

**A PREDICTIVE HABITAT OCCUPANCY MODEL OF NORTHERN
BOBWHITE IN THE DELMARVA PENINSULA, USA**

by

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A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of
the requirements for the degree of Master of Science in Wildlife Ecology

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ABSTRACT

Literature on predicting species presence contains numerous methodological recommendations that reduce bias associated with imperfect detection of individuals, measurement scale of model variables, model selection uncertainty, and spatial autocorrelation. My objective was to incorporate and test recent modeling advances to predict potential habitat occupancy of northern bobwhite. From 15 May – 15 August, 2008 and 2009, I conducted repeat-visit surveys at 360 sites within Delaware to sample the presence of bobwhite. I randomly selected half the data to model the scale-dependent relationships of bobwhite presence with metrics of site scale (500 m radius) and landscape scale habitat composition and configuration. At the site scale, bobwhite presence was negatively related to interspersed and juxtaposition of early successional and agriculture habitat, early successional to forest edge density, and agriculture to forest edge density. At the landscape scale, bobwhite presence was negatively related to cohesion of human development within 2.5 km, positively related to cohesion of early successional habitat within 2.0 km, and positively related to percentage of shrub habitat within 1.0 km. The habitat occupancy model fit the validation dataset moderately well with an area under the receiver operating characteristic curve value of 0.631. I applied my habitat occupancy model to map the predicted presence of breeding bobwhite within the Delmarva Peninsula, USA. The modeling results and distribution map will be used to guide future habitat management efforts. I also hope my methodology can serve as a basis for future habitat modeling of bobwhite and other grassland species across their range.

I then tested the efficacy of a broadcast caller for estimating density and occupancy of northern bobwhite. Density estimates while using a broadcast caller were higher and increasing passive listening survey duration from 3 to 7 min did not change density estimates. However, increasing survey duration or using a broadcast caller led to a higher detection probability. Use of a broadcast caller is inappropriate for determining density estimates through distance sampling, but may be appropriate for determining occupancy under limited conditions.

Finally, I tested if a habitat occupancy model could predict the change in occupancy of Breeding Bird Survey (BBS) routes over time in the Delmarva Peninsula, USA. I used 50 stop BBS data to calculate the percentage of stops occupied by bobwhite during 1992, 1996, 2001 and 2005. I then calculated the probability of breeding-season bobwhite occupancy at each BBS stop for each time period using the occupancy model applied to National Oceanic and Atmospheric Organization Coastal Change and Analysis Program (NOAA CCAP) land cover data. The average change in observed occupancy per year was -8.7% (\pm SE 1.3%) while the average predicted change in occupancy was 1.0% (\pm SE 0.8%). Predicted route occupancy was not related to observed route occupancy across sampling periods. Change in predicted occupancy and observed occupancy were also not related. I consider two broad reasons why observed results did not correlate to my predictive model. The first is methodological (low predictive success of model, error from applying model from one year to other years, and imperfect detection of bobwhite during BBS surveys) while the second is biological (slack in habitat configurations, differential habitat use between breeding and nonbreeding season, impact of predation and hunting, and impact of agricultural chemicals). Biologists should use caution when applying a static multi-scale occupancy model to large scale temporal habitat-population processes.

Chapter 1

AN IMPROVED APPROACH TO MODELING HABITAT OCCUPANCY OF NORTHERN BOBWHITE (*COLINUS VIRGINIANUS*)

Introduction

Although declines of northern bobwhite (*Colinus virginianus*) populations have occurred range-wide, populations at the northern end of the species' range, including those in the Mid-Atlantic, have experienced especially sharp declines. For example, populations in Delaware and Maryland have been declining by over 5% annually from 1966–2007 compared to 3% range wide (Sauer et al. 2008). Habitat loss is considered the primary cause of these declines (Brennan 1991, Williams et al. 2004, Veech 2006). Unfortunately the loss and fragmentation of bobwhite habitat is occurring at multiple scales, and at scales greater than those at which traditional research and management have focused on. Therefore, a paradigm shift has been recommended to focus research efforts to incorporate broader scale impacts (Williams et al. 2004).

Knowledge of multi-scale habitat relationships and the landscape scale distribution of habitat are important for improving bobwhite management. Models that link a species to remotely-sensed environmental variables are a common way to map potential habitat for species and have a wide use of applications (Manel et al. 2001). Methods for constructing such models vary and continue to evolve to account for biases associated with survey methods, measurement scale of independent variables, model selection, spatial autocorrelation, and model evaluation (Manel et al. 2001, Rushton et al. 2004, MacKenzie et al. 2006). Despite these advances, four limitations exist with past modeling of bobwhite habitat relationships.

First, there have been few studies modeling potential landscape scale bobwhite habitat relationships; with none published for the Mid-Atlantic region (Burger et al. 2006^{a,b,c}, Twedt et al. 2006, Roseberry and Sudkamp 2008). Recently, Burger et al. (2006^{a,b,c}) modeled habitat suitability using Breeding Bird Survey (BBS) data for Mississippi, the Central Hardwoods Bird Conservation Region (BCR) and the Southeast Coastal Plain BCR. However, because vegetative communities among general habitat types and land use vary between regions and states, these models may not provide accurate predictions of bobwhite presence for the Mid-Atlantic region (Peterson et al. 2002).

Second, there are well-recognized limitations to the use of data for habitat modeling from surveys that only visit a site once per season (e.g. Burger et al. 2006 ^{a,b,c} analysis of BBS data) (MacKenzie et al. 2006). Multiple visits to a site per season allow for the estimation of a detection probability to account for the error associated with not detecting a species at a site even though it may have been present (Mackenzie et al. 2002).

Third, the scales at which habitat variables are measured are often not biologically appropriate for the species or phenomenon being studied (McGarigal and McComb 1995, Flather and Sauer 1996, Lichstein et al. 2002). The magnitude of a species response to landscapes will vary at different scales (Roland and Taylor 1997, Holland et al. 2004, Holland et al. 2005). Therefore, measuring variables at the wrong scale can lead to under- or over-estimation of the importance of a variable in relation to other variables (Girvetz and Greco 2009). Holland et al. (2004) developed a method that measures the strength of a variable's relationship with a species at increasing landscape sizes. This can identify the scale at which the landscape variable is most strongly related to a species or phenomenon.

Fourth, in addition to recognizing the proper scale at which a species responds to a variable, it is also critical to recognize that habitat use patterns are influenced by variables operating simultaneously at multiple scales (Johnson 1980, Wiens 1989). Therefore models that

predict habitat use should also incorporate multiple scales. While many research efforts have investigated site scale characteristics of bobwhite habitat use (e.g. Roseberry and Klimstra 1984, Wilkins and Swank 1992, Kopp et al. 1999, Taylor et al. 1999, Williams et al. 2000) and others at the landscape scale (Burger et al. 2006*a,b,c*, Twedt et al. 2006, Roseberry and Sudkamp 2008), to date there has not been an effort to integrate variables at multiple scales to predict bobwhite abundance or occupancy.

My objective was to integrate recent modeling methodology to predict potential habitat occupancy using northern bobwhite in the Delmarva Peninsula, USA. More robust identification of potential habitat can be used by managers to better focus available conservations resources.

Methods

From 15 May – 15 August, 2008–2009, I conducted three replicate roadside surveys per year at 360 points (180 in 2008 and 180 in 2009) to sample the presence of bobwhite within Delaware (Figure 1.1). Although surveys were conducted primarily in Delaware for logistic and funding reasons, the model results were used to build a predictive occupancy map for bobwhite in the entire Delmarva Peninsula (which includes Delaware, parts of Maryland and Virginia), because land cover and vegetation types are similar across this region.

All survey points were placed at least one kilometer apart and adjacent to early successional and agriculture habitat along non-primary roads. No points were placed inside forests, wetlands, or developed lands as these were considered unsuitable breeding habitat. I surveyed nine points that comprised one survey route per morning from 15 minutes before sunrise until two hours after sunrise on precipitation-free days with wind speeds below 6.5 km/hr. Each point survey lasted 10 min. I randomly generated the order that routes were surveyed and alternated the order that points were surveyed within a route during replicate visits.

I listened passively during the first 7 min and then broadcast four to five recorded female bobwhite calls approximately every 10 sec at 90dB in the four cardinal directions during the last 3 min (following Guthery et al. 2001). I recorded the location of every individual bobwhite detected onto an aerial photo of the survey point and recorded the time period (passive listening vs broadcast call) when birds were first detected. After the first season, I decided to only survey the area in Delaware that is in the Mid Atlantic Coastal Plain Physiographic Region. Points that were outside of this region during the first season were not used for analysis (18 points) (Figure 1.1).

I reclassified the 22 land use/land cover types of the 2005 National Oceanic and Atmospheric Administration Coastal Change and Analysis Program (NOAA CCAP) dataset into a reduced set of 8 habitat types including High Intensity Development (HDEV), Low Intensity Development (LDEV), Agriculture (AG), Grassland (GRASS), Forest (FOR), Shrub (SHRUB), Emergent Wetland (WET), and Other (Table 1.1). I considered SHRUB and GRASS as early successional habitat and HDEV and LDEV as development. To quantify habitat composition, I measured the proportion of each habitat type (excluding Other); transforming proportion measures using the logit function to normalize the data. I also quantified habitat configuration by measuring patch cohesion of early successional habitat, a measure of how connected patches were, (ECOHES), patch cohesion of development (DCOHES), and the interspersion and juxtaposition index (IJI) of early successional habitat, a measure of how interspersed early successional with other habitat types, according to MacGarigal et al. (2002). Patch cohesion ranges from 0 to 100 and measures the physical connectedness of the patches. The IJI ranges from 0 to 100 and measures the adjacency of a patch type with other patches. I also measured the density (km/hectare) of forest to early successional habitat edge (EEDGE), and forest to agriculture edge (AGEDGE). I quantified all habitat composition and configuration variables at the survey site and landscape scales (24 variables; subscript S indicates site scale and subscript L

indicates landscape scale). Lastly, I measured the distance (km) of each survey point to the nearest divided highway (DIST) and normalized the data with a square-root transformation. This provided 25 candidate explanatory variables for the habitat modeling analysis. I liberally defined the “survey site” as the area within 500 m of an observation point, which is the 90th percentile of my observed detection distances and the detection distance threshold for bobwhite reported by Wellendorf and Palmer (2005). For each variable measured at the landscape scale, I determined the buffer radius around the site at which each variable was most strongly correlated to bobwhite presence among the set of buffer radii ranging from 0.5 km to 9.5 km (1 km to 10 km from survey point) at 500 m increments (*sensu* Holland et al. 2004) for a randomly selected subset of half ($n = 171$) of the sites. I used bootstrapping to obtain Spearman’s Rank Correlation Coefficients on 10,000 random samples of 10 points at least 10 km apart for each buffer distance. I used Student’s t-test to identify groups of ranges that were statistically similar to the range that exhibited the strongest correlation. The smallest radius within that range was used as the scale for measuring that landscape variable (e.g. Figure 1.2). Using the shortest distance was intended to reduce the overlap of landscape buffer between points.

I estimated site occupancy and detection probability using the modeling approach of Mackenzie et al. (2002), which accounts for the probability of an individual occupying the site and being detected during a survey. I used Akaike’s Information Criterion (AIC) to evaluate and select models (Burnham and Anderson 2002) and performed analysis using the program PRESENCE (Hines et al. 2006). Because I considered any variation in detection probability a nuisance parameter, I first used logistic regression to model detection probability among survey points considering explanatory variables of time of day, temperature, and wind speed, as well as constant detection probability. I selected a best model from that analysis to control for detection probability for subsequent modeling of bobwhite occupancy. I modeled bobwhite occupancy using logistic regression with the 25 covariates of site and landscape scale metrics using a

randomly selected subset of data from 50% ($n = 171$) of the survey points. The remaining 50% of the data was used to validate model-predicted occupancy.

I limited the total number of the candidate models to 40 in an iterative step-wise manner according to the following criteria:

Each model included 1–3 site-scale and 1–3 landscape-scale covariates (totaling 2–6). I selected a maximum of three variables at each scale to prevent the development of highly complex models. Models were not required to have the same number of site and landscape covariates. DIST was not considered a site or landscape scale so some models may have had 7 covariates.

Covariates that were correlated ($|r| \geq 0.5$) were not used in the same model.

All covariates were used at least once. Some covariates were used more than others because they repeatedly appeared in high-ranked models. Covariates that consistently appeared in low-ranked models were used less often. Additional covariates were individually added to high-ranked models to determine their effect on the model. Covariates that did not improve the log-likelihood estimate of the model by a value of more than two were removed.

Within the set of candidate models, I also included a global model of all 25 covariates, a global site-scale model of the 12 site-scale covariates, a global landscape-scale model of the 12 landscape-scale covariates, and a null model in which occupancy was held constant.

I calculated the small-sample-corrected information criterion AICc for all 40 models (Hurvich and Tsai 1989) because sample size was small with respect to the number of parameters (K) in the analyses. I performed multiple-model averaging to predict occupancy using those models that had substantial support for fitting the data given the candidate set of models to address model selection uncertainty (Burnham and Anderson 2002). To determine the direction and magnitude of effect sizes for covariates, I calculated the mean standardized partial regression

coefficient across all the models containing the variable of interest, and estimated precision using an unconditional variance estimator that incorporates model selection uncertainty (Burnham and Anderson 2002, p. 162).

I tested for spatial autocorrelation of the model-averaged residual values using Moran's I to test the assumption that independence of errors was met. Commonly, ecological covariates alone may be sufficient to explain spatial autocorrelation in species distributions. However, ignoring spatial autocorrelation tends to overestimate habitat effects and may reduce prediction success (Betts et al. 2006).

I validated the accuracy of my best-fit occupancy model by generating predicted occupancy values for the remaining 50% of data not used for fitting models. I used a receiver operating characteristic (ROC) curve to measure model accuracy. The ROC curve describes the relationship between model sensitivity (number of true positive predictions) and specificity (number of false positives) (Hanley and McNeil 1982). The area under the ROC curve (AUC) is an index of classification accuracy that is independent of species prevalence and arbitrary threshold effects (Manel et al. 2001). Models are considered to have low accuracy with AUC values of 0.5–0.7, medium accuracy with values of 0.7–0.9, and high accuracy with values >0.9 (Manel et al. 2001).

I also determined an optimal threshold value for assigning occupancy (sensu Pereira and Itami 1991) and measured the predictive success of the model at that value. The optimum threshold value is the value at which the percent improvement over random is largest. This is calculated using one minus specificity subtracted from the percent correctly classified as occupied at each cut off value. I then applied my model within a Geographic Information System (GIS) to produce both continuous and discrete maps of predicted bobwhite presence for the Delmarva.

Results

Bobwhites were detected at 74 of the 360 sites (20.6%) across both years (54 of the 180 sites [30%] in summer 2008 and at 20 of the 180 sites [11%] in summer 2009) (Figure 1.1). The time of day and temperature model was the highest ranked model for measuring the variation in detection probabilities. However, nine of the eleven detection models had $\Delta AIC_c \leq 2$, including a null model where detection was held constant (Table 1.2). Because the evidence ratio for the top model was not strong relative to the null model (1.66), I used the null detection model in conjunction with the habitat modeling.

