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Habitat and Conservation Suitability Assessment for Shrubland Birds in Monroe County, New York

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By

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Abstract

Shrublands and successional ecosystems are of special interest to land managers and conservation groups because to be maintained, they must be disturbed periodically. Shrubland birds rely on variation in the landscape, regular disturbance, and ephemeral patches of shrubs for breeding, foraging, and nesting. Many of these avian species are in decline, so monitoring and mapping shrublands is necessary for future conservation and management strategies (DeGraaf & Yamasaki, 2003; Howard et al., 2015; Litvaitis, 2003). Large proportions of shrubland bird populations rely on shrublands in the northeast states for breeding habitat, and the identification and land use monitoring of these regions are important for their continued survival. Remote sensing approaches were used for habitat modeling in this study because comprehensive field analyses of the status and condition of all the shrubland habitat in the study area (Monroe County, NY) would have been resource and labor intensive. To determine the quantity, distribution, and features of the quality of shrubland habitat in Monroe County, two types of models were created, and their similarities, differences, and accuracies were assessed. The first model used the National Wetland Inventory (NWI) and the National Land Cover Database (NLCD) to define optimal conditions for eight species of passerine songbirds based on habitat preferences found in literature. This classification produced an overall accuracy of 71.1% and a K coefficient of 0.65. The second model type was a supervised classification intended to find important patches of habitat not included in the NLCD classification scheme. The second classification yielded a different set of habitat requirements with an overall accuracy of 71.4% and a K coefficient of 0.66. A preliminary study on the separability of woody shrub species based on their spectral signatures was promising but inconclusive statistically and unable to be applied to high-resolution imagery to remotely determine invasive vegetation cover.

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Introduction

Conservation efforts to preserve habitat for shrubland birds have gained ecological importance considering documented decreases in the populations of many shrubland bird species (Dettmers, 2003). New York State's Comprehensive Wildlife Conservation strategy categorizes these birds as a "greatest conservation need" (New York Forest Resource Assessment and Strategy, 2015). These species rely on northeastern shrublands for stopover sites during migration, breeding sites in the summer, and foraging substrate during the summer and early fall (Oehler et al., 2006; Smith & Hatc; 2008, Bonter et al., 2009). Understanding the correlations between types of habitat changes and decline in shrubland bird species over time can help conservation groups and land managers mitigate further decreases in songbird populations and inform conservation strategies for threatened or endangered groups (Schlossberg & King, 2015). Determining where shrubland exists in a region is an important first step towards habitat assessment and management action (Burger & Liner, 2005).

Background and Trends

Shrubland and young forest habitat have been declining since the late nineteenth century, and currently constitute less than 20% of land cover in most northern states (Lorimer, 2001). These declines are due to many variables including fire suppression, change in disturbance regimes, decrease in farmland abandonment, and human development of the built environment. When a habitat type is in decline, a primary concern is the protection of species that rely on that habitat for nutrition, nesting/shelter substrate, and habitat needs (Litvaitis, 2003b; Trani et al., 2001; Howard et al., 2015).

Shrub-specialist bird species account for more than 15% of the avian biodiversity in the northeastern U.S., and although many shrubland birds have similar habitat needs, they represent a diverse group of both rare and extremely common species in North America (Dettmers, 2003). Declines in shrub-specialist species have been attributed to the loss of shrubland habitat in eastern states, due to clearing of shrublands, human development on or near shrublands, and forest maturation, which creates valuable habitat for forest species and many generalist species, but no longer supports shrubland-specialist species (Trani et al., 2001). In New England, 21 species of shrubland birds are in decline, and the proportion of declining species to increasing species is 1:3 (CEAP, 2012).

Shrublands and young forests are a unique habitat type from a conservation perspective, because they are reliant on disturbance. After a disturbance, grasses are typically the pioneer successional group, followed by shrubs. Shrublands give way to young, and then mature forests, unless disturbance is maintained. Lorimer (2001) defines early successional forest as the time frame from 0-15 years post disturbance. In a report on the benefits provided by deliberate conservation in New England, the United States Department of Agriculture Natural Resources Conservation Service states, “By their nature, shrubland habitats are ephemeral and revert to conditions unsuitable for shrubland birds and other disturbance-dependent organisms within a decade or two” (CEAP, 2012). Unlike conservation of an old growth forest, where the goal is to protect the existing ecosystem, protection and creation of shrublands requires maintenance of a natural or artificial disturbance regime (Lorimer, 2001; CEAP, 2012).

The frequency of events that create forest disturbance severe enough to trigger pioneer species and succession has decreased in the 20th and 21st centuries due to human manipulation of fire regimes, loss of beavers, and reforestation due to abandonment of young successional habitat and agricultural land. In this region, shrublands are in decline primarily due to a decrease in most types of disturbance (Litvaitis, 2003b; Lorimer, 2001; Lorimer & White, 2003; Krebs et al., 2010).

Disturbance Types

As farmland productivity per unit area has increased over the past century and the rise of large agricultural corporations has displaced small farmers, abandoned farmland has become valuable habitat in some areas. Scientists have been studying abandoned farmland worldwide, and the impact on local biodiversity depends on the intensity of the agricultural practices and the land use post-abandonment. With low impact agriculture, sometimes abandonment can lead to decreased biodiversity if the farmland was preserving biodiversity, but in other areas where a monoculture system was abandoned, the recovery of the natural ecosystem encourages native biodiversity (Queiroz et al., 2014).

In the Northeast, abandoned farmland left barren progresses through grassland, shrubland, and eventually forest successional stages (Hellesen & Matikainen, 2013; Oehler, 2003). The abandonment of farmland creates shrubland for only 5-15 years post-abandonment (DeGraaf & Yamasaki, 2003). During this period, the land has high value to shrubland birds. In New York State between 2005 and 2008, around 4% of forests were in the seedling-sapling stage, which was defined as the period between 0-19 years post-harvest or disturbance. This is an average for New England and Northeast states (Schlossberg and King, 2014). In these states, farmland abandonment has leveled off, and most will not be re-cleared or managed for shrubland, leading to forest succession and the development of canopy cover which is not desired by shrubland species. In this region, the initial peak in shrubland succession after abandonment has mostly ceased, and those areas are maturing into forests while the shrubland habitat remains in decline (Alvarez, 2007; Piché & Kelting, 2015).

Habitat Modeling for Conservation

Because large scale monitoring of wildlife populations is difficult and resource-intensive, habitat modeling using software and knowledge of ecological theory has been used for conservation in many areas including forestry, endangered species protection, and migration prediction (Mitchell, 2011). Using the highest resolution data on shrubland bird populations in Monroe County would only give data for large-scale blocks of the Breeding Bird Survey, and the rest would be extrapolation. Because there are known ecological factors that impact the abundance and distribution of shrubland species, it is possible to model ideal habitat for these species based on these factors, including patch size, preferred land cover type, and distance to other useful habitat types. When designing or implementing a conservation plan, it is necessary to use the predicted sites as a starting point, and determine the presence of the target species before implementing policy change or creating beneficial habitat (Kerr et al., 2011)

Patch Size, Edges, and Fragmentation

From a survival perspective, many small songbirds face higher predation rates and decreased safety near habitat edges (Lehnen & Rodewald, 2013; Rodewald, 2012). Forest and shrubland fragmentation increases percentage of edges/area by splitting large areas into small ones. The creation of paths, roads, utility lines, and even patch-cutting by logging operations can increase the edge ratio of a shrubland habitat (Confer& Pascoe, 2003).

One study from Ohio found that several shrub-specialist tend to avoid the edges of mature forests, and were found in higher densities 80 meters from an edge, compared to bird densities observed 20 meters from the edge. These results were found in a shrubland that was five years post-clearcutting, and the conclusions indicate that conservation planning should maximize shrubland area, while minimizing the forest/shrubland edges because they appear to be less desirable habitat for shrub-specialist species (Rodewald & Vitz, 2008).

Some species that will occasionally breed in the understory of a forest do not have the same aversion to edges that the obligate shrubland breeding birds have. Black-and-white Warblers (*Mniotilta varia)*, White-eyed Vireos (*Colinus virginianus)*, and Eastern Towhees (*Pipilio erythrophthalmus)* were not statistically found to avoid edges, while Blue-winged Warblers (*Vermivora pinus)* and Field Sparrows (*Spizella pusilla)* were found farther from edges (Schlossberg & King, 2008). Breeding success can increase or decrease depending on patch size, so these are important factors to use when identifying valuable habitat for shrubland birds (King et al., 2009; Rodewald & Vitz, 2008).

There is no singular management strategy that will cater to every type of shrubland bird, obligate or generalist. However, there are some techniques that create non-uniform patches, and keeping in mind proximity to wetland, other shrubland sites, and development can optimize a managed area for several species at once (CEAP, 2012; Buffum & McKinney, 2014). To identify the most valuable patches of habitat and avoid impact of high edge-area ratios, habitat models often include a minimum patch size, below which a patch is viewed as virtually all edge.

Proximity to Wetlands

Some species, like the Gray Catbird, are known to live in both shrublands and wetlands, and it has been speculated that proximity to wetlands is valuable for many shrubland species. Buffum and McKinney (2014) studied the effects of wetland shrubland proximity and found that shrubland species richness increased with the increased proportion of wetland shrubland within 100m of the small patches of upland shrubland where the birds were found. Compared to other factors including canopy cover, shrub height, and patch size, the only significant correlation to abundance found for shrubland specialist species was the positive correlation with increase in percent wetland within 100m (Buffum & McKinney, 2014). Other birds found to benefit from proximity to wetlands are the Chestnut-sided Warbler *(Dendroica pensylvanica),* Blue-winged Warbler (*Vermivora pinus*), Eastern Towhee *(Pipilo erythrophthalmus*), and Common Yellowthroat *(Geothlypis trichas)* (Buffum & McKinney, 2014).

Invasive Species

Invasive shrubs can have positive, negative, or neutral impacts on shrubland birds, and their roles in each ecosystem context can warrant different management techniques. Each interaction should be studied in the context of each species needs, in both seasonal and spatial context. From insect availability to protection from predators and provision of nesting sites, invasive shrubs are utilized by many species of shrubland birds and shrubland obligate breeders. The impacts on abundance, richness, nesting success, and fledging survival are just a few ways these species impact avian species. Nelson et al., (2017) created a 128-source literature review on the mechanisms and impacts of invasive plants on North American birds and found that abundance and presence of the focal species was often not impacted by the presence of invasive species, but that richness decreased in the presence of invasive plants in 41.3% of the cases in the review (Nelson et al., 2017, p. 1547)

The proliferation of invasive shrubs can be a direct or indirect threat to biodiversity of native plants and insect populations in an area. The diversity and presence of certain shrub species can impact foraging success for frugivorous and insectivorous birds and may impact the nesting substrate and brood success. It has been shown that an increase in the spread of invasive shrub species can change the insect diversity and richness of a site, with the invasive shrubs harboring less diverse and desirable insect species (Fickenscher et al., 2014; Mcchesney &

Anderson, 2015). A key study of the effects of invasive shrubs on insect communities was conducted by J.L. Fickenscher et al. (2014). The study looked not only at the responses of insect communities, but went further to provide recommendations for shrubland or thicket management. Areas with a large portion of invasive shrubs had more generalist and nuisance insect species, while there was a lack of lepidopterans and herbivorous species. These lepidopterans are known to be valuable prey for songbirds at different times of the year, so the decrease in these species where invasive shrubs make up a higher percentage of the cover could make the area less suitable for songbirds (Fickenscher et al., 2014).

The impacts of invasive species on native bird populations are varied depending on ecosystem context. Even in cases where the impacts of invasion were positive or neutral, it is important to study the mechanisms behind the relationships to advise conservation and management practices. It is also important to study the impacts and determine whether they vary with degree of invasion. Nelson et al. (2017), were careful to note that just because their findings suggest that invasive plants "do not ubiquitously degrade avian communities", their continued threat is still reshaping and changing valuable habitat, and should be studied carefully to improve understanding of ecosystem relationships at different spatial and temporal scales (Nelson et al., 2017).

Select New York Shrubland Birds and the NY State Conservation Criteria

New York State has a State Wildlife Action Plan (SWAP), which outlines the species of highest conservation priority (Howard et al., 2015). This section discusses specific species and outlines key habitat needs, illustrating the importance of conserving a variety of shrubland habitats to provide for the diverse needs of shrubland birds.

The Golden-winged Warbler (*Vermivora chrysoptera*), a shrubland specialist, is not a federally listed species, but it is listed as a "Species of Greatest Conservation Need (SGCN)-Highest Priority" as a Special Concern species in NY because its populations have seen close to a 53% decline in occupancy between 1980 and 2005. Note that this is not a decline in total abundance, it is a decline in Breeding Bird Survey sightings, which record presence/absence data year by year along preselected routes. The action plan states that one of the largest threats is the hybridization of the golden-winged warbler with the blue winged warbler, as well as the ongoing maturation of early-successional habitat.

Another shrubland bird in decline is the Northern Bobwhite (*Colinus virginianus),* a game bird. Although this is not a songbird, it is used as an indicator of the quality of early successional habitat in NY. It is noted in the SWAP that the bobwhite is experiencing "severe short- and long-term declines". This species prefers to breed and winter in shrublands, so alarming declines in this species should be considered when evaluating the overall state of shrublands and early successional habitats in NY. The Rusty Blackbird (*Euphagus carolinus)* winters in NY, and although it is a generalist shrubland user that also relies on wetlands, wet meadows, and swamps, its decline is mentioned in the SWAP under the SGCN-Highest Priority, notably caused by other bird competition and human intrusion in required habitats.

The whip-poor-will (*Caprimulgus vociferus*) is also a noted avian species of "Special Concern" (Schlossberg & King, 2007) due to their decline in NY. Their decline is not fully attributed to any one factor, but the report suggests that loss of scrubland and forest is a likely cause. The Yellow-breasted Chat *(Icteria virens)* is also a "Special Concern" shrubland species in NY, having experienced significant decline. The Blue-winged Warbler *(Vermivora cyanoptera)* and Prairie Warbler *(Setophaga discolor),* along with the Ruffed Grouse *(Bonasa* *umbellus),* a known shrubland game bird, are also both listed under the SGCN, although not under the "highest priority" column (SWAP, 2015). Not all focal species are endangered or listed as priority concerns, but declines in shrubland specialists over time can be indicators for all species that rely on a certain ecosystem type.

Using Remote Sensing and GIS to Portray Concepts in Landscape Ecology

Because so many geographic parameters factor into the ideal conditions for shrubland birds, it is helpful to use tools like GIS to combine several available datasets into one model that represents the ideal set of conditions for a species. To model for several shrubland species at once, it is useful to look at common factors, and to incorporate several land cover types to account for the varied needs of these species.

GIS software allows for the creation of models that include the spatial and ecological qualities that are preferred by one or more species. Land cover type, patch size, edge ratio, proximity to certain features, and even relative abundance can be built into a habitat model. Data for these map layers can be gathered on the ground, like the BBS results, or remotely, in the case of satellite and aerial imagery. Using combinations of the available data types, researchers have created migration models, time-series models of change, predictions of range changes, habitat suitability models, and many other types of ecological models (Lillesand, 2004; Mitchell, 2011).

Satellite imagery and RADAR help meteorologists to predict weather changes and precipitation patterns, and high-resolution aerial imagery is used to create detailed maps and surveys for companies and local governments. Landsat imagery gathered from satellites collect information across several bands of different wavelengths that are used to classify, study, and track changes in land cover and features since the early 1970s (Jensen, 2007; Stow et al., 2008).

Reflectance data are obtained by taking a measurement of the open sky to see what wavelengths are present and at what intensity while taking a parallel measurement of the object or plant from which you want to derive reflectance, and dividing the first curve by the second. Reflectance is not a form of raw data and it is calculated by compensating for the total atmospheric effects of scattering from the sun and the atmosphere, leaving only the wavelengths reflected from the object into the sensor. Different land covers cause different types of reflectance curves, and when plotted, can help differentiate between built landscape, soil, and vegetation for databases like Landsat, which is how the National Land Cover Database (NLCD) creates their land cover designations (Lillesand et al., 2004). Land cover classifications executed across intervals of time allow for the creation of time-series change analyses using GIS software. This can be used to track the growth or decline in certain habitat types in each area, and to observe trends in shape, size, or even health of a habitat type.

Remote sensing has been used for many types of environmental assessments, and has value in the fields of remediation, geology, soil science, vegetative health assessment, wildlife monitoring, and hydrology (Lillesand et al., 2004; Newton et al., 2009). Remote sensing has been used for wildlife conservation projects and habitat assessments (Jensen, 2007; Lillesand et al., 2004; Stow et al., 2008). For shrublands specifically, both spatial and temporal studies have been conducted across the United States and internationally in diverse regions such as Argentina, the Mediterranean, and Israel. Many of these studies have different goals and are working with data at different resolutions from disparate biomes, but the applications of remote sensing are similar.

Programs like ENVI and ArcGIS (Mitchell, 2012; Paz-Kagan et al., 2014; Stow, 2010) can run both supervised and unsupervised classifications, where the program extracts land cover types and groups pixels with other pixels of similar features. The features that they generate may be grouped by spectral signatures, texture, and spatial relationships to surrounding pixels (Lillesand et al., 2004). All my data were pre-processed and projected, so I matched all the coordinate systems to insure my layers functioned correctly. I used a supervised classification scheme after creating training sites and a signature file (.sig) in ArcGIS 10.4.

Stow et al. (2008) used airborne multispectral imagery to monitor shrubland habitat changes in California. To perform a change analysis of a land cover type, the land cover must be identified with a similar degree of accuracy over time. The author used visible and near-infrared wavelengths for most classifications. Much of the published literature on shrubland identification focuses on arid climates or drought conditions, but many of the methods are still applicable to shrubland classification in New York State (Blanco et al., 2016; Lippit, 2013; Paz-Kagan et al., 2014). Localized analyses using remotely sensed imagery and processing software are accepted tools used to provide models for land cover classification and habitat suitability (Lillesand, Kiefer, & Chipman, 2004; Lippit, 2013; Mitchell, 2012).

Goals and Objectives

The goal of this research is to assess the state of shrubland habitat for shrubland passerine bird species in Monroe County, NY, and to establish a spatial model using GIS and remote sensing technologies to find ideal habitat based on individual species' needs and overall requirements for shrubland species. This involves combining layers representing specific needs of shrubland birds, such as patch number, patch area, distance to advantageous and disadvantageous land covers for shrubland birds. My hypothesis is that a localized supervised classification of LANDSAT imagery could provide a more accurate map of shrubland habitat for the focal species in Monroe County, NY than the shrublands identified in the national land cover map (the 2011 National Land Cover Database). Two sets of multiple parameter habitat models were created. Model 1 uses the 2011 NLCD as the land cover database, and Model 2 uses a land cover classification limited to Monroe County. Both models are derived from Landsat imagery and are used to produce maps and models of ideal habitat parameters for the focal species that align with known shrubland habitat in Monroe County. Model results are assessed using confusion matrices and Kappa coefficients to determine which method was more successful.

