

Predicting Landscape Quality for Northern Bobwhite from Classified Landsat Imagery

Garrett L. Schairer, *Conservation Management Institute, College of Natural Resources, Virginia Polytechnic Institute and State University, 203 W. Roanoke St., Blacksburg, VA 24061-0534*

Randolph H. Wynne, *Department of Forestry, Virginia Polytechnic Institute and State University, Blacksburg, VA 24060*

Michael L. Fies, *Virginia Department of Game and Inland Fisheries, P.O. Box 996, Verona, VA 24482*

Scott D. Klopfer, *Conservation Management Institute, College of Natural Resources, Virginia Polytechnic Institute and State University, 203 W. Roanoke St., Blacksburg, VA 24061-0534*

Abstract: A detailed understanding of the spatial arrangement of northern bobwhite (*Colinus virginianus*) habitats would allow more focused efforts by wildlife managers. We used a 4-year average of northern bobwhite call-count data in conjunction with remotely sensed habitat maps to study landscape-level habitat associations. Landscape metrics were calculated for the landscape surrounding each stop and were used in 2 modeling exercises to differentiate between high and low northern bobwhite populations. Both pattern recognition (PATREC) and logistic regression models predicted levels of northern bobwhite abundance well for the modeled (73.5% and 73.9%, respectively) and independent (74.6% and 76.6%, respectively) data sets. The revised models were applied to the remotely sensed habitat maps of the eastern 2/3 of Virginia to develop maps expressing the quality of a landscape for supporting a high population of bobwhite based on existing land cover. Both models predicted similar percentages in each of the quality classes.

Proc. Annu. Conf. Southeast. Assoc. Fish and Wildl. Agencies 53:243-256

Despite the long history of management and research on northern bobwhites (bobwhite), there is insufficient knowledge regarding the spatial arrangements of habitat at a level of detail greater than the home range of a covey. The need to study bobwhite populations within landscapes was expressed during a special workshop at the Third National Quail Symposium in 1992 where biologists met to develop a National Strategic Plan for Quail (Brennan 1993, Kuvlesky et al. 1993, Roseberry

1993). Using habitat modeling, geographic information systems (GIS), and remote sensing, biologists can examine broad, landscape associations. Recently, these technologies have been used to describe the spatial relations of habitats for prairie dogs (*Cynomys ludovicianus*; Reading and Matchett 1997), black-tailed jackrabbits (*Lepus californicus*; Knick and Dyer 1997), neotropical migratory songbirds (Keller and Anderson 1992), black-tailed deer (*Odocoileus hemionus*; Borosky et al. 1996), and spotted owls (*Strix occidentalis*; Hunter et al. 1995). The goals of this research were to examine the spatial relationships of various components of bobwhite habitat and develop predictive models expressing the probability of a landscape supporting high bobwhite numbers.

Habitat modeling often simplifies the relationship between an animal population and its habitat, while recording or predicting a species' response to its environment (Schamberger and O'Neal 1984). Wildlife researchers commonly use models to predict population numbers and population responses to habitat quality and quantity (Thomas 1980, Gaudette 1986). Berry (1986) noted that responses to quality and quantity of habitat have been the basis for a number of different models, including Habitat Suitability Index (HSI) models, Pattern Recognition Models (PATREC), and Habitat Capability (HC) models.

Pattern recognition models were first used in the medical field to express the uncertainty and risk associated with diagnosing medical conditions (Williams et al. 1978). Within the wildlife profession, PATREC models have been adapted to improve managers' likelihood of making a decision that favorably impacts a species. PATREC models rely on Bayesian statistics to predict the quality of a habitat for a species given a particular set of conditions (Williams et al. 1978). Measured habitat characteristics that can be placed in mutually exclusive classes allow managers to describe a landscape (or habitat) as suitable or unsuitable for a particular population level of a species. The ability to assign a probability to an identified set of habitat conditions can guide the decision-making process (Williams et al. 1978). PATREC models have been developed for northern bobwhite (Roseberry and Sudkamp 1998), wild turkey (*Meleagris gallopavo*; Kurzejeski and Lewis 1985), bald eagles (*Haliaeetus leucocephalus*; Grubb 1988), and white-tailed deer (*Odocoileus virginianus*; Gaudette 1986).

