

APPLICATIONS OF RESOURCE SELECTION MODELING USING UNCLASSIFIED LANDSAT THEMATIC MAPPER IMAGERY

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Abstract: Geographic Information Systems (GIS) are often used for generating predictor variables for wildlife or plant resource selection models, and in producing maps of subsequent predicted values from the resulting models. Land cover class is often used as a possible covariate, if a land cover map derived from Landsat Thematic Mapper or other imagery is available for the study area of interest. We present an application where unclassified Landsat Thematic Mapper data is used to directly model wildlife habitat. We argue that using the unclassified imagery to directly model wildlife habitat selection avoids the problem of land cover classification error. Land cover classes are also often not directly related to wildlife habitat selection. This approach uses the measured spectral values in predicting wildlife habitat selection, as opposed to derived unmeasured data such as land cover classes. In this example, we model resource selection by three passerine species (alder flycatcher [*Empidonax ainorum*], blackpoll warbler [*Dendroica striata*], and savannah sparrow [*Passerculus sandwichensis*]) within the floodplain of a section of the Innoko River within the Innoko National Wildlife Refuge in West Central Alaska, using unclassified Landsat Thematic Mapper imagery.

Key words: Alaska, resource selection, alder flycatcher [*Empidonax ainorum*], blackpoll warbler [*Dendroica striata*], savannah sparrow [*Passerculus sandwichensis*], geographic information systems (GIS), Innoko National Wildlife Refuge, Landsat Thematic mapper (TM)

Geographic Information Systems (GIS) provide wildlife researchers and managers a valuable tool for modeling and managing wildlife habitat (Erickson et al. 2001, Conner 2003). Resource selection (Manly et al. 2002) studies often utilize GIS for developing model covariates and for mapping predicting values from these models (Periera and Itami 1991, Erickson et al. 1998, Suring et al. 2003). GIS data layers such as land cover, other landscape features, hydrography and elevation are becoming more readily available to the general researcher. Land cover classes are derived from Landsat Thematic Mapper (TM) or other imagery and are often subject to high classification error rates (Verbyla and Hammond 1995, Steele et al. 1998, Thomas and Jacobs 2000). Most land cover mapping is not usually developed for specific purpose of modeling wildlife habitat and the classification scheme is not usually defined for a particular species. For example, many standard land cover classifications applied in Alaska combine willow and alder into a tall shrub category, yet willow is usually a preferred forage species of moose, and alder is typically an avoided forage species.

Despite these limitations, useful models of wildlife habitat selection have been developed using GIS data layers such as land cover (Periera and Itami 1991, Aspinall and Veitch 1993, Erickson et al. 1998, Suring et al. 2003). The ability to map predictions from these models allows for study area or landscape level evaluation of selection relationships that can provide valuable information for making management decisions. One factor that limits the efficient development of such landscape level models is the land cover mapping process. This process can be costly and very time consuming because of image processing time and the need for ground truthing and accuracy assessment. Methods that expedite the process of developing these models and maps that are not so reliant on availability and accuracy of derived land cover map would be useful.

In this paper, we present a resource selection modeling application that utilizes unclassified TM imagery instead of derived land cover classes for covariates. We have found few papers that directly use the TM unclassified imagery in modeling wildlife habitat (Aspinall and Veitch 1993, Hepinstall and Sader 1997). Our approach directly utilizes the measured spectral data as opposed to derived land cover classes that are not necessarily related to the particular species of interest and often are subject to high unknown classification error rates. Furthermore, this technique would allow for a relative quick approach to generating maps of wildlife habitat in cases when the land cover mapping process is incomplete, and temporarily inconsistent (e.g., out-dated) with species survey data.

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Obvious drawbacks to this approach include the difficulty in biological interpretation of coefficients of variables associated with the spectral bands. This apparent shortcoming may be addressed through ground truthing after a resource selection map is developed, which we present. Other solutions to this drawback consist of comparisons of results to a land cover map, or further interpretation of coefficients. We evaluate the approach using documented locations of breeding alder flycatchers (*Empidonax ainorum*) blackpoll warblers (*Dendroica striata*), and savannah sparrows (*Passerculus sandwichensis*) on the Innoko National Wildlife Refuge in west central Alaska.

STUDY AREA AND METHODS

The Innoko National Wildlife Refuge is located in west central Alaska, about 270 miles southwest of Fairbanks and 290 miles northwest of Anchorage. The 3.8 million acre refuge is a relatively flat plain dominated by numerous slow-moving silty rivers and innumerable small lakes, streams, and bogs. The vegetation of the refuge reflects a transition zone between the boreal forest of interior Alaska, and the shrub-land and tundra types common in western and northern Alaska. White spruce dominates in large stands along the rivers where the soil is well-drained while black spruce muskegs or bogs develop on the poorly-drained soils outside the river corridors. Historically fires have and today continue to set vast areas back to earlier seral stages of aspen, birch and willow. River sandbars shaped by yearly flooding have bands of willow (*Salix alexensis*) and birch (*Betula papyrifera*) trees. Sloughs and marshes within the river floodplains have scattered stands of willow (*Salix pulchra*) in the lower areas as well as mature birch interspersed with grasses. Open bunch grass meadows (*Calamagrostis canadensis*) are commonly found in large tracks with stringers of birch and willow leading out from the white spruce (*Picea glauca*), alder (*Alnus incana*), and birch forested areas along the rivers.

