

THE USE OF HIGH RESOLUTION SATELLITE DATA IN WILDLIFE MODELING

by

Abigail Cohen Vitale

(Under the Direction of Robert Cooper)

ABSTRACT

With the increased capabilities of satellite sensors in recent years, there has been acute interest among researchers to utilize high-resolution satellite data in projects requiring land cover mapping. In Chapter 1 of this thesis, I investigated the advantages and limitations of three land cover classification approaches: supervised/maximum likelihood classifier, unsupervised/clustering classifier and hierarchical/rule-based knowledge classifier (HRB). I found that the two traditional approaches (supervised/unsupervised) overall performed poorly, but that each of the classification methods had notable strengths when classifying a high-resolution image. In Chapter 2, I compared the use of different data sources in bird presence/absence habitat models. I compared the performance of models that used high-resolution (<4 m) satellite data to models that used a coarser resolution (~30 m) data. I found that the results depend upon the species modeled, the scale of the features with which that species is associated and whether or not that data type can capture those features adequately.

INDEX WORDS: High-resolution image classification, Ikonos, TM, landscape modeling, avian modeling, scale, AIC

THE USE OF HIGH RESOLUTION SATELLITE DATA IN WILDLIFE MODELING

by

ABIGAIL COHEN VITALE

B.A., University of Denver, 1994

B.A., University of North Carolina, Asheville, 1999

A Thesis submitted to the graduate Faculty of University of Georgia in partial fulfillment
of the Requirements for Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2005

© 2005

Abigail Cohen Vitale

All Rights Reserved

THE USE OF HIGH RESOLUTION SATELLITE DATA IN WILDLIFE MODELING

by

ABIGAIL COHEN VITALE

Major Professor: Robert J. Cooper

Committee: Michael J. Conroy
Kathy C. Parker

Electronic Version Approved:
Maureen Grasso
Dean of the Graduate School
The University of Georgia
May 2005

DEDICATION

To my family and friends, for their unwavering support and belief that I would complete this work. I am very lucky to have you all. And to Ken Convery, my now husband-
You're fantastic!

ACKNOWLEDGEMENTS

I thank my advisor Bob Cooper for his support throughout this project. For letting me go where I wanted to go with this, although it was uncharted territory for us all. I deeply appreciated your honesty when you did not know, your willingness to help when you could, and for that door that was always open. Also a thank you to old co-advisor, Helen Whiffen for guidance and support in the early stages of the work. To committee members, Kathy Parker and Mike Conroy, I sincerely appreciated your advice and direction. In particular, Dr. Parker's support throughout the entire committee process.

A big thank you to my friends and colleagues in the Cooper Lab made the grad school experience so rich and full! To Brady Mattsson, all that and more. I sincerely appreciated all of your thoughtful advice at all hours. Thank you for asking the questions that truly helped me get my direction when I most needed it. Special thanks to Sandra Cederbaum. The voice of reason and the giver of hundreds of favors. A special thank you to John Gallagher at BF Grant for listening to his heart and ignoring the paranoia of the Dean and others...the results of this work speak for your good judgment! and to Clint Moore for your SAS APLR macro and your AIC advice, thank you for accepting all of the impromptu visits.

The Virginia Tech Statistic Consulting center provided many hours of thought and guidance for the non-linear mixed model stage of this work. In particular, Ed Boone, Penelope Pooler, Eric Smith, and Amy Hsiao. Though in the end, the work was not incorporated in the thesis, I hope that eventually we will be able to get it out! Also, a special thank you to Lola Roghair for writing the ARCGIS code that shortened the project by months!

This research was funded by the Georgia Piedmont Natural Resource Cooperative (GPNRC), National Fish and Wildlife Foundation and Warnell School of Forest Resources.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	v
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF FIGURES	viii
LIST OF APPENDICIES.....	xv
INTRODUCTION TO CHAPTERS 1 AND 2	1
CHAPTER 1 : LAND COVER CLASSIFICATION OF HIGH RESOLUTION DATA: AN EXPLORATORY ANALYSIS OF CLASSIFICATION TECHNIQUES AND METHODS USING A 4-M IKONOS IMAGE.....	4
Introduction.....	4
Methods.....	7
Results	20
Discussion.....	22
Literature Cited	29
CHAPTER 2 : THE COMPARISON OF HIGH AND LOW RESOLUTION SATELLITE DATA IN BIRD HABITAT MODELING.....	51
Introduction.....	51
Materials And Methods.....	57
Results	74
Discussion.....	82
Literature Cited	94
THESIS SUMMARY	193

LIST OF TABLES

Table 1-1: Definition of supervised classification categories for forest types.....	34
Table 1-2: Unsupervised classification land cover categories for Ikonos image before final recode.....	35
Table 1-3: Unsupervised classification land cover categories for Ikonos image after final recode.	36
Table 1-4: Hierarchical/rule-based classifier table.	37
Table 1-5: File descriptions referenced in rule-based classifier table.....	38
Table 1-6: Hierarchical rule-based (or Knowledge Classifier) classification land cover categories for Ikonos image.	39
Table 1-7: Error matrix for supervised classification.	40
Table 1-8: Accuracy assessment for supervised classification.	41
Table 1-9: Error matrix for unsupervised classification (no re-code).....	42
Table 1-10: Accuracy assessment for unsupervised classification (no re-code).	43
Table 1-11: Error matrix for unsupervised final re-code classification.	44
Table 1-12: Accuracy assessment for unsupervised final re-coded classification.....	45
Table 1-13: Error matrix for knowledge classifier.	46
Table 1-14: Accuracy assessment for knowledge classifier.	47
Table 2-1: Data Model Categories.....	108
Table 2-2: Land cover categories.....	108
Table 2-3: Percent correctly classified results from the jackknife validation method.....	109
Table 2-4: AICc differences by species and data type.	110
Table 2-5: Percent sensitivity results from the jackknife validation method.....	111
Table 2-6: Percent specificity results from the jackknife validation method..	112

LIST OF FIGURES

Figure 1-1: Distribution of training and validation vegetation points used in image classification.	
.....	48
Figure 2-1: Rule-based classification diagram of TM images. Diagram continues.	113
Figure 2-2: Total area represented by each land cover category for the Ikonos land cover classification for the year 2000.	115
Figure 2-3: Total area represented by each land cover category for the Ikonos land cover classification for the year 2001.	116
Figure 2-4: Total area represented by each land cover category for the TM land cover classification for the year 2000.	117
Figure 2-5: Total area represented by each land cover category for the TM land cover classification for the year 2001.	118
Figure 2-6: Validation results: Correct classification ranges of top ten models for each data type for the Acadian Flycatcher. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.....	119
Figure 2-7: Validation results: Correct classification ranges of top ten models for each data type for the Red-eyed Vireo. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.....	120
Figure 2-8: Validation results: Correct classification ranges of top ten models for each data type for the Yellow-billed Cuckoo. The figures represent the highest value and the lowest	

correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model. 121

Figure 2-9: Validation results: Correct classification ranges of top ten models for each data type for the Indigo Bunting. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model..... 122

Figure 2-10: Validation results: Correct classification ranges of top ten models for each data type for the Prairie Warbler. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model. 123

Figure 2-11: Validation results: Correct classification ranges of top ten models for each data type for the Yellow-breasted Chat. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model. 124

Figure 2-12: Validation results: Correct classification ranges of top ten models for each data type for closed canopy species. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model. 125

Figure 2-13: Validation results: Correct classification ranges of top ten models for each data type for early successional species. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model. 126

Figure 2-14: Ranges of AICc differences (Δ AICc) for the Acadian Flycatcher. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 127

Figure 2-15: Ranges of AICc differences (Δ AICc) for the Red-eyed Vireo. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 128

Figure 2-16: Ranges of AICc differences (Δ AICc) for the Yellow-billed Cuckoo. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 129

Figure 2-17: Ranges of AICc differences (Δ AICc) for the Indigo Bunting. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 130

Figure 2-18: Ranges of AICc differences (Δ AICc) for the Prairie Warbler. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The

lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 131

Figure 2-19: Ranges of AICc differences (Δ AICc) for the Yellow-breasted Chat. The figures

represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 132

Figure 2-20: Ranges of AICc differences (Δ AICc) for closed canopy species. The figures

represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 133

Figure 2-21: Ranges of AICc differences (Δ AICc) for the early successional species. The

figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support. 134

Figure 2-22: Sum of Akaike weights for the top ten models in each data category for all species.

The weight represents the normalized likelihood for all models in the set. When all the weights for each data type are summed for each species, they will equal one. The weight measures the empirical support the parameters have for each model..... 135

Figure 2-23: Sum of Akaike weights for the top ten models in each data category for closed

canopy species. The weight represents the normalized likelihood for all models in the set.

When all the weights for each data type are summed for each species, they will equal one.

The weight measures the empirical support the parameters have for each model..... 136

Figure 2-24: Sum of Akaike weights for the top ten models in each data category for early successional species. The weight represents the normalized likelihood for all models in the set. When all the weights for each data type are summed for each species, they will equal one. The weight measures the empirical support the parameters have for each model..... 137

Figure 2-25: Sensitivity ranges for the Acadian Flycatcher. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model. 138

Figure 2-26: Sensitivity ranges for the Red-eyed Vireo. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model. 139

Figure 2-27: Sensitivity ranges for the Yellow-billed Cuckoo. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model. 140

Figure 2-28: Sensitivity ranges for the Indigo Bunting. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model. 141

Figure 2-29: Sensitivity ranges for the Prairie Warbler. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model. 142

Figure 2-30: Sensitivity ranges for the Yellow-breasted Chat. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.	143
Figure 2-31: Sensitivity ranges for closed canopy species. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.	144
Figure 2-32: Sensitivity ranges for early successional species. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.	145
Figure 2-33: Specificity ranges for the Acadian Flycatcher. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.	146
Figure 2-34: Specificity ranges for the Red-eyed Vireo. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.	147
Figure 2-35: Specificity ranges for the Yellow-billed Cuckoo. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.	148
Figure 2-36: Specificity ranges for the Indigo Bunting. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.	149

Figure 2-37: Specificity ranges for the Prairie Warbler. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model..... 150

Figure 2-38: Specificity ranges for the Yellow-breasted Chat. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.
..... 151

Figure 2-39: Specificity ranges for the closed canopy species. The figures represent the highest value and the lowest specificity value for the models in that data group across species. The reference line placed at 70% represents the cut off point of a good specific habitat model.
..... 152

Figure 2-40: Specificity ranges for the early successional species. The figures represent the highest value and the lowest specificity value for the models in that data group across species. The reference line placed at 70% represents the cut off point of a good specific habitat model..... 153

LIST OF APPENDICIES

Appendix 1-A: GIS metadata.	49
Appendix 1-B: Land cover classification vegetation measurements.	50
Appendix 2-A: Original variable set used in models for all species (Field and GIS Variables).	154
Appendix 2-B: Habitat types.	158
Appendix 2-C: Vegetation structure definitions.	158
Appendix 2-D: Wildlife field measurements in models.	159
Appendix 2-E: GIS metadata.	160
Appendix 2-F: GIS data variables used in models.	161
Appendix 2-G: Merged land cover groups used for creating landscape metrics.	161
Appendix 2-H: Landscape metrics.	162
Appendix 2-I: Top ten AICc models from all possible logistical regressions for the Acadian Flycatcher.	163
Appendix 2-J: Top ten AICc models from all possible logistical regressions for the Red-eyed Vireo.	165
Appendix 2-K: Top ten AICc models from all possible logistical regressions for the Yellow- Billed Cuckoo.	167
Appendix 2-L: Top ten AICc models from all possible logistical regressions for the Indigo Bunting.	169
Appendix 2-M: Top ten AICc models from all possible logistical regressions for the Prairie Warbler.	171
Appendix 2-N: Top ten AICc models from all possible logistical regressions for the Yellow- breasted Chat.	173
Appendix 2-O: Acadian Flycatcher validation statistics for the top ten models.	175
Appendix 2-P: Red-eyed Vireo validation statistics for the top ten models.	177
Appendix 2-Q: Yellow-billed Cuckoo validation statistics for the top ten models.	179
Appendix 2-R: Indigo Bunting validation statistics for the top ten models.	181
Appendix 2-S: Prairie Warbler validation statistics for the top ten models.	183
Appendix 2-T: Yellow-breasted Chat validation statistics for the top ten models.	185
Appendix 2-U: Akaike weights and AICc differences (Δ AICc) for the Acadian Flycatcher... ..	187

Appendix 2-V: Akaike weights and AICc differences (Δ AICc) for the Red-eyed Vireo.	188
Appendix 2-W: Akaike weights and AICc differences (Δ AICc) for the Yellow-billed Cuckoo..	189
Appendix 2-X: Akaike weights and AICc differences (Δ AICc) for the Indigo Bunting.	190
Appendix 2-Y: Akaike weights and AICc differences (Δ AICc) for the Prairie Warbler.	191
Appendix 2-Z: Akaike Weights and AICc Differences for the Yellow-breasted Chat.	192

INTRODUCTION TO CHAPTERS 1 AND 2

Wildlife modeling has been experiencing a research shift towards issues of scale and scaling within species models for well over a decade. This shift has occurred for several reasons. First, broad scale approaches are necessary to manage our natural resources problems effectively. However, we have yet to understand completely how these broad-scale patterns and ecological processes function and affect the finer scales (Wu and Qi, 2000). Second, with the development of spatial technology such as geographical information systems (GIS), remotely sensed data sources, and the increase in computing power, effects of scale within species modeling can be addressed in ways that were previously impossible (Hay et al., 2003; Wu, 2004).

The interest in using data collected at multiple spatial scales in habitat modeling efforts comes with the recognition that all species function and are affected by patterns and processes at various scales within the landscape. In order to build an accurate habitat model, it is now widely recognized that these different habitat scales must be incorporated into the model (Cushman and McGarigal, 2002, 2004a, 2004b; Wu and Loucks, 1999). Therefore, the wildlife modeler must not only identify the environmental characteristics the species is exploiting and the landscape scales the species is affected by, but also determine which data type is best able to capture the multiple scales required to model the species effectively.

Utilizing satellite images as the sole data source for predictive habitat modeling has gained considerable attention. The increased ability of satellite sensors to capture landscape characteristics and features at finer scales has fueled speculation on the habitat modeling possibilities using this data source. Potential benefits of high-resolution satellite images to

wildlife modeling include: 1) the reduction of vegetation data collection time, expense and variability; 2) representation of continuous data across a study area; and 3) ability to capture features at multiple scales (including a fine scale $<5\text{-m}$ resolution) in a standardized format.

Currently, research utilizing high-resolution images is in the nascent stages. There is no work that compares the performance of high-resolution images to other commonly used data types in predictive habitat models. Furthermore, there is an overall lack of information that addresses the issues of working with high-resolution images in habitat modeling efforts- from classification of land cover maps to model testing. This research addresses those research gaps by assessing the performance of different land cover classification methods on a high-resolution image, comparing the predictive performance of high resolution data to standard data types for wildlife modeling, and finally, by providing an overall evaluation of high-resolution data in habitat modeling efforts.

To provide the reader some insight into how the research is organized, I will briefly outline the topics covered in this thesis. The research begins with an exploratory analysis using an Ikonos 4-m image to compare the use of three different classification methods to create high-resolution land cover maps. Commonly used classification algorithms were created for satellite images with coarser resolutions ($>30\text{-m}$) and were not designed for those of finer resolutions ($<5\text{-m}$) and at the time of image processing for this study, there was little research and no commercially available software for classifying high-resolution images. Therefore, in order to complete the second stage of the research (Chapter 2), I chose to formally contrast the use of two commonly used classification approaches (supervised and unsupervised) to a hierarchical rule-based classifier (HRB), otherwise referred to as a knowledge-based classifier, which had yet to be tested on a high resolution image classification.

Once it was determined that an acceptable land cover classification (accuracy measures >75%) could be derived from the Ikonos image using the HRB method, the second stage of the research (Chapter 2) was to contrast the performance of models created from the high-resolution data to models created from other available data sources. I was interested in contrasting models created from the more commonly used data types such as field measurements of the habitat, variables derived from Geographical Information Systems (GIS) (e.g., distance to water) and the more cost effective, coarser resolution (30-m) Thematic Mapper (TM) satellite data. The objective of the research was not to create the best models for each study species, but to compare the performance of commonly available data types with the more expensive high-resolution satellite data when modeling across a range of study species. I then provide an overall evaluation of the different data types with reference to model performance and the overall time, effort, and expense to a project

I conclude this thesis with a final closing summary of the two main chapters and the implications of the results from the entire research project.

CHAPTER 1 : LAND COVER CLASSIFICATION OF HIGH RESOLUTION DATA: AN EXPLORATORY ANALYSIS OF CLASSIFICATION TECHNIQUES AND METHODS USING A 4-M IKONOS IMAGE.

Introduction

With the increased capabilities of satellite sensors in recent years, there has been acute interest among researchers to utilize high-resolution satellite data (0.50 – 4 m) in projects requiring land cover mapping. The increased grain size (or pixels) of the images allow the detection of objects of interest within individual layers, which are of great value to those modeling across a suite of landscape levels (Wu and Qi 2000, Blaschke and Hay 2001, Hay et al. 2001, Sugumaran et al. 2002, Wu and Hobbs 2002, Hay et al. 2003, Stumpf et al. 2003, Wu 2004). From a land cover classification perspective, these objects or features can be detected because as the resolution is increased, the likelihood that neighboring pixels belong to the same land cover class of the pixel being analyzed increases. The characteristic allows for the representation of relatively homogeneous groups of pixels to be classified as real world objects of interest or “image-objects” of interest (Blaschke and Hay 2001).

Blaschke and Hay (2001) argue that the image-object definition or patch delineation within a spatial data source depends on the needs of the research. For example, in the case of urban land cover classification the target objects might be buildings (Sugumaran et al. 2002), in tree mortality studies the target objects may be individual trees (Clark et al. 2004a), or coral reefs in the case of marine mapping (Hochberg and Atkinson 2003). Whatever the objects may be, the

identification of features within the landscape at relatively detailed scales has enormous potential in modeling, mapping, and monitoring efforts. The vast potential of this data source is primarily due to the image-object scale of continuous data that can be detected via a remote sensing source. It allows for benefits such as the reduction of field data collection costs, more detailed monitoring of remote areas that otherwise are inaccessible or more detailed monitoring of landscape changes over time. Furthermore, high-resolution data are valuable for determining spatial patterns, scale influences on landscape processes, and how spatial patterns at multiple scales influence the organisms within the landscape.

However, the increased resolution and spatial variation that occur with these images also cause difficulties when deriving land cover classifications. Studies show that high-resolution data are difficult to classify using traditional classification methods, such as parallelepiped or maximum likelihood methods, because existing algorithms were not designed for the image-object spatial characteristics (Quackenbush et al. 2000, Usury 2000, Blaschke and Hay 2001, Shackelford and Davis 2003, Zhang and Wang 2003). In order to utilize the full potential of high-resolution land cover mapping, standard classification techniques will have to be modified or augmented for an appropriate analysis.

To address this issue, newer algorithms are being developed that extract contextual information such as image texture or fractal dimensions (Hay and Niemann 1994, Hay et al. 1996, Blaschke and Hay 2001, Hay et al. 2001). These algorithms utilize the fractal-net evolution and scale-space approaches and are intended to serve as a class of automatic image-object detection programs that delineate the most relevant or appropriate levels of information (patches/scales) in the image (Blaschke and Hay 2001, Hay et al. 2003).

An alternative approach of image classification is referred to as a knowledge-based classification. It is essentially a rule-based method that allows for the incorporation of different data sources within a hierarchical rule-based framework. This method allows the user to incorporate different texture and morphological features from other data sources to classify an image. Using the knowledge-based classifier, texture data can be incorporated into the classification process by first dividing the images into meaningful layers (non-vegetation/tree-vegetation/herbaceous vegetation, etc.) using indices and threshold values of the original data. The resulting layers can then be treated with traditional classification techniques and combined in a hierarchical process with a defined priority order based upon the layer (Ehlers et al. 2001).

In this research, I evaluated the performance of the hierarchical/rule-based (HRB) classification method in comparison to two different traditional classification approaches (supervised and unsupervised) on a high-resolution (4-m) Ikonos image. I chose to contrast these two methods for several reasons. First, I needed to find a way to classify a high-resolution image (4-m) to acceptable accuracy levels in order to complete the second stage of the research (Chapter 2), without having to wait for the automated image-object detection algorithm to be released commercially. Therefore, a HRB approach was very appealing to me because it could be done within land cover classification software that was readily available (ERDAS 1999b), unlike the alternative methods involving scale space or fractal net approaches.

Second, I chose to contrast this method with traditional methods because, although there were studies that acknowledged the poor performance of traditional classification algorithms, none had contrasted the methods formally at the time that this research was conducted (2000-2001). Furthermore, by evaluating the traditional approaches, I could evaluate whether or not there were any type of advantages that the algorithms could give to a high-resolution image

classification. For example, based upon the characteristics of the signature and the spatial patterns of the landscape a supervised classification may do a good job separating out perhaps one or two land cover classes, whereas the unsupervised approach may do better for separating out another group of land cover classes, although overall both methods may perform poorly. Therefore, if the supervised classification performed better at classifying the water features of the image than the unsupervised method, I would have the ability to incorporate the results of the water land cover class into the hierarchical classification. The benefit in using the hierarchical rule-based classifier is that one may incorporate different data sources into the final product.

The objective of the land cover classification was to obtain a final mapping product that would represent vegetation patterns in an ecological context for wildlife modeling as well as being suitable for management purposes. Therefore, the majority of land cover categories that I originally defined were based upon standardized wildlife habitat types for the southeast (Hamel 1992). These land cover categories were chosen specifically for predicting bird distributions and were defined before this classification was done (Table 1-1).

The focus of this chapter is to present the exploratory stages of a high-resolution image classification using a combination of methods. These exploratory results were later refined and built upon for the land cover classifications done in later years for Chapter 2.

Methods

Study Area

The area represented in the image was ~20,000 ha in Putnam County, GA, which is located in the Piedmont of Georgia approximately 145 km south of Athens. The area straddles Madison and Putnam Counties and is managed for loblolly (*Pinus taeda*) and shortleaf (*P.*

echinata) pine by the University of Georgia (Warnell School of Forest Resources 1999). A patchwork of private farms is distributed throughout the landscape. These private farms vary in use (dairy, agriculture and poultry activities).

Digital Data

Ikonos Image.—Space Imaging[®] launched its Ikonos satellite in 1999 to supply detailed imagery to commercial customers. An Eastman Kodak camera sensor aboard Ikonos collects both black and white images (1-m resolution, panchromatic) and multi-spectral images (4-m resolution, 4 bands (red, blue, green, near-infrared)). These images are still quite expensive (although the price has dropped in recent years) and are only now becoming frequently used in natural resource research and management (Auda et al. 2002, Mumby and Edwards 2002, Morisette et al. 2003, Schwarz et al. 2003, Tyson et al. 2004).

I used the Ikonos 4-m spatial resolution panchromatic image taken by the Ikonos-2 sensor on June 23, 2000. Data were projected in Universal Transverse Mercator (UTM), North Hemisphere, Zone: 17, Datum: NAD 83. The image was orthorectified and had an RMS error of 1.12 meters. The collection azimuth: 257.6 degrees at an elevation of 57.6 degrees, and the sun azimuth was 116.1 degrees at 71.0 degrees elevation. It was standard geometrically corrected and has 11 bits per pixel in a Geo TIFF format.

Ikonos Normalized Difference Vegetation Index (NDVI) data.—The Normalized Difference Vegetation Index (NDVI) is a spectral enhancement that is created by mathematically combining different bands of a satellite image. As with all image enhancement techniques, it improves image interpretability by bringing out different qualities of the data that are not readily

visible in its raw form (Lillesand and Kiefer 2000). The NDVI technique is specifically used to enhance small differences between vegetation classes. At each pixel the digital number from one band is combined with the digital number from another band using a designated mathematical equation and a new image is created with the resulting values. I created the NDVI image of the Ikonos data by combining the infrared (IR) and red (R) bands in the following way: $((IR - R) / (IR + R))$. Due to issues of integer scaling with the digital numbers, I had to use a transformed NDVI formula (TNDVI): $\text{atan}((IR - R) / (IR + R))$ (ERDAS 1999a). The tangent of the NDVI index calculation was used in order for the very small values to be visible in the NDVI image.

Digital Elevation Model (DEM).—I obtained the DEM coverage from the Georgia GIS Clearinghouse. I used the DEM file to help delineate between bottomland and upland areas in the study area. See Appendix 1-A for more metadata information.

Airborne Data Acquisition & Registration (ADAR 5500).—ADAR is a digital photography system (Positive Systems, Inc.) mounted on either a fixed wing plane or helicopter. The image produced is similar to an aerial photograph, but it captures visible and near infrared wavelengths in four spectral bands matching the first four of the Landsat TM sensor with resolutions up to 1 m. The ADAR photos in this study were used for supplemental land cover accuracy assessment points.

The photos were taken in May of 1999 and had a resolution of 2 m. They were projected in UTM, North Hemisphere, Zone: 17, Datum: NAD 83. I georeferenced and orthorectified the ADAR images to the Ikonos image using ESRI Arcview 3.2 (Redlands, CA).

Digitized Land Cover Files.—Clouds, buildings and shadows grid files used in the knowledge-based classification were all digitized on-screen as shapefiles off of the Ikonos image in Arcview and then converted to a grid file (Appendix 1-A).

Vegetation Data

All vegetation data used in the land cover classification and validation were collected in July-October 2000.

Training sites.—I established 3-7 training sites for each habitat category. Each training site consisted of nine point samples (configured in a square). The number of training sites for each land cover category varied because certain land cover types needed less data for signature purity. A pure signature has reflectance values (of the raw image) that do not overlap with the reflectance values or signature of another land cover type (Lillesand and Kiefer 2000). At each training site, I assessed vegetation characteristics within 11.3 m of the plot center (this was done due to grid configuration of training data collection). Appendix 1-B contains a complete listing of vegetation characteristics collected at each training site.

Validation sites.—I collected vegetation data at 213 validation sites. The same sampling measurements for training sites (Appendix 1-B) were also taken for validation sites. Validation points used a stratified random sampling design across the study area. This was done by breaking up the study area into ten major blocks (strata) with an effort to allocate points evenly across the landscape. All validation points were geographically referenced (UTM coordinate locations) using a Trimble global positioning system (GPS) with < 2-m accuracy. Vegetation

data were collected within a 50-m buffer surrounding the point. A homogenous land cover type was represented within the 50-m buffer. These vegetation data locations were also used later for bird census points in Chapter 2.

Supervised Classification Approach

Classification Description.—Traditional classification methods are divided into two major approaches, supervised and unsupervised. The supervised method is restrictive in the sense that all land cover values are pre-defined before the land cover classification. To begin, the user defines each land cover class by first selecting those pixels in the image that represent that land cover class in its purest form. This can be done by either georeferencing ground data (measurements of the target land cover type taken in the field) to the image (i.e., by GPS as well as by aerial photo interpretation). A training site is the identified land cover type on the ground that is georeferenced to the image reflectance values in order to “train” the classification algorithms. Once areas within the image are determined to be clear representatives of the target land cover type, the digital numbers are extracted from those areas and are referred to as the digital signature of that land cover class (Jensen 1996, ERDAS 1999a, Lillesand and Kiefer 2000).

The range of the digital signature for each land cover class has a probability density function that is based on the response pattern of the distribution of points. If it is a normal distribution, the response pattern of the land category is described by the mean vector and covariance matrix, which provide the parameters for computing a probability value. All pixels that construct the image can now be assigned a probability of membership for each land cover class. Pixels are then assigned to the class with the highest associated probability. If the probability

values are too low (a threshold set by the user) then the pixel remains unclassified (ERDAS 1999a).

The maximum likelihood classifier (MLC) is commonly used to classify normally distributed data and gives good overall results with resolutions >30-m (Avery and Berlin 1992). When the point distribution of the training data is normal, the classifier is referred to as a Gaussian maximum likelihood classifier. The assigned probabilities of the MLC are constructed using ellipsoidal “equiprobability contours,” which allow the user to visually determine where the probability of the unclassified pixel falls in relation to the location of the pure training signature that defined the land cover category (Lillesand and Kiefer 2000). It assumes equal probabilities of occurrence and costs of misclassification for all classes. The large number of computations required to classify each pixel with this method becomes a drawback when many spectral channels or classes are needed. One can reduce the number of channels or bands with techniques such as principal components analysis or canonical component transformations (Faust 1989, Jensen 1996, ERDAS 1999a). To reduce the number of classes, a decision tree or layered classifiers can be used to separate classes that are not overlapping with one another and process them in a step by step manner using a simple threshold value or a classifier that is not computationally intensive such as the parallelepiped (Lillesand and Kiefer 2000).

When the training data point distribution is not normal, a discriminant function analysis can be used, but this is not recommended due to increased difficulty in characterizing the probabilities as the number of spectral bands increase (Schott 1997). Another more viable option in the supervised approach is a feature space option which allows for a nonparametric rule to be used on those training sites that do not have a normal distribution (ERDAS 1999a).

Classification Methods.—I used Imagine software (ERDAS 1999a) to perform all classifications. I selected 17 land cover types prior to the classification with the intent that the classes represented would be used for management and wildlife modeling objectives (Table 1-1). Field collected training data were used to define vegetation land cover classes. Additional training sites were added at the time of image processing by evaluating the Ikonos image (resolution strong enough to clearly see trees) in combination with my extensive knowledge of the area and stand management data. Training sites were added to supplement overlapping land cover signatures such as open pine dense understory vegetation (OPD) and light understory (OPL) classes (Table 1-1).

The software had a combination of rules specified within the supervised classification. For training sites that had a normal distribution of points, the maximum likelihood method was used. For signatures that fell outside a normal distribution, the feature space option was used. Overlapping pixels used a parallelepiped classifier and unclassified pixels remained unclassified.

Unsupervised Approach (Clustering Classifier)

Classification Description.—Unsupervised classification allows the computer to define the land cover categories on the spectral distance of the reflectance values in the image. In this method, the user defines how many classes are wanted in the land cover, then the algorithm groups the reflectance values into the number of classes specified. The classification is based on the assumption that values within a land cover class are closer in measurement space than those values from other classes (i.e., pine vs. hardwood). Final land cover categories are defined after the classification, unlike the supervised approach, where they are defined before the classification with the training data (Lillesand and Kiefer 2000). The advantage of using this

method over supervised classification is that it potentially can identify classes that may have been previously overlooked by the user.

A common clustering algorithm in unsupervised land cover classification is the “K” means approach (Lillesand and Kiefer 2000). Here, the user defines the number of classes and the algorithm randomly places that number of seeds or points in multidimensional measurement space. Using the mean vector of the raw reflectance values, pixels are then assigned to the cluster whose vector is closest in value. As pixels are assigned to the seed clusters, the classification continues to revise the mean vectors until there are no significant changes in the location of each of the mean vectors (Avery and Berlin 1992, Lillesand and Kiefer 2000). After the algorithm is finished, the user can then assign land values to each class present.

Classification Methods.—The original unsupervised classification specified 400 land cover classes in the clustering algorithm with a convergence factor of 0.95, 10 iterations, and a skip factor of one. These specifications were chosen in order to group signatures into the most basic categories that the increased resolution could detect and potentially improve on the classification accuracy from the supervised classification.

Using training site data, my knowledge of the area and visual interpretation of the image itself, I grouped the 400 land cover classes into 22 categories (Table 1-2). These categories were different from the original categories first conceived for the supervised classification (Table 1-1). Due to the increased resolution of the data and the nature of the categories themselves, there was difficulty in obtaining an accurate classification. For example, the clearcut and pine categories signatures overlapped so much with one another that I chose to classify the pixels at a sub-component category (e.g., clearcut 0-3 years consisted of hardwood, pine, hardwood/grass,

hardwood/deciduous shrub, blackberry/pine, etc.). After performing an accuracy assessment and visually inspecting the first grouping, I further refined the classification and recoded the values for a third classification. The classification re-coded the 22 categories into 15 categories (Table 1-3). There were difficulties isolating cloud and shadows from certain land cover signatures (e.g., pine and shadows). By creating a mask of shadows and clouds, I was able to remove the majority of the trouble spots and those signatures that were mixed with them could be eliminated successfully in the re-coded image.

Hierarchical/Rule-Base (Knowledge Base) Classifier

Classification Description.—The hierarchical/rule-based classifier used in this study falls under a genre of artificial intelligence tools known as expert systems. The classifier uses an approach referred to as a knowledge base that is defined by the way it represents knowledge (e.g., rules, frames, decision trees).

The architecture of the expert system is referred to as a shell (Durkin 1998). There are six components to the shell: the knowledge base, inference engine, user interface, developer interface, explanation facility, and the system interface. The knowledge base is the location that the expert puts in specialized knowledge of the area of interest. It is a rule-based approach composed of two parts as outlined in Chadwick and Hannah (1986). The first part is the knowledge itself and it is represented in a declarative form by a set of rules, or conditional statements (IF-THEN, OR, AND; e.g., If A then B). The second part of the system is the database, which contains symbols, otherwise known as facts, assertions, or answers to the rules. For example, in the “If A then B” statement, B is a symbol because it is an answer to the rule.

The inference engine or interpreter utilizes the rules of the knowledge base to draw conclusions. It does this by scanning the condition parts of each rule to determine which rule can be run next. The database changes continually by adding or replacing symbols based upon each rule that is run. When no rules are applicable, the interpreter ends the program.

Reasoning in the rule-based system can be accomplished using two basic strategies, forward chaining and backward chaining. Forward chaining is data driven or condition driven, a bottom up approach. Backward chaining is hypothesis or goal driven; it looks for evidence that supports or contradicts the hypothesis. For example, suppose a rule-base contains three rules:

- (1) If reflectance value = 78 then pixel is pine.
- (2) If DEM = 340 then pixel is bottomland.
- (3) If reflectance value = pine and DEM=340 then pixel is bottomland pine.

The goal is to conclude that a pixel is bottomland pine. The rule-base would select rule (3) because the “then” clause matches the goal. It is not known that reflectance value 78 = pine, so this "if" statement is added to the goal list. The rule-base is again searched and this time rule (1) is selected because its then clause matches the new goal just added to the list. This time, the if-clause (reflectance value = 78 then pixel is pine) is known to be true and the operation repeats in the same way for the DEM rule. When both statements are known to be true then the goal that pixel is bottomland pine is concluded. The list of goals determines which rules are selected and used, this method is called ‘goal driven.’ The forward-chaining method uses the reverse approach. It is also possible to use a mixed strategy of backward and forward chaining. For

example, one can start off with a top-down hypothesis approach and when problems are encountered, use a bottom up or data driven approach (Chadwick and Hannah 1986).

The rules and their hierarchical order that the interpreter constructs are known as a decision tree. A decision tree begins with an initial situation and shows all possible consequences that can result from that initial situation. The decision tree is able to grow when one rule is referred to by a condition of another rule (e.g., if A then B, if B then D). The terminal hypothesis of the decision tree represents the final symbol or class of interest. When more than one rule is applicable, there are several strategies that the system can take to resolve the conflict. It is recommended that two or more strategies be employed in order to get satisfactory results (Chadwick and Hannah 1986). The rule order strategy can be employed, where the rules are ordered by highest priority within the rule base and are assigned a firing order. Another approach is ordering the data symbols so that the rule that matches the symbol with the highest priority will be chosen first. Alternatively, the rule that refers to the most recently added symbol is chosen. The possibilities are many and the more strategies that are chosen enable the user to adjust the operating system to the data that are being manipulated. The final components of the expert system are the user interface (how the user views and interacts with the system), the developer interface (the vehicle for the knowledge engineer to develop the system), the explanation facility (provides explanations on the reasoning of the system), and the system interface which links the expert system to external programs (spreadsheets, databases, algorithms, etc.), all of which are present in the hierarchical rules based program used in this research (Durkin 1998).

Classification Methods. — I used the “Expert Classifier” program in Imagine (ERDAS 1999b) to classify the image with the hierarchical rules-based approach. The knowledge-based classifier is composed of two parts. The first part of the program is called the “Knowledge Engineer,” in which the variables are identified, the rules are created, and the output classes of interest (symbols) and the decision tree are made by the “expert” who is familiar with the data. The second part of the program is the “Knowledge Classifier,” which does the actual classification using the knowledge base created in the Knowledge Engineer. Hypotheses, rules and variables generated for the classification can be found in Table 1-4 and Table 1-5.

I refined the unsupervised classification by using a combination of unsupervised and supervised classification techniques to create the base data layer in the knowledge classifier. I then recoded the grouped signatures by combining those signatures with similar categories and using a mask of the digitized cloud and shadow attributes listed in the data section because of the pixel mixing that occurred. This approach helped eliminate those classes such as cloud/building, cloud/hardwood, shadow/pine, etc. Before the rule-based part of the classification began, I chose to digitize: rivers, roads, clearcuts, clouds, shadows, etc. on screen. I also generated a mask of the digitized cloud and shadow pixels used in the rule-based classification (Appendix 1-A).

Classes that had < 69% in the accuracy assessment from the unsupervised classification were targeted in the rule-based classification for manipulation. The NDVI image was used to refine the grass and pine classes (Table 1-4; Appendix 1-A). Upland and riverine bottomland classes were separated from one another using a DEM that was digitized on screen for corrections using the training data available (Table 1-5; Appendix 1-A). Those land cover classes with values >85% from the unsupervised classification were weighted higher than classes

with low values so essentially those pixel values stayed the same. Final land cover categories are presented in Table 1-6.

Accuracy Assessment

Sampling design of accuracy assessment. —The ground data points described in the vegetation section were supplemented with a computer-generated random distribution of points using Erdas Imagine software. The land cover values of the computer-generated points were determined through aerial photo interpretation (ADAR photographs from digital data section). I used a stratified random sampling design based upon the percentage of area of each class represented in the land cover classification (Avery and Berlin 1992, Lillesand and Kiefer 2000).

Accuracy assessment measures.—Accuracy was evaluated using error matrices, accuracy assessments and Kappa statistics. Three types of information were derived from the error matrices. The error of omission, which is represented by all the non-diagonal column elements in the matrix. The error of commission, which is represented by all the non-diagonal row elements. And the number correctly classified is represented in the diagonal of the matrices (Lillesand and Kiefer 2000).

The accuracy assessments were represented by three measures: total overall accuracy, user's accuracy, and producer's accuracy. Total *overall accuracy* of a classification is derived by dividing the total number of correctly classified pixels by the total number of reference pixels. The *users accuracy* measures the classification accuracy of each class through the measure of commission error, where the diagonal (correctly classified pixels) is divided by the row total (total number of pixels classified into that cover class). The *producers accuracy* represents how

well the training set of pixels classified the image and is derived by dividing the number of correctly classified pixels for each land cover class (the diagonal) by the number of reference pixels for that category (the column total) (Avery and Berlin 1992, Lillesand and Kiefer 2000).

I also used the Kappa statistic (KHAT), which was designed for random sampling designs in accuracy assessments to adjust for the possibility of Type I errors in the overall accuracy assessment. The value of KHAT ranges between 0 and 1, where true agreement equals 1 and chance agreement is zero (no better than a random assignment of pixels). KHAT can also take on negative values, which is an indicator of very poor classification performance. Differences in overall accuracy measures (referenced above) and KHAT are to be expected because each incorporates different forms of information from the error matrix. KHAT uses products of the non-diagonal elements where as the overall accuracy measure uses data along the main diagonal of the matrix. It is recommended that both values are computed and analyzed for accuracy assessments (Avery and Berlin 1992, Jensen 1996, Lillesand and Kiefer 2000)

Results

Supervised Classification

The supervised classification performed poorly, with a low Kappa statistic (0.2448) and an overall classification accuracy of 53.17%. The largest source of error appeared to be with training signatures that overlapped with one another (< 75 % producers accuracy)(Table 1-7 and Table 1-8), which included all classes except water vegetation (algae), bare-soil, old-field, urban, rushes, pavement and pine 7-12 yrs. Although the training site signatures were relatively pure in their definition of the majority of classes, most dropped in users accuracy. For example, the pasture class overlapped enough with the old-field class so that the majority of old-field

pixels of the sample were classified as pasture (Table 1-7). The inverse was true for pasture. It was difficult to separate the Pine 7-12 yrs. class from any other class that had a pine component in it (e.g., mixed to clearcut 0-3 yrs). Water with vegetation also mixed with water and pasture, a combination of the signature itself. Pavement mixed with water and clearcut (0-3). Urban, bare-soil, and rushes classes were classified well overall (Table 1-7 and Table 1-8).

Unsupervised Classification

The unsupervised classification had mixed results. In the final two classifications (22 land cover categories /re-coded 15 land cover categories), bare-soil and building/grass had the lowest classification accuracy, falling into negative Kappa coefficients and extremely low accuracy totals due to their being spectrally inseparable from grass in some ranges (Table 1-9 - Table 1-12). In the re-coded image, water, cloud, grass, hardwood/shrub, hardwood/vine, and hardwood/grass all were spectrally separable to adequate accuracy levels using this classifier (Table 1-12).

Overall, the final unsupervised classification performed poor to fair with an overall classification accuracy of 69.26% and a Kappa statistic of 0.6429 (Table 1-12). However, the final unsupervised classification was an overall improvement over the supervised method (Kappa statistic=0.2448 and overall classification=53.17%)(Table 1-10 and Table 1-12).

Knowledge-Based Classifier

The rule-based classification performed better overall than the other classifications with a Kappa Statistic of 0.7317 (Table 1-14). Training signatures had high producers accuracies with

10 of the 13 total signatures having >70% accuracies (Table 1-13). The pine signature was improved from the unsupervised classification of 73.3% to 93.6% (producers accuracy). The bare/grass category also improved from 5.26% to 46.67% in the knowledge classifier (producers accuracy). The bottomland category seemed to over estimate riverine bottomland tracts, although there was not a problem with it mixing with other classes except for upland (Table 1-13). Bare/Grass had the lowest producers accuracy measures at 46.67%.

Discussion

Each of the classification methods was able to categorize some land cover types better than another method, but it was the knowledge-based classifier that provided a way to combine parts of the various methods into an overall stronger final product. Although the supervised classification performed poorly overall, its classification of bare-soil and buildings/urban land cover types allowed those representative pixel values to be placed at the top of the hierarchy in the knowledge based classifier. For example, overall accuracy of the building land cover class was improved when combined with other data types such as the digitized coverage that was done of the buildings in the area (Table 1-8, Table 1-12 and Table 1-14).

However, it was clear that the supervised classification method was unable to handle the complexity of the landscape and the increased variability and shadow effects represented by the high-resolution image. Major drawbacks to the supervised method were that spectral signatures of certain land cover types were so similar (e.g., upland and bottomland hardwood) that this method was unable to resolve the problem without additional data (e.g., DEM) as well as missing the opportunity to extract other land cover classes not previously defined.

It was clear under visual inspection that the unsupervised method performed well with large contiguous stands of forest or large blocks of a particular habitat type, though the classification algorithm had problems classifying individual objects of the same land cover type (e.g., a tree in a field or thin fragmented areas) where the resolution was smaller than the actual object that was in the landscape. For example, in the case of a tree in the middle of a field, the signature at the center of the tree was the strongest. Moving from the center of the tree towards the outer branches, the reflectance value changed at each pixel as vegetation became more sparse and mixed with the reflectance values of the surface below the tree, causing the edges of the object (tree) to be classified as a different vegetation category or mixed in with shadow. To resolve this issue, I looked at two different measures of texture (standard deviation and variance), but they did not provide a remedy.

Due to the patterns of this landscape in particular, I did not appear to have significant problems with this artifact, but in drier landscapes that may have large trees with sparse vegetation surrounding them (e.g., oak woodlands in western U.S), it may be more of a concern and an image-object algorithm may be more appropriate. It may be possible that I had higher sources of error in my early successional areas that had large pine trees with minimum understory growth (OPL), although a more detailed analysis of this artifact was not possible at this time.

In the future, to address this problem without an image-object algorithm, I would consider degrading the texture images to a coarser resolution to examine if that would improve the classification of a single tree or patch classifications where vegetation is sparse. With coarser resolution, a single pixel can include the reflectance of one tree or multiple trees, whereas the

high resolution can use several pixels to represent one tree with varying spectral reflectance patterns.

In general, the unsupervised classification did a fair job at extracting classes that were unobtainable from the supervised approach and in fact were not previously defined. This strength supports the use of this algorithm when exploring potential land cover classes to be extracted from high-resolution images. The refining of signatures and sub-setting of signatures not previously defined (hardwood/shrub, pine/blackberry, etc.) were valuable additions to the final product due to the overall bird/timber management goals of the project, primarily because they represent not only a category, but also a patch size that is relevant to both perspectives. In the future, I suggest performing an unsupervised classification early on, prior to collecting the majority of ground data (relying on aerial photo interpretation for reference) and using the results of that exercise along with project objectives to define the land cover categories and collect additional ground data accordingly.

The knowledge classifier performed better than both the traditional classifiers primarily because it allowed for the incorporation of other data types (and results from other methods) in a rule-based hierarchy. Due to the order in which I completed and analyzed the classifications, certain modifications to the knowledge method would have been beneficial but were not performed at the time of this study. However, the re-classification of the Ikonos image in Chapter 2, built on what was learned in this study. The bare-soil signature from the original supervised classification could have been used instead of the signature originally obtained from the recoded unsupervised classification.

Within the knowledge classifier, I employed many strategies to improve classification accuracy to a variety of classes. It was clear that land cover classes that were defined by a

structural component (e.g., Open Pine Dense (OPD), Open Pine Light (OPL)) could not be achieved using the knowledge classifier with the available data. Potentially using a combination of other texture layers supplemented with past stand history GIS layers may allow these types of classes to be obtained in the future.

Classes such as grass, bare/grass, and riverine bottomland hardwood required considerable thought. Grass had the lowest Kappa statistic (0.377), which suggested that further improvement to the rule-base needed to be done. Although I investigated different resolutions of the NDVI using 16x16-m and 24 x24-m pixels, the grass signature still needs the rule base changed for the NDVI. By using a filter to degrade the image in Imagine for areas within large areas of pasture, I had hoped to improve the signature. Unfortunately, these changes did not improve the signature of grass. Other avenues such as principal components analysis or Tasse Cap may prove to be useful (ERDAS 1999a). There is no clear indication based upon the available data that the bare/grass category could be improved as well. Analysis of the NDVI, the generation of a principal components theme, and texture measures have not given me any possible improvements for this signature. The problem may require another type of chromatic filter to normalize reflectance values before classification is undertaken.

The bottomland category seemed to overestimate riverine bottomland tracts (28 classified correctly out of 33 reference points). There was not a problem with it mixing with other classes except for upland. Performance might be improved by using a buffer around stream coverages, or by combining a decision rule using a soil coverage, stream, or flow model. Also, if a measure of fragmentation or texture of the appropriate resolution were used, small fragments less than 2 acres that are isolated from the stream area that are defined as riverine bottomland could potentially be defined differently (because they are no longer functioning as a system).

Overall, the knowledge classifier shows great promise for obtaining land cover maps derived with greater than 80% accuracy based upon high-resolution data. The results from these exploratory classifications were meant to investigate the behavior of traditional algorithms on high-resolution data and to provide a basis of knowledge to refine future classifications with the knowledge base/hierarchical classifier. The sample sizes of the accuracy assessments presented in this chapter were small. Due to the resolution of the data and my knowledge of the area, when classifications were compared with aerial photos or the raw image itself during the actual classification process, patterns and overall accuracies were easy to visually interpret for certain classes, even with low sample sizes. The classifications done in Chapter 2 were conducted under more statistically rigorous conditions for the final product used in the modeling research of this work.

Each of the methods had certain strengths associated with them, but all had major problems with removing shadows within canopy stands, along forest edges and next to individual objects (e.g., single trees). A potential remedy for this problem may be to investigate the impact of slope and aspect on the shadowing effects. Although I did create a painted relief (a relief map created from elevation, slope and aspect data) at the time of this exploratory analysis, I did not incorporate it into the knowledge-based classification. Other methods, such as a chromatic filter (Quackenbush, 2000), were used to eliminate some of the shadow problems in later classification work presented in Chapter 2.

Although this knowledge classifier shows promise, along with pre-processing techniques designed for high-resolution images (Quackenbush 2000), there seems to be more promise in developing the image-object techniques that use automatic contextual extraction and define the patch scale in the images being classified (Hay and Niemann 1994, Hay et al. 1996, Blaschke

and Hay 2001, Hay et al. 2001). There are two major reasons for this belief. First, none of these classifiers was able to classify “image-objects” well. As mentioned previously, vegetation “objects” were highly variable based upon whether or not they were mixing with the reflectance values of the surface. In essence, this mixing would significantly lower the classification accuracy of the high-resolution images that represent landscapes with fragmented vegetation patterns.

A major problem with the classifications are that there are no separation of the objects of interest or features along the vertical axis of the scale of detection. In other words, the signature that is represented for a pixel is the dominant reflectance value of the object on the highest vertical plane (e.g., tree canopy). The image-object analysis is able to address this issue with its “Scale-Space Blob Feature Detection” (Blaschke and Hay 2001). However, until there is an incorporation of the vertical plane in the methods I evaluated, the knowledge based method may not be able to address this problem as well as the image object approach for highly fragmented landscapes. Potentially, technologies such as Light Detection And Ranging (LIDAR) (Andersen et al. 2005) could be incorporated into the knowledge base classification. The second reason I suggest that the image-object approaches hold more promise at this time over the hierarchical/rule-base is due the time and labor it took to incorporate and develop all the different layers and themes that were tested and used in the hierarchical classifier. I would also not be able to use the same knowledge base created for one image on another. Finally, the overall classification success of the high-resolution image was limited by the availability of additional data.

The advantages of the approach include that it is intuitive to do, it can give adequate results depending on the classes needed and the data available, and most importantly, it is readily

available on commercial software. Whatever approach is chosen to process a high-resolution image, it was apparent that the traditional classification methods alone were unable to handle the resolution and spatial characteristics that are inherent in this type of data. The results of this exploratory study suggest that either a image-object approach or a knowledge based classifier can produce an adequate land cover map from high-resolution satellite data. The selection of a classifier for a high-resolution image will ultimately depend upon the landscape configuration, the project resources, and the availability of additional data.

Literature Cited

- Auda, Y., F. Blasco, J. P. Gastellu-Etchegorry, G. Marty, and C. Dechamp. 2002. Preliminary studies of the detection of Ambrosia populations by spatial remote sensing. *Revue Francaise D Allergologie Et D Immunologie Clinique* **42**:533-538.
- Avery, T. E., and G. L. Berlin. 1992. *Fundamentals of Remote Sensing and Airphoto Interpretation*, 5th edition. Macmillian, New York.
- Blaschke, T., and G. J. Hay. 2001. Object-Oriented Image Analysis and Scale-Space: Theory and Methods for Modeling and Evaluating Multiscale Landscape Structure. *in* M. Madden, editor. *Challenges in Geospatial Analysis, Integration and Visualization*. International Archives of Photogrammetry and Remote Sensing, Athens, GA.
- Chadwick, M., and J. A. Hannah. 1986. Expert Systems for Personal Computers-An Introduction to Artificial Intelligence. Pages 9-29 *in* Chapter 2: Principles of Rule-based Expert Systems. Sigma Press, Wilmslow, England.
- Clark, D. B., C. S. Castro, L. D. A. Alvarado, and J. M. Read. 2004. Quantifying mortality of tropical rain forest trees using high-spatial-resolution satellite data. *Ecology Letters* **7**:52-59.
- Coulter, L., D. Stow, B. Kiracofe, C. Langevin, D. M. Chen, S. Daeschner, D. Service, and J. Kaiser. 1999. Deriving current land-use information for metropolitan transportation planning through integration of remotely sensed data and GIS. *Photogrammetric Engineering and Remote Sensing* **65**:1293-1300.
- Durkin, J. 1998. Expert System Development Tools. *in* J. Liebowitz, editor. *The Handbook of Applied Expert Systems*. CRC Press LLC, Salem, MA.

- Ehlers, M., M. Gahler, and R. Janowsky. 2001. Automated Analysis of Ultra High Resolution Remote Sensing Data: GIS to the Rescue? *in* M. Madden, editor. Challenges in Geospatial Analysis, Integration and Visualization. International Archives of Photogrammetry and Remote Sensing, Athens, GA.
- Eiumnoh, A., and R. P. Shrestha. 2000. Application of DEM data to Landsat image classification: Evaluation in a tropical wet-dry landscape of Thailand. *Photogrammetric Engineering and Remote Sensing* **66**:297-304.
- ERDAS, I. 1999a. Erdas Field Guide. Pages 698 *in*. Erdas, Inc., Atlanta, GA.
- ERDAS, I. 1999b. ERDAS Imagine Expert Classifier Field Guide. *in*. ERDAS, Atlanta, GA.
- Faust, N. L. 1989. Image Enhancement. *in* A. Kent and J. G. Williams, editors. Encyclopedia of Computer Science and Technology. Marcel Dekker, Inc., New York.
- Hamel, P. B. 1992. Land Manager's Guide to the Birds of the South. Technical Report General Technical Report SE-22, US Forest Service, Chapel Hill, N.C.
- Hay, G. J., T. Blaschke, D. J. Marceau, and A. Bouchard. 2003. A comparison of three image-object methods for the multiscale analysis of landscape structure. *Isprs Journal of Photogrammetry and Remote Sensing* **57**:327-345.
- Hay, G. J., and K. O. Niemann. 1994. Visualizing 3-D Texture: A Three Dimensional Structural Approach to Model Forest Texture. *Canadian Journal of Remote Sensing* **20**:90-101.
- Hay, G. J., K. O. Niemann, and G. McLean. 2001. An Object-Specific Image Texture Analysis of H-Resolution Forest Imagery. *Remote Sensing of Environment* **55**:108-122.
- Hay, S. I., C. J. Tucker, D. J. Rogers, and M. J. Packer. 1996. Remotely sensed surrogates of meteorological data for the study of the distribution and abundance of arthropod vectors of disease. *Annals of Tropical Medicine and Parasitology* **90**:1-19.

- Hochberg, E. J., and M. J. Atkinson. 2003. Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. *Remote Sensing of Environment* **85**:174-189.
- Jensen, J. R. 1996. *Introductory Digital Image Processing: A Remote Sensing Perspective*, 2nd edition. Prentice-Hall, Englewood Cliffs, NJ.
- Lillesand, T. M., and R. W. Kiefer. 2000. *Remote Sensing and Image Interpretation*, 4th edition. John Wiley & Sons Inc., New York, NY.
- McFarland, T., and R. Parker. 1990. *Expert Systems in Education and Training*. Educational Technology Publications, Englewood Cliffs, NJ.
- Morisette, J. T., J. E. Nickeson, P. Davis, Y. J. Wang, Y. H. Tian, C. E. Woodcock, N. Shabanov, M. Hansen, W. B. Cohen, D. R. Oetter, and R. E. Kennedy. 2003. High spatial resolution satellite observations for validation of MODIS land products: Ikonos observations acquired under the NASA Scientific Data Purchase. *Remote Sensing of Environment* **88**:100-110.
- Mumby, P. J., and A. J. Edwards. 2002. Mapping marine environments with Ikonos imagery: enhanced spatial resolution can deliver greater thematic accuracy. *Remote Sensing of Environment* **82**:248-257.
- Quackenbush, L. J., P. F. Hopkins, and G. J. Kinn. 2000. Developing forestry products from high resolution digital aerial imagery. *Photogrammetric Engineering and Remote Sensing* **66**:1337-1346.
- Schott, J. R. 1997. *Remote Sensing: The Image Chain Approach*. Oxford University Press, Inc., New York.

