EVALUATING MARSH BIRD HABITAT USE AT MULTIPLE SCALES TO INFORM CONSERVATION DESIGN

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

The long-term decline of waterbird populations and the need for conservation actions directed at these species has been recognized at continental (Kushlan et al. 2002), regional (Soulliere et al. 2007), and state levels (e.g., Eagle et al. 2005). The Upper Mississippi River and Great Lakes Region Joint Venture (hereafter JV) is implementing waterbird conservation following an adaptive framework referred to as Strategic Habitat Conservation. This framework is a process consisting of four equally important components: biological planning, conservation design, implementation or program delivery, and evaluation (National Ecological Assessment Team 2006, JV 2007). The identification of limiting factors and development of models describing population-habitat relationships are core activities of biological planning, and essential to developing habitat conservation objectives that achieve population goals. The JV Waterbird Habitat Conservation Strategy (Soulliere et al. 2007) contains population-habitat models for focal waterbird species based on each species' biology and habitat requirements. However, biological information was lacking for many marsh birds when the JV models were developed, which resulted in the use of planning assumptions that require testing.

Our goal for this project was to investigate relationships between marsh bird occupancy and fine- and large-scale habitat variables in Michigan and Ohio wetlands through analyses of existing and newly collected data in an effort to reduce planning uncertainty. We focused our study on breeding use of wetlands by two "JV focal species" (Wilson's Snipe [*Gallinago delicata*] and Black Tern [*Chlidonias niger*]) and eight additional marsh bird species of management concern (Pied-billed Grebe [*Podilymbus podiceps*], American Bittern [*Botaurus lentiginosus*], Least Bittern [*Ixobrychus exilis*], Virginia Rail [*Rallus limicola*], Sora [*Porzana carolina*], Common Gallinule [*Gallinula galeata*], American Coot [*Fulica americana*], and

Forster's Tern [*Sterna forsteri*]). Three other JV focal species, Yellow Rail (*Coturnicops noveboracensis*), King Rail (*Rallus elegans*), and Black-crowned Night-Heron (*Nycticorax nycticorax*), were not detected often enough to facilitate statistical analyses. All of our 10 focal species were considered species of greatest conservation need in one or more states within the JV region (e.g., Eagle et al. 2005, Wisconsin Department of Natural Resources [DNR] 2005, Ohio DNR 2006). Our objectives were to (1) explore relationships between marsh bird occupancy and habitat variables at fine and large scales for 10 marsh bird species using multiple statistical techniques; and (2) using the information gained from these analyses, develop GIS models to predict marsh bird distributions in Michigan and Ohio.

STUDY AREAS

We combined data from several studies conducted in Michigan and Ohio spanning 2005—2013 in our analyses (Figure 1). We used the following data sets in our analyses: 1) 192 points surveyed in coastal wetlands at St. Clair Flats (Lake St. Clair) and Saginaw Bay (Lake Huron) during 2005—2007 (Monfils et. al 2014); 2) 455 points sampled in 2009 and 2010 as part of a statewide marsh bird study of glaciated portions of Ohio (Kahler 2013); 3) 32 points sampled in 2010 as part of an inventory of Waterloo State Recreation Area (Kost et al. 2010); 4) 61 points surveyed in 2011 within the Saginaw Bay watershed (Monfils unpublished data); and 4) 253 points sampled during 2010—2013 for this study as part of the Michigan Marsh Bird Survey. The combined data set represented over 2,200 point counts conducted during 2005—2013 at 993 points in Michigan and Ohio.

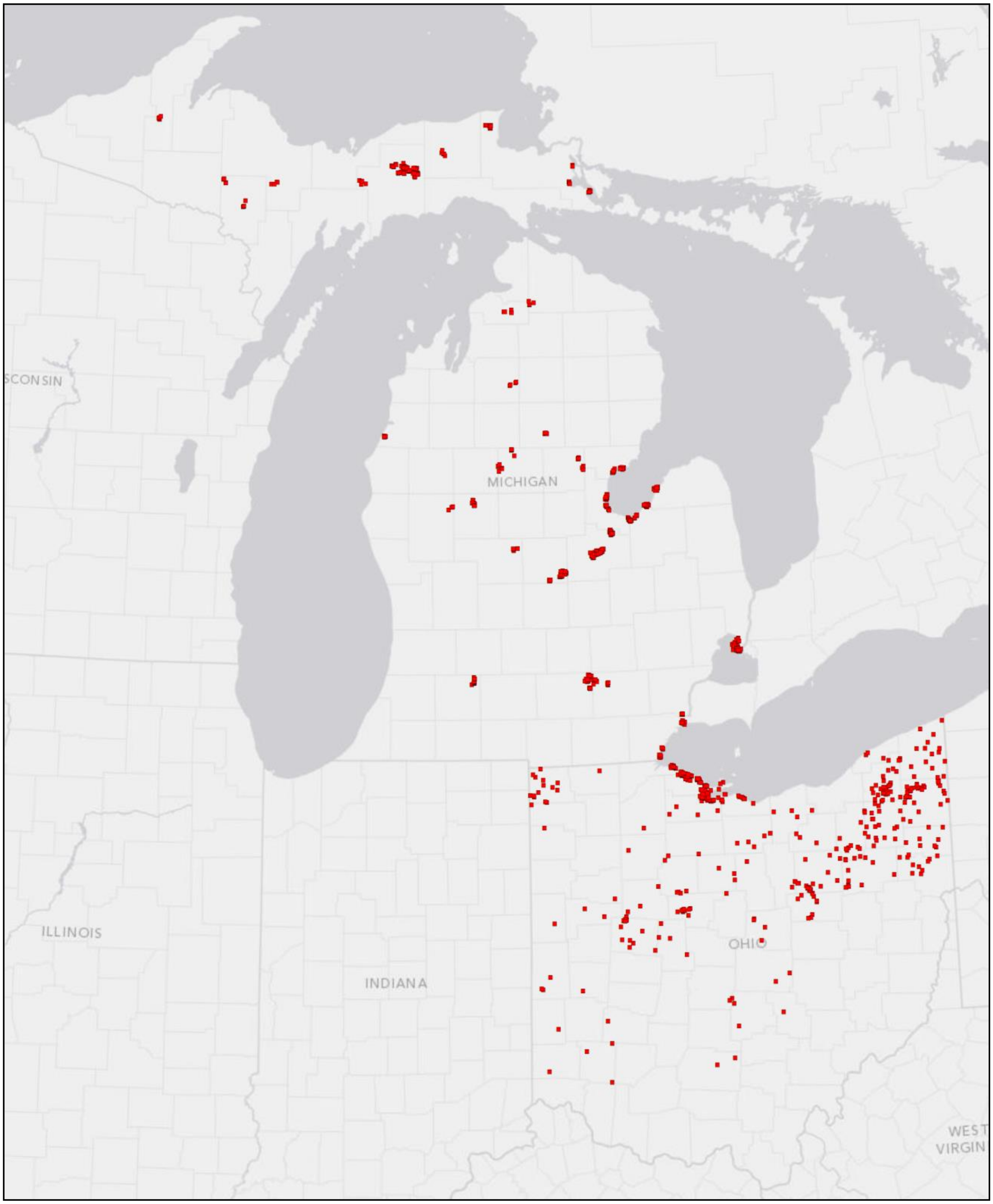

Figure 1. Locations of marsh bird survey sites surveyed during 2005—2013 in Michigan and Ohio from which data were analyzed to evaluate the influence of wetland and land cover variables at fine and large scales on marsh bird occupancy.

METHODS

Bird Surveys

Marsh bird occurrence data were collected using a standardized point-count method (Conway 2011), with avian survey stations selected randomly within emergent wetlands and spaced ≥ 400 m apart. Bird species recorded during surveys varied among the data sets used for our study. Monfils et al. (2014) recorded all wetland bird species detected, whereas Kahler (2013) focused on those species targeted by the Conway (2011) protocol (i.e., Pied-billed Grebe, American Bittern, Least Bittern, King Rail, Virginia Rail, Sora, Common Gallinule, and American Coot) and Black Tern. In addition to the species surveyed by Kahler (2013), Michigan Marsh Bird Survey participants recorded Yellow Rail, Sandhill Crane (*Grus canadensis*), Wilson's Snipe, Forster's Tern, Sedge Wren (*Cistothorus platensis*), Marsh Wren (*Cistothorus palustris*), Le Conte's Sparrow (*Ammodramus leconteii*), Swamp Sparrow (*Melospiza georgiana*), and Yellow-headed Blackbird (*Xanthocephalus xanthocephalus*).

Point counts consisted of a five-minute passive listening period followed by an audio broadcast period of secretive marsh bird calls (one-min broadcast series per species). Calls of five species were broadcasted during Michigan surveys resulting in a 10-min point count. In southern Michigan, calls of five species were played in this order: Least Bittern, Sora, Virginia Rail, King Rail, and American Bittern. In northern Michigan, calls of Least Bittern, Yellow Rail, Sora, Virginia Rail, and American Bittern were broadcasted. Calls of Least Bittern, Sora, Virginia Rail, King Rail, Pied-billed Grebe, American Bittern, and a second Least Bittern (in this order) were broadcasted during Ohio surveys, resulting in a total survey time of 12 min (Kahler 2013). We recorded all marsh birds seen or heard during each point count. Surveyors estimated distances from count stations to birds using ocular/aural estimation and/or a laser rangefinder;

distances to primary study species (i.e., grebes, bitterns, rails, coots, gallinules) were estimated to the nearest five meters, whereas detections of all other (secondary) species were placed in one of three distance categories (≤50 m, >50-100 m, and >100 m). We used only detections recorded within 100 m of stations in our analyses.

Fine-scale Wetland Characteristics

We conducted quadrat sampling to estimate several fine-scale vegetation and physical variables to be included in analyses (Table 1). In addition to the sampling done during marsh bird surveys conducted in Michigan as part of this study, we used data collected with the same methodology as part of other studies (Monfils et al. 2014, Monfils unpublished data). Three randomly selected 0.25-m^2 quadrats were sampled near each point count station. Quadrat frames were situated randomly between 1 m and 25 m along 3 compass bearings (120°, 240°, and 360°). We estimated percent cover of six plant taxa (cattail [*Typha* spp.], bulrush [*Schoenoplectus* spp.], sedge [*Carex* spp.], rush [*Juncus* spp.], common reed [*Phragmites australis*], and grass [other than common reed]) and several vegetation structural categories, plus measured water depth, depth of organic sediments, and maximum height of standing live or dead vegetation, and counted live and dead shrub and tree stems > 2 m tall within 2.5 m of the quadrat center (Riffell et al. 2001). Depth of organic sediments was estimated to the nearest cm by pushing a 1.2-m wooden rod (2-cm diameter, graduated in cm) to the bottom of the organic layer and measuring the depth of the sediments minus water depth. We also counted the number of cattail, bulrush, and common reed stems present within each quadrat. Percent cover was also estimated for the following structural groups: persistent deep-water emergents (e.g., *Typha* spp., *Schoenoplectus*

Table 1. Descriptions of fine- and large-scale variables estimated via quadrat sampling and remote sensing that were used in analyses of marsh bird occurrence in Michigan and Ohio with restricted (n = 414) and full (n = 993) data sets. An "X" indicates the variable was used in a given analysis: classification and regression tree (CART), logistic regression, and occupancy modeling.

			Restricted Data Set			Full Data Set
Variable Description	Name	Scale[1]	CART	Logistic Regression	Occupancy Modeling	CART
Quadrat Sampling						
Maximum height of live or dead vegetation	height	fine-25 m	X	X	X	
Water depth	depth	fine-25 m	X	X	X	
Organic sediment depth	organic	fine-25 m	X	X	X	
% cover emergent plants	EM	fine-25 m	X	X	X	
% cover floating plants	float	fine-25 m	X	X	X	
% cover nonpersistent shallow-water emergent plants	non_shal	fine-25 m	X	X	X	
% cover grass	grass	fine-25 m	X	X	X	
% cover *Typha* spp.	Typ_spp	fine-25 m	X	X	X	
% cover *Schoenoplectus* spp.	Sch_spp	fine-25 m	X	X	X	
% cover *Phragmites australis*	Phr_spp	fine-25 m	X	X	X	
% cover *Carex* spp.	Car_spp	fine-25 m	X	X	X	
% cover woody vegetation	wood	fine-25 m	X	X	X	
Remotely Sensed						
Vegetation to water edge density within 100 m	ED	fine-100 m	X	X	X	
Ratio of emergent:open water/aquatic bed wetland within 100 m	ratio	fine-100 m	X	X	X	
Number of vegetation patches within 100 m	nveg	fine-100 m	X	X	X	
% open water/aquatic bed wetland within 1 km	abow1km	large-1 km	X	X	X	X
% emergent wetland within 1 km	emnofor1km	large-1 km	X	X	X	X
% unsuitable anthropogenic cover within 1 km	anhab1km	large-1 km	X	X	X	X
Distance to nearest open water/aquatic bed wetland	dist2abow	large-unlimited	X	X	X	X
Distance to nearest unsuitable cover	dist2nhab	large-unlimited	X	X	X	X
Distance to nearest road	dist2rd	large-unlimited	X	X	X	X
Distance to nearest river	dist2river	large-unlimited	X	X	X	X

[1]Variable categorization (fine or large scale) and buffer distance from marsh bird survey points within which variables were estimated.

spp.), persistent shallow-water emergents (e.g., *P. australis*, *Carex* spp.), nonpersistent deep-water emergents (e.g., *Sagittaria* spp., *Zizania* spp.), nonpersistent shallow-water emergents (e.g., *Eleocharis* spp., *Polygonum* spp.), floating-leaved and free-floating vegetation (e.g., *Nuphar* spp., *Lemna* spp.), and submersed aquatic species (e.g., *Potamogeton* spp., *Chara* spp.).

Remotely Sensed Variable Estimation

We hypothesized that several remotely sensed variables (Table 1) could function as predictors of marsh bird occupancy during the breeding period based on our understanding of species life-history requirements, species habitat associations, and expert opinion. These remotely-sensed variables were generated by creating ModelBuilder workflows in ArcGIS 10.0 (ESRI, Redlands, CA) and resulted in 30 m resolution raster surfaces across a 12 km full, rounded buffer of Michigan and Ohio. See Appendix A for a detailed description of the process used for each variable.

We measured interspersion variables for all Michigan sites from 1 m resolution color infrared photos obtained from the State of Michigan Imagery Solution. Interspersion variables were not estimated for Ohio sites, because appropriate aerial imagery was not available. All photos were National Agriculture Imagery Program (NAIP) county mosaics derived from original digital orthophoto quarter quads produced for the U.S. Department of Agriculture Farm Service Agency Aerial Photography Field Office taken in summer of 2009 or 2010. We classified the photo pixels into two classes (water and vegetation) using an interactive supervised classification routine in ArcGIS 10.0. All emergent vegetation was categorized as one class because we wanted to analyze effects of interspersion of water and vegetation on bird use (see Rehm and Baldasarre 2007), not the response to variation in types of emergent/submergent vegetation. A supervised classification routine was necessary due to variation in photograph color. During a supervised classification, we "trained" a computer to recognize values of infrared light reflectivity for each class (water or vegetation) based on pixel values at defined sites. We used two training sites (water and vegetation) for each individual photo and each site consisted of at least one million pixels distributed throughout the image. Training sites with selected pixels were verified from aerial photographs and entered into the computer as one of the two classes. The computer assigned all remaining pixels to one of the two classes based on values defined by the training sites. A detailed description of the supervised image classification process is found in Appendix B.

We analyzed classified images in ArcGIS 10.0 to obtain values for cover-to-water ratio (RATIO), number of vegetation patches (NVEG), and edge density (ED) within a 100-m radius centered at Michigan survey points. We calculated the percent open-water surface area at each site, subtracted the value from 50, and multiplied the absolute value by two to obtain a RATIO measurement. Consequently, wetland with cover-to-water ratios approaching 1:1 were given values close to 0, and wetlands moving away from 1:1 ratios (e.g., 0 or 100% open water) were given values closer to 1. A detailed description of the process used to generate interspersion variables is provided in Appendix A.

Analysis

We investigated relationships between marsh bird occurrence and variables characterizing potential habitat surrounding survey stations at fine and large scales. Fine-scale variables consisted of those physically gathered within 25 m of points during quadrat sampling and remotely sensed variables collected within 100 m of points. Large-scale variables were all estimated via remote sensing within 1-km buffers surrounding points or using unlimited boundaries (i.e., distance variables). We examined overall marsh bird community structure and association with explanatory variables using multivariate analysis. We investigated relationships between individual species' occupancy and fine- and large-scale variables using three techniques: classification and regression tree (CART) analysis, logistic regression, and occupancy modeling. Prior to conducting analyses, we excluded variables highly correlated ($R \geq 0.60$) with other variables, as well as several fine-scale variables occurring on a low proportion (<15%) of quadrats. We used a final set of 22 explanatory variables (15 fine-scale and seven large-scale; Table 1) in all analyses.

We conducted all three modeling analyses on the same subset of 414 points surveyed in Michigan during 2006—2013 for which all explanatory variables were available. However, we also conducted CART analysis using data from all 993 points surveyed in Michigan and Ohio during 2005—2013 with only large-scale variables, which we used to inform the development of GIS models to depict probability of occurrence in distribution maps. We modeled relationships between marsh bird occurrence and independent variables for the following 10 species: Pied-billed Grebe, American Bittern, Least Bittern, Virginia Rail, Sora, Common Gallinule, American Coot, Wilson's Snipe, Black Tern, and Forster's Tern. We did not detect Yellow Rail, King Rail, and Black-crowned Night-Heron often enough to build statistical models.

Multivariate

We conducted nonmetric multidimensional scaling (NMDS; McCune and Grace 2002) to examine marsh bird community structure and possible associations with fine- and large-scale variables. We implemented the analysis using a subset of Michigan sites where we had both fine- and large-scale vegetation and physical variables. We included only sites where surveys were conducted for all primary and secondary target species according to the Michigan Marsh Bird Survey protocol (MiBCI 2010), which resulted in 15 species being included in the analysis. All variables were averaged by site and year prior to analysis, resulting in a final set of 79 sample units. We performed NMDS on average avian abundance using the Bray-Curtis distance measure, 250 runs on the original data matrix, and a maximum of 500 iterations. A final solution was achieved when an instability value of 0.00001 was obtained or after 500 iterations. We conducted the Monte-Carlo permutation procedure (McCune and Grace 2002) with 250 randomized runs to evaluate if axes produced by NMDS explained more variation than by chance alone. We then overlaid associations with explanatory variables based on correlations with NMDS axis scores. We conducted multivariate analysis using PC-ORD 6.15 (MjM Software, Gleneden Beach, OR).

Classification and Regression Tree

The occurrence of each species was analyzed using a classification and regression tree (CART; Breiman et al. 1984) approach. We implemented the CART analysis treating occurrence as a 0/1 categorical dependent variable, thereby providing output results reflecting predictions of whether a site would be occupied or not. We summarized species occurrence by survey point across all years. We had a full matrix of habitat variables available at both a fine and large scale for 414 survey points. Independent variables consisted of the 22 described above, and the CART analysis used these in three subsets: 1) fine-scale variables only; 2) large-scale variables only; and 3) all variables (Table 1). Large-scale analyses included independent variables measured remotely in a GIS using 1,000-m and unlimited buffers surrounding each point. Comparison of results across these variable sets allowed us to determine the relative performance of fine-scale and large-scale variables for predicting the probability of occurrence. We also conducted CART analysis using the full set of 993 survey points from Michigan and Ohio using large-scale independent variables only. This analysis was used to develop GIS models to predict and map probability of occurrence for each species within Michigan and Ohio.

The CART analyses were conducted using the rpart function with the statistical package R v2.12.2 (R Development Core Team, http://www.R-project.org). We first developed a CART for all data points and all independent variables defined for in each subset analysis. The size of the tree developed and the variables included were guided by the results of 2,000 cross-validation sub-samplings. Results of the CART analysis for each dataset provided a plot of Mallow's complexity parameter (CP) as a function of the tree size. Trees resulting from the CART analysis were "pruned" using the clip.rpart function in R. A value of CP was chosen for each species to provide a reasonable cutoff value for pruning trees to a size that provided a parsimonious representation of the data.

Logistic Regression

Logistic regression analyses were conducted as a parametric comparison to the CART analyses. Analysis focused on the restricted data set (414 points) to determine the relative effectiveness of logistic regression for developing predictions of species occurrence compared to CART. Variables were selected using a backward stepwise procedure, with final variable selection using a criterion for retention of $p < 0.05$. The logistic regression was used to make predictions of species occurrence by using a cut-off of 0.5; occupancy was predicted when the probability of occurrence exceeded 0.5, and non-detection was predicted when the logistic regression prediction was <0.5.

Occupancy Modeling

We conducted single-season occupancy modeling on a subset of 518 Michigan points for which we had both fine- and large-scale vegetation and physical variables. The likelihood-based approach presented by Mackenzie et al. (2002) was used to estimate probabilities of detection (i.e., probability of detecting species when present) and proportion of sites occupied for the 10 marsh bird species. We conducted occupancy analyses using PRESENCE 6.2 (J. Hines, U.S. Geological Survey, Patuxent Wildlife Research Center, Laurel, MD). We used a tiered approach to developing candidate models. We examined models with detection covariates first and then incorporated the best-supported detection configuration into all subsequent models (Olson et al. 2005, Kroll et al. 2006, Yates and Muzika 2006, Darrah and Krementz 2009). We began by comparing two detection models, one assuming constant probability of detection across survey periods and the second incorporating variable detection probabilities by survey period. The best-supported configuration of the two models, as indicated by Akaike's Information Criterion (AIC), was used in subsequent models containing detection covariates. We then compared models with four one-variable models containing covariates expected to most influence marsh bird detection: maximum vegetation height, percent emergent vegetation, wind speed (according to the Beaufort Scale), and noise level (ranked from 0 [no noise] to 4 [intense noise]). The best-approximating detection model was included in all subsequent occupancy models containing fine- and large-scale covariates. For each species, we compared 22 occupancy models each of which contained one occupancy covariate (Table 1). We then produced four two- and three-variable models using combinations of occupancy covariates from the top three models from our candidate sets. We conducted a goodness-of-fit test with 100 bootstraps for each species using our most parameterized model as the global model. If overdispersion appeared likely (i.e., $\hat{c}$ > 1.0), we used quasi-AIC values to rank our candidate models (Burnham and Anderson 2002).

GIS Modeling for Distribution Maps

Classification and regression tree models having only large-scale variables were generated for each species in ArcGIS 10.0 using the full data set of 993 Michigan and Ohio points. We created ModelBuilder workflows to translate final CART models into 30 m resolution prediction surfaces across Michigan and Ohio. We applied mean aggregation to each model to create images for this report at a 2-km resolution.

RESULTS

Multivariate

We used NMDS to investigate possible associations of the overall marsh bird community and fine- and large-scale independent variables. Nonmetric multidimensional scaling is an ordination technique well suited to data that are not normally distributed or are on arbitrary, discontinuous, or other scales (McCune and Grace 2002). Ordination methods aim to graphically summarize complicated relationships (e.g., many species/variables) by extracting a small number of dominant patterns from an infinite number of relationships (McCune and Grace 2002). We used NMDS to graphically arrange the sites with regard to marsh bird species occurrence and relative abundance on a reduced number of dimensions (e.g., axis 1, axis 2) and examine relative abundance of focal species among the study sites. We also correlated site scores for marsh bird use with our explanatory variables to identify possible associations between marsh bird communities and habitat/land cover variables.

Initial NMDS analysis indicated marsh bird community structure was best represented by two dimensions and a solution with equal or less stress was not likely to occur by chance alone ($P = 0.012$). After rerunning NMDS with only two dimensions, 85.5% of the variation in the original distance matrix was explained (final stress of 10.76), with most (70.5%) of the variation in marsh bird use of the sites being explained by axis 1. Marsh bird community structure appeared to be primarily arranged along axis 1, representing a gradient of sites from deep-water marshes on the negative end of the axis to shallow-water wet meadows on the positive end (Figure 2). Sites on the negative end of axis 1 tended to have greater water depths, greater percent cover of *Typha*, and greater proportions of open water/aquatic bed wetland within 1 km compared to sites toward the negative end of the axis (Figure 2). Conversely, sites on the positive end of axis 1 tended to have greater percent cover of woody vegetation, grass, and *Carex* than sites on the positive end. Relative abundances of some species appeared to be greater on the negative end of axis 1 (e.g., Pied-billed Grebe, Marsh Wren; Figure 3), indicating an association with deep-water marshes and open water, whereas other species (e.g., Sedge Wren, Wilson's Snipe; Figure 3) were more abundant at sites toward the positive end of axis 1, suggesting a relationship with greater amounts of wet meadow and woody vegetation.

