Using Bayesian Statistics, Thematic Mapper Satellite Imagery, and Breeding Bird Survey Data to Model Bird Species Probability of Occurrence in Maine

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Abstract

A Bayesian modeling technique was used to predict probability of occurrence for 14 species of Maine land birds. The relationships between bird species survey data and the spectral values of Landsat Thematic Mapper bands 4 and 5 as well as a derived texture measure were used to build conditional probabilities for input into Bayes' Theorem. The conditional probabilities form decision rules for reclassifying the input spectral data into probability of occurrence estimates with associated estimates of error inherent in the model prediction. This methodology removed the costly and time-consuming step of creating a habitat map before modeling species occurrence. The output resolution of the species predictions is not degraded from the original 30-m TM pixel size to the coarse resolution of the wildlife survey data. Model results can be compared to results from other habitat modeling techniques and used by natural resource managers to predict the effects of land-use changes on available habitat.

Introduction

Determining the habitats used by different species is an important first step in managing those habitats to sustain wildlife populations. Modeling the habitat requirements of wildlife species allows wildlife managers to predict the distribution or abundance of target wildlife species (Morrison *et al.*, 1992). Such models can take many forms, but all attempt to represent formally, through equations or decision rules, the relationships between species and their habitat.

Spatially explicit relationships between wildlife species and their habitat can be systematically tested within a geographic information system (GIS) (e.g., Lyon, 1983; Lyon *et al.*, 1987; Ormsby and Lunetta, 1987; Shaw and Atkinson, 1988; Pereira and Itami, 1991; Homer *et al.*, 1993; Herr and Queen, 1993; Rickers. *et al.*, 1995). To predict species occurrence in a spatially explicit manner, species-habitat models require a habitat map (e.g., Palmeirim 1988). Land-cover/land-use (LCLU) maps are converted into habitat-type maps according to known species-habitat associations. Because LCLU classification schemes generally are not developed with the habitat requirements of specific wildlife species in mind, accurate relationships between LCLU classes and habitat types may not exist. Errors in the aggregation of habitat types that a species use and do not use or use at different rates will lead to errors in model output.

Additionally, the accuracy of LCLU maps is often untested, leading to the introduction of errors of unknown magnitude into habitat maps. An accuracy assessment of the LCLU map would provide a confusion matrix to allow for error simulation. Because accuracy assessment of LCLU classifications is time consuming and costly, a method that could remove the LCLU classification step entirely would be useful for spatial modeling of species occurrence.

Bayesian Modeling

Bayesian statistics constitute an alternative method for building predictive relationships between species and their environment. Several studies have used Bayesian statistics to predict one variable based on its statistical relationship to other variables (Tucker *et al.*, 1997; Aspinall and Veitch, 1993; Aspinall, 1991; Bonham-Carter *et al.*, 1988; Bonham-Carter *et al.*, 1989). Further modifications of the modeled variable based on repeated comparisons with predictor variables yields a probability map and associated errors for each location on the landscape under study.

Bayes' Theorem uses *a priori* (subjective) and conditional probabilities to calculate the probability of an uncertain event occurring. *A priori* probabilities represent what the modeler believes, before testing, to be the probability of an event occurring. Conditional probabilities are probabilities that other events occur in conjunction with the original event. If species occur at a rate of 0.5 on the landscape, but occur 80 percent of the time when a closed canopy forest is present, the conditional probability of species presence for closed canopy forests is 0.80.

Aspinall (1991) used classes of land cover derived from classified satellite imagery, altitude, and accumulated frost to model habitat availability for red deer (*Cervus elaphus*) in a region of Scotland. Aspinall and Veitch (1993) simplified the procedure by removing the classification of satellite imagery, instead using unclassified satellite imagery. They created a probability of occurrence map for the Curlew (*Numenius arquata*) using grouped raw digital numbers (reflectance) from selected wavebands of satellite imagery along with a digital elevation model and species presence/absence data. Curlew survey data with coarse resolution (1-km^2 survey blocks) were used to classify the fine resolution (30-m^2) satellite image based on repeated comparisons of image pixels where Curlew were observed against image pixels where Curlew

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were not observed. The output was a probability-of-occurrence map that is similar to habitat-suitability or habitat-capability maps, but based on probability rules. Additionally, measures of error for the probability estimates were readily obtained through multiple model iterations and were included in model results. This method used the full resolution of the satellite imagery to enhance the coarse resolution of the Curlew survey data.

Proposed Method and Modeling Approach

We investigated whether the presence of Maine land birds can be predicted directly from unclassified satellite imagery and derived layers. The objectives of our study were (1) to determine if relationships exist between the raw waveband reflectance from satellite imagery and the presence and absence of bird species, (2) to use those relationships that were significant and Bayesian statistics to model potential habitat occupancy for selected land bird species breeding in Maine, and (3) to report on the variability of model input and output and on the significance of model output.