The outcome of these models could be used to advise policy decisions towards the creation and management of shrublands for native shrubland-specialist songbird species. These habitat suitability models will not only improve knowledge of the state of shrublands in New York, but will also identify and advise the most suitable sites for conservation action to take place.

To look more in-depth at invasive species in shrubland land cover classification, a field based pilot project was undertaken using spectral data collected at a local shrubland to determine whether it is feasible to separate native species from common invasive shrubs using hyperspectral imagery at the Landsat scale. I conducted a statistical analysis using canonical discrimination of these data to determine whether the difference in signatures between each genus is greater than the difference in signatures within one genus by examining their spectral profiles.

Methods

Remote sensing tools and imagery were used in lieu of an in-situ field study to identify shrubland habitat in Monroe County. Remote sensing sacrifices some level of accuracy for broad scale analyses, but is far more time- and cost-efficient than field surveys. Sources of error and uncertainty were identified and minimized as appropriate.

I used geographic data as surrogates for ecological data when forming my models and assessments. It is important to make sure data are representative of the habitat qualities that the target species need (Mitchell, 2011). I used LANDSAT and NLCD data for land cover, and Breeding Bird Survey (BBS) data and routes for bird presence and diversity. The datasets and their respective citations are displayed in Table 1.

There are three BBS routes that intersect Monroe County, and others slightly west and south of the borders. I assumed that using conservation sites as training sites will help to include factors that are beneficial to the birds, but cannot be easily seen within a 30x30 meter pixel. The geographic intersections of the highest bird relative abundance from the Breeding Bird Survey, user-classified high-quality shrubland, and adequate patch size and width indicate sites of interest for conservation and management. These overlaid maps were created for my focal species, using the parameters shown in Table 1.

The habitat models incorporated and combined GIS layers that indicate the presence and historical trends of shrubland obligate species and birds typically found in shrublands from the Breeding Bird Survey records. The presence and diversity of these species were combined with land cover data from government sources and my own data collection. I use the NLCD 2011 land use/land cover and NWI wetland classes for the first set of models, and generate my own classifications using Landsat imagery to compare a different model using the same parameters and resolution, but with training sites specific to the land use in Monroe County.

Table 1: Dataset and Image Sources. This table explains the use of each of the layers of geographic data that my models were created from. Each type is listed with the official scene or image name, the date and full citation for the dataset, the date of origin from the metadata, and how it was used in the modeling process.

Data Type	Citation	Date	Use	Scene/Notes
LANDSAT	Landsat 8 image, courtesy of the U.S. Geological Survey	2/20/2017	Land cover classification for Monroe County	LC08_L1TP_016030_20160927_20170220_01_T1
National Wetland Inventory (NWI) Watershed Boundaries	U. S. Fish and Wildlife Service. Publication date (found in metadata). National Wetlands Inventory website. U.S. Department of the Interior, Fish and Wildlife Service, Washington, D.C. http://www.fws.gov/wetlands/	10/1/17	Training sites for wet shrublands and freshwater forests	HU8_4130001, HU8_04130003, HU8_04140101 (Lower Gennessee Watershed, Oak Orchard-Twelvemile Watershed, Irondequoit-Ninemile Watershed)
National Land Cover Database (NLCD)	Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.D., Wickham, J.D., and Megown, K., 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, v. 81, no. 5, p. 345-354	2011	30m classified pixels	
County Borders NYS	NYS Civil Boundaries (includes NYS County Boundaries - Shoreline Version), Revised Oct, 2017. http://gis.ny.gov/gisdata/inventories/details.cfm?DSID=927	October, 2017	Borders and maps for scale and context	
Mendon Digital Orthophotos	Town of Mendon Digital Orthophotos, 1 ft 4 band composite of the following .jp2 files. http://gis.ny.gov/gateway/mg/2015/monroe/	2015	Small-scale classification	w_14131104_12_15100_4bd_2015.jp2, w_14161104_12_15100_4bd_2015.jp2, w_14131102_12_15100_4bd_2015.jp2, w_14161102_12_15100_4bd_2015.jp2
Breeding Bird Survey	Sauer, J. R., D. K. Niven, J. E. Hines, D. J. Ziolkowski, Jr, K. L. Pardieck, J. E. Fallon, and W. A. Link. 2017. The North American Breeding Bird Survey, Results and Analysis 1966 - 2015. Version 2.07.2017 USGS Patuxent Wildlife Research Center, Laurel, MD	1966-2015	Relative abundance statistics for target species	
BBS Routes	Sauer, J. R., D. K. Niven, J. E. Hines, D. J. Ziolkowski, Jr, K. L. Pardieck, J. E. Fallon, and W. A. Link. 2017. The North American Breeding Bird Survey, Results and Analysis 1966 - 2015. Version 2.07.2017 USGS Patuxent Wildlife Research Center, Laurel, MD	1996-2015	Areas where the BBS routes intersect the county, used to show where extrapolation was used and proximity to shrubland habitat	

The models showing potential shrubland habitat were designed based on literature values of factors known to impact the presence and abundance of shrubland bird species, both generalists and specialists, including proximity to wetlands, proximity to developed areas, patch size, patch length, edge length, and historic trends where data are available. Results show the location, quantity, and patterns in desirable shrubland habitat for native birds.

A second analysis addressed the possibility of remotely quantifying invasive species. A limited, localized field survey collected spectral data from native and invasive shrubland species to determine if there was enough difference in spectral signatures to remotely separate by species. These results were intended to allow the incorporation of invasive species coverage into a habitat suitability model. The analysis was originally intended to attempt both species and genus level separation.

Related to the first sets of models, to determine optimal habitat for shrubland species, data were obtained from field studies of shrubland bird abundance, richness, and even behavioral studies that showed cutoff points in width, area, and proximity that had a significant positive or negative effect on the abundance of individual species. These values were used as buffers and proximity measurements to show the ideal spots for nine different species. The species are: Gray Catbird (*Dumetella carolinensis*), Blue-winged Warbler (*Vermivora pinus*), Chestnut-sided Warbler (*Dendroica pensylvanica*), Prairie Warbler (*Dendroica discolor*), Common Yellowthroat (*Geothlypis trichas*), Eastern Towhee (*Pipilo erythrophthalmus*), Field Sparrow (*Spizella pusilla*), Indigo Bunting (*Passerina cyanea*), and Black-and-White Warbler (*Mniotilta varia*), which are listed with all preferred habitat qualities used in the models in Table 2.

Table 2: Focal Species Geographic Habitat Preferences. The common and scientific name and qualities of each focal species of shrubland bird. The third column shows which sources gave the information for the following columns (see footnote). Species that avoid edges are given an X in the fourth column, and area preferences are given in hectares in column 5. Columns 6 and 7 show whether a species benefits from proximity to wetlands (50-100m), or proximity to residential areas (1km). The final column notes if there is literature indicating whether this species tends to be more of a generalist (G) or specialist (S).

Common Name	Scientific Name	Sources	Edge Avoider	Proximity to Wetland	Proximity to Residential	Specialist/ Generalist
Gray catbird	*Dumetella carolinensis*	1,2,4			X	G
Blue-winged warbler	*Vermivora pinus*	1,2,7	X	X		S
Chestnut-sided warbler	*Dendroica pensylvanica*	1,2,8		X		S
Prairie warbler	*Dendroica discolor*	1,2,4,6,8	X			S
Common yellowthroat	*Geothlypis trichas*	1,2,8		X		
Eastern towhee	*Pipilo erythrophthalmus*	1,2,4,8			X	G
Field sparrow	*Spizella pusilla*	1,2,6,7,8	X	X		S
Indigo bunting	*Passerina cyanea*	1,6,7,8	X			
Black-and-white warbler	*Mniotilta varia*	1,4				G

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Model Building

Model 1 – NLCD and NWI Assigned Layers

The first set of layers created for Model 1 were extracted land use classes from the NLCD 2011 land use land cover data. Raster groups were converted into polygons for three types of land cover (shrub, forest, and low-moderate development) that have been shown in different studies to impact the abundance or presence of the focal species. The first set was land cover type, and the second set was the NWI wetlands, specifically the Freshwater Forested and Shrub Wetland category.

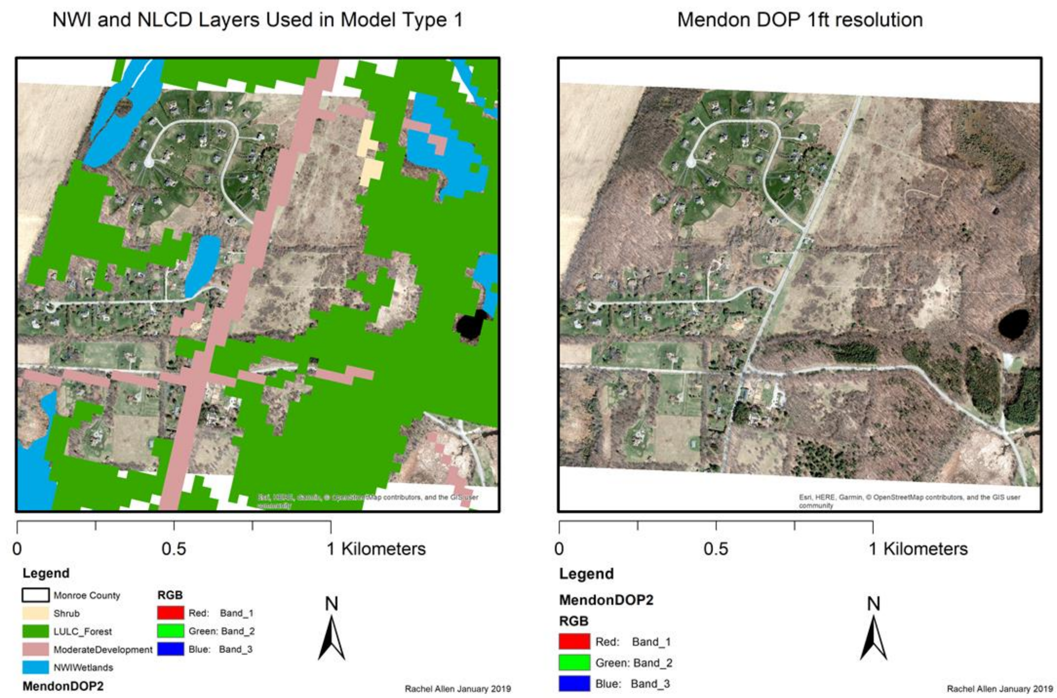


Figure 1: NLCD and NWI Layers Used in Model 1 - NLCD: This map shows development, including roads, buildings, and impervious surfaces in pink, shrublands and abandoned farmlands in tan, the forested and shrub wetlands in blue, and all (dry) forest layers from the NLCD 2011 classification in green.

The final factor in the Model 1 analysis includes several features that are known to benefit both obligate and generalist shrubland species: edge-area ratios, minimum area requirements and 100m proximity to the NWI wetlands and wet forest classes. This is intended to be a broad guideline to find shrub habitat of highest value for most shrubland-reliant species, but not all.

Model 2 – Supervised Classification

The second model was created because there were many regions known to be shrubland, including my invasive species sampling site in Mendon, NY, that were misclassified by both group 52 and 71 in the National Land Cover Database (NLCD) 2011 database. Some of this may be due to new shrubland forming and changing in the 7 years since those layers were created, but some is due to the failures of a national database on a county scale. For Model 2, I used a supervised classification approach using Landsat imagery from 2017 to identify where shrublands and other shrubland bird supportive land covers can be found in the target area, and then narrowing sites down based on the literature parameters. Supervised classification involves determining training sites of land cover types and applying the program to find additional sites that match the training sites spectral characteristics. An unsupervised classification allows the program algorithm to detect distinct classes, after which the user determines which land cover classes are included in each grouping (Mitchell, 2011; Olenicki, 2013).

The NLCD image and locations of known wetlands, forests, agricultural fields, and shrublands (Olenicki, 2013) were used to help develop training sites for the supervised classification. Aerial imagery basemaps included in ArcGIS helped to verify the digitized training sites, which were created using the Training Site Manager wizard, part of the Imagery module. These training sites were ultimately used in signature development in the supervised classification.

The NLCD definition for Shrub/Scrub classification is “areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions" (National Land Cover Database, 2016). When creating training sites, I used similar definitions, although it usually included shrub cover percentages and land cover texture, since I did not have a measure of height in my visual layers

After creating the supervised classification, I created a set of verification pixels for the model land covers independent of the training sites to check the accuracy of my classification. The supervised classifications were created based on a Landsat image from February 2017 and aerial imagery from 2015, so my classifications would be more recent than the available National Land Cover Database (2011). I used a false color combination of bands 6, 5, and 2 (Red, Green, and Blue respectively) to emphasize differences in vegetation types. The false color image is displayed in Figure 2. Figure 3 shows points representing training site locations

Once I had created a satisfactory set of training sites, I ran several supervised classifications on a Landsat image from February 2017, making small changes to improve the accuracy and remove outliers each time. I saved the one that most accurately classified the shrublands in Mendon and along the lake shore that I believed were misclassified by the NLCD. Then, similarly to the extraction of shrublands and residential areas I executed on the NLCD data, I created layers of just shrubland patches, so that I could select them for the area requirements and wetland proximity distances shown in Table 2. The supervised classification's capture of Mendon shrublands is shown in Figure 4, on the same area of the spectral sampling and the land cover comparison from Figure 1.

I used Landsat 8 imagery for a relatively coarse supervised classification (30x30m) because it matches the resolution of the NLCD 2011 land use layer. My area of interest is Monroe County, and I clipped the Landsat data and all the state and national data to the county boundaries. One difficulty in creating shrubland classifications with this 2017 Landsat image was that it was captured in February, so barren and herbaceous areas may be confused with shrublands and wet shrublands without foliage to help distinguish land cover by differences in reflectance. The February 2017 image was selected due to minimal cloud cover and year.

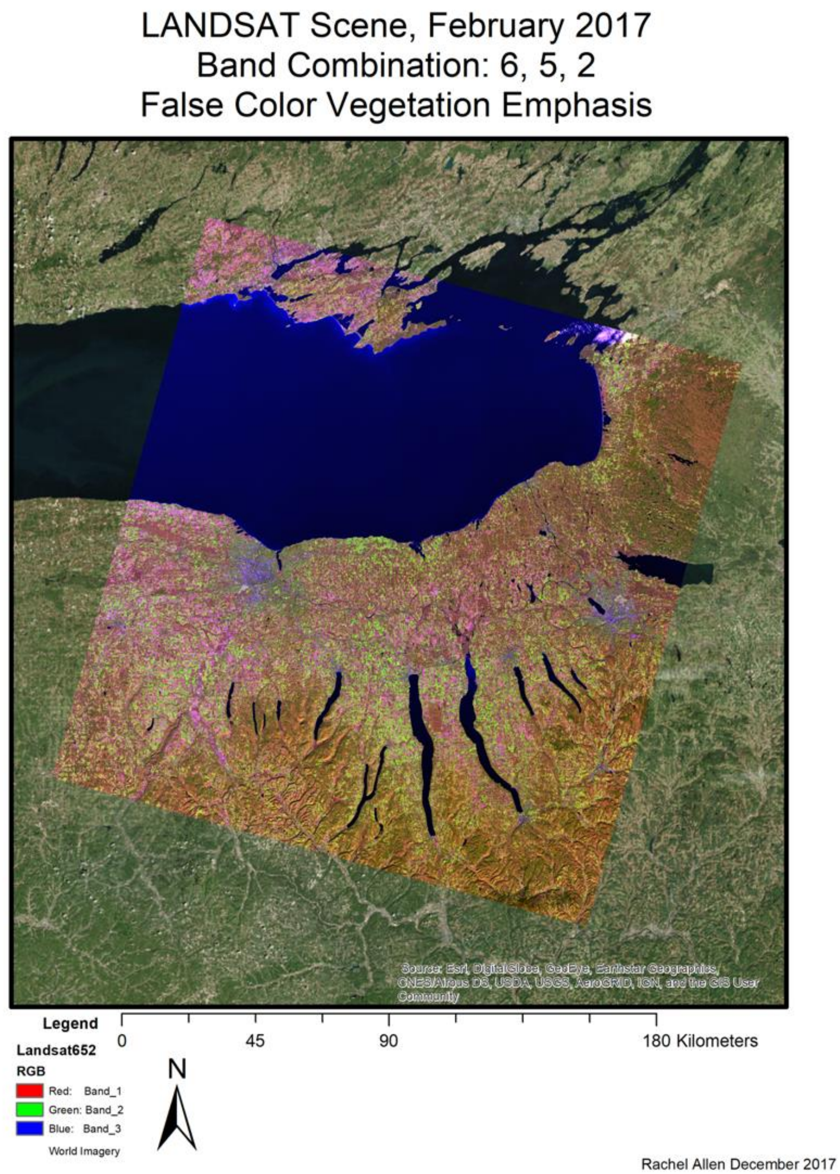


Figure 2: Landsat 8 Scene in 6,5,2 False Color. This scene is referenced in Table 2. It is derived from Landsat 8, input in ArcGIS as a composite of 7 bands, then Bands 6,5, and 2 were combined as Red, Green, and Blue respectively, to give a false color image that emphasizes differences in vegetative cover.