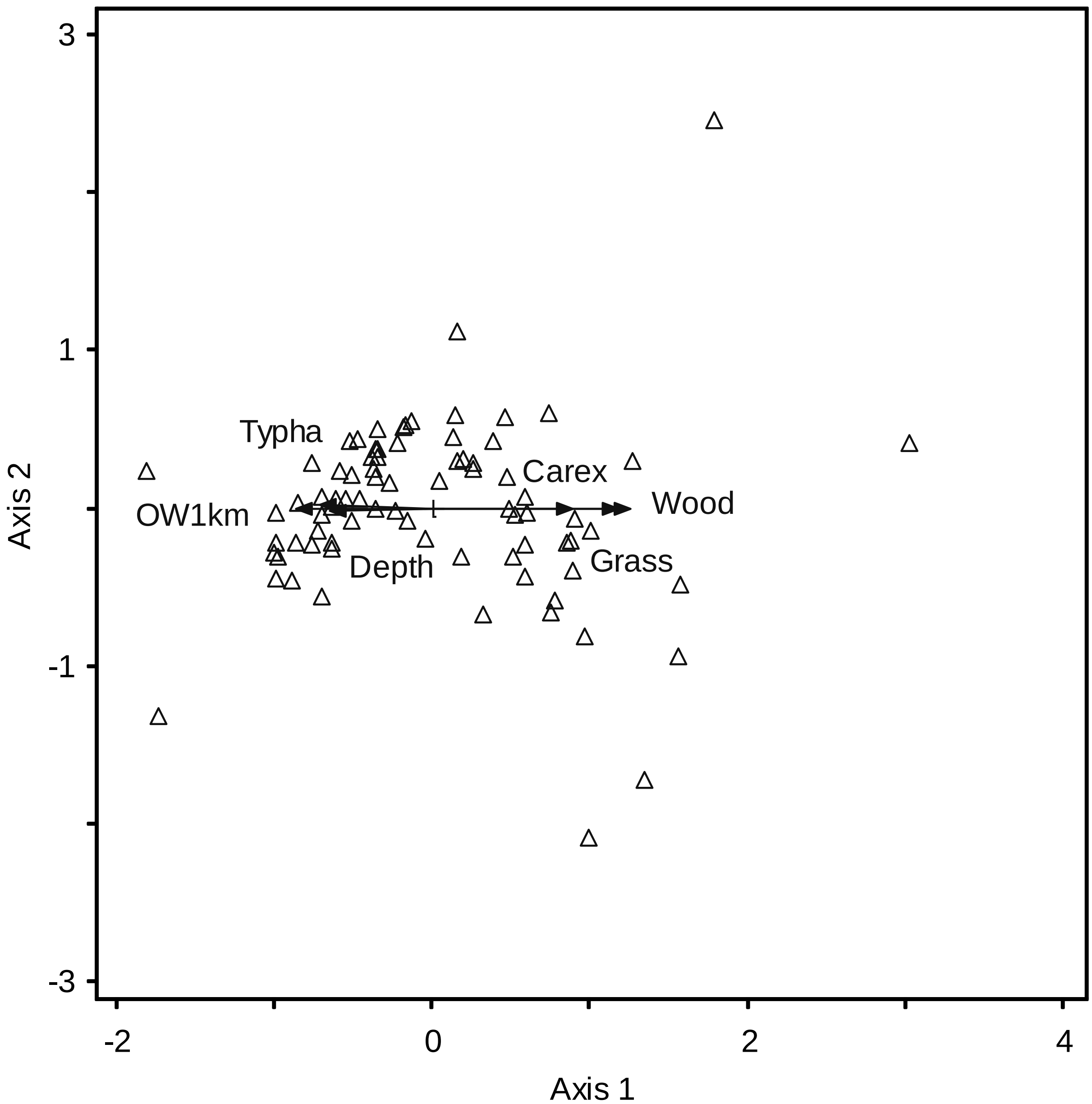

Figure 2. Biplot of first and second axes scores from non-metric multidimensional scaling (NMDS) of relative abundance of marsh bird species at 79 sites in Michigan during 2006—2013. Sites (open triangles) are overlaid by explanatory variables (labeled arrows) that were correlated with NMDS axes (r^2>0.20). Arrow length indicates strength of correlation with site scores of marsh bird use.

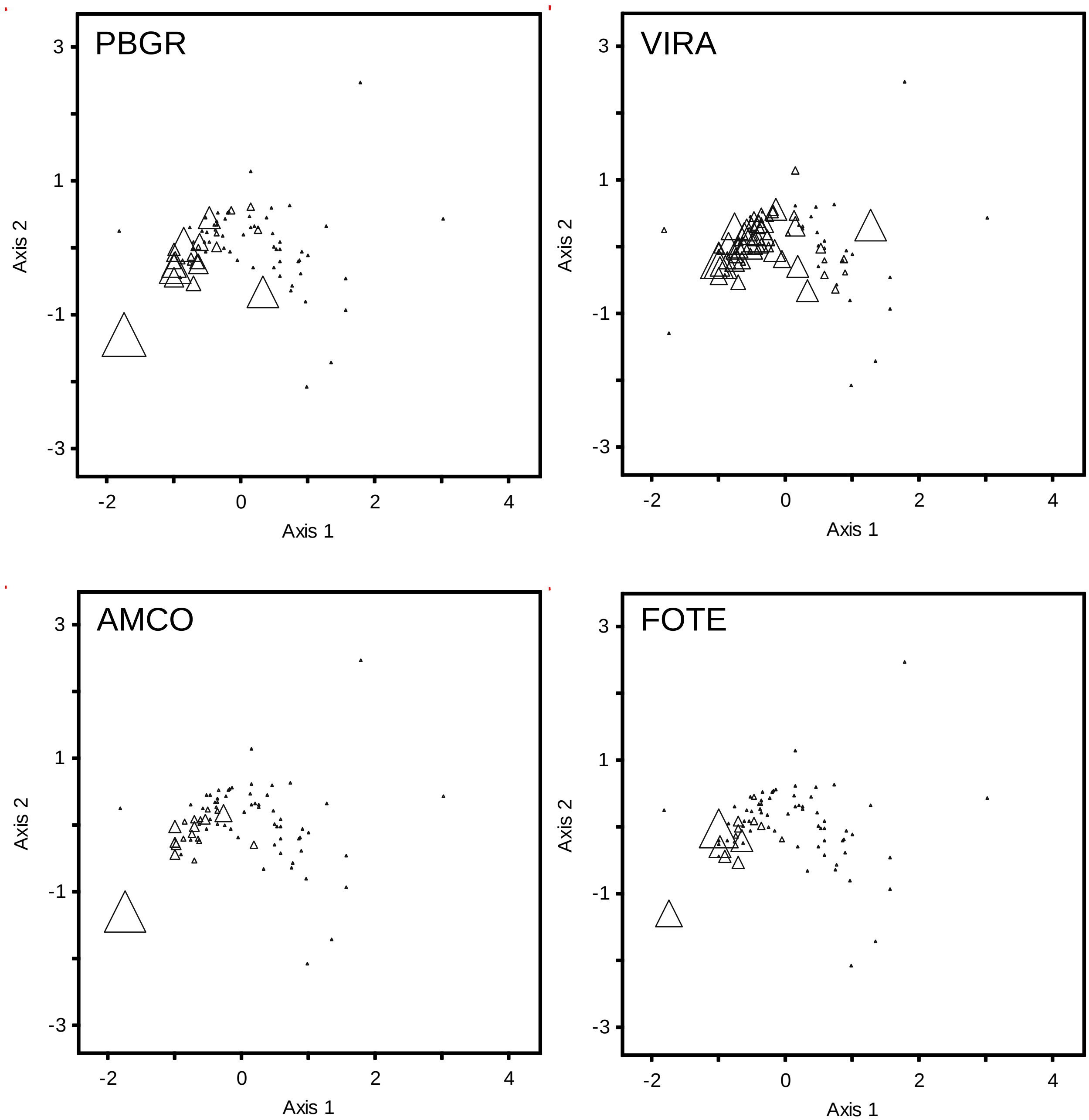

Figure 3. Biplots of first and second axes scores from nonmetric multidimensional scaling (NMDS) of relative abundance of marsh bird species at 79 sites in Michigan during 2006—2013. Sites (triangles) are proportionally scaled with regard to relative abundance of eight marsh bird species (larger triangles indicate greater abundance). Species abbreviations: AMCO = American Coot, FOTE = Forster's Tern, PBGR = Pied-billed Grebe, SACR = Sandhill Crane, SEWR = Sedge Wren, VIRA = Virginia Rail, and WISN = Wilson's Snipe.

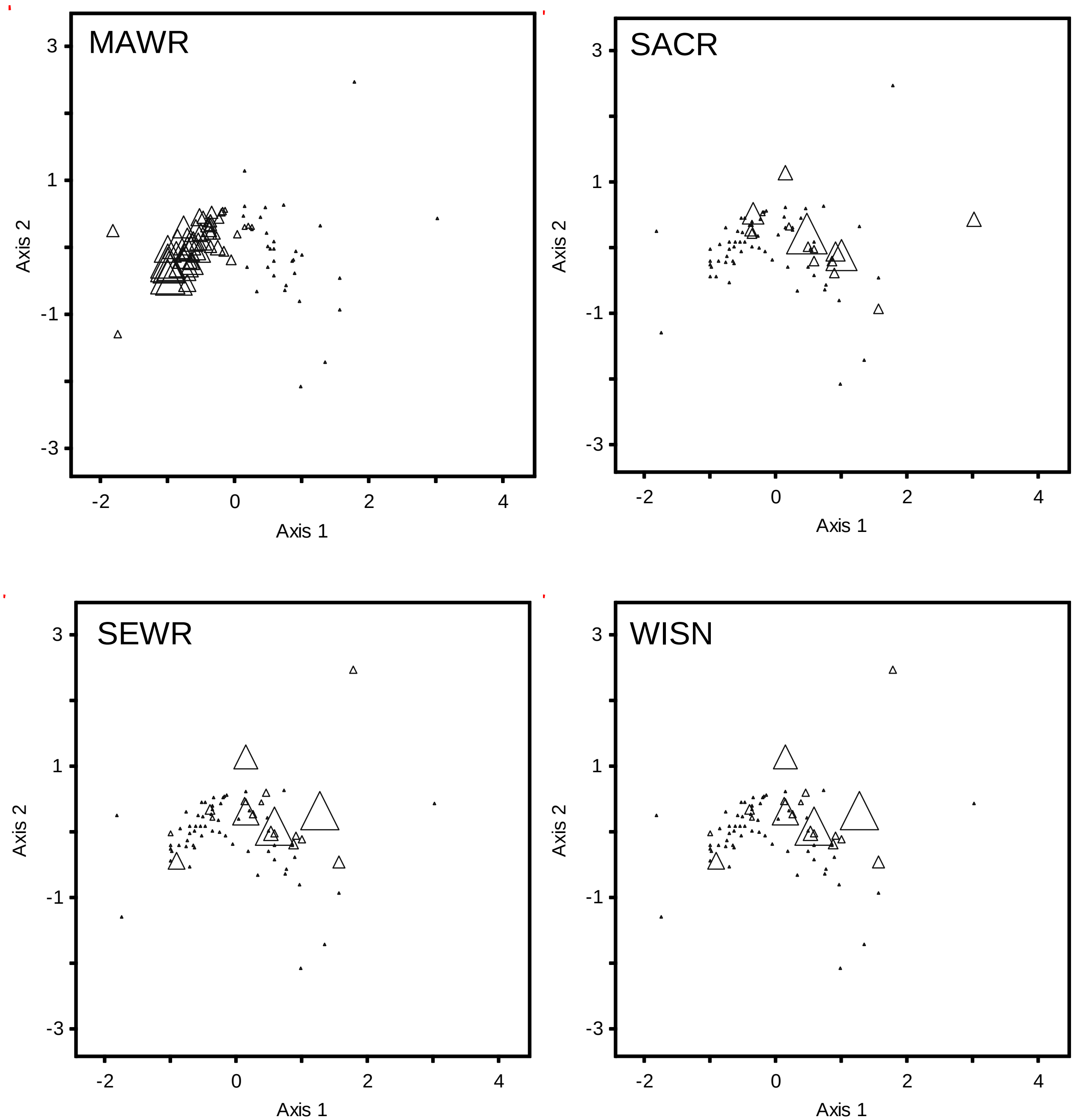

Figure 3. Continued.

CART and Logistic Regression

Percent occurrence was low for all ten species examined, and we observed similar patterns of occurrence in both the restricted and full data sets (Table 2). Virginia Rail was the most commonly detected species, being recorded at about one quarter of the points. Pied-billed Grebe, American Bittern, Least Bittern, American Coot, Common Gallinule, and Sora were detected at 10-14% of points. The remaining three species, Wilson's Snipe, Black Tern, and Forster's Tern, were even less common and occurred at 3-8% of points.

Table 2. Percent occurrence for 10 marsh bird species analyzed within the restricted and full data sets used in analyses. The restricted data set included Michigan survey points having both fine- and large-scale independent variables, whereas the full set included all survey points.

		Percent Occurrence	
Common Name	Abbreviation	Restricted Data Set (n = 414)	Full Data Set (n = 993)
Pied-bill Grebe	PBGR	6.4	10.9
American Bittern	AMBI	10.7	10.8
Least Bittern	LEBI	12.8	8.8
Virginia Rail	VIRA	26.1	22.1
Sora	SORA	12.5	13.8
Common Gallinule	COGA	4.2	9.7
American Coot	AMCO	9.6	11.6
Wilson's Snipe	WISN	4.0	2.9
Black Tern	BLTE	8.1	6.2
Forster's Tern	FOTE	3.8	6.3

Classification tree analysis with cross-validation resulted in trees for all focal species except Least Bittern, and we produced logistical regression models for all 10 species. In general, all models did an excellent job of predicting non-detection (i.e., no birds recorded at a site) with an average of 97% correct classification (Table 3). However, performance of the models in predicting points at which a species was detected varied across models (Table 4). As expected, CART models including all available variables performed best, correctly predicting an average of 47% of points where a species was present. Logistic regression on the same data did much worse, correctly predicting only 28% of points at which a species was present. The percentage of correct predictions by CART models with large-scale (average 36%) and fine-scale (average 40%) variables only did not perform as well as CART models with the full data set but still performed better than logistic regression (Table 4).

Table 3. Proportion of Michigan marsh bird survey sites correctly classified as having "non-detection" by classification and regression tree (CART) models with all variables, large-scale variables only, and fine-scale variables only, and with logistic regression using all variables.

	CART			Logistic
Species	All Variables	Large-scale Variables Only	Fine-scale Variables Only	Regression – All Variables
Pied-billed Grebe	0.96	0.98	0.98	0.98
American Bittern	0.98	0.94	0.97	0.97
Virginia Rail	0.95	0.89	0.95	0.87
Sora	0.96	0.97	0.96	0.99
Common Gallinule	0.98	1.00	0.97	0.99
American Coot	0.96	0.97	0.97	0.96
Wilson's Snipe	0.98	1.00	0.99	0.99
Black Tern	1.00	0.99	0.96	0.97
Forster's Tern	0.98	0.98	0.98	0.99
Average	0.97	0.97	0.97	0.97

Table 4. Proportion of Michigan marsh bird survey sites correctly classified as having "detection" by classification and regression tree (CART) models with all variables, large-scale variables only, and fine-scale variables only, and with logistic regression using all variables.

	CART			Logistic
Species	All Variables	Large-scale Variables Only	Fine-scale Variables Only	Regression – All Variables
Pied-billed Grebe	0.51	0.43	0.39	0.18
American Bittern	0.52	0.51	0.23	0.15
Virginia Rail	0.34	0.58	0.34	0.45
Sora	0.36	0.31	0.31	0.05
Common Gallinule	0.60	0.20	0.65	0.38
American Coot	0.51	0.44	0.44	0.40
Wilson's Snipe	0.38	0.00	0.38	0.27
Black Tern	0.33	0.27	0.50	0.19
Forster's Tern	0.70	0.54	0.39	0.43
Average	0.47	0.36	0.40	0.28

The variables included in each model differed (Tables 5, 6 and 7), but some general patterns were apparent. In the logistic regression analyses, final models contained 2 to 9 variables, with an average of 5.6 variables being significant at the 0.05 level. In the final models constructed by stepwise variable selection, the most frequently included fine-scale variables were ED, depth, EM, and Sch_spp (Table 5). Among the large-scale variables, dist2nhab, anhab1km, and dist2river were the most commonly selected variables (Table 5). In the CART analysis using all variables, the final classification trees also contained 2 to 9 variables but on average had 4.8 variables included in the final tree. Note that a test of significance is not applicable to CART analyses and that trees frequently contained multiple splits based on a single variable. As with logistic regression, depth was among the most commonly included fine-scale variable, but height, organic, and Typ_spp were also regularly selected variables in CART models. Among the large-scale variables, dist2nhab, anhab1km, and dist2river were more commonly included (as they were in logistic regression), but abow1km was also frequently chosen.

Table 5. Variables included in logistic regression analyses conducted using all variables for marsh birds detected during surveys in Michigan, 2006—2013. Variable names are as in Table 1.

	Pied-billed Grebe	American Bittern	Least Bittern	Virginia Rail	Sora	Common Gallinule	American Coot	Wilson's Snipe	Black Tern	Forster's Tern	Total
Fine-scale Variables											
height									X		1
depth	X		X			X	X	X			5
organic											0
EM		X		X		X		X			4
float			X								1
non_shal		X									1
grass		X									1
Typ_spp						X					1
Sch_spp				X		X	X		X		4
Phr_spp		X		X		X					3
Car_spp					X			X		X	3
ED				X		X	X	X	X	X	6
ratio	X										1
nveg			X	X							2
wood											0
Large-scale Variables											
emnofor1km		X		X	X						3
dist2nhab		X	X	X	X	X					5
anhab1km				X	X	X	X			X	5
abow1km		X						X		X	3
dist2abow		X									1
dist2rd							X				1
dist2river						X	X	X	X	X	5
No. variables	2	8	4	8	4	9	6	6	4	5	5.6

Table 6. Variables included in classification and regression tree (CART) analyses conducted using all variables for marsh birds detected during surveys in Michigan, 2006—2013. Variable names are as in Table 1.

	Pied-billed Grebe	American Bittern	Virginia Rail	Sora	Common Gallinule	American Coot	Wilson's Snipe	Black Tern	Forster's Tern	Total
Fine-scale Variables										
height		X	X					X	X	4
depth	X			X	X	X				4
organic	X	X						X		3
EM		X		X						2
float		X	X							2
non_shal										0
grass										0
Typ_spp		X	X	X						3
Sch_spp								X		1
Phr_spp										0
Car_spp							X		X	2
ED					X	X				2
ratio									X	1
nveg										0
wood										0
Large-scale Variables										
emnofor1km		X		X						2
dist2nhab		X		X			X			3
anhab1km		X		X	X					3
abow1km	X				X			X	X	4
dist2abow	X								X	2
dist2rd						X				1
dist2river		X		X				X	X	4
No. variables	4	9	3	7	4	3	2	5	6	4.8

Table 7. Variables included in classification and regression tree (CART) analyses conducted using only fine- or only large-scale variables for marsh birds detected during surveys in Michigan, 2006—2013. Variable names are as listed in Table 1.

	Pied-billed Grebe	American Bittern	Virginia Rail	Sora	Common Gallinule	American Coot	Wilson's Snipe	Black Tern	Forster's Tern	Total
Fine-scale Variables										
height			X			X	X	X	X	5
depth	X	X			X	X	X		X	6
organic	X			X	X			X		4
EM	X			X						2
float			X	X						2
non_shal		X								1
grass										0
Typ_spp		X	X	X	X					4
Sch_spp								X		1
Phr_spp										0
Car_spp		X					X			2
ED					X	X	X	X		4
ratio	X			X				X	X	4
nveg					X			X	X	3
wood										
Large-scale Variables										
emnofor1km	X	X	X	X		X			X	6
dist2nhab		X		X						2
anhab1km	X	X	X	X	X	X				6
abow1km	X		X	X		X			X	5
dist2abow	X		X	X	X	X		X		6
dist2rd		X	X			X			X	4
dist2river	X	X	X	X	X	X		X	X	8

CART models based only on local-scale or landscape-scale variables showed a somewhat different pattern of variable inclusion (Table 7). For fine-scale variables, ED and depth were commonly included, as they were in the CART using all variables, but height, organic, Typ_spp, and ratio were also frequently selected. Among the large-scale variables, dist2river was chosen in 8 of the 9 CART models, and all other variables were frequently included except for dist2nhab.

Occupancy Modeling

We modeled detection and occupancy probabilities for all 10 marsh bird focal species. There was considerable variation in detection probability by species and survey period (Table 8), but the probability of detecting marsh bird species when present was low, with an overall average of 0.28 for the 10 species combined. Least Bittern had the lowest detection probability (0.12—0.22), whereas greatest detection probabilities were estimated for Sora (0.62) during the first survey period and American Coot (0.52) during the second survey period. Despite having loud, resounding calls, Pied-billed Grebe and American Bittern detectability estimates were about 0.14—0.32 across the three survey periods. Detection probability appeared to vary by survey period for eight of the 10 species examined. Probability of detecting Pied-billed Grebe and Sora was greatest in the first period. American Bittern detection probabilities for the first two periods were similar and greater than the third. Least Bittern and American Coot detectability was greatest during the second survey period. Common Gallinule and Black Tern detectability estimates were greater in the later two periods compared to the first. Height was the detection covariate included most often in best-supported models. Detection probability for American Bittern, Least Bittern, Virginia Rail, Black Tern, and Forster's Tern was negatively related to vegetation height. Pied-billed Grebe and Common Gallinule detectability was negatively associated with percent cover of emergents. Wilson's Snipe was negatively related to noise level, whereas American Coot showed a positive association.

Table 8. Naïve occupancy and model-estimated occupancy (ψ) and detection probability (*p*) for 10 marsh bird species recorded at 518 points surveyed in Michigan during 2006—2013. Estimates of ψ and *p* were obtained using the best-approximating model for each species and detectability estimates are listed by survey period (*p*1, *p*2, and *p*3).

	Occupancy[1]			Detection[2]					
Species	Naïve	ψ	SE	*p*1	SE	*p*2	SE	*p*3	SE
Pied-billed Grebe	0.097	0.187	0.057	0.322	0.087	0.196	0.063	0.189	0.062
American Bittern	0.168	0.336	0.081	0.269	0.066	0.304	0.070	0.142	0.040
Least Bittern	0.106	0.276	0.078	0.122	0.042	0.226	0.063	0.115	0.038
Virginia Rail	0.270	0.380	0.051	0.398	0.038	0.390	0.039	0.381	0.040
Sora	0.143	0.244	0.046	0.618	0.098	0.214	0.048	0.049	0.021
Common Gallinule	0.081	0.112	0.031	0.244	0.078	0.425	0.110	0.378	0.108
American Coot	0.158	0.196	0.032	0.378	0.066	0.523	0.070	0.360	0.060
Wilson's Snipe	0.050	0.108	0.050	0.292	0.157	0.094	0.055	0.244	0.113
Black Tern	0.100	0.204	0.054	0.052	0.024	0.235	0.054	0.316	0.068
Forster's Tern	0.102	0.171	0.044	0.334	0.056	0.303	0.057	0.278	0.056
Average	0.128	0.221	---	0.303	---	0.291	---	0.245	---

[1]Naïve occupancy is the observed proportion of sites occupied, whereas ψ is the model-estimated proportion of sites occupied after accounting for imperfect detection.
[2]Model-estimated probability of detecting species when present.

The observed proportion of points occupied (i.e., naïve occupancy) was low for all species, with a mean of 0.13 and a range from 0.05 for Wilson's Snipe to 0.27 for Virginia Rail (Table 8). Model-estimated occupancy averaged 0.22 for all 10 species combined. After accounting for imperfect detection, model-estimated proportion of sites occupied was lowest for Common Gallinule and Wilson's Snipe at 0.11 and greatest for Virginia Rail (0.38) and American Bittern (0.34). Best-supported models for most species contained a mix of fine- and large-scale variables, whereas the best-approximating models for Pied-billed Grebe, Least Bittern, and American Coot only included fine-scale covariates. Depth was the covariate most often included in best-supported models, being present in models for five species. Four species had anhab1km as a covariate in the best-approximating model (Table 9). Three variables, non_shal, grass, and ED, were included in the best-supported models of three species. For Sora, Wilson's Snipe, and Black Tern, there was not strong support for any particular model and goodness-of-fit tests indicated overdispersion (see Appendix C for detailed occupancy modeling results).

Table 9. Occupancy covariates included in best-approximating occupancy models for marsh birds detected during surveys conducted in Michigan during 2006—2013. Positive and negative signs indicate direction of association between probability of occupancy and variable. Variable names are as listed in Table 1.

	Pied-billed Grebe	American Bittern	Least Bittern	Virginia Rail	Sora	Common Gallinule	American Coot	Wilson’s Snipe	Black Tern	Forster’s Tern	No. Species
Fine-scale Variables											
height											0
depth	+		+		+	+	+				5
organic											0
EM											0
float											0
non_shal	−	−	−								3
grass				−		−	−				3
Typ_spp			+					−			2
Sch_spp											0
Phr_spp											0
Car_spp							−	+			2
ED	+				−				+		3
ratio										−	1
nveg											0
wood									−		1
Large-scale Variables											
emnofor1km		+		+							2
dist2nhab		−									1
anhab1km				+	+	+				−	4
abow1km										+	1
dist2abow											0
dist2rd								+			1
dist2river									−		1

Patterns in Variable Inclusion

The results of analyses including all variables suggest that both fine- and large-scale variables are important in predicting marsh bird occurrence. For both CART and logistic regression, models for all but one species included both fine- and large-scale variables. Best-approximating occupancy models for seven of 10 species included both fine- and large-scale variables. Although each analytical technique resulted in at least one species having a model containing only fine-scale variables, no models contained only large-scale variables. Water depth was a commonly included fine-scale variable among all three techniques. Edge density was the fine-scale variable selected most often by logistic regression models. Height was regularly included in CART models but not in the other analyses. Dist2nhab and anhab1km were the large-scale variables selected most often in logistic regression models. Best-supported occupancy models often included anhab1km. We found that abow1km was the large-scale variable selected most often in CART models, but anhab1km and dist2nhab were regularly included as well.

The models created by CART analyses are represented by "trees" (see Appendices D and E) that provide numerical "threshold" values at each node for independent variables, above and below which greater or lesser rates of occurrence were observed for that species. Variable threshold or node values could provide guidance for management or conservation planning by identifying conditions associated with greater occupancy by marsh bird species. We examined the node values identified in CART models created using all variables (Appendix D) for the seven variables (3 fine-scale, 4 large-scale) regularly included in models across all three techniques (Table 10). Greater rates of occurrence of some species were associated with shorter vegetation (< ~0.4 m), greater water depths (> ~0.2 m), greater edge density (> ~0.2), lower proportions of anthropogenic development within 1 km, greater proportions of open water within 1 km, and shorter distances to rivers. However, patterns in variable thresholds were not always consistent among species and often conflicted (Table 10). For example, greater American Bittern occurrence was associated with vegetation > 0.15 m and Common Gallinule had greater occurrence rates with proportions of open water within 1 km that were > 31.0 and < 3.5.

Table 10. Variable patterns associated with greater proportion of sites occupied by marsh birds during surveys in Michigan, 2006—2013. Thresholds were obtained from CART analyses conducted using all variables. Variable names are as in Table 1.

	Fine-scale Variables			Large-scale Variables			
Species	Height[1]	Depth[1]	ED[2]	anhab1km[3]	abow1km[3]	dist2nhab[1]	dist2river[1]
Pied-billed Grebe		≥ 0.185			≥ 34.5		
American Bittern	≥ 0.145			< 16.5		< 15	< 685
Virginia Rail	< 0.445						
Sora		≥ 0.025		< 59.0		< 129	< 469
Common Gallinule		≥ 0.235	≥ 20.8	≥ 13.5	< 3.5 or ≥ 31.0		
American Coot		≥ 0.235	≥ 19.0				
Wilson's Snipe						< 15	
Black Tern	< 0.185				≥ 26.5		< 1734
Forster's Tern	< 0.390				≥ 19.5		< 2690

[1]Variable expressed in meters.
[2]Variable expressed as km of shared water-vegetation border per km^2.
[3]Variable expressed as the average percent of the area within 1 km of points represented by the particular land cover category.

