ASSESSING ENVIRONMENTAL ISSUES IN UPLAND GAME BIRDS

A Dissertation

by

BRIAN LESLIE PIERCE

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Nova J. Silvy
Committee Members,	Markus J. Peterson
	Fred E. Smeins
	X. Ben Wu
Head of Department,	Michael P. Masser

August 2017

Major Subject: Wildlife & Fisheries Sciences

ABSTRACT

Wildlife management is essentially the balance between maintenance of habitat and control of population density. To demonstrate the application of multivariate techniques for habitat assessment, I evaluated 4 contemporary classification schemes for use as experimental units for mourning dove (*Zenaida macroura*) research in Texas. I conducted a generalized canonical discriminant analysis (CDA) for each classification scheme using 25 habitat variables obtained adjacent to each of the 133 U.S. Fish and Wildlife Services call-count survey routes within Texas. Classification results from each CDA were used to generate a confusion matrix for each classification scheme (i.e., overall accuracy, average accuracy, and expected agreement). Because classification schemes differed in the number of categories, the Kappa Coefficient of Agreement was used to account for the proportion of agreement due to chance. The Kappa estimates were higher for the Gould (0.760) and Omernik (0.700) classification schemes, than for the Fenneman (0.618) or George (0.673) classification schemes, indicating the newer classification schemes provide a more accurate partitioning of multidimensional habitat space, and are therefore better suited for use as experimental units for mourning dove research in Texas. To demonstrate the impact of human land use on wildlife habitat, I evaluated the spatial-temporal effects of habitat loss and anthropogenic land use on grassland birds from 1993–2012. I used 8 habitat metrics corresponding to the U.S. Census of Agriculture data for Texas during this period, and northern bobwhite (*Colinus virginianus*) abundance estimates from the Breeding Bird Survey and Texas Parks and Wildlife Department as the proxy grassland bird species. The redundancy analysis indicated that economic, agricultural, and land use metrics accounted for 74.5% of the total variance in bobwhite relative abundance during the period (${R_{adj}}^2$ = 60.8%, $P <$

0.0016), and most anthropogenic land trend variables (e.g., Population Density, Market Value, Production Value) were inversely proportional to quail relative abundance. The canonical discriminant analysis indicated that economic, agricultural, and land use metrics explained 88.6% of the variability among ecoregions ($P < 0.0002$) and 99.5% of the variability among years ($P < 0.0167$). These results indicate that land values (market value and production value per hectare) and human population density may signal the onset of anthropogenic land conversion, and might be used to predict future changes that will impact grassland bird species and other natural resources. Finally, to demonstrate the feasibility of combining scientific and citizen-science data to obtain a regional estimate of grassland bird abundance, I obtained congruent estimates of northern bobwhite (*Colinus virginianus*) abundance using a double-sampling paradigm. Spring cock call-counts were conducted on 12 ranches within the Rolling Plains of Texas during 2012–2014. This sampling effort collected calls and distances at each point, yielding 1,022 total counts, detected 36,415 calls, 4,647 birds, and obtained 4,627 distances. Data were analyzed using program DISTANCE to generate local and regional estimates of quail density for each year, and to calibrate density estimates with birds heard using a double-sampling paradigm. My results demonstrated that it is economically feasible and logistically pragmatic to calibrate metrics obtained through citizen-science efforts (call-counts; relative abundance) with results obtained by more intensive scientific methods (distance sampling; density estimates). Collectively, these results illustrate that it is within the microcosm of single-species management that we test the limits of our ecological knowledge and understanding.

DEDICATION

I would like to dedicate this work to my wife, Dr. Barbara L. Pierce, for her enduring love, devotion, patience, and for being my best friend. Just to be with her, I would do it all over again. Amor aeternus est.

ACKNOWLEDGEMENTS

I am extremely grateful to my committee chair and committee members for their wisdom and guidance. Dr. Silvy served as my committee chair, mentor, and provided the historical insights that made many of these projects possible. Dr. Peterson acted as sparring partner and sounding board for many ideas, and heavily influence my rhetorical approach to scientific writing. Dr. Smeins guided me through the various perspectives on community ecology, and shaped my multivariate approach to the mourning dove habitat project. Dr. X. Ben Wu renewed my interest in spatial statistics, which provided the foundation for many of the analyses used during this research.

Each of the subsequent chapters contained in this dissertation were greatly improved by the comments and insights provided by Dr. Colin Bibby, Dr. David Buckland, Dr. M. J. Anderson, Dr. P. Legendre, and Dr. A. Zuur. Each patiently listened to my inquiries and provided sound advice which advanced my understanding of ecology and ecological statistics. Similarly, Dr. Bret Collier is responsible for dragging me, "kicking and screaming", into the R programming language and the paradigm of reproducible research. Bret, you were right!

I would like to extend my thanks to all the individuals who provided input into these various projects. Field work was completed through the tireless efforts of Jared Caton, Dawn Wentzel, Ben Toole, Mark Hess, Dr. T. Wayne Schwertner, Ryan Jones, Dustin Jones, John Tomecek, Randall Schlaudt, Zachary Johnson, and Danielle Miller. My special thanks to Dr. Silvy, Dustin Jones, and Ryan Jones who eagerly did far more than their fair share of data collection. Roel Lopez wore many hats during this period, serving as colleague, boss, and impromptu committee member. I am truly fortunate to call him a friend. Similarly, I am especially thankful to Jay Roberson of Texas Parks and Wildlife for his collaboration, determination, and support. His enthusiasm and dedication to wildlife science is a model of public service for which we can all be proud.

I owe a huge debt to Mr. Michael Frisbie, whose support, camaraderie, and intellectual insights yielded the collaborative efforts that became the methodological foundation for all distance sampling efforts within Texas Parks and Wildlife (the Mourning Dove distance sampling survey, urban dove distance sampling survey, and the deer distance sampling survey). Worse, he not-so-willingly stood beside me, and was therefore instrumental in completing the "Herculean Task" that was the Texas Dove Lethality Test. He, astonishingly, still remains a close personnel friend.

Finally, I am the product of many mentors whose tireless efforts on my behalf continues to bewilder me, long after they have all gone: Mr. Bennie Pierce, Mr. Donald Purswell, Ms. Caroline Conrads, Mr. Wayman Thorpe, Mr. Densley Utz, and Maj. Ken Jeffreys (U.S. Army). Ergo sum, quid tu creati.

CONTRIBUTORS AND FUNDING SOURCES

CONTRIBUTORS

This work was supported by a dissertation committee consisting of Professors Nova J. Silvy and Markus J. Peterson of the Department of Wildlife and Fisheries Sciences, and Professors Fred Smeins and Ben X. Wu of the Department of Ecosystems Science and Management.

The data in Chapter II was collected in part by Jared Caton, Dawn Wentzel, Ben Toole, Mark Hess, Ryan Jones, Dustin Jones, and Professor Nova J. Silvy of the Department of Wildlife and Fisheries Sciences, and Mike Frisbie, T. Wayne Schwertner, and Jay Roberson of the Texas Parks and Wildlife Department. The data in Chapter III was collected in collaboration with Israel Parker, Addie Smith, Amanda Anderson, Kevin Skow, and Ross Anderson of the Texas A&M Natural Resources Institute. The data in Chapter IV was collected in collaboration with John Tomecek, Randall Schlaudt, Zachary Johnson, and Danielle Miller of the Department of Wildlife and Fisheries Sciences. The TAMU LaTeX "Chapter Style" dissertation template was developed in collaboration with Sean Robinson of the Office of Graduate and Professional Studies.

All other work conducted for the dissertation was completed by the student independently.

FUNDING SOURCES

This work was made possible by grants from Texas Parks and Wildlife Department, The Rolling Plains Quail Research Foundation, and Texas A&M University AgriLife Extension.

The contents of this dissertation are solely the responsibility of the author and do not necessarily represent the official views of the funding agencies.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

TABLE Page

CHAPTER I

INTRODUCTION

MOURNING DOVE

Since the signing of the Migratory Bird Treaty Act in 1918, national management of mourning dove (*Zenaida macroura*) has consisted primarily of estimating population trends and establishing hunting regulations, with additional efforts to estimate various demographic parameters initiated independently within several states (National Mourning Dove Planning Committee 2004). Through these efforts a considerable amount of autecological knowledge has been gained (Baskett 1993), but this information has proven insufficient for determining the relative contribution of habitat loss (including habitat change) on either the long-term mourning dove population trend, or the long-term trend in the mourning dove call-count survey (CCS). Consequently, due to the lack of any estimate on the impact of habitat loss on mourning dove populations, the information currently available provides managers with little insight into the relative influence of proposed changes in harvest regulations on future mourning dove population trends (National Mourning Dove Planning Committee 2004). Yet bureaucratic inertia will no doubt rationalize changes in harvest regulations as the proper and necessary response to perceived declines in the mourning dove call-count index, as the exercise of regulatory authority is the means by which governmental agencies legitimize their existence under the so-called doctrine of public trust.

In the 2006 Mourning Dove Population Status Report (Dolton and Rau 2006), significant ($P \leq 0.05$) declines in the (1966–2006) CCS index trends of dove heard were reported for all 3 management units (Eastern [EMU], Central [CMU], and Western [WMU]). Of particular concern, significant declines in dove heard occurred in the 2-year

(2005–2006), 10-year (1997–2006), and 41-year (1966–2006) trends for the CMU. Texas, which comprises the largest proportional land area and the largest number of call-count survey routes (CCS; 133) within the CMU, showed a significant decline for dove heard in the 10-year (1997–2006) call-count index trend, but a non-significant decline for dove heard in the 41-year (1966–2006) trend. Surprisingly, the trends for mourning dove seen do not parallel the trends for dove heard in any management unit, which is especially troubling since both metrics are obtained concurrently from the same populations (Dolton and Rau 2006). This disparity begs the question as to which metric or trend (dove heard or dove seen) best reflects the actual trajectory of mourning dove populations. Questions of this type indicate that, at the very least, we should examine the validity of the data and associated methodology.

Further contradiction arises when we consider the annual yield from mourning dove populations. Contemplate for a moment that the mourning dove is 1 of the 10 most abundant and ubiquitous of North American bird species (Aldrich and Duvall 1958, Grue et al. 1983, Robbins et al. 1986, Baskett and Sayre 1993, Peterjohn et al. 1994), with a population size estimated to be between 350 million and 600 million birds (Dunks et al. 1982, Tomlinson 1988, Sadler 1993). Sadler (1993) reported that annual harvest in the United States averaged 45.6 million birds between 1983 and 1987, or approximately 10.8% of the estimated annual autumn population (Dunks et al. 1982, Tomlinson 1988, Sadler 1993). With such a small portion of the estimated population harvested each year, one must question the validity of existing information: would a complete moratorium on harvest reverse the presumed long-term downward trends, is population size being overestimated, is harvest being underestimated, and how important are changes in land use to the declining trends in dove heard? These questions have been asked before (Dambach 1948, Southeastern Association of Game and Fish Commissioners 1957), and bear striking resemblance to questions currently being raised by the National

Mourning Dove Planning Committee (2004).

To paraphrase Dambach (1948), my objective is not to minimize the importance of harvest regulations; rather it is to point out their limitations in terms of perpetuating the species at levels which will allow for equitable use of the resource by all parties. Similarly, I note that changes in harvest regulations are not likely to alter declines in dove abundance due to habitat depletion or downward trends resulting from survey timing (e.g., near term trend caused by CCS initiation during a population maximum; see comparison of CCS to Missouri Roadside Dove Survey in Schulz 2006). Further, the current National Mourning Dove Planning Committee (2004) explicitly states that information currently available is insufficient to predict what effect alterations in harvest regulations will have on mourning dove populations. As such, while it is anticipated that some form of harvest restrictions may be mandated if the downward trend in the CCS index continues, changes in harvest regulations will not identify, and likely will not alter, the major underlying factors influencing mourning dove populations.

NORTHERN BOBWHITE

Grassland birds are declining at an alarming rate, commensurate with losses of grassland habitat. An icon of grassland birds, the northern bobwhite (*Colinus virginianus*), is one of the most intensively studied bird species, with over 3,500 publications dedicated to it's natural history, autecology, and management. Yet, despite this enormous amount of research, the species has undergone a substantial long-term decline. While previous research has identified several biotic factors which influence abundance in a stochastic manner (i.e., short and long term weather fluctuations, disease), researchers have speculated that habitat loss due to anthropogenic land use change is the most likely cause for the long-term decline. Because land use change is both spatially and temporally variable, monitoring efforts over broad spatial and temporal scales are needed if we are to identify the signs or symptoms of impending habitat loss.

To investigate the factors influencing the decline in northern bobwhite, I utilize data from a recent multi-year survey of land trends (Anderson et al. 2014) to demonstrate the utility of commonly available anthropogenic metrics for detecting early signs of impending land use change and potential degradation of grassland bird habitat. I limit my discussion to northern bobwhite across 6 Ecoregions of Texas (Gould 1962, 1975). My habitat analysis objective is to demonstrate that common anthropogenic land use variables may be a cost effective and highly efficient method for monitoring threats to habitat quality for all grassland bird species.

To assess the potential of using citizen-science manpower to obtain abundance or relative abundance data at a higher spatial resolution, I utilize data from a recent multi-year survey of bobwhite in the Rolling Plains Ecoregion of Texas (Gould 1962, 1975) to demonstrate the utility of the double-sample calibration approach for citizen-science monitoring of northern bobwhite. I limit my discussion to conventional distances sampling for simplicity, but acknowledge that other methods for estimating the probability of detection are viable alternatives in a double-sampling paradigm. My abundance analysis objective is to demonstrate that contrary to recently published findings (Rollins et al. 2005, Applegate et al. 2011, Murray et al. 2011, Texas A&M AgriLife Extension 2013), distance sampling is an efficacious method for monitoring bobwhite abundance. Further, I assert that successful implementation of a double-sampling calibration is required for citizen-science monitoring efforts, due to spatial-temporal differences in detection probability (i.e., between periods or among habitat types). Ultimately I seek to encourage debate, further development of techniques, and illustrate alternative solutions for the use and incorporation of citizen-scientists into grassland bird monitoring efforts.

DISSERTATION THEME

This dissertation is divided into chapters, each of which represents an independent research objective in the field of Wildlife Management. Collectively, these works attempt to ascertain appropriate experimental units for statewide monitoring, which habitat variables are correlated with the annual abundance surveys, whether the habitat variables adjacent to the survey routes/points have changed over time, and if mitigating factors may have influenced the perceptions of population trajectories. As such, each chapter represents a fundamental, but typical, example of the problems and solutions faced within Wildlife Management. I note here that the "problems" faced in each chapter have existed for decades, and the solutions offered are novel attempts to address each problem using Cartesian skepticism (methodological doubt) where all previous assumptions are removed, re-evaluated, and placed back into consideration if and only if warranted within the context of the problem. The paradigm is an attempt to demonstrate the relevance of wildlife management as a field of scientific endeavor, and to demonstrate the need to re-evaluate single species management over time in order to incorporate new technology and knowledge. As such any errors in logical validity, relative truth of premises, or interpretation of results are mine alone.

Chapter I provides an introduction and overview. Chapter II questions the delineation of experimental units used for the current mourning dove call-count survey, and demonstrates a multivariate technique for evaluating classification schemes (experimental units) in species–habitat research. Chapter III investigates factors influencing the decline of northern bobwhite in Texas, and demonstrates the use of anthropogenic metrics for predicting land use change and loss of grassland bird habitat over the last 20 years. Chapter IV investigates the use of distance sampling, within a double-sampling paradigm, for potential citizen-science monitoring of grassland birds using northern bobwhite as an example. Chapter V provides a summary of these projects, and attempts to demonstrate the relevance of wildlife management as a field of science that not only increases ecological knowledge, but also provides the information necessary for natural resource management.

CHAPTER II

CHAPTER II DEFINING EXPERIMENTAL UNITS FOR MOURNING DOVE

SYNOPSIS

Ecological studies, regardless of whether they are manipulative or mensurative in nature, should clearly define the experimental units that form the basis for sampling and analysis. In order to investigate the relationship between mourning dove (*Zenaida macroura*) habitat and abundance, I evaluated 4 contemporary classification schemes for use as experimental units in Texas. I conducted a generalized canonical discriminant analysis (CDA) for each classification scheme using a response data matrix (Y) comprised of 25 habitat variables (p) obtained adjacent to each of the 133 U.S. Fish and Wildlife Services call-count survey routes (n) within Texas. The CDA for each classification was constrained by a design matrix (X) representing the categorical groups within each classification scheme. Classification results from each CDA were used to generate a confusion matrix for each classification scheme (i.e., overall accuracy, average accuracy, and expected agreement). Because classification schemes differed in the number of categories, the Kappa Coefficient of Agreement was used to account for the proportion of agreement due to chance. The Kappa estimates were higher for the Gould (0.760) and Omernik (0.700) classification schemes, than for the Fenneman (0.618) or George (0.673) classification schemes. The results indicate that the Gould (1962) and Omernik (1987) classification schemes provide a more accurate partitioning of multidimensional habitat space than the Fenneman (1928) or George (1982) classification schemes, and are therefore better suited for use as experimental units for mourning dove research in Texas.

INTRODUCTION

Experimental design encapsulates "the logical structure" of an experiment (Fisher 1971). The fundamental building block of experimental design is the experimental unit, defined as the smallest, independent subdivision of homogeneous experimental material that can be assigned a single treatment. The size and extent of each experimental unit depends upon the nature of the experiment, type of treatments, amount of replication, and the intended frame of inference. In addition, homogeneity within experimental material is of pivotal consideration, as variation among experimental units treated alike determines the magnitude of experimental error. Because we typically conceive experiments in terms of a statistical model (i.e., Response = Treatment Effect + Design Effect + Error), experimental units form the basis for all subsequent statistical analyses. It is therefore necessary for all autecological studies, regardless of whether they are manipulative or mensurative in nature, to clearly define the experimental units used within each experiment (Hurlbert 1984, 2013).

In order to investigate the relationship between mourning dove (*Zenaida macroura*) abundance and habitat, one must first identify and delineate homogeneous experimental units for the design of experiments. Because mourning doves are ubiquitous throughout Texas, any resulting experimental units are comprised of biotic and abiotic variables whose multivariate domain encompasses the n-dimensional hypervolume defining the "fundamental niche" of mourning dove (Grinnell 1917, Hutchinson 1957). To identify those variables defining the fundamental niche of mourning dove in Texas, and to make inference across the broader species range, requires an individualistic perspective (Gleason 1926, Whittaker 1956, 1967). Gleason’s (1926) individualistic concept allows us to focus attention on the identification of underlying biotic and abiotic variables that influence mourning dove abundance. Further, the individualistic concept provides the multivariate basis for the spatial delineation of similar environmental conditions (i.e., biotic and abiotic conditions), and thus areas of relatively homogeneous experimental material that can define experimental units in studies of population abundance (Goodall 1954, Bray and Curtis 1957, Whittaker 1967, Greig-Smith 1980, Gauch 1982).

Researchers have previously evaluated classifications schemes for use as experimental units in mourning dove research. Blankenship et al. (1971) compared the physiographic classification of Fenneman (1928, 1931, 1938), the potential natural vegetation classification of Küchler (1964), and a modification of the Küchler classification which accounted for cultural land use changes (agriculture) using nationwide mourning dove call-count survey results. Dove relative abundance (dove heard; 1964–1968) was analyzed by ANOVA using classification categories as treatment factors, where a higher F-ratio indicated minimization of the error variance, and therefore a better partitioning (homogeneity) of the response variable by the classification scheme. Results indicated the modified Küchler, and the original Küchler (1964) classification, were superior to the Fenneman (1928, 1931, 1938) classification in minimizing the error variance, and therefore better suited for use as experimental units in the analysis of nationwide call-count survey data (Blankenship et al. 1971). Similarly, Grue et al. (1976, 1981, 1983) conducted a study of mourning dove habitat in Texas and compared classification schemes by Fenneman (1928, 1931, 1938), Carr Jr. (1967), Godfrey et al. (1967), and Gould (1962) using the F-ratio technique of Blankenship et al. (1971). The objective of Grue et al. (1976, 1981, 1983) differed in resolution and extent, but was otherwise similar to the nationwide experimental design evaluated by Blankenship et al. (1971). The results of Grue et al. (1976, 1981, 1983) were significant for each classification scheme tested, with the Gould (1962) classification having the highest F-ratio (minimized error variance), and therefore the most suitable delineation of dove relative abundance in Texas.

I repeated the study of Grue et al. (1976, 1981, 1983) using canonical discriminant analysis (CDA; Anderson and Robinson 2003, Anderson and Willis 2003) to evaluate 4 contemporary classification schemes (Fenneman 1928, Gould 1962, George 1982, Omernik 1987) for potential use as mourning dove experimental units within Texas. These classification schemes are currently used by researchers for monitoring national mourning dove inventories (Fenneman 1928), vegetational communities (Gould 1962), regulating dove harvest (George 1982), and for monitoring and management of environmental resources within Texas and nationwide (Omernik 1987, Griffith et al. 2004, 2007). Unlike Blankenship et al. (1971) or Grue et al. (1976, 1981, 1983), the present study evaluates classification suitability using multiple environmental variables collected adjacent to each call-count transect in Texas. Note that, for this purpose, the assessment of classification categories with multiple habitat variables using CDA, MANOVA, or other multivariate techniques (Fisher 1936, ter Braak 1995, Legendre and Legendre 1998, Dale et al. 2002) is analogous to the Blankenship et al. (1971) and Grue et al. (1976, 1981, 1983) comparison of habitat classification categories using a single explanatory variable (dove heard) with ANOVA.

While previous research assumed the number of dove heard was both proportional to dove density and the product of broad-scale biotic and abiotic habitat conditions, the present study assumes that similar numbers of dove heard or dove seen can arise in areas with dissimilar mourning dove density due to differences in detectability (Burnham 1981, Burnham and Anderson 1984, Buckland et al. 2001). Likewise, similar densities may occur in areas with dissimilar habitat conditions due to chance, or to relative location within the multivariate domain defining fundamental niche conditions (Gleason 1926, Hutchinson 1957, ter Braak 1986, Jongman et al. 1995, Legendre et al. 2005). Regardless, by delineating experimental units based upon multiple habitat variables, rather than using a single proxy variable that is a combination of species abundance and detectability, I hope to alleviate any potential confounding between habitat and mourning dove abundance in future dove research efforts.

STUDY AREA

The study area covers 695,622 km^2 between 25°50’N and 36°30’N latitude (1,270 km north to south), 93°31’W and 106°38’W longitude (1,244 km east to west), within the southwestern portion of continental North America (Fig. 2.1; Alvarez et al. 2005). Elevations range from 2,667 m in the west to 0 m along the Gulf of Mexico, with a mean elevation of 520 m (Arbingast 1976). The climate of Texas is highly variable, with temperature, frost, and growing season gradients parallel to the northwest to southeast elevation gradient within the state (Arbingast 1976). A bimodal precipitation pattern (spring and fall rainfall peaks) covers the majority of the state and droughts are common, with more years of below average than above average annual rainfall (Gould 1962). Mean annual precipitation increases from west to east, with the arid west receiving >20 cm/year while the mesic east receives upward of 140 cm/year. The geology of Texas is diverse, with surface exposures dating back 600 million years (Arbingast 1976). Because of the complex interactions among climate, surface geology, and vegetation, Texas contains over 1,300 distinct soil types (Gould 1962, Alvarez and Plocheck 2005). This variation in biotic and abiotic factors across the study area illustrates the diversity of habitat conditions that must be partitioned into homogeneous experimental units for any successful study of mourning dove. The accurate delineation of experimental units is necessary for assessing spatial-temporal differences in density and detectability for any species, but is paramount for investigations of habitat generalist, such as the mourning dove.

Figure 2.1: Location and extent of study area within the United States for the 2002 mourning dove habitat study in Texas.

METHODS

DATA COLLECTION

Four classifications were selected for evaluation based upon contemporary use. The Fenneman physiographic classification (hereafter Fenneman; Fenneman 1928, 1931, 1938) covers all of North America and delineates areas based on similar geologic character (Fig. 2.3). It was selected by Foote (Foote 1959, unpublished report) as the framework for stratified random sampling in the mourning dove call-count survey (Blankenship et al. 1971, Dolton 1993). The mourning dove hunting zones for Texas (hereafter Hunt Zone; George 1982, George 1984) was designed to provide a latitudinal offset in the timing of opening day hunting to protect juvenile mourning dove, distribute equitable harvest opportunity across the state, and to simplify hunting regulations within Texas (Fig. 2.2). The Ecoregions of Texas (hereafter Omerik; Griffith et al. 2004, Griffith et al. 2007) is an integrated refinement of the hierarchical structure established by the U.S. Environmental Protection Agency, based upon the level III ecoregions initially defined by Omernik (Omernik 1987, Omernik and Griffith 2014). It was designed to delineate areas of similar environmental conditions for the research and monitoring of ecosystems (Fig. 2.4). The Gould classification (hereafter Gould; Gould 1962) covers the state of Texas and was designed to summarize the environmental factors and ecological associations defining the 10 vegetational areas within the State (Fig. 2.5).

Original maps representing each classification were compared to a geographic information systems (TNTmips; www.microimages.com) map layer containing locations for each mourning dove call-count survey transect in Texas. Routes were placed into categories for each classification, and all data was stored in a relational database (Filemaker Pro; www.filemaker.com) for subsequent analysis. The Arizona and New Mexico Mountains ecoregion of the Omerik classification extends only into the

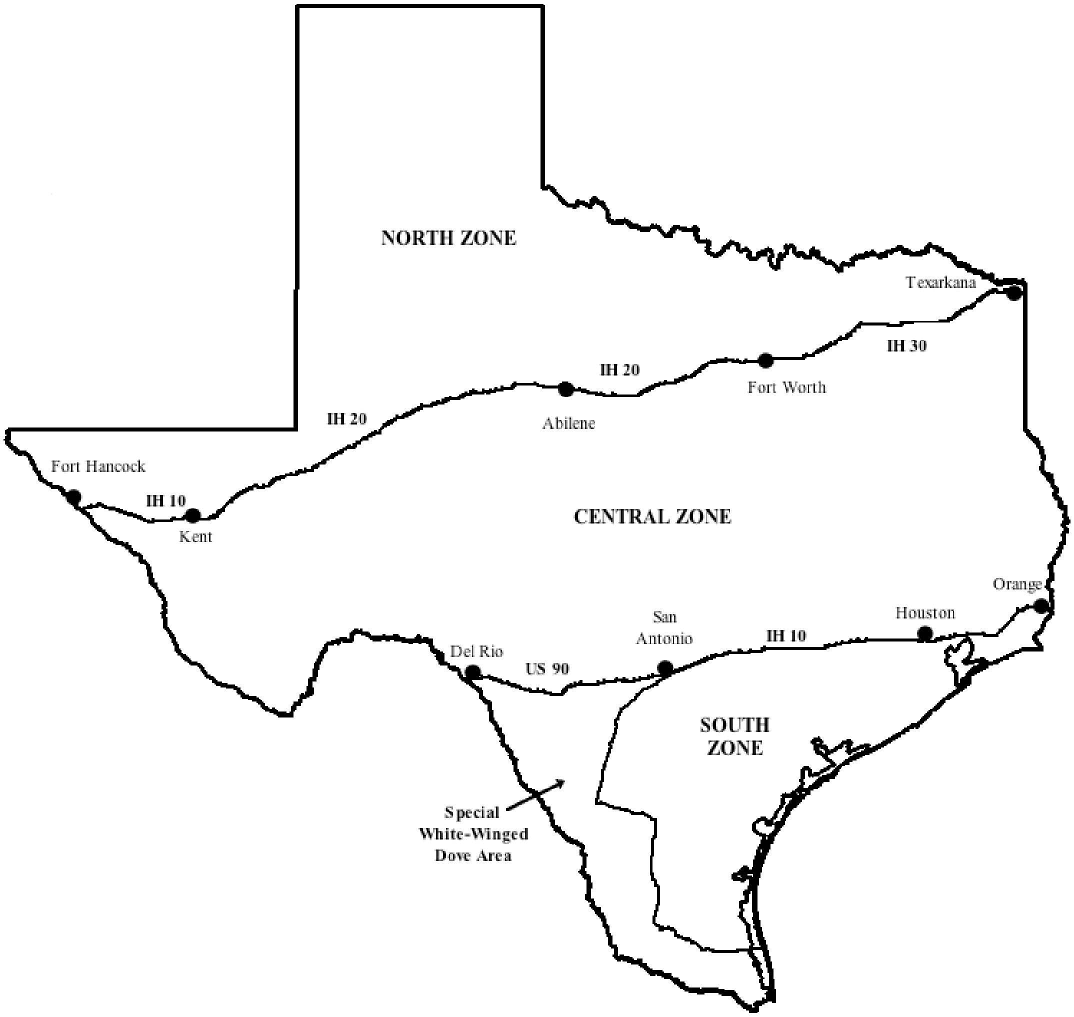


Figure 2.2: The George (George 1982) mourning dove hunting zones of Texas, used during the 2002 mourning dove habitat study in Texas.

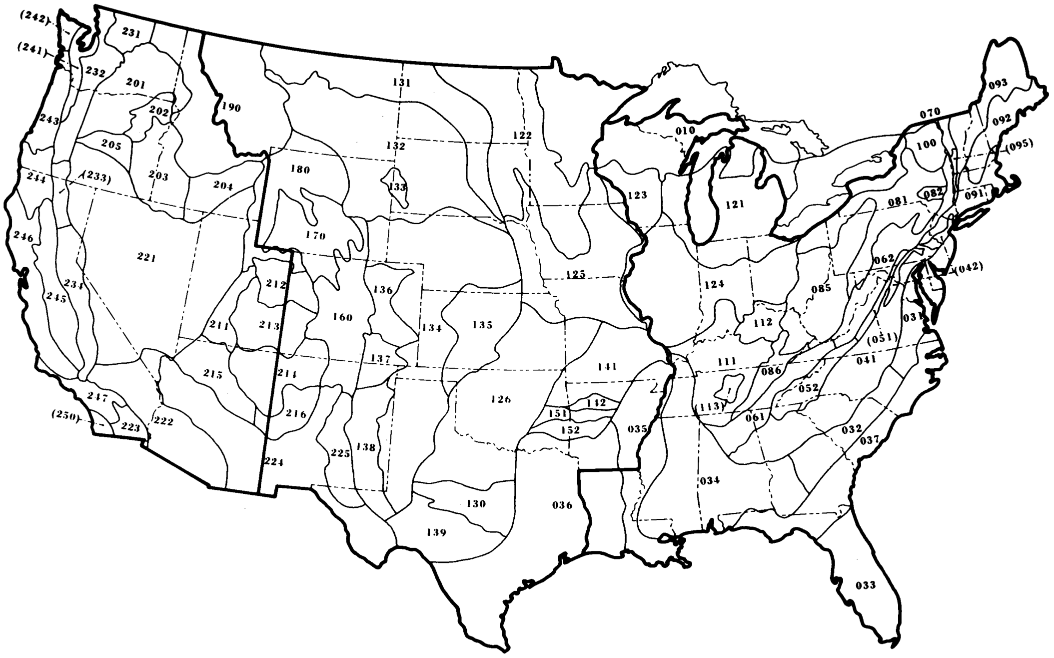


Figure 2.3: The Fenneman (Fenneman 1928) physiographic regions of the United States, used during the 2002 mourning dove habitat study in Texas.

