A Multivariate Habitat Model for Female Bobcats: A GIS Approach

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Abstract: We developed a Geographical Information System (GIS) based habitat model for female bobcats (*Lynx rufus*) and subjected the model to internal-validation, cross-validation, and validation using independent data. The model predicted probability of an area being used by female bobcats increased ($P < 0.001$) as slope and distance to mature pine stands increased. Probability of an area being used by female bobcats decreased ($P < 0.001$) with increasing distance to sapling stands, mature hardwood stands, paved roads, maintenance roads, and creeks. Forest type (non-forested, pine dominated, or hardwood dominated) also influenced ($P < 0.001$) probability of use. Internal- and cross-validation indicated the model performed relatively well (75.5% and 73% correct classification, respectively). However, when the model was tested with an independent data set, predicted values were only slightly better than random (57.5% correct classification). Our validation results indicate habitat models should not be trusted in absence of thorough verification.

Proc. Annu. Conf. Southeast Fish and Wildl. Agencies 52:232–243

For some time, there has been interest in development of wildlife habitat relationship models (Brennan et al. 1986, Capen et al. 1986, Pereira and Itami 1991, Clark et al. 1993). However, only 1 bobcat habitat relationship model (a habitat suitability index [HSI] model) has been published (Boyle and Fendley 1987). The current HSI concept may be flawed, however, because models are seldom developed and/or verified with empirical data (U.S. Fish and Wildl. Serv. 1981). Biometric habitat models (i.e., statistically developed, empirical habitat models) may have advantages over traditional HIS models because they are empirical and objectively formulated (Brennan et al. 1986, Clark et al. 1993). Unfortunately, as with most HIS models, many biometric habitat models suffer from lack of verification using independent data.

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Geographical Information Systems provided a platform for cost efficient habitat model development and application. An abundance of digital habitat data can be obtained for minimal cost. Given appropriate statistical models, these data can be used within a GIS to calculate habitat suitability (i.e., the probability of a site being used by a given species) quickly and cost-effectively (Donovan et al.1987, Pereira and Itami 1991, Clark et al. 1993, Homer et al. 1993). Further, integrating habitat and forest succession models within a GIS could allow habitat quality to be simulated as a function of proposed management. Therefore, our objectives were to develop a GIS-based biometric habitat model for female bobcats and to assess model validity using independent data. This effort represents our first attempt at developing a habitat model for predicting impacts of forest management activities (e.g., clear-cutting, stand conversion, etc.) on bobcat habitat suitability.

We thank D. Cobb, G. R. Conner, D. A. Miller, B. W. Plowman, and M. D. Weinstein for their editorial comments. Numerous technicians assisted with data collection. Funding for this project was obtained from the Mississippi Department of Wildlife, Fisheries and Parks, the U.S. Forest Service, and Georgia Pacific.

Methods

Study Areas

Our study was conducted on 2 adjacent , but distinct, areas in east-central Mississippi. The model was developed on the 142-km^2 Tallahala Wildlife Management Area (WMA) located in the Bienville National Forest. Mean annual temperature was 18 C and annual precipitation averaged 152 cm. Pine (*Pinus* spp.) stands ($\geq$70% pine dominated with mean dbh >5.0 cm) comprised 46% of the study area. Loblolly pine (*P. taeda*) was the dominant species, while shortleaf pine (*p. echinata*) and longleaf pine (*P. palustris*) occurred in scattered patches. Approximately 29% of the area was in sapling stands (forested with mean dbh $\leq$5 cm). Sapling stands averaged 13 ha in size and rarely exceeded 20 ha. Bottomland hardwoods accounted for 21% of the area and were primarily located in riparian zones along major drainages. Approximately 4% of the area was in agriculture. Pines had been regenerated by clear-cutting followed by site preparation and planting. Hardwood stands were regenerated using the shelterwood method or coppice management. Hardwood clearcutting was prohibited.

Independent data for model verification was collected on 80 km^2 owned by Georgia Pacific (GP). The GP study area was located adjacent to Tallahala WMA in Newton and Jasper counties. Weather patterns between the 2 study areas were similar. Pine stands covered 60% of the area, but 88% of pine stands were <33 cm dbh (as opposed to 18% on Tallahala WMA). Sapling (20%), hardwood (12%), and agriculture (8%) comprised the remainder of the study area. The land was managed primarily for timber production and stands were regenerated by by clearcutting and planting. Sapling stands > 100 ha were common. Larger clearcuts, intensive pine management, absence of mature timber, and lack of hardwwod stands on GP (relative to Tallahala WMA) permitted study of bobcat ecology under 2 different forest management regimes.