Predicted Marsh Bird Distributions

We conducted CART analyses using all points and large-scale variables only to identify variables that could be used in GIS models to spatially depict the probability of occurrence for eight focal species (see Appendix F). We did not produce distribution maps for Least Bittern and Sora. Least Bittern was not detected often enough to allow CART analysis and only one variable was chosen in the Sora CART model, so a useable distribution map could not be developed. Based on survey effort and associated estimates of occupancy, predictive models appeared to overestimate distributions of some species (Virginia Rail, American Coot, Wilson's Snipe), underestimate some distributions (Pied-billed Grebe, American Bittern, and Common Gallinule), and more accurately represented Black Tern and Forster's Tern.

Several areas were consistently highlighted in distributional maps as having greater likelihood of marsh bird occurrence across all species. Regardless of species and variables used, areas having concentrations of large emergent marsh/wet meadow wetlands were pronounced as having greater probability of marsh bird occupancy. The following areas overlapped among several models: 1) coastal wetlands of western Lake Erie, St. Clair River Delta, Saginaw Bay, northern Lake Huron, St. Mary's River, and northern Lake Michigan; 2) inland wetlands of the east-central Upper Peninsula (e.g., greater Seney NWR area); 3) large inland wetland complexes within the Saginaw Bay watershed (e.g., Shiawassee NWR, Shiawassee River State Game Area, Crow Island State Game Area); and 4) inland wetland complexes near Houghton Lake, Michigan.

DISCUSSION

We used three approaches (CART, logistic regression, and occupancy) to model relationships between marsh bird occurrence and fine- and large-scale covariates. There was substantial variation in results among the three statistical methods, but some general patterns emerged. Models containing both fine- and large-scale variables were better supported by the data in most cases. Other authors have observed that variables at multiple spatial scales can influence predictions of marsh bird use (e.g., Rehm and Baldassarre 2007, Bolenbaugh et al. 2011), but Valente et al. (2011) suggested local variables were most important in predicting occupancy of three common breeding species in Louisiana. Our fine-scale variable only models were slightly better on average than large-scale variable only models, suggesting the local-scale habitat characteristics may have a somewhat greater degree of control on overall marsh bird occurrence. However, our results also indicate variables at both spatial scales are influencing marsh bird occupancy. Both CART and logistic regression models did well at predicting non-detection, but CART models were better at predicting species occurrence compared to logistic regression for eight of the nine species for which both techniques could be applied. Better performance of the CART models is likely related to fewer constraints on the relationships between variables and species occurrence, indicating the non-linear, flexible CART models may be more biologically realistic than logistic regression.

We observed considerable variation in variables chosen among the three modeling techniques, but a few variables were consistently selected by two or three of the analyses. We found many of the variables selected overlapped between logistic regression and CART, but logistic regression models tended to contain more variables. Edge density was the most commonly included variable in logistic regression models, but was used less often in CART and occupancy models. Water depth was a commonly included fine-scale variable among all three techniques. Height was regularly selected in CART models but not in the other analyses. Two variables, non_shal and grass, were regularly included in best-approximating occupancy models, but were rarely selected with CART or logistic regression. In logistic regression models, dist2nhab and anhab1km were the large-scale variables selected most often. Similarly, anhab1km was included most often in occupancy models; CART models also regularly selected anhab1km and dist2nhab, but abow1km was the large-scale variable included most often. Although there was some consistency in the variables included most often in models among the three techniques, there often was variation in the species for which the variable was associated. For example, depth was a variable in models of six species, but only three species were consistent across all three analyses. Given the variation we observed in three analyses of the same data, we suggest employing multiple analytical techniques may be a valuable approach to identifying ecological relationships with the most support.

Although comparing our results to other research is difficult due to differing variables, spatial scales, and statistical techniques, we observed similarities with several studies. Water depth was one of the most regularly used fine-scale variables among all three modeling techniques and was consistently a part of Pied-billed Grebe, Common Gallinule, and American Coot models. Jobin et al. (2009) found a positive association between Least Bittern abundance and water depth and Tozer et al. (2010) observed similar relationships between water depth and abundances of both Least Bittern and Common Gallinule. Murkin et al. (1997) observed an association between American Coot abundance and area of wetland <30 cm in depth. Lor and Malecki (2006) investigated relationships between habitat variables and probability of nesting by several marsh birds. Average water depth was included in their best-approximating American

Bittern, Virginia Rail, and Sora models, and vegetation height was a variable in the Virginia Rail and Sora models (Lor and Malecki 2006). Edge density was included in at least one model for eight of the 10 species we analyzed. Measures of interspersion were associated with marsh bird abundance or occupancy in several studies (Murkin et al. 1997, Rehm and Baldassarre 2007, Darrah and Krementz 2009, Ward et al. 2010, Bolenbaugh et al. 2011).

Among the large-scale variables included in our analyses, anhab1km, abow1km, dist2nhab, and dist2river, occurred most often in models across all three techniques. DeLuca et al. (2004) observed a negative relationship between the amount of human developed land in the surrounding landscape and their index of marsh bird community integrity. Several researchers noted associations between marsh bird metrics or indices of marsh bird communities and the amount of emergent/seasonal wetland in the surrounding landscape (Craig and Beal 1992, Naugle et al. 1999, Fairbairn and Dinsmore 2001, Rehm and Baldassarre 2007, Smith and Chow-Fraser 2010) or percentage of open water at the wetland scale (Craig and Beal 1992, Murkin et al. 1997, Moore et al. 2009); however, few authors included the amount of open water in the surrounding landscape as a variable in their analyses. We found no other studies that included a variable similar to our dist2nhab and only one other study used a distance to river measure (O'Neal et al. 2008), but they did not observe an association between the variable and waterbird species richness, use days, or waterfowl brood density.

Classification and regression tree analysis is an attractive technique, because the result is a tree with several nodes and threshold values for the explanatory variables indicating associations with greater or lesser occurrence of the species. These variable thresholds could be valuable in guiding management actions or conservation planning, but when management for several species (e.g., marsh birds) is the goal, it can be difficult to identify consistent patterns in threshold values for the variables selected. For example, we observed greater occurrence of some species in areas with shorter vegetation, greater water depths, greater edge density, lower proportions of human development, greater proportions of open water within 1 km, and shorter distances to rivers. However, these associations were not always consistent among species, with sometimes conflicting patterns and widely varying threshold values. Disparity in variable thresholds among species is to be expected because of differing biology. Evaluating associations with a particular variable among multiple species is further complicated by relationships with variables in above-connecting nodes and occurrences of the same variable in multiple locations of the tree. Our analyses highlight the difficulty of planning conservation actions for multiple species, even when the species of interest use similar habitats. A better approach may be to develop specific conservation recommendations on a species-by-species basis via additional analyses. Once species-specific analyses are completed for several priority species, planning could focus on identifying areas of overlap among species, providing heterogeneity within wetlands and landscapes, and managing wetland complexes that meet the needs of multiple species.

Important Areas for Marsh Bird Conservation

We developed GIS models using large-scale variables and threshold values from CART analyses to predict the likelihood of occurrence of focal species in Michigan and Ohio. Regardless of the species and variables used, there was some spatial overlap among the distribution maps in areas identified as having the greatest probability of occurrence. These areas were generally large emergent marsh and/or wet meadow complexes, including Great Lakes coastal wetlands and large inland wetland systems in and around Seney NWR, the

Saginaw Bay watershed, and near Houghton Lake, Michigan. Our analysis suggests focusing conservation efforts (i.e., wetland protection and restoration) at or near these large wetland complexes would likely benefit marsh birds.

Refining Biological Models

Preliminary spatially explicit habitat models were developed for breeding JV focal species to guide regional marsh bird planning (Soulliere et al. 2007). However, limited population information (see Wires et al. 2010) and lack of species-specific fine-scale and landscape habitat features hampered development of correlative models. These information gaps and associated research needs were identified in the JV planning process. Likewise, expert-based planning assumptions regarding marsh bird habitat requirements were stated explicitly to target future research, as testing these assumptions and filling information gaps is critical to strategic habitat conservation. Our research moves the JV community forward in filling at least some marsh bird information gaps during the breeding period. Results of this study and other ongoing research in the region will provide information to refine models used when updating the JV Waterbird Habitat Conservation Strategy (completion target 2015).

Research Needs

We found several challenges associated with analyzing relationships between marsh bird occupancy and independent variables. The final models produced for a given species regularly differed in the variables chosen, yet their predictive capacity was often good and similar. Thus, interpreting which variables are “most important” to a particular species remains difficult, despite having models that appear to function well in predicting occupancy. Our analyses indicated that the process used to select variables to be included in analyses and the modeling approach implemented will influence the variables identified as being important, so a remaining challenge is developing sound statistical approaches for variable selection and analysis. When modeling occupancy patterns using variables from multiple spatial scales, an issue arises as to how best to use data from multiple years at the same location in CART and logistical regression analyses. In these situations, large-scale variables do not vary annually (i.e., remotely sensed data are updated at longer time intervals) but fine-scale variables can change annually or even within a season. Additional analyses that build upon this study are needed to further our ability to identify the variables driving marsh bird occupancy.

Although identification of general habitat associations (i.e., where marsh birds are more likely to occur) is an important first step toward more efficient conservation planning, more work is needed to better understand the specific breeding habitats being selected by focal species and determine if identified habitat associations are indicative of better quality conditions and increased recruitment compared to areas selected less often. Telemetry studies would help us move beyond identifying habitat associations to understanding habitat quality (i.e., survival and recruitment). Evaluations of vital rates (e.g., nest success, brood survival) across habitat gradients will be critical in determining characteristics of breeding population "source" vs. "sink" habitats and enhancing biological models that ultimately increase marsh bird conservation efficiency.

We focused on habitat variables as drivers of marsh bird occupancy, but clearly there are other factors that could be affecting where these species occur. The presence of nearby conspecifics or co-occurrence with other marsh bird species could influence probability of occupancy. Conditions on wintering and/or migration areas could also affect the health (e.g., breeding status) of marsh birds leading up to arrival on summer range and possibly alter site selection. It is also uncertain whether marsh bird species respond to habitat conditions in a strong way with little variation, or if there is an element of "chance" to site selection, implying there will always be unexplained variation no matter how "good" a predictive model may be.

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APPENDIX A

Description of Remotely Sensed Variables

Variable: abow1km
Alias: Percent (%) aquatic bed / open water wetland within 1,000 meters.

Description: Percent (%) of a 1,000 meter circular buffer from the center of a 30 meter cell classified as Palustrine or Lacustrine Aquatic Bed or Open Water wetland from the National Wetlands Inventory Program.

Data source(s): National Wetlands Inventory

Process:

1. Start with all NWI wetlands within an 18,000 meter full, rounded buffer of the Great Lakes coastline including off-shore islands (“All_wetlands.shp”; internal process file).
2. Select by Attributes all open water and aquatic bed polygons
    a. "ATTRIBUTE" LIKE '0' OR "ATTRIBUTE" LIKE '%USJ%' OR "ATTRIBUTE" LIKE '%USK%' OR "ATTRIBUTE" LIKE '%USU%' OR "ATTRIBUTE" LIKE '%USW%' OR "ATTRIBUTE" LIKE '%USY%' OR "ATTRIBUTE" LIKE '%PUB%' OR "ATTRIBUTE" LIKE '%UBF%' OR "ATTRIBUTE" LIKE '%UBG%' OR "ATTRIBUTE" LIKE '%UBH%' OR "ATTRIBUTE" LIKE '%UBJ%' OR "ATTRIBUTE" LIKE '%UBK%' OR "ATTRIBUTE" LIKE '%UBZ%' OR "ATTRIBUTE" LIKE 'PAB%' OR "ATTRIBUTE" LIKE 'L2UB/%' OR "ATTRIBUTE" LIKE '%AB%'
3. Clip to coastal zone extent (18,000 meter full rounded buffer of the Great Lakes coastline including off-shore islands; “CoastalZone.shp”; internal process file)
4. Select by Attributes all Palustrine and Lacustrine littoral wetlands
    a. "ATTRIBUTE" LIKE 'L2%' Or "ATTRIBUTE" LIKE 'P%'
5. Convert Feature to Raster; Output cell size = 10 meters, Value = 100.
6. Integer raster to convert raster to integer format.
7. Reclassify raster (100 100; NoData 0). Creates a binary raster were aquatic bed / open water wetland = 100 and everything else = 0.
8. Focal Statistics; Circle, Radius = 100 map units (meters), Statistics type=Mean, Ignore NoData in calculations = TRUE.

Variable: anhab1km

Alias: Percent (%) anthropogenic non-habitat within 1,000 meters.

Description: Percent (%) of a 1,000 meter circular buffer from the center of a 30 meter cell classified as Developed (Open Space, Low Intensity, Medium Intensity, and High Intensity) or Cultivated Crops in the 2006 National Land Cover Dataset.

Data source(s): National Land Cover Dataset, 2006.

Process:

1. Start with all NWI wetlands within an 12,000 meter full, rounded buffer of Michigan and Ohio.
2. Select by Attributes all open water and aquatic bed polygons

a. "ATTRIBUTE" LIKE '0' OR "ATTRIBUTE" LIKE '%USJ%' OR "ATTRIBUTE" LIKE '%USK%' OR "ATTRIBUTE" LIKE '%USU%' OR "ATTRIBUTE" LIKE '%USW%' OR "ATTRIBUTE" LIKE '%USY%' OR "ATTRIBUTE" LIKE '%PUB%' OR "ATTRIBUTE" LIKE '%UBF%' OR "ATTRIBUTE" LIKE '%UBG%' OR "ATTRIBUTE" LIKE '%UBH%' OR "ATTRIBUTE" LIKE '%UBJ%' OR "ATTRIBUTE" LIKE '%UBK%' OR "ATTRIBUTE" LIKE '%UBZ%' OR "ATTRIBUTE" LIKE 'PAB%' OR "ATTRIBUTE" LIKE 'L2UB/%' OR "ATTRIBUTE" LIKE '%AB%'

3. Clip to coastal zone extent (18,000 meter full rounded buffer of the Great Lakes coastline including off-shore islands; "CoastalZone.shp"; internal process file)
4. Select by Attributes all Palustrine and Lacustrine littoral wetlands
    a. "ATTRIBUTE" LIKE 'L2%' Or "ATTRIBUTE" LIKE 'P%'
5. Convert Feature to Raster; Output cell size = 10 meters, Value = 100.
6. Integer raster to convert raster to integer format.
7. Reclassify raster (100 100; NoData 0). Creates a binary raster were aquatic bed / open water wetland = 100 and everything else = 0.

8. Focal Statistics; Circle, Radius = 1000 map units (meters), Statistics type=Mean, Ignore NoData in calculations = TRUE.

Variable: dist2abow

Alias: Distance (meters) to river.

Description: Euclidean distance (meters) from the edge of a 30 m cell to another 30 m cell classified as Palustrine or Lacustrine Aquatic Bed or Open Water wetland from the National Wetlands Inventory.

Data source(s): National Wetlands Inventory

Process:

1-7. the same as abow1km

8. Aggregate; Cell factor = 3, Aggregation technique = Mean; Expand extent if needed = TRUE, Ignore NoData in calculations = TRUE
9. Euclidean Distance; Maximum distance = 12000, Output cell size = 30, Output direction raster = NULL

Variable: dist2nhab

Alias: Distance (meters) to nearest non-habitat.

Description: Euclidean distance (meters) from the edge of a 30 m cell to another 30 m cell classified as Perennial Ice/Snow, Developed (Open Space, Low Intensity, Medium Intensity, and High Intensity), Barren Land, Deciduous Forest, Evergreen Forest, Mixed Forest, and Cultivated Crops in the 2006 National Land Cover Dataset.

Data source(s): National Land Cover Dataset, 2006.

Process:

1. Start with NLCD extracted to 18,000 meter full rounded buffer of Great Lakes coastline including off-shore islands ("nlcd_18km"; internal process file).
2. Reclassify (1); (11 NoData; 12 1; 21 1; 22 1; 23 1; 24 1; 31 1; 41 1; 42 1; 43 1; 52 NoData; 71 NoData; 81 NoData; 82 1; 90 NoData; 95 NoData; NoData NoData); Change Missing values to NoData=TRUE.
3. Euclidean Distance; Maximum distance = 12000, Output cell size = 30, Output direction raster = NULL

Variable: dist2rd

Alias: Distance (meters) to nearest road.

Description: Euclidean distance (meters) from the edge of a 30 m cell to the nearest Census 2010 TIGER/Line® road vector.

Data source(s): Census 2010 TIGER/Line® Shapefiles

Process:

1. Start with all Census 2010 TIGER/Line® roads in a 12,000 m full, rounded buffer of Michigan and Ohio
2. Euclidean Distance, Maximum distance = 12000, Output cell size = 30, Output direction raster = NULL

Variable: dist2river

Alias: Distance (meters) to nearest river.

Description: Euclidean distance (meters) from the edge of a 30 m cell to the nearest National Hydrography Dataset stream/river vector.

Data source(s): National Hydrography Dataset high resolution state extracts.

Process:

1. Start with all NHD Stream/River (FType=460) within a full, rounded 12,000 m buffer of Michigan and Ohio
2. Euclidean Distance, Maximum distance = 12000, Output cell size = 30, Output direction raster = NULL

Variable: ED

Alias: Edge density (km/km^2)

Description: Line density (km/km^2) of water/vegetation shared border derived from interactive supervised classification of color infrared imagery (see Appendix B).

Data source(s): Color infrared imagery (2009 and 2010, NAIP); National Wetlands Inventory

Process:

1. Start with 1 m resolution binary raster of water (1) and vegetation (2); this is the result of step 16 from the interactive supervised image classification process (Appendix B)
2. Extract (1) to 100 m circular buffers centered at survey locations.
3. Create a Raster Domain of (2)
4. Reclassify raster (2) (1 1; 2 NoData; NoData NoData). This creates a binary raster where water = 1 and everything else = NoData.
5. Convert Raster to Polygon; Field = Value, Simplify polygons = FALSE. This converts the raster into contiguous polygons.
6. Convert Polygon to Line.
7. Calculate Line Density; Population field = NONE, Output cell size = 1; Search radius = 100; Area units = SQUARE_KILOMETERS. Limit calculation to extent of survey site buffers (3). The result is density (km/km^2) of vegetation/water interface within a 100 meter circular buffer centered at a survey location.

Variable: emnofor1km

Alias: Percent (%) emergent wetland within 1,000 meters.

Description: Percent (%) of a 1,000 meter circular buffer from the center of a 30 meter cell classified as Emergent wetland from the National Wetlands Inventory Program.

Data source(s): National Wetlands Inventory

Process:

1. Start with all NWI wetlands within a 12,000 meter full, rounded buffer of Michigan and Ohio
2. Select by Attributes all emergent polygons
    a. ATTRIBUTE LIKE '%EM%'
3. Remove forested wetlands from selection
    a. ATTRIBUTE LIKE '%FO%'
4. Clip to study area
5. Convert Feature to Raster; Output cell size = 10 meters, Value = 100.
6. Integer raster to convert raster to integer format.

7. Focal Statistics; Circle, Radius = 1,000 map units (meters), Statistics type=Mean, Ignore NoData in calculations = TRUE.

Variable: nnhab1km

Alias: Percent (%) natural non-habitat within 1,000 meters.

Description: Percent (%) of a 1,000 meter circular buffer from the center of a 30 m cell classified as Perennial Ice/Snow, Barren Land, Deciduous Forest, Evergreen Forest, Mixed Forest, and Cultivated Crops in the 2006 National Land Cover Dataset.

Data source(s): National Land Cover Dataset, 2006.

Process:

1. Start with NLCD extracted to 12,000 meter full, rounded buffer of Michigan and Ohio
2. Reclassify (1); (11 0; 12 100; 21 0; 22 0; 23 0; 24 0; 31 100; 41 100; 42 100; 43 100; 52 0; 71 0; 81 0; 82 100; 90 0; 95 0; NoData NoData); Change Missing values to NoData=TRUE.
3. Focal Statistics; Circle, Radius = 1000 map units (meters), Statistics type=Mean, Ignore NoData in calculations = TRUE.

Variable: NVEG

Alias: Number of vegetation patches within 100 meters.

Description: Number of unique, contiguous groups of 1 m cells classified as emergent vegetation through interactive supervised classification of color infrared imagery (see Appendix B) within a 100 meter circular buffer centered at a survey location.

Data source(s): Color infrared imagery (2009 and 2010, NAIP); National Wetlands Inventory

Process:

1. Start with 1 m resolution binary raster of water (1) and vegetation (2); this is the result of step 16 from the interactive supervised image classification process (Appendix B)
2. Extract (1) to 100 m circular buffers centered at survey locations.
3. Create a Raster Domain of (2)
4. Reclassify raster (2) (1 NoData; 2 1; NoData NoData).
5. Raster to Polygon; Field = Value, Simplify polygons = FALSE. This converts the raster into a vector file and groups contiguous cells together into unique polygons.
6. Polygon to Raster; Value field = OBJECTID, Cell assignment type = CELL_CENTER, Priority field = NONE, Cellsize = 1; This generates an integer raster where
7. Focal Stats; Neighborhood = Circle, Radius = 100 map units (meters), Statistics type = VARIETY, Ignore NoData in calculations = TRUE. Limit calculation to extent of survey site buffers (3).

Variable: RATIO

Alias: Ratio of vegetation to open water area within 100 meters.

Description: Ratio of the area of 1 m cells classified as emergent vegetation to the area of 1 m cells classified as water (both derived through interactive supervised image classification of color infrared imagery; see Appendix B) within a 100 meter circular buffer centered at a survey location.

Data source(s): Color infrared imagery (2009 and 2010, NAIP); National Wetlands Inventory

Process:

1. Start with 1 m resolution binary raster of water (1) and vegetation (2); this is the result of step 16 from the interactive supervised image classification process (Appendix B)
2. Extract (1) to 100 m circular buffers centered at survey locations.
3. Create a Raster Domain of (2)
4. Reclassify raster (2) (1 0; 2 100; NoData NoData). This create a binary raster where water = 0 and emergent vegetation = 100.
5. Focal Stats; Neighborhood = Circle, Radius = 100 map units (meters), Statistics type = MEAN, Ignore NoData in calculations = TRUE. Limit calculation to extent of survey site buffers (3). This results in percent (%) emergent vegetation within a 100 meter buffer centered at a survey location.
6. Convert to RATIO via Raster Calculator
    a. Abs("%Output Ratio GRID name%"-50)*2

APPENDIX B

Process Used to Classify Color Infrared Imagery

Classifying open water versus vegetation in wetlands from aerial imagery.

1. Zoom in to area of interest. Leave a buffer of >1000 m from survey points to edge of screen extent.
2. Export image file (.ecw or .sid) to grid. Make sure to export with the "use current extent" option selected.
3. Select NWI polygons that occur in the area of interest.
4. Export selected NWI polygons.
5. Use Extract by Mask to clip the image file to NWI polygons.
    a. Creates a multiband raster and a file for each individual band.
6. Open the image classification toolbar.
7. Open the Training Sample manager.
8. Select and draw open water training sites.
    a. Band 4 (infrared) is best for distinguishing water (it will appear dark gray to black).
    b. Select at least 1,000,000 pixels distributed throughout the image.
    c. Collapse training sites into a single class, assign class name "Water" and value "1".
9. Select and draw vegetation training sites.
    a. Vegetation will appear as lighter colors when using Band 4. True color or color composites can sometimes help.
    b. Select at least 1,000,000 pixels distributed throughout the image.
    c. Collapse training sites into a single class: assign class name "Vegetation" and value "2".
10. Save training sites.
11. Set the image file that you would like to classify in the image classification toolbar.
    a. Try classifications with both the multiband image and just using Band 4.
12. Click "Interactive Supervised Classification".
13. Compare classification with base image (swipe tool on the effects toolbar is useful for this assessment).
14. Export raw classification or if classification is poor, add, delete, or change training sites.
15. Run a Majority Filter on raw classification (8 cell, majority).
16. Save as classified.