Logistic regression analysis is often used in habitat quality analyses because it assumes that the variables are fixed and the response is binomial, and can take advantage of both continuous and categorical variables in the same equation. For example, logistic models have been used to predict the probability of detecting neotropical migrant bird species in forest stands of different sizes (Robbins et al. 1989), to test the cumulative effects of human disturbance on bald eagle foraging and perching (Montopoli and Anderson 1991), and to explain the differential use of subnivean access holes used by American marten (*Martes americana*; Sherburne and Bissonette 1994).

This research was supported financially by Virginia Department of Game and Inland Fisheries; the Virginia Space Grant Consortium; the Department of Fisheries and Wildlife Sciences, Virginia Tech; and the Fish and Wildlife Information Ex-

change, Virginia Tech. We thank Virginia Department of Game and Inland Fisheries personnel for conducting the bobwhite call counts and providing assistance throughout. A. B. Jones and S. W. Capel provided invaluable technical assistance. We especially thank S. A. McNulty and J. L. Waldon for reviewing earlier drafts of this manuscript.

Methods

A GIS was used to combine and manipulate bobwhite call count data and digital land cover data. We investigated 2 modeling techniques to generate useful descriptions of high quality bobwhite habitats. Both a PATREC model and a logistic regression model were developed to express the probability of an area supporting a high bobwhite population.

Our study was conducted in the coastal plain and Piedmont regions of Virginia which encompass approximately 79,560 km². The landscape in the study area is a matrix of forests (mostly conifers and mixed hardwoods) and agricultural lands. The climate and elevation are typical of the coastal plain and piedmont regions within the southeastern United States.

Data Acquisition

Habitat Data.—A remotely sensed digital land cover map was developed from spectral interpretation of Landsat TM satellite imagery (1991–1993). This land cover map contained 8 classes (row crops, pasture/hay/grass, early succession, conifer forest, deciduous forest, open water, wetlands, and urban/disturbed) with an overall estimated accuracy >70% and had a spatial resolution of 29.9 m × 29.9 m (Schairer 1999). We recognize the inadequacy of Landsat TM imagery to detect some small features such as hedgerows and wooded draws, but this was the only landscape data set available.

Population Counts.—Northern bobwhite call count data were collected each July on a set of permanent routes in Virginia and were used as an index of relative bobwhite abundance. The number of bobwhite individuals heard calling during a 2-minute sample was recorded at each of 10 stops along 14.48 km routes. Counts were performed by trained VDGIF biologists started at local sunrise. Counts were not conducted if the cloud cover was >75% or the wind was greater than 11.3 km per hour. A total of 815 independent route stops were located within the study area as some stops were not independent and some routes left the study area before completion. Route maps were converted to digital format using 1:100,000 U.S. Geological Survey (USGS) Digital Line Graph (DLG) road coverages (USGS 1996) using ArcView GIS Version 3.1 and ARC/INFO (Environ. Sys. Res. Inst., Inc. 380 New York Street, Redlands, Calif.). We used this average number of quail calling as an index to the population of bobwhite quail at that stop, recognizing that there are limitations to call count surveys (Norton et al. 1961, Robel et al. 1969, Bart et al. 1995, Link and Sauer 1998). We calculated the mean number of bobwhite heard at each stop during

the 4 years (1990–1993) leading up to and including the dates of the remotely sensed imagery. The population index was split into 2 groups, representing high (>1.0 bobwhite heard; $\bar{x}=2.156$ bobwhite/stop) and low (≤ 1.0 bobwhite heard; $\bar{x}=0.375$ bobwhite/stop) population levels. After examining the scatterplots for natural breaks and comparing the existing breaks with the perceived amount of the state capable of supporting high quail numbers we selected this threshold for our population break. Habitats in Virginia are marginal compared to other southeastern states, typically supporting a far lower quail population than elsewhere across its range. The threshold we used to differentiate between “high” and “low” populations is relative to typical bobwhite numbers in Virginia and is different than other researchers may use elsewhere. The stops were buffered using an 800-m radius circle to delineate the landscape surrounding each stop. We selected this distance because it would include all the possible locations of the calling quail and was small enough to ensure independent landscapes along the routes. We built the models using 614 stops (75.3%) and reserved 201 stops (24.7%) for an independent assessment of the model.

