# Multi-resolution approach to wildlife habitat modeling using remotely sensed imagery

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## ABSTRACT

Remotely sensed imagery, coupled with wildlife habitat models provide a powerful tool for the implementation, assessment, and monitoring of wildlife conservation/restoration initiatives. Observed, empirical relationships between a species abundance metric and landscape structure/composition are used to structure models. Habitat suitability models always represent a trade off between breadth of applicability and specificity. Large-spatial extent, coarse spatial resolution data sets may be useful for characterizing potential animal distributions at regional or continental scales; however, habitat models developed at this spatial scale may have little applicability for predicting suitability at finer spatial resolutions. Whereas numerous issues related to multi-scale analysis have been acknowledged with respect to wildlife habitat models, only recently have sources of high-resolution imagery been readily available for site-specific analyses. We outline a multi-scale approach to habitat modeling and demonstrate this approach with northern bobwhite. We developed a coarse resolution model appropriate for identifying focal regions likely to support bobwhite using classified LandSat imagery and relative abundance measures from breeding season call counts. Then we developed a fine resolution model based on 4-m multispectral IKONOS imagery and animal space-use for planning and implementing conservation practices at the local scale. We discuss the application of this hierarchical approach to conservation planning.

**Keywords:** wildlife, habitat model, habitat suitability, LandSat, IKONOS, northern bobwhite

## 1. INTRODUCTION

Increasing economic growth, modernization, and human population expansion has resulted in conversion of natural communities and habitats to other uses[1]. Meeting national and world demands for goods and services while ensuring long term sustainability of natural resources has become increasingly complex. Governmental policies and regulations such as the National Environmental Protection Act (1969) and Endangered Species Act (1973) were designed to ensure consideration of anthropogenic impacts on natural resources through documentation of potential consequences of proposed land use practices on wildlife. However, aside from endangered/threatened species, the above federal regulations do not ensure the long-term conservation of many precipitously declining wildlife species. Thus, numerous national and international conservation strategies have been developed to pro-actively restore/enhance declining wildlife populations.

Through coalitions of state, federal, and international conservation agencies and non-governmental organizations (NGOs), wildlife conservation plans such as the North American Bird Conservation Initiative (NABCI), North American Waterfowl Management Plan (NAWMP), United States Shorebird Conservation Plan, North American Waterbird Conservation Plan, Partners in Flight Bird Conservation Plan, and the Northern Bobwhite Conservation Initiative (NBCI) were developed as measures to ensure the conservation/restoration of specific groups of declining wildlife species. The approach of these conservation plans is to document historic and current species distribution and abundance, determine causes of decline, identify critical habitat issues, and propose specific habitat-based goals to reverse population declines. Habitat assessment tools, mainly wildlife habitat relationship models using remotely sensed imagery, are a crucial component to the development, implementation, and monitoring phases of these large-scale conservation plans.

Most wildlife habitat relationship models use key habitat variables that quantify the capability of the land areas to meet the life requisites of wildlife species[2] and are most commonly constructed using some measure of abundance (individuals counted, harvest, etc.) relative to measures of habitat characteristics[3,4,5,6]. Additionally, inherent in most

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models is the assumption that animal abundance is directly linked to habitat quality. However, defining the unit of area to which abundance estimates apply is often problematic, thus are arbitrarily set by the researcher with little biological basis. Extreme caution must be exercised in determining an effective sampling distance which is commensurate with the scale of the abundance and habitat data recorded for a particular species[2].

Remote sensing has widespread applications in habitat suitability assessment. Since the late 1970's, LandSat imagery has been the primary imagery source for landscape-level habitat evaluation and planning. Peery et al. (1999) and Swindle et al. (1999) used LandSat Thematic Mapper (TM) imagery to identify distribution patterns of old-forests in relation to nest site selection by Northern Spotted Owl (*Strix occidentalis*) in the central Cascade Mountains of Oregon. Rempel et al. (1997) examined the costs/benefits of competing timber harvest strategies on moose (*Alces alces*) in Ontario, Canada, using time series imagery and estimates of relative moose abundance. Using harvest as a measure of abundance, eastern wild turkey (*Meleagris gallopavo*) populations responded favorably to county level changes in forest cover detected from LandSat imagery during 1986-1993 in New York[4]. Homer et al. (1993) used LandSat TM data to identify sagebrush (*Artemisia spp*.) communities critical to sage grouse (*Centrocercus urophasianus*) wintering habitat in Wyoming. Northern bobwhite (*Colinus virginianus*) habitat models using LandSat derived land cover maps were used to assess habitat quality in Illinois[3] and Virginia[5]. Using Geographic Information Systems (GIS) databases and LandSat imagery, Roseberry et al. (1994) explored potential impacts of Conservation Reserve Program lands on northern bobwhite habitat quality in Illinois. The above habitat models incorporating LandSat imagery are suitable for generalized large-scale regional evaluations of habitat potential but have limited applications in assessing site-specific habitat quality.

