Identification of Potential Red-cockaded Woodpecker Habitat Using Landsat Thematic Mapper and Remotely Sensed Data

James A. Cox, *Tall Timbers Research Station, 13093 Henry Beadel Road, Tallahassee, FL 32312-9712*

Abstract: Identifying habitat for species with special ecological requirements can be a challenging task when procedures are based on remotely sensed data. I used georeferenced locations of red-cockaded woodpecker *(Picoides borealis)* cavity trees to evaluate the effectiveness of Landsat Thematic Mapper (TM) data and a digital elevation model in identifying oldgrowth pine forests that provide nesting habitat for this species. Remotely sensed data associated with active cavity trees (*N*=142) and polygons surrounding active cavity clusters (*N*=179) were compared to locations with unsuitable habitat (*N*=1000). Elevation was the best predictor of woodpecker locations, but some TM bands improved classifications slightly. The best classification (overall accuracy=74%, *kappa*=0.45) was based on an elevation mask and transformed TM data associated with the red, blue, and green TM bands. TM bands were transformed using linear stretching procedures and neighborhood statistics computed using a 5-by-5 pixel window. Accuracy might be further improved by analyzing patch size and shape characteristics, but such analyses would be complex and likely still fall short of common accuracy standards. Other procedures to identify potential habitat, such as aerial photo interpretation, are more appropriate for this species, and any attempt at habitat identification must allocate sufficient time for extensive field surveys.

Proc. Annu. Conf. Southeast. Assoc. Fish and Wildl. Agencies 55:534–546

Habitat delineation is an essential step in managing populations of rare species, but several factors can thwart attempts to construct accurate habitat maps. Access to private lands containing suitable habitat is often prohibited (Scepan et al. 1987, Stoms et al. 1993). Large areas often also must be surveyed, which requires considerable time and expense when field-based techniques are employed (Short 1982). Because of these and other difficulties, wildlife biologists frequently consider use of remotely sensed data for habitat mapping efforts before more intensive techniques are proposed (Stoms 1994).

Landsat Thematic Mapper TM data have been used to map potential habitat for many wildlife species, including several rare species (e.g., Hodgson et al. 1987, Jakubauskas 1992, Shaw 1989). Landsat TM data capture reflectance data from the visible to the thermal-infrared portions of the electromagnetic spectrum and have a spatial resolution of 0.09 ha (Short 1982). TM data appear to be most useful when applied to wide-ranging species such as grizzly bear (*Ursus arctos;* Craighead et al.

1982) and California condor (*Gymnogyps californianus;* Stoms et al. 1993), but attempts to map features at a finer scale also have been productive (Lauver and Whistler 1993, Shaw 1989). Landsat TM data also form the primary source of habitat information used in many GAP analysis programs (Scott et al. 1993, Stoms 1994).

The red-cockaded woodpecker *(Picoides boreals)* is an endangered species that occupies mature pine forests of the southeastern United States (Lennartz and Henry 1985). Red-cockaded woodpeckers excavate breeding and roosting cavities only in old growth (usually >80-year-old) living pine trees, and breeding groups maintain large territories (ca. 40–100 ha; Lennartz and Henry 1985) that contain a mixture of upland pine and other plant communities (Hovis and Labisky 1985). Because red-cockaded woodpeckers select nesting sites based on habitat structure and timber age as well as dominant tree species, delineation of suitable habitat can be particularly difficult using remotely sensed data.

Thomlinson (1993) analyzed TM data within polygons containing suitable woodpecker habitat and then performed standard supervised and unsupervised classification procedures (Short 1982) for a larger area. The accuracies of these classification were low (<4%). Greater accuracy might have been achieved if additional geographic data, such as elevation (Faust et al. 1991), had been included, or locations with suitable habitat conditions had been more precise. Accuracy also might have been improved if image enhancement (Short 1982), neighborhood classification (Swain et al. 1981), or patch shape analysis (McGarigal and Marks 1995) had been applied.

I used precise location information collected using a global positioning system (GPS) and more extensive classification procedures to reassess the use of TM data and other remotely sensed data (e.g., a digital elevation model) to identify potential nesting habitat for red-cockaded woodpeckers. My objective was to identify red-cockaded woodpecker habitat by comparing remotely sensed data at locations with active cavity trees to locations with unsuitable habitat conditions using discriminant function analysis (Clark et al. 1993). The data come from the population of red-cockaded woodpeckers found in the Red Hills region of northwest Florida and southwest Georgia (Engstrom and Baker 1995, Cox et al. 2001). This is the largest population remaining largely on private lands (Engstrom and Baker 1995), so identification of potential habitat is an important step for conservation of the population.