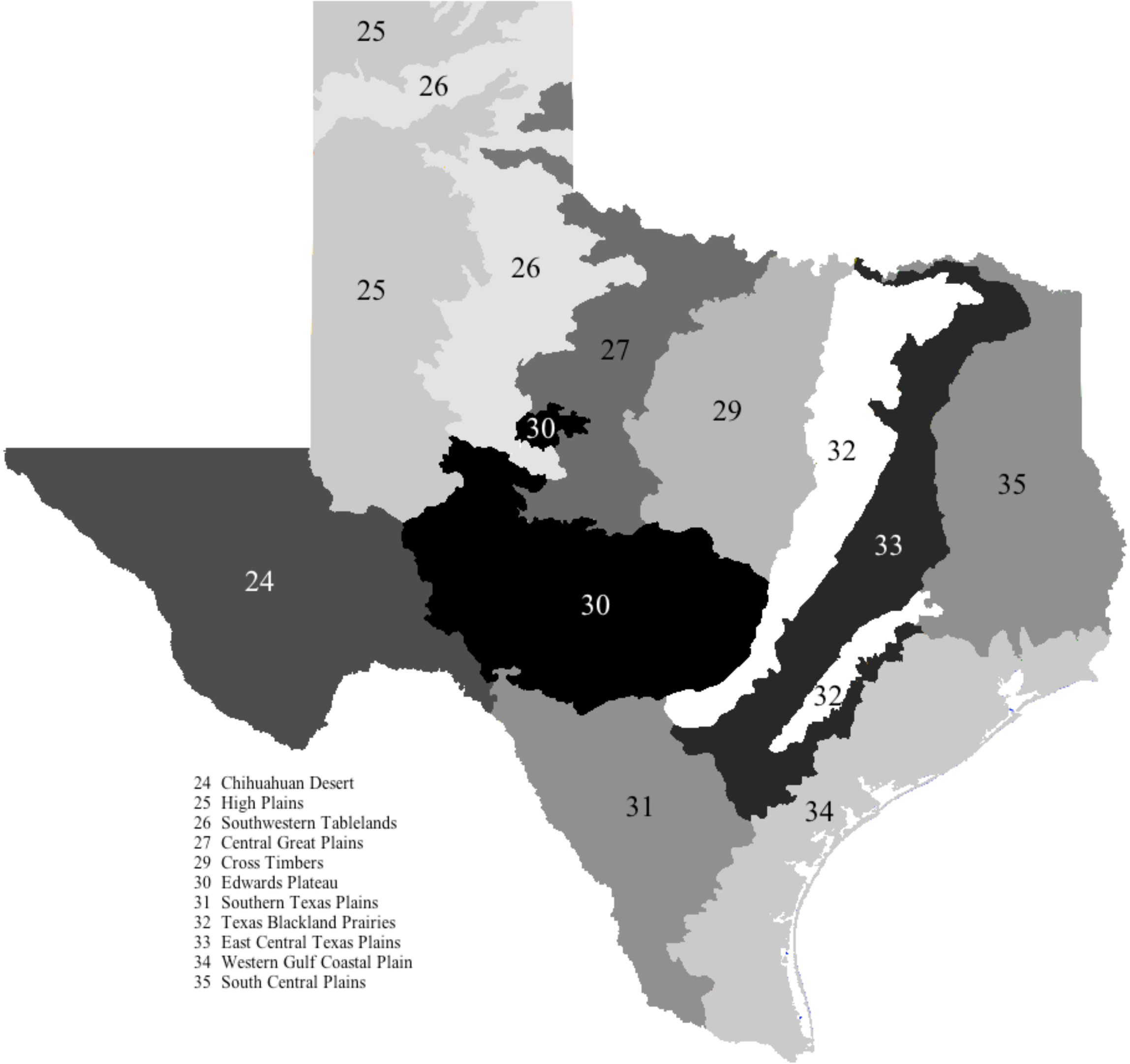


Figure 2.4: The Omernik (Omernik 1987) ecoregions of Texas, used during the 2002 mourning dove habitat study in Texas.

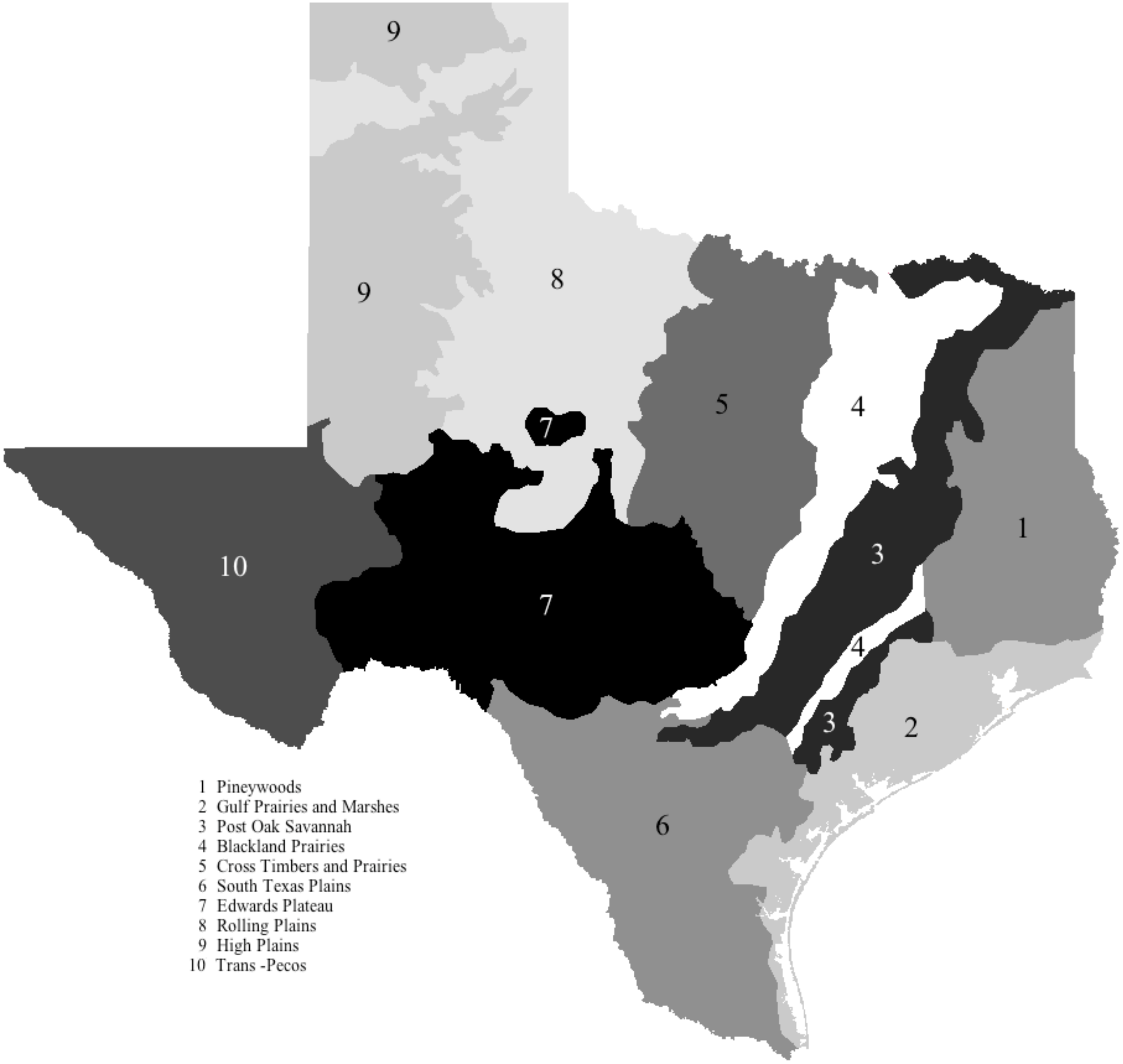


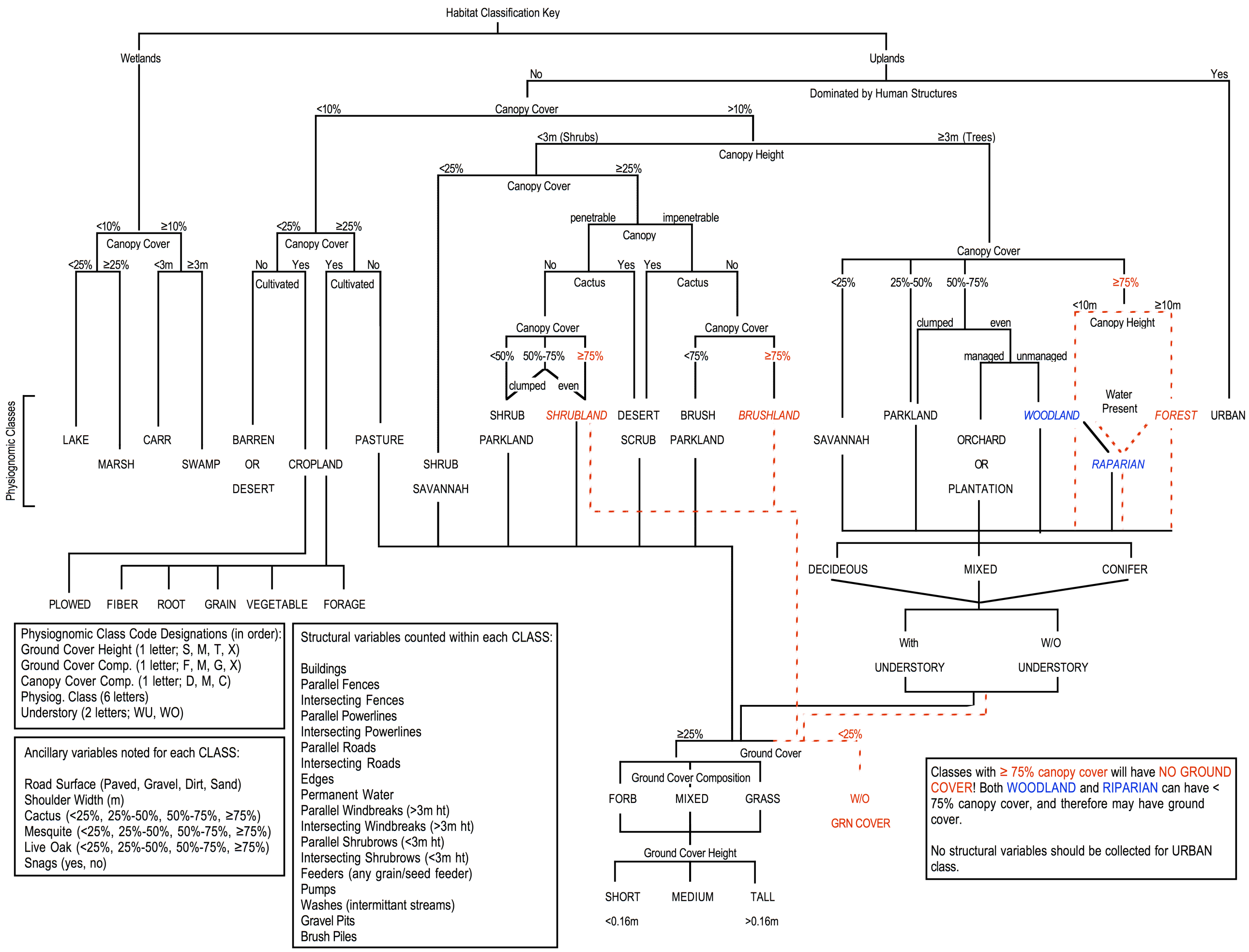
Figure 2.5: The Gould (Gould 1962) ecoregions of Texas, used during the 2002 mourning dove habitat study in Texas.

Guadalupe Mountains National Park within Texas, covering a small area that does not contain a mourning dove call-count route (Griffith et al. 2004, Griffith et al. 2007). As such, the Omerik classification was analyzed with 11, rather than 12 categories. All other classifications had at least 1 mourning dove call-count survey route within each category (Fenneman = 8, George = 3, Omerik = 11, Gould = 10) for analysis.

Habitat data were collected adjacent to each call-count survey route in Texas (*n* = 133) during the summer of 2002. All routes were located according to the stratified random sample design of the U.S. Fish and Wildlife Service mourning dove call-count survey (Dolton 1993). Environmental variables were collected at 2 spatial scales (local and regional) to assess classification suitability as experimental units for future mourning dove research. Physiognomic data were collected using the methodology of Grue et al. (1976, 1981, 1983) to gather data at the local scale, but the technique was modified to take advantage of handheld devices (HP IPAQ; www.HP.com) for faster data input and to reduce transcription errors (Fieldworker software; www.Fieldworker.com). Local surveys obtained physiognomic data, structural features, and locational information (Lat/Long; WGS84 datum). Regional agricultural and population variables were obtained from the U.S. Department of Agriculture and the U.S. Census Bureau for each county that contained a call-count survey route. Climatic variables including annual precipitation, mean temperature maximum, mean temperature minimum, and 30-year mean precipitation, maximum temperature, and minimum temperature were obtained from the PRISM Group at Oregon State University (PRISM Group; www.prism.oregonstate.edu). All spatial data were georeferenced and extracted (GPS data, raster, and vector coverages) using geographic information system software (TNTmips; www.microimages.com), and compiled within a relational database (Filemaker Pro; www.filemaker.com) for subsequent queries and analyses.

The dichotomous key of Grue et al. (1976, 1981, 1983; Fig. 2.6) was designed to exhaustively categorize all physiognomic conditions within North America (562 possible categories). While similar in outcome to the community classifications of Küchler (1964) and Daubenmire (1966), the method obtains rapid estimates of physiognomy (structure, composition, and spatial arrangement) analogous to the relevé method of Braun-Blanquet (Braun-Blanquet 1932, Westhoff and van der Maarel 1973, van der Maarel 1979, Gauch 1982). However, the categorical outcomes generated using the Grue et al. (1976, 1981, 1983) method presented several obstacles to data analysis when used as independent variables in statistical analyses: (1) the number of possible categorical outcomes (p = 562; Grue 1977:40) far exceeded the number of samples (n = 133) in the study, (2) many outcome categories were zero inflated due to limited occurrence, and (3) the redundancy of information among outcome categories produced large amounts of collinearity (Legendre and Legendre 1998, Ott and Longnecker 2001, Zuur et al. 2007). Grue (1977) avoided these problems during his evaluation of classification schemes through univariate analysis of mourning dove relative abundance, but later acknowledged that subsequent efforts to correlate habitat outcome categories with dove abundance using multiple linear regression were likely affected, resulting in spurious correlations and inflated estimates of explained variation (Grue et al. 1981). To alleviate this problem, I recoded the categorical outcomes using the decision nodes of the dichotomous key (Fig. 2.6). This recoding reduced dimensionality, with no loss of information, by replacing the categorical outcomes with the habitat variables that define the physiognomic land use types within the original key. The results of this recoding, when combined with local structural, regional agricultural, and regional climatic variables, reduced the data set to 91 variables.

The reduced set contained 91 habitat variables, which were evaluated for collinearity and interpretive suitability. Collinearity among the habitat variables was assessed using the tolerance statistic (Tolerance = 1 - R^2; reciprocal of the variance inflation factor or



Physiognomic Class Code Designations (in order):
Ground Cover Height (1 letter; S, M, T, X)
Ground Cover Comp. (1 letter; F, M, G, X)
Canopy Cover Comp. (1 letter; D, M, C)
Physiog. Class (6 letters)
Understory (2 letters; WU, WO)

Ancillary variables noted for each CLASS:

Road Surface (Paved, Gravel, Dirt, Sand)
Shoulder Width (m)
Cactus (<25%, 25%-50%, 50%-75%, ≥75%)
Mesquite (<25%, 25%-50%, 50%-75%, ≥75%)
Live Oak (<25%, 25%-50%, 50%-75%, ≥75%)
Snags (yes, no)

Structural variables counted within each CLASS:

Buildings
Parallel Fences
Intersecting Fences
Parallel Powerlines
Intersecting Powerlines
Parallel Roads
Intersecting Roads
Edges
Permanent Water
Parallel Windbreaks (>3m ht)
Intersecting Windbreaks (>3m ht)
Parallel Shrubrows (<3m ht)
Intersecting Shrubrows (<3m ht)
Feeders (any grain/seed feeder)
Pumps
Washes (intermittant streams)
Gravel Pits
Brush Piles

Classes with ≥ 75% canopy cover will have NO GROUND COVER! Both WOODLAND and RIPARIAN can have < 75% canopy cover, and therefore may have ground cover.

No structural variables should be collected for URBAN class.

Figure 2.6: Habitat classification key modified from Grue et al. (1976, 1981, 1983) for ground assessment of land cover type used during the 2002 mourning dove habitat study in Texas.

VIF), with values near zero indicating linear dependence, resulting in removal of 1 or more variables. Through this process, 66 of the 91 variables in the raw data set were removed due to collinearity. The remaining 25 variables (Table 2.1) were used in the evaluation of habitat classification schemes. One call-count survey route was not completed due to hazardous conditions (under repair), bringing the total number of samples to 132 call-count survey routes. The resulting data set used in subsequent analyses was a rectangular matrix of 132 sites (n) and 25 variables (p).

DATA ANALYSES

I used canonical analysis of principle coordinates (CAP) to conduct a generalized canonical discriminant analysis (CDA) of each classification scheme (Anderson and Robinson 2003, Anderson and Willis 2003). The CAP procedure is a 2-step process that consists of a principle coordinate analysis (PCoA; also called multidimensional scaling) followed by a CDA on the unscaled orthonormal principle coordinate axes. The CAP method differs from parametric discriminant analysis and other multi-response permutation methods, in that any symmetric distance or dissimilarity coefficient may be used (McArdle and Anderson 2001, Mielke and Berry 2001). The CDA test statistics generated by CAP are based upon canonical correlations, are invariant to changes in the distribution of the original variables, have asymptotic distributions under permutation of the observations, and group differences are not obscured by correlations among variables (Anderson and Robinson 2003, Anderson and Willis 2003). As such, the method overcomes the statistical limitations identified by Grue et al. (1976, 1981, 1983; collinearity, $p \geq n$, lack of normality, and zero inflation). All CDA analyses were based upon standardized Euclidean distances, as this symmetrical distance coefficient is appropriate for analysis of environmental descriptors, especially when zero represents the valid measurement of an environmental variable (Legendre and Legendre 1998).

Table 2.1: Local and regional habitat variable names and descriptions used during the 2002 mourning dove habitat study in Texas.

Variable Name	Description
Paved[a]	length of paved road surface
Gravel[a]	length of gravel road surface
Human[a]	length of urban landcover
CanCv0[a]	length of 0%–10% canopy cover
CanCv75[a]	length of >75% canopy cover
CanHt0[a]	length of canopy height <3m
CanHt10[a]	length of canopy height >10m
Grain[a]	length of commercial grain crops
DecCC[a]	length of deciduous canopy cover
ConCC[a]	length of coniferous canopy cover
Cact25[a]	length of cactus cover >25%
Interspersion[b]	count of physiognomic changes
P Pow[b]	count of parallel powerlines
P Wndbrk[b]	count of parallel windbreaks
Bldgs[b]	count of buildings
Wash[b]	count of ephemeral stream beds
Irrigation[b]	number of irrigation units
PopDen2000[c]	county population density in year 2000 (number/sq km)
CntyGravDen[c]	county gravel road density (km/sq km)
CntyPavedDen[c]	county paved road density (km/sq km)
CntyIrrigDen[c]	county irrigation density (ha/sq km)
CntyGrain[d]	county dove edible grain crop density (ha/sq km)
elevation(m)[e]	elevation (m)
pptnorms(mm)[e]	average annual precipitation (mm) for 1970–2000
tminnorms(c)[e]	average annual daily minimum temperature (C) for 1970–2000

[a] Variable length measured adjacent to CCS transect.

[b] Variable quantity counted adjacent to CCS transect.

[c] Variable density within the county containing the CCS transect.

[d] Wheat, oats, barley, rice, sorghum, soybean, and sunflower density within the county.

[e] Variable quantity measured at CCS transect midpoint.

Significance test were generated using 5,000 permutations. The null hypothesis of no difference among groups was expected to be false for each classification scheme *a priori* (i.e., a dull null), but tested for retroduction purposes (Romesburg 1981).

Site membership was estimated for each classification (4 thematic map classifications) using CDA based on differences in local and regional environmental variables. As such each site provided a multivariate estimate of habitat at each location, and each classification represented a generalization of predicted habitat conditions across the state of Texas. Cross-validation results (”leave-one-out” method; Lachenbruch and Mickey 1968, Seber 1984, Anderson and Robinson 2003) from each CDA were used to generate error or confusion matrices (rectangular table of categorical membership) for determining observed agreement (overall accuracy; proportion of all sites correctly classified), average accuracy (average of the proportions correct for each row and column), and to derive an unweighted Kappa coefficient (Cohen 1960, Congalton and Mead 1983, Congalton et al. 1983, Congalton 1991, Foody 2002) for each classification scheme. Kappa measures the proportion of agreement beyond what is expected by chance, and the associated *P*-value tests the null hypothesis of no agreement. Kappa was appropriate for this comparison due to the independence of raters (thematic classification versus environmental measurements), the use of unordered (nominal) categories in my analyses, and the assumption of unequal marginal distributions (disagreements between raters; Banerjee et al. 1999, Sim and Wright 2005, Vach 2005, Ludbrook 2008, Kottner and Streiner 2011).

I generated constrained (CDA) and unconstrained (PCoA) ordinations for the classification scheme with the highest kappa coefficient, and summarized correlations between the original variables and the CDA axes to identify those variables which contribute most to discrimination among groups. Analyses and plots were generated using CAP (Anderson and Robinson 2003, Anderson and Willis 2003), the R language for statistical computing (www.r-project.org), and DataGraph software (www.visualdatatools.com) on an Apple PowerMac workstation (www.apple.com).

RESULTS

All 4 classification schemes (Fenneman 1928, Gould 1962, George 1982, Omerik 1987) produced significant agreement with the multivariate habitat data, and were retained for further comparisons (Table 2.2). The George classification (Fig. 2.2; George 1982, George 1984) produced the highest average accuracy (80.6%) and observed agreement (79.5%), but consisted of only 3 latitudinal categories resulting in a low Kappa value (0.673). The Fenneman classification (Fig. 2.3; Fenneman 1928, 1931, 1938) contained 8 groups, but produced the lowest average accuracy (60.4%), observed agreement (69.7%), and Kappa value (0.618) among the classifications tested. The Omernik classification (Table 2.2, Fig. 2.4; Omernik 1987, Griffith et al. 2004, Griffith et al. 2007) contained 11 groups, produced a relatively high average accuracy (73.4%), observed agreement (72.7%) and Kappa value (0.700). Lastly, the Gould classification (Table 2.2, Fig. 2.5; Gould 1962) contained 10 groups, and produced the highest average accuracy (78.6%), observed agreement (78.8%), and Kappa value (0.760) among the classifications tested.

The Omernik (Omernik 1987, Griffith et al. 2004, Griffith et al. 2007) and Gould (1962) classifications achieved the highest overall classification accuracy and the highest Kappa scores, and were retained for further comparisons in terms of classification error among categories. The error matrix for the Omernik classification (Table 2.3, Fig. 2.4) indicates the greatest confusion (classification error) occurred in the East Central Texas Plains (category 33; 50.0%), Central Great Plains (category 27; 53.8%), Texas Blackland Prairies (category 32; 63.6%), Cross Timbers (category 29; 66.7%), and the Edwards Plateau (category 30; 66.7%) ecoregions. The Gould classification error matrix

Table 2.2: Summary of the number of categories, average accuracy, overall accuracy, chance agreement, kappa coefficient, 95 percent confidence limits, and kappa *P*-values for each classification tested during the 2002 mourning dove habitat study in Texas.

	Omernik	Gould	Fenneman	Hunt Zone
Categories	11	10	8	3
Average accuracy[a]	0.734	0.786	0.604	0.806
Observed agreement[b]	0.727	0.788	0.697	0.795
Chance agreement[c]	0.092	0.116	0.207	0.375
Kappa[d]	0.700	0.760	0.618	0.673
95% Lower CL[e]	0.614	0.681	0.520	0.555
95% Upper CL[e]	0.781	0.835	0.711	0.782
P-value[f]	<0.000	<0.000	<0.000	<0.000

[a] Average of row and column percent correct.

[b] Overall accuracy = total correct allocations/total number of samples.

[c] Chance agreement = (column * row)/(total sample size)^2.

[d] Kappa = (overall accuracy-chance agreement)/(1-chance agreement).

[e] Kappa confidence limits derived by bootstrap resampling (n=1000).

[f] Kappa test result *P*-value.

(Table 2.4, Fig. 2.5) indicates the greatest confusion occurred in the Gulf Prairies (category 2; 50.0%), Blackland Prairies (category 4; 60.0%), Post Oak Savannah (category 3; 66.7%), and Edwards Plateau (category 7; 66.7%) ecoregions. Consequently, the areas of greatest confusion were spatially congruent for both the Omernik (Omernik 1987, Griffith et al. 2004, Griffith et al. 2007) and Gould (1962) classification systems, and occurred in the central portion of the state. However, the Kappa values indicate the Gould (1962) classification provided the best partitioning of habitats within Texas, given the 25 variables selected for CDA analysis. As such, the Gould (1962) classification was retained for ordination analyses.

I used the PCoA scores from the Gould classification CDA to plot the unconstrained ordination of the call-count survey routes within Texas (Fig. 2.7). The first 2 PCoA axes explained 25.1% and 18.8% of the variability in the habitat matrix. The ordination plot illustrates that most groups are clearly influenced by the moisture gradient within the state, which is associated with PCoA axis 2 (Fig. 2.7). Similarly, many groups are strongly correlated with the elevation and temperature gradients associated with PCoA axis 1 (Fig. 2.7). However, while there is obvious alignment of many groups, distinct separation among all groups is not apparent in the unconstrained ordination.

I used canonical axis scores from the Gould classification CDA to plot a constrained ordination (Fig. 2.8) of the call-count survey routes within Texas. The CDA of the Gould (1962) classification selected $m = 25$ using the default settings, and explained 100% of the total variability among groups with squared canonical correlations of 0.945 and 0.882 for the first 2 canonical axes. Overall classification accuracy for $m = 25$ was 78.8%, and the canonical plot revealed distinct separation among all 10 groups (Fig. 2.8). While $m = p$ is permissible for CDA (Anderson and Willis 2003), a value of m that is too large may include irrelevant information in the constrained ordination. Consequently, I plotted the residual sum of squares and overall classification accuracy versus all values of m

Table 2.3: Error matrix from the canonical discriminant analysis of the Omernik (1987) classification, with canonical discriminant analysis assignments by row, and map classification memberships by column, as generated for the 2002 mourning dove habitat study in Texas.

Category[a]	24	25	26	27	29	30	31	32	33	34	35	Total[b]	Correct
24	12											12	100.0%
25		12	2	1								15	80.0%
26			10	1								11	90.9%
27			4	7	1	1						13	53.8%
29				1	10			1	3			15	66.7%
30	2			2		8						12	66.7%
31	1					1	10		1	1		14	71.4%
32					1			7	2	1		11	63.6%
33					3			1	5	1		10	50.0%
34							2	1		7		10	70.0%
35									1		8	9	88.9%
Total[c]	15	12	16	12	15	10	12	10	12	10	8	132	
Correct	80.0%	100.0%	62.5%	58.3%	66.7%	80.0%	83.3%	70.0%	41.7%	70.0%	100.0%		

[a] Omernik ecoregion 28 was removed due to size (small) and lack of a mourning dove call-count transect.

[b] Row totals for site assignments by canonical discriminant analysis.

[c] Column totals for sites grouped within map classification polygons.

Table 2.4: Error matrix from the canonical discriminant analysis of the Gould (1962) classification, with canonical discriminant analysis assignments by row, and map classification memberships by column, as generated for the 2002 mourning dove habitat study in Texas.

Category	1	2	3	4	5	6	7	8	9	10	Total[a]	Correct
1	8		1								9	88.9%
2		3		2		1					6	50.0%
3			6	2	1						9	66.7%
4			1	6	2			1			10	60.0%
5			2	1	13			1			17	76.5%
6				2		14	2				18	77.8%
7					2	1	12			3	18	66.7%
8					1		1	21			23	91.3%
9								1	13		14	92.9%
10										8	8	100.0%
Total[b]	8	3	10	13	19	16	15	24	13	11	132	
Correct	100.0%	100.0%	60.0%	46.2%	68.4%	87.5%	80.0%	87.5%	100 .0%	72.7%		

[a] Row totals for site assignments by canonical discriminant analysis.

[b] Column totals for sites grouped within map classification polygons.