- Schwarz, M., C. Steinmeier, F. Holecz, O. Stebler, and H. Wagner. 2003. Detection of windthrow in mountainous regions with different remote sensing data and classification methods. *Scandinavian Journal of Forest Research* **18**:525-536.
- Shackelford, A. K., and C. H. Davis. 2003. A hierarchical fuzzy classification approach for high-resolution multispectral data over urban areas. *Ieee Transactions on Geoscience and Remote Sensing* **41**:1920-1932.
- Sidele, J. G., D. H. Johnson, B. R. Euliss, and M. Tooze. 2002. Monitoring black-tailed prairie dog colonies with high-resolution satellite imagery. *Wildlife Society Bulletin* **30**:405-411.
- Stumpf, R. P., K. Holderied, and M. Sinclair. 2003. Determination of water depth with high-resolution satellite imagery over variable bottom types. *Limnology and Oceanography* **48**:547-556.
- Sugumaran, R., D. Zerr, and T. Prato. 2002. Improved urban land cover mapping using multi-temporal Ikonos images for local government planning. *Canadian Journal of Remote Sensing* **28**:90-95.
- Treitz, P., and P. Howarth. 2000. Integrating spectral, spatial, and terrain variables for forest ecosystem classification. *Photogrammetric Engineering and Remote Sensing* **66**:305-317.
- Tyson, B., T. Worthley, and K. Danley. 2004. Layering natural resource and human resource data for planning watershed conservation strategies. *Society & Natural Resources* **17**:163-170.
- Usury, E. L. 2000. Discussion on classification performance with high resolution images. *in* A. C. Vitale, editor., Athens, GA.

- Warnell School of Forest Resources. 1999. Visitor's Guide to Bishop F. Grant Memorial Forest.
in. Warnell School of Forest Resources, University of Georgia, Athens, GA.
- Watson, N., and D. Wilcock. 2001. Preclassification as an aid to the improvement of thematic and spatial accuracy in land cover maps derived from satellite imagery. *Remote Sensing of Environment* **75**:267-278.
- Wu, J., and Y. Qi. 2000. Dealing With Scale in Landscape Analysis: An Overview. *Geographic Information Sciences* **6**:1-5.
- Wu, J. G. 2004. Effects of changing scale on landscape pattern analysis: scaling relations. *Landscape Ecology* **19**:125-138.
- Wu, J. G., and R. Hobbs. 2002. Key issues and research priorities in landscape ecology: An idiosyncratic synthesis. *Landscape Ecology* **17**:355-365.
- Zhang, Q. F., and J. F. Wang. 2003. A rule-based urban land use inferring method for fine-resolution multispectral imagery. *Canadian Journal of Remote Sensing* **29**:1-13.

TABLES

Table 1-1: Definition of supervised classification categories for forest types (based on Hammel (1998)).

Number	Land Cover Category
1	Open pine dense understory/midstory (>51% understory and midstory)
2	Open pine light to no understory/midstory (< 25% understory/midstory)
3	Sapling Pine (12 years+) (planted)
4	Upland Hardwood (Hardwood forest that is > 480-m in elevation)
5	Riverine Bottomland Hardwood (Hardwood forest < 479-m in elevation)
6	Mixed forest (hardwood and pine mix forest that has > 25% of either)
7	Pasture
8	Old Field
9	Clear-cut (<1 yr)
10	Clear-cut natural re-growth (4-7 yr)
11	Planted pine 0-3 yr
12	Young plantation pine (7-12 yr)
13	Water
14	Rushes/water vegetation
15	Urban/housing
16	Pavement
17	Undefined

Table 1-2: Unsupervised classification land cover categories for Ikonos image before final recode.

Number	Land Cover Category
1	Cloud/Buildings
2	Cloud
3	Bare-Soil
4	Bare/Grass
5	Hardwood/Grass
6	Cloud/Grass
7	Cloud/Hardwood
8	Hardwood
9	Water Oak/ Oak
10	Hardwood/Vine
11	Hardwood/Shrub
12	Pine/Hardwood
13	Blackberry/Pine
14	Pine/Grass
15	Snag/Wood
16	Shadow
17	Pine
18	Grass/H2O Vegetation
19	Grass
20	Shadow/Pine
21	Water
22	Unclassified

Table 1-3: Unsupervised classification land cover categories for Ikonos image after final recode.

Number	Land Cover Category
1	Water
2	Grass
3	Pine
4	Shadow/Cloud
5	Blackberry/Pine
6	Pine/Hardwood
7	Hardwood/Shrub
8	Hardwood/Vine
9	Hardwood
10	Hardwood/Grass
11	Grass/Bare
12	Bare-soil
13	Algae
14	Building
15	Building/sidewalk/lawn

Table 1-4: Hierarchical/rule-based classifier table. Hypotheses are target land cover classes, rules consist of logical statements that determine which pixels are placed in the land cover type, variables used are the data sources used in the rule, and weight is the hierarchical placement of that rule in the knowledge base.

Hypotheses	Rules	Variable used	Weight
Buildings	building.grid=1	Building.grid	1
Shadows	Shadow.grid=1	Shadow.grid	1
Clouds	Cloud.grid=1	Cloud.grid	1
Water	Ik_unsuper=1	Ik_unsuper.img	.95
Pine	Ik_unsuper=115 & not Ik_unsuper.img=1	Ik_unsuper.img	.97
Hardwood/grass	Ik_unsuper=242	Ik_unsuper.img	.80
Blackberry/pine	Ik_unsuper=183	Ik_unsuper.img	.80
Pine/hardwood	Ik_unsuper=193	Ik_unsuper.img	.80
Hardwood/shrub	Ik_unsuper=195	Ik_unsuper.img	.80
Hardwood/vine	Ik_unsuper=206	Ik_unsuper.img	.80
Bare/grass	Ik_unsuper=348	Ik_unsuper.img	.75
Algae	Ik_unsuper=315	Ik_unsuper.img	1
Bottomland	Ik_unsuper=206 or Ik_unsuper=242 or Ik_unsuper=221 & Dem < 479	Ik_unsuper;Dem_recode	.95
Upland	Ik_unsuper=206 or Ik_unsuper=242 or Ik_unsuper=221 & Dem >480	Ik_unsuper;Dem_recode	.95
Grass	Ik_unsuper=88 or Ik_ndvi<.95 & not Ik_unsuper=1 & not shadow=1 & not cloud=1	Ik_unsuper;ik_ndvi.;cloud.grd; shadow grd	.90

Table 1-5: File descriptions referenced in rule-based classifier table.

File Name	File Description
Ik_bfg.img	Ikonos 4-m data
Ik_ndvi_tan.img	Normalized Difference Vegetation Index
Ik_unsuper.img	Unsupervised classification that was recoded into 27 final classes.
Ik_unsupall.img	Unsupervised classification in original format (400 land cover classes)
Knowledge.img	Land cover classification using rule-based knowledge classifier.
Supervised.img	Supervised maximum likelihood land cover classification
DEM_recode.img	DEM grid recoded into two values representative of bottomland and upland areas
Cloud Grid	Digitized cloud cover converted to raster format
Shadow Grid	Digitized shadow pixels not captured by earlier pre-processing methods; converted to raster format
Buildings Grid	Digitized buildings converted to raster format

Table 1-6: Hierarchical rule-based (or Knowledge Classifier) classification land cover categories for Ikonos image.

Number	Land Cover Category
1	Water
2	Grass
3	Pine
4	Shadow/Cloud
5	Blackberry/Pine
6	Pine/Hardwood
7	Hardwood/Shrub
8	Hardwood/Vine
9	Hardwood/Grass
10	Upland Hardwood
11	Riverine Bottomland Hardwood
12	Bare/Grass
13	Algae
14	Building
15	Undefined

Table 1-7: Error matrix for supervised classification. Diagonal values represent overall correctly classified values. Non-diagonal columns represent errors of omission. Non-diagonal rows represent errors of commission.

H20																		
	veg.			CC				CC					Plant					Row
Classified Data		OPL	H20	0-3 yrs	RBH	Bare-soil	OPD	0-3 yrs.	Mix	Upl	Past.	Old Field	Pine 0-3	Pine 7-12	Bld	Rush	Pave.	Total
Water Vegetation (Algae)	8	0	5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	14
Open Pine (Light Understory)	0	4	0	2	0	0	1	1	0	1	2	0	0	1	0	0	0	14
Water	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14
Clearcut 0-3 yrs.	0	0	0	4	0	0	0	0	0	0	9	0	0	0	0	0	1	14
Riverine Bottomland Hardwood	0	0	0	0	5	0	0	0	0	9	0	0	0	0	0	0	0	14
Bare-soil	0	0	0	0	0	11	0	0	0	0	3	0	0	0	0	0	0	14
Open Pine (Dense Understory)	0	1	0	1	0	0	6	1	1	1	0	0	0	3	0	0	0	14
Clearcut 4-7 yrs.	0	1	0	1	0	0	3	5	0	0	0	0	0	4	0	0	0	14
Mixed Forest	0	0	0	0	0	0	5	0	9	0	0	0	0	0	0	0	0	14
Upland Forest	0	0	0	0	7	0	0	0	0	7	0	0	0	0	0	0	0	14
Pasture	0	0	0	2	0	0	0	0	0	0	12	0	0	0	0	0	0	14
Old Field (wildlife food plots)	0	0	0	0	0	0	0	0	0	0	11	3	0	0	0	0	0	14
Clearcut 03 planted pine	0	0	0	3	0	0	0	0	3	0	3	1	3	1	0	0	0	14
Planted Pine 7-12 yrs	0	0	0	1	0	0	1	0	3	0	0	0	0	8	0	0	0	14
Urban (Buildings)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	1	14
Rushes	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	14
Pavement	0	0	4	2	0	0	0	0	0	0	0	0	0	0	0	0	8	14
Column Total	8	6	23	16	12	11	16	7	16	18	41	4	3	17	13	14	10	252

Table 1-8: Accuracy assessment for supervised classification. Reference totals represent the number of validation points for that class. Classified totals are the number of points classified as that category. The number correct represents number of points that were correctly classified for that category. The producers accuracy represents the accuracy of the training data used to depict the land cover category. Users accuracy represents the probability that the land cover class is correct. The Kappa statistic is a measure of overall accuracy controlling for type I error.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa Statistic
Water Vegetation (Algae)	8	14	8	100.00%	57.14%	0.5574
Open Pine (Light understory growth)	6	14	4	66.67%	28.57%	0.2683
Water	23	14	14	60.87%	100.00%	1
Clear Cut-0-3 yrs.	16	14	4	25.00%	28.57%	0.2373
Riverine Bottomland Hardwood	12	14	5	41.67%	35.71%	0.325
Bare-soil	11	14	11	100.00%	78.57%	0.7759
Open Pine (Dense understory growth)	16	14	6	37.50%	42.86%	0.3898
Clearcut 4_7 yrs	7	14	5	71.43%	35.71%	0.3388
Mixed Forest	16	14	9	56.25%	64.29%	0.6186
Upland Forest	18	14	7	38.89%	50.00%	0.4615
Pasture	41	14	12	29.27%	85.71%	0.8294
Old Field (wildlife food plots)	4	14	3	75.00%	21.43%	0.2016
Planted Pine 0-3 yrs	3	14	3	100.00%	21.43%	0.2048
Pine Plantation 7-12 yrs	17	14	8	47.06%	57.14%	0.5404
Urban (Buildings)	13	14	13	100.00%	92.86%	0.9247
Rushes	14	14	14	100.00%	100.00%	1
Pavement	10	14	8	80.00%	57.14%	0.5537
Totals	252	252	134			

Overall Kappa Statistic = 0.2448

Overall Classification Accuracy =53.17%

Table 1-9: Error matrix for unsupervised classification (no re-code). Diagonal values represent overall correctly classified values. Non-diagonal columns represent errors of omission. Non-diagonal rows represent errors of commission.

Classified Data	Grass/ Veg																						Row Total	
	Unc	H2O	Shd/ Pne	Gr	H2O	Pne	Shd	Wd	Gr	Pne	Hdw	Shb	Vne	Hoak /Oak	Hdw	Cld/ Hd	Cld/ Gr	Hdw/ Gr	Bar/ Gr	Bar/ soil	Cld	Bld	Total	
Unclassified	1	1	34	12	5	42	9	1	2	8	23	3	5	1	73	1	1	6	5	1	2	4	240	
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Shadow/Pine	3	0	0	0	0	52	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	59	
Grass	1	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	
Grass/ H2O Veg.	1	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	
Pine	1	0	0	0	0	27	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	30	
Shadow	9	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	
Snag/Wood	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
Pine/Grass	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	4	
Blackberry/Pine	2	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	8	
Pine/Hardwood	1	0	0	0	0	2	0	0	0	0	18	0	0	0	2	0	0	0	0	0	0	0	23	
Hardwood/Shrub	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	3	
Hardwood/Vine	0	0	0	0	0	0	0	0	0	2	0	0	5	0	0	0	0	1	0	0	0	0	8	
Water Oak	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	3	
Hardwood	4	0	0	0	0	5	0	0	0	1	6	0	1	0	82	0	0	0	0	0	0	0	99	
Cloud/Hardwood	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
Cloud/Grass	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	
Hardwood/Grass	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	10	
Bare/Grass	2	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	9	
Bare/Soil	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	
Cloud	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
Cloud/Bldg	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	
Column Total	33	2	34	30	13	130	9	0	6	19	50	6	11	1	161	1	1	17	5	4	2	4	540	

Table 1-10: Accuracy assessment for unsupervised classification (no re-code). Reference totals represent the number of validation points for that class. Classified totals are the number of points classified as that category. The number correct represents number of points that were correctly classified for that category. The producers accuracy represents the accuracy of the training data used to depict the land cover category. Users accuracy represents the probability that the land cover class is correct. The Kappa statistic is a measure of overall accuracy controlling for type I error.

[illegible]

Table 1-11: Error matrix for unsupervised final re-code classification. Diagonal values represent overall correctly classified values. Non-diagonal columns represent errors of omission. Non-diagonal rows represent errors of commission.

Classified Data	H2O	Grass	Pine	Shd Cld	Blckberry/ Pine	Pine/ Hdw	Hdw/ Shrub	Hdw/ Vine	Hdw/ Hdw	Hdw/ Grass	Grass/ Bare	Bare/ Soil	Algae	Bldg	Bldg/ Grass	Row Total
Water	15	0	0	0	0	0	1	0	0	0	0	0	0	0	0	16
Grass	0	14	0	0	0	0	1	0	0	1	0	0	0	0	0	16
Pine	0	2	11	1	0	3	0	0	1	0	0	0	0	0	0	18
Shadow/Cloud	0	0	1	13	0	1	0	0	0	0	0	0	0	0	0	14
Blackberry/Pine	1	0	2	0	11	0	1	0	0	1	0	0	0	0	0	16
Pine/Hardwood	1	1	2	1	0	9	0	0	2	0	0	0	0	0	0	16
Hardwood/Shrub	0	1	0	0	0	0	15	0	0	0	0	0	0	0	0	16
Hardwood/Vine	0	1	0	0	2	0	0	13	0	0	0	0	0	0	0	16
Hardwood	0	0	1	0	0	3	0	0	13	0	0	0	0	0	0	16
Hardwood/Grass	0	2	0	0	0	0	0	0	0	14	0	0	0	0	0	16
Grass/Bare	0	6	0	0	0	0	0	0	0	3	7	0	0	0	0	16
Bare-soil	0	8	0	0	0	0	0	0	0	0	7	1	0	0	0	16
Algae	2	0	0	1	0	0	0	0	0	0	0	0	13	0	0	16
Building	0	0	0	0	0	0	0	0	1	0	0	2	0	11	1	16
Building/Grass	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	16
Column Total	19	36	15	16	13	16	18	13	17	19	14	19	13	11	1	240

Table 1-13: Error matrix for knowledge classifier. Diagonal values represent overall correctly classified values. Non-diagonal columns represent errors of omission. Non-diagonal rows represent errors of commission.

(Please note: Land cover class “Undefined” is deleted).

Classified Data	Bldg	Shadow	Cloud	H2O	Pine	Hdw/ Grass	Bck Berry/ Pine	Pine/ Hdw	Hdw/ Shrub	Hdw/ Vine	Bare/ Grass	Algae	Riverine Btm Lnd Hdw	Upland	Grass	Row Totals
Buildings	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Shadows	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17
Clouds	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Water	0	1	0	25	0	0	0	0	0	0	0	0	0	0	0	0
Pine	0	0	0	1	88	1	3	6	0	0	0	0	0	0	2	26
Hardwood/Grass	0	0	0	0	0	22	0	0	0	0	0	0	0	0	3	105
Blackberry/Pine	0	0	0	1	1	1	17	0	1	0	0	0	0	0	2	25
Pine/Hardwood	0	0	0	1	5	0	0	24	0	0	0	0	0	0	0	23
Hardwood/Shrub	0	1	0	0	0	0	0	0	16	0	0	0	0	0	2	32
Hardwood/Vine	0	0	0	0	0	0	3	0	0	18	0	0	0	0	1	19
Bare/Grass	0	0	0	0	0	4	0	0	0	0	7	0	0	0	12	22
Algae	0	1	0	2	0	0	0	0	0	0	0	24	0	0	0	26
Bottomland	0	0	0	0	0	0	0	0	0	0	0	0	28	5	0	27
Upland	0	0	0	0	0	0	0	5	0	0	0	0	0	78	0	33
Grass	4	1	0	2	0	2	0	0	1	0	8	0	0	0	46	83
Column Total	21	4	0	32	94	30	23	35	18	18	15	24	28	83	68	

Table 1-14: Accuracy assessment for knowledge classifier. Reference totals represent the number of validation points for that class. Classified totals are the number of points classified as that category. The number correct represents number of points correctly classified for that category. The producers accuracy represents the accuracy of the training data used to depict the land cover category. Users accuracy represents the probability that the land cover class is correct. The Kappa statistic is a measure of overall accuracy controlling for type I error.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa Statistic
Undefined	0	1	0	---	0	0
Buildings	21	17	17	80.95%	100%	1
Shadows	4	0	0	---	80%	0
Clouds	0	0	0	---	0%	0
Water	32	26	25	78.13%	100%	0.9591
Pine	94	105	88	93.62%	87.13%	0.804
Hardwood/Grass	30	25	22	73.33%	88%	0.8729
Blackberry/Pine	23	23	17	73.91%	73.91%	0.7275
Pine/Hardwood	35	32	24	68.57%	80%	0.7327
Hardwood/Shrub	18	19	16	88.89%	87.50%	0.8367
Hardwood/Vine	18	22	18	100.00%	81.82%	0.8119
Bare/Grass	15	26	7	46.67%	28%	0.2484
Algae	24	27	24	100.00%	92.31%	0.8837
Riverine Bottomland Hardwood	28	33	28	100.00%	80%	0.8402
Upland	83	83	78	93.98%	78.26%	0.9288
Grass	68	101	46	67.65%	57.14%	0.377
Totals:	405	405	309			

Overall Classification Accuracy=76.30%

Overall Kappa Statistics=0.7317

FIGURES

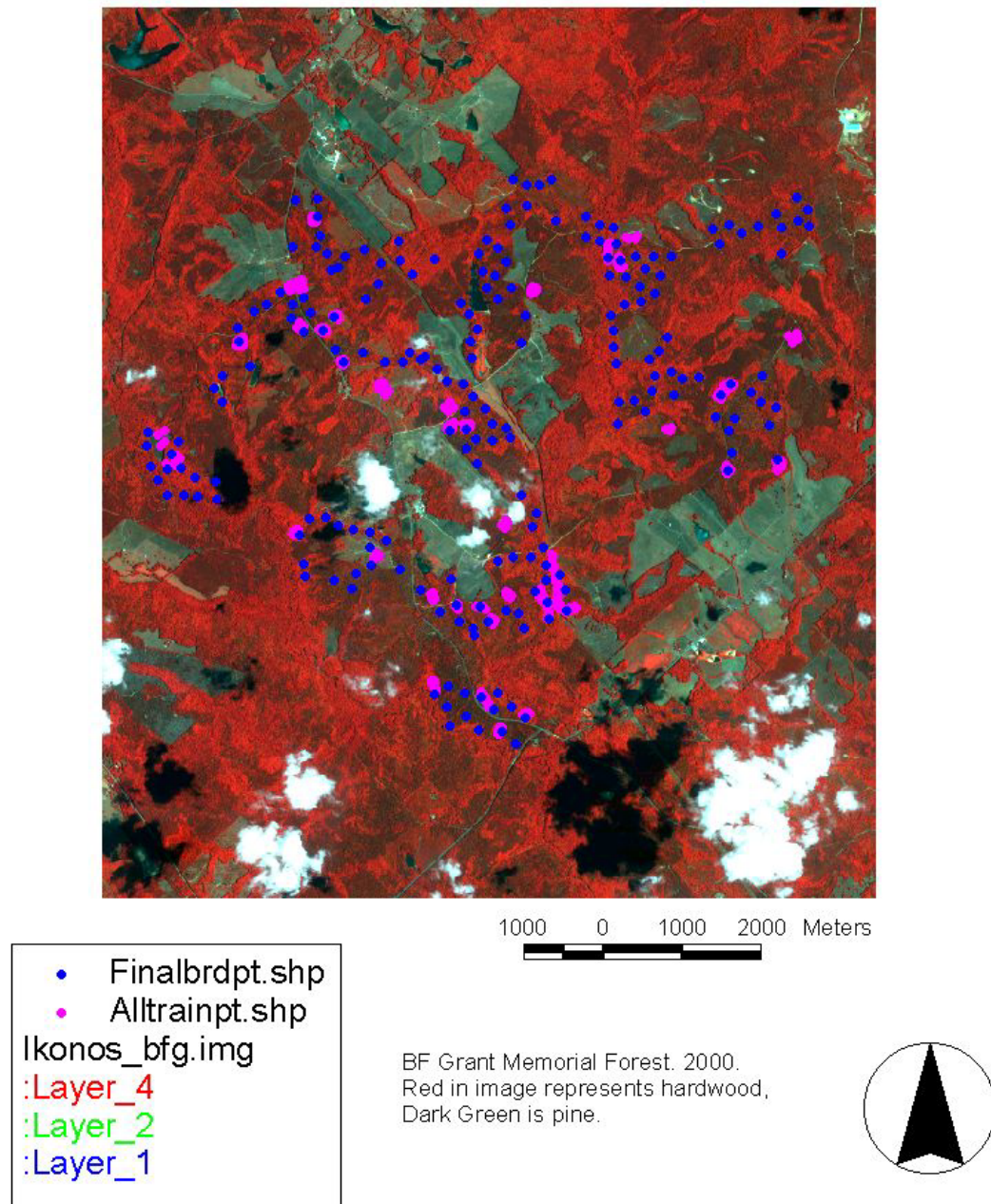


Figure 1-1: Distribution of training and validation vegetation points used in image classification.

APPENDICIES

Appendix 1-A: GIS metadata. Background information on digital data used in classifications.

Data Name	Classification Used In	Original Format	Source	Year	Scale
Clouds	Ikonos	Vector	Digitized	2000	Digitized off of 4-m data
Shadows	Ikonos	Vector	Digitized	2000	Digitized off of 4-m data
Water/Rivers	Ikonos	Vector	Digitized	2000	Digitized off of 4-m data
Roads and Highways	Ikonos	Vector	Digitized	2000	Digitized off of 4-m data
Buildings	Ikonos	Vector	Digitized	2000	Digitized off of 4-m data
Digital Elevation Model (National Elevation Dataset)	Ikonos	Raster	GA Clearinghouse	2002	1:24,000

Appendix 1-B: Land cover classification vegetation measurements. These vegetation measurements were collected within a 50-m radius from the georeferenced point (either in the configuration used for the signature training step or the validation point).

#	Training site/ Validation Measurements Used in Land Cover Classification
1	Slope
2	Aspect
3	Vegetation Cover Type
4	BAF, Tree species, DBH
5	Dominant / Co-dominant Tree Species
6	Height of Dom/codom tree every 3 rd point
7	General understory/mid-story height every 3 rd pt
8	Ground vegetation groundcover-Dominant/co-dominant
9	% groundcover shrub, herbaceous, saplings, vine and other
10	Dominant/co-dominant understory species
11	Understory density in quartiles
12	Dominant/co-dominant mid-story vegetation
13	Codified mid-story density in quartiles
14	% comparison of mid-story of hardwood, shrub, pine, vine, etc.
15	Canopy quartiles of upper/lower canopy.
16	Presence of insect irruption
17	Burned recently
18	General Management Comments

CHAPTER 2 : THE COMPARISON OF HIGH AND LOW RESOLUTION SATELLITE DATA IN BIRD HABITAT MODELING

Introduction

Research in the last 10 years has shown coarse-medium resolution satellite data (grain/pixel size > 25m) to be useful for detecting broad-scale landscape patterns associated with a variety of species distributions (Aspinall and Veitch 1993, Knick and Rotenberry 1995, Riitters et al. 1997, Dettmers and Bart 1999, Osborne et al. 2001, Mayer and Cameron 2003). Since the early 1990's, satellite data such as Landsat Thematic Mapper (TM) have been used successfully in many wildlife studies, ranging from monitoring species across large landscape scales (GrattoTrevor 1996, Hepinstall and Sader 1997), reserve design (Groves et al. 2002), determining broad scale patterns associated with species distributions (Flather and Sauer 1996, Innes and Koch 1998), to forestry applications (Cumming et al. 1994, Londo et al. 2000, Lowe and Whiffen 2000, Peng et al. 2003). TM data has now become one of the most commonly used spatial information sources in landscape management plans and species modeling efforts.

The advantage of using 30-m data lies in its affordability and ability to capture the broader landscape patterns associated with some species, but its utility is limited when addressing habitat associations at finer scales. When modeling species distributions, it is important to recognize that species exploit different features within their environment at different scales. Research has shown that many finer scale-dependent ecological processes or landscape features associated with a species' presence are not captured using 30-m image grain sizes alone.

Most often models are supplemented with other data collected at a finer scale (i.e., field measurements) to increase the performance of the models (Stoms et al. 1992, GrattoTrevor 1996, Mack et al. 1997, Debinski et al. 1999, Osborne et al. 2001, Saveraid et al. 2001).

High-resolution satellite data (< 5-m) in species modeling has been suggested for modeling across a suite of landscape scales, but its use has been significantly hampered by the exorbitant cost of the images (Andrefouet et al. 2002, Auda et al. 2002, Sidle et al. 2002, Capolsini et al. 2003, Palandro et al. 2003, Philipson and Lindell 2003, Clark et al. 2004b). Until recently, habitat data at resolutions < 5m were only available by physically measuring those characteristics in the field or by using aerial photography, both having significant drawbacks for use in landscape-level modeling.

Unlike coarse-resolution images, high-resolution images can depict features or objects of interest within individual multiple scales. Thus, the hierarchical nature of habitat use by many wildlife species can be examined through the detection of these objects or features (object-specific methods (Hay et al. 2001, Hall et al. 2004)) (Saab 1999, Gust et al. 2001, Cushman and McGarigal 2002, Wu and David 2002, Cushman and McGarigal 2004a, Nikula et al. 2004).

The assumption that increased resolution should improve model prediction has yet to be tested. This may or may not be true depending upon the species modeled and the scale of the features with which it is associated (Mack et al. 1997, Cushman and McGarigal 2002, Maeder et al. 2002, Grand and Cushman 2003, Cushman and McGarigal 2004b, a). Satellite images are limited in the features they are able to capture (i.e., reflectance values of physical features, not necessarily structural characteristics). Therefore, whether or not high-resolution satellite images are able to detect the vegetation patterns or replace field measurements of vegetation characteristics is still unknown. In recent years, studies have compared high-resolution sensors

such as Ikonos with a variety of other coarser resolution sensors including the Landsat Multispectral scanner (MSS), Landsat 7 ETM+, Terra Modis, and others in mapping projects and baseline assessments of the electromagnetic bands (Capolsini et al. 2003, Goward et al. 2003, Thome et al. 2003, Thenkabail 2004), with Ikonos data performing relatively well for the projects' objectives. To date, published studies have used high resolution satellite data to detect vegetation structure and tree mortality (Asner et al. 2002, Clark et al. 2004a), vegetation changes (Franklin et al. 2001, Allard 2003, Clark et al. 2004b), malaria control (Masuoka et al. 2003) and mapping of land use features such as tree cover, impervious surface areas, and riparian buffer zones (Asner et al. 2002, Goetz et al. 2003), but none have compared the performance of high resolution data with other data types in wildlife habitat modeling.

The use of high-resolution satellite images in wildlife habitat modeling is not without its drawbacks. The images are expensive in comparison with TM data, require stronger computing power and run times, and wildlife habitat modelers must increasingly integrate knowledge from the disciplines of remote sensing and landscape ecology to model the data correctly.

Methodological issues within each of these disciplines have arisen from the use of high-resolution data and progress towards resolving these issues is now at various stages. Many of the established processing and analytical methods (from the stage of raw data to model creation) do not function as well or at all with the increased grain size (resolution) of the images. The newness of the technology has required researchers to focus on the manipulation of existing techniques and the development of new methods over the last few years to address issues involved with the change of scale.

The main objective of this research was to compare the performance of habitat models created with high resolution satellite data with models created with other commonly available

data types to predict the presence/absence of birds across a landscape. To address whether specific habitat field measurements are necessary to build good models as well as how much a particular data category contributed to the model, I developed five different sets of models for each species using different data types.

Data type categories for the model sets were 1) field measurements only; 2) 30-m data only; 3) 4-m data only; 4) 30-m data, GIS data, and field measurements; 5) 4-m data, GIS data, and field measurements (Table 2-1). Field measurements consisted of variables commonly used in wildlife habitat models following James and Shugart (1970) (e.g., dominant species in understory, % groundcover, % canopy cover, etc). GIS data utilized various sources of spatial data manipulated in a geographical information system (e.g., distance to water, slope, aspect, stand management data, etc). The two resolutions of satellite data that represented the same geographical area during late spring/early summer were classified into land cover data, a format commonly used in wildlife modeling studies. Variables derived from those maps consisted of land cover percentages surrounding the bird survey points and landscape metrics calculated from land cover types (Appendix 2-A). It is important to note that the focus of the research was not on creating the “best” model for each species. Rather the focus was to compare how the different data types perform relative to one another for each species.

Six study species were grouped according to two general habitat types, closed canopy and early successional (open canopy) forest. These categories were selected for their common use in explaining habitat associations of groups of birds, but primarily because of the difference in the ability of satellite data to detect the layers of vegetation features in each habitat type. Changes in resolution among the data types would also likely affect the detection of features within the two habitat types differently (e.g., potentially similar results between the two image resolutions in

tracts of contiguous forest, but different results when detecting scrub/shrub vegetation in the open canopy early successional forest habitat).

It is assumed that the increased resolution in satellite data will create better predictive wildlife habitat models than data derived from coarser resolution images because of the ability of finer resolution data to capture those potential finer scaled habitat features with which a species may be associated. I constructed a priori hypotheses with the premise that this benefit will depend upon the species being modeled. Within each species and habitat grouping, I tested four hypotheses.

The following hypotheses address whether high-resolution data are necessary for all species modeled or if the 30-m data and the field measurements suffice:

Hypotheses

4-m Combination Model Hypothesis: Models containing 4-m, GIS variables, and field measurements will rank the highest in predicting presence and absence for all species. Models that contain 4-m data and the other two data types will predict presence/absence of a species the best because it combines data types that are able to capture different habitat features associated with the species, rather than representing only one set of features or scale.

Successional Stage Hypothesis: Models containing 30-m, GIS variables, and field measurements will rank higher in predicting presence and absence for the closed canopy species (CCS) than early successional (ESS) species. The 30-m resolution will be adequate for detecting large patches of forest canopy with which closed canopy species are associated but the resolution

will not be sufficient to detect the smaller patch sizes of shrubs that early successional species utilize.

The next two hypotheses address whether models created with high resolution data perform stronger than models containing only wildlife field measurements.

Closed Canopy Species Hypothesis: For closed canopy species, models containing no field measurements or only field measurements will rank lower in predicting presence and absence than models created from a combination of data types. Potentially, some of the closed canopy species are strongly associated with understory structure elements that satellite images are unable to detect. Therefore, models that do not contain data representing structure beneath the canopy (models with no field measurements) will not perform as well as models that do. However, many closed canopy species have been associated with different landscape fragmentation scales and models that do not capture these other scales (i.e., field measurement data only) will not perform as well as those that do capture landscape scale effects (models created with several data types).

Early Successional Species Hypothesis: Models containing only spatial variables for the 4-m data will have sufficient predictive ability (defined below) for ESS species. Without the presence of heavy canopy, the satellite image is able to detect understory vegetation patterns with which many early successional species may be associated. The 4-m resolution will be fine enough to pick up the smaller vegetation patches that previously were undetectable using coarser resolution. In particular, I was most interested in determining whether models created with only 4-m spatial data performed as well as field data for the early successional species. If true, the

collection of detailed habitat field measurements may not be necessary for these species. Sufficient predictive ability is defined as models having classification rates over 70 % and/or AIC differences showing sufficient empirical support ($\Delta AIC \leq 3$) (Burnham and Anderson, 2002).

A secondary overall research objective was to address the applicability of this technology in wildlife habitat modeling, specifically as to whether the predictive abilities of the high-resolution models justify the time and costs relative to other data types in this study. A final discussion will address the suitability of a data type in relation to a project's overall goals, objectives and available resources.

Materials and Methods

Study Area

The study was conducted in the Bishop F. Grant Memorial Forest (B.F. Grant), a 5261-ha tract of land located in the Piedmont of Georgia approximately 145 km south of Athens. The study area straddles Madison and Putnam Counties and is managed for loblolly (*Pinus taeda*) and shortleaf (*P. echinata*) pine by the University of Georgia (Warnell School of Forest Resources 1999). A patchwork of private farms is distributed throughout the landscape. These private farms vary in use (dairy, agriculture and poultry activities).

There are several small ponds and a waterfowl impoundment within the property. Pine stands cover approximately 50 % of the property and the remaining stands are hardwood or hardwood/pine mix. Dominant hardwood species include *Quercus spp.*, *Cary spp.*, *Acer spp.* and *Liquidambar styraciflua*. Harvest methods vary from clearcuts, to shelterwood cuts, to single-tree selection. Various other management techniques applied throughout the forest

include prescribed burns and herbicide treatments. The area is a designated wildlife management area, and is opened to the University of Georgia for research and classes (Warnell School of Forest Resources 1999).

Study Species

The six study species used in this research are neotropical migrant songbirds that breed in the southeast during the summer months. Three birds were selected for each habitat category. I focused on selecting edge-sensitive species associated with mature forest for the closed canopy habitat group and edge/patch-associated species for the early successional habitat grouping.

Closed Canopy Species.—The three species, Acadian Flycatcher (*Empidonax virescens*) (ACFL), Red-eyed Vireo (*Vireo olivaceus*) (REVI), and the Yellow-billed Cuckoo (*Coccyzus americanus*) (YBCU) have life history strategies that are associated with contiguous tracts of closed canopy mature forest and large forest patch sizes. Though associated with large tracts of deciduous woodlands, all the birds have very different habitat requirements associated with them.

The Acadian Flycatcher is associated with distance to edge landscape metrics, patch size (northern part of range), and canopy cover (Hamel 1992, Rodewald and Smith 1998, Wilson and Cooper 1998, Whitehead and Taylor 2002). In the Georgia Piedmont, the bird is a habitat specialist focusing on riparian areas (Hamel 1992, Hyder 2002). The Red-eyed Vireo's habitat requirements are associated with dense canopy cover (% of deciduous cover) and large patch size (landscape metrics)(Hamel 1992, Cimprich et al. 2000., Marshall et al. 2002, Marshall and Cooper 2004). However, research has shown that the Red-eyed Vireo responds to small canopy

gaps. (Cimprich et al. 2000., Marshall et al. 2003). The optimum habitat of the Yellow-billed Cuckoo is described as open woodlands, especially where undergrowth is thick, deciduous riparian woodland, and moist thickets (again, land cover types may prove to be useful, but the species may respond more strongly to structural characteristics)(Hamel 1992, Hughes 1999, Wilson 1999).

Edge/ Early Successional Species.—These species are associated with a variety of edge habitats (edge habitat defined as the border between different vegetation types that are markedly different in vertical height) and or early successional edge habitat. These species' life history strategies suggest a dependence on understory vegetation structure in the home range where the understory is patchily distributed across the stand or along the edges of clearcuts (i.e., birds that require an understory shrub component in an early successional habitat such as an open pine stand).

The habitat of the Indigo Bunting (*Passerina cyanea*) (INBU) consists of woodland edges, brushy fields, open deciduous woodlands and roadside thickets. The Indigo Bunting prefers areas with a few tall trees or other high perches (Hamel 1992, Payne 1992, Rodewald and Smith 1998). Prairie Warbler (*Dendroica discolor*) (PRAW) habitat suggests a dependence on patch area structure in the home range (Hamel 1992, Nolan et al. 1999). The Yellow-breasted Chat (*Icteria virens*) (YBCH) is associated with dense thickets and brush, often with thorns, along streamside tangles and dry brushy hillsides (Hamel 1992, Eckerle and Thompson 2001).

Avian Data Collection

I used the point count survey technique to assess bird habitat use across the study area. Unless noted otherwise, survey methods follow Ralph et al. (1995) and Martin et al. (1997).

Survey routes consisted of 10-13 sampling points of four overall vegetation types (Riverine Bottomland Hardwood Forest [BHD], Upland Deciduous Forest [UPL], Upland Mixed Forest [MIX], and Open Upland Pine Forest [PNE]). There were 16 survey routes in the year 2000, for a total of 184 points. One survey route was clearcut immediately after collecting bird survey data in the 2000 field season. In summer of 2001, an additional 26 points were established. I discarded two points due to questionable data quality. Total survey points from the two years of data collection are 208. There was a minimum of 30 survey points per each habitat type described above.

Bird surveys were conducted from 28 May – 1 July, 2000, and 5 May – 30 June, 2001, taking place between sunrise and 10 a.m. All birds detected within a 50-m radius of the plot center were recorded (Ralph et al. 1995). Distance between bird survey points ranged from 200 to 450-m to maintain independence from one another (Ralph and Scott 1981, Drapeau et al. 1999). I surveyed each survey point at least twice each season, with a minimum of one week between surveys (Dettmers et al. 1999). Bird surveys lasted ten minutes at each point (Barker et al. 1993, Smith et al. 1998, Drapeau et al. 1999).

Using ADAR photos (Aerial Digital Photo System [Positive Systems, Inc.]), I established survey routes by choosing stands that were large enough to contain a 50-m buffer surrounding the point and that appeared to be a homogenous representation of the vegetation type. To avoid bias due to location (e.g., all bottomland hardwood cover types placed in the same flood plain), I made a special effort to distribute the location of the survey points of each habitat type across the study area. This was done by dividing the study area into ten major blocks with an effort to spatially distribute point count routes across the landscape ($\geq$ one route per block). All survey

points were geographically referenced (Universal Transverse Mercator [UTM] coordinate locations) using a Trimble global positioning system (GPS) with < 2-m accuracy.

Vegetation Data Collection

There were three different types and uses for the vegetation measurements: 1) identifying habitat at the bird survey points (wildlife measurements); 2) training sites for classifying the satellite imagery; and 3) validation sites for assessing the accuracy of the land cover classification process. All vegetation measurements and selection of sampling points for each category differed. I collected vegetation data in July-October 2000 and June-July 2001. In 2001, due to the long growing season in GA, I re-measured field variables subject to change from the year 2000 (e.g., understory density).

Wildlife Habitat Measurements.—The designation of habitat types at the survey points was similar to categories established in previous work with avian/habitat relationships (Hamel 1992) (Appendix 2-B). Vegetation layers were very different in the two habitat types (closed canopy and early successional-open pine forest). In a closed canopy forest there are four distinct vegetation layers (ground cover, understory, midstory, canopy). In an open pine forest the midstory is not present and therefore the understory layer tends to be taller than the understory layer in a closed canopy deciduous forest. Therefore, I defined vegetation structure by height characteristics (vertical levels) and successional stage (Appendix 2-C). For a complete list of all habitat variables recorded and used in these models, see Appendix 2-D.

Land cover classification training sites.—I established 3-7 training sites for each habitat category. Each training site consisted of nine point samples (configured in a square). The

number of training sites for each land cover category varied due to signature purity. For further detail please see Chapter 1 (Appendix 1-B).

Validation sites.—Vegetation sampling sites followed the same protocol as training sites. I collected vegetation data at 213 validation sites. The same sampling measurements for training sites were also taken for validation sites. Validation points were supplemented using ADAR photo interpretation. Further details on site selection are referenced below.

Digital Data

The digital data used to create and validate the final land cover maps in this study consisted of a number of satellite images (Ikonos and two different Landsat images), high resolution digital photos, enhancement images created from the satellite images and a digital elevation model (DEM). Below, I identify the data sources and outline the methods used for themes I created.

Remotely Sensed Images.—I used the Ikonos 4-m spatial resolution panchromatic image taken by the Ikonos-2 sensor on June 23, 2000. Data were projected in UTM, North Hemisphere, Zone: 17, Datum: NAD 83. The image was orthorectified and had an RMS error of 1.12 meters. The collection azimuth: 257.6 degrees at an elevation of 57.6 degrees, and the sun azimuth was 116.1 degrees at 71.0 degrees elevation. For more detailed information about the Ikonos data, please see Chapter 1.

I used two scenes of Landsat TM data taken at different times of the year to classify the TM derived land cover map. The spatial resolutions of Landsat sensors are 15 -79 meters and

have 3-7 bands depending upon the sensor (Note: 15-m resolution is available only on the panchromatic bands on the Landsat 7 ETM+ sensor (Multispectral bands are available in 30-m resolution and are the bands used to produce land cover maps). The spring scene I used was a TM 30-m spatial resolution image taken by the Landsat 7 ETM+ sensor (7 bands) on May 30, 2000. Data were projected in UTM, North Hemisphere, zone:17, Datum: NAD 83. The sun azimuth was 125.9 degrees at 62.5 degrees elevation. The area represented in the images (Ikonos and TM) was ~20,000 ha in Putnam County, GA. I used Erdas Imagine 8.4 software to clip the TM image to the size of the Ikonos image before classifying into a land cover map.

The winter scene I used, a TM 30-m spatial resolution image taken by the Landsat 7 ETM+ sensor on December 24, 1999, was projected in UTM, North Hemisphere, zone:17, Datum: NAD 83. The sun azimuth was 155.6 degrees at 29.3 degrees elevation. The area represented in the images (Ikonos and TM) was ~20,000 ha in Putnam County, GA. I used Erdas Imagine 8.4 software to clip the TM image to the size of the Ikonos image before classifying into a land cover map. The winter scene was used in the knowledge-based classifier to refine pine and other land cover classes.

I also used Airborne Data Acquisition & Registration (ADAR 5500) digital photos for laying out point counts and land cover classification accuracy assessment. The photos were taken in May of 1999 and had a resolution of 2 m. They were projected in UTM, North Hemisphere, Zone: 17, Datum: NAD 83. The ADAR photos in this study were used for supplemental land cover accuracy assessment points.

The final digital file I used to aid in image classification was a Digital Elevation Model (DEM). The DEM file was used to help delineate between bottomland and upland areas in the study area. See Appendix 2-E for more metadata information.

Spectrally and Spatially Enhanced Images.—I used various spectral and spatial enhancements derived from the base images to help classify the data. Image enhancement techniques are modifications to the pixel values of an image to help make the image more interpretable for a particular application. Spectral enhancement transforms the value of each pixel on a multi-band basis, whereas spatial enhancements are based upon the values of individual and neighboring pixels. All image enhancement techniques can improve interpretability, reduce data redundancy, and view different qualities of the data that are not readily visible in its raw form (Lillesand and Kiefer 2000).

I used two spectral enhancement techniques (Tassled Cap, NDVI) and one spatial enhancement (Texture processing) to help classify the images in each of the satellite data types (ERDAS 1999a, Lillesand and Kiefer 2000). All remote sensing manipulations and classifications used Imagine 8.4 (Erdas, Atlanta, GA).

The Tasseled Cap Transformation (or otherwise called Kauth-Thomas Transformation) is a data reduction technique similar to Principle Components Analysis (PCA). It uses the number of multispectral bands (n) to transform the data into a new n -dimensional space. The principle axes are related more to the absorption spectra defined by the bands of the multispectral image rather than the data space (Jensen 1996, ERDAS 1999a, Lillesand and Kiefer 2000). The user then chooses the data structure axes that pertain to the features of interest. For vegetation studies, three data structure axes define vegetation information content: 1) brightness is a weighted sum of all bands based on principle variation of soil reflectance; 2) greenness is a contrast of near-infrared and visible bands and this is related to the amount of green vegetation in the scene; 3) wetness is related to canopy and soil moisture. The soil brightness index (SBI) can

be very useful in land cover classification because it emphasizes bare areas such as agricultural fields, beaches, and parking lots as the lightest features. The green vegetation index (GVI), similar to the NDVI, displays areas with healthy, green vegetation as the lightest feature. (Jensen 1996, ERDAS 1999a, Lillesand and Kiefer 2000).

The Tasseled Cap Transformation was used on Landsat TM Spring and Winter Images. I performed a tasseled cap transformation on six TM bands of each image and then utilized the SBI and GVI for the rule-based classification stage. The spring scene targeted most of the deciduous classes as well as agriculture fields, and the winter scene refined the classes that would be influenced by the presence of foliage (e.g., rivers, urban, mixed forest, pine forest, etc.). Before using the enhanced images in the rule-based classification, I performed an unsupervised classification on the enhanced themes, (200 categories, using same methods described in the classification section below) in order to select out rivers, bare area, urban, agriculture/pasture, clearcut, and mix. The use of these two indices, along with the near-IR layer (band 4), helped the land cover classification immensely for clearcut areas that had a lot of bare areas and vegetation.

The second type of enhancement used to classify the images was the NDVI, which I used on the Ikonos data. For detailed methods and background information, please see Chapter 1.

To refine further the land cover classification of clearcut with other land cover values in the TM classification, I used a clumping and sieving function in Erdas Imagine 8.4. Because clearcuts were relatively large areas on the study site, a file was generated that eliminated clumps less than 100 pixels in size for the clearcut land cover value. The file was then included in the rule-based classification for the TM image (Appendix 2-E; Figure 2-1).

GIS Data.—I obtained GIS data from the Georgia GIS Clearinghouse (<http://www.gis.state.ga.us/Clearinghouse/clearinghouse.html>) used in TM land cover classification. Supplemental data used to classify the Ikonos land cover were collected from information gathered at B. F. Grant that was either referenced using a GPS unit ≤ 1.7 -m accuracy or digitized by hand off the orthorectified image (Appendix 2-E). Variables created from the GIS software are referenced in Appendix 2-F.

Land Cover Classification

Two classification methods derived the four land cover maps from both the Landsat TM and Ikonos images. Each image had a land cover map for 2000 and 2001. I first used an unsupervised/supervised hybrid classification method to define overall classes, followed by a rule-based classification (Knowledge Classifier; Erdas Imagine 8.4) to refine target classes that had low accuracy values from step one. Further detail of the knowledge based classification method is found in Chapter 1 of this thesis.

Ikonos Classification.—The Ikonos land cover classification done in Chapter 1 was further refined in this chapter to 85% accuracy for land cover types used in the models. The unsupervised/supervised hybrid classification method is a technique that has two parts. The image was first processed using an unsupervised approach, in which the computer separates land cover classes based upon spectral reflectance values (Jensen 1996, Lillesand and Kiefer 2000). I classified the image into 400 classes or clusters. After completing the unsupervised classification where the product was a land cover theme with 400 classes, I used a supervised classification approach where the user manually defines the land cover classes to cluster the 400

land cover categories into the 17 final categories (Table 2-2; Figure 2-2 and Figure 2-3)). This was done using the training data and ADAR images. ADAR images were then geo-referenced to the Ikonos image. I then performed an accuracy assessment to identify classes that had overall correctly classified scores < 85 %. Rivers, roads, clearcuts, clouds, shadows, etc were digitized from on-screen. Additionally, I generated a mask to further eliminate cloud and shadow pixels.

The second step of the overall land cover processing targeted classes that had low accuracy values from the unsupervised classification by using a rule-based or knowledge-based classification (see Chapter 1 for detailed background information on method). The software uses a rules-based approach in multispectral image classification (ERDAS 1999b). I incorporated the digitized themes of clearcuts, cloud, shadow, building, roads, and water into the classification. Upland and riverine bottomland classes were delineated from one another using a digital elevation model and buffer. There were two separate land cover classifications done for each year and then appended to each year's data for the analysis to account for clearcuts or thins that occurred between the year 2000 and 2001. I used the tassled cap approach to clean up hardwood mixture signatures (i.e., hardwood/shrub, hardwood/vine, hardwood/grass, etc.)

Landsat TM Classification.—As with the Ikonos image, there were two separate land cover classifications done for each year and then appended to each year's data for the analysis, which accounted for the clearcuts or thins that occurred between years. I processed the image using the same methods as the Ikonos image (unsupervised/supervised hybrid approach, rule-based classifier for land cover classification refinement), but altered data sources and specific details.

To begin, the unsupervised classification clustered the spectral values into 200 land cover classes rather than 400 classes. I did not need to break the image down to the 400 land cover classes due to comparable accuracy levels at this stage. The supervised approach re-classed the signatures into 12 final land cover categories (Table 2-2; Figure 2-4 and Figure 2-5) rather than the Ikonos 17 categories. I obtained supplementary data used in the rule-based classification for the TM image from the GIS clearinghouse, as well as generated enhancement images using both winter and spring TM scenes (Appendix 2-E). Rules and supplementary data used in the rule-based classifier may be viewed (Figure 2-1). Upland and riverine bottomland classes were delineated from one another using a DEM.

Landcover Accuracy Assessment

I performed an accuracy assessment on the classified image using >4250 stratified random generated points. Validation points were a combination of 2-m ADAR photograph interpretation and independent ground-truthed points. I used the same verification points in accuracy assessments of both images. All validation sites and the ADAR images were geo-referenced to both the TM and Ikonos images (see data description for RMS error). Classification accuracy deemed acceptable had an overall accuracy > 85% per land cover class for land cover types used in the modeling effort.

Landcover Data Extraction and Variable Creation

A GPS spatially referenced bird survey points (horizontal precision < 2.33 m). Using Arcview 3.2, I created buffers in ten varying scales ranging from a radius of 50 m to 179 m

around the bird survey points that were geo-referenced by the GPS. In this analysis however, I utilized only the 80-m radius buffer, which corresponds to an area of 2 ha. I chose to examine only one scale for two reasons. First, evidence suggests that neotropical migrants respond to plot level variables; therefore, for the satellite data I chose a two hectare area surrounding the point, which approximates many of the species home range sizes (Payne 1992, Hughes 1999, Nolan et al. 1999, Cimprich et al. 2000., Eckerle and Thompson 2001, Whitehead and Taylor 2002). Second, using one spatial scale standardizes the extent of area compared between the two images, and this minimizes any spatial effects that are caused when the shape or area of analysis is different, otherwise known as effects of the modifiable areal unit problem (MAUP) (Jelinski and Wu 1996, Wu and Qi 2000).

The land cover values for each pixel/cell that were within each of the buffers surrounding the survey points were extracted in Erdas Imagine 8.4 by intersecting the buffer coverage with the land cover maps. I then extracted land cover percentage values from the four land cover maps (representing the satellite data type and either 2000 or 2001). Before deriving landscape metrics, I merged land cover classes to represent specific land cover groups (Appendix 2-G). I then derived the landscape metrics for each buffer width using the Arcview Patch Analyst Extension (Carr and Rempel 1999)(Appendix 2-H). All bird and field data were connected to spatial data using Access 2000 (Microsoft Corp., Redmond, WA) and SAS/STAT software, Version 8.0 (SAS Institute Inc., Cary, NC).

Statistical Analysis

I used logistic regression to model species presence and absence in the landscape. An information theoretic approach was used in model selection (Burnham and Anderson 2002).

Model performance was evaluated using two validation methods, a jackknife approach and Akaike's Information Criteria (AIC), which assessed the weight of evidence for each species competing models.

Pre-modeling Diagnostics.—Preliminary diagnostics were performed prior to the formal analysis or model building. First, I examined the data for violations of logistic regression assumptions using SPSS version 9.0 (SPSS, Inc., Chicago IL), unless otherwise noted. In the initial exploratory analysis, I graphed the explanatory and response variables and visually inspected scatter plots for influential observations. I assessed the influence of questionable observations by calculating the dbeta and leverage statistics. There were a few cases of observation transcription errors of the measurements, but overall I chose to leave outlier observations in the data because the measured variable appeared to be a plausible value for the site. To ensure that error terms were independent, points that were sampled over two years had one sample randomly selected from either 2000 or 2001 (n=208). I diagnosed pairwise correlations among explanatory variables. One of the two variables that had a Spearman's rank-order correlation coefficient > 0.70 was excluded from that species global model. I created interaction effects of all plausible variables, which were included in the all-possible regressions (Appendix 2-A).

Explanatory variables.—Explanatory variables were pre-selected based upon the species life history strategy or previous studies (Appendix 2-A). I expressed care to standardize the variables selected among data type models for each species. All models, when possible, contained exact subsets of other data type groups. For example, the same field and GIS variables

were used in “30-m ALL” and “4-m ALL” models for each species. The field variables placed in the “ALL” models were the same variables contained in “Field” data models. However, certain data type models contained variables that are unique to that data type (e.g., Ikonos land cover types hardwood/shrub, blackberry/pine, hardwood/vine, etc., or structural field measurements such as midstory height, canopy height, understory density, etc.), so variables represented in one specific data type and not others were included in that data type’s model only.

Model Building and Selection.—All further analyses used SAS (SAS Institute 1995), unless otherwise noted. I ran all possible regressions for each data type for each species, limiting the total number of variables allowed in each model to 7 using a macro within SAS (Moore 2000). I chose to limit the variables in the all possible combinations to reduce the chance of spurious effects and because I considered the largest possible parsimonious model to be approximately 7 variables.

AIC is an estimate of model information relative to the data and other models. In order for the estimate to be accurate, the sample size should be sufficiently large. In this study, the n/K ratio was less than 40 for the majority of the global models, where N is the number of observations and K is the number of estimable parameters in the global model. Therefore, AICc values were used (Burnham and Anderson 2002).

The information theoretic approach must also be modified to address the problem of overdispersion, which count data commonly exhibit. When overdispersion is present in a model, the estimators of model parameters usually remain unbiased, but the theoretical variances based upon the model are overestimated. To address this issue, the overdispersion needs to be modeled and then methods using the generalized likelihood inference are employed. Using simple

modifications to the AIC/AICc values, the QAIC/QAICc values are able to adjust for overdispersion (Burnham and Anderson 2002).

I first tested the global models of each species for overdispersion using Pearsons chi-square/df ($c\text{-hat}$) before conducting the formal logistic regression analysis (Burnham and Anderson 2002). Interaction effects were also included in global models. Global models that exhibited overdispersion (Indigo Bunting, Yellow-breasted Chat, and Yellow-billed Cuckoo) used the QAICc value during model selection. After performing all possible logistic regressions for each species and data category, I then compared AICc/QAICc values to select the best 10 models from the total models produced (i.e., 10 models/data category within species; 50 models/species; 300 models/six species).

