Habitat modeling of six species of landbirds at risk in Southwestern Nova Scotia

Mémoire de dominante d'approfondissement :
Gestion des Milieux Naturels

Clara Ferrari 2013-2014

Faculty tutor: Jean-Claude Gégout, AgroParisTech-ENGREF
Supervisor: Dr. Cindy Staicer, Dalhousie University

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Abstract

The habitats of six landbirds at risk – Common Nighthawk (*Chordeiles minor*), Chimney Swift (*Chaetura pelagica*), Olive-sided Flycatcher (*Contopus cooperi*), Eastern Wood-pewee (*Contopus virens*), Canada Warbler (*Cardellina canadensis*), and Rusty Blackbird (*Euphagus carolinus*) – were modeled in the Southwest Nova Biosphere Reserve, Nova Scotia, Canada. Building on earlier species distribution models created by Dalhousie University students (Halifax, Canada), this analysis revised and improved the models by resolving modeling issues, such as spatial autocorrelation, spatial bias, and important environmental features selection. The analysis also incorporated new species location data based on field surveys and public observations. The maximum entropy modeling method (MaxEnt), which uses presence-only data, was employed to model the distribution of these rare species. Wetness, structural and anthropogenic features were essential for building the models. The influence of climate change on the future potential distribution of the birds was also briefly discussed.

Résumé

Les habitats de six espèces d'oiseaux menacés – l'Engoulevent d'Amérique (*Chordeiles minor*), le Martinet ramoneur (*Chaetura pelagica*), le Moucherolle à côtés olive (*Contopus cooperi*), le Pioui de l'Est (*Contopus virens*), la Paruline du Canada (*Cardellina canadensis*) et le Quiscale rouilleux (*Euphagus carolinus*) – ont été modélisés dans la Réserve de Biosphère Southwest Nova, en Nouvelle-Ecosse, au Canada. Basée sur des modèles de distribution antérieurs réalisés pour des étudiants de l'Université de Dalhousie (Halifax, Canada), cette étude revoit et améliore ces modèles, en prenant en compte les problèmes liés à la modélisation, comme l'autocorrélation spatiale, le biais spatial et le choix des variables environnementales d'importance. Cette analyse ajoute également les données d'observation de 2014 provenant d'études de terrain et d'observations faites par le public. La méthode de modélisation de l'entropie maximale (MaxEnt), qui utilise des données de présence uniquement, a été employée pour modéliser la répartition de ces espèces rares. L'humidité, la structure de l'habitat et des variables anthropiques ont été indispensables pour construire ces modèles. L'influence du changement climatique sur la distribution potentielle future de ces oiseaux a également été brièvement discutée.

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I thank e-Bird Canada, the Breeding Bird Survey (BBS) and the Maritime Breeding Bird Atlas (MBBA) for sharing their valuable bird data. I warmly thank the members of the public who gave the time to share their bird sightings. eBird collects observations from birders through portals managed and maintained by local partner conservation organizations. The Breeding Bird Survey is a publically supported program; its data represent the combined efforts of thousands of U.S. and Canadian BBS participants who survey routes annually, as well as the work of dedicated USGS and CWS scientists and managers. I wish to thank the official sponsors of the Maritimes Breeding Bird Atlas (Bird Studies Canada, Canadian Wildlife Service, Nova Scotia Department of Natural Resources, Prince Edward Island Department of Natural Resources, Nature NB, the Nova Scotia Bird Society, and the Natural History Society of Prince Edward Island) for access to the Atlas data, and to the thousands of volunteer participants who gathered data for the project.

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Eastern Wood-pewee, © Clara Ferrari

List of abbreviations

Organizations and laws

COSEWIC: Committee on the Status of Endangered Wildlife in Canada
IPCC: Intergovernmental Panel on Climate Change
MBBA: Maritimes Breeding Bird Atlas
BBS: North American Breeding Bird Survey
MTRI: Mersey Tobeatic Research Institute
NCC: Nature Conservancy Canada
NS ESA: Nova Scotia Endangered Species Act
SARA: Species at Risk Act
DNR: Department of Natural Resources

Birds

CONI: Common Nighthawk
CHSW: Chimney Swift
OSFL: Olive-sided Flycatcher
EAWP: Eastern Wood-Pewee
CAWA: Canada Warbler
RUBL: Rusty Blackbird
SAR: Species at Risk

GIS and statistics analysis terms

AUC: Area under the curve
CGCM1: Canadian Coupled Global Climate Model
COR: Point-biserial correlation coefficient
GIS: Geographic information system
GLM: Generalized linear model
NAD: North American Datum
SDM: Species distribution model
SWC: Soil water content
UTM: Universal Transverse Mercator coordinate system

Introduction

In Canada, the Species at Risk Act (SARA) lists the species of fauna and flora that are at risk of extinction, in response to status assessments prepared by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC). In Nova Scotia, risk assessment is revisited at the provincial scale by the Nova Scotia Endangered Species Act. Landbirds at risk in Nova Scotia that inhabit forested landscapes include six species: Common Nighthawk (*Chordeiles minor*), Chimney Swift (*Chaetura pelagica*), Olive-sided Flycatcher (*Contopus cooperi*), Eastern Wood-pewee (*Contopus virens*), Canada Warbler (*Cardellina canadensis*), and Rusty Blackbird (*Euphagus carolinus)*. All are listed by COSEWIC and the province of Nova Scotia, although the federal Species at Risk Act currently omits the Eastern Wood-pewee (Table 1).