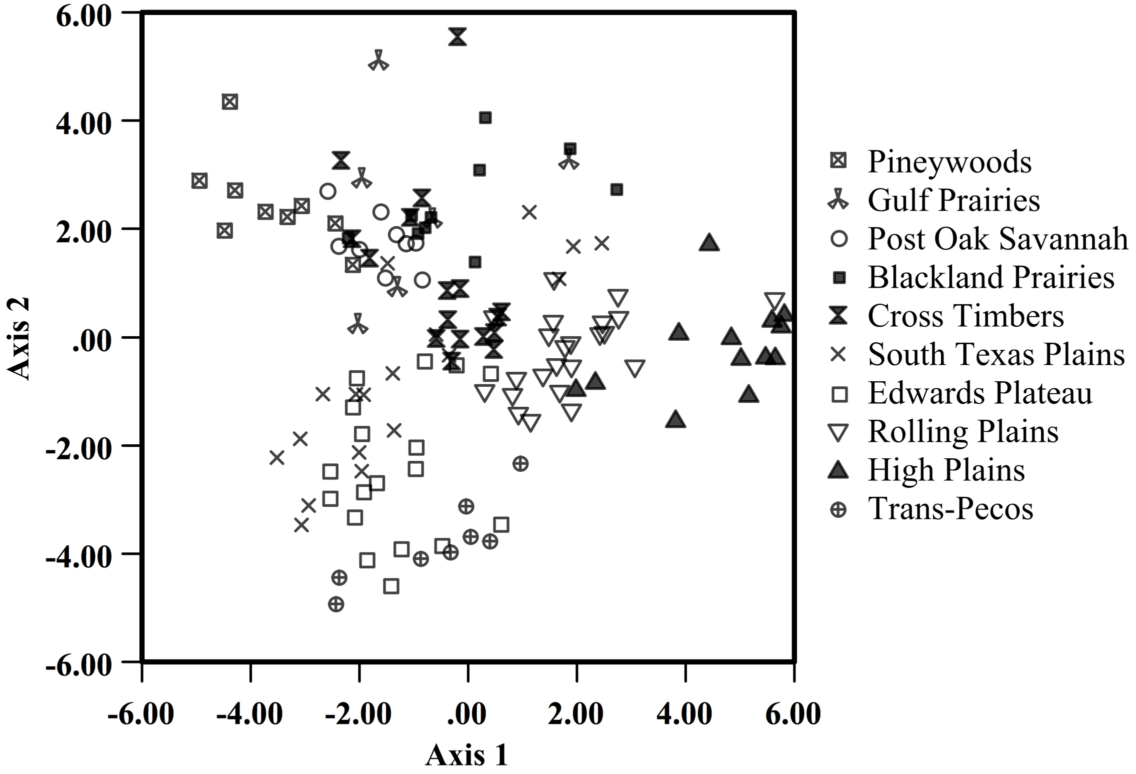


Figure 2.7: An unconstrained ordination (principal coordinates analysis or multidimensional scaling) for the Gould (Gould 1962) classification using habitat data from 132 mourning dove call-count survey sites collected during the 2002 mourning dove habitat study in Texas. Data were standardized and the Euclidean dissimilarity was calculated between all observations.

(Fig. 2.9) for the CDA analysis. This revealed $m = 17$ produced the second highest overall classification accuracy (77.3%). A CDA using $m = 17$ yielded squared canonical correlations of 0.928 and 0.840 for the first 2 canonical axes, and explained 96.1% of the total variability among groups. Therefore a CDA using $m = 17$ explained similar portions of total variability among groups, produced an ordination equivalent to that obtained with the default settings ($m = 25$; Fig. 2.8), and did not alter the final interpretation of the analysis.

Correlations between the habitat variables (Y) and the first 4 canonical axes (Q^*; Table 2.5) indicated that average precipitation, average minimal temperatures, elevation, availability of commercial grain (density in hectares harvested per square kilometer; wheat, oats, barley, rice, sorghum, soybean, and sunflower), and irrigation were important regional variables correlated with the first 3 canonical axes. In terms of structural variables, the number of parallel power lines and buildings were correlated with the first 3 canonical axes. Finally, the amount of canopy cover (less than 10% or greater than 75% canopy cover), canopy height (canopy height less than 3 m or greater than 10 m in height), presence of commercial grain, and the amount of interspersion (changes in physiognomic class) were important local variables correlated with the first 3 canonical axes. As such, these variables strongly influenced the discrimination among groups (Fig. 2.8).

DISCUSSION

I repeated the historic study of Grue et al. (1976, 1981, 1983), and evaluated 4 habitat classification schemes for use as experimental units for mourning dove research in Texas. Results (Table 2.2) indicate the more recent classification schemes, which used biotic and abiotic factors to delineate ecological communities (Gould 1962, Omernik 1987), are superior to the older classification based upon physiographic regions

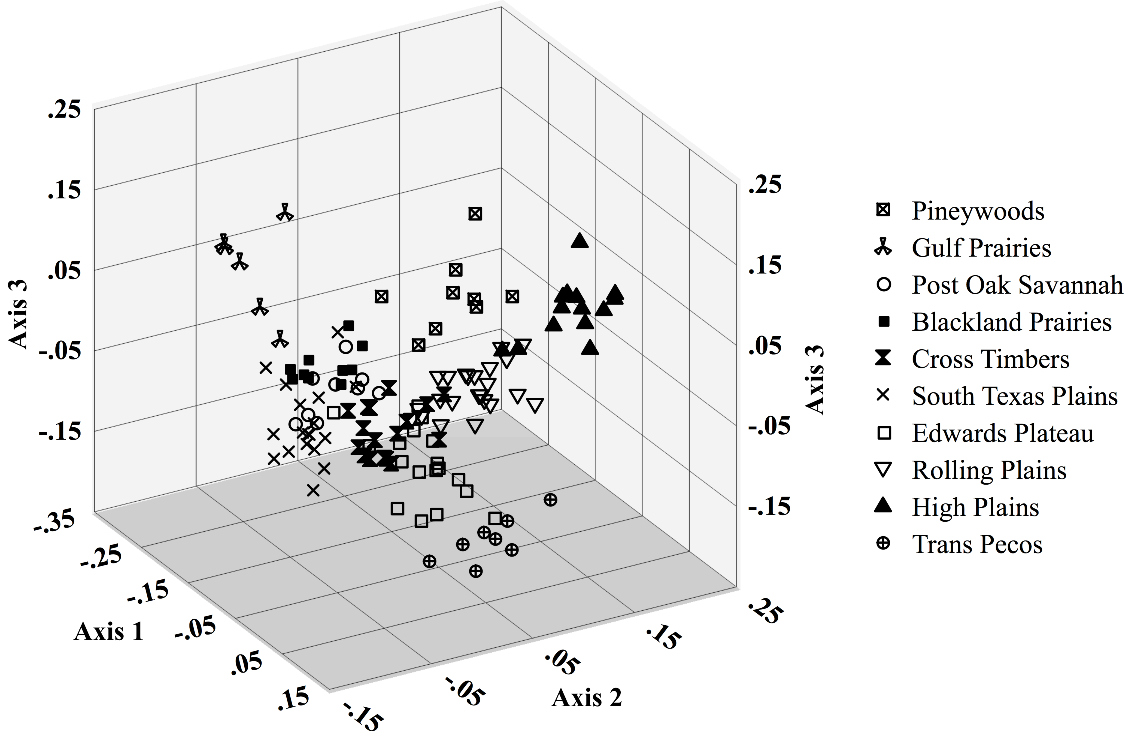


Figure 2.8: A constrained ordination (canonical discriminant analysis) for the Gould (Gould 1962) classification using habitat data from 132 mourning dove call-count survey sites collected during the 2002 mourning dove habitat study in Texas. Data were standardized and the Euclidean dissimilarity was calculated between all observations.

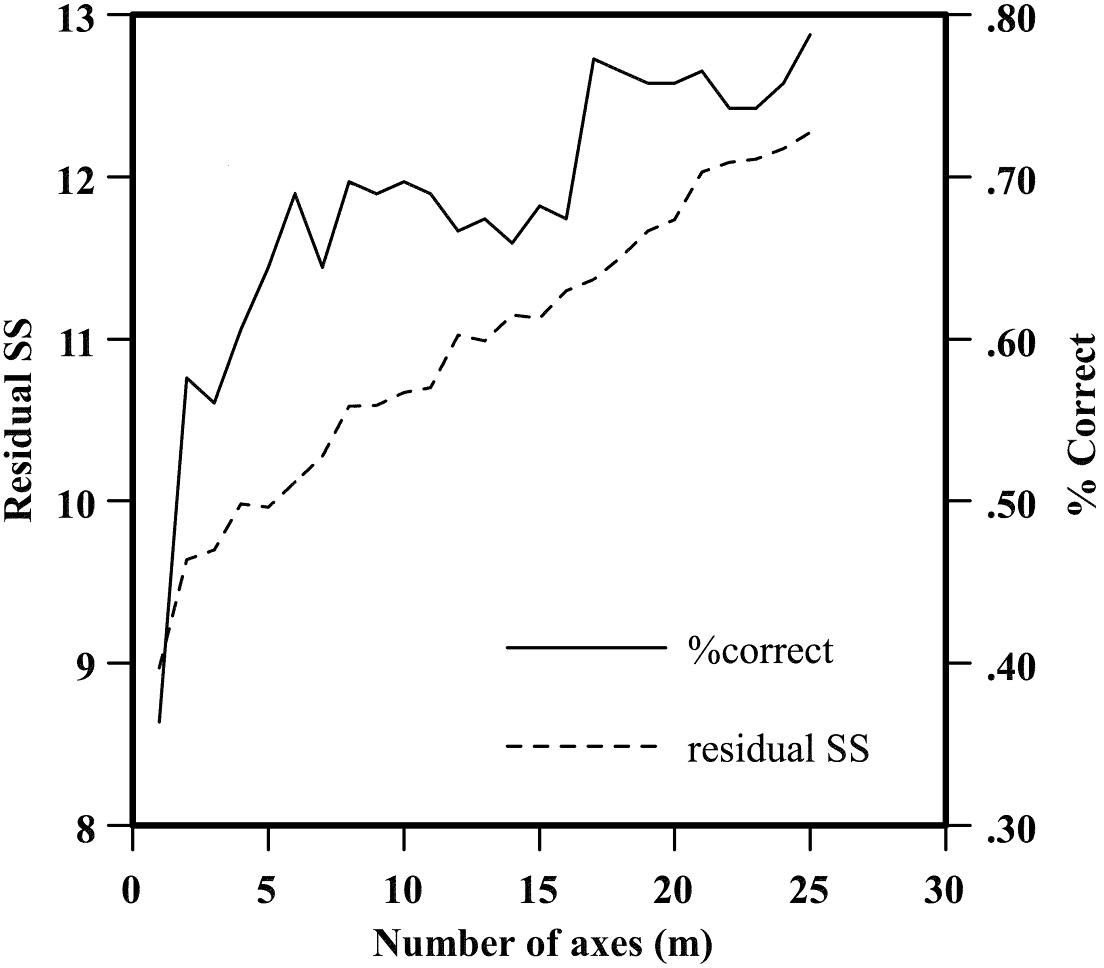


Figure 2.9: Residual sums of squares and observed proportion of agreement for all canonical axes (eigenvectors) generated in the canonical discriminant analysis of the Gould (Gould 1962) classification. Twenty-five habitat variables were collected adjacent to 132 mourning dove call-count survey transects during the 2002 mourning dove habitat study in Texas. Data were standardized and the Euclidean dissimilarity was calculated between all observations.

Table 2.5: Correlations of the first 4 canonical axes ($Q*$) with 25 habitat variables (Y) generated in the canonical discriminant analysis of the Gould (Gould 1962) classification. The habitat variables were collected adjacent to 132 mourning dove call-count survey transects during the 2002 mourning dove habitat study in Texas. Data were standardized and the Euclidean dissimilarity was calculated between all observations.

Variable	Axis 1	Axis 2	Axis 3	Axis 4
Paved[a]	-0.2020	-0.1762	-0.2372	0.3439
Gravel[a]	0.0786	-0.1018	0.0314	-0.3953
Human[a]	-0.2596	-0.0519	0.0765	-0.0395
CanCv0[a]	0.3567	0.2184	0.7668	-0.0245
CanCv75[a]	-0.6856	0.1191	-0.1144	0.2263
CanHt0[a]	0.3284	-0.0062	-0.5216	0.3453
CanHt10[a]	-0.7912	0.5142	-0.1069	0.1604
Grain[a]	0.2432	0.0974	0.5149	-0.0840
DecCC[a]	0.0522	-0.3979	0.0480	-0.2711
ConCC[a]	-0.4635	0.3250	-0.0776	0.1239
Cact25[a]	0.1780	-0.3124	-0.3725	0.5195
Interspersion[b]	0.3242	0.3102	0.6685	-0.3831
P Pow[b]	0.0826	0.1909	0.5202	-0.3229
P Wndbrk[b]	-0.2891	-0.3626	0.2121	-0.6015
Bldgs[b]	-0.6200	-0.0658	0.1273	-0.3317
Wash[b]	0.4400	-0.2208	-0.3783	0.1276
Irrigation[b]	0.3190	0.3197	0.4385	0.2230
PopDen2000[c]	-0.1553	-0.1987	0.2060	-0.0555
CntyGravDen[c]	-0.0638	0.1767	0.3339	-0.4269
CntyPavedDen[c]	0.3730	-0.1058	0.1209	-0.1107
CntyIrrigDen[c]	0.3350	0.3385	0.5499	0.2705
CntyGrain[d]	0.2136	0.0667	0.4874	-0.1070
elevation(m)[e]	0.7335	0.5727	-0.0981	0.1547
pptnorms(mm)[e]	-0.9032	-0.1064	0.2233	-0.2395
tminnorms(c)[e]	-0.5401	-0.7323	-0.0338	0.2470

[a] Variable length measured adjacent to CCS transect.

[b] Variable quantity counted adjacent to CCS transect.

[c] Variable density within the county containing the CCS transect.

[d] Wheat, oats, barley, rice, sorghum, soybean, and sunflower density within the county.

[e] Variable quantity measured at CCS transect midpoint.

(Fenneman 1928, 1931, 1938) or the Hunt Zone classification used to regulate mourning dove hunting by the Texas Parks and Wildlife Department (George 1982, 1984). This is likely due to the increased quality and quantity of the underlying data, the incorporation of anthropomorphic land use change, and the resolution of the data available to the later classification studies. Similarly, the George classification (George 1982, George 1984) produced relatively high average and observed accuracies, but the latitudinal Hunt Zone divisions were never intended to provide any delineation of habitats within the state (e.g., the xeric west Texas desert and the mesic eastern pine forest both occur within the Central Hunt Zone; Fig. 2.2). This resulted in a low Kappa value (0.673) which suggested that a substantial portion of the overall allocation accuracy was obtained due to chance.

Examination of the Gould (Fig. 2.5) and Omernik (Fig. 2.4) classification schemes show that spatial partitioning is very similar, differing mainly in the precise location of categorical boundaries. The largest difference occurs in the northern panhandle of Texas, which Gould delineated into 2 ecoregions (High Plains and Rolling Plains, and Omernik delineated into 3 ecoregions (Western High Plains, Southwestern Tablelands, and Central Great Plains). Analysis of the Gould classification (Table 2.4, Fig. 2.5) showed that 3 of 10 categories had user accuracy rates below 70% (Post Oak Savannah, Blackland Prairies, and Cross Timbers Ecoregions, respectively). Confusion within the Omernik classification also occurred in the central portion of the state (Table 2.3, Fig. 2.4), with 4 of 10 categories having user accuracy values of less than 70%. As such, misclassification error within both of these classification schemes may be the result of similarities in land use among survey routes in adjacent habitat areas (particularly anthropomorphic change), where multivariate differences between habitat units are relatively small (i.e., due to stationarity).

The CDA results were used to construct constrained and unconstrained ordinations (Figs. 2.8 and 2.7), and provided correlations between the habitat variables and the first 4 canonical axes (Table 2.5). The data span a large geographic area where changes in community composition parallel 3 distinct environmental gradients (temperature, elevation, and precipitation). Clearly, separation among groups in the unconstrained and constrained ordinations was similar, due to the alignment of multivariate habitat differences with the strong underlying environmental gradients (temperature, elevation, and precipitation). Thus, the direction of differences among groups corresponds with the axis of greatest variability in the data cloud, providing for the distinctions among some groups in the constrained ordination (Anderson and Roberson 2003, Anderson and Willis 2003). As a result, percent canopy coverage, canopy height, density of commercial grain, and interspersion were also strongly associated with the first canonical axis, as physiognomic differences arise under the influence of precipitation and temperature gradients in Texas (Figs. 2.10 and 2.11).

My study capitalized on the original work of Grue et al. (1976, 1981, 1983) and Blankenship et al. (1971) to provide an analytical paradigm for the statistical assessment of classification schemes. I used habitat data to evaluate classifications for use as experimental units. The ANOVA paradigm used by Blankenship et al. (1971) and Grue (1977) assumed an equal probability of detection for dove heard across all experimental units, and the average number of doves heard (relative abundance) on each call-count survey route contained sufficient information to delineate habitat differences within the fundamental niche of mourning dove. Subsequent studies have since contested the assumption of equal detection probabilities (Burnham 1981, Burnham and Anderson 1984, Buckland et al. 2001, Bart and Earnst 2002, Farnsworth et al. 2002, Rosenstock et al. 2002, Thompson 2002). Similarly, the assumption that relative abundance (dove heard) provides sufficient information for delineating habitat is contradicted by Baskett (1993), who concluded that unequal sex ratios, the proportion of mated to unmated males, and the stage of reproductive cycle produced high variability in dove cue rates

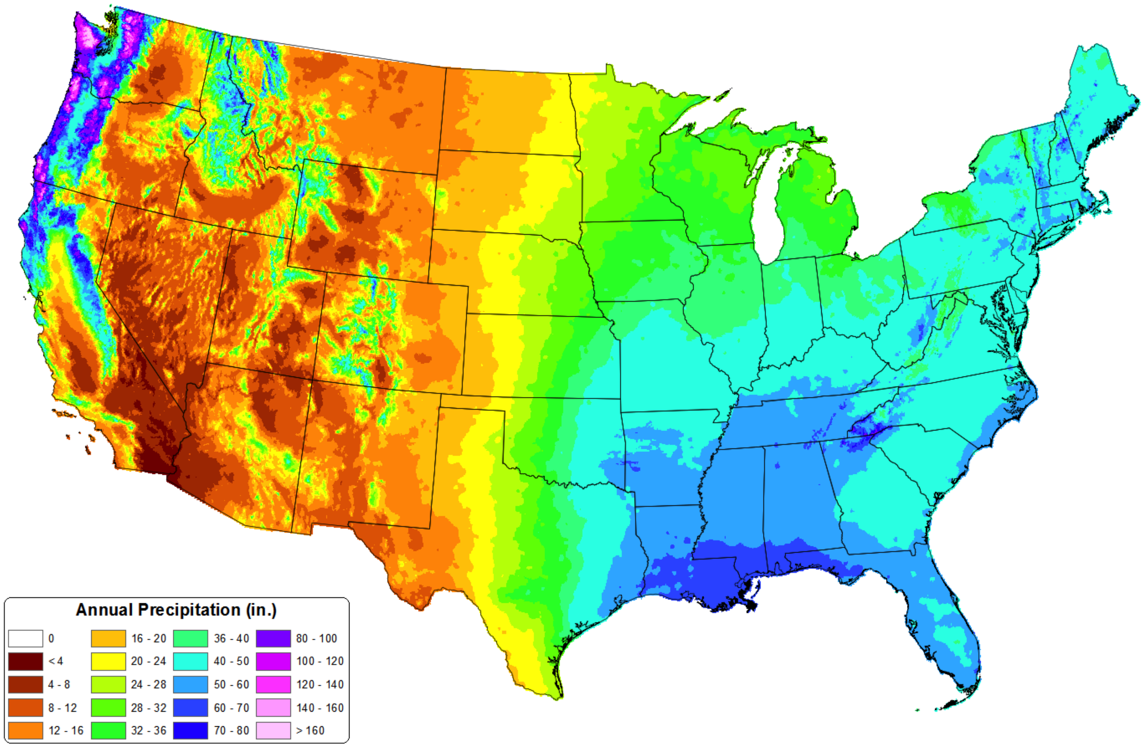


Figure 2.10: Thirty year normal average annual precipitation (1981–2010; PRISM 2013) for the United States.

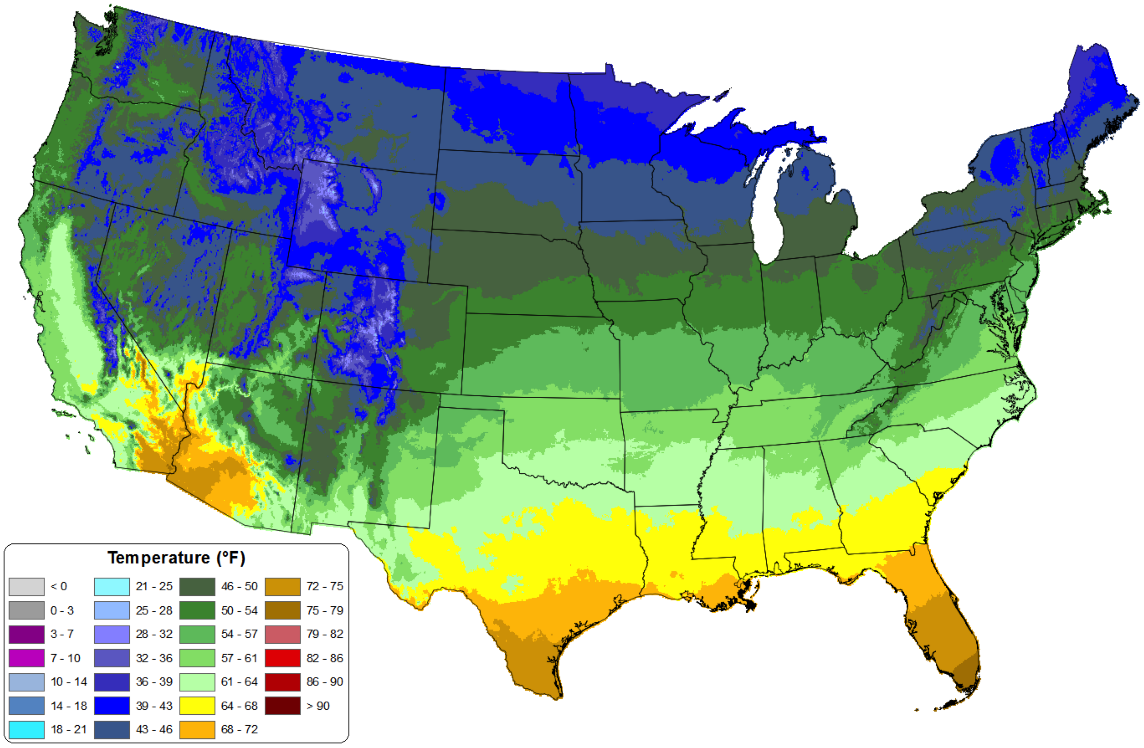


Figure 2.11: Thirty year normal average annual temperature (1981–2010; PRISM 2013) for the United States.

unrelated to habitat. As a result, variability in dove heard confounded with unequal detection probabilities may have limited the resolution (i.e., discrimination) obtainable under the ANOVA paradigm for evaluation of experimental units.

I used multivariate analysis techniques that overcame the statistical limitations prohibiting the use of multiple habitat variables for the delineation of experimental units; collinearity, $p \geq n$, lack of normality, and zero inflation. By recoding the data obtained using the decision nodes of the Grue et al. (1976, 1981, 1983; Fig. 2) habitat key, I reduced the number of variables within the original data set ($p = 562$ to $p = 25$ variables; Table 1) with no loss of information. The use of CAP to conduct a CDA based upon multivariate distances alleviated concerns associated with the distribution of habitat variables and bias due to correlation among variables (Anderson and Robinson 2003, Anderson and Willis 2003). Further, CDA provided cross-validation results that were used to generate error matrices and estimates of Kappa for each classification scheme (Table 2.2). Kappa incorporates the off-diagonal or misclassification values in the error matrix, and provides an estimate of agreement after adjusting for the probabilities of random assignment of classes (Cohen 1960, Congalton and Mead 1983, Congalton et al. 1983, Congalton 1991, Foody 2002). As a result, classifications with differing numbers of categories could be compared in an objective manner.

The need for additional information to better manage mourning dove populations has become evident (National Mourning Dove Planning Committee 2004). Research that can adequately address this need requires the identification of homogeneous experimental habitat units from within which replicate samples may be derived. Of particular concern is the association between habitat variables and call-count survey results, as the latter are unlikely to share equal probabilities of detection across diverse habitat conditions. Because location within the fundamental niche constrains demographic outcomes, delineating experimental units based upon multiple habitat variables alleviates potential conflicts between habitat and mourning dove abundance in future dove research. Further, stratification based upon environmental conditions will allow for the generation of probability density functions to correct abundance estimates for those factors responsible for imperfect detection (e.g., distance sampling), and should reduce error variance in demographic estimates for this species.

These results provide a framework for the evaluation of multivariate habitat based experimental units in autecological research. Because habitat is the essential factor regulating population trends, the impact of anthropomorphic land use requires period reassessment of experimental units relative to harvest and other demographic parameters, if we are to understand mourning dove population trends, and if we intend to properly manage mourning dove populations. The results presented here identify optimal experimental units, based upon habitat congruent with call-count survey routes, and therefore provide the foundation for future mourning dove research efforts in Texas and elsewhere.

MANAGEMENT IMPLICATIONS

Through use of habitat variables and appropriate statistical techniques, this study capitalized on the original work of Grue et al. (1976, 1981, 1983) and Blankenship et al. (1971), and provides an analytical method for assessing experimental units. My results indicate the Gould (Gould 1962; Fig. 2.5) and Omernik (Omernik 1987, Griffith et al. 2004, Griffith et al. 2007; Fig. 2.4) classifications are currently the most suitable of those evaluated for use as experimental units for mourning dove in Texas. However, while the Gould (1962) classification ranked higher, the Omernik classification has received broad acceptance as a common (standardized) classification of land cover nationwide, and should serve well as the basis for research throughout North America.

It is imperative that future researchers understand that species-habitat relationships are in constant flux, but constrained by the tolerances of each species (Gould 1983). It is also clear that as human populations grow, it will become harder to differentiate background habitat matrices from the perturbations caused by anthropomorphic influences. Because classification schemes are implicit hypotheses concerning spatial delineation of habitat, CDA (Anderson and Robinson 2003, Anderson and Willis 2003) provides a useful mechanism for the multivariate evaluation of experimental units, an intuitive requirement in all autecological studies.

CHAPTER III

ASSESSING NORTHERN BOBWHITE HABITAT

SYNOPSIS

Grassland birds are declining at an alarming rate, commensurate with the loss of grassland habitat. An icon of grassland birds, the northern bobwhite (*Colinus virginianus*), is one of the most intensively studied bird species, with over 3,500 publications dedicated to its natural history, autecology, and management. Yet, despite this enormous amount of research, the species has undergone a substantial long-term decline. While previous research has identified several biotic factors which influence abundance in a stochastic manner (i.e., short and long term weather fluctuations, disease), researchers have speculated that habitat loss due to anthropogenic land use change is the most likely cause for the long-term decline. Because land use change is both spatially and temporally variable, monitoring efforts over broad spatial and temporal scales are needed if we are to identify the signs or symptoms of impending habitat loss. As such, my efforts were not to attack the problem by attempting to characterize the macro and micro habitat variables defining the Gleasonian optimum for bobwhite. Rather, I tested familiar landscape variables that correlate with anthropogenic shifts in land use. I used canonical discriminant analysis to compare economic, agricultural, and anthropogenic metrics among ecoregions in Texas over a 20-year period (1993–2012). My comparison indicates the first 4 axes explained 88.6% of the total variance among ecoregions during that period, and the average number of frost free days, proportion of area classified as woodland, cattle density, and deviation from 30 year normal precipitation was influential in the discrimination ($P < 0.0002$, nperm = 4999). Redundancy analysis indicated the first 2 canonical eigenvalues explained 74.5% of the variance in bobwhite relative abundance during this period, as measured by the Breeding Bird Survey and Texas Parks and Wildlife Department Annual Quail Survey ($P < 0.0018$, nperm = 4999). Most metrics of anthropogenic land use were negatively correlated with quail relative abundance. These results indicate that land values (market value and production value per hectare) and human population density may signal the onset of anthropogenic land conversion, and might be used to predict future changes that will impact grassland bird species and other natural resources.

INTRODUCTION

Grassland bird conservation is a growing concern due to range contraction and/or continued declines in abundance for several species as a result of habitat loss and fragmentation (Knopf 1994, Peterjohn and Sauer 1999, Brennan and Kuvlesky 2005, With et al. 2008). Among grassland birds, the northern bobwhite (*Colinus virginianus*; hereafter bobwhite) is one of the most intensively studied species, with over 3,500 publications dedicated to its natural history, autecology, and management (Scott 1985, Hernández and Peterson 2007). Yet despite this volume of published research, bobwhite have undergone a decline in abundance throughout their range since the early 1900's (Leopold 1931, Lehmann 1937, Stoddard 1931), with substantial declines in recent decades (Brennan 1991, Peterjohn and Sauer 1999, Peterson et al. 2002). These long-term trends are frequently attributed to habitat loss associated with anthropogenic land use change and habitat fragmentation (Brennan 1991, Peterson et al. 2002, Williams et al. 2004b, With et al. 2008, Lohr et al. 2011), while short-term variations in abundance have been correlated with natural weather cycles (Bridges et al. 2001, Guthery et al. 2002, Lusk et al. 2002, Tri et al. 2012), hunting pressure (Roseberry and Klimstra 1984, Peterson and Perez 2000, Peterson 2001, Williams et al. 2004a, Tomecek et al. 2015), and grazing management (Campbell-Kissock et al. 1984, Bock and Bock 1999, Taylor et al. 2012). Combined, these factors likely account for much of the spatial-temporal variation in quail abundance noted by early quail researchers (Leopold 1931, Stoddard 1931, Jackson 1960, Rosene 1969, Lehmann 1984, Roseberry and Klimstra 1984).

To understand and reverse declines in grassland bird abundance will require comparative estimates of temporal and spatial abundance, paired with ancillary measurements of biotic and abiotic habitat variables. Unfortunately reliable estimates of quail abundance are limited (e.g., American Breeding Bird Survey, Christmas Bird Count, and Texas Parks and Wildlife Roadside Quail Survey), particularly over large areas and long periods of time (Butcher et al. 1990, Peterson 2001, Bart 2005, Link et al. 2008, Sauer et al. 2013). However, metrics defining anthropogenic land use are available from many sources (e.g., U.S. Geological Survey, U.S. Department of Agriculture), and previous researchers have used these data to define contractions in the range of bobwhites (Peterson et al. 2002, Okay 2006, Rho et al. 2015).

