0.12	0.03	0.01	-0.03	0.07	0.00	-0.07	0.11	-0.03	0.03	0.02
Mean temp Warmest qrt	0.28	0.34	0.38	0.42	0.28	0.26	0.26	0.35	0.31	0.36	0.50	0.31	0.31	0.22	0.17
Precip driest qrt	0.09	0.05	0.12	0.10	0.00	0.12	0.04	0.09	0.08	0.06	0.11	0.09	0.08	0.04	0.00
NDVI	0.22	0.29	0.10	0.19	0.24	0.17	0.28	0.12	0.20	0.32	0.56	0.36	0.23	0.23	0.41
NDVI sd	-0.16	-0.22	-0.01	-0.03	0.00	0.21	-0.02	-0.09	-0.12	-0.19	-0.32	-0.16	-0.15	-0.17	-0.19
WVP sd	0.04	-0.14	-0.01	0.09	-0.10	-0.05	0.05	-0.03	-0.16	-0.04	0.04	0.00	-0.11	-0.11	-0.07
Sunshine hrs	0.08	0.03	0.06	0.08	0.05	-0.02	0.10	0.14	0.21	0.01	0.07	-0.02	0.04	0.06	0.05
Sunshine hrs min	0.01	-0.09	0.06	0.04	0.05	0.00	-0.05	0.04	-0.02	-0.05	-0.02	-0.12	0.03	-0.01	-0.01
Aspect	0.09	0.05	0.07	0.16	-0.03	0.05	0.24	0.02	-0.06	0.10	0.25	0.24	0.06	0.04	0.10
Bulk density	-0.13	0.02	0.05	0.06	-0.16	0.19	0.16	0.05	0.09	0.01	0.01	0.15	-0.08	0.02	-0.02
Soil pH	-0.18	-0.07	-0.13	-0.17	0.03	0.05	-0.08	-0.17	-0.19	0.01	0.09	0.05	0.00	0.03	0.01
Soil diversity	0.00	-0.11	-0.06	-0.15	0.01	0.04	-0.12	-0.22	-0.24	-0.12	-0.21	-0.06	-0.05	-0.05	-0.03

qrt = Quarter; temp = Temperature; Precip = Precipitation; sd = Standard Deviation; WVP = Water Vapor Pressure; hrs = hours

APPENDIX N

STANDARDIZED REGRESSION GLM COEFFICIENT
(ABUNDANCE WINTER EV)

APPENDIX N. Standardized regression generalized linear models (GLM) coefficients (β) for winter bird abundance environmental variables (EV) models. Higher absolute values indicate more importance within model. Signs indicate relationship to abundance. β values were used to generate winter portion of Figure 3.6.

	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean diurnal Range	0.18	0.00	0.08	-0.05	0.09	0.29	-0.31	-0.01	-0.12	-0.05	0.14	0.19	0.03	0.08	-0.02
Mean temp Warmest qrt	0.40	0.42	0.83	0.78	0.56	0.84	0.20	0.37	0.47	0.60	0.42	0.47	0.41	0.33	0.53
Precip driest qrt	-0.03	-0.19	0.19	0.15	-0.08	0.22	0.34	0.15	0.18	0.02	0.01	0.04	0.15	0.05	0.01
NDVI	0.30	0.01	0.41	0.55	0.20	0.39	0.05	0.39	0.42	0.38	0.25	0.35	0.31	0.31	0.42
NDVI sd	-0.19	0.08	-0.37	-0.38	-0.11	-0.46	0.57	-0.11	-0.48	-0.38	-0.30	-0.60	-0.41	-0.27	-0.20
WVP sd	-0.15	0.11	0.16	0.32	0.06	-0.45	0.43	-0.03	-0.11	-0.05	-0.19	-0.20	-0.05	-0.05	-0.22
Sunshine hrs	0.18	0.35	0.08	0.07	0.15	0.14	-0.27	0.22	0.33	0.36	0.28	0.40	0.23	0.16	0.34
Sunshine hrs min	-0.06	0.32	-0.05	0.03	0.17	0.01	-0.06	-0.08	0.12	0.12	0.13	0.02	0.04	-0.01	0.13
Aspect	0.10	0.27	0.35	0.31	0.17	0.18	0.33	0.12	-0.06	-0.11	0.03	0.00	0.15	0.05	-0.02
Bulk density	-0.20	-0.54	0.07	0.17	-0.33	-0.06	1.11	0.27	0.09	-0.13	-0.18	-0.27	0.03	-0.02	-0.17
Soil pH	-0.27	-0.60	-0.17	0.00	-0.34	-0.05	0.87	0.01	-0.11	-0.30	-0.30	-0.47	-0.25	-0.16	-0.26
Soil diversity	0.06	-0.50	-0.22	-0.34	-0.11	-0.21	0.50	-0.20	-0.43	-0.47	-0.15	-0.31	-0.22	-0.17	-0.10

qrt = Quarter; temp = Temperature; Precip = Precipitation; sd = Standard Deviation; WVP = Water Vapor Pressure; hrs = hours

BIOGRAPHICAL SKETCH

Cameron Boehme is a second-year master's degree student working towards a degree in Applied Biological Sciences from the College of Integrative Sciences and Arts at Arizona State University. Cameron is a prior graduate from Arizona State University with a Master of Advanced studies in geographic information systems and a Bachelor of Science in wildlife and restoration ecology. While pursuing his undergraduate degree, Cameron worked for the US Forest service for four years as a biological technician on the Terrestrial Ecological Unit Inventory team. After completion of his first master's degree, he earned a commission in the US Navy as a surface warfare officer. Although his current career is far removed from natural resource management, he continues to have a passion for the natural world and regularly volunteers with outdoor recreation clubs.