Geographical Information System Development

We constructed a Geographical Information System (GIS) for each study area. We transferred stand boundaries from color infra-red photographs to 1:24,000 U.S. Geological Survey (USGS) quadrangles. We classified stands into 1 of 3 forest types: non-forested (e.g., agriculture, least diverse tree community), pine, and hardwood (most diverse tree community). Additionally, we categorized each stand into 1 of 5 condition classes: non-forested, sapling (dbh ≤5.0 cm), pole (5.1 cm < dbh <12.7 cm), pulp wood (12.8 cm < dbh < 38.1 cm), and saw-timber (dbh > 38.2 cm). We digitized stands using ARC/INFO (Environ. Systems Res. Inst. 1992).

We also constructed coverages for roads, creeks, and elevation. We classified roads as paved, gravel, or maintenance (i.e., gated roads closed to the general public) and creeks as either ephemeral or permanent. We digitized road and creek coverages directly from USGS quadrangles. We obtained digital elevation models from USGS to create elevation and slope layers. We developed 8 slope classes ranging from class 1 representing a midpoint of approximately 5.5% slope, to class 8, representing a midpoint of approximately 84.5% slope. The range of each slope class was approximately 11% (Environ. Systems Res. Inst. 1992). There were 15 habitat variables available for any location on the study areas (Table 1).

Bobcat Capture and Monitoring

We captured bobcats using Victor Soft-catch traps (Woodstream Corp., Lititz, Pa.). Following capture, we netted and drugged bobcats with ketamine hydrochloride

Table 1. Variables used to develop bobcat habitat model on Tallahala Wildlife Management Area in central Mississippi, 1989–1992. Habitat characteristics were determined using GIS technology.

Variable Name	Description
TYPE[a]	Forest type index (non-forested, pine, or hardwood)
COND[b]	Stand condition (non-forested, sapling, pole, pulp and sawtimber)
EDGE	Distance[c] to edge
SAP	Distance to nearest sapling stand
PINE	Distance to nearest non-sapling pine stand
HWD	Distance to nearest non-sapling hardwood stand
RD	Distance to nearest road
RD1	Distance to nearest paved road
RD2	Distance to nearest gravel road
RD3	Distance to nearest maintenance road
CRK	Distance to nearest creek
CRK1	Distance to nearest primary creek
CRK2	Distance to nearest ephemeral creek
ELEV	Elevation (class)
SLOPE	Slope (8 equal classes 0°–90°)

a. Forest type.

b. Stand condition

c. All distances measured in km.

(15 mg/kg body mass). We separated bobcats into 3 age classes (kitten <1.0 year; sub-adult 1–2 years; adult >2 years) based on tooth eruption, staining and wear, body size, pelage characteristics, teat condition on females, and scrotum size on males (Crowe 1975). We fitted all adult females with a radio-collar (ATS Isanti, Minn. and Wildl. Mat. Carbondale, Ill.). We monitored bobcats overnight to assess recovery prior to release at the capture site. We allowed animals 1 week to recover from capture before radio-tracking was initiated. We trapped animals during winters (7 Jan – 15 Mar) 1989–1992.

We monitored bobcats with a TRX-1000S receiver and a hand-held 3-element Yagi antenna (Wildl. Mat. Carbondale, Ill.). We estimated locations by triangulation from fixed points within the study area (Cochran 1980, Kenward 1987, White and Garrott 1990). We frequently obtained ≥3 azimuths to minimize erroneous locations. To decrease error associated with animal movement, we allowed a maximum of 15 minutes between azimuths. We converted azimuths to coordinates using the program TELEBASE (Wynn et al. 1990).

Telemetry accuracy tests indicated the standard deviation from true bearings was 6° ($N = 42$). Based on these results, a circle circumscribing the estimated location of the bobcat located 1 km from each telemetry station would have an approximate area of 3.5 ha. Approximately 90% of all telemetry bearings were taken <1 km from an animal.

We performed telemetry sampling equally throughout the diel period. To ensure sufficient locations were available for both model building and cross-validation, only those bobcats having ≥50 telemetry locations/year were used in analyses. This study was conducted on Animal Care and Use Protocol 93–032 of Mississipppi State University.

Model Development

Female bobcats select home ranges based on habitat quality, whereas males select home ranges to maximize breeding opportunities (Anderson 1987, Sandell 1989). Therefore, we chose to develop habitat models for female bobcats, assuming that female presence would make an area acceptable for males.