Table 1. Conservation status of the six studied species at risk[1]

	COSEWIC	SARA	NS ESA
Common Nighthawk (CONI)	Threatened (2007)	Threatened (2010)	Threatened (2007)
Chimney Swift (CHSW)	Threatened (2007)	Threatened (2009)	Endangered (2007)
Olive-sided Flycatcher (OSFL)	Threatened (2007)	Threatened (2010)	Threatened (2013)
Eastern Wood-Pewee (EAWP)	Special Concern (2012)	---	Vulnerable (2013)
Canada Warbler CAWA)	Threatened (2008)	Threatened (2010)	Endangered (2013)
Rusty Blackbird (RUBL)	Special Concern (2006)	Special Concern (2009)	Endangered (2013)

[1] Source: NS Endangered Species Act: Legally Listed Species; Species at Risk Public Registry; COSEWIC Wildlife Species Search). Terms are defined in Appendix 3.

All six of these species have experienced serious population declines in recent decades. Many threats weigh upon their populations, including massive use of pesticides, predation and climate change. Their major threat, however, is the modification of landscapes, leading to habitat degradation and loss (COSEWIC 2006, 2007a, 2007b, 2008a, 2008b, 2012). It is therefore essential to understand their habitat needs and the distribution of the populations.

In the last decade, a variety of species distribution models (SDMs) have been developed to quantify species' habitat distributions across a landscape (Elith and Leathwick 2009). Because the populations of these species at risk have declined significantly, relatively few records exist. Maximum entropy (MaxEnt) is a robust modeling technique introduced by Phillips et al. (2006). MaxEnt was employed to create SDMs for these species because it requires only locations of the birds (their presence) as opposed to both presence and absence data. However, several issues arose in building the first-generation MaxEnt models (Darlington-Moore 2014, Kindree 2014, Randall 2014, Westwood 2014). These issues include spatial bias, sampling bias, and selection of variables. The present analysis attempts to address these issues in building the second-generation models for the six species of landbirds at risk.

The study area was the Southwest Nova Biosphere Reserve, located in southwestern Nova Scotia, and designated by UNESCO in 2001 (MAB 2007). Acadian forest dominates this region and includes many different habitat types. These range from conifer-dominated to hardwood-dominated stands of different mixes and ages, to lakes, rivers and wetlands, as well as open areas such as barrens and cutovers. Crown-owned, private lands, and protected areas, such as the Tobeatic Wilderness Area and Kejimkujik National Park, form part of the landscape. Previous studies had established that Canada Warbler, Olive-sided Flycatcher, Rusty Blackbird and Eastern Wood-pewee prefer forested habitats, whereas Chimney Swift and Common Nighthawk use more open areas (COSEWIC 2006; 2007a; 2007b; 2008a; 2008b; 2012).

This report was written as part of a 6-month internship, concluding an Engineering school formation (AgroParisTech-Centre de Nancy), equivalent of a Master 2 and specializing in Natural Environments Management. It was hosted by Dalhousie University and the Mersey Tobeatic Research Institute, Nova Scotia, Canada.


Bald Eagle, Cape Breton © Clara Ferrari

1. Context and presentation of the study

1.1. Host organizations

Dalhousie University is located in Halifax, Nova Scotia, Canada, and was founded in 1818. It is a registered not-for-profit publicly-funded academic institution that focuses on education, training, and research and development. The first and last months of my internship were based in Cindy Staicer's Ornithology lab, in the Life Sciences Centre.

The Mersey Tobeatic Research Institute (MTRI) is a non-profit co-operative. Its mandate promotes sustainable use of natural resources and biodiversity conservation in the Southwest Nova Biosphere Reserve and beyond through research, education, and the operation of a field station. It was founded in 2004 and the office is located in Kempt, Nova Scotia, near Kejimkujik National Park. MTRI works on a diversity of projects simultaneously, including research and monitoring on species at risk, old forests and aquatic connectivity, as well as outreach initiatives. I spent 4 months at MTRI, from April to August.

1.2. Landbird Species at Risk program

My internship is part of the "Landbird Species at Risk in southwestern Nova Scotia" program, led by Dr. Cindy Staicer from Dalhousie University. She has been conducting work on landbirds and their habitat in and around Kejimkujik National Park since 1996, including monitoring programs and ornithology classes. In 2010, 2012 and 2013, Cindy Staicer and her students conducted SAR landbirds surveys in southwestern Nova Scotia. Thus, Landbird SAR is a rich, long-term program.

The program focuses on six species at risk:

- Common Nighthawk (Engoulevent d'Amérique, *Chordeiles minor*; CONI);
- Chimney Swift (Martinet ramoneur, *Chaetura pelagica*; CHSW);
- Olive-sided Flycatcher (Moucherolle à côtés olive, *Contopus cooperi*; OSFL);
- Eastern Wood-pewee (Pioui de l'Est, *Contopus virens*; EAWP);
- Canada Warbler (Paruline du Canada, *Cardellina canadensis*; CAWA);
- Rusty Blackbird (Quiscale rouilleux, *Euphagus carolinus*; RUBL).

