Spatial Analyses of Northern Bobwhite Occupancy and White-tailed Deer Hunter Distribution and Success in Ohio

Thesis

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By

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Abstract

Geospatial techniques can used to extract fine-scale spatial data and examine temporal or spatial patterns to inform wildlife conservation planning and management. The overall goal of this thesis was to apply geospatial data and analyses to investigate two systems: conservation of Northern Bobwhite (*Colinus virginianus*) and harvest management of white-tailed deer (*Odocoileus virginianus*) in Ohio. Conclusions based on these broad-scale spatial analyses can be used by managers to devise plans which will be actionable and effective for achieving regional population goals.

Northern bobwhite populations have been declining in Ohio for decades as a result of habitat loss and degradation caused by successional processes and changes in land use. Landscapes with high juxtaposition and interspersion of early successional, agricultural and forested vegetation are important to fulfill bobwhite resource requirements throughout all life stages. I applied land cover composition data to empirically derived distance to cover-type functions with the goal to predict probability of bobwhite occupancy throughout their current range in Ohio. I then compared final model accuracy to a correlational model of naïve landscape indices that similarly predicted occupancy from landscape metrics. Eighty five percent of the study area had a probability of occupancy < 0.25 during both breeding and nonbreeding seasons. This is indicative of inadequate habitat at a regional level, which has been suggested as the most appropriate level of management for this species. I assessed predictive accuracy of both models by predicting occupancy at points where Ohio Division of Wildlife (ODW) whistle count surveys were conducted and comparing predictions to presence or absence of bobwhites. Though both models were accurate to the commonly accepted threshold of 0.7, the distance to cover type model had higher area under the receiver operating curve (AUC) and kappa statistics. The

empirical distance to cover type model more accurately distinguished cases of bobwhite presence than the landscape metrics model. This finding could be used to support the value of highly detailed studies done at a fine scale for identifying patterns that can be extrapolated out to scales which are practical and useful for conservation management plans. However, since user accuracy was higher in the distance to cover type model and producer accuracy was higher in the landscape metrics model, context related to the model purpose may be needed to identify which is appropriate in a given situation.

Management of white-tailed deer is an essential task for many wildlife management agencies due to their economic, recreational and social importance. Harvest management is a key tool for capturing the benefits and mitigating some detrimental social and ecological impacts of increasingly abundant white-tailed deer populations in Ohio and other midwestern states. I used state-wide survey data of deer hunting events during 2011-2014 to evaluate factors that influenced deer hunter distribution and probability of success within potential Ohio deer management units with the goal to provide important information for harvest managers at a regional scale. While final model results were complex, the strongest relationships captured in all models showed hunters were more likely to hunt but less likely to harvest deer on public compared to private lands. I found differences in final model covariates and the impact they had on hunter use and success between DMUs, which differ based on aspects of human social, geophysical and landcover composition. For example, while all DMUs had a clear trend for hunters to select for locations with a higher percentage of forest and public land, strength of selection for these predictors and which cover types were avoided differed by DMU and, therefore, by landscape context. These results suggest that overall, incentivizing landowners to allow hunting on their property and facilitating access for hunters may be the most effective strategy to increase hunter success. Additionally, information concerning hunter behavior and outcomes in response to spatial variables can be used to devise region-specific management plans to achieve region-specific deer harvest and population goals.

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Chapter 1. Introduction

Geospatial science can be an effective tool in wildlife management decision making and environmental analysis. Low cost, varied scale, readily available datasets allow wildlife biologists to ask new questions, while geospatial tools provide a means to answer them. The field of wildlife management aims to achieve species population objectives by devising efficient management strategies, whether they address population control, maintenance, or growth objectives. Active research into social, economic, and ecological factors related to each species is essential to creating effective management plans. A broad scale understanding of habitat selection and population distribution patterns is imperative to integrate species ecology with human social influences. As human-wildlife interactions become even more frequent and pernicious, research will be indispensable if management plans are to achieve conservation goals or resolve human-wildlife conflicts. Geospatial techniques can be used to extract fine-scale spatial data and examine large-scale trends to inform practical wildlife planning and management. The overall goal of this thesis was to apply geospatial data and analyses to investigate two systems: conservation of early succession-dependent wildlife (e.g. Northern Bobwhite *Colinus virginianus*) and harvest management of White-tailed deer (*Odocoileus virginianus*) in Ohio.

Northern bobwhite populations in Ohio have been declining for decades as a result of habitat loss and degradation caused by successional process and changes in land use (Klimstra 1982, Brennan 1991, Spinola and Gates 2004, Rodewald et al. 2016). Landscapes formed by juxtaposition and interspersion of early successional, agricultural and forested edge are important to fulfill bobwhite resource requirements (Roseberry and Sudkamp 1998, Veech 2006).

Therefore, evaluating potential habitat for this species is not completely achieved by assessing quality or abundance of individual cover types. Instead, quality of potential focal management areas should also be evaluated from composition and configuration of landcover types. Being a ground-dwelling species makes bobwhite vulnerable to predation as they travel between resources. Predation has been suggested as an important suppressor of bobwhite population because land use changes which have depressed bobwhite populations may work to benefit populations of bobwhite predators (Rollins and Carroll 2001). Research concerning relationships between bobwhite use and distance to several cover types, such as lower use of cropland as distance to cover increases (Guthery and Bingham 1992) and lower use of grasslands as woody encroachment increases due to higher risk because of predator overlap (Atuo and O'Connell 2017). Proximity to necessary resources is therefore an important consideration for habitat evaluation and more broadly for evaluating population trends.

I modeled probability of Northern Bobwhite occupancy throughout their range in southern Ohio based on empirically-derived relationships between occupancy and landscape-scale habitat configuration. I modeled probability of Northern Bobwhite occupancy throughout their range in southern Ohio based on relationships between occupancy and landscape-scale habitat configuration. This probability of occupancy model approach applies distance to cover-type equations that predict probability of use at any one point as a function of interspersion with other important habitat types (Gates et al. 2017). Research on habitat requirements and cover type influences at a landscape-scale are needed to develop management plans for the species on the large-scale that is needed for range-wide population recovery. Identifying areas with requisite landscape structure can focus habitat management on those areas with greatest capacity to support bobwhite populations. Analyzing processes affecting probability of use can be applied to create additional habitat space to promote occupancy by bobwhites. With this project, I aimed to utilize land cover data and past studies that predicted bobwhite occupancy probability on small scales to predict the same values over the entirety of their current range in Ohio. I also aimed to compare final model accuracy to one of similar goals yet differing methods to investigate the potential tradeoff between high effort data collection and model correctness for when creating landscape scale models using small-scale data.

Management of White-tailed deer is an essential task for many wildlife management agencies due to their economic, recreational and social importance. Harvest management is a key tool for capturing the benefits and mitigating some detrimental social and ecological impacts of increasingly abundant white-tailed deer populations in Ohio and other midwestern states. Sustainable harvest of white-tailed deer can be an effective strategy for population control while also sustaining revenue streams and boosting public support for private and public conservation organizations. Access to acceptable hunting areas, harvest opportunity, and satisfaction with the overall hunting experience are crucial issues concerning the efficacy of harvest as a management tool. These issues become even more important as hunter participation has been decreasing for decades, which jeopardizes citizen participation support for wildlife conservation (Robinson and Ridenour 2012, Winkler and Warnke 2013). Evaluating factors that influence hunter distribution and probability of success provide important information for harvest management planning and controlling Ohio’s deer population through recreational hunting. My goal was to investigate large-scale patterns of hunter distribution and efficiency by extracting relevant fine-scale data from individual occurrences (and random points) and identifying how a location’s surrounding characteristics influence hunting opportunity. I also aimed to compare harvest efficiency patterns with deer habitat suitability to inform hunting management decisions and large-scale population control. A predictive model of hunter success can be applied by the Ohio Division of Wildlife at the level of deer management units (Karns et al. 2016) to inform efficient deer harvest monitoring and management programs. As a result, this spatial tool will contribute to strategies that better align unit level harvest objectives with hunter distribution and harvest rates to better manage deer populations and hunter satisfaction.

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Chapter 2. Spatial Analyses of Occupancy Modeling for Northern Bobwhite in Ohio

Abstract

Northern bobwhite (*Colinus virginianus*) populations have been declining in Ohio for decades as a result of habitat loss and degradation caused by successional processes and changes in land use. Landscapes with high juxtaposition and interspersion of early successional, agricultural and forested vegetation are important to fulfill bobwhite resource requirements throughout all life stages. I applied land cover composition data to empirically derived distance to cover-type functions with the goal to predict probability of bobwhite occupancy throughout their current range in Ohio. I then compared final model accuracy to a correlational model of naïve landscape indices that similarly predicted occupancy from landscape metrics. Eighty five percent of the study area had a probability of occupancy < 0.25 during both breeding and nonbreeding seasons. This is indicative of inadequate habitat at a regional level, which has been suggested as the most appropriate level of management for this species. I assessed predictive accuracy of both models by predicting occupancy at points where Ohio Division of Wildlife (ODW) whistle count surveys were conducted and comparing predictions to presence or absence of bobwhites. Though both models were accurate to the commonly accepted threshold of 0.7, the distance to cover type model had higher area under the receiver operating curve (AUC) and kappa statistics. The empirical distance to cover type model more accurately distinguished cases of bobwhite presence than the landscape metrics model. This finding could be used to support the value of highly detailed studies done at a fine scale for identifying patterns that can be extrapolated out to scales which are practical and useful for conservation management plans. However, since user accuracy was higher in the distance to cover type model and producer

accuracy was higher in the landscape metrics model, context related to the model purpose may be needed to identify which is appropriate in a given situation.

Introduction

Northern bobwhite (*Colinus virginianus*) is an important game species that have experienced population declines and range contraction in Ohio since before the 1980s (Spinola and Gates 2008). The main driver of bobwhite decline is thought to be habitat loss and degradation due to widespread land use changes (Klimstra 1982, Brennan 1991, Veech 2006). Despite decades of research and management programs, bobwhite populations continue to decline with no sign of abatement over much of the species' range. Shifts in farming practices toward intensive, large-scale cropping practices reduces landscape heterogeneity that bobwhite need to thrive, specifically by eliminating field and weedy areas that formerly provided important nesting, roosting, and foraging habitat (Klimstra 1982, Brennan 1991). Increasing populations are associated with a heterogeneous landscape of agriculture, grassland, and early successional woody vegetation, while declining populations are found in landscapes with higher proportions of forest and urban areas (Veech 2006).

As a nonmigratory bird species, adequate resources must be accessible year-round and throughout all life stages, making it even more important to increase habitat suitability in their range. Though mobility can be high between breeding and nonbreeding seasons, resources should be within close proximity to each other as bobwhite have limited capacity to move and find protective cover from predators. Being a ground-dwelling species makes bobwhite vulnerable to predation as they travel between resources. Predation has been suggested as an important suppressor of bobwhite population because land use changes which have depressed bobwhite populations may work to benefit populations of bobwhite predators (Rollins and Carroll 2001). Research has demonstrated relationships between bobwhite use and distance to several cover types, such as less use of cropland as distance to cover increases (Guthery and Bingham 1992) and lower use of grasslands as woody encroachment increases due to higher risk because of overlap between 2 avian predators (Atuo and O'Connell 2017). Other studies linked higher bobwhite survival to more shrub cover and higher distance from trees (Mosloff et al. 2021, Sinnott 2021). Proximity to necessary resources is therefore an important consideration for habitat evaluation and more broadly for evaluating population trends and threat of extirpation.

Resource selection studies are important for defining habitat requirements, which is necessary to create effective management plans. Studies of this nature assume that individuals choose available resources to maximize individual fitness via habitat selection. Bobwhite have been shown to select areas with a variety of cover types, with selection varying spatially and seasonally (Guthery et al. 2005, Hiller et al. 2007, Gates et al. 2017). For example, nonbreeding season survival limits population growth of northern populations (Folk et al. 2007, Sandercock et al. 2008, Rosenblatt 2020) and varies with severity of winter weather (Janke and Gates 2013, Janke et al. 2017). Increases in early successional woody vegetation and row crops have been linked to lower winter mortality as they increase cover and food resources, though these cover types must be in close proximity (Janke and Gates 2013, Janke et al. 2015). Habitat requirements seem to change as the breeding season progresses. Nesting bobwhite select increased litter content along with tall grassland and woody vegetation to obstruct view from predators (Taylor et al. 1999, Townsend et al. 2001, Lusk et al. 2006, Collins et al. 2009). However, daytime brooding sites favor visual obstruction and bare ground to enhance feeding efficiency during the day (Taylor et al. 1999, Burke et al. 2008, Collins et al. 2009) while litter is selected for at night to create a more hospitable microclimate before chicks are thermally independent (Taylor et al. 1999). These variable habitat requirements must also be available on a larger scale to provide essential resources throughout each season and facilitate survival and reproductive success. Therefore, effective management should focus on creating and maintaining heterogeneous landscapes to achieve population stability and growth by mitigating intense winter mortality and/or increasing reproduction (Janke and Gates 2013, Janke et al. 2017).

A usable space model quantifies the amount of habitat within an area that contributes to fitness of a focal species (Guthery et al. 2005). This method differs from habitat models that focus on translating discrete landscape measures into landscape quality. Guthery (1997) developed the usable space model for northern bobwhites defining usable space as "habitat compatible with the physical, behavioral, and physiological adaptations of bobwhites, in a time-unlimited sense". The model postulates that bobwhite density in a specific area should be proportional to the usable space found in the same area (Guthery 1997). Following this interpretation, creating more usable space should provide bobwhites with the necessary resources to recover from population decline (e.g. Guthery et al. 2005, Hiller et al. 2007). Targeted increases in usable space could also work to improve the functional connectivity of the landscape, which is important for bobwhite as they are relatively poor dispersers if adequate resources are spaced too far apart (Berkman et al. 2013, Coppola et al. 2021). Under certain methodological and ecological assumptions, Guthery et al. (2005) used use-availability data and cover type selection ratios to estimate amounts of usable space and percent usable space per cover type. Upon finding that all cover types in the study areas contributed to usable space (even avoided types), Guthery et al. concluded that variation in vegetation structure may be an important factor impacting bobwhite cover selection and therefore, how usable space is proportioned. Guthery et al.'s (2005) application of usable space investigates the overall amount of space suitable for occupancy by bobwhite.

This chapter of the thesis builds on a different method of quantifying usable space by Gates et al. (2017). The two designs differ because Gates et al. (2017) considered spatial and temporal variation on usable space, while Guthery et al. (2005) does not investigate the influence of habitat-type distributions on usable space. Gates et al. (2017) was similar to that of Guthery and colleagues by using presence-absence data to evaluate usable space; however, they departed from Guthery et al.'s work by considering the impact of landcover type interspersion by calculating distance to nearest focal cover types from points of bobwhite occupancy. Gates et al. (2017) tracked radio-marked bobwhites to measure nearest distance to each important cover type other than the one they were found in. They used logistic regression on these data along with a set of random points to create equations which predicted probability of use at a particular location within a cover type as a function of distance to other cover types. By applying this proximity-based method to data from both breeding and nonbreeding seasons, Gates et al. (2017) were able to investigate the influence of temporal and spatial variation on usable space for bobwhite. An area must have the necessary types, amounts, and distribution of habitat in order to provide adequate resources for food, cover, and nesting for bobwhite (Schroeder 1985) and the influence of cover-type distribution on probability of occupancy was specifically targeted by this approach.

Bobwhite occupancy probability models which differ in approach from the usable space and cover type interspersion and configuration techniques described above have been explored in past research. One such model created by Rosenblatt (2020) was developed to describe single-season bobwhite occupancy probability based on relevant landscape metrics. This model differs from those developed by Gates et al. (2017) in several ways: 1) the data came from point count surveys, whereas Gates et al. (2017) models were based on empirical data from radio telemetry which detailed bobwhite movement behavior in response to landcover interspersion; 2) the model variables included various landscape metrics targeting correlational relationships between bobwhite presence with landscape composition and configuration, while Gates et al. exclusively considered bobwhite habitat use in response to distance to focal cover types; 3) the study area was originally conducted with coarser data over at a broad scale similar to my own, while Gates et al. data collection and modeling were done on small study areas with fine-scale data.

Functions found to be most descriptive of bobwhite use relative to distance between focal cover types were applied over individual study sites to map bobwhite occupancy probability in the previous site-level studies (Wiley 2011, Gates et al. 2017). I applied site-level distance to cover type functions across the landscape of southern Ohio to map bobwhite distribution over this range and compare results to whistle count surveys done within the landscape to assess predictive accuracy. I applied the same model parameters identified by Rosenblatt (2020) to my study area. I contrasted model performances by comparing predictive ability between the two models. The aim of this comparison was to draw conclusions concerning how different approaches in independent variables and training data impacts model accuracy when examining species distribution.

I had two main objectives for conducting this project: 1) apply Gates et al. (2017) models to bobwhite core habitat at a large scale and evaluate for model accuracy after extrapolation; 2) compare this model’s predictive ability with that of Rosenblatt (2020) to determine which approach has better potential to describe bobwhite habitat. I expected the model results to show small, isolated patches with a particular configuration of cover types that are potentially habitable by bobwhites based on empirical knowledge of spatial patterns of habitat use from intensive studies of home ranges and daily movements of radio-marked bobwhites. I also hypothesized that my model's results would demonstrate higher accuracy in outlining bobwhite distribution than Rosenblatt (2020) obtained because of the differences in data collection methodology from which each model was created. Gates et al. (2017) models were created from empirical data which directly measures how bobwhite move and occupy the landscape in response to distance to focal cover types. Rosenblatt (2020) model differs from this by using metrics describing landscape structural characteristics which bobwhite respond to using point counts, rather than measuring the response itself. Based on these differences in methodology, I was able to investigate potential tradeoffs between data collection effort and model accuracy for a landscape-scale model.

Methods

Study Area

Though once common throughout Ohio, bobwhite core range has contracted to the southwestern and south-central areas of the state (Spinola and Gates 2008). This project was conducted on Ohio's core areas for bobwhite presence (Figure 1.1) and aligns with Ohio Department of Natural resources (ODNR) whistle count data routes (Appendix A). The western part of the study area was categorized as the Till Plain region of Ohio, which is generally categorized by flat land and land use is dominated by crops. There were also large urban areas, as the city of Cincinnati is in southwest Ohio. The south and southeastern areas tend to be hillier and include a greater amount of forested land (Lafferty 1979). The current range for northern bobwhite in Ohio aligns with the glacial boundary, which distinguishes the topography between the flatter and hillier areas of the state, and with the land use transition from the heavily cropped western site to the heavily forested eastern side of Ohio.

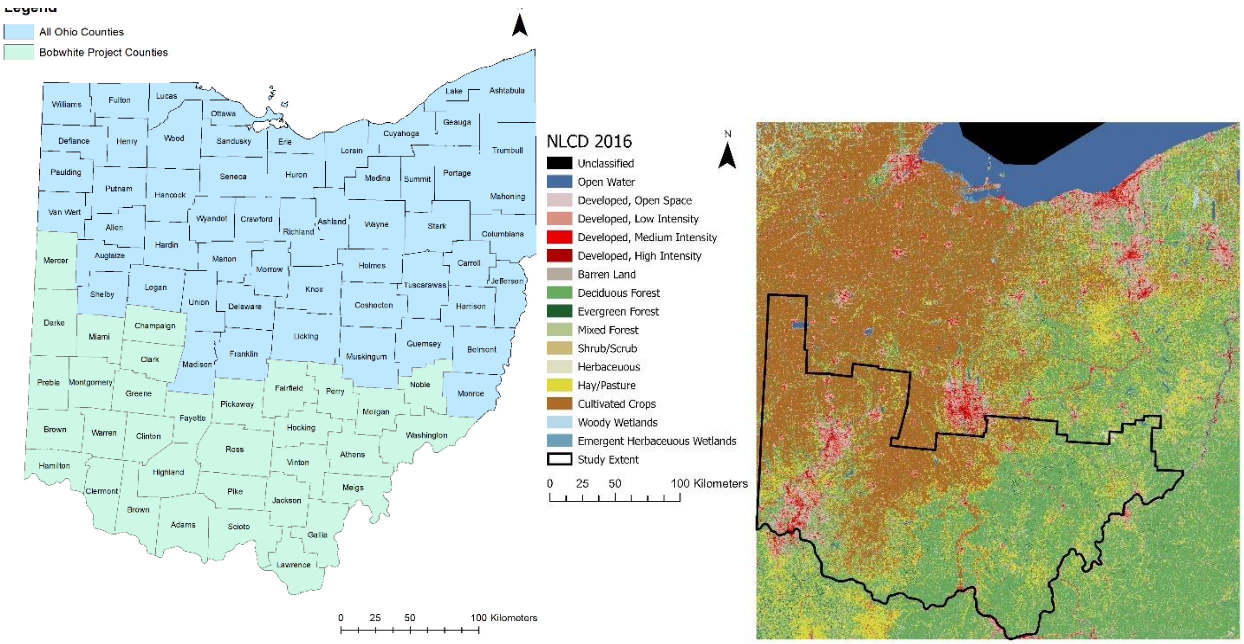

Figure 1.1. Study area based on ODNR whistle count surveys conducted in southern Ohio in 2014-2018 outlined over relevant counties (left) and overlaid on NLCD 2016 (right).

Data Sources and Methods

I acquired landcover data from the National Landcover Database (NLCD 2016) at 30-meter spatial resolution. I masked the data to the study area and reclassified NLCD landcover types into 5 new categories to better match those used in Gates et al. (2017) (Table 1.1). I used tree canopy height and percent tree cover rasters from the Global Land Analysis and Discovery (GLAD) lab (Hansen et al. 2013) to improve differentiation between forest and ES woody (Wickham et al. 2017, Wickham et al. 2021), which is especially important for bobwhite (e.g. Townsend et al. 2001, Janke and Gates 2013, Gates et al. 2017). The Calculate Raster function was used to convert forest cells with a canopy height <6 m and percent canopy cover <30% into ES woody cells to improve classification of ES woody cover. Equations predicting occupancy probability using cover-type distances as independent variables were applied from Gates et al. findings (2017) (Appendix B and Appendix C).

Original Class	Reclassified Class
Deciduous Forest	Forest
Evergreen Forest	Forest
Mixed Forest	Forest
Shrub	Early Successional Woody
Herbaceous	Early Successional Herbaceous
Pasture	Pasture
Cultivated Crops	Crops
All Other Classes	No Data

Table 1.1. Description of NLCD reclassification.

I used the Extract by Attributes tool in ArcMap to extract each cover type from the NLCD data to create a new spatial layer for each cover type. By inputting these layers into ArcMap's Euclidean distance tool, I calculated the distance from every raster cell of the study area to the nearest of each landcover class. This tool was used once on each of the 5 cover classes. A raster file delineating a single cover type and Euclidean distance rasters for each of the four other cover types were used as inputs into ArcMap's Combine tool to create a raster with an attribute table detailing distance from cells of a single cover type to nearest cells of the other 4 cover types. I then applied cover-type functions, which were created to model bobwhite occupancy probability by applying logistic regression to data which measured distance to focal cover types from radio-marked bobwhite locations (Gates et al. 2017). For each distance raster a new field was created and filled by inputting the corresponding cover-type function into ArcMap's Calculate Field tool with distances to other cover types from a particular cell as the model inputs. A new field was then created and populated by performing an inverse logit, the result of which was predicted probability of occupancy for each cell based on Gates' et al. (2017)

cover type equations. This process was repeated on the same landcover data to calculate probability of occupancy for the breeding and nonbreeding seasons. A third raster was created to obtain a composite value over both seasons by adding seasonal model cell values together and rescaling to values between 0-1. This composite raster was used for following model comparison analyses because habitat available during both seasons was expected to be important for deciding bobwhite presence because of seasonal survival.

