2018

Using a custom landscape classification to understand the factors driving site occupancy by a rapidly declining migratory songbird

Elizabeth K. Schold
Virginia Commonwealth University

Using a custom landscape classification to understand the factors driving site occupancy by a rapidly declining migratory songbird

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University

By

Elizabeth Koehler Schold
Bachelor of Arts, Harvard University, 2012

Advised by

Lesley Bulluck, Ph.D.
Department of Biology, Center for Environmental Studies
Virginia Commonwealth University

Virginia Commonwealth University
Richmond, VA
August, 2018

Acknowledgements

This thesis would not have been possible without the support of an incredible community.

I would like to thank my committee members Derek Johnson, Julie Zinnert, Catherine Viverette, and Jennifer Ciminelli for their feedback and assistance. My labmates in the Animal Ecology lab, Ben Nickley, Abby Walter, Jessie Reese, Matt DeSaix, Andy Davidson, Adele Balmer, Lauren Jurczak, and Jordan Rasure have provided incredibly helpful advice on both of my thesis chapters and multiple presentations on my research. None of this work would have been possible without lab alumnus Dan Albrecht-Mallinger's point count data, or without the patient help of Carlisle Childress in the VCU Center for Biological Complexity.

I must express my intense gratitude for my advisor, Lesley Bulluck, for her unwavering support throughout my time at Virginia Commonwealth University; I cannot imagine a better mentor. Finally, the last few years would not have been possible without the emotional support of my dear friends Logan McDonald, Ben Nettleton, Bud Stracker, and Brooke Goodnow, as well as the support of my parents Bill and Mussy Schold.

Table of Contents

Table of Tables

Table of Figures

Abstract

USING CUSTOM LANDSCAPE CLASSIFICATION TO UNDERSTAND THE FACTORS DRIVING SITE OCCUPANCY BY A RAPIDLY DECLINING MIGRATORY SONGBIRD

By Elizabeth Schold, M.S.

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University

Virginia Commonwealth University, 2018

Major Director: Lesley Bulluck, Ph.D.
Department of Biology, Center for Environmental Studies
Virginia Commonwealth University

Land cover classifications are useful in a broad range of ecological applications, yet publicly available classifications are not always useful for the needs of specific projects. Custom classifications are always a possibility, however, they can be financially or computationally out of reach for many researchers. Here we present a custom 1m resolution land cover classification created using freely available imagery and a random forest classification approach. This classification detected shrub cover more accurately and at a finer resolution than previous classifications. With the creation of this map, we were then able to examine landscape factors influencing occupancy dynamics of the golden-winged warbler, a rapidly declining shrubland

specialist, at two ecologically relevant scales. Our findings indicate that shrub cover is important in predicting warbler occupancy and persistence at scales relevant to nesting, while forest characteristics are important at scales relevant to foraging and fledgling dispersal.

Chapter 1: Using an object-based random forests classification framework to surmount the challenges of identifying shrub in a mountainous landscape

Elizabeth Schold and Lesley Bulluck, Ph.D.

Expected submission to IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing

Abstract

Land cover classification maps are essential in a wide range of ecological applications, yet publicly available land cover classifications are not always useful for the needs of specific research or management projects. Here we present a framework for classifying a high-elevation landscape in the eastern United States using freely available 4-band, 1m resolution imagery, with emphasis on capturing shrub cover in a region dominated by forest and pasture with varying levels of grazing and agriculture. Using terrain metrics, texture metrics, and segmented imagery within a random forests classification framework, we were able to produce a landscape classification with an overall accuracy of 92.4% and >80% accuracy for each land cover class. Segmented spectral data were consistently ranked as important predictors in the overall classification, though texture metrics also proved important. With the exception of elevation, terrain metrics unexpectedly ranked very low in importance in this topographically complex landscape. The results of this classification demonstrate the potential for researchers to create accurate custom classifications of their study areas on relatively limited budgets and timelines, even in complex landscapes.

Introduction to the Problem

Land cover classification maps are essential in a wide range of applications; they can be used in development planning, resource inventory, tracking landscape changes, and in ecological research. There are many existing, publicly available landcover datasets, including the National Land Cover Database (Homer et al. 2015) and more locally available datasets such as Virginia's Land Cover Dataset (Virginia Geographic Information Network 2016). Land cover datasets intended for broad use necessarily have some shortcomings for specific applications. The agencies creating the classifications are limited by time and resources in the scope of what they can produce and must therefore prioritize certain scales and classes that will be valuable to the greatest number of users. For example, the National Landcover Database, covering the entire continental United States and intended for large-scale applications, has a 30m resolution. While this may be effective for analyzing variation in large areas, it does not capture the fine-scale detail necessary for other applications. More local land cover datasets can have relatively fine-scale resolution (i.e., 1m); however, as they are often designed to capture variation across what are still relatively large areas (i.e., county, state) they capture only the most common and generally important land cover classes.

Custom classifications are therefore a necessity for projects whose goals require additional land cover classes or finer-scale resolution, but creating these classifications can require significant expenditure of resources. Creating accurate land cover classification maps is greatly simplified by using high resolution, multi-spectral data (Xie et al. 2008); however, these data can be expensive, on the order of $50-$100 per square meter, making them of limited use for management applications where budgets are often limited and/or where focal areas are large. Freely available four-band imagery (red, green, blue, and near-infrared) has limitations in comparison to multi-spectral imagery, but has been successfully used in many classifications (Frescino et al. 2005, Hurd and Civco 2009, Davies et al. 2010, Moskal et al. 2011, Hayes et al. 2014, Maxwell et al. 2014, Gonçalves et al. 2016). This imagery is also increasingly available in relatively high resolution (i.e., 1m) for the entire continental United States through the National Agricultural Imagery Program (NAIP), and occasionally available through state-level programs.

Several studies have made up for the shortcomings of four-band imagery by calculating additional object-based metrics, including texture and shape, from the original spectral bands. Texture metrics describe the variation in a user-defined window around each pixel, and have proven effective in helping to differentiate between land cover classes (Haralick et al. 1973, Hudak and Wessman 1998, Wulder et al. 1998, Thomas et al. 2003, Kluckner et al. 2009, Hayes et al. 2014, Niphadkar et al. 2017). These texture metrics incorporate the differences between adjacent cells and have been shown to improve classification accuracies by up to 10-15% (Franklin et al. 2000). Other studies have successfully used segmentation to assist in differentiating land cover classes (Ryherd S. et al. 1996, Laliberte et al. 2004). This technique groups spectrally similar neighboring pixels and can reduce noise and assist in clarifying edges between class types, especially at finer scales (e.g. Hansen and Ostler 2000, Laliberte and Rango 2009).

Shrub has proven to be a particularly elusive class to isolate from aerial imagery in various landscapes. Due to the relatively small radius of individual shrubs, they are typically not captured in images with large (>1m) pixel size. Shrub is also spectrally similar to forest in moist temperate regions; efforts to classify shrubs in arid landscapes have been more successful (Laliberte and Rango 2009). LiDAR data provides information on the elevation of landscape features and can assist in differentiating shrub from forest (Martinuzzi et al. 2009, Hellesen and

Matikainen 2013). However, LiDAR is often prohibitively expensive and logistically complex for many large-scale studies. For these reasons, many studies that do not require distinction between tree and shrub have grouped these two classes together (Cleve et al. 2008). The lack of shrub cover maps is a major stumbling block in many areas of research, as shrub is an ecologically relevant feature on the landscape. Early successional shrubland, along with the biological diversity it supports, is in decline in areas such as the northeast and mid-Atlantic region of the United States (Askins 2001); correspondingly, species dependent on these habitats have been declining throughout the northeast and mid-Atlantic region (King and Schlossberg 2014), driving a strong interest in managing for these species.

Using freely-available spectral imagery in conjunction with terrain, texture and segmentation metrics, we create an accurate landscape classification map that can assist in land management challenges relating to shrublands in a target region of the central Appalachian Mountains. We describe our methodology here, which is the first to successfully classify shrub in this moist temperate region where shrub and forest are spectrally quite similar, in hopes that this relatively simple and cost-effective approach may be replicated in other similar systems where researchers require custom classifications.

Methods

Study area

We have identified the need for a custom landscape classification in Highland County, Virginia, for use in ongoing research and management projects for the golden winged warbler (*Vermivora chrysoptera*), a declining species of migratory bird. In this region, golden-winged warblers often breed in high-elevation pasture land, where they require shrub cover to successfully nest and fledge offspring (Confer et al. 2003). A map that accurately delineates shrub cover in this region is of paramount importance to management of this and other shrub-dependent species; it will be useful in predicting these species' distributions, obtaining more accurate estimates of population size for focal species, and identifying and prioritizing areas for habitat restoration or maintenance. Existing landcover classifications do not adequately describe the shrub cover on the landscape for the needs of this project, and in fact, the shrub cover class is often missing entirely (Figure 1.1). Our goal was to create a de novo classification including five ecologically relevant classes: shrub, pasture, human infrastructure (houses and roads), water, and forest. This classification used freely available four band imagery as primary inputs, both for budgetary purposes and as a proof of concept. The framework we developed here will ideally be useful for land managers working in similar landscapes.

Highland County (Figure 1.2) is located in the Allegheny Mountains and borders West Virginia. The county is mountainous, with 22% of the landscape greater than 1000m in elevation and mountain ridges running primarily in a southwest to northeast direction. The eastern and western borders of the county include the George Washington and Jefferson National Forest and Monongahela National Forest, respectively, and much of the mountainous terrain in the center of the county is primarily forested. Thirty-six percent of the county is agricultural land situated in the valleys, with the bulk of this land being used for cattle and sheep grazing (Highland County Chamber of Commerce 2011). Shrubs tend to be found along the edges of pasture and expand into pastures when grazing pressure is low as well as in regenerating timber harvests. We define shrub as either (1) persistently low growing species such as blackberry (*rubus* sp.), multiflora rose (*Rosa multiflora*), blueberry (*Vaccinium* sect. *Cyanococcus* sp.), autumn olive (*Elaeagnus umbellata*), elderberry (*Sambuccus nigra*), and barberry (*Berberis* sp.), hawthorn (*Crataegus* sp.), as well as (2) saplings of larger tree species such as walnut (*Juglans* sp.), hackberry (*Celtis occidentalis*), black locust (*Robinia pseudoacacia*), cherry (*Prunus* sp.), maple (*Acer* sp.), apple (*Malus pumila*), crabapple (*Malus* sp.), and hickory (*Carya* sp.) (Albrecht-Malinger, unpublished data).

Highland County presents some unique problems for classification. It is mountainous, which creates shadowed regions in aerial imagery, causing the same land cover class to have different spectral signatures depending on its location on the landscape. To handle this, we incorporated the aspect of the land surface, or the direction that the slope is facing, as an input to our classification scheme. We also subdivided certain land cover classes (e.g. forest) into sun and shade categories.

Imagery and Elevation Data Acquisition

We acquired 1m resolution orthoimagery collected through the National Agricultural Imagery Project (NAIP) from the USGS Earth Explorer (USGS 2015) for Highland County, Virginia as a color-corrected Compressed-County Mosaic (CCM). These data were collected during the leaf-on period (i.e., in the growing season) of 2012 by flyover with digital cameras collecting four-band imagery. We also acquired 1ft resolution leaf-off data (i.e., not during the growing season) for Highland County through the Virginia Base Mapping Program (VBMP) (WorldView Solutions 2011) through the Earth Explorer portal. This is also a four-band image and was collected via flyover with digital camera in March and April of 2011. Though both of the imagery resources are updated every two to three years, we required older imagery for use with our biological data which were collected between 2012 and 2014. Lastly, we acquired 1/3 arc-second (approximately 10m) resolution elevation data for Highland County from the USGS National Elevation Dataset.

Training and Validation Datasets

We created training and validation data sets using the leaf-on and leaf-off high resolution orthoimagery described above. Specifically, we created polygons around areas of known cover types, informed by visual inspection, ground-truthed data (Albrecht-Mallinger and Bulluck 2016), and personal knowledge of the area (Bulluck, Schold). Seven land cover classes (shrub, pasture, human infrastructure, water, mixed/deciduous forest in shade, mixed/deciduous forest in sun, and evergreen forest) were selected for the study, based on spectral characteristics of cover types as well as on future planned uses for the classified landscape for management of shrub-dependent species. Larger polygons were divided into 10m square polygons, and 1000 of these polygons were randomly selected per training class across the entire landscape. These polygons were further randomly divided, with 500 assigned to a training set and 500 assigned to a validation data set (Figure 1.3).

Image processing

We performed image processing in ArcGIS 10.4 (Esri 2016) prior to use in classification. Inputs included 28 individual layers which can be described as either terrain, texture, spectral, or segmented. All imagery was resampled to 1m resolution and aligned with the NAIP imagery prior to further manipulation. Because we are working in a mountainous region, we needed to account for variation in reflectance resulting from differences in slope and aspect. The terrain layers of slope and aspect were calculated from our digital elevation model (DEM) using ArcGIS. A binary aspect class layer was created by reclassifying the aspect layer, with all east-facing cells categorized as a single class and all west-facing cells categorized as a single class. Texture metrics were calculated using the focal statistics tool; layers were generated to describe the range and standard deviation of cells in a 3x3 and 5x5 window around each cell in each of the two scenes (leaf-on and leaf-off). Such texture metrics have been shown to effectively predict patchy, shrubby habitat (Timm and McGarigal 2012), and visual observation of our study area suggested that the texture of shrub would be captured at a 3-5m scale. Segmentation was performed using the segment mean shift tool (Cheng 1995) on both the NAIP and VBMP inputs, producing three separate outputs for the three bands (red, green, and blue) in each of the scenes. Segmentation groups nearby cells sharing similar spectral characteristics and has been shown to reduce graininess in final classifications (Laliberte and Rango 2009). For each scene, we produced two segmented layers with different minimum allowed segment size (8 pixels and 16 pixels). Normalized difference vegetation index (NDVI) was calculated for both NAIP and VBMP imagery. NDVI has been shown to effectively characterize vegetation "greenness" and may help to discriminate shrub, pasture and forest classes (Defries and Townshend 1994). All layers were exported as GeoTIFFs for further processing in the R statistical software (R Core Team 2018).

Classification

We used a Random Forests framework (Breiman 2001) to classify the different land cover types of interest. We chose this classifier for several reasons. First and foremost, Random Forests is a powerful classification tool with high rates of accuracy; further, it can handle large datasets, and is less computationally intensive than methods with comparable accuracy (Gislason et al. 2006). The algorithm is a bootstrapping ensemble method that operates by averaging a large number of randomly generated decision trees for a single final model with low variance and high accuracy (Breiman 2001).

Classification was performed using the randomForests (Breiman and Cutler 2012) and raster (Hijmans et al. 2014) packages in R version 3.4 (R 2017). All processing was performed on the Compile cluster available through Virginia Commonwealth University. The 28 predictor layers and the training polygons described above were used as inputs to the algorithm, and a final classification layer and predictor importance ranking were generated. Several iterations of this process were run as inaccurately classified areas were identified, unimportant predictor layers were removed, and training and validation polygons were revised. We ceased the process upon achieving at least 80% accuracy of all classifications. A visual representation of this work flow can be found in Figure 1.4.

Validation

Validation of classification accuracy was performed through a pixel-to-pixel comparison of the reserved $10m^2$ validation polygons to the classified landscape. Overall accuracy of the classification was calculated, as well as user and producer accuracy for each class. Producer accuracy refers to the number of validation sites classified accurately divided by the total number of validation sites for that class (which is a complement to omission error), while user accuracy is the total number of correct classifications for a particular class divided by the total number of cells for that class (which is a complement to commission error) (Foody 2002).