1.3. Purpose and objectives

My internship was designed to revise the species distribution models (SMD) of six landbirds at risk in southwestern Nova Scotia, Canada, in order to standardize and improve those models. Field surveys were also involved, which aimed to find new sightings in the region. Indeed, little information about their habitat is known, even though field surveys had already been conducted in the region. Unfortunately, this phase was reduced because of the lack of funding for field travel. Another way to get new sightings was outreach, so that members of the community become familiar with the birds and report their observations. Due to the relative rareness of the species, the sample design assumed that only detected presences of the species were relevant, and absences were viewed as possible false negatives.

The Maximum Entropy modeling technique, or MaxEnt, was used (Phillips et al. 2006). It employs presence-only locations and environmental variables, such as climate, habitat structure and wetness, to create potential distribution maps. However, as with all modeling methods, it has weaknesses, such as spatial autocorrelation, spatial bias, and choice of relevant environmental variables that need to be considered (Kramer-Schadt et al. 2013). Therefore, a major part of this project attempted to resolve these problems.

Another aspect of my internship was to consider how to model species' habitats under the influence of climate change, in order to understand the potential distribution of the birds in the future and to protect them.

1.4.Outreach

An important part of the program is outreach, which aims to inform and raise awareness among the population of southwestern Nova Scotia. Marian Kemp and Laura Achenbach were in charge of the outreach part of the program. Several workshops on the identification of the birds and their habitats took place, widely-distributed posters and brochures (Appendix 24) were made, and a website detailing the birds' life history, habitats, and threats is currently under construction (landbirdSAR.merseytobeatic.ca). The poster, brochure, and first iteration of the workshop were developed at Dalhousie University by Dominic Cormier and Cindy Staicer in February-April 2013.

Outreach also aims to involve people in the conservation of the birds by encouraging them to submit new bird sightings. An e-mail address was available for this purpose (landbirdSAR@merseytobeatic.ca).

I assisted Marian Kemp and Laura Achenbach in offering several workshops and events:

- "Landbirds at Risk Partners in Conservation Workshop", March 21, 2014;
- "Bear River Workshop" March 25, 2014;
- "Envirothon" July 3, 2014, a Kejimkujik National Park outreach event;
- "Dawn Chorus Walk" July 12, 2014, an MTRI and Kejimkujik National Park event;
- "Night creatures talk: The Common Nighthawk", July 14, 2014, a Kejimkujik National Park Outreach event;
- CBC Land and Sea filming at Kejimkujik National Park about Landbirds at Risk in Nova Scotia, July25, 2014;
- "Atelier: Oiseaux en péril dans les paysages forestiers", French workshop on September 9, 2014 in Clare, NS.

Additionally, short videos of the Rusty Blackbird and Olive-sided Flycatcher were filmed and posted on the MTRI YouTube channel and MTRI Facebook page.

2. Materials and methods

2.1. Study species

Among the at-risk landbirds in Nova Scotia, these six species breed in forested wetlands, (OSFL, CAWA, RUBL), in rock barrens (CONI) and in upland forested landscapes (CHSW, EAWP), or in more urban areas (CHSW, CONI). They migrate each spring from the southern USA (RUBL), northern South America (CHSW, OSFL, EAWP and CAWA) and across much of South America (CONI). All the species are insectivorous. Appendices 4 to 9 present detailed descriptions of each species.

Common Nighthawk (CONI)

The Common Nighthawk (Figure 1) is characterised by white bands on the underside of long pointed wings, a notched tail and a barred underside. It breeds in North America between May and August and its territory has a very variable size. Its typical habitat is an open area with dry bare ground or rock, such as rock barrens, open woodlands, bogs, gravel pits and gravel rooftops. Like the Chimney Swift, water bodies are often nearby for feeding on the flying insects that are incubated there (COSEWIC 2008a; Cornell Lab of Ornithology 2014b).

Figure 1. Common Nighthawk
Male Rochester, NY, USA. ©Magnus Manske (Source: Wikimedia Commons)

Figure 2. Chimney Swift
©Dominic Sherony (Source: Wikimedia Commons)

Chimney Swift (CHSW)

The Chimney Swift (Figure 2) is recognizable by its cylindrical body and long slender wings. It breeds in Canada between May and August. Its natural habitat is old forest with large snags and its artificial habitat is built structures such as chimneys. Water bodies are also an important feature of its habitat for foraging (COSEWIC 2007a; Cornell Lab of Ornithology 2014).

Olive-sided Flycatcher (OSFL)

The Olive-sided Flycatcher (Figure 3) is a tyrant within the same genus as the Eastern Wood-pewee. It has a white throat, an eye-catching dark vest and no wing bars. It breeds in Canada and the western United States between June and July. It is found in coniferous and coniferous-dominated forests, with openings or edges, and snags where it perches. It also prefers open wetlands to forage (COSEWIC 2007b; Cornell Lab of Ornithology 2014b).

Figure 3. Olive-sided Flycatcher
© Dominic Sherony (Source: Wikimedia Commons)

Eastern Wood-pewee (EAWP)

The Eastern Wood- pewee (Figure 4) is a tyrant flycatcher characterised by an olive-grey color, a dusty vest and dark wings. It is a late migrant which breeds between May and September in North America. Its forested territory ranges between 2-8 hectares. It breeds in any type of wooded habitat, with a preference for deciduous and wooded riparian forests and forests edges (COSEWIC 2012; Cornell Lab of Ornithology 2014b).