APPENDIX C

Occupancy Modeling Results

Table C-1. Occupancy model selection results for 10 marsh bird species during 518 point counts conducted in Michigan during 2006—2013. Detection probability (*p*) and occupancy (ψ) covariates are coded as follows: AN1 = proportion of anthropogenic cover within 1 km; DE = water depth; D2NH = distance to nearest natural non-habitat; D2RD = distance to nearest road; D2OW1 = distance to nearest open water/aquatic bed wetland; CA = % cover *Carex* (Sedges); ED = edge density within 100 m; EM = % cover emergents; EM1 = proportion of emergent wetland within 1 km; FL = % cover floating vegetation; GR = % cover grasses; HE = maximum vegetation height; NS = % cover non-persistent shallow-water emergents; NV = no. vegetation patches within 100 m; OR = organic sediment depth; OW1 = proportion of open water/aquatic bed wetlands within 1 km; PH = % cover *Phragmites australis* (common reed); RA = ratio of emergent:open water/aquatic bed wetland within 100 m; SC = % cover *Schoenoplectus* (bulrushes); TY = % cover *Typha* (cattails); and WO = % cover woody vegetation.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	*K*	−2 Log-likelihood
Pied-billed Grebe ($\hat{c}$ = 0.89)						
ψ(DE,ED,NS),*p*(SU,EM)	432.58	0.00	0.9089	1.0000	8	416.58
ψ(ED,NS),*p*(SU,EM)	437.59	5.01	0.0742	0.0817	7	423.59
ψ(DE,ED),*p*(SU,EM)	441.93	9.35	0.0085	0.0093	7	427.93
ψ(DE,NS),*p*(SU,EM)	442.07	9.49	0.0079	0.0087	7	428.07
ψ(DE),*p*(SU,EM)	447.78	15.20	0.0005	0.0005	6	435.78
ψ(ED),*p*(SU,EM)	455.38	22.80	0.0000	0.0000	6	443.38
ψ(NS),*p*(SU,EM)	460.06	27.48	0.0000	0.0000	6	448.06
ψ(EM),*p*(SU,EM)	460.77	28.19	0.0000	0.0000	6	448.77
ψ(CA),*p*(SU,EM)	463.10	30.52	0.0000	0.0000	6	451.10
ψ(RA),*p*(SU,EM)	466.29	33.71	0.0000	0.0000	6	454.29
ψ(WO),*p*(SU,EM)	472.40	39.82	0.0000	0.0000	6	460.40
ψ(GR),*p*(SU,EM)	472.75	40.17	0.0000	0.0000	6	460.75
ψ(OW1),*p*(SU,ME)	473.32	40.74	0.0000	0.0000	6	461.32
ψ(OR),*p*(SU,EM)	473.60	41.02	0.0000	0.0000	6	461.60
ψ(FL),*p*(SU,EM)	473.62	41.04	0.0000	0.0000	6	461.62
ψ(NV),*p*(SU,EM)	475.29	42.71	0.0000	0.0000	6	463.29
ψ(SC),*p*(SU,EM)	475.88	43.30	0.0000	0.0000	6	463.88
ψ(HE),*p*(SU,EM)	477.08	44.50	0.0000	0.0000	6	465.08
ψ(.),*p*(SU,EM)	477.75	45.17	0.0000	0.0000	5	467.75
ψ(EM1),*p*(SU,EM)	478.01	45.43	0.0000	0.0000	6	466.01
ψ(TY),*p*(SU,EM)	478.03	45.45	0.0000	0.0000	6	466.03
ψ(AN1),*p*(SU,EM)	478.44	45.86	0.0000	0.0000	6	466.44
ψ(D2RD),*p*(SU,EM)	478.89	46.31	0.0000	0.0000	6	466.89
ψ(D2NH),*p*(SU,EM)	479.22	46.64	0.0000	0.0000	6	467.22
ψ(PH),*p*(SU,EM)	479.50	46.92	0.0000	0.0000	6	467.50
ψ(D2OW),*p*(SU,EM)	479.67	47.09	0.0000	0.0000	6	467.67
ψ(D2RI),*p*(SU,EM)	479.75	47.17	0.0000	0.0000	6	467.75

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	*K*	−2 Log-likelihood
ψ(.),*p*(SU,NO)	485.77	53.19	0.0000	0.0000	5	475.77
ψ(.),*p*(SU,WI)	489.05	56.47	0.0000	0.0000	5	479.05
ψ(.),*p*(SU,HE)	490.73	58.15	0.0000	0.0000	5	480.73
ψ(.),*p*(SU)	493.83	61.25	0.0000	0.0000	4	485.83
ψ(.),*p*(.)	494.33	61.75	0.0000	0.0000	2	490.33
American Bittern ($\hat{c}$ = 1.11)						
ψ(EM1,D2NH,NS),*p*(SU,HE)	627.79	0.00	0.5922	1.0000	8	678.78
ψ(EM1,D2NH),*p*(SU,HE)	628.64	0.85	0.3871	0.6538	7	681.94
ψ(EM1,NS),*p*(SU,HE)	636.25	8.46	0.0086	0.0146	7	690.39
ψ(EM1),*p*(SU,HE)	636.62	8.83	0.0072	0.0121	6	693.02
ψ(D2NH,NS),*p*(SU,HE)	637.78	9.99	0.0040	0.0068	7	692.08
ψ(D2NH),*p*(SU,HE)	640.93	13.14	0.0008	0.0014	6	697.80
ψ(NS),*p*(SU,HE)	647.95	20.16	0.0000	0.0000	6	705.59
ψ(GR),*p*(SU,HE)	648.33	20.54	0.0000	0.0000	6	706.01
ψ(DE),*p*(SU,HE)	650.19	22.40	0.0000	0.0000	6	708.07
ψ(OR),*p*(SU,HE)	650.81	23.02	0.0000	0.0000	6	708.76
ψ(TY),*p*(SU,HE)	651.00	23.21	0.0000	0.0000	6	708.97
ψ(HE),*p*(SU,HE)	651.92	24.13	0.0000	0.0000	6	709.99
ψ(D2OW),*p*(SU,HE)	652.34	24.55	0.0000	0.0000	6	710.46
ψ(.),*p*(SU,HE)	652.88	25.09	0.0000	0.0000	5	713.27
ψ(AN1),*p*(SU,HE)	653.55	25.76	0.0000	0.0000	6	711.80
ψ(.),*p*(SU)	653.62	25.83	0.0000	0.0000	4	716.32
ψ(.),*p*(SU,WI)	653.66	25.87	0.0000	0.0000	5	714.14
ψ(OW1),*p*(SU,HE)	653.83	26.04	0.0000	0.0000	6	712.11
ψ(PH),*p*(SU,HE)	654.03	26.24	0.0000	0.0000	6	712.33
ψ(D2RI),*p*(SU,HE)	654.14	26.35	0.0000	0.0000	6	712.45
ψ(FL),*p*(SU,HE)	654.24	26.45	0.0000	0.0000	6	712.57
ψ(NV),*p*(SU,HE)	654.29	26.50	0.0000	0.0000	6	712.62
ψ(EM),*p*(SU,HE)	654.44	26.65	0.0000	0.0000	6	712.79
ψ(RA),*p*(SU,HE)	654.56	26.77	0.0000	0.0000	6	712.92
ψ(CA),*p*(SU,HE)	654.60	26.81	0.0000	0.0000	6	712.97
ψ(D2RD),*p*(SU,HE)	654.70	26.91	0.0000	0.0000	6	713.08
ψ(ED),*p*(SU,HE)	654.87	27.08	0.0000	0.0000	6	713.26
ψ(WO),*p*(SU,HE)	654.88	27.09	0.0000	0.0000	6	713.27
ψ(SC),*p*(SU,HE)	654.88	27.09	0.0000	0.0000	6	713.27
ψ(.),*p*(SU,NO)	655.48	27.69	0.0000	0.0000	5	716.16
ψ(.),*p*(SU,EM)	655.49	27.70	0.0000	0.0000	5	716.17
ψ(.),*p*(.)	663.19	35.40	0.0000	0.0000	2	731.37

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	K	−2 Log-likelihood
Least Bittern ($\hat{c}$ = 0.93)						
ψ(DE,TY),*p*(SU,HE)	444.22	0.00	0.3562	1.0000	7	430.22
ψ(DE,TY,NS),*p*(SU,HE)	444.32	0.10	0.3388	0.9512	8	428.32
ψ(DE),*p*(SU,HE)	445.74	1.52	0.1666	0.4677	6	433.74
ψ(DE,NS),*p*(SU,HE)	446.11	1.89	0.1384	0.3887	7	432.11
ψ(TY,NS),*p*(SU,HE)	462.06	17.84	0.0000	0.0001	7	448.06
ψ(TY),*p*(SU,HE)	466.88	22.66	0.0000	0.0000	6	454.88
ψ(NS),*p*(SU,HE)	474.85	30.63	0.0000	0.0000	6	462.85
ψ(D2NH),*p*(SU,HE)	478.20	33.98	0.0000	0.0000	6	466.20
ψ(CA),*p*(SU,HE)	479.44	35.22	0.0000	0.0000	6	467.44
ψ(EM1),*p*(SU,HE)	480.46	36.24	0.0000	0.0000	6	468.46
ψ(AN1),*p*(SU,HE)	481.95	37.73	0.0000	0.0000	6	469.95
ψ(EM),*p*(SU,HE)	483.74	39.52	0.0000	0.0000	6	471.74
ψ(GR),*p*(SU,HE)	484.73	40.51	0.0000	0.0000	6	472.73
ψ(SC),*p*(SU,HE)	485.42	41.20	0.0000	0.0000	6	473.42
ψ(D2OW),*p*(SU,HE)	485.74	41.52	0.0000	0.0000	6	473.74
ψ(FL),*p*(SU,HE)	486.12	41.90	0.0000	0.0000	6	474.12
ψ(D2RD),*p*(SU,HE)	487.74	43.52	0.0000	0.0000	6	475.74
ψ(WO),*p*(SU,HE)	488.26	44.04	0.0000	0.0000	6	476.26
ψ(OW1),*p*(SU,HE)	488.94	44.72	0.0000	0.0000	6	476.94
ψ(.),*p*(SU,HE)	489.29	45.07	0.0000	0.0000	5	479.29
ψ(ED),*p*(SU,HE)	489.45	45.23	0.0000	0.0000	6	477.45
ψ(HE),*p*(SU,HE)	490.08	45.86	0.0000	0.0000	6	478.08
ψ(PH),*p*(SU,HE)	490.24	46.02	0.0000	0.0000	6	478.24
ψ(RA),*p*(SU,HE)	490.39	46.17	0.0000	0.0000	6	478.39
ψ(NV),*p*(SU,HE)	491.07	46.85	0.0000	0.0000	6	479.07
ψ(D2RI),*p*(SU,HE)	491.12	46.90	0.0000	0.0000	6	479.12
ψ(OR),*p*(SU,HE)	491.16	46.94	0.0000	0.0000	6	479.16
ψ(.),*p*(SU,EM)	492.74	48.52	0.0000	0.0000	5	482.74
ψ(.),*p*(SU,WI)	494.24	50.02	0.0000	0.0000	5	484.24
ψ(.),*p*(SU,NO)	496.93	52.71	0.0000	0.0000	5	486.93
ψ(.),*p*(SU)	500.48	56.26	0.0000	0.0000	4	492.48
ψ(.),*p*(.)	504.01	59.79	0.0000	0.0000	2	500.01
Virginia Rail ($\hat{c}$ = 1.25)						
ψ(GR,EM1,AN1),*p*(HE)	811.27	0.00	0.9929	1.0000	6	1001.65
ψ(GR,AN1),*p*(HE)	822.63	11.36	0.0034	0.0034	5	1018.39
ψ(GR,EM1),*p*(HE)	823.28	12.01	0.0024	0.0025	5	1019.20
ψ(EM1,AN1),*p*(HE)	824.64	13.37	0.0012	0.0012	5	1020.91

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	*K*	−2 Log-likelihood
ψ(GR),*p*(HE)	836.53	25.26	0.0000	0.0000	4	1038.31
ψ(EM1),*p*(HE)	838.19	26.92	0.0000	0.0000	4	1040.40
ψ(AN1),*p*(HE)	841.01	29.74	0.0000	0.0000	4	1043.93
ψ(CA),*p*(HE)	842.51	31.24	0.0000	0.0000	4	1045.81
ψ(DE),*p*(HE)	842.61	31.34	0.0000	0.0000	4	1045.93
ψ(FL),*p*(HE)	842.65	31.38	0.0000	0.0000	4	1045.98
ψ(EM),*p*(HE)	846.80	35.53	0.0000	0.0000	4	1051.18
ψ(HE),*p*(HE)	846.83	35.56	0.0000	0.0000	4	1051.22
ψ(WO),*p*(HE)	847.07	35.80	0.0000	0.0000	4	1051.52
ψ(NS),*p*(HE)	850.95	39.68	0.0000	0.0000	4	1056.39
ψ(TY),*p*(HE)	852.94	41.67	0.0000	0.0000	4	1058.88
ψ(NV),*p*(HE)	855.23	43.96	0.0000	0.0000	4	1061.75
ψ(SC),*p*(HE)	855.99	44.72	0.0000	0.0000	4	1062.70
ψ(OR),*p*(HE)	856.51	45.24	0.0000	0.0000	4	1063.35
ψ(OW1),*p*(HE)	856.51	45.24	0.0000	0.0000	4	1063.35
ψ(D2NH),*p*(HE)	857.49	46.22	0.0000	0.0000	4	1064.58
ψ(.),*p*(HE)	857.95	46.68	0.0000	0.0000	3	1067.67
ψ(D2RD),*p*(HE)	858.07	46.80	0.0000	0.0000	4	1065.31
ψ(D2RI),*p*(HE)	858.30	47.03	0.0000	0.0000	4	1065.60
ψ(RA),*p*(HE)	858.53	47.26	0.0000	0.0000	4	1065.88
ψ(D2OW),*p*(HE)	859.53	48.26	0.0000	0.0000	4	1067.14
ψ(PH),*p*(HE)	859.69	48.42	0.0000	0.0000	4	1067.34
ψ(ED),*p*(HE)	859.78	48.51	0.0000	0.0000	4	1067.45
ψ(.),*p*(EM)	861.68	50.41	0.0000	0.0000	3	1072.34
ψ(.),*p*(WI)	862.22	50.95	0.0000	0.0000	3	1073.01
ψ(.),*p*(.)	862.29	51.02	0.0000	0.0000	2	1075.61
ψ(.),*p*(NO)	864.28	53.01	0.0000	0.0000	3	1075.60
ψ(.),*p*(SU)	865.24	53.97	0.0000	0.0000	4	1074.29
Sora ($\hat{c}$ = 2.34)						
ψ(AN1),p(SU)	243.15	0.00	0.1390	1.0000	5	545.71
ψ(AN1,ED),p(SU)	243.90	0.75	0.0956	0.6873	6	542.78
ψ(AN1,DE),p(SU)	244.26	1.11	0.0798	0.5741	6	543.63
ψ(AN1,DE,ED),p(SU)	244.30	1.15	0.0782	0.5627	7	539.03
ψ(DE,ED),p(SU)	245.10	1.95	0.0524	0.3772	6	545.59
ψ(.),p(SU)	245.66	2.51	0.0396	0.2851	4	556.27
ψ(DE),p(SU)	245.86	2.71	0.0359	0.2579	5	552.06
ψ(ED),p(SU)	245.96	2.81	0.0341	0.2454	5	552.28
ψ(TY),p(SU)	246.45	3.30	0.0267	0.1920	5	553.44

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	*K*	−2 Log-likelihood
ψ(OR),p(SU)	246.49	3.34	0.0262	0.1882	5	553.53
ψ(D2RD),p(SU)	246.54	3.39	0.0255	0.1836	5	553.65
ψ(EM1),p(SU)	246.63	3.48	0.0244	0.1755	5	553.85
ψ(FL),p(SU)	246.64	3.49	0.0243	0.1746	5	553.87
ψ(CA),p(SU)	246.79	3.64	0.0225	0.1620	5	554.23
ψ(OW1),p(SU)	246.80	3.65	0.0224	0.1612	5	554.25
ψ(WO),p(SU)	246.86	3.71	0.0218	0.1565	5	554.39
ψ(NV),p(SU)	246.88	3.73	0.0215	0.1549	5	554.44
ψ(RA),p(SU)	246.99	3.84	0.0204	0.1466	5	554.70
ψ(EM),p(SU)	247.08	3.93	0.0195	0.1402	5	554.90
ψ(PH),p(SU)	247.09	3.94	0.0194	0.1395	5	554.94
ψ(GR),p(SU)	247.32	4.17	0.0173	0.1243	5	555.47
ψ(.),p(SU,WI)	247.40	4.25	0.0166	0.1194	5	555.65
ψ(NS),p(SU)	247.43	4.28	0.0164	0.1177	5	555.72
ψ(D2OW),p(SU)	247.53	4.38	0.0156	0.1119	5	555.97
ψ(.),p(SU,HE)	247.55	4.40	0.0154	0.1108	5	556.02
ψ(.),p(SU,EM)	247.57	4.42	0.0153	0.1097	5	556.06
ψ(D2RI),p(SU)	247.57	4.42	0.0153	0.1097	5	556.06
ψ(D2NH),p(SU)	247.61	4.46	0.0149	0.1075	5	556.15
ψ(SC),p(SU)	247.63	4.48	0.0148	0.1065	5	556.20
ψ(.),p(SU,NO)	247.64	4.49	0.0147	0.1059	5	556.22
ψ(HE),p(SU)	247.66	4.51	0.0146	0.1049	5	556.26
ψ(.),p(.)	279.26	36.11	0.0000	0.0000	2	644.27
Common Gallinule ($\hat{c}$ = 1.72)						
ψ(DE,AN1,GR),*p*(SU,EM)	221.11	0.00	0.7751	1.0000	8	353.05
ψ(DE,GR),*p*(SU,EM)	224.83	3.72	0.1207	0.1557	7	362.91
ψ(DE,AN1),*p*(SU,EM)	225.78	4.67	0.0750	0.0968	7	364.54
ψ(AN1,GR),*p*(SU,EM)	228.23	7.12	0.0220	0.0284	7	368.76
ψ(DE),*p*(SU,EM)	230.70	9.59	0.0064	0.0083	6	376.45
ψ(AN1),*p*(SU,EM)	236.57	15.46	0.0003	0.0004	6	386.55
ψ(GR),*p*(SU,EM)	237.81	16.70	0.0002	0.0002	6	388.68
ψ(WO),*p*(SU,EM)	239.37	18.26	0.0001	0.0001	6	391.38
ψ(CA),*p*(SU,EM)	239.76	18.65	0.0001	0.0001	6	392.04
ψ(ED),*p*(SU,EM)	241.30	20.19	0.0000	0.0000	6	394.69
ψ(FL),*p*(SU,EM)	242.62	21.51	0.0000	0.0000	6	396.96
ψ(EM),*p*(SU,EM)	243.72	22.61	0.0000	0.0000	6	398.86
ψ(NS),*p*(SU,EM)	244.03	22.92	0.0000	0.0000	6	399.40
ψ(TY),*p*(SU,EM)	245.97	24.86	0.0000	0.0000	6	402.74

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	K	−2 Log-likelihood
ψ(EM1),*p*(SU,EM)	247.36	26.25	0.0000	0.0000	6	405.13
ψ(RA),*p*(SU,EM)	249.77	28.66	0.0000	0.0000	6	409.27
ψ(.),*p*(SU,EM)	249.83	28.72	0.0000	0.0000	5	412.82
ψ(PH),*p*(SU,EM)	249.97	28.86	0.0000	0.0000	6	409.62
ψ(OR),*p*(SU,EM)	251.16	30.05	0.0000	0.0000	6	411.67
ψ(SC),*p*(SU,EM)	251.17	30.06	0.0000	0.0000	6	411.68
ψ(D2RD),*p*(SU,EM)	251.20	30.09	0.0000	0.0000	6	411.74
ψ(NV),*p*(SU,EM)	251.44	30.33	0.0000	0.0000	6	412.15
ψ(HE),*p*(SU,EM)	251.60	30.49	0.0000	0.0000	6	412.42
ψ(D2NH),*p*(SU,EM)	251.75	30.64	0.0000	0.0000	6	412.68
ψ(D2OW),*p*(SU,EM)	251.78	30.67	0.0000	0.0000	6	412.73
ψ(D2RI),*p*(SU,EM)	251.81	30.70	0.0000	0.0000	6	412.78
ψ(OW1),*p*(SU,EM)	251.83	30.72	0.0000	0.0000	6	412.82
ψ(.),*p*(SU,WI)	252.33	31.22	0.0000	0.0000	5	417.13
ψ(.),*p*(.)	256.30	35.19	0.0000	0.0000	2	434.29
ψ(.),*p*(SU,NO)	256.31	35.20	0.0000	0.0000	5	423.97
ψ(.),*p*(SU)	257.04	35.93	0.0000	0.0000	4	428.68
ψ(.),*p*(SU,HE)	258.29	37.18	0.0000	0.0000	5	427.38
American Coot ($\hat{c}$ = 1.36)						
ψ(DE,GR,CA),*p*(SU,NO)	439.64	0.00	0.9937	1.0000	8	577.25
ψ(DE,CA),*p*(SU,NO)	450.37	10.73	0.0046	0.0047	7	594.60
ψ(DE,GR),*p*(SU,NO)	452.49	12.85	0.0016	0.0016	7	597.49
ψ(GR,CA),*p*(SU,NO)	458.23	18.59	0.0001	0.0001	7	605.31
ψ(DE),*p*(SU,NO)	469.20	29.56	0.0000	0.0000	6	622.98
ψ(GR),*p*(SU,NO)	478.29	38.65	0.0000	0.0000	6	635.37
ψ(CA),*p*(SU,NO)	479.08	39.44	0.0000	0.0000	6	636.45
ψ(WO),*p*(SU,NO)	481.20	41.56	0.0000	0.0000	6	639.33
ψ(EM),*p*(SU,NO)	482.45	42.81	0.0000	0.0000	6	641.04
ψ(NS),*p*(SU,NO)	492.60	52.96	0.0000	0.0000	6	654.87
ψ(ED),*p*(SU,NO)	493.38	53.74	0.0000	0.0000	6	655.93
ψ(HE),*p*(SU,NO)	499.20	59.56	0.0000	0.0000	6	663.86
ψ(RA),*p*(SU,NO)	500.46	60.82	0.0000	0.0000	6	665.57
ψ(SC),*p*(SU,NO)	505.84	66.20	0.0000	0.0000	6	672.90
ψ(OW1),*p*(SU,NO)	507.02	67.38	0.0000	0.0000	6	674.52
ψ(FL),*p*(SU,NO)	508.05	68.41	0.0000	0.0000	6	675.92
ψ(EM1),*p*(SU,NO)	509.13	69.49	0.0000	0.0000	6	677.39
ψ(D2RD),*p*(SU,NO)	510.40	70.76	0.0000	0.0000	6	679.12
ψ(OR),*p*(SU,NO)	510.88	71.24	0.0000	0.0000	6	679.78

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	K	−2 Log-likelihood
ψ(AN1),*p*(SU,NO)	511.31	71.67	0.0000	0.0000	6	680.36
ψ(D2RI),*p*(SU,NO)	511.61	71.97	0.0000	0.0000	6	680.77
ψ(.),*p*(SU,NO)	512.13	72.49	0.0000	0.0000	5	684.20
ψ(PH),*p*(SU,NO)	513.76	74.12	0.0000	0.0000	6	683.70
ψ(D2OW),*p*(SU,NO)	513.83	74.19	0.0000	0.0000	6	683.79
ψ(D2NH),*p*(SU,NO)	513.94	74.30	0.0000	0.0000	6	683.95
ψ(TY),*p*(SU,NO)	513.99	74.35	0.0000	0.0000	6	684.01
ψ(NV),*p*(SU,NO)	514.07	74.43	0.0000	0.0000	6	684.12
ψ(.),*p*(SU,EM)	527.50	87.86	0.0000	0.0000	5	705.15
ψ(.),*p*(SU,HE)	534.50	94.86	0.0000	0.0000	5	714.68
ψ(.),*p*(SU)	537.18	97.54	0.0000	0.0000	4	721.06
ψ(.),*p*(.)	538.78	99.14	0.0000	0.0000	2	728.69
ψ(.),*p*(SU,WI)	539.17	99.53	0.0000	0.0000	5	721.05
Wilson’s Snipe ($\hat{c}$ = 2.22)						
ψ(CA,D2RD),*p*(SU,NO)	117.41	0.00	0.2807	1.0000	7	229.24
ψ(CA),*p*(SU,NO)	117.68	0.27	0.2452	0.8737	6	234.26
ψ(CA,D2RD,TY),*p*(SU,NO)	118.72	1.31	0.1458	0.5194	8	227.71
ψ(CA,TY),*p*(SU,NO)	118.89	1.48	0.1339	0.4771	7	232.51
ψ(D2RD,TY),*p*(SU,NO)	121.22	3.81	0.0418	0.1488	7	237.67
ψ(D2RD),*p*(SU,NO)	121.35	3.94	0.0391	0.1395	6	242.40
ψ(TY),*p*(SU,NO)	123.76	6.35	0.0117	0.0418	6	247.74
ψ(.),*p*(SU,NO)	124.54	7.13	0.0079	0.0283	5	253.91
ψ(EM1),*p*(SU,NO)	124.59	7.18	0.0077	0.0276	6	249.57
ψ(DE),*p*(SU,NO)	124.72	7.31	0.0073	0.0259	6	249.87
ψ(OR),*p*(SU,NO)	124.86	7.45	0.0068	0.0241	6	250.18
ψ(AN1),*p*(SU,NO)	124.90	7.49	0.0066	0.0236	6	250.26
ψ(.),*p*(.)	125.60	8.19	0.0047	0.0167	2	269.55
ψ(PH),*p*(SU,NO)	125.76	8.35	0.0043	0.0154	6	252.18
ψ(SC),*p*(SU,NO)	125.79	8.38	0.0043	0.0151	6	252.24
ψ(NV),*p*(SU,NO)	125.79	8.38	0.0043	0.0151	6	252.23
ψ(.),*p*(SU,HE)	125.90	8.49	0.0040	0.0143	5	256.91
ψ(FL),*p*(SU,NO)	125.99	8.58	0.0038	0.0137	6	252.68
ψ(RA),*p*(SU,NO)	126.23	8.82	0.0034	0.0122	6	253.21
ψ(OW1),*p*(SU,NO)	126.26	8.85	0.0034	0.0120	6	253.29
ψ(HE),*p*(SU,NO)	126.29	8.88	0.0033	0.0118	6	253.35
ψ(D2RI),*p*(SU,NO)	126.35	8.94	0.0032	0.0114	6	253.48
ψ(EM),*p*(SU,NO)	126.41	9.00	0.0031	0.0111	6	253.62
ψ(NS),*p*(SU,NO)	126.49	9.08	0.0030	0.0107	6	253.80

Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	K	−2 Log-likelihood
ψ(GR),*p*(SU,NO)	126.49	9.08	0.0030	0.0107	6	253.78
ψ(D2NH),*p*(SU,NO)	126.53	9.12	0.0029	0.0105	6	253.88
ψ(D2OW),*p*(SU,NO)	126.54	9.13	0.0029	0.0104	6	253.89
ψ(ED),*p*(SU,NO)	126.54	9.13	0.0029	0.0104	6	253.89
ψ(WO),*p*(SU,NO)	126.54	9.13	0.0029	0.0104	6	253.90
ψ(.),*p*(SU)	126.58	9.17	0.0029	0.0102	4	262.85
ψ(.),*p*(SU,WI)	127.35	9.94	0.0019	0.0069	5	260.14
ψ(.),*p*(SU,EM)	128.51	11.10	0.0011	0.0039	5	262.71
Black Tern ($\hat{c}$ = 3.39)						
ψ(D2RI,WO,ED),*p*(SU,HE)	117.81	0.00	0.1680	1.0000	8	389.96
ψ(D2RI,ED),*p*(SU,HE)	117.94	0.13	0.1574	0.9371	7	398.11
ψ(D2RI,WO),*p*(SU,HE)	118.62	0.81	0.1120	0.6670	7	400.70
ψ(D2RI),*p*(SU,HE)	119.08	1.27	0.0890	0.5299	6	410.12
ψ(WO),*p*(SU,HE)	120.55	2.74	0.0427	0.2541	6	415.76
ψ(WO,ED),*p*(SU,HE)	120.58	2.77	0.0420	0.2503	7	408.20
ψ(ED),*p*(SU,HE)	121.08	3.27	0.0327	0.1950	6	417.80
ψ(.),*p*(SU,HE)	121.19	3.38	0.0310	0.1845	5	425.86
ψ(SC),*p*(SU,HE)	121.27	3.46	0.0298	0.1773	6	418.50
ψ(HE),*p*(SU,HE)	121.33	3.52	0.0289	0.1720	6	418.73
ψ(D2OW),*p*(SU,HE)	121.45	3.64	0.0272	0.1620	6	419.21
ψ(RA),*p*(SU,HE)	121.63	3.82	0.0249	0.1481	6	419.88
ψ(AN1),*p*(SU,HE)	121.81	4.00	0.0227	0.1353	6	420.57
ψ(GR),*p*(SU,HE)	122.18	4.37	0.0189	0.1125	6	422.01
ψ(NS),*p*(SU,HE)	122.26	4.45	0.0182	0.1081	6	422.32
ψ(DE),*p*(SU,HE)	122.55	4.74	0.0157	0.0935	6	423.42
ψ(EM),*p*(SU,HE)	122.70	4.89	0.0146	0.0867	6	424.01
ψ(OW1),*p*(SU,HE)	122.79	4.98	0.0139	0.0829	6	424.35
ψ(OR),*p*(SU,HE)	122.82	5.01	0.0137	0.0817	6	424.45
ψ(D2RD),*p*(SU,HE)	122.84	5.03	0.0136	0.0809	6	424.53
ψ(EM1),*p*(SU,HE)	123.08	5.27	0.0120	0.0717	6	425.45
ψ(PH),*p*(SU,HE)	123.11	5.30	0.0119	0.0707	6	425.56
ψ(CA),*p*(SU,HE)	123.11	5.30	0.0119	0.0707	6	425.56
ψ(TY),*p*(SU,HE)	123.12	5.31	0.0118	0.0703	6	425.60
ψ(NV),*p*(SU,HE)	123.16	5.35	0.0116	0.0689	6	425.76
ψ(FL),*p*(SU,HE)	123.18	5.37	0.0115	0.0682	6	425.83
ψ(D2NH),*p*(SU,HE)	123.19	5.38	0.0114	0.0679	6	425.86
ψ(.),*p*(SU,EM)	130.26	12.45	0.0003	0.0020	5	460.60
ψ(.),*p*(SU)	130.37	12.56	0.0003	0.0019	4	468.69