The scale at which landscape variables were used to model bobwhite occupancy ranged from 1 km to 2.5 km from the survey location (Table 1.3). The average distance was 1.6 km (\pm SE 0.7 km). Fifteen combinations of variables were correlated (Appendix A).

Of the 40 tested habitat occupancy models, the top-ranked model included two site scale covariates and two landscape scale covariates; early successional edge density at the site, interspersed and juxtaposition index at the site, cohesion of development at the landscape, and cohesion of early successional habitat at the landscape (Table 1.4). The next two highest-ranked models also had substantial support (Model 2: early successional edge density at the site, interspersed and juxtaposition index at the site, percent of shrub habitat in the landscape, and cohesion of development at the landscape; Model 3: interspersed and juxtaposition index at the site, agriculture edge density at the site, cohesion of development at the landscape, and cohesion of early successional habitat at the landscape). The second-ranked model is very similar to the first and percentage of shrub habitat and cohesion of early successional habitat were highly correlated (0.69). Therefore, I used model averaging on the top three models. At the site scale, bobwhite presence was negatively related to interspersed and juxtaposition index, early successional edge density (range = 334 m/hectare to 584 m/hectare), and agriculture edge density (range = 416 m/hectare to 1000 m/hectare). At the landscape scale, bobwhite presence was

negatively related to the cohesion of development within 2.5 km, positively related to cohesion of early successional habitat within 2.0 km, and positively related to percent of shrub habitat within 1.0 km.

The standardized coefficients for the variables in the top models and found cohesion of development, cohesion of early successional habitat and early successional edge density had strong effects (95% confidence intervals not including zero), though of small relative magnitude (Figure 1.3). All other variables had negligible effects due to large unconditional variance. Because of these relationships, I also *post hoc* analyzed additional models with only site or landscape scale variables using the variables in the top three models. However, the smallest ΔAIC_c among this *post hoc* set of models compared to the top model of the *a priori* model set was 11.15 for the model of cohesion of development and cohesion of early successional habitat. Thus, single scale models performed poorly relative to multi-scale models.

The AUC for model-averaged predicted occupancy of the validation dataset was 0.631 (Figure 1.4). The optimum threshold value for assigning presence of bobwhite was 0.5 (Figure 1.5). At this value the model correctly predicted the occupancy status at 65.5% of sites. However, the model predicted areas where bobwhite were not detected (68.7%) better than where bobwhite were detected (55.8%). Additionally, bobwhite were detected at 41% of the sites that were predicted occupied, and were only detected in 22% of the sites that were predicted unoccupied. There was no evidence of spatial autocorrelation in model residuals (Moran's $I = -0.02$, $P = 0.14$). I produced a map that predicted where bobwhite would be present using the optimal threshold value for the Delmarva Peninsula (Figure 1.6).

Discussion

The final averaged occupancy model incorporated both site and landscape variables but had moderately weak predictive performance possibly due to data deficiencies, an imbalance

of species distributions with the environment, and model misspecification. Although multi-scale models consistently performed better than single scale models, incorporation of model selection uncertainty indicated site scale variables exhibited weak to moderate effects while landscape-scale variables had the greatest effects on occupancy. Assessing the scale at which to measure landscape variables showed there was variability among metrics, but those that had the strongest effects on occupancy were rather consistent in scale.

Guthery (1997) suggested that habitat management for bobwhites should maximize the amount of habitat used by bobwhite in both time and space. Characteristics of a habitat patch that reduces the usable space would also lower the quality of a site and the probability of the site being occupied. I was not able to measure micro-scale habitat characteristics of patches (vegetation structure and composition) that directly affect habitat quality. Although important variables at the site scale may be indirect measures of micro-scale habitat quality, it is still notable that these variables had moderate to weak effects on occupancy compared to landscape variables.

The negative relationship between edge density and occupancy at the site scale may be related to the reduction of useable space due to fragmentation of suitable habitat caused by high edge densities. The transition from forested habitat to agriculture or grassland habitats (woody edge) can provide the close proximity of grassy areas to shrubby areas favored by bobwhite. For this reason, edge habitat is considered necessary for prime bobwhite habitat (Stoddard 1931, Leopold 1933). Leopold (1933) predicted that density of edge-benefitted species would increase with increasing edge. However, above a certain density, edge becomes redundant and may have a negative effect by fragmenting the habitat (Guthery and Bingham 1992). This seems plausible for my sampling sites where the edge densities ranged from 6-10 times the threshold edge density of 60 m/ha suggested by Roseberry and Sudkamp (1998), below which bobwhite have a positive relationship with edge density.

Not all edge types have the same influence. For example, Twedt et al. (2006) found bobwhite abundance was positively related to forest edge but was negatively related to grass edge and total edge. Forest edge was likely positive because it would provide woody escape cover for bobwhite. Grass habitat provides nesting cover (Roseberry and Klimstra 1984, Taylor et al. 1999), so increasing edge would fragment and reduce the amount of breeding habitat available. Total edge may also have been a measure of fragmentation in the landscape.

The limited dispersal capabilities of bobwhite could explain both the strong effects of landscape configuration on bobwhite occupancy over landscape composition and the scale at which bobwhite appear to respond to these important landscape characteristics. The cohesion of early successional habitats and human development had stronger effects on occupancy than the simple amount. This agrees with Shumaker (1996) who found that cohesion had a higher correlation with simulated dispersal success than the amount of habitat. For example, it may be that more cohesive development acts as a stronger barrier to dispersal of bobwhite than an equivalent amount of development that is less cohesive. Human development is known to limit dispersal in terrestrial animals (e.g. juvenile cougars, *Puma concolor* [Beier 1995] and isolated populations of bobcats, *Lynx rufus*, and coyotes, *Canis latrans* [Riley et al. 2006]). Bobwhites may experience similar or more severe dispersal limitation because they have relatively restricted mobility and do not fly or disperse long distances (Kassinis and Guthery 1996, Townsend II et al. 2003, although limited exceptions can occur, see Lohr et al. 2010). Cohesion of early successional habitat and development were most correlated to occupancy at similar landscape sizes (2 km and 2.5 km radius respectively). These distances fall within the range of average dispersal distances of bobwhite reported by others; 2.8 km for adults, 3.4 for juveniles (Townsend et al. 2003), 2.1 km for adults, 1.7 for juveniles (Cook et al. 2006), and the average maximum dispersal distance of juveniles of 1.7 km (Fies et al. 2002).

The negative relationship between bobwhite occupancy and the cohesion of development can also be explained by other effects of development. First, the most immediate consequence is the reduction in the amount and quality of habitat through conversion to development. Urban environments have greater amounts of non-native shrubs and plants that are associated with lower nesting success for open-cup nesting songbirds relative to native plants (Borgmann and Rodewald 2004). Urban areas can also harbor greater densities of meso-predators (Jokimaki and Huhta 2000, Kays and DeWan 2004, Lepczyk et al. 2003 Lohr et al. 2010) which can reduce nest success of bobwhite (Rollins and Carroll 2001) and increase mortality of individuals (Lohr et al. 2010).

Despite efforts to reduce modeling errors, predictive performance of the model was moderately weak. This may have been due to several factors. First, the land cover data was collected 2–3 years prior to the collection of the occupancy data. During this time period, early successional habitats may have advanced to a later successional stage. Other land uses such as logging, development, or allowing agricultural field to go fallow could have also changed the land cover. Error in land cover data could have been corrected by constructing my own land cover map for the study area during the time of the surveys. However the time and effort that would have been needed to build these maps and test the accuracy was not practical or feasible. Timing future surveys and modeling efforts with expected updates in land cover data should eliminate temporal error.

All variables used in my model were macro-scale (e.g. agriculture, grassland, forest, etc.) measurements of habitat. Other models predicting occupancy of bobwhite with macro-scale variables do not provide a measure of model fit. So it is unknown how well our model performs compared to others. However, Mitchell et al. (2001) found coarse resolution landscape variables were most important to migrating habitat specialist migrating species. Since bobwhite are non-migratory it may be difficult to predict occupancy using these variables. Additionally, Betts et al.

(2006) found coarse-resolution variables (e.g. age of stand and cover type) calculated using aerial photos were able to predict occupancy of forest birds as well as fine-resolution variables (e.g. diameter base height and canopy cover) measured on the ground, they warned that as landscapes become more fragmented, the predictive success of coarse resolution variables will decline. For example, fencerows are considered prime escape cover and brood rearing habitat. Their loss due to clean farming is believed to be a primary reason for bobwhite declines (Brennan 1991).

However, I was not able to measure most of these areas because the resolution of the land cover data was not fine enough. The inability to measure fencerows or other fine-resolution features likely contributed to error in the model.

Species distribution models assume that the population is in equilibrium, which only occurs when colonization is greater than extinction (Levins 1969), and that the species can occur in all potential suitable habitat (Barry and Elith 2006). However, six limitations could prevent equilibrium or reduce the ability of bobwhite to occupy potential habitats. First, because bobwhite populations in the Delmarva have been declining (Sauer et al. 2008), colonization is not higher than extinction. Second, Vuilleumier and Possingham (2006) found the number of unoccupied patches can increase in heterogeneous landscapes due to asymmetrical colonization, which is common. Therefore, patches of habitat that may be suitable may not be occupied during a survey season. Third, because adult mortality of bobwhites is high, the probability of local extinction is also high, thereby increasing the number of high quality sites that are naturally unoccupied (Tyre et al. 2001). Fourth, Watson et al. (1984) found density dependent dispersal in the red grouse (*Lagopus lagopus*) and noted that when populations are low, unoccupied suitable sites may never be colonized. Fifth, if there is a time lag in the response of bobwhite population to landscape change, local populations can still persist even when surrounded by an inhospitable landscape. Sixth, Tyre et al. (2001) suggested poor habitats near high quality habitat may have a higher probability of being occupied than an isolated patch of good habitat. Therefore, bobwhite

may be present in areas with a low predicted probability of occupancy. However, false positive in predicted occupancy would increase bias more than this false negative predicted occupancy (Tyre et al. 2001). Additionally, Tyre et al. (2001) found that even under perfect conditions (e.g., no measurement error, known habitat associations, and large sample size) predictive models cannot account for all aspects of metapopulation dynamics and can produce AUC values as low as 0.80. I recommend that error related to meta-population dynamics might be reduced through long-term surveys which can account for factors affecting colonization and extinction.

Other sources of error include not accounting for interactions of variables and non-linear relationships of a variable with occupancy. I avoided models that included interactions among variables because it is impractical to account for all of them and some could lead to spurious results. However, some interactions in variables may have been important for predicting occupancy of bobwhite. Additionally, non-linear responses to variables cannot easily be accounted for using logistic regression.

Overall, this research produced important insights into the breeding habitat occupancy of bobwhite within the Mid-Atlantic Coastal Plain. I provide evidence of the importance for using factors at multiple scales when modeling habitat relationships of a species. The variation in the scales at which occupancy was related to individual landscape features supports the need to objectively assess the measurement scale of landscape features based on the data and the biology of the species rather than subjectively selecting a static or arbitrary scale. My model can also be a useful tool for conservation planning because it predicts potential locations of bobwhite and lays the groundwork for future habitat occupancy modeling efforts throughout the bobwhite range. Huxel and Hasting (1999) simulated restoration success with spatial arrangement of restored areas and found restoration adjacent to occupied habitat patches was more successful than random placement of restored areas. Increasing cohesion of habitat may be especially important because the wide areas of unoccupied habitat between the occupied

patches may be beyond the dispersal range of bobwhite. Connecting these occupied patches can increase dispersal success leading to increased colonization of empty patches and immigration from other populations, which can increase the number of occupied habitat patches (Dunning et al. 1995). Additionally, my model predicted unoccupied sites with almost 70% accuracy, and the percentage of sites bobwhite were detected was almost two times higher where they were predicted to occur. Therefore, focusing management resources to areas where bobwhite are predicted to occur should be more efficient than randomly allocating management resources.

Table 1.1. Original and reclassified land cover types based on National Oceanic and Atmospheric Administration's (NOAA) Coastal Change Analysis Program (CCAP) dataset to model northern bobwhite occupancy in Delaware, USA, from 15 May – 15 August, 2008–2009.

Reclassified Land Cover Type	Original CCAP Land Cover Type (and associated code)	% of Delmarva Peninsula
Development, High Intensity	Developed, High Intensity (2) Developed, Medium Intensity (3)	1.8
Development, Low Intensity	Developed, Low Intensity (4) Developed, Open Space (5)	7.1
Agriculture	Cultivated Crops (6) Pasture/Hay (7)	44.8
Grassland	Grassland/Herbaceous (8)	0.5
Forest	Deciduous Forest (9) Evergreen Forest (10) Mixed Forest (11) Palustrine Forested Wetland (13) Estuarine Forested Wetland (16)	32.0
Shrub	Scrub/Shrub (12) Palustrine Scrub/Shrub Wetland (14) Estuarine Scrub/Shrub Wetland (17)	4.9
Emergent Wetland	Palustrine Emergent Wetland (15) Estuarine Emergent Wetland (18)	10.8
Other	Unconsolidated Shore (19) Barren Land (20) Open Water (21) Palustrine Aquatic Bed (22)	Not Included

Table 1.2. Summary of model-selection procedure examining variables affecting the probability of detection of northern bobwhites in Delaware, USA, from 15 May – 15 August, 2008–2009. I report Akaike’s Information Criterion (AICc), the relative difference in AIC values compared to the top-ranked model (Δ AIC), the AIC model weight (W), and the number of parameters in the model (K).

Model	Δ AIC _c	W	K
TIME, TEMPERATURE	0	0.15	3
WIND	0.26	0.13	2
WIND, TEMPERATURE	0.38	0.12	3
WIND, TIME, TEMPERATURE	0.68	0.11	4
TEMPERATURE	0.69	0.11	2
NULL	1.01	0.09	2
OBSERVER	1.26	0.08	2
TIME	1.28	0.08	2
WIND, OBSERVER	1.61	0.07	3
GLOBAL	2.79	0.04	5
TIME,OBSERVER	3.33	0.03	3

AIC value of top model = 739.46

Table 1.3. Scale at which variables were measured within the landscape and mean Spearman's Rank Correlation Coefficient (r) between landscape-scale variable and northern bobwhite presence in Delaware, USA, from 15 May – 15 August, 2008–2009 based on 10,000 bootstrapped samples. The standard error for all coefficients was 0.01.

Variable	Distance from survey point	
	(km)	r
HDEV	1	-0.29
GRASS	1	-0.11
WET	1	-0.1
AG	1	0.04
SHRUB	1	0.05
FOR	1	0.13
AGEDGE	1.5	-0.07
ECOHES	2	0.2
LDEV	2.5	-0.3
DCOHES	2.5	-0.27
III	2.5	-0.15
EEDGE	2.5	0.09

Table 1.4. Summary of model-selection analysis of variables affecting the probability of occupancy of northern bobwhite in Delaware, USA, from 15 May – 15 August, 2008–2009. I report Akaike's Information Criterion (AICc), the relative difference in AIC value compared to the top-ranked model (Δ AIC), the AIC model weight (W), and the number of parameters in the model (K). Variables are described in Table 1.1. Variable subscripts denote measurement scale measurement; site = S, landscape = L.