Results

Classification Accuracy

Seven iterations of training data refinement were required to achieve our final classification. Overall accuracy of the final classified image was 92.4%. Visual examination of focal areas of known suitable habitat showed that shrub was satisfactorily classified (Figure 1.5). Producer and user accuracies for each individual class were between 84.5% and 98.6% (Table 1.1). Common misclassifications included confusion between water and human infrastructure, confusion among forest types, and occasional misclassification of shrub as forest (Table 1.2). We also noted misclassification of pasture as forest on some north-facing slopes in one atypical region of our study area (Figure 1.6).

Predictor Importance

Classification predictors were ranked in importance for determining each class as part of the output of the classification process. Results presented here are from the final classification. (Table 1.3). In previous iterations, we removed six segmented image layers (red, green, and blue layers of leaf-on segmented imagery with a minimum allowed segment size of 8 pixels, and red, green, and blue layers of leaf-off segmented imagery with a minimum allowed segment size of 16 pixels). These layers were removed due to their low ranked importance, redundancy with other segmented layers, and the computational intensity of production.

Notably, texture metrics were within the top 5 predictors for every class, with NAIP 3x3 cell standard deviation ranked within the top 5 predictors for all classes other than shrub and pasture. Segmented spectral imagery was ranked higher than unsegmented imagery for all bands and classes with the exception of the NAIP blue band, which was ranked above the blue segmented layer for all classes other than human infrastructure. Of our terrain metrics, elevation was the only metric included within the top 5 predictors of any class, and was particularly important in classifying shrub, pasture, light forest, and evergreen.

For our focal cover class, shrub, the most important predictors were the green band of segmented leaf-on imagery, the blue band of unsegmented leaf-on imagery, the red band of leaf-off segmented imagery, elevation, and one texture metric describing the range of values within 5x5m in the leaf-off imagery (Table 1.3).

Discussion

The classification has exceeded initial goals of at least 80% accuracy for each land cover class and is more than sufficient for the analysis of avian habitat for which it was initially designed. It represents substantial improvement over previous publicly available land cover classifications for Highland County, especially for applications that require knowledge of shrub distribution on the landscape.

The ranking of the most important predictors for individual land cover classes (Table 1.3) demonstrates the need for considering spectral properties of potential inputs for any classification. Rather than adding all possible inputs, it is most resource-efficient to consider only those inputs which are most likely to inform classification decisions. For future, similar projects in the focal region, we would likely eliminate several of the less important predictors to save time and reduce computational requirements.

Segmented imagery was a better predictor of most classes than unsegmented imagery, with the only exception being the NAIP blue band, which was ranked above the blue segmented layer for all classes other than human infrastructure. Leaf-on segmented imagery proved to be the first-ranked predictor of shrub, shaded forest, and evergreen forest, as well as the second-ranked predictor of pasture, human infrastructure areas, and water. This was somewhat surprising given that shrub and forest often appear similar to each other in the growing season from an aerial view (Figure 1.7A) (Feng et al. 2015), and we anticipated that texture metrics would rank more highly than spectral characteristics in differentiating these classes. However, this finding does highlight the importance of segmentation to our classification. The demonstrated importance of segmentation in this complex focal landscape supports previous studies that show object-based classification is more effective than pixel-based approaches for classifying landforms (Drăguţ and Blaschke 2006) urban areas (Myint et al. 2011), and savanna vegetation (Whiteside et al. 2011). The value of object-based, segmented imagery is that it adds spatial context to spectral information by grouping spectrally similar neighboring pixels (Hussain et al. 2013).

Leaf-off NDVI was unexpectedly the highest-ranked predictor of the pasture class. This is likely due to the dominance of cool-season grasses in our focal region (Figure 1.7B), which stand out spectrally on the otherwise relatively brown leaf-off landscape. Interestingly, neither leaf-on nor leaf-off NDVI was ranked in the top six most important predictors of any classes other than pasture. This result was surprising, as we would expect NDVI to be important in predicting evergreen forest (Defries and Townshend 1994).

Texture metrics were of intermediate importance to our land cover classification. We initially selected several potentially relevant texture metrics and scales, as the literature has suggested that different systems are best classified with differently sized windows (Laliberte et al. 2004, Feng et al. 2015). Given our primary interest in classifying shrubs, we included both range and standard deviation within 3x3m and 5x5m windows. Leaf-off 5x5m range proved to be the fifth most important predictor of shrub, which corresponds with visual observations of small clumps of shrub often appearing as much darker than surrounding pasture in the winter (leaf-off) imagery (Figure 1.7C), thus increasing the range of values within a 5x5m window where shrub is present. Leaf-on 3x3m standard deviation was the most important predictor of water, and the second most important predictor of evergreen forest, likely because these tend to be homogenous landscape features with little variation within a 3x3m window (Figure 1.7D).

Of the terrain-related predictors, elevation was relatively highly ranked for several classes (fourth for shrub, third for pasture, second for light forest, and fifth for dark forest), likely because these classes are more likely to be located at certain elevations in our focal region (Figure 1.7E) (Franklin 1995). Pasture tends to be found in valleys and lower slopes as these areas are easily cleared and worked by farmers for agriculture, while the higher elevation forests tends to be left intact along the ridges. Shrub is found most often at low to mid-elevations, and not along the forested ridges. Likewise, we also expected that slope would be important for classifying land cover in this region because steep areas are unlikely to be cleared of forest or heavily grazed. However, slope was never ranked more highly than the eighth most important predictor for any class. We also expected aspect and aspect class to aid in differentiation between dark and light forest (Figure 1.7F), though these predictors never ranked higher than 18^{th}.

Weaknesses of the Classification

The classifier confused water with human infrastructure areas relatively frequently. This is likely due to the similar spectral properties of roads (particularly dirt roads) and turbulent flowing water in full sun; both have very high albedo and a similar shape. Likewise, small farm ponds have similar spatial arrangement and spectral properties as human structures (i.e., barns and houses). The classifier also mistook some areas of steeper north-facing pasture as forest (Figure 1.6); this is likely because training polygons did not include shadowed pasture, but only flat pasture in full sun. These areas make up a small proportion of the landscape and are therefore of little concern to the current project. Further training of these areas and land cover types would likely remedy these issues.

Validation

We recognize that the clustering of training and validation pixels on the landscape within the same polygons (Figure 1.4) may bias our validation, and that the entire landscape is likely classified less accurately than our validation suggests. We plan to address this issue through random seeding of points across the landscape around which to create training and validation polygons. We will also avoid including subsets from the same polygons in both training and validation data sets.

Classification Uses and Future Directions

This landscape classification was designed with particular attention to the needs of ornithological researchers studying the golden-winged warbler. The high level of classification accuracy of the cover classes of interest (shrub, pasture, and forest) will enable us to examine the relationship of landscape metrics to known distributions and occupancy dynamics of these birds, as well as to predict the likelihood of occurrence in previously unsurveyed areas. Such analyses will uncover the broader scale habitat requirements for this species, which have never been quantified due to the lack of an accurate shrub layer, better enabling land managers to identify potential areas for restoration or conservation. This is a major advancement, as this species is under consideration for the US Endangered Species list, and there are ongoing efforts and funding programs to facilitate habitat creation and management on public and private lands in this region.

There are better data sources for construction of landscape classification maps of complex, shrubby landscapes than were used in the current study, but none that are as readily available and affordable. LiDAR data, which can be used to create a three-dimensional landscape model, is useful in discriminating shrubs from trees and grasses due to differences in feature height (Dalponte et al. 2008, Antonarakis et al. 2008). Higher resolution imagery is almost always preferable (Yu et al. 2006), and, depending on the application, can be necessary for accurate classification (Kalliola and Syrjanen 1991, Harvey and Hill 2001). Multi-spectral and hyper-spectral imagery is also preferable to simple three- or four-band imagery (Robinove 1981). Combining both LiDAR and high-resolution imagery produces the most precise and accurate classifications (Mundt et al. 2006, Ke et al. 2010). The advantages of our classification framework lie in its cost- and labor-efficiency; while perhaps not as accurate as a classification using more expensive source data, the framework compromises with a useful product for the resources expended and is a significant improvement over the complete absence or inaccurate representation of shrub cover in current land cover maps. We anticipate that remote sensing technology will continue to increase in quality and decrease in cost, therefore eventually being within the scope of the majority of researchers and land managers; however, when working on time-sensitive projects, we must work with the best tools available at present.

Our classification system using public domain imagery makes us optimistic for the future of low-cost, accessible classifications for the needs of specific projects. We are already implementing this particular classification framework for 5 more counties in western Virginia for use in golden-winged warbler research and management. The additions of texture and segmentation in a classification framework would likely enable classifications in other ecosystem types containing ecologically important shrub, such as coastal dune ecosystems, heath balds, sagebrush steppes, sage scrub, and grasslands. Thoughtful consideration of the textural and spectral features of the classes of interest, along with biological considerations that may predict or limit the presence of classes in certain locations, can assist in the development of accurate classifications with limited expenditure.

Table 1.1. Producer and user accuracy for each landscape class in this study.

Class	Producer Accuracy	User Accuracy
Shrub	88.3%	89.5%
Pasture	98.0%	98.6%
Human Infrastructure	84.5%	90.3%
Water	96.3%	96.8%
Forest (Light)	96.2%	91.7%
Forest (Shadow)	89.6%	92.1%
Evergreen	87.1%	91.3%

Table 1.2. Validation confusion matrix of correctly and incorrectly classified sites. Values represent the number of 1m cells in each category

		Actual Cover Class							
		Shrub	Pasture	Human Infrastructure	Water	Forest, Light	Forest, Dark	Evergreen	Total
Value in Classification	Shrub	22457	430	170	64	307	1159	512	25099
	Pasture	121	35550	322	4	7	44	12	36060
	Human Infrastructure	126	182	9915	721	31	1	1	10977
	Water	9	1	765	23848	1	2	2	24628
	Forest, Light	476	8	136	9	36698	1493	1214	40034
	Forest, Dark	1783	77	335	56	844	33777	1566	38438
	Evergreen	454	45	95	50	263	1229	22316	24452
	Total	25426	36293	11738	24752	38151	37705	25623	199688

Table 1.3. Variable importance rankings for each predictor layer used in the land cover classification for each land cover type in Highland County, VA. The top five predictor layers for each cover type are highlighted in green. All layers are described in more detail in the methods.

Layer	Shrub	Pasture	Human infrastructure	Water	Light Forest	Dark Forest	Evergreen
NAIP segmented imagery, green band	1	2	2	2	4	1	1
NAIP blue band	2	13	8	5	1	3	4
VBMP segmented imagery, red band	3	7	7	4	3	2	3
Elevation	4	3	6	9	2	11	5
VBMP 5x5 cell range	5	10	13	6	7	8	7
NAIP 3x3 cell standard deviation	6	8	4	1	5	4	2
NAIP red band	7	17	14	11	9	12	8
NAIP segmented imagery, blue band	8	15	3	10	8	14	9
NAIP infrared band	9	5	15	12	12	10	6
VBMP segmented imagery, green band	10	4	1	3	6	6	14
NAIP 5x5 cell standard deviation	11	21	10	16	15	13	11
VBMP green band	12	12	5	13	10	5	12
VBMP blue band	13	16	17	17	17	15	16
Slope	14	14	11	8	14	9	18
VBMP red band	15	6	9	21	16	7	13
NAIP segmented imagery, red band	16	18	12	14	13	17	17
VBMP NDVI	17	1	16	7	11	20	10
NAIP 5x5 cell range	18	9	19	27	19	16	15
NAIP green band	19	19	20	15	18	19	19
VBMP 3x3 cell range	20	22	18	20	21	24	21
NAIP NDVI	21	27	21	26	23	18	25
NAIP 3x3 cell range	22	23	24	23	27	26	27
Aspect	23	26	23	18	28	28	22
VBMP segmented imagery, blue band	24	24	28	25	25	22	20
Aspect Class	25	25	25	24	24	23	23
VBMP 3x3 cell standard deviation	26	11	26	19	20	21	24
VBMP 5x5 cell standard deviation	27	20	27	28	26	25	26
VBMP infrared band	28	28	22	22	22	27	28

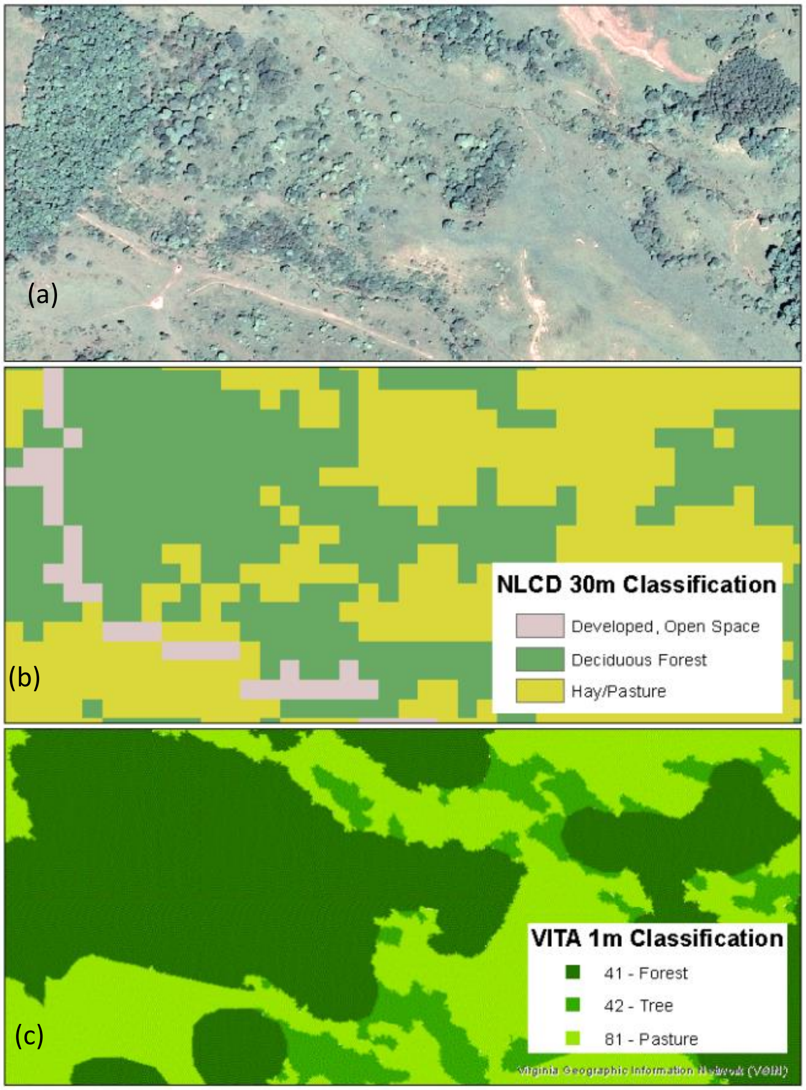

Figure 1.1. Three views of a single extent of potential golden-winged warbler habitat in Highland County, VA, including (a) 1m resolution NAIP imagery from Highland county, VA, (b) the 30m resolution National Land Cover Dataset, and (c) the 1m resolution Virginia Information Technologies Agency classification. Both classification schemes fail to capture any of the shrub cover apparent within the first scene.