Model Validation.—The first set of measures used to validate models was derived from the jackknifing method. The top models for each species were evaluated using the jackknife procedure. Jackknife refers to the approach that builds the model with all of the data except one randomly selected observation. Then, the model performance can be validated by comparing the predicted value based upon the data set ($n-1$) to the held out observation value. This is an iterative process so that overall measures of performance can be determined for each of the models. The cutoff point used to predict an event or non-event in the validation procedure used the proportion of birds present in the landscape (total number of points a species was detected / total bird survey points) rather than an arbitrary value of 0.50. Models were ranked using total percentage of observations correctly classified, sensitivity and specificity. Percent correctly classified is a measure of the overall performance of a model, whereas sensitivity and specificity measures address specific classification components of the models. Sensitivity is a ratio

consisting of the number of correctly classified events over the total number of events. In the case of a bird species, it is the percent of birds that were correctly classified as present that were actually present. Similarly, specificity is a ratio of the number of correctly classified non-events over the total number of non-events. In this case, it is the percent of birds that were correctly classified as absent that were absent.

The second measure of model performance used the information criteria approach, which consisted of AICc differences (Δ AICc) and Akaike weights (Burnham and Anderson 2002). Δ AICc values allow one to compare models among a relative scale and are useful for ranking purposes. The individual AICc value by itself is not interpretable; it can only be used relative to other AICc values in the model set. They are computed by subtracting the AICc model value from the lowest model AICc value. The larger the AICc difference, the less plausible the model is the best model given the data.

Akaike weights allow for the interpretation of the relative likelihood of a model (the relative strength of evidence for a model), and allow one to quantify the plausibility of each model being the best model in relation to the model set. The relative likelihood is normalized to the sum of one. The method provides a way to scale and interpret the AICc differences (Burnham and Anderson 2002). The weight values are derived from the likelihood estimate and provide a good measure of a “data-based” weight of evidence for each model. In this case, models are comparable by species and we can determine which models in which data type have the strongest weights of evidence.

Assessment of Model Performance.—The jackknife validation measures were evaluated for all of the hypotheses in the following ways: 1) the best performing or worst performing

models for % correctly classified, % sensitivity, % specificity; 2) overall difference between the contrasted models and other data models of that species. If the difference between these models was $< 5\%$, it was deemed not substantial for the objectives of this project; 3) if the overall range of the 10 models for that data type was above 70%, the data type was deemed effective for those models. If the ranges of a data category overlapped with other data categories, I considered measures similar among the overlapping data types. I chose the 5% and 70% cutoff points because I felt these were acceptable levels of model accuracy and minimal model differences for my project. Data will be presented in raw format and the cutoff points can be interpreted to what the reader finds acceptable for their project goals.

AICc differences were interpreted using the general guidelines from Burnham and Anderson (2002). All models with values < 2 were considered to have substantial empirical support, values 4-7 have substantially less empirical support and models with values > 10 were considered to have no empirical support. AIC weights were compared among data types within each species. Those data groups that had the most weight attributed to them were considered to be the best models in relation to the other data groups for that species.

Results

I have presented the top 10 models for each species and all data categories using AICc (after running all possible logistic regressions) in Appendix 2-I - Appendix 2-N. All statistics produced during model validation using the jackknife method are in Appendix 2-O - Appendix 2-T. All model Akaike weights and AICc differences are presented in Appendix 2-U - Appendix 2-Z. The specificity and sensitivity results are presented after the percentage correctly classified and AIC measures.

Results for 4-m Combination Model Hypothesis

Models containing a combination of data derived from 4-m resolution, GIS variables and field measurements will rank the highest in validation measures for all species.

Jackknife Validation Results.—Model performance differed between the closed canopy and early successional species. For both habitat groups, the “4-m All” data models were the best or 2nd best performing models, although the difference between competing models was typically small (< 5%) (Table 2-3). In fact, for closed canopy species, the performance of “30-m All” models was comparable to the “4-m All” models (Table 2-3). While the “4-m All” models performed well for closed canopy species, the field data models performed the best for 2 of 3 early successional species. Among species, the Prairie Warbler had the largest difference of 4% between the best models (Table 2-3). Although the results for the Indigo Bunting were similar to those of the Prairie Warbler, the top models from the different data types were closer for the Indigo Bunting (Table 2-3). In the jackknife validation, it is clear that “4-m All” model performance is very similar to other competing data categories for each species when the best models for each data type were evaluated.

When evaluating the ranges of correct classification percentages that the top 10 models for each category span, the results also indicate high degrees of overlap with most of the data types (Figure 2-6 - Figure 2-13), with a notable exception being, “30-m Only” models. Performance of the top 10 models exceeded 70% correct classification for all species except the Yellow-billed Cuckoo and the Indigo Bunting (Figure 2-8 and Figure 2-9).

Results for the Range of AICc/QAICc Differences and Weights.—Five of the six species had the “4-m All” data category ranked highest with the most empirical support when comparing AICc differences among species (Figure 2-14 - Figure 2-19; Table 2-4). The Prairie Warbler was the only species where the “Field” models ranked higher than the “4-m All” models (Figure 2-18; Table 2-4). When viewing the range of AICc differences by species groups (Figure 2-20 and Figure 2-21), the ranges of all “4-m All” models show smaller variation in Δ AICc values and hold more empirical support over other data types. Although the trend did not hold across all species, the AICc differences by habitat group depict the overall superior performance of the “4-m All” data models.

The patterns described above using validation measures and Δ AICc values were supported by the Akaike weights. Figure 2-22 depicts the Akaike weights for species in both habitat groups. For the parameters of “4-m All” models the graphs depict strong weights of evidence overall, except for the Prairie Warbler. Closer inspection reveals that for the Prairie Warbler, “Field” data models have more supporting empirical evidence than the “4-m All” models (Appendix 2-Y). The “4-m All” models had the most AICc weight among five of the six species and exhibited overall stronger empirical support when viewing AICc differences by habitat group. The results of the AICc analyses exhibited a stronger overall pattern in support of the “4-m All” data models.

In summary, I tested whether the combination models containing 4-m satellite data were the best models. They were “technically” not the top models across all species, primarily because the “Field” models did very well with the Prairie Warbler species. Overall “4-m All” models performed the best across both groups of species, with >70% classification rates for 4 of 6 species and strong empirical support measured by the AICc methods.

Results for the Successional Stage Hypothesis

Models containing 30-m, GIS variables, and field measurements will rank higher in validation results for the closed canopy species than early successional species.

Jackknife Validation Results.—When ranked by best overall model in closed canopy species, “4-m All” and “30-m All” models were tied for the best model for the ACFL and Red-eyed Vireo, and the “30-m All” models ranked second for the Yellow-billed Cuckoo by only 2% (Table 2-3). When evaluating the performance of this model type with the early successional species, “30-m All” ranked fourth for the Indigo Bunting and Yellow-breasted Chat with a difference of 3% and 5% (respectively) correctly classified compared with the top model (Table 2-3). The Prairie Warbler’s best “30-m All” model ranked third with a 3% difference to the top data model for the species. The results support the hypothesis that “30-m All” models perform better for closed canopy species than early successional species, although the differences in classification values between the best models and the “30-m All” models are again small (< 5%; Table 2-3).

The results from the evaluation of the top overall model in each category are tempered by relatively small differences, which were further exhibited when viewing the top 10 model ranges within each of the data categories. The “30-m All” ranges overlap consistently with other data types, although overlapping data types vary by species (Figure 2-6 - Figure 2-13).

In summary, mixed jackknife validation results gave little support overall for the hypothesized results. When the top data categories were ranked among species modeled, the hypothesis was supported, although these results were tempered with the fact that overall

differences between both habitat groups were < 5%. The most notable pattern to emerge was that the “30-m All” models appeared to perform comparably to “4-m All” models.

Results for the Range of AICc/QAICc Differences and Weights.—Two of the six species (Acadian Flycatcher and Prairie Warbler) had the “30-m All” data category ranked > 10, which means that there was no empirical support for those model groups using the Δ AICc scale (Table 2-4; Figure 2-14 and Figure 2-18). The remaining species in the closed canopy habitat group showed “30-m All” models ranked closely with the highest ranked “4-m All” models. The “30-m All” models in the remaining early successional species did not rank as highly as the two remaining closed canopy species (Table 2-4). Given this, the analysis of AICc differences supports the hypothesis. The Akaike weights show this same trend (Figure 2-22).

The best models in the jackknife validation supported the results of the AICc differences and weights analyses; although that agreement diverged when relatively small differences among the model rankings were taken into account with the jackknife validation. The somewhat mixed results of the two analyses could not support the hypothesis strongly. The most notable result found concerned the performance of “30-m All” models for closed canopy species; models containing “30-m All” data performed comparably to “4-m All” data models.

Results for Closed Canopy Species Hypothesis

For closed canopy species, models containing no field measurements or only field measurements will rank lower in validation measures than models created from a combination of data types.

Jackknife Validation Results.—The hypothesis was technically supported when evaluating the overall best model; non-combination models consistently ranked the lowest among all data types. However, differences were below 5% when compared with the next best combination model (Table 2-3). The effect became clearer in the evaluation of the ranges of the top 10 models for each data category. Model ranges with 4-m spatial data only and field variables only overlapped with the combination data models for all species. The hypothesis was not supported when evaluating the number of models 70% correct classification. Model performances for closed canopy species exhibited one notable pattern. The “30-m Only” data models were the worst performing and had no overlap with the combination models for 2 of the 3 species (Acadian Flycatcher and Red-eyed Vireo) (Figure 2-6 -Figure 2-8).

Results for the Range of AICc/QAICc Differences and Weights.—Three of the closed canopy species models containing only field measurements or only spatial data ranked worse than the combination models (Figure 2-14 - Figure 2-16; Table 2-4). This was clearly illustrated by the distinct ranges of the Δ AICc values for the contrasted model categories, where the majority of the spatial data only and field measurement models had little to no empirical support across 2 of 3 species (Acadian Flycatcher, Red-eyed Vireo) (Figure 2-14 and Figure 2-15; Table 2-4). The exception occurred with the Yellow-billed Cuckoo, where all models had a range of empirical support (Figure 2-16). For this species, the models containing no field or only field data exhibited lower empirical evidence in comparison with the combination data models.

The results from the AICc weight analysis also supported the hypothesis. Figure 2-23 shows that for closed canopy species the parameters of “4-m All” models and “30-m All” models

have much stronger weights of evidence than the contrasted models of “4-m Only”, “30-m Only”, and “Field” data models.

In summary, the hypothesis was supported by most of the results. In particular, models containing only variables derived from 30-m spatial data performed especially poorly.

Results for Early Successional Hypothesis

Models containing only spatial variables for the 4-m data will have sufficient predictive ability ($PCC \geq 70\%$) or empirical support ($\Delta AIC \leq 3$) for early successional species.

Jackknife Validation Results.—The results for the Prairie Warbler did not support the hypothesis concerning differences among data type models, but the overall ranges of “4-m Only” data models were satisfactory given the 70% cutoff for overall model performance (Table 2-3). The best “4-m Only” models were closely clustered with minor differences near the top models and all classification values fell above or around 70% overall accuracy. Differences between “4-m Only” data and the top model were 0 to 6% correctly classified (Indigo Bunting-1%; Prairie Warbler-6%; Yellow-breasted Chat-0%) (Table 2-3).

Results for the Range of $AIC_c/QAIC_c$ Differences and Weights.—The results of the AIC_c differences were highly variable across early successional species. The “4-m Only” models for the Prairie Warbler had no empirical support (Figure 2-18) while the two remaining species had mixed results. Although the “4-m Only” data did fairly well for the Yellow-breasted Chat (Figure 2-19), it did not do as well for the Indigo Bunting (Figure 2-17). Overall, “4-m Only” model support ranged from none to just below substantial across this group of species (Table 2-

4; Figure 2-17 - Figure 2-19), which is clearly indicated by the range in the graph representing AICc differences grouped by habitat group (Figure 2-21). AICc differences were interpreted to not support the stated hypothesis, due to mixed patterns among the three species.

The Akaike weights showed that the “4-m Only” models did not improve prediction in comparison to the other model data types for the early successional species (Figure 2-24).

Although the Yellow-breasted Chat “4-m Only” models had the most empirical support out of the three species, it was still not as strong as “4-m All” data type. Overall, Akaike weights indicated that there was very little weight of evidence that “4-m Only” data performed effectively outside of the Yellow-breasted Chat models. Therefore, the hypothesis was not supported because of the mixed results.

In summary, when evaluating 4-m satellite data for predicting the presence/absence of an early successional species, the mixed results from both analysis methods indicated a lack of support for this hypothesis. Although overall ranges of the “4-m Only” data type fell above 70% and there were relatively minor differences among the hypothesized data and the top models, the mixed results from the AICc analyses (ranging from no empirical support to some) across the species implied to me that there were no notable trends. It is clear that the results of this hypothesis are dependent upon the species modeled.

Percent Sensitivity and Specificity Results

The clearest pattern to emerge for sensitivity measures was that “30-m Only” data had the poorest sensitivity measures for closed canopy species (Figure 2-25 - Figure 2-27, Table 2-5). Patterns of specificity were slightly more widespread. The poorest specificity measures for closed canopy species were produced by “Field” data, while “30-m Only” data represented the

poorest performance for early successional species (Figure 2-40; Table 2-6). There was also evidence to suggest that models containing only 4-m data had high specificity values ($>70\%$) when modeling early successional species (Figure 2-40). However, results were highly variable within the top 10 models of the “4-m Only” data category for each species (Figure 2-36 – Figure 2-38). The rest of the results for these measures were generally mixed and patterns questionable, depending upon the species.

Discussion

The objectives of this research were to address whether high-resolution satellite data improved species habitat models over other available data types. Though there was overall support for 4-m data, the results indicate that there is no data type that can model every species the best. Ultimately, the results depend upon the species modeled, the scale of the features with which the species is associated and whether or not that data type can capture those features adequately.

I found that the scale that the data type represented appeared to influence model performance among the habitat groups. For closed canopy species, models that contained a combination of data types or multiple scales had more empirical support than models created from data that represented one landscape scale, especially if the scale of the data was too coarse, as in the case of “30-m Only” models. Although “4-m All” models were ranked as the best performing models for three closed canopy species, they were tied in performance with “30-m All” models for two of the three species. These results indicated that the 30-m resolution data were an adequate scale to detect those features associated with most of the birds when coupled with finer scaled data types such as field measurements. These results suggest that birds

associated with closed canopy forests appeared to be responding to vegetation patterns represented at multiple scales and that the landscape scale can be sufficiently captured for the majority of these species using 30-m data or less (in combination models).

In general, early successional species modeling efforts produced better results with finer scaled data; in particular, with field measurements only and 4-m combination models, although the results were mixed and no strong pattern appeared for “4-m Only” data among the species. One or more of the following explanations could cause these results: A) land cover extraction scale was not appropriate; B) inherent variability in early successional land cover types; C) members of the habitat group need to be based upon more detailed habitat requirements; D) species not associated as strongly to land cover variables and derived metrics; or E) effects from the modifiable areal unit problem (see below).

A topic that was beyond the scope of this study, but deserves mentioning is one of scaling issues. Currently, it is unclear how changing the scale of observation affects research results (30-m versus 4-m resolution change). It is well documented that relationships change among the studied phenomenon when the scale of observation is changed. This effect, known as the “modifiable areal unit problem” or MAUP, was first identified in geography research in 1934 (Gehlke and Biehl 1934), and later became a focus of study in the 1980’s (Openshaw and Taylor 1979, 1981, Openshaw 1984). The modifiable area unit problem refers to when the shape or size of a spatial area is changed and the resulting correlations or statistical models change (Jelinski and Wu 1996). Why this occurs is still subject to intense debate. Whether or not the phenomenon occurs because of the inherent scale within ecological systems, improper use of analysis methods, or another yet to be recognized reason is now a current research focus in landscape ecology (Wu and Qi 2000). Although simple “scaling laws” exist in ecology,

methods, models and theories used to integrate and extrapolate information from one spatial scale to another are still needed (Jelinski and Wu 1996, Qi and Wu 1996, Wu and Loucks 1999, Wu and Qi 2000, Wu and Hobbs 2002, Hay et al. 2003). It is unclear if there are MAUP effects in this analysis, but with more research being done on this issue it will be clear at a later date if the results are impacted by this phenomenon.

Jackknife and AIC Validation

The analyses in this study used two different methods for assessing model performance, jackknifing techniques and AIC. I selected the jackknife validation because it accommodated the original data set for model construction and testing without producing significant bias. Furthermore, it is a well-established statistical technique (Tukey 1958, SAS Institute 1995, Ang 1998, Sarle 2002). I employed AIC to contrast the results derived by the jackknife validation and to provide greater support to the analysis. The methods used in jackknife validation and AIC provide different measures of model performance and theoretically, results of both methods should agree given sufficient sample size.

The results from these two techniques support each other, although there were a few cases where they did not. The disagreement may have occurred because of low sample size or excessive variability in the data. I considered the results that had agreement between the two methods to have strong support, and those that did not, I placed more weight in the AIC analysis because the method accounts for the number of model parameters whereas the jackknife validation method does not (Ang 1998, Burnham and Anderson 2002, Sarle 2002). There were two salient patterns depicted by both the jackknife validation (overall percent correctly

classified) and AIC analyses with a number of weaker trends that were not addressed specifically by a hypothesis.

4-m Combination Model Hypotheses.—Models containing a combination of high-resolution data, field and GIS measurements performed well in comparison with other data types. The models ranked highest in 5 of 6 species using AICc, and 4 of 6 species using the jackknife method (though top models were tied for best model in 3 of the species). Furthermore, the best model among data types showed that the “4-m All” models never dropped below 70 percent correctly classified (Table 2-3) and AIC differences showed the majority of “4-m All” models to have substantial empirical support (Table 2-4; Figure 2-20 and Figure 2-21).

Although this overall pattern supported the a priori expectations concerning the performance of 4-m combination models, the hypothesis did not hold across all the species. In particular, both the jackknife and AIC analyses supported the “Field” model for the Prairie Warbler. Although the 4-m combination models had “Field” variables within them, they still did not perform as well as models containing “Field” data only. The top 10 “4-m All” models contained a combination of field and 4-m data (no GIS variables were selected, only 4-m and field measurements). Clearly, the “Field” variables were more strongly associated with the species than the 4-m land cover data. Reasons for this result remain unclear, but a possible explanation is that the inherent variability that was introduced to the “4-m All” models from the 4-m land cover variables was higher than the variability inherent in field measurement variables.

The variability that exists in land cover classifications originates from many sources. One source is from the inherent classification errors (or processing errors), which are highest at boundaries between different land cover classes. These errors are often under estimated using

common accuracy assessments (Edwards and Lowell 1996, Foody 2002, Plourde and Congalton 2003, Langford et al. 2004). Maps created from a higher resolution satellite image are particularly at risk for this type of variability. When land cover maps derived from high-resolution images are used, the classification error at borders heightens due to the increased number of patches detected by the amplified resolution. The effect is more pronounced in habitats that exhibit high fragmentation such as early successional vegetation, rather than in habitats where fragmentation is commonly lower (i.e., mature contiguous forest) (Edwards and Lowell 1996, Congalton and Green 1999, Plourde and Congalton 2003, Langford et al. 2004), which may help explain why 4-m models did not perform well for the Prairie Warbler.

Another potential source of variability with the satellite data in this study is temporal. I derived the 4-m land cover classification from an image that was taken during the first year of the study. The study was located in a part of the southeastern U.S. that experiences a nine-month growing season. Although measurement differences between years are generally not a problem for many habitat types, “Field” measurements representing understory and ground densities of grass, saplings, and shrubs were re-estimated the second year because of noticeable changes between year one and two of the study. This could not be done for either of the land cover classifications. The effect may be more apparent in the high-resolution land cover map, because the small changes in patches are detected by the 4-m resolution and not by the 30-m resolution.

Research is now being conducted on the best way to represent the accuracy of a land cover map given issues with the spatial distribution of error, but land cover accuracy assessment and the appropriate metrics is still a field for greater development and at this time remains a source of uncertainty in most accuracy assessments (Foody 2002), including this study.

Successional Stage Hypothesis.—There were no strong patterns supporting this hypothesis due to the mixed results among the species modeled and the jackknife validation results. Although not addressed specifically by the hypothesis, a general pattern emerged among closed canopy species where performance of “30-m All” models was comparable to “4-m All” models. These results suggest that the 30-m land cover data are comparable to 4-m land cover data when coupled with additional data sources for some closed canopy species.

The mixed results among the species for this hypothesis may be explained by differences in habitat requirements. It is possible that the two general habitat groups that birds were divided into were not specific enough to have generalized results relevant to the hypotheses. Although a group of species may be generally associated with mature forests or early successional forests, the details of those life history habitat associations differ widely on the strength and type of other characteristics associated with each species distribution (e.g., understory structure, landscape indices, ground cover, etc.). For example, the Prairie Warbler has a known association with patch area of early successional vegetation (Nolan et al. 1999), while the Indigo Bunting appears to be more associated with the presence of taller perching trees in early successional habitats (Payne 1992). Both habitat associations are dramatically different in specific characteristics, but the birds are often found in the same areas. Therefore, this would be a pattern worth examining by including more species in the habitat groups as well investigating more detailed life history habitat associations among species.

Closed Canopy Species Hypothesis.—The second notable pattern to emerge when analyzing models that contain only one data source was the overall poor performance of the “30-m Only” models. In 5 of 6 species, the “30-m Only” best models consistently ranked the lowest

among all the data types using the jackknife validation (Table 2-3). Although, the results of the Yellow-billed Cuckoo analysis caused the poor performance of the “30-m Only” pattern to break (Figure 2-8) for the closed canopy species, none of the model groups performed well for this species. The AIC differences and weights supported the results from the jackknifing method (Figure 2-14 - Figure 2-21; Figure 2-23; Table 2-4).

It appears that the resolution of “30-m Only” data are too coarse of a scale to depict patch features, especially those of early successional habitats, in relation to other available data types. This statement is supported by the results that depict all “30-m Only” models for early successional species falling below 70% correctly classified in the jackknife validation, as well as having no empirical support in the AIC analysis in relation to other data types.

Early Successional Species Hypothesis.—There were no clear patterns among habitat groups for any models constructed with 4-m data due to the mixed results among the species modeled and the validation results. Explanations for this result may be in the data extraction scale used for 4-m land cover types and the inherent variability in some early successional land cover categories discussed previously.

Sensitivity and Specificity Measures

The patterns depicted in the sensitivity and specificity measures from the jackknife validation were clear. Models created from 30-m data had poor sensitivity measures for closed canopy species and poor specificity measures for early successional species. “Field” models showed poor specificity measures for closed canopy species. There were no clear patterns among habitat groups for any models constructed with 4-m data. The management implications of these findings suggest that models constructed with only 30-m data should be avoided due to

their poor performance when trying to either delineate areas for a closed canopy species or find areas where early successional species are not present. It is interesting to note that “Field” models did a poor job predicting the absence of a species associated with closed canopy forests, but they did better predicting presence, with the majority of “Field” models above 70% sensitivity and the range just dropping slightly under 70% for closed canopy species (Figure 2-31). However, there was overlap in all data types, which weakened the pattern.

Implications for Data Type Selection

Outside of the patterns previously discussed, this research showed no other trends to determine guidelines for what data type to use in wildlife habitat models, though it is important to discuss the drawbacks and limitations of working with these data sources, in particular, the satellite images.

The project’s objectives and available resources (financial, computing power, labor, and time frame) will determine which data types are appropriate. The collection of field measurements is generally unavoidable. All species management projects will have to have some form of measurements taken in the field, whether to provide a training or validation set of data for land cover classification or to capture those vegetation characteristics associated with the species (field measurements). This research suggests that field measurements are still important for wildlife modeling, although depending upon the species modeled and the alternative data sources available, a project’s objectives may be met with data solely derived from satellite images. In the end, it is up to the modeler to determine whether the differences between the data types warrant the use of high-resolution images, or if the project resources are better utilized with alternative data types.

Ikonos 4-m Data.—The ability of the 4-m image to detect feature-objects in the landscape is what makes this data source so appealing and is the main benefit of selecting it. When used in land cover maps, high-resolution data allows for the extraction of more detailed land cover classes as opposed to the coarser 30-m resolution data. However, the scale in which the image can detect feature-objects is only relevant if those are features of interest to the species being modeled or the detection of those feature objects do not contain too much variability from the land cover classification. Another benefit to using satellite images is that they provide data over a much larger area with less effort than that expended for common field measurements, which again is only relevant if the satellite data represent the appropriate scale associated with the management objectives.

However, the drawbacks of high-resolution data are considerable. It is not only in the initial cost of the image, which is approximately 10 times more expensive than the coarser 30-m resolution Landsat 7 data (Morissette et al. 2003), but in the labor expended to perform the image processing tasks, land cover classifications, and data extraction methods to bring the data into a modeling format. Land cover classifications of high-resolution images are problematic and often need supplemental data at higher resolutions or comparable resolutions to help facilitate the land cover classification (Chapter 1). The more fragmented the landscape, the more difficult the land cover classification becomes with high-resolution data. Highly fragmented landscapes in high-resolution images are generally more expensive situations in which to perform classifications due to the potential need for the collection of more field data for training and validation sites and the extra labor required to improve the cover types to suitable error levels. Also, once the land cover classification is complete with high-resolution images, substantial computing power is needed to extract values from the classification (e.g., 2 GHZ processor, 1 GB RAM). A project must have

these computing resources available or labor costs increase dramatically from an already high labor cost.

Other considerations involving the size of the study area and the change of features of interest over time should be accounted for when deciding whether to use high-resolution data. A high-resolution data scene (image) size is smaller in area represented than a 30-m resolution image. If there is more than one high-resolution scene in a study, processing times are increased because each land cover classification must be developed independently, because moisture, sun angle, and other environmental factors alter reflectance values on a scene-by-scene basis. This problem causes great difficulties with the applicability of a model or a developed land cover classification across scenes (Londo et al. 2000, Lowe and Whiffen 2000). The change in vegetation features over time may also affect the utility of 4-m data given the associated cost of the image into a usable modeling format. If one was planning to use the scene to detect features that are that highly variable from year to year then these data might not be recommended. If the features of interest are stable over a period of years as well as the size of the landscape justifies the use of this data source to project budgets, then it would be recommended.

Landsat TM Data.—The benefits to using TM Landsat 30-m data over Ikonos 4-m data lie largely in its affordability, large scene sizes, image availability over time (present and past), and the developed processing and land cover classification algorithms. The limitations of this data type lie in the fact that the scale of resolution is too coarse for some species, which was exhibited by the results for “30-m Only” data type models in the study. Land cover maps derived from 30-m data are often not enough as a data source to create species absence/presence models in comparison to the availability of other data types. This limitation can be tempered for

some species by incorporating other data types into the models, such as in the case of “30-m All” models. Generally, performance of “4-m All” and “30-m All” models for closed canopy species were comparable, which has important implications for many projects that are limited in their available resources.

Conclusions

Although no detailed cost comparison is available for this study, the 4-m data were unquestionably the most labor intensive and time consuming to obtain. The implications of the modeling study suggest that the costs of working with high-resolution data far outweigh any small differences seen in model performance for small projects. Part of the high labor and time costs were due to the lack of established land cover classification techniques, processing times for the immense file sizes during data extraction and manipulation, and compatibility issues stemming from very large file sizes when using various software programs. At this time, it would not be feasible for most studies to use this data source because of the reasons stated above, although with the development of increased computing power for very large file sizes, standardized satellite image pre-processing techniques and classification algorithms these considerations would not be as substantial and economically limiting as they were for this study. As the cost of high-resolution images continue to decrease and their use becomes more widespread, we will find that many of these problems mentioned may be alleviated by developments in the remote sensing and computing fields.

Until those methods and techniques are developed for handling high-resolution data, the majority of projects may find that the combination data with the 30-m data would be a suitable choice for modeling efforts, although obviously the project’s objectives and resources ultimately

decide this fact. It was also interesting to note that for early successional species, the performance of models that contained solely data from field measurements held empirical support in AIC results and had high sensitivity measures in models for closed canopy species. The results did indicate comparability among 30-m and 4-m combination models for 2 out of the 3 closed canopy species. Though AIC empirical support was weaker for data types that did not contain high-resolution data for early successional species, these models did show reasonable empirical support for the “30-m All” or “Field” models. However, the 30-m data alone is clearly unsuitable for modeling bird species in early successional habitats.

That said, if either the project objectives were for a multi-resource project where several species were being managed, or the identified features of interest were captured at the 4-m data type’s scale and remained relatively stable through time, I would recommend the use of high-resolution satellite data. In my opinion, it would be plausible to select a high-resolution data source coupled with other data if the project objectives were to model a large number of important species, as well as if the project had other multi resource goals in which the data could be utilized. Although further consideration into the type of species to be modeled, the fragmentation of the landscape, the size of the study area and the resources available to the project all should determine the utility of high-resolution data to the overall project goals. Areas of future research that would build upon this study would be the inclusion of more species in habitat groupings to define clearer patterns, further investigation into potential home range sizes of early successional species, more detailed analysis of landscape configuration or overall spatial patterns of the study area to determine scale and spatial pattern effects in the models, improvements on land cover accuracy assessment of patch edges and the relationship between vegetation patch densities and the high resolution signatures in land cover classification.

Literature Cited

- Allard, A. 2003. Detection of vegetation degradation on Swedish mountainous heaths at an early stage by image interpretation. *Ambio* **32**:510-519.
- Andersen, H. E., R. J. McGaughey, and S. E. Reutebuch. 2005. Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment* **94**:441-449.
- Andrefouet, S., R. Berkelmans, L. Odriozola, T. Done, J. Oliver, and F. Muller-Karger. 2002. Choosing the appropriate spatial resolution for monitoring coral bleaching events using remote sensing. *Coral Reefs* **21**:147-154.
- Ang, R. P. 1998. Use of the jackknife statistic to evaluate result replicability. *Journal of General Psychology* **125**:218.
- Asner, G. P., M. Palace, M. Keller, R. Pereira, J. N. M. Silva, and J. C. Zweede. 2002. Estimating canopy structure in an Amazon Forest from laser range finder and Ikonos satellite observations. *Biotropica* **34**:483-492.
- Aspinall, R., and N. Veitch. 1993. Habitat Mapping From Satellite Imagery and Wildlife Survey Data Using a Bayesian Modeling Procedure in a Gis. *Photogrammetric Engineering and Remote Sensing* **59**:537-543.
- Auda, Y., F. Blasco, J. P. Gastellu-Etchegorry, G. Marty, and C. Dechamp. 2002. Preliminary studies of the detection of Ambrosia populations by spatial remote sensing. *Revue Francaise D Allergologie Et D Immunologie Clinique* **42**:533-538.
- Avery, T. E., and G. L. Berlin. 1992. *Fundamentals of Remote Sensing and Airphoto Interpretation*, 5th edition. Macmillian, New York.
- Barker, R. J., J. R. Sauer, and W. A. Link. 1993. Optimal Allocation of Point-Count Sampling Effort. *Auk* **110**:752-758.

- Blaschke, T., and G. J. Hay. 2001. Object-Oriented Image Analysis and Scale-Space: Theory and Methods for Modeling and Evaluating Multiscale Landscape Structure. *in* M. Madden, editor. Challenges in Geospatial Analysis, Integration and Visualization. International Archives of Photogrammetry and Remote Sensing, Athens, GA.
- Burnham, K. P., and D. R. Anderson. 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach, 2nd edition. Springer-Verlag, New York.
- Capolsini, P., S. Andrefouet, C. Rion, and C. Payri. 2003. A comparison of Landsat ETM+, SPOT HRV, Ikonos, ASTER, and airborne MASTER data for coral reef habitat mapping in south pacific islands. *Canadian Journal of Remote Sensing* **29**:187-200.
- Carr, A., and D. R. Rempel. 1999. Patch Analyst User's Manual. Ontario Min. Natural Resources Northwest Science & Technology Thunder Bay, Ont. TM-002. 16 pp + Append.
- Chadwick, M., and J. A. Hannah. 1986. Expert Systems for Personal Computers-An Introduction to Artificial Intelligence. Pages 9-29 *in* Chapter 2: Principles of Rule-based Expert Systems. Sigma Press, Wilmslow, England.
- Cimprich, D. A., F. R. Moore, and M. P. Guilfoyle. 2000. Red-eyed Vireo (*Vireo olivaceus*). *in* A. Poole and F. Gill, editors. The Birds of North America. The Birds of North America, Inc., Philadelphia.
- Clark, D. B., C. S. Castro, L. D. A. Alvarado, and J. M. Read. 2004a. Quantifying mortality of tropical rain forest trees using high-spatial-resolution satellite data. *Ecology Letters* **7**:52-59.

- Clark, D. B., J. M. Read, M. L. Clark, A. M. Cruz, M. F. Dotti, and D. A. Clark. 2004b. Application of 1-M and 4-M resolution satellite data to ecological studies of tropical rain forests. *Ecological Applications* **14**:61-74.
- Congalton, R. G., and K. Green. 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Lewis Publishers, Boca Raton, FL.
- Cumming, S. G., P. J. Burton, S. Prahacs, and M. R. Garland. 1994. Potential Conflicts between Timber Supply and Habitat Protection in the Boreal Mixedwood of Alberta, Canada - a Simulation Study. *Forest Ecology and Management* **68**:281-302.
- Cushman, S. A., and K. McGarigal. 2002. Hierarchical, multi-scale decomposition of species-environment relationships. *Landscape Ecology* **17**:637-646.
- Cushman, S. A., and K. McGarigal. 2004a. Hierarchical analysis of forest bird species-environment relationships in the Oregon Coast Range. *Ecological Applications* **14**:1090-1105.
- Cushman, S. A., and K. McGarigal. 2004b. Patterns in the species-environment relationship depend on both scale and choice of response variables. *Oikos* **105**:117-124.
- Debinski, D. M., K. Kindscher, and M. E. Jakubauskas. 1999. A remote sensing and GIS-based model of habitats and biodiversity in the Greater Yellowstone Ecosystem. *International Journal of Remote Sensing* **20**:3281-3291.
- Dettmers, R., and J. Bart. 1999. A GIS modeling method applied to predicting forest songbird habitat. *Ecological Applications* **9**:152-163.
- Dettmers, R., D. A. Buehler, J. G. Bartlett, and N. A. Klaus. 1999. Influence of point count length and repeated visits on habitat model performance. *Journal of Wildlife Management* **63**:815-823.

- Drapeau, P., A. Leduc, and R. McNeil. 1999. Refining the use of point counts at the scale of individual points in studies of bird-habitat relationships. *Journal of Avian Biology* **30**:367-382.
- Durkin, J. 1998. Expert System Development Tools. *in* J. Liebowitz, editor. *The Handbook of Applied Expert Systems*. CRC Press LLC, Salem, MA.
- Eckerle, K. P., and C. F. Thompson. 2001. Yellow-breasted Chat. *in* A. Poole and F. Gill, editors. *The Birds of North America*. The Birds of North America, Inc., Philadelphia.
- Edwards, G., and K. E. Lowell. 1996. Modeling uncertainty in photointerpreted boundaries. *Photogrammetric Engineering and Remote Sensing* **62**:377-391.
- Ehlers, M., M. Gahler, and R. Janowsky. 2001. Automated Analysis of Ultra High Resolution Remote Sensing Data: GIS to the Rescue? *in* M. Madden, editor. *Challenges in Geospatial Analysis, Integration and Visualization*. International Archives of Photogrammetry and Remote Sensing, Athens, GA.
- ERDAS, I. 1999a. Erdas Field Guide. Pages 698 *in*. Erdas, Inc., Atlanta, GA.
- ERDAS, I. 1999b. ERDAS Imagine Expert Classifier Field Guide. *in*. ERDAS, Atlanta, GA.
- Faust, N. L. 1989. Image Enhancement. *in* A. Kent and J. G. Williams, editors. *Encyclopedia of Computer Science and Technology*. Marcel Dekker, Inc., New York.
- Flather, C. H., and J. R. Sauer. 1996. Using landscape ecology to test hypotheses about large-scale abundance patterns in migratory birds. *Ecology* **77**:28-35.
- Foody, G. M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* **80**:185-201.

- Franklin, S. E., M. A. Wulder, and G. R. Gerylo. 2001. Texture analysis of Ikonos panchromatic data for Douglas-fir forest age class separability in British Columbia. *International Journal of Remote Sensing* **22**:2627-2632.
- Gehlke, C., and K. Biehl. 1934. Certain effects of grouping upon the size of the correlation coefficient in census tract material. *Journal of American Statistical Association* **29**:169.
- Goetz, S. J., R. K. Wright, A. J. Smith, E. Zinecker, and E. Schaub. 2003. Ikonos imagery for resource management: Tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region. *Remote Sensing of Environment* **88**:195-208.
- Goward, S. N., P. E. Davis, D. Fleming, L. Miller, and J. R. Townshend. 2003. Empirical comparison of Landsat 7 and Ikonos multispectral measurements for selected Earth Observation System (EOS) validation sites. *Remote Sensing of Environment* **88**:80-99.
- Grand, J., and S. A. Cushman. 2003. A multi-scale analysis of species-environment relationships: breeding birds in a pitch pine-scrub oak (*Pinus rigida*-*Quercus ilicifolia*) community. *Biological Conservation* **112**:307-317.
- GrattoTrevor, C. L. 1996. Use of Landsat TM imagery in determining important shorebird habitat in the outer Mackenzie delta, northwest territories. *Arctic* **49**:11-22.
- Groves, C. R., D. B. Jensen, L. L. Valutis, K. H. Redford, M. L. Shaffer, J. M. Scott, J. V. Baumgartner, J. V. Higgins, M. W. Beck, and M. G. Anderson. 2002. Planning for biodiversity conservation: Putting conservation science into practice. *Bioscience* **52**:499-512.
- Gust, N., J. H. Choat, and M. I. McCormick. 2001. Spatial variability in reef fish distribution, abundance, size and biomass: a multi-scale analysis. *Marine Ecology-Progress Series* **214**:237-251.

- Hall, O., G. J. Hay, A. Bouchard, and D. J. Marceau. 2004. Detecting dominant landscape objects through multiple scales: An integration of object-specific methods and watershed segmentation. *Landscape Ecology* **19**:59-76.
- Hamel, P. B. 1992. Land Manager's Guide to the Birds of the South. Technical Report General Technical Report SE-22, US Forest Service, Chapel Hill, N.C.
- Hay, G. J., T. Blaschke, D. J. Marceau, and A. Bouchard. 2003. A comparison of three image-object methods for the multiscale analysis of landscape structure. *Isprs Journal of Photogrammetry and Remote Sensing* **57**:327-345.
- Hay, G. J., and K. O. Niemann. 1994. Visualizing 3-D Texture: A Three Dimensional Structural Approach to Model Forest Texture. *Canadian Journal of Remote Sensing* **20**:90-101.
- Hay, G. J., K. O. Niemann, and G. McLean. 2001. An Object-Specific Image Texture Analysis of H-Resolution Forest Imagery. *Remote Sensing of Environment* **55**:108-122.
- Hay, S. I., C. J. Tucker, D. J. Rogers, and M. J. Packer. 1996. Remotely sensed surrogates of meteorological data for the study of the distribution and abundance of arthropod vectors of disease. *Annals of Tropical Medicine and Parasitology* **90**:1-19.
- Hepinstall, J. A., and S. A. Sader. 1997. Using Bayesian statistics, Thematic Mapper satellite imagery, and breeding bird survey data to model bird species probability of occurrence in Maine. *Photogrammetric Engineering and Remote Sensing* **63**:1231-1237.
- Hochberg, E. J., and M. J. Atkinson. 2003. Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. *Remote Sensing of Environment* **85**:174-189.
- Hughes, J. M. 1999. Yellow-billed Cuckoo (*Coccyzus americanus*). *in* A. Poole and F. Gill, editors. *The Birds of North America*. The Birds of North America, Inc.

- Hyder, S. 2002. Investigation of the relationship between floodplain geomorphology and riparian songbird communities. MS. University of Georgia, Athens, GA.
- Innes, J. L., and B. Koch. 1998. Forest biodiversity and its assessment by remote sensing. *Global Ecology and Biogeography* **7**:397-419.
- Jelinski, D. E., and J. G. Wu. 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology* **11**:129-140.
- Jensen, J. R. 1996. *Introductory Digital Image Processing: A Remote Sensing Perspective*, 2nd edition. Prentice-Hall, Englewood Cliffs, NJ.
- Knick, S. T., and J. T. Rotenberry. 1995. Landscape Characteristics of Fragmented Shrubsteppe Habitats and Breeding Passerine Birds. *Conservation Biology* **9**:1059-1071.
- Langford, W. T., S. E. Gergel, T. G. Dietterich, and W. Cohen. 2004. Are Estimates of Habitat Fragmentation Incorrect? The Impact of Map Missclassification on Landscape Metrics. *Ecological Applications* **submitted for publication**.
- Lillesand, T. M., and R. W. Kiefer. 2000. *Remote Sensing and Image Interpretation*, 4th edition. John Wiley & Sons Inc., New York, NY.
- Londo, H. A., P. A. Glass, D. L. Evans, K. L. Belli, R. C. Parker, T. G. Matney, and E. B. Schultz. 2000. Integration of Remote Sensing, GPS with Traditional Forest Inventory Procedures. *in* A. Vitale, editor. 3rd Southern Forestry GIS Conference, Athens, GA.
- Lowe, T., and H. J.-H. Whiffen. 2000. Estimating Pine Basal Area Using Landsat Thematic Mapper Satellite Images. *in* 3rd Southern Forestry GIS Conference, Athens, GA.
- Mack, E. L., L. G. Firbank, P. E. Bellamy, S. A. Hinsley, and N. Veitch. 1997. The comparison of remotely sensed and ground-based habitat area data using species-area models. *Journal of Applied Ecology* **34**:1222-1228.

- Maeder, J., S. Narumalani, D. C. Rundquist, R. L. Perk, J. Schalles, K. Hutchins, and J. Keck. 2002. Classifying and mapping general coral-reef structure using Ikonos data. *Photogrammetric Engineering and Remote Sensing* **68**:1297-1305.
- Marshall, M., R. J. Cooper, J. A. DeCecco, J. Strazanac, and L. Butler. 2002. Effects of experimentally reduced prey abundance on the breeding ecology of the Red-eyed Vireo. *Ecological Applications* **12**:261-280.
- Marshall, M. R., and R. J. Cooper. 2004. Territory size of a migratory songbird in response to caterpillar density and foliage structure. *Ecology* **85**:432-445.
- Martin, T. E., C. Paine, C. J. Conway, W. M. Hochachka, P. Allen, and W. Jenkins. 1997. BBIRD Field Protocol. *in*. Montana Cooperative Wildlife Research Unit, University of Montana, Missoula, MT. 59812.
- Masuoka, P. M., D. M. Claborn, R. G. Andre, J. Nigro, S. W. Gordon, T. A. Klein, and H. C. Kim. 2003. Use of Ikonos and Landsat for malaria control in the Republic of Korea. *Remote Sensing of Environment* **88**:187-194.
- Mayer, A. L., and G. N. Cameron. 2003. Landscape characteristics, spatial extent, and breeding bird diversity in Ohio, USA. *Diversity and Distributions* **9**:297-311.
- McFarland, T., and R. Parker. 1990. Expert Systems in Education and Training. Educational Technology Publications, Englewood Cliffs, NJ.
- Moore, C. 2000. SAS Macro APLR (All Possible Logistic Regressions). *in*. University of Georgia., Athens, GA.
- Morisette, J. T., J. E. Nickeson, P. Davis, Y. J. Wang, Y. H. Tian, C. E. Woodcock, N. Shabanov, M. Hansen, W. B. Cohen, D. R. Oetter, and R. E. Kennedy. 2003. High spatial resolution satellite observations for validation of MODIS land products: Ikonos

- observations acquired under the NASA Scientific Data Purchase. *Remote Sensing of Environment* **88**:100-110.
- Mumby, P. J., and A. J. Edwards. 2002. Mapping marine environments with Ikonos imagery: enhanced spatial resolution can deliver greater thematic accuracy. *Remote Sensing of Environment* **82**:248-257.
- Nikula, A., S. Heikkinen, and E. Helle. 2004. Habitat selection of adult moose *Alces alces* at two spatial scales in central Finland. *Wildlife Biology* **10**:121-135.
- Nolan, V. J., E. D. Ketterson, and C. A. Buerkle. 1999. Prairie Warbler. *The Birds of North America: Life Histories for the 21st century* **455**:1-27.
- Openshaw, S. 1984. *The Modifiable Areal Unit Problem.*, Norwich.
- Openshaw, S., and P. Taylor. 1979. A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. Pages 127-144 *in* N. Wrigley, editor. *Statistical Applications in the Spatial Sciences*. Pion, London.
- Openshaw, S., and P. Taylor. 1981. The modifiable areal unit problem. Pages 60-69 *in* N. Wrigley and R. Bennett, editors. *Quantitative Geography: A British View*. Routledge and Kegan Paul, London.
- Osborne, P. E., J. C. Alonso, and R. G. Bryant. 2001. Modelling landscape-scale habitat use using GIS and remote sensing: a case study with great bustards. *Journal of Applied Ecology* **38**:458-471.
- Palandro, D., S. Andrefouet, P. Dustan, and F. E. Muller-Karger. 2003. Change detection in coral reef communities using Ikonos satellite sensor imagery and historic aerial photographs. *International Journal of Remote Sensing* **24**:873-878.

- Payne, R. B. 1992. Indigo Bunting. *in* A. Poole, P. Stettenheim, and F. Gill, editors. The Birds of North America. The Academy of Natural Sciences, Philadelphia.
- Peng, W. L., D. B. Wheeler, J. C. Bell, and M. G. Krusemark. 2003. Delineating patterns of soil drainage class on bare soils using remote sensing analyses. *Geoderma* **115**:261-279.
- Philipson, P., and T. Lindell. 2003. Can coral reefs be monitored from space? *Ambio* **32**:586-593.
- Plourde, L., and R. G. Congalton. 2003. Sampling method and sample placement: How do they affect the accuracy of remotely sensed maps? *Photogrammetric Engineering and Remote Sensing* **69**:289-297.
- Qi, Y., and J. G. Wu. 1996. Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. *Landscape Ecology* **11**:39-49.
- Quackenbush, L. J., P. F. Hopkins, and G. J. Kinn. 2000. Developing forestry products from high resolution digital aerial imagery. *Photogrammetric Engineering and Remote Sensing* **66**:1337-1346.
- Ralph, C. J., S. Droege, and J. R. Sauer. 1995. Monitoring Bird Populations by Point Counts. General Technical Report PSW-GTR-149, USDA Forestry Service Publications, Albany, CA.
- Ralph, C. J., and M. J. Scott, editors. 1981. Estimating numbers of Terrestrial Birds. Allen Press Inc, Lawrence Kansas.
- Riitters, K. H., R. V. Oneill, and K. B. Jones. 1997. Assessing habitat suitability at multiple scales: A landscape- level approach. *Biological Conservation* **81**:191-202.

- Rodewald, P. G., and K. G. Smith. 1998. Short-term effects of understory and overstory management on breeding birds in Arkansas oak-hickory forests. *Journal of Wildlife Management* **62**:1411-1417.
- Saab, V. 1999. Importance of spatial scale to habitat use by breeding birds in riparian forests: A hierarchical analysis. *Ecological Applications* **9**:135-151.
- Sarle, W. S. 2002. What are cross-validation and bootstrapping? *in*. Usenet FAQ's.
- SAS Institute, I. 1995. Logistic Regression Examples Using the SAS System. Version 6, 1 edition. SAS Institute Inc., Cary, NC.
- Saveraid, E. H., D. M. Debinski, K. Kindscher, and M. E. Jakubauskas. 2001. A comparison of satellite data and landscape variables in predicting bird species occurrences in the Greater Yellowstone Ecosystem, USA. *Landscape Ecology* **16**:71-83.
- Schott, J. R. 1997. Remote Sensing: The Image Chain Approach. Oxford University Press, Inc., New York.
- Schwarz, M., C. Steinmeier, F. Holecz, O. Stebler, and H. Wagner. 2003. Detection of windthrow in mountainous regions with different remote sensing data and classification methods. *Scandinavian Journal of Forest Research* **18**:525-536.
- Shackelford, A. K., and C. H. Davis. 2003. A hierarchical fuzzy classification approach for high-resolution multispectral data over urban areas. *Ieee Transactions on Geoscience and Remote Sensing* **41**:1920-1932.
- Sidle, J. G., D. H. Johnson, B. R. Euliss, and M. Tooze. 2002. Monitoring black-tailed prairie dog colonies with high-resolution satellite imagery. *Wildlife Society Bulletin* **30**:405-411.

- Smith, W. P., D. J. Twedt, P. B. Hamel, R. P. Ford, D. A. Wiedenfeld, and R. J. Cooper. 1998. Increasing point-count duration increases standard error. *Journal of Field Ornithology* **69**:450-456.
- Stoms, D. M., F. W. Davis, and C. B. Cogan. 1992. Sensitivity of Wildlife Habitat Models to Uncertainties in Gis Data. *Photogrammetric Engineering and Remote Sensing* **58**:843-850.
- Stumpf, R. P., K. Holderied, and M. Sinclair. 2003. Determination of water depth with high-resolution satellite imagery over variable bottom types. *Limnology and Oceanography* **48**:547-556.
- Sugumaran, R., D. Zerr, and T. Prato. 2002. Improved urban land cover mapping using multi-temporal Ikonos images for local government planning. *Canadian Journal of Remote Sensing* **28**:90-95.
- Thenkabail, P. S. 2004. Inter-sensor relationships between Ikonos and Landsat-7 ETM+ NDVI data in three ecoregions of Africa. *International Journal of Remote Sensing* **25**:389-408.
- Thome, K. J., S. F. Biggar, and W. Wisniewski. 2003. Cross comparison of EO-1 sensors and other Earth resources sensors to Landsat-7 ETM+ using Railroad Valley Playa. *Ieee Transactions on Geoscience and Remote Sensing* **41**:1180-1188.
- Tukey, J. W. 1958. Bias and confidence in not-quite large samples. *Annals of Mathematical Statistics* **29**:614.
- Tyson, B., T. Worthley, and K. Danley. 2004. Layering natural resource and human resource data for planning watershed conservation strategies. *Society & Natural Resources* **17**:163-170.

- Usury, E. L. 2000. Discussion on classification performance with high resolution images. *in* A. C. Vitale, editor., Athens, GA.
- Warnell School of Forest Resources. 1999. Visitor's Guide to Bishop F. Grant Memorial Forest. *in*. Warnell School of Forest Resources, University of Georgia, Athens, GA.
- White, D. H., B. R. Chapman, J. H. Brunjes, R. V. Raftovich, and J. T. Seginak. 1999. Abundance and reproduction of songbirds in burned and unburned pine forests of the Georgia Piedmont. *Journal of Field Ornithology* **70**:414-424.
- Whitehead, D. R., and T. Taylor. 2002. Acadian Flycatcher (*Empidonax virescens*). *in* A. Poole and F. Gill, editors. The Birds of North America. The Birds of North America, Inc., Philadelphia.
- Wilson, J. K. 1999. Breeding biology of the yellow-billed cuckoo relative to timber harvest in a bottomland hardwood forest. MS. University of Georgia, Athens, GA.
- Wilson, R. R., and R. J. Cooper. 1998. Acadian Flycatcher Nest Placement: Does Nest Placement Influence Reproductive Success? *Condor* **100**:673--679.
- Wu, J., and O. L. Loucks. 1999. Hierarchy and Scaling: Extrapolating Information Along a Scaling Ladder. *Canadian Journal of Remote Sensing* **25**:367-380.
- Wu, J., and Y. Qi. 2000. Dealing With Scale in Landscape Analysis: An Overview. *Geographic Information Sciences* **6**:1-5.
- Wu, J. G. 2004. Effects of changing scale on landscape pattern analysis: scaling relations. *Landscape Ecology* **19**:125-138.
- Wu, J. G., and J. L. David. 2002. A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. *Ecological Modelling* **153**:7-26.

- Wu, J. G., and R. Hobbs. 2002. Key issues and research priorities in landscape ecology: An idiosyncratic synthesis. *Landscape Ecology* **17**:355-365.
- Zhang, Q. F., and J. F. Wang. 2003. A rule-based urban land use inferring method for fine-resolution multispectral imagery. *Canadian Journal of Remote Sensing* **29**:1-13.

TABLES

Table 2-1: Data Model Categories. The design of the project was to contrast models created from different data types.

MODEL TYPE	DATA TYPES			
	Field	GIS	30-m	4-m
1. Field Only	X			
2. 30-m Only			X	
3. 4-m Only				X
4. All Types (30-m)	X	X	X	
5. All Types (4-m)	X	X		X

Table 2-2: Land cover categories. Land cover categories derived from the rule-based classification (Id. 13-19 are only available in the Ikonos Land Cover Map).

ID NUMBER	LAND COVER CODE	CLASSIFIED LAND COVER CATEGORIES
1	BLD	Urban
2	RDS	Roads
3	CCB	Clearcut-bare ground
4	H2O	Water
5	PNE	Upland Pine Forest
6	MIX	Upland Mix Forest
7	BPN	Riverine Bottomland Pine
8	BMX	Riverine Bottomland Mix
9	BHD	Riverine Bottomland Hardwood
10	UPL	Upland Hardwood Forest
11	GRS	Agriculture/pasture/grass
12	UND	Undefined
13	RIV	Rivers/streams
14	HGS	Hardwood/Grass
15	BLP	Blackberry/Pine
16	HSB	Hardwood Shrub
17	HVN	Hardwood/Vine
18	BRG	Bare/grass
19	AGE	Algae

Table 2-3: Percent correctly classified results from the jackknife validation method. Percent correctly classified represents how well the model predicted overall.

HABITAT GROUP	SPECIES	DATA TYPE	% CORRECT MINIMUM (POOREST MODEL)	% CORRECT MAXIMUM (BEST MODEL)
Closed Canopy	ACFL	4M_ALL	80	83
		30M_ALL	78	83
		4M_ONLY	81	82
		FIELD	77	81
		30M_ONLY	73	75
	REVI	4M_ALL	72	76
		30M_ALL	74	76
		4M_ONLY	72	73
		FIELD	68	73
		30M_ONLY	68	71
	YBCU	4M_ALL	64	70
		30M_ALL	63	68
		30M_ONLY	63	67
		4M_ONLY	60	65
		FIELD	62	64
Early Successional	INBU	FIELD	64	73
		4M_ALL	67	72
		4M_ONLY	70	72
		30M_ALL	68	70
		30M_ONLY	61	63
	PRAW	FIELD	84	87
		4M_ALL	80	83
		30M_ALL	78	82
		4M_ONLY	78	81
		30M_ONLY	63	67
	YBCH	4M_ALL	77	81
		4M_ONLY	75	81
		FIELD	75	78
		30M_ALL	73	76
		30M_ONLY	65	68

Table 2-4: AICc differences by species and data type. AICc differences measure the level of empirical support for a model. A model can only be compared to other models within a species. They cannot be compared across species.