Human activity is characterized and measured by various agencies with other interests, such as the U.S. Department of Agriculture, the U.S. Census Bureau, and the Internal Revenue Service. These entities either enhance, or plague our lives, depending upon perspective. What can not be disputed is the information they collect monitors human activity in a meticulous manner. If population density and anthropogenic land use are the primary casual factors behind habitat degradation and loss, then monitoring societal metrics may provide an early warning of when and where habitat change will likely occur. Given the data available, I believe that refocusing research efforts toward the identification of factors portending degradation in habitat quality will provide the most pragmatic strategy for reversing the decline in grassland birds, especially northern bobwhite.

I suggest a change in our collective research focus is necessary, if we are to halt and reverse declines in grassland bird species. I utilize data from a recent multi-year survey of land trends (Anderson et al. 2014) to demonstrate the utility of commonly available anthropogenic metrics for detecting early signs of impending land use change and potential degradation of grassland bird habitat. I limit my discussion to northern bobwhite across 6 Ecoregions of Texas (Gould 1962, 1975), but acknowledge that early detection of habitat degradation is desirable for evaluating all natural resource use and conservation efforts. My objective is to demonstrate that common anthropogenic land use variables may be a cost effective and highly efficient method for monitoring threats to habitat quality for all grassland bird species. However, my objective is not to minimize the importance of intensive demographic research, nor to quell perseverations on harvest regulations and disease; rather it is to point out their limitations in terms of protecting the quality and quantity of the resources which support grassland species. Ultimately I seek to encourage debate, promote the development of new techniques, and illustrate alternative solutions for future researchers and research efforts.

STUDY AREA

I collected data from counties within Texas (169 of 254) whose geographic centers are congruent with the Gulf Coastal Prairies and Marshes, Cross Timbers, South Texas Plains, Edwards Plateau, Rolling Plains, and High Plains Ecoregions of Texas (Gould 1962, 1975). The study covered an area of between 25°50’N and 36°30’N latitude (1,270 km north to south), 93°31’W and 106°38’W longitude (1,244 km east to west), within the southwestern portion of continental North America (Alvarez and Plocheck 2005). Elevations range from 2,667 m in western Texas to 0 m along the Gulf of Mexico, with a mean elevation of 520 m (Arbingast 1976). The climate within Texas is highly variable, with the northwest to southeast elevation gradient roughly paralleled by similar temperature, frost, and growing season gradients. Most of the state has a bimodal precipitation pattern (spring and fall rainfall peaks), due to the annual advance and retreat of the subtropical high pressure zone. As a result, precipitation is particularly variable across Texas and droughts are common, with more years below, than above, average annual rainfall (Gould 1975). Mean annual precipitation increases from west to east, with the arid west receiving >20 cm per year while the mesic east receives upward of 140 cm per year. The geology of Texas also is varied, with surface exposures dating back 600 million years in geologic time (Arbingast 1976). Because of the complex interactions among climate, surface geology, and vegetation, over 1,300 distinct soil types occur in Texas, which arguably is the greatest natural resources within the state (Gould 1962, 1975, Arbingast 1976, Alvarez and Plocheck 2005). While my description of the study area is general by necessity, it fairly illustrates the variability of habitat conditions across Texas.

METHODS

The database used in this study was compiled from data obtained from the U.S. Department of Agriculture (USDA National Agricultural Statistics Service; USDA Natural Resource Conservation Service), U.S. Geological Service (USGS Land Cover Institute), U.S. Census Bureau, Texas State Comptroller of Public Accounts, and the Texas Almanac, using methods previously described in Kjelland et al. (2007). These data were available either for Independent School Districts (ISDs) or counties, and were obtained in either text, raster, vector, or pdf format. Data in pdf format required transformation to a text format prior to manipulation, while data in text, vector, and raster formats could be downloaded and manipulated directly. Metrics were compiled by county or ISD, and aggregated by Gould Ecoregions for 1997, 2002, 2007, and 2012 to coincide with USDA Census of Agriculture data. Assignments to ecoregions were made using a spatial join of counties or ISD to ecoregions by geographic information system (ArcGIS or R). Data were extracted for the 6 ecoregions surveyed for northern bobwhite by the

Texas Parks and Wildlife Department (TPWD) each year (Peterson and Perez 2000).

I obtained the number of frost free days, human population density, livestock density, the proportion of woodland, cropland, pastureland, average value, average production value, deviation from 30-year normal precipitation, Breeding Bird Survey average birds per route, and TPWD average birds per route for Texas counties, ISDs, or ecoregions from 1997 to 2012. Average number of frost free days for each of the 254 Texas counties were obtained from the Texas Almanac. Census data for each Texas county was obtained from the Texas State Data Center (U.S. Census Bureau). Livestock (sheep, goats, and cattle), agricultural land use (woodland, pastureland, cropland) and ownership sizes for each county were obtained from the USDA Agricultural Statistics Service. Average land value data and coverages for Texas ISDs were obtained from the Texas State Comptroller of Public Accounts. Annual precipitation and 30-year average annual precipitation data were obtained from Oregon State University (PRISM), and annual precipitation anomalies were generated by subtraction of the 30-year normal coverage (1981–2010) from annual data for each year. Breeding Bird Survey relative abundance data for northern bobwhite (birds per route) were obtained from the U.S. Geological Survey (Patuxent Wildlife Research Center, North American Breeding Bird Survey). Texas Parks and Wildlife Department Roadside Quail Survey relative abundance data for northern bobwhite (birds per route aggregated by ecoregion) was obtained from TPWD.

I evaluated the resulting 12 habitat variables for collinearity using the variance inflation factor (VIF), estimated by sequential regression of each habitat variable against the remaining habitat variables in the data set within a general linear model. VIF values greater than 10 indicated linear dependence, or collinearity, among variables. When this occurred, I eliminated or retained variables of a collinear pair based upon ecological interpretive suitability. Through this process 4 variables in the raw data set were eliminated due to collinearity. The resulting data sets used in subsequent analyses were composed of a rectangular $X(env)$ matrix ($n = 24$, $p = 8$), an $X(eco)$ matrix ($n = 24$, $p = 1$; codes for ecoregion), an $X(yr)$ matrix ($n = 24$, $p = 1$; codes for year), and rectangular $Y(quail)$ matrix ($n = 24$, $p = 2$) containing bobwhite relative abundance indices for each ecoregion and year.

I conducted a canonical redundancy analysis (RDA) to determine if available habitat metrics could account for the change in northern bobwhite spatial-temporal relative abundance (Jongman et al. 1995, Legendre and Legendre 1998). I generated a response matrix representing bobwhite relative abundance $Y(quail)$ and an environmental matrix representing habitat variables $X(env)$. The response matrix was centered while the environmental matrix was standardized (z scores), and the analysis was conducted using Euclidean distances, as this symmetrical distance coefficient is deemed more appropriate for analysis of environmental descriptors when zero represents a valid measurement (Legendre and Legendre 1998). Significance test results were generated using 5,000 permutations under a null hypothesis of no relationship between matrices.

Redundancy analysis (RDA) is a direct gradient analysis technique which summaries the linear relationships between a set of response variables and a set of explanatory variables. As a result, the method extracts the variation in the response variables that can be explained by the explanatory variables. RDA is an extension of multiple linear regression which allows for regression of multiple response variables by multiple explanatory variables by using matrix regression followed by principle component analysis. The significance of the RDA model is determined by permutation, and is interpreted in analogous fashion to multiple linear regression or ANOVA. If the model is significant, the proportion of constrained variance explained indicates how much of the total variance may be accounted for by the variables in your model. Ordinations may focus on sites (distance biplot, scaling 1) or correlations among variables (correlation biplot, scaling 2), depending on the study requirements (Legendre 1998).

I used canonical analysis of principle coordinates (CAP) to conduct a generalized canonical discriminant analysis (CDA) to compare ecoregions and years (Anderson and Willis 2003, Anderson and Robinson 2003). I generated a design matrix representing ecoregions X(eco) and years X(yr), and then tested each matrix under a null hypothesis of no difference among groups using a response matrix Y(env) composed of habitat data. These analyses were based upon standardized variables (z scores) using Euclidean distances, as this symmetrical distance coefficient is deemed more appropriate for analysis of environmental descriptors when zero represents a valid measurement, thus indicating the true absence of a variable at a sample location (Legendre and Legendre 1998). Significance test results (t2 and t3) were generated using 5,000 permutations.

CAP uses principle coordinate analysis (PCoA) of the response data matrix Y as the initial step, where the resulting axes (*m*) are orthonormal and contain sequentially decreasing amounts of the variance. A constrained ordination of sites (Y) is then generated using a design matrix X, which represents the group assignment, and the ordination axes are drawn in order to maximize the differences or discrimination between groups (X). The number of axes (*m*) to be used in the canonical analysis is determined by minimizing the misclassification error via the ”leave-one-out” method (Lachenbruch and Mickey 1968, Seber 1984, Anderson and Willis 2003), where each observation is sequentially ”left out” of the ordination procedure, and then classified into the resulting canonical space. The proportion of incorrect allocations relative to the hypothesized group structure yields the percent misclassification error. The test statistics (t2 and t3; Anderson and Robinson 2003) are based upon canonical correlations, and have asymptotic distributions under permutation of the observations. As a result, these statistics are invariant to changes in the distribution of the original variables, and group differences are not obscured by correlations among variables. The trace statistic (t2) is analogous to Pillais trace in MANOVA, and is the more powerful test when group differences occur across more than one dimension. The greatest root statistic (t3) is analogous to Roys Greatest Root in MANOVA, and is the more powerful test when group differences occur along a single dimension.

RESULTS

I conducted a RDA of northern bobwhite relative abundance versus habitat variables covering 6 ecoregions of Texas from 1997–2012. The 2 canonical eigenvectors account for 71.5% and 2.9% percent of the total variance in quail relative abundance, with an R^2 = 74.5% (${R_{adj}}^2$ = 60.8%, $P < 0.0016$). A biplot of the results showing all variables within the model indicates that most anthropogenic land trend variables (e.g., Population Density, Market Value, Production Value) are inversely proportional to quail relative abundance indices (Fig. 3.1).

I conducted a CDA of habitat metrics by ecoregion for the 6 ecoregions of Texas from 1997–2012. The program defaults selected *m* = 4 principal coordinate axes, which obtained the maximum proportion of correct allocations 100%, and explained 88.6% of the variability among ecoregions. The first 2 canonical axes had squared canonical correlations of ${\delta_1}^2 = 0.9947$ and ${\delta_2}^2 = 0.9550$, and both trace statistics (t2 and t3) were significant ($P < 0.0002$). A plot of ecoregions on the first 2 canonical axes scores illustrates the differences among ecoregions (Fig. 3.2).

I conducted a CDA of habitat metrics by year for the 4 years corresponding to the Census of Agriculture data for Texas from 1997–2012. The program defaults selected m = 7 principal coordinate axes, which obtained the maximum proportion of correct allocations 54.2%, and explained 99.5% of the variability among years. The first 2 canonical axes had squared canonical correlations of ${\delta_1}^2 = 0.9500$ and ${\delta_2}^2 = 0.4275$, and both trace statistics (t2 and t3) were significant ($P < 0.0167$). A plot of years sampled on the first 2 canonical axes scores illustrates there are differences among years (Fig. 3.3).

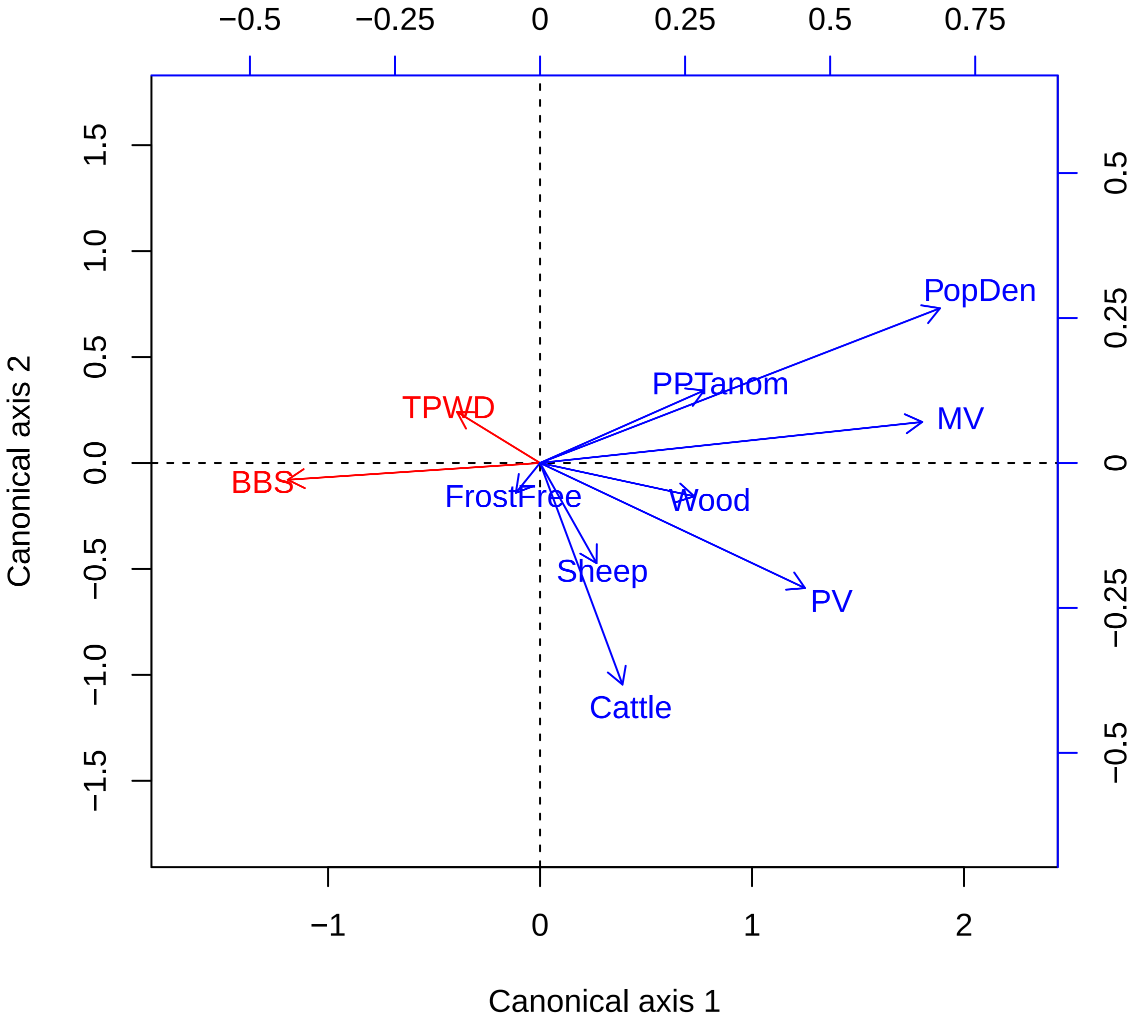


Figure 3.1: Redundancy analysis biplot for 2 quail relative abundance indices (red), and 8 habitat variables (blue) for 6 ecoregions surveyed in Texas during 1997–2012.

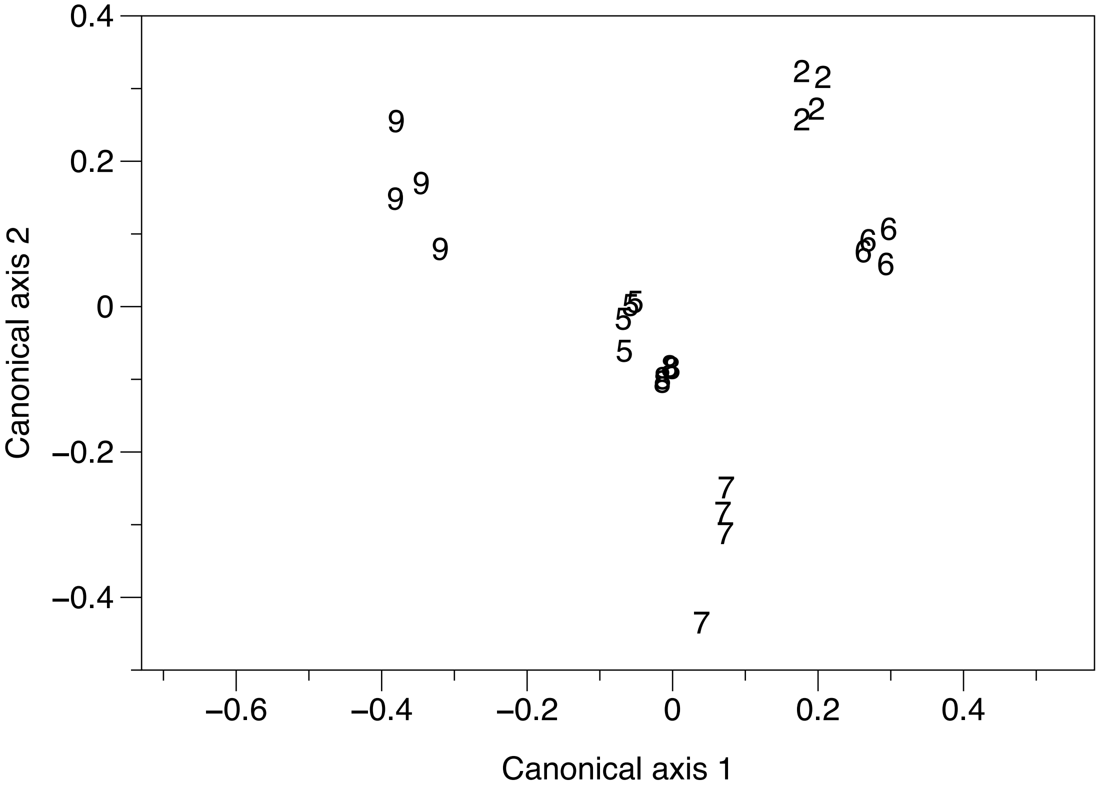


Figure 3.2: A plot of the first 2 canonical discriminant analysis scores for the 6 ecoregions surveyed in Texas during 1997–2012. Gould Ecoregions are Gulf Coastal Prairies (2), Cross Timbers (5), South Texas Plains (6), Edwards Plateau (7), Rolling Plains (8), and High Plains (9).

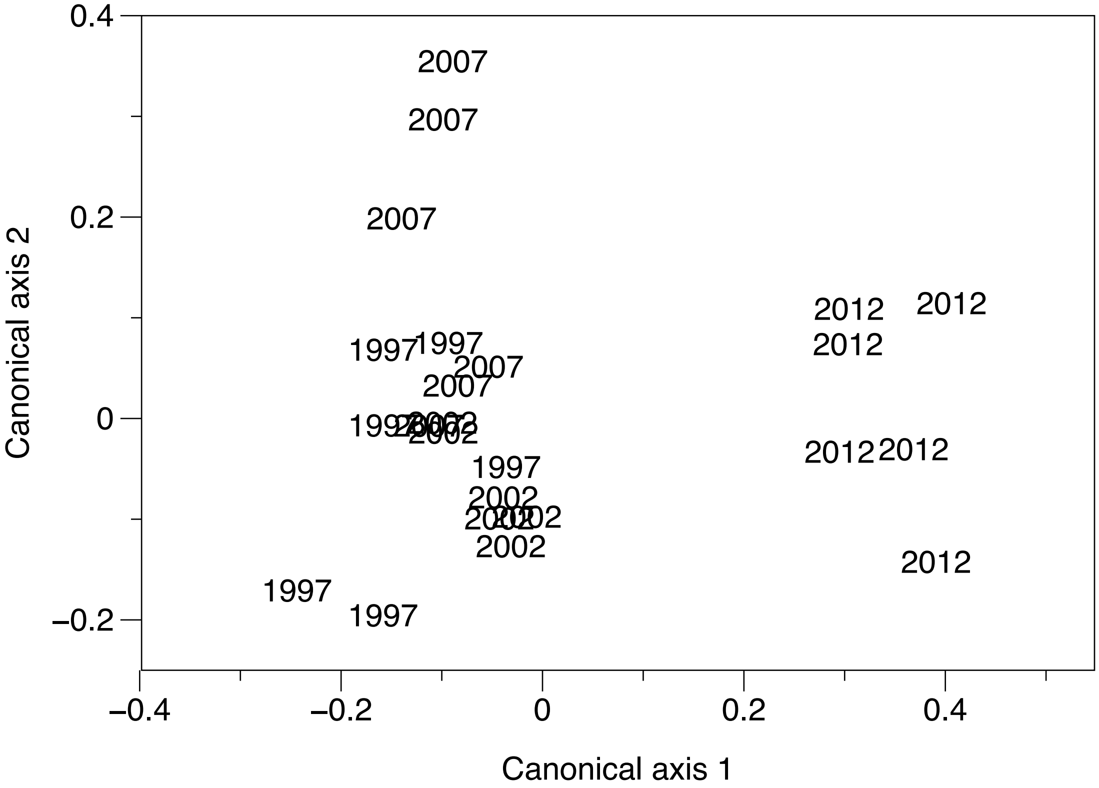


Figure 3.3: A plot of the first 2 canonical discriminant analysis scores for the 4 years surveyed in Texas during 1997–2012. Here years are 1997, 2002, 2007, and 2012 respectfully.

DISCUSSION

Texas is comprised of approximately 56.7 million ha of private farms, ranches and forests, leading the nation in land area devoted to privately owned working lands (www.Texaslandtrends.org). These working lands account for 83% of the land area within the state, and provide substantial economic, environmental, and recreational resources that benefit many Texans. Further, these private lands provide most of the vital habitat that supports the native flora and fauna of Texas. Yet these lands are under increasing land conversion pressure driven by rapid population growth, suburbanization, and rural development. For instance, during 1997–2012 the Texas population grew from 19 million to 26 million residents, an increase of 36%. My RDA analysis (Fig. 3.1) clearly indicates that most anthropogenic land use metrics are inversely related to both indices of quail relative abundance. Habitat variables within RDA analysis explained R^2 = 74.5% (${R_{adj}}^2$ = 60.8%, $P < 0.0016$) of the variance in bobwhite relative abundance during the 1997–2012 period. The CDA analyses revealed significant differences in habitat variables among ecoregions (Fig. 3.2), but less substantial differences among the small sample of years (Fig. 3.3). However, I note that 2012 was arguably the peak of the recent drought in Texas, and it is distinctly different among the years sampled (Fig. 3.3). Regardless, my results provide incontrovertible evidence that anthropogenic habitat degradation and loss is largely responsible for the ongoing decline in northern bobwhite and other grassland birds.

Large monitoring efforts covering broad regions are typically costly, and focus on measuring population demographics. These activities generate metrics that characterize the trajectory, but do not identify causal mechanisms, of species declines. I have demonstrated that a shift in research focus toward monitoring anthropogenic metrics is both economically feasible and yields results that can be utilized for crafting responsive habitat management. More importantly, by shifting the focus to the monitoring of anthropogenic land use metrics, I have identified several metrics that can be used to predict shifts in habitat quality (Human Population Density, Average Market Value per Hectare, Avg Production Value per Hectare). As such, these analyses provide inputs for determining where best to utilize conservation capital in order to maximizing return on investment.

Many grassland bird species are undergoing range contractions and declines in abundance. One such grassland bird, the northern bobwhite, is among the most studied species in North America, and yet it continues to decline. To understand these declines in grassland bird abundance will require the collection of comparative environmental and synecological information over broad temporal and spatial areas. However, in order to halt or reverse species declines will require early identification of factors associated with habitat degradation and loss. As such, my findings are particularly relevant because this paradigm can easily be incorporated into long-term, broad-scale monitoring efforts for other species and habitat. And while I have demonstrated that a shift in research focus toward monitoring anthropogenic metrics is economically feasible and yields useful results over broad areas, I caution that information is useful only if acted upon in a deliberate and timely manner.

MANAGEMENT IMPLICATIONS

My results demonstrate: (1) modeling of species relative abundance as a function of anthropogenic land use metrics indicates habitat change is largely responsible for the continued decline in northern bobwhite, (2) the monitoring of anthropogenic land use metrics provides early indication of likely habitat degradation and loss, and (3) the monitoring of anthropogenic land use metrics is economically feasible and yields actionable information for habitat management. I therefore believe this shift in research focus toward habitat and anthropogenic metrics influencing habitat quality provides a useful management paradigm that can be applied to other species and ecosystems.

CHAPTER IV

ASSESSING NORTHERN BOBWHITE ABUNDANCE

SYNOPSIS

Grassland birds are declining at an alarming rate, commensurate with declines in grassland habitat. Northern bobwhite (*Colinus virginianus*) are one of the most intensively studied grassland bird species, with over 3,500 publications dedicated to its natural history, autecology, and management. Yet, despite this enormous amount of research, the species continues to decline. Monitoring efforts are needed over broad spatial and temporal scales if we are to identify proximate and ultimate causes in order to halt or reverse these declines. However, the manpower required for this scale of monitoring is economically daunting. While the incorporation of citizen volunteers has been proposed as a potential solution, questions remain regarding the accuracy of data produced by volunteers and the validity of the intended methods. I conducted spring cock call-counts on 12 ranches within the Rolling Plains of Texas during 2012–2014. I completed 1,022 total counts, detected 36,415 calls, 4,647 birds, and obtained 4,627 distances. Data were analyzed using program DISTANCE to generate local and regional estimates of quail density each year, and to assess the feasibility of a double-sample calibration for the proposed Texas Quail Index. To evaluate potential outcomes for proposed field and analytical methods, I conducted separate analyses of our distance data using 3 sampling methods from the literature that utilized fixed distance intervals for point counts of bobwhite quail. Our results indicate that *apriori* fixed sampling intervals obfuscate model fit, often resulting in inaccurate estimates of density. This is particularly true if the *apriori* fixed sampling intervals do not match the shape of the detection function. Our results indicate that double-sampling calibration of point counts, using

distance sampling with exact distances, provides an economically feasible paradigm for incorporating citizen science participation into grassland bird monitoring projects. I discuss some potential problems associated with fixed interval distance sampling in grassland birds, and the use of double-sampling for calibration and quality control in citizen-science efforts.

INTRODUCTION

Grassland bird conservation is a growing concern due to range contraction and continued declines in abundance for several species as a result of habitat loss and fragmentation (Knopf 1994, Peterjohn and Sauer 1999, Brennan and Kuvlesky 2005, With et al. 2008). Among grassland birds, the northern bobwhite (Colinus virginianus; hereafter bobwhite) is one of the most intensively studied species, with over 3,500 publications dedicated to its natural history, autecology, and management (Scott 1985, Hernández and Peterson 2007). Despite this volume of published research, bobwhite have undergone a decline in abundance throughout their range since the early 1900's (Leopold 1931, Stoddard 1931, Lehmann 1937), with substantial declines in recent decades (Brennan 1991, Peterjohn and Sauer 1999, Peterson et al. 2002). These long-term trends are frequently attributed to habitat loss associated with anthropogenic land use change and habitat fragmentation (Brennan 1991, Peterson et al. 2002, Williams et al. 2004*b*, With et al. 2008, Lohr et al. 2011), while variation in abundance among years has been correlated with natural weather cycles (Bridges et al. 2001, Guthery et al. 2002, Lusk et al. 2002, Tri et al. 2012). Combined, these factors likely account for much of the spatial-temporal variation in quail abundance noted by early quail researchers (Leopold 1931, Stoddard 1931, Jackson 1960, Rosene 1969, Lehmann 1984, Roseberry and Klimstra 1984).

To understand and reverse declines in grassland bird abundance will require comparative synecological information from many areas, especially estimates of temporal and spatial abundance. Unfortunately reliable estimates of animal abundance are costly to collect, particularly over large areas. To overcome this problem, many research efforts have utilized volunteers, or citizen-scientists, to provide the manpower and spatial coverage necessary for data collection over broad spatial and temporal scales (Greenwood 2007, Couvet et al. 2008, Dickinson et al. 2010, Conrad and Hilchey 2011, Jiguet et al. 2012). Citizen-science research partnerships have been used to monitor birds (Audubon Christmas Bird Count, ebird.org, birdsleuth.org), insects (e-butterfly.org, bumblebeewatch.org, BugGuide.net), marine mammals (wildwhales.org), herptiles (aza.org/frogwatch), plants (budburst.org), asteroids (cosmoquest.org), and weather (oldweather.org). These efforts are not exclusive to private interests, as demonstrated by the European Breeding Bird Surveys (Wretenberg et al. 2006, Jiguet et al. 2012), the North American Breeding Bird Survey, and the Christmas Bird Count (Butcher et al. 1990, Bart 2005, Link et al. 2008, Sauer et al. 2013). Furthermore, due to geographic extent and fiscal limitations, the majority of these efforts would not have been undertaken without the use of volunteer input (Greenwood 2007, Couvet et al. 2008, Dickinson et al. 2010, Conrad and Hilchey 2011, Jiguet et al. 2012).

Research has shown that citizen volunteers are unlikely to have the experience, training, or expertise necessary to conduct many of the more intensive abundance estimation techniques (mark-resight, time-to-detection, double-observer; Greenwood 2007, Couvet et al. 2008, Dickinson et al. 2010, Conrad and Hilchey 2011, Jiguet et al. 2012), including the ability to unequivocally discern animal calls or to accurately estimate distances (Scott et al. 1981, Bart 2005, Alldredge et al. 2007, Efford and Dawson 2009, Nadeau and Conway 2013). Consequentially, most citizen-science efforts rely upon the use of relative indices. Yet indices of relative abundance (raw counts) have been widely criticized for being incomplete counts of unknown proportions of a population (Burnham 1981, Anderson 2001, MacKenzie and Kendall 2002, Pollock et al. 2002, Rosenstock et al. 2002, Thompson 2002, Anderson 2003, Ellingson and Lukacs 2003, Buckland and Handel 2006). Without ancillary data for correction, relative indices are a confounding of detection probability and density. As a result, relative index data derived from even the most standardized methods are unlikely to be comparable between areas or between years (Rosenstock et al. 2002, Thompson 2002, Ellingson and Lukacs 2003, Buckland and Handel 2006).