Figure 4. Eastern Wood-Pewee
Brown Road, Kempt, NS
© Clara Ferrari

Figure 5. Canada Warbler
©William H. Majoros (Source: Wikimedia Commons)

Canada Warbler (CAWA)

The Canada Warbler (Figure 5) is a wood-warbler characterized by its yellow throat, breast and belly, and its dark streaked necklace across its chest. It spends little time on its breeding ground (June-July). Its territory is small (0.4-1.5 ha) and it often returns to the same site year after year. Its habitat includes deciduous undergrowth in mature riparian forests and forested wetlands. It needs a dense layer of tall shrubs and ferns to nest (COSEWIC 2008b; Cornell Lab of Ornithology 2014b).

Rusty Blackbird (RUBL)

The Rusty Blackbird (Figure 6) is characterised by a dark coloration, a medium-length tail, and pale eyes. It breeds mainly in Canada between April and September. Its territory is approximately 10 hectares. It breeds in any type of forest, mainly nesting in coniferous saplings near water. Wooded wetlands, beaver ponds, and stream and lake edges are part of its foraging habitat (COSEWIC 2006; Cornell Lab of Ornithology 2014b).

Silver River NCC property,
Digby county, NS
© Clara Ferrari

2.2.Study area: Southwest Nova Biosphere Reserve

The study area (Figure 7) consisted of the southwestern end of the peninsular province of Nova Scotia, Canada. It contained five counties: Annapolis, Digby, Queens, Shelburne and Yarmouth. Included in this area are a national park (Kejimkujik National Park), 11 nature reserves, 6 wilderness areas and numerous provincial parks. Together they made up the Southwest Nova Biosphere Reserve, designated by UNESCO in 2001. The core protected area includes the Tobeatic Wilderness Area and Kejimkujik National Park.

Evergreen-deciduous Acadian forests dominate the landscape (79%), as well as shallow lakes, wetlands and rivers, as a result of glaciation. Coniferous species include balsam fir (*Abies balsamea*), red spruce (*Picea rubens*), white pine (*Pinus strobus*) and hemlock (*Tsuga canadensis*). Deciduous species include red maple (*Acer saccharum*), red oak (*Quercus rubra*), yellow birch (*Betula alleghaniensis*) and American beech (*Fagus grandifolia*) (Cameron and Richardson 2006). The temperate climate is greatly influenced by the sea: the Bay of Fundy in the North and Atlantic Ocean in the South. The annual mean temperature is 5-7°C and the total precipitation is 1200-1600 mm. The topography is relatively flat. The soil is mainly thin and acidic, and fresh water is acidic and nutrient-poor (Drysdale et al. 2008; Bourque and Hassan 2008).