Despite widespread use as a tool for large-scale monitoring and evaluation, LandSat imagery is less useful for predicting habitat quality for species that respond to fine-scale habitat characteristics. The utility of LandSat imagery for monitoring habitat change is a function of the spatial resolution at which focal species perceive and use habitat patches. Relatively low spatial resolution (28.5m) of LandSat data is suitable for coarse-grained habitat selectors, habitat generalists, or species requiring large homogeneous habitat patches. However, many species perceive their environment at smaller spatial resolution. Low spatial resolution imagery, relative to the animal's perception of the environment, may not be sufficient to detect proximate and ultimate cues leading to habitat utilization[5]. Detection of pertinent habitat features becomes increasingly problematic when considering species which are dependent upon high interspersion of multiple habitat patches relative to imagery resolution.

Wildlife habitat models are built upon empirical relationships observed between 2 primary types of input data: one measuring abundance, density, distribution, population performance or space-use; and a second measuring landscape and/or vegetation composition and structure. Johnson (1980) defined a hierarchical framework where habitat selection may occur at 4 primary spatial scales: 1) the species geographic distribution 2) location of a home range within the geographic distribution 3) time allotted to habitat types within a home range, and 4) use of specific structures or resources within each habitat type. Spatial and organizational scale of model inputs have been shown to have substantial effects on precision and accuracy of model predictions[13,14,15,16,17]. Therefore, prediction across scales is problematic and often lead to spurious results[18]. Consequently, wildlife habitat relation models must be constructed using input data (population/animal characteristics) and land cover data that is consistent with the scale of analyses and application.

A fundamental question of concern for all large-scale conservation initiatives is "How do we distribute technical expertise, cost-shared practices, and other resources in a manner that optimizes conservation benefit/investment ratios?" Conservation investments should be placed in the landscape in regions that have potential for greatest population response and highest probability of eliciting a sustained response. Such regions might be characterized as already sustaining extant populations of the species of interest, yet having extensive quantities of potentially usable habitat available for enhancement. Tracts large in size and in close proximity to existing suitable habitat should receive priority status. Using northern bobwhite conservation as an illustration, previous state-level initiatives have selectively allocated resources using a variety of subjective and objective criteria so as to maximize return on investment. Objective, empirically-based criteria are needed for defining spatially explicit allocation of effort and resources for regional northern bobwhite conservation initiatives. Abundance/land cover based habitat models provide tools for defining large-scale extant habitat quality and may be useful for identifying areas with greatest opportunity for habitat/population enhancement while fine-scale habitat models can be used to identify specific habitat deficiencies in a scale consistent with the species perception of its environment. In this paper we outline a multi-scale approach to habitat modeling and demonstrate this approach with northern bobwhite. We developed a coarse resolution model appropriate for identifying focal regions likely to support bobwhite using classified LandSat imagery and relative abundance measures from breeding season call counts. Then we developed a fine resolution model based on 4-m multispectral IKONOS imagery and animal space-use estimated from radio-marked bobwhite for planning and implementing conservation practices at the local scale.

## 2. METHODOLOGY

### 2.1 Study site

This study was conducted at the Black Prairie Wildlife Management Area (BPWMA) and on privately-owned land in Clay and Lowndes counties within the Black Prairie Physiographic Region of northeast Mississippi during 2001-2002. For a more detail description of BPWMA see Smith (2001). Privately-owned study sites (n = 6) were selected based on cropping practices, landscape composition (approximately 60-80% corn and soybean rowcrop), soil associations, and landowner cooperation to maximize homogeneity among study sites. Much of the area has been rowcropped for more than 50 years. Other agricultural activities include forage and livestock production. Frost-free days range from 200-230. Mean annual total precipitation for Lowndes and Clay counties are 139 and 129 cm, respectively. Mean annual temperatures are lowest for January (6-8$^{o}$C) and highest for July (27$^{0}$C). Soils are neutral to alkaline, poorly drained to well-drained, fine, montmorillonitic, silty clays and loams developed over chalk or marl[20,21,22]. Predominant soil series present include: Okolona, Brooksville, Kipling, Vaiden, and Sumter upland soils with Griffith soils occurring in lowland floodplains. Slopes range from level to gently sloping with Kipling soils having the greatest potential slope of 8%. Soils of these types have fair to good potential for cultivated crops such as soybeans, corn, cotton, small grain, and pasture plants; but may require special management practices due to their erosion potential and clayey, sticky nature when moist.