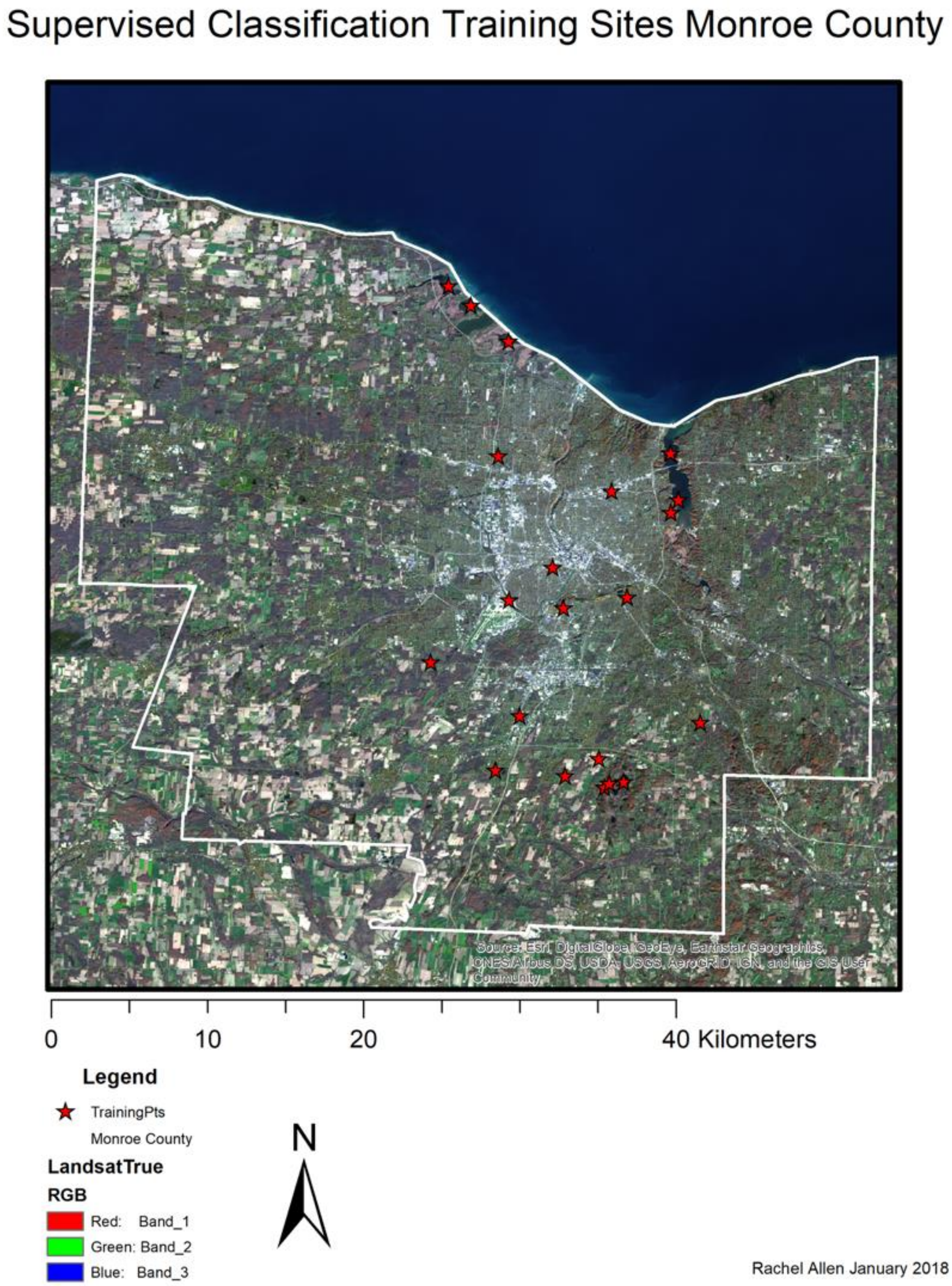


Figure 3: Training Areas Used to Create Supervised Classifications in Figure 19. Each red star represents different polygons created to train the Supervised Classification tool in ArcGIS 10.4. These polygons represented ideal and relatively uniform examples of six land cover types: water, forest, shrubland, wetland, cultivated, and developed. Because some of these polygons were only several dozen pixels, each site is represented by a star to show the distribution of training sites throughout Monroe county.

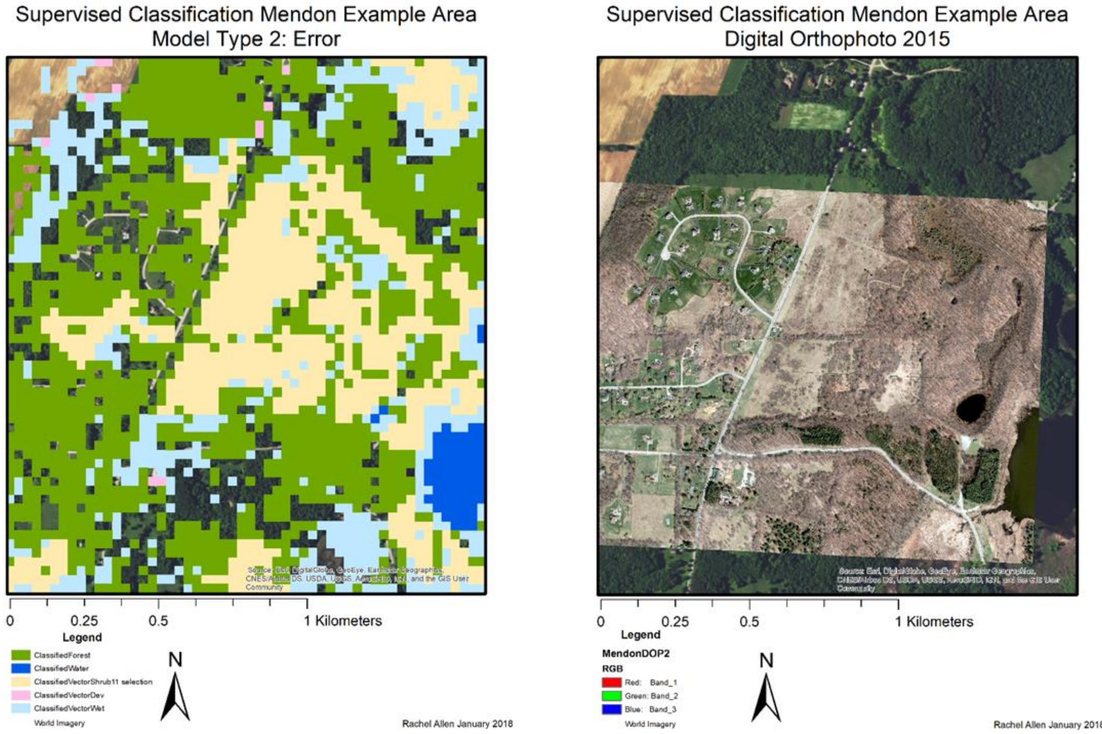


Figure 4: Supervised Classification in Mendon. The panel on the right shows the layers from my supervised classification, zoomed into my focus area in Mendon to examine accuracy. The second panel shows 1ft resolution orthoimages of the same image, at the same scale.

Wetland Proximity Variables

Because several species benefit from proximity to wetlands, I included NWI wetlands to run a proximity model. There are three main watersheds in Monroe County, and I downloaded all features from the Lower Genesee Watershed, Oak-Orchard Twelve-mile Watershed, and Irondequoit-Nine-mile Watershed. I used the "Merge" command in ArcGIS to create a complete index of wetland types within the boundaries of the county, then selected by attribute for Wetland Type =Freshwater Forest/Shrub Wetland. Since the database doesn't distinguish between the two vegetative classes, I used this category and assumed that birds that benefit from proximity to lowland shrublands and wetland would benefit from these types of wetland.

Model Steps

Both models followed similar processes. Below is an overview of these steps using NWI and NLCD data to determine ideal habitat for one focus species, the blue-winged warbler (*Vermivora pinus*). The literature says that the Blue-winged Warbler will nest in patches as small as 0.3ha, but benefits from patch sizes 0.4ha or larger (Askins et al., 2007). After selecting by polygon area greater than or equal to 0.4ha, the potentially viable habitat patch count drops to 2354 from 5559 initial sites (Figure 5).

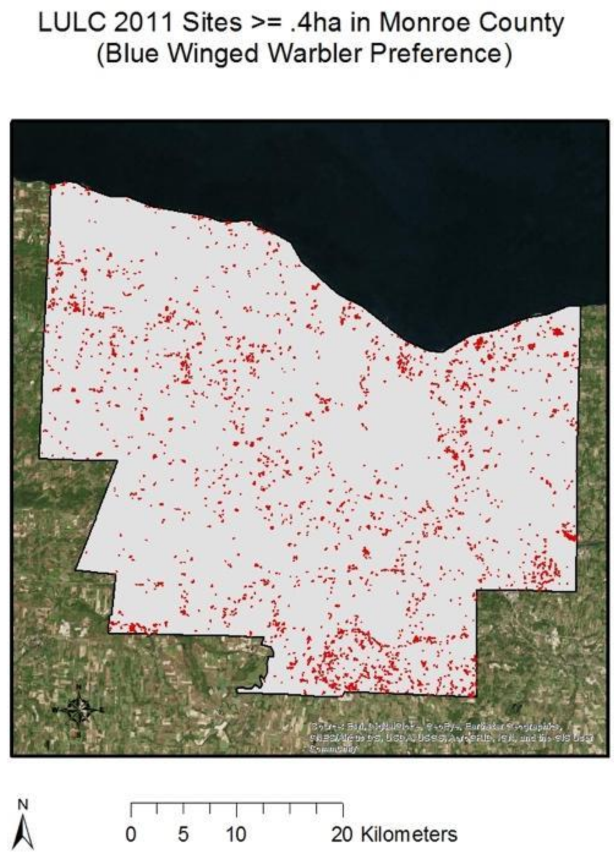


Figure 5: Blue Winged Warbler Sites First Iteration. Sites in Monroe County greater than or equal to 0.4 hectares in red. Monroe County shown in light grey with a black outline.

Each habitat parameter added a habitat constraint to the current results, paring down available sites. The second iteration, proximity to wetlands, was used to identify potential blue-winged warbler sites within 50m of a wetland, as defined by the NWI in Wetland Type = Freshwater Forest/Shrub Wetland. Only 557 of the 2354 first iteration patches greater than 0.4ha fit this proximity parameter (Figure 6). Increasing the buffer distance to 100 meters retained 793 patches (Figure 7). According to the literature, there was not a significant difference in benefits to birds when they are 50 or 100m from a wetland, so I used the 100-meter proximity selection for the next steps of the model, as it includes more viable patches.

Figure 6: Blue-winged Warbler Sites Second Iteration. Sites in Monroe County that are greater than or equal to 0.4 hectares and within 50m of a NWI Shrub Wetland/Freshwater Forest site.

Figure 7: Blue-winged Warbler Sites Third Iteration. The shrubland sites greater than or equal to 0.4 hectares that within 100 meters of an NWI shrub wetland or forested wetland.

Following this pattern, eight more models were created, comparing the habitat preferences of my focus species. Some differences in preferences include an increase in gray catbird with proximity to low-intensity residential areas within 1km and within 200m of other shrublands. The Prairie Warbler, conversely, decreases in abundance with proximity to other shrublands, and benefits from patch sizes at least 1.1ha. The Breeding Bird Survey did not include significant records of the Prairie Warbler (*Dendroica discolor)* as far north as Monroe County, so although it is an example of a good shrubland reference bird, it was removed from my results. It is interesting to note that birds like the Prairie Warbler (*Dendroica discolor)*, who do not benefit from proximity to other shrublands, may not do well in the study area due to the patchwork style of the landscape and distribution of the patches surrounding the city of Rochester.

Error Assessment Methods

There are two main types of error in classification of a certain land cover in a landscape. When creating supervised and unsupervised landscape classifications, there will be errors of omission, where a shrubland exists, but is classified as some other type of land cover on the map. The second type of error is an error of commission, where areas that are not shrubland are mistakenly classified as shrubland. Based on the resolution and accuracy of the data and the type of classification system used, the amount of each type of error will vary. Using known training sites that have been verified by ground truth and comparing results to high resolution aerial photography (DOPs) can help decrease both types of error when classifying shrublands (Olenicki, 2013). An independent set of 60 points was created for each of the six land cover classes (water, forest, wetland, shrubland, cultivated, and developed) and then converted to a raster to check the accuracy of my supervised classification (Map and GIS Library, 2013).

Using the "combine" command, the reference point raster layer was joined with the classified image. This generated an attribute table that was used to create the confusion matrix of classes. This attribute table contained the counts for the number of each of my reference pixels and the classes they were either accurately placed into or misplaced. I exported this table into Microsoft Excel and created a pivot table to show error within and between each class, as well as a Kappa coefficient and overall accuracy percentage. This step was then replicated using the NLCD Land cover classes and the same reference point raster layer of reference pixels to compare the successes and failures of each model type.

Invasive Species Spectral Data

As an initial exploratory project to help assess the level of invasiveness in a shrubland area, I collected specific shrubland reflectance data from Mendon Ponds in October of 2016. This information would then be used to prioritize conservation efforts by site. These spectra were collected using a SpectraVista HR1024i Field Portable Spectroradiometer. This meter collects data from 350 to 2500nm, a full range that includes important signatures of vegetation. Each sample includes a .sig file with the full spectral data and an image of the target area that was captured by the instrument at the time of the reading, as well as the time and GPS coordinates of the site. Ideally, these field data would enable me to add an invasive species coverage to the model, to be able to determine which areas contain large amounts of Honeysuckle (*Lonicera spp.)*, Autumn Olive (*Eleagnus umbellata)*, Common Buckthorn (*Rhamus cathartica),* and Multi-flora Rose (*Rosa multiflora)*, and which sites have high concentrations of natives like dogwood and viburnum species. Adding this component to the model helps determine the quality of sites for nesting and foraging, and brood success based on shrub structure of native and invasive species (Rodewald, 2012).

Using SAS and a script developed by Dr. Van Aardt, I ran a subset of wavelengths in values 463nm to 680nm through statistical tests to determine whether any were significantly different than others, this wavelength range have been used in other studies of canopy separation using hyperspectral data. The range of 450-950nm was used by Cochrane (2000) for species level classification, and I used a sub-sample of wavelengths in the VNIR range between 460 and 680nm. This range of the spectrum generated simpler models that used less than 30 main components to build an equation separating features.

Results and Discussion

Model 1 Results and Discussion

The first species I ran Model 1 for was the Gray Catbird (*Dumetella carolinensis*) (Figure 8). The high relative abundance (RAStat) value for Monroe County indicates the abundance of the species in relation to the presence of the other birds along the route. As shown in Table 2, these birds are generalists. One of the model features that catbirds display is an affinity for developed areas near shrublands. After selecting for their preferred patch size minimum, I selected patches that are within 1km of a light to moderately developed area. These patches are overlaid on a color map showing the BBS RAStat values, to provide simple visual verification based on a long-term survey.

The Blue-winged Warbler (*Vermivora pinus*) model (Figure 9) patch results are relatively uniformly distributed throughout the county, except for the center of the city. The highest relative abundance is in the south half of the county, away from the lake shores, however, the BBS routes do not intersect the northern areas of Monroe County, so the lower RAStat values in the northwestern area is based on data extrapolation. Blue-winged warblers are considered a characteristic species of successional old field habitat in New York (Edinger, 2015), and the presence of this species can be used as an indicator of quality shrublands and forest opening. The step methodology for all focal species followed a similar model to this species, as shown in Figures 8-16.

The Chestnut-sided Warbler is not common in Monroe County, and according the BBS data, this warbler is more common in the city and more residential and outlying shrublands to the southeast of the county than in the more forested quadrant to the northwest of the county. The Prairie Warbler *(Dendroica discolor)* is occasionally found in Monroe County (Figure 11), but upon creation of the species preference map, it became clear that there are few sites in this area that met the needs of this bird. The BBS relative abundance statistic shows that it is either not present, or not breeding in this area of western New York. In some cases where the relative abundance does not match the predicted model, it is indicative of an error in assumptions or a failure to extract the correct layers for ecological surrogates. In others, it may be that the area of interest does not contain the habitat type that is sought.

The Common Yellowthroat (*Geothlypis trichas)* is common throughout Monroe County (Figure 12). It is important to note that where light blue indicated a relative abundance value of 0 or <1 in several earlier maps, the BBS layer for this species has a RAStat of 10+ across the whole County.

The Eastern Towhee is one of the less common species in Monroe County, according to the patch numbers and the BBS RAstat value (Figure 13). The Field Sparrow relative abundance is relatively even across the County, with a higher value in the Southwestern portion (Figure 14). The Indigo Bunting is more prevalent throughout the County and according to the BBS relative abundance values, with the highest relative abundance (10+) found in the Southwestern block of the image (Figure 15).

The Black-and-white Warbler can benefit from proximity to forest, and is described in some literature is a shrub and forest generalist. It is not common in Monroe County according to the relative abundance statistic from the BBS. It is found most in the north-western area of the county, which is where there tends to be a concentration of forest according to the NLCD 2011 forest classes (evergreen, deciduous, mixed) that were combined into one layer. This relation is shown in Figures 16 and 17.

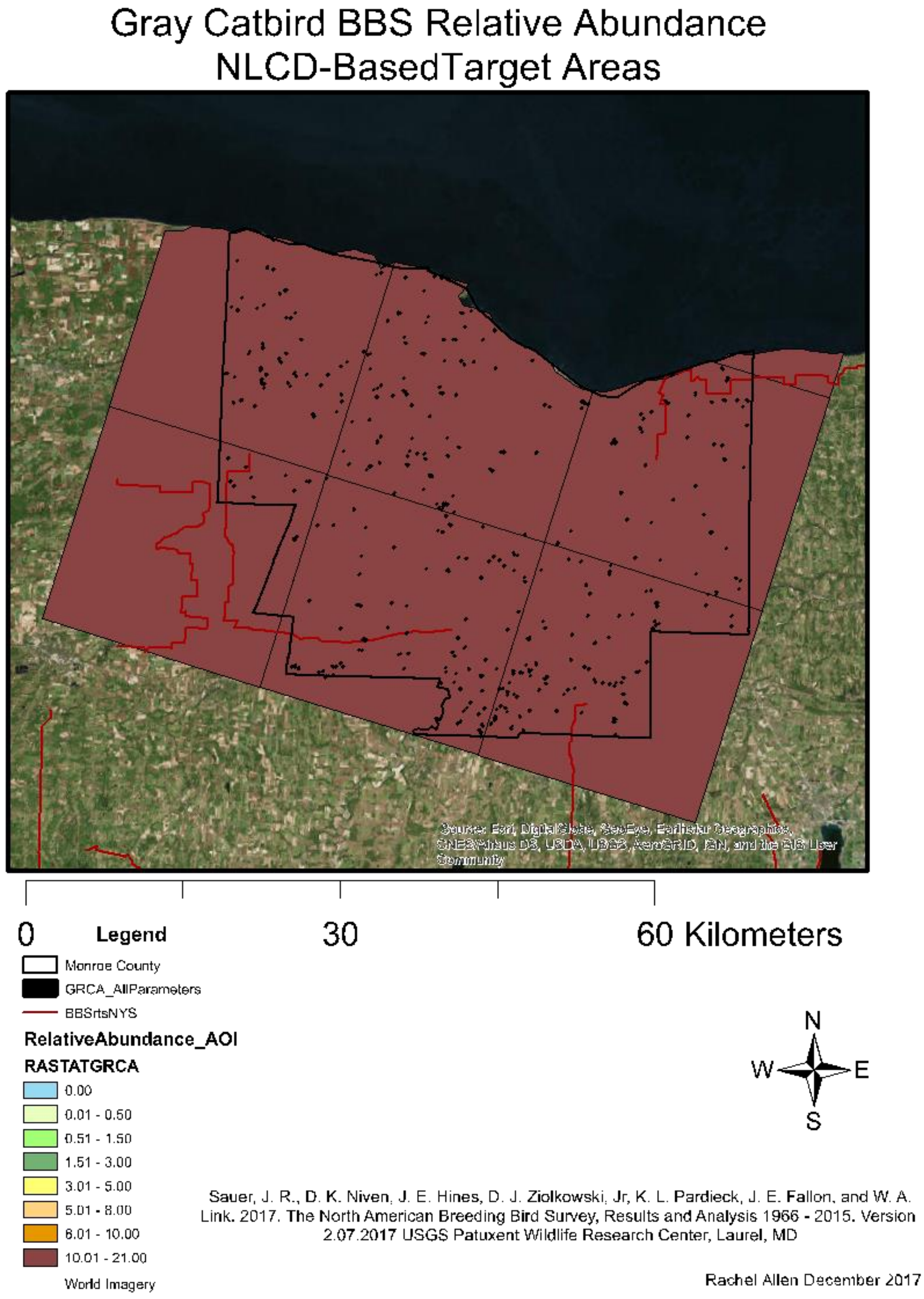


Figure 8: Gray Catbird (*Dumetella carolinensis*) Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Gray Catbird in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015), with brown showing the highest RAStat, and blue showing the lowest. Note: The size of the sites is slightly exaggerated for visibility in this format.