C. Ambrose, L. Brennan, T. Engstrom, J. Meyers, and an anonymous reviewer provided helpful comments on earlier drafts of this paper. I also thank J. van Zyl and W. Baker for assistance in developing the data sets used in these analyses.

Methods

The Red Hills physiographic region covers 24,000 km^2 of Jefferson, Leon, and Gadsden counties, Florida, and Grady and Thomas counties, Georgia. Upland forests are a mixture of second-growth loblolly *(Pinus taeda),* shortleaf *(P. echinata),* and longleaf pines *(P. palustris)* and some relatively undisturbed, old-growth stands of longleaf pine (Engstrom and Baker 1995).

Cox et al. (2001) visited cavity clusters in 1999 and georeferenced each cavity tree using a Trimble GeoExplorer II unit (Trimble Navigation Ltd., Sunnyvale, Calif.). The 2-dimensional variation in georeferenced locations was <3 m (Cox et al. 2001). Cavity trees also were classified as "active" (occupied within the past few months) or "inactive" (not recently occupied) using criteria in Jackson (1977). Only active cavity trees were used in these analyses. I created polygons depicting core cluster areas by connecting cavity trees (both active and inactive) in the cluster with a minimum convex polygon (Lipscomb and Williams 1995). Only core polygons containing at least 1 active cavity were used in the analyses.

Landsat 7 TM data (Earth Resour. Observ. Systems Data Ctr., Sioux Falls, S.D.) collected on 24 December 1999 were obtained from the Florida Department of Environmental Protection. TM data were georeferenced using digital orthographic quadrangles obtained from the Georgia Geographic Information Systems (GIS) Clearinghouse (Atlanta, Ga.) to attain a root mean square error of 0.5 (<7 m). Each TM band was then converted to the raster format used in ArcView Spatial Analyst (Environ. Systems Res. Inst., Redlands, Calif.). A digital elevation model obtained from the Georgia GIS Clearinghouse (1:24,000) also was converted to a raster format. I processed all GIS data layers using a Universal Transversed Mercator projection (Zone 16, North Am. Datum 1983). All GIS procedures were performed using ArcView and ArcView Spatial Analyst, and supplemental programs developed for ArcView (e.g., Hooge et al. 1999, Rempel et al. 1999).

Locations of unsuitable habitat conditions were generated using 2 methods. First, aerial photographs taken in 1994 (1:24,000) were used to digitize marshes, lakes, fields, pine plantations, urban areas, and other land cover features >0.25 ha. These features were digitized in conjunction with a study of upland ground cover (C. Ambrose, unpubl. rep., Tall Timbers Res. Sta., Tallahassee, Fla.) and did not include floodplain forests and upland hardwood forests. Point locations (N=750) were created randomly within these digitized polygons with the stipulation that locations were >15 m from exterior edges (Hooge et al. 1999).

The second method to establish unsuitable locations focused on floodplain forests and upland hardwood forests not digitized above. These cover types were identified from digital orthographic quadrangles, and I generated x-, y-locations (N=250) by digitizing sites directly in the GIS. Locations generated in this manner were >500 m apart to minimize spatial autocorrelation (see below).

I performed statistical comparisons of locations with suitable habitat (i.e., active clusters) to locations with unsuitable habitat (fields, urban areas, lakes, forested wetlands, etc.) using Systat (Wilkinson 1998). Elevation values and spectral signatures for TM data were compiled at each location, and multivariate discriminant function analysis (DFA) was used to identify variables that best discriminated between suitable and unsuitable locations (Clark et al. 1993, Wilkinson 1998). Effectiveness of different variables was determined by comparing F-ratios and tolerance statistics (Wilkinson 1998). Tolerance statistics gauge the redundancy of variables included in a DFA (Wilkinson 1998). The *kappa* statistic (Titus et al. 1984) was used to assess the overall accuracy of classifications (Wilkinson 1998).

I used probability and box plots (Wilkinson 1998) to check for violations of normality. Because cavity trees were aggregated by clusters, timber stands, and ownerships. I also investigated the extent to which data were spatially correlated. A high degree of spatial autocorrelation could lead to artificially inflated sample sizes in situations where several active trees were in close proximity. Semivariograms depicting spatial dissimilarity among points based on standardized covariances (Deutsch and Journel 1998, Wilkinson 1998) were used to check for spatial autocorrelation. I also used *P*-values adjusted by Bonferroni approximations (Wilkinson 1998) in cases where multiple comparisons were made using *t*-tests.