Field Methods

A systematic sample of transects with a random start for the first transect were located within the middle section of the Innoko River floodplain (Figure 1). Surveys were conducted between 0300 and 1100 hours from June 1st until June 30th for five consecutive years (1998 – 2002). Line transects were followed by using a predetermined compass heading perpendicular to the river. Transects were walked slowly with three to five minute stops every 30 meters while looking and listening for targeted bird species. More precise locations of all birds verified either visually or auditorily were gathered using a PLGR+96 GPS. Transects were followed until either 1100 hours when bird activity noticeably declined or until the vegetation changed signifying the outer limits of the floodplain. Birds were not recorded on the transects while returning to the river.

Originating at each bird location, the dominant overstory plant species were recorded on four transects orientated north, south, east, and west. Ten records were taken on each of the four transects or 40 total records at each bird location. Each of the four transects were 25 meters in length and plant species information was recorded at points at 2.5 meter intervals. When more than one species occurred at a point in the overstory, only the upper species was recorded.

GIS Methods

Field data for bird observations and transect lines were entered into an Access database and from this four ArcInfo coverages were generated: 3 point coverages representing the three observed species and one line coverage portraying the transects. A polygon coverage representing the Innoko River floodplain (i.e., study area) was then delineated by using the transect lines, TM imagery, and years of on-the-ground observations.

With ArcInfo GRID, the study area polygon was converted into an image with 30-meter cells, coincident with TM imagery taken on August 26, 1991. A total of eleven raster layers were co-registered with the study area and used in subsequent processing including spectral values from TM bands 1-5, and 7, from August 26, 1991, elevation (from 1:63,360-scale DEM's), slope, aspect, distance to rivers, and distance to lakes. For each bird observation, the values of each of the above eleven layers were recorded for every pixel within a 3.5 pixel (105 m)-radius of the observation point and stored in Access tables. The same buffer size and raster layers were used to generate similar tables for systematically-sampled pixels within the study area as a whole (5094 samples out of 616,754 pixels). A final table was constructed from buffering every point within the study area. Derived variables within each 105 m buffer included the mean and standard deviation of spectral values for each TM band, the proportion of the buffer with aspects of north, south, east, and west, and the mean elevation, slope, distance to river and distance to lake (Table 1).

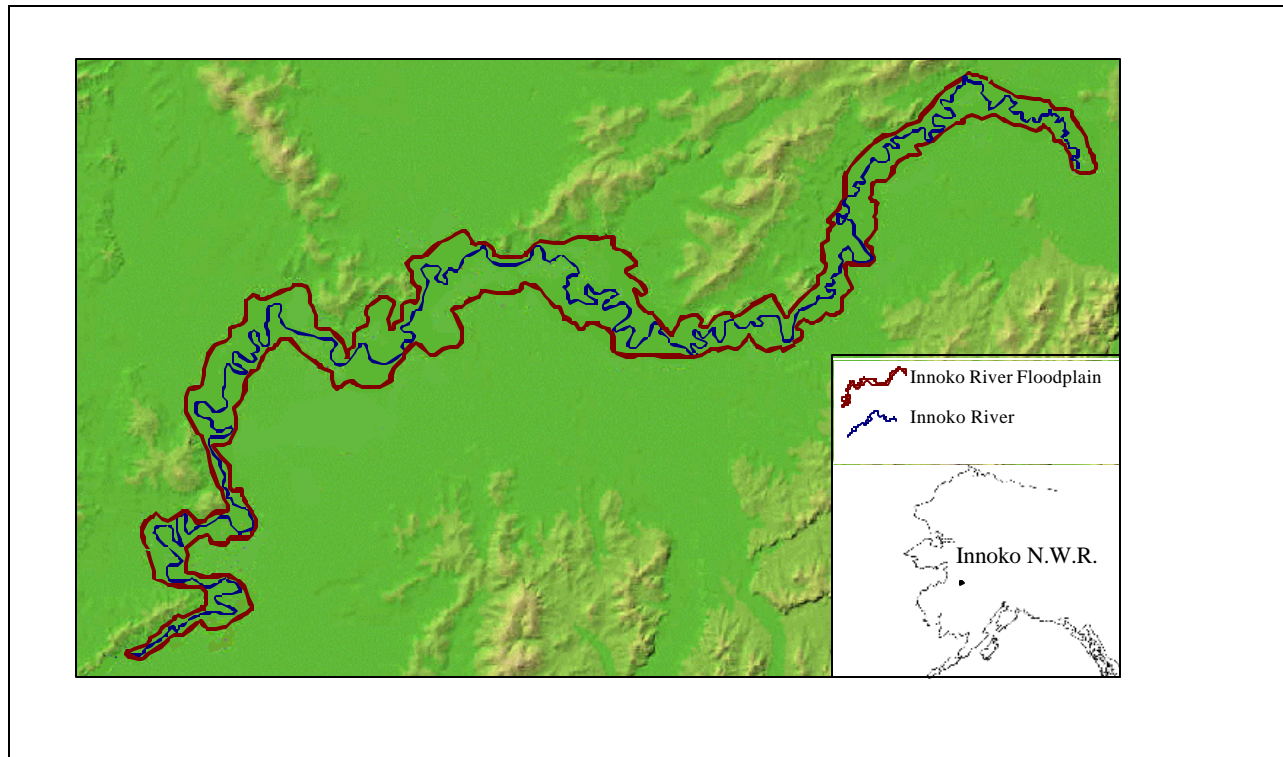


Figure 1. Location of study area within the Innoko National Wildlife Area and the transect locations.