Model ^a	Δ AIC _c	W	K	Rank
EEDGE _S , IJI _S , DCOHES _L , ECOHES _L	0	0.49	6	1
EEDGE _S , IJI _S , SHRUB _L , DCOHES _L	2.38	0.15	6	2
IJI _S , AGEDGE _S , DCOHES _L , ECOHES _L	2.39	0.15	6	3
AGEDGE _S , IJI _S , DCOHES _L	3.35	0.09	5	4
EEDGE _S , IJI _S , ECOHES _L , LDEV _L	4.59	0.05	6	5
IJI _S , DCOHES _L	5.29	0.03	4	6
ECOHES _S , AGEDGE _S , DCOHES _L	7.11	0.01	5	7
AGEDGE _S , DCOHES _L	8.05	0.01	4	8
AGEDGE _S , FOR _S , DCOHES _L , ECOHES _L	8.38	0.01	6	9
AGEDGE _S , AG _L , DCOHES _L , SHRUB _L	10.68	0	6	10
AGEDGE _S , ECOHES _L , LDEV _L	11.2	0	5	11
ECOHES _S , EEDGE _S , IJI _S , IJI _L	12.26	0	6	12
SHRUB _S , DCOHES _L , ECOHES _L , EEDGE _L	14.53	0	6	13
EEDGE _S , AGEDGE _S , EEDGE _L , AGEDGE _L	16.16	0	6	14
LDEV _S , LDEV _L	16.56	0	4	15
ECOHES _S , SHRUB _S , DCOHES _L , SHRUB _L	18.27	0	6	16
SHRUB _S , EEDGE _L , ECOHES _L , HDEV _L	19.37	0	6	17
IJI _S , WET _S , AG _L , IJI _L	19.99	0	6	18
IJI _S , FOR _L	20.96	0	4	19
SHRUB _S , AGEDGE _S , IJI _L	22.22	0	5	20
HDEV _S , HDEV _L	22.33	0	4	21
EEDGE _S , GRASS _S , HDEV _S , EEDGE _L , HDEV _L	22.63	0	7	22
AGEDGE _S , FOR _L , DIST	23.09	0	5	23
LDEV _S , FOR _S , IJI _L , WET _L	23.33	0	6	24

^aAIC value of top model = 343.51

Table 1.4. (continued)

Model ^a	ΔAIC_c	W	K	Rank
Global _L	24.19	0	14	25
HDEV _S , FOR _S , GRASS _L , HDEV _L	26.31	0	6	26
NULL	26.73	0	2	27
WET _S , WET _L	28.8	0	4	28
GRASS _S , GRASS _L	30.19	0	4	29
AGEDGE _S , AG _L , DCOHES _L , ECOHES _L	101.37	0	6	30
ECOHES _S , EEDGE _S , IJ _S ECOHES _L , DCOHES _L	101.97	0	7	31
ECOHES _S , DCOHES _L	102.38	0	4	32
ECOHES _S , ECOHES _L ,	114.21	0	4	33
ECOHES _S , AGEDGE _L	115.92	0	4	34
EEDGE _S , DCOHES _L , ECOHES _L , SHRUB _L	902.16	0	6	35
ECOHES _S , DCOHES _S , ECOHES _L , DCOHES _L	977.75	0	6	36
ECOHES _S , IJ _S , DCOHES _L , ECOHES _L , GRASS _L	980.81	0	8	37
AGEDGE _S , DCOHES _S , ECOHES _S , EEDGE _L , SHRUB _L , DIST	982.08	0	8	38
Global _S	989.62	0	14	39
Global _{L,S}	1002.58	0	27	40

^aAIC value of top model = 343.51

Figure 1.1. Locations of all survey sites and whether northern bobwhite were detected within Delaware USA, from 15 May – 15 August, 2008–2009.

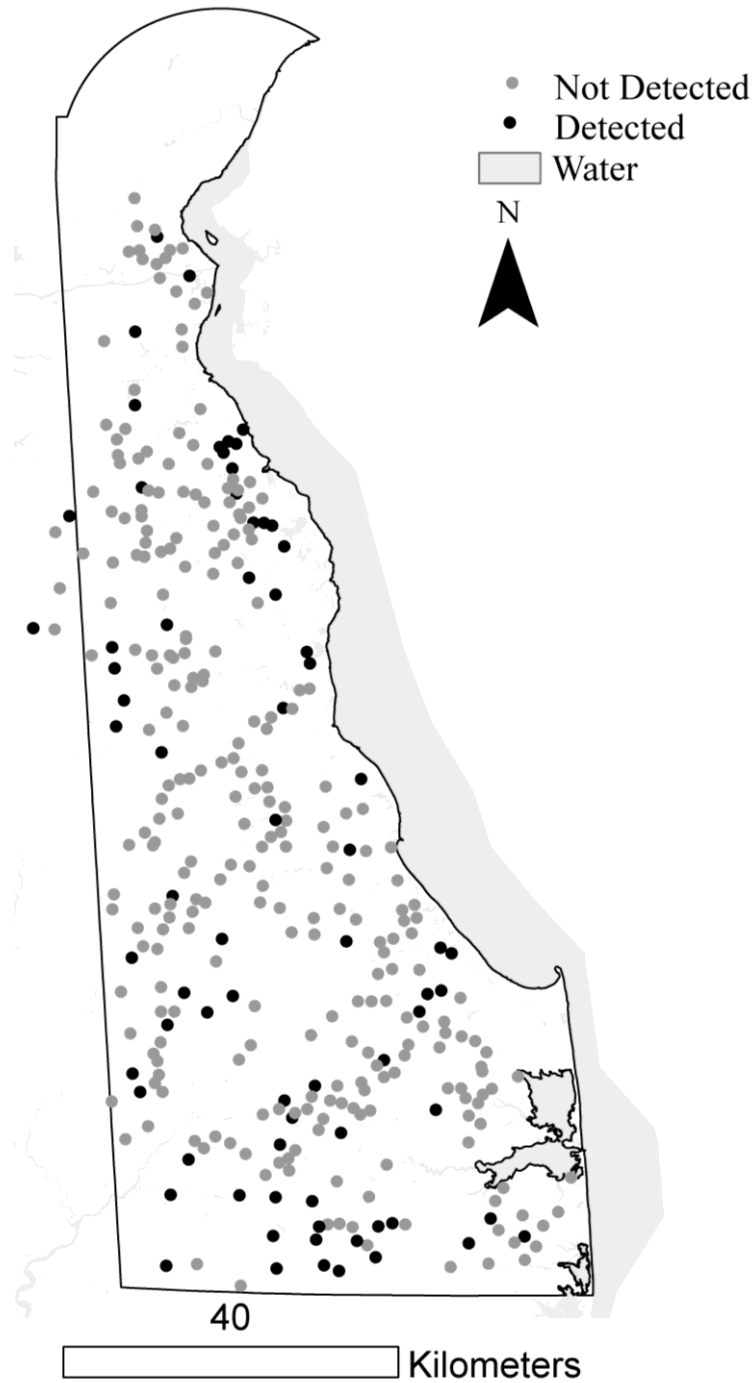
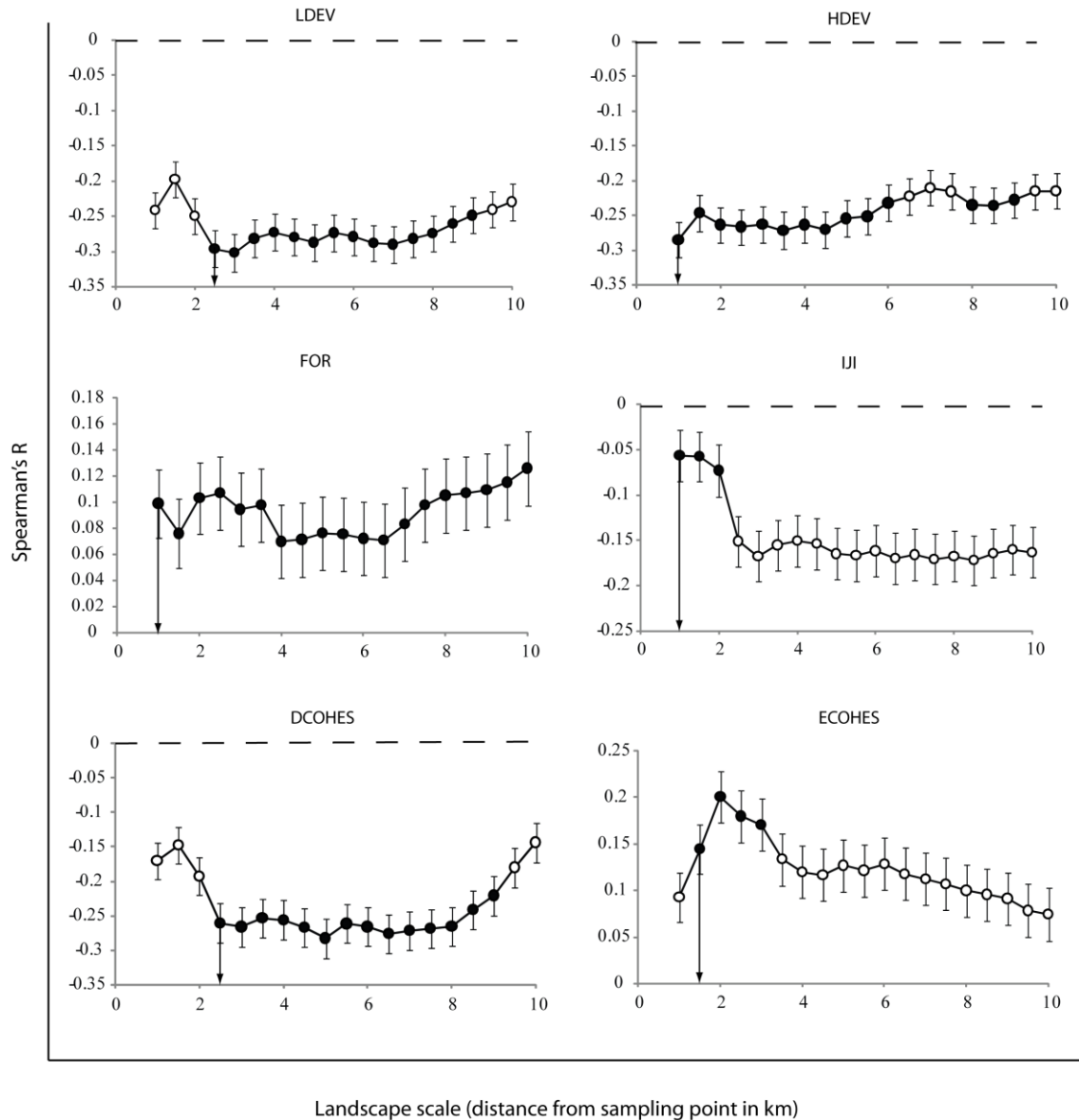


Figure 1.2. Mean and 95% confidence intervals of Spearman's Rank Correlation Coefficient between northern bobwhite presence and explanatory variables measured within buffers of 0.5 km to 9.5 km in 0.5 km increments around the site. Black points indicate distances statistically similar to the buffer distance with the strongest correlation. Arrows indicate distance used.



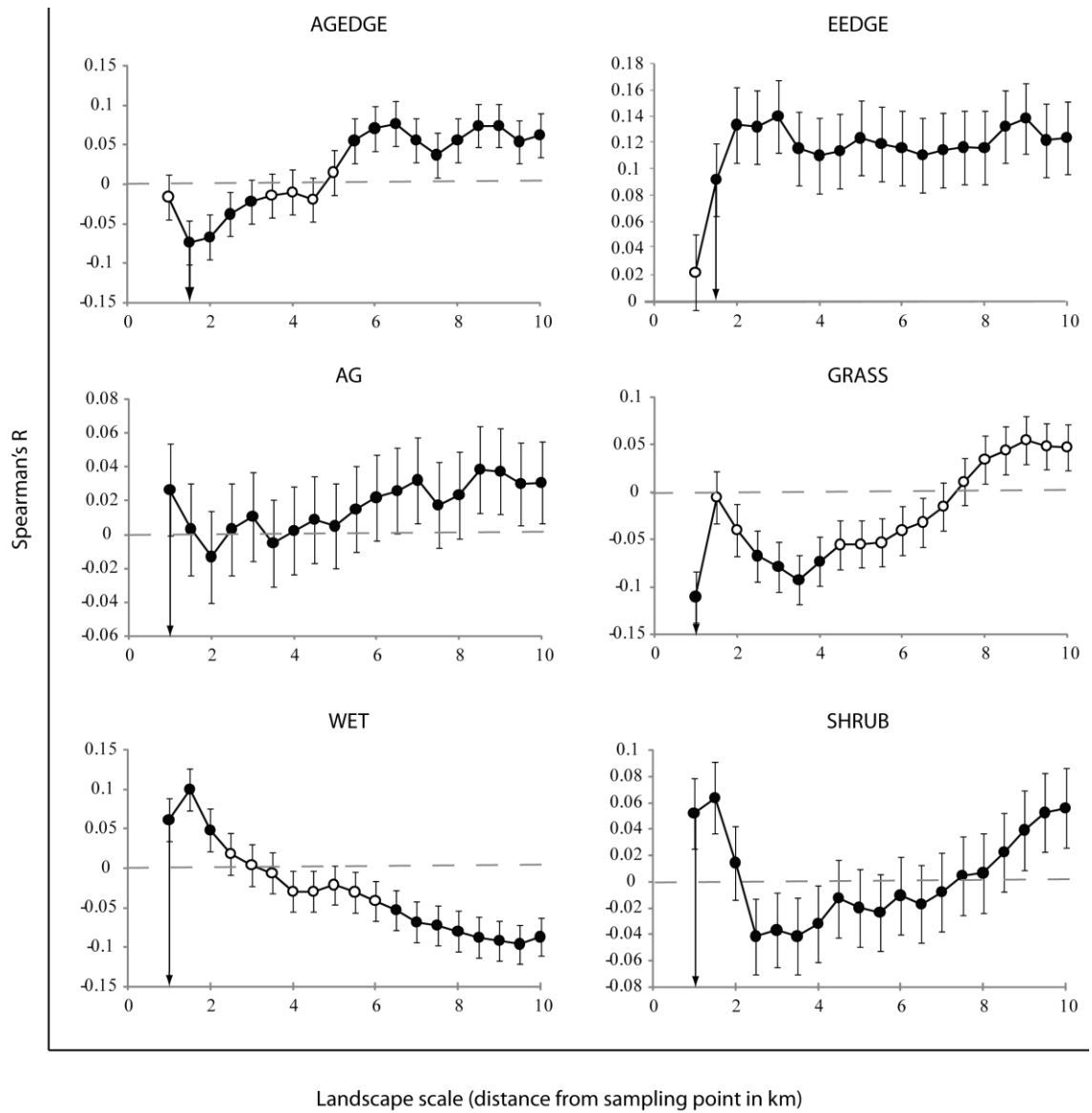


Figure 1.3. Direction and relative effect size (standardized model-averaged partial regression coefficient) for variables in the top models. Error bars denote 95% confidence intervals of effects size based on unconditional variance estimate.