I evaluated several types of image enhancement (e.g., masking and linear stretches; Short 1982), neighborhood analysis (Swain et al. 1981), and pattern recognition (McGarigal and Marks 1995) procedures. An elevation mask (Swain et al. 1981) was used to analyze TM data above the minimum elevation observed for woodpeckers (31.3 m above mean sea level). Linear contrast stretches (Short 1982) were applied to selected TM bands that appeared to discriminate between suitable and unsuitable locations. Linear stretches were truncated using 90% of the range of values (Short 1982). Neighborhood statistics (Swain et al. 1981) were computed for selected TM bands transformed using linear stretching. Neighborhood statistics were created by examining a 5-by-5 pixel window and assigning the central pixel with 2 statistics: (1) average spectral value of pixels within the window, and (2) standard deviation of pixels within the window. Finally, patch size and shape characteristics were considered for a subset of the region. Unsuitable features such as small pastures and food plots have regular geometric shapes that might be identified using patch characteristics such as area-to-perimeter ratios, fractal dimension, and neighborhood heterogeneity (McGarigal and Marks 1993).

Results

TM Data for Active Trees and Core Areas

Only the low-and high-gain thermal bands differed in the comparison of TM data associated with active cavity trees to TM data associated with core cluster polygons (Table 1). DFA of suitable and unsuitable sites based on TM data for active cavity trees had an overall accuracy of 67%, while a similar DFA based on core cluster polygons had an accuracy of 60%. Red and blue TM bands best distinguished suitable and unsuitable sites for both cavity trees and core polygons. In the case of cavity tree locations, the red TM band alone correctly classified 46% of active trees, and estimates of statistical tolerances (Table 2) indicated the red TM band was correlated with other TM bands having fair discrimination. Further analyses were limited to comparisons of active cavity trees and unsuitable locations.

Probability and box plots (Wilkinson 1998) suggested that 3 variables deviated from normality, but only for locations associated with unsuitable habitat. Attempts to transform these 3 variables resulted in deviations from normality for data recorded at suitable locations, so data transformations were not performed. Lindman (1974)

Table 1. TM data associated with active cavity trees ($N = 428$), polygons surrounding clusters of cavity trees ($N = 179$), and unsuitable sites ($N = 1000$). F-ratios are based on comparisons of active cavity trees or active cluster polygons to unsuitable locations.

	Active cavities			Core cluster polygons			Unsuitable sites	
TM Band	Avg.	SD	F	Avg.	SD	F	Avg.	SD
Panchromatic	32.45	2.83	38.58	31.85	3.07	0.08	31.86	3.41
Blue	52.08	1.36	55.17	52.33	1.58	34.48	53.66	2.50
Green	35.00	1.24	18.11	35.23	1.49	0.70	36.29	2.78
Red	31.48	3.01	93.08	31.92	2.94	42.24	32.75	5.12
Near infrared	58.37	4.23	4.74	57.74	4.49	1.37	57.12	7.62
Mid infrared	45.29	5.67	19.08	47.02	6.03	1.33	50.03	13.44
Far infrared	26.52	3.61	14.07	27.26	3.91	7.43	30.35	9.18
LG thermal[a]	115.02	0.62	0.96	115.15	0.71	2.04	115.09	1.54
HG thermal[a]	121.40	0.94	4.45	121.54	1.036	9.90	121.45	2.56
Elevation	65.54	12.14	136.60	65.11	11.77	125.45	56.70	14.57

a. Differed in comparisons of active clusters and core cluster polygons, $t_{604} > 3.0$, Bonferroni-adjusted $P \leq 0.05$.

Table 2. Discriminant function analysis of Landsar TM bands and elevation data at sites that were suitable ($N = 142$) or unsuitable ($N = 1000$) for red-cockaded woodpeckers. Variables are sorted by decreasing F-ratios (Wilkinson 1998), which help gauge the importance of variables in distinguishing between suitable and unsuitable locations. Tolerance (Wilkinson 1998) measures covariation among variables and is low (<0.1) when a variable is highly correlated with another variable. Canonical functions represent the weightings applied in the classifications.

Variable	*F*	Tolerance	Standard canonical functions
Elevation	120.98	0.91	0.65
Red	114.85	0.11	1.85
Green	43.01	0.12	–1.13
Blue	40.12	0.25	–0.75
Far infrared	26.59	0.33	–0.53
Panchromatic	16.01	0.69	0.29
High gas thermal	12.08	0.09	0.25
Mid infrared	11.26	0.18	–0.01
Near infrared	8.04	0.38	0.42
Low gain thermal	0.91	0.10	–0.08

demonstrated that DFA was robust to violations of the assumptions of homogeneity of variances and normality.

As expected, spatial autocorrelations of TM data was generally high (γ [h] >0.45) for proximal locations (i.e., <500 m apart); however spatial autocorrelation fell sharply (γ [h]<0.20) once distances >500 m were achieved. Because the median distance among active clusters in this region was 516 m (Cox et al. 2001), I used av-

Table 3. Results of discriminant function analysis of neighborhood statistics obtained from transformed TM bands (see text). Variables are sorted by decreasing F-ratios (Wilkinson 1998). Canonical functions represent the weightings applied in the classifications.