Statistical Methods

Univariate T-tests were calculated to compare the mean values of the used and available locations for each variable. These T-tests compared the sample mean of the used points to the mean of the available points. Because such a large number of available points were sampled for this study (5094 points), the mean of the available points was considered to come from a census and contain no error, and thus the T-test statistic became,

$$t = \frac{Mean(used) - Mean(available)}{SE_{used}}$$

Degrees of freedom for the test were the number of sampled used points for the bird species minus one. The results of these T-tests were used to determine which variables to drop from the model building process once multicollinearity was detected. If two variables were highly correlated (Pearson's correlation coefficient of 0.80 was used as the cut-off), then the variable with the largest p-value from the univariate T-tests for all three species was dropped. For example, if the mean of spectral values from band 1 for each 105 meter buffer was highly correlated with the mean of values for band 5, and the p-values for univariate T-test for bands 1 and 5 averaged across the three bird species were 0.25 and 0.11, respectively, then band 1 was dropped to break the collinearity. The final list of variables considered during the model building process is in Table 1.

Logistic regression was used to estimate the resource selection function or RSF (Manly et al. 2002),

$$w(x) = \exp\{b_1(x_1) + \dots + b_p(x_p)\}$$

where $w(x)$ is the estimated relative probability of selection of a point in the landscape given the values of the variables x_1 through x_p at that point and the estimated coefficients, b_1 through b_p , for variables in the model. There were twelve variables available for estimating the RSF. For each species (3), all 4095 ($2^{12} - 1 = 4095$) possible main effects models were fit. Quadratic variables and interaction terms were ignored for this study. The 4095 models were then ranked according to Schwartz's Bayesian Criterion (BIC) (Schwartz, 1978). The top five models (i.e., smallest BICs) from this set were reported as our final models. BIC is defined as $-2\log(Likelihood) + p \log(n)$, where p was the number of variables in the model, n was the number of bird locations plus the number of available locations, $Likelihood$ was the value of the logistic likelihood, and \log was the natural logarithm.

Table 1. Variables considered in resource selection models. All variables derived within a 105 m buffer of the bird locations and available sample.

Variable Name	Description	Used ^a	Variable Name	Description	Used ^a
BAND 1	average of band 1 within buffer	X	STD BAND1	standard deviation of band 1 within buffer	X
BAND 2	average of band 2 within buffer		STD BAND2	standard deviation of band 2 within buffer	
BAND 3	average of band 3 within buffer		STD BAND3	standard deviation of band 3 within buffer	X
BAND 4	average of band 4 within buffer	X	STD BAND4	standard deviation of band 4 within buffer	X
BAND 5	average of band 5 within buffer	X	STD BAND5	standard deviation of band 5 within buffer	
BAND 7	average of band 7 within buffer		STD BAND7	standard deviation of band 7 within buffer	X
ELEV	average elevation	X	RIVER	average distance from river (meters)	X
SLOPE	average slope	X	LAKE	average distance from lake (meters)	X
ASPECT	4 categorical variables, % within north, south, east, west aspect	X			

^aThese variables were retained for resource selection modeling based on results of the correlation analysis.

Relative probabilities of use were calculated based on importance value weights for the top five models. Importance values (Burnham and Anderson 1998) for each variable were calculated using the top five models. The importance value is a weighted proportion (weights w_i) of models where the variable was included. Each model was used to predict the relative probability of selection and each of the five predictions were weighted according to the BIC weights. This weighting procedure is similar to the Akaike weights (Burnham and Anderson, 1998, p124). For each of the top five models for each buffer size and species the BIC differences were calculated as,

$\Delta_i = BIC_i - \min(BIC)$ where BIC_i is the BIC for the i th model and $\min(BIC)$ is the minimum BIC value for the five models. The BIC weights were then calculated as,

$$w_i = \frac{\exp\left(-\frac{1}{2}\Delta_i\right)}{\sum_{i=1}^5 \exp\left(-\frac{1}{2}\Delta_i\right)}$$

Maps of the model averaged relative probability of use were generated for the study area. The relative probabilities were calculated for each pixel as a weighted average of relative probabilities obtained from each of the top five models, with weights equal to the importance values for each model. These predictions were calculated for all available locations within the study area (5094 locations on a 30mX30m grid). For mapping, the predicted relative probabilities of use for every available point were ranked and classified into five categories. The five categories were defined as: very low selection (RSF value lower than the 25% percentile of the RSF values for used locations), low selection (RSF value between 25th and 50th percentiles of the RSF values for used points), moderate selection (50-75th percentile), high selection (RSF value >75th percentile of RSF values for used locations). Predictions were mapped for each bird species, resulting in three maps of the predicted relative probability of use in the study area. Mapping was done using ArcView® GIS 3.2 software with the Spatial Analyst® extension.