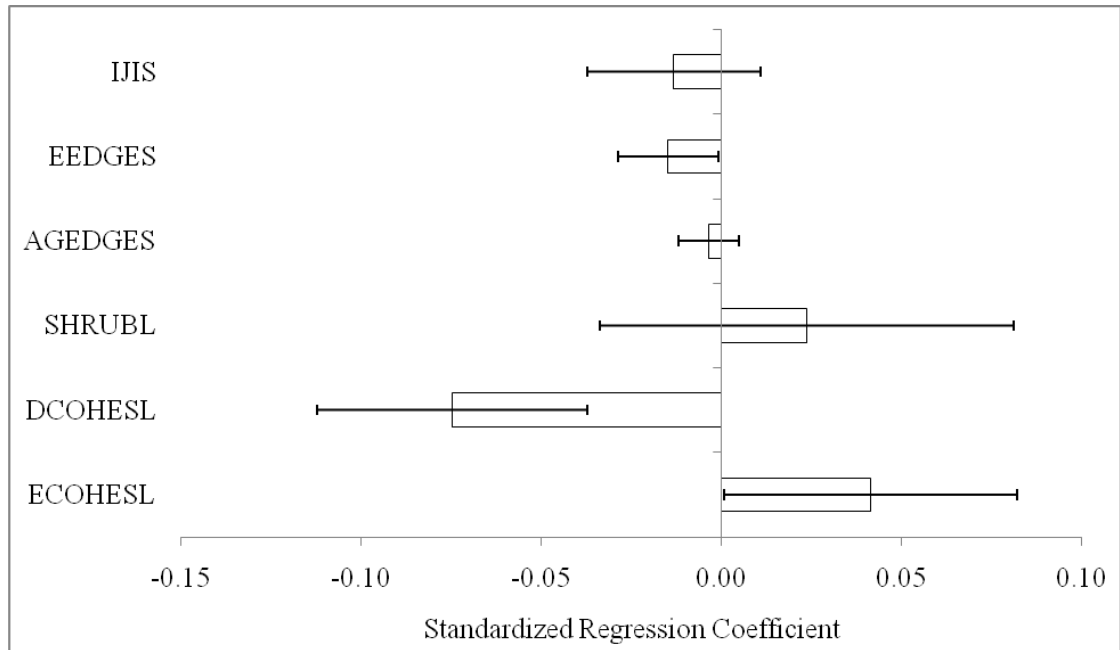


Figure 1.4. Receiver operating characteristic (ROC) curve for validation survey points of northern bobwhite breeding season occupancy within early successional habitats of Delaware, USA, from 15 May – 15 August, 2008–2009.

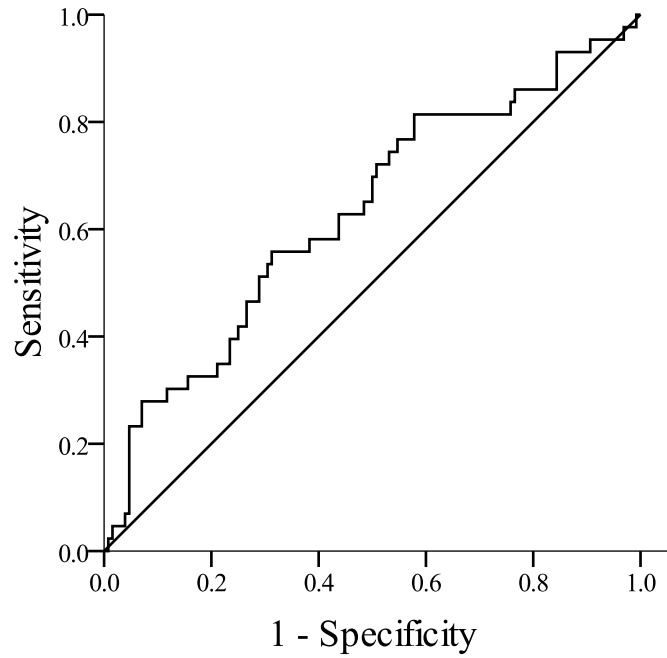


Figure 1.5. Percent improvement in accuracy of site occupancy classification using predictive habitat model over random classification across threshold values ranging from 0-1.

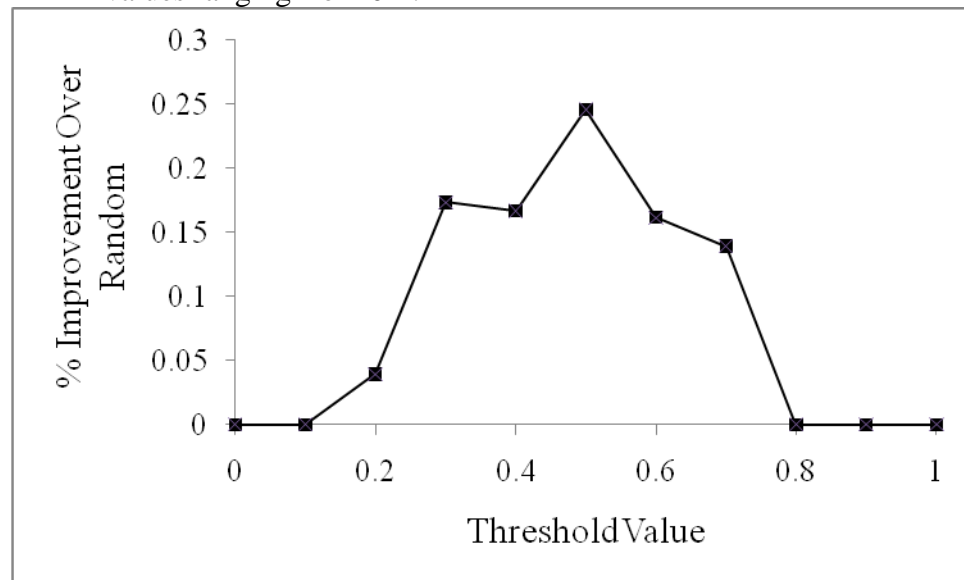


Figure 1.6. Predicted probability of breeding season occupancy of northern bobwhite within early successional habitats of the Delmarva Peninsula, USA, from 15 May – 15 August, 2008–2009.

Figure 1.7. Predicted breeding season occupancy of northern bobwhite within early successional habitats of the Delmarva Peninsula, USA, from 15 May – 15 August, 2008–2009.



Chapter 2

EFFECTS OF BROADCAST CALLER ON ESTIMATING DENSITY AND OCCUPANCY OF NORTHERN BOBWHITE

Introduction

Northern bobwhite (*Colinus virginianis*) are experiencing steep range-wide declines (Sauer et al. 2008). These declines have led to the formation of the Northern Bobwhite Conservations Initiative (NBCI) whose goal is to restore bobwhite populations to 1980 levels. A standardized and cost-effective large-scale monitoring protocol that estimates a biologically meaningful population size is needed to determine when or if this goal is met (Bill Palmer, personal communication).

Call count surveys of whistling northern bobwhite are a common method for surveying bobwhite populations to estimate relative abundance (Fowler 1988, Curtis et al. 1989, Hansen and Guthery 2001). These surveys may provide an accurate assessment of population trends if rigorous sampling protocols are followed (e.g. repeat visits to sites during peak calling periods and good weather conditions). However, they are not useful for estimating population size (Hansen and Guthery 2001) and may not always provide accurate trend estimates despite rigorous sampling protocol (Thompson 2002).

Unbiased estimates of bird density can be obtained using distance sampling, which allows for modeling distance-related changes in detection if certain assumptions are met (Buckland et al. 2001). These include 1) all individuals at zero distance from the observer are detected, 2) detectability declines monotonically with distance from the observer, 3) individuals do not move before they are detected, and 4) distance to the individual is estimated accurately. However, the relatively low detectability of bobwhite

due to their cryptic coloration, secretive behavior, and low abundance pose a logistical problem for obtaining a minimum sample size of 75-100 detections to reliably model a detection function (Buckland et al. 2001).

Broadcasting a female bobwhite call during surveys may improve the detection of males by eliciting a courtship behavior response (e.g. whistling) (Coody 1991). Broadcast calls do increase the number of detections of marsh birds (Gibbs and Melvin 1993, Conway and Gibbs 2005), western burrowing owls (*Athen cunicularia hypugaea*) (Conway and Simon 2003), and band-tailed pigeons (*Patagioenas fasciata*) (Kirkpatrick et al 2007). However, Hansen and Guthery (2001) found the caller did not increase the number of detected male bobwhite. Additionally, broadcasting a female bobwhite call has been shown to increase movement of penned male bobwhite (Coody 1991), which suggests that the assumption of no movement prior to detection could be violated if the caller induces free-ranging males to move before being detected. Thus, rigorous distance sampling to produce density estimates may not be possible when using broadcast calls.

Surveying site occupancy does not rely on detecting all individuals and may reduce bias due to imperfect detection associated with call count surveys. Surveys that estimate the number of sites occupied can also be less expensive and easier to conduct than distance sampling surveys (Mackenzie et al. 2002). Estimating occupancy of a site relies on repeat visits to reduce the probability of not detecting an individual when a site is actually occupied and to model changes in probability of detection ($P_{(D)}$). Occupancy surveys can accommodate movement prior to detection, therefore a broadcast caller may be useful for improving $P_{(D)}$ and occupancy estimates. Past surveys using broadcast callers for marsh birds (Gibbs and Melvin 1993, Conway and Gibbs 2005), western burrowing owls (Conway and Simon 2003), and band-tailed pigeons (Kirkpatrick et al.

2007) did increase the number of sites considered occupied. However, it is not known how a caller would affect the number of sites that bobwhite are detected.

Increasing survey duration can also increase the number of detections and probability of detecting an individual if the site is occupied (Dettmers et al. 1999, Hansen and Guthery 2001, Gooch et al. 2006). Gooch et al. (2006) found longer surveys had a higher number of Anurans detected per site, but 87% of detections occurred in the first 3 min. Dettmers et al. (1999) found predictive habitat models for forest birds with low detection probability performed better with longer surveys. However, when detection probability was high, increased survey time did not improve their habitat models. Hansen and Guthery (2001) found 6 min surveys had 0.57-0.92 more singing males than 3 min surveys. Although increased survey duration may increase detection probability, there are two potential negative consequences. First, increased survey time may allow bobwhites to move prior to detection. Second, the number of sites that can be surveyed within a given amount of time will be reduced. Therefore, it is important biologists consider the costs and benefits of survey duration when monitoring a population.

I tested the null hypothesis that the use of broadcast callers and increased survey duration do not affect detection probability, estimated density, and estimated occupancy of breeding bobwhite. Results from my study are important for improving the accuracy of large-scale surveys to monitor bobwhite populations.

Methods

From 15 May - 15 Aug 2009, I conducted 3 replicate roadside surveys at 180 points to sample the presence and density of bobwhite within Delaware. I conducted 9 point count surveys, within one survey route, per morning from 15 min before sunrise

until 2 hr after sunrise on precipitation-free days when the wind speed was below 6.5 km/hr. Each point survey lasted 10 min. I randomly generated the order that routes were surveyed and alternated the order that points were surveyed within a route during replicate visits. Surveys were split into three time periods that were 3 min, 4 min, and 3 min in duration. I listened passively for bobwhite during the first 7 min (first and second time periods) and then broadcast 4 – 5 recorded female bobwhite calls approximately every 10 sec at 90dB in the four cardinal directions during the last 3 min (third time period) (following Guthery et al. 2001). I recorded the location of every individual bobwhite detected onto an aerial photo of the survey point and recorded the time period when each individual was detected. All bobwhite detected in the third time period were recorded even if they had been detected previously.

I digitized bobwhite locations from aerial photos into a Geographic Information System to determine the detection distance (to the nearest meter) of each bobwhite from the observation point. I used program DISTANCE (Thomas et al. 2005) to estimate the effective detection distance and density of bobwhite for the passive and broadcast call surveys. I compared effective detection distance and density for the first and third time period to ensure even effort between passive and broadcast caller periods and between the 3 min and 7 min passive surveys to determine the effect of increased survey duration. I therefore had three treatments: 3 min of passive listening, 7 min of passive listening, and 3 min of broadcast caller. I grouped observations into 10 equal distance bands from 0 - 600 m. I selected this number of distance bands to provide enough detail to model the detection curve and to prevent spurious spikes in the detection function that result from heaping or inaccurate distance measurements (Buckland et al 2001). I selected 600 m as the maximum distance so all detections were

included; however, I truncated the furthest 10% of detections. I determined the fit of the model based on distance bands using the chi-square goodness of fit test ($\alpha = 0.05$).

I used Akaike's Information Criterion for small samples (AIC_c) to compare detection function models where detection was held constant or allowed to vary across treatments. For all models I fit the half normal, half normal + cosine expansion, half normal + simple polynomial expansion, half normal + Hermite polynomial expansion, uniform, and uniform + cosine expansion key functions. I then used Student's t-test to determine if effective detection distance and estimated densities were significantly different. If results were not significant I ran a power analysis to determine the sample size needed to detect a difference, if one existed.

I estimated separate detection probabilities for each survey treatment by analyzing occupancy histories using multi-method analysis (Nichols et al. 2008) in program PRESENCE (Hines 2006) where I considered each treatment as a different method. I used AIC_c to rank models of the $P(D)$ and weigh the probability of each model being the best-fit model given the data and set of candidate models. The model with the lowest AIC_c value was considered the best model. Models with $\Delta AIC_c \leq 2$ were considered to have substantial support.

Results

I detected 48 bobwhite across 23 (Appendix B) sites during the 3 min passive listening survey, with 30 additional bobwhite detections and 7 additional sites with detections during the full 7 min passive listening survey. I detected 75 bobwhite at 28 sites during the 3 min broadcast calling survey. I found 92% concordance of overall site occupancy between the 3 min passive listening and 3 min broadcast calling treatments, with 61% (17 out of 28) overlap of occupied sites among those with

detections during either survey treatment. I found 94% concordance of overall site occupancy between the 7 min passive listening and 3 min broadcast calling treatments; with 73% (22 out of 30) overlap of occupied sites among those with detections during either survey treatment. Detection rates of bobwhite were 0.09 bobwhite/visit for the 3 min passive survey, 0.14 bobwhite/visit for the 7 min passive survey and 0.14 for the broadcast caller survey. Bobwhite were observed flying toward the observer and some bobwhite were only detected because of these movements.

Separating survey treatments to model density fit the data better than pooling treatments ($\Delta AIC=7.82$). The uniform key with a cosine function was the best function to model detection for the 3 and 7 min passive listening surveys and fit the distribution of the detections ($\chi^2=8.55, 3.28$, $df=6$ for both and $P=0.20, 0.77$ respectively) (Figure 2.1). The half normal key with cosine expansion function was the best function to model detection during the broadcast call survey; however, it did not fit the distribution of detections ($\chi^2=18.81$ $df=6$ and $P<0.01$).

The maximum distance a bobwhite was detected in the passive surveys was 573 m and 508 m for the broadcast period. The effective detection distance was higher during the 3 min passive listening survey (326 ± 39 m) and 7 min passive listening survey (331 ± 31 m) than the broadcast call survey (174 ± 14 m) ($P<0.001$ for both) but was not different between passive listening surveys ($P=0.91$). The estimated density of bobwhite was 7.08 times higher based on the broadcast call survey (4.127 ± 0.668 quail/km²) than the 3 min passive listening survey (0.649 ± 0.156 quail/km²) ($P<0.001$) and 3.75 times higher than the 7 min passive listening survey (1.012 ± 0.192 quail/km²) ($P<0.001$). The density in the 7 min passive survey was 1.66 times higher than the 3 min passive survey but was not significantly different ($P=0.15$). A sample

size of 326 and 665 was needed to detect an effect size of double the estimate with a power of 0.5 and 0.8, respectively.