Model Comparisons

Both the usable space and landscape metrics models were applied to the same set of whistle count data collected by ODNR over 27 counties in southern Ohio (Appendix A) during mid-May to late-June 2014-2018. Surveys were done at 325 randomly selected road routes each with 6 stops. Observers recorded numbers of bobwhite seen or heard over 1 minute survey intervals at each stop. The data were converted from count to occupancy by aggregating over the 4 years and denoting presence when at least 1 bird was recorded at a single stop. Both models were applied to data at stop and route levels.

Whistle count surveys represent presence or absence over a certain detection radius while the distance to cover type functions predict presence at a specific point. For this reason, a secondary model construction was needed to account for occupancy probability of the detection within the point count radius, rather than the actual survey point. To accomplish this, I calculated three related metrics: Euclidean distance to a pixel of certain occupancy probability, proportion of probabilities above and below certain probability thresholds, and mean probability. Probability thresholds for the first two metrics were tested between 0.1-0.9 at intervals of 0.2. The latter two metrics were calculated over a 630-m buffer to approximate breeding season home range (Liberati 2013). After exploring other methods (e.g. logistic regression, random forest classification), we decided to apply quadratic discriminant analysis (QDA) to this model selection because it can be used to identify non-linear boundaries between classes and does not assume equal covariance among classes. As a result, QDA provided a better fit for our data and goals (Qin 2018). After testing several combinations of variables listed above, the best performing model was chosen for subsequent analyses.

I examined final model results from Rosenblatt (2020) to apply their landscape metric-based model to compare accuracy with to the distance to cover type-based model. Rosenblatt created their model using logistic regression to test landscape metrics hypothesized to predict bobwhite presence based on point count surveys conducted for the Ohio Breeding Bird Atlas (2006-2011). Rosenblatt's study area extent was similar to that of ODNR whistle count survey and my own study, though it did not extent as far north on the eastern side (Figure 1.2). The final model consisted of 5 variables: forest cohesion, percent agriculture, percent agriculture squared, percent barren land and percent herbaceous land. Rosenblatt calculated these metrics using R package 'landscapemetrics' (Hesselbath et al. 2019) on NLCD landcover data over a 630 m buffer to approximate summer home range size (Liberati 2013), methods which I followed in my study.

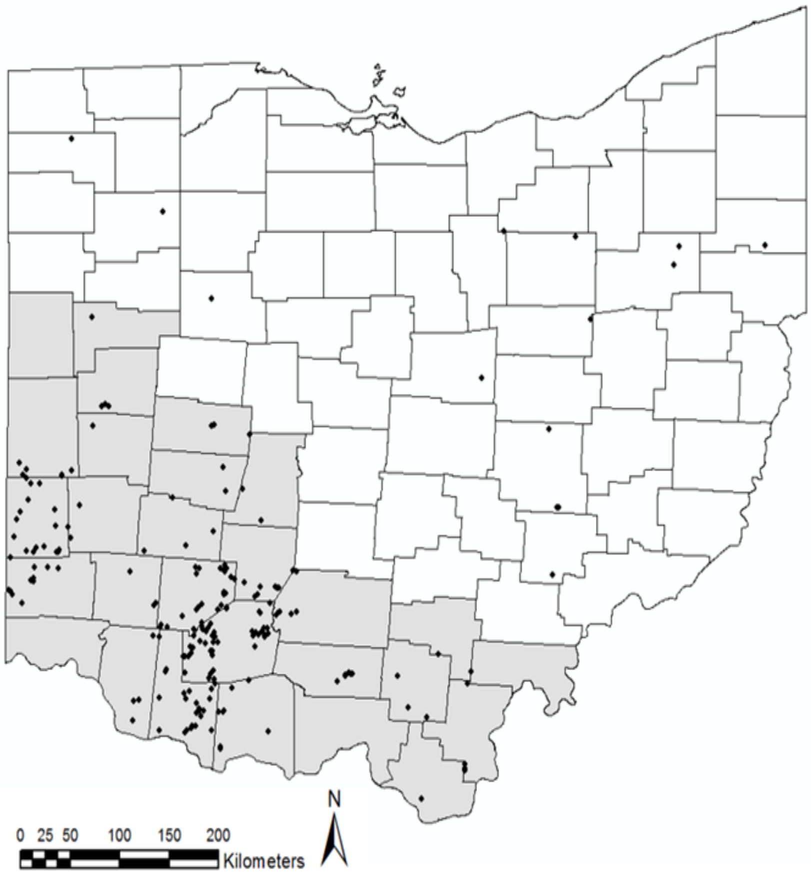

Figure 1. 2. Study area from Rosenblat (2020) where points represent bobwhite locations from Ohio Breeding Bird Atlas Survey during 2006-2011. Gray areas represent modeling study area.

I evaluated accuracy of both modeling approaches and compared the results. Quadratic discriminant analysis was applied to both models. Since the data was skewed towards absent points, I used and compared a receiver operating characteristic (ROC) curve and a precision-recall curve (PRC) to summarize model performance at different thresholds using 'pROC' (Robin et al. 2011) and 'precrec' (Saito and Rehmsmeier 2017) R packages, respectively. Though both ROC and PRC curves summarize model accuracy at different thresholds, they differ in the accuracy metrics used. ROC reports true positive rate (i.e. sensitivity) as $\frac{\text{True Positives}}{\text{True Positives + False Negatives}}$ on the y-axis and false positive rate (i.e. 1 - specificity) as

$\frac{\text{False Positives}}{\text{False Positives + True Negatives}}$ on the x-axis. PRC accounts for data that are unbalanced between positive and negative data points by reporting positive predictive value (i.e. precision) as $\frac{\text{True Positives}}{\text{True Positives + False Positives}}$ on the y axis and recall on the x-axis, where recall is equal to sensitivity . By not including true negatives in the equations, PRC accounts for datasets where absences are much more frequently observed than positives (Davis and Goadrich 2006).

I calculated several model performance metrics at the proportional probability threshold (above which indicates presence, below indicates absence) calculated by number of negatives in the data divided by total data points and at the "optimal threshold" which was calculated using the 'ROCit' package (Khan and Brandenburger 2020) in R software. The optimal threshold is defined as the one that maximizes the difference between the true positive rate and false positive rate. I calculated sensitivity, specificity, positive predictive value, negative predictive value and kappa value at the proportional and optimal thresholds to evaluate model predictive ability. Sensitivity (i.e. producer's accuracy) (Liu et al. 2007) describes the model's ability to predict an outcome of presence when bobwhites are present. Specificity describes the how often the model will predict an absence when the location is absent of bobwhite. Positive predictive value (i.e. user's accuracy) (Liu et al. 2007) is calculated by $\frac{\text{True positives}}{\text{True positives + False positives}}$ and represents the ratio of positives that were correctly predicted out of all positives predicted by the model. Similarly, the negative predictive value is calculated by $\frac{\text{True negatives}}{\text{True negatives + False negatives}}$ and represents the ratio of correctly predicted negative outcomes compared to total negative predictions by the model. Lastly I computed kappa statistic, which describes the accuracy of the model compared to what would be expected of random chance predictions.

Results

Maps displaying final probabilities of bobwhite occupancy generally demonstrated vast areas of low occupancy values (non-habitat), smaller areas of median level values and much smaller pockets of high occupancy probability (Figures 1.2, 1.3, 1.4). Areas with probability of occupancy < 0.25 comprised about 85% of the study area during both breeding and nonbreeding seasons (Tabe 1.2). Comparing the results for breeding and nonbreeding seasons, areas of median probability of occupancy were clumped into small patches in the breeding season while they were more spread in the nonbreeding season. The southeastern AOI had similarly low occupancy probability in both seasons as this highly forested portion had sparse, median level values. Values of high occupancy probability were more condensed during the breeding season (Table 1.2). The map of nonbreeding season occupancy probability shows more spread areas of higher occupancy, with relatively large areas of very high probability west of Circleville (Figure 1.3). In both cases, though, there was a clear pattern where higher occupancy occurred around the transition zone from intensive crop areas to heavily forested areas. The composite map had lower percentage of probability values at the two extremes and a higher percentage towards the lower median.

Probability Range	% Breeding	% Nonbreeding	% Composite
0 – 0.24	85.0	85.7	81.8
0.25 – 0.49	5.7	5.6	12.6
0.50 – 0.74	4.2	5.5	4.5
0.75 - 1	5.1	3.2	1.1

Table 1.2. Percent of cells within certain probability of occupancy ranges for breeding, nonbreeding and composite models results using a model based on distance between important cover types for Northern bobwhite throughout southern Ohio.

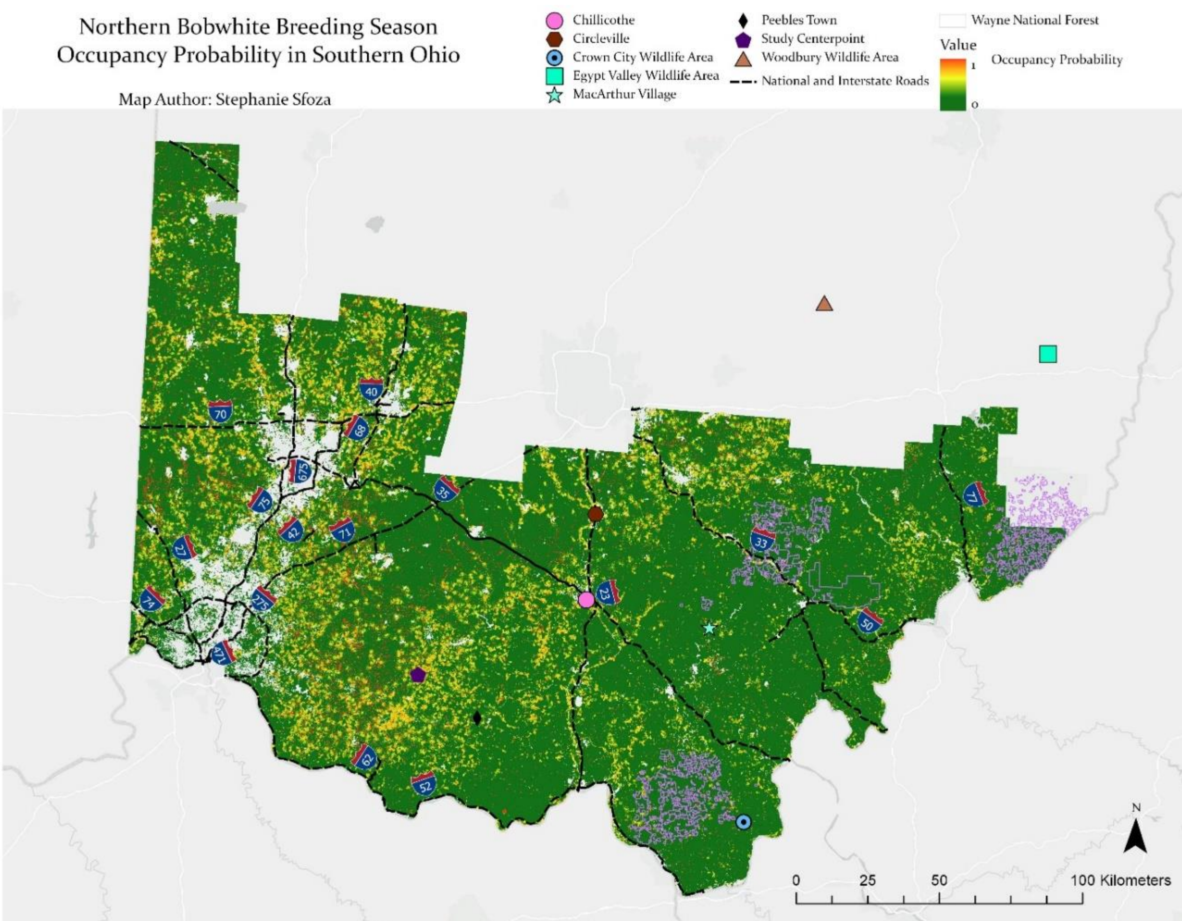

Figure 1. 3. Map displaying model values predicting occupancy probability of northern bobwhite in the breeding season over southern Ohio based on distance to cover type functions.

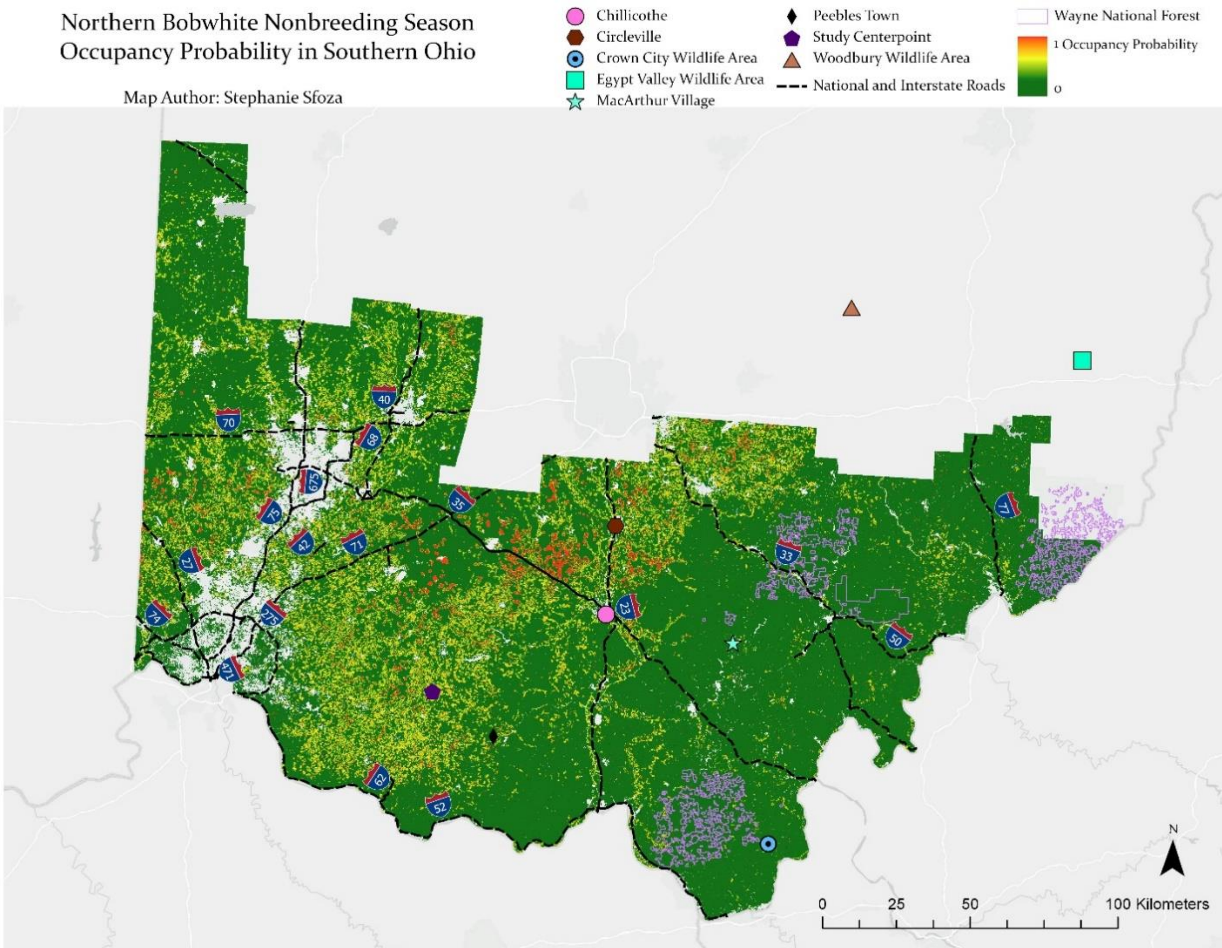

Figure 1. 4. Map displaying model values predicting occupancy probability of northern bobwhite in the nonbreeding season over southern Ohio based on distance to cover type functions.

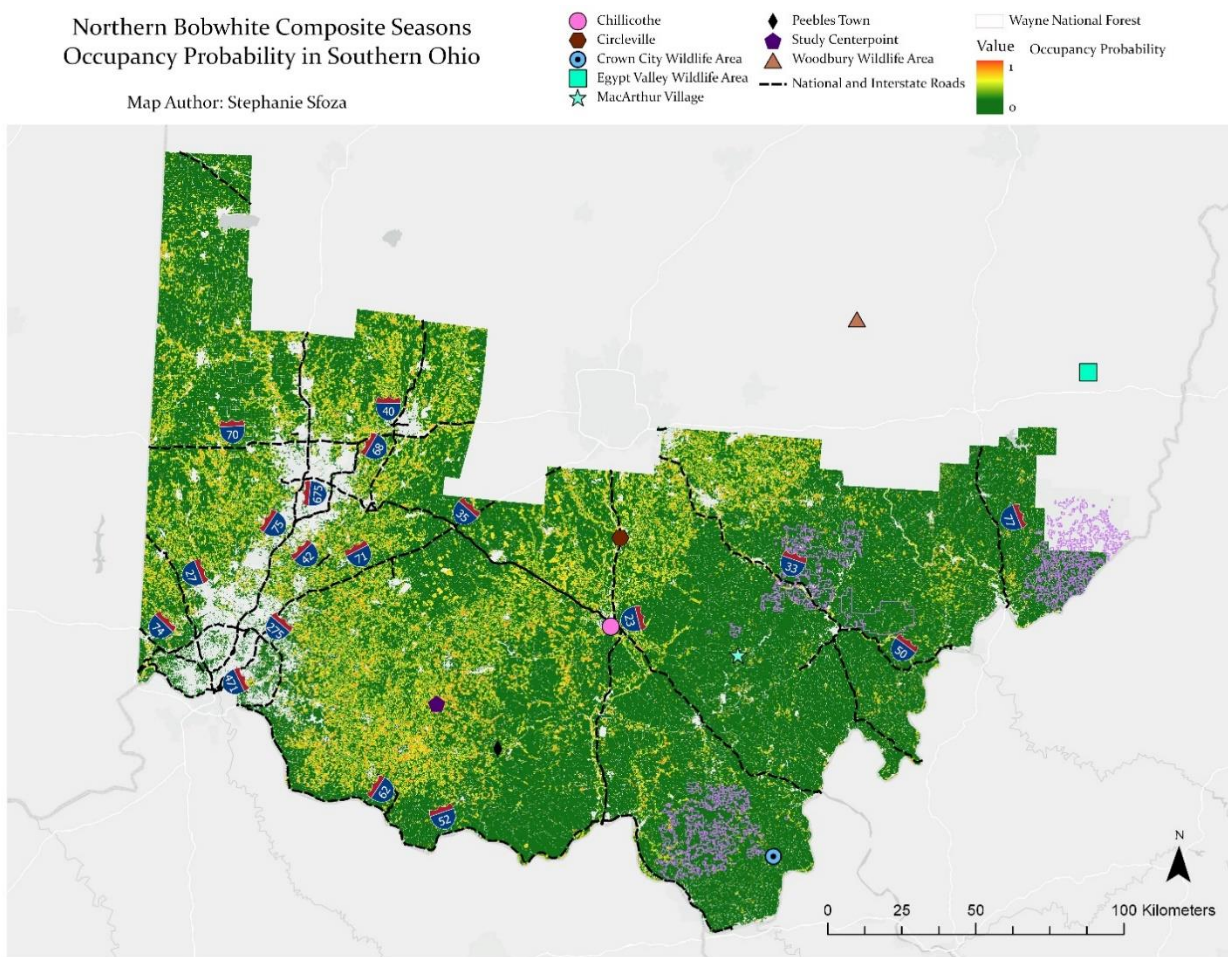

Figure 1.5. Map displaying composite model values predicting occupancy probability of northern bobwhite over southern Ohio based on distance to cover type functions.

Whistle count survey data used to calculate accuracy indices for each model totaled 1881 observations at the stop level and 315 observations at the route level. The final model designated for accuracy analysis of the distance to cover type probability model was:dist.1*Mean+dist.3*Mean+dist.5*Mean+dist.7*Mean+dist.9*Mean, where dist._ indicates the Euclidean distance to a cell of at least 0.1 to 0.9 occupancy probability and Mean indicates the mean occupancy probability within the 630 meter buffer.

Model Comparisons

At the stop level the distance to cover type model predictions were correct at about 80% of the points while the landscape metrics model predictions were correct at about 71% of points (Table 1.3). At the route level these values were about 68% for the distance to cover type model and 66% for the landscape metrics model (Table 1.4). These calculations were made using the proportional probability threshold. Using the optimal threshold, the stop level the distance to cover type model predictions were correct at about 46% of the points while the landscape metrics model predictions were correct at about 44% of points (Table 1.5). At the route level these values were about 68% for the distance to cover type model and 57% for the landscape metrics model (Table 1.6).

	Distance to Cover Type model					Landscape Metrics model			
		Predicted					Predicted		
Observed		Absent	Present		Observed		Absent	Present	
	Absent	1210	448	73%		Absent	1439	219	87%
	Present	94	129	58%		Present	164	59	26%
		93%	22%				90%	21%	

Table 1.3. Confusion matrices using ODNR bobwhite whistle count surveys between 2014-2018 at the stop level for both cover type distance and landscape metrics based bobwhite occupancy models. Conducted using proportion of class probability threshold.

	Distance to Cover Type model					Landscape Metrics model			
		Predicted					Predicted		
Observed		Absent	Present		Observed		Absent	Present	
	Absent	141	77	65%		Absent	138	80	63%
	Present	24	73	75%		Present	28	69	71%
		85%	49%				83%	46%	

Table 1.4. Confusion matrices using ODNR bobwhite whistle count surveys between 2014-2018 at the route level for both cover type distance and landscape metrics based bobwhite occupancy models. Conducted using proportion of class probability threshold.

	Distance to Cover Type model					Landscape Metrics model			
		Predicted					Predicted		
		Absent	Present				Absent	Present	
Observed	Absent	674	984	41%	Observed	Absent	621	1037	37%
	Present	29	194	87%		Present	18	205	91.93%
		95.87%	16%				97%	17%	

Table 1.5. Confusion matrices using ODNR bobwhite whistle count surveys between 2014-2018 at the stop level for both cover type distance and landscape metrics based bobwhite occupancy models. Conducted using optimal probability threshold 0.41 for cover type distance and 0.32 for landscape metrics model.

	Distance to Cover Type model					Landscape Metrics model			
		Predicted					Predicted		
		Absent	Present				Absent	Present	
Observed	Absent	143	75	66%	Observed	Absent	91	127	42%
	Present	27	70	72%		Present	10	87	89.69%
		84.12%	48%				90%	41%	

Table 1.6. Confusion matrices using ODNR bobwhite whistle count surveys between 2014-2018 at the route level for both cover type distance and landscape metrics based bobwhite occupancy models. Conducted using optimal thresholds 0.74 for cover type distance and 0.37 for the LSM (right).