The debate concerning the practical tradeoffs between accurate and expensive estimation techniques, versus inexpensive, but potentially inaccurate, relative indices also is not new (Caughley 1977, Lancia et al. 1994, Pierce et al. 2012). However, the use of accurate wildlife research techniques is expensive, requires training and experience to achieve good results, and the requisite expertise cannot be acquired through short training sessions (Scott et al. 1981, Alldredge et al. 2007, Freitag and Pfeffer 2013, Paul et al. 2014, Riesch and Potter 2014). Of the various possible solutions, double-sampling is in many ways the most pragmatic approach for improving grassland bird monitoring efforts (Neyman 1938, Tikkiwal 1960, Caughley 1977, Eberhardt and Simmons 1987, Collins 2007). Double-sampling is a method for calibrating the results from a simple, inexpensive method with the results from an intensive, more expensive method (Eberhardt and Simmons 1987, Bart and Earnst 2002, Pollock et al. 2002, Collins 2007). This combination of professional expertise and volunteer effort is one of the most efficient ways to improve data quality (verifying accuracy and/or precision) in broad-scale, citizen-science monitoring efforts when the underlying assumptions can be met (Eberhardt and Simmons 1987, Bart and Earnst 2002, Pollock et al. 2002, Collins 2007).

During the most recent bobwhite decline within Texas and Oklahoma (2009–2014) a privately funded research venture (Operation Idiopathic Decline; OID) was initiated to determine if epidemiological factors were correlated with declines in quail abundance.

This required congruent estimates of bobwhite abundance, disease prevalence, and environmental conditions across a broad geographic area. Because reliable estimates of animal abundance are costly to collect, OID researchers partnered with Texas AgriLife Extension to revive a volunteer-based bobwhite abundance and habitat monitoring effort called the Texas Quail Index (TQI; Rollins et al. 2005, Reyna 2008, Texas A&M AgriLife Extension 2013). Project managers believed the use of citizen volunteers would provide the manpower and spatial coverage necessary for data collection at the scale required to investigate this hypothesis. However, these monitoring efforts may be limited by the quality of the sampling design and data collection methodology if remedial steps are not taken (Reyna 2008, Dickinson et al. 2010, Freitag and Pfeffer 2013, Paul et al. 2014, Riesch and Potter 2014).

Distance sampling is but one of several available methods for correcting empirical counts for incomplete or imperfect detection (Buckland et al. 1993, 2001). Distance sampling can be conducted using line transects or point counts, may incorporate covariates (Zerbini 2006, Marques et al. 2007, Rexstad 2007, Johnson et al. 2010), and can account for heterogeneity in detection through use of mark-resight models (mrds; Laake et al. 2011). Due to efficacy, ease of use, and perhaps as a shibboleth with respect to relative indices (Engeman 2003, Hutto and Young 2003, Johnson 2008), various forms of conventional distance sampling are increasingly used for grassland bird counts in favor of fixed-radius (Reidy et al. 2011) or variable circular plot indices (Roeder et al. 1987, Bollinger et al. 1988). However, despite the advent of modern equipment which makes distance sampling accessible (e.g., laser rangefinders and GPS), several valid issues brought forth in the debate concerning the utility of relative indices (Thompson 2002, Johnson 2008) and convenience sampling (Anderson 2001) continue to persist. Principal among these problems is insufficient sample size (observations; n), insufficient sample effort (sample points; k), inaccurate distance estimates, and the advent of a new paradigm termed convenience analysis, where analytical tools are assumed robust to deficiencies in sample design, field methodology, or incorrect assumptions concerning detection function shape with respect to the species of interest (DeSante 1981, 1986, Rollins et al. 2005, Applegate et al. 2011, Murray et al. 2011).

I provide data from a recent multi-year survey of bobwhite in the Rolling Plains Ecoregion of Texas (Gould 1962, 1975) to demonstrate the utility of the double-sample calibration approach for citizen-science monitoring of grassland birds. I limit my discussion to conventional distances sampling of northern bobwhite for simplicity, but acknowledge that covariate distance sampling, mark-recapture distance sampling, mark-recapture, double-observer, time-to-detection, and other methods for estimating the probability of detection are viable alternatives that might be used in a double-sampling paradigm. Our objective is to demonstrate that contrary to recently published findings (Rollins et al. 2005, Applegate et al. 2011, Murray et al. 2011, Texas A&M AgriLife Extension 2013), distance sampling is an efficacious method for monitoring bobwhite (and other grassland bird) abundance. Further, I assert that successful implementation of a double-sampling calibration is required for TQI, and similar citizen-science monitoring efforts, due to spatial-temporal differences in detection probability (i.e., between periods or among habitat types), and discuss some of the problems with this approach that I feel are common to point counts for all grassland bird species. Ultimately I seek to encourage debate, further development of techniques, and illustrate alternative solutions for the use and incorporation of citizen-scientists into grassland bird monitoring efforts. And to be clear, I do not condemn, but rather commend the efforts of our colleagues (Rollins et al. 2005, Applegate et al. 2011, Murray et al. 2011, Texas A&M AgriLife Extension 2013) whose results I use here to illustrate solutions to common sampling problems: it is through their publications that I am able to identify and overcome obstacles that would otherwise plague future researchers and research efforts.

STUDY AREA

The Rolling Plains ecoregion is the semi-arid portion of the Great Plains grassland that extends into northwestern Texas (Gould 1962, 1975). Elevations range from 200 m to 950 m, and topography is characterized by flat or gentle rolling plains bisected by valleys draining in a predominantly southeasterly direction. May and September are the wettest months, with annual precipitation increasing from 550 mm to 760 mm along a west to east gradient. Soils vary from neutral coarse sands to slightly basic calcareous packed grey clays, or red clays and shales. The area is primarily rangeland, with much of the flatter regions converted to cropland. Prairie communities are dominated by native bunch grass species, including little bluestem (*Schizachyrium scoparium*), big bluestem (*Andropogon gerardii*), sand bluestem (*Andropogon hallii*), Indian grass (*Sorghastrum nutans*), sideoats grama (*Bouteloua curtipendula*), switchgrass (*Panicum virgatum*), hairy grama (*Bouteloua hirsuta*), blue grama (*Bouteloua gracilis*), and western wheatgrass (*Agropyron smithii*). On clay soils the common invasive species include Buffalograss (*Buchloe dactyloides*), curly mesquite (*Hilaria belangeri*), tobosa grass (*Pleuraphis mutica*), three-awn (*Aristida spp.*), and sand dropseed (*Sporobolus cryptandrus*). In sandy soils sand sage (*Artemisia filifolia*) and shinnery oak (*Quercus harvardii*) are common invasive species. Where heavy grazing occurs sandburs (*Cenchrus spp.*), red grama (*Bouteloua trifida*), Texas grama (*Bouteloua rigidiseta*), croton (*Croton texensis*), western ragweed (*Ambrosia psilostachya*), and many other common annuals and perennials increase in frequency. Riparian areas support several woody species including oaks (*Quercus spp.*), eastern cottonwood (*Populus delitoides*), elms (*Ulmus spp.*), and junipers (*Juniperus spp.*).

METHODS

We conducted spring cock call-counts on 12 study sites within the Rolling Plains of Texas during 2012–2014. Study sites were selected randomly from a list of 33 privately owned properties, and ranged in size from 1,600 to over 100,000 ha. The ranches selected were highly variable in terms of land cover and management, and therefore captured much of the variability in land conditions across the region (i.e., geology, soil type, vegetation, and topography). All study sites experienced drier conditions during 2012–2013 due to ongoing drought, and 4 ranches experienced wildfires during 2011 that removed all vegetation on greater than 50% of each area.

We used GIS (TNTmips; Microimages.com) to delineate non-habitat on each property and adjacent properties that might influence detectability or quail abundance (cropland [cotton], buildings, roads, wind turbines, oil field infrastructure, cattle pens), and distributed 9–12 sample points (depending on site size) adjacent to unimproved ranch roads or pasture boundaries within the habitat area. All points were placed at least 1 km apart (euclidean distance, not road length) to minimize counting of the same individuals at more than one point. As such, study sites were probabilistically sampled, with count points placed systematically to provide maximal coverage (i.e., a "convenience" sample with potential habitat bias). However, ranch roads were typically unimproved trails, had very little traffic, and consisted of two bare wheel tracks with a vegetated median surrounded by viable quail habitat. As such, quail were frequently seen on and near the road while conducting counts or while transiting between count locations. We therefore believe these paths neither attracted nor repelled quail, and thus any perturbation was due to presence of the observer. Finally, this procedure created count points similar to those established on ranches by TQI surveyors, and therefore provides inference to results obtained from methods recommended in this program (Rollins et al. 2005, Reyna 2008, Texas A&M AgriLife Extension 2013).

We conducted counts from 10 May to 5 June each year during 20122014. Surveys started 30 minutes after sunrise and continued until 4 hours after sunrise. Surveys were replicated 24 times each year, with starting points reversed for each replication. At each point we recorded the ranch name, point, date, surveyor, start time, wind velocity, temperature, time interval (0–3 minutes, 3–6 minutes), distance, and bearing to each bird detected during a 6 minute count period. Environmental metrics were measured using a handheld weather meter (Kestrel; Kestrelmeters.com). Time intervals and bearings were measured by stop watch and electronic compass (GPS; garmin.com) attached to each plastic clipboard (non-magnetic). Upon detection, surveyors turned to face the calling individual to determine bearing, and then measured distance to the individuals location using a laser rangefinder (Leupold; leupold.com). Observers watched and listened for bobwhite as they approached each count location, and recorded any bird seen or heard that might have been displaced by the approach of the observer (distance and bearing). During the count, if vegetation blocked the line of sight to a bird or calling location, observers moved a short distance to a location perpendicular to the count point with clear visibility to the call origin, and then measured either the distance to the bird or to vegetation where the calls originated. Birds for which no distance could be obtained were annotated as such on the data sheets. All calls detected during the count period were tabulated separately for each time interval using a mechanical tally counter, which allowed the surveyor to tabulate calls while focusing attention on detecting individuals (distance and bearing). At the conclusion of each count observers were allowed to verify or obtain distances to birds they identified during the count period.

All surveyors received extensive field training in the technique prior to the study using digital callers (Foxpro; gofoxpro.com), and conducted practice counts on live quail as a group at the start of each field season. Each observer learned the protocol, variations in bobwhite calls, distance sampling theory, proper use of a laser range finder and GPS unit. During training sessions surveyors checked their distance measurements against known distances to each digital caller from their count point. During practice sessions, surveyors completed counts at each point individually, and then compared information (e.g., calls, birds, distances and bearings) with other surveyors in the group. This type of training provided immediate feedback on possible errors, which is necessary to instilled confidence and proficiency with all equipment and procedures among surveyors (Gibson and Bergman 1954, Hodge 1981, Scott et al. 1981, Thompson 1982).

We used Program DISTANCE (version 6; Thomas et al. 2010) to estimate detection probability and density for each ranch and year. We assessed data for violation of distance sampling assumptions (Buckland et al. 2001, Buckland and Handel 2006) and determined truncation width by plotting histograms of the distance data (ungrouped and grouped) by year and observer. We used conventional distance sampling (CDS) to generate models using uniform, half-normal, and hazard-rate key functions with a maximum of 3 cosine, hermite polynomial, or simple polynomial series expansion terms. Model fit was assessed using QQ plots, histograms of fitted models, and the Cramér-von Mises test (Darling 1957). Akaikes Information Criterion (AIC) was used to select among candidate models.

We generated summaries of calls, birds, and average density for each year (regional estimates) and each ranch x year (local estimates) to assess method precision as well as spatial-temporal variability in bobwhite relative abundance and density. To quantify differences in relative indices, we compared the number of calls and the number of birds detected by year and ranch x year using Kruskal-Wallis test. We compared histograms of model fits, effective detection radii, and density estimates from our results, to results generated using three published research methods for bobwhite spring cock call-counts (Rollins et al. 2005, Applegate et al. 2011, Murray et al. 2011, Texas A&M AgriLife

Extension 2013). Through comparison we demonstrate potential problems associated with data collection methods that use, or intend to use, *apriori* fixed distance intervals. Further, we discuss how these problems and misconceptions about auditory detection, distance estimation, and surveyor training, might impact citizen-science results from point count surveys (Scott et al. 1981, Bart et al. 2004, Alldredge et al. 2007, Nadeau and Conway 2013).

We used the ratio estimation procedure (Neyman 1938, Caughley 1977, Eberhardt and Simmons 1987) to assess correlations between average calls and density for bobwhite in the Rolling Plains. We compare coefficients of determination among regressions to assess double-sampling calibration, and discuss potential use with respect to citizen-science monitoring efforts (Eberhardt and Simmons 1987, Bart and Earnst 2002, Pollock et al. 2002, Collins 2007). We use summaries of our findings to address recent criticisms of distance sampling for quail, and to discuss potential problems relevant to distance sampling and citizen-science monitoring of bobwhite in Texas.

RESULTS

We conducted spring cock call-counts on 12 ranches within the Rolling Plains of Texas during 2012–2014. The amount of replication differed between years due to weather during the count period. We completed 1,022 total counts which detected 36,415 calls, 4,647 birds, and obtained 4,627 distances. The number of calls per point (n = 384, $H_2{}^2$ = 59.4978, $P < 0.000$) and the number of birds per point (n = 384, $H_2{}^2$ = 72.714, $P < 0.000$) differed between years (Table 4.1, Fig. 4.1). Similarly, the number of calls per point (n = 36, $H_{35}{}^2$ = 250.8391, $P < 0.000$) and the number of birds per point (n = 36, $H_{35}{}^2$ = 258.7566, $P < 0.000$) differed between ranch x years (Table 4.2, Fig. 4.2).

Distances differed among years (n = 4,627, $H_2{}^2$ = 314.9836, $P < 0.000$; Fig. 4.3), and among ranch x years (n = 4,627, $H_{35}{}^2$ = 772.6298, $P < 0.000$; Fig. 4.4). The

Table 4.1: Mean calls per point and mean birds per point, by year, for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Year	Points	Calls	Average	SD	SE	Birds	Average	SD	SE
2012	256	6,456	25.22	30.45	1.90	836	3.27	2.52	0.16
2013	382	16,212	42.44	41.77	2.14	1,674	4.38	3.06	0.16
2014	384	13,747	35.80	33.79	1.72	2,137	5.58	4.88	0.25

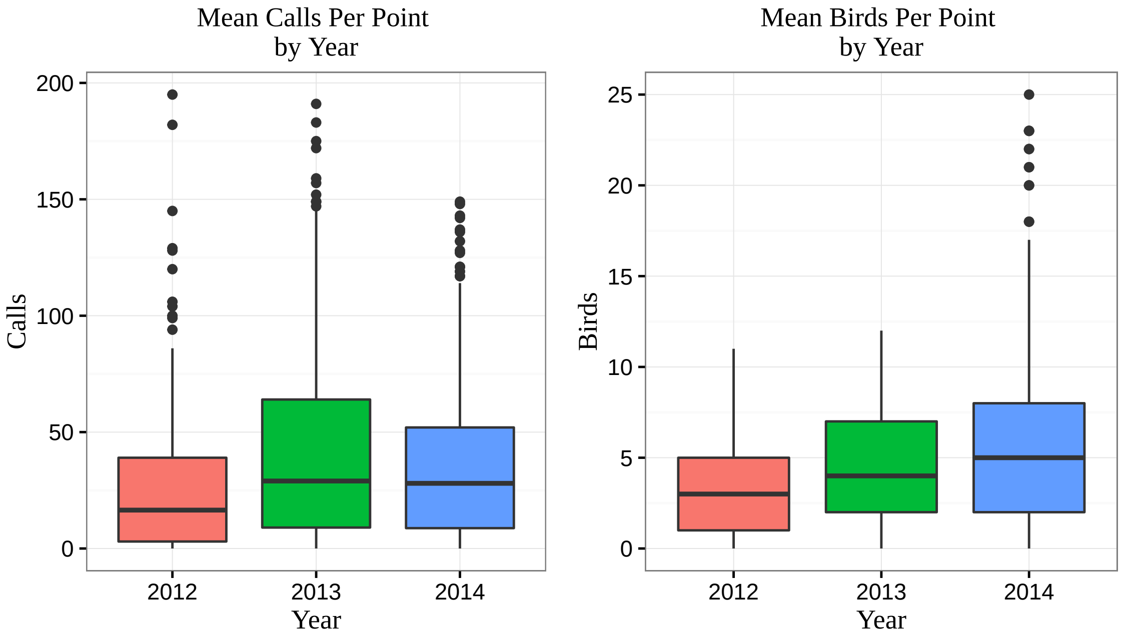


Figure 4.1: Mean calls per point and mean birds per point, by year, for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Table 4.2: Mean calls per point and mean birds per point by ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Ranch	Year	Calls	Average	SD	SE	Birds	Average	SD	SE
TX2C	2012	596	27.09	21.25	4.53	81	3.68	2.03	0.43
TX2C	2013	604	27.45	22.72	4.84	75	3.41	2.26	0.48
TX2C	2014	555	16.82	14.10	2.45	98	2.97	1.90	0.33
TX4N	2012	95	4.32	9.32	1.99	19	0.86	1.25	0.27
TX4N	2013	403	18.32	20.82	4.44	51	2.32	2.19	0.47
TX4N	2014	931	28.21	26.63	4.64	147	4.45	3.08	0.54
TX7N	2012	172	7.82	13.62	2.90	22	1.00	1.60	0.34
TX7N	2013	1,299	59.05	44.44	9.48	110	5.00	3.35	0.71
TX7N	2014	3,161	95.79	36.63	6.38	531	16.09	5.09	0.89
TX7S	2012	552	25.09	24.16	5.15	83	3.77	2.84	0.61
TX7S	2013	1,420	64.55	40.74	8.69	128	5.82	2.40	0.51
TX7S	2014	104	3.15	7.78	1.35	11	0.33	0.82	0.14
TX6S	2012	708	35.40	17.65	3.95	88	4.40	1.76	0.39
TX6S	2013	1,479	73.95	38.16	8.53	144	7.20	1.88	0.42
TX6S	2014	1,085	36.17	21.28	3.89	132	4.40	1.79	0.33
TX6C	2012	367	16.68	13.27	2.83	75	3.41	1.89	0.40
TX6C	2013	1,482	33.68	29.99	4.52	177	4.02	2.69	0.41
TX6C	2014	1,106	33.52	22.80	3.97	159	4.97	2.62	0.46
TX2N	2012	1,732	78.73	48.00	10.23	141	6.41	1.94	0.41
TX2N	2013	3,354	76.23	45.68	6.89	283	6.43	2.30	0.35
TX2N	2014	2,298	69.64	31.15	5.42	344	10.42	2.94	0.51
TX1N	2012	106	4.82	7.29	1.56	20	0.91	0.92	0.20
TX1N	2013	1,493	33.93	35.13	5.30	166	3.77	2.97	0.45
TX1N	2014	1,116	33.82	21.03	3.66	196	5.94	3.06	0.53
TX1S	2012	304	13.82	14.31	3.05	64	2.91	2.02	0.43
TX1S	2013	361	8.20	12.34	1.86	73	1.66	1.72	0.26
TX1S	2014	1,055	31.97	24.16	4.20	143	4.33	2.42	0.42
TX4S	2012	998	45.36	31.17	6.65	112	5.09	1.60	0.34
TX4S	2013	1,849	84.05	55.96	11.93	166	7.55	2.58	0.55
TX4S	2014	942	28.55	21.91	3.81	136	4.12	2.45	0.43
TX2S	2012	482	26.78	30.54	7.20	66	3.67	3.07	0.72
TX2S	2013	573	15.92	14.57	2.43	92	2.56	2.16	0.36
TX2S	2014	281	10.41	10.90	2.10	55	2.04	2.24	0.43
TX4C	2012	344	17.20	14.44	3.23	65	3.25	1.55	0.35
TX4C	2013	1,895	47.38	36.68	5.80	209	5.22	3.06	0.48
TX4C	2014	1,113	37.10	29.81	5.44	185	6.17	3.32	0.61

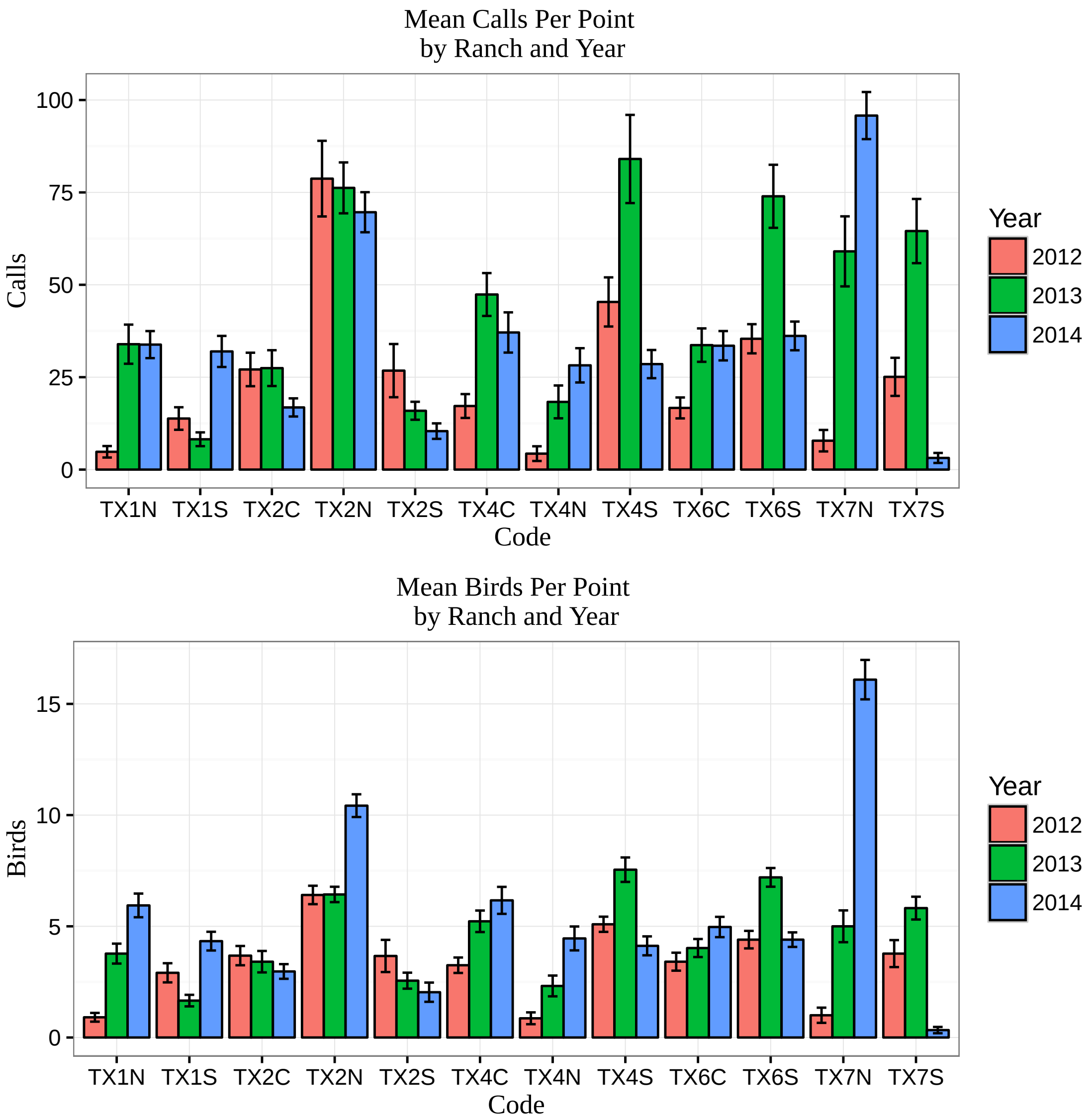


Figure 4.2: Mean calls per point and mean birds per point, by ranch and year, for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

histogram of 4,627 distances collected during the 3 year study shows that bobwhite detections increase as a function of radial area out to 70 m, and rapidly declined beyond 100 m (Fig. 4.5). The 95th, 50th, and 25th quantiles for detection occurred at 241 m, 86 m, and 57 m, respectively, with an average detection distance of 105.5 m. The largest detection distance observed during the 3 year study occurred at 532 m.

Model selection was conducted using exact distances with data truncated at 360 m to improve model fit (Buckland et al. 2001). A hazard-rate model with a single 4th order polynomial adjustment term was selected based upon AIC value (AIC = 49,681) and model fit (Cramér-von Mise, $P = 0.05$; Fig. 4.6), with a finite detection probability of 0.10 at 360 m (Buckland et al. 2001, Buckland et al. 2006). The effective distance radius was 113.7 m (*SE* = 1.37 m), and the coefficient of variation for the slope of the probability density function evaluated at distance zero, $h(0)$, was 2.4$\%$. Histograms showed no differences in detection function shape among observers or years, and analysis by observer and year did not improve model fit. We therefore pooled distances among observers and years to model the detection function, but stratified encounter rates by year and ranch x year for estimates of density.

Point estimates of density increased from 2012 to 2014 (Table 4.3), and density estimates varied among ranch x years (Table 4.4). Coefficients of Variation for regional density estimates were < 3$\%$ for each year (Table 4.3), and < 10$\%$ for all but 4 ranches during the survey period (Table 4.4). We note that changes in precipitation and differences in grazing management among individual ranches may have influenced bobwhite abundance and detectability across the region, which has experienced severe drought since 2009 (Tomeček et al. 2017, submitted). However, we detected no significant difference in density among years or ranch x years during the drought of 2012–2014 (Table 4.3, Table 4.4).

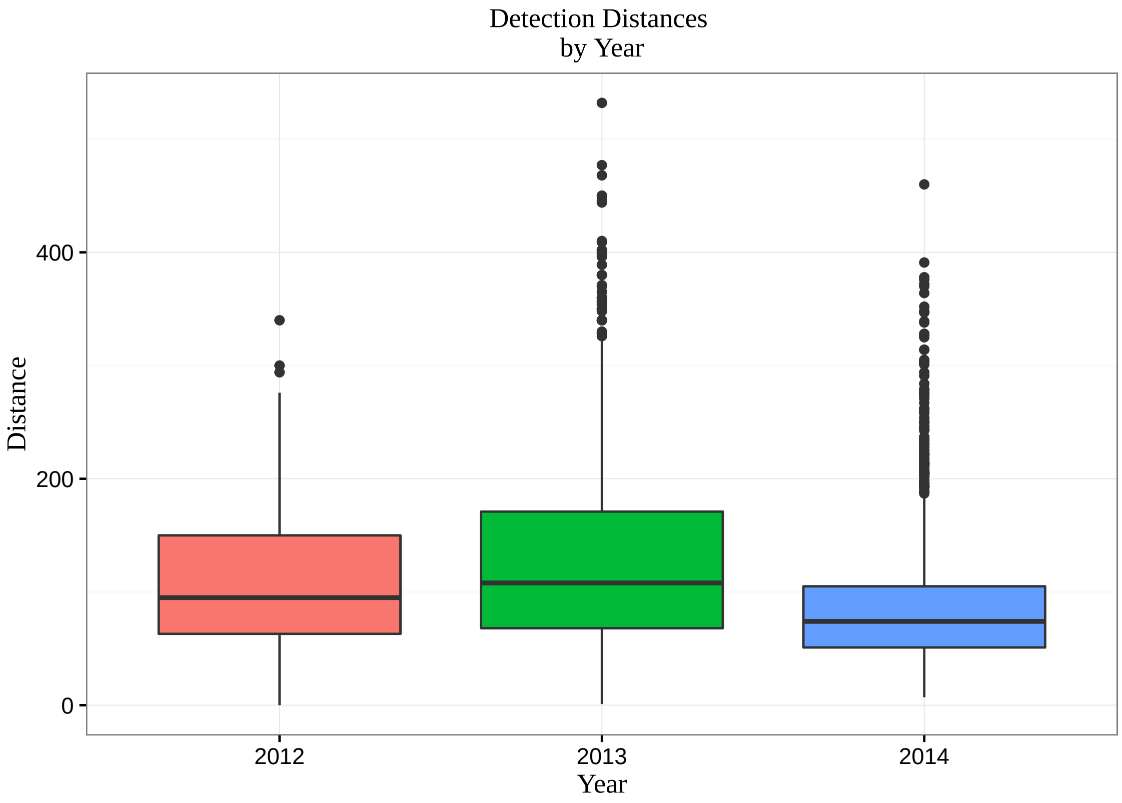


Figure 4.3: Boxplots of distances by year for all bobwhite detected during the annual survey of 12 ranches within the Rolling Plains Ecoregion of Texas during 2012–2014.

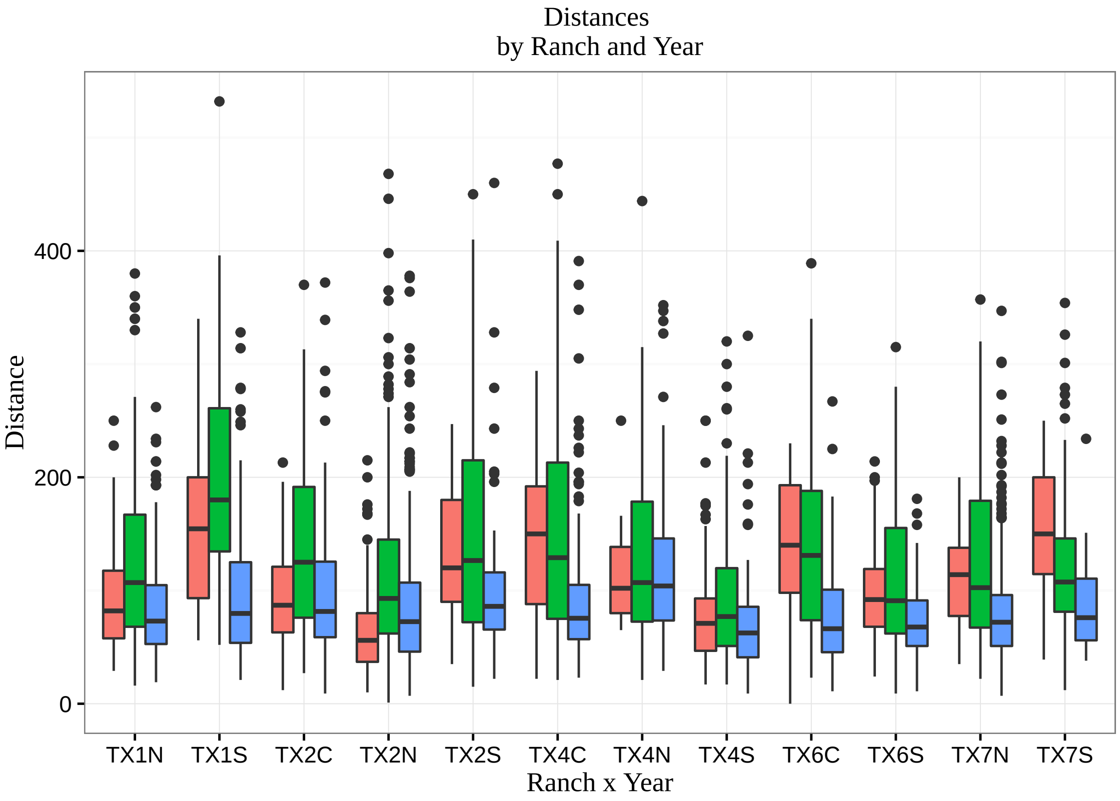


Figure 4.4: Boxplots of distances by ranch and year for all bobwhite detected during the annual survey of 12 ranches within the Rolling Plains Ecoregion of Texas during 2012–2014.