Testing for the effect of treatment on occupancy modeling among 5 models, I found that separating detection probabilities among all treatments was the top ranked model with a model weight of 0.92. Constant detection among all treatments and visits was the second best model ($\Delta AICc = 6.73$, $w = 0.03$), grouping passive listening surveys and separating the broadcast caller survey was the third model ($\Delta AICc = 7.52$, $w = 0.02$), variable detection probability by time and method was the fourth model ($\Delta AICc = 7.92$, $w = 0.02$) and variable detection probability among visits with constant detection between methods was the lowest ranked model ($\Delta AICc = 8.82$, $w = 0.01$). The detection probability for bobwhite during a single visit was 0.52 ± 0.07 during 3 min of passive listening, 0.79 ± 0.06 for 7 min of passive listening, and 0.74 ± 0.06 using the broadcast call. The cumulative probability of detecting a bobwhite (P_{dc}) in at least one of the three surveys if the site was occupied was 0.88 for 3 min of passive listening, 0.99 for 7 min of passive listening, and 0.98 when using the broadcast call. This was calculated using the formula: $P_{dc} = 1 - (1 - P(D))^3$.

Discussion

Use of a broadcast caller increased detections and distance-based density estimates of bobwhites compared to passive listening. However, evidence from my study suggests that density estimates derived from caller surveys were biased high (i.e. 3-7 times that estimated from passive listening) because of movement prior to detection. Although Buckland et al. (2001) suggest random and slow movements relative to the observer and prior to detection do not cause large biases in line transect sampling, I often observed bobwhites running on the ground or flying directly toward the observer

when using the broadcast caller. These visual detections occurred in close proximity to the observer, producing an excess number of detections in the first distance band. Consequently, the broadcast caller detection function fit poorly to the data and dropped more steeply as distance from the observer increased as compared to passive listening. Additionally, the effective detection distance for broadcast caller surveys was also shorter. Alternatively, the loud volume of the broadcast caller could have limited my ability to detect bobwhite vocalizations at long distances. However, the call was not played constantly; therefore its impact on detection was likely low.

My results indicate increasing the duration of surveys may be a better way to increase number of detections rather than using a broadcast caller because it does not appear to violate any assumptions of distance sampling. The 7 min passive survey had greater precision of the effective detection distance while not affecting the value of the effective detection distance, the estimated density, or the precision of the density estimate. Increasing survey duration will increase the probability of random movement of individuals. Because random movements are more likely to be detected when the individuals are near the observer, increasing survey duration will lead to an upward bias in the density estimate (Buckland et al. 2001). In contrast, short duration surveys can miss detections near the observer which will bias density estimates low (Buckland 2006). I did not have the power to detect a difference between the 3min and 7min passive survey periods, and true density was also unknown. However, the 7 min passive survey's detection function had a better fit than the other two methods while also obtaining the recommended sample size of Buckland et al. (2001). Therefore, I believe if bias in the density estimate of the 7min passive surveys exists it is minimal when compared to the 3 min passive survey. However, the detection rate and survey duration

without bias from movement will likely vary by study and should be tested using a pilot study.

In addition to testing survey duration and caller effects on density estimates, I was also interested in measuring their effect on determining occupancy. Increasing the probability of detection at a site reduces bias of not detecting present individuals (Gu and Swihart 2004). Methods that increase detection probability (e.g., broadcasting female call) should therefore increase the predictive performance of an occupancy model. However, broadcasting calls may produce false positive occupancy by attracting a bird into a sampling area that it normally wouldn't occupy; a violation of occupancy modeling (MacKenzie et al. 2006, Royle and Link 2006).

Broadcasting calls may also create error because the effective response distance of birds to the broadcast caller is unknown and the sampling area cannot be accurately defined. Positive responses from bobwhite, while using a caller, have been observed up to 200 m (Coody 1991). However, it is likely effective at greater distances. For example, I observed bobwhite responding to the caller from up to ~ 300 m. I suspect that the effective distance of the caller was not greater than 350 m because site occupancy based on caller surveys was similar to that of passive listening surveys, in which birds were effectively detected out to ~350 m. Further research should be conducted to determine the effective distance of a broadcast caller. This will allow researchers to know the area that is sampled when using a caller.

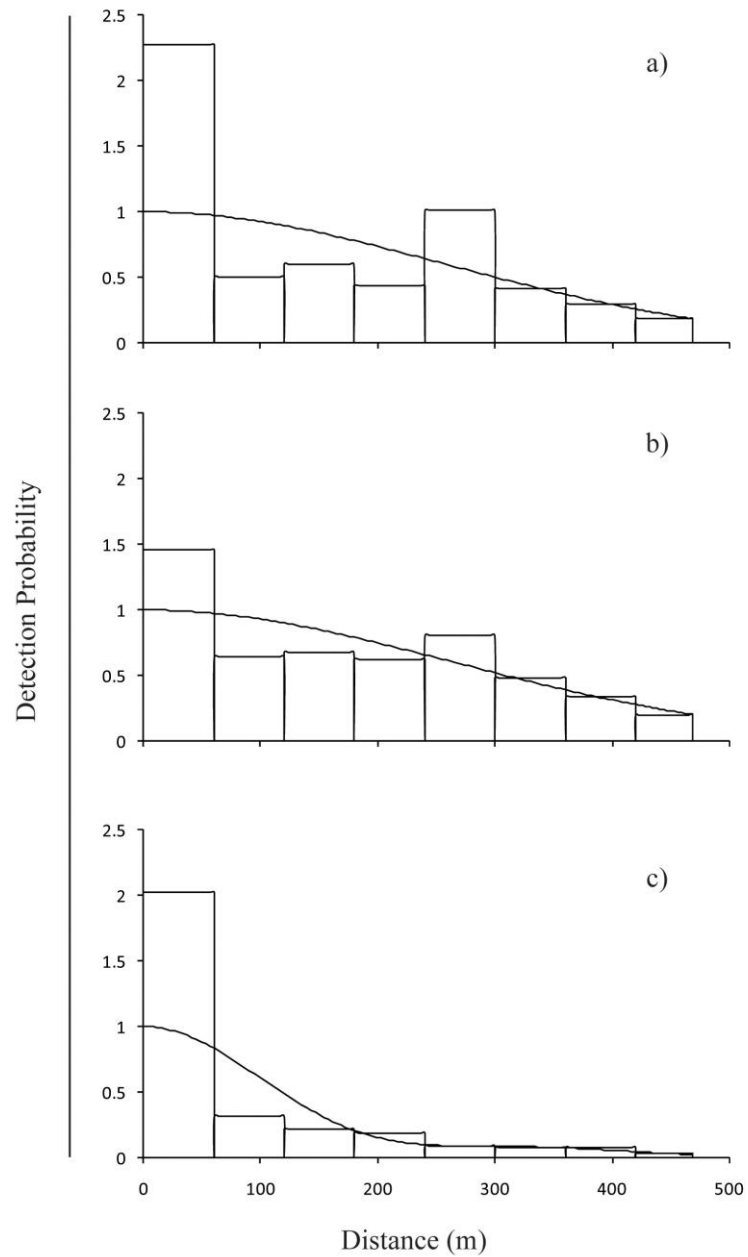
Calling intensity of bobwhite may be lower for small populations (Coody 1991, Wellendorf and Palmer 2005). Passive listening surveys may only be detecting bobwhites that are vocal and/or close to the observer, therefore biasing occupancy low. I encourage future researchers to further investigate the potential effects of variable

bobwhite densities on calling intensity and whether the benefits of a caller will outweigh their costs to improve occupancy estimation.

Management Implications

Use of a broadcast caller is inappropriate for determining bobwhite density estimates through distance sampling. Additionally, increasing the number of sampling sites or duration of surveys is more appropriate for increasing the number of detections for distance sampling than broadcasting calls. However, increasing survey duration may lead to biased density estimates. It is important to identify potential sources of bias for each survey. A broadcast caller may, however, improve occupancy estimates under certain conditions. First, a caller may also be useful for increasing calling rates for a small population by giving the illusion of more conspecifics in the area. Second, use of a caller may also be acceptable when funding or logistical constraints limit survey effort. I recommend using a caller at sampling sites located more than 500 m from the edge of a study area or more than 1 km from another sampling site.

Figure 2.1. Histograms of observed detection probability with distance from observer for the a) 3 min passive listening, b) 7 min passive listening, and c) broadcast caller surveys. Lines depict modeled detection probabilities using the uniform key with cosine function for the passive listening surveys and the uniform key + cosine expansion function for the broadcast caller survey.



**LINKING LONG-TERM HABITAT CHANGES TO NORTHERN BOBWHITE
POPULATIONS: ASSESSING THE PREDICTIVE POWER OF A STATIC
MULTI-SCALE OCCUPANCY MODEL**

Introduction

Broad-scale habitat loss is believed to be the primary cause of declining northern bobwhite (*Colinus virginianus*) populations (Brennan 1991, Williams et al. 2004). However, past research and management have not focused on habitat loss at this scale (Williams et al. 2004). Information gained from research at fine scales cannot necessarily be extrapolated to the landscape scale (McCarty 1956) where habitat loss and fragmentation is occurring. Thus, bobwhite declines associated with fine-scale habitat loss or degradation cannot necessarily be used as evidence that habitat loss at a broad scale is the primary cause of population declines.

Although several studies have addressed bobwhite population dynamics at large scales (e.g. Church et al. 1993, Lusk et al. 2002, Peterson et al. 2002, Williams et al. 2003), only a few studies have attempted to examine the relationship of landscape scale habitat loss to population changes. Twedt et al. (2006) analyzed the landscape around Breeding Bird Survey (BBS) routes in 1980 and 1992 to predict bobwhite abundance in the West Gulf Coastal Plain. They further applied their 1992 model to 2004 land cover data and found predicted abundance was more correlated to observed abundance of bobwhite than random predictions. This result implied land cover changes may relate to population changes, but this relationship was not directly tested. Veech (2006) also analyzed the landscape around increasing, decreasing, and extinct populations of bobwhite using BBS data and National Resource Inventory land cover data from 1997 across the bobwhite distributional range. He found the amounts of forest

and unsuitable habitat for bobwhite were higher in decreasing and extinct populations. Although this evidence linked landscape characteristics with population changes, landscape change was not explicitly measured. Consequently, data quantifying both long-term trends of bobwhite populations and land cover changes are needed to directly assess the relationship of landscape change with population change.

The BBS provides the longest duration and broadest spatial extent dataset of breeding bird populations in North America. However, there are some obstacles for using the dataset. BBS survey sites are visited only once per breeding season, and bird *abundance* data from a single visit are unreliable because variation in detection cannot be accounted for (Hansen and Guthery 2001, Mackenzie et al. 2002). Alternatively, *occupancy* of BBS routes may be more useful because it does not require all individuals to be detected. However, occupancy estimates are still not adjusted for probability of detection and can be biased (MacKenzie et al. 2006). If these limitations are to be addressed, repeat site visits are required to measure variability in detection and model factors affecting it.

The relationships between bobwhite populations and landscape characteristics are complex, and best measured using multi-variable models (Roseberry and Sudkamp 1998, Burger et al. 2006 *a,b,c*, Twedt et al. 2006, Duren 2010). Therefore, change in any one variable may not predict landscape scale effects on bobwhite population change; however, changes in a suite of variables through time may have a stronger relationship. Measuring changes in the landscape by predicted change in a multivariate model through time may show a stronger relationship with bobwhite populations.

Bobwhite populations in the Mid-Atlantic have experienced some of the steepest declines in the country (Sauer et al. 2008) while experiencing increased landuse

development (Long and Williams 2010). Therefore this system has the potential to provide an important case study for measuring the impacts of changing habitat availability on bobwhite occupancy. Specifically, I tested if a previously established static multi-scale habitat-based occupancy model for bobwhite (Duren 2010) could predict the change in occupancy of BBS routes over time in the Delmarva Peninsula, USA. This information could be useful for scaling habitat management to a landscape scale (Williams et al. 2004) and assisting future conservation efforts.

Study Area

The Delmarva Peninsula is entirely located in the Mid-Atlantic Coastal Plain physiographic region and is comprised mostly of row crop agriculture and oak (*Quercus* spp.), poplar (*Populus* spp.) and maple (*Acer* spp.) forest in the north and areas of pine (*Pinus* spp.) forest in the south (Table 3.1). Between 1992 and 2005, high-density development had the greatest relative increase and grassland habitat had the greatest relative decrease in area. However, the absolute change in area among land use/cover types was minor, with low density development having the largest increase of 5,040 ha.

Methods

BBS Route Occupancy

I estimated observed occupancy for BBS routes in the Delmarva Peninsula for two year periods surrounding NOAA CCAP data sets estimated for 1992, 1996, 2001, and 2005. BBS surveys are 39.4 km long routes with stops every 0.8 km. Surveyors record every bird heard or seen within 0.4 km radius of the point for 3 min.

Each survey starts one-half hour before sunrise and last about 5 hours. I averaged the probability of occupancy for each of the fifty stops (sites) within routes. Each year was considered a repeat visit. The first year in the primary sampling period started the year before the land cover data or the year of the land cover data depending on availability of BBS data. Whenever possible, I was consistent with the start of the primary sampling period relative to year of the land cover data within routes. I pooled stop data across all time periods for modeling detection probability using the change in temperature (TEMP), change in sky cover (SKY), end time of survey (TIME), presence of a second observer (OBS), and wind speed (WIND) at the beginning of the survey as covariates. I used model averaging on all detection probability models with a $\Delta AIC_C \leq 2$ to estimate the number of sites occupied for each route and sampling period. I estimated the number of BBS route stops occupied using multi-year occupancy modeling in program PRESENCE (Hines 2006).

Predictive Habitat Occupancy Model

Duren (2010) modeled 2008–2009 breeding-season bobwhite occupancy across the Delmarva Peninsula, USA, based on 2005 land cover data from the National Oceanic and Atmospheric Organization Coastal Change and Analysis Program (NOAA CCAP). The model predicted bobwhite occupancy based on habitat variables at the survey site and surrounding landscape scales. The composite model incorporated the influence of six habitat variables averaged among three individual models. At the site scale, bobwhite presence was negatively related to interspersed and juxtaposition index of early successional and agriculture habitat (IJI_S [where subscript S indicates site level]) in all models, early successional to forest edge density ($EEDGE_S$) in two models and agriculture to forest edge density ($AGEDGE_S$) in one model. At the landscape scale,

bobwhite presence was negatively related to cohesion of development ($DCOHES_L$ [where subscript L indicates landscape level]) within a 3.0 km radius around sites in all models, positively related to cohesion of early successional habitat ($ECOHES_L$) within a 2.0 km radius around sites in two models, and positively related to percentage of shrub habitat ($SHRUB_L$) within a 1.5 km radius around sites in one model. Each variable measured at the landscape scale was determined as the buffer radius around the site at which each variable was most strongly correlated to bobwhite presence among the set of buffer radii ranging from 0.5 km to 9.5 km (1 km to 10 km from survey point) at 500 m increments (sensu Holland et al. 2004). Further analysis of effect size of the standardized coefficients for these 6 variables found $DCOHES_L$, $ECOHES_L$ and $EEDGE_S$ had the strongest effects.