Model validation was conducted based on methods described in Howlin et al. (2003). A randomly selected sample of 25% of the observations (validation use sample) was used to evaluate the predictive abilities of the model. The model under validation was refit without the validation use sample, and predictions were made from this model for the available data and the validation use sample. The predicted values were then scaled to the number of use points in the validation sample. Data from the available set were grouped into 20 bins based on the percentiles of the predicted relative probability of use from the model under validation. Data from the validation use sample were put into bins based on the same 20 break points. The observed selection in each bin (number of use points) was compared to the predicted selection in each bin (sum of the scaled predicted values) using simple linear regression. We repeated the random selection of validation use points 5 times and calculated the model validation slope for each set of use points.

The slope of the regression model, with the predicted selection as the predictor of observed selection, is a measure of the predictive ability of the model. When the slope is not significantly different from zero there is no correlation between the predictions and actual resource use, we categorized the predictive abilities of the model as poor. When the slope is positive and significantly different from zero there is a fair amount of positive correlation between predictions and actual use, and the predictive abilities of the model is fair. We categorized a model as

having good predictive ability when the slope of the relationship between predicted and observed selection is not significantly different from 1 and significantly different than 0.

RESULTS

Pearson correlations were calculated and variables with high ($r > 0.8$) correlations were eliminated, leaving twelve variables as candidates for the resource selection models (Table 1).

Alder Flycatcher

During the field surveys, 109 locations of alder flycatchers were obtained for model building purposes. The top five models for alder flycatcher resource selection are found in Table 2. Elevation (ELEV) and the average of band 4 (BAND 4) were included in all of the top five models, the standard deviation of band 3 was in four of the top five, while distance to river (RIVER) was included in three of the top five. The probability of use increased as the elevation and distance to river decreased (negative coefficients). This probability increased as the average of band 4 and standard deviation of band 3 decreased (positive coefficients). Model validation results suggested a good-fitting model, since the confidence interval between the slope of the regression between predicted RSF values and observed RSF values for the 25% validation sample did not capture the value 0, and did capture the value 1 for each validation run (Table 3). The variables ELEV, BAND 4, and STD BAND 3 had the highest importance values (Table 4). A general pattern of higher probability of use near the river in the southern section of the study area was apparent (Figure 2).

Blackpoll Warbler

During the field surveys, 105 locations of blackpoll warblers were obtained for model building purposes. The top five models for blackpoll warbler resource selection are found in Table 2. The average of band 4 (BAND 4) and elevation were included in all of the top 5 models, and the average of band 1 was included in the top 3 models. The probability of use increased as the elevation and average of band 1 decreased (negative coefficients). This probability increased as the average of band 4 increased (positive coefficients). Model validation results suggested a fair-fitting model, since the confidence interval of the slope of the regression between predicted RSF values and observed RSF values for the 25% validation sample did not capture the value 0, but also tended to capture the value 1 occasionally (Table 3). As with alder flycatchers, the variables BAND 4, ELEV, and BAND 1 had the highest importance values (Table 4).

Savannah Sparrow

During the field surveys, 71 locations of savannah sparrows were obtained for model building purposes. The top five models for savannah sparrow resource selection are found in Table 3. Distance to lake (LAKE) and elevation was included in all of the top 5 models, the average of band 1 and standard deviation of band 1 was included in 4. The probability of use increased as the distance to lake and elevation decreased (negative coefficients). This probability increased as the average of band 1 and standard deviation of band 1 increased (positive coefficients). Model validation results suggested a good-fitting model, since the confidence intervals of the slope of the regression between predicted RSF values and observed RSF values for the 25% validation sample did not capture the value 0, and did capture the value 1 for each validation run (Table 3). The variables LAKE, ELEV, BAND 1, and STD BAND 1 had the highest importance values (Table 4).

Vegetation Surveys at Bird Locations

The three birds species were found in different parts of the meadow/shrub/forest complex along the Innoko River riparian corridor based on mean overstory vegetation percent cover comparisons (Table 5). Savannah sparrows was shown to be associated with bluejoint grass, the dominant herbaceous plant of the meadows. Blackpoll warblers, a forest species, was shown to be associated with paper birch (*Betula papyrifera*), the dominant tree within forested areas of the study area. Alder flycatchers were associated with diamondleaf willow (*Salix pulchra*), the most common shrub in the zone between the forests and the meadows. Alder flycatchers were also associated strongly with feltleaf willow (*Salix alexensis*), the willow species that grows only on the sandbars of the Innoko River.

Table 2. Top 5 models (lowest BIC) for alder flycatcher, blackpoll warbler and savannah sparrow. Model based on averages and standard deviations of variables in a 105m-radius buffer around each sampled point in the landscape. Available sample comes from the corridor-wide area. Description of variable names are found in Table 1.