Variable	F	Tolerance	Standard canonical functions
Elevation	109.56	0.78	0.59
Avg. red	52.31	0.31	–0.77
SD blue	44.53	0.54	0.54
SD green	22.30	0.39	–0.45
Avg. blue	16.81	0.73	0.29
Avg. far infrared	15.54	0.36	0.39
SD far infrared	13.43	0.42	0.34
SD panchromatic	13.43	0.53	–0.30
SD red	11.29	0.23	0.42
Avg. panchromatic	11.05	0.89	–0.21

erage TM and elevation values for all active cavity trees in clusters containing >1 active cavity (N=142).

DFA Using Evaluation Data and Enhanced Imagery

When elevation and TM data were considered simultaneously, elevation was the best predictor of suitable locations (Table 2) and correctly classified 61% and 62 % of the suitable and unsuitable, respectively. A classification based on elevation and raw TM data for 5 bands with high (>15.0) F-ratios (Table 2) contrasted elevation and the panchromatic and red TM bands against the blue, green, and far infrared TM bands. This classifications had an overall accuracy of 65%, but *kappa* was low (0.31), indicating poor discrimination.

Application of the elevation mask (31.3 m above mean sea level) eliminated 232 unsuitable locations. The DFA performed on the remaining locations indicated that red, green, blue, and far infrared bands best distinguished locations (F=37.37, 36.67, 105.15, and 24.89, respectively), but overall accuracy was 68%, which was indistinguishable from that obtained without using the elevation mask. *Kappa* also was low (0.36).

DFA performed following application of linear stretching to 5 TM bands with high ratios (>15.0; Table 2) revealed that elevation was still the best predictor of suitable locations (F=126.34), but the panchromatic TM band was the second strongest predictor (F=33.89). However, the classification based on these transformed TM data was not significantly improved (overall accuracy of 62%; *kappa*=0.21).

Neighborhood Analysis

A DFA performed using elevation and neighborhood statistics led to better discrimination of sites. Elevation still best distinguished between suitable and unsuitable locations (Table 3); however, the average value of the red band, standard devia-

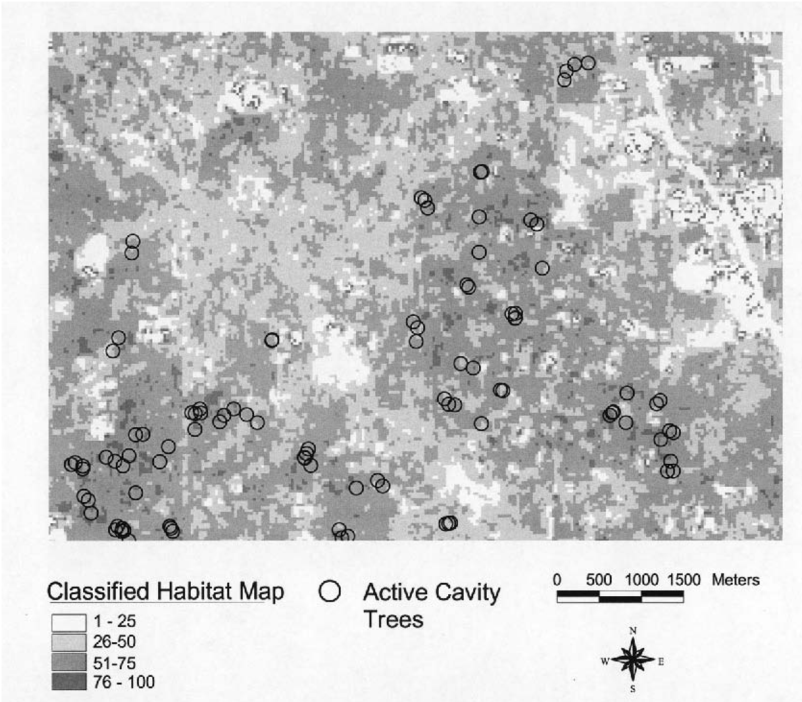

Figure 1. Classified map of potential re-cockaded woodpecker habitat in an area of the Red Hills region. This map was scaled 0–100 with greater values corresponding to suitable locations (avg. = 68.6, SD = 8.6) and lower values corresponding to unsuitable sites (avg. = 55.7, SD = 16.85). Overall classification accuracy was 74% with *kappa* = 0.45.

tion of the blue band, average value of the blue band, and standard deviation of the green band appeared to separate groups better than other TM data considered to this point. The overall classification derived from this DFA was 74% with *kappa*=0.45. When these same neighborhood statistics were analyzed following application of the elevation mask, results were similar to those above, but the classification had a slightly lower overall accuracy (71%) and *kappa* was 0.42. A large proportion of suitable sites (85%) was correctly classified, but only 66% of the unsuitable sites were correctly classified.