Being able to identify unused habitats is beneficial when developing habitat models. However, it is impossible to identify unused habitats with certainty (e.g., if the site was used when the animal was not monitored) (Clark et al. 1993). Therefore, we generated random points such that no random point occurred within 200 m of a used location. By placing this restriction on random points, we hoped to reduce probability that a random point occurred at a site that was actually used by a bobcat. We overlaid bobcat telemetry locations and random points onto GIS layers and determined habitat characteristics (Table 1) at each point.

Selection of variables for habitat modeling without prior indication of their ecological importance should be avoided (Johnson 1981; Rexstad et al. 1988, 1990; Taylor 1990). Therefore, we passed habitat variables through 3 filters before entering the model. The first filter determined significance ($P < 0.01$; using a 2-sample t-test or

χ^2 test) of individual habitat variates by comparing variable values between used and random locations. Because of our relatively large sample size (N = 4,052 locations), we chose a conservative alpha level ($P < 0.01$) to reduce number of variables used in further model development.

To further reduce the variable set, we subjected remaining continuous variates to a second filter to remove correlated variables. If variables were correlated ($P < 0.05$; $|r| > 0.4$) we omitted the least significant variable (univariate statistic; above) from further model building efforts (Brennan et al. 1986).

We used stepwise logistic regression as the final filter and statistical tool to develop the habitat model. The stepwise selection procedure permitted variable inclusion or exclusion based on a variable's relative contribution when additional variables exist in the model. This procedure has advantages over discriminant function analysis because multivariate normality and equality of covariance matrices are not assumed (Afifi and Clark 1990). Further, when a mixture of continuous and discrete predictor variables is used, logistic regression is superior to discriminant function analysis (Efron 1975, Press and Wilson 1978). Type of location (bobcat or random) served as the binary response variable in modeling attempts.

We calculated posterior probabilities (i.e., probability of bobcat use) using Equation 1. These probabilities were treated as a HSI for bobcats (Brennan et al. 1986).

$$P\left(\frac{1}{x}\right) = \frac{1}{1 + e^{(\beta_0 + \beta_1 X_1 + \ldots \beta_i X_i)}} \qquad \text{Eq. 1}$$

Where: $P\frac{1}{x}$ = probability of a bobcat using a vector of habitat variables (x)

β_i= logistic regression coefficients

X_i= habitat values

Model Testing

We subjected the model to 3 increasingly rigorous levels of testing. We used internal-validation to evaluate model predictions with data used in model construction. We withheld approximately 20% of bobcat locations and random locations from model building efforts. We used these locations to cross-validate model predictions as an evaluation of model validity on Tallahala WMA.

To test model generality, we used bobcat and random locations obtained on the GP study areas as independent data for model testing (Capen et al. 1986, Verbyla and Litvaitis 1989, Taylor 1990). If our model predicted well on GP, we could assume the model was sufficiently general to apply on a variety of southern, forested landscapes.

We considered a point suitable for female bobcats if the posterior probability was ≥ 0.5. We calculated sensitivity (i.e., bobcat location predicted correctly as a bobcat location), specificity (i.e., random location predicted correctly as a random location), and total correct classification for all evaluation tests (SAS Inst. 1992). For cross-validation and validation using independent data, we overlaid all locations onto the appropriate study area coverages and determined habitat attributes associated with each location. A SAS (SAS Inst. 1992) program was written to calculate posterior probabilities for each cross-validation and independent data point. A frequency distribution of posterior probabilities was derived for cross-validation and independent data sets.

Results

Bobcats were monitored from January 1989 to December 1993 on Tallahala WMA. We used 2,026 locations from 14 female bobcats and an equal number of random locations to construct the habitat model. Significant (P <0.01, Table 2) non-correlated (P ≥0.05, $|r|$ <0.04, Table 3) variates subjected to stepwise logistic regression were SLOPE, SAP, RD1, RD2, RD3, CRK, HWD, PINE, COND, and TYPE. All variables except COND and RD2 were retained (P <0.001) by the stepwise procedure.

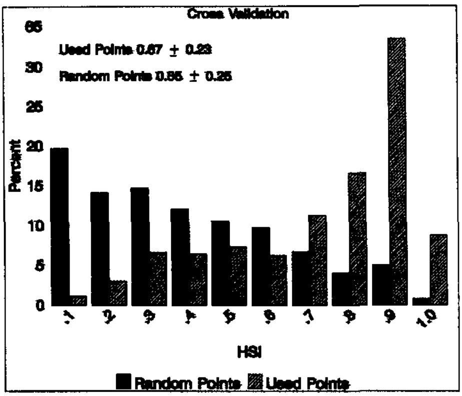
Probability of bobcat use increased as distance to sapling stands, primary roads, maintenance roads, creeks and hardwood stands decreased. Whereas probability of bobcat use increased as slope and distance to pine stands increased. Probability of bobcat use was highest for agriculture, lowest for hardwoods, and intermediate for

Table 2. Results of univariate tests among habitat variables[a]; associated with sites used by female bobcats and random locations on Tallahala Wildlife Management Area in central Mississippi, 1989–1992.