We used 1991 Thematic Mapper satellite imagery for Maine coupled with 1990 Breeding Bird Survey (BBS) data to predict probability of occurrence for land bird species. Birds were selected for this study because of the availability of a landscape-level database (BBS data) and the recent concern over the status of many land bird species (Terborgh, 1989; DeGraaf and Rappole, 1995; Martin and Finch, 1995). We used Bayes' Theorem to formalize the relationship between species presence and reflectance values of the satellite imagery. Bayes' Theorem modifies *a priori* probabilities of an uncertain event occurring according to the conditional probabilities of related themes. For our study, the frequency of association between the presence (or absence) of a species and the presence (or absence) of a particular reflectance value or digital number (DN) from the satellite imagery formed the conditional probabilities used in Bayes' Theorem. The output of Bayes' theorem is the *a posteriori* probability of species occurrence for each pixel present in the input themes. The output, therefore, has the same spatial resolution as the input theme with the highest resolution and is not degraded to the lowest resolution data. Our modeling procedure allowed for testing of model input variability and significance and of model output variability and significance. Standard error propagation methods (Burrough, 1986) were used to calculate variability in model output. Our approach removed the intermediate steps of creating land-cover/land-use maps and assigning habitat types, thereby removing the errors inherent in those steps and the time and expense involved in creating a credible land-cover/land-use map.

Our methodology, although similar to that employed by Aspinall and Veitch (1993), differed in several significant ways. First, the landscape of Maine is a much more heterogeneous landscape than the moorland and grassland study area of Aspinall and Veitch. We included a spatial texture measure in our analysis to determine if species were correlated with heterogeneity of the landscape. Second, the large area of Maine (approximately 85,000 km^2) allowed us to use the conditional probabilities of individual digital numbers from each data theme rather than grouping the reflectance values of the satellite imagery as Aspinall and Veitch did for their small study area (1500 km^2). Our increased spectral resolution provided for more precise correlations to be made between species presence or absence and each data theme. Finally, our study focused on all land bird species with sufficient survey data rather than a single species.

Study Area

Maine is located in a transition zone between northern hardwoods in the south and boreal conifer forests to the north. Steep environmental gradients result in many species of plants and animals reaching their northern or southern range limits in the state (McMahon, 1990; Boone, 1996). Large portions of northern Maine forests are in industrial forest ownership and managed primarily for pulpwood production. Seymour (1994) described the characteristics of northeastern U.S. forests and the silvicultural systems used in this region.

Maine Land Birds

Approximately 150 species of land birds have been documented as breeding regularly in Maine (Boone, 1996; Gawler *et al.*, 1996). The abundance and life history characteristics of Maine's land birds may help to determine which species will be modeled successfully using the approach we have outlined. Habitat generalists, rare species, and species poorly sampled by the BBS (e.g., raptors, nocturnal birds, seabirds, shorebirds) are not expected to provide clear relationships between species presence and satellite-derived data themes. Bird species that may be modeled successfully using this approach include common species that are relatively specialized in their habitat requirements.

Methods

Breeding Bird Survey

The Breeding Bird Survey (BBS), initiated in 1966, gathers data on breeding birds in North America through annual roadside point counts. Survey points (stops) are every 0.8 km along 39.4-km routes for a total of 50 data points for each route. All birds seen or heard within a 0.4-km radius during three minutes are recorded. Approximately 50 routes are located in Maine, of which roughly 40 are run each year. Each survey route is run during the peak of the breeding season, with certain guidelines for time of day and weather conditions intended to reduce biases in the data (Robbins *et al.*, 1986; Peterjohn and Sauer, 1993; Droege, 1990).

BBS stop-level data for 1990 were obtained in digital format. Unique records for each route-stop combination included each species American Ornithologist Union (AOU) number and the number of individuals observed. BBS routes were digitized from route maps obtained from the Patuxent Wildlife Research Center. Digital Line Graph (DLG) files for the state transportation network were used to identify the roads in BBS routes and stop locations were added every 0.8 km along each route. Thirty-eight routes were run in 1990 from which eight were removed from the modeling procedure because of problems associated with the recording of data on those routes. BBS stops for those 30 routes were individually buffered at a radius of 0.4 km according to the established guidelines for BBS surveys for recording all species seen or heard within 0.4 km of a stop location (Figure 1:1).

Landsat Thematic Mapper

A 1991 three-band Landsat Thematic Mapper (TM) statewide image mosaic of Maine was available from the Maine Image Analysis Laboratory at the University of Maine. Bands 3 (reflected red), 4 (near-IR), and 5 (mid-IR) are well suited for vegetation discrimination (Horler and Ahern, 1986). Several data themes were derived from the three available TM bands. A Normalized Difference Vegetation Index (NDVI) was calculated from the normalized ratio of band 3 to band 4, and provided the greatest range of differences between vegetation and non-vegetation in green biomass. NDVI images are often used for land-cover/land-use mapping and change detection (Tucker *et al.*, 1985; Sader and Winne, 1992; Sader, 1995). Measurements of the spatial texture of imagery can be calculated from an NDVI image and are useful in determining landscape-level heterogeneity of vegetation (Cohen, 1994). Two