Patch Characteristics in Classified Map

I created a classified map of potential habitat (Fig. 1) by applying the standardized canonical functions in Table 3 and summing the appropriate GIS layers. The elevation mask was used to limit the classification to regions >31.3 m. The classification (Fig. 1) was further scaled to range 0–100 with greater values corresponding to suitable locations (avg.=68.6, SD=8.6) and lower values corresponding to unsuitable sites (avg. 55.7, SD=16.85). Regions with the greatest number of misclassified loca-

Table 4. Patch variables considered in a classified map of potential habitat (Fig. 1). The map had 3 total classes: (1) unsuitable, (2) possibly suitable/unsuitable, and (3) suitable (see text). Patches consisted of similarly valued cells (1–3) within a search radius of 30 m along diagonal axes; aggregations of patches were based on a search radius of 300m. Analyses were restricted to < 300 m of locations (N = 226) misclassified in other analyses. The range is provided in parentheses. Variable acronyms were used in Table 5.

Variable name	Acronym	Description
Aggregation area	AREA	Sum for patches in aggregation (0.103–118.37 ha).
Aggregation area standard deviation	ASD	Root mean squared error for patches in aggregation (0.00–11.32).
Aggregation shape index	ASI	Sum of edge segments divided by total area^{-2} (1.00–3.12).
Area-weighted aggregation fractal dimension	AWFD	Measures patch complexity as shapes deviate from simple circle (=1) to shapes with complex perimeters (=2); weighted by area (1.0–1.19).
Area-weighted mean aggregation shape index	AWSI	Sum of patch perimeters divided by patch area^{-2} (m^2);weighted by area (1.0–7.2).
Dissimilar patches within 300 m	DISSIM	N patches of other class within aggregation (0–17).
Aggragation edge density	ED	Sum of edge segments divided by area (0.03–10.28).
Largest patch index	LPI	Percent area of largest patch compared to total area (0.01–3.20).
Median patch area	MDPA	Median patch size in an aggregation (0.06–18.82 ha).
Mean patch area	MPA	Aggregation area divided by number of patches (0.06–16.97 ha).
Mean perimeter-to-area ratio	MPAR	Sum of perimeter-to-area ratios divided by N patches (193.3–1772.1).
Mean patch edge	MPE	Total edge length divided by N patches (120.3–4771.1 m)
Mean patch fractal dimension	MPFD	Log patch perimeter (m) divided by the log patch area (m^2) divided by the number of patches.
Number of patches	NUMP	N patches within an aggregation (1–30).
Aggregation perimeter	PERIM	Length surrounding aggregation; includes internal holes (128.3–43422.7 m).
Perimeter	PERIM	Length of outermost edge of aggregation (120.2–32,272.4 m).
Similar patches within 300 m	SIMIL	N patches of a similar class within an aggregation (1–10).
Total aggregation edge	TE	Sum of edge lengths within an aggregation (121.0–37,798.1).
Neighborhood variety	VAR	N distinctive classes within 300 m (1–3).

tions (i.e., values in the range 50–65) contained roughly 25% of all locations and covered 60,234 ha (approximately 32% of the total area).

Figure 1 was aggregated into 3 categories of suitability to assess patch size and shape characteristics. The categories were (1) “probably unsuitable” (classes 0–49), (2) “suitable or unsuitable” (classes 50–65), and (3) “probably suitable” (classes 66–100). Eighteen shape neighborhood metrics (Table 4) were calculated (Rempel et al. 1999) for each patch. Patches were defined as cells with similar values (1–3)

Table 5. *F*-ratios and tolerance statistics for 18 patch and shape variables derived from a classified map of potential habitat (Fig. 1). Variable descriptions provided in Table 4. The overall accuracy of the classification of suitable and unsuitable locations misclassified in previous classifications was 47%; *kappa* = 0.26.