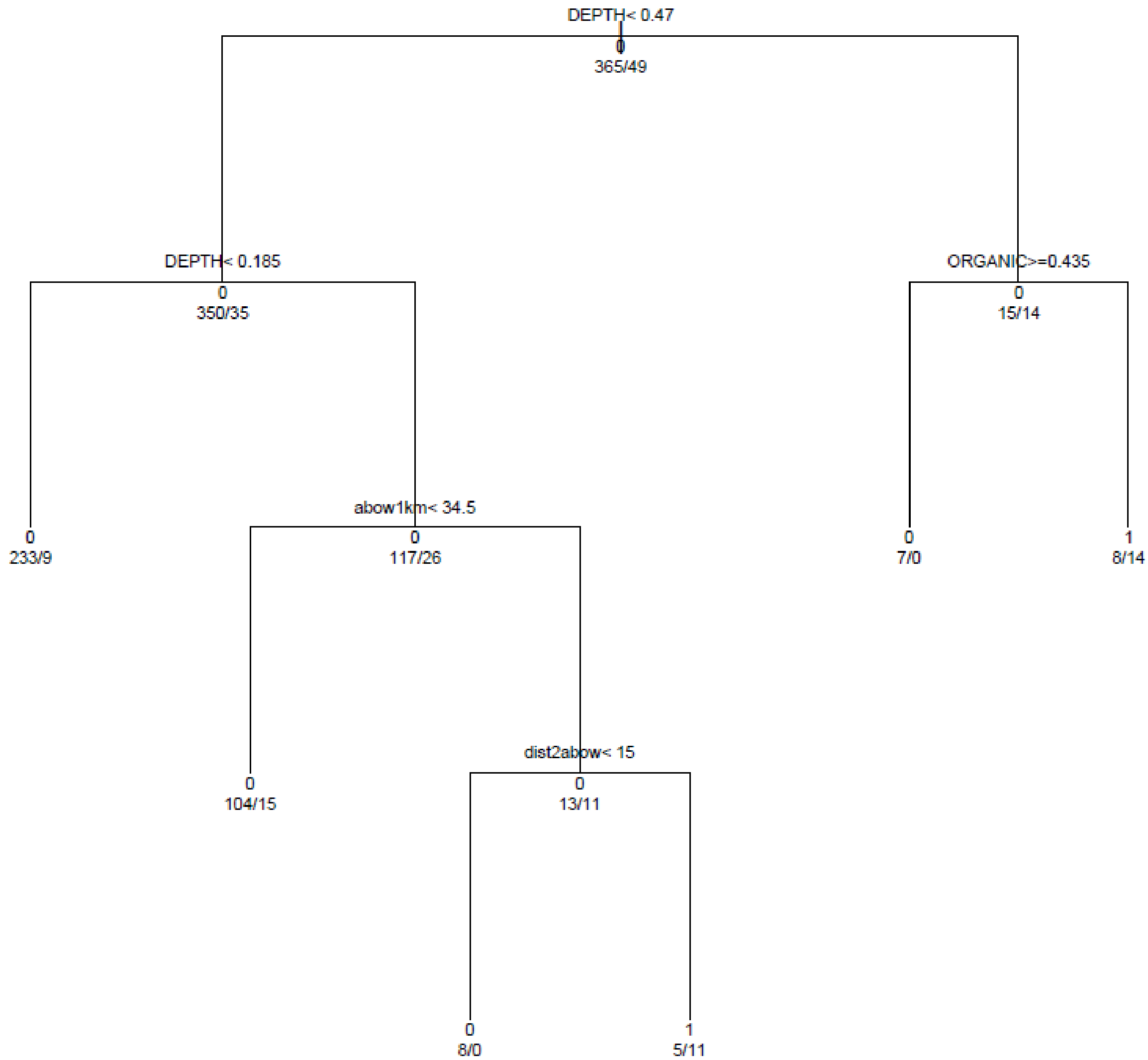
Table C-1. Continued.

Species and Model	QAIC	ΔQAIC	w_i	Model Likelihood	*K*	−2 Log-likelihood
ψ(.),*p*(SU,NO)	131.22	13.41	0.0002	0.0012	5	464.28
ψ(.),*p*(SU,WI)	132.30	14.49	0.0001	0.0007	5	468.42
ψ(.),*p*(.)	134.88	17.07	0.0000	0.0002	2	501.29
Forster's Tern ($\hat{c}$ = 1.81)						
ψ(RA,OW1,AN1),*p*(HE)	236.83	0.00	0.6567	1.0000	6	406.98
ψ(RA,AN1),*p*(HE)	238.43	1.60	0.2951	0.4493	5	413.51
ψ(RA,OW1),*p*(HE)	242.71	5.88	0.0347	0.0529	5	421.25
ψ(OW1,AN1),*p*(HE)	244.84	8.01	0.0120	0.0182	5	425.10
ψ(RA),*p*(HE)	249.16	12.33	0.0014	0.0021	4	436.54
ψ(OW1),*p*(HE)	253.59	16.76	0.0002	0.0002	4	444.56
ψ(AN1),*p*(HE)	258.93	22.10	0.0000	0.0000	4	454.23
ψ(D2OW),*p*(HE)	260.83	24.00	0.0000	0.0000	4	457.68
ψ(ED),*p*(HE)	262.62	25.79	0.0000	0.0000	4	460.92
ψ(CA),*p*(HE)	269.68	32.85	0.0000	0.0000	4	473.69
ψ(EM),*p*(HE)	270.47	33.64	0.0000	0.0000	4	475.13
ψ(WO),*p*(HE)	272.14	35.31	0.0000	0.0000	4	478.15
ψ(HE),*p*(HE)	272.16	35.33	0.0000	0.0000	4	478.18
ψ(D2RD),*p*(HE)	273.21	36.38	0.0000	0.0000	4	480.09
ψ(SC),*p*(HE)	274.82	37.99	0.0000	0.0000	4	483.00
ψ(NV),*p*(HE)	275.11	38.28	0.0000	0.0000	4	483.53
ψ(TY),*p*(HE)	278.84	42.01	0.0000	0.0000	4	490.28
ψ(D2RI),*p*(HE)	278.90	42.07	0.0000	0.0000	4	490.38
ψ(NS),*p*(HE)	278.93	42.10	0.0000	0.0000	4	490.44
ψ(OR),*p*(HE)	279.82	42.99	0.0000	0.0000	4	492.04
ψ(.),*p*(HE)	280.08	43.25	0.0000	0.0000	3	496.14
ψ(GR),*p*(HE)	280.10	43.27	0.0000	0.0000	4	492.55
ψ(D2NH),*p*(HE)	280.10	43.27	0.0000	0.0000	4	492.56
ψ(FL),*p*(HE)	281.24	44.41	0.0000	0.0000	4	494.61
ψ(DE),*p*(HE)	281.84	45.01	0.0000	0.0000	4	495.70
ψ(EM1),*p*(HE)	281.89	45.06	0.0000	0.0000	4	495.79
ψ(PH),*p*(HE)	282.02	45.19	0.0000	0.0000	4	496.04
ψ(.),*p*(EM)	282.62	45.79	0.0000	0.0000	3	500.73
ψ(.),*p*(NO)	284.28	47.45	0.0000	0.0000	3	503.75
ψ(.),*p*(WI)	290.03	53.20	0.0000	0.0000	3	514.16
ψ(.),*p*(.)	292.25	55.42	0.0000	0.0000	2	521.79
ψ(.),*p*(SU)	296.16	59.33	0.0000	0.0000	4	521.63

APPENDIX D

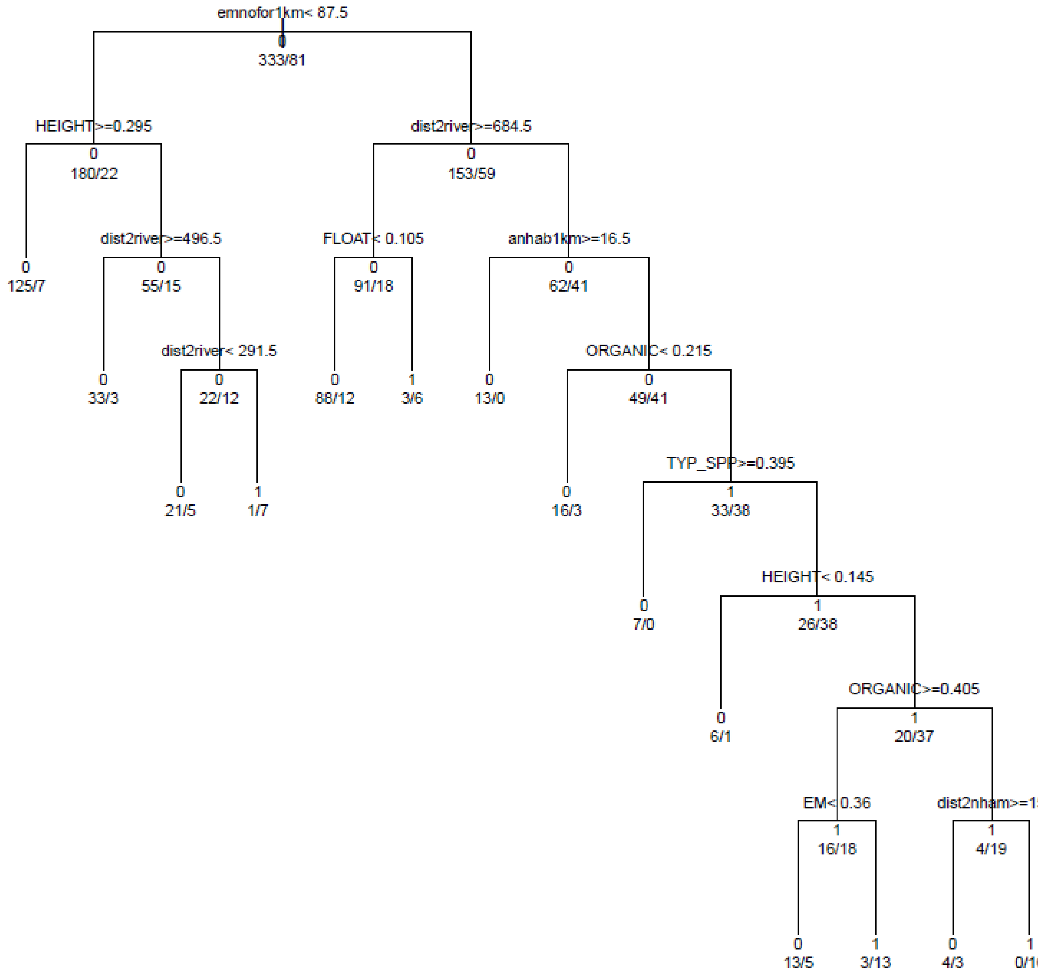
Classification and Regression Trees Using All Variables

PBGR

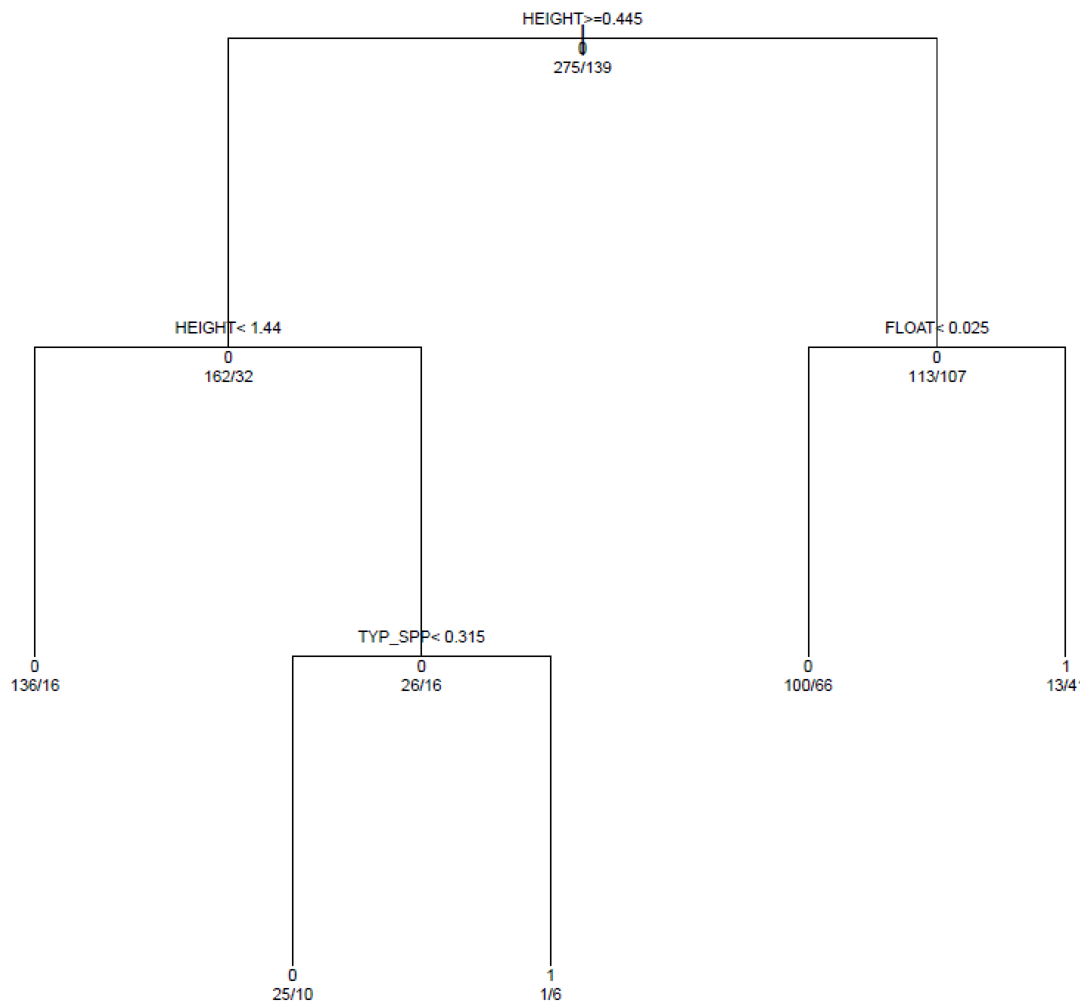


DEPTH< 0.47
0
365/49
DEPTH< 0.185
0
350/35
ORGANIC>=0.435
0
15/14
0
233/9
abow1km< 34.5
0
117/26
0
7/0
1
8/14
0
104/15
dist2abow< 15
0
13/11
0
8/0
1
5/11

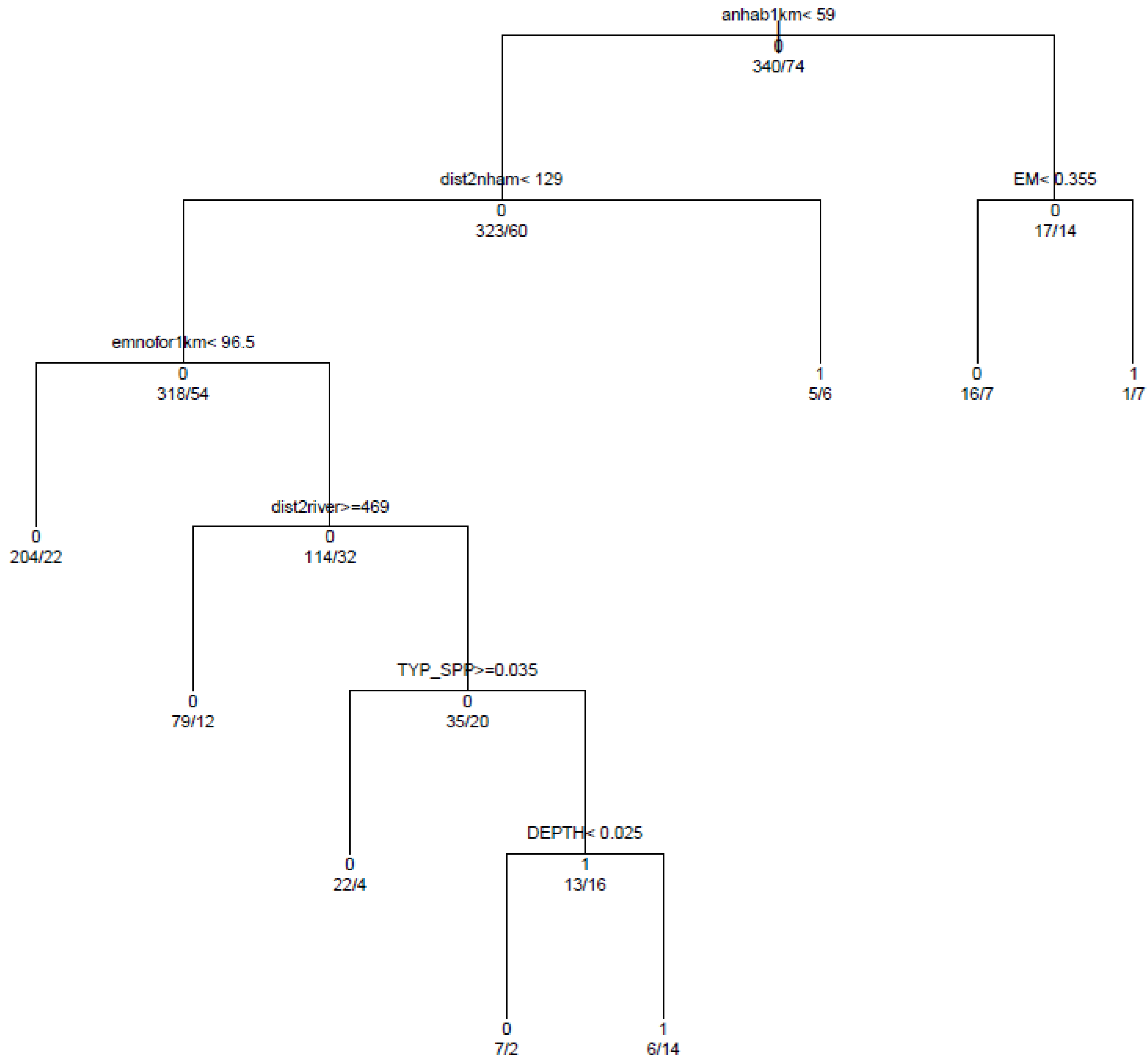
AMBI


emnofor1km< 87.5
0
333/81
HEIGHT>=0.295
0
180/22
dist2river>=684.5
0
153/59
0
125/7
dist2river>=496.5
0
55/15
FLOAT< 0.105
0
91/18
anhab1km>=16.5
0
62/41
0
33/3
dist2river< 291.5
0
22/12
0
88/12
1
3/6
0
13/0
ORGANIC< 0.215
0
49/41
0
21/5
1
1/7
0
16/3
TYP_SPP>=0.395
1
33/38
0
7/0
HEIGHT< 0.145
1
26/38
0
6/1
ORGANIC>=0.405
1
20/37
EM< 0.36
1
16/18
dist2nham>=15
1
4/19
0
13/5
1
3/13
0
4/3
1
0/16

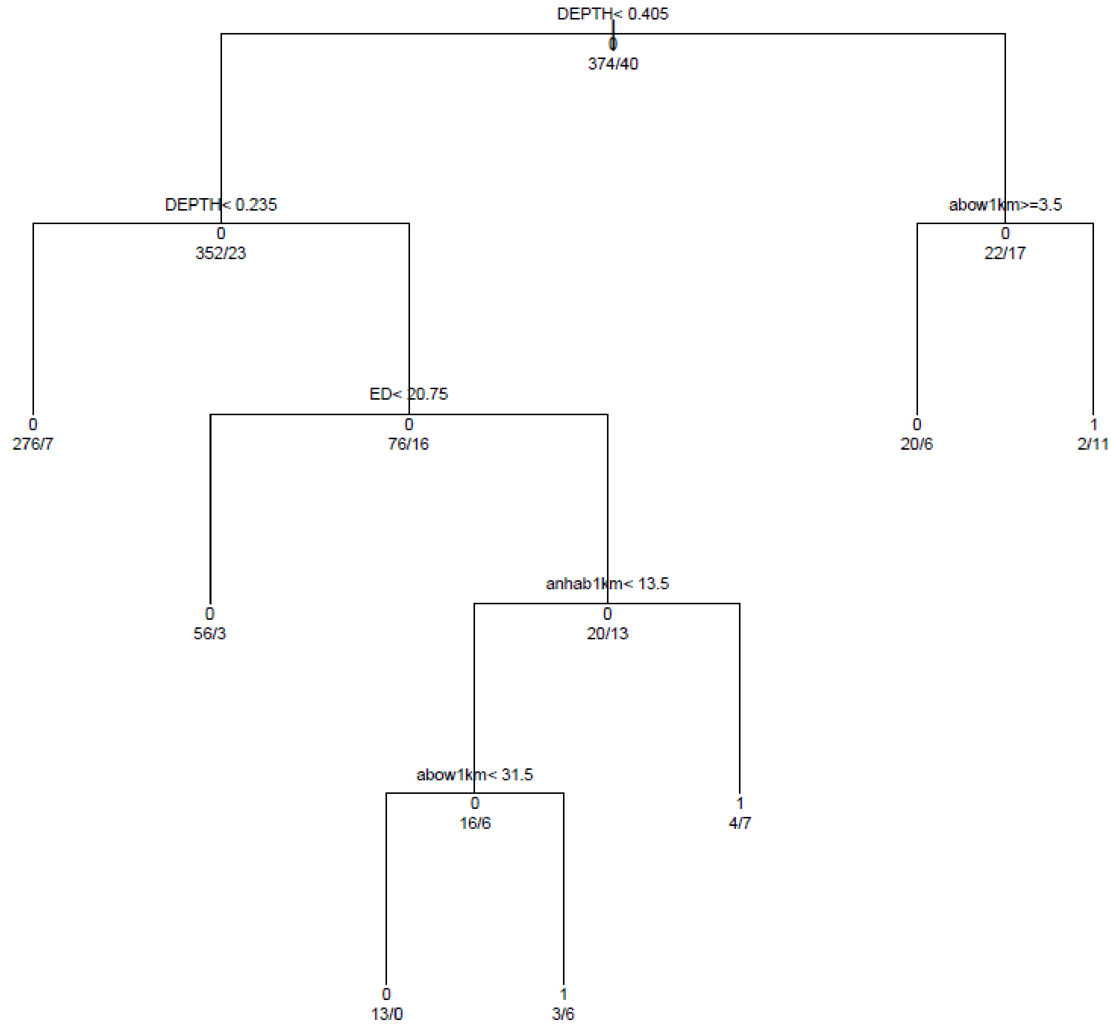
VIRA


HEIGHT>=0.445
0
275/139
HEIGHT< 1.44
0
162/32
FLOAT< 0.025
0
113/107
TYP_SPP< 0.315
0
26/16
0
136/16
0
100/66
1
13/41
0
25/10
1
1/6