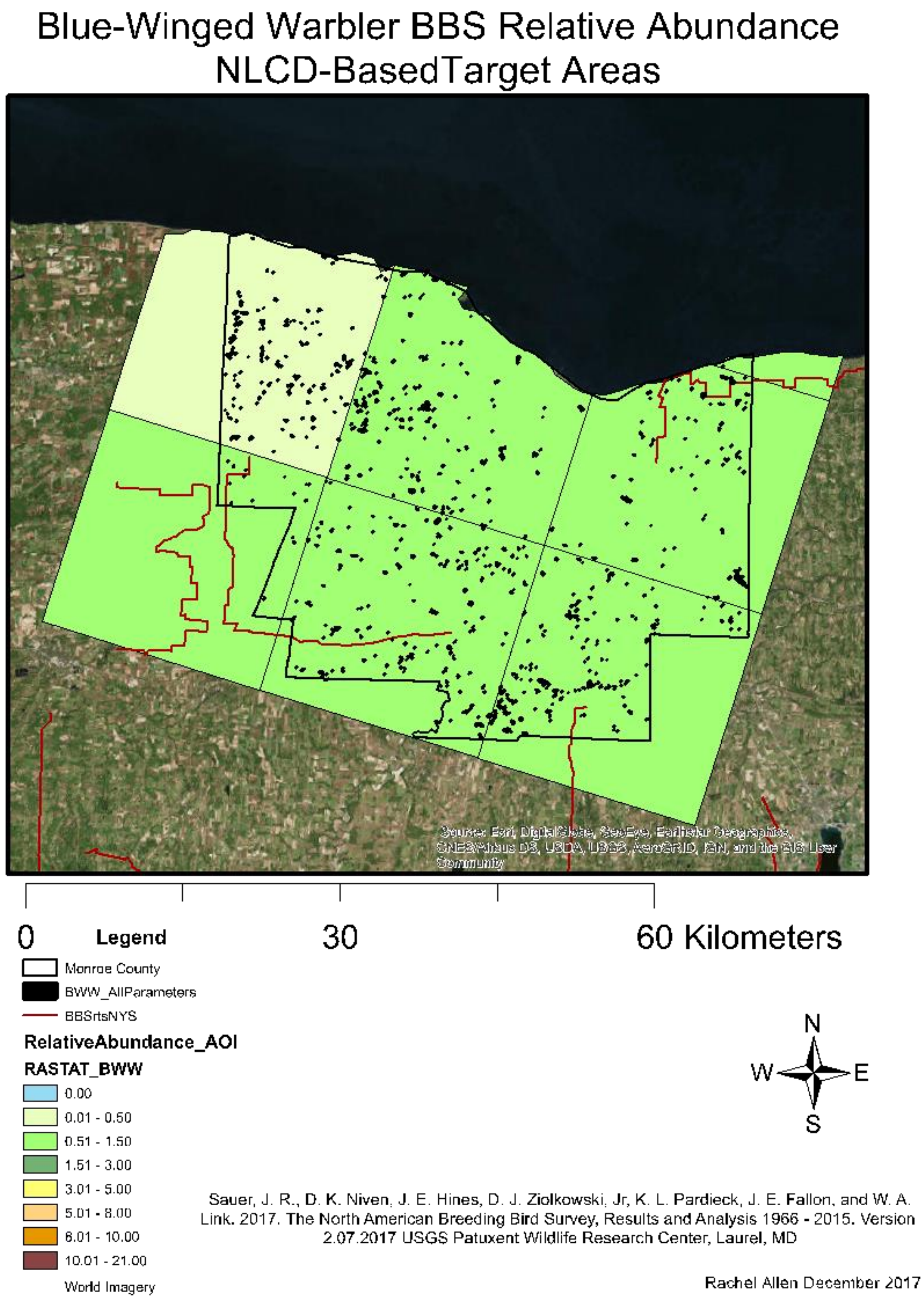


Figure 9: Blue-winged Warbler (*Vermivora pinus*) Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Blue-winged Warbler in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015). Note: The size of the sites is slightly exaggerated for visibility in this format.

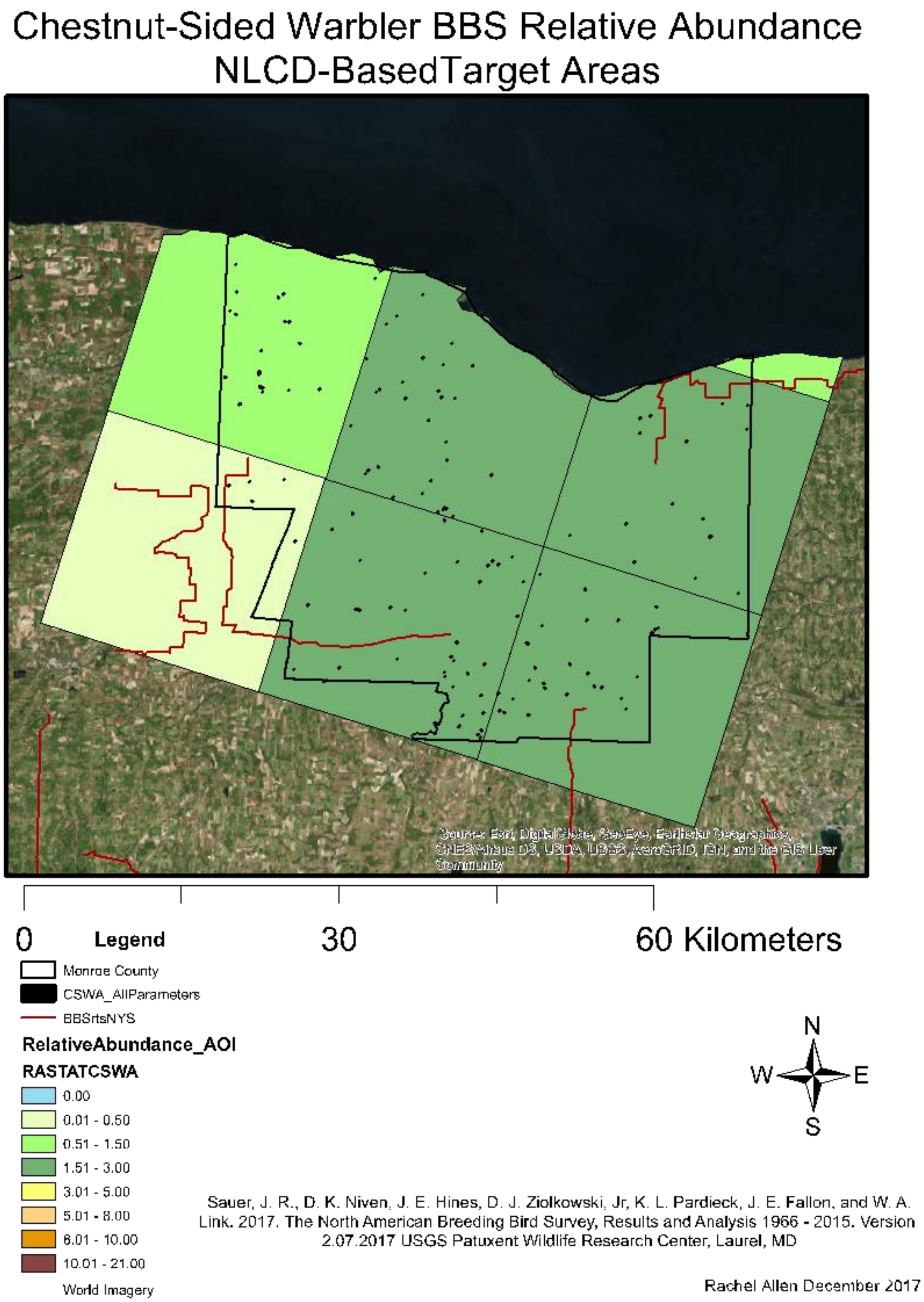


Figure 10: Chestnut-sided Warbler (*Dendroica pensylvanica*) Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Chestnut-sided Warbler in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015), with red showing the highest RAStat, and blue showing the lowest. Note: The size of the sites is slightly exaggerated for visibility in this format.

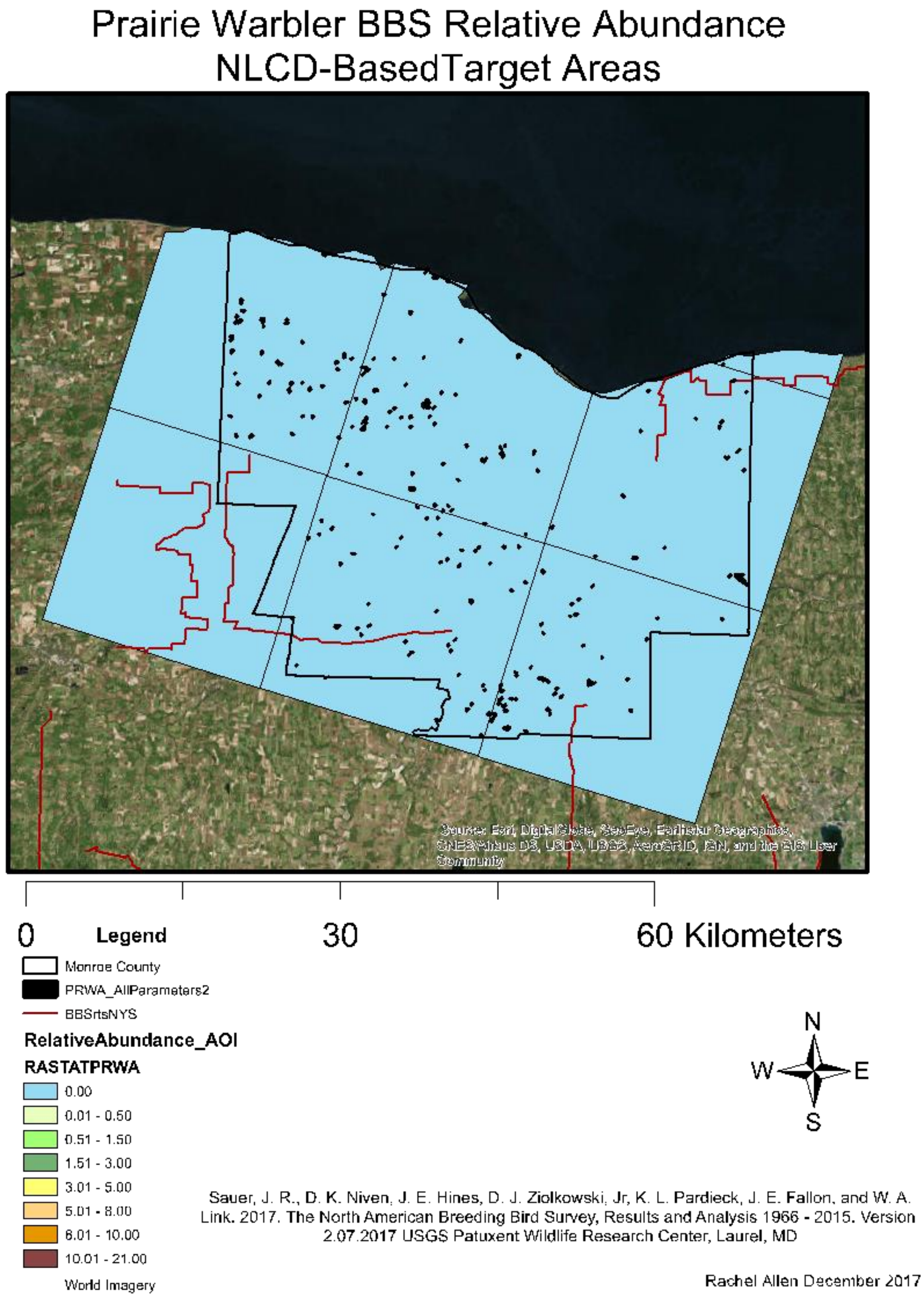


Figure 11: Prairie Warbler (*Dendroica discolor*) Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Prairie Warbler in black. The all-blue background represents the low relative abundance values from the Breeding Bird Survey (1966-2015). Note: The size of the sites is slightly exaggerated for visibility in this format.

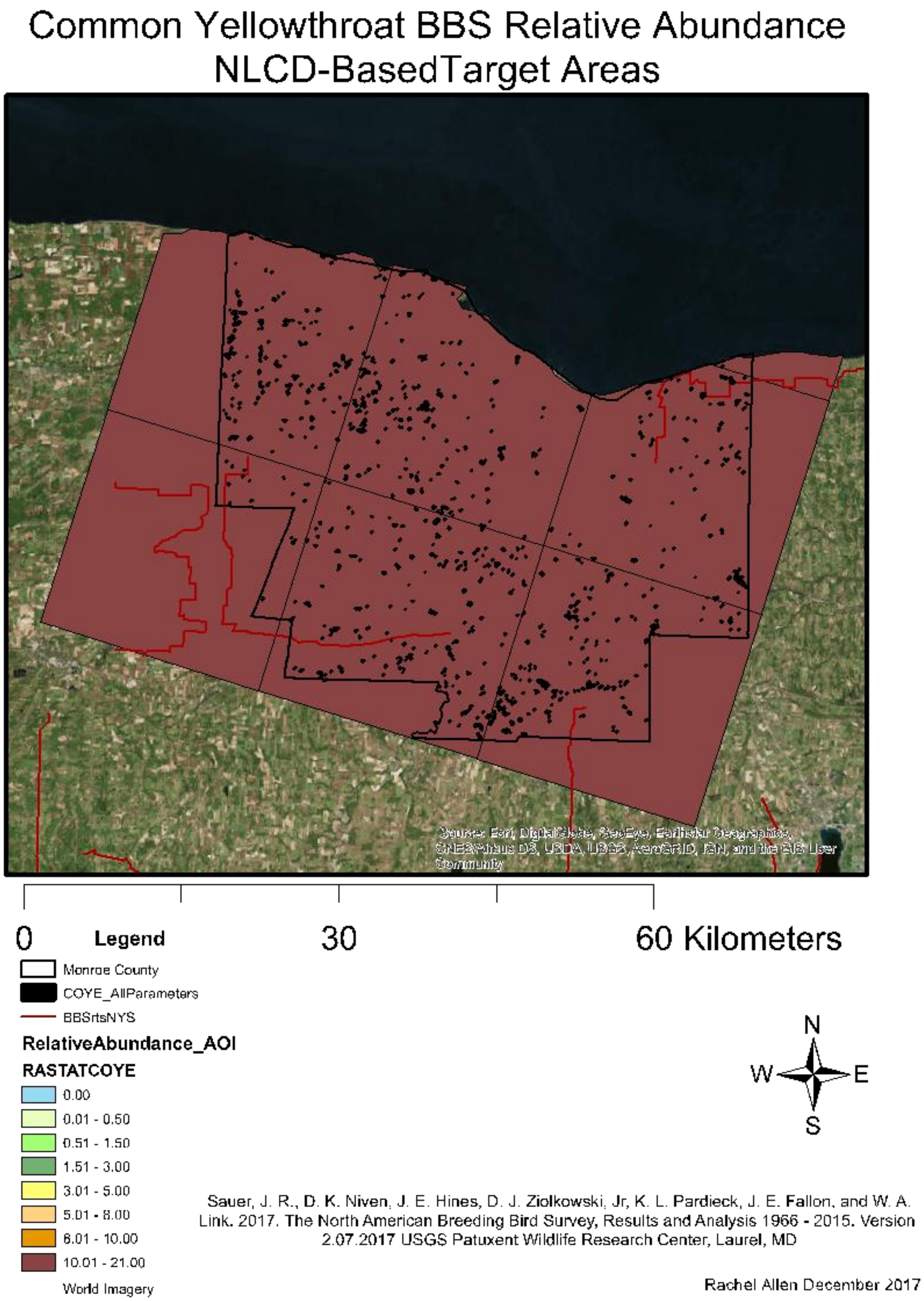


Figure 12: Common Yellowthroat (*Geothlypis trichas)* Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Common Yellowthroat in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015), with brown showing the highest RAStat, and blue showing the lowest. Note: The size of the sites is slightly exaggerated for visibility in this format.

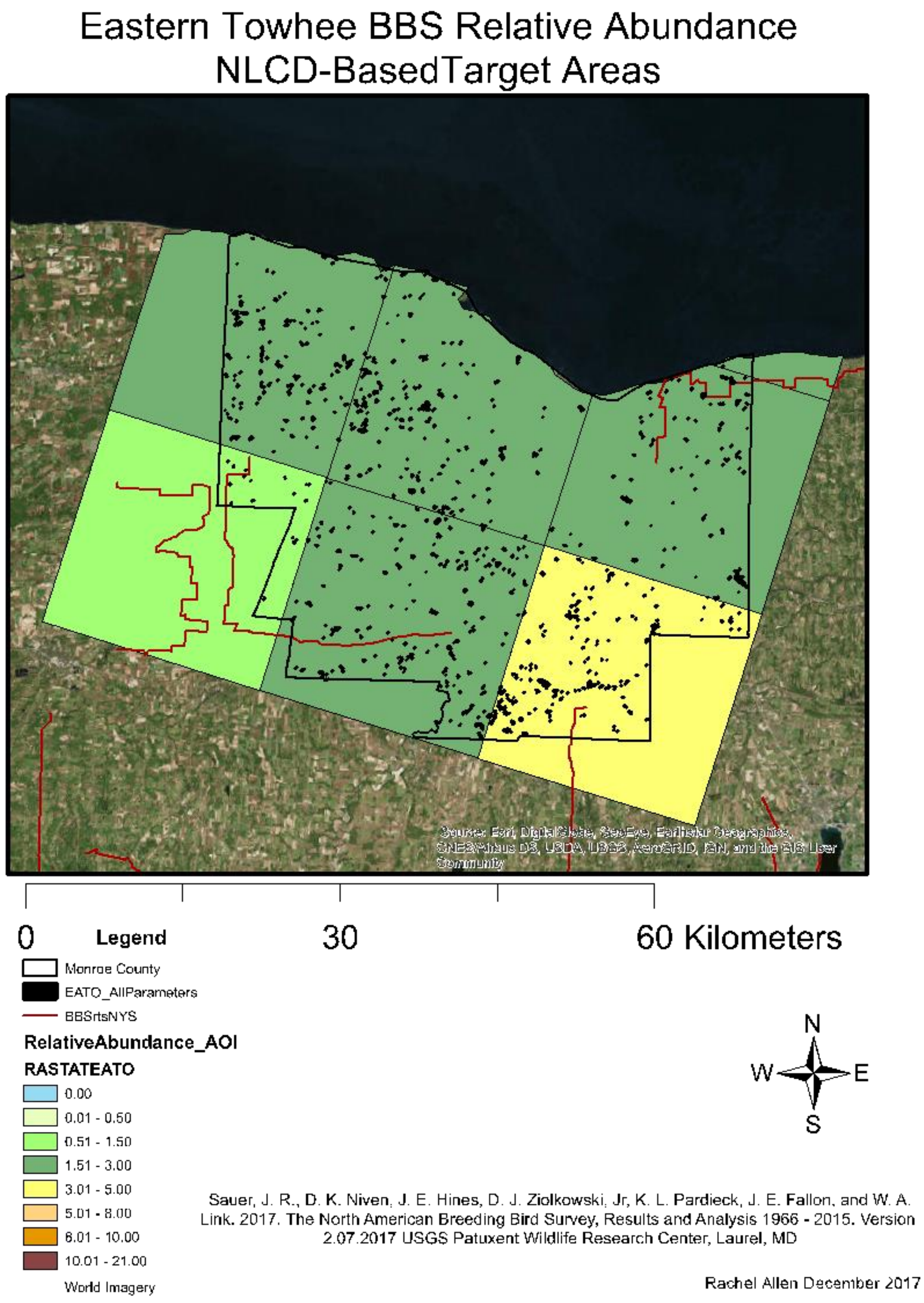


Figure 13: Eastern Towhee *(Pipilo erythrophthalmus)* Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Eastern Towhee in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015). Note: The size of the sites is slightly exaggerated for visibility in this format.