Landscape Metrics.—Landscape composition and pattern were examined using a number of landscape metrics calculated in ArcView 3.1 similar to those used in FRAGSTATS, a U.S. Department of Agriculture Forest Service program for analyzing spatial patterns (McGarigal and Marks 1995). We chose the percentage of the landscape, the mean patch size, and the mean edge contrast index for each of the land cover types, and a patch-per-unit measure expressing landscape contagion (Frohn 1998) as our landscape metrics (Table 1). These 19 metrics were chosen based on our knowledge of the landscape metrics calculated by FRAGSTATS and by examining similar landscape studies (e.g., Roseberry and Sudkamp 1998, Michener et al. 1998).

Table 1. Nineteen landscape metrics calculated at each quail call count stop location, eastern Virginia, 1990–1993.

Landscape Metric	Landscape Metric Description
Percent of the landscape in row crops	Percentage of the 800-m radius landscape in the cover type
Percent of the landscape in early succession	
Percent of the landscape in pasture/hay/grass	
Percent of the landscape in coniferous forest	
Percent of the landscape in deciduous forest	
Percent of the landscape in open water	
Mean patch size of row crops	Mean patch size of all the patches of the cover type
Mean patch size of early succession	
Mean patch size of pasture/hay/grass	
Mean patch size of coniferous forest	
Mean patch size of deciduous forest	
Mean patch size of open water	
Mean edge contrast index row crops	Mean of weighted edges as they might appear to bobwhite
Mean edge contrast index early succession	
Mean edge contrast index pasture/hay/grass	
Mean edge contrast index coniferous forest	
Mean edge contrast index deciduous forest	
Mean edge contrast index open water	
Patch per unit	A better measure of contagion in raster environments

PATREC Modeling.—Hall et al. (1997) defined habitat quality as “the ability of the environment to provide conditions appropriate for individual and population persistence.” When we use the term habitat quality, we are implying the ability of a habitat to provide the life requisites for bobwhite.

A PATREC model was built to predict habitat quality for bobwhite in the Piedmont and coastal plain of Virginia using the 19 landscape metrics. Relationships between variables were tested using Pearson product-moment correlation coefficients (Zar 1984; PROC CORR, SAS Inst. 1990). All statistical tests were statistically significant at an $\alpha=0.10$ level. Any pair of variables with a correlation greater than 0.5 was examined to see if 1 variable could be dropped from the modeling phase. We used Wilcoxon signed rank tests to compare differences between the high and low population levels for each of the remaining metrics (Zar 1984). Mutually exclusive categories for each landscape variable were defined by examining scatter plots of the bobwhite call count and the landscape metric so that the categories differentiated between the population levels. Each mutually exclusive category had 2 conditional probabilities expressing the probability for that level of the landscape metric, one given the habitat was suitable and the other given the habitat was not suitable. An equation based on Bayes theorem of conditional probability was used to combine the conditional and prior probabilities into one final PATREC model probability (Williams et al. 1978). The model was tested on the independent set of stops to determine the accuracy of the model. We also examined the model fit for the modeled data set.

Logistic Regression Modeling.—A stepwise logistic regression model was developed in SAS (PROC LOGISTIC; SAS Inst. 1990) that predicted the probability of a high population existing on a landscape in eastern Virginia. We maintained the same split between high and low populations and used the same 19 landscape metrics as the PATREC model. The model was assessed using the randomly selected set of independent stops by applying the logistic regression equation to the landscape variables collected at the stop. Again, we applied the resulting equation to the modeled data set to ensure that the equation fit the modeled data. Finally, Pearson product-moment correlation coefficients were calculated between the final logistic probability for a stop and its bobwhite call count to evaluate the model prediction.

Comparing and Applying Models

The PATREC posterior probabilities were compared to the logistic regression probabilities to evaluate the fit of both models. Pearson product-moment correlation coefficients were calculated between the final PATREC posterior probability and the logistic regression model in SAS.

Both final models were applied to the entire study area to gain insight about locations of potentially high quality bobwhite habitats within the study area. We sampled 200 random points within the study area, collecting the final probabilities for each of the models. Correlation coefficients were used to examine these pairs of values to see if the models were predicting probabilities similar to each other across the study area.