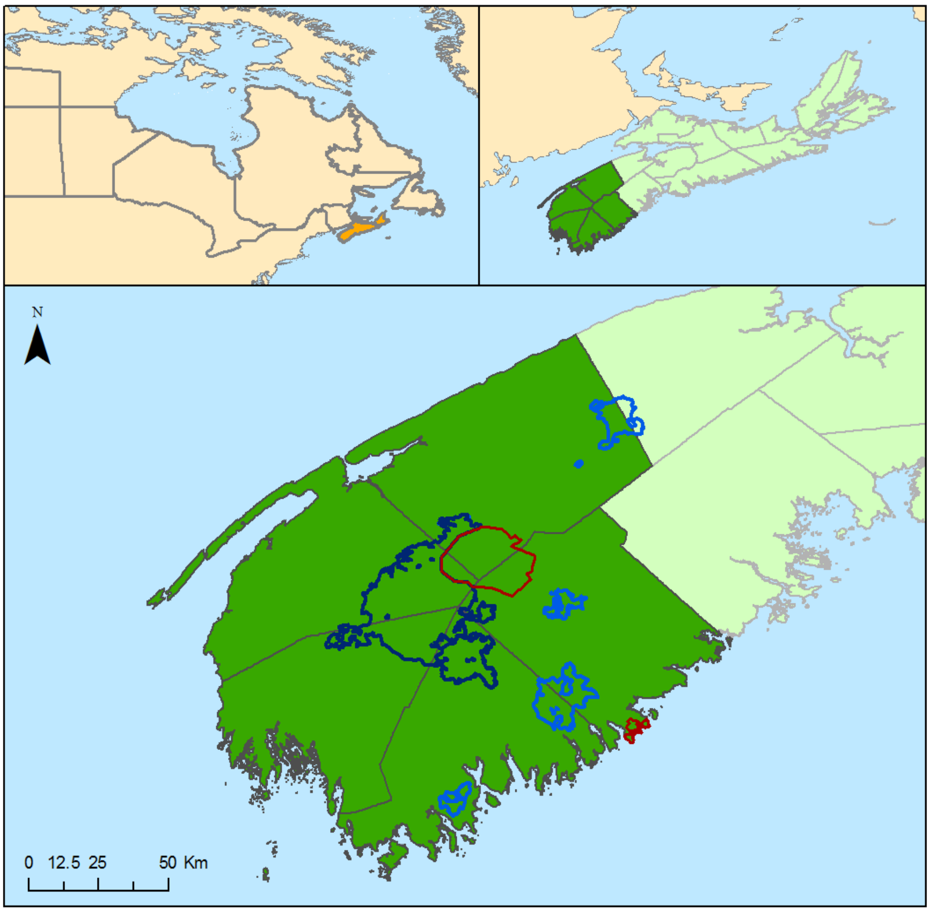

Figure 7. Study area location

Top left: Nova Scotia in eastern Canada (orange). Top right: Nova Scotia (light green) and Southwest Nova Biosphere Reserve (dark green). Bottom: Southwest Nova Biosphere Reserve (dark green), Kejimkujik National Park (red), Tobeatic Wilderness area (dark blue) and other wilderness areas (light blue). Sources: Geobase.ca, Dalhousie GIS Department, Commission for Environmental Cooperation.

2.3. Revision of the models

2.3.1. MaxEnt, a Maximum Entropy species distribution model program

MaxEnt is a distribution modeling technique introduced by Phillips et al. (2006). MaxEnt estimates the potential geographic distribution of a species based on its known locations and environmental variables displayed geographically. It uses presence-only data, unlike other models that use presence and absence data. MaxEnt creates a sample of background locations, which can be referred as "pseudo-absences" to offset the presence-only data. It uses the probability distribution of maximum entropy constrained by the environmental variables, so that the mean of each variable under the predicted distribution is close to the observed mean of the observed sample (Yates et al. 2010).

The main advantage of this specific modeling technique is that it only requires presence data. It is able to deal with sparse, irregularly-sampled or spatially-biased records. MaxEnt is a popular tool, easy to use and widely recognized as one of the best species distribution modeling methods in terms of predictive performance (Syfert et al. 2013; Kramer-Schadt et al. 2013). For these reasons it was chosen for this study. For more information about MaxEnt software, see Phillips et al. (2006), Elith et al. (2011), and Merow et al. (2013).

Another benefit of MaxEnt is its great adaptability: many settings can be modified in order to maximize the species distribution model. Indeed, specific settings reflect assumptions and hypotheses that need to be justified. These include the background data, the control of sampling bias, the functional forms of the environmental variables, the regulation of model complexity and the type of outputs (Phillips et al. 2006, Merow et al. 2013) An important part of this project was to test and improve the settings, which was not done in the first-generation models made by Cindy Staicer's students at Dalhousie University (Darlington-Moore 2014, Kindree 2014, Randall 2014, Westwood 2014).

2.3.2. ArcGIS process

ArcMap (ESRI 2010a) is a geographic information system (GIS) software package and the main component of ArcGIS program. ArcMap was used for working with environmental geographic data and for bird sighting data.

The raster extent was set to the southwestern Nova Scotia region, containing the boundaries of the five counties (Annapolis, Digby, Queens, Shelburne, Yarmouth). The same extent and cell size were used for every raster data. GRID and ASCII format were employed.

The spatial reference system is NAD 1983 UTM Zone 20. GIS coordinates used for a bird sighting sometimes corresponded to where the observer stood, and not to where the bird actually was. If the bird location relative to the observer was known (direction and distance), the observation was manually moved in a spreadsheet software. The revised locations were clipped for southwestern Nova Scotia and exported as a .CSV file.

2.3.3. Bird data source

For the second-generation models, bird observations were based on:

- The Maritime Breeding Bird Atlas (MBBA) from 2006 to 2010
- The North American Breeding Bird Surveys (BBS) from 2006 to 2014
- E-bird data Canada between 2011 and 2013 (Cornell Lab of Ornithology 2014a)
- The Staicer Ornithology team (2006-2013), including Alana Westwood's field work (2012-2013)
- Sightings from the public e-mailed to Cindy Staicer or to landbirdSAR@merseytobeatic.ca

From the E-bird data, only the dates matching the species' breeding season were kept (Table 2).

Table 2. Dates used for breeding season for each landbird at risk (C. Staicer, Pers. Com.)

Species	Beginning	End
CONI	June 1	July 31
CHSW	June 1	July 31
OSFL	June 1	July 15
EAWP	June 1	July 15
CAWA	May 25	July 15
RUBL	April 25	June 30

New sightings were obtained through field work and from the public in 2014. These new data were used in the second-generation models.

2.3.4. Field surveys 2014

Field surveys were conducted between May and June 2014, for four species at risk: Olive-sided Flycatcher, Eastern Wood-Pewee, Canada Warbler, and Rusty Blackbird. The surveys took place between sunrise and 12:00, under good weather conditions: wind was less than 20 km/h and no steady rain was falling. The protocol was based on Dalhousie's 2012-2013 species at risk surveys supervised by Dr. Cindy Staicer and developed by Ph.D. student Alana Westwood.