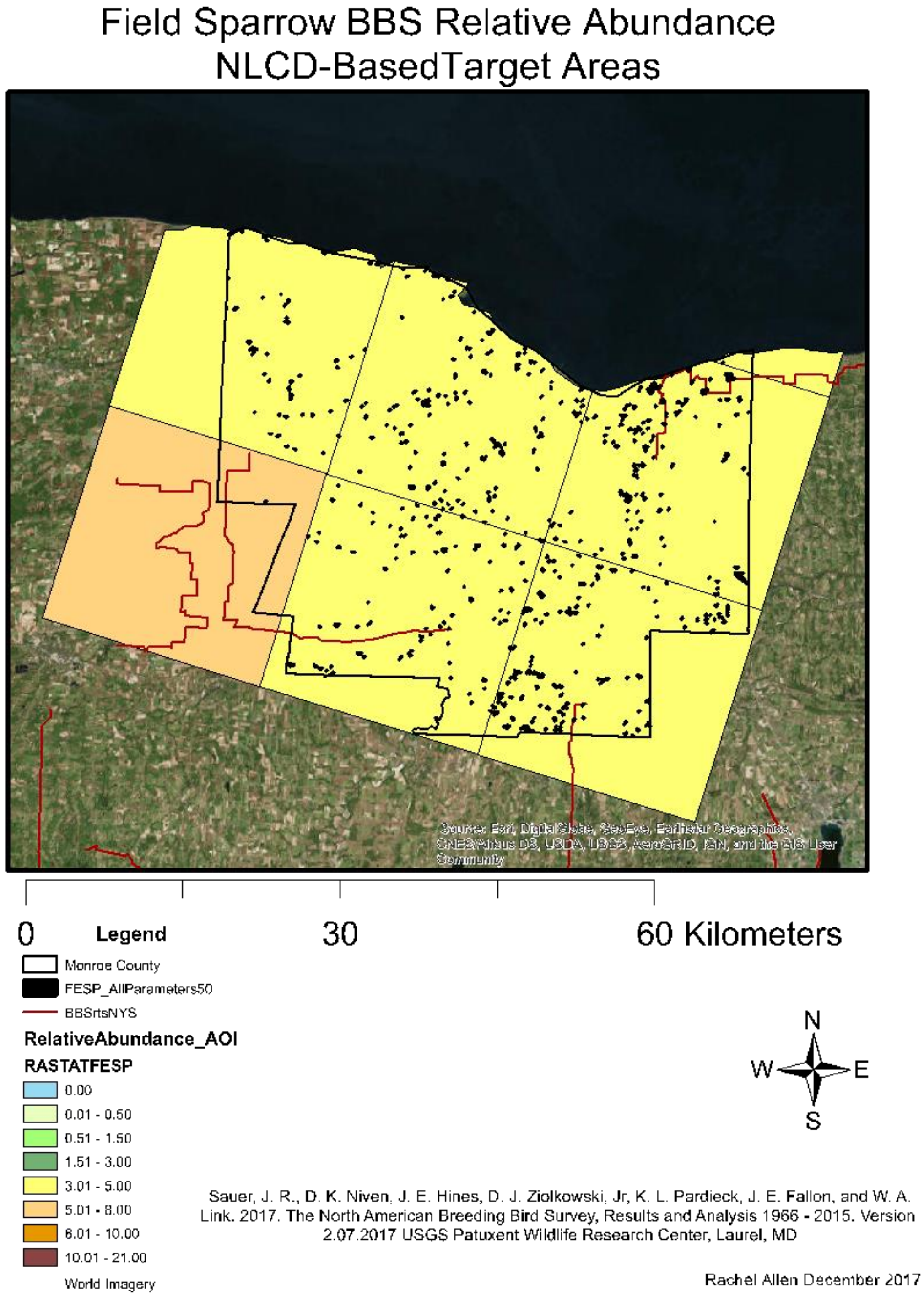


Figure 14: Field Sparrow *(Spizella pusilla)* Sites. This map shows the areas determined by the literature values in Table 2 best suited for the Field Sparrow in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015). Note: The size of the sites is slightly exaggerated for visibility in this format.

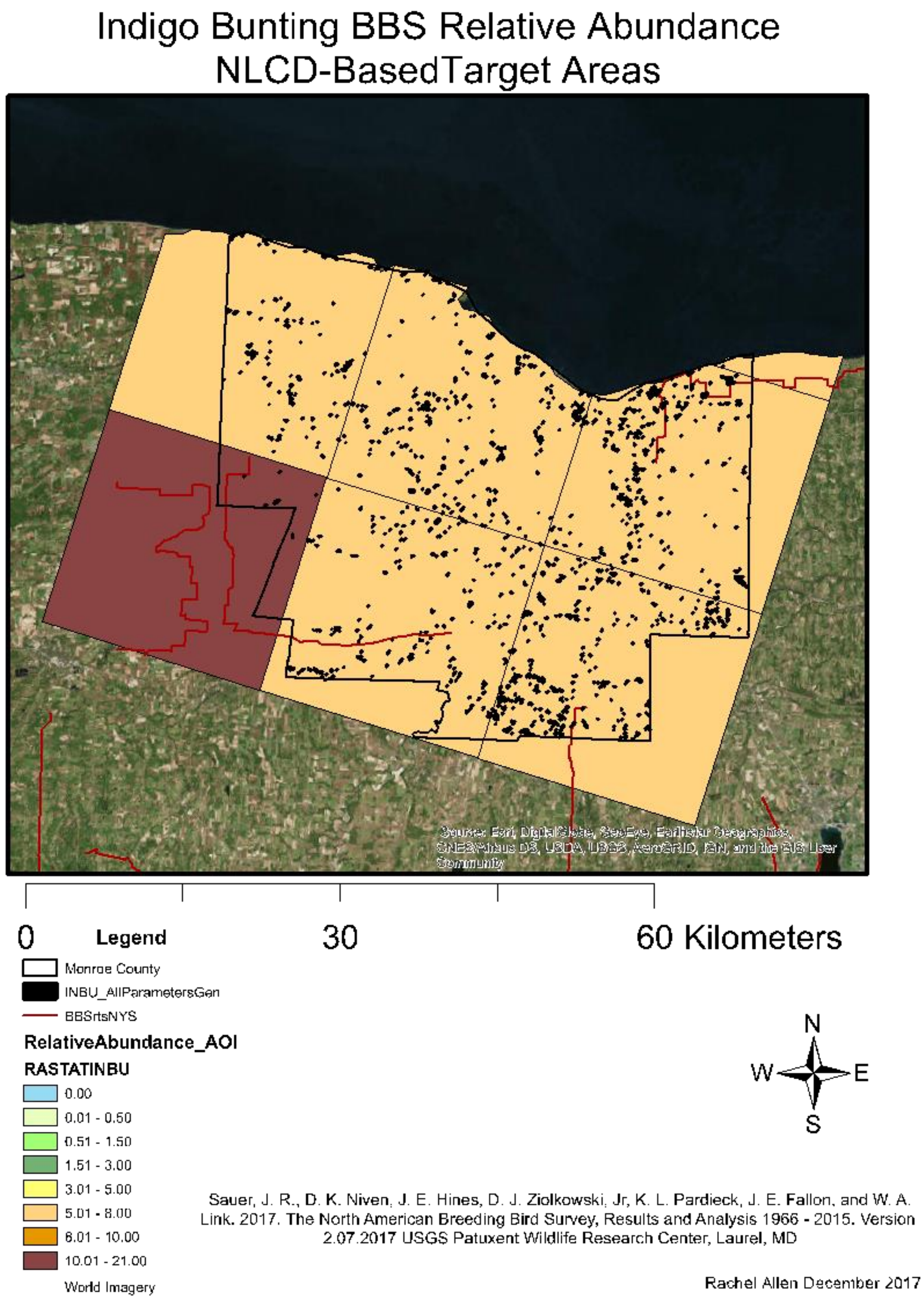


Figure 15: Indigo Bunting (*Passerina cyanea*) Sites. The areas determined by the literature values in Table 2 best suited for the Indigo Bunting in black. The colors of the blocks represent the relative abundance values from the Breeding Bird Survey (1966-2015), with brown showing the highest RAStat, and orange showing lower values. Note: The size of the sites is slightly exaggerated for visibility in this format.

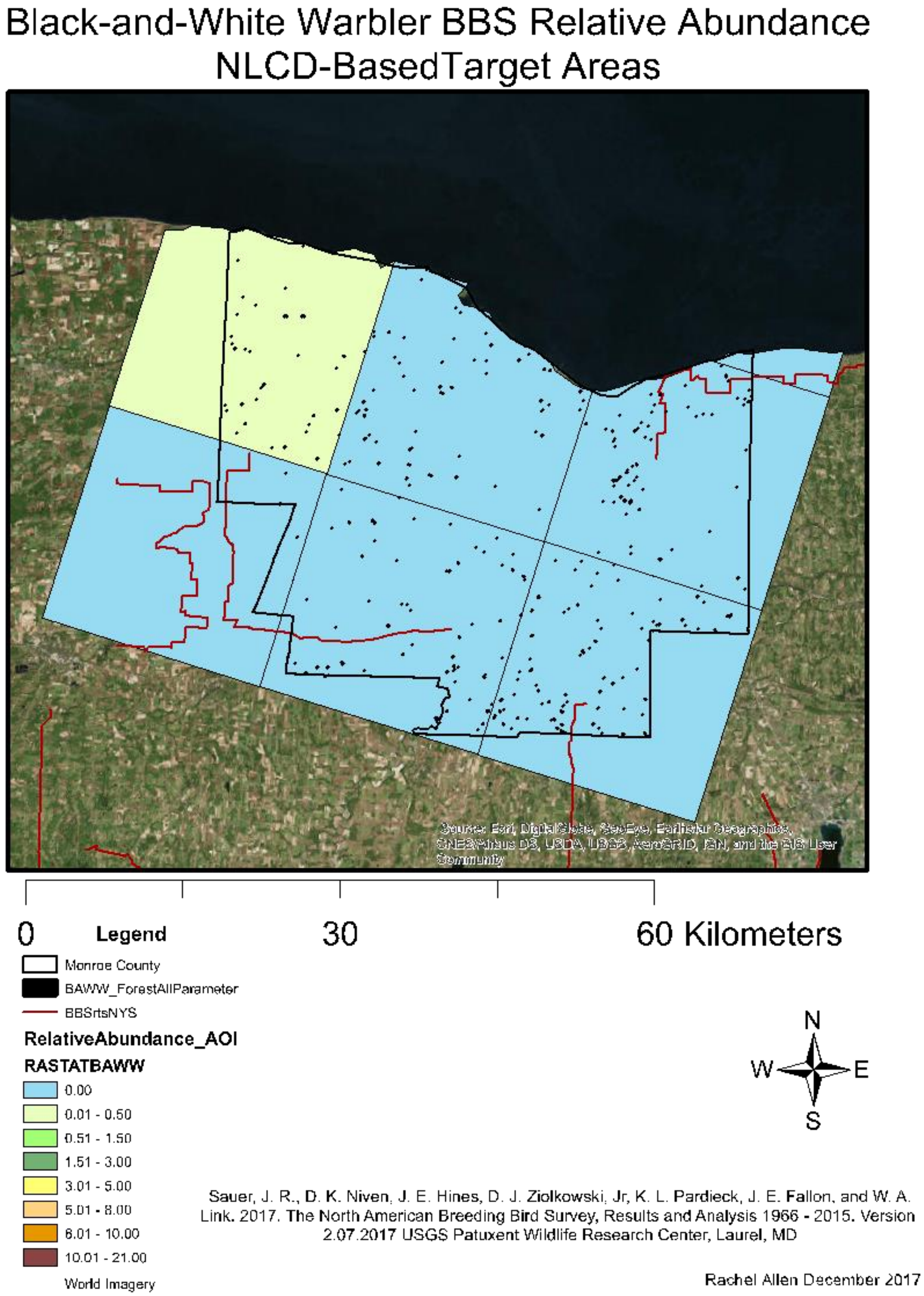


Figure 16: Black-and-white Warbler *(Mniotilta varia)* Sites. The areas determined by the literature values in Table 2 best suited for the Black-and-white Warbler in black. The colors of the blocks represent the RAStat values from the Breeding Bird Survey (1966-2015), with brown being the highest possible RAStat, and blue being the lowest. Note: The size of the sites is slightly exaggerated for visibility in this format.

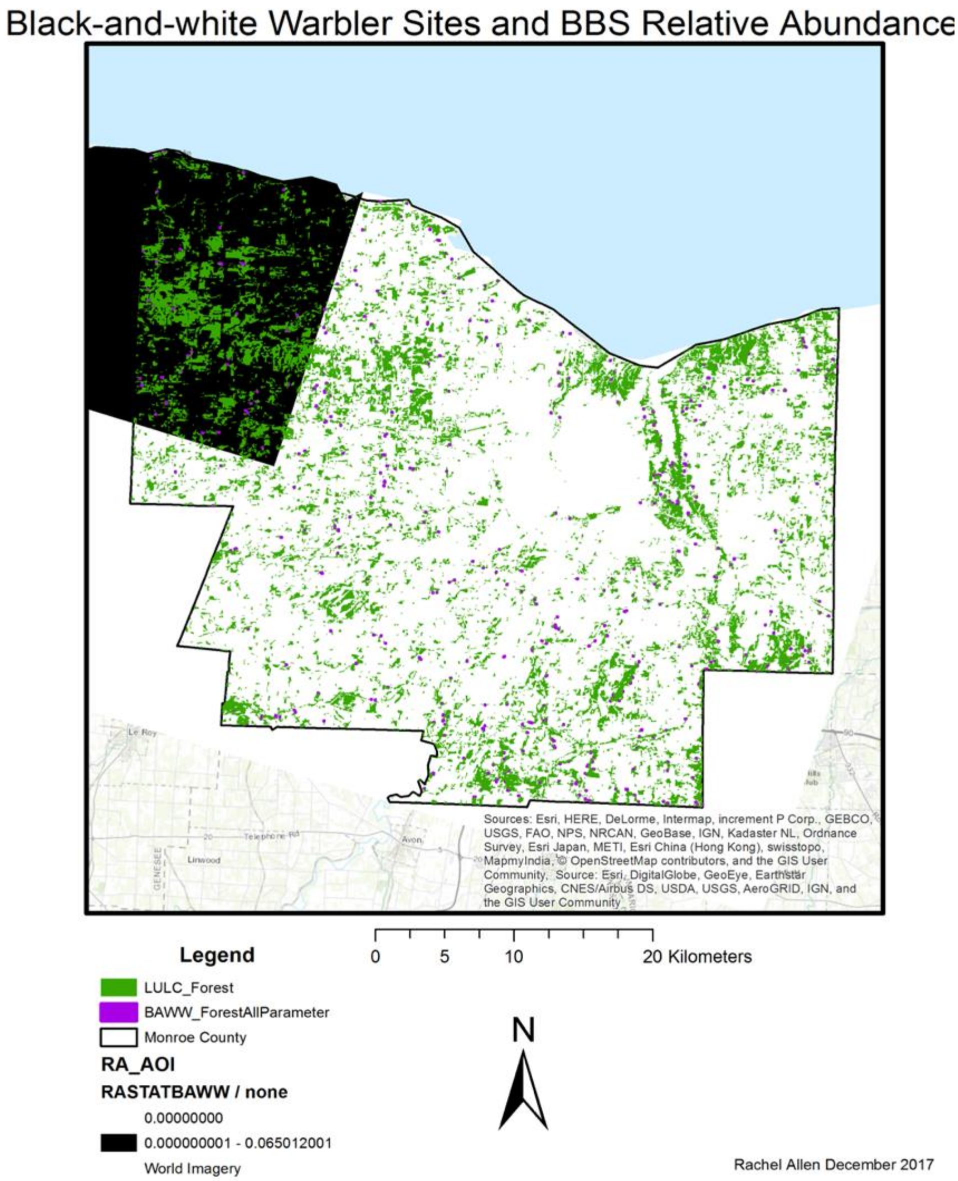


Figure 17: Black-and-white Warbler with Forest Overlay. The forest overlay shows a possible ecological explanation for the slight increase in BAWW relative abundance in the northwestern corner of Monroe County.

The final Model 1 that was generated is a generalized model (Fig. 18), containing parameters from Table 2 that benefit the most birds. This includes 100m proximity to wetland, and a patch size greater than 1.1ha, both to reduce edge influence, and avoid other impacts of fragmentation.