Results

PATREC Modeling

Of the 614 stops used to build the model, 444 had a mean ≤ 1.0 bobwhite heard, leading to prior probabilities of 0.28 and 0.73 for high and low populations, respectively. Eight metrics were found to be statistically significant between the habitat quality levels (Table 2). High bobwhite populations were found in areas with a greater percentage of the landscape in row crops, a lower percentage in deciduous forest, a higher mean patch size for row crops, a lower mean patch size of deciduous forest, lower mean edge contrast indices for row crops and water, and higher mean edge contrast edge indices for pasture and deciduous forest than areas with low bobwhite populations (Table 2). The 8 metrics were split into 2 or 3 classes that attempted to explain the differences between high and low bobwhite call counts (Table 3). Three variables were removed from the model because we determined that the model did not adequately differentiate between population levels or they contributed little to the overall model. Table 4 provides an example of how conditional probabilities for each landscape variable were combined into 1 final probability.

Of the 201 independent stops reserved to assess the accuracy of the models, 74.6%

Table 2. Summary statistics for Wilcoxon Sign Rank tests (S) for the 8 variables entered in the PATREC model, eastern Virginia, 1990–1993. Low population is defined as having an average ≤ 1.0 bobwhite heard at a stop ($N = 444$) and high populations are defined as having an average number heard > 1.0 at a stop ($N = 170$).

Parameter	Mean	S	P
Percent row crops			
Low	275.55		
High	390.96	66462.5	0.0001
Percent deciduous forest			
Low	328.64		
High	252.28	60785.0	0.0001
Mean patch size—row crops			
Low	281.14		
High	376.34	63977.5	0.0001
Mean patch size—deciduous forest			
Low	329.43		
High	250.22	42537.0	0.0001
Mean edge contrast index—row crops			
Low	329.88		
High	249.05	42338.0	0.0001
Mean edge contrast index—pasture/grass/hay			
Low	297.32		
High	334.08	56793.0	0.0216
Mean edge contrast index—deciduous forest			
Low	288.33		
High	357.56	60785.0	0.0001
Mean edge contrast index—open water			
Low	314.91		
High	288.14	48983.5	0.0567

Table 3. Conditional probabilities used in summer northern bobwhite PATREC model for eastern piedmont and coastal plain regions of Virginia, 1990–1993.

Feature	Habitat Quality Classes	
	High Population Conditional Probabilities	Low Population Conditional Probabilities
1. Percent of the landscape in row crops		
a. <20.0%	0.388	0.667
b. 20.0–60.0%	0.582	0.332
c. >60.0%	0.029	0.001
2. Mean patch size of row crops		
a. <10.0 ha	0.829	0.955
b. ≥10.0 ha	0.171	0.045
3. Mean patch size of deciduous forest		
a. <1.0 ha	0.453	0.241
b. ≥1.0 ha	0.547	0.745
4. Mean edge contrast index—row crops		
a. <29.0	0.594	0.408
b. ≥29.0	0.406	0.592
5. Mean edge contrast index—pasture/hay/grass		
a. <15.0	0.288	0.356
b. 15.0–50.0	0.647	0.597
c. >50.0	0.065	0.047

Table 4. Sample PATREC model calculations¹ using 1 bobwhite call count stop, showing the steps taken to calculate the posterior condition probabilities (CP) of that stop supporting a high bobwhite population based on the habitat characteristics of the sampled stop.

Variable	CP(high)	CP(low)
Percent in row crops = 42	0.38	0.13
Mean patch size row crops = 15.3	0.11	0.02
Mean patch size deciduous forest = 0.75	0.45	0.24
Mean edge contrast index row crops = 20	0.59	0.41
Mean edge contrast index pasture/hay/grass = 5	0.29	0.36

1. Posterior probabilities are calculated to express the probability of a particular stop supporting a high bobwhite population given the existing habitat features. Based on Bayes' theorem, the formula used is:

$$P(S|E) = \frac{P(S)P(E|S)}{P(S)P(E|S) + P(U)P(E|U)}$$

where P(S) equals the prior probability of suitable habitat; P(U) equals the prior probability of unsuitable habitat; P(E|S) equals the likelihood of sample result E given suitable habitat; P(E|U) equals the likelihood of sample result E given unsuitable habitat; and P(S|E) equals the revised or posterior probability of suitable habitat given sample result E.