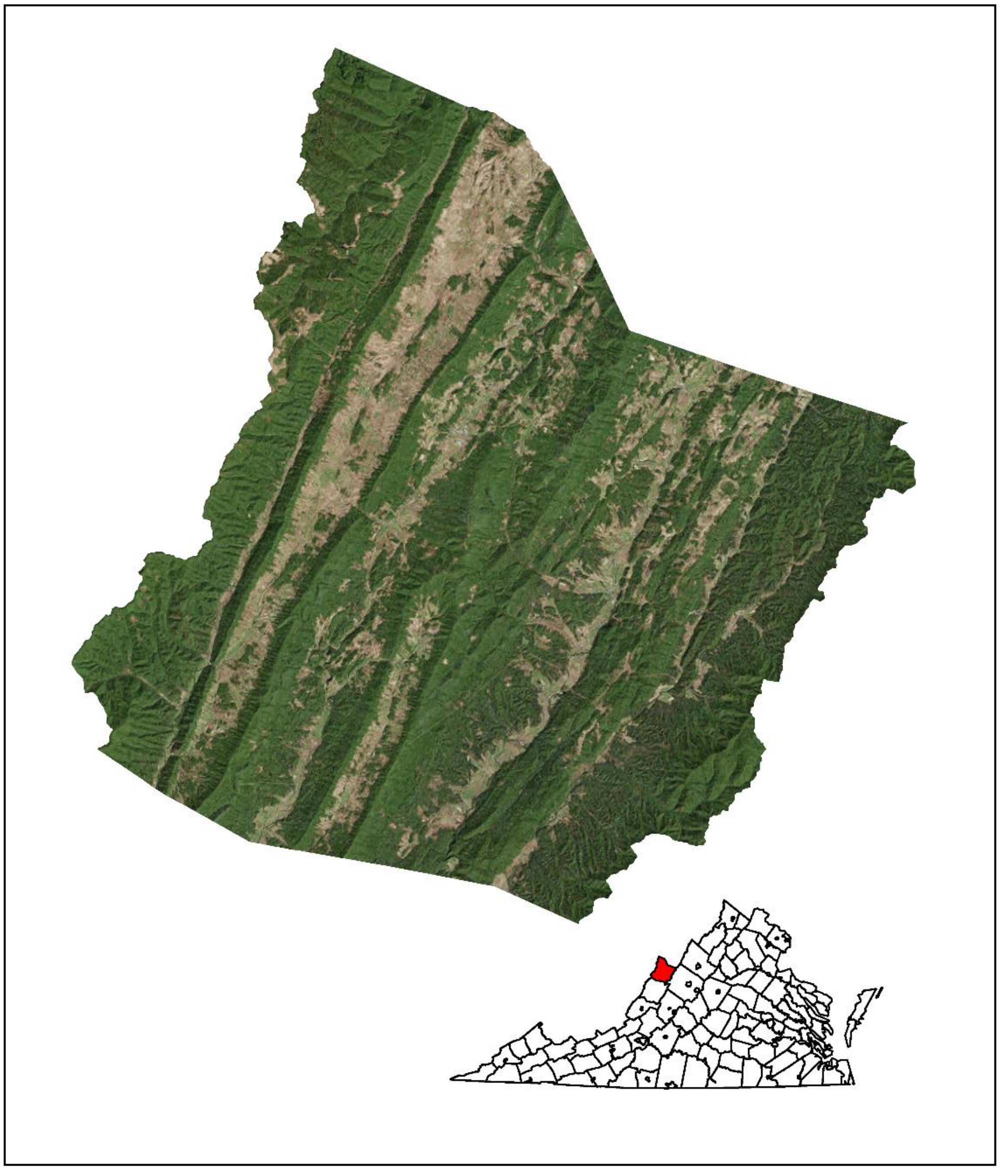

Figure 1.2. Aerial imagery of Highland County, VA, illustrating general regional topography, with green forested mountain ridges running from southwest to northeast and cleared brown/grey pastureland in the valleys between mountains. Red shading in lower-right inset indicates location within the state of Virginia.

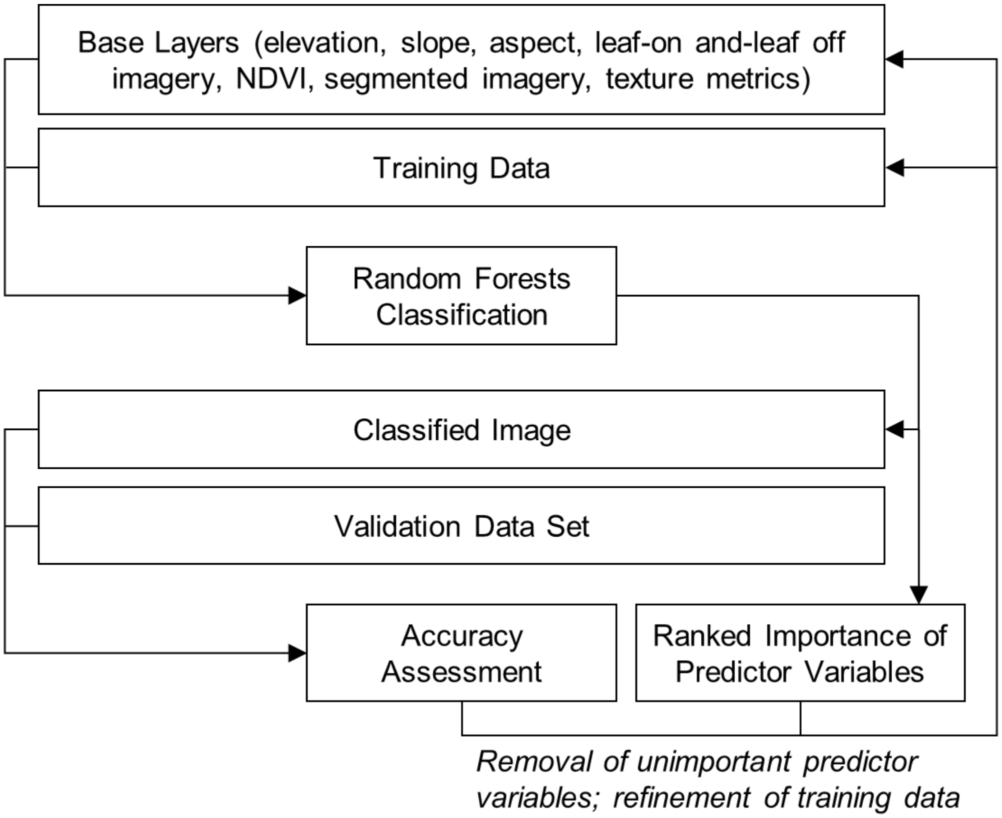

Figure 1.3. Workflow for Random Forests classification.

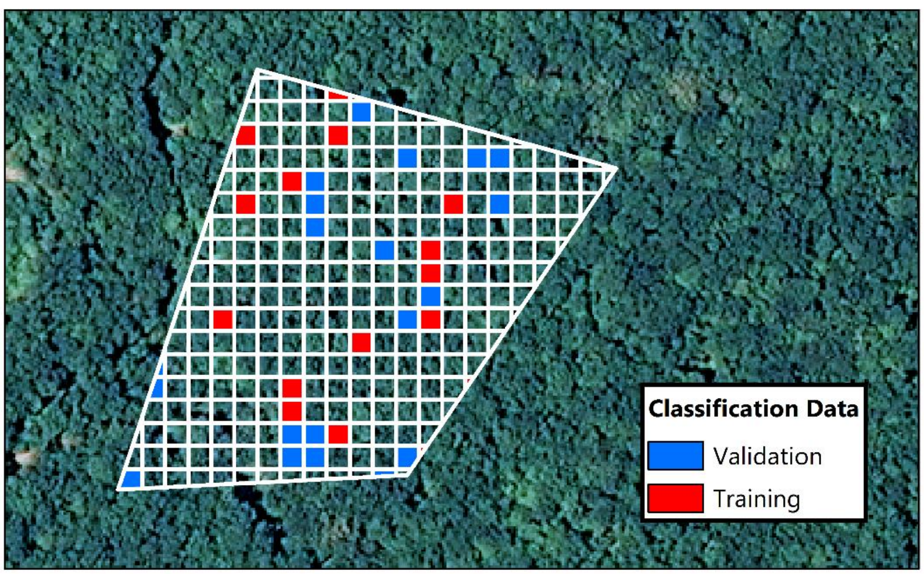

Figure 1.4. Example of polygon division and subsetting in an area of mature forest in Highland County, VA. Each small square represents a 10m x 10m validation (blue) or training (red) polygon. Five hundred training polygons and five hundred validation polygons were created for each land cover class across the landscape.

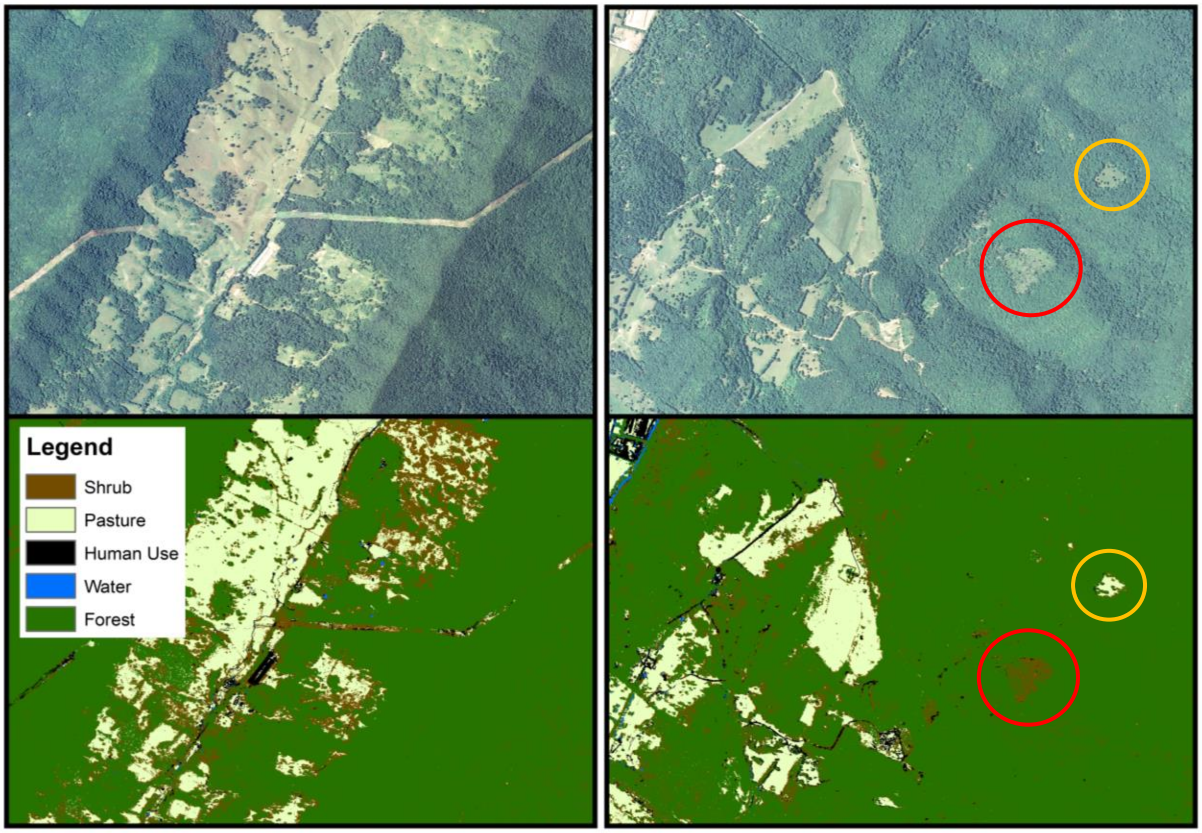

Figure 1.5. Two example landscapes from NAIP imagery and corresponding classification from Highland County, VA where each color represents a certain cover type. The left two panels show an area known to contain a considerable amount of shrubland, correctly identified in the classification. The right two panels show mainly forest with some pasture and human structures as well as two openings in the forest; the first (red circle) is regenerating from a timber harvest and accurately identified as shrub; the second (yellow circle) is maintained as a mowed field with sparse trees, also correctly identified in the classification.

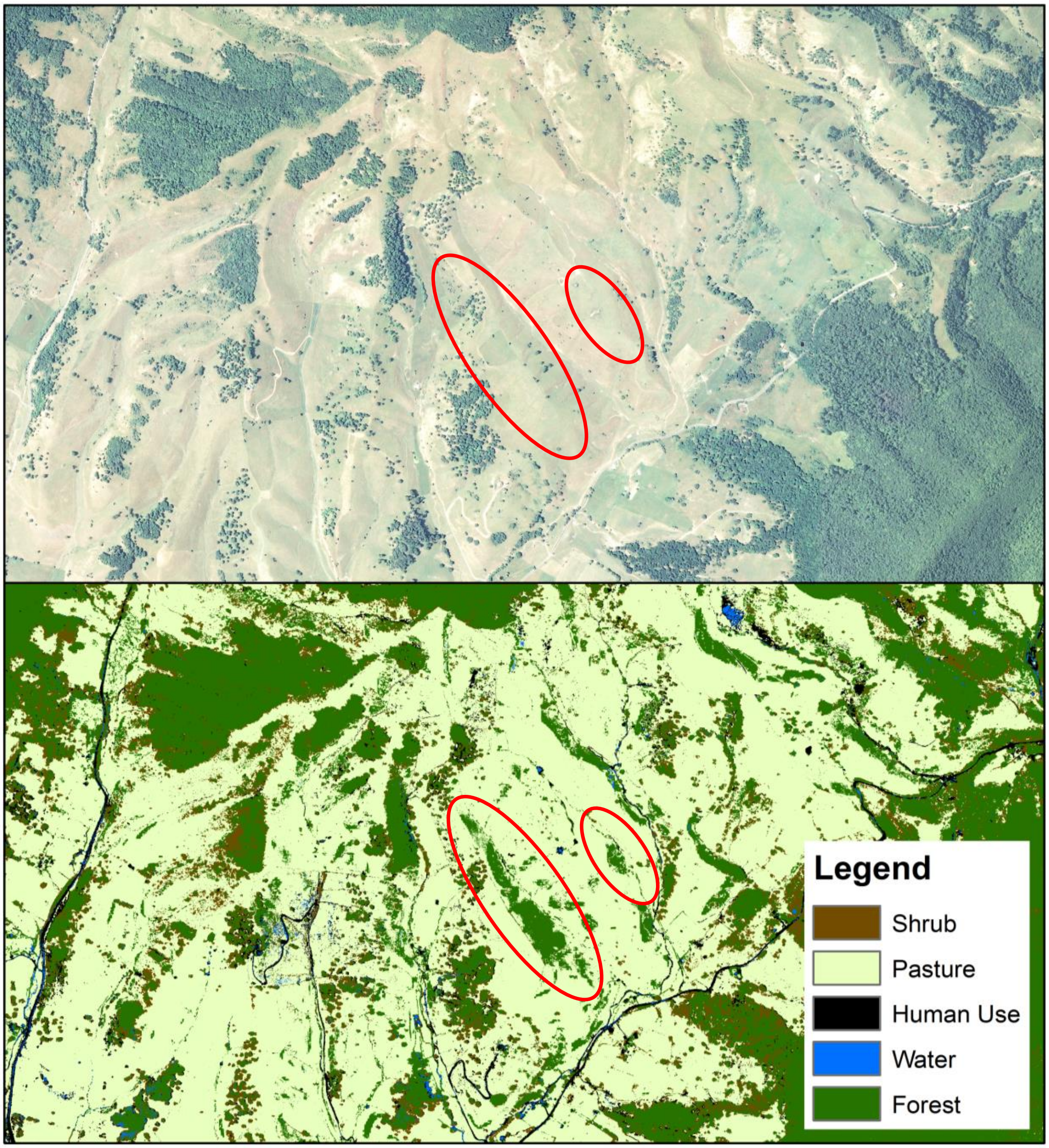

Figure 1.6. Notable areas of poor performance included north-facing pasture slopes (red circles) with some shrub cover, here classified as forest.