At the stop level, the model calculated using distance to cover type selection functions generally outperformed the landscape metrics model in all categories except specificity which was about 0.03 higher for the landscape metrics model (Table 1.7). Sensitivity was more than 2 time higher, positive and negative predictive values were marginally higher ($\Delta = 0.01$, $\Delta = 0.03$ respectively) and the kappa value was higher by more than half the value for the landscape metrics model ($\Delta = 0.063$). Both models showed AUC values which were substantially higher than the baseline for ROC and PRC measures (Figure 1.6, Figure 1.7). Though the landscape metrics model had a higher AUC value under the ROC curve ($\Delta = 0.0056$), the model based on cover type distance resulted in a higher AUC under the PRC curve ($\Delta = 0.0264$). The optimal probability threshold was 0.7439 and 0.3201 for the cover type distance and landscape metrics based models, respectively. After applying these thresholds the comparison results were different than with weighted probability (by proportion of positives) thresholds (Table 1.7). At optimal thresholds, sensitivity was higher in the landscape model (Δ = 0.049). Positive and negative predictive values and kappa value were similar for both models, though higher in the landscape metrics model (Δ = 0.0004; Δ = 0.0131; Δ = 0.0018). The distance to cover type model had a higher specificity value (Δ = 0.0131).

	Proportional Threshold		Optimal Thresholds	
Metric	Cover Type Distance	Landscape Metrics	Cover Type Distance	Landscape Metrics
Sensitivity	0.5785	0.2646	0.8700	0.9193
Specificity	0.0721	0.1023	0.0413	0.0282
Positive Predictive Value	0.2236	0.2122	0.1647	0.1651
Negative Predictive Value	0.9279	0.8977	0.9587	0.9718
Kappa	0.1827	0.1197	0.0969	0.0987

Table 1.7. Accuracy metrics using southern Ohio northern bobwhite whistle count surveys between 2014-2018 at the stop level for both cover type distance and landscape metrics based models. Accuracy metrics were conducted using proportion of class probability threshold (left) and optimal thresholds 0.41 for cover type distance and 0.32 for landscape metrics model (right).

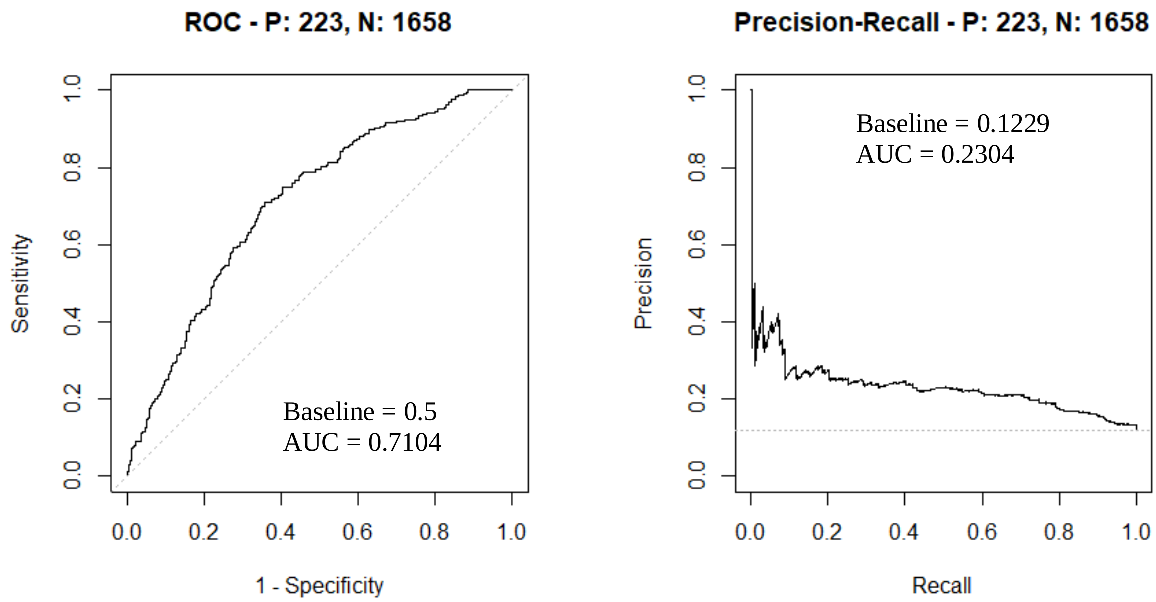

Figure 1.6. ROC and PRC curves (black lines) demonstrating model performance compared to a random classifier or baseline (dotted line) for the cover type distance-based model at stop level observations of southern Ohio northern bobwhite whistle count surveys conducted in between 2014-2018.

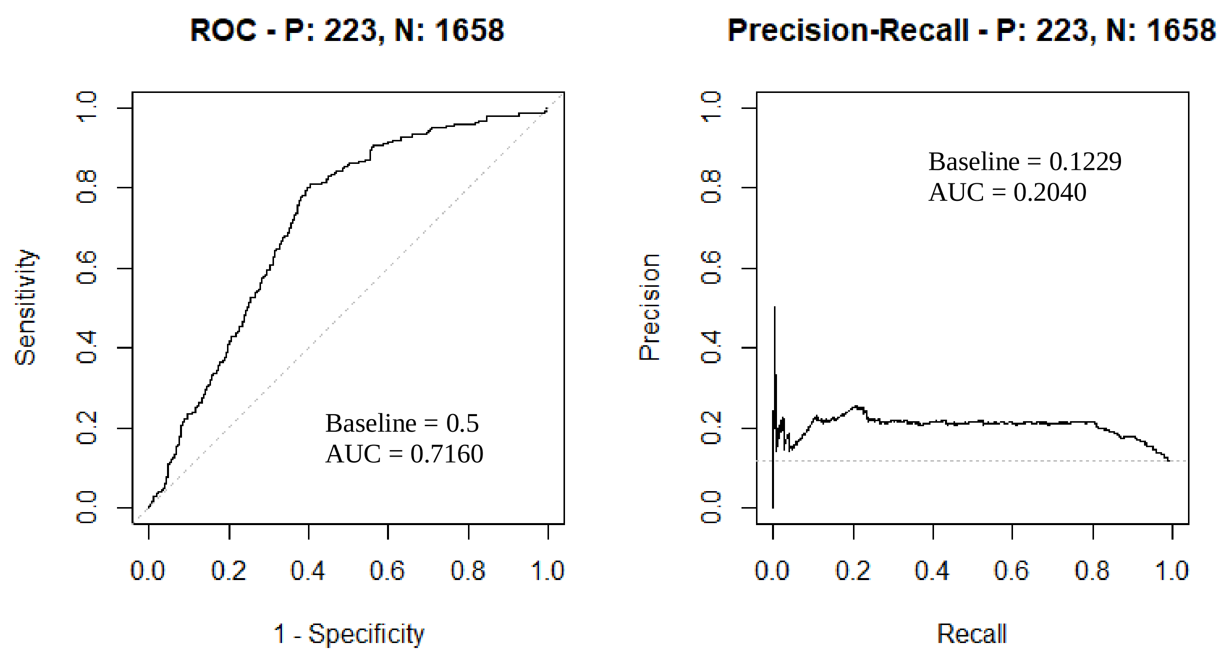

Figure 1.7. ROC and PRC curves (black lines) demonstrating model performance compared to a random classifier or baseline (dotted line) for the landscape metrics based model at stop level observations of southern Ohio northern bobwhite whistle count surveys conducted between 2014-2018.

At the route level, the cover type distance model scored higher in sensitivity (Δ = 0.0413), slightly higher positive and negative predictive values (Δ = 0.0236, Δ = 0.0232) and higher in the kappa value (Δ = 0.047) (Table 1.8). The landscape metrics model had a higher specificity (Δ = 0.0232) (Table 1.8). Once again, both models had AUC values which were substantially higher than the baseline for ROC and PRC measures (Figure 1.8, Figure 1.9). The distance to cover types model had higher AUC values for both ROC and PRC curves (Δ = 0.0722, Δ = 0.1206). The optimal threshold at the route level for the distance to cover type model was 0.4118 and 0.3701 for the landscape metrics model. After applying these thresholds, the distance to cover type had higher specificity (Δ = 0.0598), positive predictive value (Δ = 0.0763) and kappa value (Δ = 0.0965) while sensitivity (Δ = 0.1753) and negative predictive value was higher in the landscape metrics model (Δ = 0.0598) (Table 1.8).

	Proportional Threshold		Optimal Threshold	
Metric	Cover Type Distance	Landscape Metrics	Cover Type Distance	Landscape Metrics
Sensitivity	0.7526	0.7113	0.7216	0.8969
Specificity	0.1455	0.1687	0.1588	0.0990
Positive Predictive Value	0.4867	0.4631	0.4828	0.4065
Negative Predictive Value	0.8545	0.8313	0.8412	0.9010
Kappa	0.3468	0.2998	0.3320	0.2355

Table 1.8. Accuracy metrics using southern Ohio northern bobwhite whistle count surveys between 2014-2018 at the route level for both cover type distance and landscape metrics based models. Accuracy metrics were conducted using proportion of class threshold (left) and optimal thresholds 0.74 for cover type distance and 0.37 for the LSM (right).

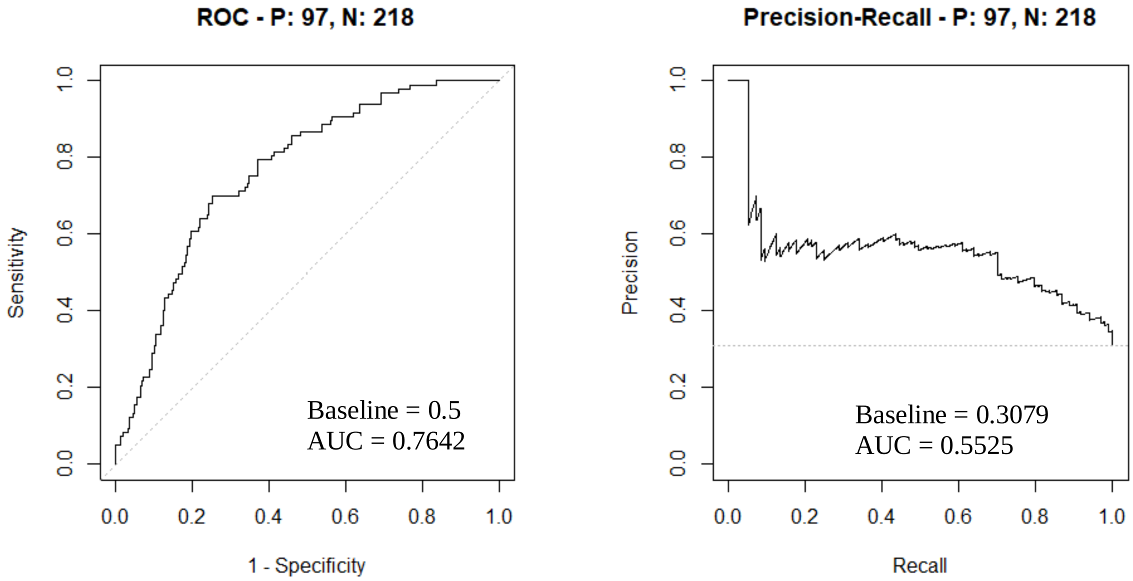

Figure 1.8. ROC and PRC curves (black lines) demonstrating model performance compared to a random classifier or baseline (dotted line) for the cover type distance-based model at route level observations of southern Ohio northern bobwhite whistle count surveys conducted in between 2014-2018.

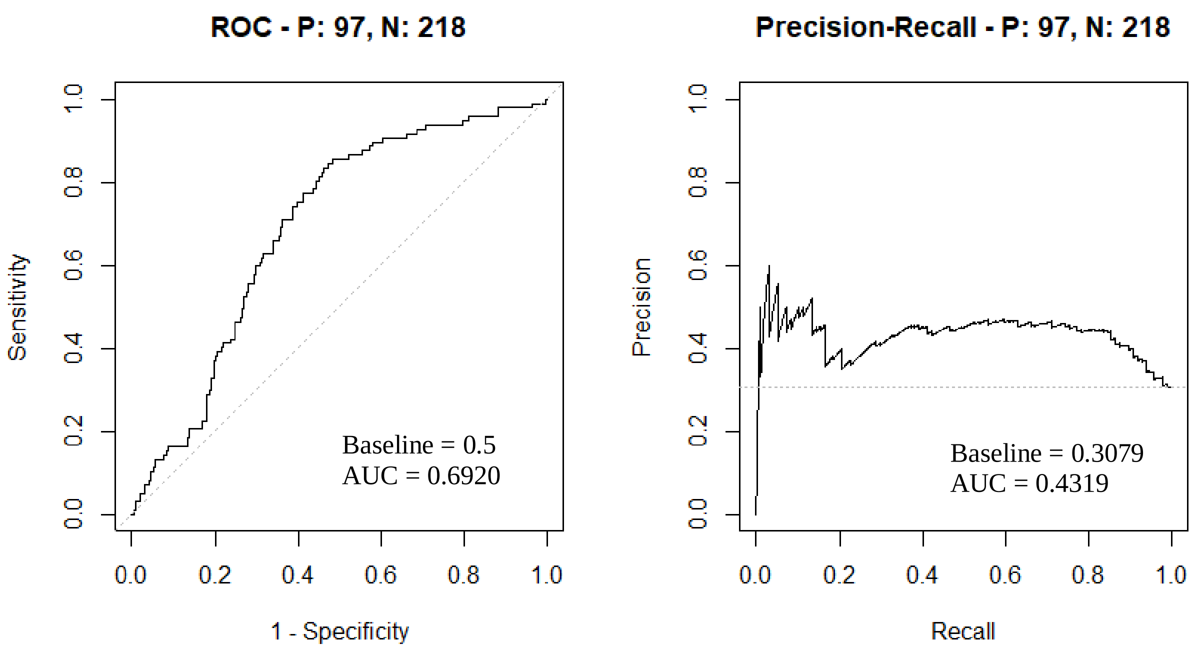

Figure 1.9. ROC and PRC curves (black lines) demonstrating model performance compared to a random classifier or baseline (dotted line) for the landscape metrics based model at route level observations of southern Ohio northern bobwhite whistle count surveys conducted in between 2014-2018.

There were mixed results in accuracy assessment values between proportional and optimal thresholds. At the stop level the distance to cover type model had higher sensitivity (Δ = 0.2915) and negative predictive value (Δ = 0.0308) at the optimal threshold, yet lower values in specificity (Δ = -0.0308), positive predictive value (Δ = -0.0589) and kappa value (Δ = -0.0858). Using the optimal threshold at the route level this model had lower sensitivity (Δ = -0.031), positive and negative predictive values (Δ = -0.0039) and kappa value (Δ = -0.0148), yet higher specificity (Δ = 0.0133). These mixed results are due to tradeoffs between error types from prior to posterior probability thresholds at both data levels. Mixed results were also found comparing results from both thresholds in the landscape metrics model. At the stop level results from the optimal threshold were higher for sensitivity (Δ = 0.6547) and negative predictive value (Δ = 0.0741), yet lower for specificity (Δ = -0.0741), positive predictive value (Δ = -0.0471) and kappa value (Δ = -0.021). These trends were the same at the route level with optimal threshold results being higher for sensitivity (Δ = 0.1856) and negative predictive value, while lower for specificity (Δ = -0.0697), positive predictive value (Δ = -0.0566) and kappa value (Δ = -0.0643).

For the distance to cover type model AUC values were higher at the route level than the stop level for ROC and PRC curves (Δ = 0.0538, Δ = 0.1371 respectively). The landscape metrics model decreased in AUC for the ROC curve (Δ = -0.024) and increased for the PRC curve (Δ = 0.0429) at the route compared to stop level. At the proportional threshold all accuracy assessment results for the distance to cover type model increased at the route level compared to the stop level, except for negative predictive value. At the optimal threshold sensitivity and negative predictive value decreased at the route level while the other metrics increased. The same trends occurred for the landscape metrics accuracy results.

The distance to cover type and landscape metrics models displayed similar patterns related to error distribution. In both cases there were areas where several false negatives were located. This is likely related to the clumped nature of areas where bobwhite were present, which is a requirement for a false negative to result from the model predictions. Interestingly, the most southern areas of central and eastern Ohio where forest cover predominates had more false negatives in both models.

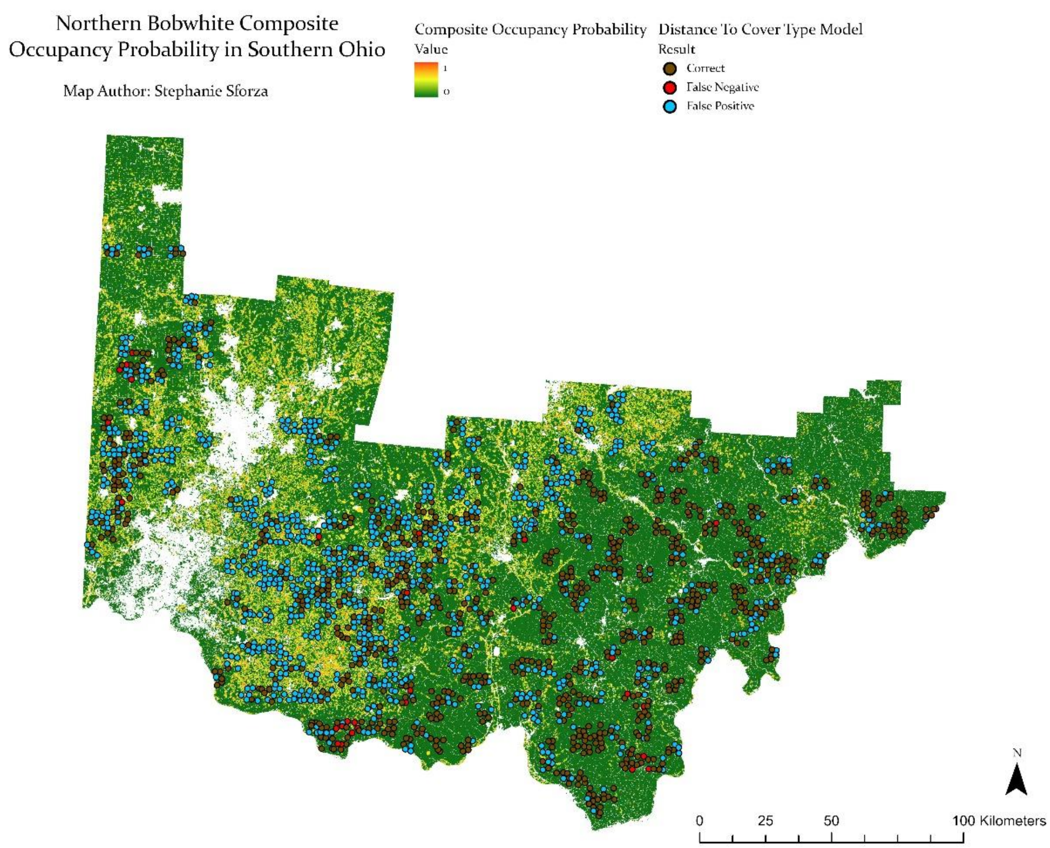

Figure 1.10. Map results of model predicting northern bobwhite occupancy based on distance to focal cover types. The model was applied to predict occurrence at stops of ODNR whistle count survey conducted in southern Ohio between 2014-2018.

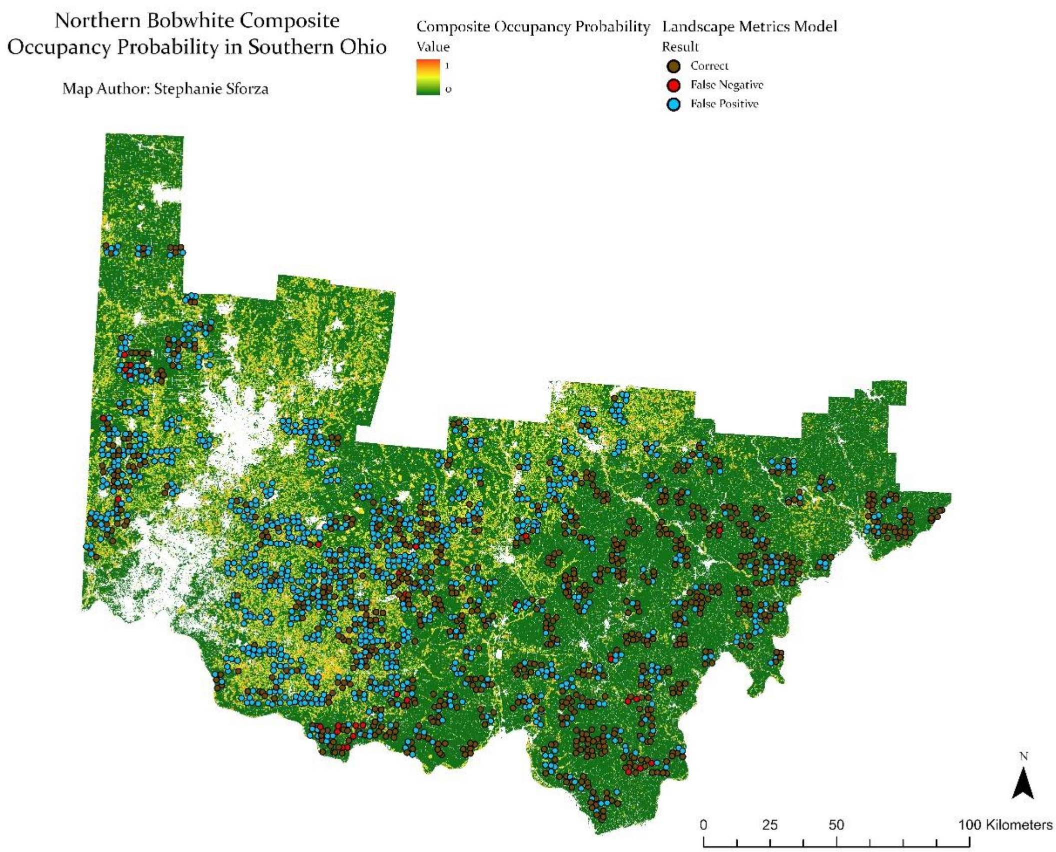

Figure 1.11. Map results of model predicting northern bobwhite occupancy based on landcover metrics. The model was applied to predict occurrence at stops of ODNR whistle count survey conducted in southern Ohio between 2014-2018.

Discussion

The current bobwhite range is characterized by large areas of a single continuous landcover type such as northwestern Ohio that is dominated by row crop. Knowing that bobwhite require an interspersion of several cover types to meet requirements throughout their life stages (Shroder 1985, Roseberry and Sudkamp 1998, Hiller et al. 2007), we expected the study to show only small pockets of areas that are potentially habitable for this species. This prediction appears to have been correct as 85% of the study area had a probability of occupancy less than 0.25 in both breeding and nonbreeding seasons. This is indicative of inadequate habitat at a regional level, which has been suggested as the most appropriate level of management for this species (Williams et al. 2004). The final maps of occupancy probability over the study area emphasize that bobwhite were more likely to be found in the transition zone between forest and agricultural dominated lands than in areas where a single cover type dominates. These maps could also be used to address the issue of fragmentation, the solution to which may be creating more connected habitat over a board scale to have a meaningful impact on conservation goals for this species (Miller et al. 2019). Targeted habitat improvement in areas where occupancy probability was high and bobwhite were absent proximate to areas where they were present could increase functional connectivity for the species. This could in turn increase bobwhite survival (Coppola et al. 2021), dispersal and geneflow (Berkman et al. 2013), and ultimately local population persistence (Sans et al. 2012, Miller et al. 2019)

The final maps visually aligned with expectations based on general knowledge of bobwhite presence in Ohio in some areas, though not as well in others (Appendix A). Known populations exist in southern Ohio near Peebles town and the areas studied in Gates et al. (2017). Likewise, there are known populations in southwestern Ohio, near the Indiana border. Both seasons show pronounced areas of mediate (yellow) and high (red) occupancy probability in these areas. On the other hand, known populations near Crown City wildlife area do not seem to be as well represented in the produced maps. The reason for this may be differences in general landcover between south and southwestern Ohio where Gates et al. (2017) study was conducted which is dominated by row crop and pasture with some wooded areas, compared to the heavily forested landscape seen in southeastern Ohio. These results may hint that cover type selection between populations in the two landscapes differs and could be an avenue for future research. On the other hand, small, declining populations in this region could be a symptom of the lack of adequate habitat in the area (Spinola and Gates 2004, ODNR 2017).