As a part of another study examining the effects of herbaceous field borders, 54.3 ha of field borders (6.09 m in width) were planted along agriculturally related field edges (fence rows, drainage ditches, access roads, and contour filter strips) on 3 of the privately-owned study sites during winter 2000. Field borders were planted with a Kobe lespedeza (*Lespedeza striata*) and partridge pea (*Chamaecrista fasciculata*) mixture at rates of 11.2 kg/ha and 3.36 kg/ha, respectively.

### 2.2 Focal species

This study uses northern bobwhite as a representative species for habitat model development. Northern bobwhite are non-migratory birds with relatively limited mobility[23] requiring a diversity of seral stages to meet daily and seasonal life requisites[24,25]. Specifically, bobwhites are dependent upon early successional stage plant communities that provide essential seed and invertebrate resources in a vegetation structure consistent with their morphological adaptations[24,26,27,28]. Given that the spatial arrangement of habitat patches often dictate the usability of multiple habitats, relatively small home range sizes, and relative ease in identifying these specific habitat requirements, the northern bobwhite is a suitable “model species” for the study of wildlife-habitat relationships[2].

### 2.3 Imagery

Consistent with other large-scale, coarse resolution wildlife habitat models, we used LandSat ETM 7 data for northeast Mississippi (path 22, row 37) for development of the abundance-based model. We further restricted the scope of our analyses to a 3,583.3 km$^2$ section of the Black Prairie Physiographic region of Mississippi. We used imagery from 2 dates (Jan 99 and Jul 02) to develop land cover layers. Although the Jan 99 image may not reflect current land cover conditions, our use of this imagery was primarily to delineate agricultural fields and forestland, which had not changed substantively between 1999 and 2001. We employed the supervised classification procedure in ERDAS IMAGINE (version 8.5). Training areas (n = 23) were selected based on land cover designations from 4 GIS thematic layers developed previously from 1:24,000 digital ortho quad maps. GIS thematic layers were ground truthed and annually updated. Classification accuracy was subjectively evaluated using the above GIS thematic layers. We grouped land cover designations into 4 broad habitat classes based on similarities in vegetation structural characteristics and potential importance to bobwhite. Pasture/hay fields, CRP fields, and grassy field borders (GRASS) were grouped together due to similarity in structural characteristics, species composition, and lack of disturbance. Woodlots, fence rows and ditches, and road right of ways containing woody vegetation were grouped as WOOD. ROWCROP habitats consisted of soybeans, corn, grain food plots, or annual weed communities associated with soil disturbance. Residential areas, roads, and water bodies were classified as ODD habitats. Approximately 48% of the landscape was classified as

GRASS, 35% as WOOD, 10.3% in ROWCROP, and the remainder (6.7%) in ODD habitats. Although we initially investigated other sources of readily available classified LandSat land cover layers such as the National Land Cover Data (NLCD) and the Mississippi GAP Analysis Program, both land cover sources were less accurate than our resulting classified image.

We used 4-m multispectral IKONOS imagery of a 100 $km^2$ subset of the Black Prairie Physiographic region described above to develop a land cover layer for the fine resolution space-use models. Scenes from Sept 02 and May 03 were used to discriminate among vegetation types. We used the same classification procedure, subjective accuracy assessment protocol, and habitat classification scheme as that of the abundance-based model land cover layer. However, we used a new set of training areas (n = 18) located within the IKONOS image from which to develop classification signatures. To reduce the “graininess” of the resulting classified image, we employed a 3 x 3 neighbourhood filter. Similar to the LandSat derived land cover layer, 40% of the resulting IKONOS derived land cover layer was in GRASS, 36.2% in ROWCROP, 22.9% in WOOD, and 0.9% in ODD habitats.