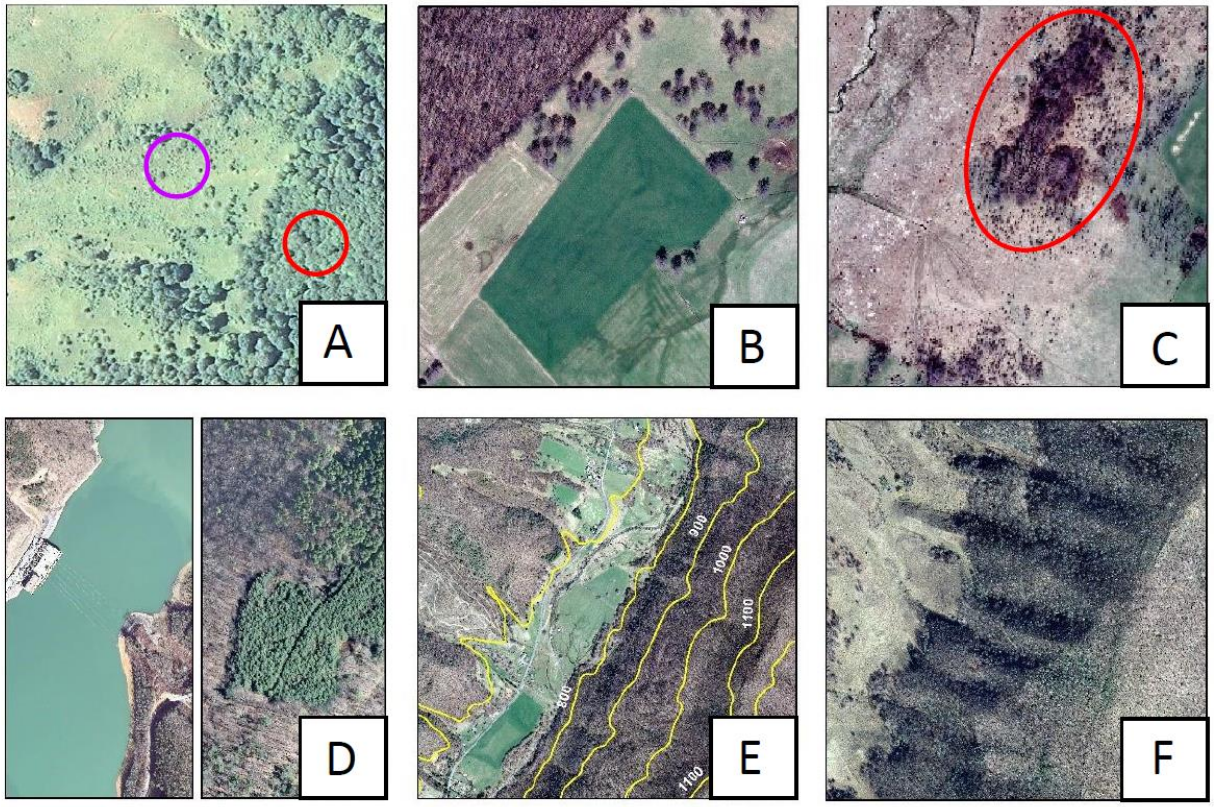

Figure 1.7. Scenes from Highland County, VA, exhibiting various characteristics important when considering classification, including (A) similar spectral characteristics of trees (red circle) and shrub (magenta circle) in leaf-on imagery; (B) presence of cool-season grasses in leaf-off scenes; (C) spectral contrast of shrub (red circle) from background of pasture in leaf-off imagery; (D) visual homogeneity of water (left) and evergreen (right); (E) elevational and topographical restrictions of certain cover classes, such as pasture, which is found only at low elevations and on relatively flat terrain; and (F) spectral differences in shaded and sunny regions of same cover type caused by sun angle and topography.

Chapter 2: Scale-dependent predictors of golden-winged warbler (*Vermivora chrysoptera*) occupancy dynamics in western Virginia

Elizabeth Schold, Dan Albrecht-Mallinger, and Lesley Bulluck, Ph.D.

Expected submission to *The Journal of Wildlife Management*

Abstract

Conservation planning for declining avian species requires an understanding of how landscape level habitat characteristics affect individuals. These habitat effects will often have differing effects at different scales (e.g., nest site scale, territory scale, or foraging area scale). The majority of studies to date have used traditional ground vegetation surveys to identify factors that predict occurrence of individuals at a site. We use a custom landscape classification with fine (1m) resolution to assess the association of landscape characteristics of interest at multiple scales with probability of site occupancy and persistence by the golden-winged warbler, a shrub-dependent species of conservation concern. We expected that shrub characteristics would be important at small scales used for nesting, while forest characteristics would be important at larger scales used for foraging and fledgling dispersal. Using data collected from three years of point counts across high elevation pasture lands in Highland County, VA, we developed and tested occupancy, colonization, and extinction models in an information theoretic framework. While our initial predictions about factors important at different scales were correct, we also found evidence that birds prefer a more homogenous landscape at smaller scales and a more diverse landscape at larger scales. We anticipate that the findings of this study will provide

helpful information for land managers seeking to improve habitat for golden-winged warblers in the southern Appalachians.

Introduction

Conservation of declining species requires a thorough understanding of how landscape composition and complexity influence their distribution. For decades, studies have examined how vegetation characteristics may affect wildlife abundance or occurrence (Macarthur and Macarthur 1961, James and Shugart 1970), which is of critical importance considering that habitat loss has been recognized as the leading cause of species decline worldwide (Sala et al. 2009). These studies have traditionally prioritized the role of fine scale vegetation structure (i.e., within patch, 11.3m radius plot) rather than broader scale habitat features such as landscape composition and complexity. This level of detail can be informative, especially in understanding how vegetation impacts a particular activity, such as nesting or foraging; however, it fails to capture larger scale variation which can be particularly important at broader scales of habitat selection (Mayor et al. 2009). Further, species that use different components of a landscape for different purposes (habitat complementation) are likely to use larger scale patterns when selecting habitat. For example, some bird species require mature forest for breeding, and young dense forests for the post breeding period when predation rates are highest (Pacen 2000, King et al. 2009); such species will therefore prefer to breed in landscapes where a mix of forest age classes are available. Management practices that focus on landscape composition will be more effective for these species than those that focus solely on fine scale vegetation structure.

More recently, as spatial data and the technology to analyze those data have become readily available, studies have investigated how characteristics at scales of hectares or square kilometers influence species occurrence dynamics (Thogmartin 2010, Lee and Carroll 2014). Understanding vegetation characteristics at both the within-patch and broader landscape scales can provide a more complete picture of the habitat needs of threatened species and provide important information for land managers. For example, thresholds in habitat use are more likely to emerge where the affinity for certain characteristics may be important at one scale but not at another (Leblond et al. 2011). Despite widespread recognition of the value of multi-scale habitat assessments, explicitly assessing the scale dependence of habitat selection is rarely done in practice (McGarigal et al. 2016). Another advantage of the availability of landscape-scale data is the ability to assess not only the amount of certain habitat types, but also the arrangement, or spatial complexity, of those habitat types. This is especially important where species rely on complex mosaics of habitats within a landscape, as is the case for many species that rely on early successional shrublands during part or all of their annual cycle (Askins 2001).

Early successional habitats are of key importance to the golden-winged warbler, a shrubland-dependent species of significant conservation concern that is currently being considered for federal protection under the Endangered Species Act (Lyder 2011). The golden-winged warbler is declining across its breeding range in eastern North America, but populations in the southern Appalachian region are showing particularly concerning patterns (8.5% annual declines, versus 2.6% range-wide) (Sauer et al. 2011) and have been listed as a Tier 1 species of greatest conservation need by the Virginia Wildlife Action plan (VDGIF 2015). This species occupies habitats with a complex mosaic of cover types that includes shrubs, saplings, grasses and forbs within a forested landscape (Buehler et al. 2007). It is well known that these birds rely on shrub cover when constructing their nests (Klaus and Buehler 2001, Confer et al. 2003, Bulluck and Buehler 2008). Recent telemetry studies tracking adults and fledglings in Minnesota demonstrated that golden-winged warblers in both life stages will use mature forest habitat (Streby et al. 2012, Streby and Andersen 2013a). Despite a significant amount of research effort in recent years on this declining species, very few studies have assessed landscape level habitat patterns and none have assessed whether habitat composition and complexity predict changes in occupancy over time. This is likely due in part to the absence of maps that accurately show the location of shrub cover. Shrubs are often misclassified as forests or grassland in most national and state-level land cover classifications (Cleve et al. 2008). With the creation of a new 1m resolution land cover classification (Chapter 1), it is now possible to model how broader-scale habitat characteristics predict golden-winged warbler site occupancy, as well as changes in occupancy over time (i.e., probability of local colonization and extinction).

Occupancy modeling is a useful tool for assessing the probability of species occurrence within a given area, as it takes into account detection probability, thus accounting for the fact that observers will not always detect an animal present in a surveyed area (Thompson et al. 1998, MacKenzie et al. 2002, Lancia et al. 2005). Dynamic occupancy modeling takes multiple surveys into account over the course of a single breeding season and/or across years and can model how birds move between sampling locations (Betts et al. 2008, Frey et al. 2012). These models produce estimates of detection and site occupancy, as in traditional occupancy modeling, but also provide estimates of colonization and extinction rates as a function of habitat covariates. While a high probability of occupancy at a site may be an indicator of suitable habitat, continuous occupancy, or persistence – as assessed with colonization and extinction models – may also illustrate factors that cause sites to be less suitable and therefore only occupied sporadically.

In this study, we examine whether relatively broad scale patterns in habitat features predict the probability of golden-winged warbler site occupancy, as well as the probability of site colonization and extinction between survey years. Landscape metrics are best assessed at biologically meaningful scales; we expect that some characteristics may be important at more local scales (100m), while others are important at broader scales (500m). The 100m radius is approximately the size of a golden-winged warbler breeding territory (~3ha) (Streby et al. 2012). The 500m radius represents the area a single adult bird might reasonably venture from its territory to nearby resources (Streby and Andersen 2013a) and that a fledgling will disperse when still reliant on parental care (Streby et al. 2012). Based on what we know of the breeding biology of golden-winged warblers, we expect that shrub characteristics (both amount and complexity of shrub cover) will be important at the smaller 100m scale, while forest cover will be important at the broader 500m scale. Relating occupancy dynamics to land cover composition and heterogeneity at these different scales will provide valuable information about the scale at which habitat attributes are most important for golden-winged warblers.

Methods

Study Area

This work was conducted in Highland County, Virginia, located in the Allegheny Mountains on the border with West Virginia. Twenty-two percent of the county is higher than 1000m in elevation, and the landscape is a mosaic of forest and agricultural land, primarily under private ownership (Highland County Chamber of Commerce 2011). High-elevation pasturelands in the region frequently contain shrubby patches consisting of persistently low growing species such as blackberry (*Rubus* sp.), multiflora rose (*Rosa multiflora*), blueberry (*Vaccinium* sect. *Cyanococcus* sp.), autumn olive (*Elaeagnus umbellata*), elderberry (*Sambucus nigra*.), and barberry (*Berberis* sp.); as well as saplings of larger tree species such as hawthorn (*Crataegus* sp.), walnut (*Juglans* sp.), hackberry (*Celtis occidentalis*), black locust (*Robinia pseudoacacia*), cherry (*Prunus* sp.), maple (*Acer* sp.), apple (*Malus pumila*), crabapple (*Malus* sp.), and hickory (*Carya* sp.) (Albrecht-Malinger, unpublished data).

Point Count Surveys

Our analyses utilized point count data that were collected for a previous study of golden-winged warblers (Albrecht-Mallinger and Bulluck 2016). These data were collected throughout Highland County in habitat on private lands that could potentially support breeding golden-winged warblers, defined as greater than 600m in elevation with at least 30% shrub cover. Fixed radius point count surveys (100m) were conducted during the breeding seasons (April 28 – June 18) of 2012 – 2014 at 173 points across 60 private properties each year (Figure 2.1). Each point was surveyed three times over the course of each season to account for potential within-season variation in detection. Points were placed at least 200-300m apart to ensure there was no double counting of individuals at more than one point, a decision informed by the average golden-winged warbler breeding territory size (approximately 3ha) (Streby et al. 2012). Point counts were 9 minutes in duration and included two periods of golden-winged warbler male song being broadcast. The broadcast of male song during surveys is warranted for cryptic species with low detection probability such as the golden-winged warbler as it significantly increases the likelihood of detection (Kubel and Yahner 2007, Aldinger and Wood 2014, McNeil et al. 2014).

Landscape Metrics

Using ArcGIS version 10.4 (Esri 2016), we created 100m and 500m buffers around each of the 173 surveyed points, for a total of 346 polygons of interest. We then clipped a 1m resolution landscape classification raster (Chapter 1) to each polygon. The landscape classification included areas defined as shrub, pasture, human infrastructure (roads and buildings), water, and forest. The resulting 346 rasters were exported to Fragstats version 4.2.1 (MacGarigal and Marks 1995) in order to calculate class and landscape level metrics within the buffers around each survey point. We wanted to determine whether landscape composition and/or landscape complexity were important for predicting golden-winged warbler occupancy dynamics and therefore focused on metrics that we thought best characterized these factors (Table 2.1). Landscape composition metrics consisted of percent of the landscape composed of shrub and percentage of the landscape composed of forest; landscape complexity metrics consisted of a shrub clumpiness index, which represents the degree of shrub dispersion/aggregation, and Simpson's diversity index for richness and evenness of cover types. After calculating these metrics, they were summarized and assessed for variation. Because many of the outputs from Fragstats tend to be highly correlated, all metrics were assessed for co-linearity and variables with r values > |0.7| (Dormann et al. 2013) were noted and not included within the same model. The remaining variables were used to develop occupancy models.

O*ccupancy Modeling*

Dynamic occupancy models estimate the probability of site occupancy, colonization and local extinction as a function of covariates (MacKenzie et al. 2003). We developed multi-season occupancy models using the colext function (Kéry and Chandler 2012) in Package Unmarked (Fiske and Chandler 2011) in program R (R 2017). The three annual surveys (2012-2014) were considered the primary sample periods between which extinction and colonization are possible, and the three surveys within each breeding season were the secondary sample periods, with an assumption of population closure (no extinction or colonization) during that time. All observation- and site-level covariates were normalized for better model convergence, and then back-transformed for model interpretation and visualization. We compared candidate models using the Akaike Information Criterion (AIC) (Akaike 1974).

One major benefit of occupancy models is that researchers can explicitly model variation in detection probability and incorporate that variation into models of occupancy. We tested five linear detection models with the following covariates: time of day, day of year, temperature, percent forest cover within the 100m survey radius, and viewshed within the 100m survey radius. Time of day and day of year are known factors that can impact detection probability of songbirds as they typically sing less later in the day and later in the season; temperature may also impact detection, particularly on cold mornings when birds may sing less often (Nichols et al. 2000, Nadeau et al. 2008, Conway and Gibbs 2011). Forest cover may impact detection as birds foraging in or along forest edges may be seen and heard less frequently than those foraging in more open habitats. Viewshed is the proportion of the point count radius that was visible to the observer based on topography and was calculated using a digital elevation model in ArcGIS (Esri 2016). We hypothesized that birds may be less likely to be detected in point count locations where a larger portion of the count radius is not visible. The best model for detection probability was then incorporated into all models of occupancy, colonization, and extinction.