So: for this stop: P(S)=0.277; P(U)=0.723; P(E|S) = ((0.38)(0.11)(0.45)(0.59)(0.29))=0.0032184; P(E|U) = ((0.13)(0.02)(0.24)(0.41)(0.36)) = 0.0000924; and

$$P(S|E) = \frac{(0.28)(0.0032184)}{(0.28)(0.0032184) + (0.72)(0.0000924)} = 0.93125.$$

Table 5. Final PATREC and logistic regression classification table for bobwhite population abundance for the modeled bobwhite call count stops and the independent set of stops, eastern Virginia, 1990–1993.

Observed Population Abundance	Predicted Population Abundance											
	PATREC Model						Logistic Regression Model					
	Modeled Data (<i>N</i> = 614)			Independent Data (<i>N</i> = 201)			Modeled Data (<i>N</i> = 614)			Independent Data (<i>N</i> = 201)		
	High	Low	% Correct	High	Low	% Correct	High	Low	% Correct	High	Low	% Correct
High	56	114	32.9	22	29	43.1	21	149	12.3	9	42	17.6
Low	49	395	89.0	22	128	85.3	11	433	97.5	5	145	96.7
Percent correct	53.3	77.6	73.5	50.0	81.5	74.6	65.6	74.4	73.9	64.3	77.5	76.6

Table 6. Logistic regression parameter estimation for 2-variable model predicting high/low bobwhite populations in eastern Virginia, 1990–1993.

Variable	Parameter Estimates	SE	χ^2	<i>P</i>
Intercept	-1.4220	0.1696	70.2827	0.0001
% in row crops	0.0448	0.00717	39.0565	0.0001
Mean patch size of deciduous forest	-0.0401	0.0187	4.5874	0.0322

were correctly classified (Table 5). When the model was applied to the modeled data, it also performed well, yielding an accuracy of 73.5%. This model under-predicted the quality of the landscape at a number of the modeled stops, but performed slightly better on the independent set than the modeled data set. Of the independent data set, there was no distinct trend towards erroneously predicting either population level (Table 5).

Logistic Regression Modeling

Two of the 19 landscape metrics entered into a stepwise logistic equation model were significant factors in describing the differences between bobwhite population levels (Table 6). This model had a concordance of 69.5% and accurately predicted bobwhite populations at 73.9% of the modeled stops and at 76.6% of the independent verification stops (Table 5). On both the independent and modeled data stops, this model tended to under-predict the quality of the landscape, predicting most of the stops had low habitat quality class. The majority of the erroneous stops predicted a low population when there was a high population (Table 5).

Model Comparison and Application

Pearson product-moment correlation coefficients between the logistic regression probability and the posterior probabilities from the PATREC model indicated that the models were highly correlated ($R=0.85768$, $N=815$, $P=0.0001$). Pairs of

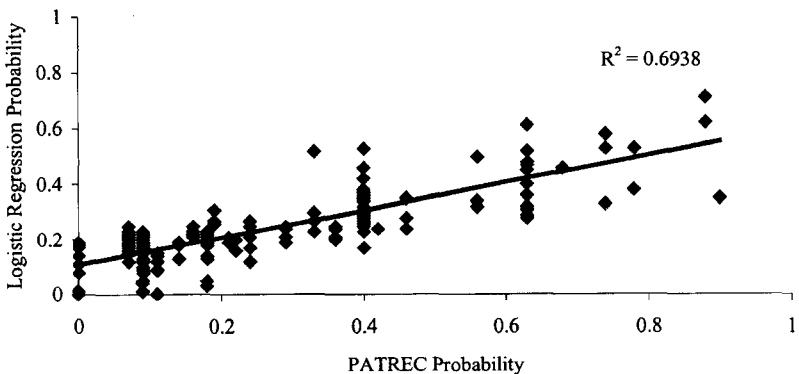


Figure 1. Comparison of PATREC and Logistic Regression probabilities from 200 randomly selected points on the landscape. The graph shows that the models predict similar probabilities across eastern Virginia, 1990–1993.