## 2.4 Abundance-based model development

Breeding season call counts were conducted in mid-June to index yearly bobwhite breeding density during 2001 and 2002. Counts were conducted from sunrise to 0900 hr with wind speeds <15 mph. We recorded number of calling males heard during a 5 minute listening period at 87 geo-referenced stations. Stations were $\geq$ 800 m apart and located on a grid encompassing each study site. We conducted counts 3 times/year at each station during a 4-day sampling period to estimate mean number of calling males/station. We used the mean number of calling males/station averaged over both years to index relative abundance.

We used binary response, multiple logistic regression for model development. Similar to Schairer et al. (1999), we used 2 groups representing high (>1 calling male/station) and low ($\leq$1 calling male/station) bobwhite population levels. Presumptively, breeding density reflects habitat suitability in some region surrounding the point. Therefore, we buffered each call count station by 800 m (range of audible detection) for the coarse scale habitat models. Each buffered region was clipped to the underlying classified LandSat image to delineate habitat characteristics within the region. FRAGSTATS[29] was used to compute class and landscape metrics for each buffered count station. For a more detailed description of FRAGSTATS metrics see McGarigal and Marks (1995). Pair-wise t-tests were used to identify landscape metrics that differed between high and low abundance stations, eliminating non-significant metrics from further analysis[30]. We used this subset of landscape metrics in model selection procedures. We used the SCORE option in PROC LOGISTIC[31] to generate a set of competing models incorporating 1 – 4 habitat metrics. We then used a modified information-theoretic approach[32,33], based on Akaike Information Criteria[34], $\chi^2$ Goodness of Fit tests, and overall correct classification rates for final model selection.

## 2.5 Space-use model development

Northern bobwhites were captured in late winter (Feb - Mar) with baited walk-in funnel traps[24] or by night netting[35]. Birds were sexed, aged (adult/sub-adult), weighed, banded with a #7 aluminum leg band, fitted with a 5 - 6 g pendant style radio transmitter (American Wildlife Enterprises, Tallahassee, Florida, USA), and released at the capture site. Radio transmitters operated on 148.000 - 151.000 MHz bands and were equipped with a motion sensitive 12 hr mortality switch. Capture, handling, tagging, and radio-marking procedures were consistent with Mississippi State University Institutional Animal Care and Use Committee (IACUC permit no. #99-212) guidelines and the American Ornithologist’s Union Report of Committee on the Use of Wild Birds in Research (American Ornithological Union 1988).

We used a programmable scanning receiver with a 3 element Yagi antennae to locate radio-marked birds. Wide-ranging birds were located using fixed wing aircraft. Radio-marked birds were located $\geq$5 times/week from 15 Apr - 15 Sept by homing to $\leq$25 m and triangulating from positions geographically referenced with a Trimble Geo-Explorer II (Trimble 1999) hand-held global positioning system (GPS) unit. GPS locations were differentially corrected and presumed accurate to within 1-3 m. Utilization distributions depicting relative intensity of use were computed for each bird using the Animal Movement extension[36] in Arcview 3.2 (ESRI 1999). We buffered each utilization peak by 400 m to create circular ranges equivalent in area to the median home range size. Utilization ranges were clipped to the classified image to delineate habitat characteristics within each utilization range. FRAGSTATS[29] was used to compute landscape and class level habitat metrics within each clipped home range. Similarly, landscape metrics were computed for an equal number of randomly located circular ranges equivalent in size to the median home range for each year.

Logistic regression models were developed in a similar fashion as the abundance-based models except that utilization ranges and random ranges were used as the binary response variable.

## 3. RESULTS

We used calling information from 87 call count stations. High abundance call count stations averaged 2.71 calling males/station (SE = 0.20) while low abundance stations averaged 0.35 calling males/station (SE = 0.06). We used radio-telemetry locations from 53 northern bobwhite to construct utilization distributions. Median home range size was 53.3 ha (range 13.7 – 371.92ha).

Our best predictive abundance-based model contained the variables: grass class area (GR_CA, parameter = 0.008, SE = 0.008, $\chi^2_1$ = 0.911, P = 0.340), number of rowcrop patches (ROW_NP, parameter = 0.162, SE = 0.058, $\chi^2_1$ = 7.787, P = 0.005), and the Shannon Diversity Index (SHDI, parameter = -2.915, SE = 0.1.491, $\chi^2_1$ = 3.822, P = 0.051; Table 1). Stations from which >1 calling male was observed had greater amounts of grassy vegetation (high $\bar{x}$ = 136.73, SE = 5.87, low $\bar{x}$ = 102.15, SE = 7.79, P <0.001), more patches of rowcrop (high $\bar{x}$ = 14.40, SE = 1.04, low $\bar{x}$ = 10.97, SE = 0.88, P = 0.017), but a lower Shannon Diversity Index score (high $\bar{x}$ = 0.72, SE = 0.05, low $\bar{x}$ = 0.88, SE = 0.05, P = 0.018; Table 2). Overall correct classification rate was 72.7%.