Comparisons of model accuracy in predicting bobwhite occupancy between my broad scale application of distance to cover type resource selection equations and Rosenblatt (2020) landscape metrics model yielded mixed results. Aggregating data from stop to route level generally increased AUC value, except for the ROC curve for the landscape metrics model. On the other hand, using more generalized data could result in losing important variation and introducing higher bias. Route level analysis also generally resulted in higher values for the accuracy assessment tables. Higher model accuracy of spatially aggregated data may result from both models using data inputs at the scale of bobwhite home range size, meaning covariates may be more relevant at a broader scale. Due to the increases in accuracy at the route level, the remaining discussion will focus on comparing results of route level accuracy analyses between models.

Both models produced AUC results ≥ 0.7, which is a commonly used threshold of model accuracy at which point a model is deemed fairly accurate. Though both models met this threshold, the distance to cover type model performed better than the landscape metrics model in AUC. These results indicate that the distance to cover type model may be more capable of distinguishing between cases of bobwhite presence and absence.

Though AUC values are useful as a general measure of separability, more specific measures of accuracy are needed depending on research questions and management techniques being explored through model results. It is imperative to acknowledge that all types of error are not equal when evaluating models concerning bobwhite distribution. In the case of false positives, there could be fine-scale habitat characteristics that are not captured by these models which precludes bobwhite presence, despite adequate cover type interspersion or landscape structure. Such errors of commission could be used for management planning as a step to identify areas where restoration could be used to improve fine-scale aspects of habitat quality with the goal of increasing areas which can support bobwhite occupancy. On the other hand, false negatives are less acceptable because this result indicates bobwhite presence where the model predicted absence. Errors of omission indicate that a model did not identify habitat as adequate when bobwhite were present, meaning bobwhite responded to a habitat characteristic not accounted for in the model.

Sensitivity is an important metric to consider because it includes measures of true positive and false negative predictions. Sensitivity was highest in the landscape model using the optimal threshold, meaning this model was better able to predict presence when presence was observed. This model also demonstrated the higher negative predictive value, which indicates that this model was more correct when it predicted absence than the distance to cover type model also at the optimal threshold. On the other hand, the distance to cover type model demonstrated higher specificity, meaning it was better able to predict absence when absence was observed. When comparing sensitivity and specificity, both models demonstrated much higher sensitivity values, suggesting that identifying actual cases of presence comes with the tradeoff of a high rate of false positives. The distance to cover type model also had a higher positive predictive value, which indicates that this model was more correct when it predicted presence than the landscape metrics model at the optimal threshold.

Context is needed to evaluate which metrics are most relevant to a given situation and, therefore, which model is more appropriate. For instance, if a bobwhite manager were to use the results of one model to identify areas where bobwhite were present, the distance to cover type model would be more appropriate since it yields better odds of presence when presence is predicted. However, from the perspective of a researcher deciding which modeling approach will more often predict presence when presence is the observed result, the landscape metrics model would be more appropriate. These tradeoffs between user and producer accuracy are complex and should be evaluated depending on intended model use.

I began these model comparisons with the hypothesis that my distance to cover type model would display increased ability to discern areas of bobwhite occupancy because the cover type selection equations were trained on bobwhite movement and habitat use data. Based on the two more general measures of AUC and kappa values, the distance to cover type model was better at predicting bobwhite occupancy. That said, conclusions about which model is appropriate are dependent on the context intended use.

The distance to cover type equations were originally created with empirical, fine-scale data collected on smaller study sites, which makes the extrapolation of results to the entire species range in Ohio even more interesting. Since the landscape metrics model was created based on coarser data collected over a broad scale, it is important to note that this model generally performed at a lower level than one created based on highly specific, yet fine scale empirical data. This finding could be used to support the value of highly detailed, higher effort studies done at a fine scale for identifying trends which can be extrapolated out to scales which are practical and useful for conservation management plans. On the other hand, benefits of taking an approach similar to that of Rosenblatt (2020) are that field data collection is not needed since this data is open-source and model performance was similar to the distance to cover types, even higher in the case of producer accuracy. As discussed above, the context of use is significant to decide which model is more appropriate. User vs. producer accuracies, available resources and level of accuracy needed should be accounted for.

Future studies could make necessary changes which would improve this model. First, applying distance to cover type selection equations to landcover data which differentiates over seasons. Although NCLD is useful as an easily accessible, large-scale dataset, seasonal differences in landcover and vegetation types are represented. Since the model created in this study cannot account for seasonal changes in vegetation, it may overestimate probability of use where certain cover types are present in the breeding season but diminished in the nonbreeding season, such as early successional woody cover. Additionally, we likely did not represent early successional woody cover or discriminate grassland from other herbaceous cover as Gates et al. (2017) were able to do at the site scale due to using NLCD which is coarser and less able to make certain distinguishments via remote sensing. Another improvement to the model would be including data concerning urbanization, which has been linked to declining bobwhite populations (Veech 2006, Miller et al. 2019) as this could narrow down potential management areas with the ability to support sustained or increasing populations.

Management Implications

This study evaluated potential for Northern Bobwhite occupancy on a regional scale, which could be used to inform future conservation management over their range in southern Ohio. The final maps of occupancy probability over the study area emphasize that bobwhite were more likely to be found in the transition zone between forest and agricultural dominated lands than in areas of Ohio where a single cover type dominates. Map results could be used to identify areas which would benefit from habitat restoration to meet year-round landcover needs where populations are known to be present and declining due to lack of adequate habitat. Loss of adequate habitat has been identified as a driving factor in bobwhite declines (Brennan 1991, Guthery 1997, Veech 2006). Management of the species could benefit from information related to the current state of potential for bobwhite occupancy for certain conservation techniques such as reintroduction and habitat restoration. Focusing management efforts in areas with the highest potential for benefit to the species will be important for reversing long-term population declines (Roseberry and Sudkamp 1998).

This study also demonstrates the importance of small-scale, high effort data collection for the purpose of evaluating large-scale trends in vulnerable populations. This approach of extrapolating highly specific findings related to habitat use could be applied to other early-successional dependent species which are declining throughout their range, as I did in this study.

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Chapter 3. Spatial Analyses of Regional Patterns of White-Tailed Deer Hunter Distribution and Success in Ohio

Abstract

Management of white-tailed deer (*Odocoileus virginianus*) is an essential task for many wildlife management agencies due to their economic, recreational and social importance. Harvest management is a key tool for capturing the benefits and mitigating some detrimental social and ecological impacts of increasingly abundant white-tailed deer populations in Ohio and other midwestern states. I used state-wide survey data of deer hunting events during 2011-2014 to evaluate factors that influenced deer hunter distribution and probability of success within potential Ohio deer management units with the goal to provide important information for harvest managers at a regional scale. While final model results were complex, the strongest relationships captured in all models showed hunters were more likely to hunt but less likely to harvest deer on public compared to private lands. I found differences in final model covariates and the impact they had on hunter use and success between DMUs, which differ based on aspects of human social, geophysical and landcover composition. For example, while all DMUs had a clear trend for hunters to select for locations with a higher percentage of forest and public land, strength of selection for these predictors and which cover types were avoided differed by DMU and, therefore, by landscape context. These results suggest that overall, incentivizing landowners to allow hunting on their property and facilitating access for hunters may be the most effective strategy to increase hunter success. Additionally, information concerning hunter behavior and outcomes in response to spatial variables can be used to devise region-specific management plans to achieve region-specific deer harvest and population goals.

Introduction

White-tailed Deer (*Odocoileus virginianus*) have great economic, social, and ecological significance in Ohio, where this species became the state mammal in 1988. Due to being a habitat generalist, this species can be found in a variety of habitat types including forests, agricultural landscapes (Nixon et al. 1970), wetlands (Hummel et al. 2018) and shrublands (Iverson and Iverson 1999). This species demonstrates a high degree of adaptability to human interaction, which allows them to occupy areas in urban settings such as metroparks and residential areas (Iverson and Iverson 1999; Kilpatrick and Spohr 2000). Areas characterized by high edge amount and interspersion of cover types can benefit this species by providing cover and forage resources nearby each other throughout the year (Alverson et al. 1988, Quinn et al. 2013, Cain et al. 2019).

By 1860 European settlement had begun taking a toll on Ohio's white-tailed deer population through a combination of reducing forest area and intense hunting, ultimately extirpating the species here and in nearby states by 1905 (Nixon 1970). Efforts to grow the population consisted of restocking, restricted hunting policies and reforestation (Nixon 1970). Ohio's deer population has generally increased since this time, estimated to be 17,000 in 1970 and 700,000 in 2006 (ODNR 2006).

Management strategies to reduce negative sociological and ecological impacts of high white-tailed deer abundance in Ohio have become an important concern. To devise an effective management plan concerning the widespread impacts of Ohio's herd, large-scale research and planning is needed. Hunting is the most preferred method of deer management for state level managers because it generates income while also advancing management agency population goals. Unfortunately, hunting participation in North America has declined in recent decades.

U.S. Fish and Wildlife Service 2016 hunting levels were the lowest seen in 25 years. Reasons for hunter decline include low recruitment in young, non-white, non-male and non-hunter populations (Mehmood et al. 2003, Poudyal et al. 2008, Gude et al. 2012); increased interest in virtual entertainment and urban lifestyles (Robinson and Ridenour 2012, Karns et al. 2015); and a lack of time, land access and game (Mehmood et al. 2003, Miller and Vaske 2003). If declines continue this way, the future of hunting as a viable strategy to generate funds for conservation and manage deer populations is questionable due to lack of participation (Winkler and Wanke, 2013).

Opinions on necessary changes to deer density and related management techniques vary widely depending on the stake that people have in the issue and their perception of acceptable deer population size compared to their perception of current abundance. D'Angelo and Grund (2015) found that 51% of farmers in Minnesota supported reduction of deer densities, despite their perception that damage due to deer was insignificant. Of hunters surveyed in the same study, 62% indicated that deer densities should be increased. Kilpatrick et al. (2007a) found that most homeowners in Connecticut did not allow hunting on their own land, despite being open to lethal management techniques for reducing human-deer conflicts. This link between hunter and landowner attitudes becomes significant to management strategies in light of the strain that access to hunting land can impose. When potentially deer-rich private, subdivided land parcels (Lovely et al. 2013) do not allow access to hunters, this can create a negative scenario for all parties due to financial losses to farmers, nuisances to homeowners and loss of successful opportunities for hunters (Haden et al. 2005, Proffitt et al. 2013).

Studies focusing on factors influencing hunter distribution and success have been conducted in the past. Diefenbach et al. (2005) found that deer hunters were 1.5 times less likely to hunt for every 5% increase in slope while 87% of hunters stayed within 0.5 km of the nearest road, making slope and distance to road potentially important predictors of hunter density. Unfortunately, hunters seem to experience a lower chance of success in areas near roads (Iverson and Iverson 1999, Cooper et al. 2002, Lebel et al. 2012, Rowland et al. 2021). Increased development and parcelization of land can limit hunter access, thereby reducing harvest pressure and acting as refugia for deer (Harden et al. 2005, Lovely et al. 2013). On the other hand, fragmented forests can increase resources and potentially carrying capacity for deer (Alverson et al. 1988). More fragmented forest landscapes can increase vulnerability of deer to harvest by reducing dense cover, leading to a higher hunter of success rates if accessibility needs are met (Foster et al. 1997, Lebel et al. 2012).

Unevenness in hunter distribution causes gaps where hunting does not occur (either due to lack of access or being unpreferable) despite high deer densities, creating areas with low harvest risk that act as refugia (Harden et al. 2005, Lovely et al. 2013). As the efficacy of hunting decreases as a technique for population reduction and income generation, wildlife managers are pressed to deal with overabundant species with smaller funds. Each of the variables mentioned above can be measured in relation to individual, fine-scale incidents of hunting or other human-wildlife interactions, however these distinct experiences cannot directly inform population management strategies. In order to make conclusions about regional patterns related to deer hunting, fine-scale characteristics can be analyzed along with the relevant outcome (hunter presence and/or success) over a region. Using this approach, results will theoretically reflect patterns occurring at a scale which is useful to managers looking to make changes to regional hunting regulations and population trends.

Dynamics of deer population and harvest management are scale-dependent (Foster et al. 1997). Delineation of relevant regions is imperative to consider for analyses of variation patterns in deer hunter behavior and harvest at broad spatial scales to inform broad management goals. Rather than analyzing trends over biologically arbitrary boundaries such as counties, results are more relevant and useful to coarse-scale management planning if regions contain areas that display similarities in ecological and sociocultural factors. Karns et al. (2016) used this method to propose deer management units (DMUs) over Ohio with the purpose of creating a framework that would facilitate effective regional deer population and harvest management. This study found that percent farmland, proportion of noncrop area within farmland and per capita deer permit sales at the county level worked best to delineate regions of homogeneous deer harvest dynamics. I investigated factors influencing hunter distribution and success within these potential DMUs to compare impactful factors between regions and develop conclusions which could be applied by managers at an appropriate scale. To my knowledge, this study is novel in that it evaluates harvest trends through a spatial framework based on factors relevant to game management. Future changes to harvest and game management grounded in these conclusions should improve in predictability and efficiency compared to those based on less relevant management boundaries.

With the overall aim to investigate landscape factors that influence Ohio deer hunting, this project had three main objectives: 1) Identify factors impacting hunter distribution; 2) Identify factors influencing probability of hunter success; 3) Contrast results between proposed deer management units to draw conclusions at a regional level. I predicted that likelihood of hunter presence will decrease as distance to nearest road and slope increase. I also predicted that likelihood hunter presence will increase with amount of forest and in public land over private.

Regarding probability of hunter success, I predicted hunters will have a higher rate of success than their public land counterparts, though the strength of this trend will vary between DMUs. I expected increased forest and forest edge to increase hunter success in all cases, with stronger trends in DMUs where forest amount is lower and other cover types are more dominant. Candidate model sets informed by expert opinion and relevant literature were created to test a priori hypotheses regarding how geospatial characteristics influence hunting outcomes. Generally, these methods could inform and be applied to other geographic areas to investigate landscape-hunter relationships.

Methods

Study Area

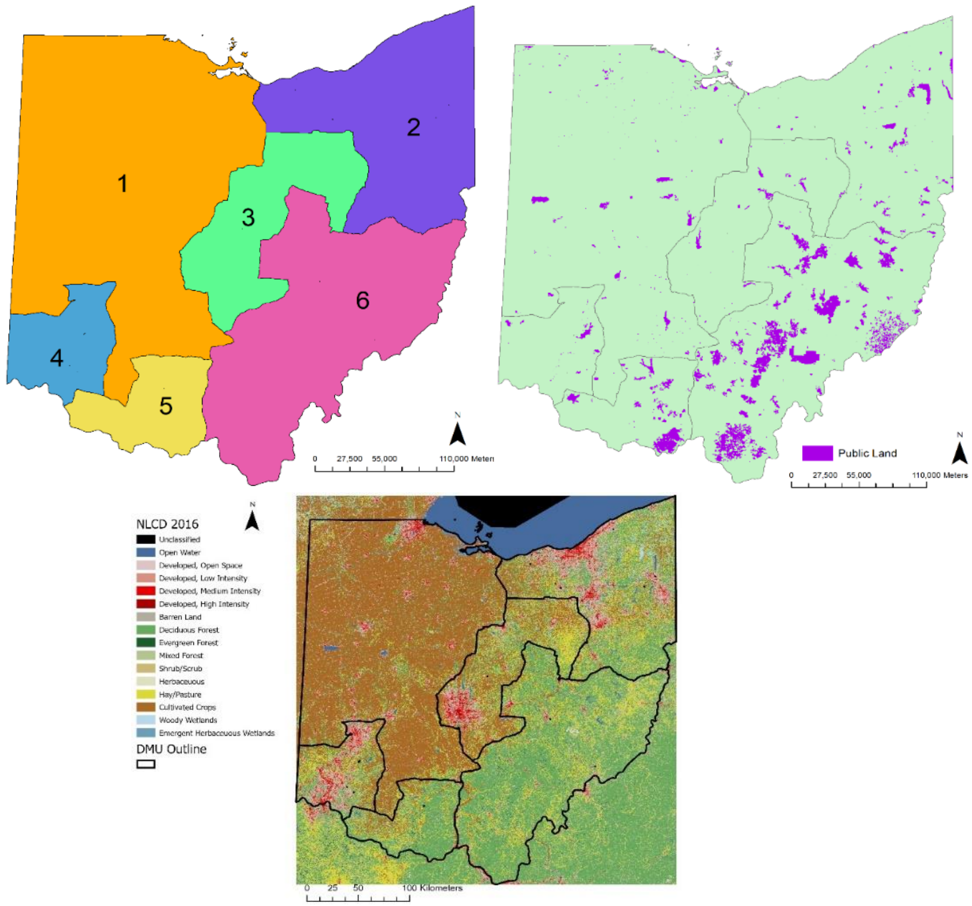

Figure 2.1. Deer management units proposed by Karns et al. (2016) (top left). Areas designated as publicly owned lands outlined (top right). NLCD 2016 landcover including DMU outline (bottom).

Landcover Type	DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6
% Low Urban	8.3	19.8	13.9	27.4	5.3	6.7
% High Urban	1.7	4.4	4.5	7.7	0.6	0.8
% Forest	8.4	38.3	24.0	27.4	58.0	66.8
% Shrub	0.0	0.5	0.2	0.1	0.9	0.9
% Herbaceous	0.4	0.9	0.3	0.4	1.2	1.0
% Hay/Pasture	4.5	18.7	21.3	14.4	18.2	18.9
% Crop	75.0	12.7	34.8	22.0	15.5	4.1

Table 2.1. Percentage cells belonging to each relevant landcover class within each of the 6 proposed deer management units in Ohio.

This project used hunter survey data from all 6 of Ohio's proposed deer management units (Karns et al. 2016) (Figure 2.1). Land use in DMU 1 consisted heavily of cropland. DMU 2 was characterized by large pockets of urban areas as Cleveland is within this unit, while also including a mix of agricultural and some forested areas. DMU 3 also has a pocket of urban area as it includes Columbus, though it is mostly agricultural land outside the city. DMU 4 included Cincinnati, and so consisted mostly of urban area and some agricultural pockets. DMU 5 was made up of forest and agricultural land, it acts as a gradient between the mode single-type dominated DMUs. DMU 6 was largely forested with areas of crop use. Past glaciation in western Ohio has caused differences in topography where the western side is largely flat and the eastern side consists of much greater topographic variation.

Data Collection

In July-August of 2014 95,000 Ohio hunters were asked via email to complete an online survey that requested several fields of data concerning a single hunting event. Hunters were allowed to delineate hunt location by point or rectangle, if the latter was used the center point of the resulting polygon was used during data collection. Respondents were asked whether the hunt was successful, which county it occurred in and year in which it occurred with options 2011-2012, 2012-2013 and 2013-2014. About 10,000 surveys were returned. Throughout the state there were a total of 4,853 successful hunts and 6,119 unsuccessful hunts. To analyze patterns in hunter distribution within a DMU, random points were created to match the total number of data points within the region. Random point locations were only bounded by the boundaries of the DMU in order to test whether hunters distributed themselves differently than a random distribution of points.

I obtained digital elevation model rasters from the Ohio Geographically Referenced Information Program (OGRIP) and converted to degree slope using ArcMap Slope tool. Road centerline data was also obtained from OGRIP through their Local Based Response System (LBRS) project. LBRS contains centerlines for all public and private roads, including paved and unfinished gravel roads. Centerlines were merged into a single polyline file at the DMU level for analysis. ArcMap's near tool was applied to the merged centerlines to calculate the distance from each data point to the nearest feature. Polygon files outlining publicly owned lands were obtained from Ohio Division of Wildlife (ODW). Parcel shapefiles for each county were downloaded from the county auditor's website or map office. Parcel shapefiles were merged and converted to raster by parcel size to estimate mean parcel sizes. Landcover data were obtained from NLCD (2016). I reclassified NLCD to reduce the number of classes by combining them or leaving out those not relevant to the study area (Table 2.2). Distance to nearest road was calculated for each point location using the Near Distance tool (ArcMap). I used the 'landscapemetrics' package (Hesselbarth et al. 2019) in R software to calculate landscape metrics surrounding each data point. I calculated metrics describing percent landcover and amount of edge per landcover type within a buffer. Slope, mean parcel size, and landscape metrics were collected at 3 spatial scales (100m, 200m, 300m) to find which best suited the data and explained hunter responses. To decide between the 3 spatial scales, I applied initial data exploration by creating single variable models using each buffer size and comparing variation explained and variable significance. Following this initial exploration, I found that the 300m buffer was most appropriate and applied this to the model creation. Principal component analysis was applied to the percent land cover type variables to reduce the dimensionality and intercorrelation these data.

NLCD Classification	New Classification
Developed, Open Space Developed, Low Intensity	Low Urban
Developed, Medium Intensity Developed, High Intensity	High Urban
Barren Land	Barren Land
Deciduous Forest Evergreen Forest Mixed Forest	Forest
Shrub/scrub	Shrub
Herbaceous Hay/pasture Cultivated crops	Herbaceous Hay/pasture Cultivated crops
Woody wetlands Emergent herbaceous wetlands	Woody wetlands Emergent herbaceous wetlands

Table 2.2. Reclassification of NLCD 2016 class types to those which were used to model effects on hunter distribution and success and white-tailed deer habitat suitability over proposed DMUs for Ohio.

I also created a habitat suitability model (HSI) for white-tailed deer based on available literature (Roseberry and Woolf 1998, Miranda and Porter 2003) which was then adapted to our goals and study area by incorporating expert opinion. I added the food and cover coefficients (Table 2.3) as separate fields in an NLCD raster before exporting those fields into two new rasters, each showing either food value coefficients or cover value coefficients. I then used the focal statistics tool to find the maximum coefficient values within a functional distance to account for high quality resources available for use in the surrounding landscape. A 500 m buffer was applied to food value coefficients while a 200 m buffer was applied to cover value coefficients (Roseberry and Woolf 1998). The final HSI was calculated for each value by averaging all 4 values.

Landcover Class	Food Coefficient	Cover Coefficient
Developed Open	0.7	0.6
Developed Low	0.4	0.4
Developed Medium	0.2	0.2
Deciduous Forest	0.4	1.0
Evergreen Forest	0.1	1.0
Mixed Forest	0.3	1.0
Shrubland	0.5	1.0
Herbaceous	0.5	0.3
Pasture/Hay	0.6	0.1
Cultivated Crop	0.5	0.4
Woody Wetland	0.3	0.2
Emergent Herbaceous Wetland	0.0	0.7

Table 2.3. Coefficients used to assign value for each food and cover metric in the HSI model.