	Suitable		Unsuitable			
Variable	Avg.	SD	Avg.	SD	*F*	Tolerance
AREA	43.36	62.58	37.25	59.29	0.00	0.01
ASD	3.00	3.06	4.31	5.83	0.25	0.01
ASI	1.49	0.41	1.44	0.29	0.00	0.00
AWFD	1.11	0.06	1.12	0.07	0.43	0.02
AWSI	2.07	0.81	2.40	1.65	0.04	0.01
DISSIM	8.30	4.40	8.14	4.61	1.13	0.74
ED	1.10	1.07	1.72	2.84	0.62	0.00
LPI	0.32	0.29	0.52	0.89	0.08	0.01
MDPA	1.66	3.57	1.20	2.53	0.34	0.03
MPA	3.64	3.60	3.25	2.88	0.01	0.01
MPAR	695.10	293.53	745.43	296.80	0.03	0.32
MPE	1152.03	959.89	1041.82	727.54	0.07	0.00
MPFD	1.06	0.04	1.06	0.03	0.03	0.01
NUMP	4.17	4.43	5.83	8.23	1.38	0.03
PERIM	1333.34	1737.16	1154.31	1628.21	0.00	0.01
SIMILAR	2.41	2.10	2.79	2.62	2.35	0.56
TE	4061.14	3944.74	6333.03	10435.98	0.62	0.00
VARIETY	2.11	0.64	2.04	0.66	0.32	0.86

within a search radius of 30 m along diagonal axes. Because of the complexity of the analysis, it was limited to a 300 m area surrounding 226 locations misclassified using variables in Table 3 (suitable=24, unsuitable=202). Just under half (46%) of the area consisted of "suitable or unsuitable" cells, while "probably unsuitable" and "probably suitable" cells made up 24.3% and 29.7% of the area, respectively.

Few geometric shape variables differed in this comparison (Table 5). Variables with the greatest *F*-ratios (DISSIM, SIMILAR, and NUMP) measured the heterogeneity of locations (Appendix 1) or edge features (ED and TE). Low tolerance statistics (Table 5) suggested several of these variables were redundant. Suitable sites misclassified in previous classifications tended to have fewer nearby patches with similar values and also a smaller total number of neighboring patches with similar values. The overall accuracy of a new classifications of previously misclassified sites based on shape variables was 47% with *kappa*=0.26.

Discussion

Classification of potential habitat for the red-cockaded woodpecker using TM data can be improved when these data are used in combination with elevation data and accurate occurrence information. Thomlinson (1993) processed TM data for polygons averaging about 30 ha and had little success identifying potential habitat. Core polygons created for woodpecker clusters in the Red Hills averaged only 1.6 ha and closely matched the data associated with active cavity trees. When a classification was performed using TM data associated with core polygons, the overall accuracy was 60% and the *kappa* statistic was 0.23 as compared to *kappa* statistics <0.04 obtained by Thomlinson (1993) using larger polygons. Use of polygons >2–5 ha may exacerbate common classification problems such as the "mixed-pixel effect" (Short 1982).

On the other hand, elevation data, not TM data, proved to be the best predictor of suitable habitat, and inclusion of elevation data was essential to improving the accuracy of all classifications. TM data improved classifications slightly after image enhancement procedures were performed (e.g., linear stretches), but similar improvements may not be realized on public lands where most large woodpecker populations now reside (James 1995). The effectiveness of TM data in the Red Hills probably hinged on the diversity of cover types that existed. Urban areas, agricultural fields, roads, pastures, and other treeless features found in the Red Hills can be easily distinguished from forest lands using TM data (C. Ambrose, unpubl. rep., Tall Timbers Res. Sta., Tallahassee, Fla., 2000), but these cover types will be less common on many public lands. Thomlinson (1993) could not distinguish timber stands (e.g., mature sawtimber, immature sawtimber, sparse sawtimber, etc.) that varied in a subtle manner on the Sam Houston National Forest. Similarly, I found several young, dense pine plantations with small patches of thinned canopies that were classified as "suitable."

With a low overall accuracy <75%, the best classification of potential habitat (Fig. 1) contained large areas where red-cockaded woodpeckers were not likely to occur. Comparison of unsuitable sites to digital orthographic quadrangles revealed that many unsuitable locations classified as "suitable" occurred in small (<3.5 ha) fields surrounded by appropriate habitat, near edges of fields and unpaved trails, and in hardwood areas where canopy cover appeared to be sparse compared to nearby forested areas. Common errors associated with remotely sensed data obviously contribute to these inaccuracies, but another constraint lies in the biology of red-cockaded woodpeckers. Habitat occupancy is strongly influenced by low dispersal rates and the number of nearby active territories (Thomlinson 1993, Cox et al. 2001). Sites far removed from active woodpecker clusters and lacking suitable cavities will not be occupied regardless of the quality of the habitat. Such life-history traits make field surveys imperative in any attempt to map habitat for this species.

Scores of new variables could have been developed either for use in the classification of TM data or for the evaluation of patch shape characteristics, but it seems unlikely that new variables could improve the classification. Shape variables considered here improved the classification only by approximately 10% (i.e., 47% of the 30% of locations misclassified initially), and it would be difficult to perform such an analysis for the entire region. The subregion considered here included about 25% of the total region and involved >17,000 polygons. Many GIS software packages are not capable of analyzing the >80,000 polygons that might be found in a comprehensive regional analysis.