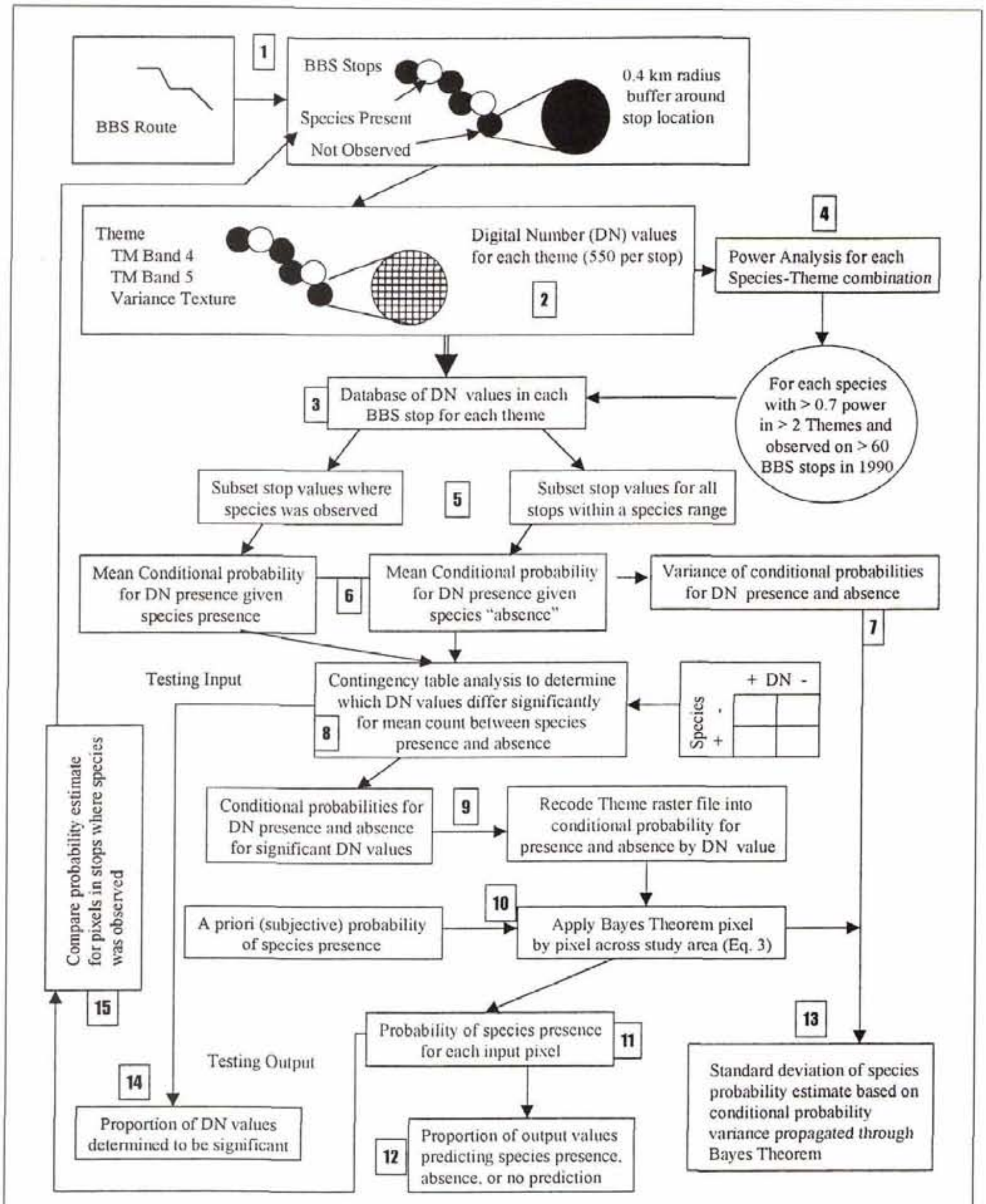

Figure 1. Flow chart of the modeling approach. Numbers 1 to 15 relate to the sequence of processing steps described in the text.

spatial texture measures were calculated from the NDVI image (ERDAS, 1994):

7- by 7-pixel window, variance

$$V = \text{Sum } (x_{ij} - m)^2 \;/\; (n - 1) \tag{1}$$

7- by 7-pixel window, skewness

$$S = |\ \text{Sum } (x_{ij} - m)^3\ | \;/\; (n - 1)V^{3/2} \tag{2}$$

where

x_{ij} = DN value of pixel$_{i,j}$,
n = number of pixels in analysis window (7 by 7 pixels),
m = mean of pixels in analysis window, and
V = variance of pixels in analysis window (as calculated in Equation 1).

Pixel vales for each theme within the 0.4-km radius buffer for each BBS stop were appended to a database file (Figure 1:2-3)

We used a power analysis as a diagnostic tool for determining, *a priori*, which species were most likely to be modeled successfully and which data themes to use for each species (Steidl *et al.*, 1997). The power analysis compared species-specific differences between the average digital number (DN) value for species presence and the average DN value for all BBS stops surveyed in 1990 (Figure 1:4). For each data theme, spectral reflectance values within a 0.4-km radius of BBS survey points (stops) were compared to determine if the effect size was large enough to detect a difference given an alpha level of 0.05, and sample sizes relating to the number of stops a particular species was observed at and the total number of stops surveyed. If the calculated power was above 0.70 (a conservative value) in at least two data themes, the species was selected for the inductive modeling procedure.