Modeling Approach

I fit logistic regression models to predict probability of hunter presence and success given certain data points. There are 3 general classes of factors known to influence deer hunter distribution and success, each of which can be represented with multiple variables. As a result, I decided the number of variables to be tested were too complex to be tested within a single candidate model set. Candidate model sets were created for 3 separate categories of predictors including habitat characteristics, land accessibility to hunters, and physical difficulty. Models were constructed *a priori* according to hypotheses developed based on review of literature and expert opinion. I used delta AIC value >2 to identify the highest-ranked models. In the case of an AIC < 2, I identified the simpler model as highest ranked. After comparing models within a category, the top model was added to the final candidate model set and combined into a single model. Interactions not included in the category models which were predicted to have an impact were then added to the combined model. A quadratic term was tested using likelihood ratio test on variables slope, distance to road, parcel size, and all principal components to account for non-linear relationships. If deemed significant by this test, the quadratic term was added to the candidate model sets in addition to the single term.

The access candidate model set was the same for distribution (Table 2.4) and success (Table 2.5). I predicted that hunters would be more likely to use public land due to ease of access, despite lower probability of success on public land due to deer avoidance of areas where hunters are dense. Lovely et al. (2013) found that percentage of land hunted increased with mean parcel size, while deer density seemed to increase at lower mean parcel sizes. To test these findings in this study, I added the mean parcel size to both candidate model sets. Physical exertion to reach a hunting location was accounted for in the difficulty category, since I predicted that hunters are inclined to hunt in areas closer to roads and at a lower slope (Diefenbach et al. 2005, Rowland et al. 2021). An interaction was added between slope and road for the distribution model as hunters may be less inclined to walk farther as slope increases (Table 2.4). Percent landcover and edge metrics were included to investigate how habitat influences hunter distribution and success. Since we know white-tailed deer populations vary with habitat characteristics, I examined whether land cover composition influence hunter distribution and success. A similar question was investigated with HSI values in the success models, though in a way that attempted to directly compare deer habitat and probability of hunting success (Table 2.5). The final hunter distribution candidate model set included an additional interaction to test whether hunter distance to road changes with amount of forest cover as this represents a cover type which is physically more difficult to walk through and could influence the distance hunters walk (Table 2.4). The interaction added in the final set of the hunter success portion aimed to test whether the influence of forest land cover changes on public land. I predicted the effect of forest percent on probability of success would be lower on public than private land due to lower deer densities (Table 2.5).

Category	Model Sets
Access	PublicLand
	PublicLand+MeanParcelSize
Difficulty	Slope
	RoadDist
	Slope+RoadDist
	Slope+RoadDist+Slope:RoadDist
Landscape Metrics	PC1+PC2+PC3
	PC1+PC2+PC3+ForestEdge
Final	TopModels
	TopModels+PC[b]:RoadDist

[a] PC refers to principial components describing percentage landcover type over a 300m buffer
[b] Specific principal component will be chosen based on which demonstrates a gradient to forest
Table 2.4. Candidate model sets used to fit hunter distribution models using hunter survey data related to hunts which occurred between 2011-2014 over each of 6 proposed DMUs in Ohio.

Category	Model Sets
Access	PublicLand
	PublicLand+MeanParcelSize
Difficulty	Slope
	RoadDist
	Slope+RoadDist
Landscape Metrics	HSI
	PC1+PC2+PC3
	PC1+PC2+PC3+ForestEdge
	PC1+PC2+PC3+ForestEdge+CropEdge
Final	TopModels
	TopModels+PC[b]:PublicLand

[a] PC refers to principial components describing percentage landcover type over a 300m buffer
[b] Specific principal component will be chosen based on which demonstrates a gradient to forest
Table 2.5. Candidate model sets used to fit hunter success models using hunter survey data related to hunts which occurred between 2011-2014 over each of 6 proposed DMUs in Ohio. *Results*

Results

I used hunter data from all 6 DMUs to create models predicting hunter distribution and success (Table 2.6).

	DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6
Harvest	1054	980	498	294	324	1703
Non-Harvest	1437	1187	601	342	402	2150
Random	2491	2167	1099	636	726	3853

Table 2.6. Number of data points located in each proposed Ohio DMU in the hunter survey data concerning hunts which occurred between 2011-2014, which was used to create the distribution and success models.

DMU	Slope (°)	Distance to Road (m)	Parcel Size (km^2)	% Forest	% Low Urban	% High Urban	% Herbaceous	% Pasture	% Crop
1	1.10 (0.01 - 13.92)	292.92 (0.04 - 2296.73)	0.41 (0.001 - 17.15)	16.34 (0 – 100)	6.71 (0 – 100)	1.00 (0 - 91.64)	0.45 (0 - 26.52)	5.97 (0 - 84.71)	64.73 (0 – 100)
2	3.59 (0.01 - 27.44)	239.60 (0.06 - 1181.11)	0.50 (0.0005 - 30.36)	44.12 (0 – 100)	14.61 (0 – 100)	2.82 (0 - 95.25)	0.89 (0 - 54.89)	18.37 (0 - 93.95)	11.88 (0 – 100)
3	2.93 (0.03 - 21.87)	239.96 (0.06 - 1002.40)	0.31 (0.001 - 18.42)	31.04 (0 – 100)	10.54 (0 - 99.04)	2.45 (0 - 95.19)	0.25 (0 - 15.19)	20.16 (0 – 100)	32.65 (0 – 100)
4	3.42 (0.05 - 24.12)	219.54 (0.19 - 1086.57)	0.31 (0.0005 - 14.01)	38.70 (0 – 100)	19.76 (0 - 98.41)	4.79 (0 - 97.74)	0.39 (0-19.85)	14.05 (0 - 98.42)	20.21 (0 – 100)
5	7.01 (0.01 - 29.64)	322.75 (0.45 - 1610.24)	1.06 (0.003 - 35.01)	62.15 (0 – 100)	5.02 (0 - 84.24)	0.39 (0 - 43.99)	1.12 (0 - 72.79)	17.62 (0 - 95.21)	11.55 (0 – 100)
6	9.32 (0.02 - 32.35)	265.39 (0.02 - 1810.47)	0.80 (0.001 - 42.87)	70.10 (0 – 100)	6.13 (0 - 97.80)	0.48 (0 - 88.92)	0.78 (0 - 99.73)	17.15 (0 - 99.68)	3.30 (0 – 100)

Table 2.7. Means and (range) of covariates used to model hunter distribution and success from hunter survey data concerning hunts which occurred between 2011-2014.

Distribution

The top models for each category were supported with < 2 ΔAICc (Appendix F). Principal component analysis applied to the percent cover variables yielded 3 principal components to be tested in the candidate model sets (Appendix D) Overall, top models for each DMU were either the result of combining all variables from the category level top models or this combination of models plus an interaction term between distance to road and the principal component corresponding to forest amount. These two top models were often within 2 ΔAICc of each other, in which case the simpler version was chosen as the final model (Appendix F). Public land, the three principal components, and slope variables were present in all 6 final models. Distance to road in was present in all final models except that of DMU 6. Total forest edge was included in models for DMUs 1, 3 and 5. Mean parcel size was only included in the final model for DMU 2. Final models for DMUs 2 and 3 included an interaction between slope and distance to road. Public land demonstrated the highest odds ratio in every model, ranging from 1.7704 to 10.492 (Table 2.8) and was significant ($P<0.01$) for all DMU models except DMU 3. Principal components demonstrating a gradient towards increasing forest percentage had consistently positive relationships with hunter presence, while principal components which decreased as forest percentage increased had a negative effect on hunter presence (Table 2.8, Figure 2.3).

The top model for DMU 1 encompassing the agricultural landscape of northwestern and west-central Ohio ($w_i = 0.498$) included 11 variables. Public land had a positive effect on use ($\beta = 2.3506$, $P < 0.0001$). Principal component 1 accounted for 29% of the variation (Appendix D) and represented the landscape shifting from forested area to more crop dominated. Probability of hunter use was negatively associated with principal component 1 ($\beta = -0.4432$, $P < 0.0001$) (Table 2.8). Principal component 2 explained 20% of the variation and represented a gradient from higher forested area towards urban dominated. Hunter use had a negative relationship with principal component 2 ($\beta = -0.3608$, $P < 0.0001$). Principal component 3 corresponded to a shift towards areas with higher shrubby and herbaceous vegetation and explained 15% of the variation. There was a positive relationship between principal component 3 and hunter use ($\beta = 0.0769$, $P = 0.0419$). Quadratic terms were included for principal components 1 ($\beta = -0.1726$, P

<0.0001) and 2 (β = 0.0306, P =0.0425) in DMU 1. Slope was included in the model yet had no significant effect on use (β = 0.0018, P = 0.9749). Distance to road had a positive effect on use (β = 0.0019, P < 0.0001) and was included as a quadratic term. Amount of forest edge showed a positive relationship with use (β = 0.0003, P < 0.0001).

The top model for DMU 2 encompassing the unglaciated mixed urban and forest landscape of northeastern and east central Ohio (w_i = 0.729) included 13 variables. Public land had a positive effect on use (β = 0.7324, P < 0.0001). Principal component 1 accounted for 26% if the variation (Appendix D) and corresponded to a gradient from urban landscapes to more forested areas. Principal component had a positive effect on hunter use (β = 0.2598, P < 0.0001) (Table 2.8). Principal component 2 explained 21% of the variation and represented a shift from pasture and crop dominated landscapes towards more forested land. Hunter use increased with principal component 2 (β = 0.1283, P = 0.0011). Principal component 3 accounted for 15% of the variation and demonstrated a gradient from cropland to higher pasture land. This component did not have a significant impact on hunter use (β = -0.0077, P =0.8221). Quadratic terms were included for principal components 1 (β = -0.1181, P <0.0001) and 2 (β = -0.0825, P = 0.0003) in DMU 2. Slope did not influence use (β = 0.0214, P = 0.377). Distance to road increased probability of use (β = 0.0015, P = 0.0044) and was also included as a quadratic term. Mean parcel size (β < 0.0001, P = 0.2849) and the interaction between slope and distance to road (β = <0.0001, P = 0.8677) were not significant predictors of use.

The top model identified for DMU 3 the mixed forest, urban and agricultural landscape of central Ohio included 10 variables (w_i = 0.431). Public land had a positive, yet not statistically significant influence on hunter use (β = 0.6114, P = 0.0595). Principal component 1 in DMU 3 accounted for 25% of the variation (Appendix D) and constituted a change in the landscape as it shifted from urban areas to cropland. There was no significant relationship between hunter use and principal component 1 (β = 0.1537, P = 0.15). Principal component 2 demonstrated a landscape gradient from crop dominated to forested areas and explained 22% of the variation. There was a positive relationship between hunter use and principal component 2 (β = 0.2602, P < 0.0001) (Table 2.8). Principal component 3 explained 17% of the variation and represented a shift in the landscape from areas with high amount of pasture towards forested land. Principal component 3 did not have a significant effect on hunter use (β = -0.0185, P = 0.4957). Hunter use increased as amount of forest edge (β = 0.0002, P = 0.0041). Distance to nearest road did not have a strong impact on use (β = 0.0015, P = 0.0848) increased. The interaction between slope and distance to road was insignificant (β = -0.0001, P = 0.3703).

The top model for DMU 4 including the variable terrain and predominantly forested landscape of southeastern Ohio included 8 variables (w_i = 0.349). Public land increased probability of use compared to private (β = 1.2918, P = 0.0009). Principal component 1 represented a change in the landscape from forested to urban and accounted for 26% of the variation (Appendix D). Principal component 1 had a negative impact on hunter use (β = -0.572, P < 0.0001) (Table 2.8). Principal component 2 explained 21% of the variation and corresponded to a gradient from cropland to forested dominated. There was a positive relationship between principal component 1 and hunter use (β = 0.3544, P < 0.0001). A quadratic term for principal component 2 was also included in the final model (β = -0.0218, P = 0.6441). Principal component 3 in DMU 4 accounted for 15% of the variation and represented a shift towards landscapes high in pasture area, though it did not impact hunter use (β = -0.0094, P = 0.8962). Percent slope did not impact hunter use (β = 0.0205, P =0.3211). Distance from nearest road (β = 0.0031, P = 0.0033) increased use probability, distance to road was also included as a quadratic term.

The top model for DMU 5 encompassing the mixed urban-agriculture-forested landscape of south-central Ohio included 9 variables (w_i = 0.719). Public land resulted in increased use probability (β = 0.6723, P = 0.0002). Principal component 1 represented a shift in the landscape from forested areas to pasture and crop dominated. This component accounted for 31% of the variation (Appendix D) and demonstrated a negative relationship with hunter use (β = -0.1535, P = 0.0035). Principal component 2 accounted for 19% of the variation and described a gradient from urban areas to cropland. There was a negative relationship between hunter use and principal component 2 (β = -0.1109, P = 0.0293). Principal component 3 corresponded to a shift towards areas higher in shrubby and herbaceous vegetation. This principal component accounted for 15% of the variation, though it did not significantly impact hunter use (β = -0.0948, P = 0.0826). Slope did not impact use either (β = 0.0149, P = 0.6451). Amount of forest edge (β = 0.0002, P = 0.003) and distance from nearest road (β = 0.0021, P = 0.0016) increased use probability, distance to road was also included as a quadratic term.

Lastly, the top model for DMU 6 DMU which encompassed the mixed forest and urban landscape of southwestern Ohio included 8 variables (w_i = 1.0). Public land increased probability of hunter use (β = 0.6669, P < 0.0001). Principal component 1 accounted for 30% (Appendix D) of the variation and demonstrated a shift in the landscape from areas with high amounts of pasture towards forested areas. The relationship between principal component 1 and hunter use was no significant (β = 0.0396, P = 0.1228). Principal component 2 accounted for 19% of the variation and described a landscape shifting towards urban areas, but did not have a significant effect on hunter use (β = 0.0177, P = 0.5855). Principal component 3 explained 16% of the variation and corresponded to a gradient towards increasing amounts of shrubby and herbaceous vegetation. Principal component 3 had a negative impact on hunter use ($\beta = -0.0969$, $P = 0.0001$). Slope did not impact use ($\beta = 0.0150$, $P = 0.3179$).

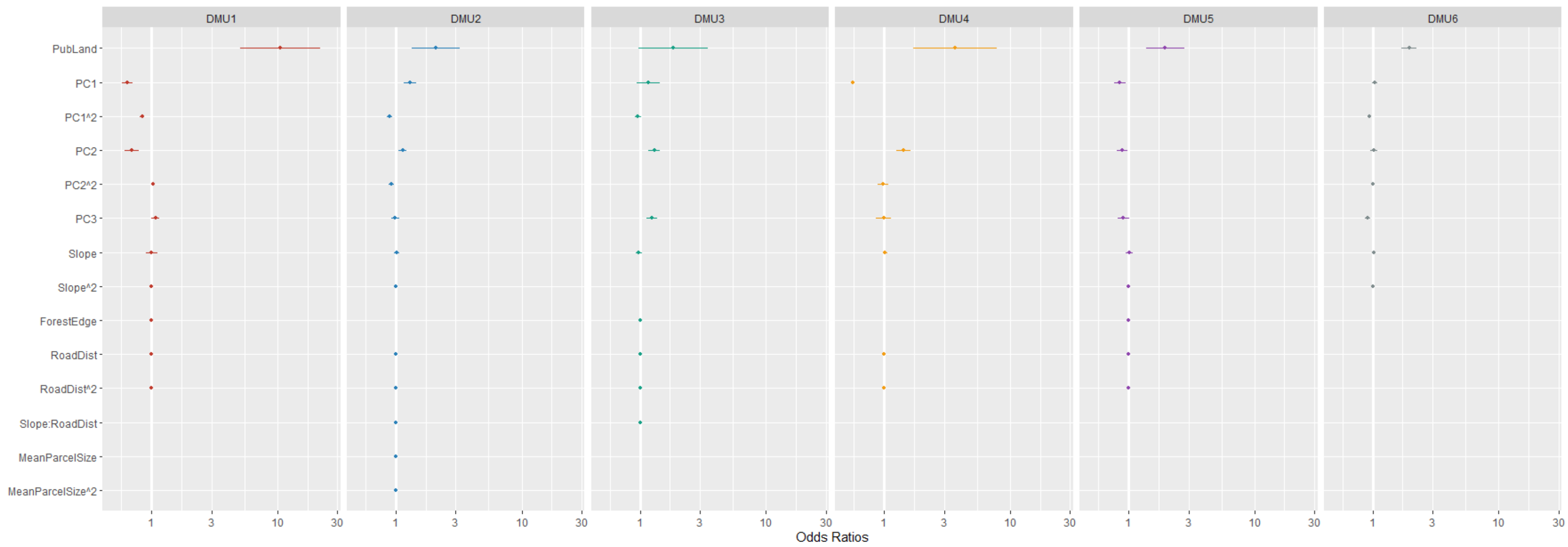

Figure 2.2. Odd Ratios with confidence interval bars for variables included in top models predicting hunter distribution over all 6 proposed DMUs in Ohio using hunter survey data concerning hunts which occurred between 2011-2014.

DMU	Covariate[a]	β[b]	Odds ratio	SE[c]	*P*[d]
1	(Intercept)	-0.4588	0.6321	0.0997	<0.0001
	PublicLand	2.3506	10.492	0.3731	<0.0001
	PC1	-0.4432	0.642	0.0483	<0.0001
	I(PC1^2)	-0.1726	0.8415	0.0211	<0.0001
	PC2	-0.3608	0.6971	0.0632	<0.0001
	I(PC2^2)	0.0306	1.031	0.0151	0.0425
	PC3	0.0769	1.08	0.0378	0.0419
	Slope	0.0018	1.0018	0.0558	0.9749
	I(Slope^2)	0.0002	1.0002	0.0071	0.9765
	RoadDist	0.0019	1.0019	0.0003	<0.0001
	I(RoadDist^2)	<0.0001	1.0000	<0.0001	0.0057
	ForestEdge	0.0003	1.0003	0.0001	<0.0001
2	(Intercept)	0.0382	1.0387	0.104	0.7148
	PublicLand	0.7324	2.0801	0.2242	0.0011
	PC1	0.2598	1.2967	0.0564	<0.0001
	I(PC1^2)	-0.1181	0.8886	0.0244	<0.0001
	PC2	0.1283	1.1369	0.0392	0.0011
	I(PC2^2)	-0.0825	0.9209	0.0226	0.0003
	PC3	-0.0077	0.9923	0.0342	0.8221
	Slope	0.0214	1.0216	0.0242	0.377
	I(Slope^2)	-0.0019	0.9981	0.0013	0.1405
	RoadDist	0.0015	1.0015	0.0005	0.0044
	I(RoadDist^2)	<0.0001	1.0000	<0.0001	0.0013
	Slope:RoadDist	<0.0001	1.0000	<0.0001	0.8677
	MeanParcelSize	<0.0001	1.0000	<0.0001	0.2849
	I(MeanParcelSize^2)	<0.0001	1.0000	<0.0001	0.4194
3	(Intercept)	-0.2926	0.7463	0.1656	0.0772
	PublicLand	0.6114	1.843	0.3244	0.0595
	PC1	0.1537	1.1662	0.1068	0.15
	I(PC1^2)	-0.0335	0.967	0.0293	0.2517
	PC2	0.2602	1.2971	0.0552	<0.0001
	PC3	0.2210	1.2473	0.0469	<0.0001
	Slope	-0.0185	0.9816	0.0272	0.4957
	ForestEdge	0.0002	1.0002	0.0002	0.0041
	RoadDist	0.0015	1.0015	0.0009	0.0848
	I(RoadDist^2)	<0.0001	1.0000	<0.0001	0.0603
	Slope:RoadDist	-0.0001	0.9999	0.0001	0.3703

Continued

[a]PC refers to a principal component based on percentage landcover type. The number indicates which component it is.
[b] Variable coefficients [c] Standard error [d] P-value

Table 2.8. Model regression summary for top models predicting hunter distribution over all 6 proposed DMUs in Ohio using hunter survey data concerning hunts which occurred between 2011-2014.

Table 2.8 Continued

DMU	Covariate[a]	β[b]	Odds ratio	SE[c]	*P*[d]
4	(Intercept)	-0.4513	0.6368	0.1761	0.0104
	PublicLand	1.2918	3.6395	0.3883	0.0009
	PC1	-0.572	0.5644	0.0683	<0.0001
	PC2	0.3544	1.4254	0.0689	<0.0001
	I(PC2^2)	-0.0218	0.9784	0.0472	0.6441
	PC3	-0.0094	0.9906	0.0724	0.8962
	Slope	0.0205	1.0207	0.0206	0.3211
	RoadDist	0.0031	1.0031	0.0011	0.0033
	I(RoadDist^2)	<0.0001	1.0000	<0.0001	0.0038
5	(Intercept)	-0.5988	0.5495	0.2251	0.0078
	PublicLand	0.6723	1.9587	0.1786	0.0002
	PC1	-0.1535	0.8577	0.0526	0.0035
	PC2	-0.1109	0.8951	0.0509	0.0293
	PC3	-0.0948	0.9096	0.0546	0.0826
	Slope	0.0149	1.015	0.0324	0.6451
	I(Slope^2)	-0.0020	0.998	0.0014	0.1534
	ForestTE300	0.0002	1.0002	0.0002	0.003
	RoadDist	0.0021	1.0021	0.0007	0.0016
	I(RoadDist^2)	<0.0001	1.0000	<0.0001	0.0008
6	(Intercept)	0.0086	1.0086	0.0847	0.9194
	PublicLand	0.6669	1.9482	0.0679	<0.0001
	PC1	0.0396	1.0403	0.0256	0.1228
	I(PC1^2)	-0.0651	0.9369	0.0127	<0.0001
	PC2	0.0177	1.0179	0.0325	0.5855
	I(PC2^2)	0.0110	1.011	0.0058	0.0568
	PC3	-0.0969	0.9076	0.0241	0.0001
	Slope	0.0150	1.0151	0.0151	0.3179
	I(Slope^2)	-0.0012	0.9988	0.0006	0.0561

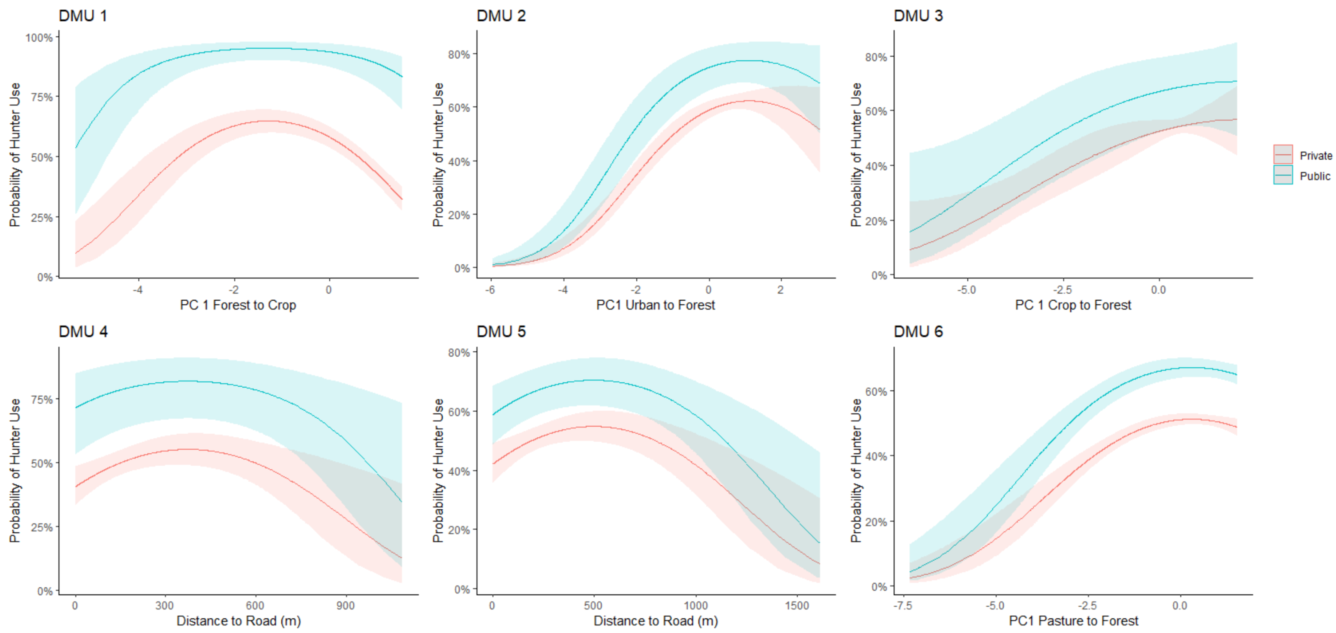

Figure 2.3. Graphed relationship between probability of hunter use and most significant variables which included a quadratic term described on X axis. Models were created using survey data from Ohio deer hunters concerning hunts which occurred during 2011-2014 seasons and random points, final models chosen based on AIC. Shaded regions represent 95% confidence intervals.