We developed separate models to predict the probability of occupancy, extinction, and colonization for each of our two focal scales (100m and 500m). We included linear and quadratic functions for all landscape variables listed in Table 2.1. We used quadratic functions because we expected there may be some non-linear relationships and/or optimal ranges for some landscape metrics. All univariate models (i.e., only including one variable for each response) were tested, as well as null and global models. We also tested models including additive effects and interaction terms between the covariates from all univariate models performing better than the null model. The best model for occupancy at each scale was incorporated into models of colonization and extinction at the same scale.

Results

All landscape metrics used in these analyses were calculated and examined for variation across sites (Table 2.2). Before incorporating landscape metrics into potential occupancy, colonization, and extinction models, we assessed all potential variables for co-linearity at each of our scales. There were no correlations with $r > |0.7|$.

Detection Probability Models

The best supported model for detection probability incorporated percent forest cover within a 100m radius of the point (Table 2.3, Table 2.4). In the absence of forest cover, detection probability was 72.2%, and declined linearly with increasing percentage of forest cover within the survey radius (Figure 2.2). The impact of forest cover on detection probability was carried forward into all further models.

Occupancy Modeling

At the 100m scale, the best supported model using only single predictors included the shrub clumpiness index; however, this model performed only slightly better than the other top performing models. We proceeded to develop models incorporating additive and interaction terms between our predictors from all models performing better than the null model. An additive model incorporating percent shrub cover and Simpson's diversity index performed best, and a model incorporating an interaction between percent shrub cover and Simpson's diversity index performed similarly (ΔAIC = 1.43, Table 2.5). Because these models do not differ markedly (both indicate a positive relationship between shrub cover and the probability of occupancy that varies with the diversity of cover types) (Table 2.3), we present the simpler additive model that performs best. The positive relationship between shrub cover and golden-winged warbler occupancy is strongest when the diversity of cover types is high (i.e., a 100m radius includes forest, pasture, shrub and water/human infrastructure) and weakest when the diversity of cover types is low (i.e., a 100m radius includes just shrub and pasture) (Figure 2.3). There is a negative relationship between Simpson's diversity index and probability of occupancy at this scale such that occupancy is uniformly high when the diversity of cover types is low (Figure 2.3).

At the 500m scale, the top ranked occupancy model was the global additive model which included all four landscape variables (Table 2.6) where Simpson's diversity index, shrub clumpiness and percent forest cover were all significantly positively associated with golden-winged warbler site occupancy (Table 2.3, Figure 2.4, panels A-C). Percent shrub cover was not a significant predictor of occupancy ($p = 0.99$) at this scale. The second ranked model (ΔAIC = 2.89) incorporated percent forest cover as a quadratic term with the maximum probability of golden-winged warbler site occupancy between 40-60% forest cover within a 500m radius around the survey location (Figure 2.4, panel D).

Colonization and Extinction

In our system, 22.0% of our sites experienced a likely colonization, while 32.4% experienced a likely extinction. No models of golden-winged warbler site colonization between survey years ranked better than the null model at the 100m scale (Table 2.7) or the 500m scale (Table 2.8). However, the highest ranked model for site extinction between survey years at the 100m scale incorporated percent shrub cover (Table 2.9), indicating that the probability of golden-winged warbler site extinction decreases as shrub cover increases within the survey radius (Table 2.3). Specifically, sites have an approximately 0.25 probability of extinction when shrub cover is less than 10% and approaches 0 as shrub cover is greater 40% within 100m around the survey location (Figure 2.5).

At the 500m scale, the top ranked model predicting golden-winged warbler site extinction was the global additive model (Table 2.10); however, percent forest cover was the only significant predictor in that model, having a negative relationship with probability of occupancy (Table 2.3, Figure 2.6a). The second ranked extinction model at 500m included only a quadratic percent forest cover term, with the probability of site extinction decreasing with increasing percent forest cover up to about 40% forest cover at which point the probability of site extinction is very low. Though there is a slight apparent increase in the probability of extinction with high (>80%) forest cover, this may be a function of the large standard error (and low sample size) at these extreme values. (Figure 2.6b).

Discussion

This study has confirmed the importance of land cover characteristics at multiple scales when investigating predictors of occupancy and persistence. Generally, as expected, we found that shrub characteristics best predicted occupancy at the 100m scale, and that forest characteristics best predicted occupancy at the 500m scale. Interestingly, this trend was complicated by diversity of cover types – at the smaller scale, high land cover diversity reduced the probability of occupancy, while the opposite was true at the 500m scale. We found no support for any colonization models at either scale. The best extinction models mirrored our findings for occupancy, with shrub cover being important at smaller scales and forest cover being important at larger scales. In considering colonization and extinction, it is important to note that golden-winged warblers tend to have high site fidelity (Confer 1992, Schlossberg 2009, Albrecht-Mallinger and Bulluck 2016). Site extinction typically occurs only with mortality or if a pair experienced low nest success and therefore does not return the following year. Site colonization typically occurs either when a second-year bird is looking for a territory for its first breeding season or when a bird previously experienced low nest success and is seeking a better territory.

Detection Probability

Our best model for detection probability incorporated percent forest cover within the 100m survey radius, with detection probability declining with higher forest cover. While this is an intuitive finding, it highlights the potential importance of incorporating spatial land cover data into detection modeling. This technique seems to be more common in literature concerning visual detection of mammals (Belt and Krausman 2012, Ransom et al. 2012). Few ornithological studies to date have incorporated such covariates into detection models and many researchers could therefore potentially be over- or underestimating detection probabilities, and this will bias the resulting probabilities of site occupancy. While this result does not negate the well-known impact of factors such as time of day, date, and temperature on detection probability (Nichols et al. 2000, Nadeau et al. 2008, Conway and Gibbs 2011), we recommend also exploring spatial factors that could potentially have an impact.

Occupancy and Extinction at the 100m scale

At the 100m scale, our most supported model predicting occupancy incorporated shrub cover as well as Simpson's diversity index of cover types (Figure 2.3). As hypothesized, shrub was important in predicting occupancy, supporting the idea that shrub cover is important within a defensible territory used for nesting, as found in multiple other studies (Confer and Knapp 1981, Confer et al. 2003, Askins et al. 2007, Bulluck and Harding 2010). However, the relationship between shrub cover and predicted occupancy was not as strong when diversity of cover types was low. Areas with low diversity of cover types typically only contained shrub and pasture; when a relatively high diversity of cover types was present, the other classes beyond shrub and pasture were typically forest, and less often human infrastructure and water. Therefore, it appears that the amount of shrub cover is a more important predictor of occupancy when cover types unsuitable for nesting (primarily forest, but also including human infrastructure and water) are present in a potential nesting area.

Extinction at the 100m scale was also best predicted by percent shrub cover in the landscape, with less shrub cover predicting a higher probability of extinction. This may indicate that low shrub cover is indicative of reduced breeding success, as found in previous studies (Confer et al. 2003, Bulluck and Buehler 2008), leading birds to seek new territories in future breeding seasons. This is in line with what we know of golden-winged warbler breeding biology, as shrub has proven to be a key factor in predicting occupancy and nest success in many studies (Bulluck and Harding 2010, Bakermans et al. 2015, Leuenberger et al. 2017), though no studies to date have demonstrated this relationship at a broader spatial scale or using remotely sensed land cover metrics as we have done here.

Occupancy and Extinction at the 500m scale

At the 500m scale, our best supported model predicting golden-winged warbler site occupancy incorporated all four of our land cover variables. Out of these four terms, percent forest, shrub clumpiness, and diversity of cover types all had significant, positive relationships with probability of occupancy. This supports previous knowledge of the importance of forest for breeding season behaviors of golden-winged warblers, as adults have been shown to forage in forest edges and fledglings tend to disperse into forested areas (Streby et al. 2012, Streby and Andersen 2013a). Shrub clumpiness is, interestingly, important at the 500m scale, where it was not important at the 100m scale in which shrub attributes were hypothesized to best predict occupancy. This may be related to the distribution of shrub on the landscape. The edges of forests in our study area often have contiguous shrubby edges; therefore, the importance of shrub clumpiness may actually be an indicator of the importance of forest edges, which tend to have higher densities of insect prey (Helle and Muona 1985, Winnet-Murray 1986, Murcia 1995), and have been shown to be associated with golden-winged warbler territories (Rossell et al. 2003).

Greater diversity of cover types predicts higher occupancy at the 500m scale, while the opposite is true at the smaller 100m scale. This suggests that having a more even distribution of forest, shrub, and pasture (the three main cover types on the landscape) within a 500m radius area is an indicator of suitable habitat, potentially providing enough shrub for successful nesting as well as enough forest for foraging and dispersal of fledglings. At the 100m radius scale, a high diversity of cover types implies less of the preferred nesting habitat – shrub – and more habitat unsuitable for nesting (mainly forest, but also including water and human infrastructure). These findings, both for occupancy being linked to increased shrub aggregation and more cover types, highlights the importance of habitat complexity at the larger 500m scale.

The second best supported model of golden-winged warbler site occupancy at the 500m scale is also potentially informative of the habitat needs of golden-winged warblers. This model suggests that within a 500m radius, these birds require approximately 50% of their habitat to be forested (i.e., approximately 40ha within an 80ha area). This knowledge provides a clear, easily implemented recommendation for land management practices to increase the likelihood of golden-winged warbler occurrence.

At the 500m scale, the top-ranked extinction model was the global additive model, including percent shrub cover, percent forest cover, shrub clumpiness, and Simpson's diversity index. Out of these terms, however, only percent forest proved significant ($p < 0.05$), with a negative relationship between forest cover and probability of extinction. This model implies that at this broader scale, birds are less likely to return to breed at a site if there is not sufficient forest cover. The second-ranked model for site extinction at the 500m scale incorporated percent forest cover squared. The probability of extinction is highest when percent forest cover is less than approximately 40% of a 500m radius area. There is also a slight trend toward higher probability of extinction when forest cover is greater than 80%, though not as exaggerated a trend as when forest cover is low. This is likely due to the fact that very few of our survey locations (N = 4) had forest cover >80%. This finding expands upon the results of our top 500m scale occupancy model, demonstrating that forest cover is important not only for occupancy, but also for persistence.

Future Directions

This study is the first to model how broad scale land cover metrics influence the occupancy dynamics of the golden-winged warbler, a species of high conservation concern and for which management recommendations at these scales have been lacking or based on anecdotal observations. Despite the importance of this study, there is room for improvement in future iterations. None of our colonization models had more support than the null model, indicating that none of the landscape metrics we examined affect colonization at the scales we examined. Colonization may be driven by interactions with blue-winged warblers, which hybridize with and compete with golden-winged warblers on the breeding grounds. Studies of landscape partitioning between the two species suggest that golden-winged warblers prefer higher elevation habitats (Welton 2003, Patton et al. 2010) than blue-winged warblers. As the blue-winged warbler range expands and as climate change influences temperature and rainfall at higher elevations, golden-winged warblers may be pushed into higher elevation sites. We would recommend incorporating site elevation into future colonization models. The scale at which we examined potential variables may also have been an issue, as birds selecting habitat may do so based on scales that are broader than 500m, as has been demonstrated for other species (Wiens et al. 1987, Orians and Wittenberger 1991, Mayor et al. 2009, Harms et al. 2017). However, our point count locations are too close to warrant broader buffers that would overlap considerably and therefore decrease independence among survey points.

We also recommend that future studies assess the influence of golden-winged warbler site occupancy at nearby points by including a spatial autocovariate (Lee and Carroll 2014). Birds will often interpret the presence of conspecifics as an indicator of suitable habitat, and there is some evidence that golden-winged warblers, in particular, may be more likely to breed in areas near conspecifics (Albrecht-Mallinger and Bulluck 2016). Accounting for such spatial autocorrelation will lead to improved model estimates (Betts et al. 2006).

While the results of this study can likely be extended to other Appalachian regions where pasture is an important component of the habitat (e.g., West Virginia, North Carolina), they may not be applicable to areas of the Great Lakes region. Future studies should test the ability of these models to predict occupancy dynamics in these other regions, though the lack of shrub cover maps likely precludes this in the near term.

Management Implications

As funding for conservation of non-game avian species is extremely limited, it is important to have as much information as possible to make informed decisions about how to invest resources. The findings of this study have clear and important management implications for golden-winged warblers. It is apparent that golden-winged warblers require significant forested areas within their breeding season habitat, as has been suggested, but never quantified, in previous studies from the Great Lakes region (Streby et al. 2012, Streby and Andersen 2013b). Additionally, this study has confirmed the importance of shrub at smaller scales. We show here that these land cover characteristics promote not only occurrence of golden-winged warblers on the breeding grounds, but also persistence between years. We have also found that *diversity* of cover types is a strong predictor of occurrence, with low diversity of cover types predicting higher occupancy at smaller scales and high diversity of cover types predicting higher occupancy at larger scales.

Our findings can assist land managers in setting restoration goals and prioritizing potential restoration sites. The golden-winged warbler is a focal species in an ongoing effort to create and maintain habitat on private lands (Working Lands for Wildlife) that is funded by the Natural Resources Conservation Service. Using the findings of this study in conjunction with our land cover classification, identification of potentially occupied areas that have not yet been surveyed should be possible, which is particularly important in our study system, as the majority of golden-winged warbler habitat is found on private lands. We hope that our model results will assist land managers in seeking sites important to not only golden-winged warblers, but other focal shrubland species as well as identifying potential landowner restoration partners.

Table 2.1. Landscape metrics used as predictors for the probability of site occupancy, colonization and extinction, calculated separately for 100m and 500m scales.

Landscape Metric	Description
Percentage Shrub	The percentage of pixels within a raster classified as shrub.
Percentage Forest	The percentage of pixels within a raster classified as forest.
Shrub Clumpiness Index	A metric of the aggregation of shrub pixels, where a value of 1 indicates maximum aggregation, a value of -1 indicates maximum disaggregation, and a value of 0 indicates random distribution of shrub pixels.
Simpson's Diversity Index	A measure of richness and evenness of cover classes within a raster, where a value of 0 indicates minimum diversity (dominated by one cover type) and a value of 1 indicates maximum diversity (even mix of five different land cover types).

Table 2.2. Summary of all landscape metrics used in creating and testing detection, occupancy, colonization and extinction models for golden-winged warblers in Highland County, VA. Detection covariates describe the area within the 100m fixed radius point count.

Landscape Metric	Mean	Standard Error	Minimum	Maximum
Detection covariates				
Visibility	0.540	0.014	0.101	0.993
Percent Forest Cover	39.331	1.435	5.057	90.644
100m radius patch covariates				
Percent Shrub Cover	24.582	0.945	3.973	60.642
Percent Forest Cover	39.331	1.435	5.057	90.644
Shrub Clumpiness Index	0.618	0.004	0.449	0.778
Simpson's Diversity Index	0.598	0.008	0.171	0.742
500m radius patch covariates				
Percent Shrub Cover	16.307	0.552	3.658	34.647
Percent Forest Cover	47.788	1.286	9.200	83.970
Shrub Clumpiness Index	0.635	0.004	0.525	0.802
Simpson's Diversity Index	0.581	0.007	0.280	0.731

Table 2.3. Parameter estimates for most supported models of golden-winged warbler detection, site occupancy and site extinction models.