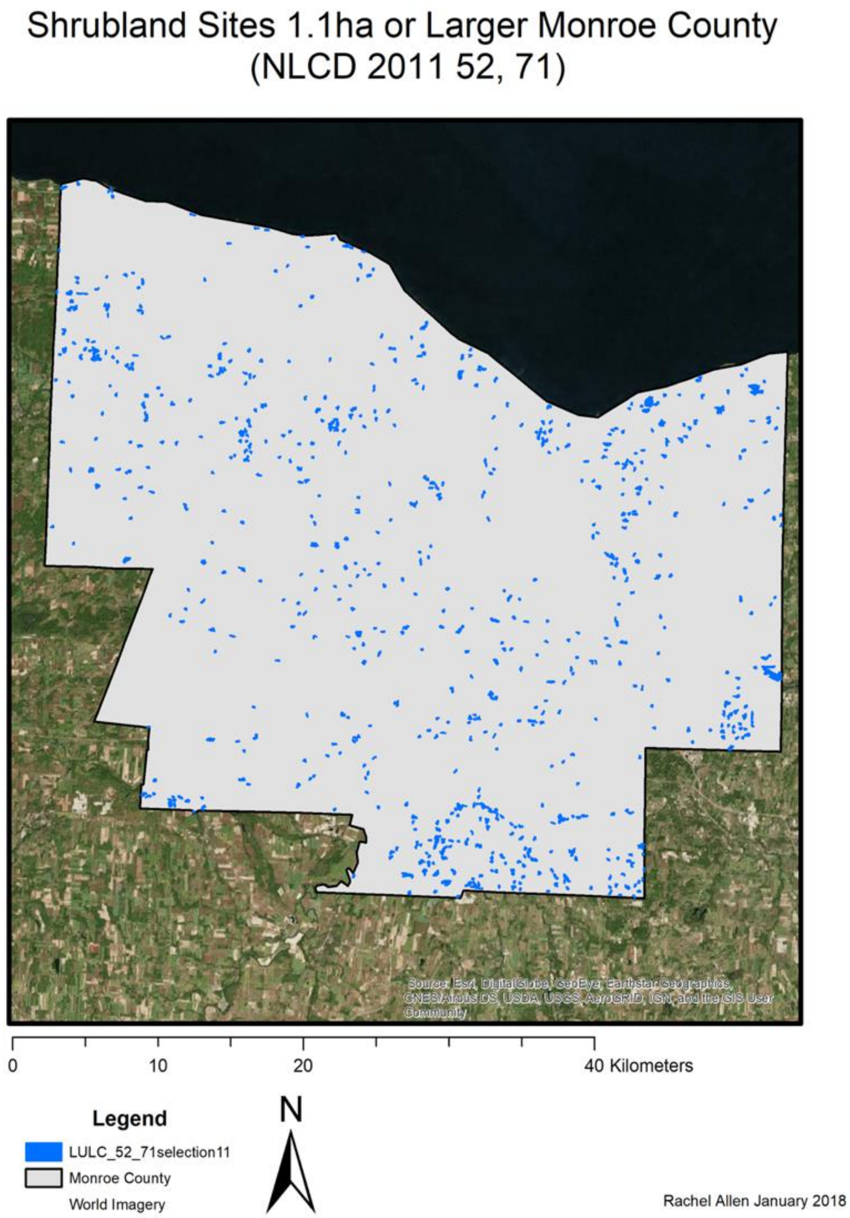


Figure 18: Shrubland Sites for Songbirds that Benefit from Proximity to Wetlands using NLCD LULC data. This map shows in blue the LULC classes 52 and 71 that are greater than or equal to 1.1 hectares, and within 100m of a wetland, characteristics that have been found to increase abundance of many shrubland species.

A few areas of shrubland omission, including my sampling area of Mendon were apparent in the Model one results, so I created a supervised classification (Model 2) to determine whether I could reduce the error, and more accurately capture the shrubland habitat. For individual species results, Figures 8-18 display the patch results visually. Table 3 displays the number of patches and total area of suitable habitat for each of the focal species according to Model 1. Some of these species have large number of patches, but a relatively small area. This usually indicates a high edge/area ratio that is undesirable for many shrubland species, however the patch size was a limiting factor in model creation, and these patches are all within the preferred size limits for each species. The species with the smallest total area include the Chestnut-sided Warbler, the Prairie Warbler, and the Black-and-White Warbler. The species with the highest total patches and total area are the Common Yellowthroat, Eastern Towhee, Field Sparrow, and Indigo Bunting. The Gray Catbird, despite being a common species in the region, had a low patch number and total area due to its preference for shrublands near residential areas. Catbirds use urban shrublands and benefit from proximity to development, so it may be that they are successfully utilizing most of the patches, so the low overall number does not necessarily mean inadequate habitat. For land cover classification and shrubland modeling based on parameters, I found that Model 1 was better at identifying small, distinct patches, with less noise. The supervised classification from Model 2 contained more patches, but also more noise.

Table 3: Patch Size and Number (Model 1 - NLCD). For the individual species maps, the results show the number of suitable patches within the county, as well as the total area (hectares) of all the patches.

Species	Number of Patches	Area (ha) Total
Common Yellowthroat	970	1047
Eastern Towhee	961	1034
Prairie Warbler	210	489
Black and White Warbler	474	85
Field Sparrow	559	1178
Indigo Bunting	1134	1654
Chestnut-Sided Warbler	177	55
Blue-Winged Warbler	793	992
Gray Catbird	506	179

Model 2 Results and Discussion

Model 2 was my supervised classification model to compare to the general shrubland sites from Model 1. With supervised classification, it is important to check the accuracy of your model and determine the Kappa coefficient for your classification. Since my supervised classification contained larger, irregular patches, calculating complex models often yielded the same results as the "general" model for several shrubland birds. My output for Model 2 (Figure 19) is a set of polygons that represent habitat that would benefit shrubland birds that benefit from proximity to wetlands and require a patch size no smaller than 1.1 hectares. Selecting by location to wetlands when using classified wetlands yielded the same results as the select by area function at >1.1ha.This meant that every single patch identified as suitable habitat was within 100m of a wetland. While it is possible that this is how the distribution of wetlands and shrublands exists in Monroe County, I checked this classification with the NWI layer, to see if my supervised classification may have overclassified the wetlands, so I re-ran the model with the NWI wetland layer from Model 1, and generated a different result, displayed in Figure 20.

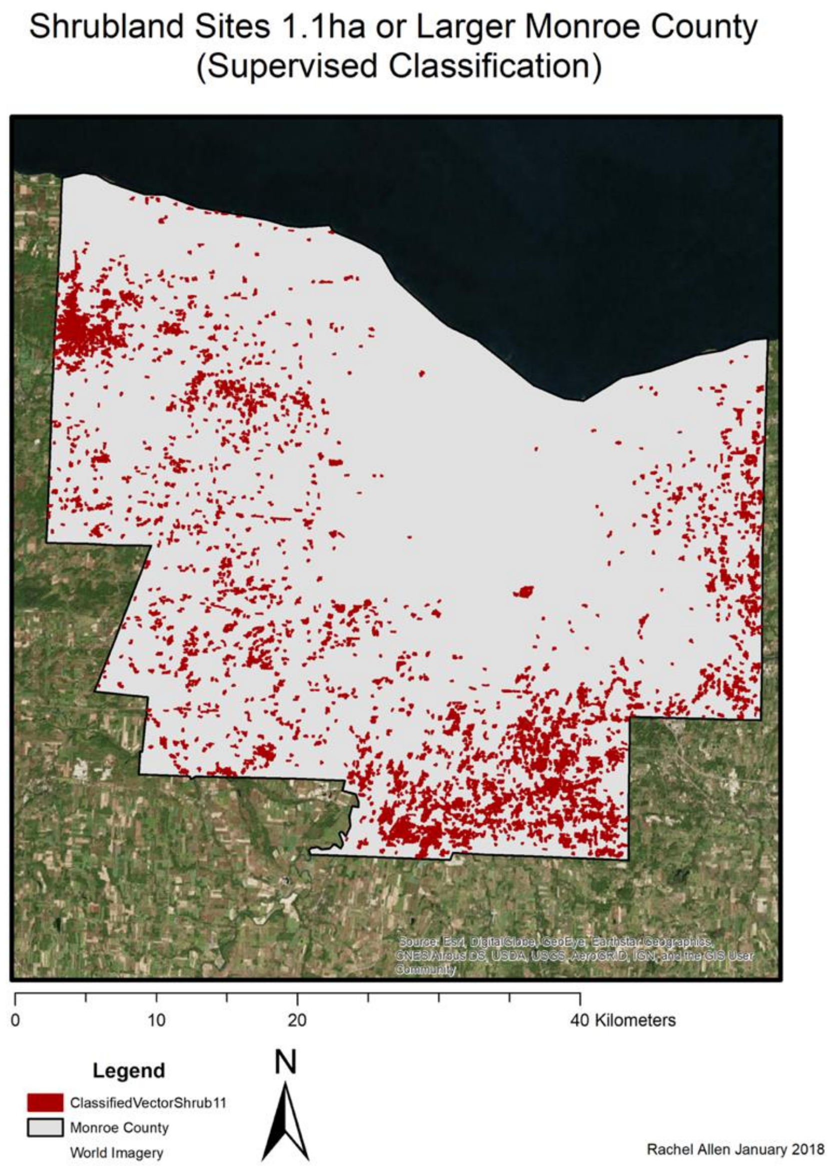


Figure 19: All (Supervised) Shrubland Sites Greater than 1.1 Hectare Within Monroe County. Red represents all of the shrubland derived from the supervised classification that met general minimum requirements for the target birds, including 100m proximity to the wetlands determined by the supervised classification. Patches less than 1.1ha were excluded from this model.

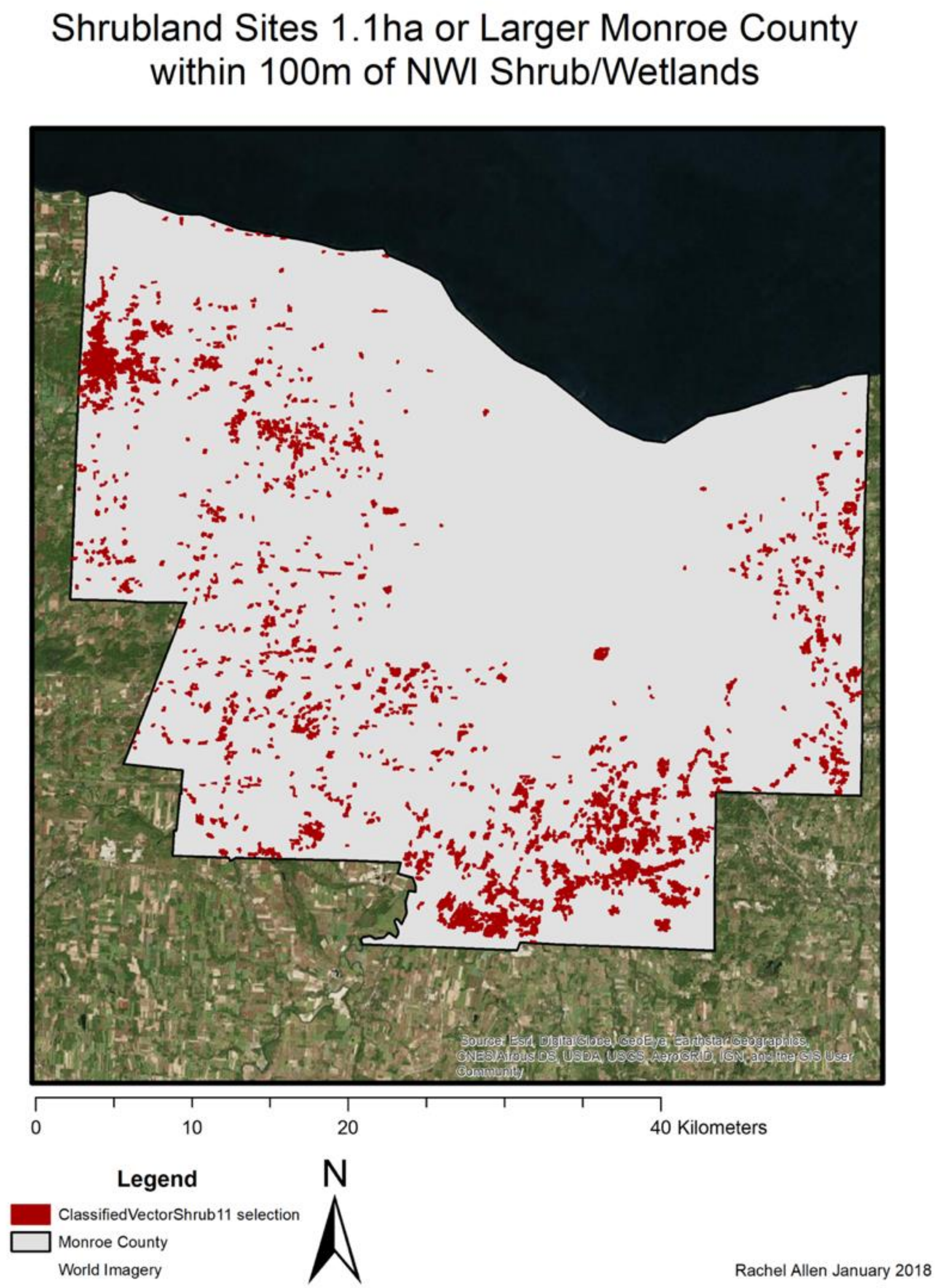


Figure 20: Hybrid Model Shrubland Sites. The red on this map represents sites greater than 1.1 ha in Monroe County, but instead of running a proximity to my classified wetlands, I instead ran a 100m proximity selection to the NWI wetlands, creating a hybrid of the two models for a general shrubland habitat map.

There were fewer total patches when the classified shrublands were eliminated if they were not within 100m of an NWI wetland. Because 57/60 wetland patches were correctly identified as wetland in my supervised classification, and only 48/60 wetland patches were correctly identified in the NLCD database, I would not have used the NLCD groups to run this combined model. Since the NWI database is created specifically for wetland classification, I decided it was the best layer to use for wetland proximity models.

To compare with aerial imagery in Mendon, I also overlaid my supervised classification, which matched the shrublands in that area much more closely than Model 1 which can be seen in Mendon between Figure 1 and Figure 4 but for the whole county, the overall accuracy percentages were virtually the same.

Union and Intersect Discussion

To visualize all of the patches identified in either model, I ran a geometric union of the results of Model 1 (generic shrubland species) and Model 2 (Figure 21).

To see which areas were identified as shrubland bird habitat in both Model 1 and Model 2, I ran an "Intersect" geometric function on the results of both models (Figure 22). This image accentuates that there were significant differences in the models, and that only a small number of shrubland patches were identified by both models. The results shown in intersect are not just the raw intersect, but the intersection where patches are within 100m of each other. Both the union and intersect are displayed in Figure 23. Showing the union and intersect in one image highlights that there were more areas not shared between the two models than areas that they had in common.

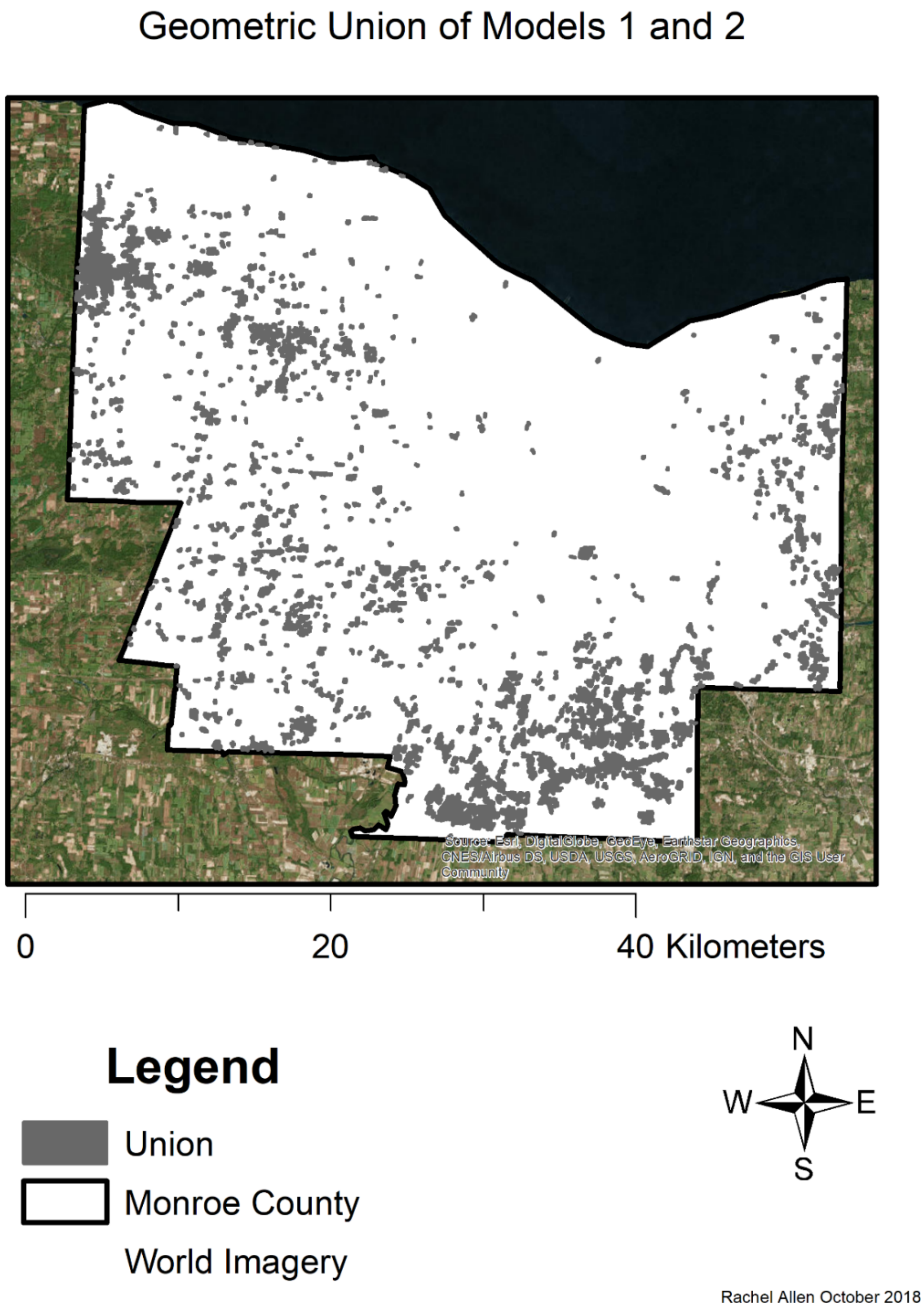


Figure 21: This figure shows the geometric union of the result polygons from Model 1 and Model 2. These represent some of the best habitat areas for native shrubland birds as identified by both a supervised classification, and a layer selection model. Note: These sites are also enlarged for visibility.