Variable	Test[b]	Used	Random	P
TYPE	X^2	N/A[c]	N/A	<0.001
COND	X^2	N/A	N/A	<0.001
EDGE	t	0.10±0.002[d]	0.11±0.002	0.17
SAP	t	0.07±0.002	0.18±0.004	<0.001
PINE	t	0.13±0.003	0.10±0.004	<0.001
HWD	t	0.38±0.007	0.40±0.01	0.01
RD	t	0.39±0.006	0.40±0.007	0.10
RD1	t	1.29±0.02	1.64±0.02	<0.001
RD2	t	0.73±0.01	0.54±0.01	<0.001
RD3	t	0.80±0.02	1.68±0.02	<0.001
CRK	t	0.21±0.003	0.25±0.004	<0.001
CRK1	t	0.83±0.01	0.82±0.01	0.55
CRK2	t	0.26±0.005	0.31±0.005	<0.001
ELEV	t	2.47±0.02	2.47±0.02	0.93
SLOPE	t	2.78±0.02	2.67±0.02	<0.001

a. Variable descriptions in Table 1.
b. Univariate statistical test employed.
c. Ordinal data, means not applicable.
d. Means ± SE

pine forest types (Table 4). Internal-validation procedures indicated 75.5% (sensitivity = 0.79, specificity = 0.72) correct classification. Cross-validation was performed on 468 bobcat locations and 635 random locations. The model correctly predicted 73% of all cross-validation locations (sensitivity = 0.76, specificity = 0.71). When the model was applied to GP data (562 used and 562 random locations), it correctly predicted 57.5% of all locations sensitivity = 0.48, specificity = 0.67) (Fig. 1).



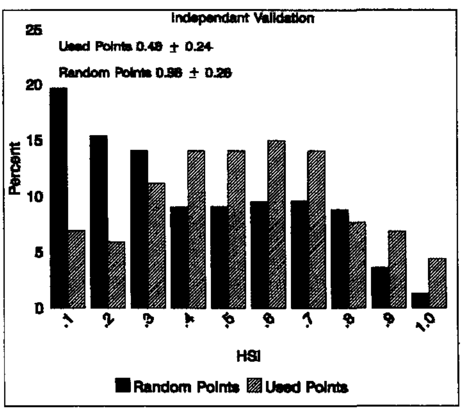


Figure 1. Distribution of bobcat and random locations relative to habitat suitability index (HSI) values of a female bobcat HSI model developed on Tallahala Wildlife Management Area in central Mississippi, 1989–1992. Percentages represent percent of locations with a given Habitat Suitability Index (HSI). Cross-validation represents data collected on the same study area; independent validation represents data collected on an adjacent study area.

Table 3. Correlation coefficents of continuous habitat variables associated with bobcat telemetry and random locations,[a] Tallahala Wildlife Management Area in central Mississippi, 1989–1992.

Variable[b]	SAP	PINE	HWD	RD1	RD2	RD3	CRK	CRK2	SLOPE
SAP	1.0								
PINE	−0.18	1.0							
HWD	−0.09	−0.29	1.0						
RD1	0.20	−0.14	−0.17	1.0					
RD2	−0.06	−0.01	−0.11	−0.02	1.0				
RD3	0.20	−0.15	0.21	0.18	−0.08	1.0			
CRK	0.08	−0.08	0.03	0.03	0.29	0.37	1.0		
CRK2	0.018	−0.02	−0.11	0.14	0.23	0.36	0.83	1.0	
SLOPE	−0.10	−0.10	0.14	−0.05	−0.03	−0.03	0.01	−0.07	1.0

a. Correlation coefficients for variables that significantly differ between telemetry and random locations (Table 2).
b. Variable descriptions in Table 1.

Discussion

The proliferation of digital spatial data makes habitat model development based on GIS technology appealing (Donovan et al. 1987, Pereira and Itami 1991, Clark et al. 1993, Homer et al. 1993). Our model development and testing methods offer a relatively inexpensive way to develop and test wildlife habitat models for a variety of species. Moreover, if models are to be applied to multiple areas, models based on GIS technology would be easier to use and more cost effective than models based on extensive field sampling.