Bayes' Theorem

Bayes' Theorem has four parts: *a priori* probabilities of presence and absence and conditional probabilities of presence and absence (Equation 3). For analysis based on conditional probabilities from multiple themes, each conditional probability for presence or absence is multiplied together as input into the theorem. In our study, *a priori* probabilities were the probabilities that a specific species would or would not occur at a site. Our conditional probabilities were based on the associations between the presence or absence of each DN in relation to the presence or absence of a species. For our analysis, Bayes' Theorem took the form:

$$P_P = \frac{S_p * (P_{Theme})}{(S_p * (P_{Theme})) + (S_a * (A_{Theme}))} \tag{3}$$

where

S_p = Subjective (*a priori*) probability of species presence,
S_a = Subjective (*a priori*) probability of species absence,
P_{Theme} = Product of the conditional probabilities of species presence for DN '*x*' for each theme,
A_{Theme} = Product of the conditional probabilities of species absence for DN '*x*' for each theme, and
P_P = *a posteriori* probability of species presence.

Subjective Probabilities

We considered two methods to calculate *a priori* species presence: (1) dividing the number of stops a species was observed on by the total number of stops surveyed in 1990 or (2) assuming an equal probability for species presence and absence (Aspinall, 1991). The first method has the disadvantage of potentially severely underestimating the actual probability of species occurrence because of the brief snapshot in time the BBS survey design represents. For example, a species may be observed at 200 of the 1500 surveyed in 1990, yielding an *a priori* probability of species presence of 0.133. The actual probability of species presence will likely be higher than 0.133 because the BBS only records those species heard or seen in a single 3-minute point count.

The second method is potentially a closer approximation of the probability of actual species presence and absence and provides more tractable results: output probability of occurrence values greater than 0.5 are assumed to predict species presence because the conditional probabilities of the theme attributes increased the *a posteriori* probability estimate up from the *a priori* probability of presence; values less than 0.5 predict absence. We used conditional probabilities of 0.5 for *a priori* species presence and absence in our models.

Conditional Probabilities

We calculated conditional probability of species presence and absence for each DN for each theme. Conditional probability of species presence for DN '*x*' was the proportion of stops where species '*y*' was observed that contained DN '*x*' (Figure 1:5). Conditional probability of species absence was based on the frequency of occurrence of each DN for all routes surveyed in 1990 and within a species range, as defined by those routes where a species had been observed at least once during the history of the BBS (Figure 1:6). For example, if a species was observed on 100 stops of the 1500 stops surveyed within that species' range, and DN 32 was observed 90 of the 100 presence stops and 1000 of the 1500 stops surveyed, then DN 32's conditional probability of presence is 90/100 = 0.90 and conditional probability of absence is 1000/1500 = 0.67.

We calculated both the mean and variance of the conditional probability for each DN for species presence. These conditional probabilities were based on 100 iterations of 90 percent random subsets of stops where a species was observed in 1990. We calculated conditional probability for species absence based on 100 iterations of 10 percent random subsets of all stops surveyed with a species range to equalize sample size between presence and absence subsets.

Bayes' Theorem assumes that observed relative frequencies of occurrence are adequate measures of conditional probabilities. This assumption is generally met when sample sizes are large. Small sample size leads to imprecise probability values that may not adequately represent the probability of an event occurring (Gelman *et al.*, 1995). To maximize our potential for successful modeling of species presence and absence, we limited our analysis to those species observed at 60 or more stops, and with power values higher than 0.70 in at least two data themes. The selection of 60 stops and a power of 0.70 in two or more themes was arbitrary, but considered conservative in limiting modeling to the most likely species to show clear relationships with the available data.

Testing the Significance of Each Theme Value

For those species that met the selection criteria listed above, we tested for significant differences between conditional probability of presence and absence for individual DN values for each theme using a 2 by 2 contingency table analysis (Aspinall and Veitch, 1993; Aspinall, 1991). We used the original count data (i.e., the number of species presence stops where DN '*x*' occurred) for DN presence and absence against species presence and absence (Figure 1: 8). The conditional probability of DN values that were significantly different were selected as input into Bayes' Theorem. Non-significant DN values were assigned 1.0 for both presence and absence, eliminating them and the variability they represented from inclusion in the model. The overall significance of each theme was determined from the proportion of DN values that were significantly different between species presence and random frequencies generated from 100 iterations of 100 random stops.

Applying Bayes' Theorem

Each element of Bayes' Theorem was input into the formula on a pixel-by-pixel basis. The conditional probabilities calculated in the previous steps represented decision rules in the form of reclass tables that were used to recode the input data's DN values into conditional probabilities (Figure 1:9-11). An ARC/INFO (ESRI, 1995) grid represented each data theme. Grid algebra, reclass tables for conditional probability values, and ARC macro language (AML) were used to create predicted probability of occurrence output for each species.