Term	Estimate	Standard Error	p
Detection			
Intercept	0.545	0.0779	<0.001
Percent Forest	-0.204	0.0750	<0.01
100m Occupancy			
Intercept	0.815	0.184	<0.001
Simpson's Diversity Index	-0.555	0.225	<0.05
Percent Shrub	0.538	0.219	<0.05
100m Extinction			
Intercept	-1.88	0.253	<0.001
Percent Shrub	-0.580	0.273	<0.05
500m Occupancy – Global			
Intercept	0.854	0.195	<0.001
Percent Shrub	-0.005	0.295	0.99
Percent Forest	0.872	0.297	<0.01
Shrub Clumpiness Index	0.589	0.272	<0.05
Simpson's Diversity Index	0.956	0.338	<0.01
500m Occupancy – (Forest Cover)^2			
Intercept	1.442	0.270	<0.001
Percent Forest	0.231	0.179	<0.05
(Percent Forest)^2	-0.636	0.172	<0.001
500m Extinction - Global			
Intercept	-2.155	0.471	<0.001
Percent Shrub	-0.680	0.474	0.15
Percent Forest	-1.182	0.411	<0.05
Shrub Clumpiness Index	0.058	0.393	0.88
Simpson's Diversity Index	-0.139	0.887	0.88
500m Extinction – (Forest Cover)^2			
Intercept	-2.462	0.386	<0.001
Percent Forest	-0.716	0.323	<0.05
(Percent Forest)^2	0.514	0.302	<0.05

Table 2.4. Model selection results for factors influencing golden-winged warbler detection probability in surveys carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AIC Weight	Cumulative Weight
Percent Forest	1694.86	0.00	0.708	0.71
Date	1698.25	3.39	0.130	0.84
Null	1700.15	5.29	0.050	0.89
Viewshed	1700.31	5.45	0.046	0.93
Time of Day	1700.39	5.53	0.044	0.98
Temperature	1701.89	7.03	0.021	1.00

Table 2.5. Model selection results for factors influencing golden-winged warbler occupancy within a 100m radius around survey locations carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AICwt	Cumulative Weight
Simpson's Diversity Index + Percent Shrub	1688.95	0.00	0.42	0.42
Simpson's Diversity Index * Percent Shrub	1690.38	1.43	0.20	0.62
Simpson's Diversity Index + Percent Shrub + Shrub Clumpiness Index + Percent Forest	1692.86	3.91	0.06	0.68
(Shrub Clumpiness Index)^2	1693.41	4.46	0.04	0.72
Simpson's Diversity Index + (Shrub Clumpiness Index)^2	1693.54	4.59	0.04	0.76
Simpson's Diversity Index * (Shrub Clumpiness Index)^2	1695.54	4.59	0.04	0.81
Percent Shrub + (Shrub Clumpiness Index)^2	1693.79	4.84	0.04	0.84
Simpson's Diversity Index	1694.20	4.85	0.04	0.88
Percent Shrub	1694.20	5.24	0.03	0.91
Null	1694.86	5.91	0.02	0.93
Shrub Clumpiness Index	1695.36	6.41	0.02	0.95
(Percent Shrub)^2	1695.67	6.72	0.01	0.96
(Simpson's Diversity Index)^2	1695.68	6.73	0.01	0.98
Percent Shrub * (Shrub Clumpiness Index)^2	1696.43	7.47	0.01	0.99
Percent Forest	1696.86	7.91	0.01	0.99
(Percent Forest)^2	1697.58	8.62	0.01	1.00

Table 2.6. Model selection results for factors influencing golden-winged warbler site occupancy within 500m around survey locations carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AICwt	Cumulative Weight
Simpson's Diversity Index + Percent Shrub + Shrub Clumpiness Index + Percent Forest	1680.28	0.00	0.73	0.73
(Percent Forest)^2	1683.18	2.89	0.17	0.90
(Shrub Clumpiness Index)^2	1686.48	6.20	0.03	0.93
Percent Shrub	1686.73	6.45	0.03	0.96
Shrub Clumpiness Index	1687.22	6.94	0.02	0.98
(Percent Shrub)^2	1688.32	8.04	0.01	1.00
Simpson's Diversity Index	1692.44	12.16	0.00	1.00
(Simpson's Diversity Index)^2	1693.54	13.26	0.00	1.00
Null	1694.86	14.58	0.00	1.00
Percent Forest	1696.62	16.34	0.00	1.00

Table 2.7. Model selection results for factors influencing golden-winged warbler site colonization within 100m around survey locations carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AICwt	Cumulative Weight
Null	1688.95	0.00	0.168	0.17
Percent Forest	1689.21	0.26	0.148	0.32
(Simpson's Diversity Index)2	1689.22	0.26	0.148	0.46
Percent Shrub	1689.72	0.77	0.115	0.58
Shrub Clumpiness Index	1689.73	0.77	0.114	0.69
(Shrub Clumpiness Index)2	1690.48	1.52	0.079	0.77
Percent Shrub + Shrub Clumpiness Index + Percent Forest + Simpson's Diversity Index	1690.86	1.91	0.065	0.84
Simpson's Diversity Index	1690.92	1.96	0.063	0.90
(Percent Forest)2	1691.13	2.18	0.057	0.96
(Percent Shrub)2	1691.66	2.70	0.044	1.00

Table 2.8. Model selection results for factors influencing golden-winged warbler site colonization within 500m around survey locations carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AICwt	Cumulative Weight
Null	1680.28	0.00	0.25	0.25
Shrub Clumpiness Index	1680.84	0.56	0.19	0.43
Percent Forest	1682.10	1.82	0.10	0.53
(Shrub Clumpiness Index)2	1682.22	1.94	0.09	0.63
Percent Shrub	1682.27	1.98	0.09	0.72
Simpson's Diversity Index	1682.28	2.00	0.09	0.81
(Simpson's Diversity Index)2	1682.29	2.01	0.09	0.90
(Percent Forest)2	1683.62	3.34	0.05	0.95
(Percent Shrub)2	1684.13	3.84	0.04	0.98
Percent Shrub + Shrub Clumpiness Index + Percent Forest + Simpson's Diversity Index	1685.56	5.28	0.02	1.00

Table 2.9. Model selection results for factors influencing golden-winged warbler site extinction within 100m around survey locations carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AICwt	Cumulative Weight
Percent Shrub	1685.59	0.00	0.40	0.40
(Percent Shrub)^2	1687.07	1.48	0.19	0.59
(Shrub Clumpiness Index)^2	1688.46	2.87	0.10	0.68
Null	1688.95	3.36	0.07	0.76
Shrub Clumpiness Index	1689.28	3.68	0.06	0.82
(Simpson's Diversity Index)^2	1689.41	3.82	0.06	0.88
Simpson's Diversity Index	1690.01	4.42	0.04	0.92
Percent Forest	1690.19	4.60	0.04	0.96
Percent Shrub + Shrub Clumpiness Index + Percent Forest + Simpson's Diversity Index	1691.52	5.93	0.02	0.98
(Percent Forest)^2	1691.71	6.12	0.02	1.00

Table 2.10. Model selection results for factors influencing golden-winged warbler site extinction within 500m around survey locations carried out in Highland County, VA, 2012-2014.

Model	AIC	ΔAIC	AICwt	Cumulative Weight
Percent Shrub + Shrub Clumpiness Index + Percent Forest + Simpson's Diversity Index	1672.29	0	0.515	0.51
(Percent Forest)^2	1674.05	1.75	0.2142	0.73
Percent Forest	1674.21	1.91	0.1977	0.93
Percent Shrub	1677.95	5.66	0.0304	0.96
(Percent Shrub)^2	1679.28	6.99	0.0156	0.97
Null	1680.28	7.99	0.0095	0.98
Shrub Clumpiness Index	1680.98	8.69	0.0067	0.99
(Shrub Clumpiness Index)^2	1681.18	8.89	0.0061	1
Simpson's Diversity Index	1682.25	9.96	0.0035	1
(Simpson's Diversity Index)^2	1684.14	11.84	0.0014	1

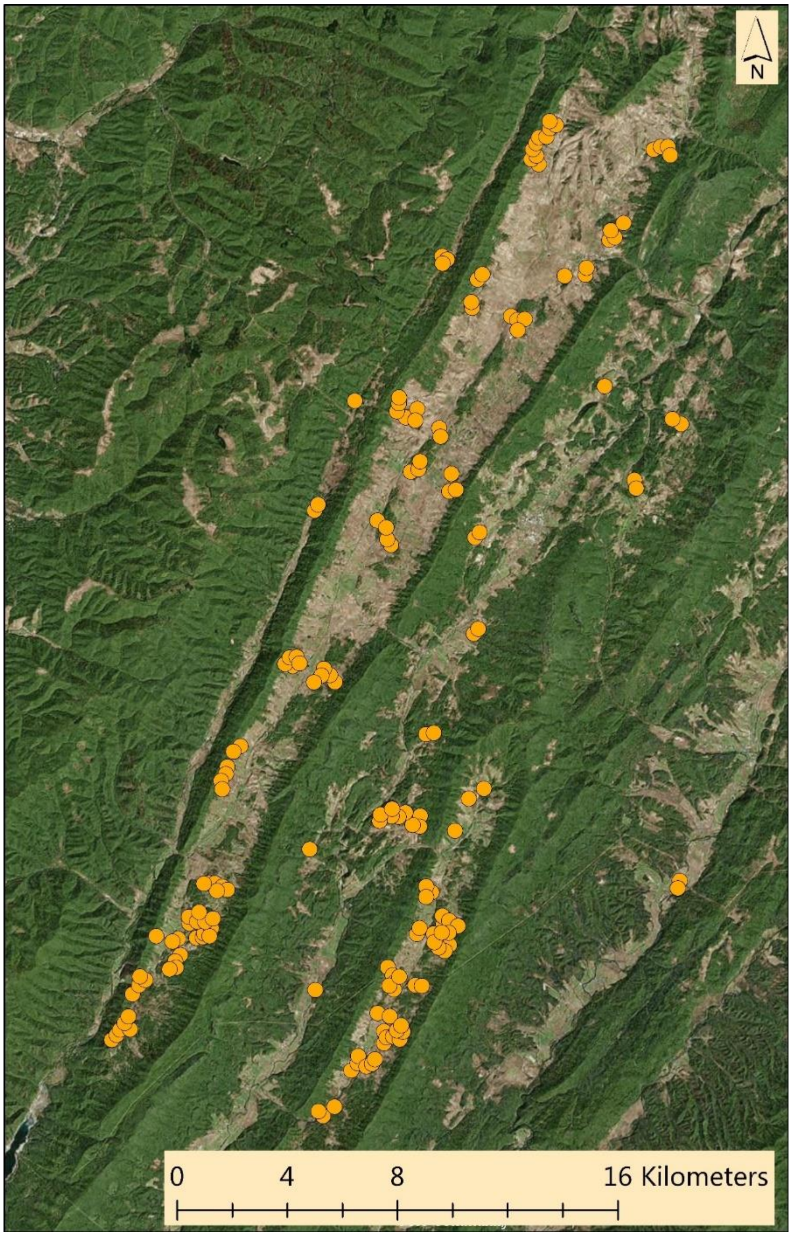

Figure 2.1. Map of 173 survey locations within Highland County, VA.

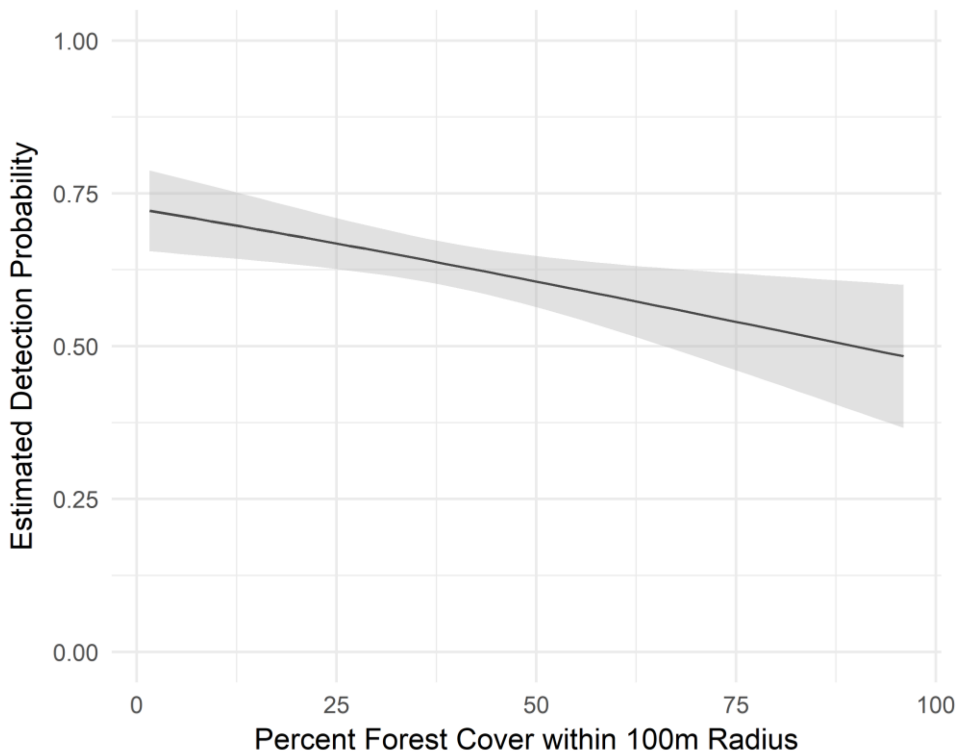

Figure 2.2. Estimated detection probability of golden-winged warblers during 9-minute fixed radius point counts as a function of percent forest cover within a 100m radius of the surveyed point. Error bars represent 95% confidence intervals.

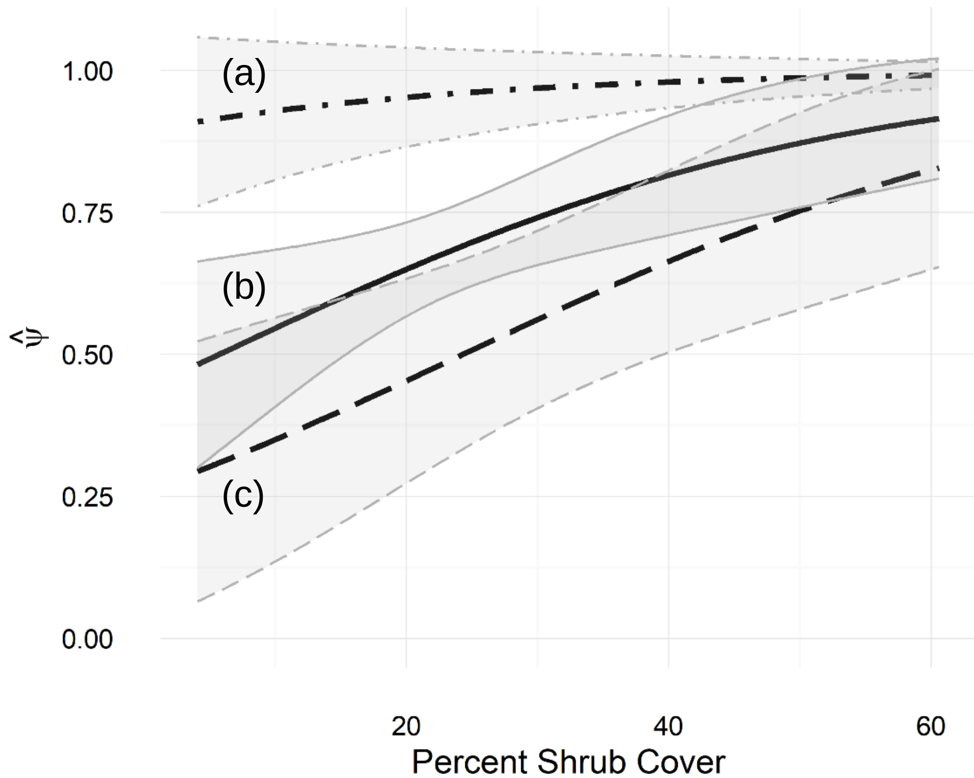

Figure 2.3. Probability of golden-winged warbler site occupancy (Ψ) at the 100m scale as a function of shrub cover stratified by (a) minimum (0.17), (b) mean (0.60), and (c) maximum (0.74) values of Simpson's diversity index across our study sites. Error bars represent 95% confidence intervals.