Most variables in our model can be explained by prey abundance. Although prey abundance varied temporally, relative prey abundance among habitats did not change. Preliminary results of scat analyses on Tallahalla WMA indicate small mammals and rabbits comprise over 90% of bobcat prey (M. Chamberlain unpubl. data). On Tallahala WMA, these prey were most abundant in early successional habitats

Table 4. Logistic regression coefficients of a female bobcat habitat suitability model developed on Tallahala Wildlife Management Area in central Mississippi, 1989–1992.

Variable[a]	Coefficient	*P* (Coefficient = 0)
SLOPE	0.18	<0.001
SAP	−2.56	<0.001
RD1	−0.70	<0.001
RD3	−1.16	<0.001
CRK	−1.18	<0.001
HWD	−0.63	<0.001
PINE	2.48	<0.001
TYPE	−0.70	<0.001

a. SLOPE = slope class, SAP= distance to sapling stand, RD1 = distance to paved road, RD3 = distance to maintenance road, CRK = distance to creek, HWD = distance to hardwood stand, PINE = distance to pine stand, TYPE = stand type.

(e.g., agriculture field edges and sapling stands) and least abundant in mature pine stands (Conner 1991). Drift piles along creeks harbor abundant prey (Maser and Trappe 1984) and may explain the relationship between distance to creeks and probability of bobcat use. Conversely, bobcats may use creeks as travel corridors between prey rich habitats (Rolley 1983, Shiflet 1984). Bobcat use of roads for travel and/or hunting (McCord 1974, Hall and Newsom 1976) best explains inclusion of distance to paved and maintenance roads in our model.

The importance of slope and distance to hardwood stands in our model can not be explained by prey abundance. Distance to mature hardwood stands was inversely related to probability of bobcat use, yet prey density was low in mature hardwoods (Conner 1991). However, hardwood stands contained abundant hollow trees and logs and had virtually complete canopy closure during summer. Therefore, hardwood stands may have been important to bobcats for den sites, cover, and protection from summer heat (Hall and Newsom 1976, Heller and Fendley 1982). There is no obvious relationship between slope and bobcat prey abundance. Therefore, we believe bobcats preferred steeper slopes because of the relative seclusion offered by such areas (Zezulak and Schwab 1979, Hamilton 1982).

Internal and cross-validation procedures yielded similar results and indicated the model performed relatively well. In general, random locations were predicted with less accuracy than were used locations. Because it was impossible to determine non-used locations, some random locations likely fell in suitable bobcat habitat (Clark et al. 1993).

When independent data were used to assess the model, classification success was disappointing. The model correctly identified only 48% of bobcat locations. We previously reported no study-area specific differences in stand level habitat preference (Conner and Leopold 1996). However, because the habitat model developed on Tallahala WMA performed poorly on GP, habitat preference in multivariate space must have differed between the areas.

Bobcat habitat quality is often equated with prey abundance (Anderson 1987, Conner and Leopold 1996). Unfortunately, it was impossible to sample prey abundance associated with each bobcat location. Our model may have actually predicted the spatial arrangement of habitat features on Tallahala WMA that were conducive to prey abundance. There is no reason to believe, given different forest management procedures on GP, that similar habitat arrangements would be equally valuable to bobcat prey. For example, most of Tallahala WMA was comprised of mature pine forests. These stands had low prey abundance (Conner 1991). However, the roads passing through mature pine stands provided edge habitat beneficial to bobcat prey. Therefore, bobcats may have preferred roads on Tallahala WMA because of prey abundance associated with road edges. In contrast, the GP study area was dominated by younger pine stands, which had high prey abundance (Conner 1991). On GP, the relative importance of roads as habitat for prey may be small; thus, roads may have been less important to bobcats on GP. Therefore, differences in forest management practices between the 2 areas provide the most logical explanation for poor model performance on GP.

Management Implications and Future Research Needs

The procedures used to develop our habitat model are applicable to a wide variety of species. Further, biometric habitat models can provide a tool to ask 'what if' questions to aid in management decisions. For example, a forest manager could evaluate long-term effects of a proposed timber harvest strategy by linking habitat models to forest succession models and modeling future habitat conditions.

Building habitat models is an iterative process. As models are developed and tested, the test results should be used to further refine the model. In this paper, we present only the first stage of model development. Our goal was to develop a model that could predict impacts of various forest management activities on bobcat habitat. Our first attempt failed to adequately predict bobcat habitat on industrial forest. Future research should focus on generalizing the model such that it predicts well in a variety of forested landscapes.

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