Testing Model Output

Model output was evaluated in three ways. First, the percentage of the state that was not modified by Bayes Theorem was calculated (Figure 1:12). These areas indicated a non-significant difference in conditional probabilities for all data themes used in the model building. Species with no model prediction for more than 55 percent of Maine were considered to have been modeled unsuccessfully. Second, the standard deviation of the model output was calculated by propagating the variability of the input conditional probabilities through Bayes' Theorem (Figure 1:13) as discussed in Burrough (1986). Burrough provides standard procedures for calculating the aggregate variability of model output based on the variability of the input and the types of mathematical operations performed. The number of input themes used for each species determined how many operations and, therefore, which derivation of the error propagation equation was used. Estimates of standard deviation propagated through the modeling process were grouped into six levels.

Finally, model output for each species was tested against model input. Model predictions for the overall area of stop locations where a species was observed in 1990 (0.4-km ra-

Table 1. Percentages of DN Values in Each Data Theme with Significantly Different Conditional Probabilities for Species Presence and Absence According to a 2 by 2 Contingency Table Analysis.

	Data Theme		
Species	TM Band 4	TM Band 5	Variance Texture
Eastern Phoebe	24.7	17.1	
Bobolink	23.2	31.6	
Red-winged Blackbird	35.3	44.6	43.0
House Finch	14.2	11.4	38.5
American Goldfinch	22.1	18.7	36.0
Savannah Sparrow	11.1	26.9	
Song Sparrow	21.1	31.6	46.5
Nashville Warbler	23.2	22.3	
Northern Parula	31.6	35.2	
Yellow Warbler	7.4	16.6	29.5
Black-throated Green Warbler		44.6	45.0
Gray Catbird	14.7	14.5	
Winter Wren	36.3	40.4	48.5
Red-breasted Nuthatch	31.1	19.7	

dius buffer) were compared by the percentage of predicted species presence, absence, and no prediction (not modified).

Results

Thirty-eight of 54 Maine BBS routes were surveyed in 1990. Thematic Mapper bands 4 and 5 and the variance texture theme derived from an NDVI image were used in model building. Haze contamination in TM band 3 eliminated it from consideration. Differences in DN frequencies of association for bird species presence and absence for the NDVI and skewness texture themes were minimal, resulting in low power and removal of these themes from inclusion in the modeling phase.

Of the 151 species observed in 1990, 52 were observed at enough stops (> 60) to potentially provide enough data to build conditional probabilities that adequately represented the probability of certain DN values being associated with species presence and absence. Of these 52, only 23 had power greater than 0.70 in two or more of the data themes used and only 14 of these species had what we felt were satisfactory results. The remaining species models had large areas of the state (> 55 percent) that were not modified from *a priori* probabilities and were, therefore, considered not to have been modeled successfully.

Testing Model Input

The proportions of DN values for each data theme-species combination that were determined to be significant by the 2 by 2 contingency table analysis are listed in Table 1. Higher percentages indicate that more DN values had significantly different conditional probability values for species presence and absence.

Testing Model Output

Table 2 summarizes predicted species presence, absence, or no prediction as percentages of Maine's land area. Table 2 also includes major habitat types used by each species, themes used in the analysis, number of BBS stops each species was observed on in 1990, and relative magnitude of variability of the model predictions.

Model output predictions for those areas where a species was observed in 1990 are presented in Table 3 as proportions of the area that the model predicts species presence, absence, and no prediction. Presumably, species models should predict species presence for a majority of the area where the species occurred in 1990.

Discussion

Fourteen of the 23 species modeled had satisfactory results. The summary results (Table 2) indicate several general trends in those species that we were able to model successfully. All 14 species successfully modeled can be considered habitat generalists within the general habitat categories of forest, grassland-open, aquatic, and suburban/residential. These habitat categories, although broad, are discrete and very different structurally. Common species using habitats indiscriminately, such as crows, did not have clear relationships between species presence and our available data themes. This result was expected given our methodology.

No connection existed between the percentage of significant DN conditional probabilities (Table 1), the number of themes used as model input, and the percentage of unmodified areas in model output (Table 2). We had expected that models with higher percentages of significant DN conditional probabilities would have overall lower percentages of unmodified areas in the model output. This unexpected result may be due to the spatial relationship of the DN values that were significant in each theme. If all significant DN values were at the same spatial location in each theme, the percentage of the state that was modified by the model would be lower than if the significant DN values from each theme did

Table 2. Summary Table Showing Species Model Predictions as a Percentage of Maine's Landscape, Habitat Types Each Species Is Primarily Associated with, Data Themes Used in Building Each Model, and the Number of BBS Stops Each Species Was Observed at in 1990.