	Alder Flycatcher		Blackpoll Warbler		Savannah Sparrow	
Model	Variable	Estimate	Variable	Estimate	Variable	Estimate
1	RIVER	-0.0008	BAND 1	-0.2315	LAKE	-0.0013
	BAND 4	0.0412	BAND 4	0.0694	BAND 1	0.3339
	STD BAND 3	0.2278	STD BAND 3	0.2124	STD BAND 1	0.5839
	STD BAND 4	0.0393	ELEV	-0.1399	ELEV	-0.2527
	ELEV	-0.1191				
BIC(weight)	911.36(0.376)		866.92(0.673)		499.89(0.71)	
2	BAND 4	0.0471	BAND 1	-0.1817	LAKE	-0.0014
	STD BAND 3	0.2347	BAND 4	0.0740	BAND 1	0.3078
	STD BAND 4	0.0517	STD BAND 7	0.1386	BAND 4	0.0153
	ELEV	-0.1228	ELEV	-0.1305	STD BAND 1	0.5777
					ELEV	-0.2583
BIC(weight)	912.35 (0.229)		869.31(0.203)		504.85(0.065)	
3	RIVER	-0.0008	RIVER	-0.0004	LAKE	-0.0013
	BAND 4	0.0433	BAND 1	-0.2022	BAND 1	0.3294
	STD BAND 1	-0.7367	BAND 4	0.0664	BAND 4	0.0261
	STD BAND 3	0.2940	STD BAND 3	0.1920	STD BAND 7	0.1684
	STD BAND 7	0.2039	ELEV	-0.1336	ELEV	-0.2446
	ELEV	-0.1231				
BIC(weight)	912.50(0.213)		872.16(0.049)		504.98(0.061)	
4	RIVER	-0.0013	RIVER	-0.0007	LAKE	-0.0012
	BAND 4	0.0332	BAND 4	0.0603	BAND 5	0.0822
	STD BAND 7	0.1933	ELEV	-0.1078	STD BAND 1	0.5629
	ELEV	-0.1018			STD BAND 4	0.0551
					ELEV	-0.2453
BIC(weight)	913.81(0.111)		872.45(0.042)		505.13(0.056)	
5	BAND 4	0.0479	BAND 4	0.0654	LAKE	-0.0013
	STD BAND 1	-0.9981	ELEV	-0.1134	BAND 1	0.3454
	STD BAND 3	0.3839			STD BAND 1	1.1452
	STD BAND 7	0.2149			STD BAND 3	-0.2531
	ELEV	-0.1343			ELEV	-0.2537
BIC(weight)	914.72(0.070)		872.962(0.033)		505.45(0.048)	

DISCUSSION

This study is an observational study (Hurlbert 1984), and analyses should be considered exploratory as opposed to confirmatory (Burnham and Anderson 1998). Differences in patterns of resource use was compared to resource availability for these three species, based on derived GIS variables, some of which had no direct biological meaning. We acknowledge that in confirmatory analyses, model selection criteria such as AIC and BIC require a well defined and relatively small set of candidate models for the theory to hold up. We have not attempted to portray our results as confirmatory, and acknowledge the exploratory nature of the analyses. We also selected BIC, since we have observed it to select smaller models, although AIC and many other model selection criteria may be considered appropriate, especially in exploratory analyses.

The study area, and subsequent definition of available habitat was based on the extent of the line transects used in the bird study. The bird surveys were conducted within the Innoko River floodplain. The survey area for the bird surveys was limited to the floodplain to allow for relatively convenient access to the transects from boats from the Innoko Refuge field camp or from fixed wing aircraft on floats. Most areas away from the major river corridor would only be accessible via helicopter, and costs would have been prohibitive. Inferences from resource selection

Table 3. Model validation results using methods by Howlin et al. (2003). Regression slopes are from predicted RSF and the observed RSF from 25% training set. Slopes with confidence intervals that overlap 1, and do not overlap 0 suggest a good model. Slopes with confidence intervals that do not overlap 0, and also do not overlap 1 are considered a fair model. Slopes with confidence intervals that overlap 0 are considered poor models.

Validation			95% CI for slope (b1)	
Run	Intercept	Slope	LL	UL
Alder flycatcher				
1.00	-0.145	1.108	0.93	1.29
2.00	0.154	0.886	0.68	1.09
3.00	0.321	0.762	0.51	1.02
4.00	-0.256	1.189	0.94	1.44
5.00	0.041	0.970	0.80	1.14
Blackpoll warbler				
1.00	-0.679	1.522	1.20	1.84
2.00	-0.571	1.439	1.20	1.67
3.00	-0.196	1.151	0.90	1.40
4.00	-0.527	1.405	1.14	1.67
5.00	0.009	0.993	0.84	1.15
Savannah sparrow				
1.00	0.123	0.901	0.80	1.00
2.00	0.064	0.949	0.86	1.04
3.00	0.016	0.987	0.88	1.10
4.00	-0.071	1.057	1.00	1.11
5.00	0.148	0.882	0.76	1.01

studies are limited to the definition of availability, which was somewhat arbitrary and limited by costs, as is the case in most studies. The vegetation communities of the floodplain are distinctive from the surrounding upland communities and provide some biological basis for our definition of availability. Inferences from this study are limited to resource selection within habitats of the Innoko river floodplain.