Production of potential habitat maps using less complicated methods should be considered as an alternative approach for this species. Pestana (1986), for example, used 1:65,000 color infrared photographs to map potential red-cockaded woodpecker habitat in southern Missouri. Interpretation of aerial photographs also is generally better understood by many wildlife biologists, and this approach might cover a large area as effectively as a GIS-based processes involving remotely sensed data and scores of transformed variables. Also, given the influence of nearby active territories on habitat occupancy (Thomlinson 1993, Cox et al. 2001), time must be allocated for field surveys regardless of the methods used to delineate habitat. Most of the habitat occupied by this Red Hills population was largely known prior to initiating an analysis of TM data, so extensive field surveys, coupled with quick assessments of potential habitat made using convenient aerial maps, might be better strategies to pursue.

Higher resolution imagery might eventually improve the overall accuracy of habitat maps created for species with special requirements, but at least one attempt to map woodpecker habitat using high-resolution imagery was not successful. K. Slocum (pers. commun., Topographic Eng. System, Army Corps Eng.) collected multi-spectral imagery with a spatial resolution of 1 m and attempted to distinguish areas with mature longleaf pine used for nesting by red-cockaded woodpeckers from areas with younger loblolly pines that were not used. Reflectance data were centered at 450, 550, 650, and 800 nanometers, but separation of sites containing longleaf was poor. Imagery collected in different seasons might have helped in this instance (Thomlinson 1993), but again aerial photo interpretation and other less sophisticated techniques, might be more easily applied by wildlife biologists.

Although attempts to map red-cockaded woodpecker habitat using remotely sensed TM data will not likely meet common accuracy standards (Stoms et al. 1994), TM data may have some utility when used to develop a coarse map of potential habitat in and immediately surrounding cavity clusters. Less technical approaches involving aerial photography should be considered first, but the classified map (Fig. 1) developed here has helped to estimate foraging habitat for several woodpecker clusters, and, in combination with other analyses (Cox et al. 2001), to identify sites where artificial clusters (Copeyon et al. 1991) might be constructed. The classification also highlights areas in the Red Hills where woodpeckers are not known to occur and additional field surveys are warranted. If TM data are to be used in a similar manner elsewhere, the analyses should be based on a large sample of precise and recent (<2-year-old) occurrence records.

Literature Cited

Clark, J. D., J. E. Dunn, and K. G. Smith. 1993. A multivariate model of female black bear habitat using a geographic information system. J. Wildl. Manage. 57:519–526.

Copeyon, C. K., J. R. Walters, and J. H. Carter, III. 1991. Induction of red-cockaded woodpecker group formation by artificial cavity construction. J. of Wildl. Manage. 55:549–556.

Cox, J., W. W. Baker, and R. T. Engstrom. 2001 Red-cockaded woodpeckers in the Red Hills region: a GIS-based assessment. Wildl. Soc. Bull. 28:278–288.

Craighead, J. J., J. S. Sumner, and G. B. Scaggs. 1982. A definitive system for analysis of grizzly bear habitat and other wilderness resources, utilizing LANDSAT multispectral imagery and computer technology. Wildl.-Wildlands Inst. Monogr. 1. Univ. Mont., Missoula.

Deutsch, C. and A. G. Journel. 1998. GSLIB: Geostatistical Software Library and User's Guide, 2nd ed. Oxford Univ. Press, New York. 340pp.

Engstrom, R. T. and W. W. Baker. 1995. Red-cockaded woodpeckers on Red Hills hunting plantations: inventory, management, and conservation. Pages 489–493 *in* D.L. Kulhavy, R. G. Hooper, and R. Costa, eds. Red-cockaded woodpecker: recovery, ecology, and management. Ctr. Appl. Stud., Coll. For., Stephen F. Austin State Univ., Nacogdoches, Texas. 551pp.

Faust, N. L., W. H. Anderson, and J. L. Star. 1991. Geographic information systems and remote sensing future computing environment. Photogramm. Eng. and Remote Sens. 57:655–668.

Hodgson, M. E., J. R. Jensen, H. E. Mackey, Jr., and M. C. Coulter. 1987. Remote sensing of wetland habitat: a wood stork example. Photogramm. Eng. and Remote Sens. 53:1075–1080.

Hooge, P. N., W. Eichenlaub, and E. Solomon. 1999. The animal movement program. U.S. Geol. Surv., Alaska Biol. Sci. Ctr., Anchorage. 28pp.

Hovis, J. A. and R. F. Labisky. 1985. Vegetative associations of red-cockaded woodpecker colonies in Florida. Wildl. Soc. Bull. 13:307–314.

Jackson, J. A. 1977. Determination of the status of red-cockaded woodpecker colonies. J. Wildl. Manage. 41:448–452.