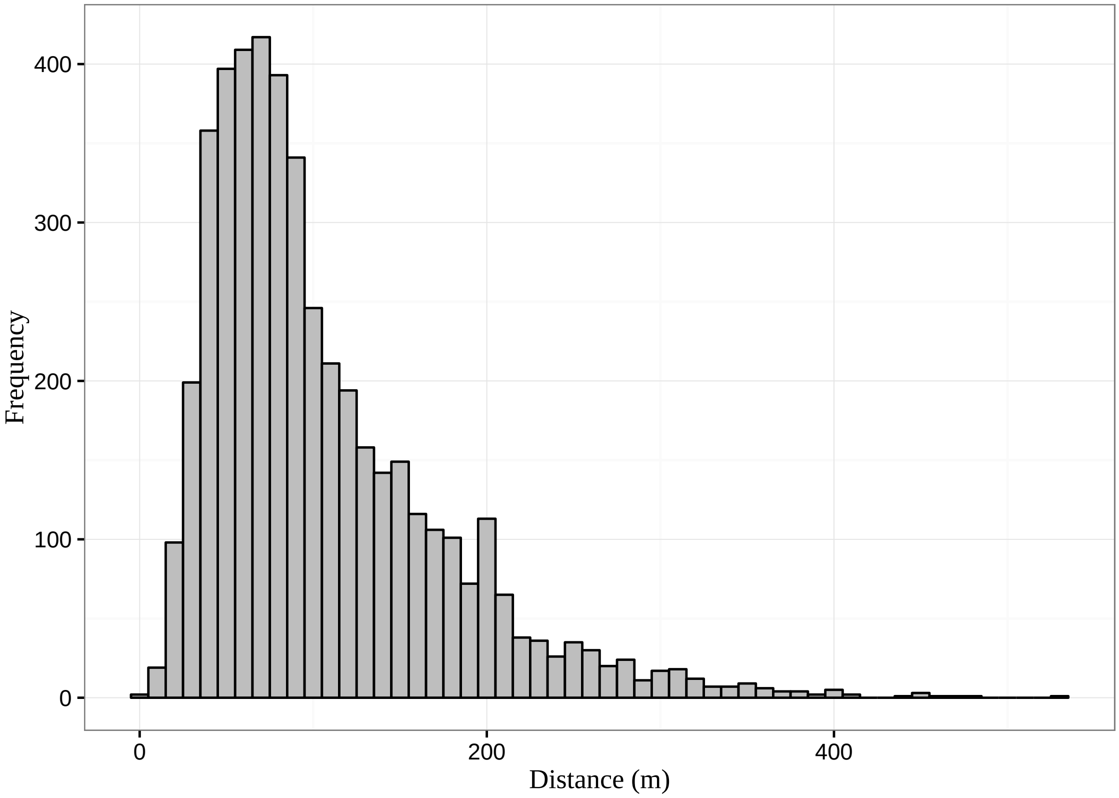


Figure 4.5: Histogram of distances for all bobwhite detected during the annual survey of 12 ranches within the Rolling Plains Ecoregion of Texas during 2012–2014.

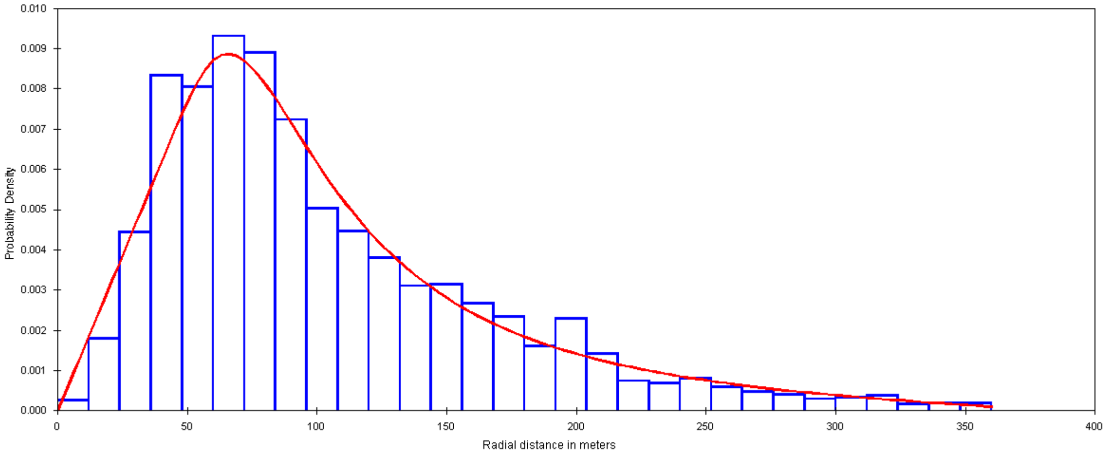


Figure 4.6: Probability density plot from program DISTANCE showing the fit of a hazard-rate model with one, 4th-order, simple polynomial adjustment term, to the histogram of distances obtained for all bobwhite detections within 360 m on the 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Table 4.3: Estimates of bobwhite density obtained using exact distances for each year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Year	Encounter Rate	Density	%CV	df	95% LCL	95% UCL
2012	3.20	0.79	2.52	4,693.15	0.75	0.83
2013	4.32	1.06	2.47	4,939.17	1.01	1.12
2014	5.55	1.37	2.65	4,382.37	1.30	1.44

We conducted separate analyses of our distance data using 3 techniques suggested for point counts of northern bobwhite that employed *apriori* distance intervals during data collection (Rollins et al. 2005, Applegate et al. 2011, Murray et al. 2011, Texas A&M AgriLife Extension 2013). All analysis steps were identical, and differed only in the number and size of distance intervals. This standardized the distance data, and ensured that identical encounter rates and distances were used for each method (i.e., therefore the same distribution of observations; 95$\%$ of all observations occurred within 241 m). Model selection differed by method, but each selected a hazard-rate model with either 0, 1, or 2 adjustment terms based on AIC. Model fit was good for all but the method of Rollins et al. (2005, Texas A&M AgriLife Extension 2013), which exhibited relatively poor fit near the distance zero (Fig.s 4.7 and 4.8; Table 4.5). We observed differences in $h(0)$ (the probability density function evaluated at distance zero) among methods due to sampling methodology (i.e., exact distances vs. *apriori* distance intervals), which created differences among density estimates and inflation of variance in the density estimates (Table 4.6). Results were similar for all but the Rollins et al. (2005) method, which produced estimates approximately 3 times lower than the other methods (Table 4.5).

The Rollins et al. (Rollins et al. 2005, Texas A&M AgriLife Extension 2013) method used 3 equal intervals (0-200 m, 200-400 m, and 400-600 m), generated 4150, 464, and 13 detections, and was fit using a hazard-rate model without adjustment terms (Fig.s 4.7 and 4.8; Table 4.5). The effective detection radius was 176.5 m, and the coefficient of variation for the slope of the probability density function evaluated at distance zero, $h(0)$, was 5.74$\%$ (Table 4.6).

The method of Murray et al. (2011) used 7 unequal intervals (0-50 m, 50-100 m, 100-150 m, 150-200 m, 200-300 m, 300-400 m, and 400-500 m; note Figure 2 in Murray et al. 2011 uses only 6 unequal bins, removing the 400-500 m interval) resulting in 853, 1892, 896, 509, 378, 86, and 12 detections, and was fit using a hazard-rate model with 4th

Table 4.4: Estimates of bobwhite density obtained using exact distances for each ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Ranch	Year	Density	%CV	df	95% LCL	95% UCL
TX2C	2012	0.91	5.64	31.34	0.81	1.02
TX2C	2013	0.83	7.30	26.41	0.71	0.96
TX2C	2014	0.72	4.28	68.15	0.66	0.79
TX4N	2012	0.21	8.51	24.79	0.18	0.25
TX4N	2013	0.56	9.67	23.85	0.46	0.68
TX4N	2014	1.10	6.90	41.43	0.95	1.26
TX7N	2012	0.25	11.93	22.81	0.19	0.31
TX7N	2013	1.23	10.50	23.39	0.99	1.53
TX7N	2014	3.96	5.44	49.39	3.55	4.42
TX7S	2012	0.93	10.04	23.63	0.75	1.14
TX7S	2013	1.43	5.11	34.58	1.29	1.59
TX7S	2014	0.08	6.52	42.84	0.07	0.09
TX6S	2012	1.08	4.26	40.83	0.99	1.18
TX6S	2013	1.77	3.44	72.45	1.65	1.90
TX6S	2014	1.08	3.42	112.26	1.01	1.16
TX6C	2012	0.84	5.35	32.92	0.75	0.94
TX6C	2013	0.98	4.78	76.88	0.89	1.08
TX6C	2014	1.21	4.69	58.78	1.10	1.33
TX2N	2012	1.58	3.60	68.15	1.47	1.69
TX2N	2013	1.57	3.07	279.40	1.47	1.66
TX2N	2014	2.52	3.44	121.35	2.35	2.70
TX1N	2012	0.22	4.88	36.60	0.20	0.25
TX1N	2013	0.92	5.94	61.47	0.81	1.03
TX1N	2014	1.46	5.35	50.17	1.31	1.63
TX1S	2012	0.51	6.26	28.88	0.45	0.58
TX1S	2013	0.39	4.79	76.77	0.35	0.42
TX1S	2014	1.07	4.73	58.10	0.98	1.18
TX4S	2012	1.25	3.32	92.27	1.17	1.34
TX4S	2013	1.86	4.67	38.85	1.69	2.04
TX4S	2014	1.01	5.01	53.88	0.92	1.12
TX2S	2012	0.90	14.46	17.98	0.67	1.22
TX2S	2013	0.62	5.65	52.15	0.55	0.69
TX2S	2014	0.49	9.84	29.40	0.40	0.60
TX4C	2012	0.80	4.42	38.31	0.73	0.87
TX4C	2013	1.24	5.10	64.31	1.12	1.37
TX4C	2014	1.50	6.43	39.15	1.32	1.71

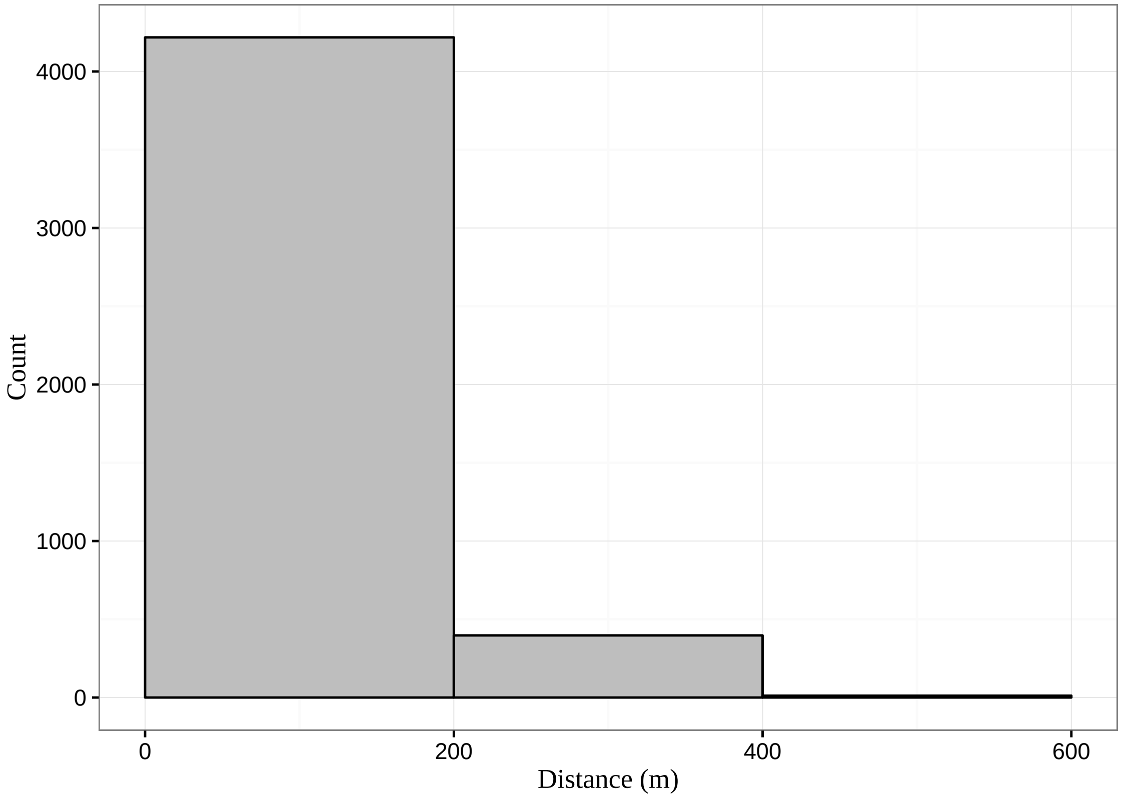


Figure 4.7: Histogram of distances obtained using the method defined by Rollins et al. (2005) for bobwhite detected during the annual survey of 12 ranches within the Rolling Plains Ecoregion of Texas during 2012–2014.

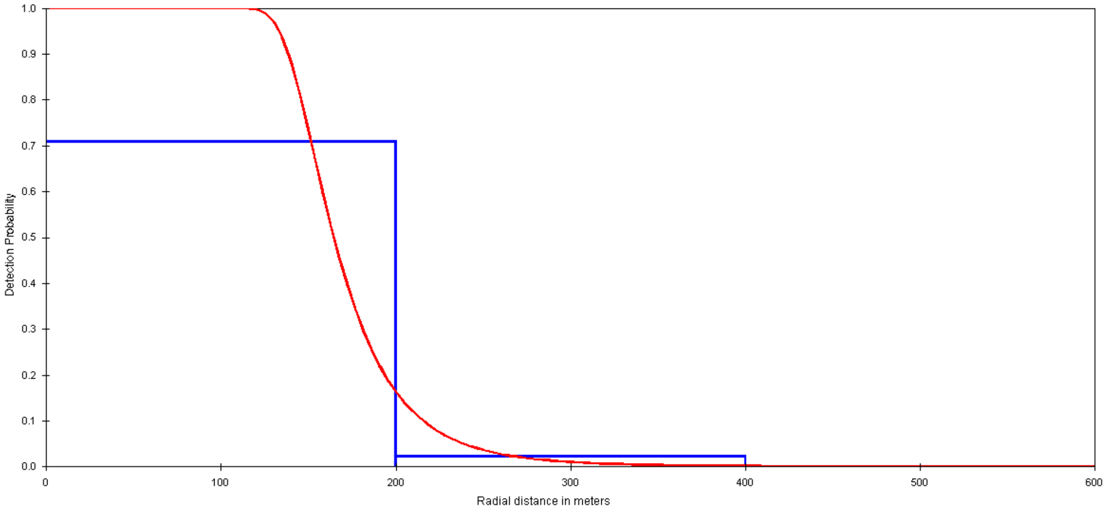


Figure 4.8: Probability density plot from program DISTANCE showing the fit of a hazard-rate model with no adjustment term, to the histogram of distances obtained using the method of Rollins et al. (2005) for bobwhite detections within 600 m on the 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Table 4.5: Estimates of bobwhite density obtained using the method of Rollins et al. (2005) for each ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Ranch	Year	Density	%CV	df	95% LCL	95% UCL
TX2C	2012	0.38	7.68	107.17	0.32	0.44
TX2C	2013	0.35	8.91	61.29	0.29	0.42
TX2C	2014	0.30	6.81	366.41	0.27	0.35
TX4N	2012	0.09	9.98	46.84	0.07	0.11
TX4N	2013	0.24	11.02	39.53	0.19	0.30
TX4N	2014	0.46	8.65	101.94	0.38	0.54
TX7N	2012	0.10	13.02	32.35	0.08	0.13
TX7N	2013	0.51	11.72	36.35	0.40	0.65
TX7N	2014	1.64	7.53	179.84	1.42	1.91
TX7S	2012	0.39	11.31	38.09	0.31	0.48
TX7S	2013	0.59	7.30	142.47	0.51	0.69
TX7S	2014	0.03	8.35	114.61	0.03	0.04
TX6S	2012	0.45	6.73	248.16	0.39	0.51
TX6S	2013	0.74	6.25	707.62	0.65	0.83
TX6S	2014	0.45	6.24	1,046.18	0.40	0.51
TX6C	2012	0.35	7.47	124.06	0.30	0.40
TX6C	2013	0.41	7.02	377.16	0.36	0.47
TX6C	2014	0.50	7.01	286.40	0.44	0.58
TX2N	2012	0.66	6.34	600.00	0.58	0.74
TX2N	2013	0.66	6.03	2,672.52	0.59	0.74
TX2N	2014	1.06	6.24	1,139.23	0.93	1.19
TX1N	2012	0.09	7.14	165.93	0.08	0.11
TX1N	2013	0.38	7.91	189.75	0.33	0.45
TX1N	2014	0.61	7.47	188.21	0.52	0.70
TX1S	2012	0.21	8.15	82.60	0.18	0.25
TX1S	2013	0.16	7.08	355.15	0.14	0.19
TX1S	2014	0.45	7.04	278.25	0.39	0.51
TX4S	2012	0.52	6.18	947.87	0.46	0.59
TX4S	2013	0.77	7.00	193.00	0.67	0.89
TX4S	2014	0.42	7.23	229.18	0.37	0.49
TX2S	2012	0.37	15.37	22.96	0.27	0.51
TX2S	2013	0.26	7.65	181.06	0.22	0.30
TX2S	2014	0.21	10.81	50.42	0.17	0.26
TX4C	2012	0.33	6.83	214.94	0.29	0.38
TX4C	2013	0.53	7.28	266.72	0.46	0.62
TX4C	2014	0.63	8.28	107.00	0.54	0.74

Table 4.6: Estimates of the probability density function evaluated at distance zero, coefficient of variation for the probability density estimate, effective detection radius, and coefficient of variation for the effective detection radius generated using the exact distance method of the present paper, the Rollins et al. (2005), Murray et al. (2011), Applegate et al. (2011) methods using distance data obtained from all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Method	h(0)	%CV	EDR	%CV
Rollins et al. 2005	0.000064	5.74	176.47	2.87
Murray et al. 2011	0.000152	2.76	114.76	1.38
Applegate et al. 2011	0.000149	3.08	116.05	1.54
Pierce et al.	0.000155	2.40	113.73	1.20

and 6th order adjustment terms (Fig.s 4.9 and 4.10; Table 4.7). The effective detection radius was 114.8 m, and the coefficient of variation for the slope of the probability density function evaluated at distance zero was 2.76% (Table 4.6).

The method of Applegate et al. (2011) used 4 unequal intervals (0-25 m, 25-50 m, 50-100 m, and 100-600 m; note Applegate et al. 2011 used all detections greater than 100 m in their final interval), generated 113, 740, 1892, and 1882 detections, and was fit using a hazard-rate model without adjustment terms (Fig. 4.11 and 4.12; Table 4.8). The effective detection radius was 116.1 m, and the coefficient of variation for the slope of the probability density function evaluated at distance zero was 1.54% (Table 4.6).

We used the ratio method to assess double-sampling for bobwhite with distance sampling as the intensive method and a relative index derived from birds heard during timed point counts as the rapid or low cost method (Neyman 1938, Caughley 1977, Eberhardt and Simmons 1987). Data for this calibration was obtained simultaneously, as recommended by Eberhardt and Simmons (1987). The intercept for the regression of average calls per point versus density was not significantly different from zero (Table 4.9), and logically the calibration should pass through the origin (if density = 0, then calls = 0; however see Collins 2007). As such, the regression of average calls per point versus density (Fig. 4.13), through the origin, produced an R^2 = 0.925 (Table 4.10). The coefficient of determination and precision of estimate indicates a double-sample calibration is both scientifically and economically feasible (Bart and Earnst 2002, Collins 2007). We note that because distance sampling relies upon encounter rate to estimate density,

$$D = \frac{E(n) \cdot h(0)}{2\pi k}$$

it is by definition a linear product of encounter rate (birds per point) and $h(0)$, and

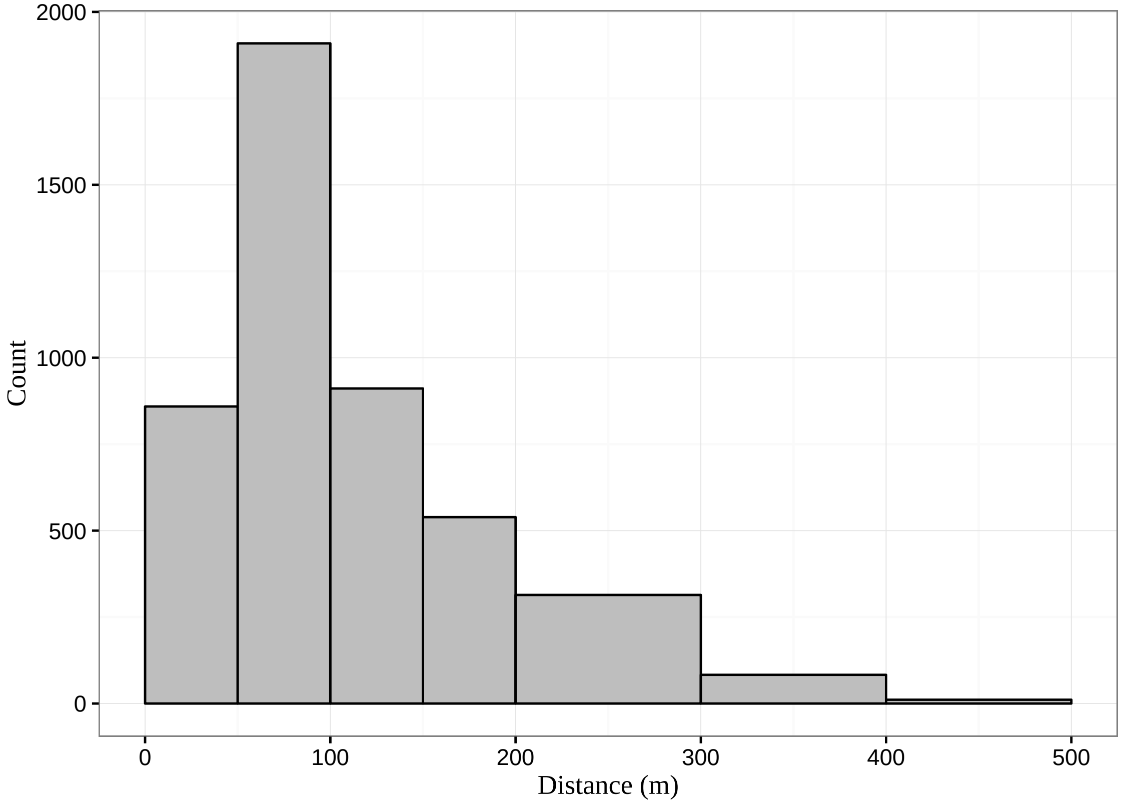


Figure 4.9: Histogram of distances obtained using the method defined by Murray et al. (2011) for bobwhite detected during the annual survey of 12 ranches within the Rolling Plains Ecoregion of Texas during 2012–2014.

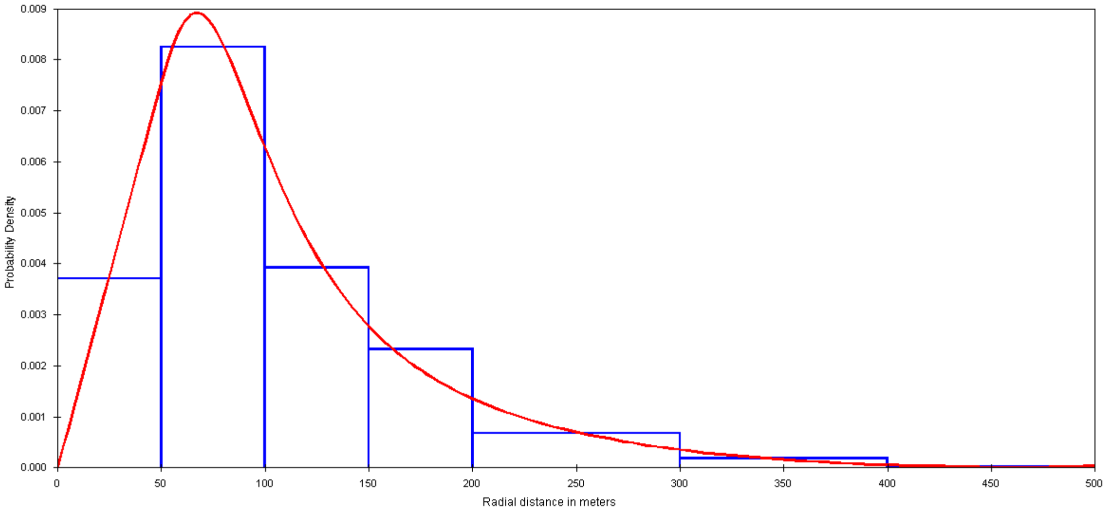


Figure 4.10: Probability density plot from program DISTANCE showing the fit of a hazard-rate model with 4th and 6th order adjustment terms, to the histogram of distances obtained using the method of Murray et al. (2011) for bobwhite detections within 500 m on the 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Table 4.7: Estimates of bobwhite density obtained using the method of Murray et al. (2011) for each ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Ranch	Year	Density	%CV	df	95% LCL	95% UCL
TX2C	2012	0.89	5.80	35.13	0.79	1.00
TX2C	2013	0.82	7.35	28.48	0.71	0.96
TX2C	2014	0.72	4.59	78.55	0.66	0.79
TX4N	2012	0.21	8.62	26.08	0.17	0.25
TX4N	2013	0.56	9.81	24.78	0.46	0.69
TX4N	2014	1.08	7.03	44.75	0.93	1.24
TX7N	2012	0.24	12.01	23.41	0.19	0.31
TX7N	2013	1.21	10.58	24.19	0.97	1.50
TX7N	2014	3.89	5.61	55.82	3.48	4.35
TX7S	2012	0.91	10.13	24.51	0.74	1.12
TX7S	2013	1.41	5.29	39.70	1.26	1.56
TX7S	2014	0.08	6.66	46.68	0.07	0.09
TX6S	2012	1.06	4.47	49.65	0.97	1.16
TX6S	2013	1.74	3.70	96.97	1.62	1.87
TX6S	2014	1.06	3.68	150.37	0.99	1.14
TX6C	2012	0.82	5.52	37.36	0.74	0.92
TX6C	2013	0.97	4.90	92.40	0.88	1.07
TX6C	2014	1.19	4.88	69.17	1.08	1.31
TX2N	2012	1.55	3.85	89.07	1.44	1.67
TX2N	2013	1.56	3.31	444.60	1.46	1.67
TX2N	2014	2.50	3.68	166.22	2.32	2.69
TX1N	2012	0.22	5.06	42.58	0.20	0.24
TX1N	2013	0.91	6.11	67.99	0.80	1.02
TX1N	2014	1.44	5.52	56.92	1.29	1.60
TX1S	2012	0.51	6.41	31.70	0.44	0.58
TX1S	2013	0.38	4.98	89.70	0.35	0.42
TX1S	2014	1.05	4.92	68.19	0.96	1.16
TX4S	2012	1.23	3.59	125.79	1.15	1.32
TX4S	2013	1.82	4.86	45.79	1.65	2.01
TX4S	2014	1.00	5.20	62.17	0.90	1.11
TX2S	2012	0.89	14.53	18.30	0.65	1.20
TX2S	2013	0.62	5.76	58.98	0.55	0.69
TX2S	2014	0.49	9.57	30.95	0.41	0.60
TX4C	2012	0.79	4.62	45.99	0.72	0.86
TX4C	2013	1.26	5.26	74.30	1.14	1.40
TX4C	2014	1.49	6.58	42.77	1.31	1.70

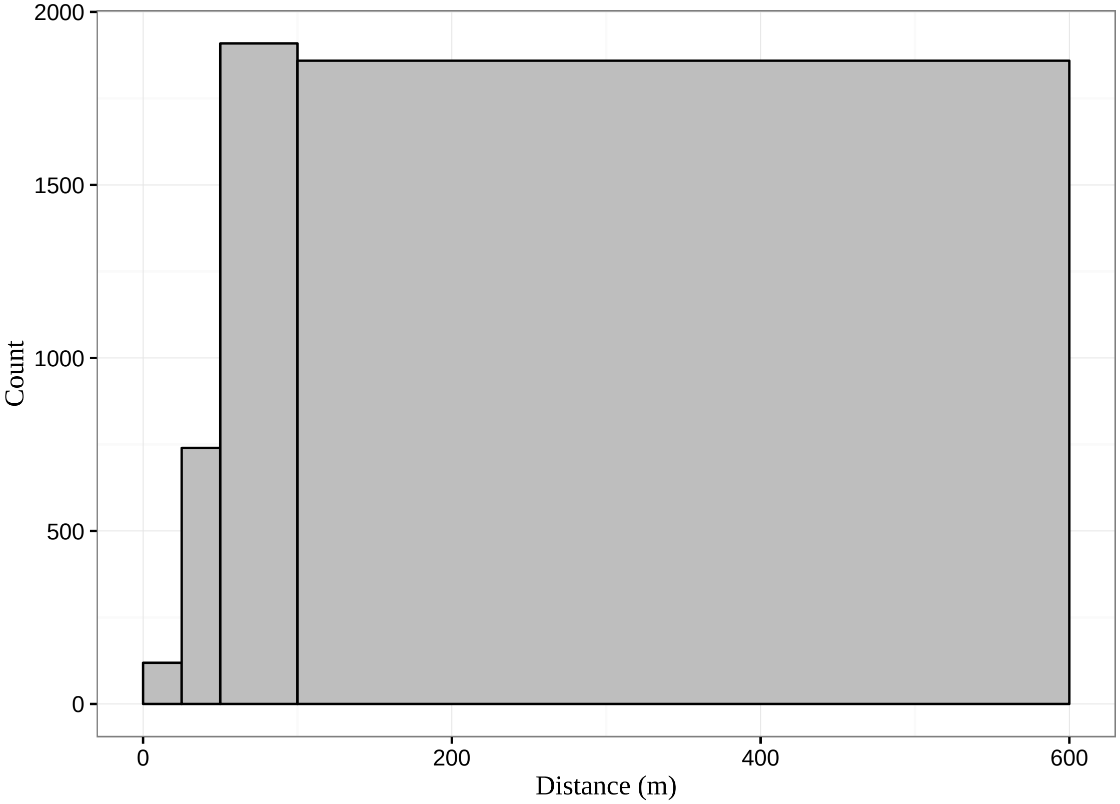


Figure 4.11: Histogram of distances obtained using the method defined by Applegate et al. (2011) for bobwhite detected during the annual survey of 12 ranches within the Rolling Plains Ecoregion of Texas during 2012–2014.