HABITAT GROUP	SPECIES	DATA TYPE	QAICC/ AICC VALUE	AICC DIFF. MIN.	AICC DIFF. MAX.	LEVEL OF EMPIRICAL SUPPORT
Closed Canopy	ACFL	4M_ALL	162.680	0	3	Substantial
		4M_ONLY	173.970	12	14	None
		30M_ALL	182.201	19	22	None
		FIELD	195.459	34	35	None
		30M_ONLY	212.110	51	52	None
	REVI	4M_ALL	203.764	0	2	Substantial
		30M_ALL	204.956	2	4	Substantial
		4M_ONLY	209.392	6	8	Considerably Less
		FIELD	228.704	25	27	None
		30M_ONLY	232.349	29	31	None
	YBCU	4M_ALL	221.249	0	1	Substantial
		30M_ALL	221.163	0	1	Substantial
		FIELD	225.518	3	5	Substantial to Considerably Less
		4M_ONLY	228.984	6	8	Considerably Less to None
		30M_ONLY	229.901	7	9	Considerably Less to None
Early Successional	INBU	4M_ALL	195.872	0	2	Substantial
		30M_ALL	199.052	4	5	Considerably Less
		4M_ONLY	202.735	7	9	Considerably Less to None
		FIELD	203.061	8	9	Considerably Less to None
		30M_ONLY	220.163	24	26	None
	PRAW	FIELD	109.150	0	2	Substantial
		4M_ALL	112.333	5	6	Considerably Less
		4M_ONLY	120.690	12	14	None
		30M_ALL	121.229	12	14	None
		30M_ONLY	170.981	62	64	None
	YBCH	4M_ALL	83.590	0	2	Substantial
		4M_ONLY	86.803	3	5	Substantial to Considerably
		FIELD	90.067	7	8	Considerably Less
		30M_ALL	90.378	8	9	Considerably Less to None
		30M_ONLY	100.186	17	18	None

Table 2-5: Percent sensitivity results from the jackknife validation method. Sensitivity represents how well the model predicted the presence of the species.

HABITAT GROUP	SPECIES	DATA TYPE	% SENSITIVITY MINIMUM (POOREST MODEL)	% SENSITIVITY MAXIMUM (BEST MODEL)
Closed Canopy	ACFL	4M_ALL	82	85
		FIELD	81	84
		30M_ALL	78	82
		4M_ONLY	81	82
		30M_ONLY	70	74
	REVI	FIELD	74	87
		4M_ALL	72	83
		4M_ONLY	74	79
		30M_ALL	74	78
		30M_ONLY	64	68
	YBCU	4M_ONLY	56	74
		FIELD	66	71
		4M_ALL	59	67
		30M_ALL	54	63
		30M_ONLY	47	57
Early Successional	INBU	30M_ALL	64	70
		30M_ONLY	64	70
		4M_ALL	63	69
		FIELD	62	66
		4M_ONLY	59	62
	PRAW	FIELD	89	94
		4M_ALL	77	89
		30M_ALL	80	89
		30M_ONLY	74	86
		4M_ONLY	77	80
	YBCH	4M_ALL	78	85
		30M_ALL	76	83
		30M_ONLY	74	81
		4M_ONLY	85	80
		FIELD	72	78

Table 2-6: Percent specificity results from the jackknife validation method. Specificity represents how well the model predicted the absence of a species.

HABITAT GROUP	SPECIES	DATA TYPE	% SPECIFICITY MINIMUM (POOREST MODEL)	% SPECIFICITY MAXIMUM (BEST MODEL)
Closed Canopy	ACFL	30M_ALL	75	85
		4M_ALL	79	83
		4M_ONLY	81	83
		30M_ONLY	75	79
		FIELD	72	78
	REVI	30M_ALL	73	77
		4M_ALL	70	74
		30M_ONLY	69	74
		4M_ONLY	68	71
		FIELD	60	67
	YBCU	4M_ALL	66	75
		30M_ALL	66	74
		30M_ONLY	67	74
		4M_ONLY	52	67
		FIELD	59	63
Early Successional	INBU	FIELD	64	81
		4M_ONLY	77	80
		4M_ALL	67	75
		30M_ALL	69	72
		30M_ONLY	55	59
	PRAW	FIELD	83	86
		4M_ALL	80	83
		4M_ONLY	77	82
		30M_ALL	77	81
		30M_ONLY	60	65
	YBCH	4M_ONLY	75	82
		4M_ALL	77	81
		FIELD	75	79
		30M_ALL	71	75
		30M_ONLY	62	64

FIGURES

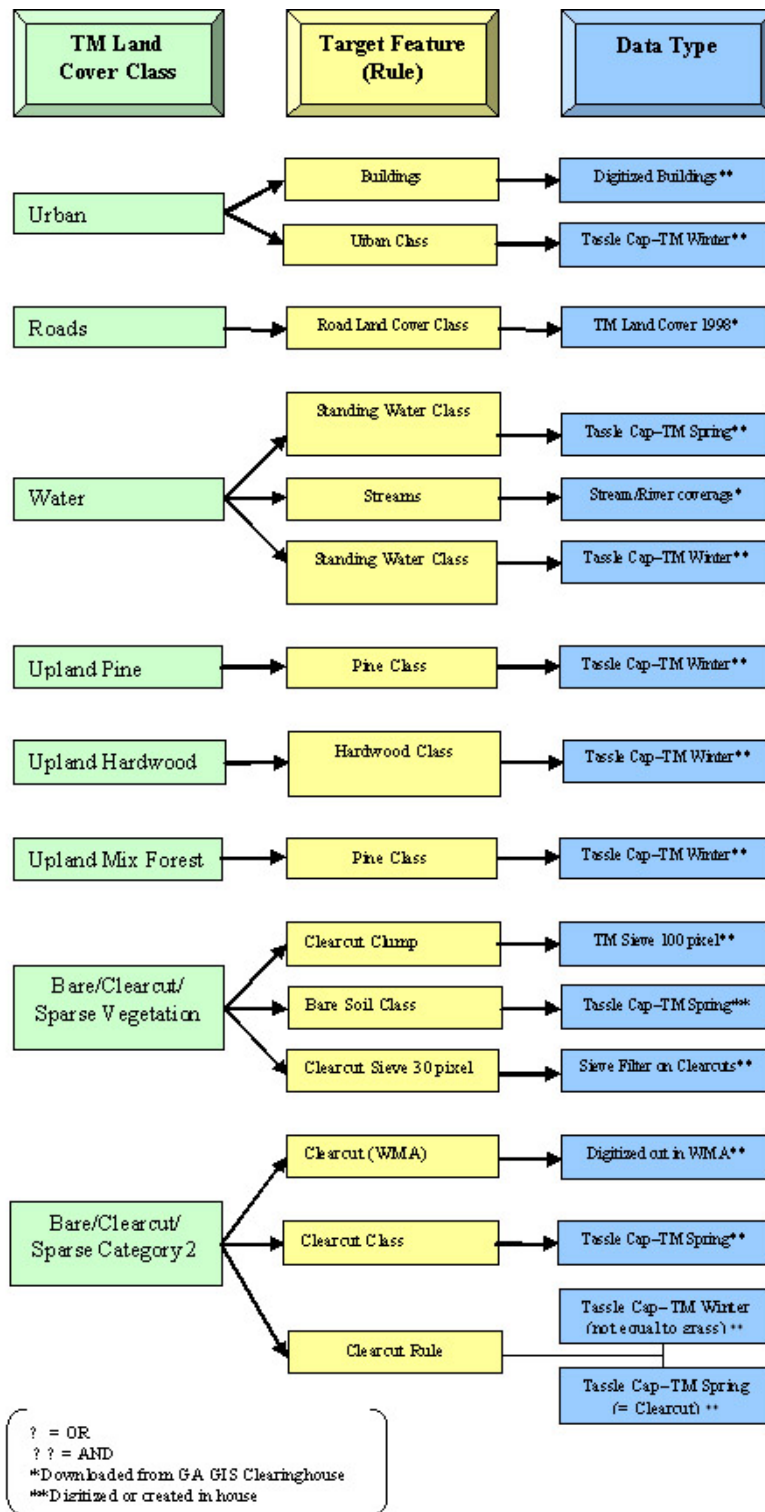


Figure 2-1: Rule-based classification diagram of TM images. Diagram continues.

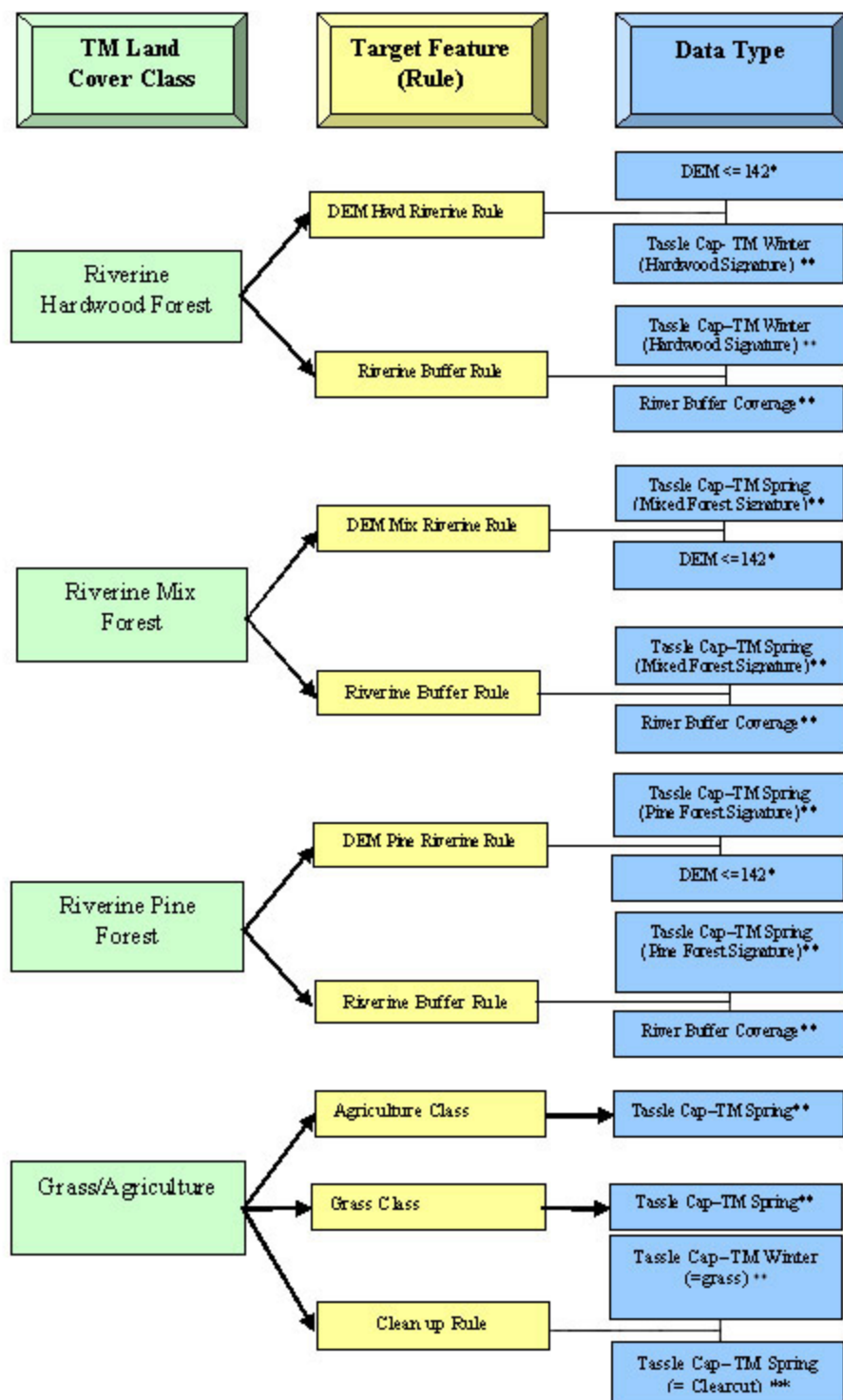


Figure 2-1: Rule-based classification diagram of TM images continued.

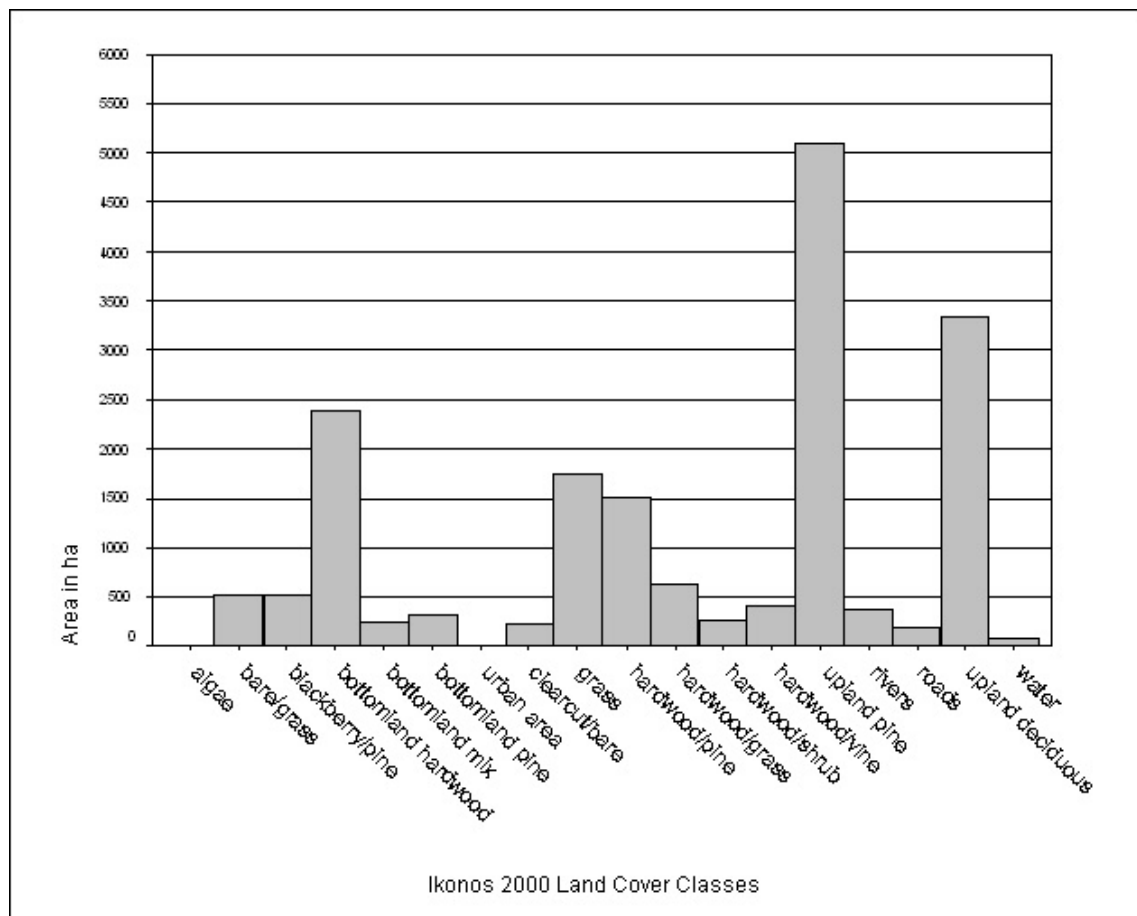


Figure 2-2: Total area represented by each land cover category for the Ikonos land cover classification for the year 2000.

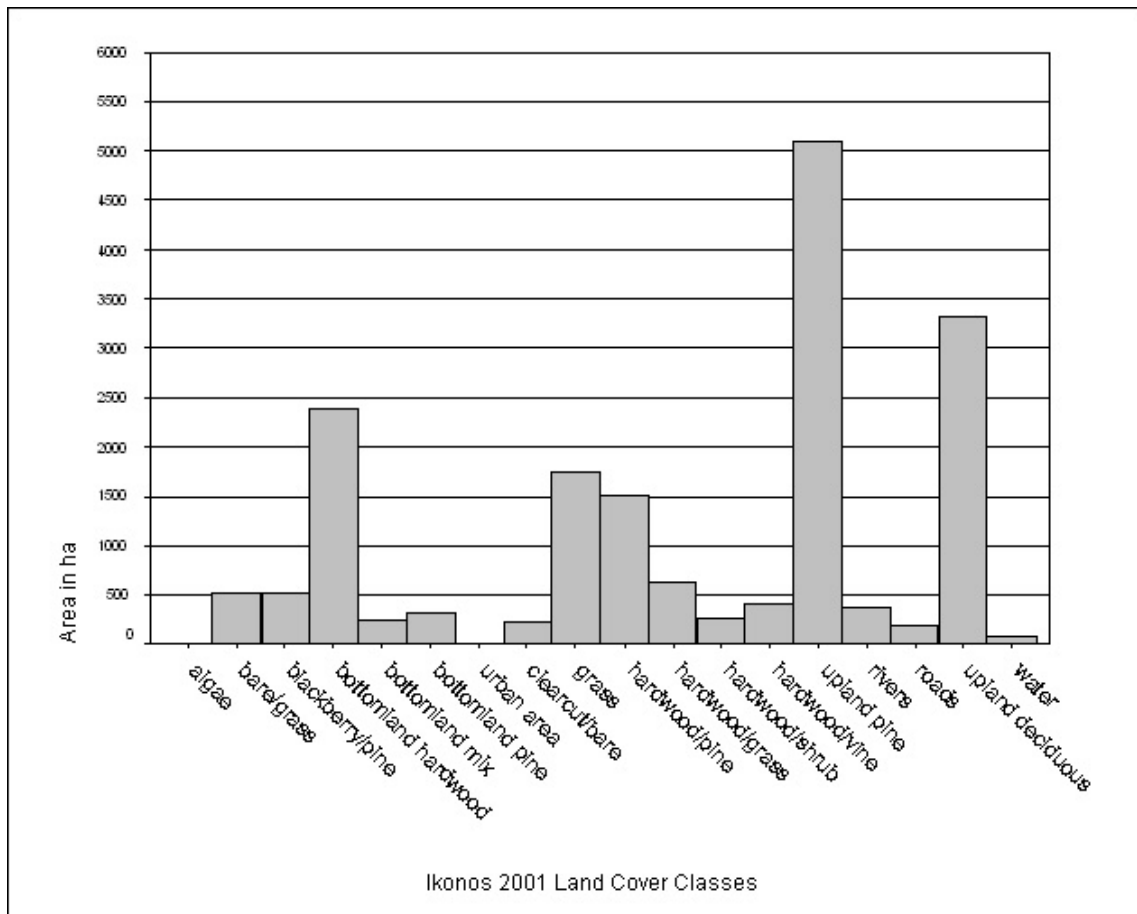


Figure 2-3: Total area represented by each land cover category for the Ikonos land cover classification for the year 2001.

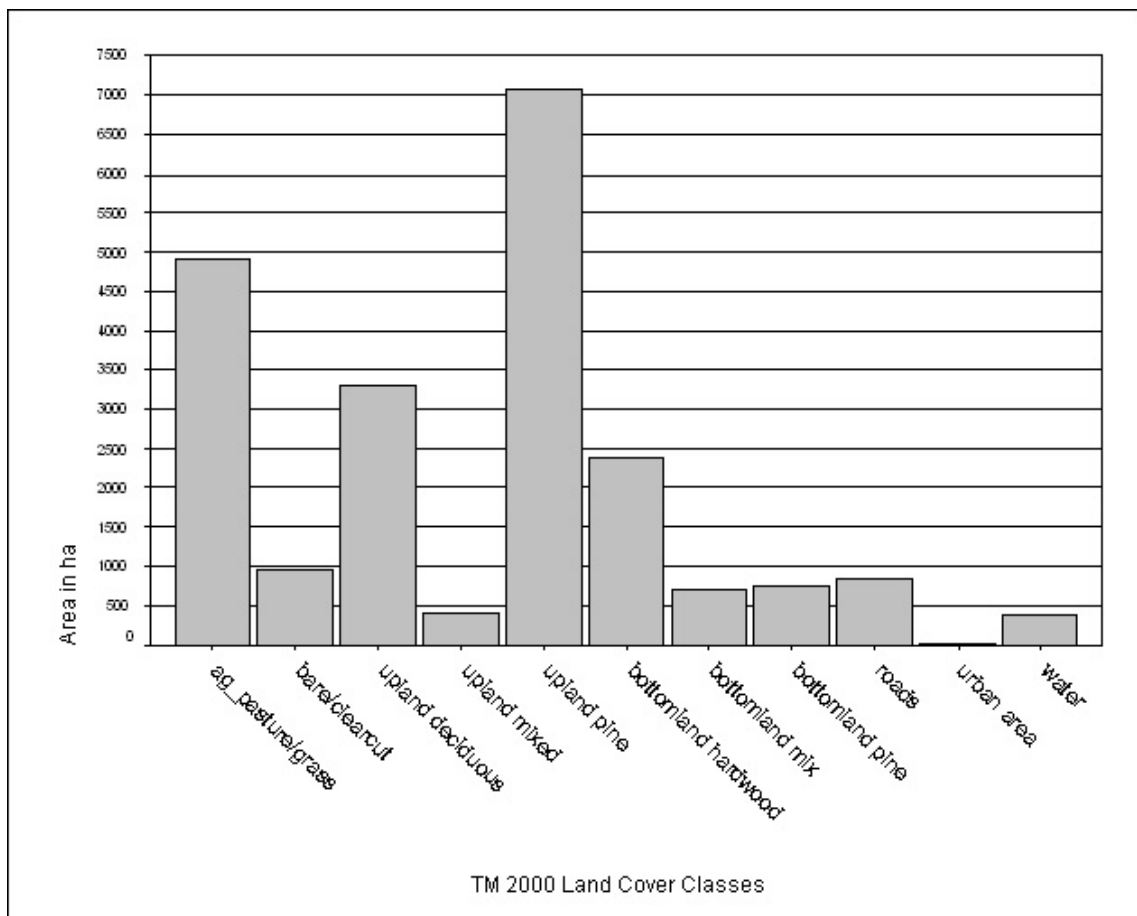


Figure 2-4: Total area represented by each land cover category for the TM land cover classification for the year 2000.

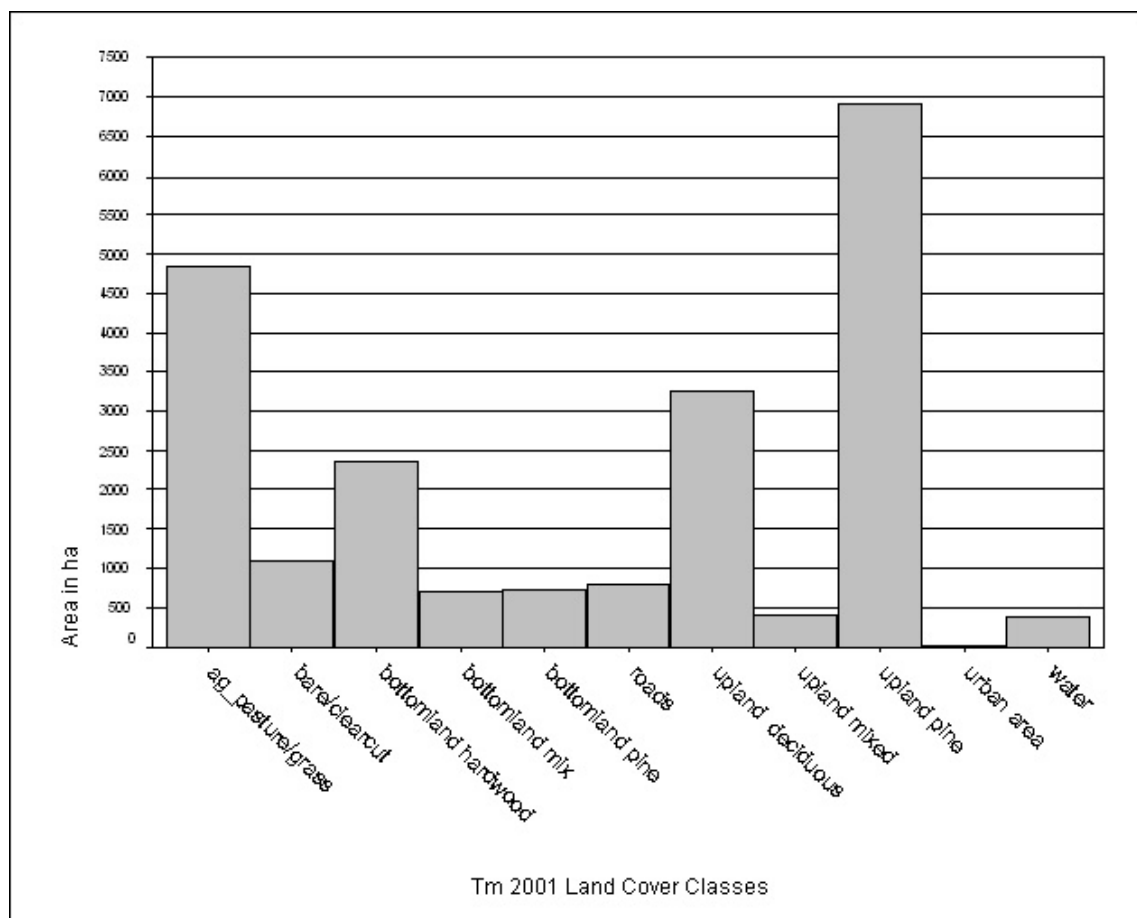


Figure 2-5: Total area represented by each land cover category for the TM land cover classification for the year 2001.

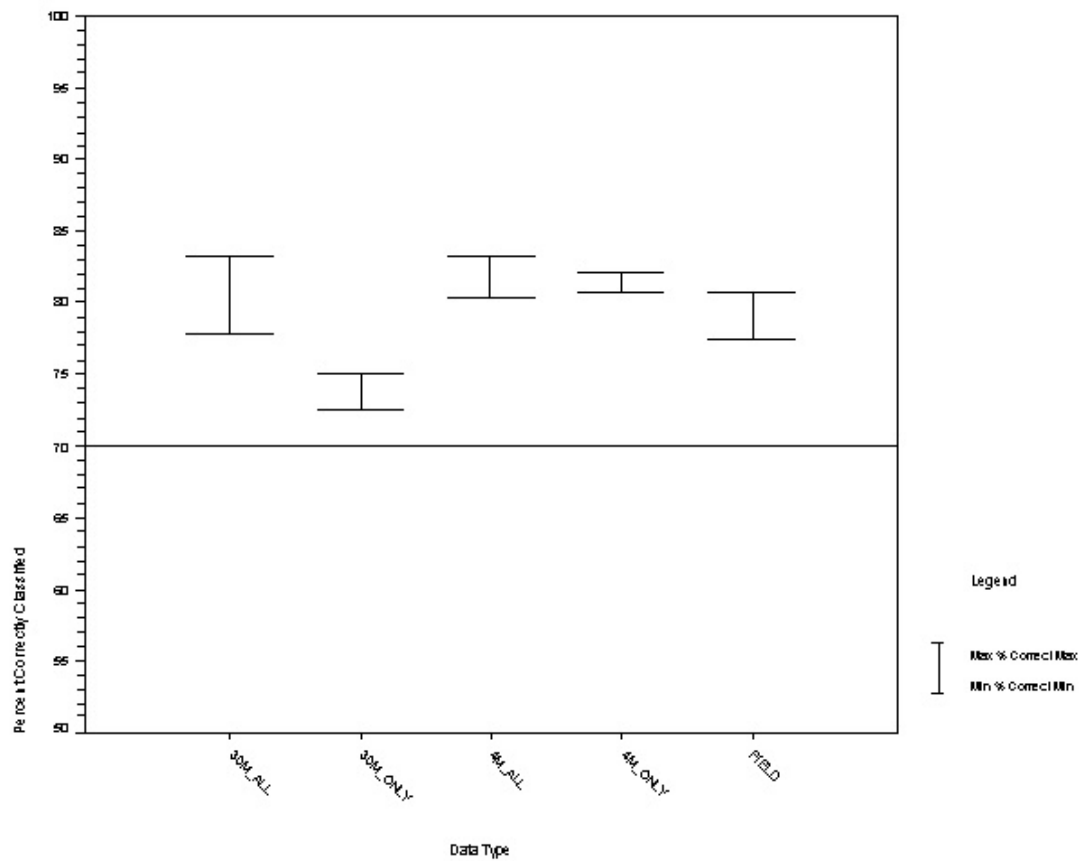


Figure 2-6: Validation results: Correct classification ranges of top ten models for each data type for the Acadian Flycatcher. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

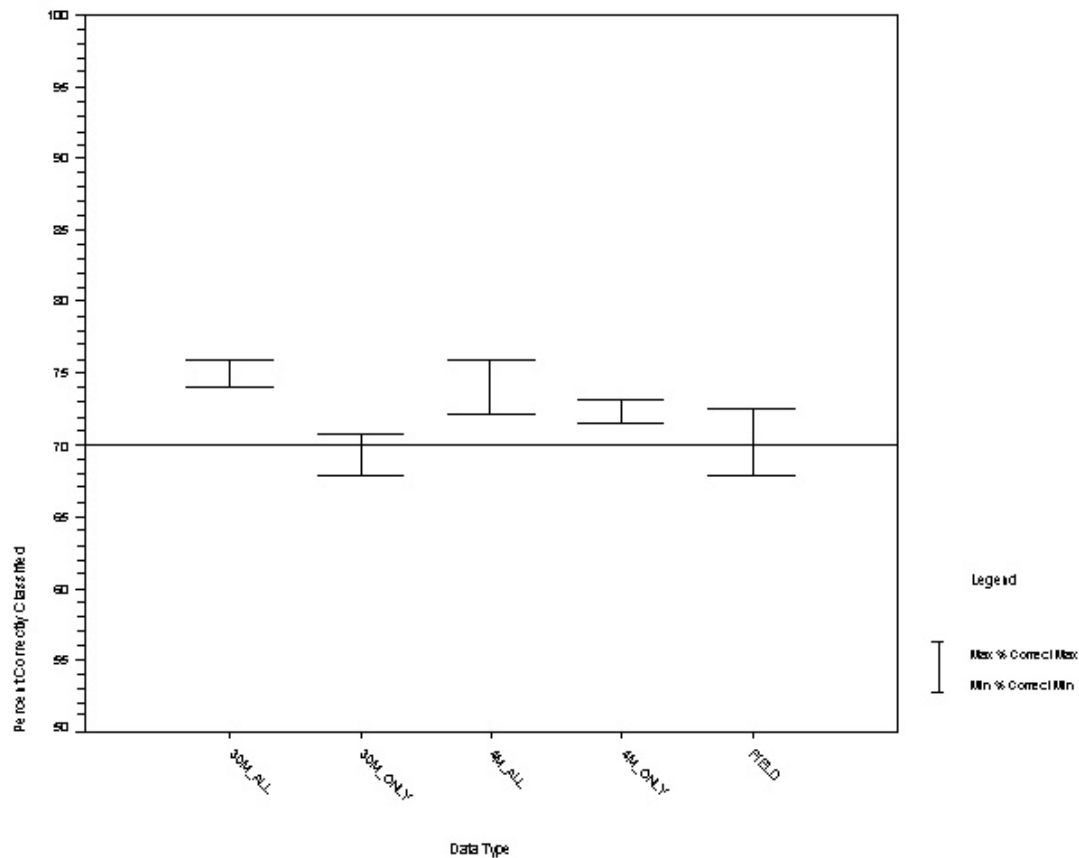


Figure 2-7: Validation results: Correct classification ranges of top ten models for each data type for the Red-eyed Vireo. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

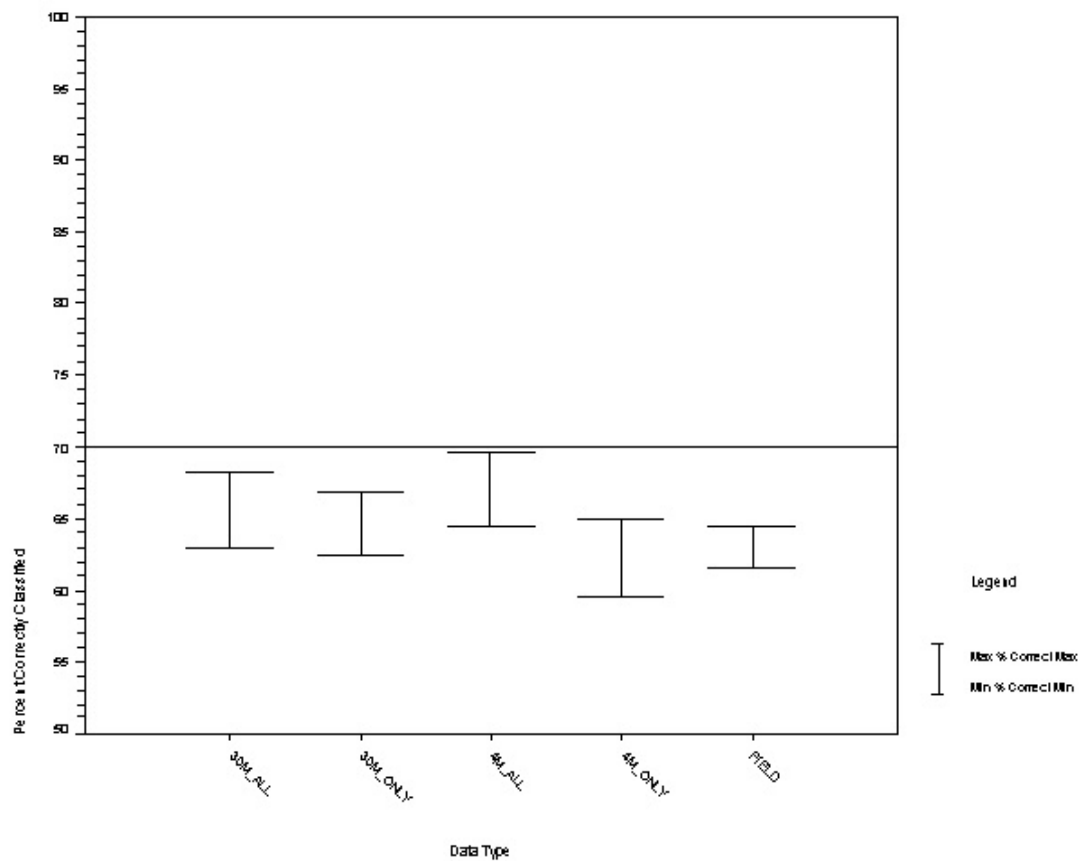


Figure 2-8: Validation results: Correct classification ranges of top ten models for each data type for the Yellow-billed Cuckoo. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

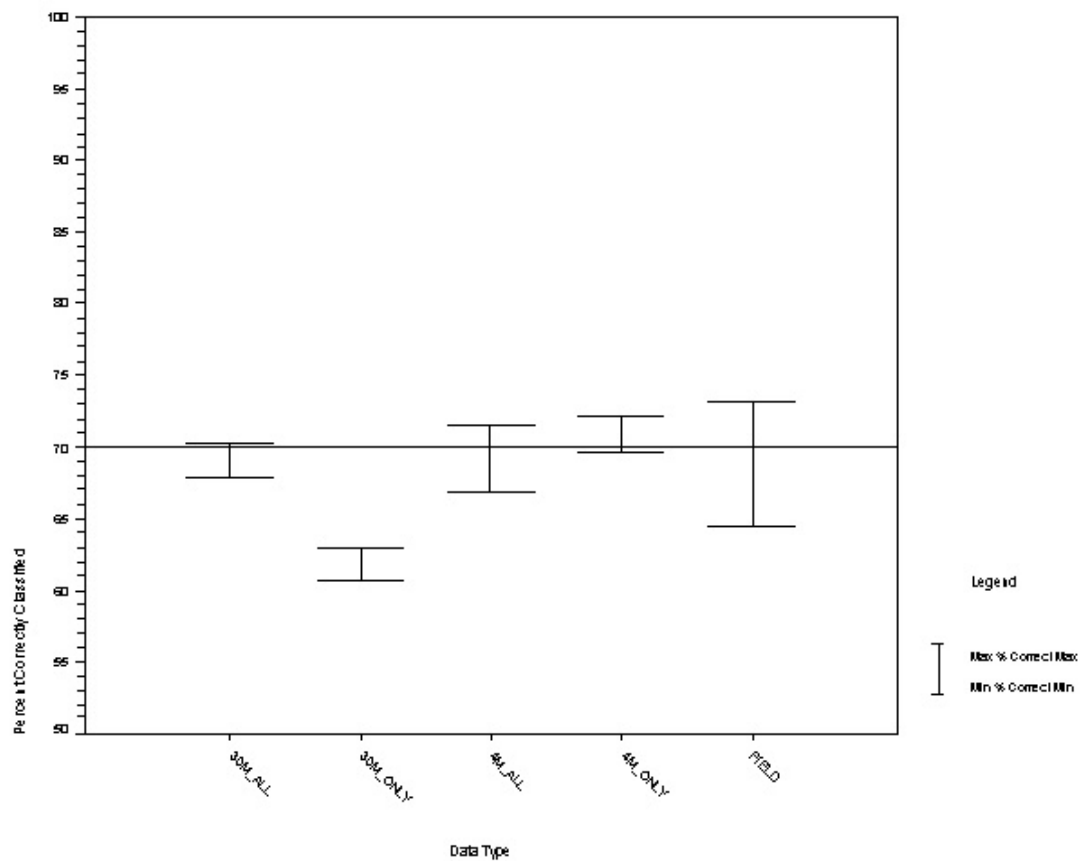


Figure 2-9: Validation results: Correct classification ranges of top ten models for each data type for the Indigo Bunting. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

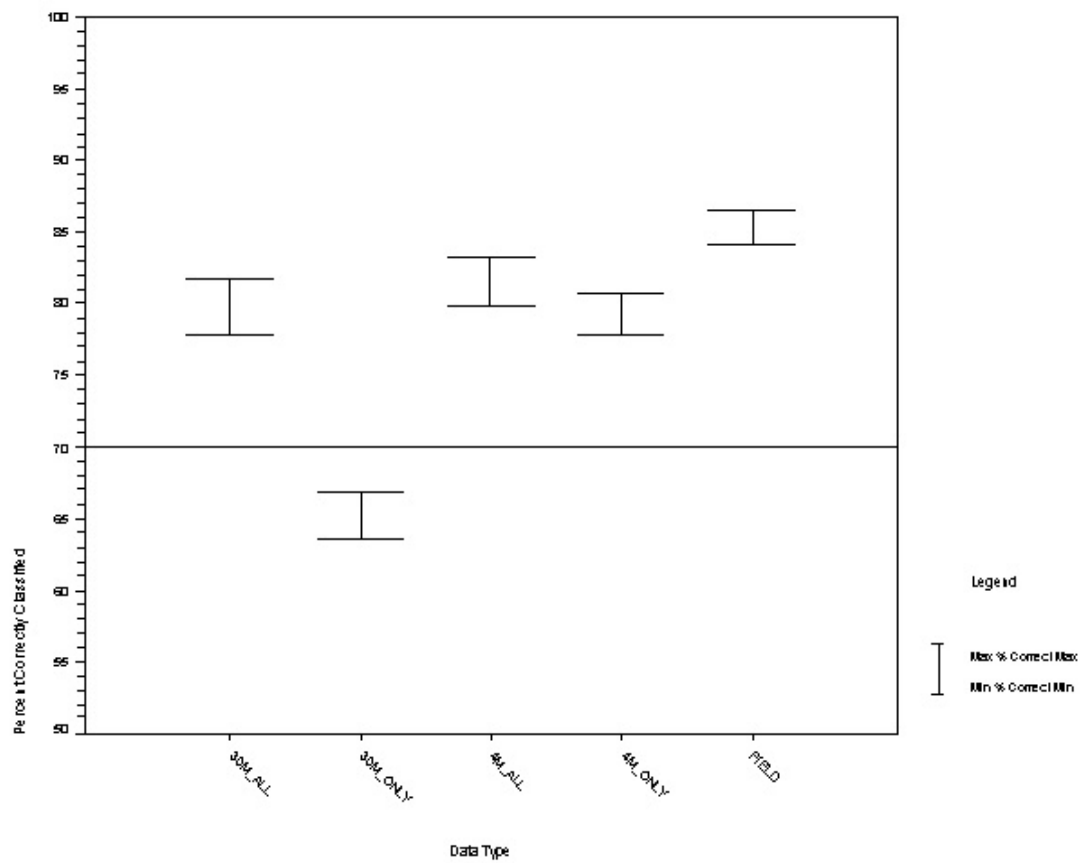


Figure 2-10: Validation results: Correct classification ranges of top ten models for each data type for the Prairie Warbler. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

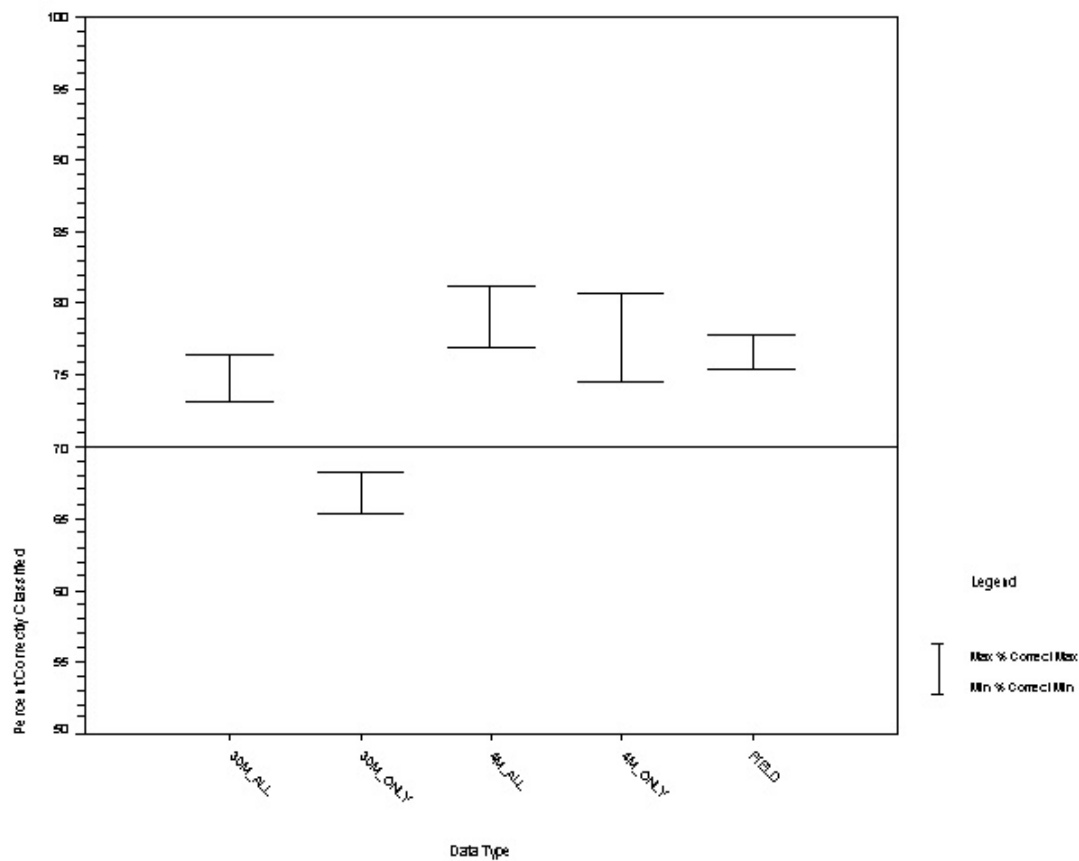


Figure 2-11: Validation results: Correct classification ranges of top ten models for each data type for the Yellow-breasted Chat. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

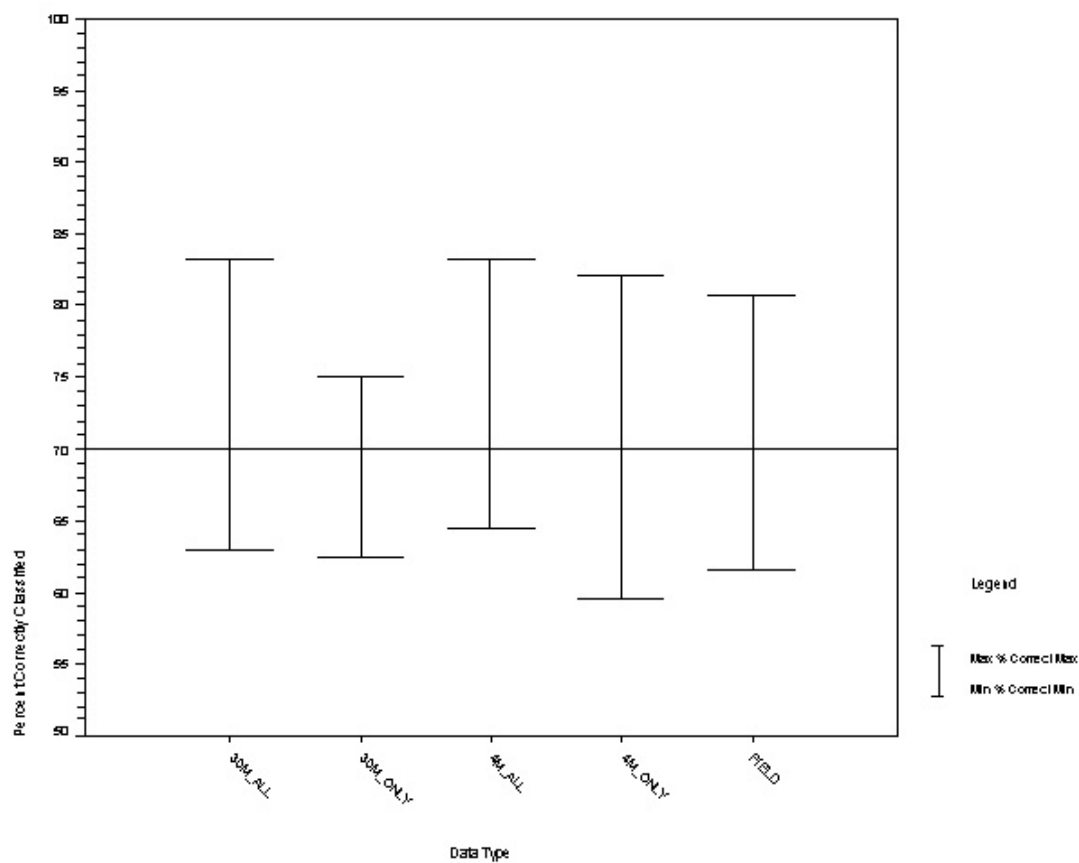


Figure 2-12: Validation results: Correct classification ranges of top ten models for each data type for closed canopy species. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

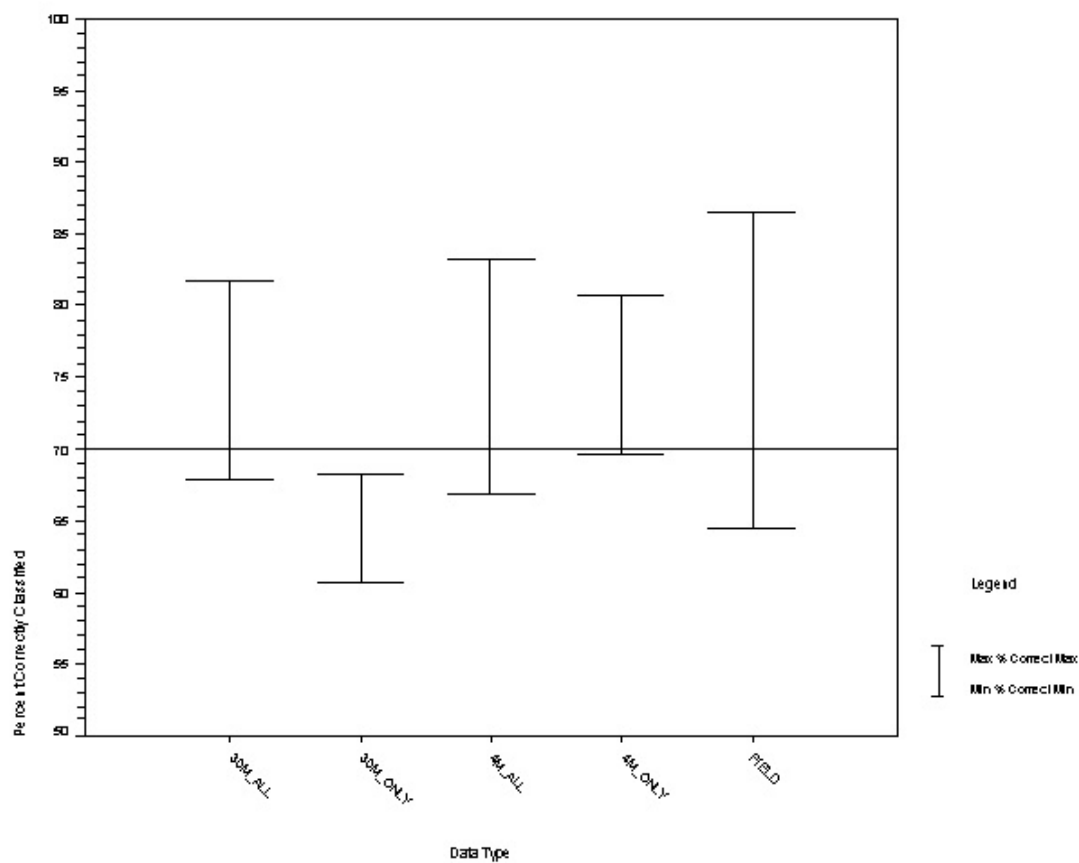


Figure 2-13: Validation results: Correct classification ranges of top ten models for each data type for early successional species. The figures represent the highest value and the lowest correctly classified value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good overall habitat model.