Hunter Success

Principal components analysis was also applied to these datasets to reduce dimensionality and intercorrelation of percentage landcover type data where the result was 3 principal components per DMU (Appendix E). Certain category level models were not separated from the null model by at least 2 ΔAICc (Appendix G), in which case these were not tested in the final model. Final models were supported by a ΔAICc>2 in every case. Models which predict hunter success were created using hunter survey data showing successful and unsuccessful hunting attempts (Table 2.6). Public land is the only variable to be included in top models for all DMUs (Table 2.9, Figure 2.4). Public land had the strongest negative effect on success probability in all models with odds ratios between 0.2805 and 0.6357 and was significant in every model

(P<0.01). Principal components were included in 4 out of 6 top models where HSI replaced them in DMU 3 and no landscape metrics were included in DMU 5.

The top model for DMU 1 encompassing the agricultural landscape of northwestern and west-central Ohio included 6 variables (w_i = 0.724). Public land decreased probability of success (β = -1.0009, P < 0.0001) (Table 2.9). Principal component 1 in DMU 1 accounted for 27% of the variation (Appendix E) and represented a change from crop dominated landscapes towards forested areas. There was a positive relationship between principal component 1 and hunter success (β = 0.1002, P = 0.0035). Principal component 2 explained 20% of the variation and corresponded to a gradient from urban areas towards forested land. The relationship between hunter success and principal component 2 was statistically insignificant (β = 0.0802, P = 0.2186). Principal component 3 accounted for 15% of the variation and demonstrated a shift from shrubby and herbaceous vegetation towards landscapes with higher pasture area. There was a positive relationship between principal component 3 and hunter success (β = 0.1106, P = 0.0123). Distance to road did not impact success (β = 0.0003, P = 0.1137).

The top model selected for DMU 2 encompassing the unglaciated mixed urban and forest landscape of northeastern and east central Ohio included 7 variables (w_i = 0.676). Public land decreased probability of success compared to private land (β = -1.1596, P < 0.0001). Principal component 1 in DMU 2 accounted for 24% of the variation (Appendix E) and constituted a shift from forested are towards pasture and crop dominated land. Principal component 1 did not have a significant impact on hunter success (β = -0.0006, P = 0.9906). Principal component 2 explained 21% of the variation and described a shift from urban areas towards pasture and crop dominated lands. There was a negative relationship between principal component 2 and hunter success (β = -0.1362, P = 0.013). Principal component 3 accounted for 15% of the variation and represented a gradient from croplands towards pasture dominated areas, though it did not significantly impact success (β = -0.0527, P = 0.2478). Slope increased probability of success (β = 0.1043, P = 0.0008) and it was included as a quadratic term.

The top model for DMU 3 the mixed forest, urban and agricultural landscape of central Ohio included 3 variables (w_i = 0.629). Public land decreased probability of hunt success (β = -0.8245, P = 0.0308). Mean parcel size did not affect success probability (β = <0.0001, P = 0.1276). Habitat suitability for deer had a positive impact on success (β = 1.4774, P = 0.0255) and was only included in this DMU's final model.

The top model for DMU 4 including the variable terrain and predominantly forested landscape of southeastern Ohio included 8 variables (w_i = 0.699). Public land decreased probability of success (β = -1.2711, P = 0.0004). Principal component 1 in DMU 4 explained 25% of the variation (Appendix E) and represented a shift from forested landscapes towards croplands. Principal component 2 accounted for 23% of the variation and demonstrated a gradient from urban areas towards croplands. Principal component 3 explained 16% and described a gradient from pasture to crop dominated landscapes. Principal components 1 (β = -0.0896, P = 0.3289), 2 (β = 0.1383, P = 0.1152) and 3 (β = 0.1357, P = 0.1402) did not have significant impacts on hunter success in DMU 4 (Table 2.9). Crop edge had a negative impact on success (β = -0.0006, P = 0.0001). Effects on success from forest edge (β = <0.0001, P = 0.743), distance to road (β = -0.0007, P = 0.1861) or slope (β = 0.0021, P = 0.9302) were not found.

The model for DMU 5 encompassing the mixed urban-agriculture-forested landscape of south-central Ohio only included 2 variables (w_i = 1.0). Public land had a negative impact on success (β = -0.7873, P = 0.0010), while mean parcel size did not have a strong impact (β = <0.0001, P = 0.0473).

Finally, the top model for DMU 6 DMU which encompassed the mixed forest and urban landscape of southwestern Ohio included 8 variables (w_i = 0.64). Public land decreased probability of success compared to private land hunters (β = -0.4531, P < 0.0001) (Table 2.9). Principal component 1 explained 30% of the variation (Appendix E) and described a shift from forested landscapes towards those with more pasture area. Principal component 1 did not significantly impact hunter success (β = -0.0274, P = 0.4226). Principal component 2 explained 20% of the variation and represented a gradient away from more urban landscapes. There was a positive relationship between principal component 2 and hunter success (β = 0.0996, P = 0.0360). Principal component 3 accounted for 16% of the variation and described a shift towards areas with more shrubby and herbaceous vegetation. Principal component 3 was associated with a decrease in hunter success (β = -0.0852, P = 0.0134). Forest edge (β = 0.0004, P = 0.0986) and mean parcel size (β < 0.0001, P = 0.0003) did not strongly impact success

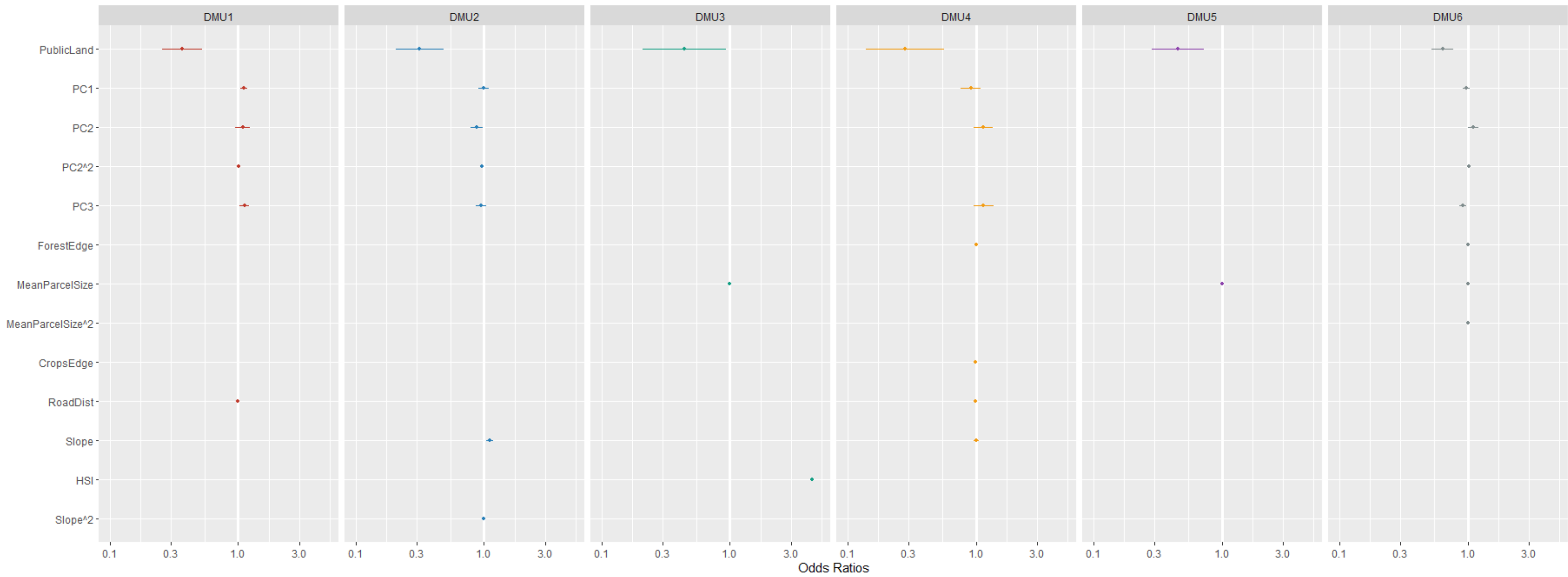

Figure 2.4. Odd Ratios including confidence interval bars for variables included in top models predicting hunter success probability over all 6 proposed DMUs in Ohio using hunter survey data concerning hunts which occurred between 2011-2014.

DMU	Covariate[a]	β[b]	Odds ratio	SE[c]	*P*[d]
1	(Intercept)	-0.3528	0.7027	0.0733	<0.0001
	PublicLand	-1.0009	0.3676	0.1844	<0.0001
	PC1	0.1002	1.1054	0.0344	0.0035
	PC2	0.0802	1.0835	0.0652	0.2186
	I(PC2^2)	0.0078	1.0079	0.0075	0.2996
	PC3	0.1106	1.1169	0.0442	0.0123
	RoadDist	0.0003	1.0003	0.0002	0.1137
2	(Intercept)	-0.3280	0.7204	0.081	0.0001
	PublicLand	-1.1596	0.3136	0.2178	<0.0001
	PC1	-0.0006	0.9994	0.0474	0.9906
	PC2	-0.1362	0.8727	0.0548	0.013
	I(PC2^2)	-0.0336	0.9669	0.0172	0.0499
	PC3	-0.0527	0.9486	0.0456	0.2478
	Slope	0.1043	1.1099	0.0311	0.0008
	I(Slope^2)	-0.0048	0.9952	0.0019	0.0135
3	(Intercept)	-1.0941	0.3349	0.4551	0.0162
	PublicLand	-0.8245	0.4384	0.3818	0.0308
	MeanParcelSize	<0.0001	1	<0.0001	0.1276
	HSI	1.4774	4.3817	0.6614	0.0255
4	(Intercept)	0.4986	1.6464	0.2918	0.0875
	PublicLand	-1.2711	0.2805	0.3579	0.0004
	PC1	-0.0896	0.9143	0.0917	0.3289
	PC2	0.1383	1.1483	0.0878	0.1152
	PC3	0.1357	1.1454	0.092	0.1402
	ForestEdge	<0.0001	1	0.0004	0.743
	CropEdge	-0.0006	0.9994	0.0001	0.0001
	RoadDist	-0.0007	0.9993	0.0005	0.1861
	Slope	0.0021	1.0021	0.0240	0.9302
5	(Intercept)	-0.0200	0.9802	0.0835	0.8106
	PublicLand	-0.7873	0.4551	0.2401	0.0010
	MeanParcelSize	<0.0001	1	<0.0001	0.0473
6	(Intercept)	-0.1970	0.8212	0.0800	0.0139
	PublicLand	-0.4531	0.6357	0.0970	<0.0001
	PC1	-0.0274	0.973	0.0341	0.4226
	PC2	0.0996	1.1047	0.0475	0.0360
	I(PC2^2)	0.0180	1.0181	0.0077	0.0190
	PC3	-0.0852	0.9183	0.0345	0.0134
	ForestEdge	0.0004	1.0001	<0.0001	0.0986
	MeanParcelSize	<0.0001	1	<0.0001	0.0003
	I(MeanParcelSize^2)	<0.0001	1	<0.0001	0.0156

[a]PC refers to a principal component based on percentage landcover type. The number indicates which component it is. [b] Variable coefficients [c] Standard error [d] P-value

Table 2.9. Model regression summary for top models predicting hunter success over all 6 proposed DMUs in Ohio using hunter survey data concerning hunts which occurred between 2011-2014.

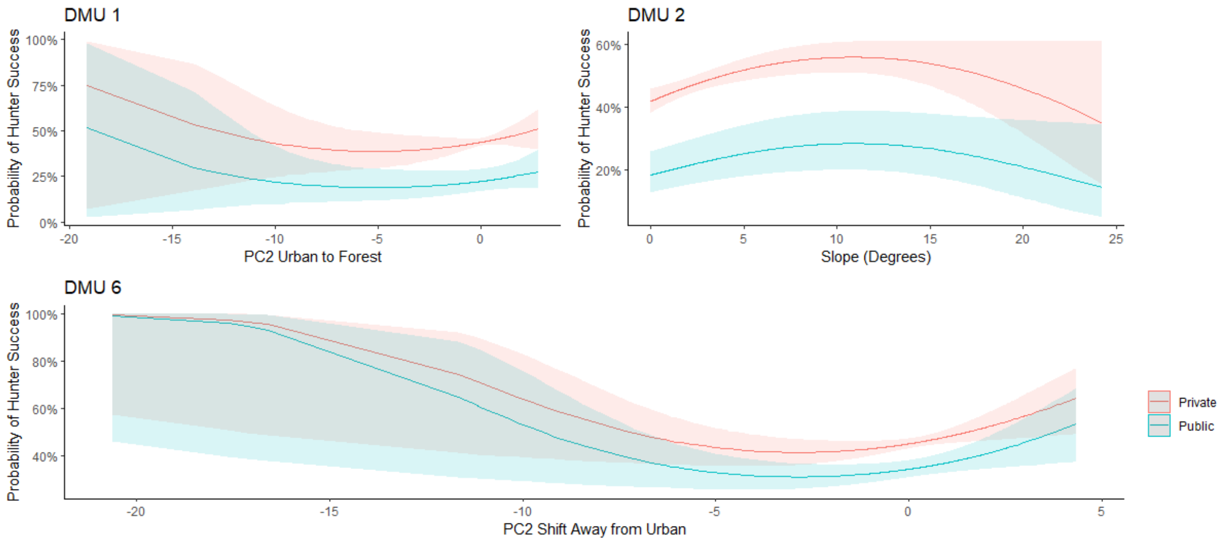

Figure 2.5. Graphed relationship between probability of hunter success and most significant variables which included a quadratic term described on X axis. Models were created using survey data from Ohio deer hunters concerning hunts which occurred during 2011-2014 seasons, final models chosen based on AIC. Shaded regions represent 95% confidence intervals.

Discussion

The effect of fine-scale environmental characteristics on larger-scale hunter distribution and success is an important, yet not well understood phenomenon in game harvest management. Though previous research has been conducted on the subject, to my knowledge past studies included a narrower set of environmental variables than I explored (e.g. Diefenbach et al. 2005, Lovely et al. 2013), data were often summarized at a much coarser (county level) scale (Foster et al. 1997) and comparisons were not made among regions with different landscape under a single state's regulatory framework such as done here between deer management units (Lebel et al. 2013, Rowland et al. 2021).

Though distance to nearest road and slope both appeared in most of the top distribution models, these results deviated from our predictions and past literature (Diefenbach et al. 2005, Rowland et al. 2021). Hunters were more likely to be found farther away from the nearest road than closer to them in all DMUs except 6, where this variable did not appear in the top model.

Where Diefenbach et al. found hunters were 3 times less likely to hunt in a location for every 0.5 km increase from the nearest road, I found that hunters were 2-4 times more likely for every 0.5 km increase, depending on the relevant DMU. For each top model including distance to nearest road of any kind recorded by LBRS data, the variable was also included as a quadratic, meaning this effect levels off and this seems to occur between 400-1000 m. These results could mean that hunters in these DMUs believe there is a better chance of success by walking a length from the road, but success may be offset by the physical costs of walking past these threshold values. Though distance to road did appear in two of the final success models, I found no significant effects between this variable and chance of harvest. Such results do not concur with literature which found distance to roads to have a detrimental effect on harvest probability (Cooper et al. 2002, Lebel et al. 2012, Rowland et al. 2021).

Though none were statistically significant, variables indicating a positive relationship between probability of use and slope were found in every top model except for DMU 3, making these results different from the literature (Diefenbach et al. 2005, Rowland et al. 2021). These results also differ from my predictions as I thought hunters would choose not to go up steeper slopes due to physical exertion and perceived lack of relationship to chances of success. The difference between this finding and that of Diefenbach et al. (2005) could be due to large differences in slopes found between the study areas. Where the slope for my study area had a maximum of about 32° (Table 2.7), Diefenbach et al. (2005) study area located within Pennsylvania had slopes up to 61°. My findings suggest that hunters do not choose locations based on slope regardless of region in the state, which is unexpected as the east side of Ohio has much higher variation in topography than the west side. Also unexpectedly, DMU 2 demonstrated a positive relationship between slope and harvest success, which may indicate that there is some benefit (e.g. improved line of sight) to higher slopes in this unit.

Hunters selected for forest dominated landscapes in every DMU. This finding aligns with the prediction that deer hunters seek out forested areas to hunt in, likely because it is seen as good deer habitat. This relationship presented itself in different, yet predictable ways depending on DMU general landcover abundance. For example, DMU 1 principal component 1 documented a shift in forest to crop dominated locations, meaning this gradient captured the most variation out of the landcover type combinations for the DMU. Top model results showed that increases in this principal component translated to decreases in hunter use (odds ratio=0.642, SE=0.0483). From these findings it can be inferred that, out of the tested landscape variables, hunters in DMU 1 select most strongly for forest and against crop which is expected from a management unit where agricultural land is much more abundant than forested. Similarly, DMUs 2 and 4 first principal components described gradients between urban and forested areas and demonstrated a positive relationship with predicted use as the landscape became more forested (odds ratio=1.2967, SE=0.0564; odds ratio=-0.572, SE=0.0683 respectively). This demonstrates strong selection for forest and against urban landcover in the context of a DMU where urban land areas are more common than forest. Though DMU 6 principal component 1 did describe a gradient towards forest that increased positively with use this effect was not significant ($P>0.05$), likely because forested landcover is the most abundant in this unit.

To my knowledge there is only one other study that investigated hunter distribution in relation to amount of forest cover. Rowland et al. (2021) found that both successful and unsuccessful mule deer (*Odocoileus hemionus)* hunters using rifles as their method of take were less likely to hunt in more forested areas. The results of my study indicated a significant positive relationship between forest cover and success only in DMU 1, which may be a result of small forest pockets providing necessary cover resources to deer in a landscape almost entirely consisting of crop areas. Contrary to the literature which found that small, fragmented forest patches increase hunter success (Foster et al. 1997, Lebel et al. 2012), I found no evidence of this. Top models which included forest-related principal components showed positive, mostly insignificant relationships between use by successful hunters and percentage forest area. Additionally, amount of forest edge did not appear in most models and did not have significant effects when it did.

Hunter success and habitat suitability index only appeared in the top model for DMU 3. HSI had a strong positive relationship with success in this unit, meaning better deer habitat translated to higher success chances in this DMU only. Principal components detailing trends in percentage landcover type generally outcompeted HSI in the success models. These findings may indicate that deer do not distribute themselves according to higher habitat quality in other DMUs or that my habitat suitability model is not accurate over most DMUs.

Mean parcel size did not notably impact hunter distribution or success according to my results, which contradicts the literature. Lovely et al. (2013) found that percentage of land hunted increased with parcel size, while deer density increased at lower parcel sizes. Lovely et al. and Haren et al. (2005) concluded that increased development restricted hunter access and created refugia with higher deer populations where hunters were excluded. Though I did find that hunters avoided urban areas and DMU 2 success increased as crop areas shifted towards urban, I did not find conclusive evidence that more developed areas reduced harvest success rates.

As predicted, this study found strong relationships between hunter distribution, success and whether they hunted on publicly owned land. Hunters in every DMU were more likely to hunt on public land than private, while also being between 36-72% less likely to succeed on public land. These findings are in line with the hypotheses for this project and with general findings from Ohio Division of Wildlife deer hunter statistics. ODW reported 32% of resident hunters were on public land during the 2014-2015 season, though public land accounts for only 4% of land area over the entire state (ODW 2016). In the same season, hunters on private land had a success rate of 28.3% compared to 13% on public land (ODW 2016). Interestingly, the strength of the relationship found in this study varied widely over the deer management units. According to the results, hunters in DMU 1 were 10.5 times more likely to hunt on public land than private, yet 0.37 times less likely to be successful (Table 2.8, Table 2.9). This intense selection for public land could be a result of the overwhelming agricultural landscape characterized by DMU 1 (Figure 2.1). In a landscape where hunting access to forested areas are hard to find and privately owned farming land is abundant, access to deer hunting locations may be limited to public land. DMU 4 hunters were 3.64 times as likely to use public land than private and 0.28 times as likely to succeed, which are the second and first highest odds ratios respectively, again in a region where forest cover is not the dominant cover type. On the other hand, DMUs 5 and 6 had lower odds ratios for use (1.9587, 1.9482 respectively) and higher for success (0.4551, 0.6357) in regions which consisted of relatively high amounts of forested area. Additional potential reasons for selecting public land could be ease of access, abundance of public land, and it could be seen as good deer habitat. Public land demonstrated the strongest relationship with success in models for all DMUs, though the relationships were negative in these models. Demonstrating strong, opposite effects in both distribution and success models, statewide selection for public land despite lower success probabilities demonstrates Ohio hunters are not distributing themselves in a way that provides the highest probability of success.

Identifying differences in model results between DMUs can provide valuable information for region-specific game management plans. I found important differences between which principal components were created for each DMU and the impact they had on hunter use depending on the overall regional landcover context. While all DMUs saw a clear trend of hunters selecting for locations with a higher percentage of forest, landcover types selected against and strength of selection for forest depended on the context of other abundant cover types. There was strong selection for forest areas by hunters in the least forested DMU, while the same effect was not statistically significant in the most forested DMU. Dominant landcover types other than forest were often selected against, for example crop being selected against in cropland dominated DMU 1 and urban areas being selected against in DMU 4, which had the highest urban area. Contrary to my predictions, I did not find significant differences between DMUs related to the impact of slope and distance to road on use, despite variation in their topography and dominant landcover types some of which are more difficult to walk through.

In a few instances the effect of certain cover types on success changed by DMU. I found this to be true in DMU 2 where landscapes with more urban area increased success compared to DMU 6 where the same variable decreased success. Variation in effect of certain landcover types on success could result from changes in deer resource use between landscapes of different dominant cover types. Where urban areas may provide important refugia within the private land and crop dominated landscape of DMU 1, it may not provide enough food and cover resources compared to areas in the heavily forested DMU 6. DMU 1 was the only region where increased forest significantly increased success, which could also be due to important resources for deer in forested areas compared to the agricultural landscape. These findings exemplify how impacts of a single variable can change between deer management units. As with the distribution predictive models, I concluded that these differences were due to the overall deer management unit landcover context and how this changes hunter and deer resources. Differences between DMUs based on landcover context likely also applies to the public land versus private land findings as well. Areas where forest land was abundant usually demonstrated less strong selection for public land than in DMUs where forest was less abundant. Results from the success models demonstrated more detrimental impacts of public land on harvest chances in DMUs where public land and forested land were relatively less abundant. This may be a result of many hunters converging on accessible public lands which consist of relatively rare, preferred cover types in these DMUs, resulting in lower success and potentially providing deer refugia outside of those areas.