Consistent with our current knowledge of northern bobwhite habitat ecology, our best space-use model contained the variables grass cohesion index (GR_COH, parameter = 0.440, SE = 0.193, $\chi^2_1$ = 5.202, P = 0.023), rowcrop edge density (ROW_ED, parameter = 0.017, SE = 0.004, $\chi^2_1$ = 17.251, P < 0.001), rowcrop clumpiness index (ROW_CLUMP, parameter = -11.147, SE = 5.552, $\chi^2_1$ = 4.032, P = 0.045), and the splitting index (SPLIT, parameter = -0.462, SE = 0.218, $\chi^2_1$ = 4.475, P = 0.034; Table 3). Patches of GRASS habitats were more contiguous within utilization ranges ($\bar{x}$ = 99.03, SE = 0.16) than random ranges ($\bar{x}$ = 97.18, SE = 0.43, P < 0.001; Table 4). Furthermore, utilization ranges ($\bar{x}$ = 230.29, SE = 12.12) had more rowcrop habitat edges than random ranges ($\bar{x}$ = 147.05, SE = 10.49, P < 0.001; Table 4). Rowcrop patches were less aggregated in utilization ranges ($\bar{x}$ = 0.86, SE = 0.01) than in random ranges ($\bar{x}$ = 0.91, SE = 0.01, P < 0.001; Table 4). However, utilization ranges ($\bar{x}$ = 3.28, SE = 0.19) had lower Splitting Index values than random ranges ($\bar{x}$ = 4.06, SE = 0.27, P = 0.017) indicating less overall fragmentation across all habitat types. Correct classification was 80.2%.

## 4. DISCUSSION

Peterson et al. (2002) suggest that scientifically defensible, spatially explicit management plans for northern bobwhite are badly needed and spatially consistent, temporally persistent patterns in relationships between land cover and bobwhite abundance suggest that landscape-based explanations for abundance should be possible. To this point, no large-scale bobwhite conservation initiative has used empirical, statistical models of habitat suitability to define focal areas for allocation of conservation effort. However, several large-scale, empirical statistical models of bobwhite habitat suitability have been developed for regional and state-level spatial extents.

Roseberry and Sudkamp (1998) developed a Pattern Recognition (PATREC) model, based on classified LandSat imagery and 2 sources of population abundance data (county level harvest data and breeding bird survey). They quantified landscape structure and composition using LandSat data and FRAGSTATS and compared landscape metrics with indices of bobwhite abundance. PATREC is a method of assessing habitat suitability based on probabilities that a particular habitat condition is consistent with a set of observed environmental attributes. They empirically related landscape variables (proportion of rowcrops and grassland, woody edge density, contagion, and latitude) to bobwhite distribution and abundance. Each variable was described by a set of mutually exclusive categories representing alternative states (contagion < 65%, contagion $\geq$ 65%) and each alternative state had a set of 2 conditional probabilities that described the chances that, given an overall landscape condition (e.g. suitable, unsuitable) a particular characteristic would exist. Higher bobwhite densities were associated with diverse patchy landscapes with moderate amounts of edge and rowcrop and abundant woody edge.

Schairer et al. (1999) developed PATREC and logistic regression models for Virginia using 1993 LandSat TM land cover data and breeding season call counts from 815 geo-referenced points as an index to population abundance. They constructed conditional probabilities for PATREC models using percentage of landscape in rowcrops, mean patch size of rowcrops, mean patch size of deciduous forest, mean edge contrast index of rowcrops, and mean edge contrast of grasslands as predictor variables. Higher bobwhite populations were associated with greater percentage of landscape in rowcrops, lower percentage in deciduous forest, higher mean patch size for rowcrops, lower mean patch size for water and higher mean edge contrast indices for pasture and deciduous forest. The PATREC model had an overall correct classification rate of 73.5% on modeled data and 74.6% on independent data. They also developed a logistic regression habitat suitability model after Brennan et al. (1986). Two of 19 variables entered into a stepwise logistic regression were retained as useful predictors of relative quality (high density vs. low density). Posterior probability of being high quality increased with increasing percentage rowcrops and decreasing mean patch size of deciduous forests. The logistic regression model had an overall correct classification rate of 73.9% for modeled data and 76.6 % on independent data. Both modeling approaches accurately predicted low quality sites but grossly under predicted high quality sites. Schairer et al. (1999) suggested that using these models in a predictive sense will help wildlife manage avoid applying management actions on "islands" of good habitat within otherwise low quality landscapes.