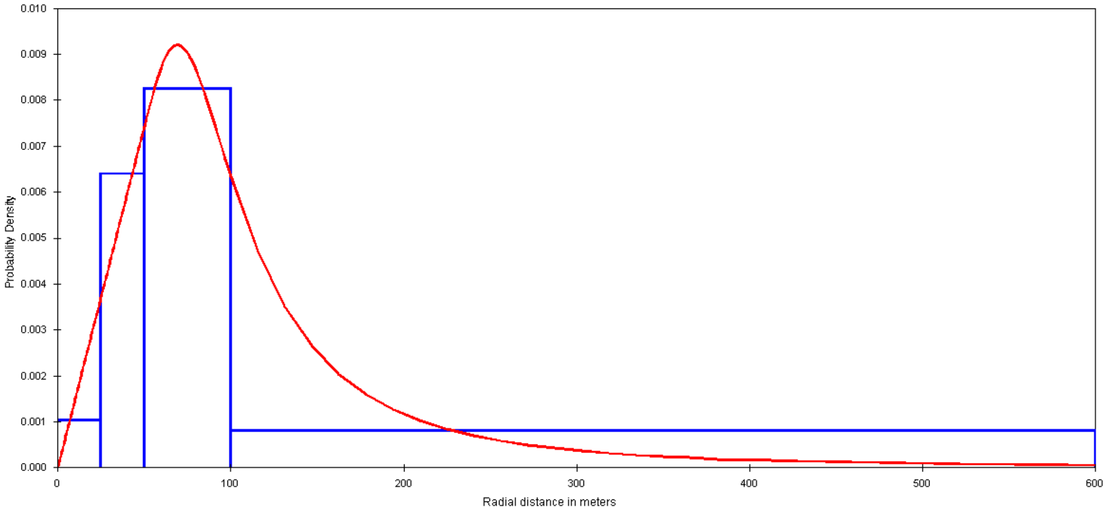


Figure 4.12: Probability density plot from program DISTANCE showing the fit of a hazard-rate model with 4th and 6th order adjustment terms, to the histogram of distances obtained using the method of Applegate et al. (2011) for bobwhite detections within 500 m on the 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Table 4.8: Estimates of bobwhite density obtained using the method of Applegate et al. (2011) for each ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Ranch	Year	Density	%CV	df	95% LCL	95% UCL
TX2C	2012	0.87	5.96	39.11	0.77	0.98
TX2C	2013	0.81	7.48	30.47	0.69	0.94
TX2C	2014	0.70	4.79	92.91	0.64	0.77
TX4N	2012	0.20	8.73	27.40	0.17	0.24
TX4N	2013	0.55	9.90	25.75	0.45	0.67
TX4N	2014	1.05	7.16	48.18	0.91	1.22
TX7N	2012	0.24	12.09	24.02	0.18	0.30
TX7N	2013	1.18	10.67	25.00	0.95	1.47
TX7N	2014	3.80	5.77	62.60	3.39	4.27
TX7S	2012	0.89	10.22	25.41	0.72	1.10
TX7S	2013	1.38	5.46	45.13	1.23	1.53
TX7S	2014	0.08	6.80	50.67	0.07	0.09
TX6S	2012	1.04	4.68	59.26	0.95	1.14
TX6S	2013	1.70	3.94	124.70	1.57	1.84
TX6S	2014	1.04	3.93	193.34	0.96	1.12
TX6C	2012	0.81	5.69	42.04	0.72	0.90
TX6C	2013	0.95	5.08	107.16	0.85	1.05
TX6C	2014	1.16	5.07	80.31	1.05	1.28
TX2N	2012	1.51	4.08	112.52	1.40	1.64
TX2N	2013	1.53	3.58	593.03	1.42	1.64
TX2N	2014	2.44	3.93	213.65	2.26	2.64
TX1N	2012	0.21	5.24	48.96	0.19	0.24
TX1N	2013	0.89	6.26	74.92	0.78	1.00
TX1N	2014	1.40	5.69	64.05	1.25	1.57
TX1S	2012	0.49	6.55	34.64	0.43	0.56
TX1S	2013	0.38	5.16	103.54	0.34	0.42
TX1S	2014	1.03	5.11	79.00	0.93	1.14
TX4S	2012	1.20	3.84	163.91	1.12	1.30
TX4S	2013	1.78	5.05	53.25	1.61	1.97
TX4S	2014	0.97	5.37	70.98	0.88	1.08
TX2S	2012	0.87	14.59	18.63	0.64	1.17
TX2S	2013	0.60	5.92	65.74	0.54	0.68
TX2S	2014	0.48	9.66	32.22	0.40	0.59
TX4C	2012	0.77	4.82	54.31	0.70	0.85
TX4C	2013	1.23	5.44	84.56	1.11	1.38
TX4C	2014	1.46	6.72	46.52	1.27	1.67

therefore average birds per point versus density is an unsuitable regression (confounded) for use in this double-sampling procedure (Fig. 4.14).

DISCUSSION

We used point distance sampling (Buckland et al. 2001) to generate local and regional estimates of bobwhite density in the Rolling Plains Ecoregion of Texas. We used 2–3 observers each year during a 14 day period, and obtained a sufficient number of observations (*n* = 4.627) to generate a model fit (Fig. 4.6) that resulted in relatively precise estimates of density by year and by ranch x year (Table 4.3, Table 4.4). As such, our results demonstrate that contrary to published findings (Applegate et al. 2011, Murray et al. 2011), distance sampling can be successfully and economically (man-hours) used to obtain estimates of density for northern bobwhite.

Like all methods, distance sampling may fail to provide anticipated results for a multitude of reasons. However, in many cases it is difficult to tell if the problem lies with the sample design, field methodology, surveyors, analytical technique, or due to circumstances beyond the control of the investigators. Common deficiencies include insufficient sample size, imprecise distance estimation, and "convenience analysis", where analytical tools are assumed robust to deficiencies in sample design, methodology, or training. To illustrate, we used our data to generate results with *apriori* distance intervals defined in Rollins et al. 2005 (also see Texas A&M AgriLife Extension 2013), Murray et al. 2011, and Applegate et al. 2011. For point distance sampling the slope of the probability density function evaluated at distance zero, $h(0)$, is the critical component for estimating density

$$D = \frac{E(n) \cdot h(0)}{2\pi k}$$

where $E(n)$ is the expected number of animals in the survey area, and k is the number of

Table 4.9: Linear regression of density versus average calls per point for each ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.196	0.101	1.935	0.061
Average Calls	0.025	0.002	10.659	0.000

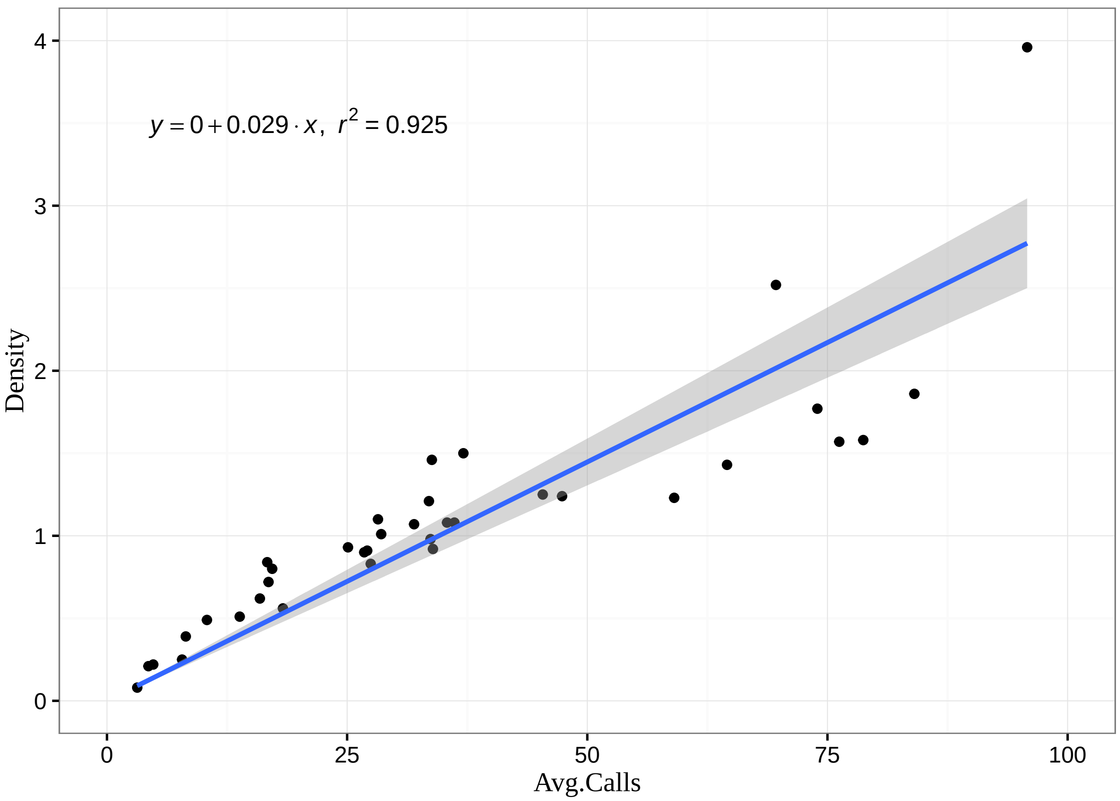


Figure 4.13: Linear regression, through the origin, of the average calls per point versus density for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Table 4.10: Linear regression, through the origin, of density versus average calls per point for each ranch and year for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014.

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
Average Calls	0.029	0.001	20.713	0.000

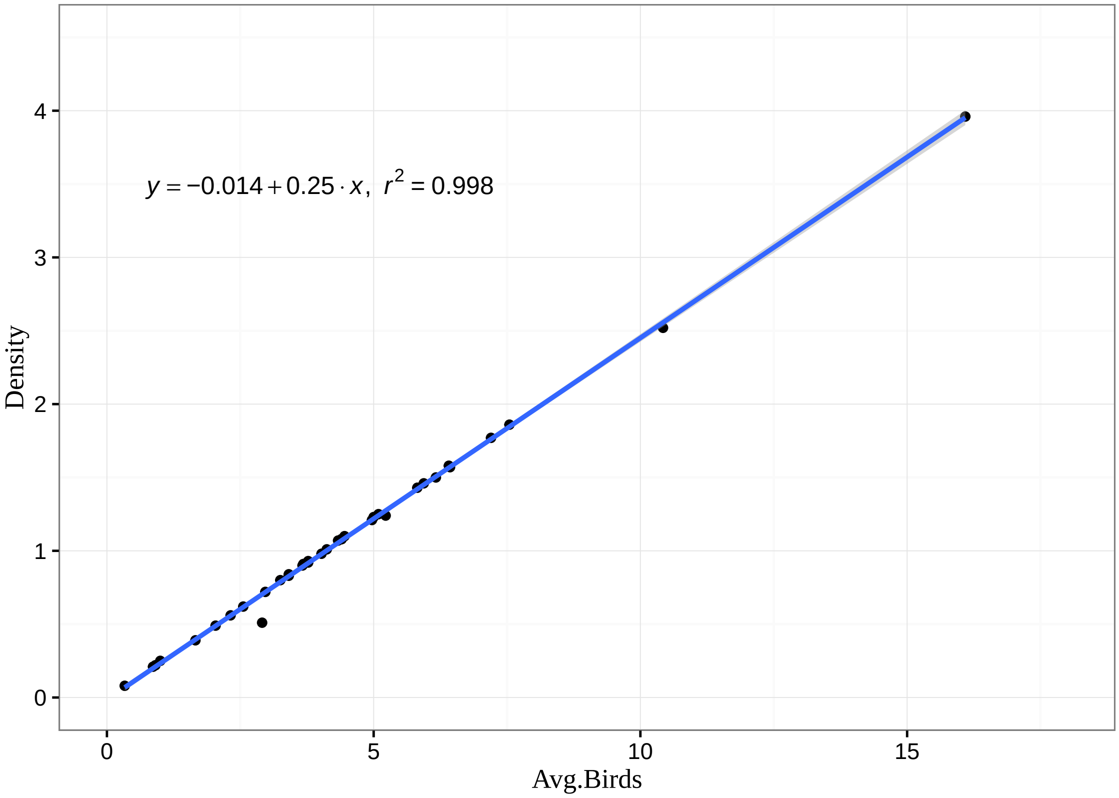


Figure 4.14: Confounded linear regression of the average birds per point versus density for all 12 ranches surveyed in the Rolling Plains of Texas during the spring of 2012–2014. Because DISTANCE estimates of density are the product of encounter rate (birds per point) and $h(0)$, the regression of average birds per point versus density is an unsuitable regression for use in this double-sampling procedure.

points surveyed (Buckland et al. 2001). It is $h(0)$ that is modeled through use of distances. Because the coefficient of variation (CV) for $h(0)$ describes model fit in terms of the relative magnitude of the squared residuals, a lower CV indicates smaller residuals, and therefore a better fit of the model to the data. Because all of our comparative estimates were obtained using the same data, the CV for $h(0)$ serves as the ideal metric for comparing results between these methods.

The methodology proposed by of Rollins et al. (2005) has been expanded to a statewide citizen-science monitoring effort (Texas A&M AgriLife Extension 2013). It recommends the use of 3 equal distance intervals for point counts of 5 minutes in duration. While the authors state that distance sampling is a "labor intensive method" for estimating quail abundance, and is usually restricted to research projects, we believe it could be successfully incorporated into a citizen-science survey with proper training and the application of distance sampling in a double-sampling effort. However, an examination of their methodology indicates the inappropriate use of *apriori* distance intervals to overcome inaccuracy in distance estimation. The 3 proposed distance intervals (0-200 m, 200-400 m, and 400-600 m) are too broad (Buckland et al. 2001:42), and appear to have been arbitrarily selected with disregard for the shape of the true detection function. We used the *apriori* distance intervals of Rollins et al. (2005, Texas A&M AgriLife Extension 2013) to generate results using our survey data. The histogram of distances obtained (Fig. 4.7) showed that 3 intervals were too broad, and the probability density plot (Fig. 4.8) demonstrated poor model fit despite a large number of observations (n = 4,627). Results derived from their methodology had a higher CV for $h(0)$, and therefore higher CV's for all density estimates (Table 4.6, Table 4.5). As a result of poor model fit near distance zero, this method produced density estimates 2-3 times lower than those obtained using exact distances (Table 4.4). As such, we believe the use of distance sampling for this project is limited, unless incorporated as part of a double-sampling effort with exact distances collected by trained observers. This is not to say that distance sampling is too difficult for citizen-scientist, rather there appears to be no economically feasible paradigm for providing the standardized training and equipment necessary to obtain adequate results at this time (i.e., the incorporation of rangefinders, collection of exact distances, and sufficient observer training in the field).

The study of Murray et al. (2011) obtained 925 observations of bobwhites from an unspecified number of points along 14 routes over 2 years, but recommended use of the removal method (Farnsworth et al. 2002) due to better precision and suspected violation of distance assumptions. The authors state that poor sample design (bias due to location near roadways), movement away from the point in response to the observers, reduced singing rates in response to observers, and poor accuracy in estimates of distance were likely responsible for violation of distance assumptions and poor performance of the distance method. Certainly inadequate sample design, combined with reduced calling rates and movement away from the observer may have biased estimates, but each should have been corrected prior to sampling. Likewise, inaccuracy in distance estimation should have been identified and corrected during training. However, we used the *apriori* distance intervals of Murray et al. (2011) to generate results using our data to determine if their use of distance intervals or models that demonstrated "a lack of fit" near distance zero (Murray et al. 2011:1076) further influenced their comparison among methods. The histogram of distances obtained using our data was peaked near 100 m (Fig. 4.9). A hazard rate model with 2 simple polynomial adjustment terms (4^th and 6^th order) was selected via AIC, and the probability density plot (Fig. 4.10) demonstrated a successful model fit. Results derived using their distance intervals had a slightly elevated CV for $h(0)$ in comparison with results obtained using exact distances (Table 4.6), and therefore produce elevated CV's for most density estimates (Table 4.7). This indicates that while the *apriori* distance intervals used by Murray et al. (2011) likely constrained model fit, they happened to capture the shape of the underlying detection function. While fortuitous, our results demonstrate Murray et al. (2011) were unable to obtain a proper model fit with their data due to inadequate sample design and methodology, resulting in violation of distance assumptions and biased results. Clearly *apriori* fixed distance intervals can hinder model fit, and may not adequately represent the true detection function. As such, exact distances should be collected in the field whenever possible, with post-hoc application of distance intervals for smoothing, when necessary, during the analytical phase.

Applegate et al. (2011) obtained 635 observations of bobwhites from 110 points over 6 years, but recommended that alternatives to distance sampling be used in future studies due to poor results. An examination of their methodology indicates that detection function fit was inhibited by poor model selection and inappropriate use of *apriori* distance intervals to overcome inaccuracy in distance estimation. The 4 intervals used (0-25, 26-51, 51-100, and greater than 100 m) were too broad (Buckland et al. 2001:42), and selected either without knowledge of, or with disregard for, the likely shape of the true detection function. Their model fitting was limited to half-normal and uniform functions, when under these constraints a hazard rate function may have provided better results due to the inherent shape for this family of models (Buckland et al. 2001:47). Hence, their detection function "shoulder" was obfuscated by the coarse, *apriori* distance intervals, resulting in model fits where detection probability increased as a function of radial distance (i.e., monotonically increasing). When we used the *apriori* distance intervals of Applegate et al. (2001) to generate results using our data, the histogram of distances obtained (Fig. 4.11) was indeed similar to Applegate et al. (2001:118), but the probability density plot (Fig. 4.12) demonstrated that a relatively successful model fit could be obtained with appropriate model selection. However, results derived from their analytical methodology had a higher CV for $h(0)$, and therefore higher CV's for all density estimates (Tables 4.8 and Table 4.6).

Our results demonstrate that calibration of bobwhite relative abundance (raw counts of birds heard) with density estimates derived from distance sampling is both straightforward and efficacious (Table 4.10, Fig. 4.13). Further, our results demonstrate that with a valid sampling design, a distance sampling based, double-sampling procedure (Neyman 1938, Caughley 1977, Eberhardt and Simmons 1987) can easily be incorporated into a larger citizen-science monitoring effort for bobwhite in Texas (e.g., the Texas A&M AgriLife Texas Quail Index). These findings are relevant because many research efforts require some measure of abundance or relative abundance to make management decisions. Yet indices of relative abundance (raw counts) have been widely criticized for being incomplete counts of unknown proportions of a population. Based upon our results, and the results of previous research (Bart and Earnst 2002, Collins 2007), we believe double-sampling may be the most practical, yet underutilized solution, for obtaining reliable knowledge from studies using indices of relative abundance.

Large monitoring efforts covering broad regions are costly, and to overcome this problem many research efforts have incorporated citizen-scientists to provide the necessary manpower at reduced costs. However, researchers from various backgrounds have indicated that citizen volunteers are unlikely to have the experience, training, or supervision necessary to conduct many of the more intensive abundance estimation techniques used by professional biologists. Our results agree with the findings of previous researchers, and demonstrate that it is possible to calibrate metrics obtained through citizen-science efforts with results obtained by more intensive scientific methods. As such, our findings support the supposition that citizen-science results can be economically incorporated into scientific research, so long as the endeavor is buttressed with reproducible scientific results obtained under a valid sampling design.

Many grassland bird species are undergoing range contractions and declines in abundance. One such grassland bird, the northern bobwhite quail, is among the most studied species in North America, and yet it continues to decline. To understand and reverse declines in grassland bird abundance will require collection of comparative environmental and synecological information over broad areas, especially estimates of temporal and spatial abundance. The scale of these efforts suggests that only participation by landowners and the public (i.e., citizen scientists) can meet both the fiscal and manpower requirements of these future projects. Project outcomes will therefore depend upon the successful conversion of volunteer effort into valuable scientific data, and consequently the integrity of the experimental design, sampling methodology, training, and analytical methods.

MANAGEMENT IMPLICATIONS

What we have demonstrated that: (1) distance sampling can be used to obtain accurate estimates of bobwhite if sufficient observations are obtained for each area of inference, (2) modeling of the detection function is inhibited by small sample sizes, (3) modeling of the detection function is inhibited by inappropriate use of *apriori* distance intervals (i.e., distance intervals derived to overcome inaccuracy in distance estimation with disregard for ability to accurately model the shape of the true probability density function), (4) inappropriate use of *apriori* distance intervals inflates variance of the density estimates (information loss due to categorization of a continuous variable), (5) density estimates derived from distance sampling may be used to obtain a double-sampling regression with auditory detections (i.e., a common relative index for grassland birds), and therefore (6) a double-sampling paradigm is likely a pragmatic solution for obtaining reliable information from citizen-science surveys of northern bobwhite and other grassland birds.

CHAPTER V

CONCLUSIONS

MOURNING DOVE

In recent years, the need for additional information to better manage mourning dove populations has become evident (National Mourning Dove Planning Committee 2004). Research that can adequately address this need requires the identification of homogeneous experimental habitat units from within which replicate samples may be derived. Of particular concern is the association between habitat variables and relative abundance indices, as the latter are unlikely to share equal probabilities of detection across diverse habitat conditions. My evaluation of experimental units for mourning dove research in Texas used habitat variables at 2 spatial scales, but did not incorporate annual call-count survey (CCS) results into the analysis. This approach assumes a relationship between habitat and species niche, but alleviates any potential bias due to differences in detectability among sites and confounding due to tautological incorporation of abundance survey results into a model that predicts abundance. Through use of habitat variables and appropriate statistical techniques, this study capitalized on the original work of Grue et al. (1976, 1981, 1983) and Blankenship et al. (1971), and provides an analytical paradigm for the statistical assessment of classification schemes.

My results indicate that the (Gould 1962) classification is currently the most suitable for delineation of experimental units in Texas. However, the vegetation based classification of Gould (1962, 1975) is only available for Texas. Conversely, the Omernik (Omernik 1987, Griffith et al. 2004) classification method is standardized and available for the continental United States. Further, the Omernik (Omernik 1987, Griffith et al. 2004) classification was derived from a cartographic paradigm that included variables for potential natural vegetation, soils, physiography, and anthropomorphic land use. In doing so, Omernik (Omernik 1987, Griffith et al. 2004) acknowledged that land cover classifications must contain not only habitat variables defining the background state of the ecological matrix (dominant gradients influencing potential habitat condition), but also some measure of anthropomorphic effects (contemporary land use), which act to perturb the underlying system. It is therefore imperative that future researchers understand that species-habitat relationships are in constant flux, but constrained by the tolerances of each species. Because classification schemes are implicit hypotheses concerning spatial delineation of habitat into multivariate experimental units, CDA (Anderson and Robinson 2003, Anderson and Willis 2003) may provide a useful mechanism for the periodic future assessment of classifications (whether cartographic or quantitatively based).

Finally, these results provide a framework for testing the earlier hypothesis of Dambach (1948) who concluded that habitat was the essential factor regulating population trends:

> “The chief factor determining long term trends in game populations in Ohio is land use. Only as far as the major use of the land can be modified to meet the needs of wildlife can any appreciable influence on game populations be expressed. Hunting restrictions, artificial propagation, predator control, winter feeding and related efforts are incidental compared to natural production.”

I propose that anthropomorphic land use must be periodically evaluated, relative to harvest and other demographic parameters, if we are to understand ecological trends, and if we intend to properly manage wildlife, and particularly mourning dove, populations. Results presented here identify currently optimal experimental units, based upon habitat congruent with CCS routes, and therefore provide the foundation for future mourning dove research efforts in Texas and elsewhere.

NORTHERN BOBWHITE HABITAT

Grassland bird conservation is a growing concern due to range contraction and/or continued declines in abundance for several species as a result of habitat loss and fragmentation. These long-term trends are frequently attributed to changing anthropogenic land use. Texas is comprised of approximately 56.7 million ha of private farms, ranches and forests, leading the nation in land area devoted to privately owned working lands. While these working lands account for 83% of the land area within the state, and provide substantial economic, environmental, and recreational benefits, these private lands also provide most of the available habitat supporting native flora and fauna. Yet these lands are being consumed by rapid population growth, suburbanization, and rural development. Our spatial-temporal analysis of bobwhite habitat clearly indicates that many contemporary anthropogenic land uses are inversely related to quail abundance. For instance, our habitat analysis explained R^2 = 74.5% (${R_{adj}}^2$ = 60.8%, $P < 0.0016$) of the variance in bobwhite relative abundance during the 1997–2012 period in Texas, and revealed significant regional differences in habitat variables through time. As such, our results provide incontrovertible evidence that anthropogenic habitat degradation is largely responsible for the ongoing decline in northern bobwhite and other grassland birds.

The outcome of this research is both informative and hopeful. If the primary cause of habitat loss is contemporary human land use, then we can work to alter and transform human land management to minimize negative impacts and maximize our natural resources. That which has been created by human endeavors, can be altered by human ingenuity and effort. We therefore suggest that refocusing research efforts toward the identification of spatial-temporal land management factors that degrade or improve natural productivity in habitat quality will provide the most pragmatic strategy for reversing the decline in grassland birds, especially the northern bobwhite.

The results from my assessment of northern bobwhite habitat in Texas demonstrates that a shift toward monitoring of anthropogenic metrics is economically feasible, and can be used to develop new forms of responsible habitat management. More importantly, we have identified available metrics that can be used to predict shifts in habitat quality (Human Population Density, Average Market Value per Hectare, Average Production Value per Hectare). As such, my analyses provide inputs for determining what metrics can be monitored to assess changes in habitat quality over time, and where to utilize conservation capital in order to maximizing return on investment.

NORTHERN BOBWHITE ABUNDANCE

Many grassland bird species are undergoing range contractions and declines in abundance. To understand and reverse these declines will require collection of environmental and synecological information over broad spatial and temporal scales, especially estimates of abundance. Yet the manpower required for monitoring at this scale is large and economically daunting, which suggests that only participation by landowners and the public citizen scientists can meet both the fiscal and manpower requirements of these future monitoring efforts. Citizen-science project outcomes will therefore depend upon the successful conversion of volunteer effort into valuable scientific data.

Numerous research projects have utilized relatively untrained volunteers, often termed citizen-scientists, to provide the manpower necessary for data collection over large areas, timescales, and a multitude of species: birds (ebird.org, birdsleuth.org), insects (e-butterfly.org, bumblebeewatch.org, BugGuide.net), marine mammals (wildwhales.org), herptiles (aza.org/frogwatch), plants (budburst.org), asteroids (cosmoquest.org), weather (oldweather.org), and the search for extra-terrestrial intelligence (seti.org, setiathome.berkeley.edu). However, ecological research has shown that most citizen volunteers are unlikely to have the experience, training, or expertise necessary to conduct many of the more intensive abundance estimation techniques, such as mark-resight, time-to-detection, and double-observer (Greenwood 2007, Couvet et al. 2008, Dickinson et al. 2010, Conrad and Hilchey 2011, Jiguet et al. 2012), including the ability to unequivocally discern animal calls or to accurately estimate distances (Gibson and Bergman 1954, Scott et al. 1981, Hodge 1981, Alldredge et al. 2007, Efford and Dawson 2009, Nadeau and Conway 2013). This is not to say that there are not highly-trained lay individuals, such as many birding enthusiasts, that maintain a better command of field craft and bird call identification than most scientists. Rather, it demonstrates the need for incorporation of scientific expertise into citizen-science efforts to ensure appropriate methodology, experimental design, and training regimes are established to yield the level of accuracy and precision required for successful analysis and inference from crowd-sourced data.

I developed a pilot scale study to demonstrate the feasibility of combining scientific expertise, with citizen-science participation effort, to obtain a regional estimate of northern bobwhite abundance. Our objective was to use distance sampling density estimates to calibrate bobwhite call-count surveys within a double-sampling paradigm (Caughley 1977, Eberhardt and Simmons 1987, Bart and Earnst 2002, Pollock et al. 2002, Collins 2007). Spring cock call-counts were conducted on 12 ranches within the Rolling Plains of Texas during 2012–2014. This sampling effort collected calls and distances at each point, yielding 1,022 total counts, detected 36,415 calls, 4,647 birds, and obtained 4,627 distances (Tables 4.1 and 4.2). Data were analyzed using program DISTANCE to generate local and regional estimates of quail density for each year (Tables 4.3 and 4.4), and to calibrate density estimates with birds heard (Fig 4.13). These results support the findings of previous researchers (Caughley 1977, Eberhardt and Simmons 1987, Bart and Earnst 2002, Pollock et al. 2002, Collins 2007), and demonstrate that it is economically feasible and logistically pragmatic to calibrate metrics obtained through citizen-science efforts (call-counts; relative abundance) with results obtained by more intensive scientific methods (distance sampling; density estimates). As such, our findings support the supposition that citizen-science results can be incorporated into scientific research, so long as the endeavor is buttressed with reproducible scientific results, obtained with the proper equipment, methodology, and training, under a valid sampling design. Finally, our results represent prima facie evidence that with a valid experimental design and appropriate training, a distance sampling based, double-sampling procedure can easily be incorporated into a larger citizen-science monitoring effort for grassland birds, such as the Texas A&M AgriLife Texas Quail Index.

WILDLIFE MANAGEMENT

This dissertation represents my attempts to address several wildlife management problems using novel combinations of existing research tools and methodology. Collectively, these works represent independent research into 3 aspects of autecology that are central to all wildlife management endeavors: defining experimental units, identifying habitat factors that regulate populations, and estimating animal abundance.