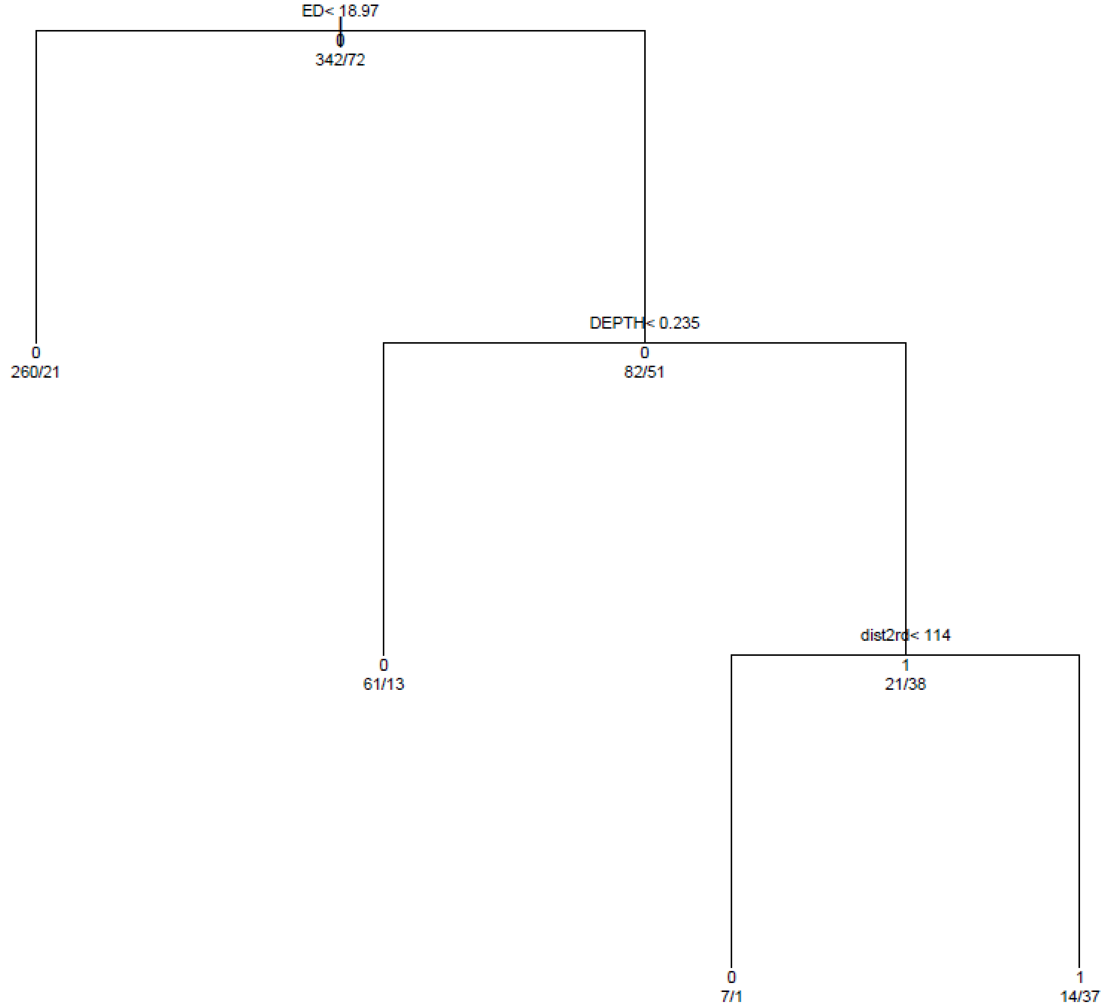
SORA

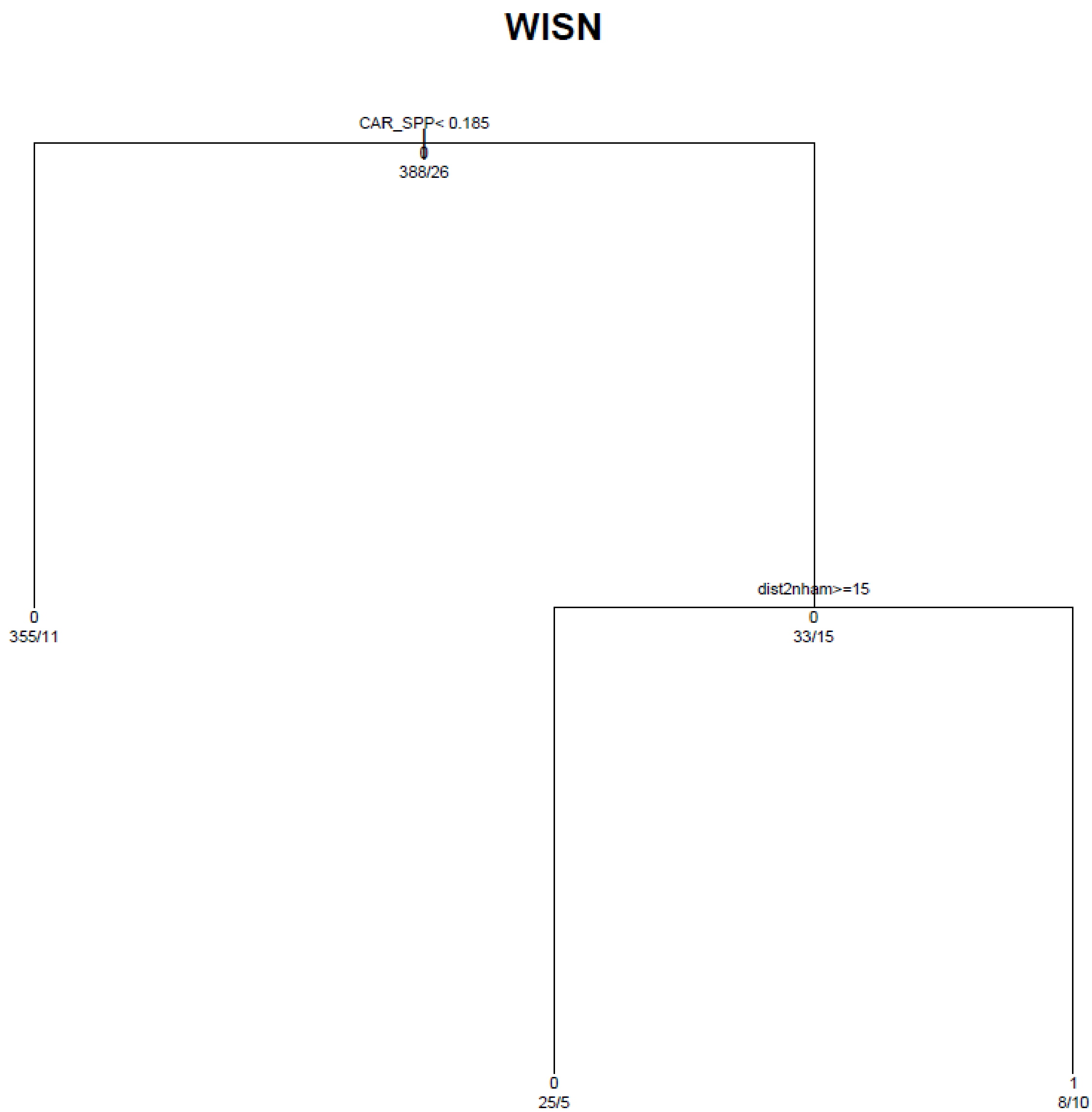

anhab1km< 59
0
340/74
dist2nham< 129
0
323/60
EM< 0.355
0
17/14
emnofor1km< 96.5
0
318/54
1
5/6
0
16/7
1
1/7
dist2river>=469
0
114/32
0
204/22
TYP_SPP>=0.035
0
35/20
0
79/12
DEPTH< 0.025
1
13/16
0
22/4
0
7/2
1
6/14

COGA

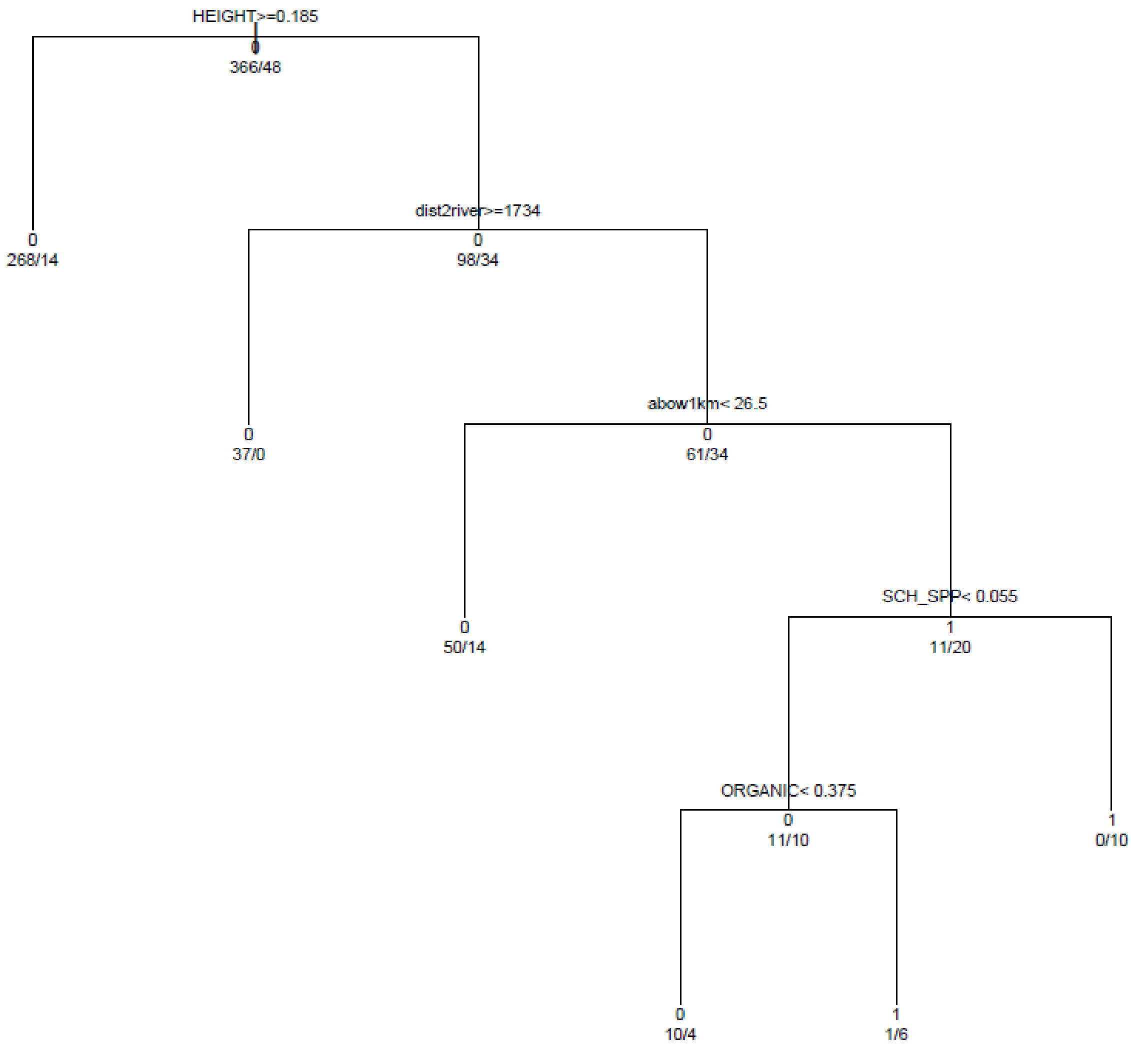

DEPTH< 0.405
0
374/40
DEPTH< 0.235
0
352/23
abow1km>=3.5
0
22/17
0
276/7
ED< 20.75
0
76/16
0
20/6
1
2/11
0
56/3
anhab1km< 13.5
0
20/13
abow1km< 31.5
0
16/6
1
4/7
0
13/0
1
3/6

AMCO

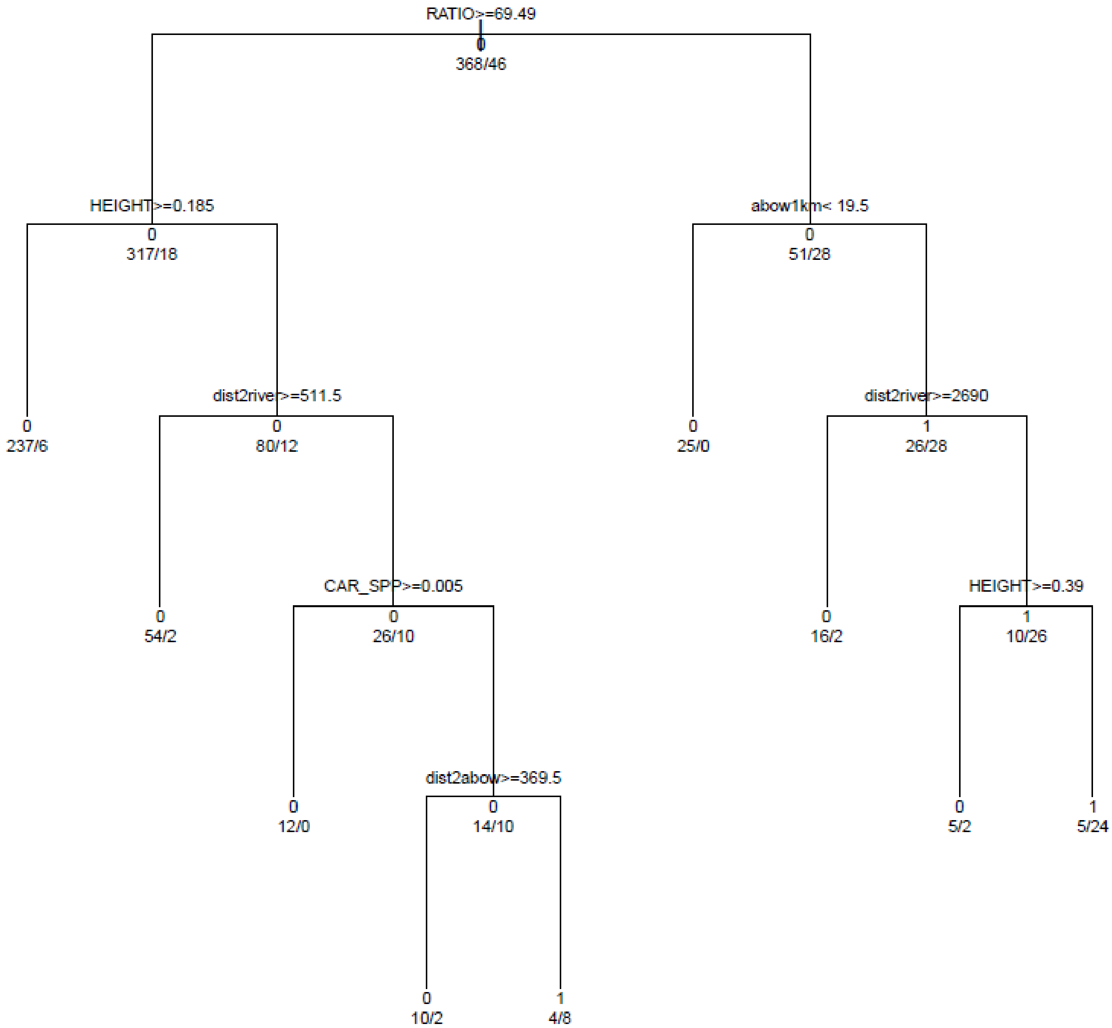

ED< 18.97
0
342/72
0
260/21
DEPTH< 0.235
0
82/51
0
61/13
dist2rd< 114
1
21/38
0
7/1
1
14/37


WISN
CAR_SPP< 0.185
0
388/26
0
355/11
dist2nham>=15
0
33/15
0
25/5
1
8/10

BLTE


HEIGHT>=0.185
0
366/48
0
268/14
dist2river>=1734
0
98/34
0
37/0
abow1km< 26.5
0
61/34
0
50/14
SCH_SPP< 0.055
1
11/20
ORGANIC< 0.375
0
11/10
1
0/10
0
10/4
1
1/6

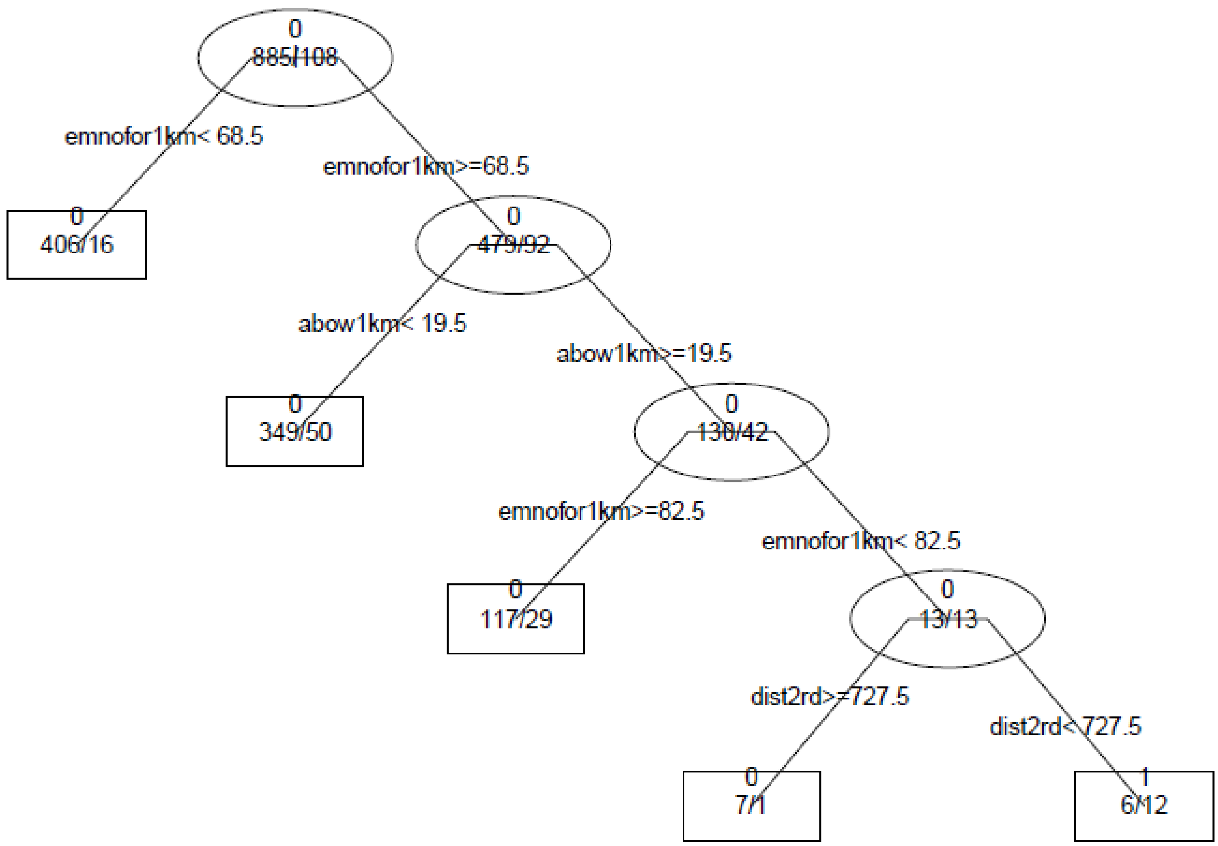
FOTE


RATIO>=69.49
0
368/46
HEIGHT>=0.185
0
317/18
abow1km< 19.5
0
51/28
0
237/6
dist2river>=511.5
0
80/12
0
25/0
dist2river>=2690
1
26/28
0
54/2
CAR_SPP>=0.005
0
26/10
0
16/2
HEIGHT>=0.39
1
10/26
0
12/0
dist2abow>=369.5
0
14/10
0
5/2
1
5/24
0
10/2
1
4/8

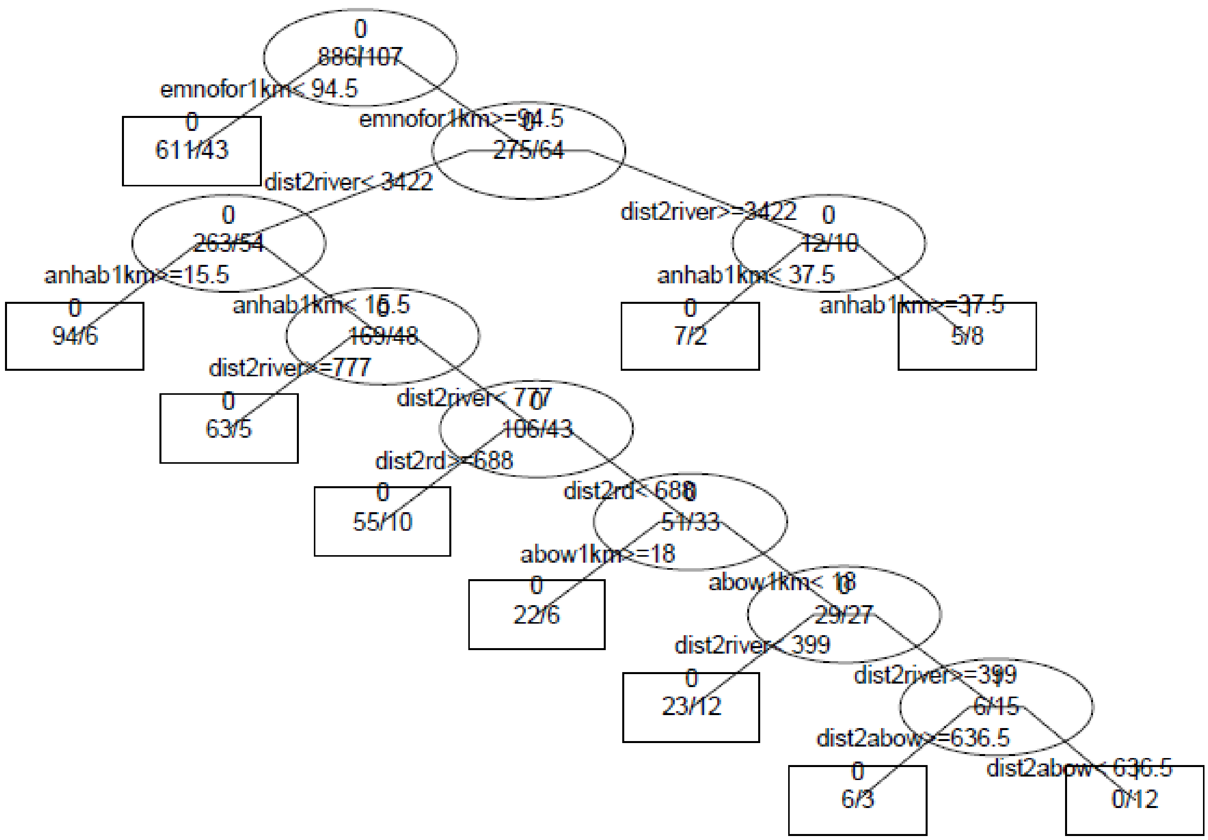
APPENDIX E

Classification and Regression Trees Using Large-scale Variables Only

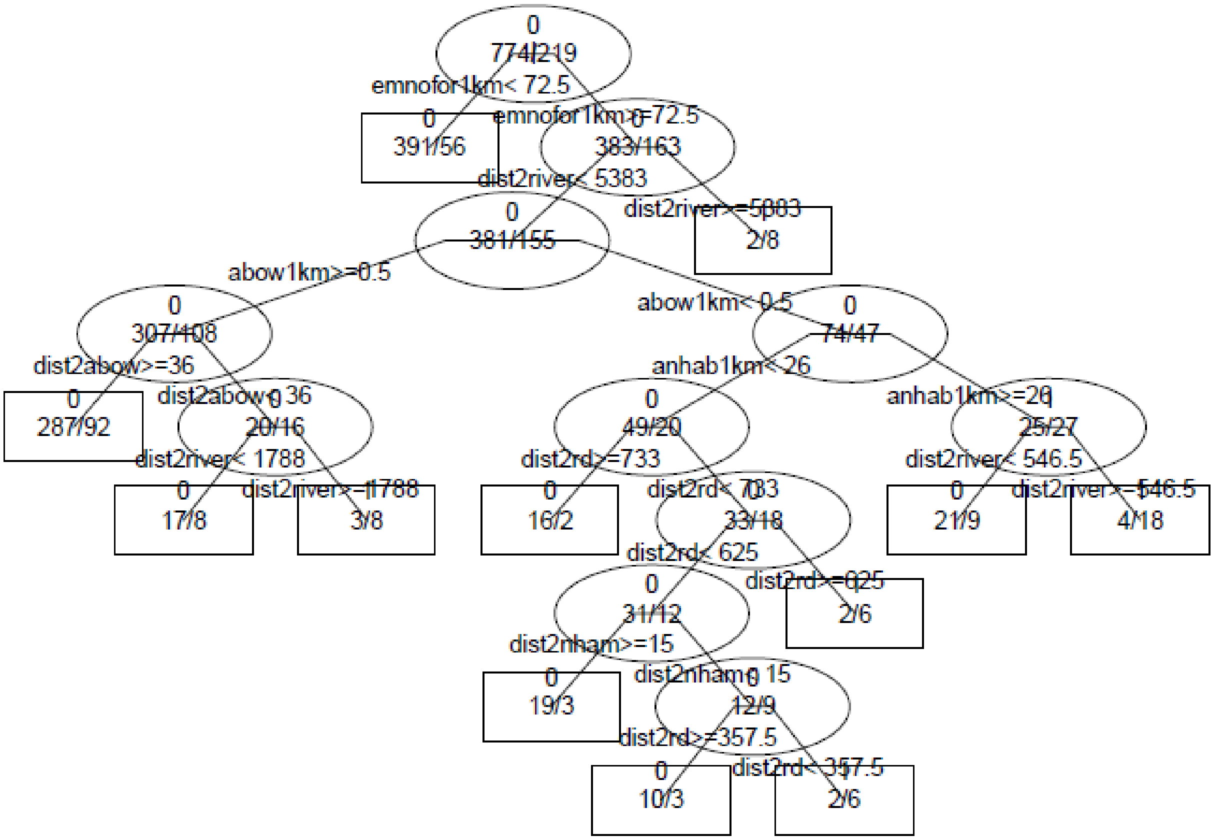
PBGR LAND


0
885/108
emnofor1km< 68.5
emnofor1km>=68.5
0
406/16
0
479/92
abow1km< 19.5
abow1km>=19.5
0
349/50
0
130/42
emnofor1km>=82.5
emnofor1km< 82.5
0
117/29
0
13/13
dist2rd>=727.5
dist2rd< 727.5
0
7/1
1
6/12

AMBI LAND

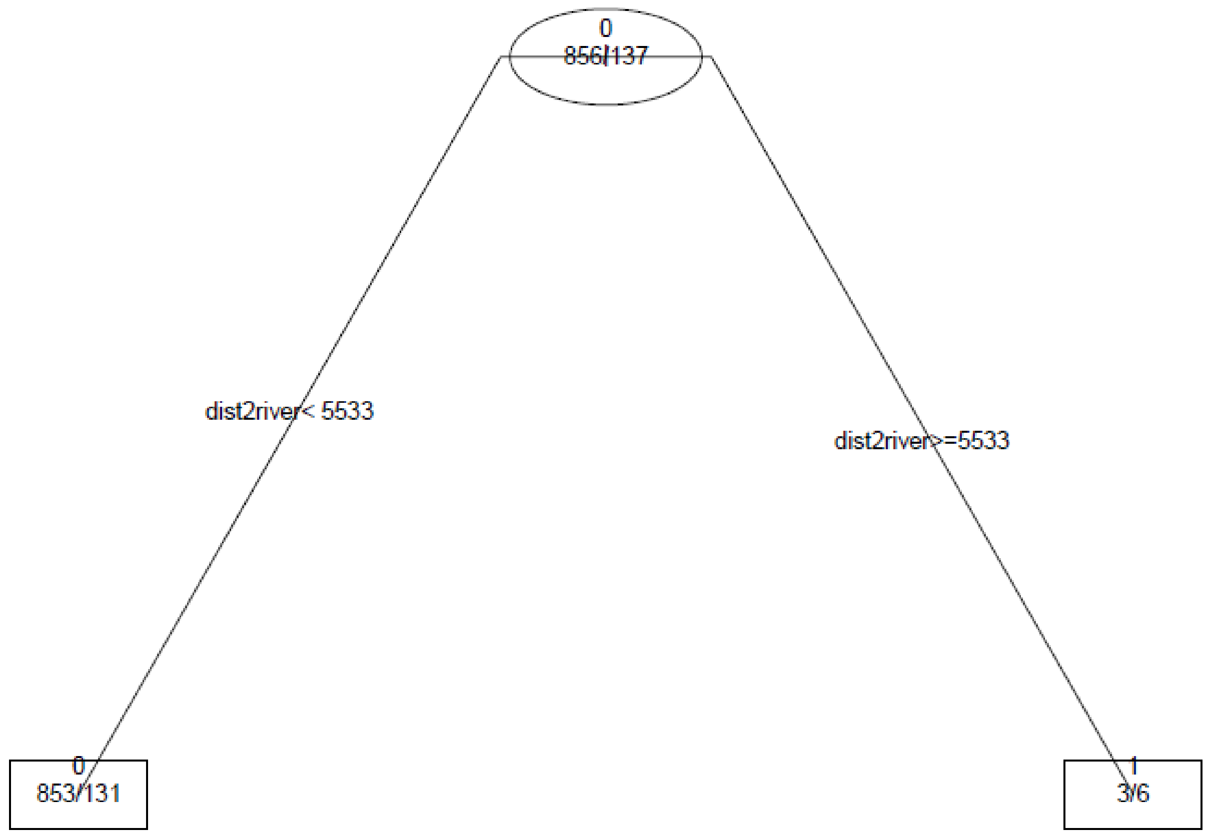

0
886/107
emnofor1km< 94.5
emnofor1km>=94.5
0
611/43
0
275/64
dist2river< 3422
dist2river>=3422
0
263/54
0
12/10
anhab1km>=15.5
anhab1km< 15.5
anhab1km< 37.5
anhab1km>=37.5
0
94/6
0
169/48
0
7/2
1
5/8
dist2river>=777
dist2river< 777
0
63/5
0
106/43
dist2rd>=688
dist2rd< 688
0
55/10
0
51/33
abow1km>=18
abow1km< 18
0
22/6
0
29/27
dist2river< 399
dist2river>=399
0
23/12
1
6/15
dist2abow>=636.5
dist2abow< 636.5
0
6/3
1
0/12