Burger et al. (1998) developed an organism-centered, logistic regression habitat model for northern bobwhite in northern Missouri. Separate models were developed for breeding and non-breeding seasons. The model is based on animal space-use as estimated from radio-marked northern bobwhite in 2 landscapes in northern Missouri. The posterior probability from a logistic regression model was used to predict habitat suitability based on landscape metrics describing structural complexity of winter and summer ranges and random circles of mean home range size. During winter, 3 -variable logistic regression models incorporating shape index of rowcrop fields, edge density of CRP fields, and edge density of woody patches predicted overall selection with a 90-95% posterior correct classification rate. During summer, the best approximating model contained the variables: landscape edge density, number of grass waterway patches, landscape number of patches, fallow habitat mean perimeter to area ratio, and CRP mean patch edge. Correct classification rates based on posterior probabilities for all observed and random ranges were 92.0% and 94.7%, respectively. Winter and summer habitat suitability models were back applied to a vector model of the landscape to generate raster surface models where the cell values equaled the probability of occupancy given the surrounding landscape composition and structure. An overall suitability index was calculated as the mean of summer and winter suitability. This habitat suitability model was deployed in an internet-based, integrated resource management system designed to provide decision-support for natural resource planners[40].

We suggest that our LandSat-based habitat modeling efforts, as well as those reported by Roseberry and Sudkamp (1998) and Schraier et al. (1999), support Peterson et al. (2002) contention that landscape-based explanations for abundance of northern bobwhite are possible. Furthermore, we contend that large spatial extent, coarse resolution, abundance-based models adequately address the need for scientific, objective identification of focal areas in which to allocate conservation effort under regional and national conservation initiatives such as the Northern Bobwhite Conservation Initiative. Focal areas could be defined in terms of contiguous areas of suitable habitat in sufficiently large patches to support sustainable populations. Once identified, these areas could be targeted for habitat enhancement based on either greatest deficiencies or optimal allocation of limited fiscal resources. However, these models may have little utility for conservation planning *within* these focal areas.

Guthery (1997) contends that the goal of habitat management for bobwhite lies not in elevating habitat quality, but rather creation of "usable space." Organism-centered space-use models have been previously used to predict probability of occupancy (usable space) over relatively large landscapes[39]. This biologically-based approach utilizes animal space-use patterns obtained from radio-marked individuals within the landscape of interest, thereby overcoming problems associated with earlier models (arbitrarily set study boundaries and scale of analysis, surrounding landscape effects, abundance as a proxy measure of quality). These models offer a more effective link between fine scale selection of structural and compositional attributes of habitat by animals and macro-scale remote sensing habitat assessments. We suggest that site-specific models based on high-resolution imagery and animal space-use provide a better tool for identifying habitat quality and deficiencies at small spatial scales. Such models could be deployed as conservation planning tools integrated in GIS tool kits for use by federal resource management agencies such as the Natural Resource Conservation Service (NRCS) and other state conservation agencies. Such tools would allow resource planners to conduct site-specific (farm-level) evaluations of habitat suitability, identify habitat deficiencies, and predict hypothetical habitat suitability under alternative management regimes employing various conservation practices. Taken together, these models illustrate a hierarchical approach to habitat modeling using response variables and land cover data that vary in organizational and spatial resolution so that predictions are made at a scale appropriate to the processes being predicted.

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Table 1. Model parameters and coefficients, $\chi^2$ Goodness of Fit statistic, relative $AIC_c$, and predictive ability of abundance-based habitat suitability models for northern bobwhite developed within the Black Prairie Physiographic region, MS, 2001 - 2002.