I used this predictive habitat occupancy model to estimate the change in occupancy between time periods for individual BBS routes in the Delmarva Peninsula. First, I produced 30-m-resolution raster grid surfaces of the predicted probability of occupancy for each year of historic land cover data. I used Global Positioning System (GPS) coordinates, if they were available, to identify the locations of stops within routes. When GPS coordinates were missing, I used 50 equally-spaced points along a route for stop locations. I then averaged the probability of occupancy among grid cells that coincided with 50 stop locations within routes.

Data Analysis

Using linear regression ($\alpha \leq 0.05$), I assessed the relationships between a) predicted and observed route occupancy pooled across years, b) changes in predicted and observed route occupancy between each successive time period (~ 4 years) pooled across all time intervals, c) changes of each of the 6 predictive occupancy model

covariates and changes in observed route occupancy between time periods pooled across all time intervals and d) changes of each of the 6 predictive occupancy model covariates and changes in observed route occupancy between 1992-2005. Last, to see how long-term change in habitat was related to long-term trends in occupancy I compared change in predicted occupancy to change in observed occupancy between 1992 to 2005 (17-year interval) using linear regression ($\alpha \leq 0.05$).

Results

I used data from 15 BBS routes in 1992, 19 in 1996, 24 in 2001 and 22 in 2005 to obtain 57 measures of observed occupancy change during any two consecutive time periods from 1992-2005 and 14 measures of observed occupancy change during 1992 -2005 (Fig. 3.1). Observed bobwhite route occupancy declined sharply over time while predicted occupancy based on multi-scale habitat characteristics was stable (Fig. 3.2). Observed route occupancy among years ranged from 2.2% in 2005 to 100% in 1992 and the average change in observed occupancy per year was -8.7% (\pm SE 1.3%). The relationships between change in observed occupancy and the 6 variables of the model pooled across all time intervals were all poor and none were significant (Fig 3.3). However, change in SHRUB and EEDGE from 1992-2005 were significantly related to change in occupancy, both were negative, and all other variables were not (Figure 3.4). Additionally, change in observed occupancy was large, especially when compared to the percent change in the variables of the model (Fig 3.5)

Predicted route occupancy among years ranged from 3.6% in 1996 to 53.9% in 2001 and the average change in predicted occupancy was 1.0% (\pm SE 0.8%). Predicted route occupancy for each time step was not related to observed route occupancy across sampling periods ($F_{1,56} = 0.34$, $P = 0.56$, $r^2 = 0.004$) (Fig. 3.6).

Additionally, changes in predicted and observed occupancy were not related ($F_{1,56} = 0.16$ $P = 0.69$ $r^2 = 0.003$) (Fig. 3.7). Lastly, predicted change in occupancy was not related to observed change in occupancy from 1992-2005 ($F_{1,13} = 1.69$ $P = 0.22$, $r^2 = 0.12$) (Fig. 3.8).

Discussion

The static multi-scale occupancy model of Duren (2010) failed to predict change of occupancy through time. I consider two broad types of reasons why I did not find significant results and discuss how future researchers may be able to improve this modeling effort. First I will discuss potential methodological reasons including a) an inaccurate or imprecise predictive occupancy model, b) changes in patch occupancy not at equilibrium, and c) biased occupancy estimates from Breeding Bird Survey data. Second, I discuss potential biological relationships that may be causing observed occupancy declines even if habitat changes are nominal including: a) slack in habitat configurations, b) differential habitat use between breeding and nonbreeding seasons, c) high predation and harvest rates, and d) possible reduction in food supply from agricultural chemicals.

Methodologically, the ability to detect a relationship between observed and predicted occupancy relies on the accuracy and precision of the predictive model. Unfortunately, Duren (2010) found the predictive ability of the model was moderately low (which in itself can be attributed to potential methodological and biological biases). Thus, model uncertainty may have introduced enough error (noise) to obscure the signal in the data I was looking to detect.

Second, a static occupancy model constructed from data at one time point may not be appropriate to apply at other time points because of dynamic metapopulation

processes affecting occupancy (Clinchy et al. 2001). For example, Twedt et al. (2006) found the percent grass, the amount of clumping of agricultural habitat, total edge, and grass edge were important variables for predicting bobwhite abundance in 1980. However, in 1992 percent grass and forest edge were the most important variables for predicting bobwhite abundance. Peterson et al. (2002) also found the strength of the relationship of bobwhite abundance from BBS surveys to land cover variables changed through time. These results may be evidence that the relationship of landscape characteristics with occupancy may change through time or could have risen from methodological problems (e.g. imperfect detection of bobwhite). Regardless they illustrate how applying a static landscape scale occupancy model to data from other years may create error.

Third, confounding the possibility of inaccurately predicting change in occupancy, the estimates of route occupancy for the BBS routes may be biased. Repeat visits to a site are necessary to reduce detection error. Additionally, the population should be closed to emigration or immigration between repeat visits (MacKenzie et al 2006). This is not possible using BBS data because points are only surveyed once a year. I attempted to use repeat visits for the BBS data by assuming the site occupancy status would not change in a year. This assumption may have been violated because births and deaths would have occurred between surveys, especially for bobwhite which have high reproductive output and annual mortality (Sandercock et al. 2007). Colonization or extinction events between visits would bias the probability of detection low, reducing the precision of the observed occupancy of the route. The survey length also likely reduces the probability of occupancy. Duren (2010) found the probability of detection was 0.52 for 3 min surveys. Additionally, for analysis of the BBS data, I did not meet the 3-4 repeat visits to sites per season recommended by MacKenzie and Royle

(2005). These factors would further reduce the precision of the estimated occupancy of a route. While using three years of BBS data as repeat visits would have been preferable, it would have increased the probability of violating the closed population assumption and reduced the number of routes that could be analyzed. Finding a relationship between change in occupancy and change in two of the individual variables is evidence of a flawed methodology. The results are not consistent, with landscape change showing a relationship with occupancy change only in two variables. A good methodology should reveal more consistent results.

There are also biological explanations of the poor association between predicted and observed occupancy change assuming methodological problems were minor. My predictive occupancy was based on macro-scale habitat configuration, therefore change in the predicted occupancy is a surrogate measure of landscape change from 1992-2005. Additionally, I measured changes in variables considered important for predicting bobwhite occupancy (Duren 2010). Landscape change, according to the model and the individual variables, was small relative to the change in bobwhite occupancy for the same time period. In addition, changes in the predicted occupancy and the variables tested were not closely related to change in occupancy of bobwhite. Betts et al. (2002) found that macro-scale variables were able to predict habitat as well as micro scale variables. However, they suggest this would not happen in fragmented landscapes where a disconnect between measures of habitat quantity and configuration and habitat quality can exist. Therefore, changes in macro-scale habitat variables that I measured may not reflect changes in micro-scale habitat variables that may be driving population declines.

Additionally, the relationship of bobwhite occupancy to landscape variables may be flexible. This is supported by the idea of “slack” in bobwhite habitat which

occurs when the interactive effects of multiple habitat configurations still provide optimum bobwhite habitat (Guthery 1999). Therefore, some change in patch configuration can occur while not reducing the overall quality of the landscape for bobwhite.

My results that large-scale habitat changes were not related to bobwhite declines do not necessarily contradict the ideas of Brennan (1991) and Williams et al. (2004) or the useable space hypothesis of Guthery (1999). Changes to the micro scale characteristics of the land cover would not have been quantified using the model because of the coarse resolution of land cover data. Changes in these characteristics of a land cover will directly affect availability and quality of habitat for bobwhite. For example, changes in farming and silviculture practices that reduce the *quality* of agricultural fields but do not affect the *quantity* of habitat available would not have been measured. These may be more critical to bobwhite declines (Brennan, 1991 and Williams et al. 2004) and grassland bird populations (Murphy 2003). Additionally, Dures and Cumming (2010) found diversity of birds across an urban gradient were closely related to micro-scale characteristics of a patch and not related to any macro-scale habitat metrics.

A second potential biological bias could have occurred because of a slight differential use of habitat use between breeding and nonbreeding seasons (Roseberry and Klimstra 1984). I used a breeding season habitat model to predict changes in occupancy of bobwhite. The Delmarva Peninsula is near the northern extent of bobwhite range making it more vulnerable to winter weather catastrophes (Brennan 1999). Therefore, changes in winter escape cover may be more of a limiting factor of useable space for bobwhite, but was not measured in this study.

Third, predation and hunting were the greatest sources of mortality in Missouri (Burger et al. 1995) and Oklahoma (DeMaso et al. 1998). Brennan (1991) suggested bobwhite evolved with a variety of predators and if habitat needs are met then bobwhite populations should be able to withstand predator and hunting pressure. However, Rollins and Carrol (2001) suggest a modern landscape may change the impact of predators on bobwhite populations. These changes may be a result of increased predator populations and changes in predator community composition and predator search efficiency. Similarly, search efficiency of hunters may also increase in modern landscapes. Williams et al. (2000) found harvest mortality was higher for coveys that selected more woody cover in a rangeland study area. This area had fewer patches of woody cover than an agricultural study area where harvest mortality was not influenced by cover type selection. They suggest that hunters were able to target areas where bobwhite would be easier when there is less escape cover. This can lead to overharvest and sharp declines in populations, especially if natural mortality factors are also higher.

Fourth, although the effects of predation and harvest are well documented and known for bobwhite, the effects of agriculture chemicals on bobwhite survival are less known. Organophosphates are commonly used agriculture chemicals that are highly toxic and have negative short term effects on bobwhite (Brennan 1991). Additionally, White (1990) suggests organophosphates may be a possible source of mortality. Indirect effects of chemicals on bobwhite are even less understood than direct effects. Pesticides and herbicides are used to reduce insects and weedy plants that would inhibit crop growth. Weedy plant seeds are an important source of energy for bobwhite in winter (Robel et al. 1979) and insects are an important source of protein for bobwhite (Palmer et al 2001). Additionally, Lochmiller et al. (1993) found reduced growth rates in bobwhite chicks when their diet consisted of <15% protein. Factors affecting bobwhite

chick survival are unknown but wild turkey (*Meleagris gallapovo*) chick survival increased when they were able to fly and avoid predators (Spears et al. 2005). Therefore, slower growth rates from a low quality diet could decrease survival.

Management Implications

Based on my approach, I was unable to detect a relationship between short-term landscape changes and bobwhite occupancy. Therefore I encourage future researchers and managers to use caution when considering the use of a single predictive habitat occupancy model to predict temporal relationships. Improving the accuracy and precision of predictive models and accounting for changes in associations between bobwhite occupancy and landscape features through time could improve this methodology. Specifically, I encourage use of within-season replicated population surveys instead of relying on BBS and use of finer scale land-use cover maps (as is sometimes available at state levels). However, if my results reflect truth about quail biology, researchers and managers should focus on other factors influencing population declines such as predators, over-harvesting, agricultural chemicals, or additive effects of these with habitat loss, rather than focus solely on habitat change.

Table 1. Total hectares (%) of habitat types in the Delmarva Peninsula, USA during 1992, 1996, 2001, and 2005.

	Year				% change 1992– 2005
	1992	1996	2001	2005	
Low Density Development	71,114 (4.8)	73,705 (5.0)	75,669 (5.1)	76,154 (5.1)	7.1
High Density Development	24,169 (1.6)	24,893 (1.7)	25,791 (1.7)	26,938 (1.8)	11.5
Forest	477,261 (32.2)	475,827 (32.1)	473,991 (32)	473,240 (32.0)	-0.8
Wetland	162,952 (11.0)	161,504 (10.9)	160,668 (10.8)	160,123 (10.8)	-1.7
Shrubland	68,367 (4.6)	71,210 (4.8)	72,374 (4.9)	72,587 (4.9)	6.2
Agriculture	667,586 (45.0)	665,891 (44.9)	668,108 (45.1)	662,930 (44.8)	-0.7
Grassland	10,544 (0.7)	9,026 (0.6)	5,106 (0.3)	7,770 (0.5)	-26.3

Figure 3.1. Location and name of all Breeding Bird Survey routes in the Delmarva Peninsula, USA.

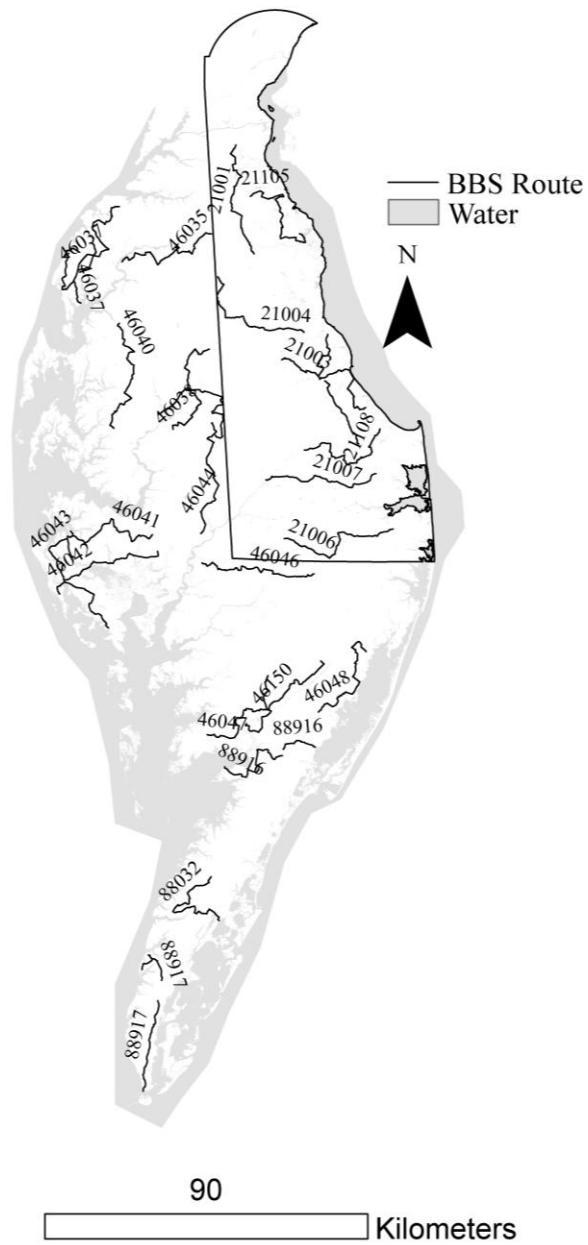


Figure 3.2. Percent of BBS stops observed and predicted to be occupied (\pm SE), in the Delmarva Peninsula, USA, 1992-2005.