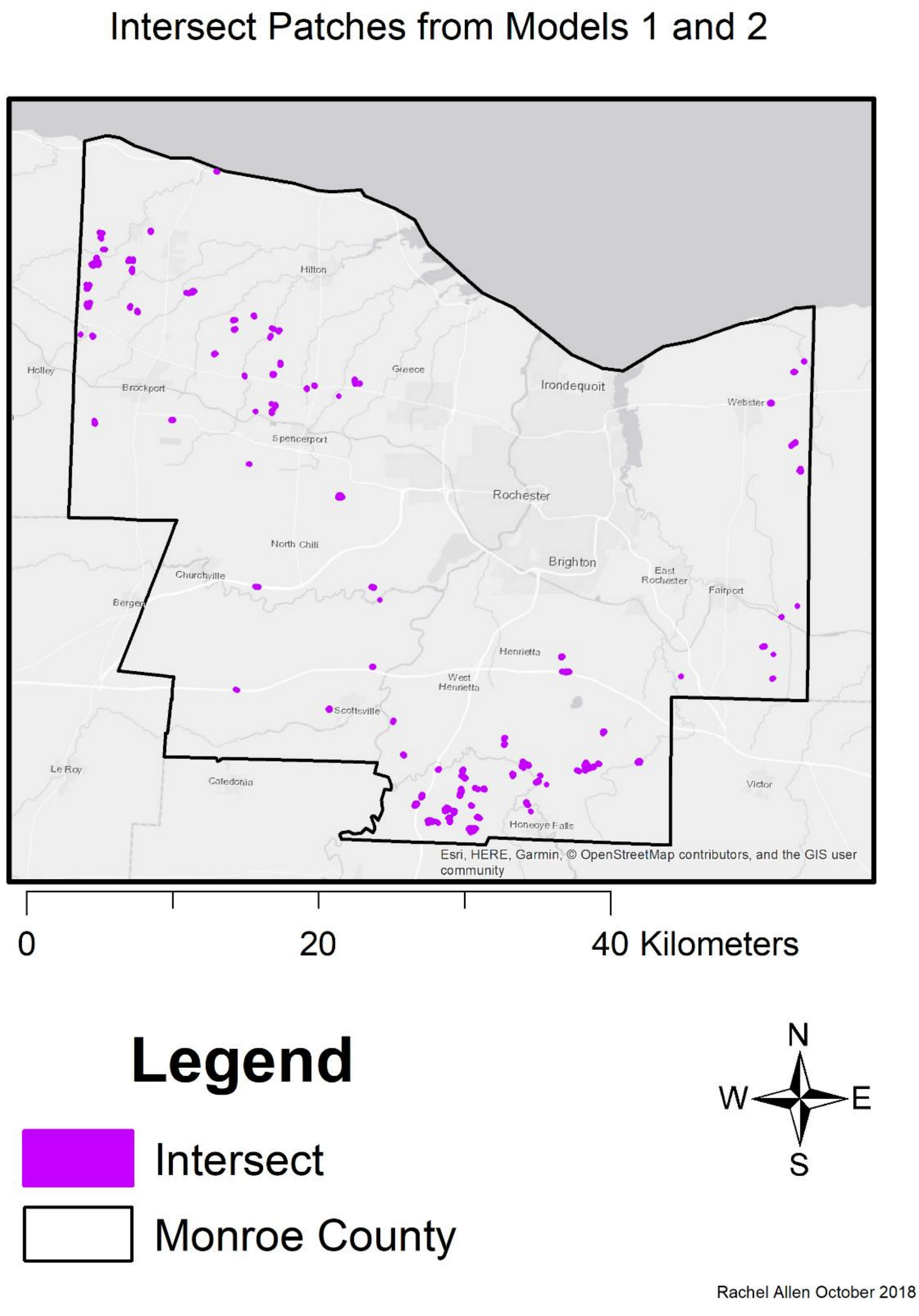


Figure 22: This map shows an overlay by town and location to give spatial context to the intersection of both models. The area in purple is an (exaggerated scale) demonstration of the patches shared between the models or within 100m.

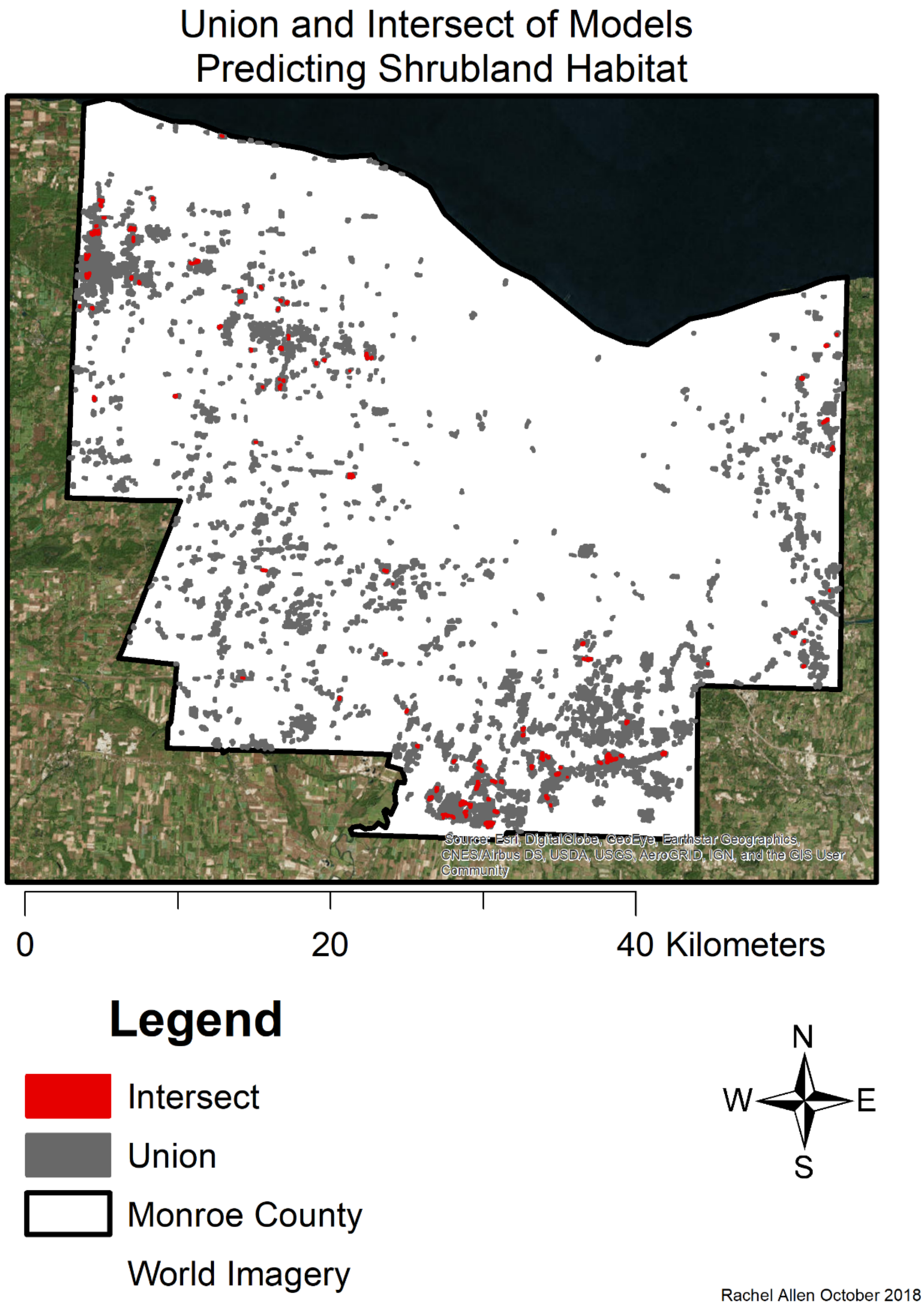


Figure 23: This figure shows both the union and the intersection of Model 1 and Model 2. The union is shown in grey and represents all of the identified shrubland habitat in the county, where the red only shows the areas where both models identified the same area as ideal for shrubland birds.

Accuracy Results and Discussion:

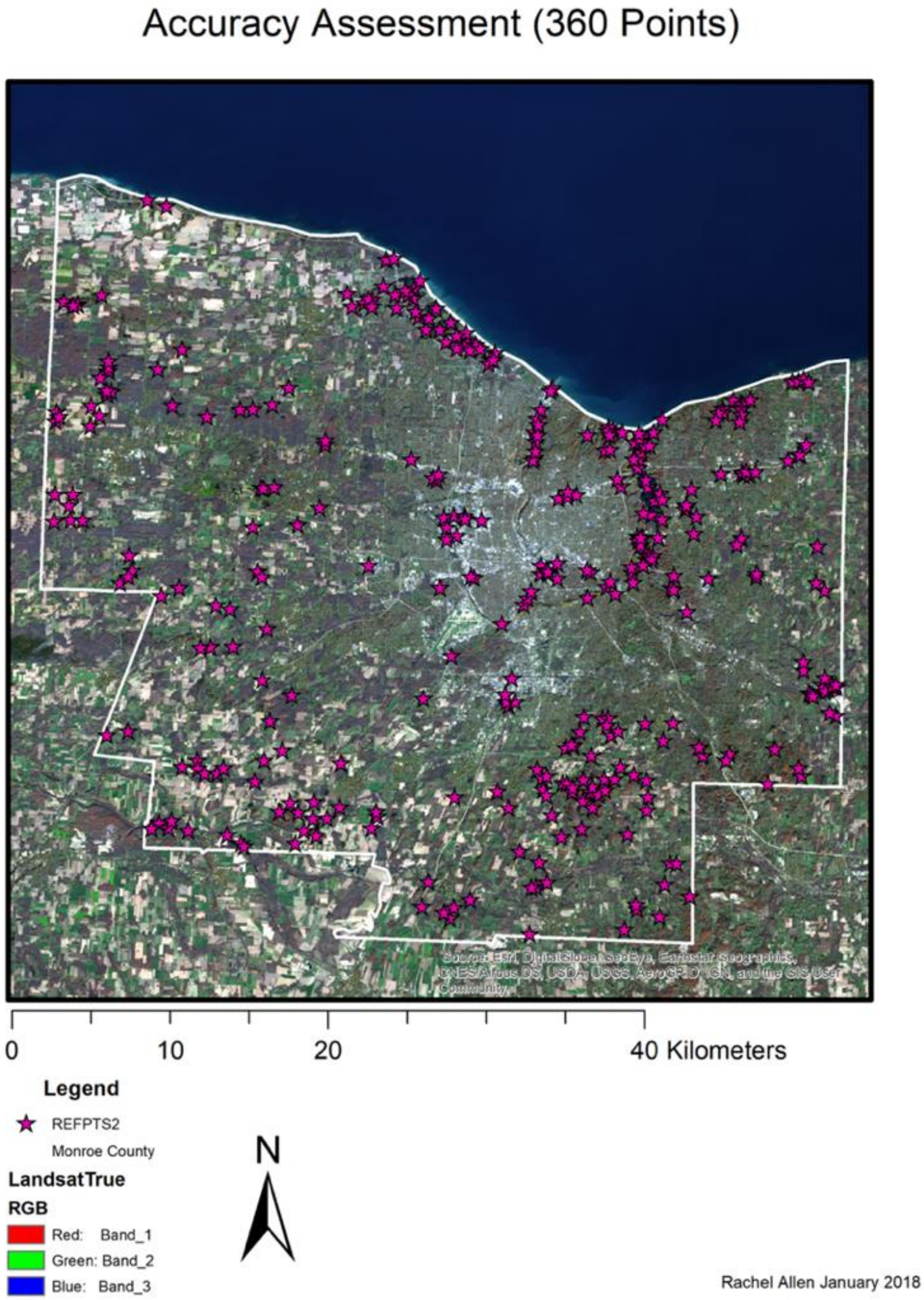


Figure 24: Accuracy Reference Points. Each star shows the location of a reference point used to generate the confusion matrix in Table 4. There are a total of 360 points, 60 for each of 6 classes.

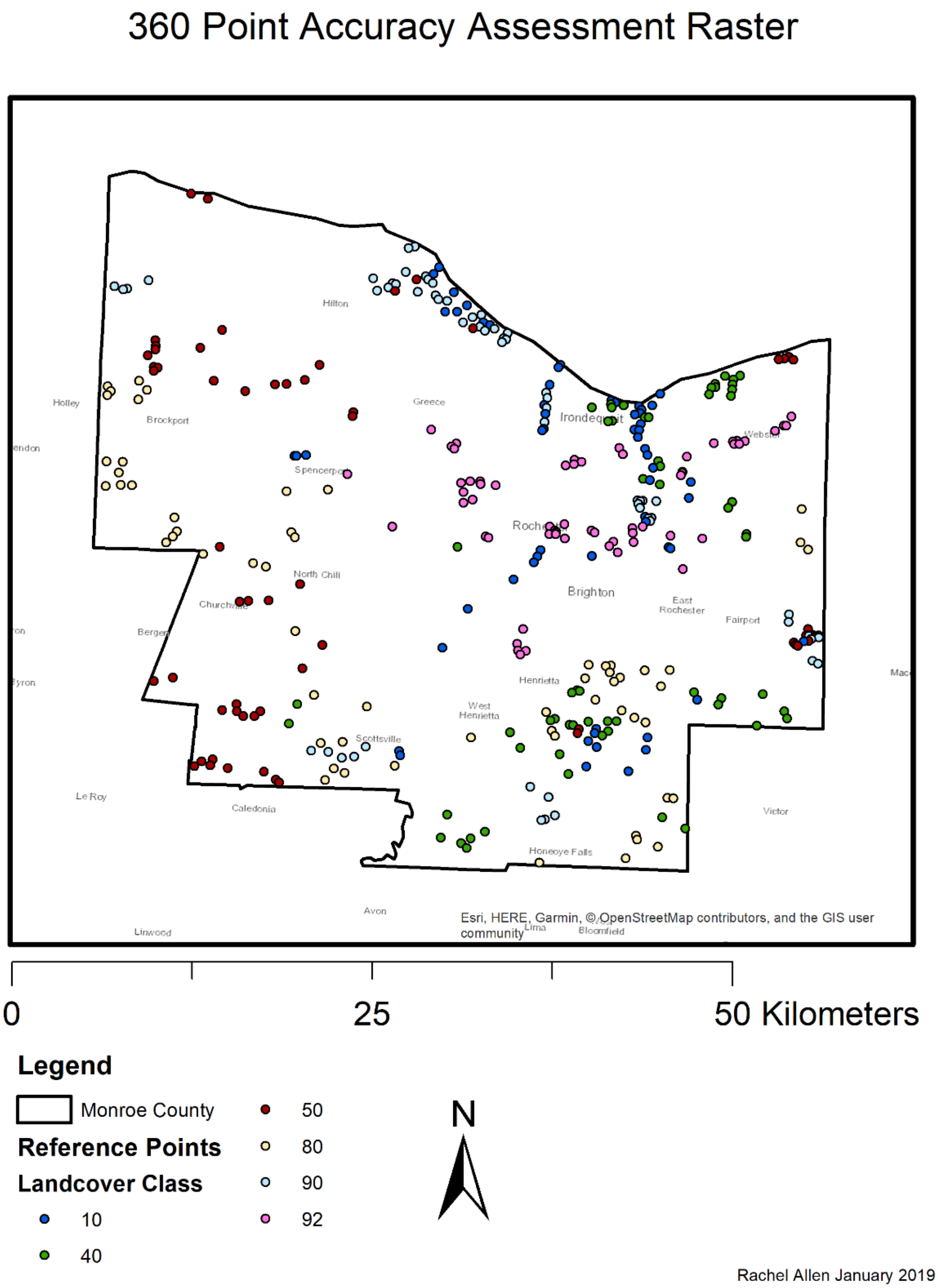


Figure 25: Accuracy Assessment Points as Raster. This map shows each reference point as a pixel with a land cover type and value color coded to show the distribution of the reference pixels throughout the county. Land cover class 10 signifies open water, 40 is forests, 50 is shrubland, 80 is barren/crop, 90 is wetland, and 92 is developed or roadways.

Both models are very similar in overall accuracy percent 71.1% vs 71.4% (Table 4 and Table 5). These accuracies were below 80% overall, which would be considered high accuracy. The supervised classification worked well in Mendon and other known shrub/scrub areas that were originally classified as wetland or cultivated fields in the NLCD database, but that provide valuable habitat for native birds. One problem that was encountered with the wetland classification is that it was almost always adjacent to shrublands, so selecting by location for proximity to shrub wetlands led to minimal narrowing of the Model 2 results.

The clusters of sites generated for each species could be used as reference points for bird point counts, population surveys, and breeding studies. Understanding other factors like management and disturbance regime timing, predation, and phenological changes would require site-specific data for the birds.

Table 4: Confusion Matrix for NLCD Accuracy (Model 1). This matrix shows the accuracy of the NLCD LULC categories using the same reference points derived from aerial imagery and ground reference that were created for Table 3. The inaccurate classifications fall in different categories, but the overall accuracy percentage is very similar, around 70%.

NLCD		Classification							
Ref	LC Type	Water	Forest	Shrubland	Cultivated	Wetland	Developed	Grand Total	Producer's
	Water	51			2	5	2	60	85%
	Forest		37		2	20	1	60	62%
	Shrubland		23	4	11	21	1	60	7%
	Cultivated				58		2	60	97%
	Wetland		7		4	48	1	60	80%
	Developed			2			58	60	97%
	Grand Total	51	67	6	77	94	65	360	
	User's	100.00%	55.22%	66.67%	75.32%	51.06%	89.23%		
	Overall	71.11%							
	Kappa Coeff	65.33							

Table 5: Confusion Matrix of Supervised Classification (Model 2). This matrix shows the reference points and their counts in each category in the rows, and the classifications assigned to them in the columns. The overall accuracy was 71.39%, the user's accuracy percentage is displayed below the total values for each column, while the producer's accuracy percentage is displayed to the right of the totals for each row. The Kappa Coefficient is 0.65, or expressed as a percentage, 65.67%.

Supervised		Classification							
Ref	LC Type	Water	Forest	Shrubland	Cultivated	Wetland	Developed	Grand Total	Producer's
	Water	50				5	5	60	83%
	Forest		36	3	2	19		60	60%
	Shrubland		5	26	3	26		60	43%
	Cultivated		10		29	21		60	48%
	Wetland			3		57		60	95%
	Developed				1		59	60	98.3%
	Grand Total	50	51	32	35	128	64	360	
	User's	100.00%	70.59%	81.25%	82.86%	44.53%	92.19%		
	Overall	71.39%							
	Kappa Coeff	65.67							

The overall accuracies of these two matrices are so close that it was not possible to determine which one is more accurate using the 360 reference points based on overall accuracy percentage alone. However, some important values were found in the User and Producer accuracy columns. The intersection results had a low accuracy (19/60) in shrubland when compared to the shrubland and wetland categories of accuracy points from the overall error assessment points. The supervised classification did successfully identify more of the shrubland reference points (26) than the NLCD classification (4), or 43% to the NLCD model's 7%. This suggests that Model 2 is the more accurate model for shrubland identification. Additionally, there were errors of commission in the shrubland category where one forest reference point and three wetland points were classified as shrublands. Knowing that these types of land cover have many features in common, it is not unreasonable for them to be confused in remotely sensed classification. Additionally, it is possible that if they are similar enough to shrublands to be mistakenly classified as shrubland, they may provide usable habitat for bird species that prefer shrublands and shrub/wetlands. There would have been a higher accuracy of shrubland classification in the supervised model, but the errors of commission in the other areas led to a very similar overall accuracy between the models. Because the best available Landsat image for this time period was a cloudless February 2017 image, identifying shrubland was not based on foliage reflectance, which likely influence the accuracy in the supervised classification. The accuracy statistics are better than a random model, but the addition of foliage in another Landsat scene could provide the ideal threshold of accuracy classification (80%).