| Model | $\chi^2$ | $AIC_c$[1] | %[2] | Sensitivity | Specificity |
|---|---|---|---|---|---|
| 1 Variable | | | | | |
| -2.018 + 0.020 (GR_CA) | 11.39 | 98.21 | 63.6 | 71.4 | 54.3 |
| -2.175 + 0.039 (GR_PLAND) | 11.37 | 98.23 | 63.6 | 71.4 | 54.3 |
| -1.553 + 0.031 (GR_LPI) | 9.64 | 100.23 | 61.0 | 69.0 | 51.4 |
| 2 Variable | | | | | |
| 0.908 + 0.184 (ROW_NP) – 3.852 (SHDI) | 18.63 | 91.62 | 70.1 | 73.8 | 65.7 |
| 0.910 + 0.368 (ROW_PD) – 3.851 (SHDI) | 18.61 | 91.65 | 70.1 | 73.8 | 65.7 |
| -3.311 + 0.022 (GR_TCA) + 0.131 (ROW_NP) | 16.89 | 93.78 | 70.1 | 76.2 | 62.9 |
| 3 Variable | | | | | |
| 1.891 + 0.203 (ROW_NP) – 10.174 (SHDI) + 5.888 (MSIDI) | 20.40 | 91.65 | 70.1 | 73.8 | 65.7 |
| 1.893 + 0.406 (ROW_PD) – 10.177 (SHDI) + 5.890 (MSIDI) | 20.38 | 91.68 | 70.1 | 73.8 | 65.7 |
| -0.496 + 0.008 (GR_CA) + 0.162 (ROW_NP) – 2.915 (SHDI) | 19.69 | 92.94 | 72.7 | 76.2 | 68.6 |
| 4 Variable | | | | | |
| -1.764 + 0.037 (GR_CPLAND) + 0.182 (ROW_NP) – 12.590 (SHDI) + 17.877 (SIDI) | 22.40 | 91.18 | 67.5 | 73.8 | 60.0 |
| -1.756 + 0.018 (GR_TCA) + 0.182 (ROW_NP) – 12.570 (SHDI) + 17.834 (SIDI) | 22.39 | 91.19 | 67.5 | 73.8 | 60.0 |
| -1.76 + 0.037 (GR_PLAND) + 0.365 (ROW_PD) - 12.602 (SHDI) + 17.895 (SIDI) | 22.38 | 91.20 | 67.5 | 73.8 | 60.0 |

[1] Akaike Information Criteria corrected for small sample sizes

[2] Overall correct classification rate

Table 2. Differences and correlation coefficients for landscape variables ($P \leq 0.05$) and within a 800m buffer between high (n=42) and low (n=35) abundance call count stations within the Black Prairie Physiographic region, MS, 2001-2002.

| Variable Code | Variable Description | $\bar{X}$ High | SE | $\bar{X}$ Low | SE | P-value | $\rho$[4] | P-value |
|---|---|---|---|---|---|---|---|---|
| GR_CA | Grass class area[1] | 136.73 | 5.87 | 102.15 | 7.79 | <0.001 | 0.32 | 0.004 |
| GR_PLAND | Grass percentage of landscape[1] | 68.35 | 2.93 | 51.08 | 3.89 | <0.001 | 0.32 | 0.004 |
| GR_LPI | Grass largest patch index[1] | 64.13 | 3.49 | 46.42 | 4.20 | 0.002 | 0.28 | 0.012 |
| GR_TCA | Grass total core area[1] | 97.81 | 6.69 | 66.99 | 6.84 | 0.002 | 0.29 | 0.010 |
| GR_CPLAND | Grass core area percentage of landscape[1] | 48.90 | 3.35 | 33.50 | 3.42 | 0.002 | 0.29 | 0.010 |
| ROW_NP | Rowcrop number of patches[1] | 14.40 | 1.04 | 10.97 | 0.88 | 0.017 | 0.21 | 0.071 |
| ROW_PD | Rowcrop patch density[1,3] | 7.20 | 0.52 | 5.48 | 0.44 | 0.017 | 0.21 | 0.071 |
| SHDI | Shannon Diversity Index[2] | 0.72 | 0.05 | 0.88 | 0.05 | 0.018 | -0.24 | 0.038 |
| SIDI | Simpson Diversity Index[2] | 0.41 | 0.03 | 0.49 | 0.03 | 0.034 | -0.23 | 0.044 |
| MSIDI | Modified Simpson Diversity Index[2] | 0.57 | 0.05 | 0.73 | 0.05 | 0.029 | -0.23 | 0.042 |

[1] Class level metric

[2] Landscape level metric

[3] In patches/100ha

[4] Pearson correlation coefficient

Table 3. Model parameters and coefficients, $\chi^2$ Goodness of Fit statistic, relative $AIC_c$, and predictive ability of space-use habitat suitability models for northern bobwhite developed within the Black Prairie Physiographic region, MS, 2001 - 2002.