	Prediction Statewide (%)						
Species Name	Absence	N.Mod.	Presence	Habitat	Theme	# Stops	Std. Level
American Goldfinch	5.4	42.5	52.1	S	4,5, V	83	3
Song Sparrow	14.3	39.7	46.0	S	4,5, V	361	3
Eastern Phoebe	6.3	48.4	45.3	F	4,5	127	4
Gray Catbird	9.9	51.2	38.9	S	4,5	178	2
Winter Wren	60.0	14.6	25.4	F	4,5, V	212	1
Savannah Sparrow	47.0	42.1	10.9	G/A	4,5	88	6
Northern Parula	45.9	23.6	30.6	F	4,5	169	3
Nashville Warbler	40.1	26.6	33.3	F	4,5	131	4
Black-throated Gr. Warbler	39.6	38.1	22.2	F	5, V	95	3
Red-breasted Nuthatch	39.0	38.4	22.6	F	4,5	77	6
Yellow Warbler	34.2	52.0	13.8	S	4,5, V	187	3
House Finch	30.1	44.8	25.0	R	4,5, V	160	3
Bobolink	27.8	39.6	32.6	G	4,5	112	5
Red-winged Black Bird	22.9	54.3	22.8	A	5, V	145	4

(N.Mod. = not modified/no prediction; Habitat: S = shrub open; F = forest generalist; R = suburban/residential; G = grassland-open; A = aquatic; Them.: 4 = TM Band 4; 5 = TM Band 5; V = variance texture; Std. (standard deviation) Level: 1 = low; 6 = high) not align spatially. Species with higher percentages of significant DN conditional probabilities did, as expected, have relatively lower values for the error standard deviation (Table 2).

The inclusion of spatial texture measures proved useful in this study. Seven of the successful models included data from the theme for variance texture. This theme measured the spatial heterogeneity of the area surrounding each BBS stop at a scale of 4.4 hectares (7- by 7-pixel analysis window). High variance texture measures indicated high variability in the amount of vegetation and, therefore, variable habitat types. Six of the seven species models using the variance texture theme had positive correlations with that theme. These six species are associated with mixed habitat types such as forest edge, suburban yards, brushy undergrowth, or abandoned farmland. The spatial heterogeneity of these environments is high as reflected in large texture values. Black-throated Green Warblers were the only species modeled that are primarily associated with mature forests and the only species modeled that had a significant negative correlation with the variance texture theme. Maps of the distribution of predicted species presence and absence and the propagated variability of those estimates provide for a visual interpretation of model results. Black-throated Green Warblers are predicted in areas of the state that are dominated by larger tracts of mature softwood or mixed softwood-hardwood forest, as expected by the habitat preferences of the species.

Model predictions for where species were observed in 1990 (Table 3) consistently (13 of 14 species) contained a higher percentage by area (2.7 to 46.5 percent) of predicted presence pixels than in the statewide results (Table 2), indicating model results were correctly predicting species presence for those test areas. Model results for these areas also contained consistently lower predicted species absence than present in statewide results.

Although our model predicts only presence or absence, it is possible to infer relative abundance of a species according to the prevalence of presence pixels in a region. Regions with concentrations of pixels that indicate species presence are equivalent to a prediction of higher abundance for a species than an area with few presence pixels interspersed with absence pixels.

Because we evaluated each DN value separately (rather than grouping into several levels) in each theme and eliminated non-significant DN values from input into Bayes' Theorem, each data theme on its own contained numerous pixels that were non-significant. Using the power analysis discussed above to eliminate those species-theme combinations that were unlikely to have significant relationships reduced the number of analyses required.

Errors in BBS route stop location may have biased our results. The iterative approach we used to build the correlations between the BBS data and the satellite imagery will minimize problems associated with determining the exact location of BBS stops. Each 0.4-km buffer (all species within this radius are recorded during the BBS) around each stop contains 550, 30-m^2 pixels. A deviation of one tenth of a mile in stop placement would result in a 50 percent change in the pixels comprising the 0.4-km buffer around each stop. Although a deviation in stop location of a tenth of a mile is allowed when running a BBS route, such a deviation would not be systematically biased in any one direction.

TABLE 3. PERCENT OF AREA IN EACH SPECIES 1990 PRESENCE STOPS PREDICTING SPECIES PRESENCE, NO PREDICTION, AND PREDICTING ABSENCE.

	Percentage		
Species Name	Absence	No Prediction	Presence
Eastern Phoebe	2.6	29.3	68.1
Bobolink	12.3	38.1	49.6
Red-winged Blackbird	7.4	42.2	50.4
House Finch	8.8	39.2	52.0
American Goldfinch	0.8	17.2	82.0
Savannah Sparrow	22.3	49.5	28.2
Song Sparrow	3.9	20.3	75.8
Nashville Warbler	28.5	29.7	41.8
Northern Parula	31.9	25.0	43.1
Yellow Warbler	4.5	35.2	60.3
Black-throated Green Warbler	35.7	43.0	21.3
Gray Catbird	3.7	41.8	54.5
Winter Wren	51.7	18.5	29.8
Red-breasted Nuthatch	32.9	41.8	25.3

Conclusions

Our study determined that relationships exist between the unclassified satellite imagery and species presence for 14 of 23 species tested. Furthermore, we were able to use those relationships, in the form of conditional probabilities, to model the probability of occurrence for 14 land birds in Maine. Our modeling procedure also provided measures of variability in model input, the modeling procedure itself, and model output. Variability in the input data guided model building to those DN values that had the greatest difference in conditional probabilities for species presence and absence. Measures of variability in model output were useful in determining the reliability of predicted species presence and absence.