Former model distribution maps were used to find suitable patches of habitat for those species. Unfortunately, the lack of funding for field travel (truck and gasoline) during this summer prevented numerous field surveys. Only a few new locations were surveyed:

- Rusty Blackbird survey (April-May 2014)
- Silver River NCC property (June 3-4, 2014)
- Port Joli Bird Society property (June 11-12, 2014)
- Bowers Meadow and Round Bay NCC properties (June 11-12, 2014)
- Kempt, NS, near MTRI (June-July 2014)
- BBS Survey (#036, Kejjimkujik; June 12, 2014)
- Kejimkujik National Park backcountry trail (June 20-24, 2014)
- Tupper Lake, Old Annapolis Road (July 4, 2014)

In those locations, suitable habitat maps were made for each bird and the high-suitability areas were surveyed. When a typical habitat for one of the birds was encountered, a playback survey was conducted and the exact waypoint was marked using an eTrek 10 GARMIN GPS. During a 5-min listening period, all the birds heard were recorded on a point count data sheet (a copy can be found in Appendix 20), as well as their relative location to the observer. This was followed by a series of four 30-second playbacks interspersed by a 30-second listening period, one for each bird. A playback is a recording of a specific species of bird played in order to attract the bird and prompt it to vocalize, therefore allowing surveyors to detect it more easily than simply listening. A playback data sheet (a copy can be found in Appendix 21) was filled out at the same time as the point count sheet: time, relative location to the observer, and behaviour were recorded every time a target species was detected. The habitat information was also recorded on a habitat data sheet (a copy can be found in Appendix 22). The entire survey was also recorded by an H2N stereo microphone, so that the recording could be listened to if doubts remained about the aural identification of a species.

2.3.5. Estimates to compare the models

AUC

MaxEnt mainly uses AUC (area under the curve) for assessing a model. AUC is the probability that the model evaluates a presence site higher than a random site from the study area. It is used to assess the discriminatory capacity of species distribution models (SDM), i.e., how well the model discriminates presence from background locations (Merow et al. 2013; Jiménez-Valverde 2012; S. J. Phillips et al. 2009).

AUC ranks between 0 and 1, 1 being a perfect model. 0.5 indicates a model no better than random, and below 0.5 a model worse than random. Generally, models with an AUC superior to 0.7 is considered to have a good discriminatory power (Phillips et al. 2009; Blach-Overgaard et al. 2010; Kramer-Schadt et al. 2013; Syfert et al. 2013; Millar and Blouin-Demers 2012; Lobo and Tognelli 2011). AUC is calculated in MaxEnt (Phillips et al. 2010).

AUC is widely used to estimate the performance of a model. Among its benefits, it avoids adopting a threshold between presence and absence, which is used for other estimates and can be arbitrary. Many other estimates are available for presence-absence models, but the number of estimates are limited for presence-only models, and AUC seems the most accurate estimate for the last ones (Jiménez-Valverde 2012; Kramer-Schadt et al. 2013; Merow et al. 2013).

AUC estimates the discriminatory power of a model but it is not an absolute estimate. For example, it does not give information on model calibration[1] (Millar and Blouin-Demers 2012). Therefore, other estimates were sought. Many estimates are available for presence-absence dataset, but fewer remain for presence-only dataset.

[1] Calibration and discrimination are two independent notions of model quality. Discrimination is the ability to correctly differentiate presence and absence sites and can be estimated with AUC. Calibration is the agreement between predicted probabilities of presence and observed distribution of presence (Phillips and Elith 2010).

COR

The point-biserial correlation coefficient (COR) represents the correlation between the presence and pseudo-absence, and the model predictions. It is mathematically equivalent to the Pearson coefficient and it is used when one of the two sets of data is dichotomous, taking only two values (Phillips et al. 2009; Millar and Blouin-Demers 2012). It is mentioned in several papers as a good complement to AUC (Phillips et al. 2009, Blach-Overgaard et al. 2010, Millar and Blouin-Demers 2012, Syfert et al. 2013). Unlike AUC, COR takes in account both discrimination and calibration. It ranks between 0 and 1; the higher COR is, the better the model (Millar and Blouin-Demers 2012). COR was calculated thanks to the ROCR package in R (Sing et al. 2005), that gives the performance of scoring classifiers.

Gain

The regularised training gain estimates the contribution of the predictors to the model, i.e., how strictly the model is concentrated around the presence locations (Blach-Overgaard et al. 2010; Kramer-Schadt et al. 2013). Closely related to deviance, gain is defined as the average log probability of the presence samples, minus a constant so that the uniform distribution has a gain of zero (Phillips 2005).

2.3.6. Tests used to compare the distribution models

Different statistical tests can be used to compare models. First, the Shapiro-Wilk normality test was used to assert the normal distribution of the model estimates. If the results of those tests show that the estimates were not normally distributed, a Wilcoxon rank sum test was used to compare the models, as demonstrated in many papers (S. J. Phillips et al. 2009; Blach-Overgaard et al. 2010; Millar and Blouin-Demers 2012; Syfert et al. 2013). These tests were computed using R-studio (Ripley 2001).

2.4. Presentation and issues of the former models

2.4.1. Landbirds distribution models already completed

First-generation species distribution models were made for each of these birds using MaxEnt software (Phillips et al. 2006) by four students: Jennifer Randall (Common Nighthawk; Randall 2013), Meagan Kindree (Chimney Swift; Kindree 2014), Siobhan Darlington-Moore (Eastern Wood-Pewee; Darlington-Moore 2014), and a Ph.D candidate, Alana Westwood (Canada Warbler, Olive-sided Flycatcher and Rusty Blackbird; Westwood 2014).