| Model | $\chi^2$ | $AIC_c$[1] | %[2] | Sensitivity | Specificity |
|---|---|---|---|---|---|
| 1 Variable | | | | | |
| -2.477 + 0.028 (ROW_PD) | 37.18 | 108.86 | 75.5 | 71.7 | 79.2 |
| -4.189 + 0.593 (ROW_LSI) | 35.69 | 110.65 | 73.6 | 67.9 | 79.2 |
| -5.096 + 0.018 (PD) | 32.79 | 112.47 | 76.4 | 77.4 | 75.5 |
| 2 Variable | | | | | |
| 123.2 – 1.003 (SPLIT) – 1.273 (AI) | 42.68 | 99.00 | 79.2 | 81.1 | 77.4 |
| -4.230 + 0.025 (ED) – 1.019 (SPLIT) | 42.47 | 99.23 | 79.2 | 81.1 | 77.4 |
| -5.848 + 1.435 (LSI) – 1.019 (SPLIT) | 42.44 | 99.27 | 79.2 | 81.1 | 77.4 |
| 3 Variable | | | | | |
| 88.081 + 0.012 (ROW_PD) – 0.769 (SPLIT) – 0.920 (AI) | 46.62 | 98.34 | 76.4 | 77.4 | 75.5 |
| -4.024 + 0.013 (ROW_PD) + 0.018 (ED) – 0.780 (SPLIT) | 46.47 | 98.44 | 75.5 | 75.5 | 75.5 |
| -4.022 + 0.013 (ROW_PD) + 0.0004 (TE) – 0.779 (SPLIT) | 46.47 | 98.45 | 75.5 | 75.5 | 75.5 |
| 4 Variable | | | | | |
| -34.891 + 0.440 (GR_COH) + 0.017 (ROW_ED) – 11.147 (ROW_CLUMP) – 0.462 (SPLIT) | 49.93 | 96.19 | 80.2 | 81.1 | 79.2 |
| -24.658 + 0.385 (GR_COH) + 0.021 (ROW_ED) – 0.157 (ROW_COH) – 0.488 (SPLIT) | 49.25 | 96.69 | 79.2 | 81.1 | 77.4 |
| 470.700 + 0.021 (ROW_NP) + 7.446 (ED) – 420.500 (LSI) – 0.806 (SPLIT) | 49.18 | 96.10 | 76.4 | 75.5 | 77.4 |

[1] Akaike Information Criteria corrected for small sample sizes

[2] Overall correct classification rate

Table 4. Differences in landscape variables ($P \leq 0.05$) between circular utilization and random northern bobwhite ranges within the Black Prairie Physiographic region, MS, 2001 - 2002.

| Variable Code | Variable Description | $\bar{X}$ Utilization | SE | $\bar{X}$ Random | SE | P-value |
|---|---|---|---|---|---|---|
| GR_COH | Grass cohesion | 99.03 | 0.16 | 97.18 | 0.43 | <0.001 |
| ROW_NP | Rowcrop number of patches | 61.89 | 3.25 | 28.75 | 3.00 | <0.001 |
| ROW_PD | Rowcrop patch density | 123.75 | 6.50 | 57.49 | 5.99 | <0.001 |
| ROW_ED | Rowcrop edge density | 230.29 | 12.12 | 147.05 | 10.49 | <0.001 |
| ROW_LSI | Rowcrop Landscape Shape Index | 8.58 | 0.28 | 5.60 | 0.30 | <0.001 |
| ROW_CLUMP | Rowcrop Clumpiness Index | 0.86 | 0.01 | 0.91 | 0.01 | <0.001 |
| ROW_COH | Rowcrop cohesion | 95.92 | 0.80 | 97.83 | 0.28 | 0.025 |
| PD | Patch density | 330.39 | 10.34 | 233.94 | 9.64 | <0.001 |
| TE | Total edge | 17649.81 | 477.62 | 13859.17 | 590.17 | <0.001 |
| ED | Edge Density | 352.93 | 9.55 | 277.11 | 11.80 | <0.001 |
| LSI | Landscape Shape Index | 7.36 | 0.17 | 6.02 | 0.21 | <0.001 |
| SPLIT | Splitting Index | 3.28 | 0.19 | 4.06 | 0.27 | 0.017 |
| AI | Aggregation Index | 93.16 | 0.19 | 94.68 | 0.23 | <0.001 |

[1] Class level metric

[2] Landscape level metric

[3] In patches/100ha