Although only 14 species were successfully modeled in this study, successful modeling of other species, especially less common habitat specialists, might be possible using multiple years of BBS data surrounding the acquisition dates of satellite imagery. Because we found only 23 species of 59 had measurable relationships to the Thematic Mapper bands and derived layers we used, it is likely that other layers TM bands or other derived layers might provide a better correlate to environmental variables important to bird species. Inclusion of other data themes might increase the numbers of species that could be successfully modeled.

The results from this study indicate that our Bayesian modeling technique shows promise for providing landscape-level habitat assessments for some land birds in Maine. The technique used in this study provides a potentially faster and less expensive approach to predicting species presence and absence than those techniques requiring new LCLU maps. The spatially explicit results produced by our method and the fine spatial resolution of the data used to model these species and the resulting high resolution of model predictions makes this methodology an attractive alternative to more generalized methods. The methodology also represents a feasible method to test for the effects of differing spatial scales of heterogeneity and area effects.

Comparisons of our results to results using this methodology with habitat maps as model input or other methods using habitat maps would provide a better understanding of the problems with our analysis. Such a study is currently underway with results anticipated this fall. Future studies, especially in areas of large physiographic relief, could include other data themes such as slope, aspect, and elevation, which are commonly used as ancillary data to improve LCLU classifications of satellite imagery and, therefore, improve the predictive ability of the Bayesian models.

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References

Aspinall, R.J., 1991. Use of an inductive modeling procedure based on Bayes Theorem for analysis of spatial data, *Computer Modeling in the Environmental Sciences* (D.G. Farmer and M.J. Rycroft, editors), Institute of Mathematics and its Applications Conference Series No. 28, Oxford University Press, Oxford, pp. 325–339.

Aspinall, R., and N. Veitch, 1993. Habitat mapping from satellite imagery and wildlife survey data using a Bayesian modeling procedure in a GIS, *Photogrammetric Engineering & Remote Sensing*, 59(4):537–543.

Bonham-Carter, G.F., F.P. Agterberg, and D.F. Wright, 1988. Integration of geological datasets for gold exploration in Nova Scotia, *Photogrammetric Engineering & Remote Sensing*, 54:1585–1592.

———, 1989. Weights of evidence modeling: A new approach to mapping mineral potential, *Statistical Applications in the Earth Sciences* (F.P Agterberg and G.F. Bonham-Carter, editors), Geological Survey of Canada, Paper 89-9, pp. 171–183.

Boone, R.B., 1996. *An Analysis of Terrestrial Vertebrate Diversity in Maine*, unpublished Ph.D. Dissertation, University of Maine, Orono, Maine, 222 p.

Burrough, P.A., 1986. *Principles of Geographical Information Systems for Land Resources Assessment*, Clarendon Press, Oxford, 194 p.

Cohen, W.B., 1994. GIS applications perspective: Current research on remote sensing of forest structure, *Remote Sensing and GIS in Ecosystem Management* (V.A. Sample, editor), Island Press, Washington, D.C., pp. 91–107.

DeGraaf, R.M., and J.H. Rappole, 1995. *Neotropical Migratory Birds: Natural History, Distribution, and Population Change*, Cornell University Press, 676 p.

Droege, S., 1990. The North American Breeding Bird Survey, *Survey Designs and Statistical Methods for the Estimation of Avian Population Trends* (J.R. Sauer and S. Droege, editors), U.S. Fish Wildl Serv., Biol Rep. 90(1), pp. 1–4.

ERDAS, 1994. *ERDAS Field Guide*, Erdas, Inc., Atlanta, Georgia, 628 p.

ESRI, 1995. *ARC/INFO, Version 7.0.3.*, ESRI, Inc., Redlands, California.

Gawler, S.C., J.J. Albright, P.D. Vickery, and F.C. Smith, 1996. *Biological Diversity in Maine: An Assessment of Status and Trends in the Terrestrial and Freshwater Landscape*, report prepared for the Maine Forest Biodiversity Project, Maine Natural Areas Program, Department of Conservation, 80 p. plus appendices.

Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin, 1995. *Bayesian Data Analysis*, Chapman & Hall, 525 p.

Herr, A.M., and L.P. Queen, 1993. Crane habitat evaluation using GIS and remote sensing, *Photogrammetric Engineering & Remote Sensing*, 59(10):1531–1538.

Homer, C.G., T.C. Edwards, Jr., R.D. Ramsey, and K.P. Prince, 1993. Use of remote sensing methods in modelling sage grouse winter habitat, *J. Wildl. Manage.*, 57(1):78–84.

Horler, D.N.H., and F.J. Ahern, 1986. Forestry information content of Thematic Mapper data, *Int. J. Remote Sensing*, 7:405–428.