VIRA LAND

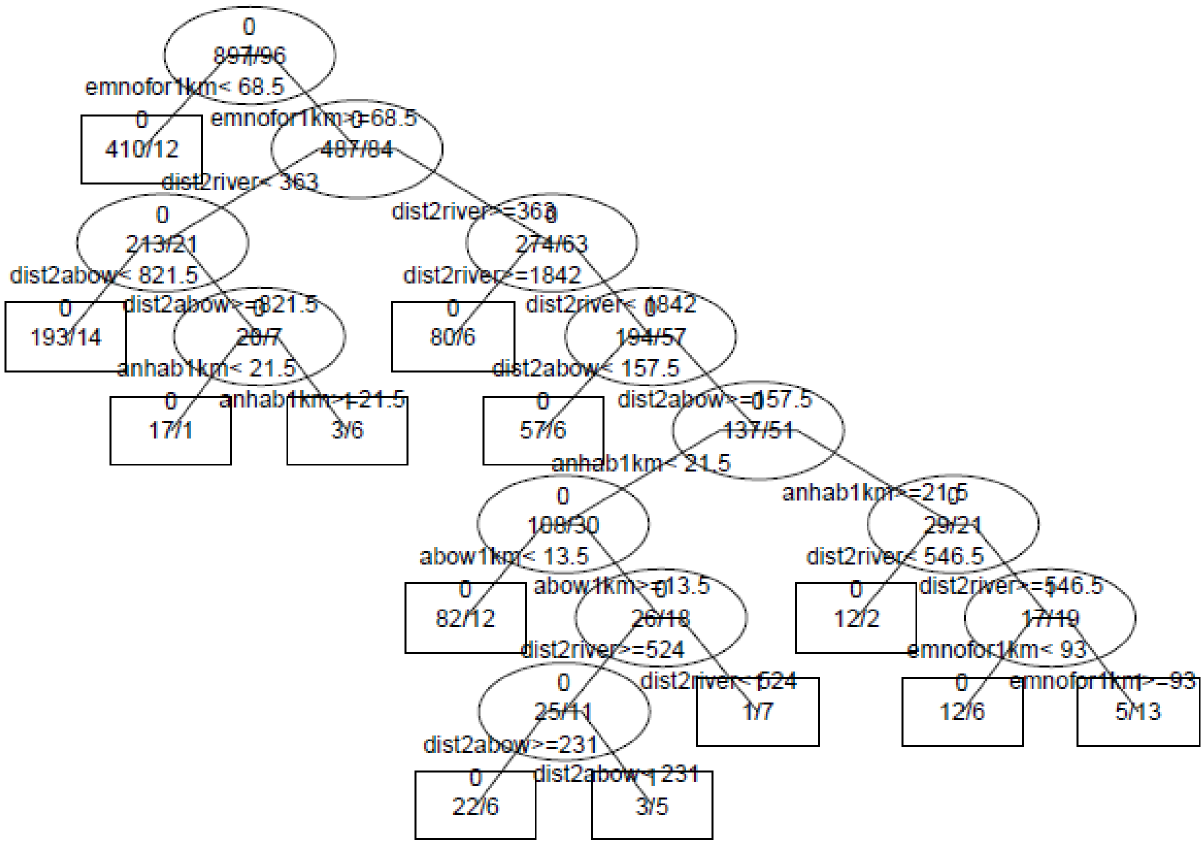


0
774/219
emnofor1km< 72.5
emnofor1km>=72.5
0
391/56
0
383/163
dist2river< 5383
dist2river>=5383
0
381/155
1
2/8
abow1km>=0.5
abow1km< 0.5
0
307/108
0
74/47
dist2abow>=36
dist2abow< 36
0
287/92
0
20/16
anhab1km< 26
anhab1km>=26
0
49/20
1
25/27
dist2river< 1788
dist2river>=1788
0
17/8
1
3/8
dist2rd>=733
dist2rd< 733
0
16/2
0
33/18
dist2river< 546.5
dist2river>=546.5
0
21/9
1
4/18
dist2rd< 625
dist2rd>=625
0
31/12
1
2/6
dist2nham>=15
dist2nham< 15
0
19/3
0
12/9
dist2rd>=357.5
dist2rd< 357.5
0
10/3
1
2/6

SORA LAND

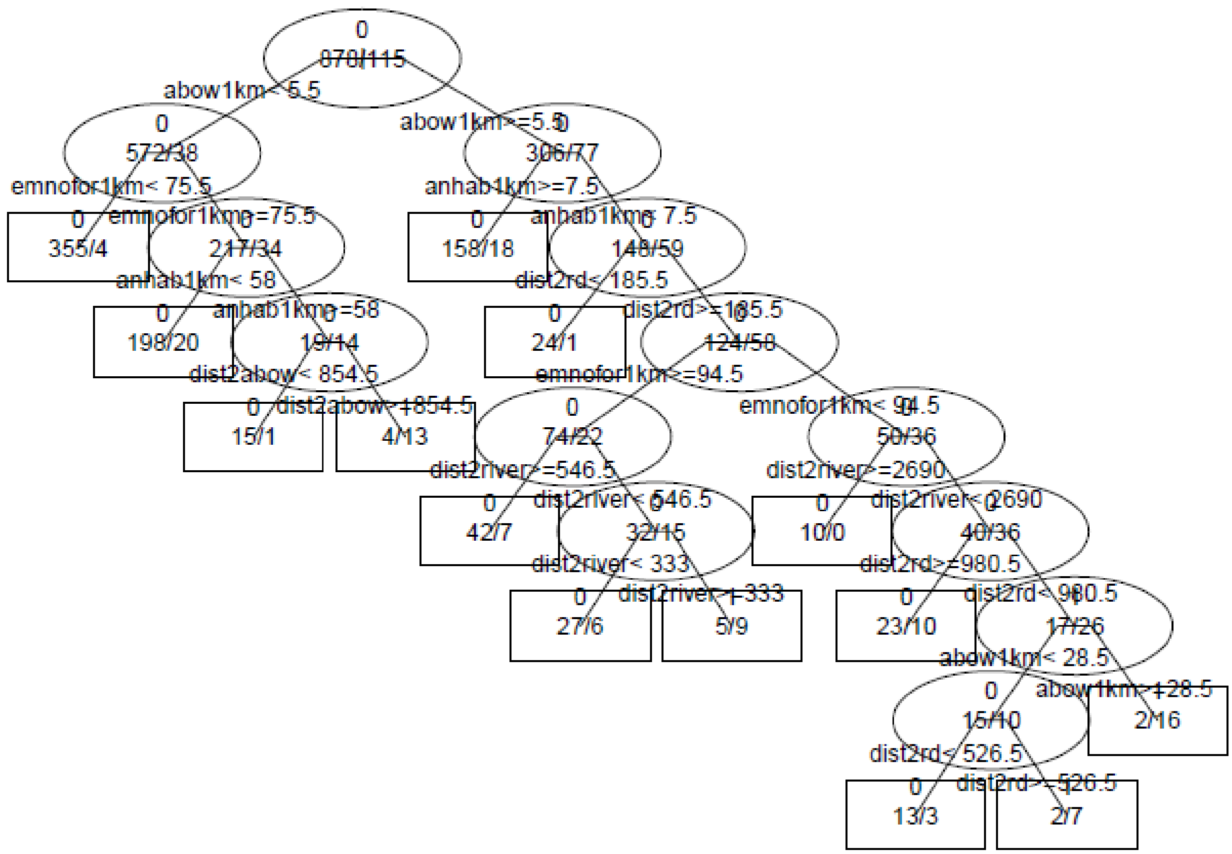


COGA LAND

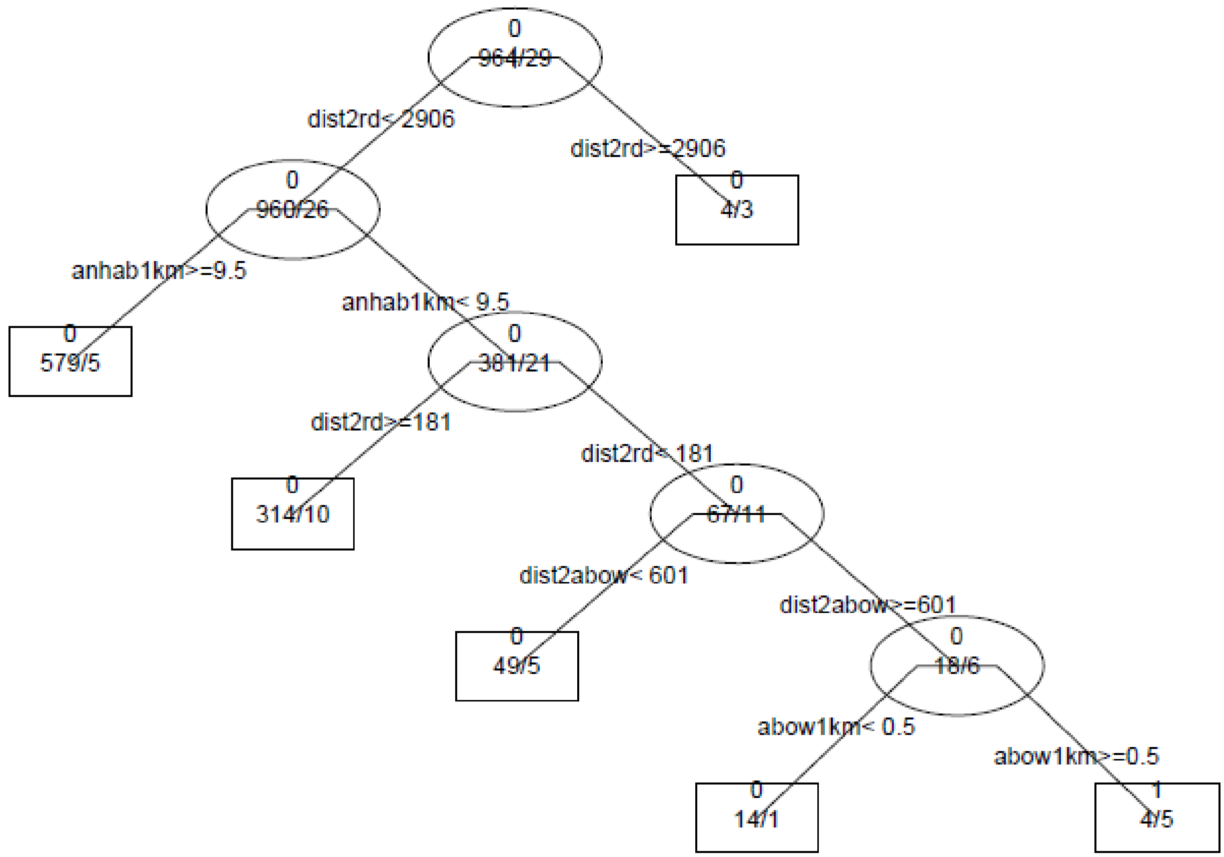


0
897/96
emnofor1km< 68.5
emnofor1km>=68.5
0
410/12
0
487/84
dist2river< 363
dist2river>=363
0
213/21
0
274/63
dist2abow< 821.5
dist2abow>=821.5
0
193/14
0
20/7
dist2river>=1842
dist2river< 1842
0
80/6
0
194/57
anhab1km< 21.5
anhab1km>=21.5
0
17/1
1
3/6
dist2abow< 157.5
dist2abow>=157.5
0
57/6
0
137/51
anhab1km< 21.5
anhab1km>=21.5
0
108/30
0
29/21
abow1km< 13.5
abow1km>=13.5
0
82/12
0
26/18
dist2river< 546.5
dist2river>=546.5
0
12/2
1
17/19
dist2river>=524
dist2river< 524
0
25/11
1
1/7
emnofor1km< 93
emnofor1km>=93
0
12/6
1
5/13
dist2abow>=231
dist2abow< 231
0
22/6
1
3/5

AMCO LAND

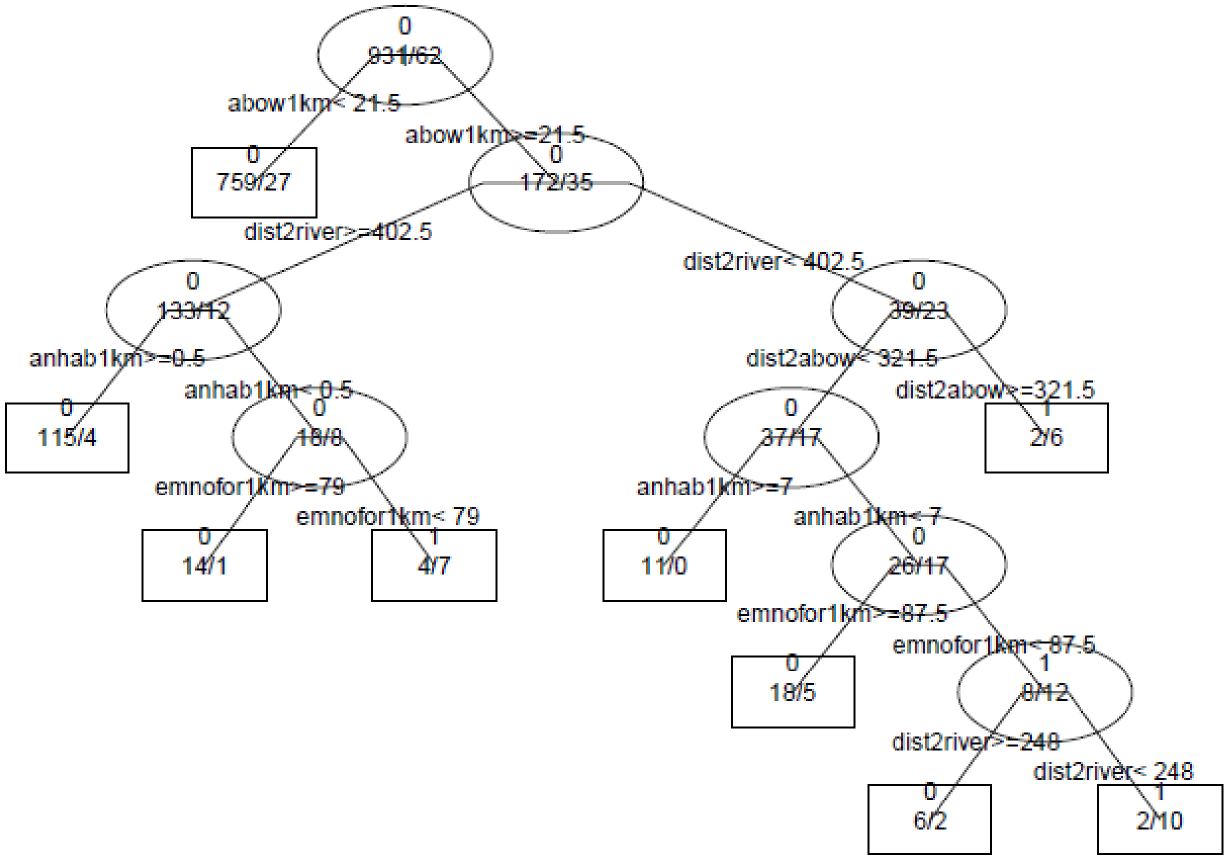

0
878/115
abow1km< 5.5
abow1km>=5.5
0
572/38
0
306/77
emnofor1km< 75.5
emnofor1km>=75.5
anhab1km>=7.5
anhab1km< 7.5
0
355/4
0
217/34
0
158/18
0
148/59
anhab1km< 58
anhab1km>=58
dist2rd< 185.5
dist2rd>=185.5
0
198/20
0
19/14
0
24/1
0
124/58
dist2abow< 854.5
dist2abow>=854.5
emnofor1km>=94.5
emnofor1km< 94.5
0
15/1
1
4/13
0
74/22
0
50/36
dist2river>=546.5
dist2river< 546.5
dist2river>=2690
dist2river< 2690
0
42/7
0
32/15
0
10/0
0
40/36
dist2river< 333
dist2river>=333
dist2rd>=980.5
dist2rd< 980.5
0
27/6
1
5/9
0
23/10
1
17/26
abow1km< 28.5
abow1km>=28.5
0
15/10
1
2/16
dist2rd< 526.5
dist2rd>=526.5
0
13/3
1
2/7

WISN LAND



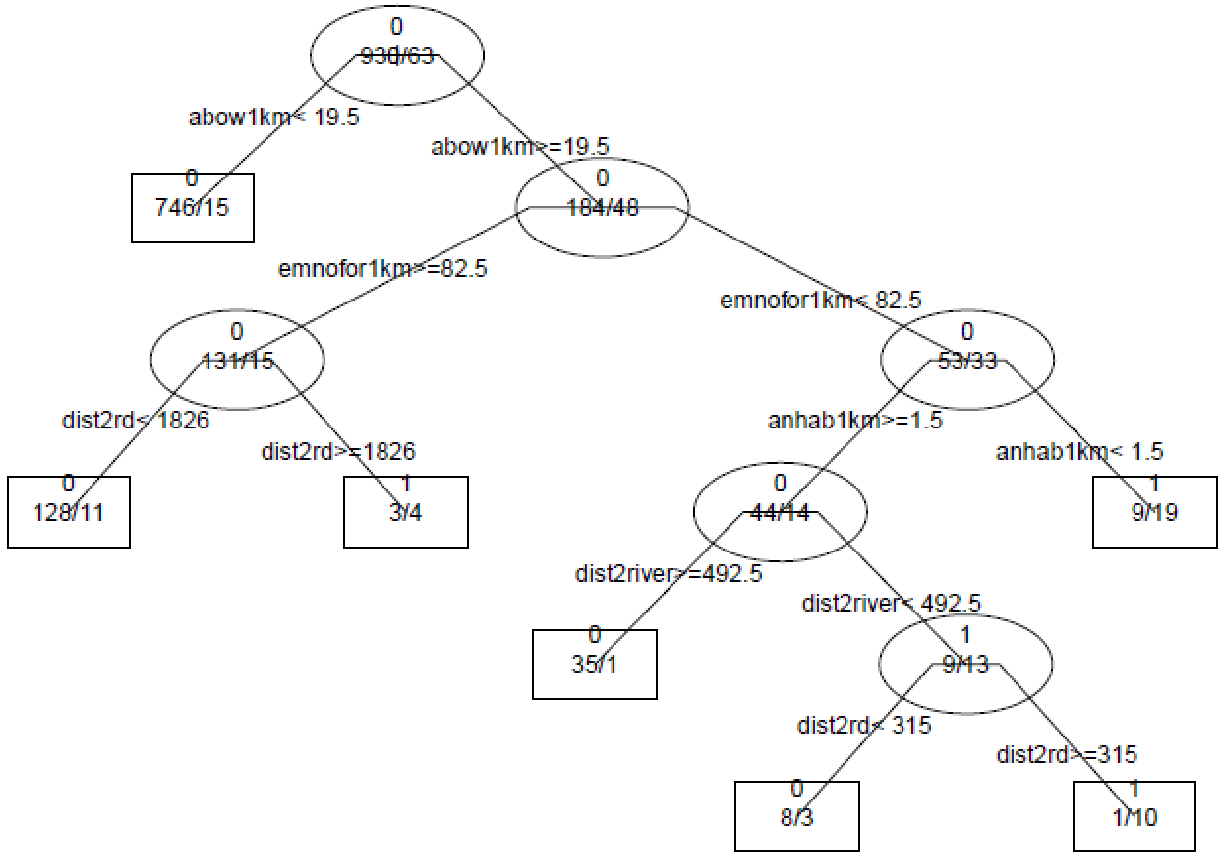
0
964/29
dist2rd< 2906
dist2rd>=2906
0
960/26
0
4/3
anhab1km>=9.5
anhab1km< 9.5
0
579/5
0
381/21
dist2rd>=181
dist2rd< 181
0
314/10
0
67/11
dist2abow< 601
dist2abow>=601
0
49/5
0
18/6
abow1km< 0.5
abow1km>=0.5
0
14/1
1
4/5

BLTE LAND



0
931/62
abow1km< 21.5
abow1km>=21.5
0
759/27
0
172/35
dist2river>=402.5
dist2river< 402.5
0
133/12
0
39/23
anhab1km>=0.5
anhab1km< 0.5
dist2abow< 321.5
dist2abow>=321.5
0
115/4
0
18/8
0
37/17
1
2/6
emnofor1km>=79
emnofor1km< 79
anhab1km>=7
anhab1km< 7
0
14/1
1
4/7
0
11/0
0
26/17
emnofor1km>=87.5
emnofor1km< 87.5
0
18/5
1
8/12
dist2river>=248
dist2river< 248
0
6/2
1
2/10

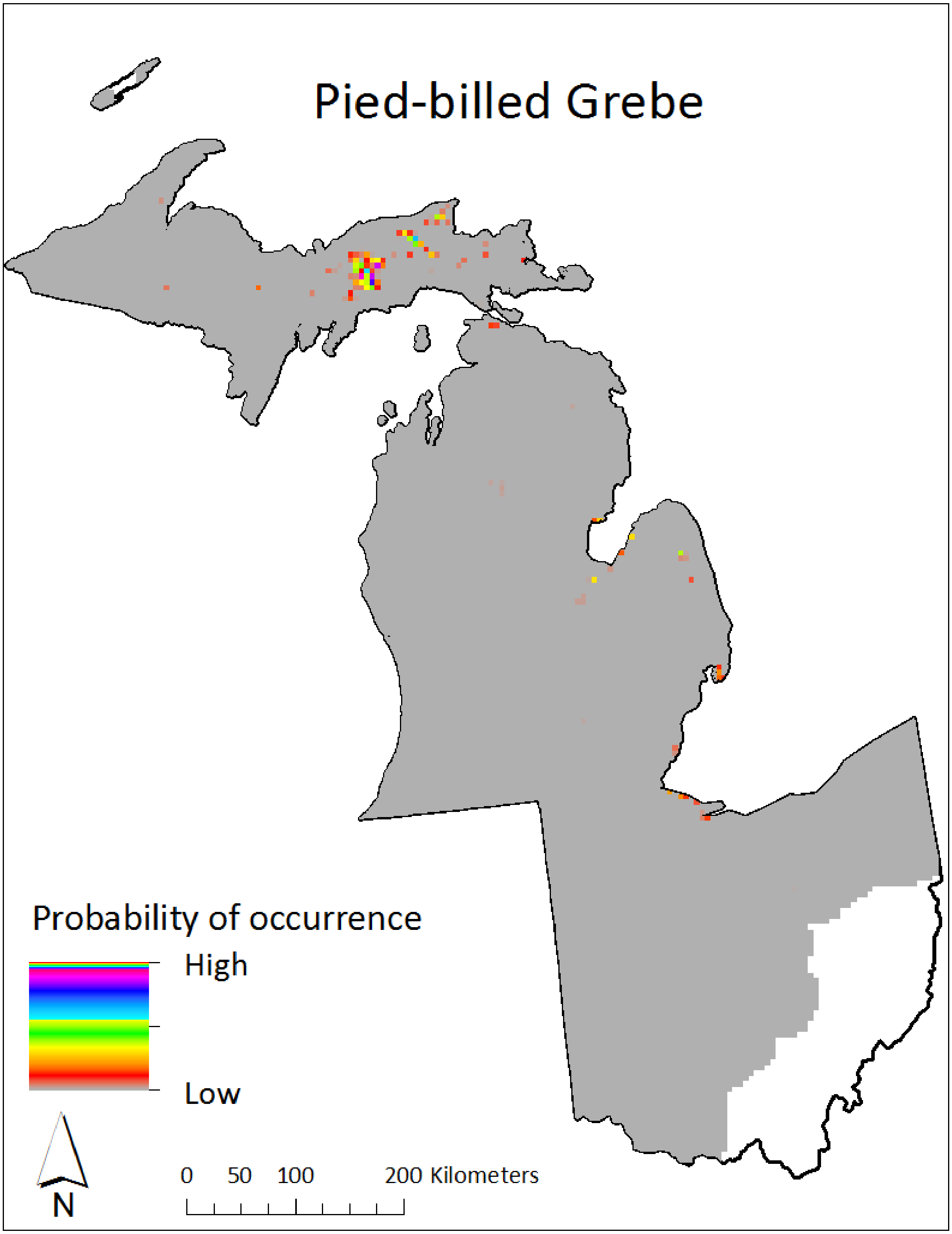
FOTE LAND


0
930/63
abow1km< 19.5
abow1km>=19.5
0
746/15
0
184/48
emnofor1km>=82.5
emnofor1km< 82.5
0
131/15
0
53/33
dist2rd< 1826
dist2rd>=1826
anhab1km>=1.5
anhab1km< 1.5
0
128/11
1
3/4
0
44/14
1
9/19
dist2river>=492.5
dist2river< 492.5
0
35/1
1
9/13
dist2rd< 315
dist2rd>=315
0
8/3
1
1/10