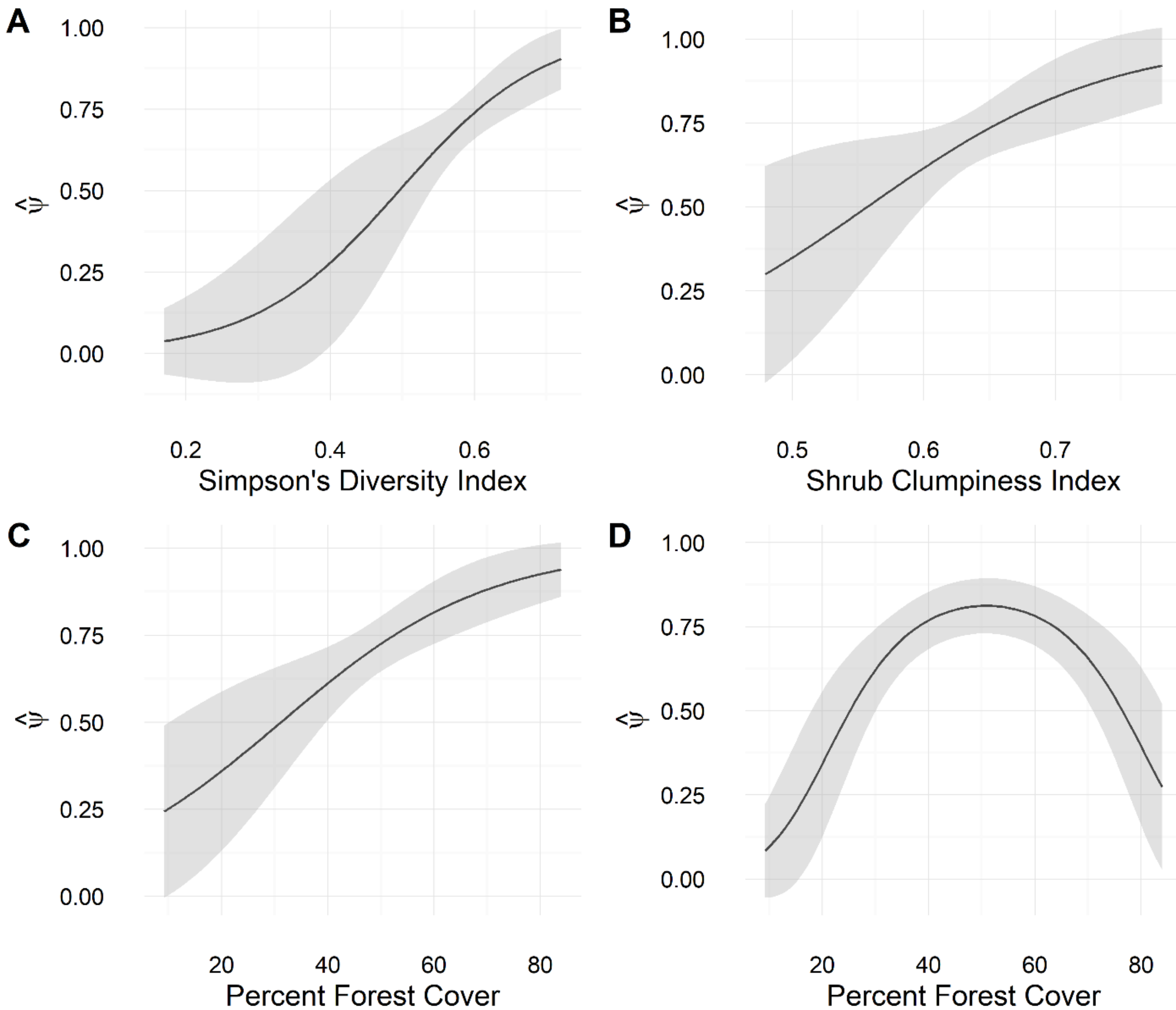

Figure 2.4. Probability of site occupancy (Ψ) by golden-winged warblers within a 500m radius around survey points (~80ha). Panels A-C show probability of occupancy as predicted by single terms within the top-ranked global model when other terms are set to their respective means. Panel D shows probability of occupancy as predicted by percent forest cover squared, our second-ranked model. Error bars represent 95% confidence intervals.

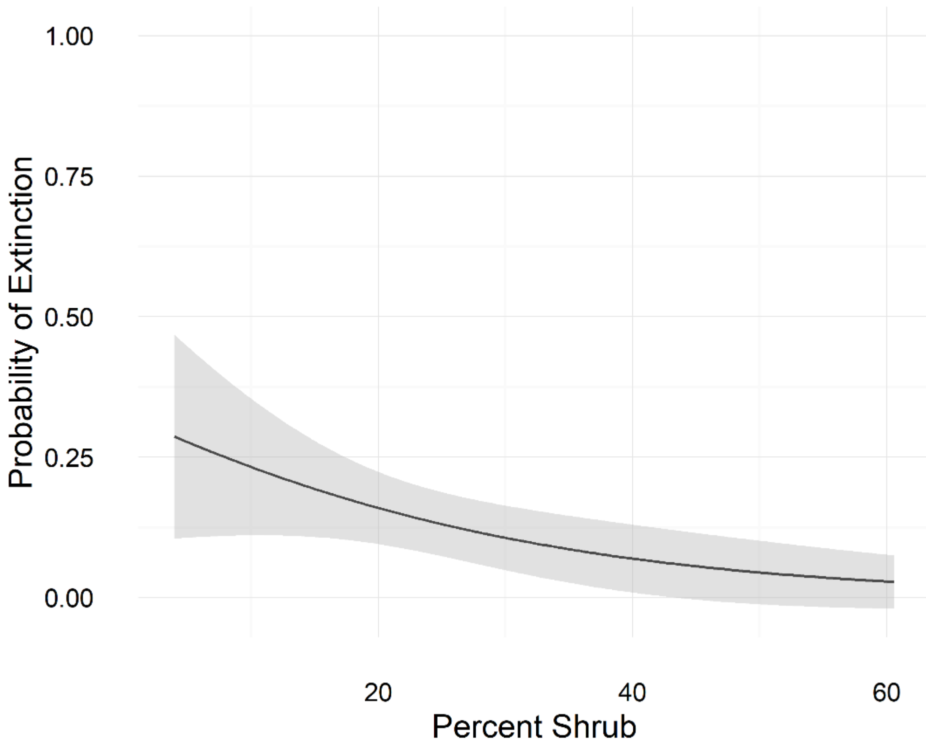

Figure 2.5. Probability of golden-winged warbler site extinction between survey years as a function of percent shrub cover within a 100m radius of the survey point (3.14ha). Probability of extinction decreases with increasing shrub cover. Error bars represent 95% confidence intervals.

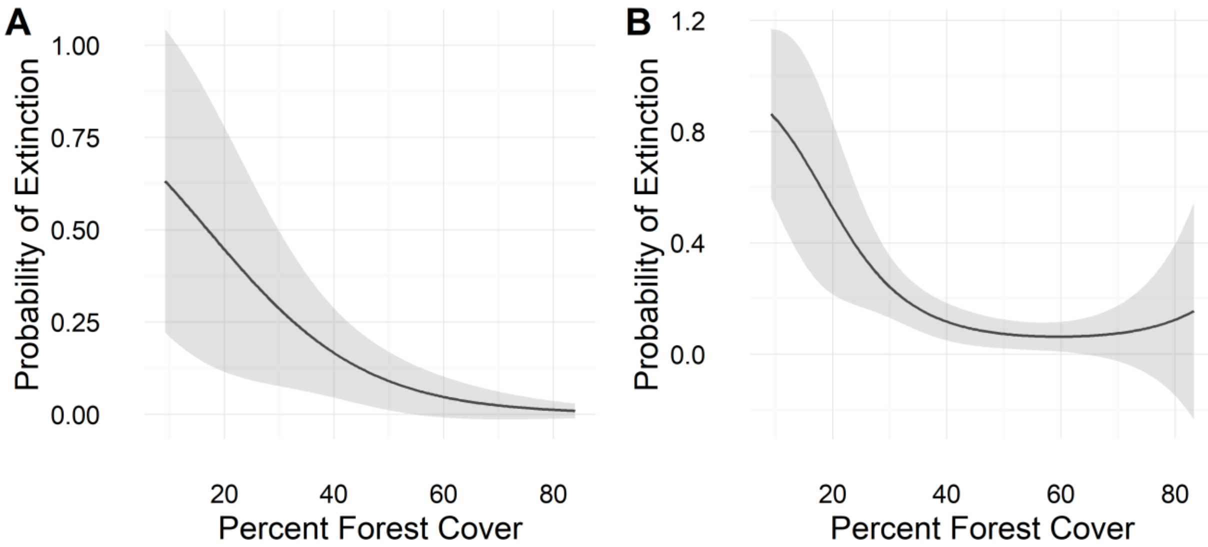

Figure 2.6. Probability of golden-winged warbler site extinction at the 500m scale as a function of (A) percent forest cover (a single term within the top-ranked global model when other terms are set to their respective means) and (B) percent forest cover squared, the second-ranked model. Error bars represent 95% confidence intervals.

Literature Cited

Akaike, H. 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control 19:716–723.

Albrecht-Mallinger, D. J., and L. P. Bulluck. 2016. Limited evidence for conspecific attraction in a low-density population of a declining songbird, the Golden-winged Warbler (*Vermivora chrysoptera*). The Condor 118:451–462.

Aldinger, K. R., and P. B. Wood. 2014. Golden-winged warblers in high-elevation pasturelands 126:279–287.

Antonarakis, A. S., K. S. Richards, and J. Brasington. 2008. Object-based land cover classification using airborne LiDAR. Remote Sensing of Environment 112:2988–2998.

Askins, R. A., B. Zuckerberg, and L. Novak. 2007. Do the size and landscape context of forest openings influence the abundance and breeding success of shrubland songbirds in southern New England? Forest Ecology and Management 250:137–147.

Askins, R. a. 2001. Sustaining Biological Diversity in Early Successional communities: The Challange of Managing Unpopular Habitats. Wildlife Society bulletin 29:407–412.

Bakermans, M. H., C. L. Ziegler, and J. L. Larkin. 2015. American woodcock and golden-winged warbler abundance and associated vegetation in managed habitats. Northeastern Naturalist 22:690–703.

Belt, J. J., and P. R. Krausman. 2012. Evaluating population estimates of mountain goats based on citizen science. Wildlife Society Bulletin 36:264–276.

Betts, M. G., A. W. Diamond, G. J. Forbes, M. A. Villard, and J. S. Gunn. 2006. The importance of spatial autocorrelation, extent and resolution in predicting forest bird occurrence. Ecological Modelling 191:197–224.

Betts, M. G., N. L. Rodenhouse, T. Scott Sillett, P. J. Doran, and R. T. Holmes. 2008. Dynamic occupancy models reveal within-breeding season movement up a habitat quality gradient by a migratory songbird. Ecography 31:592–600.

Breiman, L. 2001. Random forests. Machine Learning 45:5–32.

Breiman, L., and A. Cutler. 2012. Breiman and Cutler's random forests for classification and regression. Package "randomForest":29.

Buehler, D. a, A. M. Roth, R. Vallender, T. C. Will, J. L. Confer, R. a Canterbury, S. B. Swarthout, K. V Rosenberg, and L. P. Bulluck. 2007. Status and Conservation Priorities of Golden-Winged. The Auk 124:1439–1445.

Bulluck, L. P., and D. A. Buehler. 2008. Factors influencing golden-winged warbler (*Vermivora* *chrysoptera*) nest-site selection and nest survival in the Cumberland Mountains of Tennesse. The Auk 125:551–559.

Bulluck, L. P., and S. Harding. 2010. Golden-winged Warbler Patch Occupancy and Habitat Use in Bath and Highland Counties, Virginia. Department of Biology, Virginia Commonwealth University. Richmond, VA.:1–34.

Cleve, C., M. Kelly, F. R. Kearns, and M. Moritz. 2008. Classification of the wildland–urban interface: A comparison of pixel- and object-based classifications using high-resolution aerial photography. Computers, Environment and Urban Systems 32:317–326.

Confer, J. L. 1992. Golden-winged Warbler (*Vermivora chrysoptera*). The Birds of North America Online 123:962–966.

Confer, J. L., and K. Knapp. 1981. American Ornithological Society Golden-Winged Warblers and Blue-Winged Warblers : The Relative Success of a Habitat Specialist and a Generalist 98:108–114.

Confer, J. L., J. L. Larkin, and P. E. Allen. 2003. Effects of Vegetation, Interspecific Competition, and Brood Parasitism on Golden-Winged Warbler (Vermivora Chrysoptera) Nesting Success. The Auk 120:138.

Conway, C. J., and J. P. Gibbs. 2011. Summary of intrinsic and extrinsic factors affecting detection probability of marsh birds. Wetlands 31:403–411.

Dalponte, M., L. Bruzzone, and D. Gianelle. 2008. Fusion of Hyperspectral and LIDAR Remote Sensing Data for Classification of Complex Forest Areas. IEEE Transactions on Geoscience and Remote Sensing 46:1416–1427.

Davies, K. W., S. L. Petersen, D. D. Johnson, D. Bracken Davis, M. D. Madsen, D. L. Zvirzdin, and J. D. Bates. 2010. Estimating Juniper Cover From National Agriculture Imagery Program (NAIP) Imagery and Evaluating Relationships Between Potential Cover and Environmental Variables. Rangeland Ecology & Management 63:630–637.

Defries, R. S., and J. R. Townshend. 1994. Ndvi-Derived Land Cover Classifications At a Global Scale. International Journal of Remote Sensing 15:3567–3586.

Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Marquéz, B. Gruber, B. Lafourcade, P. J. Leitão, T. Münkemüller, C. Mcclean, P. E. Osborne, B. Reineking, B. Schröder, A. K. Skidmore, D. Zurell, and S. Lautenbach. 2013. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography 36:027–046.

Drăguţ, L., and T. Blaschke. 2006. Automated classification of landform elements using object-based image analysis. Geomorphology 81:330–344.

Esri. 2016. ArcMap 10.4.1.

Feng, Q., J. Liu, and J. Gong. 2015. UAV Remote sensing for urban vegetation mapping using random forest and texture analysis. Remote Sensing 7:1074–1094.

Fiske, I., and R. Chandler. 2011. ‘ unmarked ’: an R package for Fitting Hierarchichal Models of

Wildlife Occurence and Abundance. Journal of Statistical Software 43:1–23.

Foody, G. M. 2002. Status of land cover classification accuracy assessment. Remote Sensing of Environment 80:185–201.

Franklin, J. 1995. Predictive vegetation mapping: geographical modelling of biospatial patterns in relation to environmental gradients. Progress in Physical Geography 19:474–499.

Franklin, S. E., R. J. Hall, L. M. Moskal, A. J. Maudie, and M. B. Lavigne. 2000. Incorporating texture into classification of forest species composition from airborne multispectral images. International Journal of Remote Sensing 21:61–79.