PATREC posterior probabilities and logistic regression probabilities differed (Wilcoxon signed rank test: $S=104.5$, $N=815$, $P<0.0001$), with a mean difference between the models of 11.6%. The probabilities from each of the 2 models collected at 200 random points across the landscape revealed that the models predicted similar probabilities (Fig. 1, $R=0.83294$, $N=200$, $P<0.001$), indicating that the models did not depart significantly from each other in their estimation of the quality of individual landscapes.

When the models were applied to the entire study area, both models predicted comparable amounts in the low (91.8% PATREC and 95.3% logistic regression) and the high quality (8.2% PATREC and 4.7% logistic regression) classes. The majority of eastern Virginia appears to have low probability of supporting a high bobwhite population according to both of our models.

Discussion

PATREC Model

Landscapes with 20%–60% in row crops appeared optimal for bobwhite in Virginia. The optimal percent of the landscape was 30%–70% in Illinois (Roseberry and Sudkamp 1998), 30%–35% in Georgia (Michener et al. 1998), and 50%–60% in Missouri (Dailey 1989). The mean patch size of row crops was also a significant variable in our PATREC model. It has been hypothesized that increasing field or patch sizes has a negative effect on bobwhite populations due to the loss of edges and larger core field area (Roseberry and Klimstra 1984, Brennan 1991). The optimum mean patch size in our study area was <10.0 ha, which included the optimum of 2–3 ha described by Michener et al. (1991) in Georgia. Lower populations of bobwhite were detected on landscapes with a mean patch size of deciduous forest that was >1.0 ha. Moderate amounts of edge with open land types (row crops and pasture/hay/grass) also appeared beneficial.

Logistic Regression Model

The logistic regression model contained 2 significant variables, both of which were significant variables in the PATREC model. The percentage of the landscape in row crops was positively associated with a high population index. The importance of crops and early succession habitats has been well documented (Roseberry and Klimstra 1984, Michener et al. 1998, Roseberry and Sudkamp 1998). The mean patch size of deciduous forest was also significant, being negatively related to bobwhite populations. This variable in our model approximates the negative association a closed canopy forest has with bobwhite populations. As patches of deciduous forest get larger, there is less of the other, high quality habitats for bobwhite in the landscape.

Model Comparison

We achieved similar results with the PATREC and logistic regression models. They were both structured to predict the probability of supporting a high bobwhite

population, using the same high/low population levels. Correlation coefficients between model outputs showed comparable results between models, and the overall percentage of the study area being classified with a high probability was comparable between models. Some feel PATREC models are more useful when only landscape level, coarse-scale habitat data are available, such as from remotely sensed images (Roseberry and Sudkamp 1998). The final PATREC model appeared to fit the data reasonable well and was consistent with other similar studies.

The PATREC model was more difficult and time consuming to generate. Conversely, the logistic model was easier to create, is easier to explain to non-modelers, included fewer variables, and had a slightly better fit than the PATREC model. Despite similar overall accuracy between the models, the PATREC model appeared to better predict those areas capable of supporting high bobwhite numbers than the logistic regression model because the nature of the logistic regression model was to predict most areas as being of low quality. We believe that quail management will be better served if it is based upon a model better able to identify high quality habitats than one that has a slightly better fit.

Model Application

The logistic regression and PATREC models showed areas that have the potential to support high bobwhite populations based on existing landscape conditions. Both models predicted little of the study area in the high habitat quality class, but the PATREC model appeared to better approximate the amount of the study area likely to support high bobwhite numbers than the logistic regression model. Despite small sample sizes in the high quality class, we feel that the PATREC model better depicted habitat quality for bobwhite than the logistic regression model.

The model accuracy may have been influenced by the size of the defined landscape. We opted for an 800-m radius circle, which may have included too much unsuitable habitat; however, Roseberry and Sudkamp (1998) used a similar sized landscape in Illinois (909-m radius circle). Our decision to include this amount of area was based on the landscape sizes used by Roseberry and Sudkamp (1998) and our desire to include the landscape surrounding any potential bobwhite location heard at the stop.

Conclusions and Management Implications

Northern bobwhites on the coastal plain and Piedmont of eastern Virginia were predicted to occur in high numbers in areas with certain landscape characteristics. The predictive capability of these models will allow wildlife managers to concentrate their work in an area likely to support a high bobwhite population. By targeting an area likely to respond to management actions, managers can reduce the possibility of taking management actions on "islands" of good habitat within lower-quality landscapes. These models will also serve as a monitoring tool to quantify changes in the amounts of high and low quality habitat over time caused by changing land use patterns and changes in habitat due to habitat management programs.