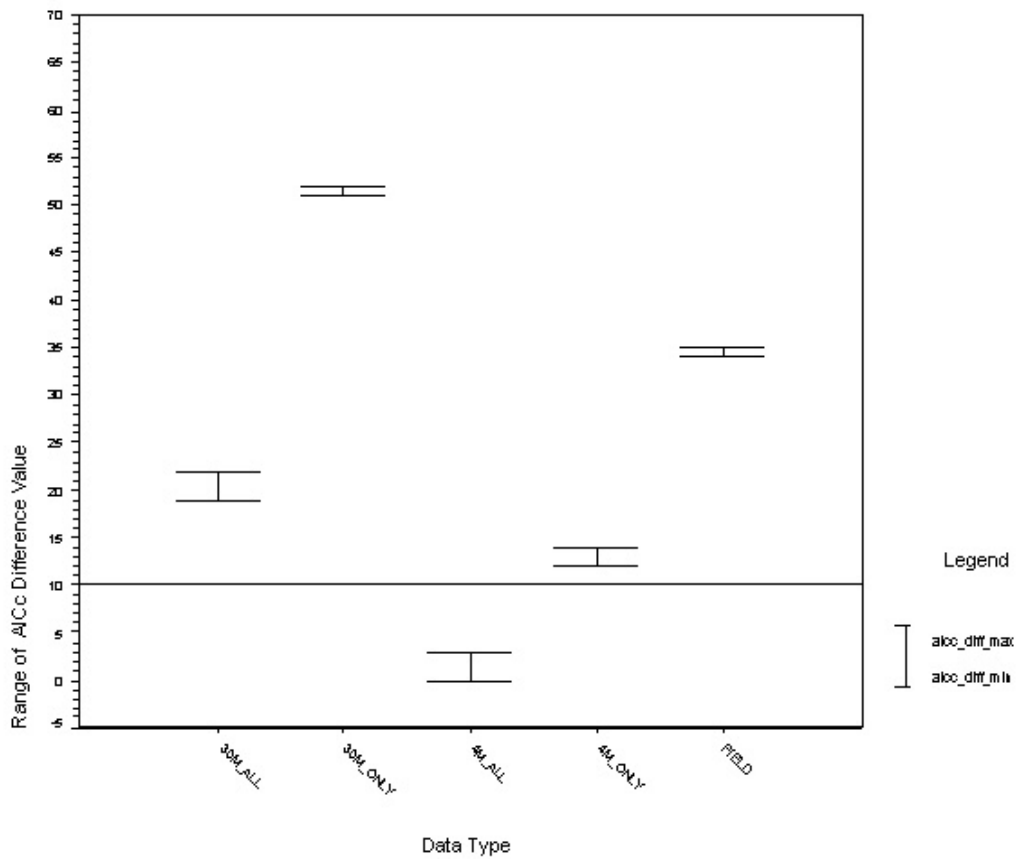


Figure 2-14: Ranges of AICc differences (Δ AICc) for the Acadian Flycatcher. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

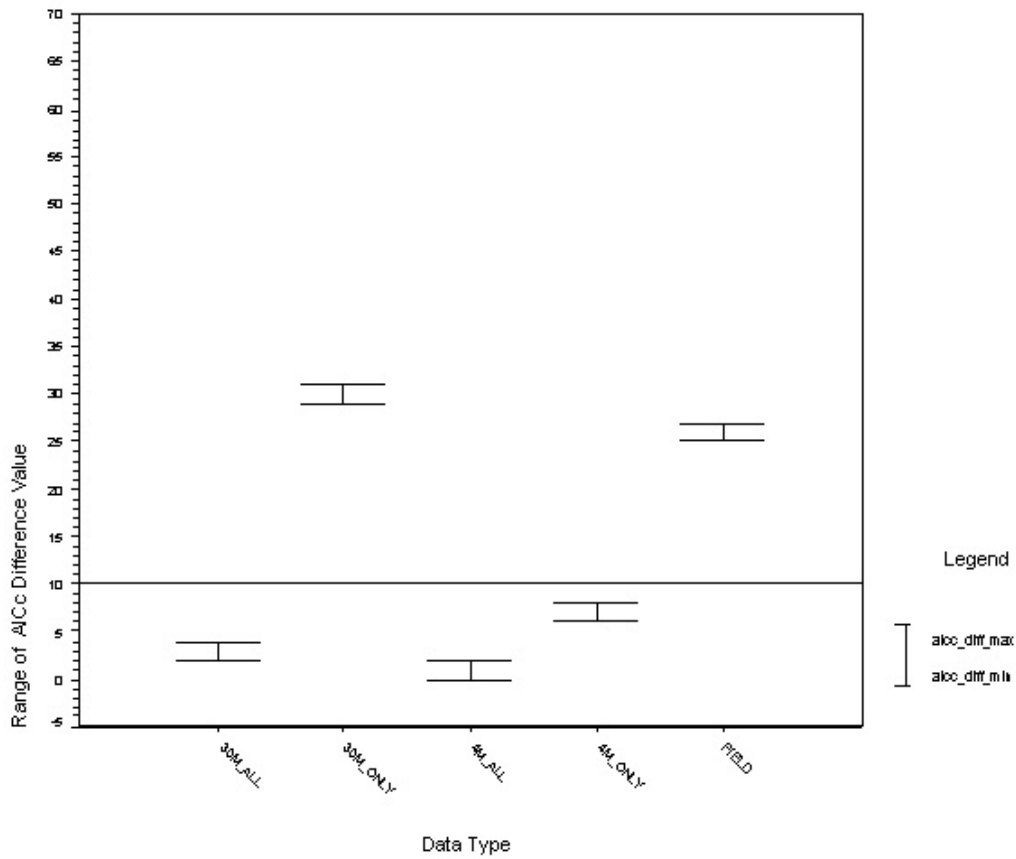


Figure 2-15: Ranges of AICc differences (Δ AICc) for the Red-eyed Vireo. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

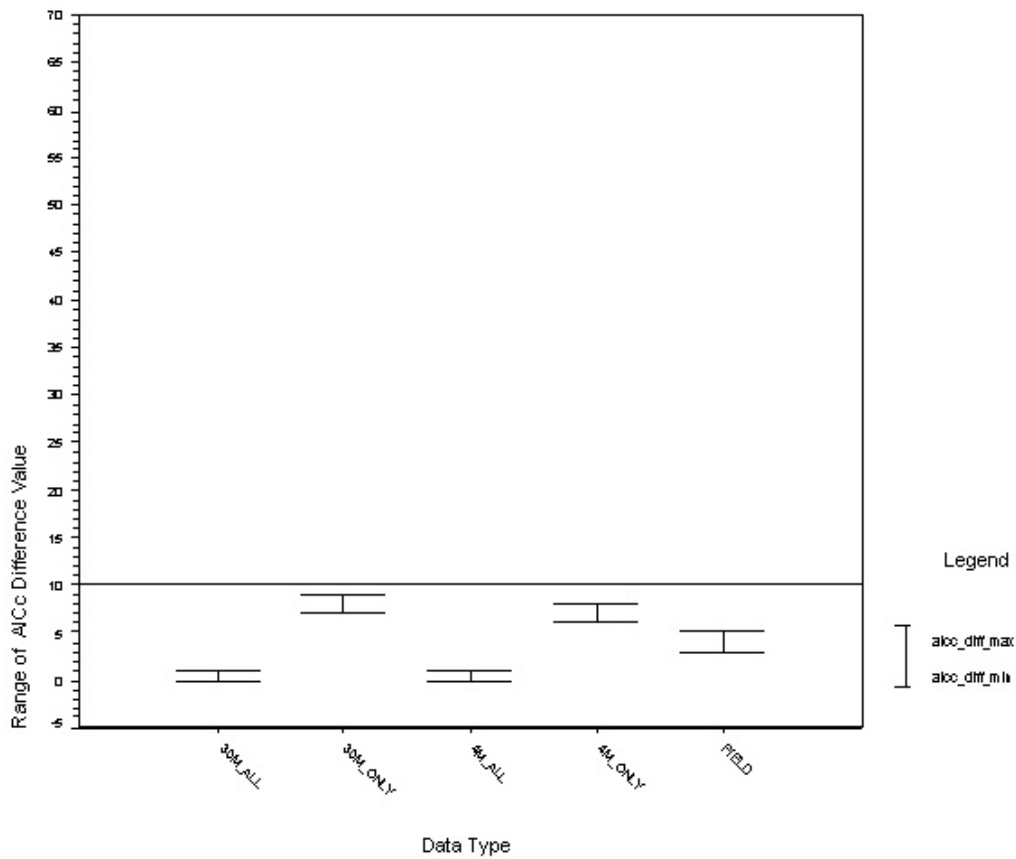


Figure 2-16: Ranges of AICc differences ($\Delta AICc$) for the Yellow-billed Cuckoo. The figures represent the highest and the lowest $\Delta AICc$ value for the models in that data group. $\Delta AICc$ are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

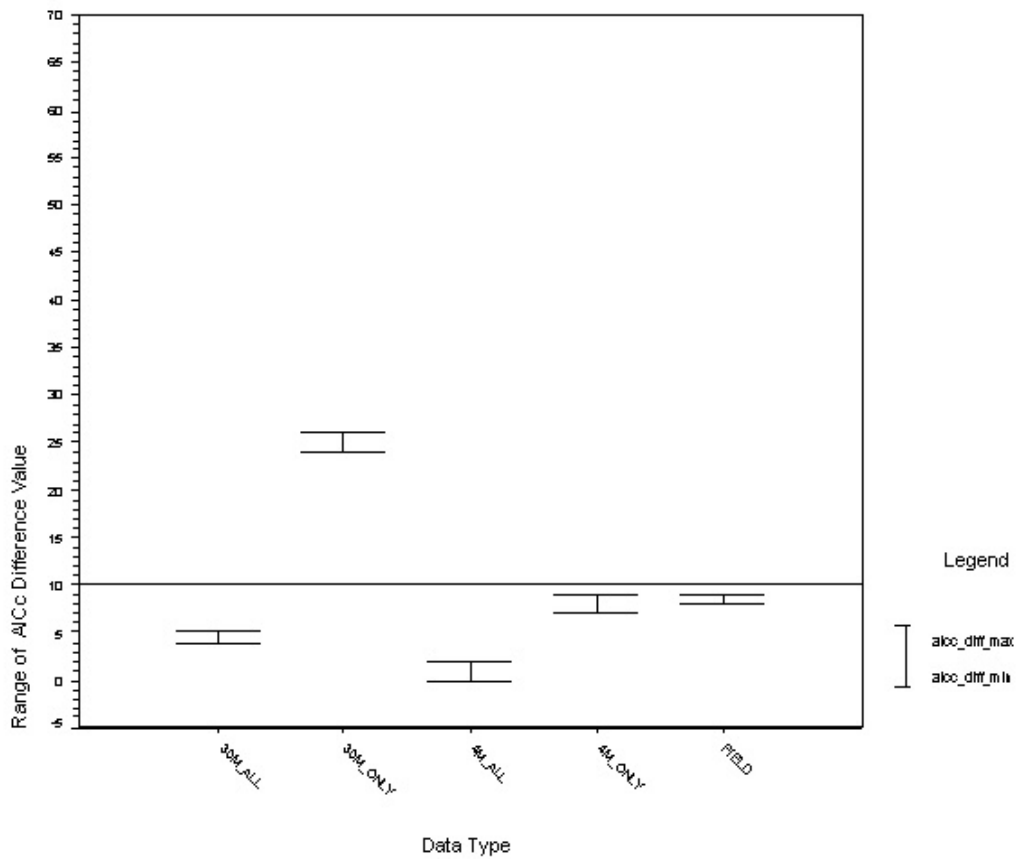


Figure 2-17: Ranges of AICc differences (Δ AICc) for the Indigo Bunting. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

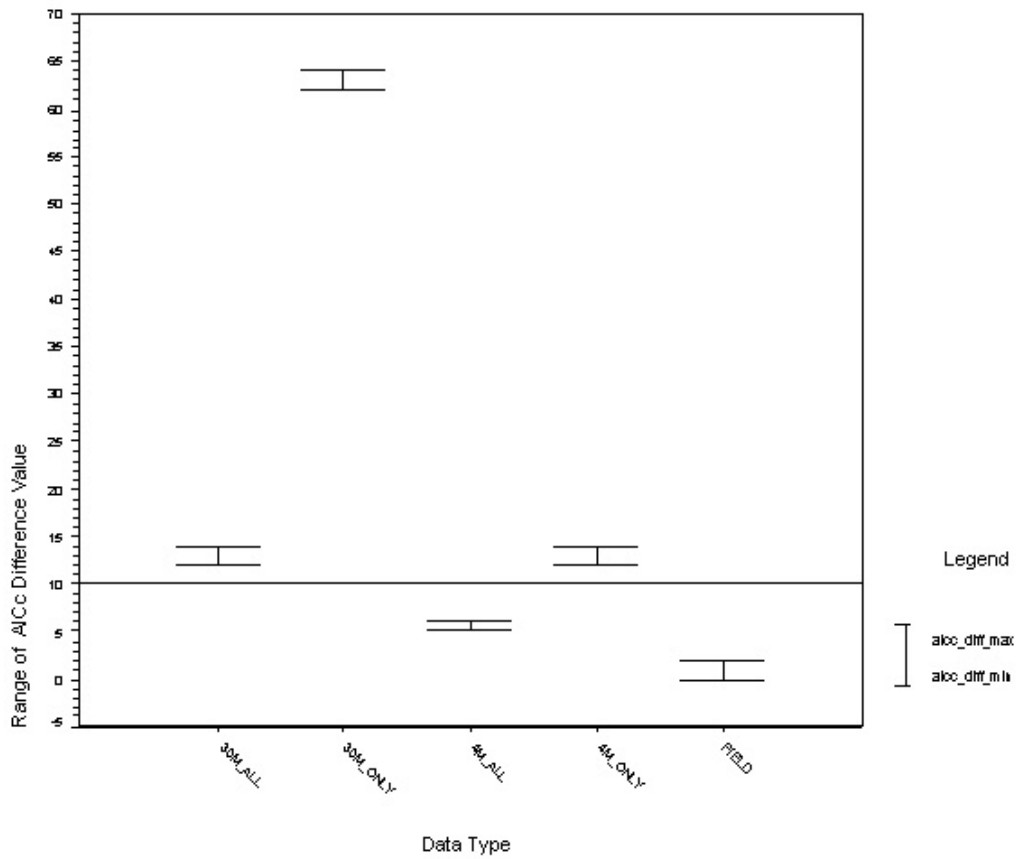


Figure 2-18: Ranges of AICc differences (Δ AICc) for the Prairie Warbler. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

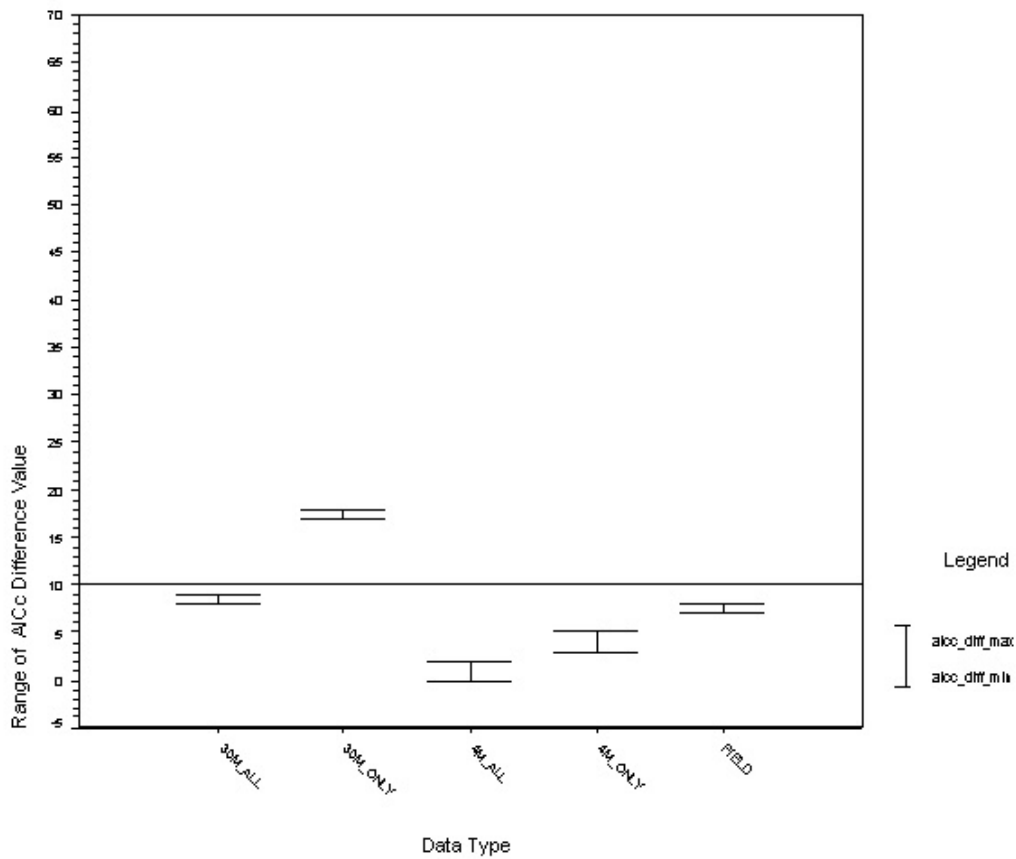


Figure 2-19: Ranges of AICc differences (Δ AICc) for the Yellow-breasted Chat. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

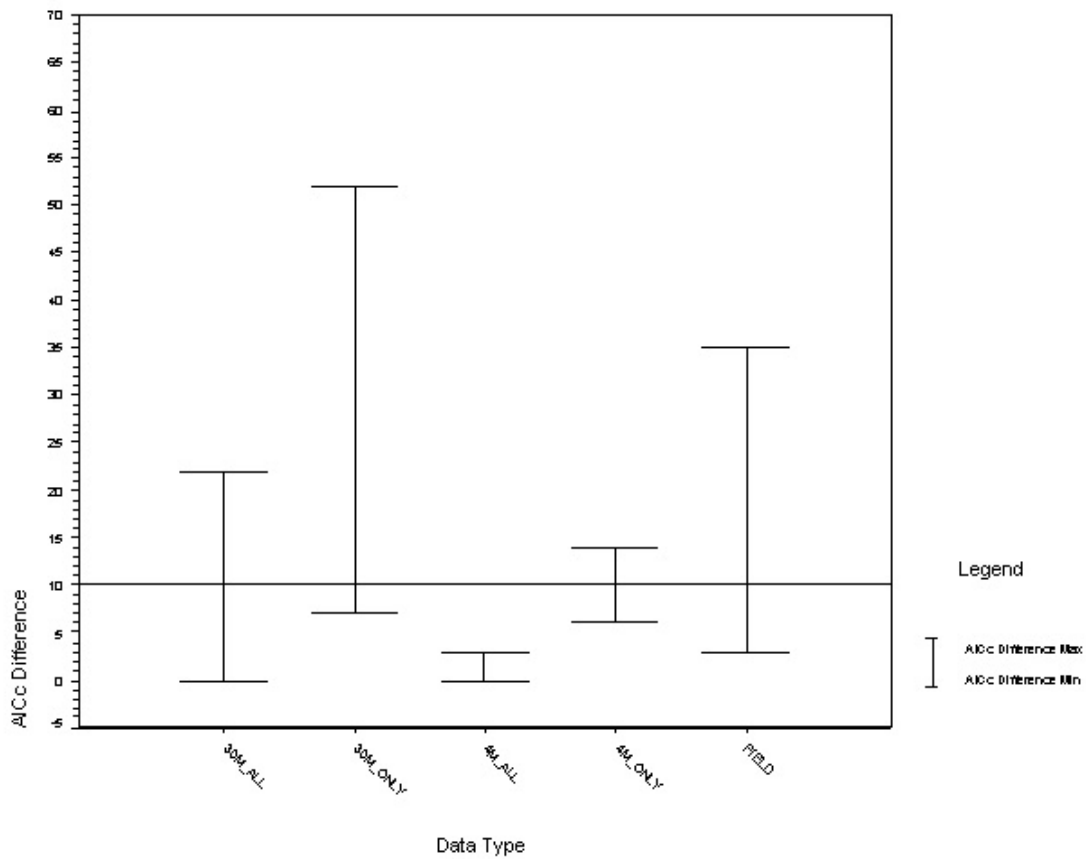


Figure 2-20: Ranges of AICc differences (Δ AICc) for closed canopy species. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

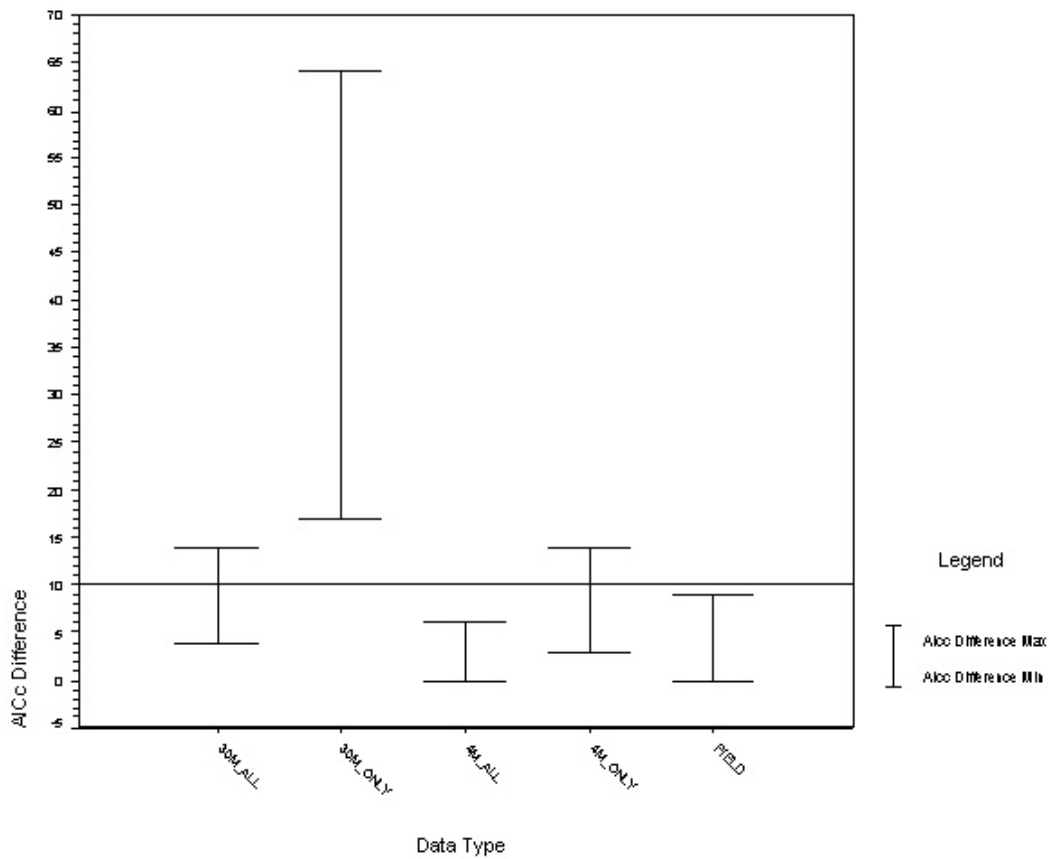


Figure 2-21: Ranges of AICc differences (Δ AICc) for the early successional species. The figures represent the highest and the lowest Δ AICc value for the models in that data group. Δ AICc are a measure of empirical support a model has relative to the other models. The lower the value the stronger the supporting evidence. Models having values greater than 10 (reference line on the graph) have essentially no empirical support.

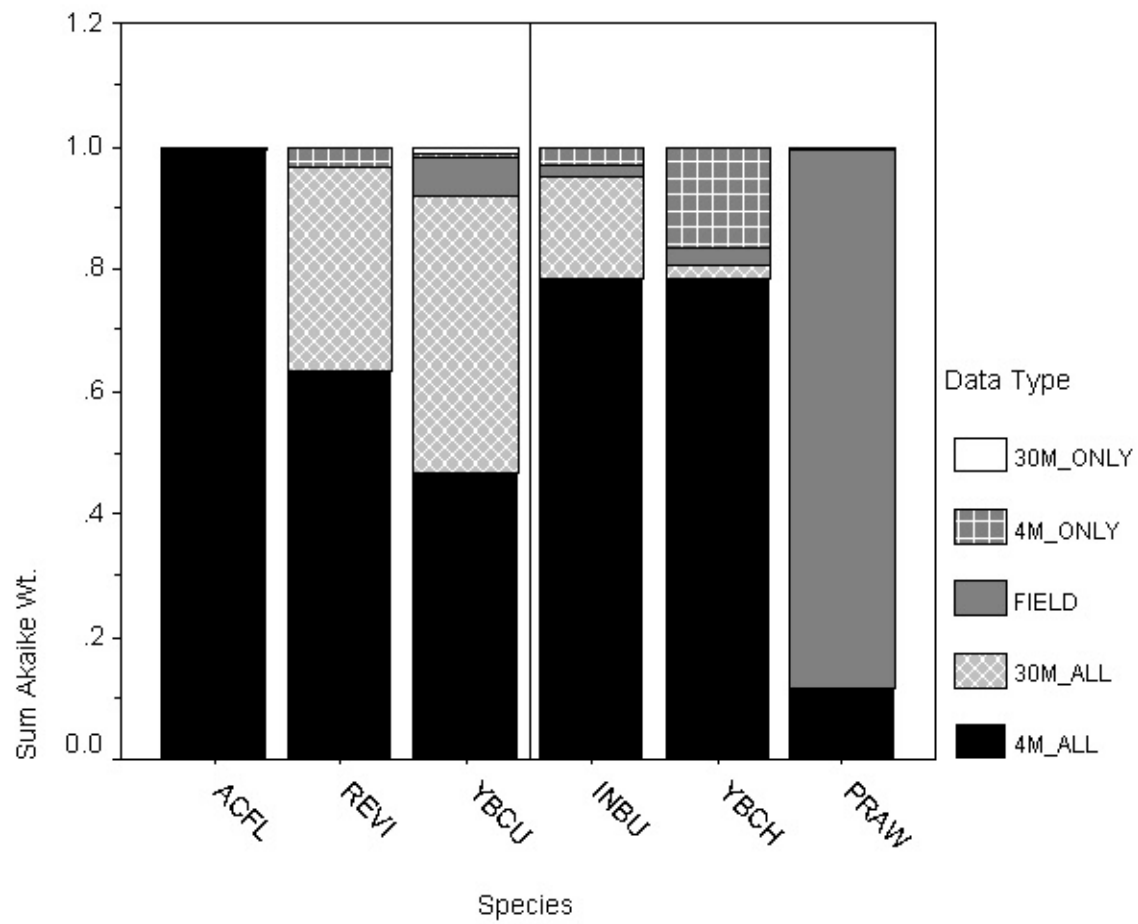


Figure 2-22: Sum of Akaike weights for the top ten models in each data category for all species. The weight represents the normalized likelihood for all models in the set. When all the weights for each data type are summed for each species, they will equal one. The weight measures the empirical support the parameters have for each model.

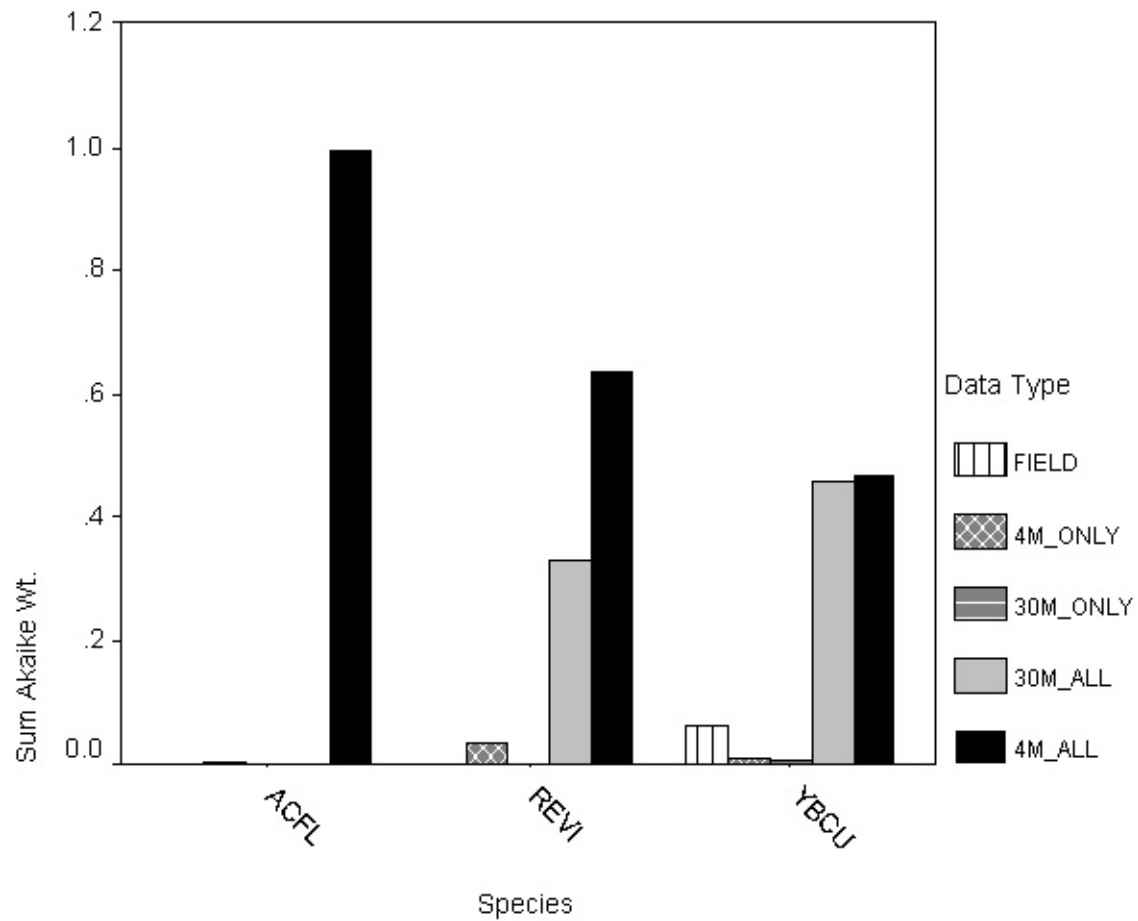


Figure 2-23: Sum of Akaike weights for the top ten models in each data category for closed canopy species. The weight represents the normalized likelihood for all models in the set. When all the weights for each data type are summed for each species, they will equal one. The weight measures the empirical support the parameters have for each model.

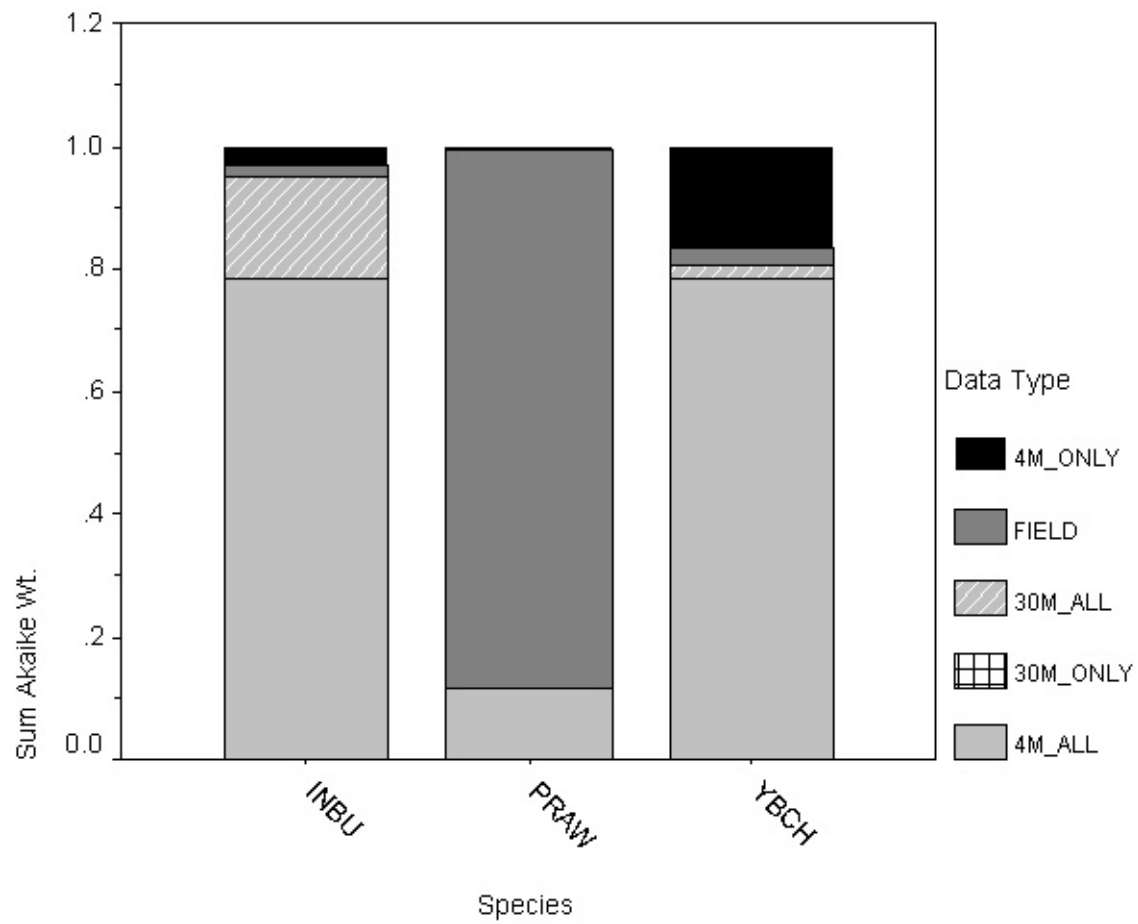


Figure 2-24: Sum of Akaike weights for the top ten models in each data category for early successional species. The weight represents the normalized likelihood for all models in the set. When all the weights for each data type are summed for each species, they will equal one. The weight measures the empirical support the parameters have for each model.

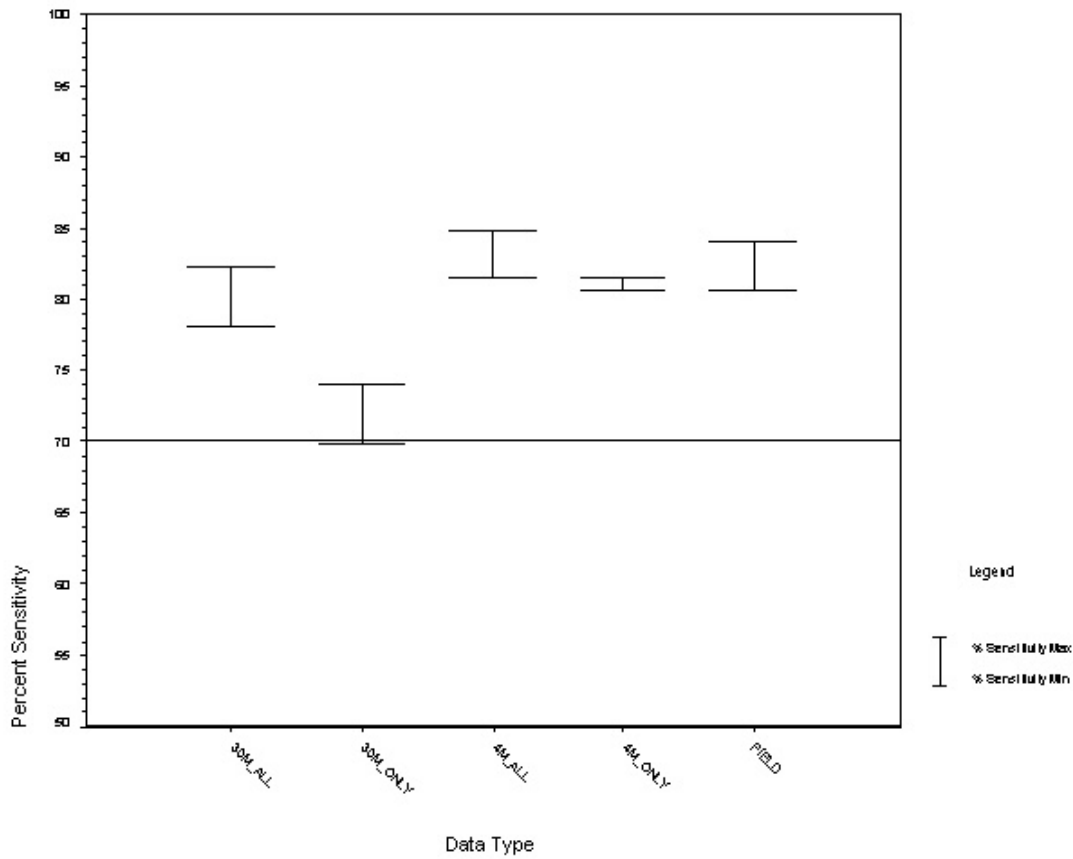


Figure 2-25: Sensitivity ranges for the Acadian Flycatcher. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

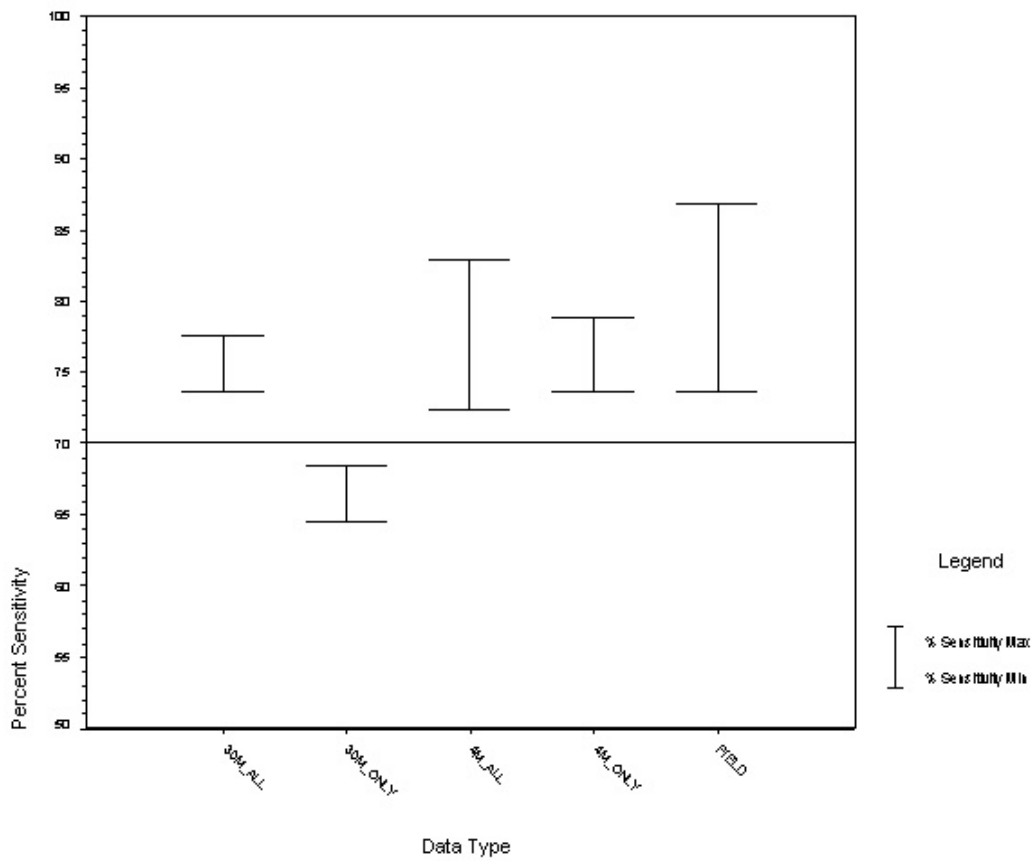


Figure 2-26: Sensitivity ranges for the Red-eyed Vireo. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

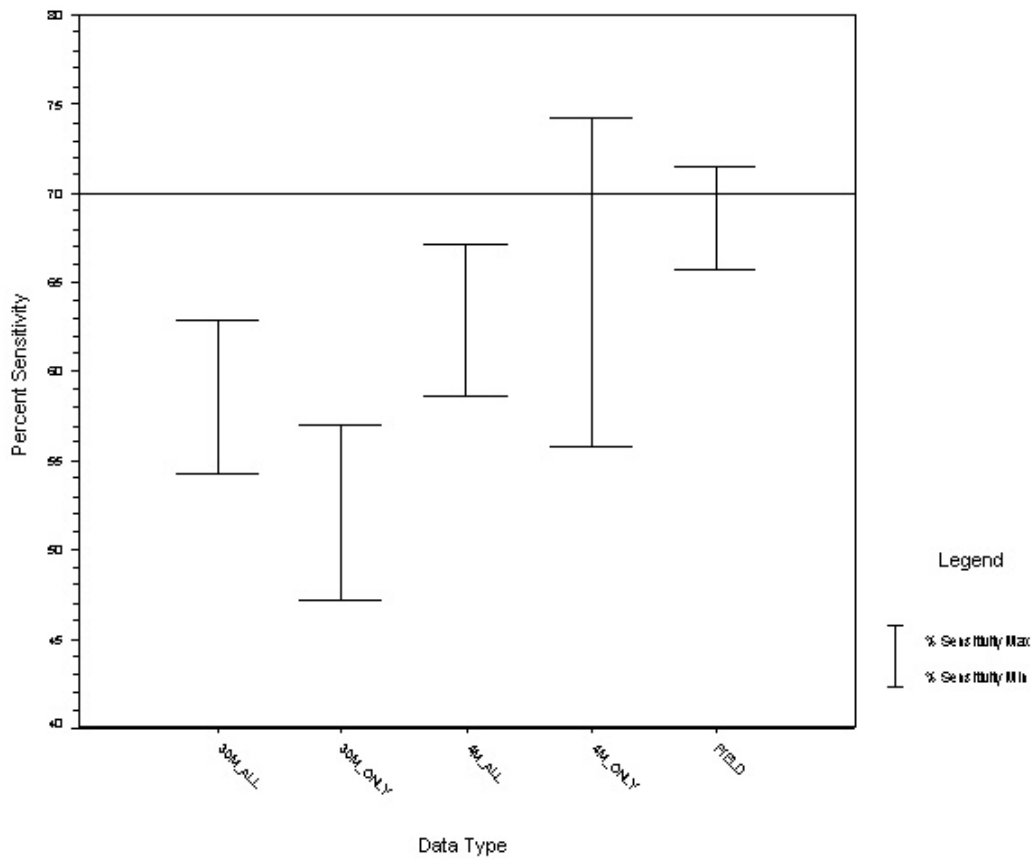


Figure 2-27: Sensitivity ranges for the Yellow-billed Cuckoo. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

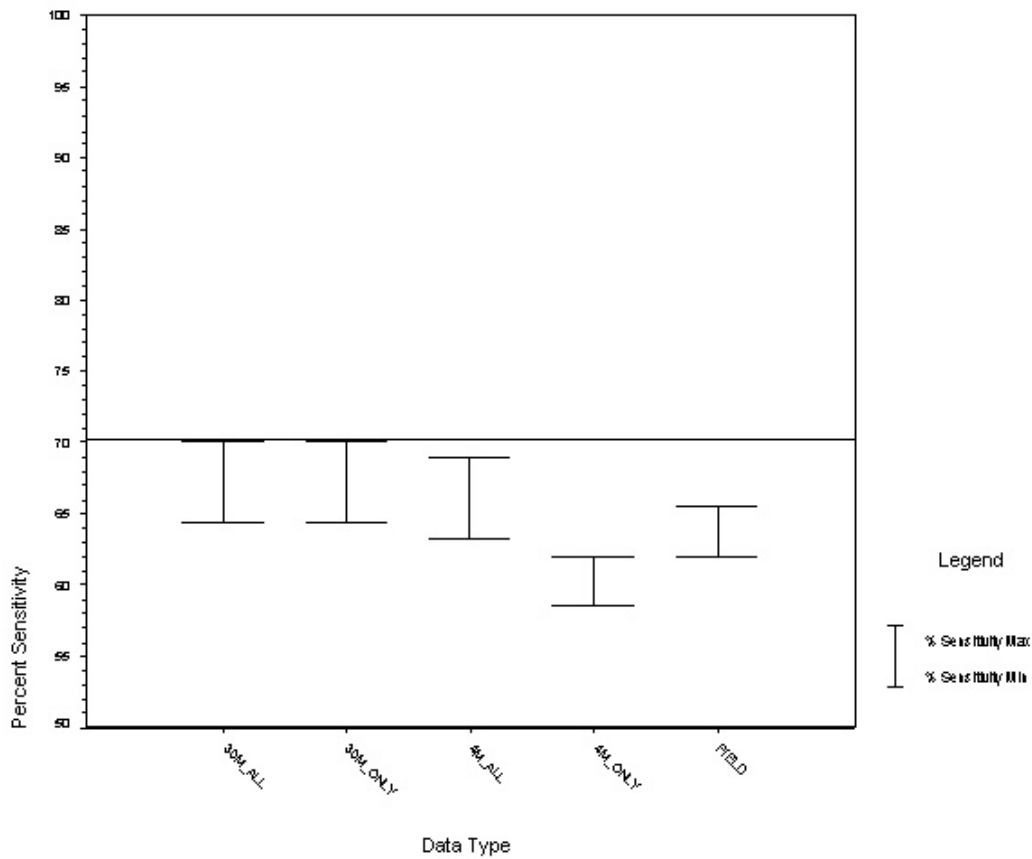


Figure 2-28: Sensitivity ranges for the Indigo Bunting. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

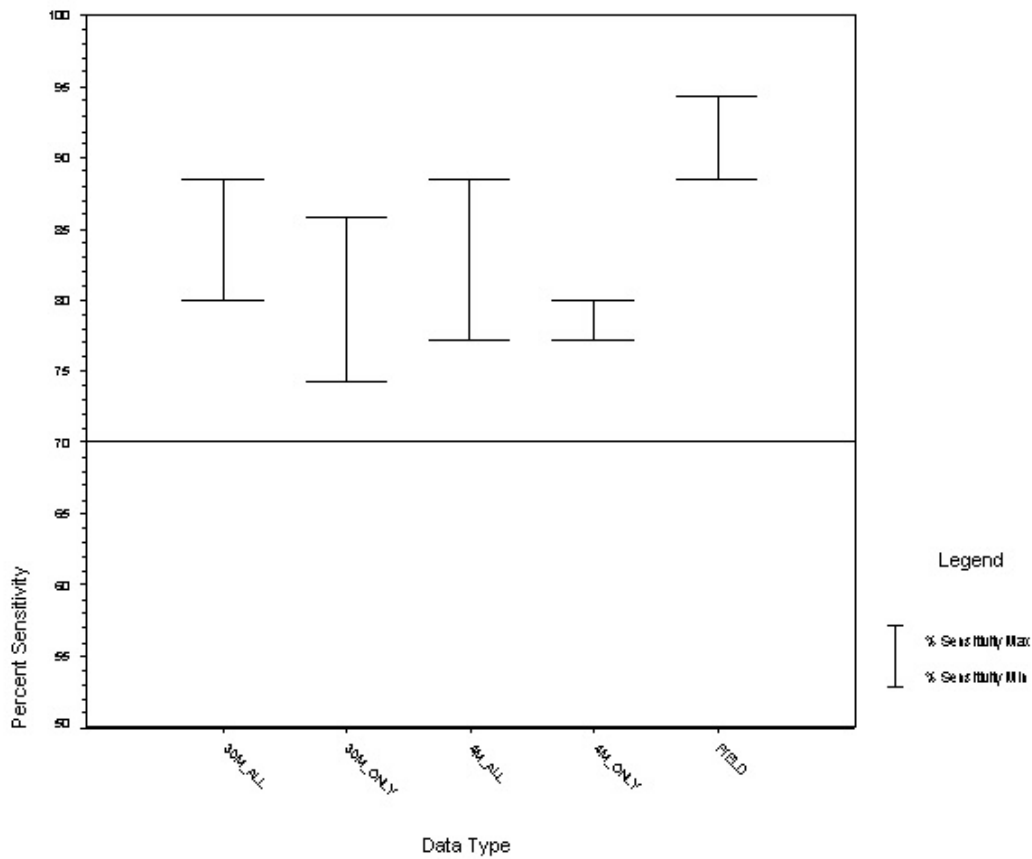


Figure 2-29: Sensitivity ranges for the Prairie Warbler. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

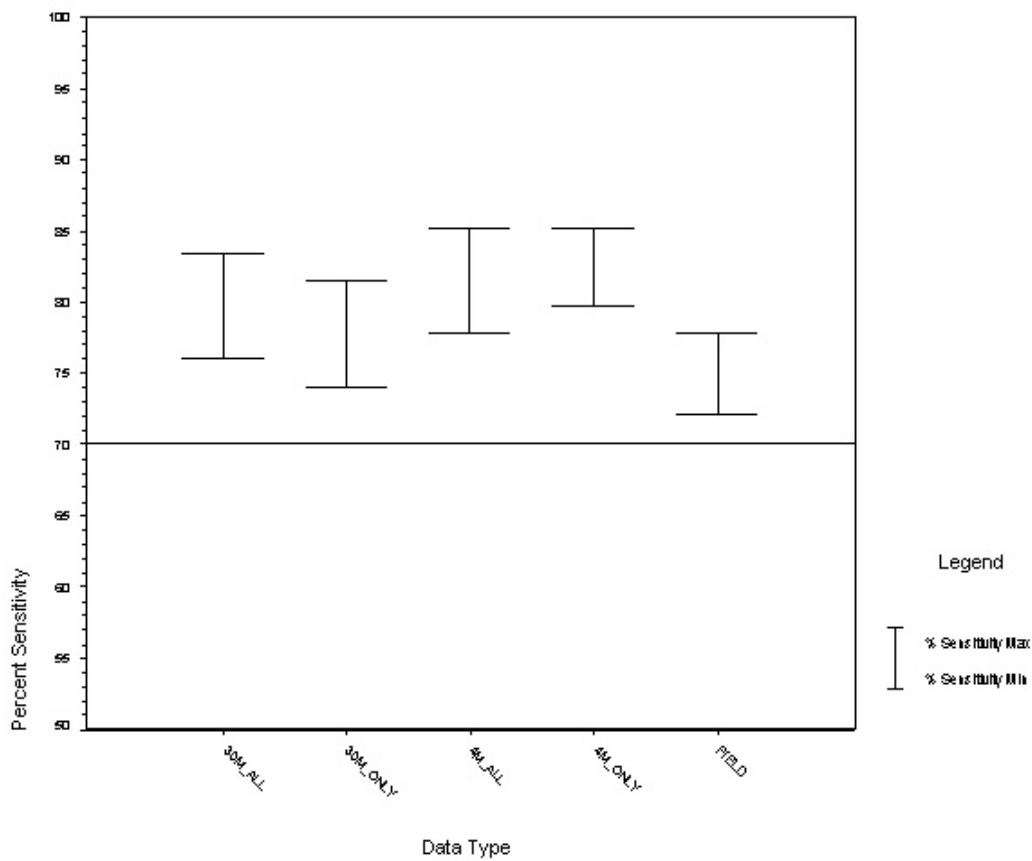


Figure 2-30: Sensitivity ranges for the Yellow-breasted Chat. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

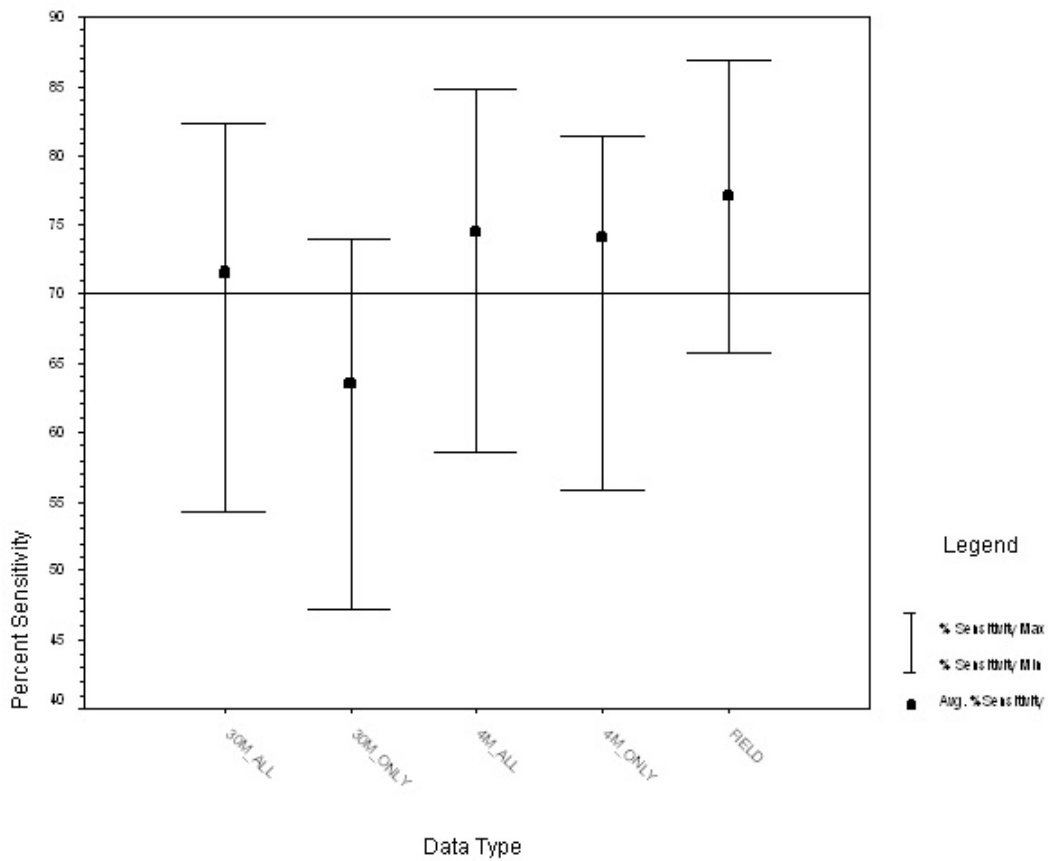


Figure 2-31: Sensitivity ranges for closed canopy species. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

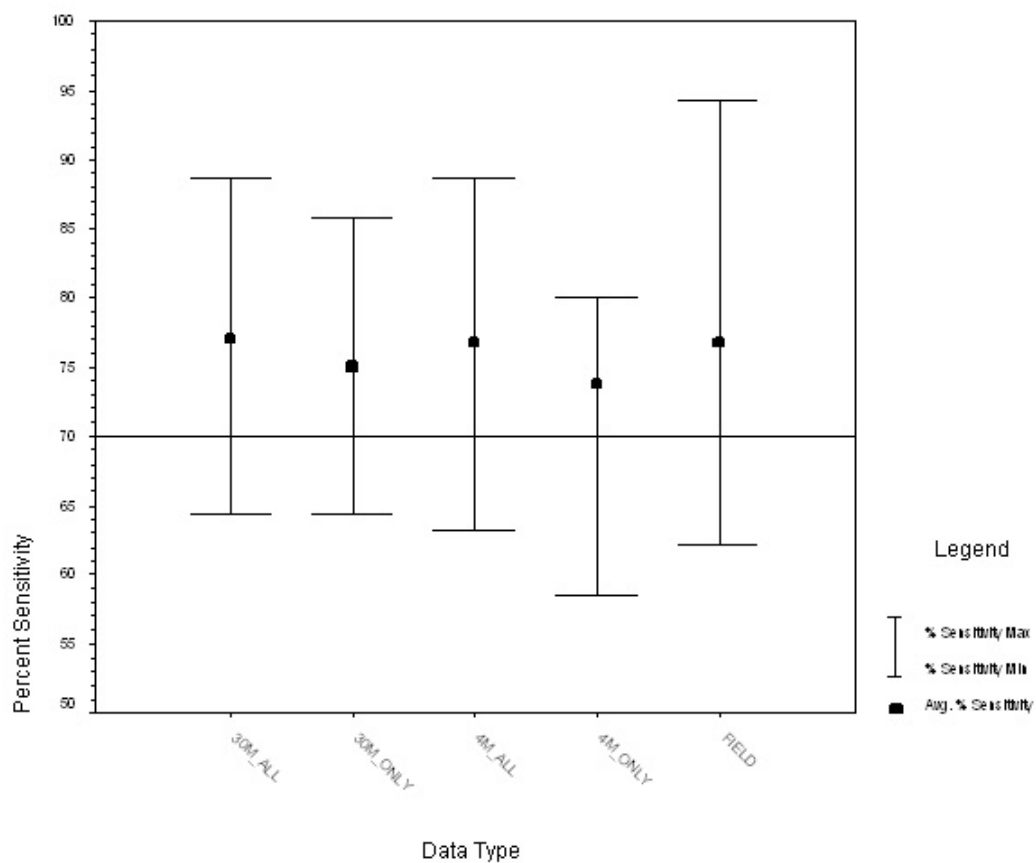


Figure 2-32: Sensitivity ranges for early successional species. The figures represent the highest and the lowest sensitivity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good sensitive habitat model.

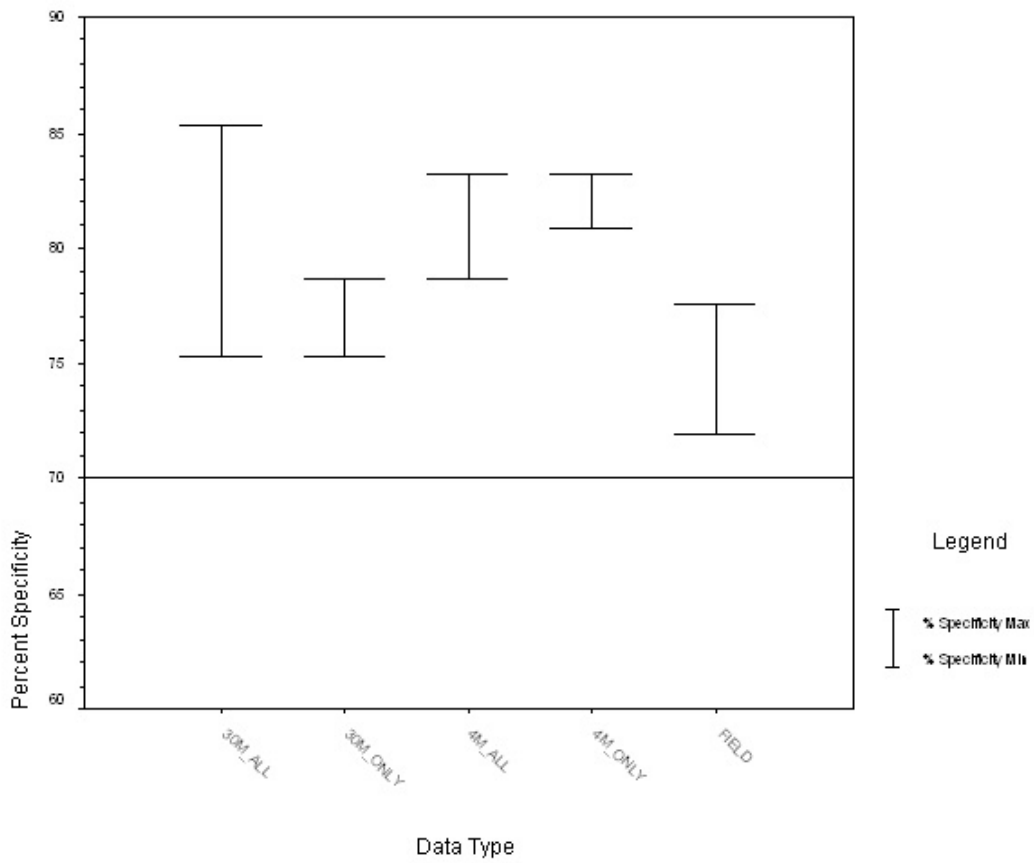


Figure 2-33: Specificity ranges for the Acadian Flycatcher. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.

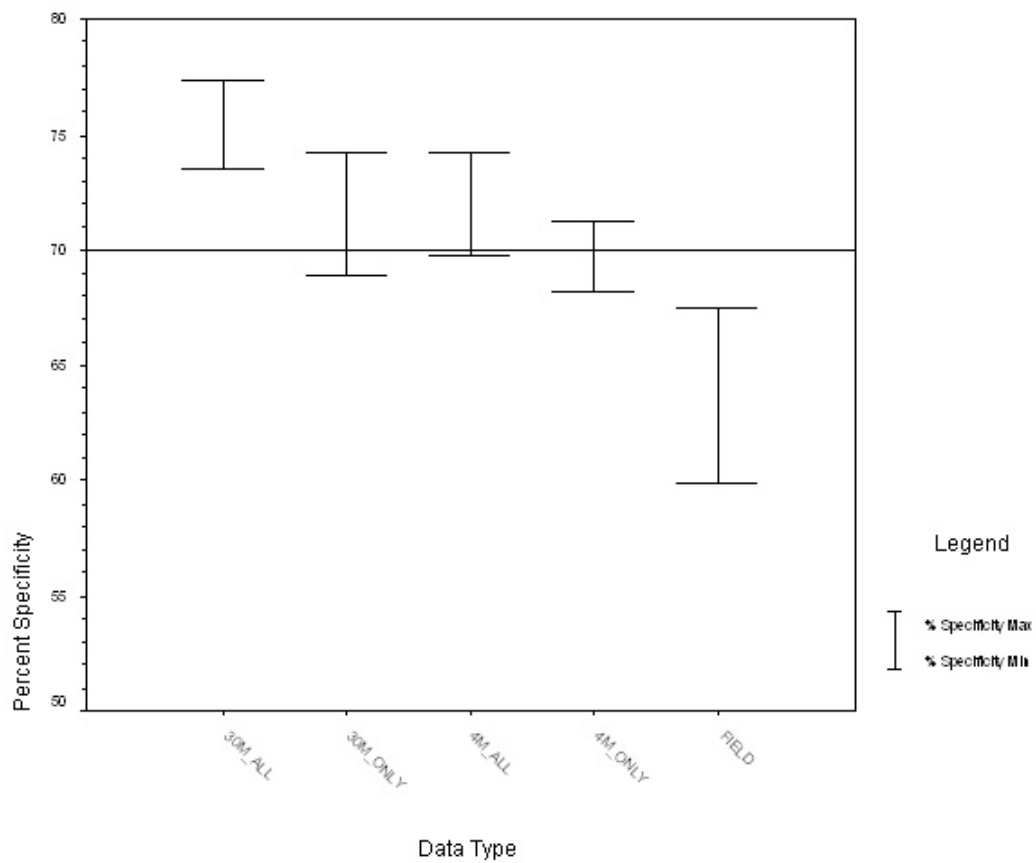


Figure 2-34: Specificity ranges for the Red-eyed Vireo. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.