We decided to use a buffer of the used and available locations for development of the covariates, to account for potential inaccuracies in the GPS locations of the birds, and to provide information on the habitat surrounding the bird locations. The size of the buffer was selected arbitrarily. Future work might consider varying the size of buffers (Erickson et al. 1998), or using a size most relevant to home range size of the species modeled (White and Garrott 1990, Erickson et al. 2001, Manly et al. 2002).

The primary purpose of the modeling effort was to develop predictions of relative probability of use on the landscape. We did not provide much interpretation of the coefficients associated with the variables considered, and believe direct interpretation for certain variables in the model such as functions of spectral values may be difficult and could be considered a shortcoming in this paper. For example, we included the standard deviation of the mean spectral values to incorporate indices to variation in vegetation characteristics of the landscape, but we did not attempt to interpret the coefficient for the standard deviations. Other variables such the normalized difference vegetation index (NDVI), which is calculated from the normalized ratio of band 3 to 4, is often used to improve discrimination between vegetation and non-vegetation (Tucker et al. 1985, Sader 1995). We did not consider using this index as a variable, and do not know if such a transformation would have improved the models. The use of such indices may have provided more direct biological interpretation of the coefficients of the models.

Table 4. Importance values (weighted proportion of top five models including variable with BIC weights w_i) and sign of coefficient for each variable for each species.

Variable	Alder Flycatcher	Blackpoll Warbler	Savannah Sparrow
RIVER	0.7 (-)	0.09 (-)	0
LAKE	0	0	1 (-)
BAND 1	0	0.93 (-)	0.95 (+)
BAND 4	1 (+)	1 (+)	0.13 (+)
BAND 5	0	0	0.06 (+)
STD BAND 1	0.28 (-)	0	0.94 (+)
STD BAND 3	0.89 (+)	0.72 (+)	0.05 (-)
STD BAND 4	0.61 (+)	0	0.06 (+)
STD BAND 7	0.39 (+)	0.20 (+)	0.06 (+)
ELEV	1 (-)	0.93 (-)	1 (-)
SLOPE	0	0	0
ASPECT	0	0	0

We believe the shortcoming regarding lack or difficulty of interpretation could be overcome by either ground-truthing the final resource selection maps, developing an accurate land cover map after the models have been developed, interpreting the coefficients of the variables considered, or using more standard variables used in land cover mapping. If a land cover map is available, this may be used to provide some limited information on interpretation of the selection map depending of the detail in the land cover map. The primary biological interpretation of the models was based on ground-truthing of observed bird locations, although a better validation approach would have been to select samples in the various levels of probability of use as depicted in the maps (Figures 2 and 3). Additional interpretation could have been gained by correlating the variables considered in the resource selection models (e.g., spectral means and standard deviations) at the bird locations to the vegetation characteristics from ground observations at the bird locations. We also only considered main effects models. Quadratic or other non-linear relationships of the variables with the relative probability of use may exist and may have provided better models.

We have not tested whether better models are obtained when using the raw imagery or the classified land cover map (Hepinstall 2000). We suspect it may depend on the study area, species, and the quality of both the imagery and the land cover map. We suspect that a combination of both unclassified imagery and classified imagery (e.g., land cover) may yield superior models compared to models from either data set individually.

Models and maps were very different for savannah sparrow compared with both blackpoll warbler and alder flycatcher. The models and maps do appear to identify the grassland areas used by savannah sparrows that are not used by the other more shrub/tree associated species. The maps and models for alder flycatchers did appear to isolate the sandbar habitat and other willow and shrub habitat that is associated with this species. The blackpoll warbler maps overlap the alder flycatcher maps to some extent, and the model validation results suggest the blackpoll models were not as good as the models for the other two species. These results are apparent in small scale views of the resource selection probability maps for a portion of the study area (Figure 3).

Resource selection modeling and mapping for GIS are tools managers use to understand and protect wildlife habitat. The ability to create such models and maps is often limited by the availability and reliability of GIS data layers. Land cover is often considered a covariate(s) in modeling resource selection, but may not be available for the study area of interest, may be outdated, or may not be at a scale relevant to the species under consideration. Land cover is also a variable derived from TM images, so that the measured data for land cover are the unclassified spectral values. TM is becoming more easily accessible and available for the average GIS user. In this paper, we have successfully demonstrated an approach for modeling resource selection that utilizes the unclassified imagery in directly developing predictors of wildlife resource selection. This approach avoids several problems associated with land cover mentioned above, and could definitely reduce the time for mapping wildlife habitat, especially when an expedited process is needed.