Future research on this subject could improve and elaborate on these findings in a few areas. The first would be adding in potentially important variables not explored here such as weather, hunter effort and CRP lands. Another study could investigate variables which influence success specifically on public lands to get an idea of why it seems to be a distinct factor in lowering hunting success. Lastly, it would be interesting to compare changes in factors influencing hunter distribution and success between different methods of take to tailor potential harvest management plans to those categories of hunters.

Management Implications

Spatial data extracted at a small scale seemed to influence hunter distribution and success differently depending on the regional landcover context. Information concerning hunter behavior and outcomes in response to spatial variables within certain DMUs can be used to devise region-specific management plans to achieve region-specific deer harvest and population goals. Overall, incentivizing landowners to allow hunting on their property and facilitating access for hunters may be the most effective strategy to increase hunter success, which could then increase satisfaction (Miller and Graefe 2001, Black and Jensen 2018) and, in turn, hunter participation (Mehmood et al. 2003). Identifying influences on hunter selection and success rates can be used to delineate areas where over and underharvest may occur. Areas of high selection and harvest rates may experience overharvest while the opposite is true for underharvest, which should be accounted for through targeted management plans based on agency goals. Management plans that take these results into account may have a better chance of sustaining harvest as a practical and effect technique to control deer populations while also generating various economic and social benefits.

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Appendix A. Results of Northern Bobwhite Whistle Count Survey

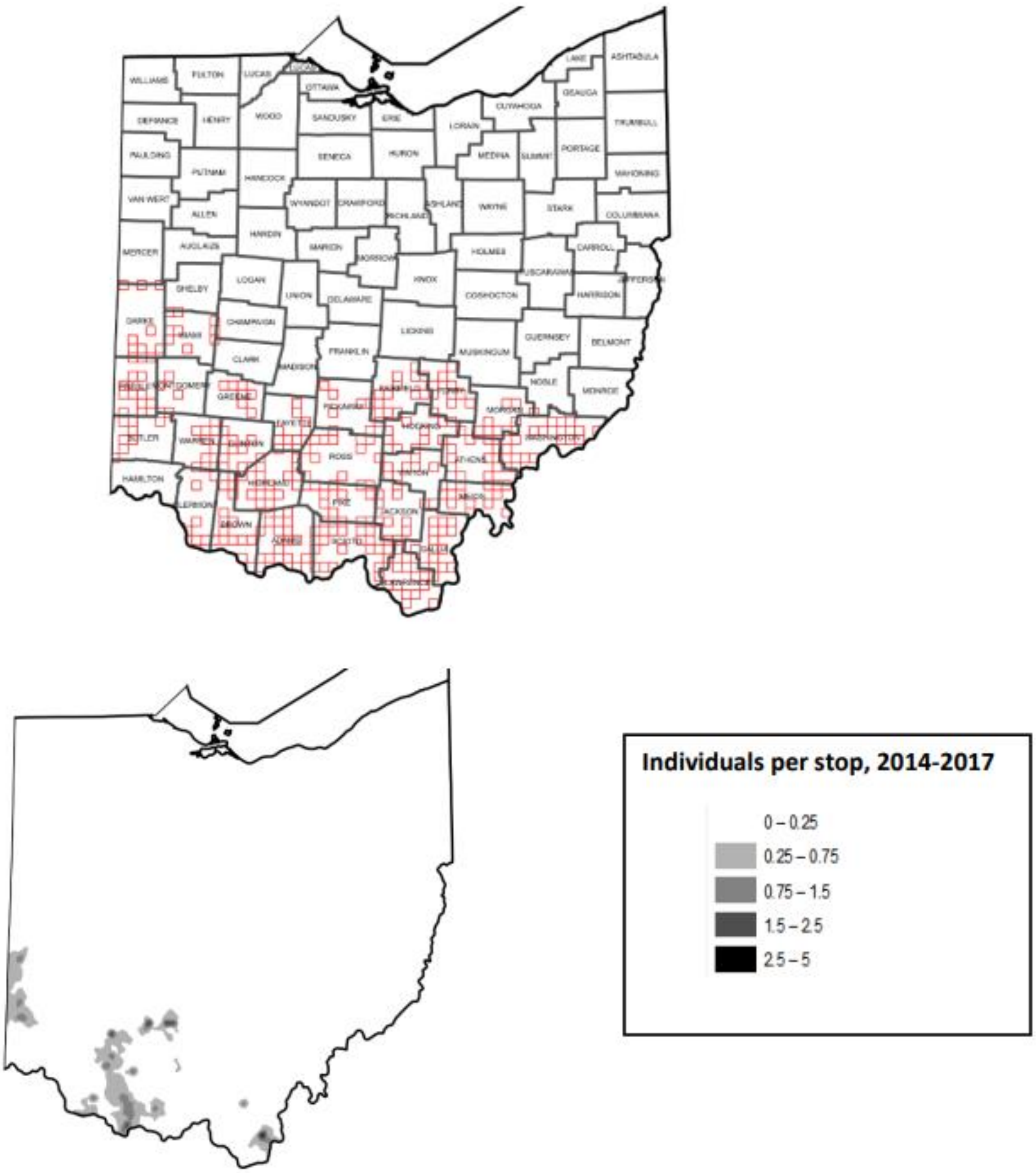

Figure A.1. Map of Northern Bobwhite quail survey done by Ohio department of natural resources (top). Each square represents a route in which 6 stops were surveyed. There is also a map which visualizes the results of this study over 2014-2017 (bottom).

Appendix B. Distance to Cover Type Models Breeding

Cover Type[a]	Covariate	β[b]	SE[c]	P[d]
ES Herb	(Intercept)	0.1265	0.1537	0.4105
	ESWoody	-0.0046	0.0010	0.0000
	Forest	0.0027	0.0005	0.0000
	RowCrop	0.0009	0.0009	0.3069
	PastureHay	-0.0020	0.0003	0.0000
	ESWoody:PastureHay	0.0000	0.0000	0.0000
	Forest:RowCrop	0.0000	0.0000	0.0000
	Forest:PastureHay	0.0000	0.0000	0.0086
ES Woody	(Intercept)	0.2658	0.1806	0.1410
	ESHerb	-0.0009	0.0006	0.1277
	Forest	0.0033	0.0006	0.0000
	RowCrop	0.0008	0.0019	0.6788
	PastureHay	-0.0028	0.0005	0.0000
	ESHerb:RowCrop	-0.0001	0.0000	0.0011
	ESHerb:PastureHay	0.0000	0.0000	0.0114
	Forest:RowCrop	0.0000	0.0000	0.0066
	Forest:PastureHay	0.0000	0.0000	0.0005
	RowCrop:PastureHay	0.0000	0.0000	0.0671
Forest	(Intercept)	1.7577	0.2337	0.0000
	ESHerb	0.0000	0.0010	0.9809
	ESWoody	-0.0113	0.0021	0.0000
	RowCrop	0.0077	0.0020	0.0001
	PastureHay	0.0001	0.0007	0.9095
	ESHerb:ESWoody	0.0000	0.0000	0.1217
	ESHerb:RowCrop	-0.0001	0.0000	0.0000
	ESHerb:PastureHay	0.0000	0.0000	0.0000
	ESWoody:PastureHay	0.0000	0.0000	0.0000
	RowCrop:PastureHay	-0.0001	0.0000	0.0000

Continued

[a] Cover type to which models will be applied [b] RC = row crop; PH = pasture/hay; F = forest; ESW = early successional woody; ESH = early successional herbaceous [c] k = number of parameters; AIC = Akaike's information criteria; ΔAIC = difference between AIC for best model and model i; wi = Akaike weight

Table B.1. Candidate model sets of factors influencing probability of use of cover by northern bobwhites radio-tracked on 4 study sites in southwestern Ohio during the breeding season (April-September 2010- 2011).

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Table B.1 Continued

Cover Type[a]	Covariate	β[b]	SE[c]	P[d]
Pasture/Hay	(Intercept)	1.7428	0.3448	0.0000
	ESHerb	-0.0022	0.0010	0.0312
	ESWoody	-0.0033	0.0018	0.0685
	RowCrop	-0.0045	0.0041	0.2705
	Forest	-0.0005	0.0010	0.6091
	ESHerb:RowCrop	-0.0001	0.0000	0.0001
	ESWoody:RowCrop	0.0000	0.0000	0.0361
	RowCrop:Forest	0.0000	0.0000	0.0949
Row Crop	(Intercept)	0.5486	0.2058	0.0077
	ESHerb	-0.0035	0.0007	0.0000
	ESWoody	0.0063	0.0013	0.0000
	PastureHay	-0.0008	0.0004	0.0301
	Forest	0.0044	0.0007	0.0000
	ESHerb:PastureHay	0.0000	0.0000	0.0000
	ESHerb:Forest	0.0000	0.0000	0.1100
	ESWoody:Forest	0.0000	0.0000	0.0000

Appendix C. Distance to Cover Type Models Nonbreeding

Cover Type[a]	Covariate	β[b]	SE[c]	P[d]
ES Herb	(Intercept)	1.8815	0.1576	0.0000
	ESWoody	-0.0095	0.0014	0.0000
	Forest	-0.0009	0.0005	0.1023
	RowCrop	-0.0133	0.0012	0.0000
	PastureHay	-0.0014	0.0003	0.0001
	ESWoody:PastureHay	0.0000	0.0000	0.0005
	Forest:PastureHay	0.0000	0.0000	0.0077
	RowCrop:PastureHay	0.0000	0.0000	0.0460
ES Woody	(Intercept)	0.7279	0.1135	0.0000
	ESHerb	0.0003	0.0004	0.4150
	Forest	0.0014	0.0005	0.0028
	RowCrop	-0.0056	0.0007	0.0000
	PastureHay	-0.0020	0.0003	0.0000
	ESHerb:Forest	0.0000	0.0000	0.0000
	ESHerb:RowCrop	0.0000	0.0000	0.0293
	ESHerb:PastureHay	0.0000	0.0000	0.0219
	Forest:PastureHay	0.0000	0.0000	0.0050
Forest	(Intercept)	1.4349	0.1654	0.0000
	ESHerb	0.0017	0.0006	0.0021
	ESWoody	-0.0024	0.0008	0.0016
	RowCrop	0.0061	0.0020	0.0027
	PastureHay	0.0005	0.0004	0.2299
	ESHerb:RowCrop	-0.0001	0.0000	0.0000
	ESHerb:PastureHay	0.0000	0.0000	0.0000
	RowCrop:PastureHay	-0.0001	0.0000	0.0000

Continued

[a] Cover type to which models will be applied [b] RC = row crop; PH = pasture/hay; F = forest; ESW = early successional woody; ESH = early successional herbaceous [c] k = number of parameters; AIC = Akaike's information criteria; ΔAIC = difference between AIC for best model and model i; wi = Akaike weight

Table C.1. Candidate model sets of factors influencing probability of use of cover by northern bobwhites radio-tracked on 4 study sites in southwestern Ohio during the non-breeding season (October-March 2009- 2011).

Table C.1 Continued

Cover Type[a]	Covariate	β[b]	SE[c]	P[d]
Pasture/Hay	(Intercept)	0.7903	0.3004	0.0085
	ESHerb	0.0015	0.0010	0.1541
	ESWoody	0.0156	0.0028	0.0000
	RowCrop	-0.0158	0.0042	0.0002
	Forest	0.0015	0.0013	0.2380
	ESHerb:ESWoody	-0.0001	0.0000	0.0009
	ESHerb:RowCrop	0.0000	0.0000	0.1102
	ESWoody:Forest	-0.0001	0.0000	0.0000
	RowCrop:Forest	0.0000	0.0000	0.0696
Row Crop	(Intercept)	1.6217	0.2808	0.0000
	ESHerb	-0.0001	0.0006	0.8814
	ESWoody	-0.0090	0.0025	0.0003
	PastureHay	-0.0010	0.0007	0.1433
	Forest	-0.0007	0.0010	0.4661
	ESHerb:ESWoody	0.0000	0.0000	0.0088
	ESHerb:PastureHay	0.0000	0.0000	0.0000
	ESWoody:PastureHay	0.0000	0.0000	0.1449
	ESWoody:Forest	0.0000	0.0000	0.0003
	PastureHay:Forest	0.0000	0.0000	0.0197

Appendix D. Hunter Distribution Models Principal Component Results

DMU	Principal Component	Low Urban	High Urban	Forest	Shrub	Herbaceous	Pasture	Crops
1	1	-0.4401	-0.3720	-0.6414	-0.1082	-0.2016	-0.5394	0.9614
	2	0.7433	0.7431	-0.5285	-0.1012	0.0708	-0.3173	0.1007
	3	-0.0209	-0.0727	0.0561	0.5920	0.7443	-0.3219	0.0418
2	1	-0.8150	-0.7453	0.7227	0.1661	0.0660	0.1660	-0.0208
	2	0.2707	0.2292	0.6091	0.1317	0.2314	-0.6094	-0.7323
	3	0.0778	-0.0214	-0.0064	-0.4697	0.0997	0.6701	-0.5938
3	1	-0.8634	-0.7968	0.2226	0.0918	-0.2408	0.0754	0.5059
	2	-0.1086	-0.1977	0.8261	0.0457	0.1692	0.2840	-0.8304
	3	0.0019	0.1332	0.4632	0.2628	0.0926	-0.9297	0.1443
4	1	0.8392	0.7574	-0.6029	-0.1530	-0.1686	-0.2908	-0.2221
	2	0.2130	0.0877	0.7032	0.2749	0.2687	-0.2683	-0.8469
	3	0.0328	-0.0104	-0.0710	-0.3038	-0.1847	0.8460	-0.4771
5	1	0.5341	0.4037	-0.9436	-0.1982	-0.1598	0.6652	0.5538
	2	-0.6615	-0.7279	-0.2146	-0.0370	-0.1479	0.1926	0.5156
	3	0.0302	0.0614	-0.1930	0.4510	0.6799	-0.3835	0.4155
6	1	-0.5020	-0.3611	0.9789	0.0044	-0.0887	-0.7292	-0.4360
	2	0.6705	0.7347	0.1637	-0.1325	-0.1569	-0.3914	-0.3278
	3	0.0377	0.1081	-0.0678	0.7350	0.7303	-0.1369	-0.1974

Table D.1. Factor loadings resulting from principal component analysis of percentage landcover type over a 300m buffer used in the hunter distribution analysis for each proposed Ohio Deer Management Unit.

DMU	Landcover Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
1	Low Urban	-0.310	0.605	-0.021	-0.038	0.042	-0.674	-0.283
	High Urban	-0.262	0.605	-0.072	-0.104	-0.156	0.714	-0.124
	Forest	-0.452	-0.430	0.056	0.096	-0.562	0.003	-0.531
	Shrub	-0.076	-0.082	0.587	-0.800	0.051	-0.006	-0.007
	Herbaceous	-0.142	0.058	0.737	0.567	0.306	0.111	-0.069
	Pasture	-0.380	-0.258	-0.319	-0.122	0.746	0.137	-0.311
	Cultivated Crops	0.678	0.082	0.041	-0.033	0.073	0.069	-0.722
2	Low Urban	-0.607	0.223	0.076	0.061	0.017	0.608	0.450
	High Urban	-0.555	0.189	-0.021	0.049	0.050	-0.780	0.206
	Forest	0.538	0.501	-0.006	0.097	-0.232	-0.107	0.620
	Shrub	0.124	0.108	-0.461	0.294	0.817	0.039	0.067
	Herbaceous	0.049	0.191	0.098	-0.910	0.344	-0.007	0.075
	Pasture	0.124	-0.502	0.657	0.135	0.342	-0.092	0.397
	Cultivated Crops	-0.015	-0.603	-0.583	-0.228	-0.200	-0.027	0.452
3	Low Urban	-0.651	-0.088	0.002	-0.008	0.070	-0.666	0.346
	High Urban	-0.601	-0.160	0.122	0.003	0.168	0.729	0.197
	Forest	0.168	0.667	0.424	0.184	0.092	0.043	0.551
	Shrub	0.069	0.037	0.240	-0.951	0.174	-0.022	0.039
	Herbaceous	-0.182	0.137	0.085	-0.161	-0.953	0.078	0.032
	Pasture	0.057	0.229	-0.850	-0.188	0.003	0.128	0.412
	Cultivated Crops	0.382	-0.670	0.132	0.034	-0.141	0.014	0.605
4	Low Urban	0.621	0.175	0.032	0.034	0.014	0.606	0.463
	High Urban	0.560	0.072	-0.010	0.090	-0.007	-0.784	0.241
	Forest	-0.446	0.577	-0.068	-0.340	-0.008	-0.127	0.575
	Shrub	-0.113	0.226	-0.293	0.589	0.710	0.008	0.012
	Herbaceous	-0.125	0.221	-0.178	0.644	-0.699	0.025	0.037
	Pasture	-0.215	-0.220	0.816	0.337	0.088	-0.041	0.342
	Cultivated Crops	-0.164	-0.695	-0.460	0.024	-0.023	-0.011	0.526
5	Low Urban	0.364	-0.572	0.030	-0.006	0.042	-0.714	-0.167
	High Urban	0.275	-0.629	0.061	0.044	0.240	0.678	-0.078
	Forest	-0.643	-0.185	-0.190	-0.060	0.123	-0.015	-0.705
	Shrub	-0.135	-0.032	0.445	0.863	-0.171	-0.020	-0.091
	Herbaceous	-0.109	-0.128	0.671	-0.480	-0.525	0.071	-0.101
	Pasture	0.453	0.166	-0.378	0.107	-0.603	0.156	-0.473
	Cultivated Crops	0.377	0.445	0.410	-0.086	0.507	-0.005	-0.476
6	Low Urban	-0.349	0.584	0.035	0.033	0.023	-0.693	-0.235
	High Urban	-0.251	0.640	0.101	-0.136	-0.032	0.698	-0.103
	Forest	0.680	0.143	-0.063	-0.004	-0.028	0.015	-0.715
	Shrub	0.003	-0.115	0.686	-0.193	0.684	-0.014	-0.107
	Herbaceous	-0.062	-0.137	0.681	0.087	-0.700	-0.028	-0.119
	Pasture	-0.507	-0.341	-0.128	0.516	0.137	0.175	-0.543
	Cultivated Crops	-0.303	-0.285	-0.184	-0.818	-0.143	-0.033	-0.319

Table D.2. Eigen values resulting from principal component analysis of percentage landcover type over a 300m buffer used in the hunter distribution analysis for each proposed Ohio Deer Management Unit.

DMU	Metric	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
1	Variance	2.011	1.510	1.019	0.976	0.844	0.532	0.107
	Proportion Variance	0.287	0.216	0.146	0.139	0.121	0.076	0.015
2	Variance	1.802	1.475	1.039	0.987	0.970	0.629	0.099
	Proportion Variance	0.257	0.211	0.148	0.141	0.139	0.090	0.014
3	Variance	1.758	1.534	1.195	0.986	0.965	0.526	0.036
	Proportion Variance	0.251	0.219	0.171	0.141	0.138	0.075	0.005
4	Variance	1.827	1.485	1.076	1.039	0.890	0.666	0.017
	Proportion Variance	0.261	0.212	0.154	0.148	0.127	0.095	0.002
5	Variance	2.153	1.340	1.027	0.977	0.950	0.537	0.017
	Proportion Variance	0.308	0.191	0.147	0.140	0.136	0.077	0.002
6	Variance	2.070	1.319	1.149	0.961	0.868	0.614	0.019
	Proportion Variance	0.296	0.188	0.164	0.137	0.124	0.088	0.003

Table D.3. Variance explained by axes resulting from principal component analysis of percentage landcover type over a 300m buffer used in the hunter distribution analysis for each proposed Ohio Deer Management Unit.

Appendix E. Hunter Success Models Principal Component Results

DMU	Principal Component	Low Urban	High Urban	Forest	Shrub	Herbaceous	Pasture	Crops
1	1	0.3001	0.2177	0.7295	0.2011	0.1673	0.5231	-0.9469
	2	-0.7877	-0.7774	0.3895	0.0661	-0.1512	0.1386	-0.0644
	3	0.0412	0.0613	-0.1179	-0.6313	-0.6664	0.4529	-0.0653
2	1	0.4133	0.3885	-0.9368	-0.2016	-0.0503	0.4324	0.4866
	2	-0.7153	-0.6551	-0.1252	0.0275	-0.2656	0.4112	0.5081
	3	0.0573	-0.1026	0.0295	-0.2220	-0.0682	0.7471	-0.6728
3	1	-0.8513	-0.7775	0.1306	0.0957	-0.2703	-0.1879	0.5423
	2	0.1674	0.2104	-0.9440	-0.0116	-0.0770	0.0594	0.7759
	3	0.1682	0.3435	0.2603	0.1362	-0.2037	-0.9438	0.2412
4	1	0.2678	0.3701	-0.9667	-0.1876	-0.2140	0.3729	0.5916
	2	-0.8202	-0.7034	-0.0074	-0.0570	-0.1131	0.3293	0.5327
	3	0.0006	0.0076	-0.0896	0.4421	0.4037	-0.6536	0.5467
5	1	0.5609	0.4307	-0.9394	-0.1618	-0.1824	0.6655	0.5434
	2	-0.6563	-0.7404	-0.2231	0.0049	-0.1791	0.3267	0.4199
	3	0.0225	-0.0494	0.1983	-0.6697	-0.5060	0.3226	-0.4055
6	1	0.4991	0.3485	-0.9771	0.0264	0.1062	0.7611	0.4329
	2	-0.6860	-0.7523	-0.1725	0.1515	0.2032	0.3541	0.3256
	3	0.0554	0.1222	-0.0336	0.7137	0.7144	-0.0901	-0.2986

Table E.1. Factor loadings resulting from principal component analysis of percentage landcover type over a 300m buffer used in the hunter success analysis for each proposed Ohio Deer Management Unit.