This application of remote-sensing technology to assess and, in the future, monitor bobwhite habitat holds great promise, permitting managers to both spatially

identify areas of interest for bobwhite management and evaluate habitat management programs over large regions. Applications to other species will no doubt follow in coming years.

We selected certain sized landscapes and landscape metrics we thought were biologically meaningful and consistent with the literature. Continued research in both of these areas may reveal additional information of value to quail managers. In Virginia, we used a population threshold of ≥ 1.0 to indicate areas with high quail populations, which may be an arbitrary level for quail and is extremely low compared to other portions of the Northern bobwhite range. An examination of the effect of this threshold may reveal some different conclusions.

Literature Cited

- Bart, J., M. Hofschien, and B. G. Peterjohn. 1995. Reliability of the Breeding Bird Survey: Effects of restricting surveys to roads. *Auk* 112:758–761.
- Berry, K. H. 1986. Introduction: Development, testing, and application of wildlife-habitat models. Pages 3–4 in J. Verner, M. L. Morrison, and C. J. Ralph, eds. *Wildlife 2000: Modeling habitat relationships of terrestrial vertebrates*. Univ. Wisc. Press, Madison. 469pp.
- Boroski, B. B., R. H. Barrett, I. C. Timossi, and J. G. Kie. 1996. Modeling habitat suitability for black-tailed deer (*Odocoileus hemionus columbianus*) in heterogeneous landscapes. *For. Ecol. and Manage.* 88:157–165.
- Brennan, L. A. 1991. How can we reverse the northern bobwhite population decline. *Wildl. Soc. Bull.* 19:544–55.
- . 1993. Strategic plan for quail management and research in the United States: Introduction and background. Pages 160–169 in K. E. Church and T. V. Dailey, eds. *Quail III: National Quail Symposium*. Kans. Dep. Wildl. and Parks, Pratt.
- Dailey, T. V. 1989. Modeling bobwhite quail habitat relationships on 4 central Missouri wildlife management areas. Mo. Dep. Conserv., Fed. Aid in Wildl. Restor. Proj. W-13-R-43, Final Rep. 19pp.
- Frohn, R. C. 1998. Remote sensing for landscape ecology. Lewis Publ., Boca Raton, Fla. 88pp.
- Gaudette, M. T. 1986. Modeling winter habitat for white-tailed deer in southwestern Virginia. M.S. Thesis, Va. Polytechnic Inst. and State Univ., Blacksburg. 68pp.
- Grubb, T. G. 1988. Pattern recognition—a simple model for evaluating wildlife habitat. U.S. Dep. Agric. (USDA) For. Serv. Rocky Mtn. For. and Range Exp. Sta., RM-487, Fort Collins, Col. 5pp.
- Hall, L. S., P. R. Krausman, and M. L. Morrison. 1997. The habitat concept and a plea for standard terminology. *Wildl. Soc. Bull.* 25:173–182.
- Hunter, J. E., R. J. Gutierrez, and A. B. Franklin. 1995. Habitat configuration around spotted owl sites in northwestern California. *Condor* 97:684–693.
- Keller, M. E. and S. H. Anderson. 1992. Avian use of habitat configurations created by forest cutting in southeastern Wyoming. *Condor* 94:55–65.
- Knick, S. T. and D. L. Dyer. 1997. Distribution of black-tailed jack rabbit habitat determined by GIS in southwestern Idaho. *J. Wildl. Manage.* 61:75–85.
- Kurzejeski, E. W. and J. B. Lewis. 1985. Application of PATREC modeling to wild turkey