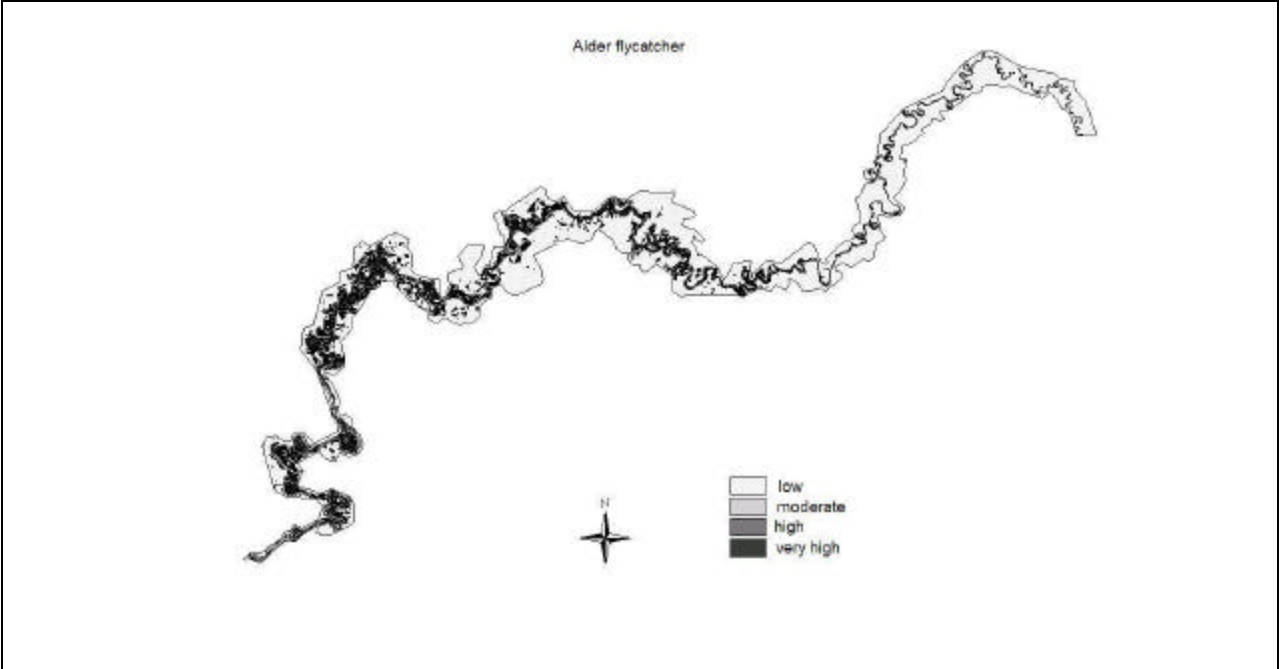


Figure 2. Map of the predicted relative probability of alder flycatcher selecting a point on the landscape.