While I used 2 game bird species as examples (mourning dove and northern bobwhite), it is important to note the outcomes of each effort have broader ecological application. The target species within each effort are interchangeable with other bird species in each guild, and the philosophical approach to each problem is universal (methodological skepticism). Similarly, the scientific methods used in each of these research efforts are common, and relevant for both single-species and community ecology. Yet, both ”game species” and ”single-species management” are viewed with disdain by many contemporary conservation biologists. This is unfortunate, because game species are relatively common and, funding is available due to management necessities arising from human exploitation. Of greater importance is the ancillary political shift toward ”community ecology” and ”bioconservation”, as it represents a further embrace of the Clementian “ecosystems as an organism” perspective, and a move away from the Gleasonian Individualistic Concept.

To whit; we are now in an age where computational processing power and statistical advances in multivariate research will allow us to investigate niche interactions as envisioned by Gleason (1926) and Hutchinson (1957). Therefore, the ability to investigate multivariate factors defining the fundamental niche of a single species provides the knowledge necessary to advance our understanding of species interactions within an ecosystem. As such, to condemn investigations into single species for political dogma will, to some extent, hinder our ability to elucidate understanding of the natural world.

My research, and this conclusion, is an argument which attempts to demonstrate the relevance of wildlife management as a field of scientific endeavor, and to advocate the need to re-evaluate single species management over time in order to incorporate new technology and knowledge, and advance human understanding. While I believe I have adequately made my case, any errors in logical or validity, relative truth of premises, or interpretation of results, are mine alone.

LITERATURE CITED

Aldrich, J., and A. Duvall. 1958. Distribution and migration of races of the mourning dove. Condor 60:108–128.

Alldredge, M., T. Simons, and K. Pollock. 2007. A field evaluation of distance measurement error in auditory avian point count surveys. Journal of Wildlife Management 71:2759–2766.

Alvarez, E. C., and R. Plocheck, editors. 2005. Texas almanac 2006-2007: sesquicentennial edition 1857-2007. Dallas Morning News, Dallas, USA.

Anderson, D. R. 2001. The need to get the basics right in wildlife field studies. Wildlife Society Bulletin 29:1294–1297.

Anderson, D. R. 2003. Response to Engeman: index values rarely constitute reliable information. Journal of Wildlife Management 31:288–291.

Anderson, M., and J. Robinson. 2003. Generalized discriminant analysis based on distances. Australian and New Zealand Journal of Statistics 45:301–318.

Anderson, M., and T. Willis. 2003. Canonical analysis of principal coordinates: a useful method of constrained ordination for ecology. Ecology 84:511–525.

Anderson, R., A. Engeling, A. Grones, R. R. Lopez, B. L. Pierce, K. Skow, and T. Snelgrove. 2014. Status update and trends of Texas rural working lands. Texas Land Trends 1:1–13.

Applegate, R. D., R. E. Kissell Jr, E. D. Moss, E. L. Warr, and M. L. Kennedy. 2011. Problems with avian point counts for estimating density of northern bobwhite-a case study. Journal of Fish and Wildlife Management 2:117–121.

Arbingast, S. 1976. Atlas of Texas. University of Texas, Bureau of Business Research, Austin, USA.

Banerjee, M., M. Capozzoli, L. McSweeney, and D. Sinha. 1999. Beyond kappa: a review of interrater agreement measures. Canadian Journal of Statistics 27:3–23.

Bart, J. 2005. Monitoring the abundance of bird populations. The Auk 122:15–25.

Bart, J., S. Droege, P. Geissler, B. Peterjohn, and C. J. Ralph. 2004. Density estimation in wildlife surveys. Wildlife Society Bulletin 32:1242–1247.

Bart, J., and S. Earnst. 2002. Double sampling to estimate density and population trends in birds. The Auk 119:36–45.

Baskett, T. S., 1993. Biological evaluation of the call-count survey. Pages 253–268 *in* T. S. Baskett, M. W. Sayre, R. E. Tomlinson, and R. E. Mirarchi, editors. Ecology and management of the mourning dove. Stackpole Books, Harrisburg, Pennsylvania, USA.

Baskett, T. S., and M. W. Sayre, 1993. Characteristics and importance. Pages 1–6 *in* T. S. Baskett, M. W. Sayre, R. E. Tomlinson, and R. E. Mirarchi, editors. Ecology and management of the mourning dove. Stackpole Books, Harrisburg, Pennsylvania, USA.

Blankenship, L. H., A. B. Humphrey, and D. MacDonald. 1971. A new stratification for mourning dove call-count routes. Journal of Wildlife Management 35:319–326.

Bock, C. E., and J. H. Bock. 1999. Response of winter birds to drought and short-duration grazing in southeastern Arizona. Conservation Biology 13:1117–1123.

Bollinger, E. K., T. A. Gavin, and D. C. McIntyre. 1988. Comparison of transects and circular-plots for estimating bobolink densities. Journal of Wildlife Management 52:777–786.

Braun-Blanquet, J. 1932. Plant sociology; the study of plant communities. McGraw-Hill, New York, New York, USA.

Bray, J. R., and J. T. Curtis. 1957. An ordination of the upland forest communities of southern Wisconsin. Ecological Monographs 27:326–349.

Brennan, L. A. 1991. How can we reverse the northern bobwhite population decline? Wildlife Society Bulletin 19:544–555.

Brennan, L. A., and J. Kuvlesky, William P. 2005. North American grassland birds: an unfolding conservation crisis? Journal of Wildlife Management 69:1–13.

Bridges, A. S., M. J. Peterson, N. J. Silvy, F. E. Smeins, and X. B. Wu. 2001. Differential influence of weather on regional quail abundance in Texas. Journal of Wildlife Management 65:10–18.

Buckland, S. T., D. R. Anderson, K. P. Burnham, and J. L. Laake. 1993. Distance sampling: estimating abundance of biological populations. Chapman and Hall, London, England, UK.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.

Buckland, S. T., and C. Handel. 2006. Point-transect surveys for songbirds: robust methodologies. The Auk 123:345–357.

Burnham, K. P. 1981. Summarizing remarks: environmental influences. Studies in Avian Biology 6:324–325.

Burnham, K. P., and D. Anderson. 1984. The need for distance data in transect counts. Journal of Wildlife Management 48:1248–1254.

Butcher, G. S., M. R. Fuller, L. S. McAllister, and P. H. Geissler. 1990. An evaluation of the Christmas Bird Count for monitoring population trends of selected species. Wildlife Society Bulletin 18:129–134.

Campbell-Kissock, L., L. H. Blankenship, and L. D. White. 1984. Grazing management impacts on quail during drought in the northern Rio Grande Plain, Texas. Journal of Range Management 37:442–446.

Carr Jr., J. T. 1967. The climate and physiography of Texas. Report no. 53. Texas Water Development Board, Austin, USA.

Caughley, G. 1977. Analysis of vertebrate populations. Wiley, New York, New York, USA.

Cohen, J. 1960. A coefficient of agreement for nominal scales. Educational and Psychological Measurement 20:37–46.

Collins, B. T. 2007. Guidelines for using double sampling in avian population monitoring. The Auk 124:1373–1387.

Congalton, R. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment 37:35–46.

Congalton, R., and R. Mead. 1983. A quantitative method to test for consistency and correctness in photointerpretation. Photogrammetric Engineering and Remote Sensing 49:69–74.

Congalton, R., R. Oderwald, and R. Mead. 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogrammetric Engineering and Remote Sensing 49:1671–1678.

Conrad, C. C., and K. G. Hilchey. 2011. A review of citizen science and community-based environmental monitoring: issues and opportunities. Environmental Monitoring and Assessment 176:273–291.

Couvet, D., F. Jiguet, R. Julliard, H. Levrel, and A. Teyssedre. 2008. Enhancing citizen contributions to biodiversity science and public policy. Interdisciplinary Science Reviews 33:95–103.

Dale, M., P. Dixon, M.-J. Fortin, P. Legendre, D. Myers, and M. Rosenberg. 2002. Conceptual and mathematical relationships among methods for spatial analysis. Ecography 25:558–577.

Dambach, C. A. 1948. The relative importance of hunting restrictions and land use in maintaining wildlife populations in Ohio. The Ohio Journal of Science 48:209–229.

Darling, D. A. 1957. The Kolmogorov-Smirnov, Cramer-von Mises tests. The Annals of Mathematical Statistics 28:838–823.

Daubenmire, R. F. 1966. Vegetation: identification of typal communities. Science 151:291–298.

DeSante, D. F. 1981. A field test of the variable circular-plot censusing technique in a California coastal scrub breeding bird community. Studies in Avian Biology 6:177–185.

DeSante, D. F. 1986. A field test of the variable circular-plot censusing method in a Sierran subalpine forest habitat. Condor 88:129–142.

Dickinson, J. L., B. Zuckerberg, and D. N. Bonter. 2010. Citizen science as an ecological research tool: challenges and benefits. Annual Review Of Ecology, Evolution, And Systematics 41:149–172.

Dolton, D., 1993. The call-count survey: Historic development and current procedures. Pages 1–6 *in* T. S. Baskett, M. W. Sayre, R. E. Tomlinson, and R. E. Mirarchi, editors. Ecology and management of the mourning dove. Stackpole Books, Harrisburg, Pennsylvania, USA.

Dolton, D., and R. Rau. 2006. Mourning dove population status, 2006. U.S. Department of the Interior, Fish and Wildlife Service, Laurel, Maryland, USA.

Dunks, J., R. Tomlinson, H. Reeves, D. Dolton, C. Braun, and T. Zapatka. 1982. Migration, harvest, and population dynamics of mourning doves banded in the Central Management Unit, 1967–77. U.S. Department of the Interior, Fish and Wildlife Service, Laurel, Maryland, USA.

Eberhardt, L. L., and M. A. Simmons. 1987. Calibrating population indices by double sampling. Journal of Wildlife Management 51:665–675.

Efford, M. G., and D. K. Dawson. 2009. Effect of distance-related heterogeneity on population size estimates from point counts. The Auk 126:100–111.

Ellingson, A., and P. Lukacs. 2003. Improving methods for regional landbird monitoring: a reply to Hutto and Young. Wildlife Society Bulletin 31:896–902.

Engeman, R. M. 2003. More on the need to get the basics right: population indices. Wildlife Society Bulletin 31:286–287.

Farnsworth, G. L., K. H. Pollock, J. D. Nichols, T. R. Simons, J. E. Hines, and J. R. Sauer. 2002. A removal model for estimating detection probabilities from point-count surveys. The Auk 119:414–425.

Fenneman, N. M. 1928. Physiographic divisions of the United States. Annals of the Association of American Geographers 18:261–353.

Fenneman, N. M. 1931. Physiography of western United States. McGraw-Hill Book Company, Inc., New York, New York, USA.

Fenneman, N. M. 1938. Physiography of eastern United States. McGraw-Hill Book Company, Inc., New York, New York, USA.

Fisher, R. 1936. The use of multiple measurements in taxonomic problems. Annals of Eugenics 7:179–188.

Fisher, S., RA. 1971. The design of experiments. Hafner Publishing Company, New York, New York, USA.

Foody, G. M. 2002. Status of land cover classification accuracy assessment. Remote Sensing of Environment 80:185–201.

Freitag, A., and M. Pfeffer. 2013. Process, not product: investigating recommendations for improving citizen science "success". PLoS One 8:e64079.

Gauch, H. 1982. Multivariate analysis in community ecology. Cambridge University Press, Cambridge, England, U. K.

George, R. R. 1982. Three-zone dove hunting considered for 1983-84 season. Texas Parks and Wildlife Department, Austin, USA.

George, R. R. 1984. Job no. 1: Mourning dove density, distribution, movement, and harvest. Texas Parks and Wildlife Department, Austin, USA.

Gibson, E. J., and R. Bergman. 1954. The effect of training on absolute estimation of distance over the ground. Journal of Experimental Psychology 48:473.

Gleason, H. A. 1926. The individualistic concept of plant associations. Bulletin of the Torrey Botany Club 53:7–26.

Godfrey, C. L., C. R. Carter, and G. S. McKee. 1967. Resource areas of Texas. Bulletin 1070. Texas A&M University, Texas Agricultural Experiment Station, College Station, USA.

Goodall, D. 1954. Objective methods for the classification of vegetation: an essay in the use of factor analysis. Australian Journal of Botany 2:304–324.

Gould, F. 1962. Texas plants; a checklist and ecological summary. Agricultural and Mechanical College of Texas, Texas Agricultural Experiment Station, College Station, USA.

Gould, F. 1975. Texas plants: a checklist and ecological summary. Agricultural and Mechanical College of Texas, Texas Agricultural Experiment Station, College Station, USA.

Greenwood, J. J. 2007. Citizens, science and bird conservation. Journal of Ornithology 148:77–124.

Greig-Smith, P. 1980. The development of numerical classification and ordination. Vegetatio 42:1–9.

Griffith, G., J. Bryce, J. Omerick, A. Comstock, A. Rogers, B. Harrison, S. Hatch, and D. Bezanson. 2004. Ecoregions of Texas. U. S. Environmental Protection Agency, Corvallis, Oregon, USA.

Griffith, G. E., S. Bryce, J. Omernik, and A. Rodgers. 2007. Ecoregions of Texas. Texas Commission on Environmental Quality, Austin, USA.

Grinnell, J. 1917. The niche-relations of the California thrasher. The Auk 34:427–433.

Grue, C., R. R. Reid, and N. J. Silvy. 1983. Correlation of habitat variables with mourning dove call counts in Texas. Journal of Wildlife Management 47:186–195.

Grue, C. E., R. R. Reid, and N. J. Silvy. 1976. A technique for evaluating the breeding habitat of mourning doves using call-count transects. Proceedings of the Annual Conference, Southeastern Association of Game and Fish Commissioners 30:667–673.

Grue, C. E., R. R. Reid, and N. J. Silvy, 1981. A windshield and multivariate approach to the classification, inventory, and evaluation of wildlife habitat: an exploratory study. Pages 124–140 *in* D. E. Capen, editor. The use of multivariate statistics in studies of wildlife habitat. Department of the Interior, U. S. Department of Agriculture, Washington D. C., USA.

Guthery, F., J. Lusk, D. Synatzske, J. Gallagher, S. DeMaso, R. George, and M. Peterson, 2002. Weather and age ratios of northern bobwhites in south Texas. Pages 99–105 *in* S. DeMaso, W. Kuvlesky, F. Hernández, and M. Berger, editors. Quail V: Proceedings of the Fifth National Quail Symposium. Texas Parks and Wildlife Department, Austin, USA.

Hernández, F., and M. J. Peterson, 2007. Northern bobwhite ecology and life history. Pages 40–64 *in* L. Brennan, editor. Texas Quails: Ecology and Management. Texas A&M University Press, College Station, USA.

Hodge, M. H. 1981. Land-based range estimation. Department of the Army, U.S. Army Research Institute for the Behavioral and Social Sciences, Fort Belvoir, Virginia, USA.

Hurlbert, S. 1984. Pseudoreplication and the design of ecological field experiments. Ecological Monographs 54:187–211.

Hurlbert, S. 2013. Affirmation of the classical terminology for experimental design via a critique of casella's statistical design. Agronomy Journal 105:412–418.

Hutchinson, G. E. 1957. Concluding remarks. Cold Spring Harbor Symposia on Quantitative Biology 22:415–427.

Hutto, R. L., and J. S. Young. 2003. On the design of monitoring programs and the use of population indices: a reply to Ellingson and Lukacs. Wildlife Society Bulletin

31:903–910.

Jackson, A. 1960. A handbook for bobwhite quail management in the west Texas Rolling Plains. Texas Parks and Wildlife Department, Austin, USA.

Jiguet, F., V. Devictor, R. Julliard, and D. Couvet. 2012. French citizens monitoring ordinary birds provide tools for conservation and ecological sciences. Acta Oecologica 44:58–66.

Johnson, D., J. Laake, and J. Ver Hoef. 2010. A model-based approach for making ecological inference from distance sampling data. Biometrics 66:310–318.

Johnson, D. H. 2008. In defense of indices: the case of bird surveys. Journal of Wildlife Management 72:857–868.

Jongman, R. H. G., C. J. F. ter Braak, and O. F. R. van Tongeren. 1995. Data analysis in community and landscape ecology. Cambridge University Press, Cambridge, England, U. K.

Kjelland, M., U. Kreuter, G. Clendenin, R. Wilkins, X. Wu, E. Afanador, and W. Grant. 2007. Factors related to spatial patterns of rural land fragmentation in Texas. Environmental Management 40:231–244.

Knopf, F. L. 1994. Avian assemblages on altered grasslands. Studies in Avian Biology 15:247–257.

Kottner, J., and D. L. Streiner. 2011. The difference between reliability and agreement. Journal of Clinical Epidemiology 64:701–702.

Küchler, A. W. 1964. Potential natural vegetation of the conterminous United States. American Geographical Society, New York, New York, USA.

Laake, J., B. Collier, M. Morrison, and R. Wilkins. 2011. Point-based mark-recapture distance sampling. Journal of Agricultural, Biological, and Environmental Statistics 16:1–20.

Lachenbruch, P., and M. Mickey. 1968. Estimation of error rates in discriminant analysis.

Technometrics 10:1–11.

Lancia, R. A., J. D. Nichols, and K. H. Pollock, 1994. Estimating the number of animals in wildlife populations. Pages 215–253 *in* T. Bookout, editor. Research and management techniques for wildlife and habitats. The Wildlife Society, Bethesda, Maryland. USA.

Legendre, P., D. Borcard, and P. Peres-Neto. 2005. Analyzing beta diversity: Partitioning the spatial variation of community compostion data. Ecological Monographs 75:435–450.

Legendre, P., and L. Legendre. 1998. Numerical ecology. Elsevier Science B. V., Amsterdam, The Netherlands.

Lehmann, V. W. 1937. Increase quail by improving their habitat. Texas Game, Fish, and Oyster Commission, Austin, USA.

Lehmann, V. W. 1984. Bobwhites in the Rio Grande Plain of Texas. Texas A&M University Press, College Station, USA.

Leopold, A. 1931. Report on a game survey of the north central states. Democrat Printing, Madison, Wisconsin, USA.

Link, W. A., J. R. Sauer, and D. K. Niven. 2008. Combining Breeding Bird Survey and Christmas Bird Count data to evaluate seasonal components of population change in northern bobwhite. Journal of Wildlife Management 72:44–51.

Lohr, M., B. M. Collins, C. K. Williams, and P. M. Castelli. 2011. Life on the edge: northern bobwhite ecology at the northern periphery of their range. Journal of Wildlife Management 75:52–60.

Ludbrook, J. 2008. Statistics in biomedical laboratory and clinical science: applications, issues and pitfalls. Clinical and Experimental Pharmacology and Physiology 17:1–13.

Lusk, J., F. Guthery, R. George, M. Peterson, and S. DeMaso. 2002. Relative abundance of bobwhites in relation to weather and land use. Journal of Wildlife Management

66:1040–1051.

MacKenzie, D. I., and W. L. Kendall. 2002. How should detection probability be incorporated into estimates of relative abundance? Ecology 83:2387–2393.

Marques, T., L. Thomas, S. Fancy, S. Buckland, and C. Handel. 2007. Improving estimates of bird density using multiple-covariate distance sampling. The Auk 124:1229–1243.

McArdle, B., and M. Anderson. 2001. Fitting multivariate models to community data: a comment on distance-based redundancy analysis. Ecology 82:290–297.

Mielke, P. W., and K. J. Berry. 2001. Permutation methods : a distance function approach. Springer, New York, New York, USA.

Murray, L. D., R. J. Gates, and R. M. Spinola. 2011. Evaluation of three methods to estimate density and detectability from roadside point counts. Journal of Wildlife Management 75:1072–1081.

Nadeau, C. P., and C. J. Conway. 2013. Field evaluation of distance-estimation error during wetland-dependent bird surveys. Wildlife Research 39:311–320.

National Mourning Dove Planning Committee. 2004. Mourning dove national strategic harvest management plan. U. S. Department of the Interior, Fish and Wildlife Service, Laurel, Maryland, USA.

Neyman, J. 1938. Contribution to the theory of sampling human populations. Journal of the American Statistical Association 33:101–116.

Okay, A., 2006. Spatial pattern and temporal dynamics of northern bobwhite abundance and agricultural landuse, and potential casual factors. Dissertation, Texas A&M University, College Station, USA.

Omernik, J. 1987. Ecoregions of the conterminous United States. Annals of the Association of American Geographers 77:118–125.

Omernik, J., and G. Griffith. 2014. Ecoregions of the conterminous United States:

evolution of a hierarchical spatial framework. Environmental Management 54:1249–1266.

Ott, R. L., and M. Longnecker. 2001. An introduction to statistical methods and data analysis. Duxbury, Pacific Grove, California, USA.

Paul, K., M. Quinn, M. Huijser, J. Graham, and L. Broberg. 2014. An evaluation of a citizen science data collection program for recording wildlife observations along a highway. Journal of Environmental Management 139:180–187.

Peterjohn, B. G., and J. R. Sauer. 1999. Population status of North American grassland birds from the North American Breeding Bird Survey, 1966–1996. Studies in Avian Biology 19:27–44.

Peterjohn, B. G., J. R. Sauer, and W. A. Link. 1994. The 1992 and 1993 summary of the North American Breeding Bird Survey. Bird Populations 2:46–61.

Peterson, M. 2001. Northern bobwhite and scaled quail abundance and hunting regulation: a Texas example. Journal of Wildlife Management 65:828–837.

Peterson, M., and R. Perez, 2000. Is quail hunting self regulatory? Northern bobwhite and scaled quail abundance and quail hunting in Texas. Pages 85–91 *in* L. Brennan, W. Palmer, L. Burger, and T. Pruden, editors. Quail IV: Proceedings of the Fourth National Quail Symposium. Tall Timbers Research Station, Tallahassee, Florida, USA.

Peterson, M. J., X. B. Wu, and P. Rho, 2002. Rangewide trends in landuse and northern bobwhite abundance: an exploratory analysis. Pages 35–44 *in* S. J. DeMaso, J. Kuvlesky, W. P., F. Hernández, and M. E. Berger, editors. Quail V: Proceedings of the Fifth National Quail Symposium. Texas Parks and Wildlife Department, Austin, USA.

Pierce, B. L., R. R. Lopez, and N. J. Silvy, 2012. Estimating animal abundance. Pages 284–310 *in* N. J. Silvy, editor. The Wildlife Techniques Manual. Johns Hopkins University Press, Baltimore, Maryland, USA.

Pollock, K. H., J. D. Nichols, T. R. Simons, G. L. Farnsworth, L. L. Bailey, and J. R.

Sauer. 2002. Large scale wildlife monitoring studies: statistical methods for design and analysis. Environmetrics 13:105–119.

Reidy, J. L., F. R. Thompson, and J. W. Bailey. 2011. Comparison of methods for estimating density of forest songbirds from point counts. Journal of Wildlife Management 75:558–568.

Rexstad, E. 2007. Point and interval estimates of abundance using multiple covariate distance sampling: an example using great bustards. Centre for Research into Ecological and Environmental Modelling (CREEM), University of St Andrews, St. Andrews, Scotland, UK.

Reyna, K., 2008. The Texas Quail Index: evaluating predictors of quail abundance using citizen science. Dissertation, Texas A&M University, College Station, USA.

Rho, P., X. B. Wu, F. E. Smeins, N. J. Silvy, and M. J. Peterson. 2015. Regional land cover patterns, changes and potential relationships with scaled quail (Callipepla squamata) abundance. Journal of Ecology and Environment 38:185–193.

Riesch, H., and C. Potter. 2014. Citizen science as seen by scientists: methodological, epistemological and ethical dimensions. Public Understanding of Science 23:107–120.

Robbins, C., D. Bystrak, and P. Geissler. 1986. The breeding bird survey: it's first fifteen years, 1965–1979. U. S. Fish and Wildlife Service, Resource Publication 157:1–196.

Roeder, K., B. Dennis, and E. O. Garton. 1987. Estimating density from variable circular plot censuses. Journal of Wildlife Management 51:224–230.

Rollins, D., J. Brooks, N. Wilkins, and D. Ransom. 2005. Counting quail. Texas Cooperative Extension Service, Texas A&M University, College Station, USA.

Romesburg, H. C. 1981. Wildlife science: gaining reliable knowledge. Journal of Wildlife Management 45:293–313.

Roseberry, J. L., and W. D. Klimstra. 1984. Population ecology of the bobwhite. Southern Illinois University Press, Carbondale, USA.

Rosene, W. 1969. The bobwhite quail, its life and management. Rutgers University Press, New Brunswick, New Jersey, USA.

Rosenstock, S. S., D. R. Anderson, K. M. Giesen, T. Leukering, and M. F. Carter. 2002. Landbird counting techniques: current practices and an alternative. The Auk 119:46–53.

Sadler, K., 1993. Mourning dove harvest. Pages 449–458 *in* T. S. Baskett, M. Sayer, R. E. Tomlinson, and R. E. Mirarchi, editors. Ecology and management of the mourning dove. Stackpole Books, Harrisburg, Pennsylvania, USA.

Sauer, J. R., W. A. Link, J. E. Fallon, K. L. Pardieck, and D. J. Ziolkowski. 2013. The North American Breeding Bird Survey 1966–2011: summary analysis and species accounts. North American Fauna 79:1–32.

Schulz, J. H. 2006. 2006 mourning dove population and research status report. Missouri Department of Conservation, Columbia, USA.

Scott, J. M., F. L. Ramsey, and C. B. Kepler. 1981. Distance estimation as a variable in estimating bird numbers from vocalizations. Studies in Avian Biology 6:334–340.

Scott, T. G. 1985. Bobwhite thesaurus. International Quail Foundation, Edgefield, South Carolina, USA.

Seber, G. A. F. 1984. Multivariate observations. Wiley, New York, New York, USA.

Sim, J., and C. C. Wright. 2005. The kappa statistic in reliability studies: use, interpretation, and sample size requirements. Physical Therapy 85:257–268.

Southeastern Association of Game and Fish Commissioners. 1957. Mourning dove investigations 1948-1956. Southeastern Association of Game and Fish Commissioners, Columbia, South Carolina, USA.

Stoddard, H. 1931. The bobwhite quail: its habits, preservation and increase. Charles Scribner's Sons, New York, New York, USA.

Taylor, C. A., D. Twidwell, N. E. Garza, C. Rosser, J. K. Hoffman, and T. D. Brooks.

2012. Long-term effects of fire, livestock herbivory removal, and weather variability in Texas semiarid savanna. Rangeland Ecology and Management 65:21–30.

ter Braak, C. 1986. Canonical correspondence analysis: a new eigenvector technique for multivariate direct gradient analysis. Ecology 67:1167–1179.

ter Braak, C., 1995. Calibration. Pages 78–90 *in* R. Jongman, C. ter Braak, and O. van Tongeren, editors. Data analysis in community and landscape ecology. Cambridge University Press, Cambridge, UK.

Texas A&M AgriLife Extension, 2013. Texas quail index: team handbook. <http://wildlife.tamu.edu/files/2013/12/TQI_handbook.pdf>. Accessed 1 June 2017.

Thomas, L., S. Buckland, E. Rexstad, J. Laake, S. Strindberg, S. Hedley, J. Bishop, T. Marques, and K. Burnham. 2010. Distance software: design and analysis of distance sampling surveys for estimating population size. Journal of Applied Ecology 47:5–14.

Thompson, T. J. 1982. Range estimation training and practice: a state of the art review. Department of the Army, U.S. Army Research Institute for the Behavioral and Social Sciences, Fort Benning, Georgia, USA.

Thompson, W. L. 2002. Towards reliable bird surveys: accounting for individuals present but not detected. The Auk 119:18–25.

Tikkiwal, B. 1960. On the theory of classical regression and double sampling estimation. Journal of the Royal Statistical Society. Series B (Methodological) 22:131–138.

Tomeček, J., B. Pierce, and M. Peterson. 2015. Quail abundance, hunter effort, and harvest of two Texas quail species: implications for hunting management. Wildlife Biology 21:1–9.

Tomlinson, R. E. 1988. Migration, harvest, and population characteristics of mourning doves banded in the western management unit, 1964–1977. U.S. Department of the Interior, Fish and Wildlife Service, Washington, D.C., USA.

Tri, A. N., J. P. Sands, M. C. Buelow, D. Williford, E. M. Wehland, J. A. Larson, K. A.

Brazil, J. B. Hardin, F. Hernández, and L. A. Brennan. 2012. Impacts of weather on northern bobwhite sex ratios, body mass, and annual production in south Texas. Journal of Wildlife Management 77:579–586.

Vach, W. 2005. The dependence of Cohen's kappa on the prevalence does not matter. Journal of Clinical Epidemiology 58:655–661.

van der Maarel, E. 1979. Transformation of cover-abundance values in phytosociology and its effects on community similarity. Vegetatio 39:97–114.

Westhoff, V., and E. van der Maarel, 1973. The Braun-Blanquet approach. Pages 617–726 *in* R. Whittaker, editor. Ordination and Classification of Communities. Handbook of Vegetation Science. Part V. Springer, The Hague, The Netherlands.

Whittaker, R. 1956. Vegetation of the Great Smokey Mountains. Ecological Monographs 26:1–80.

Whittaker, R. 1967. Gradient analysis of vegetation. Biological Reviews 49:207–264.

Williams, C., R. Lutz, R. Applegate, and W. Palmer. 2004*a*. Winter survival and additive harvest in northern bobwhite coveys in Kansas. Journal of Wildlife Management 68:94–100.

Williams, C. K., F. S. Guthery, R. D. Applegate, and M. J. Peterson. 2004*b*. The northern bobwhite decline: scaling our management for the twenty-first century. Wildlife Society Bulletin 32:861–869.

With, K. A., A. W. King, and W. E. Jensen. 2008. Remaining large grasslands may not be sufficient to prevent grassland bird declines. Biological Conservation 141:3152–3167.

Wretenberg, J., Å. Lindström, S. Svensson, T. Thierfelder, and T. Pärt. 2006. Population trends of farmland birds in sweden and england: similar trends but different patterns of agricultural intensification. Journal of Applied Ecology 43:1110–1120.

Zerbini, A., 2006. Improving precision in multiple covariate distance sampling: a case study with whales in Alaska. Ph.D. thesis, University of Washington, Seattle, USA.

Zuur, A. F., E. N. Ieno, and G. M. Smith. 2007. Analysing ecological data. Springer, New York, New York, USA.