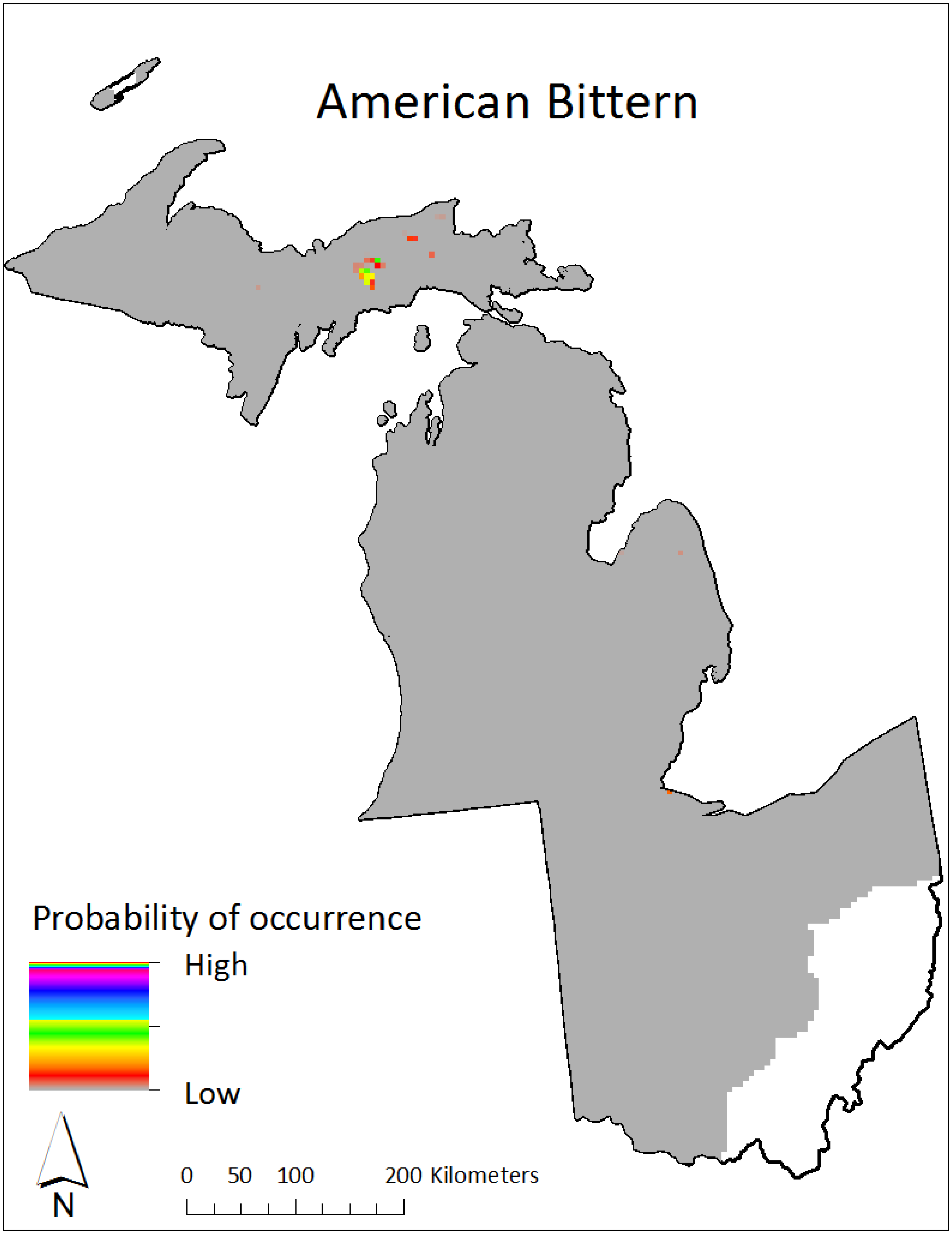
APPENDIX F

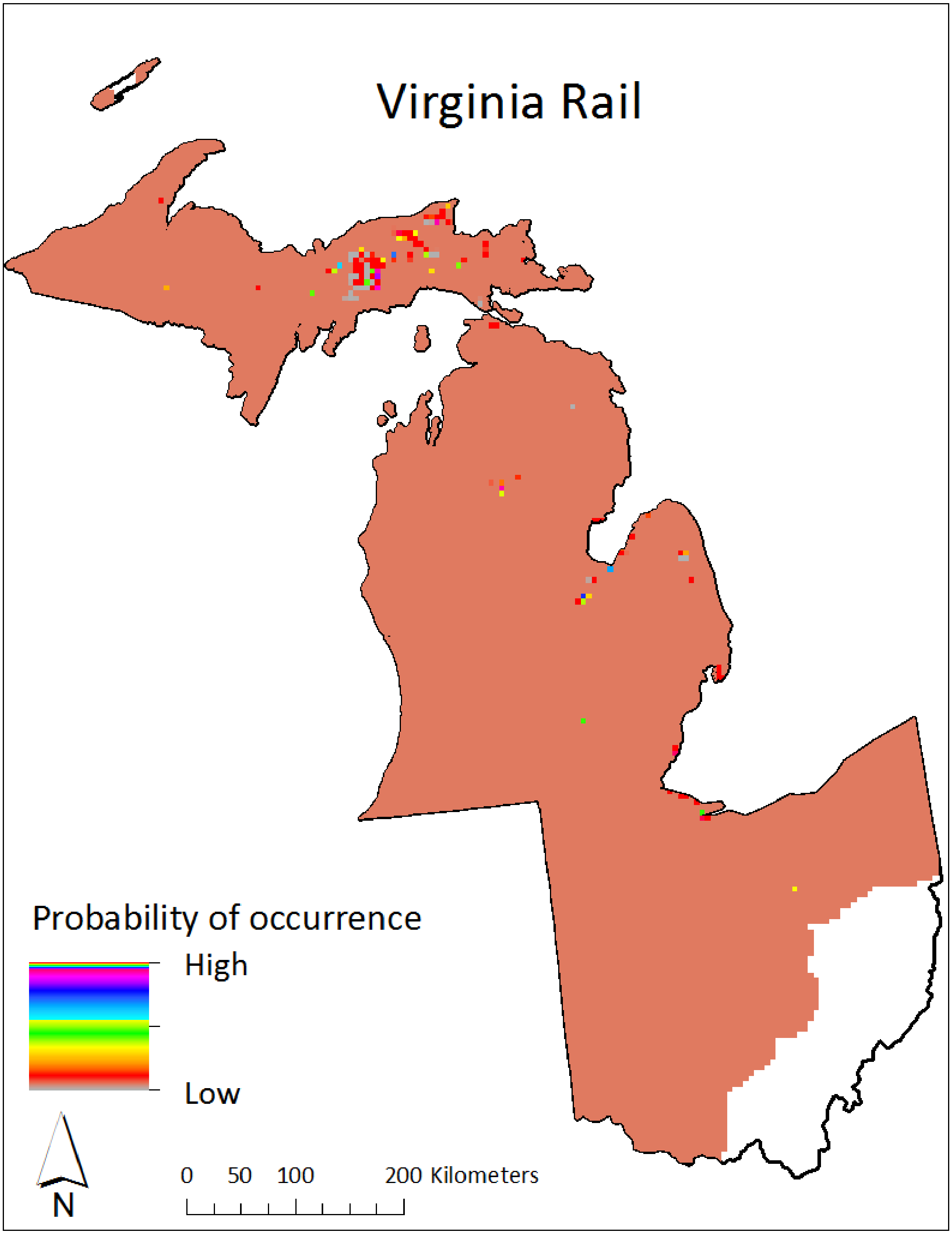
Marsh Bird Distribution Maps

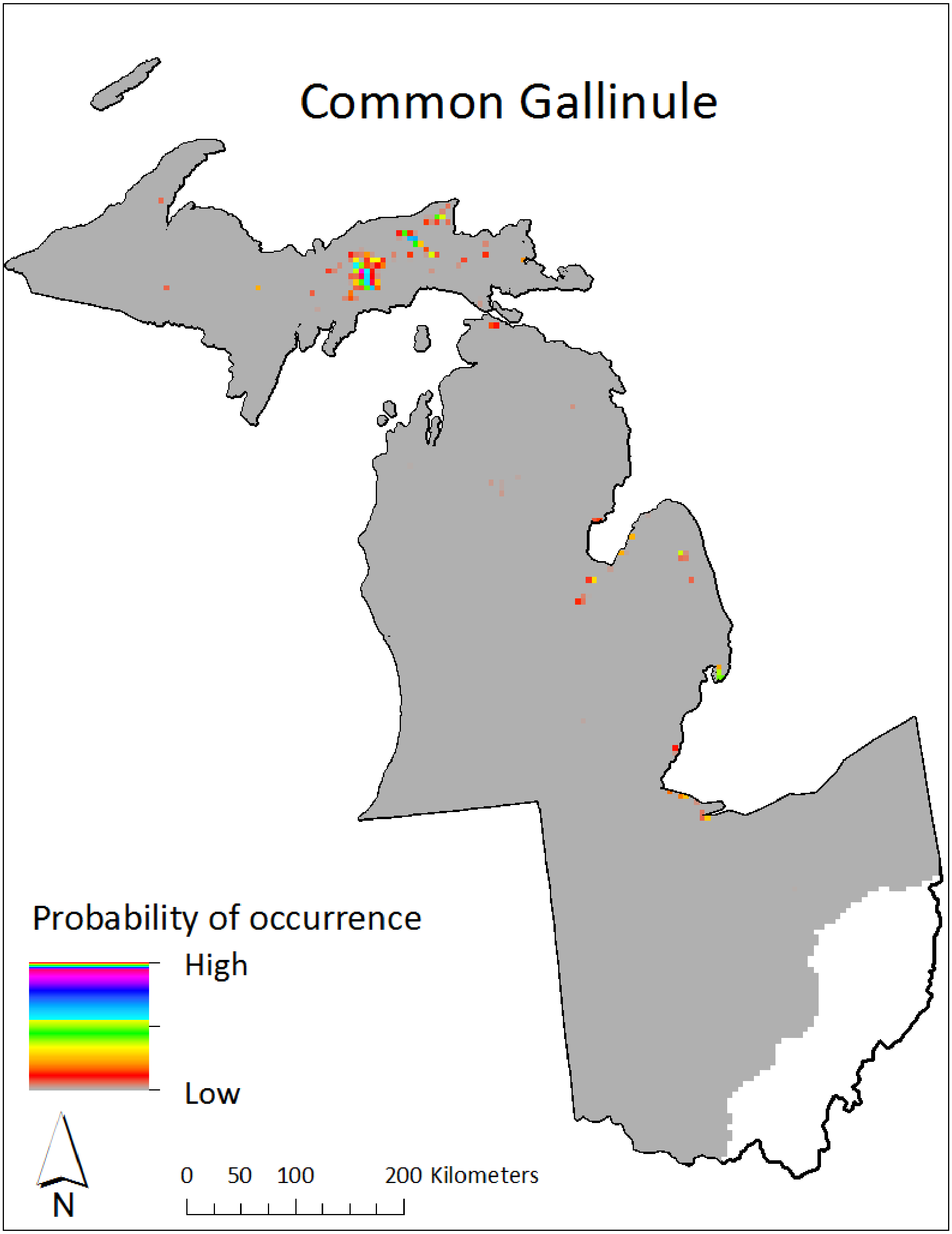
Note: The estimated probability of marsh bird species occurrence depicted in the following maps is based on classification and regression tree (CART) models developed using only large-scale, remotely sensed landscape variables. Models incorporated marsh bird occupancy and large-scale independent variables estimated at 993 points surveyed in Michigan and Ohio during 2005—2013. Least Bittern was not detected often enough for CART analysis to function. A distribution map was not produced for Sora, because the model was too simple (one variable) to reasonably predict likelihood of occurrence.

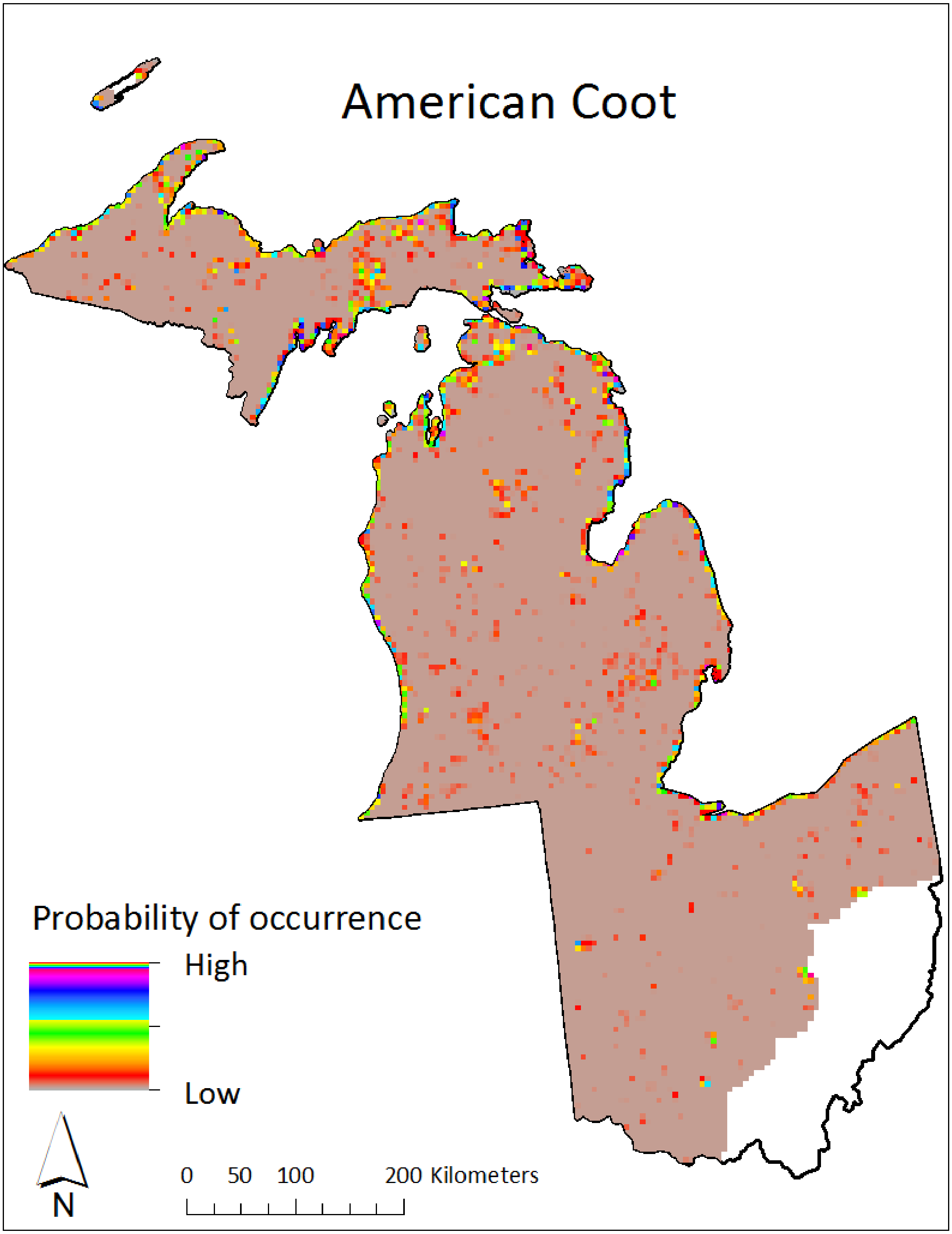


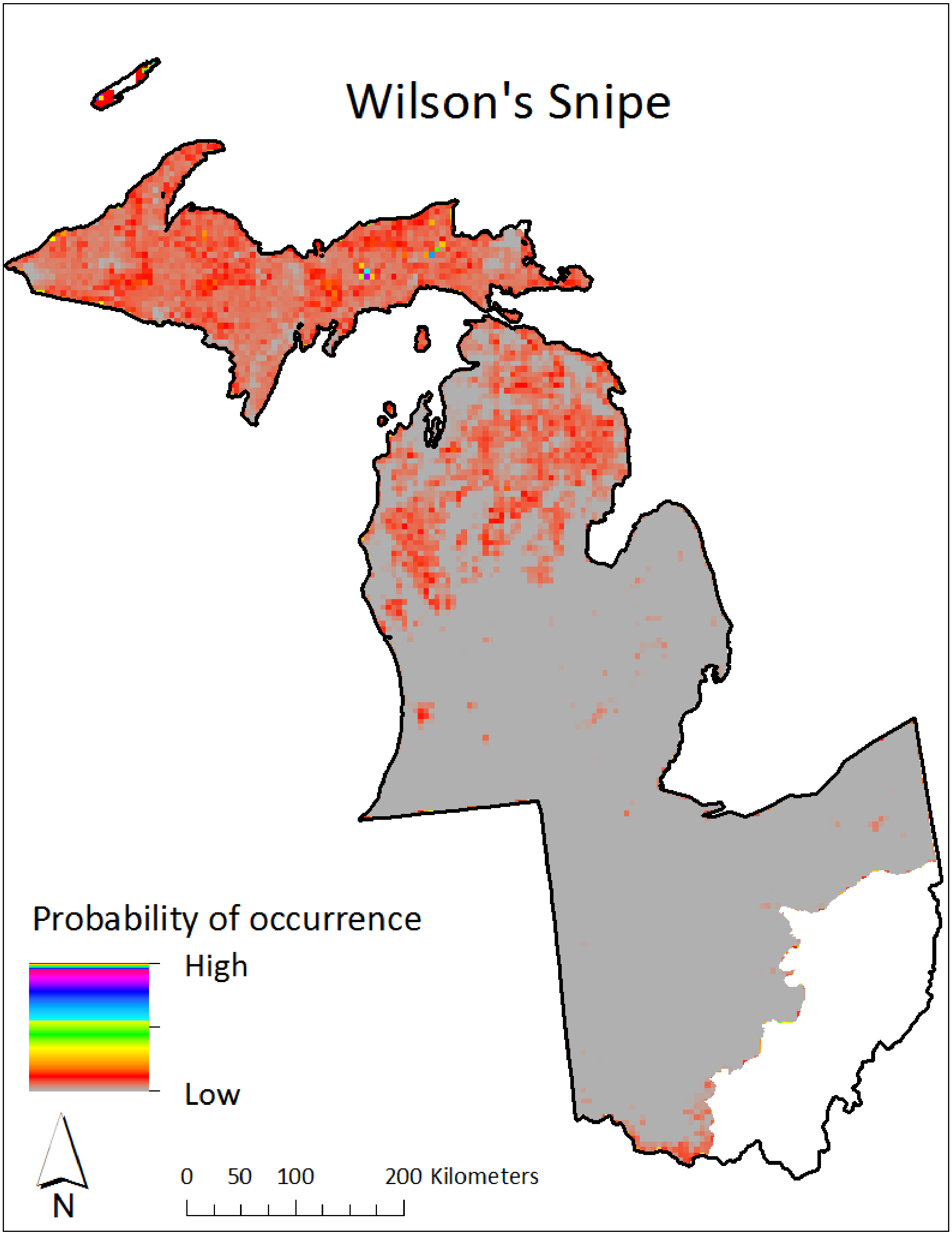
Pied-billed Grebe
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers

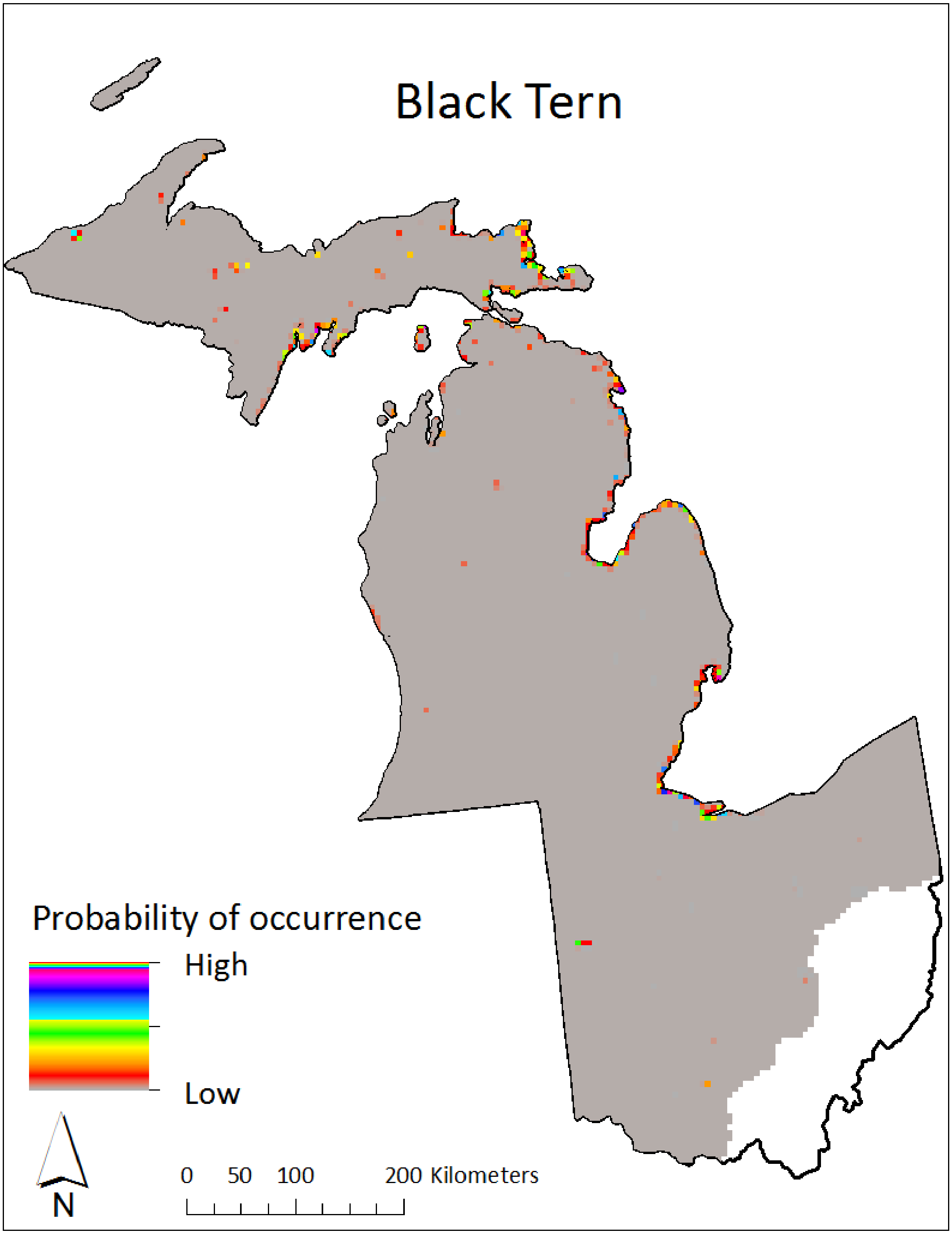

American Bittern
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers

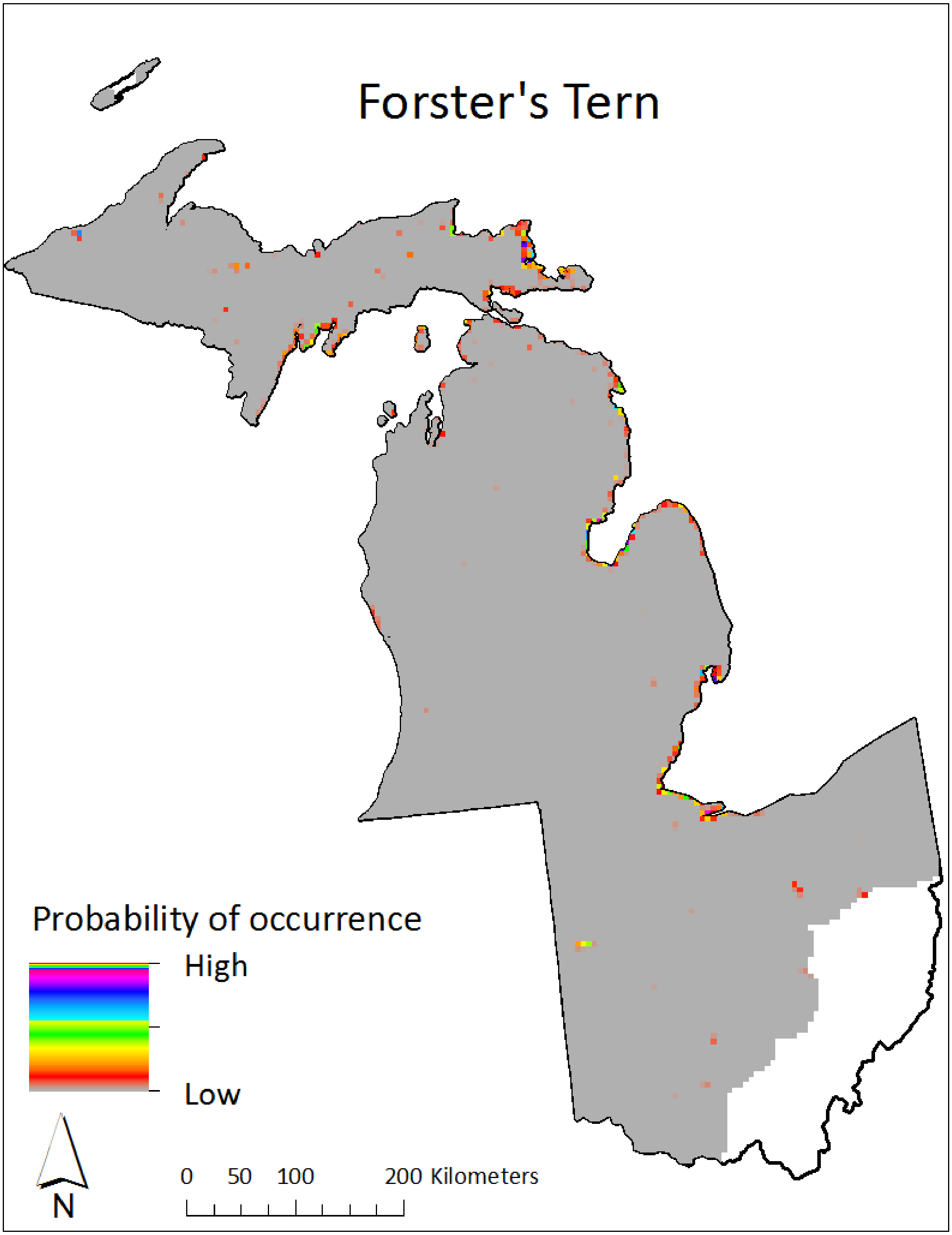

Virginia Rail
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers


Common Gallinule
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers


American Coot
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers


Wilson's Snipe
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers


Black Tern
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers



Forster's Tern
Probability of occurrence
High
Low
N
0 50 100 200 Kilometers