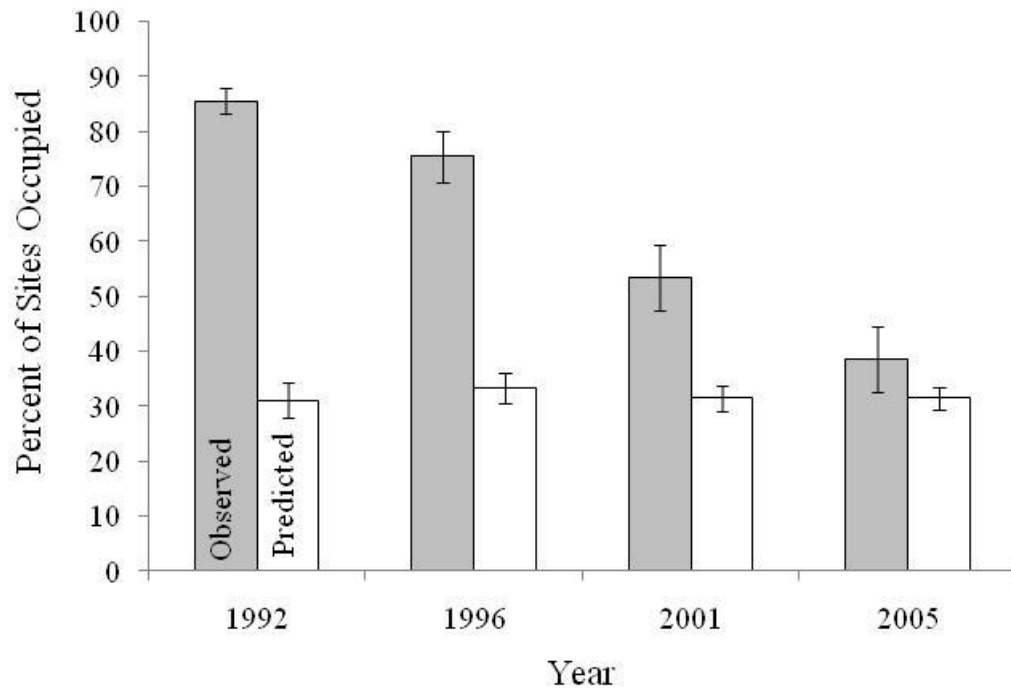


Figure 3.3. Percent change of each variable in the model and change in observed occupancy of northern bobwhite in BBS routes in the Delmarva Peninsula, USA, 1992-2005. Data pooled across intervals 1992-1996, 1996-2001 and 2001-2005.

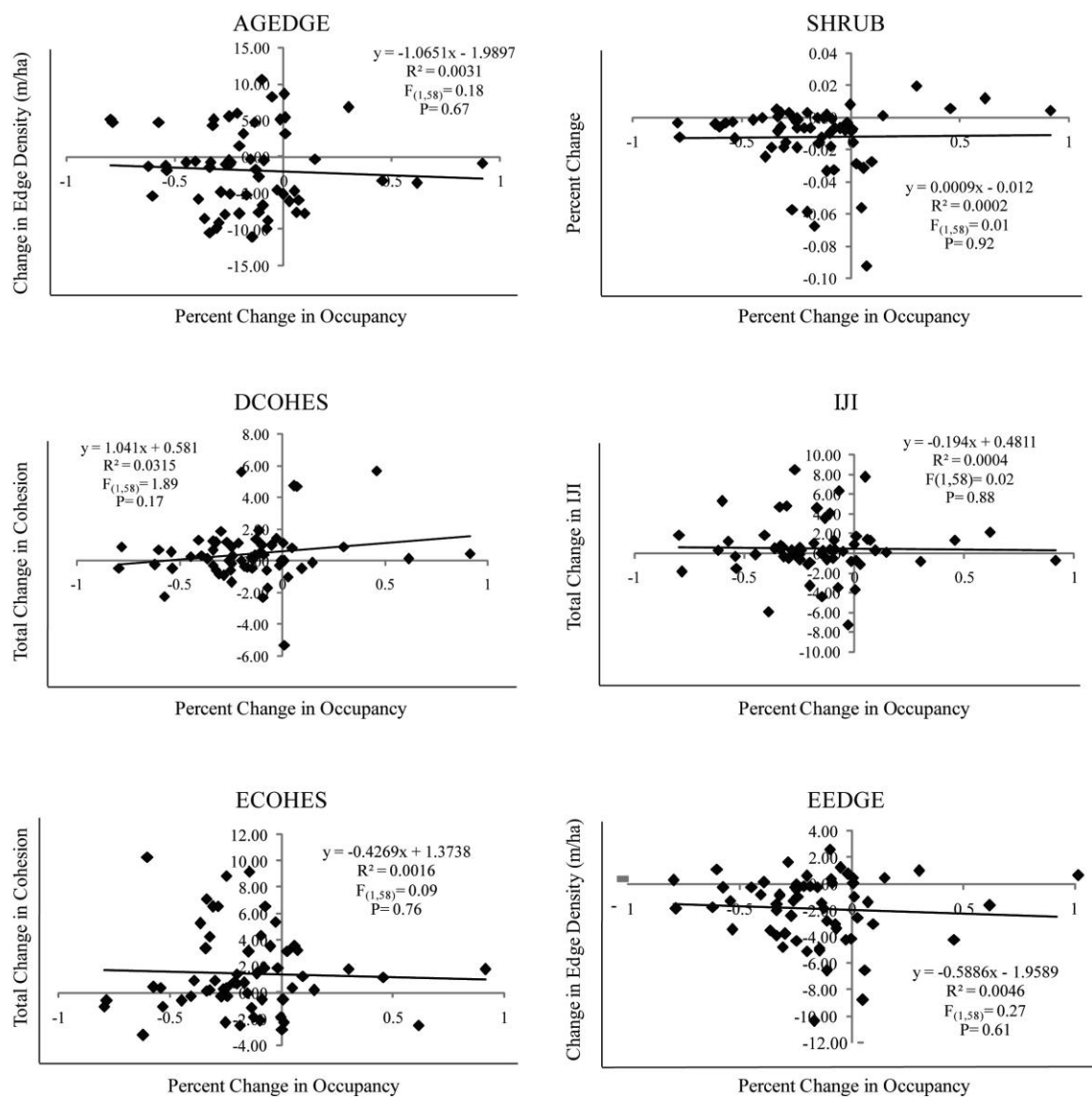


Figure 3.4. Percent change of each variable in the model and change in observed occupancy of northern bobwhite in BBS routes in the Delmarva Peninsula, USA, 1992-2005. Data pooled from 1992, 1996, 2001, and 2005.

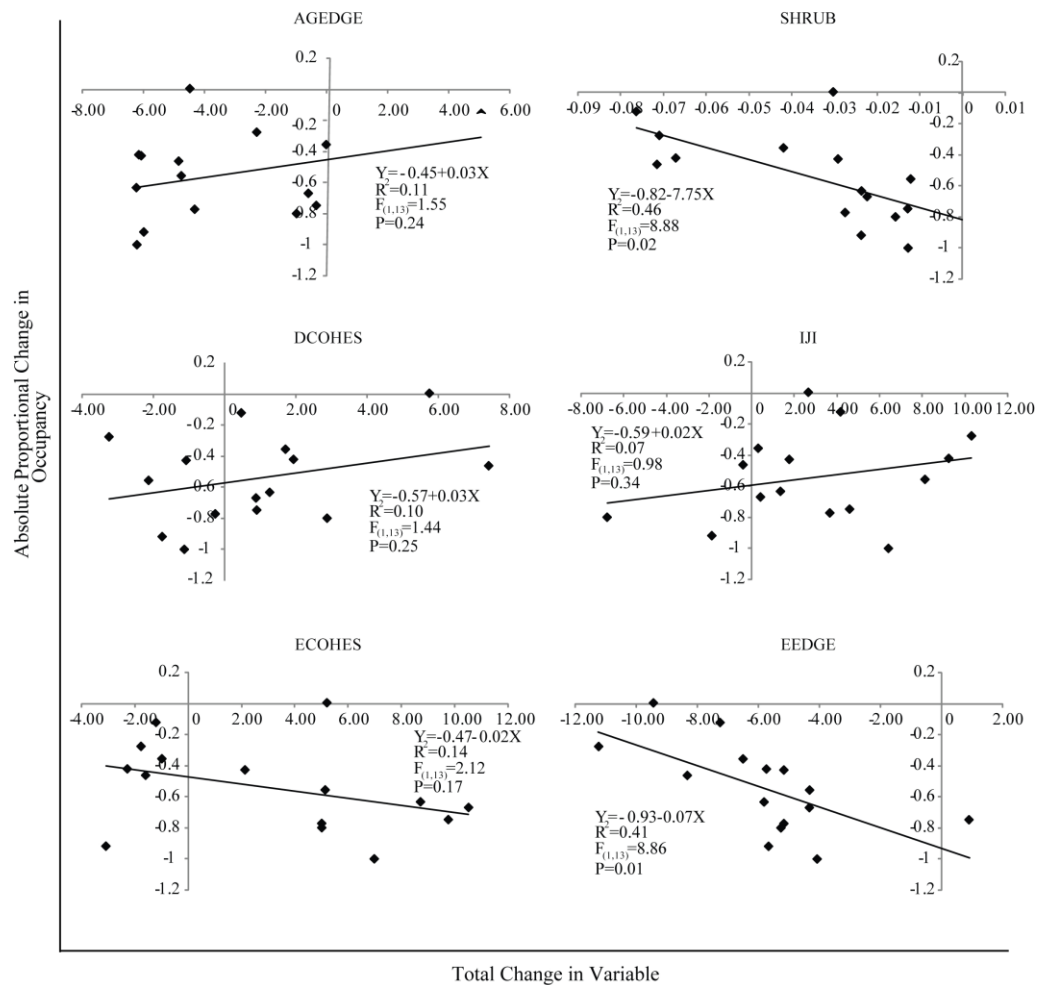


Figure 3.5. Boxplot of percent change of each variable in the model and predicted change in occupancy of northern bobwhite in BBS routes in the Delmarva Peninsula, USA, Data pooled across intervals 1992-1996, 1996-2001 and 2001-2005.

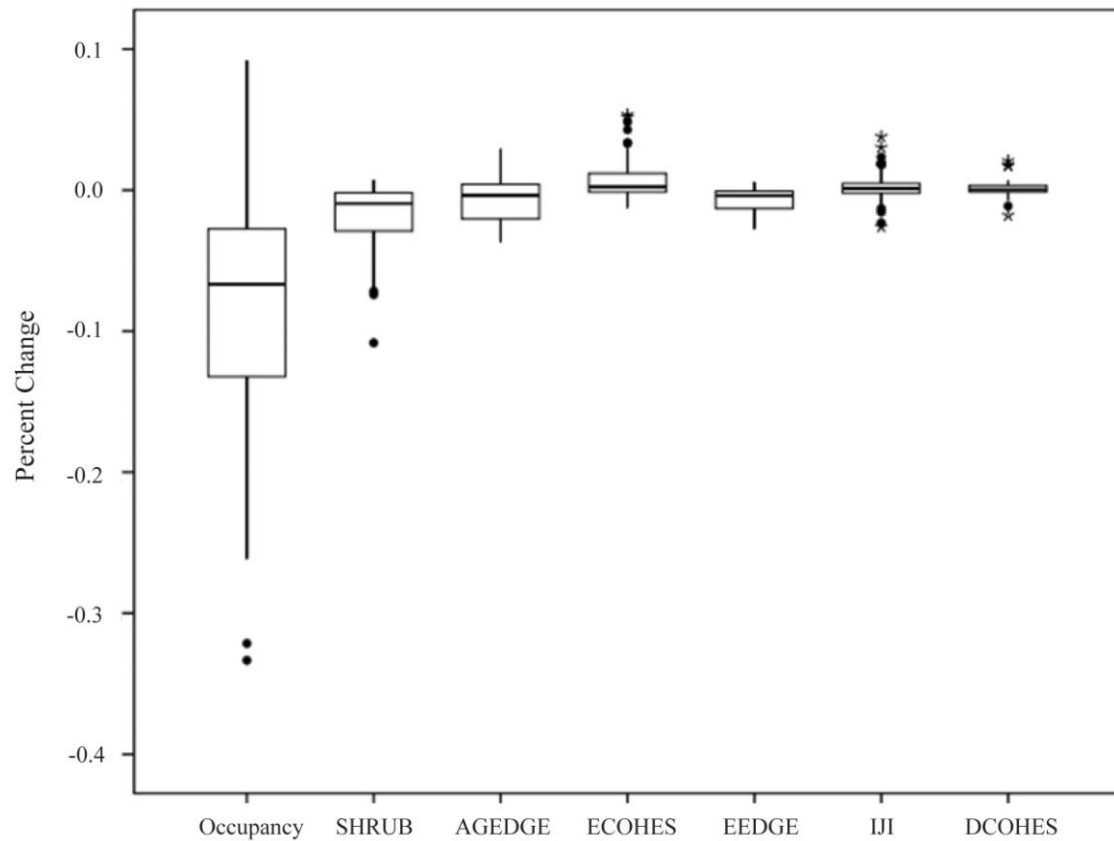


Figure 3.6. Predicted and observed percent of occupied sites of northern bobwhite in BBS routes in the Delmarva Peninsula, USA. Data pooled from 1992, 1996, 2001, and 2005.

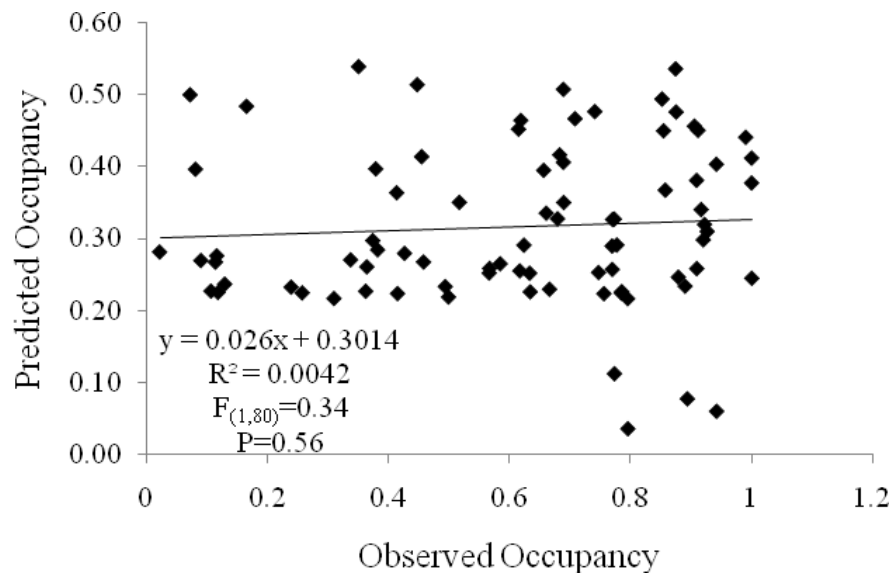


Figure 3.7. Predicted and observed percent change in occupancy of northern bobwhite in BBS routes in the Delmarva Peninsula, USA. Data pooled across intervals 1992-1996, 1996-2001 and 2001-2005.