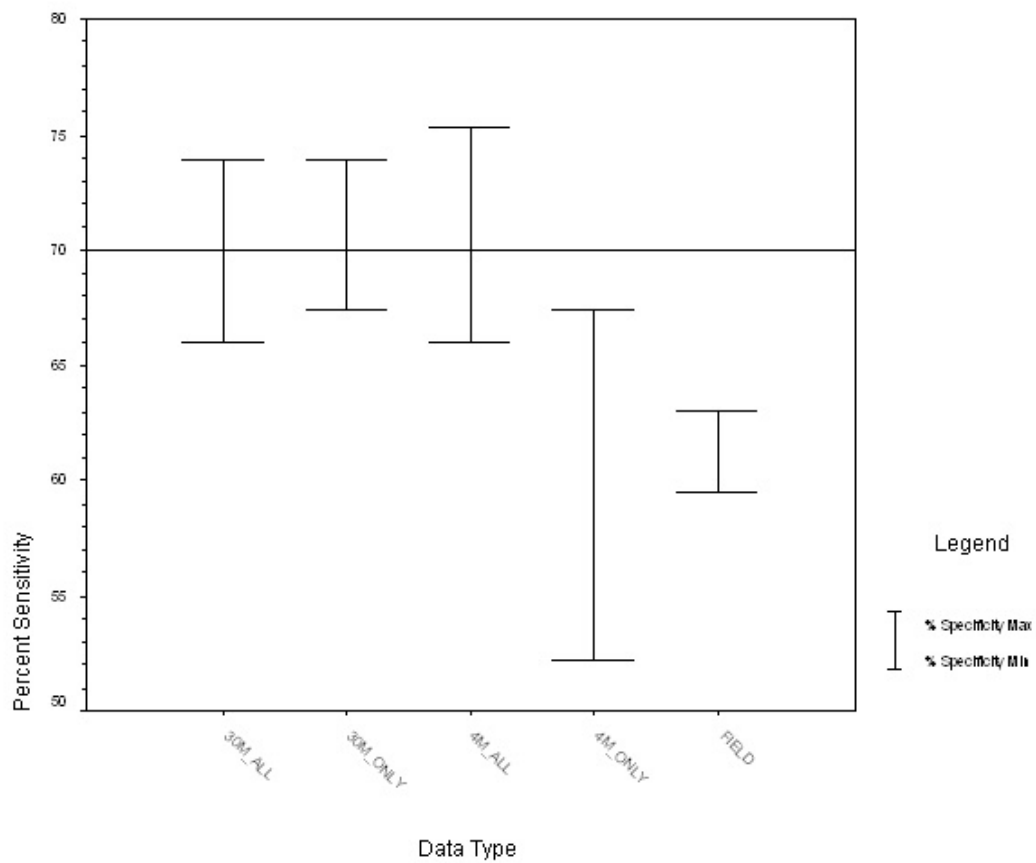


Figure 2-35: Specificity ranges for the Yellow-billed Cuckoo. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.

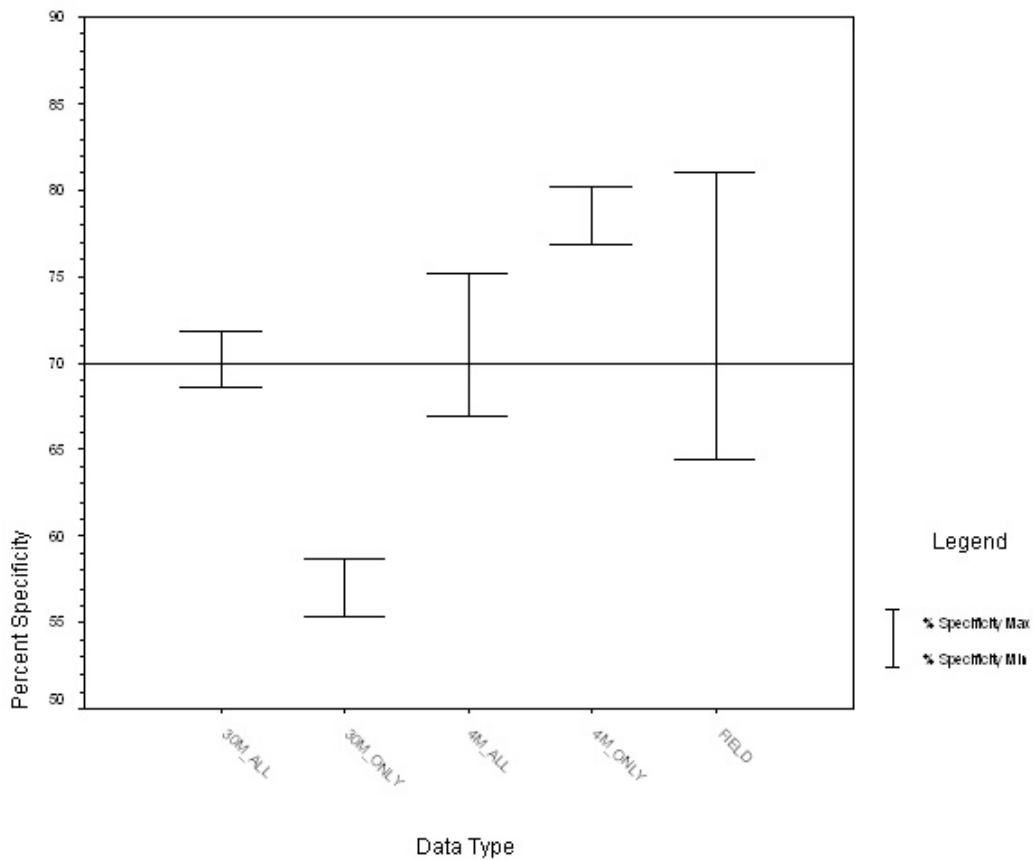


Figure 2-36: Specificity ranges for the Indigo Bunting. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.

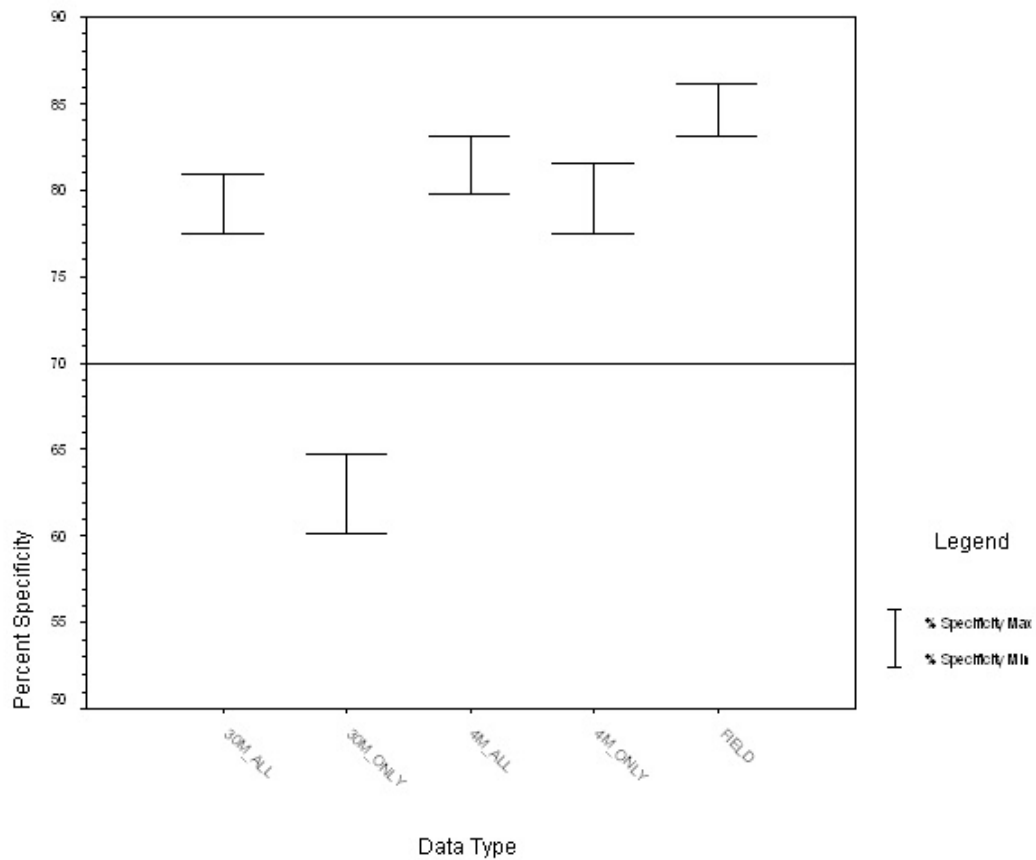


Figure 2-37: Specificity ranges for the Prairie Warbler. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.

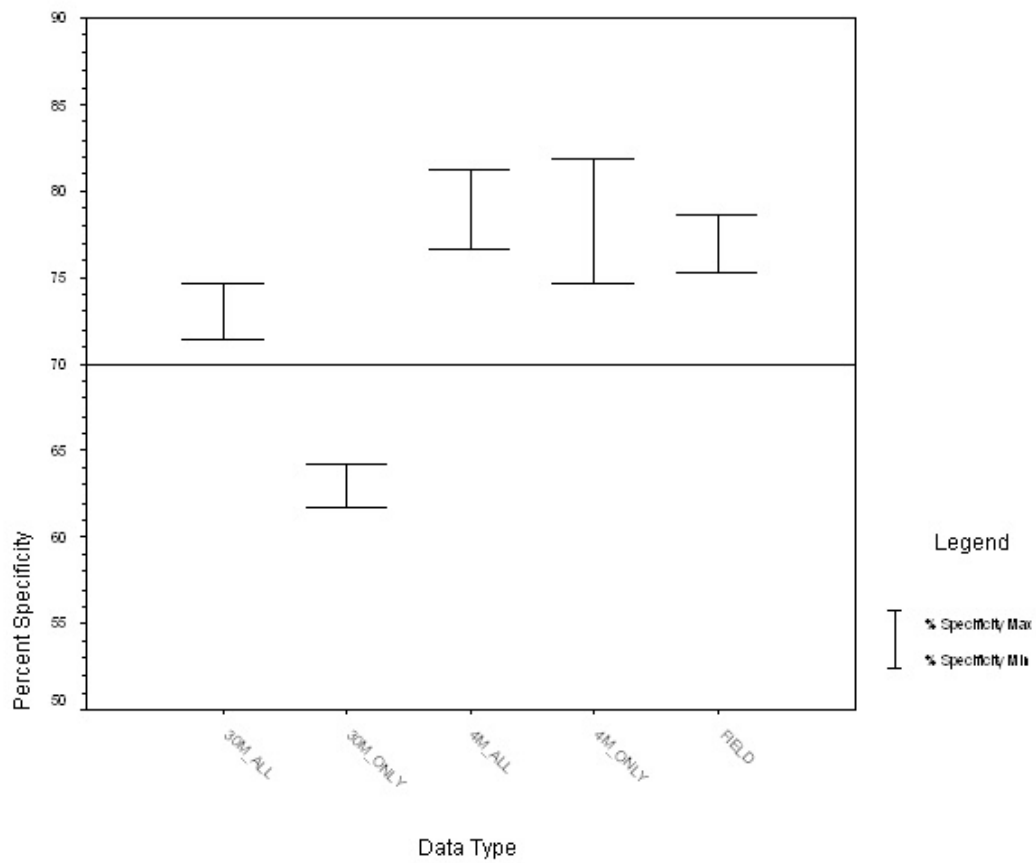


Figure 2-38: Specificity ranges for the Yellow-breasted Chat. The figures represent the highest value and the lowest specificity value of the top ten models in that data group. The reference line placed at 70% represents the cut off point of a good specific habitat model.

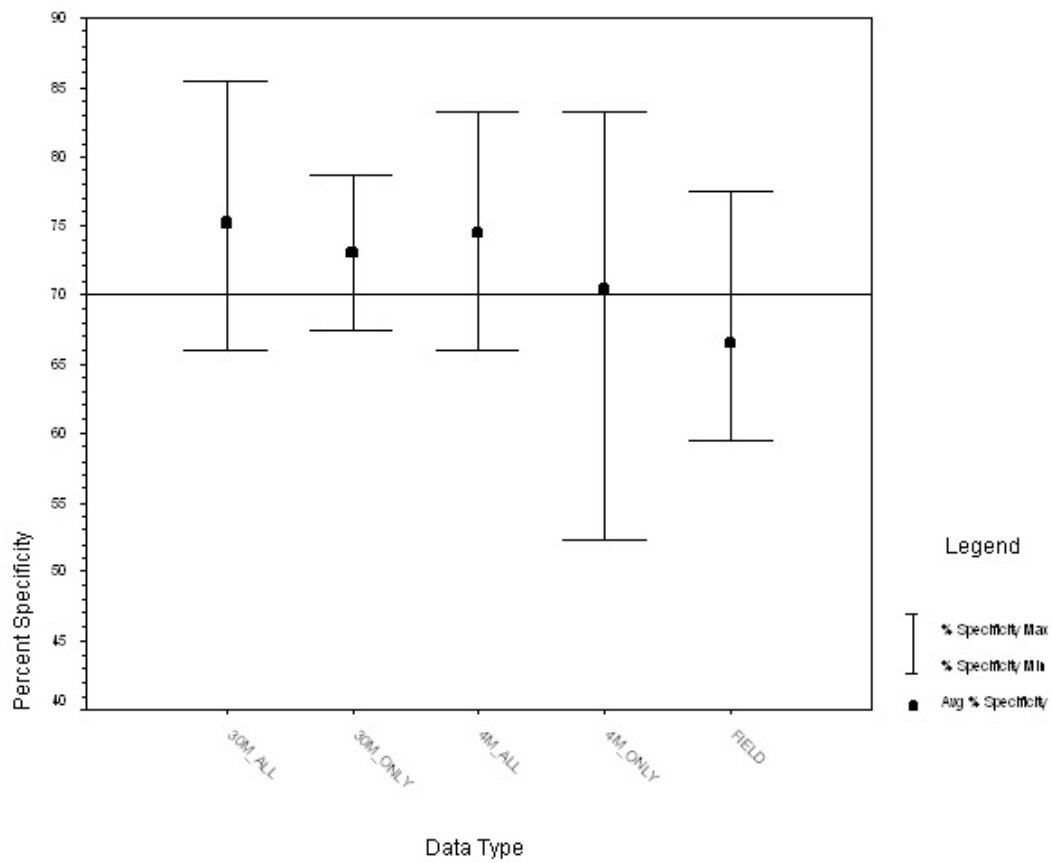


Figure 2-39: Specificity ranges for the closed canopy species. The figures represent the highest value and the lowest specificity value for the models in that data group across species. The reference line placed at 70% represents the cut off point of a good specific habitat model.

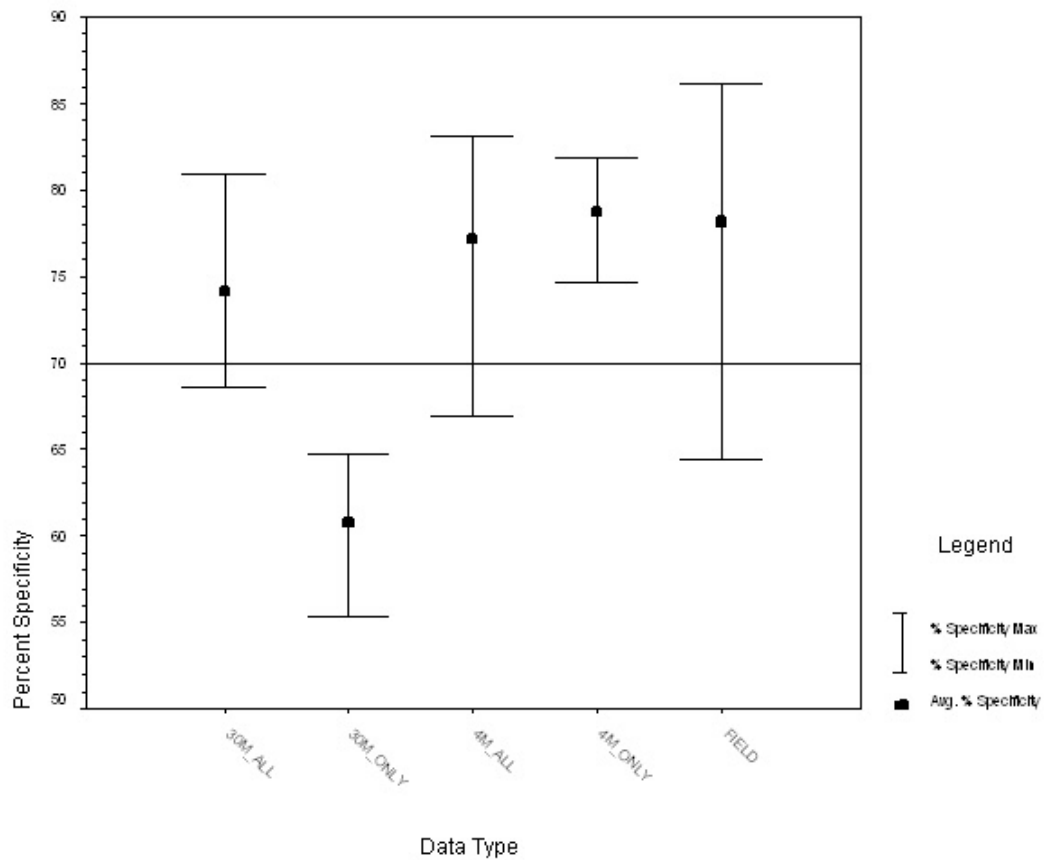


Figure 2-40: Specificity ranges for the early successional species. The figures represent the highest value and the lowest specificity value for the models in that data group across species. The reference line placed at 70% represents the cut off point of a good specific habitat model.

APPENDICIES

Appendix 2-A: Original variable set used in models for all species (Field and GIS Variables). Table continues on next page.

Data Type	Variables (Definitions are in Tables 2-4, 11)	Code	Mean	Min	Max	ACFL	INBU	PRAW	REVI	YBCH	YBCU
FIELD	% Canopy Cover	CP	59.68	12.50	87.50	x	x		x		x
FIELD	% Grass Ground Cover	G_GRASS	17.79	0.00	95.00		x	x		x	x
FIELD	% Midstory Hardwood	M_HDWD	89.28	3.00	100.00	x					x
FIELD	% Midstory Pine	M_PINE	4.55	0.00	97.00	x					
FIELD	% Midstory Shrub	M_SHRB	2.49	0.00	75.00						x
FIELD	% Midstory Vine	M_VINE	3.72	0.00	50.00	x	x	x		x	x
FIELD	% Seedlings Ground Cover	G_SEED	17.78	0.00	85.00			x		x	x
FIELD	% Standing Dead Wood	DEAD	0.07	0.00	1.00		x				
FIELD	% Understory Density (Living)	U_DENSITY	50.28	0.00	87.50	x		x	x	x	
FIELD	% Understory Saplings	U_SAPLING	66.47	0.00	100.00	x	x	x	x	x	
FIELD	% Understory Shrubs	U_SHRB	8.21	0.00	98.00			x		x	
FIELD	% Understory Vine	U_VINE	11.97	0.00	98.00						x
FIELD	% Vine Groundcover	G_VINE	11.65	0.00	75.00			x		x	x
FIELD	Canopy Height	HT_CANOPY	28.29	10.00	75.00	x		x			x
FIELD	H20 Present within 100m of Census	H20 PRESENT	0.22	0.00	1.00	x	x		x		x
FIELD	Midstory Density	M_DENSITY	56.78	10.00	87.50	x		x		x	
FIELD	Percent Hardwood (derived from habitat type)	PER_HDWD	54.51	12.50	87.50	x	x	x	x	x	x
FIELD	Trees with DBH >14	DBH_14IN	4.36	0.00	19.00		x	x		x	
FIELD	Understory/Midstory Height	UM_HEIGHT	11.65	1.00	38.34			x	x	x	x
GIS	Time Since Last Burn (Quadratic Transformation)	BURNQ	381.30	0.07	2401.00			x		x	x
GIS	Time Since Last Cut	LASTCUT	20.99	1.00	51.00	x	x		x		

Appendix 2-A: Original variable set used in models for all species (Ikonos Variables (4-m)). Table continues on next page.

Data Type	Variables (Definitions are in Tables 2-4, 11)	Code	Mean	Min	Max	ACFL	INBU	PRAW	REVI	YBCH	YBCU
Ikonos	All deciduous forest (area in m2)	%DECID	7246.10	0.00	18948.90				x		x
Ikonos	All roads (area in m2)	%RDS	245.39	0.00	2575.59	x		x	x	x	
Ikonos	Bottomland hardwood (area in m2)	%BHD	4191.59	0.00	18594.08	x					x
Ikonos	Bottomland mix (area in m2)	%BMX	375.82	0.00	3252.50	x			x		
Ikonos	Clearcut areas/bare (area in m2)	%CCB	312.75	0.00	18798.10	x	x	x	x	x	
Ikonos	Grass (area in m2)	%GRS	180.57	0.00	6318.39		x	x		x	
Ikonos	Hardwood/grass (area in m2)	%HGS	117.50	0.00	2172.10	x		x		x	
Ikonos	Hardwood/shrub (area in m2)	%HSB	182.49	0.00	2502.43		x		x		
Ikonos	Hardwood/vine (area in m2)	%HVN	278.96	0.00	3076.02	x		x		x	
Ikonos	Pine (area in m2)	%PNE	7351.40	0.00	19134.26	x	x	x		x	x
Ikonos	Rivers (area in m2)	%RIV	390.03	0.00	5191.54	x			x		x
Ikonos	Upland (area in m2)	%UPL	3054.51	0.00	18846.07		x	x		x	x
Ikonos	Upland mix (area in m2)	%MIX	2131.66	0.00	5073.43	x	x	x	x	x	x
Ikonos	Water body (area in m2)	%H2O	4.32	0.00	527.78	x	x	x		x	
Ikonos	All Early Successional Total Edge	IESA_TE	379.99	0.00	2302.05	x		x	x	x	
Ikonos	All Forest Cover Total Edge	IALL_TE	834.08	287.76	2364.99			x		x	
Ikonos	Deciduous Forest Edge Density	IDFO_ED	4.17	0.00	18.50				x		
Ikonos	Deciduous Forest # Patches	IDFO_NUMP	27.58	0.00	81.00	x					
Ikonos	Deciduous Forest Total Edge	IDFO_TE	1476.32	0.00	2956.39	x			x		
Ikonos	Early Successional Shrub # Patches	IESS_NUMP	6.71	0.00	39.00			x		x	
Ikonos	Early Successional Shrub Edge Density	IESS_ED	5.29	0.00	55.07		x				x
Ikonos	Mixed Forest Mean Patch Edge	IDMF_MPE	94.83	0.00	1051.67						x
Ikonos	Mixed Forest # Patches	IDMF_NUMP	31.34	0.00	92.00			x		x	
Ikonos	Mixed Forest Total Edge	IDMF_TE	1796.12	0.00	3187.88		x				
Ikonos	Pine Forest Edge Density	IPFO_ED	5.25	0.00	21.49		x				
Ikonos	Pine Forest Mean Patch Edge	IPFO_MPE	118.00	17.99	1015.02	x					
Ikonos	Pine Forest # Patches	IPFO_NUMP	22.33	1.00	57.00						x

Appendix 2-A: Original variable set used in models for all species ((TM) Variables (30-m)). Table continues on next page.

Data Type	Variables (Definitions are in Tables 2-4, 11)	Code	Mean	Min	Max	ACFL	INBU	PRAW	REVI	YBCH	YBCU
TM	All roads (area in m2)	%RDS	731.13	0.00	10563.32	x		x	x	x	
TM	Bottomland hardwood (area in m2)	%BHD	4291.93	0.00	19979.85	x					x
TM	Bottomland mix (area in m2)	%BMX	802.82	0.00	10824.87	x		x			
TM	Clearcut areas/bare (area in m2)	%CCB	393.55	0.00	16691.31	x	x	x	x	x	
TM	Grass (area in m2)	%GRS	924.00	0.00	9333.26		x	x		x	
TM	Pine (area in m2)	%PNE	7251.93	0.00	20004.27	x	x	x		x	x
TM	Upland (area in m2)	%UPL	3264.96	0.00	19802.52		x	x	x	x	x
TM	Upland mix (area in m2)	%MIX	1061.59	0.00	9691.20	x	x	x	x	x	x
TM	Water body (area in m2)	%H2O	429.64	0.00	6573.22	x	x		x		x
TM	All Forest Total Edge	TALL_TE	563.86	250.72	937.85			x		x	
TM	Deciduous Forest Edge Density	TDFO_ED	2.82	0.00	6.82	x			x		
TM	Deciduous Forest # Patches	TDFO_NUMP	1.77	0.00	7.00	x					
TM	Deciduous Forest Total Edge	TDFO_TE	0.57	0.00	2.00				x		
TM	Early Successional All Total Edge	TESA_TE	141.10	0.00	884.76	x		x	x	x	
TM	Early Successional Shrub Edge Density	TESS_ED	3.30	0.00	63.56		x				x
TM	Early Successional Shrub # Patches	TESS_NUMP	0.22	0.00	3.00			x		x	
TM	Mixed Forest Mean Patch Edge	TDMF_MPE	300.72	0.00	850.13						x
TM	Mixed Forest # Patches	TDMF_NUMP	2.23	0.00	8.00			x		x	
TM	Mixed Forest Total Edge	TDMF_TE	519.84	0.00	1073.40		x				
TM	Pine Forest Mean Patch Edge	TPFO_MPE	285.64	0.00	869.87	x					
TM	Pine Forest # Patches	TPFO_NUMP	2.05	0.00	7.00						x
TM	Pine Forest Total Edge	TPFO_TE	496.26	0.00	1121.59		x				

Appendix 2-A: Original variable set used in models for all species (Interaction effects).

Data Type	Variables (Definitions are in Tables 2-4, 11)	Code	Mean	Min	Max	ACFL	INBU	PRAW	REVI	YBCH	YBCU
Interactions	Last Burn X % Grass Ground Cover	BURNQ_G GRASS	n/a	n/a	n/a						x
Interactions	Last Burn X % Seedling Ground Cover	BURNQ_G SEED	n/a	n/a	n/a						x
Interactions	Last Burn X % Vine Ground Cover	BURNQ_G VNE	n/a	n/a	n/a						x
Interactions	Last Burn X % Vine Under Cover	BURNQ_UVN	n/a	n/a	n/a						x
Interactions	% Canopy Cover X % Grass Ground Cover	CP_G GRASS	n/a	n/a	n/a		x				x
Interactions	% Canopy Cover X % Seedling Ground Cover	CP_G SEED	n/a	n/a	n/a						x
Interactions	% Canopy Cover X % Vine Ground Cover	CP_G VNE	n/a	n/a	n/a						x
Interactions	% Canopy Cover X % Midstory Hardwood	CP_M_HWD	n/a	n/a	n/a						x
Interactions	% Canopy Cover X % Midstory Density	CP_M_DEN	n/a	n/a	n/a	x					
Interactions	% Canopy Cover X % Midstory Pine	CP_M_PNE	n/a	n/a	n/a	x					
Interactions	% Canopy Cover X % Midstory Shrub	CP_M_SHB	n/a	n/a	n/a						x
Interactions	% Canopy Cover X % Midstory Vine	CP_M_VNE	n/a	n/a	n/a		x				x
Interactions	% Canopy Cover X % Understory Density	CP_U_DEN	n/a	n/a	n/a	x			x		
Interactions	% Canopy Cover X % Understory Seedlings	CP_U_SAP	n/a	n/a	n/a	x	x		x		
Interactions	% Canopy Cover X % Understory Vine	CP_U_VNE	n/a	n/a	n/a						x
Interactions	Trees with DBH >14 X % Grass Ground Cover	DBH14_G GRASS	n/a	n/a	n/a		x			x	
Interactions	Trees with DBH >14 X % Seedling Ground Cover	DBH14_G SEED	n/a	n/a	n/a					x	
Interactions	Trees with DBH >14 X % Vine Ground Cover	DBH14_G VNE	n/a	n/a	n/a					x	
Interactions	Trees with DBH >14 X % Sapling Understory	DBH14_U SAP	n/a	n/a	n/a		x			x	
Interactions	Trees with DBH >14 X % Shrub Understory	DBH14_U-SHB	n/a	n/a	n/a					x	
Interactions	% Canopy Cover X % Year Last Cut	CP_LC	n/a	n/a	n/a	x	x		x		
Interactions	Year Last Cut X % Midstory Density	LC_M_DEN	n/a	n/a	n/a	x					
Interactions	Year Last Cut X % Understory Density	LC_U_DEN	n/a	n/a	n/a	x			x		
Interactions	% Midstory Density X % Understory Density	M_DEN_U_DEN	n/a	n/a	n/a	x				x	
Interactions	% Midstory Density X % Sapling Understory	M_DEN_U_SAP	n/a	n/a	n/a	x				x	
Interactions	% Midstory Density X % Shrub Understory	M_DEN_U_SHB	n/a	n/a	n/a					x	
Interactions	% Hardwood X % Canopy Cover	PHDWD_CP	n/a	n/a	n/a	x					
Interactions	% Hardwood X Trees with DBH >14	PHDWD_DBH14	n/a	n/a	n/a					x	
Interactions	% Hardwood X % Grass Ground Cover	PHDWD_G GRASS	n/a	n/a	n/a		x			x	x
Interactions	% Hardwood X % Seedling Ground Cover	PHDWD_G SEED	n/a	n/a	n/a					x	x
Interactions	% Hardwood X % Vine Ground Cover	PHDWD_G VNE	n/a	n/a	n/a					x	x
Interactions	% Hardwood X % Sapling Understory	PHDWD_U SAP	n/a	n/a	n/a		x		x	x	
Interactions	% Hardwood X % Shrub Understory	PHDWD_U_SHB	n/a	n/a	n/a					x	
Interactions	% Hardwood X % Vine Understory	PHDWD_U_VNE	n/a	n/a	n/a						x
Interactions	% Under Density X % Grass Ground Cover	U_DEN_G GRASS	n/a	n/a	n/a					x	
Interactions	% Under Density X % Seedling Ground Cover	U_DEN_G SEED	n/a	n/a	n/a					x	
Interactions	% Under Density X % Vine Ground Cover	U_DEN_G VNE	n/a	n/a	n/a					x	

Appendix 2-B: Habitat types. Survey points were placed in these pre-selected habitat types throughout the landscape. Definitions of habitat types derived from Hammel, 1999.

Forest Type	Code	Description
Upland Deciduous Forest	UPL	All deciduous forest located above 450-m elevation. The forest type is made up of >75% deciduous hardwood species.
Upland Pine Forest	PNE	All pine forest located above 450-m elevation. The forest type is made up of >75% conifer tree species.
Upland Mixed Forest	MIX	All mix forest located above 450-m elevation. The forest type is 26-74% deciduous hardwood species and the remaining percentage is conifer species.
Riverine Bottomland Deciduous Forest	BHD	All deciduous forest located below 450-m elevation. The forest type is made up of >75% deciduous hardwood species.
Riverine Bottomland Pine Forest	BPN	All deciduous forest located below 450-m elevation. The forest type is made up of >75% conifer tree species.
Riverine Bottomland Mixed Forest	BMX	All deciduous forest located below 450-m elevation. The forest type is 26-74% deciduous hardwood species and the remaining percentage is conifer species.

Appendix 2-C: Vegetation structure definitions. Vegetation layers were very different from one another, especially when contrasting closed canopy and early successional forests. In order to account for the structural differences in the vegetation layers, I defined them in the following way.

Vegetation	Habitat	Categories
Structure Type	Open Pine Habitats	Mixed / Hardwood Habitats
Groundcover	All vegetation < 1 m tall	All vegetation < 0.5 m tall
Understory	All vegetation 1.1 to 3 m tall	All vegetation 0.6 to 2m tall
Midstory	All vegetation 3.1 to 10 m tall	All vegetation 2.1 to 10m tall

Appendix 2-D: Wildlife field measurements in models. These field measurements were taken at every location that had its avian population surveyed. All are estimates of the stated variables within a set 50-m radius from the survey point.

Code	Description
G_GRASS	% Grass Ground Cover
G_LITTER	% Groundcover of Leaf Litter
G_SEED	% Groundcover of Tree Seedlings
G_VINE	% Groundcover of Vines
G_HERB	% Groundcover of Herbs
G_FERN	% Groundcover of Ferns
G_ROCK	% Groundcover of Rock
G_SOIL	% Groundcover of Bare Soil
U_HERB	% of Understory Herbs
U_VINE	% of Understory Vines
U_SAPLING	% of Understory Tree Sapling Species
U_SHRB	% of Understory Shrub Species
DEAD	# of Dead understory trees surrounding bird survey point (BAF 10 Prism).
U_DENSITY	% Understory Density
M_HDWD	% Midstory Hardwood
M_PINE	% Midstory Pine
M_SHRUB	% Midstory Shrub
M_VINE	% Midstory Vine
M_DENSITY	Midstory Tree Density
C_TYPE	Cover Type from Definitions in Table 5.
PHWD	% Hardwood derived from definitions of cover type (Table 5).
SLOPE	% Slope
ASPECT	Degree Aspect
CP	% Canopy Cover
HT_CANOPY	Height of Average Sized Tree in Canopy (ft)
UM_HEIGHT	Height of Understory (Early Successional) /Midstory (Closed Canopy) (ft)
BA_N_SNG	Basal Area surrounding point using BAF Prism, not including snags.
H20_PRESENT	The presence of water within 100m of the survey point.
DBH02	Number of trees measuring 0-2 inch DBH surrounding bird survey point
DBH24	Number of trees measuring 2-4 inch DBH surrounding bird survey point
DBH46	Number of trees measuring 4-6 inch DBH surrounding bird survey point
DBH68	Number of trees measuring 6-8 inch DBH surrounding bird survey point
DBH810	Number of trees measuring 8-10 inch DBH surrounding bird survey point
DBH1012	Number of trees measuring 10-12 inch DBH surrounding bird survey point
DBH1214	Number of trees measuring 12-14 inch DBH surrounding bird survey point
DBH14	Number of trees measuring >= 14 inch DBH surrounding bird survey point

Appendix 2-E: GIS metadata. Background information on the data used in the GIS software.

Data Name	Classification Used In	Original Format	Source	Year	Scale
Clouds	Ikonos	Vector	Digitized	2002	Digitized off of 4-m data
Shadows	Ikonos	Vector	Digitized	2002	Digitized off of 4-m data
Water/Rivers	Ikonos	Vector	Digitized	2002	Digitized off of 4-m data
Roads and Highways	Ikonos	Vector	Digitized	2002	Digitized off of 4-m data
Buildings	Ikonos	Vector	Digitized	2002	Digitized off of 4-m data
ADAR Images	TM and Ikonos	Raster	Plane	1999	2-m Resolution
Streams and Rivers	TM	Vector	GA Clearinghouse	2000	1:24,000
Roads and Highways	TM	Vector	GA Clearinghouse	1997	1:12,000
Digital Elevation Model (National Elevation Dataset)	TM	Raster	GA Clearinghouse	2002	1:24,000
Clearcuts and Thins	TM	Vector	Digitized	2002	Digitized off of 4-m data
TM Land Cover	TM	Raster	GA Clearinghouse	1998	30-m Resolution
Seive 7x7 Window (9 pixel size)	TM	Raster	From TM Image	2000/2001	30-m Resolution
Seive 7x7 Window (100 pixel size)	TM	Raster	From TM Image	2000/2001	30-m Resolution
Water/Rivers	TM	Vector	GA Clearinghouse	2000	1:24,000
River Buffer	TM	Vector	From Waters/Rivers Coverage	2002	Digitized off of 4-m data
Tassle-cap Transformation (Winter Scene)	TM	Raster	From TM Image	1999	30-m Resolution
Tassle-cap Transformation (Spring Scene)	TM	Raster	From TM Image	2000	30-m Resolution

Appendix 2-F: GIS data variables used in models. All variables were derived using GIS software from georeferenced data.

GIS Variable	Description
BURNQ	Number of years since stand was burned. Variable transformed into a quadratic distribution
LASTCUT	Number of years since stand received a cut, thin, etc.
MAIN_RDS	Distance between bird point and main roads (Road size > 6-m) in meters
H20DISTANCE_M	Distance between bird point and water (rivers, streams, lakes) in meters
ROADS_M	Distance between bird point and all roads (including logging roads) in meters
SLOPE	Average slope surrounding bird point at 50m radius
ASPECT	Average aspect surrounding bird point at 50m radius

Appendix 2-G: Merged land cover groups used for creating landscape metrics. In order to derive meaningful metrics for a species, land cover classes were grouped into the following categories prior to calculating landscape metrics.

Codes	Land Cover Type	Land Cover Value Of Tm (Table 2-2)	Land Cover Value Of Ikonos (Table 2-2)	Definition
DFO	Deciduous Forest Only	7, 8	9,10	Riverine bottomland Hardwood and Upland Forests
DMF	Deciduous and Mixed Forests	7,8,12	8-10,12	Riverine Bottomland Hardwood, Upland Forests, and All Mixed Forest Types
PFO	Pine Forest Only	10,11	7,11	Pine Forest
ALL	All Forest	7-12	7-12	Riverine Bottomland Hardwood, Upland, All Mixed, and Pine Forest Types
ESA	Early Successional All	3,5	5,6,13-17	Agriculture/Grass and Clearcut
ESS	Early Successional Shrub	3	5,14-17	Clearcut
ESG	Early Successional Grass	5	6,13	Agriculture/Grass and Bare/Grass
ENG	Early Successional Shrub	n/a	5,15-17	Clearcut with no grass components in Ikonos classification

Appendix 2-H: Landscape metrics. Metrics were created from the grouped land cover types. Area statistics are expressed in hectares.

Landscape Metric Codes	Definition
CA	Class area. Sum of all patches belonging to a given class.
TLA	Total Landscape Area. Sum of areas of all patches in a landscape.
NUM	Number of Patches for the land cover class selected.
MPS	Average Patch Size.
AWMSI	Area Weighted Mean Shape Index ≥ 1 . Increases without limit as the patch shapes become more irregular. AWMSI equals the average shape index of patches of the corresponding patch type (Equals 1 when all are circular (vector) or square (raster)). The measure is weighted by patch area so that larger patches weigh more than smaller patches.
ED	Edge Density= TE/TLA . Amount of edge relative to the landscape area.
MPE	Mean Patch Edge= $TE/NUMP$. Average amount of edge per patch.
TE	Total Edge. Sum of the perimeter of all patches for the specified land cover.

Appendix 2-I: Top ten AICc models from all possible logistical regressions for the Acadian Flycatcher. Table continues on next page. Model variables defined in Appendix 2-A, D, F,G.

Species	Data Type	Model #	Model	# Parms.	Log Likelihood	QAICc /AICc
ACFL	4M_ALL	1	%PNE %CCB IESA TE U SAPLING CP CP USAP	6	-72.751	160.061
ACFL	4M_ALL	2	%PNE %CCB IESA TE U SAPLING M DENSITY U DENSITY	6	-73.250	161.059
ACFL	4M_ALL	3	%PNE %CCB IESA TE U SAPLING M DENSITY	5	-74.326	161.069
ACFL	4M_ALL	4	%BHD %PNE %CCB IESA TE U SAPLING M DENSITY	6	-73.389	161.338
ACFL	4M_ALL	5	%PNE IESA TE U SAPLING M DENSITY CP CP USAP	6	-73.614	161.789
ACFL	4M_ALL	6	%PNE IESA TE U SAPLING U DENSITY CP CP USAP	6	-73.926	162.411
ACFL	4M_ALL	7	%PNE %CCB IESA TE U SAPLING M DENSITY CP	6	-73.978	162.516
ACFL	4M_ALL	8	%PNE %CCB IESA TE U SAPLING M DENSITY M VINE	6	-74.046	162.651
ACFL	4M_ALL	9	%PNE %CCB IESA TE LASTCUT U SAPLING M DENSITY	6	-74.046	162.652
ACFL	4M_ALL	10	%PNE %CCB IESA TE U SAPLING M DENSITY M PINE	6	-74.060	162.680
ACFL	4M_ONLY	1	%PNE %CCB IESA TE	3	-81.944	172.085
ACFL	4M_ONLY	2	%BHD %PNE %CCB IESA TE	4	-80.895	172.087
ACFL	4M_ONLY	3	%PNE %CCB IPFO MPE IESA TE	4	-81.176	172.648
ACFL	4M_ONLY	4	%BHD %PNE %CCB IPFO MPE IESA TE	5	-80.257	172.932
ACFL	4M_ONLY	5	%BHD %PNE %CCB %HGS IESA TE	5	-80.542	173.502
ACFL	4M_ONLY	6	%PNE %CCB %HGS IESA TE	4	-81.666	173.628
ACFL	4M_ONLY	7	%PNE %MIX %CCB IESA TE	4	-81.671	173.639
ACFL	4M_ONLY	8	%PNE %BMX %CCB IESA TE	4	-81.804	173.905
ACFL	4M_ONLY	9	%RIV %PNE %CCB IESA TE	4	-81.815	173.928
ACFL	4M_ONLY	10	%PNE %RDS %CCB IESA TE	4	-81.837	173.970
ACFL	30M_ALL	1	%MIX TDFO ED TESA TE U SAPLING M DENSITY LASTCUT	6	-82.080	178.719
ACFL	30M_ALL	2	%MIX %CCB TDFO ED U SAPLING M DENSITY LASTCUT	6	-82.459	179.478
ACFL	30M_ALL	3	%MIX TDFO ED TESA TE U SAPLING M DENSITY CP	6	-82.962	180.484
ACFL	30M_ALL	4	%MIX %CCB TDFO ED U SAPLING M DENSITY CP	6	-83.225	181.011
ACFL	30M_ALL	5	%CCB TDFO ED U SAPLING M DENSITY CP LASTCUT	6	-83.261	181.082
ACFL	30M_ALL	6	TDFO ED TDFO NUMP TESA TE U SAPLING M DENSITY LASTCUT	6	-83.437	181.434
ACFL	30M_ALL	7	TDFO ED TESA TE U SAPLING M DENSITY CP LASTCUT	6	-83.455	181.471
ACFL	30M_ALL	8	%MIX TPFO MPE TDFO ED TESA TE U SAPLING M DENSITY	6	-83.577	181.713
ACFL	30M_ALL	9	%MIX %CCB TPFO MPE U SAPLING M DENSITY CP	6	-83.706	181.971
ACFL	30M_ALL	10	%CCB TDFO ED TDFO NUMP U SAPLING M DENSITY LASTCUT	6	-83.820	182.201

Appendix 2-I: Top ten AICc models from all possible logistical regressions for the Acadian Flycatcher. Table continued.

Species	Data Type	Model #	Model	# Parm.	Log Likelihood	QAICc /AICc
ACFL	FIELD	1	PHDWD U SAPLING M DENSITY CP M HDWD M PINE	6	-89.547	193.655
ACFL	FIELD	2	PHDWD U SAPLING M DENSITY CP	4	-92.019	194.335
ACFL	FIELD	3	PHDWD U SAPLING M DENSITY CP CP USAP	5	-91.111	194.639
ACFL	FIELD	4	PHDWD U SAPLING M DENSITY CP MIDDEN USAP	5	-91.132	194.683
ACFL	FIELD	5	PHDWD U SAPLING M DENSITY U DENSITY M HDWD M PINE	6	-90.114	194.789
ACFL	FIELD	6	PHDWD U SAPLING M DENSITY M HDWD M PINE M VINE	6	-90.167	194.894
ACFL	FIELD	7	PHDWD H20 PRESENT U SAPLING M DENSITY CP	5	-91.252	194.921
ACFL	FIELD	8	PHDWD H20 PRESENT U SAPLING M DENSITY CP MIDDEN USAP	6	-90.360	195.281
ACFL	FIELD	9	PHDWD U SAPLING M DENSITY U DENSITY CP CP USAP	6	-90.361	195.282
ACFL	FIELD	10	PHDWD H20 PRESENT U SAPLING M DENSITY CP CP USAP	6	-90.449	195.459
ACFL	30M ONLY	1	%MIX TPFO MPE TDFO ED TDFO NUMP TESA TE	5	-99.297	211.013
ACFL	30M ONLY	2	%H20 %MIX TPFO MPE TDFO ED TDFO NUMP TESA TE	6	-98.228	211.016
ACFL	30M ONLY	3	% PINE %MIX TDFO ED TDFO NUMP TESA TE	5	-99.385	211.188
ACFL	30M ONLY	4	%H20 %MIX TDFO ED TDFO NUMP TESA TE	5	-99.493	211.405
ACFL	30M ONLY	5	%H20 % PINE %MIX TDFO ED TDFO NUMP TESA TE	6	-98.474	211.508
ACFL	30M ONLY	6	%H20 %MIX %BMX TDFO ED TDFO NUMP TESA TE	6	-98.485	211.530
ACFL	30M ONLY	7	%MIX %RDS TPFO MPE TDFO ED TDFO NUMP TESA TE	6	-98.614	211.787
ACFL	30M ONLY	8	%MIX %BMX TDFO ED TDFO NUMP TESA TE	5	-99.704	211.826
ACFL	30M ONLY	9	%MIX %BMX TPFO MPE TDFO ED TDFO NUMP TESA TE	6	-98.725	212.011
ACFL	30M ONLY	10	%BHD %MIX TPFO MPE TDFO ED TDFO NUMP TESA TE	6	-98.775	212.110

Appendix 2-J: Top ten AICc models from all possible logistical regressions for the Red-eyed Vireo. Model variables defined in Appendix 2-A, D, F,G. Table continues on next page.

Species	Data Type	Model #	Model	# Parms.	Log Likelihood	QAICc /AICc
REVI	4M_ALL	1	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_SAPLING U_DENSITY	7	-92.324	201.373
REVI	4M_ALL	2	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_SAPLING	6	-93.896	202.353
REVI	4M_ALL	3	H20_PRESENT %DECID %CCB %HSB IDFO_TE IDFO_ED U_SAPLING	7	-93.075	202.873
REVI	4M_ALL	4	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_DENSITY	6	-94.241	203.042
REVI	4M_ALL	5	H20_PRESENT %DECID IDFO_TE IESA_TE IDFO_ED U_SAPLING U_DENSITY	7	-93.207	203.137
REVI	4M_ALL	6	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_SAPLING CP	7	-93.232	203.188
REVI	4M_ALL	7	H20_PRESENT %DECID %HSB IDFO_TE U_SAPLING U_DENSITY	6	-94.321	203.203
REVI	30M_ALL	1	%BMX %H20 %CCB TESA_TE U_SAPLING HT_CANOPY CP	7	-93.244	203.212
REVI	30M_ALL	2	%BMX %H20 %RDS TESA_TE U_SAPLING HT_CANOPY CP	7	-93.334	203.391
REVI	4M_ALL	8	H20_PRESENT %DECID %HSB IDFO_TE U_SAPLING	5	-95.569	203.555
REVI	4M_ALL	9	H20_PRESENT %DECID %HSB IDFO_TE U_SAPLING UM_HEIGHT U_DENSITY	7	-93.480	203.683
REVI	4M_ALL	10	H20_PRESENT %DECID %CCB IDFO_TE IESA_TE IDFO_ED U_SAPLING	7	-93.520	203.764
REVI	30M_ALL	3	%BMX %H20 TESA_TE U_SAPLING UM_HEIGHT HT_CANOPY CP	7	-93.568	203.861
REVI	30M_ALL	4	%H20 %UPL %CCB TESA_TE U_SAPLING HT_CANOPY CP	7	-93.655	204.033
REVI	30M_ALL	5	%BMX %H20 TESA_TE U_SAPLING HT_CANOPY CP	6	-94.843	204.247
REVI	30M_ALL	6	%H20 %CCB TESA_TE U_SAPLING UM_HEIGHT HT_CANOPY CP	7	-93.955	204.633
REVI	30M_ALL	7	%H20 %UPL TESA_TE U_SAPLING UM_HEIGHT HT_CANOPY CP	7	-93.984	204.693
REVI	30M_ALL	8	%BMX %H20 TESA_TE U_SAPLING U_DENSITY HT_CANOPY CP	7	-94.057	204.838
REVI	30M_ALL	9	%BMX %H20 TESA_TE TDFO_ED U_SAPLING HT_CANOPY CP	7	-94.095	204.914
REVI	30M_ALL	10	%H20 TESA_TE U_SAPLING UM_HEIGHT U_DENSITY HT_CANOPY CP	7	-94.116	204.956
REVI	4M_ONLY	1	%RIV %DECID %HSB IDFO_TE IDFO_ED	5	-97.711	207.840
REVI	4M_ONLY	2	%RIV %DECID %CCB %HSB IDFO_TE IDFO_ED	6	-96.776	208.112
REVI	4M_ONLY	3	%RIV %DECID IDFO_TE IDFO_ED	4	-99.053	208.403
REVI	4M_ONLY	4	%MIX %DECID %HSB IDFO_TE IDFO_ED	5	-98.136	208.690
REVI	4M_ONLY	5	%RIV %DECID %CCB IDFO_TE IESA_TE IDFO_ED	6	-97.147	208.854
REVI	4M_ONLY	6	%RIV %DECID %CCB IDFO_TE IDFO_ED	5	-98.244	208.906
REVI	4M_ONLY	7	%RIV %DECID IDFO_TE IESA_TE IDFO_ED	5	-98.294	209.006
REVI	4M_ONLY	8	%MIX %DECID IDFO_TE IESA_TE IDFO_ED	5	-98.352	209.123
REVI	4M_ONLY	9	%RIV %MIX %DECID %HSB IDFO_TE IDFO_ED	6	-97.282	209.123
REVI	4M_ONLY	10	%MIX %DECID IDFO_TE IDFO_ED	4	-99.547	209.392

Appendix 2-J: Top ten AICc models from all possible logistical regressions for the Red-eyed Vireo. Table continued.

Species	Data Type	Model #	Model	# Parm.	Log Likelihood	QAICc /AICc
REVI	FIELD	1	H20_PRESENT U_DENSITY CP	3	-109.196	226.590
REVI	FIELD	2	H20_PRESENT U_SAPLING U_DENSITY CP	4	-108.286	226.869
REVI	FIELD	3	H20_PRESENT U_SAPLING CP	3	-109.361	226.919
REVI	FIELD	4	H20_PRESENT CP	2	-110.555	227.228
REVI	FIELD	5	PHDWD H20_PRESENT U_DENSITY CP	4	-108.762	227.821
REVI	FIELD	6	PHDWD H20_PRESENT U_SAPLING U_DENSITY CP	5	-107.823	228.064
REVI	FIELD	7	PHDWD H20_PRESENT U_SAPLING CP	4	-108.923	228.144
REVI	FIELD	8	H20_PRESENT UM_HEIGHT U_DENSITY CP	4	-109.006	228.309
REVI	FIELD	9	PHDWD H20_PRESENT CP	3	-110.150	228.498
REVI	FIELD	10	H20_PRESENT U_SAPLING UM_HEIGHT U_DENSITY CP	5	-108.143	228.704
REVI	30M_ONLY	1	%H20 %CCB %RDS TESA_TE TDFO_ED	5	-108.988	230.393
REVI	30M_ONLY	2	%BMX %H20 %CCB %RDS TESA_TE TDFO_ED	6	-107.934	230.428
REVI	30M_ONLY	3	%H20 %UPL %CCB %RDS TESA_TE TDFO_ED	6	-107.975	230.509
REVI	30M_ONLY	4	%H20 %UPL %CCB %RDS TDFO_TE TESA_TE	6	-108.204	230.968
REVI	30M_ONLY	5	%H20 %CCB %RDS TDFO_TE TESA_TE	5	-109.291	231.000
REVI	30M_ONLY	6	%BMX %H20 %CCB %RDS TDFO_TE TESA_TE	6	-108.253	231.065
REVI	30M_ONLY	7	%H20 %MIX %CCB %RDS TESA_TE TDFO_ED	6	-108.615	231.790
REVI	30M_ONLY	8	%H20 %CCB TESA_TE TDFO_ED	4	-110.804	231.906
REVI	30M_ONLY	9	%H20 %UPL %CCB TESA_TE TDFO_ED	5	-109.860	232.138
REVI	30M_ONLY	10	%H20 %RDS TESA_TE TDFO_ED	4	-111.026	232.349

Appendix 2-K: Top ten AICc models from all possible logistical regressions for the Yellow-Billed Cuckoo. Model variables defined in Appendix 2-A, D, F,G. Table continues on next page.

Species	Data Type	Model #	Model	# Parns.	Log Likelihood	QAICc /AICc
YBCU	4M ALL	1	%MIX %DECID G VINE M HDWD M VINE BURNQ	6	-115.100	220.485
YBCU	30M ALL	1	TPFO NUMP G VINE M HDWD M VINE BURNQ	5	-116.325	220.491
YBCU	4M ALL	2	%MIX VINE G GRASS M HDWD M VINE BURNQ	6	-115.120	220.521
YBCU	30M ALL	2	%MIX TPFO NUMP U VINE CP BURNQ BURNQ UVNE	6	-115.206	220.673
YBCU	4M ALL	3	%RIV %DECID IDMF MPE G VINE G GRASS BURNQ	6	-115.261	220.769
YBCU	4M ALL	4	%MIX %DECID G VINE G GRASS M HDWD M VINE	6	-115.262	220.771
YBCU	30M ALL	3	%MIX TDMF MPE TPFO NUMP U VINE BURNQ BURNQ UVNE	6	-115.264	220.775
YBCU	4M ALL	5	%MIX %DECID G VINE BURNQ	4	-117.715	220.811
YBCU	30M ALL	4	TPFO NUMP U VINE CP BURNQ CP UVIN BURNQ UVNE	6	-115.332	220.896
YBCU	30M ALL	5	TPFO NUMP G VINE U VINE CP BURNQ BURNQ UVNE	6	-115.345	220.918
YBCU	4M ALL	6	%MIX %DECIDG VINE G GRASS M HDWD BURNQ	6	-115.365	220.954
YBCU	30M ALL	6	TPFO NUMP G VINE G GRASS M HDWD M VINE BURNQ	6	-115.376	220.973
YBCU	30M ALL	7	%MIX TPFO NUMP VINE CP BURNQ	5	-116.599	220.976
YBCU	4M ALL	7	%MIX %DECID G VINE G GRASS MSHB BURNQ	6	-115.381	220.983
YBCU	4M ALL	8	%MIX %DECID G VINE UVNE BURNQ	5	-116.651	221.069
YBCU	30M ALL	8	TDMF MPE TPFO NUMP G VINE U VINE BURNQ BURNQ UVNE	6	-115.471	221.142
YBCU	4M ALL	9	%MIX %DECID IDMF MPE G VINE G GRASS BURNQ	6	-115.471	221.142
YBCU	30M ALL	9	TPFO NUMP U VINE M HDWD M VINE BURNQ BURNQ UVNE	6	-115.477	221.152
YBCU	30M ALL	10	TDMF MPE TPFO NUMP U VINE BURNQ BURNQ UVNE	5	-116.704	221.163
YBCU	4M ALL	10	%MIX %DECID IDMF MPE VINE BURNQ	5	-116.753	221.249
YBCU	FIELD	1	G VINE G GRASS M HDWD M VINE CP	5	-118.110	223.652
YBCU	FIELD	2	G VINE G GRASS M HDWD M VINE CP CP G SEED	6	-117.434	224.617
YBCU	FIELD	3	G VINE G GRASS UM HEIGHT M HDWD M VINE CP	6	-117.453	224.651
YBCU	FIELD	4	G VINE G GRASS M HDWD M VINE CP CP M HDWD	6	-117.593	224.898
YBCU	FIELD	5	G VINE G GRASS M HDWD CP	4	-120.085	225.008
YBCU	FIELD	6	G VINE G GRASS M HDWD M VINE CP CP G GRASS	6	-117.881	225.408
YBCU	FIELD	7	G VINE G GRASS U VINE M HDWD M VINE CP	6	-117.901	225.444
YBCU	FIELD	8	H20 PRESENT VINE G GRASS M HDWD M VINE CP	6	-117.918	225.475
YBCU	FIELD	9	G VINE G GRASS M HDWD M VINE CP CP MVINE	6	-117.939	225.511
YBCU	FIELD	10	G VINE G GRASS G SEED M HDWD M VINE CP	6	-117.943	225.518

Appendix 2-K: Top ten AICc models from all possible logistical regressions for the Yellow-Billed Cuckoo. Table continued.