2.4.2. Former models issues

Each of the first-generation models used different features, including different environmental variables and MaxEnt features. This resulted in two potential problems. First, the input data varied from one model to the other. The source of the locations data and environmental variables may have been different, as well as the scale and extent chosen to build GIS layers. Table 3 indicates the different variables used to build each first-generation model, which reflect the wetness and the structure of the habitats, as well as landscape features. Second, in most of these first-generation MaxEnt models, the default parameters were selected with no real reflection on why they were used, for lack of time. MaxEnt offers many different parameters that can be refined, like the number of background points, the number of replicates, the bias file etc., and parameter choice is an important step to building a consistent model (Merow et al. 2013).

Table 3. Environmental variables used for each first-generation model, made by Dalhousie students [1]

Common Nighthawk	Chimney Swift	Olive-sided Flycatcher	Eastern Wood pewee	Canada Warbler	Rusty Blackbird
Canopy closure	Distance to big trees	Canopy closure	Canopy closure	Canopy closure	Canopy closure
Distance to waterways	Distance to cliffs	Distance to suitable forest	First canopy height in meters	Distance to suitable forest	Distance to suitable forest
Distance to open bogs	Distance to dead trees	Distance to clearcuts and barrens and rock barrens	Depth to water table	Distance to **relevant** wetland vegetation	Distance to clearcuts
Distance to clear-cuts	Distance to urban areas	Distance to relevant wetland vegetation	Distance to burnt areas	Depth to water table	Distance to relevant wetland vegetation
Distance to gravel pits	Distance to waterways		Distance to agricultural lands		Depth to water table
Distance to blueberry fields	Distance to wetland		Distance to inland water bodies		
Distance to rock barrens			Distance to road corridors		
Distance to burnt areas			Distance to uneven aged stands		
			Distance to a set of preferred trees		
			Distance to protected areas		

[1] Sources: Darlington-Moore 2014, Kindree 2014, Randall 2014, Westwood 2014.

2.5. Selection of the environmental variables in MaxEnt models

2.5.1. Choice of the environmental variables used

The environmental variables used in the second-generation models were chosen based on the previous works, both models and species studies. Table 3 shows all the predictor variables used in the first-generation models. Table 4 shows the list of the chosen variables and Appendix 1 details the sources for each variable. The source of the GIS data is Nova Scotia Forest Inventory, Nova Scotia forest wetlands layer and Nova Scotia wet areas mapping.

Other environmental variables that could potentially explain a part of the birds' distributions were investigated. Literature generally differentiates several types of variables: climatic and non-climatic variables, the latter ones including features controlling species habitat, and disturbance (natural and human-induced) (Guisan and Thuiller 2005; Blach-Overgaard et al. 2010).

Table 4. Environmental variables used in MaxEnt models

Environmental variable	Name in GIS	Environmental variable	Name in GIS
First story canopy height	1story_canopy	Distance to wetlands	d_wtl
Second story canopy height	2story_canopy	Distance to red maple forest	d_red_maple
Canopy cover	canopy_cover	Distance to uneven aged stands	d_uneven_age
Depth to water table	depth_wtbl	Distance to urban areas	d_urban
Distance to agricultural lands	d_agria	Distance to protected areas	d_protecteda
Distance to burnt areas	d_burnta	Distance to CAWA suitable forest	cawafortypedist
Distance to clear cut	d_clearcut	Distance to CAWA wetlands	cawawetlanddist
Distance to cliffs, dunes & coastal rocks	d_cliff	Distance to OSFL suitable forest	osflfortypedist
Distance to dead trees	d_dead	Distance to OSFL wetlands	osflwetlanddist
Distance to gravel and rocky areas	d_gravela	Distance to RUBL suitable forest	rublfortypedist
Distance to inland water bodies	d_wways	Distance to RUBL wetlands	rublwetlanddist
Distance to low shrub areas	d_low_shrub	Forest type	for_typ
Distance to open wetlands	d_open_wtl	Land cover	land_cover
Distance to shrubby wetlands	d_shrubby_wtl	Type of wetlands	lc_wtl
Distance to treed wetlands	d_treed_wtl		

Climatic variables are sometimes used for fauna (Hu and Jiang 2011; Cumming et al. 2010), but mainly only when the spatial extent is large and the climate can influence the species distribution (Cumming et al. 2010). The Southwest Nova Biosphere is relatively small (around 15000 km^2 (MAB 2007)), therefore climate influence was ignored. Moreover, edaphic variables such as soil type and geologic bedrock were also neglected because they don't seem related to bird habitat (Vaughan and Ormerod 2003; Mackey and Lindenmayer 2001). Structure of the habitats was focused on, as with the previous MaxEnt models.

One of the structural variables is land cover, which is commonly used for fauna, because it easily represents the structure and features of the habitat, whereas climatic and edaphic variables do not (Cumming et al. 2010; Kramer-Schadt et al. 2013). However, the variable land cover used in the models repeats itself with some variables that represent the distance to a specific feature of the environment: urban areas, dead trees, wetlands, gravel areas, barrens, agricultural areas and burnt areas. Therefore, close attention was paid to the influence of these variables and their possible correlation with the other variables. Indeed, distance to specific feature seemed interesting to model bird distribution, because birds are expected to be found close to their preferable habitat. The same goes for type of wetlands and distance to open, shrubby, and treed wetlands. Note that the distance to wetlands (d_wtl) is distance to treed (d_treed_wtl), open (d_open_wtl), and shrubby wetlands (d_shrubby_wtl) all together. Raster layers representing the distance to the nearest polygon were built using the Euclidean Distance tool in ArcGIS.