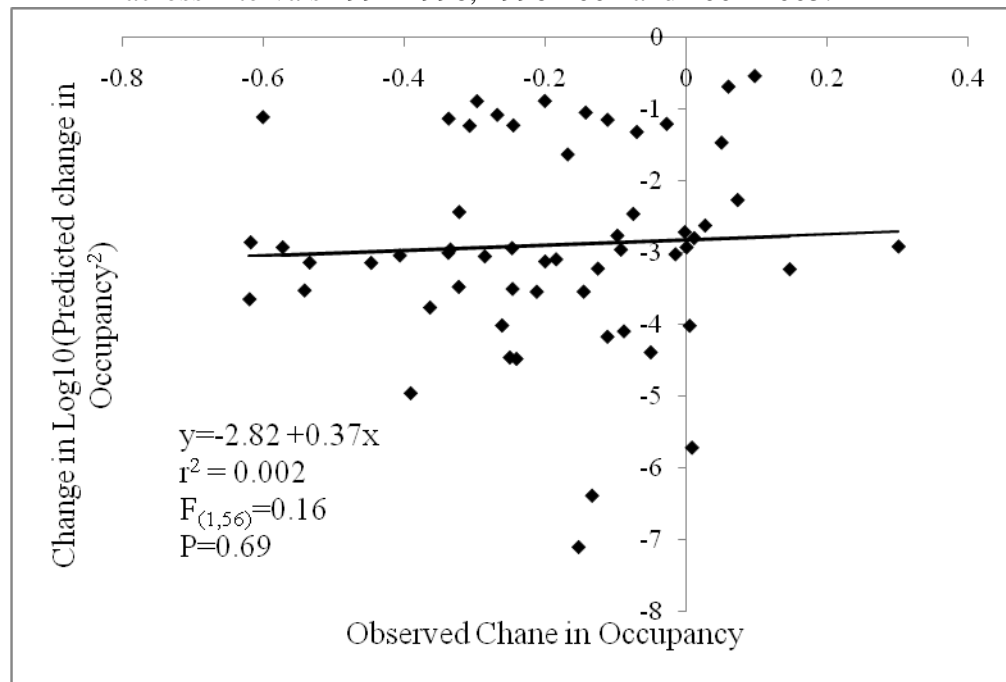
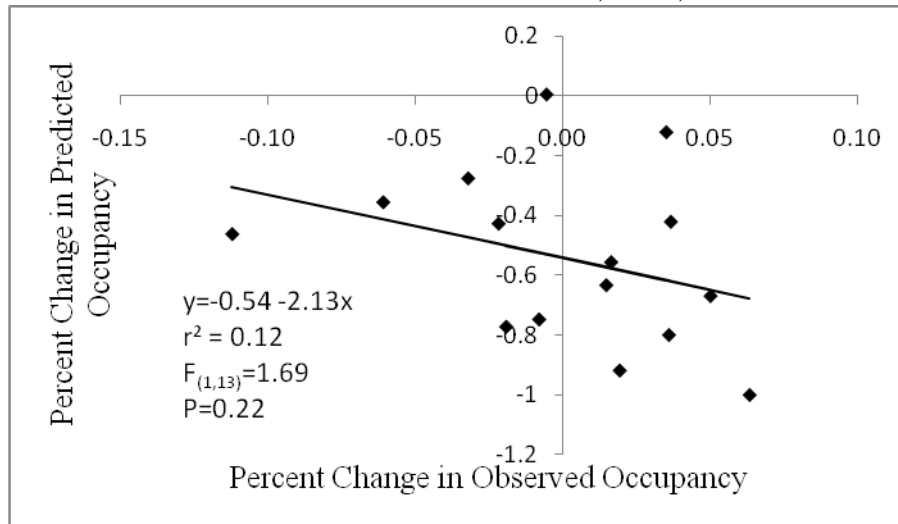


Figure 3.8. Predicted and observed percent change in occupancy of northern bobwhite in BBS routes in the Delmarva Peninsula, USA, 1992-2005.



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Appendix A

CORRELATIONS BETWEEN EXPLANATORY VARIABLES. CORRELATIONS > |0.5| ARE HIGHLIGHTED.

	<i>LDEVS</i>	<i>HDEVS</i>	<i>FORS</i>	<i>SHRUBS</i>	<i>AGS</i>	<i>GRASSS</i>	<i>WETS</i>	<i>DCOHESS</i>	<i>ECOHESS</i>	<i>IJIS</i>
LDEVS	1									
HDEVS	0.43	1								
FORS	0.08	0.03	1							
SHRUBS	0.17	0.2	0.42	1						
AGS	-0.24	-0.18	-0.64	-0.57	1					
					-					
GRASSS	0.3	0.35	0.13	0.28	0.27	1				
					-					
WETS	-0.09	-0.17	0.18	0.19	0.23	-0.01	1			
					-					
DCOHESS	0.52	0.42	-0.13	0.1	0.29	0.22	-0.04	1		
					-					
ECOHESS	0.03	0.04	0.3	0.71	0.44	0.18	-0.04	-0.04	1	
IJIS	-0.03	-0.08	-0.15	-0.02	0.01	0.07	-0.22	0.39	-0.11	1
AGEDGES	-0.18	-0.11	-0.52	-0.42	0.53	-0.21	-0.24	0.14	-0.21	0.15
					-					-
EEDGES	0.13	0.12	0.06	0.44	0.13	0.19	-0.17	0.04	0.49	0.03
					-					
LDEVL	0.39	0.38	0	0.02	0.09	0.23	-0.01	0.52	-0.04	0.04

	<i>LDEVS</i>	<i>HDEVS</i>	<i>FORS</i>	<i>SHRUBS</i>	<i>AGS</i>	<i>GRASSS</i>	<i>WETS</i>	<i>DCOHESS</i>	<i>ECOHESS</i>	<i>IJIS</i>
					-					
HDEVL	0.42	0.47	-0.01	0	0.01	0.18	-0.22	0.39	0.07	0.07
					-					-
FORL	0.06	0.19	0.21	0.09	0.02	0.08	-0.37	-0.16	0.22	0.08
					-					-
SHRUBL	0.14	0.22	0.22	0.43	0.36	0.35	-0.03	0.12	0.44	0.03
					-					-
AGL	-0.13	-0.1	-0.03	-0.05	0.29	-0.2	-0.34	-0.22	-0.06	0.07
					-					-
GRASSL	0.1	0.26	0.07	0.24	0.12	0.4	-0.11	0.14	0.3	0.07
					-					-
WETL	0.06	-0.11	0.07	0.12	0.31	0.03	0.32	-0.05	-0.12	0.14
					-					-
DCOHESL	0.25	0.26	-0.01	-0.05	0.01	0.11	0.01	0.35	-0.1	0.01
					-					-
ECOHESL	-0.05	-0.01	0.05	0.14	0.17	0.13	-0.08	-0.15	0.34	0
IJIL	0.29	0.15	-0.14	-0.01	-0.1	0.06	0.24	0.4	-0.21	0.07
AGEDGEL	-0.13	-0.09	-0.18	-0.17	0.21	-0.16	-0.07	-0.11	-0.13	0
					-					-
EEDGEL	-0.02	0.04	0	0.18	0.14	0.16	-0.18	-0.02	0.32	0.01
					-					-
DIST	-0.21	-0.22	0.09	0.07	0.04	-0.12	0.14	-0.36	-0.02	0.03

	<i>AGEDGES</i>	<i>EEDGES</i>	<i>LDEVL</i>	<i>HDEVL</i>	<i>FORL</i>	<i>SHRUBL</i>	<i>AGL</i>	<i>GRASSL</i>	<i>WETL</i>	<i>DCOHESL</i>
AGEDGES	1									
EEDGES	-0.13	1								
LDEVL	-0.03	0.00	1							
HDEVL	-0.09	0.05	0.51	1						
FORL	0.00	0.25	-0.05	0.18	1					
SHRUBL	-0.19	0.34	0.13	0.22	0.33	1				
AGL	0.09	0.05	-0.20	-0.08	0.46	-0.22	1			
GRASSL	-0.08	0.30	0.17	0.17	0.26	0.40	-0.08	1		
WETL	-0.01	-0.08	-0.10	-0.19	-0.53	-0.13	-0.33	-0.13	1	
DCOHESL	0.01	-0.04	0.88	0.39	-0.04	0.02	-0.10	0.10	-0.08	1
ECOHESL	-0.08	0.25	-0.12	0.04	0.28	0.69	-0.19	0.32	-0.11	-0.12
IJIL	-0.01	-0.18	0.66	0.28	-0.60	-0.18	-0.41	-0.08	0.41	0.60
AGEDGEL	0.06	-0.20	-0.15	-0.11	-0.22	-0.36	0.11	-0.24	0.06	-0.10
EEDGEL	-0.08	0.31	-0.04	0.11	0.22	0.72	-0.17	0.25	-0.09	-0.12
DIST	-0.08	-0.07	-0.49	-0.39	0.08	-0.02	0.09	-0.10	-0.09	-0.46

	<i>ECOHESL</i>	<i>IJIL</i>	<i>AGEDGEL</i>	<i>EEDGEL</i>	<i>DIST</i>
ECOHESL	1				
IJIL	-0.29	1			
AGEDGEL	-0.13	0.14	1		
EEDGEL	0.75	-0.25	-0.16	1	
DIST	-0.05	-0.45	0.01	-0.10	1

Appendix B

TOTAL BIRD SPECIES DETECTED DURING BREEDING SEASON POINT COUNT SURVEYS THROUGHOUT THE STATE OF DELAWARE IN 2008 AND 2009. SURVEYS CONDUCTED THREE TIMES EACH YEAR AMONG 360 SITES.

Common Name	Scientific Name	Number Detected
American Crow	<i>Corvus brachyrhynchos</i>	260
American Goldfinch	<i>Spinus tristis</i>	456
American Redstart ¹	<i>Setophaga ruticilla</i>	3
American Robin	<i>Turdus migratorius</i>	1251
American Tree Sparrow	<i>Spizella arborea</i>	16
Bald Eagle ¹	<i>Haliaeetus leucocephalus</i>	7
Baltimore Oriole ²	<i>Icterus galbula</i>	3
Barn Swallow	<i>Hirundo rustica</i>	404
Barred Owl ²	<i>Strix varia</i>	3
Black Vulture	<i>Coragyps atratus</i>	55
Black-and-White Warbler ²	<i>Mniotilta varia</i>	2
Black-bellied Plover ²	<i>Pluvialis squatarola</i>	20
Blue Grosbeak	<i>Passerina caerulea</i>	555
Blue Jay	<i>Cyanocitta cristata</i>	44
Blue-gray gnatcatcher	<i>Poliophtila caerulea</i>	2
Bobolink ²	<i>Dolichonyx oryzivorus</i>	11
Brown Thrasher ²	<i>Toxostoma rufum</i>	36
Brown-headed Cowbird	<i>Molothrus ater</i>	123
Canada Goose	<i>Branta canadensis</i>	255
Carolina Chickadee	<i>Poecile carolinensis</i>	42
Carolina Wren	<i>Thryothorus ludovicianus</i>	170
Cattle Egret ²	<i>Bubulcus ibis</i>	56
Cedar Waxwing	<i>Bombycilla cedrorum</i>	38
Chimney Swift ²	<i>Chaetura pelagica</i>	17
Chipping Sparrow	<i>Spizella passerina</i>	366

Common Grackle	<i>Quiscalus quiscula</i>	1498
Common Yellowthroat	<i>Geothlypis trichas</i>	307
Cooper's Hawk ¹	<i>Accipiter cooperii</i>	2
Dickcissel	<i>Spiza americana</i>	5
Downy Woodpecker	<i>Picoides pubescens</i>	5
Eastern Bluebird	<i>Sialia sialis</i>	130
Eastern Kingbird ²	<i>Tyrannus tyrannus</i>	91
Eastern Meadowlark	<i>Sturnella magna</i>	42
Eastern Phoebe	<i>Sayornis phoebe</i>	14
Eastern Towhee ²	<i>Pipilo erythrophthalmus</i>	42
Eastern Wood-pewee	<i>Contopus virens</i>	24
European Starling	<i>Sturnus vulgaris</i>	1804
Field Sparrow ²	<i>Spizella pusilla</i>	403
Fish Crow	<i>Corvus ossifragus</i>	34
Glossy Ibis ²	<i>Plegadis falcinellus</i>	11
Grasshopper Sparrow ²	<i>Ammodramus savannarum</i>	317
Gray Catbird	<i>Dumetella carolinensis</i>	118
Great Blue Heron ²	<i>Ardea herodias</i>	40
Great Crested Flycatcher	<i>Myiarchus crinitus</i>	42
Greater Yellowlegs ²	<i>Tringa melanoleuca</i>	2
Green Heron	<i>Butorides virescens</i>	11
Great Egret	<i>Ardea alba</i>	19
Hairy Woodpecker	<i>Picoides villosus</i>	3
Horned Lark	<i>Eremophila alpestris</i>	464
House Finch	<i>Carpodacus mexicanus</i>	40
House Sparrow	<i>Passer domesticus</i>	201
House wren	<i>Troglodytes aedon</i>	26
Indigo Bunting	<i>Passerina cyanea</i>	1243
Killdeer	<i>Charadrius vociferus</i>	116
Laughing Gull	<i>Larus atricilla</i>	96
Little Blue Heron ²	<i>Egretta caerulea</i>	7
Mallard	<i>Anas platyrhynchos</i>	53
Marsh Wren ²	<i>Cistothorus palustris</i>	62
Mourning Dove	<i>Zenaida macroura</i>	636
Northern Bobwhite ²	<i>Colinus virginianus</i>	701
Northern Cardinal	<i>Cardinalis cardinalis</i>	703
Northern Flicker ²	<i>Colaptes auratus</i>	13

Northern Mockingbird	<i>Mimus polyglottos</i>	548
Orchard Oriole	<i>Icterus spurius</i>	45
Osprey ¹	<i>Pandion haliaetus</i>	4
Ovenbird	<i>Seiurus aurocapillus</i>	1
Pileated Woodpecker	<i>Dryocopus pileatus</i>	5
Pine Warbler	<i>Dendroica pinus</i>	10
Prairie Warbler	<i>Dendroica discolor</i>	37
Purple Martin	<i>Progne subis</i>	812
Red-bellied Woodpecker	<i>Melanerpes carolinus</i>	34
Red-eyed Vireo	<i>Vireo olivaceus</i>	68
Red-headed Woodpecker ¹	<i>Melanerpes erythrocephalus</i>	1
Red-tailed hawk	<i>Buteo jamaicensis</i>	21
Red-winged Blackbird	<i>Agelaius phoeniceus</i>	920
Ring-billed Gull	<i>Larus delawarensis</i>	10
Ring-necked Pheasant	<i>Phasianus colchicus</i>	4
Rock Pigeon	<i>Columba livia</i>	123
Rose-breasted Grosbeak	<i>Pheucticus ludovicianus</i>	10
Ruby-throated Hummingbird	<i>Archilochus colubris</i>	19
Sanderling	<i>Calidris alba</i>	4
Scarlet Tanager ²	<i>Piranga olivacea</i>	3
Seaside Sparrow ¹	<i>Ammodramus maritimus</i>	5
Snowy Egret ²	<i>Egretta thula</i>	5
Song Sparrow	<i>Melospiza melodia</i>	302
Tree Swallow	<i>Cathartes aura</i>	360
Tufted Titmouse	<i>Baeolophus bicolor</i>	60
Turkey Vulture	<i>Tachycineta bicolor</i>	108
Vespers Sparrow	<i>Pooecetes gramineus</i>	21
White-breasted Nuthatch	<i>Sitta carolinensis</i>	2
Wild Turkey	<i>Meleagris gallopavo</i>	8
Willet ²	<i>Catoptrophorus semipalmatus</i>	4
Wood Thrush ¹	<i>Hylocichla mustelina</i>	31
Yellow Warbler	<i>Dendroica petechia</i>	74
Yellow-breasted Chat ²	<i>Icteria virens</i>	56

¹ Tier 1 species of conservation concern in Delaware.

² Tier 2 species of conservation concern in Delaware.