Species	Data Type	Model #	Model	# Parm.	Log Likelihood	QAICc /AICc
YBCU	4M_ONLY	1	%DECID	1	-124.738	226.948
YBCU	30M_ONLY	1	TDMF_MPE TPFO_NUMP	2	-124.055	227.817
YBCU	4M_ONLY	2	%MIX %DECID	2	-124.077	227.857
YBCU	4M_ONLY	3	%DECID IDMF_MPE	2	-124.283	228.220
YBCU	4M_ONLY	4	%DECID IESS_ED	2	-124.495	228.596
YBCU	4M_ONLY	5	%RIV %DECID	2	-124.547	228.689
YBCU	4M_ONLY	6	%PNE %MIX	2	-124.579	228.744
YBCU	30M_ONLY	2	% PINE TDMF_MPE TPFO_NUMP	3	-123.502	228.936
YBCU	4M_ONLY	7	%DECID %UPL	2	-124.703	228.964
YBCU	4M_ONLY	8	%DECID %BHD	2	-124.703	228.964
YBCU	4M_ONLY	9	%UPL %BHD	2	-124.703	228.964
YBCU	4M_ONLY	10	%DECID IPFO_NUMP	2	-124.714	228.984
YBCU	30M_ONLY	3	%H20 TDMF_MPE TPFO_NUMP	3	-123.605	229.119
YBCU	30M_ONLY	4	%MIX TDMF_MPE TPFO_NUMP	3	-123.611	229.129
YBCU	30M_ONLY	5	% PINE TPFO_NUMP	2	-124.809	229.152
YBCU	30M_ONLY	6	%BHD TDMF_MPE TPFO_NUMP	3	-123.789	229.445
YBCU	30M_ONLY	7	%UPL %BHD TPFO_NUMP	3	-123.968	229.763
YBCU	30M_ONLY	8	%MIX %UPL %BHD TPFO_NUMP	4	-122.821	229.851
YBCU	30M_ONLY	9	TDMF_MPE TPFO_NUMP TESS_ED	3	-124.029	229.870
YBCU	30M_ONLY	10	% PINE %MIX TDMF_MPE TPFO_NUMP	4	-122.849	229.901

Appendix 2-L: Top ten AICc models from all possible logistical regressions for the Indigo Bunting. Model variables defined in Appendix 2-A, D, F,G. Table continues on next page.

Species	Data Type	Model #	Model	# Parms.	Log Likelihood	QAICc /AICc
INBU	4M ALL	1	%UPL %H20 IDMF TE CP M VINE CP MVINE	6	-110.210	193.705
INBU	4M ALL	2	%UPL %H20 IDMF TE CP	4	-113.772	195.122
INBU	4M ALL	3	%UPL %MIX %H20 CP M VINE CP MVINE	6	-111.190	195.278
INBU	4M ALL	4	%H20 IDMF TE G GRASS CP M VINE CP MVINE	6	-111.342	195.522
INBU	4M ALL	5	%UPL %H20 IHSB IDMF TE CP	5	-112.800	195.701
INBU	4M ALL	6	%H20 IDMF TE CP M VINE CP MVINE	5	-112.845	195.774
INBU	4M ALL	7	%UPL %H20 IDMF TE CP M VINE	5	-112.862	195.802
INBU	4M ALL	8	%UPL %PNE %H20 IHSB IDMF TE G GRASS	6	-111.537	195.836
INBU	4M ALL	9	%PNE %H20 IDMF TE CP M VINE CP MVINE	6	-111.539	195.838
INBU	4M ALL	10	%PNE %H20 IHSB IDMF TE G GRASS	5	-112.906	195.872
INBU	30M ALL	1	%UPL %H20 G GRASS CP M VINE CP MVINE	6	-112.800	197.863
INBU	30M ALL	2	%GRS %H20 G GRASS CP M VINE CP MVINE	6	-112.857	197.955
INBU	30M ALL	3	%H20 G GRASS CP M VINE CP MVINE	5	-114.346	198.185
INBU	30M ALL	4	%UPL %GRS %H20 G GRASS CP DBH14	6	-113.084	198.319
INBU	30M ALL	5	%UPL %GRS %H20 G GRASS CP	5	-114.434	198.326
INBU	30M ALL	6	%UPL %GRS %H20 CP M VINE CP MVINE	6	-113.113	198.367
INBU	30M ALL	7	%UPL %GRS %H20 USAP CP DBH14	6	-113.277	198.630
INBU	30M ALL	8	%H20 G GRASS CP UND DEAD M VINE CP MVINE	6	-113.404	198.834
INBU	30M ALL	9	%UPL %GRS %H20 CP DBH14	5	-114.794	198.904
INBU	30M ALL	10	%H20 G GRASS USAP CP M VINE CP MVINE	6	-113.540	199.052

Appendix 2-L: Top ten AICc models from all possible logistical regressions for the Indigo Bunting. Table continued.

Species	Data Type	Model #	Model	# Params.	Log Likelihood	QAICc /AICc
INBU	4M_ONLY	1	%PNE %HSB IPFO_ED IDMF_TE	4	-117.006	200.315
INBU	4M_ONLY	2	%PNE %GRS %HSB IPFO_ED IDMF_TE	5	-116.240	201.226
INBU	4M_ONLY	3	%PNE %HSB IDMF_TE	3	-118.949	201.316
INBU	4M_ONLY	4	%UPL %PNE %HSB IPFO_ED IDMF_TE	5	-116.597	201.799
INBU	4M_ONLY	5	%PNE %HSB IEES_ED IPFO_ED IDMF_TE	5	-116.744	202.035
INBU	FIELD	1	G GRASS CP M_VINE CP_MVINE PERHWD_G GRASS	5	-116.844	202.196
INBU	FIELD	2	PHDWD_G GRASS PERHWD_G GRASS	3	-119.552	202.284
INBU	4M_ONLY	6	%PNE %H20 %HSB IPFO_ED IDMF_TE	5	-116.994	202.436
INBU	4M_ONLY	7	%PNE %CCB %HSB IPFO_ED IDMF_TE	5	-116.999	202.446
INBU	4M_ONLY	8	%MIX %PNE %HSB IPFO_ED IDMF_TE	5	-117.004	202.453
INBU	4M_ONLY	9	%UPL %PNE %GRS %HSB IPFO_ED IDMF_TE	6	-115.832	202.732
INBU	4M_ONLY	10	%PNE %GRS %HSB IDMF_TE	4	-118.513	202.735
INBU	FIELD	3	G GRASS U_SAPLING CP M_VINE CP_MVINE PHWD_G GRSS	6	-115.834	202.735
INBU	FIELD	4	PHDWD_G GRASS CP M_VINE CP_MVINE PERHWD_G GRASS	6	-115.841	202.748
INBU	FIELD	5	PHDWD_G GRASS	2	-121.164	202.774
INBU	FIELD	6	PHDWD_G GRASS CP M_VINE CP_MVINE	5	-117.250	202.848
INBU	FIELD	7	G GRASS CP_UND_DEAD M_VINE CP_MVINE PHWD_G GRSS	6	-115.979	202.969
INBU	FIELD	8	G GRASS CP PERHWD_G GRASS	3	-119.990	202.988
INBU	FIELD	9	H20_PREST G GRASS CP M_VINE CP_MVINE PHWD_G GRSS	6	-115.996	202.997
INBU	FIELD	10	PHDWD_G GRASS U_SAPLING PERHWD_G GRASS	4	-118.715	203.061
INBU	30M_ONLY	1	% PINE %GRS %CCB	3	-129.355	218.028
INBU	30M_ONLY	2	% PINE %GRS	2	-130.906	218.420
INBU	30M_ONLY	3	%UPL % PINE %GRS %CCB	4	-128.682	219.066
INBU	30M_ONLY	4	%UPL % PINE %GRS	3	-130.018	219.092
INBU	30M_ONLY	5	% PINE %GRS TESS_ED	3	-130.236	219.442
INBU	30M_ONLY	6	%MIX % PINE %GRS %CCB	4	-129.211	219.915
INBU	30M_ONLY	7	% PINE %GRS %CCB %H20	4	-129.252	219.982
INBU	30M_ONLY	8	% PINE %GRS %CCB TPFO_TE	4	-129.256	219.988
INBU	30M_ONLY	9	% PINE %GRS %CCB TDMF_TE	4	-129.354	220.146
INBU	30M_ONLY	10	% PINE %GRS %H20	3	-130.685	220.163

Appendix 2-M: Top ten AICc models from all possible logistical regressions for the Prairie Warbler. Model variables defined in Appendix 2-A, D, F,G. Table continues on next page.

Species	Data Type	Model #	Model	# Parns.	Log Likelihood	QAICc /AICc
PRAW	FIELD	1	PHDWD G GRASS G SEED U SAPLING CP PERHWD USAP	6	-46.135	106.829
PRAW	FIELD	2	PHDWD G SEED U SAPLING CP CP G SEED PERHWD USAP	6	-46.435	107.429
PRAW	FIELD	3	PHDWD G GRASS G SEED U SAPLING M VINE PERHWD USAP	6	-46.619	107.797
PRAW	FIELD	4	PHDWD G GRASS G SEED U SAPLING CP CP G SEED	6	-46.808	108.176
PRAW	FIELD	5	PHDWD G GRASS G SEED U SAPLING PERHWD USAP	5	-47.935	108.287
PRAW	FIELD	6	PHDWD G GRASS G SEED CP CP G SEED PERHWD G GRASS	6	-46.922	108.405
PRAW	FIELD	7	PHDWD G GRASS G SEED U SAPLING PERHWD G SEED PERHWD USAP	6	-46.944	108.448
PRAW	FIELD	8	PHDWD G GRASS G SEED U SAPLING PERHWD G GRASS PERHWD USAP	6	-46.947	108.453
PRAW	FIELD	9	PHDWD G GRASS G SEED U SAPLING HT CANOPY PERHWD USAP	6	-47.143	108.846
PRAW	FIELD	10	PHDWD G GRASS G SEED CP PERHWD G GRASS	5	-48.366	109.150
PRAW	4M_ALL	1	%PNE %GRS IESA TE UM HEIGHT CP	5	-49.708	111.833
PRAW	4M_ALL	2	%PNE %GRS IESA TE CP	4	-50.777	111.852
PRAW	4M_ALL	3	%PNE %GRS IESA TE G GRASS CP	5	-49.771	111.960
PRAW	4M_ALL	4	%PNE IESA TE G GRASS UM HEIGHT USAP CP	6	-48.779	112.118
PRAW	4M_ALL	5	%PNE IESA TE G GRASS CP	4	-50.924	112.145
PRAW	4M_ALL	6	%PNE IESA TE G GRASS USAP CP	5	-49.884	112.186
PRAW	4M_ALL	7	%PNE %GRS IESA TE G GRASS M VINE CP	6	-48.824	112.207
PRAW	4M_ALL	8	%PNE %GRS IESA TE G GRASS UM HEIGHT CP	6	-48.864	112.289
PRAW	4M_ALL	9	%PNE IESA TE G GRASS UM HEIGHT CP	5	-49.951	112.320
PRAW	4M_ALL	10	%PNE IESA TE UM HEIGHT CP	4	-51.018	112.333

Appendix 2-M: Top ten AICc models from all possible logistical regressions for the Prairie Warbler. Table continued.

Species	Data Type	Model #	Model	# Parms.	Log Likelihood	QAICc /AICc
PRAW	4M_ONLY	1	%PNE %GRS IESA TE	3	-55.260	118.717
PRAW	30M_ALL	1	%MIX BURNQ G GRASS G SEED CP BURNQ G SEED	6	-52.215	118.990
PRAW	30M_ALL	2	BURNQ G GRASS G SEED M VINE CP BURNQ G SEED	6	-52.237	119.035
PRAW	4M_ONLY	2	%PNE %GRS %RDS IESA TE	4	-54.586	119.469
PRAW	4M_ONLY	3	%PNE %GRS %HGS IESA TE	4	-54.688	119.674
PRAW	4M_ONLY	4	%PNE %GRS IDMF ED2 IESA TE	4	-54.787	119.871
PRAW	4M_ONLY	5	%PNE IESA TE	2	-56.989	120.095
PRAW	4M_ONLY	6	%PNE %GRS %CCB IESA TE	4	-54.899	120.095
PRAW	4M_ONLY	7	%PNE %RDS IESA TE	3	-55.966	120.130
PRAW	30M_ALL	3	BURNQ G GRASS G SEED CP BURNQ G SEED	5	-53.889	120.196
PRAW	30M_ALL	4	BURNQ G GRASS G SEED CP CP G GRASS BURNQ G SEED	6	-52.821	120.202
PRAW	4M_ONLY	8	%PNE %GRS %RDS %HGS IESA TE	5	-53.945	120.307
PRAW	30M_ALL	5	BURNQ G GRASS G SEED M VINE CP BURNQ G GRASS	6	-52.879	120.318
PRAW	30M_ALL	6	%MIX BURNQ G GRASS G SEED CP BURNQ G GRASS	6	-53.001	120.562
PRAW	4M_ONLY	9	%PNE %GRS IPFO ED IESA TE	4	-55.184	120.665
PRAW	4M_ONLY	10	%PNE %GRS IDFO NUMP IESA TE	4	-55.196	120.690
PRAW	30M_ALL	7	TPFO ED BURNQ G GRASS G SEED CP BURNQ G SEED	6	-53.159	120.878
PRAW	30M_ALL	8	BURNQ G GRASS G SEED UM HEIGHT CP BURNQ G SEED	6	-53.236	121.032
PRAW	30M_ALL	9	%MIX G GRASS G SEED M VINE CP CP G SEED	6	-53.276	121.112
PRAW	30M_ALL	10	%MIX G GRASS G SEED M VINE CP CP G GRASS	6	-53.334	121.229
PRAW	30M_ONLY	1	% PINE %GRS %CCB %RDS TPFO ED	5	-78.260	168.939
PRAW	30M_ONLY	2	% PINE %GRS %RDS TPFO ED	4	-79.652	169.601
PRAW	30M_ONLY	3	% PINE %GRS %CCB %RDS TDMF ED2	5	-78.674	169.765
PRAW	30M_ONLY	4	% PINE %GRS %CCB %RDS TPFO ED TDFO NUMP	6	-77.931	170.422
PRAW	30M_ONLY	5	% PINE %GRS %CCB %RDS TDMF ED2 TPFO ED	6	-77.987	170.534
PRAW	30M_ONLY	6	% PINE %UPL %GRS %CCB %RDS TPFO ED	6	-77.992	170.544
PRAW	30M_ONLY	7	% PINE %GRS %CCB TPFO ED	4	-80.162	170.621
PRAW	30M_ONLY	8	% PINE %GRS %CCB %RDS TDFO NUMP	5	-79.141	170.701
PRAW	30M_ONLY	9	% PINE %GRS %CCB %RDS TPFO ED TALL MPS2	6	-78.167	170.894
PRAW	30M_ONLY	10	% PINE %GRS %RDS TDFO NUMP	4	-80.342	170.981

Appendix 2-N: Top ten AICc models from all possible logistical regressions for the Yellow-breasted Chat. Model variables defined in Appendix 2-A, D, F,G. Table continues on next page.

Species	Model #	Data Type	Model	# Parm.	Log Likelihood	QAICc /AICc
YBCH	1	4M ALL	IDMF NUMP IESA TE M DENSITY	3	-78.343	81.768
YBCH	2	4M ALL	%RDS IDMF NUMP IESA TE M DENSITY	4	-76.525	82.229
YBCH	3	4M ALL	IDMF NUMP IESA TE M VINE M DENSITY	4	-76.544	82.245
YBCH	4	4M ALL	%RDS IDMF NUMP IESA TE M VINE M DENSITY	5	-74.854	82.844
YBCH	5	4M ALL	IDMF NUMP IESA TE USAP M DENSITY	4	-77.267	82.905
YBCH	6	4M ALL	IDMF NUMP IESA TE UM HEIGHT M DENSITY	4	-77.698	83.298
YBCH	7	4M ALL	%RDS IDMF NUMP IESA TE UM HEIGHT M DENSITY	5	-75.507	83.440
YBCH	8	4M ALL	IDMF NUMP IESA TE G VINE M DENSITY	4	-77.891	83.475
YBCH	9	4M ALL	%CCB IDMF NUMP IESA TE M DENSITY	4	-77.955	83.533
YBCH	10	4M ALL	IDMF NUMP IESA TE BURNQ M DENSITY	4	-78.017	83.590
YBCH	1	4M ONLY	IDMF NUMP IESA TE	2	-84.151	84.967
YBCH	2	4M ONLY	%RDS IDMF NUMP IESA TE	3	-82.019	85.121
YBCH	3	4M ONLY	%PNE %RDS IDMF NUMP IESA TE	4	-80.364	85.731
YBCH	4	4M ONLY	%PNE IDMF NUMP IESA TE	3	-82.707	85.749
YBCH	5	4M ONLY	%RDS %HGS IDMF NUMP IESA TE	4	-80.615	85.960
YBCH	6	4M ONLY	%HGS IDMF NUMP IESA TE	3	-83.093	86.101
YBCH	7	4M ONLY	%PNE IESA TE	2	-85.846	86.513
YBCH	8	4M ONLY	%PNE %RDS %HGS IDMF NUMP IESA TE	5	-79.008	86.634
YBCH	9	4M ONLY	%PNE %HVN	2	-86.057	86.706
YBCH	10	4M ONLY	%PNE %RDS IESA TE	3	-83.863	86.803

Appendix 2-N: Top ten AICc models from all possible logistical regressions for the Yellow-breasted Chat. Table continued.

Species	Model #	Data Type	Model	# Parms.	Log Likelihood	QAICc /AICc
YBCH	1	FIELD	PHDWD USAP M_DENSITY	3	-86.404	89.121
YBCH	2	FIELD	PHDWD M_DENSITY	2	-89.037	89.425
YBCH	1	30M_ALL	%PNE TESA_TE G_SEED M_DENSITY	4	-84.423	89.434
YBCH	3	FIELD	PHDWD M_VINE M_DENSITY	3	-86.750	89.437
YBCH	4	FIELD	PHDWD G_VINE M_DENSITY PHD_G_VINE	4	-84.445	89.454
YBCH	5	FIELD	PHDWD G_VINE M_DENSITY	3	-86.770	89.455
YBCH	6	FIELD	PHDWD USAP M_VINE M_DENSITY	4	-84.479	89.485
YBCH	2	30M_ALL	%PNE TESA_TE G_SEED M_VINE M_DENSITY	5	-82.178	89.527
YBCH	3	30M_ALL	%PNE TESA_TE M_VINE M_DENSITY	4	-84.575	89.572
YBCH	4	30M_ALL	%PNE TDMF_NUMP TF M_VINE M_DENSITY	5	-82.391	89.721
YBCH	7	FIELD	PHDWD G_VINE M_VINE M_DENSITY PHD_G_VINE	5	-82.517	89.835
YBCH	8	FIELD	PHDWD G_VINE USAP M_DENSITY	4	-84.900	89.869
YBCH	5	30M_ALL	%PNE TDMF_NUMP TESA_TE G_SEED M_DENSITY	5	-82.605	89.916
YBCH	9	FIELD	PHDWD G_VINE USAP M_DENSITY PHD_G_VINE	5	-82.636	89.944
YBCH	6	30M_ALL	%PNE MRDS TDMF_NUMP TESA_TE M_VNE M_DEN	6	-80.296	89.971
YBCH	7	30M_ALL	MRDS TDMF_NUMP TESA_TE M_VINE M_DENSITY	5	-82.678	89.982
YBCH	8	30M_ALL	%PNE TDMF_NUMP TESA_TE G_SEED M_VNE M_DEN	6	-80.371	90.040
YBCH	10	FIELD	PHDWD G_VINE M_VINE M_DENSITY	4	-85.117	90.067
YBCH	9	30M_ALL	%PNE MRDS TESA_TE M_VINE M_DENSITY	5	-82.859	90.147
YBCH	10	30M_ALL	%PNE TESA_TE M_DENSITY	3	-87.781	90.378
YBCH	1	30M_ONLY	% PINE TDMF_NUMP TESA_TE	3	-96.523	98.353
YBCH	2	30M_ONLY	% PINE %RDS TDMF_NUMP TESA_TE	4	-94.438	98.571
YBCH	3	30M_ONLY	% PINE %RDS %GRS TDMF_NUMP TESS_NUMP	5	-93.360	99.728
YBCH	4	30M_ONLY	% PINE %RDS %UPL TDMF_NUMP TESA_TE	5	-93.381	99.747
YBCH	5	30M_ONLY	% PINE %GRS TDMF_NUMP TESS_NUMP	4	-95.777	99.792
YBCH	6	30M_ONLY	% PINE %UPL TDMF_NUMP TESA_TE	4	-95.905	99.909
YBCH	7	30M_ONLY	% PINE TALL TE TDMF_NUMP TESA_TE	4	-95.971	99.969
YBCH	8	30M_ONLY	% PINE %MIX TDMF_NUMP TESA_TE	4	-96.098	100.085
YBCH	9	30M_ONLY	% PINE %GRS %CCB TDMF_NUMP	4	-96.188	100.167
YBCH	10	30M_ONLY	% PINE %MIX TESA_TE	3	-98.532	100.186

Appendix 2-O: Acadian Flycatcher validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Table continues on next page.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensitivity	% Specificity	False Positive	False Negative	% Concordant	% Discordant	% Tied	Pairs	C	R-Square	Max re-scale R-Square
ACFL	30M_ALL	10	0.57	77.88	78.99	76.40	18.26	26.88	89.8	10.1	0.1	10591	0.9	0.398	0.560
ACFL	30M_ALL	6	0.57	78.37	79.83	76.40	18.10	26.09	89.8	10.1	0.1	10591	0.9	0.377	0.552
ACFL	30M_ALL	5	0.57	78.85	80.67	76.40	17.95	25.27	90	10	0	10591	0.9	0.425	0.576
ACFL	30M_ALL	4	0.57	79.33	82.35	75.28	18.33	23.86	89.6	10.3	0.1	10591	0.9	0.453	0.590
ACFL	30M_ALL	9	0.57	79.33	78.99	79.78	16.07	26.04	88.9	11	0.2	10591	0.89	0.416	0.570
ACFL	30M_ALL	8	0.57	79.81	78.15	82.02	14.68	26.26	89.3	10.6	0.1	10591	0.89	0.404	0.564
ACFL	30M_ALL	7	0.57	80.29	81.51	78.65	16.38	23.91	89.9	10	0.1	10591	0.9	0.410	0.568
ACFL	30M_ALL	2	0.57	80.77	81.51	79.78	15.65	23.66	90	9.9	0.1	10591	0.9	0.421	0.578
ACFL	30M_ALL	3	0.57	80.77	80.67	80.90	15.04	24.21	89.7	10.2	0.1	10591	0.9	0.442	0.586
ACFL	30M_ALL	1	0.57	83.17	81.51	85.39	11.82	22.45	89.9	10	0.1	10591	0.9	0.385	0.563
ACFL	30M_ONLY	5	0.57	72.60	70.59	75.28	20.75	34.31	84.7	15.2	0.1	10591	0.85	0.354	0.466
ACFL	30M_ONLY	10	0.57	73.08	69.75	77.53	19.42	34.29	85	14.8	0.2	10591	0.85	0.335	0.454
ACFL	30M_ONLY	4	0.57	73.56	71.43	76.40	19.81	33.33	84.2	15.6	0.2	10591	0.84	0.342	0.454
ACFL	30M_ONLY	6	0.57	73.56	70.59	77.53	19.23	33.65	84.7	15.2	0.1	10591	0.85	0.349	0.463
ACFL	30M_ONLY	9	0.57	73.56	71.43	76.40	19.81	33.33	85.1	14.8	0.2	10591	0.85	0.345	0.460
ACFL	30M_ONLY	2	0.57	74.04	71.43	77.53	19.05	33.01	85.1	14.7	0.1	10591	0.85	0.354	0.467
ACFL	30M_ONLY	1	0.57	74.52	72.27	77.53	18.87	32.35	84.8	15.1	0.1	10591	0.85	0.340	0.454
ACFL	30M_ONLY	3	0.57	74.52	73.95	75.28	20.00	31.63	84.4	15.4	0.2	10591	0.85	0.343	0.455
ACFL	30M_ONLY	8	0.57	74.52	73.11	76.40	19.44	32.00	84.4	15.4	0.2	10591	0.85	0.335	0.449
ACFL	30M_ONLY	7	0.57	75.00	72.27	78.65	18.10	32.04	84.9	14.9	0.2	10591	0.85	0.338	0.456
ACFL	4M_ALL	5	0.57	80.29	81.51	78.65	16.38	23.91	91.8	8.1	0.1	10591	0.92	0.524	0.667
ACFL	4M_ALL	9	0.57	81.25	82.35	79.78	15.52	22.83	91.7	8.1	0.1	10591	0.92	0.469	0.640
ACFL	4M_ALL	2	0.57	81.73	82.35	80.90	14.78	22.58	92	7.9	0.1	10591	0.92	0.510	0.661
ACFL	4M_ALL	8	0.57	81.73	82.35	80.90	14.78	22.58	91.6	8.2	0.2	10591	0.92	0.465	0.637
ACFL	4M_ALL	3	0.57	82.21	82.35	82.02	14.04	22.34	91.6	8.2	0.1	10591	0.92	0.482	0.644
ACFL	4M_ALL	10	0.57	82.21	82.35	82.02	14.04	22.34	91.8	8.2	0.1	10591	0.92	0.482	0.645
ACFL	4M_ALL	1	0.57	82.69	84.03	80.90	14.53	20.88	91.8	8.1	0.1	10591	0.92	0.519	0.668
ACFL	4M_ALL	4	0.57	82.69	84.03	80.90	14.53	20.88	91.9	8.1	0	10591	0.92	0.517	0.664
ACFL	4M_ALL	6	0.57	83.17	84.87	80.90	14.41	20.00	91.6	8.3	0.1	10591	0.92	0.545	0.676
ACFL	4M_ALL	7	0.57	83.17	83.19	83.15	13.16	21.28	91.8	8.1	0.1	10591	0.92	0.488	0.648

Appendix 2-O: Acadian Flycatcher validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Continued table.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensitivity	% Specificity	False Positive	False Negative	% Concordant	% Discordant	% Tied	Pairs	C	R-Square	Max re-scale R-Square
ACFL	4M ONLY	3	0.57	80.77	80.67	80.90	15.04	24.21	89.9	9.9	0.1	10591	0.9	0.468	0.607
ACFL	4M ONLY	4	0.57	80.77	80.67	80.90	15.04	24.21	90.4	9.5	0.1	10591	0.9	0.492	0.623
ACFL	4M ONLY	1	0.57	81.25	80.67	82.02	14.29	23.96	89.9	10.1	0	10591	0.9	0.461	0.600
ACFL	4M ONLY	2	0.57	81.25	80.67	82.02	14.29	23.96	90.1	9.8	0.2	10591	0.9	0.486	0.618
ACFL	4M ONLY	6	0.57	81.25	80.67	82.02	14.29	23.96	89.9	10	0.1	10591	0.9	0.460	0.601
ACFL	4M ONLY	5	0.57	81.73	81.51	82.02	14.16	23.16	90.1	9.7	0.2	10591	0.9	0.489	0.621
ACFL	4M ONLY	8	0.57	81.73	80.67	83.15	13.51	23.71	89.7	10.1	0.1	10591	0.9	0.458	0.600
ACFL	4M ONLY	9	0.57	81.73	80.67	83.15	13.51	23.71	89.8	10.1	0.2	10591	0.9	0.460	0.601
ACFL	4M ONLY	10	0.57	81.73	80.67	83.15	13.51	23.71	89.9	10	0.1	10591	0.9	0.461	0.601
ACFL	4M ONLY	7	0.57	82.21	81.51	83.15	13.39	22.92	89.9	10	0.1	10591	0.9	0.471	0.606
ACFL	FIELD	6	0.57	77.40	80.67	73.03	20.00	26.14	87.4	12.3	0.3	10591	0.88	0.406	0.534
ACFL	FIELD	1	0.57	77.88	81.51	73.03	19.83	25.29	87.5	12.4	0.2	10591	0.88	0.428	0.549
ACFL	FIELD	2	0.57	77.88	80.67	74.16	19.33	25.84	86.8	12.8	0.3	10591	0.87	0.411	0.528
ACFL	FIELD	4	0.57	77.88	80.67	74.16	19.33	25.84	86.9	12.6	0.4	10591	0.87	0.417	0.536
ACFL	FIELD	3	0.57	78.85	83.19	73.03	19.51	23.53	87	12.6	0.4	10591	0.87	0.417	0.536
ACFL	FIELD	9	0.57	78.85	84.03	71.91	20.00	22.89	87.1	12.6	0.3	10591	0.87	0.395	0.528
ACFL	FIELD	10	0.57	78.85	82.35	74.16	19.01	24.14	87	12.7	0.3	10591	0.87	0.373	0.516
ACFL	FIELD	5	0.57	79.33	82.35	75.28	18.33	23.86	87.3	12.6	0.1	10591	0.87	0.407	0.535
ACFL	FIELD	7	0.57	79.33	82.35	75.28	18.33	23.86	87	12.8	0.2	10591	0.87	0.362	0.506
ACFL	FIELD	8	0.57	80.77	83.19	77.53	16.81	22.47	87	12.7	0.3	10591	0.87	0.375	0.517

Appendix 2-P: Red-eyed Vireo validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Table continues on next page.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensitivity	% Specificity	False Positive	False Negative	% Concordant	% Discordant	% Tied	Pairs	C	R-Square	Max re-scale R-Square
REVI	30M_ALL	4	0.38	74.04	75.00	73.48	38.04	16.38	85	14.9	0.1	10032	0.851	0.317	0.451
REVI	30M_ALL	10	0.38	74.04	75.00	73.48	38.04	16.38	84.8	15	0.2	10032	0.849	0.314	0.447
REVI	30M_ALL	7	0.38	75.00	76.32	74.24	36.96	15.52	84.8	15.1	0.2	10032	0.848	0.31	0.445
REVI	30M_ALL	8	0.38	75.00	76.32	74.24	36.96	15.52	84.8	15	0.1	10032	0.849	0.324	0.452
REVI	30M_ALL	1	0.38	75.48	76.32	75.00	36.26	15.38	85.2	14.6	0.2	10032	0.853	0.326	0.458
REVI	30M_ALL	2	0.38	75.48	77.63	74.24	36.56	14.78	85.2	14.7	0.1	10032	0.853	0.334	0.462
REVI	30M_ALL	9	0.38	75.48	76.32	75.00	36.26	15.38	84.9	14.9	0.1	10032	0.85	0.317	0.449
REVI	30M_ALL	3	0.38	75.96	73.68	77.27	34.88	16.39	84.9	15	0.1	10032	0.85	0.328	0.458
REVI	30M_ALL	5	0.38	75.96	76.32	75.76	35.56	15.25	84.6	15.3	0.1	10032	0.846	0.318	0.445
REVI	30M_ALL	6	0.38	75.96	77.63	75.00	35.87	14.66	85.3	14.6	0.1	10032	0.854	0.317	0.450
REVI	4M_ALL	4	0.38	72.12	72.37	71.97	40.22	18.10	85.1	14.8	0.1	10032	0.851	0.343	0.462
REVI	4M_ALL	3	0.38	72.60	77.63	69.70	40.40	15.60	85.1	14.7	0.2	10032	0.852	0.372	0.484
REVI	4M_ALL	5	0.38	72.60	76.32	70.45	40.21	16.22	85.3	14.5	0.1	10032	0.854	0.365	0.480
REVI	4M_ALL	10	0.38	72.60	76.32	70.45	40.21	16.22	84.8	15	0.1	10032	0.849	0.384	0.489
REVI	4M_ALL	6	0.38	73.08	76.32	71.21	39.58	16.07	85.5	14.4	0.1	10032	0.855	0.361	0.477
REVI	4M_ALL	2	0.38	73.56	78.95	70.45	39.39	14.68	85.2	14.7	0.1	10032	0.853	0.36	0.474
REVI	4M_ALL	7	0.38	75.00	80.26	71.97	37.76	13.64	85.4	14.5	0.1	10032	0.855	0.329	0.454
REVI	4M_ALL	1	0.38	75.48	77.63	74.24	36.56	14.78	86	13.9	0.1	10032	0.86	0.36	0.481
REVI	4M_ALL	9	0.38	75.48	82.89	71.21	37.62	12.15	85.4	14.5	0.1	10032	0.855	0.328	0.458
REVI	4M_ALL	8	0.38	75.96	81.58	72.73	36.73	12.73	84.7	15.1	0.2	10032	0.848	0.335	0.451
REVI	4M_ONLY	2	0.38	71.63	76.32	68.94	41.41	16.51	83.7	16.2	0.1	10032	0.837	0.336	0.445
REVI	4M_ONLY	5	0.38	71.63	75.00	69.70	41.24	17.12	83.7	16.1	0.1	10032	0.838	0.351	0.452
REVI	4M_ONLY	6	0.38	71.63	75.00	69.70	41.24	17.12	83.2	16.7	0.1	10032	0.833	0.35	0.446
REVI	4M_ONLY	3	0.38	72.12	73.68	71.21	40.43	17.54	83	16.8	0.1	10032	0.831	0.311	0.419
REVI	4M_ONLY	4	0.38	72.12	78.95	68.18	41.18	15.09	83	16.8	0.1	10032	0.831	0.325	0.432
REVI	4M_ONLY	7	0.38	72.12	75.00	70.45	40.63	16.96	83.4	16.4	0.2	10032	0.835	0.32	0.428
REVI	4M_ONLY	9	0.38	72.12	76.32	69.70	40.82	16.36	83.6	16.3	0.1	10032	0.837	0.328	0.438
REVI	4M_ONLY	10	0.38	72.12	76.32	69.70	40.82	16.36	82.5	17.3	0.2	10032	0.826	0.325	0.424
REVI	4M_ONLY	1	0.38	72.60	76.32	70.45	40.21	16.22	83.5	16.3	0.2	10032	0.836	0.319	0.431
REVI	4M_ONLY	8	0.38	73.08	77.63	70.45	39.80	15.45	83.2	16.7	0.1	10032	0.833	0.331	0.434

Appendix 2-P: Red-eyed Vireo validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Continued table.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensitivity	% Specific	False Pos.	False Neg.	% Concord	% Discord	% Tied	Pairs	C	R-Square	Max re-scale R-Square
REVI	FIELD	5	0.38	67.79	76.32	62.88	45.79	17.82	78.5	20	1.5	10032	0.792	0.203	0.302
REVI	FIELD	1	0.38	68.75	80.26	62.12	45.05	15.46	77.5	19.4	3.1	10032	0.791	0.219	0.309
REVI	FIELD	8	0.38	69.23	78.95	63.64	44.44	16.00	79.2	20.2	0.6	10032	0.795	0.236	0.320
REVI	FIELD	2	0.38	69.71	73.68	67.42	43.43	18.35	79.2	20.4	0.4	10032	0.794	0.239	0.326
REVI	FIELD	4	0.38	69.71	86.84	59.85	44.54	11.24	68.3	12	19.8	10032	0.781	0.22	0.302
REVI	FIELD	9	0.38	69.71	86.84	59.85	44.54	11.24	73.9	16.1	10	10032	0.789	0.198	0.291
REVI	FIELD	7	0.38	70.19	82.89	62.88	43.75	13.54	78.9	20.2	0.9	10032	0.794	0.221	0.312
REVI	FIELD	10	0.38	70.67	76.32	67.42	42.57	16.82	79.8	19.9	0.2	10032	0.799	0.235	0.325
REVI	FIELD	3	0.38	71.63	81.58	65.91	42.06	13.86	77.9	20.5	1.7	10032	0.787	0.236	0.319
REVI	FIELD	6	0.38	72.60	84.21	65.91	41.28	12.12	79.7	20	0.3	10032	0.798	0.233	0.325
REVI	30M ONLY	1	0.38	67.79	65.79	68.94	45.05	22.22	78.7	21	0.3	10032	0.789	0.222	0.312
REVI	30M ONLY	5	0.38	67.79	65.79	68.94	45.05	22.22	78.6	21.1	0.3	10032	0.788	0.22	0.309
REVI	30M ONLY	10	0.38	68.27	65.79	69.70	44.44	22.03	77.6	22	0.3	10032	0.778	0.204	0.289
REVI	30M ONLY	2	0.38	68.75	67.11	69.70	43.96	21.37	79.3	20.4	0.2	10032	0.795	0.223	0.319
REVI	30M ONLY	7	0.38	68.75	67.11	69.70	43.96	21.37	79.1	20.7	0.2	10032	0.792	0.221	0.313
REVI	30M ONLY	8	0.38	68.75	64.47	71.21	43.68	22.31	77.7	21.9	0.3	10032	0.779	0.205	0.291
REVI	30M ONLY	6	0.38	69.23	67.11	70.45	43.33	21.19	79.2	20.7	0.2	10032	0.792	0.221	0.315
REVI	30M ONLY	4	0.38	69.71	67.11	71.21	42.70	21.01	79.3	20.5	0.2	10032	0.794	0.227	0.319
REVI	30M ONLY	3	0.38	70.19	68.42	71.21	42.22	20.34	79.3	20.5	0.2	10032	0.794	0.229	0.322
REVI	30M ONLY	9	0.38	70.67	64.47	74.24	40.96	21.60	78.4	21.3	0.3	10032	0.785	0.211	0.301

Appendix 2-Q: Yellow-billed Cuckoo validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Table continues on next page.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R Square	Max re-scale R Square
YBCU	30M_ALL	6	0.35	62.98	57.14	65.94	54.02	24.79	73.7	26.1	0.2	9660	0.738	0.153	0.213
YBCU	30M_ALL	9	0.35	63.46	54.29	68.12	53.66	25.40	72.7	26.8	0.4	9660	0.730	0.153	0.213
YBCU	30M_ALL	1	0.35	64.42	57.14	68.12	52.38	24.19	73.6	26.1	0.3	9660	0.737	0.147	0.204
YBCU	30M_ALL	7	0.35	66.35	62.86	68.12	50.00	21.67	73.1	26.4	0.4	9660	0.733	0.145	0.201
YBCU	30M_ALL	2	0.35	67.31	61.43	70.29	48.81	21.77	73.5	26.1	0.3	9660	0.737	0.161	0.220
YBCU	30M_ALL	5	0.35	67.79	62.86	70.29	48.24	21.14	73.6	26	0.4	9660	0.738	0.154	0.214
YBCU	30M_ALL	3	0.35	66.83	57.14	71.74	49.37	23.26	73.4	26.3	0.3	9660	0.736	0.158	0.217
YBCU	30M_ALL	4	0.35	68.27	61.43	71.74	47.56	21.43	72.7	26.9	0.5	9660	0.729	0.159	0.217
YBCU	30M_ALL	8	0.35	67.31	55.71	73.19	48.68	23.48	73.4	26.2	0.4	9660	0.736	0.152	0.212
YBCU	30M_ALL	10	0.35	67.79	55.71	73.91	48.00	23.31	72.5	27.1	0.4	9660	0.727	0.144	0.199
YBCU	30M_ONLY	4	0.35	63.46	55.71	67.39	53.57	25.00	67.8	31.8	0.4	9660	0.680	0.084	0.117
YBCU	30M_ONLY	10	0.35	63.94	57.14	67.39	52.94	24.39	68.7	30.9	0.4	9660	0.689	0.089	0.125
YBCU	30M_ONLY	8	0.35	63.94	54.29	68.84	53.09	25.20	68.8	30.7	0.5	9660	0.691	0.090	0.127
YBCU	30M_ONLY	5	0.35	65.38	57.14	69.57	51.22	23.81	66.5	32.6	0.9	9660	0.669	0.074	0.103
YBCU	30M_ONLY	7	0.35	62.50	47.14	70.29	55.41	27.61	67.1	32	0.9	9660	0.675	0.081	0.113
YBCU	30M_ONLY	3	0.35	64.90	52.86	71.01	51.95	25.19	68	31.5	0.5	9660	0.683	0.084	0.117
YBCU	30M_ONLY	9	0.35	65.38	54.29	71.01	51.28	24.62	67.7	31.9	0.4	9660	0.679	0.079	0.112
YBCU	30M_ONLY	2	0.35	66.83	57.14	71.74	49.37	23.26	68.1	31.5	0.4	9660	0.683	0.084	0.118
YBCU	30M_ONLY	1	0.35	66.35	54.29	72.46	50.00	24.24	67.6	31.8	0.6	9660	0.679	0.080	0.112
YBCU	30M_ONLY	6	0.35	64.90	47.14	73.91	52.17	26.62	67.9	31.6	0.5	9660	0.681	0.082	0.115
YBCU	4M_ALL	4	0.35	66.35	67.14	65.94	50.00	20.18	74.6	25.1	0.3	9660	0.747	0.154	0.215
YBCU	4M_ALL	1	0.35	64.42	60.00	66.67	52.27	23.33	73.5	26.2	0.3	9660	0.736	0.156	0.217
YBCU	4M_ALL	6	0.35	64.42	60.00	66.67	52.27	23.33	73.8	25.9	0.3	9660	0.739	0.154	0.214
YBCU	4M_ALL	8	0.35	65.87	64.29	66.67	50.55	21.37	73	26.8	0.2	9660	0.731	0.139	0.197
YBCU	4M_ALL	5	0.35	64.90	60.00	67.39	51.72	23.14	72	27.7	0.3	9660	0.721	0.135	0.187

Appendix 2-Q: Yellow-billed Cuckoo validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Continued table.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concord	% Discord.	% Tied	Pairs	C	R Square	Max re-scale R Square
YBCU	4M_ONLY	6	0.35	59.62	74.29	52.17	55.93	20.00	67.4	31.9	0.6	9660	0.677	0.074	0.104
YBCU	4M_ONLY	2	0.35	62.98	64.29	62.32	53.61	22.52	67	32.6	0.4	9660	0.672	0.080	0.111
YBCU	4M_ONLY	4	0.35	64.42	61.43	65.94	52.22	22.88	66.7	32.8	0.5	9660	0.669	0.077	0.107
YBCU	4M_ONLY	7	0.35	62.98	55.71	66.67	54.12	25.20	67	32.4	0.6	9660	0.673	0.074	0.104
YBCU	4M_ONLY	8	0.35	62.98	55.71	66.67	54.12	25.20	67	32.4	0.6	9660	0.673	0.074	0.104
YBCU	4M_ONLY	9	0.35	62.98	55.71	66.67	54.12	25.20	67	32.4	0.6	9660	0.673	0.074	0.104
YBCU	4M_ONLY	10	0.35	63.46	57.14	66.67	53.49	24.59	66.7	32.9	0.4	9660	0.669	0.075	0.104
YBCU	4M_ONLY	3	0.35	64.90	61.43	66.67	51.69	22.69	67.1	32.4	0.5	9660	0.673	0.079	0.109
YBCU	4M_ONLY	1	0.35	63.94	57.14	67.39	52.94	24.39	66.7	32.8	0.5	9660	0.670	0.074	0.104
YBCU	4M_ONLY	5	0.35	64.42	58.57	67.39	52.33	23.77	66.8	32.7	0.5	9660	0.671	0.076	0.106
YBCU	FIELD	3	0.35	61.54	65.71	59.42	54.90	22.64	73.5	26.2	0.2	9660	0.737	0.135	0.189
YBCU	FIELD	5	0.35	61.54	65.71	59.42	54.90	22.64	70.1	29.5	0.4	9660	0.703	0.111	0.157
YBCU	FIELD	8	0.35	61.54	65.71	59.42	54.90	22.64	73.2	26.5	0.3	9660	0.734	0.128	0.182
YBCU	FIELD	1	0.35	63.46	71.43	59.42	52.83	19.61	73.2	26.5	0.3	9660	0.734	0.126	0.179
YBCU	FIELD	7	0.35	63.46	70.00	60.14	52.88	20.19	73.3	26.4	0.2	9660	0.735	0.130	0.183
YBCU	FIELD	10	0.35	63.94	71.43	60.14	52.38	19.42	72.8	26.8	0.4	9660	0.730	0.130	0.183
YBCU	FIELD	4	0.35	63.94	70.00	60.87	52.43	20.00	73.1	26.5	0.4	9660	0.733	0.130	0.185
YBCU	FIELD	9	0.35	64.42	71.43	60.87	51.92	19.23	73.1	26.6	0.3	9660	0.732	0.127	0.181
YBCU	FIELD	6	0.35	63.46	67.14	61.59	53.00	21.30	73.1	26.5	0.4	9660	0.733	0.128	0.182
YBCU	FIELD	2	0.35	63.94	65.71	63.04	52.58	21.62	73	26.7	0.3	9660	0.731	0.134	0.189
YBCU	4M_ALL	10	0.35	65.87	62.86	67.39	50.56	21.85	72.6	27.2	0.2	9660	0.727	0.142	0.198
YBCU	4M_ALL	9	0.35	64.90	58.57	68.12	51.76	23.58	73.6	26.3	0.2	9660	0.736	0.151	0.212
YBCU	4M_ALL	7	0.35	66.83	60.00	70.29	49.40	22.40	73.9	25.7	0.4	9660	0.741	0.152	0.213
YBCU	4M_ALL	2	0.35	66.83	58.57	71.01	49.38	22.83	72.8	27	0.2	9660	0.729	0.156	0.217
YBCU	4M_ALL	3	0.35	69.71	58.57	75.36	45.33	21.80	73.9	25.9	0.2	9660	0.740	0.153	0.214

Appendix 2-R: Indigo Bunting validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Table continues on next page.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R Square	Max re-scale R Square
INBU	30M_ALL	8	0.4	69.23	70.11	68.60	38.38	23.85	79	20.8	0.2	10527	0.8	0.224	0.31
INBU	30M_ALL	3	0.4	68.75	67.82	69.42	38.54	25.00	78.2	21.6	0.2	10527	0.8	0.223	0.304
INBU	30M_ALL	5	0.4	67.79	64.37	70.25	39.13	26.72	78.3	21.6	0.2	10527	0.8	0.228	0.307
INBU	30M_ALL	2	0.4	68.27	65.52	70.25	38.71	26.09	79.1	20.7	0.2	10527	0.8	0.236	0.321
INBU	30M_ALL	1	0.4	68.75	66.67	70.25	38.30	25.44	79.1	20.8	0.1	10527	0.8	0.236	0.321
INBU	30M_ALL	10	0.4	69.71	68.97	70.25	37.50	24.11	78.9	20.9	0.2	10527	0.8	0.222	0.308
INBU	30M_ALL	4	0.4	68.75	65.52	71.07	38.04	25.86	78.8	21	0.2	10527	0.8	0.236	0.319
INBU	30M_ALL	6	0.4	69.23	65.52	71.90	37.36	25.64	79.3	20.5	0.2	10527	0.8	0.239	0.321
INBU	30M_ALL	9	0.4	69.71	66.67	71.90	36.96	25.00	77.8	21.9	0.2	10527	0.8	0.224	0.303
INBU	30M_ALL	7	0.4	70.19	67.82	71.90	36.56	24.35	78.8	20.9	0.2	10527	0.8	0.232	0.316
INBU	30M_ONLY	8	0.4	60.58	67.82	55.37	47.79	29.47	69.8	29.9	0.3	10527	0.7	0.106	0.145
INBU	30M_ONLY	4	0.4	60.58	66.67	56.20	47.75	29.90	69.1	30.2	0.7	10527	0.7	0.103	0.139
INBU	30M_ONLY	9	0.4	60.58	65.52	57.02	47.71	30.30	69.7	29.9	0.4	10527	0.7	0.106	0.145
INBU	30M_ONLY	10	0.4	61.54	67.82	57.02	46.85	28.87	68.6	30.8	0.6	10527	0.7	0.097	0.131
INBU	30M_ONLY	5	0.4	60.58	64.37	57.85	47.66	30.69	69.1	30.4	0.6	10527	0.7	0.099	0.135
INBU	30M_ONLY	1	0.4	61.54	66.67	57.85	46.79	29.29	69.7	29.9	0.5	10527	0.7	0.107	0.146
INBU	30M_ONLY	7	0.4	61.54	66.67	57.85	46.79	29.29	69.6	30	0.4	10527	0.7	0.109	0.147
INBU	30M_ONLY	6	0.4	62.98	70.11	57.85	45.54	27.08	69.7	29.8	0.5	10527	0.7	0.108	0.147
INBU	30M_ONLY	2	0.4	61.54	65.52	58.68	46.73	29.70	68.6	30.8	0.6	10527	0.7	0.095	0.128
INBU	30M_ONLY	3	0.4	62.02	66.67	58.68	46.30	29.00	70.3	29.1	0.6	10527	0.7	0.113	0.153
INBU	4M_ALL	4	0.4	67.31	67.82	66.94	40.40	25.69	79.1	20.7	0.2	10527	0.8	0.246	0.334
INBU	4M_ALL	6	0.4	67.31	66.67	67.77	40.21	26.13	78.3	21.5	0.2	10527	0.8	0.235	0.32
INBU	4M_ALL	10	0.4	66.83	63.22	69.42	40.22	27.59	78	21.8	0.2	10527	0.8	0.237	0.321
INBU	4M_ALL	7	0.4	68.75	66.67	70.25	38.30	25.44	78.2	21.6	0.2	10527	0.8	0.233	0.319
INBU	4M_ALL	3	0.4	69.71	68.97	70.25	37.50	24.11	79.3	20.6	0.1	10527	0.8	0.247	0.336
INBU	4M_ALL	8	0.4	67.79	63.22	71.07	38.89	27.12	78.5	21.2	0.3	10527	0.8	0.246	0.334

Appendix 2-R: Indigo Bunting validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Continued table.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R Square	Max re-scale R Square
INBU	4M ONLY	3	0.4	69.71	59.77	76.86	35.00	27.34	74.5	25.2	0.3	10527	0.7	0.191	0.259
INBU	4M ONLY	6	0.4	70.19	60.92	76.86	34.57	26.77	75.9	23.9	0.2	10527	0.8	0.204	0.278
INBU	4M ONLY	8	0.4	70.19	60.92	76.86	34.57	26.77	75.9	24	0.2	10527	0.8	0.204	0.278
INBU	4M ONLY	10	0.4	70.67	62.07	76.86	34.15	26.19	75	24.7	0.3	10527	0.8	0.193	0.263
INBU	4M ONLY	5	0.4	70.19	59.77	77.69	34.18	27.13	76.1	23.6	0.3	10527	0.8	0.205	0.28
INBU	4M ONLY	7	0.4	70.67	59.77	78.51	33.33	26.92	75.7	24	0.3	10527	0.8	0.204	0.278
INBU	4M ONLY	1	0.4	71.15	60.92	78.51	32.91	26.36	75.8	23.9	0.2	10527	0.8	0.205	0.279
INBU	4M ONLY	2	0.4	71.15	58.62	80.17	32.00	27.07	77.2	22.5	0.2	10527	0.8	0.208	0.285
INBU	4M ONLY	4	0.4	72.12	60.92	80.17	31.17	25.95	76.4	23.3	0.3	10527	0.8	0.207	0.282
INBU	4M ONLY	9	0.4	72.12	60.92	80.17	31.17	25.95	77.5	22.2	0.3	10527	0.8	0.210	0.288
INBU	FIELD	6	0.4	64.42	64.37	64.46	43.43	28.44	75.8	23.5	0.7	10527	0.8	0.205	0.277
INBU	FIELD	4	0.4	67.31	64.37	69.42	39.78	26.96	77.2	22.1	0.7	10527	0.8	0.201	0.283
INBU	FIELD	3	0.4	68.27	64.37	71.07	38.46	26.50	78	21.7	0.3	10527	0.8	0.196	0.279
INBU	FIELD	7	0.4	68.27	64.37	71.07	38.46	26.50	77.4	21.7	0.9	10527	0.8	0.199	0.281
INBU	FIELD	9	0.4	68.75	64.37	71.90	37.78	26.27	77.5	21.6	0.9	10527	0.8	0.193	0.277
INBU	FIELD	1	0.4	70.19	65.52	73.55	35.96	25.21	76.6	22.2	1.2	10527	0.8	0.187	0.268
INBU	FIELD	8	0.4	69.71	63.22	74.38	36.05	26.23	72.7	23.5	3.9	10527	0.7	0.143	0.224
INBU	FIELD	10	0.4	71.63	63.22	77.69	32.93	25.40	75.5	24	0.5	10527	0.8	0.159	0.241
INBU	FIELD	5	0.4	72.12	64.37	77.69	32.53	24.80	73.6	23.5	2.8	10527	0.8	0.168	0.232
INBU	FIELD	2	0.4	73.08	62.07	80.99	29.87	25.19	73.6	23.7	2.8	10527	0.8	0.131	0.219
INBU	4M ALL	1	0.4	68.75	65.52	71.07	38.04	25.86	79.5	20.3	0.2	10527	0.8	0.251	0.344
INBU	4M ALL	2	0.4	69.23	64.37	72.73	37.08	26.05	77.2	22.6	0.2	10527	0.8	0.228	0.311
INBU	4M ALL	9	0.4	70.67	67.82	72.73	35.87	24.14	79.1	20.7	0.2	10527	0.8	0.243	0.332
INBU	4M ALL	5	0.4	71.63	66.67	75.21	34.09	24.17	77.7	22.1	0.3	10527	0.8	0.234	0.319