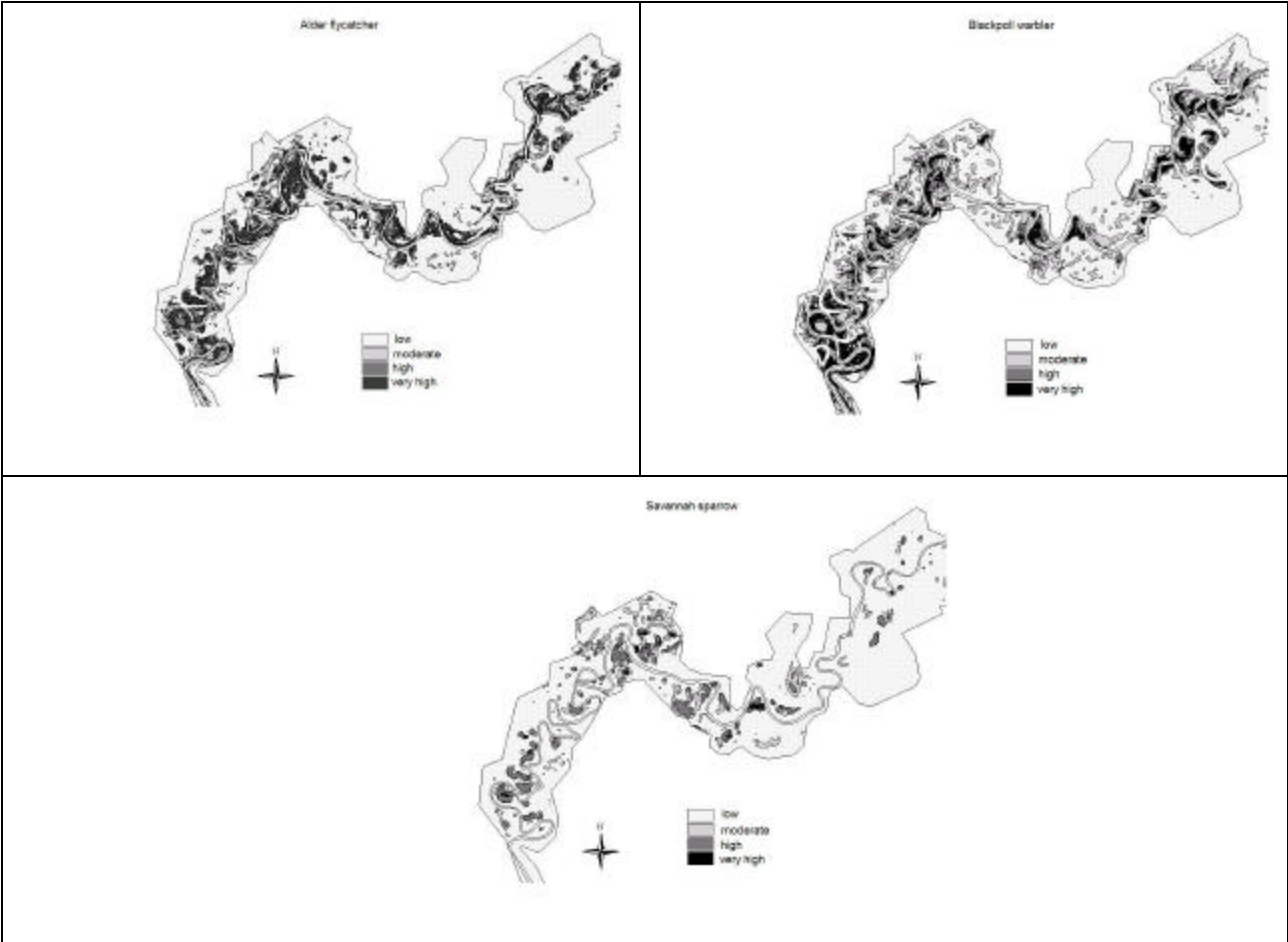


Figure 3. Magnified view of resource selection probability maps for all three species.

Table 5. Mean percent cover, standard deviations and t-test comparisons for alder flycatchers (alfl), blackpoll warblers (blpo) and savannah sparrows (sasp) locations based on field measurements. Only groups/species that yielded t-test p-values less than 0.05 are reported.

Group/Species	Alder		Blackpoll		Savannah		t-test p-values		
	Flycatcher		Warbler		Sparrow		alfl vs	alfl vs	sasp vs.
	%	sd	%	sd	%	sd	blpo	sasp	blpo
<u>Forbs</u>									
<i>Equisetum palustre</i>	0.26	1.37	0.00	0.00	1.92	6.49	0.648	0.003	0.002
<i>Equisetum silvaticum</i>	0.20	0.86	0.27	0.97	0.00	0.00	0.592	0.084	0.034
<i>Equisetum</i> subtotal	0.46	1.98	0.50	1.97	2.09	6.52	0.946	0.008	0.014
Total	1.61	4.28	1.10	2.64	3.01	8.68	0.558	0.108	0.040
<u>Grasses</u>									
<i>Arctogrostis latifolia</i>	0.13	0.66	0.00	0.00	0.00	0.00	0.047	0.049	1.000
<i>Calamagrostis canadensis</i>	27.09	17.60	14.83	12.91	61.34	33.64	0.000	0.000	0.000
<i>Carex rostrata</i>	1.43	4.68	0.53	2.37	12.02	26.55	0.694	0.000	0.000
<i>Carex</i> subtotal	1.51	4.76	0.67	2.61	12.26	26.54	0.713	0.000	0.000
<i>Glyceria maxima</i>	0.08	0.76	0.00	0.00	0.48	2.49	0.729	0.071	0.043
Total	28.80	17.64	15.93	14.44	74.86	29.33	0.000	0.000	0.000
<u>Shrubs</u>									
<i>Alnus crispa</i>	2.02	6.48	6.93	15.28	0.00	0.00	0.001	0.166	0.000
<i>Alnus incana</i>	1.48	3.36	1.97	4.67	0.10	0.65	0.346	0.009	0.001
<i>Alnus</i> subtotal	3.49	8.48	8.90	16.10	0.10	0.65	0.001	0.036	0.000
<i>Rosa articularis</i>	1.10	2.46	2.20	3.58	0.03	0.29	0.005	0.007	0.000
<i>Salix alexensis</i>	10.33	22.98	0.80	4.27	0.00	0.00	0.000	0.000	0.741
<i>Salix bebbiana</i>	5.28	8.37	5.60	10.14	2.57	8.60	0.817	0.053	0.042
<i>Salix pulchra</i>	26.84	22.47	17.90	21.00	6.99	14.27	0.004	0.000	0.001
<i>Salix</i> subtotal	42.45	23.33	24.33	26.28	9.59	18.21	0.000	0.000	0.000
Total	48.67	20.48	37.40	23.78	13.90	22.94	0.001	0.000	0.000
<u>Trees</u>									
<i>Betula nana</i>	0.87	3.27	0.63	2.33	4.25	14.50	0.854	0.009	0.008
<i>Betula papyrifera</i>	14.69	15.40	39.13	25.20	0.89	2.90	0.000	0.000	0.000
<i>Betula</i> subtotal	15.56	15.70	39.87	24.74	5.21	14.81	0.000	0.000	0.000
<i>Picea glauca</i>	0.69	2.32	2.93	6.32	0.00	0.00	0.000	0.240	0.000
<i>Populus tremuloides</i>	1.33	5.87	2.37	8.53	0.07	0.59	0.260	0.176	0.021
Total	17.58	16.87	45.17	25.64	5.65	15.76	0.000	0.000	0.000

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