Frescino, T. S., G. G. Moisen, L. Deblander, and M. Guerin. 2005. The Investigation of Classification Methods of High-Resolution Imagery.

Frey, S. J. K., A. M. Strong, and K. P. McFarland. 2012. The relative contribution of local habitat and landscape context to metapopulation processes: A dynamic occupancy modeling approach. Ecography 35:581–589.

Gislason, P. O., J. A. Benediktsson, and J. R. Sveinsson. 2006. Random forests for land cover classification. Pattern Recognition Letters 27:294–300.

Gonçalves, J., R. Henriques, P. Alves, R. Sousa-Silva, A. T. Monteiro, Â. Lomba, B. Marcos, and J. Honrado. 2016. Evaluating an unmanned aerial vehicle-based approach for assessing habitat extent and condition in fine-scale early successional mountain mosaics. Applied Vegetation Science 19:132–146.

Hansen, D. J., and W. K. Ostler. 2000. An evaluation of new high resolution image collection and processing techniques for estimating shrub cover and detecting landscape changes associated with military training in arid lands. 1999 Annual Meeting of the Ecological Society of America, Snowbird, UT (US), 08/06/2000--08/10/2000.

Haralick, R. M., K. Shanmugam, and I. Dinstein. 1973. Textural Features for Image Classification. IEEE Transactions on Systems, Man, and Cybernetics SMC-3:610–621.

Harms, T. M., K. T. Murphy, X. Lyu, S. S. Patterson, K. E. Kinkead, S. J. Dinsmore, and P. W. Frese. 2017. Using landscape habitat associations to prioritize areas of conservation action for terrestrial birds. PLoS ONE 12:1–21.

Harvey, K. R., and G. J. E. Hill. 2001. Vegetation mapping of a tropical freshwater swamp in the Northern Territory, Australia: a comparison of aerial photography, Landsat TM and SPOT satellite imagery. International Journal of Remote Sensing 22:2911–2925.

Hayes, M. M., S. N. Miller, and M. A. Murphy. 2014. High-resolution landcover classification using Random Forest. Remote Sensing Letters 5:112–121.

Helle, P., and J. Muona. 1985. Invertebrate numbers in edges between clear-fellings and mature forests in northern Finland. Silva Fennica 19:281–294.

Hellesen, T., and L. Matikainen. 2013. An Object-Based Approach for Mapping Shrub and Tree Cover on Grassland Habitats by Use of LiDAR and CIR Orthoimages. Remote Sensing 5:558–583.

Highland County Chamber of Commerce. 2011. Land Use. http://www.highlandcova.org/Compplan/Landverb.htm.

Homer, C. G., J. A. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. D. Herold, J. D. Wickham, and K. Megown. 2015. Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. Photogrammetric Engineering and Remote Sensing 81:345–354.

Hudak, A. T., and C. A. Wessman. 1998. Textural analysis of historical aerial photography to characterize woody plant encroachment in South African savanna. Remote Sensing of Environment. 66(3): 317-330.:317–330.

Hurd, J. D., and D. L. Civco. 2009. Creating an Image Dataset To Meet Your Classification Needs : a Proof-of-Concept Study. ASPRS 2009 Anual Conference.

Hussain, M., D. Chen, A. Cheng, H. Wei, and D. Stanley. 2013. Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS Journal of Photogrammetry and Remote Sensing 80:91–106.

James, F. C., and H. H. J. Shugart. 1970. A Quantitative Method of Habitat Description. Audubon Field Notes 24:727–736.

Kalliola, R., and K. Syrjanen. 1991. To what extent are vegetation types visible in satellite imagery? Annales Botanici Fennici 28:45–57.

Ke, Y., L. J. Quackenbush, and J. Im. 2010. Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification. Remote Sensing of Environment 114:1141–1154.

Kéry, M., and R. B. Chandler. 2012. Dynamic occupancy models in unmarked. R package version 094:1–24.

King, D. I., R. B. Chandler, S. Schlossberg, and C. C. Chandler. 2009. Habitat use and nest success of scrub-shrub birds in wildlife and silvicultural openings in western Massachusetts, USA. Forest Ecology and Management 257:421–426.

King, D. I., and S. Schlossberg. 2014. Synthesis of the conservation value of the early-successional stage in forests of eastern North America. Forest Ecology and Management 324:186–195.

Klaus, N. A., and D. A. Buehler. 2001. Golden-Winged Warbler Breeding Habitat Characteristics and Nest Success in Clearcuts in the Southern Appalchian Mountains. Source: The Wilson Bulletin Wilson Bull 113:297–301.

Kluckner, S., T. Mauthner, P. M. Roth, and H. Bischof. 2009. Semantic Classification in Aerial Imagery by Integrating Appearance and Height Information. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 5995 LNCS:477–488.

Kubel, J. E., and R. H. Yahner. 2007. Detection Probability of Golden-Winged Warblers during Point Counts with and without Playback Recordings. Journal of Field Ornithology 78:195–

205.

Laliberte, A. S., and A. Rango. 2009. Texture and scale in object-based analysis of subdecimeter resolution unmanned aerial vehicle (UAV) imagery. IEEE Transactions on Geoscience and Remote Sensing 47:1–10.

Laliberte, A. S., A. Rango, K. M. Havstad, J. F. Paris, R. F. Beck, R. McNeely, and A. L. Gonzalez. 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. Remote Sensing of Environment 93:198–210.

Lancia, R. A., W. L. Kendall, K. H. Pollock, and J. D. Nichols. 2005. Estimating the number of animals in wildlife populations. Pages 106–153 Techniques for Wildlife Investigations and Management.

Leblond, M., J. Frair, D. Fortin, C. Dussault, J. P. Ouellet, and R. Courtois. 2011. Assessing the influence of resource covariates at multiple spatial scales: An application to forest-dwelling caribou faced with intensive human activity. Landscape Ecology 26:1433–1446.

Lee, M. B., and J. P. Carroll. 2014. Relative importance of local and landscape variables on site occupancy by avian species in a pine forest, urban, and agriculture matrix. Forest Ecology and Management 320:161–170.

Leuenberger, W., D. J. McNeil, J. Cohen, and J. L. Larkin. 2017. Characteristics of Golden-winged Warbler territories in plant communities associated with regenerating forest and abandoned agricultural fields. Journal of Field Ornithology 88:169–183.

Lyder, J. 2011. Federal Register.

Macarthur, R. H., and J. W. Macarthur. 1961. On Bird Species Diversity. Ecology 42:594–598.

MacGarigal, K., and B. J. Marks. 1995. FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. Reference Manual. Forest Science Department, Oregon State University, Corvallis, OR.

MacKenzie, D. I., J. D. Nichols, J. E. Hines, M. G. Knutson, and A. B. Franklin. 2003. Estimating site occupancy, colonization, and local extinction when a species is detected imperfectly. Ecology 84:2200–2207.

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, A. A. Royle, and C. A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology 83:2248–2255.

Martinuzzi, S., L. A. Vierling, W. A. Gould, M. J. Falkowski, J. S. Evans, A. T. Hudak, and K. T. Vierling. 2009. Mapping snags and understory shrubs for a LiDAR-based assessment of wildlife habitat suitability. Remote Sensing of Environment 113:2533–2546.

Maxwell, A. E., M. P. Strager, T. A. Warner, N. P. Zégre, and C. B. Yuill. 2014. Comparison of NAIP orthophotography and RapidEye satellite imagery for mapping of mining and mine reclamation. GIScience & Remote Sensing 51:301–320.

Mayor, S. J., D. C. Schneider, J. A. Schaefer, and S. P. Mahoney. 2009. Habitat selection at multiple scales. Écoscience 16:238–247.

McGarigal, K., H. Y. Wan, K. A. Zeller, B. C. Timm, and S. A. Cushman. 2016. Multi-scale habitat selection modeling: a review and outlook. Landscape Ecology 31:1161–1175.

McNeil, D. J., C. R. V Otto, and G. J. Roloff. 2014. Using audio lures to improve golden-winged warbler (*Vermivora chrysoptera*) detection during point-count surveys. Wildlife Society Bulletin 38:586–590.

Moskal, L. M., D. M. Styers, and M. Halabisky. 2011. Monitoring Urban Tree Cover Using Object-Based Image Analysis and Public Domain Remotely Sensed Data. Remote Sensing 3:2243–2262.

Mundt, J. T., D. R. Streutker, and N. F. Glenn. 2006. Mapping Sagebrush Distribution Using Fusion of Hyperspectral and Lidar Classifications. Photogrammetric Engineering & Remote Sensing 72:47–54.

Murcia, C. 1995. Edge effects in fragmented forests: implications for conservation. Trends in Ecology & Evolution 10:58–62.

Myint, S. W., P. Gober, A. Brazel, S. Grossman-Clarke, and Q. Weng. 2011. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. Remote Sensing of Environment 115:1145–1161.

Nadeau, C. P., C. J. Conway, B. S. Smith, E. Thomas, C. P. Nadeau, C. J. Conway, B. S. Smith, and T. E. Lewis. 2008. Maximizing Detection Probability of Wetland-Dependent Birds during Point-Count Surveys in Northwestern Florida 120:513–518.

Nichols, J. D., J. E. Hines, J. R. Sauer, J. E. Fallon, and P. J. Heglund. 2000. A Double-Observer Approach for Estimating Detection Probability and Abundance from Point Counts. The Auk 117:393–408.

Niphadkar, M., H. Nagendra, C. Tarantino, M. Adamo, and P. Blonda. 2017. Comparing Pixel and Object-Based Approaches to Map an Understorey Invasive Shrub in Tropical Mixed Forests. Frontiers in Plant Science 8:1–18.

Orians, G. H., and J. F. Wittenberger. 1991. Spatial and Temporal Scales in Habitat Selection Published by. The American Naturalist 137:29–49.

Pacen, R. W. 2000. Breeding and Post-Breeding Habitat Use By Forest Migrant Songbirds in the Missouri Ozarks. The Condor 102:738–747.

Patton, L. L., D. S. Maehr, J. E. Duchamp, S. Fei, J. W. Gassett, and J. L. Larkin. 2010. Do the Golden-winged Warbler and Blue-winged Warbler Exhibit Species-specific Differences in their Breeding Habitat Use? Avian Conservation and Ecology 5.

R Core Team. 2018. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

R, D. C. T. 2017. R: A language and environment for statistical computing.

Ransom, J. I., P. Kaczensky, B. C. Lubow, O. Ganbaatar, and N. Altansukh. 2012. A collaborative approach for estimating terrestrial wildlife abundance. Biological Conservation 153:219–226.

Robinove, C. J. 1981. The logic of multispectral classification and mapping of land. Remote Sensing of Environment 11:231–244.

Rossell, C. R., S. C. Patch, and S. P. Wilds. 2003. Attributes of golden-winged warbler territories in a mountain wetland. Wildlife Society Bulletin 31:1099–1104.

Ryherd S., Woodcock C., S. Ryherd, and C. Woodcock. 1996. Combining Spectral and Texture Data in the Segmentation of Remotely Sensed Images. Photogrammetric Engineering Remote Sensing 62:181–194.

Sala, O. E., S. Chapin, J. Armesto, E. Berlow, J. Bloomfield, R. Dirzo, E. Huber-Sanwald, L. Huenneke, R. B. Jackson, A. Kinzig, R. Leemans, D. M. Lodge, H. A. Mooney, M. Oesterheld, L. Poff, M. T. Sykes, B. H. Walker, M. Walker, and D. H. Wall. 2009. Global Biodiversity Scenarios for the Year 2100. Science 287:1770–1774.

Sauer, J. R., W. A. Link, J. E. Fallon, K. L. Pardieck, and D. J. Ziolkowski. 2011. The North American Breeding Bird Survey 1966–2011: Summary Analysis and Species Accounts. North American Fauna 79:1–32.

Schlossberg, S. 2009. Site Fidelity of Shrubland and Forest Birds. The Condor 111:238–246.

Streby, H. M., and D. E. Andersen. 2013a. Survival of Fledgling Ovenbirds : Influences of Habitat Characteristics at Multiple Spatial Scales 115:403–410.

Streby, H. M., and D. E. Andersen. 2013b. Testing common assumptions in studies of songbird nest success. Ibis 155:327–337.

Streby, H. M., J. P. Loegering, and D. E. Andersen. 2012. Spot-mapping underestimates song-territory size and use of mature forest by breeding golden-winged warblers in Minnesota, USA. Wildlife Society Bulletin 36:40–46.

Thogmartin, W. E. 2010. Modeling and Mapping Golden-winged Warbler Abundance to Improve Regional Conservation. Environmental Sciences 5:12.

Thomas, N., C. Hendrix, and R. G. Congalton. 2003. A Comparison of Urban Mapping Methods Using High-Resolution Digital Imagery. Photogrammetric Engineering & Remote Sensing 69:963–972.

Thompson, W. L., G. C. White, and C. Gowan. 1998. Monitoring Vertebrate Populations. Page Monitoring Vertebrate Populations.

Timm, B. C., and K. McGarigal. 2012. Fine-scale remotely-sensed cover mapping of coastal dune and salt marsh ecosystem at Cape Cod National Seashore using Random Forest. Remote Sensing of Environment 127:106–117.

USGS. 2015. USGS EarthExplorer.

VDGIF. 2015. Virginia’s 2015 Wildlife Action Plan.

Virginia Geographic Information Network. 2016. Virginia Land Cover Map Service.

Welton, M. 2003. Status and distribution of the Golden-winged warbler in Tennessee. Migrant 74:61–82.

Whiteside, T. G., G. S. Boggs, and S. W. Maier. 2011. Comparing object-based and pixel-based classifications for mapping savannas. International Journal of Applied Earth Observation and Geoinformation 13:884–893.

Wiens, J. A., J. T. Rotenberry, B. Van Horne, J. A. Wiens, J. T. Rotenberry, and B. Van Horne. 1987. Nordic Society Oikos Habitat Occupancy Patterns of North American Shrubsteppe Birds : The Effects of Spatial Scale. Oikos 48:132–147.

Winnet-Murray, K. 1986. Variation in the behavior and food supply of four neotropical wrens. University of Florida.

WorldView Solutions, I. 2011. Technical Plan of Operations: Virginia Statewide Land Cover Data Development. Richmond, VA.

Wulder, M. A., E. F. LeDrew, S. E. Franklin, and M. B. Lavigne. 1998. Aerial Image Texture Information in the Estimation of Northern Deciduous and Mixed Wood Forest Leaf Area Index (LAI). Remote Sensing of Environment 64:64–76.

Xie, Y., Z. Sha, and M. Yu. 2008. Remote sensing imagery in vegetation mapping: a review. Journal of Plant Ecology 1:9–23.

Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schirokauer. 2006. Object-based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery. Photogrammetric Engineering & Remote Sensing 72:799–811.

Vita

Elizabeth Schold was born on May 2, 1990 in Lowell, MA. She received her Bachelors of Arts in 2012 in Organismic and Evolutionary Biology from Harvard University, where she conducted her undergraduate research on avian phylogenetics and immunological genetics in the lab of Dr. Scott Edwards. Upon graduating, she spent a field season monitoring seabirds in Nova Scotia with the Edwards lab before a year-long internship at Archbold biological station, where she worked on the long-term Florida scrub jay project. She spent several years in Ann Arbor, Michigan, working as a laboratory technician at University of Michigan and as an intern at Michigan Tech Research Institute, where she discovered a fondness for plants and for remote sensing. She joined the Avian Ecology laboratory with Dr. Lesley Bulluck in April 2016 and has enjoyed working on various field projects within the lab in addition to her thesis research.