Appendix 2-S: Prairie Warbler validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Table continues on next page.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R Square	Max re-scale R Square
PRAW	FIELD	1	0.17	84.13	88.57	83.24	48.33	2.70	94.4	5.5	0	6055	0.944	0.569	0.705
PRAW	FIELD	2	0.17	84.13	88.57	83.24	48.33	2.70	93.7	6.2	0.1	6055	0.937	0.657	0.748
PRAW	FIELD	6	0.17	84.13	88.57	83.24	48.33	2.70	94	5.9	0.1	6055	0.940	0.503	0.669
PRAW	FIELD	5	0.17	84.62	88.57	83.82	47.46	2.68	93.6	6.4	0.1	6055	0.936	0.486	0.655
PRAW	FIELD	9	0.17	84.62	88.57	83.82	47.46	2.68	94	5.9	0.1	6055	0.940	0.497	0.665
PRAW	FIELD	10	0.17	84.62	88.57	83.82	47.46	2.68	93.7	6.1	0.2	6055	0.938	0.426	0.626
PRAW	FIELD	3	0.17	85.10	88.57	84.39	46.55	2.67	94.1	5.9	0	6055	0.941	0.550	0.692
PRAW	FIELD	7	0.17	85.10	91.43	83.82	46.67	2.03	93.9	6	0.1	6055	0.939	0.497	0.666
PRAW	FIELD	4	0.17	86.06	94.29	84.39	45.00	1.35	94	5.8	0.2	6055	0.941	0.358	0.612
PRAW	FIELD	8	0.17	86.54	88.57	86.13	43.64	2.61	94.2	5.8	0.1	6055	0.942	0.545	0.688
PRAW	4M ALL	5	0.17	79.81	80.00	79.77	55.56	4.83	92.4	7.4	0.1	6055	0.925	0.397	0.595
PRAW	4M ALL	3	0.17	80.77	77.14	81.50	54.24	5.37	92.8	7	0.2	6055	0.929	0.423	0.615
PRAW	4M ALL	4	0.17	80.77	82.86	80.35	53.97	4.14	93.2	6.7	0.1	6055	0.933	0.526	0.668
PRAW	4M ALL	2	0.17	81.25	80.00	81.50	53.33	4.73	92.7	7.2	0.1	6055	0.928	0.452	0.621
PRAW	4M ALL	8	0.17	82.21	80.00	82.66	51.72	4.67	93.3	6.5	0.1	6055	0.934	0.486	0.649
PRAW	4M ALL	9	0.17	82.21	82.86	82.08	51.67	4.05	93.2	6.8	0.1	6055	0.932	0.459	0.629
PRAW	4M ALL	1	0.17	82.69	82.86	82.66	50.85	4.03	93.1	6.8	0.1	6055	0.931	0.503	0.651
PRAW	4M ALL	6	0.17	82.69	88.57	81.50	50.79	2.76	92.8	7	0.1	6055	0.929	0.457	0.629
PRAW	4M ALL	10	0.17	82.69	85.71	82.08	50.82	3.40	92.9	7.1	0	6055	0.929	0.480	0.632
PRAW	4M ALL	7	0.17	83.17	82.86	83.24	50.00	4.00	93.3	6.6	0.1	6055	0.934	0.464	0.640
PRAW	30M ALL	9	0.17	77.88	80.00	77.46	58.21	4.96	92.1	7.8	0.1	6055	0.921	0.472	0.613
PRAW	30M ALL	1	0.17	79.33	85.71	78.03	55.88	3.57	92.4	7.5	0.1	6055	0.925	0.452	0.610
PRAW	30M ALL	6	0.17	79.33	82.86	78.61	56.06	4.23	92.4	7.6	0	6055	0.924	0.428	0.594
PRAW	30M ALL	7	0.17	79.33	85.71	78.03	55.88	3.57	92.2	7.8	0.1	6055	0.922	0.493	0.625
PRAW	30M ALL	10	0.17	79.33	82.86	78.61	56.06	4.23	92.5	7.4	0.1	6055	0.925	0.465	0.609
PRAW	30M ALL	3	0.17	80.29	85.71	79.19	54.55	3.52	91.8	8.2	0	6055	0.918	0.461	0.603
PRAW	30M ALL	8	0.17	80.77	88.57	79.19	53.73	2.84	91.9	8	0	6055	0.919	0.492	0.623
PRAW	30M ALL	2	0.17	81.25	85.71	80.35	53.13	3.47	92.1	7.8	0	6055	0.921	0.524	0.646
PRAW	30M ALL	4	0.17	81.25	82.86	80.92	53.23	4.11	92.2	7.7	0.1	6055	0.923	0.495	0.628
PRAW	30M ALL	5	7	81.73	85.71	80.92	52.38	3.45	92.3	7.7	0	6055	0.923	0.493	0.626

Appendix 2-S: Prairie Warbler validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Continued table.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R - Square	Max re-scale R Square
PRAW	4M ONLY	5	0.17	77.88	80.00	77.46	58.21	4.96	90.6	9.3	0.1	6055	0.907	0.389	0.546
PRAW	4M ONLY	7	0.17	79.33	77.14	79.77	56.45	5.48	90.8	9.1	0.1	6055	0.909	0.405	0.561
PRAW	4M ONLY	3	0.17	79.81	80.00	79.77	55.56	4.83	91.1	8.8	0.1	6055	0.912	0.391	0.564
PRAW	4M ONLY	1	0.17	80.29	80.00	80.35	54.84	4.79	90.9	8.9	0.2	6055	0.910	0.395	0.562
PRAW	4M ONLY	6	0.17	80.29	80.00	80.35	54.84	4.79	91.1	8.8	0.1	6055	0.912	0.397	0.565
PRAW	4M ONLY	9	0.17	80.29	80.00	80.35	54.84	4.79	91	8.9	0.2	6055	0.911	0.396	0.563
PRAW	4M ONLY	10	0.17	80.29	77.14	80.92	55.00	5.41	91.1	8.8	0.1	6055	0.911	0.392	0.561
PRAW	4M ONLY	2	0.17	80.77	77.14	81.50	54.24	5.37	91	8.8	0.1	6055	0.911	0.416	0.577
PRAW	4M ONLY	4	0.17	80.77	80.00	80.92	54.10	4.76	91	8.8	0.1	6055	0.911	0.400	0.567
PRAW	4M ONLY	8	0.17	80.77	77.14	81.50	54.24	5.37	91.3	8.7	0	6055	0.913	0.416	0.581
PRAW	30M ONLY	2	0.17	63.46	80.00	60.12	71.13	6.31	77.1	22.5	0.4	6055	0.773	0.139	0.225
PRAW	30M ONLY	3	0.17	63.94	82.86	60.12	70.41	5.45	77.5	22.2	0.4	6055	0.777	0.151	0.240
PRAW	30M ONLY	4	0.17	63.94	77.14	61.27	71.28	7.02	78.5	21.3	0.2	6055	0.786	0.146	0.244
PRAW	30M ONLY	5	0.17	63.94	82.86	60.12	70.41	5.45	78.2	21.3	0.5	6055	0.785	0.146	0.243
PRAW	30M ONLY	7	0.17	63.94	74.29	61.85	71.74	7.76	77.4	22.2	0.5	6055	0.776	0.125	0.212
PRAW	30M ONLY	1	0.17	64.90	82.86	61.27	69.79	5.36	78.5	21.1	0.4	6055	0.787	0.140	0.238
PRAW	30M ONLY	8	0.17	64.90	74.29	63.01	71.11	7.63	77.5	22.2	0.3	6055	0.776	0.145	0.232
PRAW	30M ONLY	9	0.17	64.90	82.86	61.27	69.79	5.36	79.1	20.7	0.3	6055	0.792	0.143	0.240
PRAW	30M ONLY	6	0.17	65.38	85.71	61.27	69.07	4.50	78.6	21	0.4	6055	0.788	0.135	0.237
PRAW	30M ONLY	10	0.17	66.83	77.14	64.74	69.32	6.67	76.3	23.1	0.5	6055	0.766	0.137	0.217

Appendix 2-T: Yellow-breasted Chat validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Table continues on next page.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R Square	Max re-scale R Square
YBCH	4M_ALL	7	0.25	81.25	81.48	81.17	39.73	7.41	88.4	11.5	0.1	8316	0.884	0.349	0.505
YBCH	4M_ALL	5	0.25	81.25	83.33	80.52	40.00	6.77	87.7	12.1	0.2	8316	0.878	0.313	0.477
YBCH	4M_ALL	1	0.25	80.77	85.19	79.22	41.03	6.15	87.6	12.3	0.1	8316	0.876	0.311	0.469
YBCH	4M_ALL	2	0.25	80.29	81.48	79.87	41.33	7.52	88.1	11.8	0.2	8316	0.881	0.335	0.492
YBCH	4M_ALL	10	0.25	80.29	83.33	79.22	41.56	6.87	87.4	12.4	0.1	8316	0.875	0.310	0.471
YBCH	4M_ALL	8	0.25	79.81	83.33	78.57	42.31	6.92	87.2	12.6	0.2	8316	0.873	0.299	0.466
YBCH	4M_ALL	9	0.25	79.81	85.19	77.92	42.50	6.25	87.6	12.3	0.1	8316	0.876	0.309	0.470
YBCH	4M_ALL	6	0.25	79.33	79.63	79.22	42.67	8.27	87.7	12.2	0.1	8316	0.878	0.322	0.479
YBCH	4M_ALL	4	0.25	78.85	79.63	78.57	43.42	8.33	88.6	11.4	0.1	8316	0.886	0.367	0.518
YBCH	4M_ALL	3	0.25	76.92	77.78	76.62	46.15	9.23	87.9	11.9	0.2	8316	0.88	0.345	0.497
YBCH	4M_ONLY	2	0.25	80.77	77.78	81.82	40.00	8.70	86.6	13.2	0.2	8316	0.867	0.330	0.456
YBCH	4M_ONLY	5	0.25	80.77	79.63	81.17	40.28	8.09	86.6	13.2	0.2	8316	0.867	0.340	0.470
YBCH	4M_ONLY	1	0.25	77.88	77.78	77.92	44.74	9.09	85.4	14.4	0.2	8316	0.855	0.304	0.429
YBCH	4M_ONLY	6	0.25	77.88	79.63	77.27	44.87	8.46	85.5	14.3	0.2	8316	0.856	0.305	0.436
YBCH	4M_ONLY	3	0.25	76.92	75.93	77.27	46.05	9.85	86.9	13	0.2	8316	0.869	0.327	0.465
YBCH	4M_ONLY	4	0.25	76.44	77.78	75.97	46.84	9.30	86	13.8	0.2	8316	0.861	0.301	0.436
YBCH	4M_ONLY	9	0.25	76.44	79.63	75.32	46.91	8.66	85.4	14.4	0.1	8316	0.855	0.203	0.363
YBCH	4M_ONLY	7	0.25	75.96	77.78	75.32	47.50	9.38	85.2	14.5	0.3	8316	0.854	0.278	0.404
YBCH	4M_ONLY	8	0.25	75.48	72.22	76.62	48.00	11.28	87	12.8	0.2	8316	0.871	0.331	0.475
YBCH	4M_ONLY	10	0.25	74.52	74.07	74.68	49.37	10.85	85.9	13.9	0.3	8316	0.86	0.296	0.426
YBCH	FIELD	1	0.25	77.88	77.78	77.92	44.74	9.09	83.7	15.7	0.7	8316	0.84	0.282	0.402
YBCH	FIELD	3	0.25	77.40	74.07	78.57	45.21	10.37	81.8	13.8	4.4	8316	0.84	0.293	0.406
YBCH	FIELD	6	0.25	77.40	77.78	77.27	45.45	9.16	84.9	14.7	0.4	8316	0.851	0.318	0.435
YBCH	FIELD	5	0.25	76.92	74.07	77.92	45.95	10.45	82.4	16.1	1.5	8316	0.831	0.239	0.377
YBCH	FIELD	8	0.25	76.92	75.93	77.27	46.05	9.85	83.7	16.1	0.3	8316	0.838	0.273	0.407
YBCH	FIELD	9	0.25	76.44	72.22	77.92	46.58	11.11	84.9	14.7	0.5	8316	0.851	0.310	0.442
YBCH	FIELD	4	0.25	76.44	74.07	77.27	46.67	10.53	83.8	15	1.2	8316	0.844	0.291	0.420
YBCH	FIELD	2	0.25	76.44	77.78	75.97	46.84	9.30	78.6	13	8.4	8316	0.828	0.254	0.370
YBCH	FIELD	10	0.25	75.96	77.78	75.32	47.50	9.38	84.1	15.2	0.8	8316	0.845	0.267	0.402
YBCH	FIELD	7	0.25	75.48	74.07	75.97	48.05	10.69	84.9	14.4	0.7	8316	0.852	0.299	0.436

Appendix 2-T: Yellow-breasted Chat validation statistics for the top ten models. These are the models selected by QAICc/AICc values from the all possible logistic regression analysis. Continued table.

Species	Data Type	Valid model #	Prob Level	% Correct	% Sensit.	% Specific.	False Pos.	False Neg.	% Concordant	% Discordant	% Tied	Pairs	C	R Square	Max re-scale R Square
YBCH	30M_ALL	2	0.25	76.44	81.48	74.68	46.99	8.00	86.2	13.7	0.1	8316	0.863	0.326	0.453
YBCH	30M_ALL	3	0.25	76.44	81.48	74.68	46.99	8.00	85.2	14.6	0.1	8316	0.853	0.314	0.432
YBCH	30M_ALL	1	0.25	75.96	79.63	74.68	47.56	8.73	85.1	14.7	0.2	8316	0.852	0.287	0.418
YBCH	30M_ALL	4	0.25	75.48	81.48	73.38	48.24	8.13	86	13.9	0.1	8316	0.861	0.318	0.447
YBCH	30M_ALL	7	0.25	75.00	77.78	74.03	48.78	9.52	85.9	13.9	0.1	8316	0.86	0.299	0.435
YBCH	30M_ALL	6	0.25	75.00	79.63	73.38	48.81	8.87	87	12.9	0.1	8316	0.87	0.324	0.464
YBCH	30M_ALL	5	0.25	74.52	81.48	72.08	49.43	8.26	85.9	13.8	0.2	8316	0.86	0.290	0.431
YBCH	30M_ALL	8	0.25	74.52	83.33	71.43	49.44	7.56	87	12.9	0.1	8316	0.87	0.325	0.464
YBCH	30M_ALL	10	0.25	73.08	75.93	72.08	51.19	10.48	83.8	16	0.2	8316	0.839	0.264	0.383
YBCH	30M_ALL	9	0.25	73.08	77.78	71.43	51.16	9.84	85.8	14.2	0.1	8316	0.858	0.324	0.448
YBCH	30M_ONLY	2	0.25	68.27	79.63	64.29	56.12	10.00	80.4	19.4	0.2	8316	0.805	0.216	0.313
YBCH	30M_ONLY	3	0.25	68.27	79.63	64.29	56.12	10.00	82.6	17.1	0.2	8316	0.827	0.183	0.301
YBCH	30M_ONLY	10	0.25	68.27	81.48	63.64	56.00	9.26	77.2	22.6	0.2	8316	0.773	0.188	0.268
YBCH	30M_ONLY	8	0.25	67.31	75.93	64.29	57.29	11.61	78.8	21	0.2	8316	0.789	0.206	0.296
YBCH	30M_ONLY	1	0.25	66.83	75.93	63.64	57.73	11.71	78.5	21.4	0.1	8316	0.786	0.200	0.289
YBCH	30M_ONLY	9	0.25	66.83	75.93	63.64	57.73	11.71	79.3	20.4	0.3	8316	0.794	0.198	0.290
YBCH	30M_ONLY	6	0.25	66.35	74.07	63.64	58.33	12.50	78.2	21.6	0.2	8316	0.783	0.210	0.300
YBCH	30M_ONLY	7	0.25	66.35	79.63	61.69	57.84	10.38	78.8	21.1	0.2	8316	0.788	0.208	0.298
YBCH	30M_ONLY	4	0.25	65.38	74.07	62.34	59.18	12.73	80.4	19.4	0.3	8316	0.805	0.227	0.326
YBCH	30M_ONLY	5	0.25	65.38	74.07	62.34	59.18	12.73	80.4	19.4	0.2	8316	0.805	0.175	0.280

Appendix 2-U: Akaike weights and AICc differences (Δ AICc) for the Acadian Flycatcher. Weights are relative to one another for each species and sum to one.

Species	Data Type	Model #	Model Variables	AIC Diff.	Akaike Wt.
ACFL	4M_ALL	1	%PNE %CCB IESA TE U SAPLING CP CP USAP	0.00	0.21760
ACFL	4M_ALL	2	%PNE %CCB IESA TE U SAPLING MID_DENSITY U_DENSITY	1.00	0.13211
ACFL	4M_ALL	3	%PNE %CCB IESA TE U SAPLING MID_DENSITY	1.01	0.13146
ACFL	4M_ALL	4	%BHD %PNE %CCB IESA TE U SAPLING MID_DENSITY	1.28	0.11490
ACFL	4M_ALL	5	%PNE IESA TE U SAPLING MID_DENSITY CP CP USAP	1.73	0.09174
ACFL	4M_ALL	6	%PNE IESA TE U SAPLING U_DENSITY CP CP USAP	2.35	0.06719
ACFL	4M_ALL	7	%PNE %CCB IESA TE U SAPLING MID_DENSITY CP	2.45	0.06378
ACFL	4M_ALL	8	%PNE %CCB IESA TE U SAPLING MID_DENSITY M_VINE	2.59	0.05960
ACFL	4M_ALL	9	%PNE %CCB IESA TE LASTCUT U SAPLING MID_DENSITY	2.59	0.05958
ACFL	4M_ALL	10	%PNE %CCB IESA TE U SAPLING MID_DENSITY M_PINE	2.62	0.05876
ACFL	4M_ONLY	1	%PNE %CCB IESA TE	12.02	0.00053
ACFL	4M_ONLY	2	%BHD %PNE %CCB IESA TE	12.03	0.00053
ACFL	4M_ONLY	3	%PNE %CCB IPFO_MPE IESA TE	12.59	0.00040
ACFL	4M_ONLY	4	%BHD %PNE %CCB IPFO_MPE IESA TE	12.87	0.00035
ACFL	4M_ONLY	5	%BHD %PNE %CCB %HGS IESA TE	13.44	0.00026
ACFL	4M_ONLY	6	%PNE %CCB %HGS IESA TE	13.57	0.00025
ACFL	4M_ONLY	7	%PNE %MIX %CCB IESA TE	13.58	0.00025
ACFL	4M_ONLY	8	%PNE %BMX %CCB IESA TE	13.84	0.00021
ACFL	4M_ONLY	9	%RIV %PNE %CCB IESA TE	13.87	0.00021
ACFL	4M_ONLY	10	%PNE %RDS %CCB IESA TE	13.91	0.00021
ACFL	30M_ALL	1	%MIX TDFO_ED TESA TE U SAPLING MID_DENSITY LASTCUT	18.66	0.00002
ACFL	30M_ALL	2	%MIX %CCB TDFO_ED U SAPLING MID_DENSITY LASTCUT	19.42	0.00001
ACFL	30M_ALL	3	%MIX TDFO_ED TESA TE U SAPLING MID_DENSITY CP	20.42	0.00001
ACFL	30M_ALL	4	%MIX %CCB TDFO_ED U SAPLING MID_DENSITY CP	20.95	0.00001
ACFL	30M_ALL	5	%CCB TDFO_ED U SAPLING MID_DENSITY CP LASTCUT	21.02	0.00001
ACFL	30M_ALL	6	TDFO_ED TDFO_NUMP TESA TE U SAPLING MID_DENSITY LCUT	21.37	0.00000
ACFL	30M_ALL	7	TDFO_ED TESA TE U SAPLING MID_DENSITY CP LASTCUT	21.41	0.00000
ACFL	30M_ALL	8	%MIX TPFO_MPE TDFO_ED TESA TE U SAPLING MID_DENSITY	21.65	0.00000
ACFL	30M_ALL	9	%MIX %CCB TPFO_MPE U SAPLING MID_DENSITY CP	21.91	0.00000
ACFL	30M_ALL	10	%CCB TDFO_ED TDFO_NUMP U SAPLING MID_DENSITY LCUT	22.14	0.00000
ACFL	FIELD	1	PHDWD U SAPLING MID_DENSITY CP M_HARDWOOD M_PINE	33.59	0.00000
ACFL	FIELD	2	PHDWD U SAPLING MID_DENSITY CP	34.27	0.00000
ACFL	FIELD	3	PHDWD U SAPLING MID_DENSITY CP CP_USAP	34.58	0.00000
ACFL	FIELD	4	PHDWD U SAPLING MID_DENSITY CP MIDDEN_USAP	34.62	0.00000
ACFL	FIELD	5	PHDWD U SAP MID_DENSITY U_DENSITY M_HWOOD M_PINE	34.73	0.00000
ACFL	FIELD	6	PHDWD U SAPLING MID_DENSITY M_HWOOD M_PINE M_VINE	34.83	0.00000
ACFL	FIELD	7	PHDWD H20_PRESENT U SAPLING MID_DENSITY CP	34.86	0.00000
ACFL	FIELD	8	PHDWD H20_PRESENT U SAP MID_DENSITY CP MIDDEN_USAP	35.22	0.00000
ACFL	FIELD	9	PHDWD U SAPLING MID_DENSITY U_DENSITY CP CP_USAP	35.22	0.00000
ACFL	FIELD	10	PHDWD H20_PRESENT U SAPLING MID_DENSITY CP CP_USAP	35.40	0.00000
ACFL	30M_ONLY	1	%MIX TPFO_MPE TDFO_ED TDFO_NUMP TESA TE	50.95	0.00000
ACFL	30M_ONLY	2	%H20 %MIX TPFO_MPE TDFO_ED TDFO_NUMP TESA TE	50.95	0.00000
ACFL	30M_ONLY	3	%PNE %MIX TDFO_ED TDFO_NUMP TESA TE	51.13	0.00000
ACFL	30M_ONLY	4	%H20 %MIX TDFO_ED TDFO_NUMP TESA TE	51.34	0.00000
ACFL	30M_ONLY	5	%H20 %PNE %MIX TDFO_ED TDFO_NUMP TESA TE	51.45	0.00000
ACFL	30M_ONLY	6	%H20 %MIX %BMX TDFO_ED TDFO_NUMP TESA TE	51.47	0.00000
ACFL	30M_ONLY	7	%MIX %RDS TPFO_MPE TDFO_ED TDFO_NUMP TESA TE	51.73	0.00000
ACFL	30M_ONLY	8	%MIX %BMX TDFO_ED TDFO_NUMP TESA TE	51.76	0.00000
ACFL	30M_ONLY	9	%MIX %BMX TPFO_MPE TDFO_ED TDFO_NUMP TESA TE	51.95	0.00000
ACFL	30M_ONLY	10	%BHD %MIX TPFO_MPE TDFO_ED TDFO_NUMP TESA TE	52.05	0.00000

Appendix 2-V: Akaike weights and AICc differences (Δ AICc) for the Red-eyed Vireo. Weights are relative to one another for each species and sum to one.

Species	Data Type	Model #	Model Variables	AIC Diff.	Akaike Wt.
REVI	4M_ALL	1	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_SAP U_DENSITY	0.00	0.13513
REVI	4M_ALL	2	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_SAPLING	0.98	0.08277
REVI	4M_ALL	3	H20_PRESENT %DECID %CCB %HSB IDFO_TE IDFO_ED U_SAPLING	1.50	0.06382
REVI	4M_ALL	4	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_DENSITY	1.67	0.05864
REVI	4M_ALL	5	H20_PRESENT %DECID IDFO_TE IESA_TE IDFO_ED U_SAP U_DENSITY	1.76	0.05592
REVI	4M_ALL	6	H20_PRESENT %DECID %HSB IDFO_TE IDFO_ED U_SAPLING CP	1.82	0.05450
REVI	4M_ALL	7	H20_PRESENT %DECID %HSB IDFO_TE U_SAPLING U_DENSITY	1.83	0.05411
REVI	30M_ALL	1	%BMX %H20 %CCB TESA_TE U_SAPLING HT_CANOPY CP	1.84	0.05387
REVI	30M_ALL	2	%BMX %H20 %RDS TESA_TE U_SAPLING HT_CANOPY CP	2.02	0.04925
REVI	4M_ALL	8	H20_PRESENT %DECID %HSB IDFO_TE U_SAPLING	2.18	0.04537
REVI	4M_ALL	9	H20_PRESENT %DECID %HSB IDFO_TE U_SAP UM_HT U_DENSITY	2.31	0.04256
REVI	4M_ALL	10	H20_PRESENT %DECID %CCB IDFO_TE IESA_TE IDFO_ED U_SAPL	2.39	0.04087
REVI	30M_ALL	3	%BMX %H20 TESA_TE U_SAPLING UM_HEIGHT HT_CANOPY CP	2.49	0.03895
REVI	30M_ALL	4	%H20 %UPL %CCB TESA_TE U_SAPLING HT_CANOPY CP	2.66	0.03573
REVI	30M_ALL	5	%BMX %H20 TESA_TE U_SAPLING HT_CANOPY CP	2.87	0.03211
REVI	30M_ALL	6	%H20 %CCB TESA_TE U_SAPLING UM_HEIGHT HT_CANOPY CP	3.26	0.02647
REVI	30M_ALL	7	%H20 %UPL TESA_TE U_SAPLING UM_HEIGHT HT_CANOPY CP	3.32	0.02569
REVI	30M_ALL	8	%BMX %H20 TESA_TE U_SAPLING U_DENSITY HT_CANOPY CP	3.47	0.02389
REVI	30M_ALL	9	%BMX %H20 TESA_TE TDFO_ED U_SAPLING HT_CANOPY CP	3.54	0.02299
REVI	30M_ALL	10	%H20 TESA_TE U_SAPLING UM_HEIGHT U_DENSITY HT_CANOPY CP	3.58	0.02252
REVI	4M_ONLY	1	%RIV %DECID %HSB IDFO_TE IDFO_ED	6.47	0.00532
REVI	4M_ONLY	2	%RIV %DECID %CCB %HSB IDFO_TE IDFO_ED	6.74	0.00465
REVI	4M_ONLY	3	%RIV %DECID IDFO_TE IDFO_ED	7.03	0.00402
REVI	4M_ONLY	4	%MIX %DECID %HSB IDFO_TE IDFO_ED	7.32	0.00348
REVI	4M_ONLY	5	%RIV %DECID %CCB IDFO_TE IESA_TE IDFO_ED	7.48	0.00321
REVI	4M_ONLY	6	%RIV %DECID %CCB IDFO_TE IDFO_ED	7.53	0.00313
REVI	4M_ONLY	7	%RIV %DECID IDFO_TE IESA_TE IDFO_ED	7.63	0.00297
REVI	4M_ONLY	8	%MIX %DECID IDFO_TE IESA_TE IDFO_ED	7.75	0.00280
REVI	4M_ONLY	9	%RIV %MIX %DECID %HSB IDFO_TE IDFO_ED	7.75	0.00280
REVI	4M_ONLY	10	%MIX %DECID IDFO_TE IDFO_ED	8.02	0.00245
REVI	FIELD	1	H20_PRESENT U_DENSITY CP	25.22	0.00000
REVI	FIELD	2	H20_PRESENT U_SAPLING U_DENSITY CP	25.50	0.00000
REVI	FIELD	3	H20_PRESENT U_SAPLING CP	25.55	0.00000
REVI	FIELD	4	H20_PRESENT CP	25.86	0.00000
REVI	FIELD	5	PHDWD H20_PRESENT U_DENSITY CP	26.45	0.00000
REVI	FIELD	6	PHDWD H20_PRESENT U_SAPLING U_DENSITY CP	26.69	0.00000
REVI	FIELD	7	PHDWD H20_PRESENT U_SAPLING CP	26.77	0.00000
REVI	FIELD	8	H20_PRESENT UM_HEIGHT U_DENSITY CP	26.94	0.00000
REVI	FIELD	9	PHDWD H20_PRESENT CP	27.13	0.00000
REVI	FIELD	10	H20_PRESENT U_SAPLING UM_HEIGHT U_DENSITY CP	27.33	0.00000
REVI	30M_ONLY	1	%H20 %CCB %RDS TESA_TE TDFO_ED	29.02	0.00000
REVI	30M_ONLY	2	%BMX %H20 %CCB %RDS TESA_TE TDFO_ED	29.06	0.00000
REVI	30M_ONLY	3	%H20 %UPL %CCB %RDS TESA_TE TDFO_ED	29.14	0.00000
REVI	30M_ONLY	4	%H20 %UPL %CCB %RDS TDFO_TE TESA_TE	29.60	0.00000
REVI	30M_ONLY	5	%H20 %CCB %RDS TDFO_TE TESA_TE	29.63	0.00000
REVI	30M_ONLY	6	%BMX %H20 %CCB %RDS TDFO_TE TESA_TE	29.69	0.00000
REVI	30M_ONLY	7	%H20 %MIX %CCB %RDS TESA_TE TDFO_ED	30.42	0.00000
REVI	30M_ONLY	8	%H20 %CCB TESA_TE TDFO_ED	30.53	0.00000
REVI	30M_ONLY	9	%H20 %UPL %CCB TESA_TE TDFO_ED	30.77	0.00000
REVI	30M_ONLY	10	%H20 %RDS TESA_TE TDFO_ED	30.98	0.00000

Appendix 2-W: Akaike weights and AICc differences (Δ AICc) for the Yellow-billed Cuckoo.

Species	Data Type	Model #	Model Variables	AIC Diff.	Akaike Wt.
YBCU	4M_ALL	1	%MIX %DECID G_VINE M_HDWD MG_VINE BURNQ	0.00	0.05619
YBCU	30M_ALL	1	TPFO_NUMP G_VINE M_HDWD MG_VINE BURNQ	0.01	0.05602
YBCU	4M_ALL	2	%MIX G_VINE G_GRASS M_HDWD MG_VINE BURNQ	0.04	0.05519
YBCU	30M_ALL	2	%MIX TPFO_NUMP U_VINE CP BURNQ BURNQ_UVNE	0.19	0.05116
YBCU	4M_ALL	3	%RIV %DECID IDMF_MPE G_VINE G_GRASS BURNQ	0.28	0.04875
YBCU	4M_ALL	4	%MIX %DECID G_VINE G_GRASS M_HDWD MG_VINE	0.29	0.04869
YBCU	30M_ALL	3	%MIX TDMF_MPE TPFO_NUMP U_VINE BURNQ BURNQ_UVNE	0.29	0.04859
YBCU	4M_ALL	5	%MIX %DECID G_VINE BURNQ	0.33	0.04773
YBCU	30M_ALL	4	TPFO_NUMP U_VINE CP BURNQ CP_UVIN BURNQ_UVNE	0.41	0.04574
YBCU	30M_ALL	5	TPFO_NUMP G_VINE U_VINE CP BURNQ BURNQ_UVNE	0.43	0.04525
YBCU	4M_ALL	6	%MIX %DECID G_VINE G_GRASS M_HDWD BURNQ	0.47	0.04443
YBCU	30M_ALL	6	TPFO_NUMP G_VINE G_GRASS M_HDWD MG_VINE BURNQ	0.49	0.04403
YBCU	30M_ALL	7	%MIX TPFO_NUMP G_VINE CP BURNQ	0.49	0.04394
YBCU	4M_ALL	7	%MIX %DECID G_VINE G_GRASS M_SHRB BURNQ	0.50	0.04381
YBCU	4M_ALL	8	%MIX %DECID G_VINE UVNE BURNQ	0.58	0.04196
YBCU	30M_ALL	8	TDMF_MPE TPFO_NUMP G_VINE U_VINE BURNQ BURNQ_UVNE	0.66	0.04046
YBCU	4M_ALL	9	%MIX %DECID IDMF_MPE G_VINE G_GRASS BURNQ	0.66	0.04045
YBCU	30M_ALL	9	TPFO_NUMP U_VINE M_HDWD MG_VINE BURNQ BURNQ_UVNE	0.67	0.04025
YBCU	30M_ALL	10	TDMF_MPE TPFO_NUMP U_VINE BURNQ BURNQ_UVNE	0.68	0.04003
YBCU	4M_ALL	10	%MIX %DECID IDMF_MPE G_VINE BURNQ	0.76	0.03835
YBCU	FIELD	1	G_VINE G_GRASS M_HARDWOOD MG_VINE CP	3.17	0.01153
YBCU	FIELD	2	G_VINE G_GRASS M_HARDWOOD M_VINE CP CP_G_SEED	4.13	0.00712
YBCU	FIELD	3	G_VINE G_GRASS UM_HEIGHT M_HARDWOOD M_VINE CP	4.17	0.00700
YBCU	FIELD	4	G_VINE G_GRASS M_HARDWOOD M_VINE CP CP_M_HDWD	4.41	0.00619
YBCU	FIELD	5	G_VINE G_GRASS M_HARDWOOD CP	4.52	0.00586
YBCU	FIELD	6	G_VINE G_GRASS M_HARDWOOD M_VINE CP CP_G_GRASS	4.92	0.00479
YBCU	FIELD	7	G_VINE G_GRASS U_VINE M_HARDWOOD M_VINE CP	4.96	0.00471
YBCU	FIELD	8	H20_PRESENT G_VINE G_GRASS M_HARDWOOD M_VINE CP	4.99	0.00464
YBCU	FIELD	9	G_VINE G_GRASS M_HARDWOOD M_VINE CP CP_MVINE	5.03	0.00455
YBCU	FIELD	10	G_VINE G_GRASS G_SEED M_HARDWOOD M_VINE CP	5.03	0.00454
YBCU	4M_ONLY	1	%DECID	6.46	0.00222
YBCU	30M_ONLY	1	TDMF_MPE TPFO_NUMP	7.33	0.00144
YBCU	4M_ONLY	2	%MIX %DECID	7.37	0.00141
YBCU	4M_ONLY	3	%DECID IDMF_MPE	7.73	0.00117
YBCU	4M_ONLY	4	%DECID IESE_ED	8.11	0.00097
YBCU	4M_ONLY	5	%RIV %DECID	8.20	0.00093
YBCU	4M_ONLY	6	%PNE %MIX	8.26	0.00090
YBCU	30M_ONLY	2	%PNE TDMF_MPE TPFO_NUMP	8.45	0.00082
YBCU	4M_ONLY	7	%DECID %UPL	8.48	0.00081
YBCU	4M_ONLY	8	%DECID %BHD	8.48	0.00081
YBCU	4M_ONLY	9	%UPL %BHD	8.48	0.00081
YBCU	4M_ONLY	10	%DECID IPFO_NUMP	8.50	0.00080
YBCU	30M_ONLY	3	%H20 TDMF_MPE TPFO_NUMP	8.63	0.00075
YBCU	30M_ONLY	4	%MIX TDMF_MPE TPFO_NUMP	8.64	0.00075
YBCU	30M_ONLY	5	%PNE TPFO_NUMP	8.67	0.00074
YBCU	30M_ONLY	6	%BHD TDMF_MPE TPFO_NUMP	8.96	0.00064
YBCU	30M_ONLY	7	%UPL %BHD TPFO_NUMP	9.28	0.00054
YBCU	30M_ONLY	8	%MIX %UPL %BHD TPFO_NUMP	9.37	0.00052
YBCU	30M_ONLY	9	TDMF_MPE TPFO_NUMP TESS_ED	9.38	0.00051
YBCU	30M_ONLY	10	%PNE %MIX TDMF_MPE TPFO_NUMP	9.42	0.00051

Appendix 2-X: Akaike weights and AICc differences (Δ AICc) for the Indigo Bunting.

Species	Data Type	Model #	Model Variables	AIC Diff.	Akaike Wt.
INBU	4M_ALL	1	%UPL %H20 IDMF_TE CP M_VINE CP_M_VINE	0.00	0.17578
INBU	4M_ALL	2	%UPL %H20 IDMF_TE CP	1.42	0.08654
INBU	4M_ALL	3	%UPL %MIX %H20 CP M_VINE CP_M_VINE	1.57	0.08004
INBU	4M_ALL	4	%H20 IDMF_TE G_GRASS CP M_VINE CP_M_VINE	1.82	0.07087
INBU	4M_ALL	5	%UPL %H20 IHSB IDMF_TE CP	2.00	0.06479
INBU	4M_ALL	6	%H20 IDMF_TE CP M_VINE CP_M_VINE	2.07	0.06248
INBU	4M_ALL	7	%UPL %H20 IDMF_TE CP MG_VINE	2.10	0.06161
INBU	4M_ALL	8	%UPL %PNE %H20 IHSB IDMF_TE G_GRASS	2.13	0.06056
INBU	4M_ALL	9	%PNE %H20 IDMF_TE CP M_VINE CP_M_VINE	2.13	0.06049
INBU	4M_ALL	10	%PNE %H20 IHSB IDMF_TE G_GRASS	2.17	0.05947
INBU	30M_ALL	1	%UPL %H20 G_GRASS CP M_VINE CP_M_VINE	4.16	0.02198
INBU	30M_ALL	2	%GRS %H20 G_GRASS CP M_VINE CP_M_VINE	4.25	0.02099
INBU	30M_ALL	3	%H20 G_GRASS CP M_VINE CP_M_VINE	4.48	0.01871
INBU	30M_ALL	4	%UPL %GRS %H20 G_GRASS CP DBH14	4.61	0.01750
INBU	30M_ALL	5	%UPL %GRS %H20 G_GRASS CP	4.62	0.01744
INBU	30M_ALL	6	%UPL %GRS %H20 CP M_VINE CP_M_VINE	4.66	0.01708
INBU	30M_ALL	7	%UPL %GRS %H20 U_SAPLING CP DBH14	4.92	0.01498
INBU	30M_ALL	8	%H20 G_GRASS CP DEAD M_VINE CP_M_VINE	5.13	0.01353
INBU	30M_ALL	9	%UPL %GRS %H20 CP DBH14	5.20	0.01306
INBU	30M_ALL	10	%H20 G_GRASS U_SAPLING CP M_VINE CP_M_VINE	5.35	0.01213
INBU	4M_ONLY	1	%PNE %HSB IPFO_ED IDMF_TE	6.61	0.00645
INBU	4M_ONLY	2	%PNE %GRS %HSB IPFO_ED IDMF_TE	7.52	0.00409
INBU	4M_ONLY	3	%PNE %HSB IDMF_TE	7.61	0.00391
INBU	4M_ONLY	4	%UPL %PNE %HSB IPFO_ED IDMF_TE	8.09	0.00307
INBU	4M_ONLY	5	%PNE %HSB IESS_ED IPFO_ED IDMF_TE	8.33	0.00273
INBU	FIELD	1	G_GRASS CP M_VINE CP_M_VINE PERHWD_G_GRASS	8.49	0.00252
INBU	FIELD	2	PHDWD G_GRASS PERHWD_G_GRASS	8.58	0.00241
INBU	4M_ONLY	6	%PNE %H20 %HSB IPFO_ED IDMF_TE	8.73	0.00223
INBU	4M_ONLY	7	%PNE %CCB %HSB IPFO_ED IDMF_TE	8.74	0.00222
INBU	4M_ONLY	8	%MIX %PNE %HSB IPFO_ED IDMF_TE	8.75	0.00221
INBU	4M_ONLY	9	%UPL %PNE %GRS %HSB IPFO_ED IDMF_TE	9.03	0.00193
INBU	4M_ONLY	10	%PNE %GRS %HSB IDMF_TE	9.03	0.00192
INBU	FIELD	3	G_GRASS U_SAPLING CP M_VINE CP_M_VINE PHWD_G_GRASS	9.03	0.00192
INBU	FIELD	4	PHDWD G_GRASS CP M_VINE CP_M_VINE PERHWD_G_GRASS	9.04	0.00191
INBU	FIELD	5	PHDWD G_GRASS	9.07	0.00189
INBU	FIELD	6	PHDWD G_GRASS CP M_VINE CP_M_VINEINE	9.14	0.00182
INBU	FIELD	7	G_GRASS CP DEAD M_VINE CP_M_VINE PERHWD_G_GRASS	9.26	0.00171
INBU	FIELD	8	G_GRASS CP PERHWD_G_GRASS	9.28	0.00169
INBU	FIELD	9	H20_PRESENT G_GRASS CP M_VINE CP_M_VINE PHWD_GGRASS	9.29	0.00169
INBU	FIELD	10	PHDWD G_GRASS U_SAPLING PERHWD_G_GRASS	9.36	0.00163
INBU	30M_ONLY	1	%PNE %GRS %CCB	24.32	0.00000
INBU	30M_ONLY	2	%PNE %GRS	24.71	0.00000
INBU	30M_ONLY	3	%UPL %PNE %GRS %CCB	25.36	0.00000
INBU	30M_ONLY	4	%UPL %PNE %GRS	25.39	0.00000
INBU	30M_ONLY	5	%PNE %GRS TESS_ED	25.74	0.00000
INBU	30M_ONLY	6	%MIX %PNE %GRS %CCB	26.21	0.00000
INBU	30M_ONLY	7	%PNE %GRS %CCB %H20	26.28	0.00000
INBU	30M_ONLY	8	%PNE %GRS %CCB TPFO_TE	26.28	0.00000
INBU	30M_ONLY	9	%PNE %GRS %CCB TDMF_TE	26.44	0.00000
INBU	30M_ONLY	10	%PNE %GRS %H20	26.46	0.00000

Appendix 2-Y: Akaike weights and AICc differences (Δ AICc) for the Prairie Warbler. Weights are relative to one another for each species and sum to one.

Species	Data Type	Model #	Model Variables	AIC Diff.	Akaike Wt.
PRAW	FIELD	1	PHDWD G_GRASS G_SEED U_SAPLING CP PERHWD_USAP	0.00	0.16365
PRAW	FIELD	2	PHDWD G_SEED U_SAPLING CP CP_G_SEED PERHWD_USAP	0.60	0.12126
PRAW	FIELD	3	PHDWD G_GRASS G_SEED U_SAPLING M_VINE PERHWD_USAP	0.97	0.10089
PRAW	FIELD	4	PHDWD G_GRASS G_SEED U_SAPLING CP CP_G_SEED	1.35	0.08347
PRAW	FIELD	5	PHDWD G_GRASS G_SEED U_SAPLING PERHWD_USAP	1.46	0.07896
PRAW	FIELD	6	PHDWD G_GRASS G_SEED CP CP_G_SEED PERHWD_G_GRASS	1.58	0.07445
PRAW	FIELD	7	PHDWD G_GRASS G_SEED U_SAPLING PERHWD_G_SEED PERHWD_USAP	1.62	0.07286
PRAW	FIELD	8	PHDWD G_GRASS G_SEED U_SAPLING PERHWD_G_GRASS PERHWD_USAP	1.62	0.07266
PRAW	FIELD	9	PHDWD G_GRASS G_SEED U_SAPLING HT_CANOPY PERHWD_USAP	2.02	0.05971
PRAW	FIELD	10	PHDWD G_GRASS G_SEED CP PERHWD_G_GRASS	2.32	0.05128
PRAW	4M_ALL	1	%PNE %GRS IESA_TE UM_HEIGHT CP	5.00	0.01341
PRAW	4M_ALL	2	%PNE %GRS IESA_TE CP	5.02	0.01329
PRAW	4M_ALL	3	%PNE %GRS IESA_TE G_GRASS CP	5.13	0.01259
PRAW	4M_ALL	4	%PNE IESA_TE G_GRASS UM_HEIGHT U_SAPLING CP	5.29	0.01163
PRAW	4M_ALL	5	%PNE IESA_TE G_GRASS CP	5.32	0.01147
PRAW	4M_ALL	6	%PNE IESA_TE G_GRASS U_SAPLING CP	5.36	0.01124
PRAW	4M_ALL	7	%PNE %GRS IESA_TE G_GRASS M_VINE CP	5.38	0.01112
PRAW	4M_ALL	8	%PNE %GRS IESA_TE G_GRASS UM_HEIGHT CP	5.46	0.01068
PRAW	4M_ALL	9	%PNE IESA_TE G_GRASS UM_HEIGHT CP	5.49	0.01051
PRAW	4M_ALL	10	%PNE IESA_TE UM_HEIGHT CP	5.50	0.01044
PRAW	4M_ONLY	1	%PNE %GRS IESA_TE	11.89	0.00043
PRAW	30M_ALL	1	%MIX BURNQ_G_GRASS G_SEED CP BURNQ_G_SEED	12.16	0.00037
PRAW	30M_ALL	2	BURNQ_G_GRASS G_SEED M_VINE CP BURNQ_G_SEED	12.21	0.00037
PRAW	4M_ONLY	2	%PNE %GRS %RDS IESA_TE	12.64	0.00029
PRAW	4M_ONLY	3	%PNE %GRS %HGS IESA_TE	12.84	0.00027
PRAW	4M_ONLY	4	%PNE %GRS IDMF_ED IESA_TE	13.04	0.00024
PRAW	4M_ONLY	5	%PNE IESA_TE	13.27	0.00022
PRAW	4M_ONLY	6	%PNE %GRS %CCB IESA_TE	13.27	0.00022
PRAW	4M_ONLY	7	%PNE %RDS IESA_TE	13.30	0.00021
PRAW	30M_ALL	3	BURNQ_G_GRASS G_SEED CP BURNQ_G_SEED	13.37	0.00020
PRAW	30M_ALL	4	BURNQ_G_GRASS G_SEED CP CP_G_GRASS BURNQ_G_SEED	13.37	0.00020
PRAW	4M_ONLY	8	%PNE %GRS %RDS %HGS IESA_TE	13.48	0.00019
PRAW	30M_ALL	5	BURNQ_G_GRASS G_SEED M_VINE CP BURNQ_G_GRASS	13.49	0.00019
PRAW	30M_ALL	6	%MIX BURNQ_G_GRASS G_SEED CP BURNQ_G_GRASS	13.73	0.00017
PRAW	4M_ONLY	9	%PNE %GRS IPFO_ED IESA_TE	13.84	0.00016
PRAW	4M_ONLY	10	%PNE %GRS IDFO_NUMP IESA_TE	13.86	0.00016
PRAW	30M_ALL	7	TPFO_ED BURNQ_G_GRASS G_SEED CP BURNQ_G_SEED	14.05	0.00015
PRAW	30M_ALL	8	BURNQ_G_GRASS G_SEED UM_HEIGHT CP BURNQ_G_SEED	14.20	0.00013
PRAW	30M_ALL	9	%MIX G_GRASS G_SEED M_VINE CP CP_G_SEED	14.28	0.00013
PRAW	30M_ALL	10	%MIX G_GRASS G_SEED M_VINE CP CP_G_GRASS	14.40	0.00012
PRAW	30M_ONLY	1	%PNE %GRS %CCB %RDS TPFO_ED	62.11	0.00000
PRAW	30M_ONLY	2	%PNE %GRS %RDS TPFO_ED	62.77	0.00000
PRAW	30M_ONLY	3	%PNE %GRS %CCB %RDS TDMF_ED	62.94	0.00000
PRAW	30M_ONLY	4	%PNE %GRS %CCB %RDS TPFO_ED TDFO_NUMP	63.59	0.00000
PRAW	30M_ONLY	5	%PNE %GRS %CCB %RDS TDMF_ED TPFO_ED	63.70	0.00000
PRAW	30M_ONLY	6	%PNE %UPL %GRS %CCB %RDS TPFO_ED	63.71	0.00000
PRAW	30M_ONLY	7	%PNE %GRS %CCB TPFO_ED	63.79	0.00000
PRAW	30M_ONLY	8	%PNE %GRS %CCB %RDS TDFO_NUMP	63.87	0.00000
PRAW	30M_ONLY	9	%PNE %GRS %CCB %RDS TPFO_ED TALL_MPS	64.07	0.00000
PRAW	30M_ONLY	10	%PNE %GRS %RDS TDFO_NUMP	64.15	0.00000

Appendix 2-Z: Akaike Weights and AICc Differences for the Yellow-breasted Chat. Weights are relative to one another for each species and sum to one.

Species	Data Type	Model #	Model Variables	AIC Diff.	Akaike Wt.
YBCH	4M_ALL	1	IDMF_NUMP IESA_TE M_DENSITY	0.00	0.13340
YBCH	4M_ALL	2	%RDS IDMF_NUMP IESA_TE M_DENSITY	0.46	0.10593
YBCH	4M_ALL	3	IDMF_NUMP IESA_TE M_VINE M_DENSITY	0.48	0.10504
YBCH	4M_ALL	4	%RDS IDMF_NUMP IESA_TE M_VINE M_DENSITY	1.08	0.07787
YBCH	4M_ALL	5	IDMF_NUMP IESA_TE U_SAPLING M_DENSITY	1.14	0.07554
YBCH	4M_ALL	6	IDMF_NUMP IESA_TE UM_HEIGHT M_DENSITY	1.53	0.06206
YBCH	4M_ALL	7	%RDS IDMF_NUMP IESA_TE UM_HEIGHT M_DENSITY	1.67	0.05780
YBCH	4M_ALL	8	IDMF_NUMP IESA_TE G_VINE M_DENSITY	1.71	0.05681
YBCH	4M_ALL	9	%CCB IDMF_NUMP IESA_TE M_DENSITY	1.77	0.05519
YBCH	4M_ALL	10	IDMF_NUMP IESA_TE BURNQ M_DENSITY	1.82	0.05364
YBCH	4M_ONLY	1	IDMF_NUMP IESA_TE	3.20	0.02694
YBCH	4M_ONLY	2	%RDS IDMF_NUMP IESA_TE	3.35	0.02494
YBCH	4M_ONLY	3	%PNE %RDS IDMF_NUMP IESA_TE	3.96	0.01839
YBCH	4M_ONLY	4	%PNE IDMF_NUMP IESA_TE	3.98	0.01822
YBCH	4M_ONLY	5	%RDS %HGS IDMF_NUMP IESA_TE	4.19	0.01640
YBCH	4M_ONLY	6	%HGS IDMF_NUMP IESA_TE	4.33	0.01528
YBCH	4M_ONLY	7	%PNE IESA_TE	4.75	0.01244
YBCH	4M_ONLY	8	%PNE %RDS %HGS IDMF_NUMP IESA_TE	4.87	0.01171
YBCH	4M_ONLY	9	%PNE %HVN	4.94	0.01129
YBCH	4M_ONLY	10	%PNE %RDS IESA_TE	5.04	0.01076
YBCH	FIELD	1	PHDWD U_SAPLING M_DENSITY	7.35	0.00337
YBCH	FIELD	2	PHDWD M_DENSITY	7.66	0.00290
YBCH	30M_ALL	1	%PNE TESA_TE G_SEED M_DENSITY	7.67	0.00289
YBCH	FIELD	3	PHDWD M_VINE M_DENSITY	7.67	0.00288
YBCH	FIELD	4	PHDWD G_VINE M_DENSITY PHD_G_VINE	7.69	0.00286
YBCH	FIELD	5	PHDWD G_VINE M_DENSITY	7.69	0.00286
YBCH	FIELD	6	PHDWD U_SAPLING M_VINE M_DENSITY	7.72	0.00281
YBCH	30M_ALL	2	%PNE TESA_TE G_SEED M_VINE M_DENSITY	7.76	0.00276
YBCH	30M_ALL	3	%PNE TESA_TE M_VINE M_DENSITY	7.80	0.00269
YBCH	30M_ALL	4	%PNE TDMF_NUMP TESA_TE M_VINE M_DENSITY	7.95	0.00250
YBCH	FIELD	7	PHDWD G_VINE M_VINE M_DENSITY PHD_G_VINE	8.07	0.00236
YBCH	FIELD	8	PHDWD G_VINE U_SAPLING M_DENSITY	8.10	0.00232
YBCH	30M_ALL	5	%PNE TDMF_NUMP TESA_TE G_SEED M_DENSITY	8.15	0.00227
YBCH	FIELD	9	PHDWD G_VINE U_SAPLING M_DENSITY PHD_G_VINE	8.18	0.00224
YBCH	30M_ALL	6	%PNE MRDS TDMF_NUMP TESA_TE M_VINE M_DENSITY	8.20	0.00221
YBCH	30M_ALL	7	MRDS TDMF_NUMP TESA_TE M_VINE M_DENSITY	8.21	0.00219
YBCH	30M_ALL	8	%PNE TDMF_NUMP TESA_TE G_SEED M_VINE M_DENSITY	8.27	0.00213
YBCH	FIELD	10	PHDWD G_VINE M_VINE M_DENSITY	8.30	0.00210
YBCH	30M_ALL	9	%PNE MRDS TESA_TE M_VINE M_DENSITY	8.38	0.00202
YBCH	30M_ALL	10	%PNE TESA_TE M_DENSITY	8.61	0.00180
YBCH	30M_ONLY	1	%PNE TDMF_NUMP TESA_TE	16.59	0.00003
YBCH	30M_ONLY	2	%PNE %RDS TDMF_NUMP TESA_TE	16.80	0.00003
YBCH	30M_ONLY	3	%PNE %RDS %GRS TDMF_NUMP TESS_NUMP	17.96	0.00002
YBCH	30M_ONLY	4	%PNE %RDS %UPL TDMF_NUMP TESA_TE	17.98	0.00002
YBCH	30M_ONLY	5	%PNE %GRS TDMF_NUMP TESS_NUMP	18.02	0.00002
YBCH	30M_ONLY	6	%PNE %UPL TDMF_NUMP TESA_TE	18.14	0.00002
YBCH	30M_ONLY	7	%PNE TALL_TE TDMF_NUMP TESA_TE	18.20	0.00001
YBCH	30M_ONLY	8	%PNE %MIX TDMF_NUMP TESA_TE	18.32	0.00001
YBCH	30M_ONLY	9	%PNE %GRS %CCB TDMF_NUMP	18.40	0.00001
YBCH	30M_ONLY	10	%PNE %MIX TESA_TE	18.42	0.00001

THESIS SUMMARY

This research presented had two main objectives. The first objective was to classify the high-resolution image into a land cover map with acceptable accuracy levels ($>75\%$), using commercially available software. At the time when the first objective was carried out, there was limited knowledge on the best ways to create land cover maps from high-resolution images ($<5\text{-m}$). Therefore, I investigated the limitations and benefits of three land cover classification approaches: supervised/maximum likelihood classifier, unsupervised/ clustering classifier and hierarchical/rule-based knowledge classifier (HRB). I found that the two traditional approaches (supervised/unsupervised) overall performed poorly, but that each of the classification methods were able to categorize some land cover types better than another. The HRB classifier provided a way to combine parts of the two methods as well as additional data into an overall stronger final product. All classification algorithms had problems classifying individual objects as the same land cover type (e.g., a tree in a field or thin fragmented areas) where the resolution was smaller than the actual object that was in the landscape. Using the HRB, I was able to use additional data to refine classification categories to higher accuracy levels ($> 85\%$) later in the study (Chapter 2). However, though the HRB was able to minimize the object classification problems to acceptable accuracy levels in Chapter 2, it was unable to fully correct them. Therefore, the HRB approach may not work as well on landscapes that exhibit high fragmentation in its features.

The second objective of the research was to compare the performance of different data sources in habitat models using presence/absence bird models. By comparing the performance of models that used high-resolution satellite data (Ikonos 4-m) and models that used a more

commonly available coarser resolution data (TM Landsat 30-m), along with other data sources (i.e. field measurements, GIS derived data), I was able to determine which data types produced the best models among a variety of bird species.

Using AIC and jackknifing validation measures, I found that:

- 1) Combination models created from field measurements, GIS data, and land cover data derived from 4-m resolution (4-m All), overall performed the best across all species (with some exceptions);
- 2) Combination models created from field data, GIS measurements, and either 4-m satellite data (4-m All) or 30-m satellite data (30-m All) were comparable in performance for closed canopy bird species;
- 3) The use of solely 30-m land cover data in species models was clearly inferior, perhaps due to the being too coarse for detecting species associations;
- 4) In general, early successional species modeling efforts produced better results with finer scaled data, in particular, with field measurements only and 4-m combination models, though the results were mixed and no strong pattern appeared for “4-m Only” data among the species.
- 5) In general, models for closed canopy species that contained a combination of data types or multiple scales had more empirical support than models created from data that represented one landscape scale.

Though there was overall support for 4-m data, the results indicate that there is no one data type can model **every** species the “best.” Ultimately, the results depend upon the species modeled; the scale of the features that species is associated and whether or not that data type can capture those features adequately.

There was no detailed cost comparison available for this study, although the 4-m data were unquestionably the most labor intensive and time consuming to process. At this time, it would not be feasible for most studies to use this data, although as the cost of high-resolution images continue to decrease and its use becomes more widespread, we will find that many of the problems may be alleviated by developments in the remote sensing and computing fields. This modeling study suggests that the costs of working with high-resolution data may outweigh the differences seen in model performance for those projects that are small in scale. Until those methods and techniques are developed for handling high-resolution data and overall costs are reduced, the majority of projects may find that the combination data with the 30-m data would be a suitable choice for modeling efforts, although obviously the project's objectives, goals and resources ultimately decide this fact.