- management in Missouri. Pages 269–283 in J. Earl and M. C. Kennamer, eds. Proc. Fifth Natl. Wild Turkey Symp., Des Moines, Iowa.
- Kuvlesky Jr., W. P., B. D. Leopold, P. D. Curtis, J. L. Roseberry, and T. Hutton. 1993. Strategic plan for quail management and research in the United States: issues and strategies: Population dynamics and effects of hunting. Pages 180–181 in K. E. Church and T. V. Dailey, eds. Quail III: National Quail Symposium. Kans. Dep. Wildl. and Parks, Pratt.
- Link, W. A. and J. R. Sauer. 1998. Estimating population change from count data: Application to the North American Breeding Bird Survey. *Ecol. Appl.* 8:258–268.
- McGarigal, K. and B. J. Marks. 1995. FRAGSTATS: spatial pattern analysis programs for quantifying landscape structure. U.S. For. Serv. Gen. Tech. Rep. PNW-351, Pacific Northwest For. Exp. Sta., Portland, Ore. 122pp.
- Michener, W. K., J. B. Atkinson, P. F. Houhoulis, P. M. Johnson, R. N. Smith, and J. W. Jones. 1998. Northern bobwhite quail: responses to landscape configuration. Tech. Pap., 64th Annu. Meet. Am. Soc. for Photogrammetry and Remote Sensing, Tampa, Fla. 10pp.
- Montopoli, G. J. and D. A. Anderson. 1991. A logistic regression model for the cumulative effects of human intervention on bald eagle habitat. *J. Wildl. Manage.* 55:290–293.
- Norton, H. W., T. G. Scott, W. R. Hanson, and W. D. Klimstra. 1961. Whistling-cock indices and bobwhite populations in autumn. *J. Wildl. Manage.* 25:398–403.
- Reading, R. P. and R. Matchett. 1997. Attributes of black-tailed prairie dog colonies in north-central Montana. *J. Wildl. Manage.* 61:664–673.
- Robbins, C. S., D. K. Dawson, and B. A. Dowell. 1989. Habitat area requirements of breeding forest birds of the middle Atlantic states. *Wildl. Monogr.* 103. 34pp.
- Robel, R. J., D. J. Dick, and G. F. Krause. 1969. Regression coefficients used to adjust bobwhite quail whistle count data. *J. Wildl. Manage.* 33:662–668.
- Roseberry, J. L. 1993. Bobwhite and the “new biology.” K. E. Church and T. V. Dailey, eds. Pages 16–20 in Quail III: National Quail Symposium. Kans. Dep. Wildl. and Parks, Pratt.
- and W. D. Klimstra. 1984. Population ecology of the bobwhite. South. Ill. Univ. Press, Carbondale. 259pp.
- and S. D. Sudkamp. 1998. Assessing the suitability of landscapes for northern bobwhite. *J. Wildl. Manage.* 62:895–902.
- SAS Institute, Inc. 1990. SAS/STAT user’s guide. Vers. 6.0. SAS Inst., Inc., Cary, N.C. 1686pp.
- Schairer, G. L. 1999. Landscape level evaluation of northern bobwhite habitats in eastern Virginia using Landsat TM imagery. M.S. Thesis, Va. Polytechnic Inst. and State Univ., Blacksburg. 168pp.
- Schamberger, M. and J. O’Neal. 1984. Concepts and constraints of habitat model testing. Pages 5–10 in J. Verner, M. L. Morrison, and C. J. Ralph, eds. *Wildlife 2000: Modeling habitat relationships of terrestrial vertebrates*. Univ. Wisc. Press, Madison. 469pp.
- Sherburne, S. S. and J. A. Bissonette. 1994. Marten subnivean access point use: response to subnivean prey levels. *J. Wildl. Manage.* 58:400–405.
- Thomas, J. W. 1980. Wildlife-habitat modeling—cheers, fears, and introspection. Pages xix–xxv in J. Verner, M. L. Morrison, and C. J. Ralph, eds. *Wildlife 2000: Modeling habitat relationships of terrestrial vertebrates*. Univ. Wisc. Press, Madison. 469pp.
- United States Geological Survey (USGS). 1996. U.S. GeoData Digital Line Graphs USGS FS-078–96. 74pp.

- Williams, G. L., K. R. Russell, and W. K. Seitz. 1978. Pattern recognition as a tool in the ecological analysis of habitat. Pages 521–531 *in* Classification, inventory, and analysis of fish and wildlife habitat: proceedings of a national symposium. U.S. Fish and Wildl. Serv. Biol. Serv. Prog. FWS/OBS-78/76.
- Zar, J. H. 1984. Biostatistical analysis. Second Ed. Prentice-Hall Inc., Englewood Cliffs, N.J. 718pp.