Lyon, J.G., 1983. Landsat-derived land-cover classifications for locating potential Kestral nesting habitat, *Photogrammetric Engineering & Remote Sensing*, 43(2):245–250.

Lyon, J.G., J.T. Heinen, R.A. Mead, and N.E.G. Roller, 1987. Spatial data for modeling wildlife habitat, *J. Surv. Eng.*, 113(2):88–100.

Martin, T.E., and D.M. Finch, 1995. *Ecology and Management of Neotropical Migratory Birds*, Oxford University Press, New York, 489 p.

McMahon, J.S., 1990. *The Biophysical Regions of Maine: Patterns in the Landscape and Vegetation*, unpublished Ph.D. Dissertation, University of Maine, Orono, Maine.

Morrison, M.L., B.G. Marcot, and R.W. Mannan, 1992. *Wildlife-Habitat Relationships: Concepts and Applications*, The University of Wisconsin Press, Madison, Wisconsin, 364 p.

Ormsby, J.P., and R.S. Lunetta, 1987. Whitetail deer food availability maps from Thematic Mapper data, *Photogrammetric Engineering & Remote Sensing*, 53(8):1081–1085.

Palmeirim, J.M., 1988. Automatic mapping of avian species habitat using satellite imagery, *Oikos*, 52:59–68.

Periera, J.M.C., and R.M. Itami, 1991. GIS-based habitat modeling using logistic multiple regression: A study of the MT. Graham Red Squirrel, *Photogrammetric Engineering & Remote Sensing*, 57(11):1475–1486.

Peterjohn, B.G., and J.R. Sauer, 1993. North American Breeding Bird Survey annual summary: 1990-1991, *Bird Populations*, 1:1–15.

Rickers, J.R., 1995. A proximity-based approach to assessing habitat, *Landscape Ecology*, 10(5):309–321.

Ritter, K.H., R.V. O'Neill, C.T. Hunsaker, J.D. Wickham, D.H. Yankee, S.P. Timmins, K.B. Jones, and B.L. Jackson, 1995. A factor analysis of landscape pattern and structure metrics, *Landscape Ecol.*, 10(1):23–39.

Robbins, C.S., D. Bystrak, and P.H. Geissler, 1986. *The Breeding Bird Survey: Its First Fifteen Years, 1965–1979*, U.S. Fish Wildl. Serv., Resour. Publ. 157, 196 p.

Sader, S.A., 1995. Spatial characteristics of forest clearing and vegetation regrowth as detected by Landsat Thematic Mapper imagery, *Photogrammetric Engineering & Remote Sensing*, 61(9): 1145–1151.

Sader, S.A., and J.C. Winne, 1992. RGB-NDVI colour composites for visualizing forest change dynamics, *Int. J. Remote Sensing*, 13(16):3055–3067.

Seymour, R.S., 1994. The northeastern region, *Regional Silviculture of the United States* (J.W. Barrett, editor), John Wiley & Sons, Inc., pp. 31–78.

Shaw, D.M., and S.F. Atkinson, 1988. GIS applications for Golden-cheeked warbler habitat description, *Proceedings of the 1988 GIS/LIS conference*, San Antonio, pp. 401–406.

Steidl, R.J., J.P. Hayes, and E. Schauber, 1997. Statistical power analysis in wildlife research, *J. Wildl. Manage.*, 61(2):270–279.

Terborgh, J., 1989. *Where Have all the Birds Gone?* Princeton University Press, Princeton, New Jersey, 207 p.

Tucker, C.J., J.R.G. Townshend, and T.E. Geoff, 1985. African land cover classification using satellite data, *Science*, 227:369–375.

Tucker, K., S.P. Rushton, R.A. Sanderson, E.B. Martin, and J. Blaiklock, 1997. Modelling bird distributions — A combined GIS and Bayesian rule-based approach, *Landscape Ecology*, 12(2):77–93.

LIFE INSURANCE PLAN IMPROVEMENTS AND CREDIT ANNOUNCED

Members insured in the ASPRS Life Insurance Plan as of March 31, 1997 will receive a credit of 40 percent of their semiannual premium due on the October 1, 1997 renewal. This marks the 33rd time since the inception of the Program that premium credits have been granted by the Life Insurance Trust. These credits have effectively lowered member's annual premiums by an average of 20 percent over the last 5 years, thus reducing the cost of coverage for eligible insured members and their families.

Because of the Plan's excellent experience, the carrier has also agreed to two valuable enhancements for the ASPRS Term Life Plan. New York Life has implemented an increase in maximum benefit for members and spouses (except in Texas) from the current *$300,000 to* **$600,000**. In Texas, the maximum spouse benefit is increasing from $150,000 to $300,000. They have also increased the Accelerated Death Benefit from the current 25 percent to 50 percent.

For more information on the ASPRS Insurance Program, please contact: **Administrator, ASPRS Group Insurance Program, 1255 23rd Street, NW, Washington, DC 20037** or **call toll-free (800-424-9883)**. In the District of Columbia, call 202-457-6820.