DMU	Landcover Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
1	Low Urban	0.217	-0.659	0.040	-0.012	-0.061	0.687	0.200
	High Urban	0.158	-0.651	0.059	-0.209	0.171	-0.686	0.069
	Forest	0.528	0.326	-0.114	-0.139	0.502	0.027	0.574
	Shrub	0.146	0.055	-0.610	-0.605	-0.487	-0.009	-0.007
	Herbaceous	0.121	-0.127	-0.644	0.724	-0.071	-0.139	0.077
	Pasture	0.379	0.116	0.438	0.209	-0.682	-0.186	0.329
	Cultivated Crops	-0.685	-0.054	-0.063	-0.045	-0.086	-0.048	0.715
2	Low Urban	0.320	-0.593	0.055	0.108	0.130	0.627	-0.347
	High Urban	0.301	-0.543	-0.099	0.036	0.128	-0.757	-0.119
	Forest	-0.726	-0.104	0.028	0.185	-0.028	-0.113	-0.644
	Shrub	-0.156	0.023	-0.214	-0.642	0.715	0.049	-0.061
	Herbaceous	-0.039	-0.220	-0.066	-0.704	-0.663	0.021	-0.100
	Pasture	0.335	0.341	0.719	-0.200	0.070	-0.134	-0.438
	Cultivated Crops	0.377	0.421	-0.648	0.073	-0.101	-0.003	-0.496
3	Low Urban	-0.642	0.133	0.152	-0.030	-0.135	-0.665	-0.293
	High Urban	-0.586	0.168	0.311	0.020	-0.032	0.721	-0.101
	Forest	0.098	-0.752	0.235	-0.070	0.013	0.072	-0.599
	Shrub	0.072	-0.009	0.123	0.976	-0.154	-0.033	-0.050
	Herbaceous	-0.204	-0.061	-0.184	0.183	0.940	-0.041	-0.035
	Pasture	-0.142	0.047	-0.853	0.069	-0.216	0.173	-0.410
	Cultivated Crops	0.409	0.618	0.218	-0.057	0.161	0.018	-0.611
4	Low Urban	0.205	-0.653	0.001	0.018	0.019	0.631	0.363
	High Urban	0.283	-0.560	0.007	0.032	0.021	-0.762	0.155
	Forest	-0.739	-0.006	-0.086	0.180	0.023	-0.135	0.629
	Shrub	-0.143	-0.045	0.423	-0.559	0.697	-0.016	0.019
	Herbaceous	-0.163	-0.090	0.386	-0.549	-0.716	-0.025	0.038
	Pasture	0.285	0.262	-0.625	-0.546	0.005	-0.035	0.400
	Cultivated Crops	0.452	0.424	0.523	0.234	-0.025	-0.022	0.535
5	Low Urban	0.380	-0.566	0.022	-0.005	-0.012	0.710	-0.172
	High Urban	0.292	-0.639	-0.049	-0.103	-0.136	-0.685	-0.077
	Forest	-0.636	-0.192	0.197	-0.039	-0.132	0.007	-0.707
	Shrub	-0.110	0.004	-0.665	-0.681	0.263	0.059	-0.099
	Herbaceous	-0.124	-0.154	-0.502	0.697	0.456	-0.056	-0.110
	Pasture	0.451	0.282	0.320	-0.098	0.582	-0.138	-0.498
	Cultivated Crops	0.368	0.362	-0.402	0.171	-0.590	-0.011	-0.441
6	Low Urban	0.344	-0.588	0.052	0.004	-0.021	-0.697	0.217
	High Urban	0.240	-0.645	0.115	0.124	0.111	0.693	0.078
	Forest	-0.674	-0.148	-0.032	-0.003	0.041	0.014	0.722
	Shrub	0.018	0.130	0.670	0.450	-0.566	0.002	0.106
	Herbaceous	0.073	0.174	0.670	-0.227	0.672	-0.052	0.096
	Pasture	0.525	0.303	-0.085	-0.457	-0.272	0.176	0.558
	Cultivated Crops	0.298	0.279	-0.280	0.722	0.373	-0.021	0.305

Table E.2. Eigen values resulting from principal component analysis of percentage landcover type over a 300m buffer used in the hunter success analysis for each proposed Ohio Deer Management Unit.

DMU	Metric	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
1	Variance	1.908	1.427	1.071	0.931	0.909	0.588	0.166
	Proportion Variance	0.273	0.204	0.153	0.133	0.130	0.084	0.024
2	Variance	1.666	1.455	1.080	0.994	0.973	0.681	0.151
	Proportion Variance	0.238	0.208	0.154	0.142	0.139	0.097	0.022
3	Variance	1.758	1.575	1.223	0.997	0.956	0.445	0.047
	Proportion Variance	0.251	0.225	0.175	0.142	0.137	0.064	0.007
4	Variance	1.713	1.576	1.093	1.075	0.886	0.630	0.027
	Proportion Variance	0.245	0.225	0.156	0.154	0.127	0.090	0.004
5	Variance	2.180	1.344	1.015	0.987	0.952	0.502	0.021
	Proportion Variance	0.311	0.192	0.145	0.141	0.136	0.072	0.003
6	Variance	2.104	1.362	1.136	0.950	0.855	0.568	0.025
	Proportion Variance	0.301	0.195	0.162	0.136	0.122	0.081	0.004

Table E.3. Variance explained by axes resulting from principal component analysis of percentage landcover type over a 300m buffer used in the hunter success analysis for each proposed Ohio Deer Management Unit.

Appendix F. Hunter Distribution Candidate Models

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICc Wt
1	Access	PublicLand +MeanParcelSize	3	-3347.06	6700.13	0.0000	0.681
		PublicLand	2	-3348.82	6701.64	1.512	0.319
		Null	1	-3453.26	6908.52	208.391	0.0000
	Difficulty	Slope+I(Slope^2)+RoadDist+I(RoadDist^2)	5	-3292.14	6594.3	0.0000	0.67
		Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+Slope:RoadDist	6	-3291.85	6595.71	1.412	0.33
		Slope+I(Slope^2)	3	-3371.26	6748.53	154.237	0.0000
		RoadDist+I(RoadDist^2)	3	-3379.68	6765.37	171.076	0.0000
		Null	1	-3453.26	6908.52	314.223	0.0000
	Landscape	PC1+I(PC1^2)+PC2+I(PC2^2) +PC3	7	-2956.68	5927.37	0.0000	1
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+ForestEdge	6	-2975.36	5962.73	35.356	0.0000
		Null	1	-3453.26	6908.52	981.145	0.0000
	Final	PublicLand+Slope+I(Slope^2)+ RoadDist+I(RoadDist^2)+ PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+ForestEdge +(PC1:RoadDist)	13	-2890.25	5806.57	0.0000	0.502
		PublicLand+Slope+I(Slope^2)+ RoadDist+I(RoadDist^2)+ PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+ForestEdge	12	-2891.26	5806.58	0.013	0.498
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+ForestEdge	7	-2956.68	5927.37	120.807	0.0000
		Slope+I(Slope^2)+RoadDist+ I(RoadDist^2)	5	-3292.14	6594.3	787.73	0.0000
		PublicLand	2	-3348.82	6701.64	895.075	0.0000
		Null	1	-3453.26	6908.52	1101.953	0.0000
2	Access	PublicLand +MeanParcelSize+ I(MeanParcelSize ^2)	4	-2973.69	5955.4	0.0000	0.87
		PublicLand	2	-2977.6	5959.19	3.798	0.13
		Null	1	-3004.1	6010.2	54.805	0.0000

Continued

[a] PC refers to principal components calculated from precent landcover variables within 300m buffer

Table F.1. Candidate model set results for the hunter distribution analysis over all DMUs.

Table F.1 Continued

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICc Wt
	Difficulty	Slope+I(Slope^2)+RoadDist+ I(RoadDist^2)+(Slope:RoadDist)	6	-2937.44	5886.9	0.0000	0.969
		Slope+I(Slope^2)+RoadDist+I(RoadDist^2)	5	-2941.89	5893.8	6.897	0.031
		RoadDist+I(RoadDist^2)	3	-2954.73	5915.47	28.568	0.0000
		Slope+I(Slope^2)	3	-2991.6	5989.21	102.307	0.0000
		Null	1	-3004.1	6010.2	123.297	0.0000
	Landscape	PC1+I(PC1^2)+PC2+I(PC2^2) +PC3	6	-2785.49	5583.01	0.0000	0.6060
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+ForestEdge	7	-2784.92	5583.87	0.8590	0.3940
		Null	1	-3004.1	6010.2	427.195	0.0000
	Final	PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+(Slope:RoadDist)+PublicLand +parcel300+I(parcel300^2)	14	-2765.16	5558.41	0.0000	0.7290
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+(Slope:RoadDist)+PublicLand +MeanParcelSize+I(MeanParcelSize^2)+PC2:RoadDist	15	-2765.14	5560.39	1.983	0.2710
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3	6	-2785.49	5583.01	24.597	0.0000
		Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+(Slope:RoadDist)	6	-2937.44	5886.9	328.495	0.0000
		PublicLand +MeanParcelSize+I(MeanParcelSize^2)	4	-2973.69	5955.4	396.987	0.0000
		Null	1	-3004.1	6010.2	451.792	0.0000
3	Access	PublicLand	2	-1515.18	3034.36	0.0000	0.7090
		PublicLand +MeanParcelSize	3	-1515.07	3036.15	1.782	0.2910
		Null	1	-1523.54	3049.08	14.713	0.0000
	Difficulty	Slope+RoadDist+I(RoadDist^2)+ (Slope:RoadDist)	5	-1500.86	3011.76	0.0000	0.7690
		Slope+ RoadDist+I(RoadDist^2)	4	-1503.1	3014.21	2.454	0.2260
		RoadDist+I(RoadDist^2)	3	-1507.91	3021.82	10.067	0.0050
		Slope	2	-1517.42	3038.85	27.094	0.0000
		Null	1	-1523.54	3049.08	37.322	0.0000

Continued

Table F.1 Continued

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICc Wt
	Landscape	PC1+I(PC1^2)+PC2+PC3+Forest Edge	6	-1428.95	2869.93	0.0000	0.9690
		PC1+I(PC1^2)+PC2+PC3	5	-1433.39	2876.81	6.874	0.0310
		Null	1	-1523.54	3049.08	179.145	0.0000
	Final	PC1+I(PC1^2)+PC2+PC3+Forest Edge +PublicLand+Slope+ RoadDist+ I(RoadDist^2)+ (Slope:RoadDist)	11	-1422.85	2867.81	0.0000	0.4310
		PC1+I(PC1^2)+PC2+PC3+Forest Edge +PublicLand+Slope+ RoadDist+I(RoadDist^2)+(Slope:RoadDist)+(PC2:RoadDist)	12	-1421.86	2867.87	0.052	0.4200
		PC1+I(PC1^2)+PC2+PC3+Forest Edge	6	-1428.95	2869.93	2.117	0.1490
		Slope+ RoadDist+ I(RoadDist^2)+(Slope:RoadDist)	5	-1500.86	3011.76	143.941	0.0000
		PublicLand	2	-1515.18	3034.36	166.549	0.0000
		Null	1	-1523.54	3049.08	181.262	0.0000
4	Access	PublicLand	2	-864.73	1733.47	0.0000	0.7240
		PublicLand +MeanParcelSize	3	-864.69	1735.4	1.93	0.2760
		Null	1	-881.68	1765.37	31.902	0.0000
	Difficulty	Slope+RoadDist+I(RoadDist^2)+(Slope:RoadDist)	5	-829.23	1668.51	0.0000	0.6170
		Slope+RoadDist+I(RoadDist^2)	4	-830.71	1669.46	0.951	0.3830
		RoadDist+I(RoadDist^2)	3	-852.88	1711.77	43.264	0.0000
		Slope	2	-860.95	1725.91	57.401	0.0000
		Null	1	-881.68	1765.37	96.863	0.0000
	Landscape	PC1+PC2+I(PC2^2)+PC3	5	-759.36	1528.76	0.0000	0.7330
		PC1+PC2+I(PC2^2)+PC3+Forest Edge	6	-759.36	1530.78	2.019	0.2670
		Null	1	-881.68	1765.37	236.61	0.0000
	Final	PC1+PC2+I(PC2^2)+PC3+Slope +RoadDist+I(RoadDist^2)+PublicLand+(RoadDist:PC2)	10	-746.84	1513.86	0.0000	0.6510
		PC1+PC2+I(PC2^2)+PC3+Slope +RoadDist+I(RoadDist^2)+ PublicLand	9	-748.48	1515.1	1.247	0.3490
		PC1+PC2+I(PC2^2)+PC3	5	-759.36	1528.76	14.904	0.0000
		Slope+RoadDist+I(RoadDist^2)	4	-830.71	1669.46	155.601	0.0000
		PublicLand	2	-864.73	1733.47	219.612	0.0000
		Null	1	-881.68	1765.37	251.514	0.0000

Continued

Table F.1 Continued

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICc Wt
5	Access	PublicLand	2	-997.96	1999.93	0.0000	0.7310
		PublicLand +MeanParcelSize	3	-997.96	2001.93	2.002	0.2690
		Null	1	-1006.45	2014.9	14.969	0.0000
	Difficulty	Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+(Slope:RoadDist)	6	-993.74	1999.54	0.0000	0.6760
		Slope+I(Slope^2)+RoadDist+I(RoadDist^2)	5	-995.6	2001.24	1.702	0.2890
		RoadDist+I(RoadDist^2)	3	-999.92	2005.85	6.31	0.0290
		Slope+I(Slope^2)	3	-1001.49	2009	9.465	0.0060
		Null	1	-1006.45	2014.9	15.364	0.0000
	Landscape	PC1+PC2+PC3+ForestEdge	5	-990.9	1991.84	0.0000	0.9690
		PC1+PC2+PC3	4	-995.36	1998.75	6.912	0.0310
		Null	1	-1006.45	2014.9	23.063	0.0000
	Final	PC1+PC2+PC3+ForestEdge +Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+PublicLand	10	-973.39	1966.93	0.0000	0.7190
		PC1+PC2+PC3+ForestEdge +Slope+I(Slope^2)+RoadDist+I(RoadDist^2)+PublicLand+(RoadDist:PC1)	11	-973.31	1968.81	1.879	0.2810
		PC1+PC2+PC3+ForestEdge	5	-990.9	1991.84	24.906	0.0000
		PublicLand	2	-997.96	1999.93	33	0.0000
		Slope+I(Slope^2)+RoadDist+I(RoadDist^2)	5	-995.60	2001.24	34.308	0.0000
		Null	1	-1006.45	2014.9	47.969	0.0000
6	Access	PublicLand +MeanParcelSize+I(MeanParcelSize^2)	4	-5274.51	10557.02	0.0000	0.5670
		PublicLand	2	-5276.78	10557.56	0.5370	0.4330
		Null	1	-5341.39	10684.78	127.763	0.0000
	Difficulty	Slope+I(Slope^2)+RoadDist	4	-5328.28	10664.57	0.0000	0.4200
		Slope+I(Slope^2)+RoadDist+(Slope:RoadDist)	5	-5327.59	10665.2	0.6260	0.3070
		Slope+I(Slope^2)	3	-5329.72	10665.44	0.8690	0.2720
		Null	1	-5341.39	10684.78	20.216	0.0000
		RoadDist	2	-5340.62	10685.24	20.669	0.0000

Continued

Table F.1 Continued

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICc Wt
	Landscape	PC1+I(PC1^2)+PC2+I(PC2^2) +PC3	6	-5283.58	10579.18	0.0000	0.6950
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+ForestEdge	7	-5283.41	10580.83	1.6520	0.3050
		Null	1	-5341.39	10684.78	105.61	0.0000
	Final	PublicLand+ PC1+I(PC1^2)+PC2+I(PC2^2) +PC3+Slope+I(Slope^2)	9	-5227.91	10473.85	0.0000	1.0000
		PublicLand	2	-5276.78	10557.56	83.705	0.0000
		PC1+I(PC1^2)+PC2+I(PC2^2) +PC3	6	-5283.58	10579.18	105.322	0.0000
		Slope+I(Slope^2)	3	-5329.72	10665.44	191.585	0.0000
		Null	1	-5341.39	10684.78	210.931	0.0000

Appendix G. Hunter Success Candidate Models

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICcWt
1	Access	PublicLand	2	-1684.43	3372.86	0.0000	0.716
		PublicLand +(MeanParcelSize)	3	-1684.35	3374.71	1.853	0.284
		Null	1	-1697.07	3396.14	23.282	0.000
	Difficulty	RoadDist	2	-1694.41	3392.82	0.0000	0.608
		RoadDist+Slope	3	-1694.37	3394.74	1.919	0.233
		Null	1	-1697.07	3396.14	3.318	0.116
		Slope	2	-1697.06	3398.12	5.303	0.043
	Landscape	PC1+PC2+I(PC2^2)+PC3	5	-1688.33	3386.68	0.000	0.491
		PC1+PC2+I(PC2^2)+PC3+ ForestEdge+CropEdge	7	-1686.74	3387.52	0.839	0.323
		PC1+PC2+I(PC2^2)+PC3+ForestEdge	6	-1688.33	3388.68	2.004	0.18
		Null	1	-1697.07	3396.14	9.459	0.004
		HSI	2	-1697	3398.00	11.319	0.002
	Final	PC1+PC2+I(PC2^2)+PC3+PublicLand +RoadDist	7	-1670.2	3354.44	0.0000	0.724
		PC1+PC2+I(PC2^2)+PC3+PublicLand +RoadDist+PC1:PublicLand	8	-1670.15	3356.37	1.927	0.276
		PublicLand	2	-1684.43	3372.86	18.419	0.000
		PC1+PC2+I(PC2^2)+PC3	5	-1688.33	3386.68	32.242	0.000
		RoadDist	2	-1694.41	3392.82	38.383	0.000
		Null	1	-1697.07	3396.14	41.701	0.000
2	Access	PublicLand+MeanParcelSize	3	-1474.89	2955.79	0.000	0.549
		PublicLand	2	-1476.09	2956.18	0.393	0.451
		Null	1	-1492.15	2986.3	30.512	0.000
	Difficulty	RoadDist+Slope+I(Slope^2)	4	-1480.33	2968.67	0.000	0.48
		Slope+I(Slope^2)	3	-1481.35	2968.71	0.037	0.471
		Slope	2	-1484.64	2973.28	4.609	0.048
		RoadDist	2	-1490.49	2984.99	16.316	0.000
		Null	1	-1492.15	2986.3	17.628	0.000
	Landscape	PC1+PC2+I(PC2^2)+PC3	5	-1486.98	2983.99	0.000	0.397
		HSI	2	-1490.58	2985.17	1.178	0.22
		PC1+PC2+I(PC2^2)+PC3+ForestEdge	6	-1486.86	2985.77	1.779	0.163
		Null	1	-1492.15	2986.3	2.311	0.125
		PC1+PC2+I(PC2^2)+PC3+ForestEdge +CropEdge	7	-1486.39	2986.83	2.842	0.096

Continued

Table G.1. Candidate model set results for the hunter success analysis over all DMUs.

Table G.1 Continued

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICcWt
3	Access	PublicLand+MeanParcelSize	3	-749.55	1505.11	0.000	0.79
		PublicLand	2	-751.89	1507.79	2.681	0.207
		Null	1	-756.93	1515.87	10.76	0.004
	Difficulty	Null	1	-756.93	1515.87	0.000	0.516
		Slope	2	-756.83	1517.67	1.794	0.211
		RoadDist	2	-756.91	1517.83	1.954	0.194
		Slope+RoadDist	3	-756.8	1519.63	3.755	0.079
	Landscape	HSI	2	-754.91	1513.84	0.000	0.425
		PC1+PC2+PC3+ForestEdge+CropEdge	6	-751.1	1514.29	0.448	0.34
		Null	1	-756.93	1515.87	2.036	0.154
		PC1+PC2+PC3	4	-755.15	1518.34	4.501	0.045
		PC1+PC2+PC3+ForestEdge	5	-754.36	1518.78	4.94	0.036
	Final	HSI+PublicLand+MeanParcelSize	4	-747.03	1502.09	0.000	0.629
		HSI+PublicLand+MeanParcelSize+ HSI:MeanParcelSize	5	-747.03	1504.11	2.013	0.23
		PublicLand	3	-749.55	1505.11	3.02	0.139
		HSI	2	-754.91	1513.84	11.744	0.002
		Null	1	-756.93	1515.87	13.78	0.001
4	Access	PublicLand	2	-432.94	869.9	0.000	0.514
		PublicLand+MeanParcelSize	3	-431.99	870.03	0.127	0.483
		Null	1	-439.03	880.06	10.166	0.003
	Difficulty	Slope+RoadDist	3	-430.42	866.88	0.000	0.727
		Slope	2	-432.44	868.9	2.025	0.264
		RoadDist	2	-435.98	875.98	9.109	0.008
		Null	1	-439.03	880.06	13.188	0.001
	Landscape	PC1+PC2+PC3+ForestEdge+CropEdge	6	-418.76	849.65	0.000	0.999
		PC1+PC2+PC3	4	-427.69	863.45	13.804	0.001
		PC1+PC2+PC3+ForestEdge	5	-427.66	865.41	15.766	0.000
		HSI	2	-435.65	875.31	25.663	0.000
		Null	1	-439.03	880.06	30.415	0.000
	Final	PC1+PC2+PC3+ForestEdge+CropEdge+ PublicLand+ Slope+RoadDist	9	-409.62	837.52	0.000	0.699
		PC1+PC2+PC3+ForestEdge+CropEdge+ PublicLand+ Slope+RoadDist +PC1:PublicLand	10	-409.43	839.22	1.695	0.3
		PC1+PC2+PC3+ForestEdge+CropEdge	6	-418.76	849.65	12.126	0.002
		Slope+RoadDist	3	-430.42	866.88	29.353	0.000
		PublicLand	2	-432.94	869.9	32.376	0.000
		Null	1	-439.03	880.06	42.542	0.000

Continued

Table G.1 Continued

DMU	Category	Model	K	logLik	AICc	ΔAICc	AICcWt
5	Access	PublicLand+MeanParcelSize	3	-484.06	974.15	0.000	0.891
		PublicLand	2	-487.17	978.35	4.209	0.109
		Null	1	-499.03	1000.06	25.914	0.000
	Difficulty	Slope	2	-497.86	999.74	0.000	0.363
		Null	1	-499.03	1000.06	0.322	0.309
		RoadDist	2	-498.65	1001.31	1.573	0.165
		Slope+RoadDist	3	-497.66	1001.35	1.613	0.162
	Landscape	Null	1	-499.03	1000.06	0.000	0.52
		HSI	2	-499.02	1002.05	1.993	0.192
		PC1+PC2+PC3+ForestEdge+CropEdge	6	-495.04	1002.2	2.14	0.178
		PC1+PC2+PC3+ForestEdge	5	-496.93	1003.94	3.876	0.075
		PC1+PC2+PC3	4	-498.72	1005.5	5.436	0.034
	Final	PublicLand+MeanParcelSize	3	-484.06	974.15	0.000	1
		Null	1	-499.03	1000.06	25.914	0.000
6	Access	PublicLand+MeanParcelSize+ I(MeanParcelSize^2)	4	-2600.84	5209.69	0.000	1
		PublicLand	2	-2610.9	5225.8	16.114	0.000
		Null	1	-2644.71	5291.42	81.731	0.000
	Difficulty	Null	1	-2644.71	5291.42	0.000	0.44
		Slope	2	-2644.22	5292.45	1.03	0.263
		RoadDist	2	-2644.59	5293.18	1.759	0.182
		Slope+RoadDist	3	-2644.05	5294.1	2.681	0.115
	Landscape	PC1+PC2+I(PC2^2)+PC3+ForestEdge	6	-2631.61	5275.24	0.000	0.628
		PC1+PC2+I(PC2^2)+PC3 +ForestEdge+CropEdge	7	-2631.61	5277.24	2.004	0.231
		PC1+PC2+I(PC2^2)+PC3	5	-2634.1	5278.22	2.988	0.141
		Null	1	-2644.71	5291.42	16.183	0.000
		HSI	2	-2644.5	5293	17.765	0.000
	Final	PC1+PC2+I(PC2^2)+PC3+ForestEdge+ PublicLand+MeanParcelSize+ I(MeanParcelSize^2)	9	-2593.65	5205.34	0.000	0.64
		PC1+PC2+I(PC2^2)+PC3+ForestEdge+ PublicLand+MeanParcelSize+ I(MeanParcelSize^2)+PC1:PublicLand	10	-2593.44	5206.94	1.602	0.287
		PublicLand+MeanParcelSize+ I(MeanParcelSize^2)	4	-2600.84	5209.69	4.351	0.073
		PC1+PC2+I(PC2^2)+PC3+ForestEdge	6	-2631.61	5275.24	69.899	0.000
		Null	1	-2644.71	5291.42	86.081	0.000