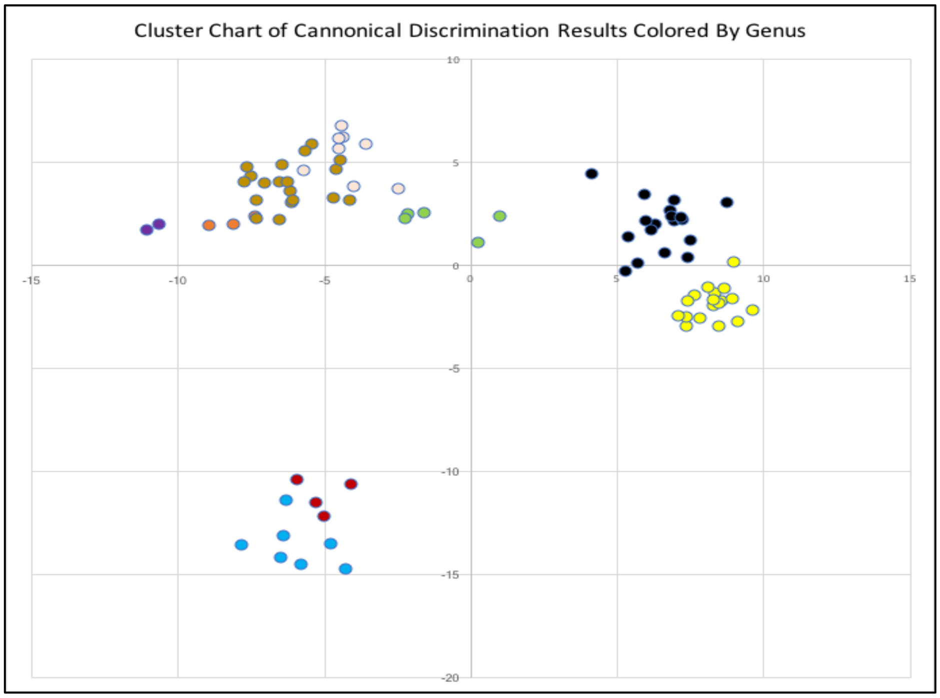
The errors of commission were most prominent in the cultivated and wetland categories, where land cover types of almost every other category were misclassified as wetlands or cultivated land. These errors are what brought the overall accuracy of both models below the standard 80% value. The wetland commission is likely due to excess moisture in the soils, making shrublands look like wetlands. It is often difficult to separate cultivated land with crop residue from shrublands without foliage because of the reflective properties of low-growth vegetation using satellite data. Fortunately, some cultivated land, especially fields that have been abandoned for several years, also qualify as good habitat for shrubland birds, so these errors may not indicate a lack of habitat for the target species.

Similar errors between models included the commission error where forest is categorized as shrubland, and where open water is included in the shrubland count. Young forests can share common spectral signatures with shrublands. Wetland shrublands, especially those without foliage in wet conditions may be confused with open water. A young forest (classified forest) or a shrub/wetland (classified wetland) may add value to adjacent shrubland and foster foraging or breeding habitat for generalist species, while a parking lot or open pool of water may not. The categories with the highest accuracy in both models were water and developed land.

The Kappa coefficient differs from the overall accuracy calculation in that it also takes into account the success of the model compared to a random fit model. K coefficients greater than 50% indicate that both the supervised classification-based model and the NLCD model were more successful at separating the land cover types than a random fit model. A Kappa coefficient of 0.80 or higher would be representative of a high-accuracy model, and neither of my models met that threshold, showing that while they are better than a randomized model, they have room for improvement. For the NLCD model, using the 2016 dataset may fit the accuracy points obtained from the 2015 aerial imagery better, if shrubland has changed to other land cover. For the supervised classification model, using an image from the growing season would likely improve the accuracy.

Spectral Results and Discussion

The field analysis of spectral properties of shrubs was intended to provide fine scale opportunity for remote classification of shrubland habitat to include invasive species. Due to limited time with the equipment, the number of samples collected was too small to draw statistical conclusions that would allow the results to be directly applied to the classification models. Ranking sites by invasive cover was not possible due to the scale of the project. However, the near-infrared sampling of wavelengths ~460-680nm showed success in clustering signatures by genus. Although the small size of my study did not allow for a complete statistical analysis, I was able to generate some formulae and charts to demonstrate potential relationships and separability of the shrubs in the pilot study. Although no statistically significant conclusions can be drawn from this pilot study, using this range of wavelengths appears to separate certain genera, allowing for the remote identification of native and invasive shrub species (Figure 26).



Key:

Lonicera	Vitis
Cornus	Rubus
Rhamnus	Malus
Elaeagnus	Prunus
Rosa	

Figure 26: Scatter plot of the genus data collected from Mendon Ponds (Separated by canonical discrimination). This figure shows the maximized separability of the shrub genera. *Vitis*, *Rubus*, *Malus*, and *Prunus* are shown in bright colors and show native species, but very small sample size. The largest sample sizes are from *Lonicera* (yellow), *Eleagnus* (black), and *Cornus* (brown). These species were sorted by genus depending on changes in reflectance between wavelengths 463nm and 680nm.

In Figure 26, *Malus sp.* and *Rubus sp.* are clearly separated from other native species and the main invasive species: Multiflora rose, Honeysuckle, Autumn Olive, and Buckthorn. *Lonicera sp*. was displayed in yellow, and may be grouped more closely with *Eleagnus* than any of the other species. All the *Rosa* samples in this study were invasive (*Rosa multiflora),* distinguishable from *Rhamnus*, but mixed in with the *Cornus* species, which are mostly native. It may be possible to separate some of the invasive species *(Lonicera*, *Eleagnus)* from (*Prunus*, *Malus*, *and Rubus*), but these preliminary assumptions would need to be proven statistically using a large-scale database before drawing any definitive conclusions.

Conclusions

My models produced several sets of habitat patch data, including area, location, and certain ecosystem parameters that are necessary for each species, and a general shrubland model of the conditions that would benefit the largest number of my shrubland species. Model 1 (NLCD and NWI) provides very specific habitat conditions for each species. These model patches could suggest areas to protect a certain species with declining habitat or declining population, especially those reliant on wetlands, because Model 1 uses the NWI pre-classified wetlands that may not have been properly captured by a single Landsat image from a February scene. The combination of these datasets provides a more robust wetland classification. Model 2 (Supervised) would be best for conservation efforts that intend to maximize the number of species in a region, because even though the error values between models are comparable, Model 2 more accurately captured shrubland habitat and areas of shrubland best suited for generalist species due to proximity to other advantageous land cover types. It is possible that aligning the upcoming 2016 LULC Data with 2016 imagery could remedy some of the omitted shrublands from the Model 1 results. The combination model (Figure 20) that used the supervised classification data, the best overall shrubland conditions, and proximity to NWI wetlands would be useful to wetland and shrubland conservation groups, to determine how to best protect these two habitat types that are both beneficial to shrubland-reliant birds. I also calculated the geometric union and intersection of the two models, to find the total ideal shrubland area as determined by either model (Figure 21), and the areas shared by both, which therefore fit the ideal criteria for shrubland birds according to both models (Figures 22, 23).

The overall accuracy of my supervised model was slightly below a “very accurate” model. The Landsat image from 2017 included training errors due to seasonal lack of leaves. Future analyses using these model steps could use the sequential NLCD databases to create a time series to track the changing trends and locations of shrublands. The NLCD 2016 database should become available sometime in 2019, and using 2016 or 2017 cloudless Landsat imagery, 2016 validation data, and the most recent (2015 or later) high-resolution orthoimagery would avoid potential temporal errors cause by shrubland succession and seasonal differences. Aligning datasets temporally, will likely give the most accurate habitat assessment possible, and future studies should aim for at least an 80% overall accuracy in supervised classification.

Results can also be verified by long-term expert and citizen-science databases. E-Bird, a citizen science and birding records website, can provide access to their research database (ERD) for relevant projects, and the Breeding Bird Survey has data and statistics for decades of route surveys. Checking the BBS database against the E-Bird database, an online database for citizen scientists and birding records, would provide insight as to the success of the model in locating habitat for the focal species. I had planned to include the E-Bird professional and research database as part of my project, but was unable to access that data during my research.

Future research on shrubland conservation should look more in depth at forested areas, and the value of forest patches in proximity to shrublands for generalist species. In large patches of forest, powerline corridors, utility ROW's and patch- or clear-cuts can be valuable conservation tools. GIS software could determine optimal areas for patch cuts by using tools like proximity selection to determine whether the patches would meet literature criteria to potentially draw in shrubland birds, and inversely, analyzing the surrounding forest to insure the large patches of forest left would still be adequate in terms of the recorded needs of forest obligate breeders. Maintaining a database of these patches and their total area would be a valuable addition to a time-series to track if preferred habitat for certain species was shrinking or changing across the county.

The results of my pilot spectral analysis are promising for future research on separating shrubland and invasive species by genus. For a statistically sound model, future studies will need a significantly larger sampling size per genus. To maintain consistency and reduce error, these measurements should be made with a fixed angle and many samples of foliage, complete branches, and even fruit and twigs. Taking measurements across several days would increase the number of samples, but could increase the error due to weather conditions and the angle of the sun. Spectral indices and databases will be important for the future of remote sensing and invasive species detection, so increasing the amount of data is one of the most valuable parts of current research. The addition of species composition to model layers would create a more complete ecological representation of these patches. Shrub species composition in these models would be valuable to advise conservation plans, to help determine invasive species control plans, native plant management for the benefit of shrubland birds.

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Appendix: Spectral Data

There were 84 samples across 25 different sites, taken October 10th, 2016 for the spectral separation pilot project. The raw data contained a sample number, sample site number, time stamp, genus, species when possible, a senescence value, and all values of wavelengths from 300-2500nm.

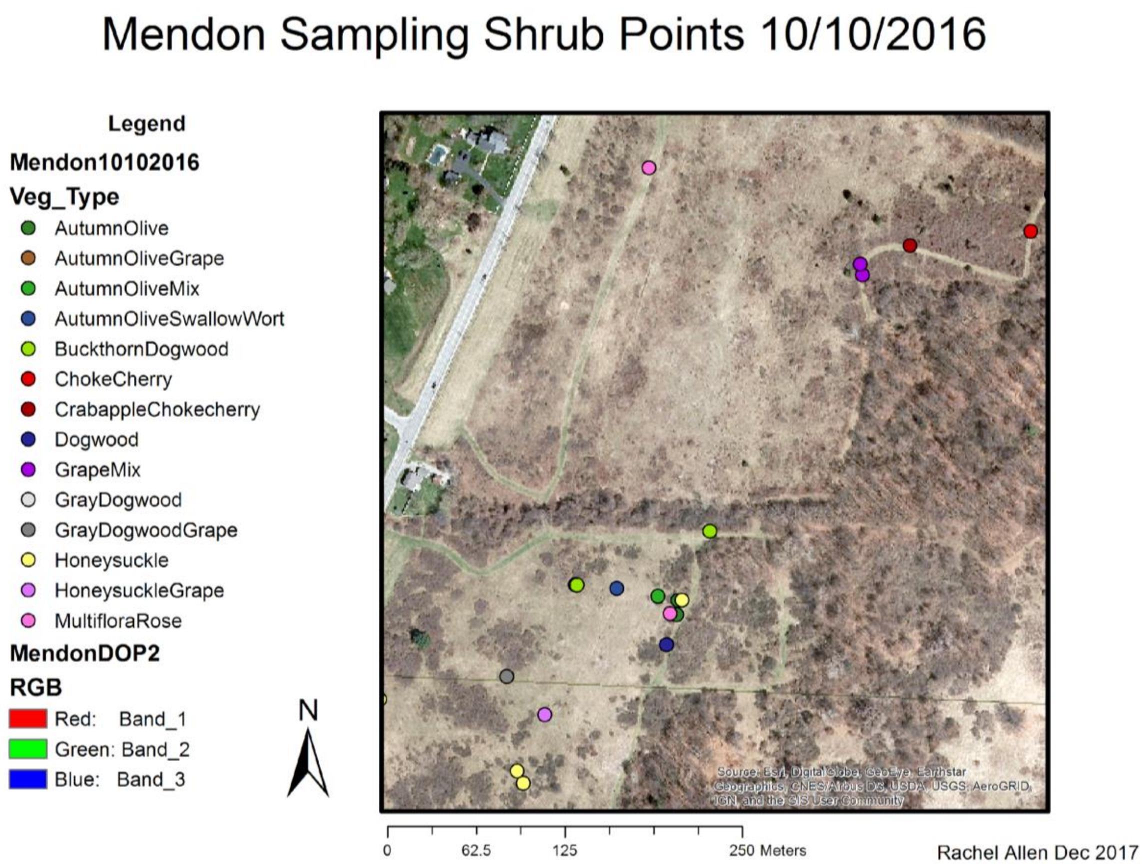

Figure 1a: Mendon Shrub Sampling Points 10/10/2016
This map shows the area of the shrublands in Mendon where samples were taken on 10/10/2016. The colors indicate the predominant species mixtures present at each sampling site.

Table 1a: Spectral Data Sampling Table. Sample # indicates distinct samples, sample site indicates order of sampling, with multiple samples collected at each location. Field discrimination was only certain to genus level for several shrubs, but species were recorded when certain. Presence of visible senescence is indicated by a 1, while lack is indicated by a 0.

Sample #	Sample Site	Time	Genus	Species	Senescence
1	0	12:16:31 PM	Lonicera		0
2	1	12:19:02 PM	Lonicera		0
3	1	12:19:26 PM	Lonicera		0
4	1	12:19:50 PM	Lonicera		0
5	2	12:34:09 PM	Lonicera		0
6	2	12:34:30 PM	Lonicera		0
7	2	12:34:49 PM	Lonicera		0
8	2	12:35:14 PM	Lonicera		0
9	3	12:43:55 PM	Lonicera		0
10	3	12:44:15 PM	Lonicera		0
11	3	12:44:34 PM	Lonicera		0
12	4	12:51:23 PM	Cornus	Racemosa	1
13	4	12:51:41 PM	Cornus	Racemosa	1
14	4	12:51:58 PM	Cornus	Racemosa	1
15	5	1:01:24 PM	Cornus	Racemosa	1
16	5	1:01:40 PM	Cornus	Racemosa	1
17	5	1:01:57 PM	Cornus	Racemosa	1
18	5	1:02:14 PM	Cornus	Racemosa	1
19	5	1:02:31 PM	Cornus	Racemosa	1
20	6	1:05:41 PM	Rhamnus	Cathartica	1
21	6	1:06:00 PM	Rhamnus	Cathartica	1
22	6	1:06:22 PM	Rhamnus	Cathartica	1
23	7	1:12:41 PM	Elaeagnus	Umbellata	1
24	7	1:13:00 PM	Elaeagnus	Umbellata	1
25	7	1:13:27 PM	Elaeagnus	Umbellata	1
26	7	1:13:48 PM	Elaeagnus	Umbellata	1
27	8	1:24:19 PM	Cornus		1
28	8	1:24:36 PM	Cornus		1
29	8	1:24:53 PM	Cornus		1
30	8	1:25:11 PM	Cornus		1
31	9	1:35:43 PM	Elaeagnus	Umbellata	0
32	9	1:36:00 PM	Elaeagnus	Umbellata	0
33	9	1:36:21 PM	Elaeagnus	Umbellata	0
34	10	1:44:19 PM	Rosa	Multiflora	0
35	10	1:44:45 PM	Rosa	Multiflora	0
36	10	1:45:13 PM	Rosa	Multiflora	0
37	10	1:45:39 PM	Rosa	Multiflora	0
38	11	1:54:50 PM	Elaeagnus	Umbellata	0
39	11	1:55:07 PM	Elaeagnus	Umbellata	0
40	11	1:55:25 PM	Elaeagnus	Umbellata	0
41	11	1:55:43 PM	Elaeagnus	Umbellata	0
42	12	2:01:16 PM	Elaeagnus	Umbellata	0

43	12	2:01:58 PM	Elaeagnus	Umbellata	0
44	12	2:02:18 PM	Elaeagnus	Umbellata	0
45	13	2:05:44 PM	Lonicera		0
46	13	2:06:03 PM	Lonicera		0
47	13	2:06:20 PM	Lonicera		0
48	14	2:14:36 PM	Rhamnus	Cathartica	0
49	14	2:15:07 PM	Rhamnus	Cathartica	0
50	15	2:20:11 PM	Cornus	Racemosa	1
51	15	2:20:30 PM	Cornus	Racemosa	1
52	15	2:20:54 PM	Cornus	Racemosa	1
53	16	2:32:11 PM	Vitis	Riparia	1
54	16	2:32:29 PM	Vitis	Riparia	1
55	16	2:32:56 PM	Vitis	Riparia	1
56	17	2:36:05 PM	Rubus		1
57	17	2:36:23 PM	Rubus		1
58	17	2:36:42 PM	Rubus		1
59	17	2:36:57 PM	Rubus		1
60	18	2:42:09 PM	Vitis	Riparia	1
61	18	2:42:29 PM	Vitis	Riparia	1
62	18	2:42:50 PM	Vitis	Riparia	1
63	18	2:43:07 PM	Vitis	Riparia	1
64	19	2:50:24 PM	Malus		0
65	19	2:50:49 PM	Malus		0
66	19	2:51:09 PM	Malus		0
67	20	3:00:50 PM	Prunus	Virginiana	1
68	20	3:01:11 PM	Prunus	Virginiana	1
69	21	3:11:36 PM	Cornus	Racemosa	1
70	21	3:11:57 PM	Cornus	Racemosa	1
71	21	3:12:18 PM	Cornus	Racemosa	1
72	21	3:12:37 PM	Cornus	Racemosa	1
73	22	3:20:07 PM	Elaeagnus	Umbellata	1
74	22	3:20:26 PM	Elaeagnus	Umbellata	1
75	22	3:20:44 PM	Elaeagnus	Umbellata	1
76	22	3:21:04 PM	Elaeagnus	Umbellata	1
77	23	3:29:28 PM	Rosa	Multiflora	0
78	23	3:29:46 PM	Rosa	Multiflora	0
79	23	3:30:03 PM	Rosa	Multiflora	0
80	23	3:30:38 PM	Rosa	Multiflora	0
81	24	3:44:58 PM	Lonicera		0
82	24	3:45:20 PM	Lonicera		0
83	25	3:55:44 PM	Lonicera		1
84	25	3:56:09 PM	Lonicera		1