Jakubauskas, M. 1992. Modeling endangered bird species habitat with remote sensing and geographic information systems. ASPRS/ASCM 1992 Annu. Convention and Exposition, Albuquerque, N.M. 362pp.

James, F. 1995. The status of the red-cockaded woodpecker in 1990 and the prospect for recovery. Pages 439–451 *in* D.L. Kulhavy, R. G. Hooper, and R. Costa, eds. Red-cockaded woodpecker: recovery, ecology, and management. Ctr. Appl. Stud., Coll. For., Stephen F. Austin State Univ., Nacogdoches, Texas. 551pp.

Lauver, C. L. and J. L. Whistler. 1993. A hierarchical classification of Landsat TM imagery to identify natural grassland areas and rare species habitat. J. Photogramm. Eng. And Remote Sens. 59:161–174.

Lennartz, M R. and V. G. Henry. 1985. Red-cockaded woodpecker recovery plan. U.S. Fish and Wildl. Serv., Atlanta, Ga. 88pp.

Lindman, H. R. 1974. Analysis of variance in complex experimental designs. W. H. Freeman and Co., San Francisco, Calif. 256pp.

Lipscomb, D.J. and T. M. Williams. 1995. Use of geographic information systems for determination of red-cockaded woodpecker management areas. Pages 137–143 *in* D. L. Kulhavy, R. G. Hooper, and R. Costa, eds. Red-cockaded woodpecker: recovery, ecology, and management. Ctr. Appl. Stud., Coll. For., Stephen F. Austin State Univ., Nacogdoches, Texas. 551pp.

McGarigal, K. and B. Marks. 1995. Fragstat: a spatial pattern analysis program for quantifying landscape and structure. U.S. Dep. Of Agri. For. Serv. Gen. Tech. Rep. PNW-GTR-351, U.S. Dep. Agric., For. Serv. Pacific Northwest Res. Sta., Portland, Ore. 122pp.

Pestana, K.E. 1986. Remote sensing technique for identifying potential red-cockaded woodpecker habitat. Pages 106–116 *in* F. J. Singer, ed. Proceedings of the Foruth Conference on Research in National Parks and Equivalent Reserves: Wildlife Management and Habitats. George Wright Soc. And Natl. Park Serv., Washington, D.C. 218pp.

Rempel, R.S., A. Carr, and P. Elke. 1999. Patch analyst and patch analyst (grid) function reference. Ctr. North. For. Ecosystem Res., Ontario Ministry Nat. Resour., Lakehead Univ., Thunder Bay, Ontario.

Scepan, J., F. Davis, and L. Blum. 1987. A geographic information system for managing California condor habitat. Proc. Annu. Internatl .Conf. Geogr. Inf. Systems, San Francisco, Calif. Pp. 476–486.

Scott, J.M., F. Davis, B. Csuti, R. Noss, B. Butterfield, C. Groves, H. Anderson, S. Caicco, F. D'Erichia, T. Edwards, Jr., J. Ullman, and R. Wright. 1993. Gap analysis: a geographic approach to protection of biological diversity. Wildl. Monogr. 123:1–41.

Shaw, D. M. 1989. Applications of GIS and remote sensing for the characterization of habitat for threatened and endangered species. Ph.D. Diss., Univ. North Texas, Denton. 325pp.

Short, N.M. 1982. The Landsat tutorial workbook. Natl. Aeronautics and Space Assoc. Ref. Publ. No. 1073. U.S. Gov. Printing Off., Washington, D.C. 637pp.

Stoms, D.M.F. 1994. Actual vegetation layer. Pages 1.1–1.6 *in* J. M. Scott and M. D. Jennings, eds. A handbook for Gap analysis. Idaho Coop. Fish and Wildl. Res. Unit, Univ. Idaho, Moscow, Idaho.

———, F. W. Davis, C. B. Cogan, M. O. Painho, B. W. Duncan, J. Scepan, and J. M. Scott. 1993. Geographical analysis of California condor sighting data. Conserv. Biol. 7:148–159.

Swain, P. H., S. B. Vardeman, and J. C. Tilton. 1981. Contextual classification of multispectral image data. Pattern Recognition 13:429–441.

Thomlinson, J. 1993. Landscape ecological characteristics of habitat of the red-cockaded woodpecker *(Picoides borealis).* Ph.E. Diss., Univ North Texas, Denton. 201pp.

Titus, K., J. Mosher, and B. Williams. 1984. Chance-corrected classification for use in discriminant analysis: ecological applications. Am. Midl. Nat. 111:1–7.

Wilkinson, L. 1998. Systat. Version 8.0. SPSS Sci. Marketing Dep., Chicago, Ill. 751pp.