To model the human influence, Blach-Overgaard et al. (2010) used several indexes, such as the human influence index and human population density data. We chose to use only the distance to urban areas, which seemed a good approximation for the human influence. Urban areas include all types of residential and industrial areas, road corridors and human-related structures.

2.5.2. Selection of the variables in MaxEnt models

Correlation between explanatory variables must be avoided or minimized in order to have a consistent model. Several statistical analyses can be led to measure the correlation between variables. We used the Pearson correlation coefficient, computed in R (Ripley 2001). Two variables with a Pearson correlation coefficient <0.7 – 0.8 are generally seen as not correlated (Merow et al. 2013; Syfert et al. 2013).

By default, MaxEnt takes into account all the available variables. But risk of overfitting arises when there are too many environmental variables for too few occurrences. It is generally recommended to have a least ten times more sightings than explanatory variables (Vaughan and Ormerod 2003; Lobo and Tognelli 2011; Kramer-Schadt et al. 2013).

MaxEnt uses regularization to select relevant explanatory variables (Merow et al. 2013). Regularization penalizes too many variables: the environmental variables are weighted according to their addition to model complexity, and the sum of those establish how much the probability of occurrences is penalized to avoid overfitting (Phillips 2005; Fridley 2010). We chose the default regularization parameter, based on the results of Phillips and Dudík (2008) where many different species were used to set an optimal regularization parameter.

However, MaxEnt does not have the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) diagnostics to choose which variables to remove, as in the generalized linear models (Daudin et al. 2001). Therefore, the variables were selected manually. All possibly relevant variables were input into MaxEnt, and the variables which show a small percent contribution or permutation importance[2] were removed and a new model with less variables were tested. This process was repeated until AUC and COR decreased greatly when variables are removed.

[2] The percent contribution is based on the increase or decrease in regularized gain due to a particular variable for each iteration of the training algorithm. For each environmental variable in turn, the permutation importance is determined by measuring the decrease in training AUC when the values of this variable are randomly permuting for the training set. This second estimate does not depend on the path that MaxEnt use to get the optimal solution, whereas the first estimate does (Phillips 2005).

2.6. Sample bias issues and creation of correcting backgrounds

2.6.1. MaxEnt, a presence-only model

MaxEnt was used because it is a modeling method that does not require absence data. Indeed, "true" absences were hardly available for the studied birds. The absence of a species during a survey does not necessarily mean that the species does not use this location. The species can be undetected at the visited site or it can be temporary absent. For example, when a species has a large home range, the bird can be in another part of its habitat (Lütolf et al. 2006; Brotons et al. 2004). Most of the six species had large territories or home ranges.

The Dalhousie's 2012-2013 species at risk surveys can be seen as the most reliable absences available, because some entire surveys with playbacks were conducted. However, it does not guarantee genuine absences and only a small part of southwestern Nova Scotia was sampled during those two spring and summer surveys. Moreover, the six bird species are at risk in the region. So, quite rare and incidental observations are a main source of information, especially for CONI and CHSW that are more urban. Indeed, CAWA, OSFL, EAWP and RUBL are more reclusive, living in more remote habitats. Consequently, presence-only models were chosen to avoid false-absence issues (Pearson 2010).

2.6.2. Sample bias

A sample is unbiased in environmental space if "*it samples each combination of environmental covariates proportionately to the amount of the study area that has those covariate values*" (Phillips et al. 2009). Sample bias has several causes. In literature, it is mentioned that a sample is usually biased toward easy access areas, such as roads, population centres, or protected areas. Some surveys also focused on particular landscapes, regions, and vegetation types while ignoring other types (Phillips and Elith 2010; Kramer-Schadt et al. 2013). Sample bias must not be confused with spatial autocorrelation, which occurs when samples are more clustered or dispersed than a random sample.

The basic MaxEnt hypothesis states the uniform sample assumption, even though sample bias can be seen as a major challenge for presence-only models, because absence data cannot balance the sample bias (Merow et al. 2013). However, a large part of MaxEnt modeling papers do not take the sample bias into account, and few studies have addressed this issue (Lobo and Tognelli 2011; Kramer-Schadt et al. 2013). In the first-generation landbird SAR models, this issue was not considered. Many papers strongly recommend attempting to account for sampling bias (Merow et al. 2013).

Spatial bias can influence all the accuracy measures, such as AUC and gain (Phillips et al. 2009; Lobo and Tognelli 2011). Moreover, a spatially biased model can reflect the sampling effort rather than the species distribution (Syfert et al. 2013; Kramer-Schadt et al. 2013).

2.6.3. How to deal with spatial bias?

Sample bias is particularly an issue in presence-only modeling method because of the lack of "true" absence. By default, the model generates randomly distributed background data, or "pseudo-absence" data.

One way to deal with spatial bias is to use a biased prior: the background sample can be selected to have the same bias as the occurrence data, so that the model does not focus on the sample selection bias but on actual differences between the occurrence and pseudo-absence locations (Phillips et al. 2009; Kramer-Schadt et al. 2013; Merow, Smith and Silander 2013). Two different biased prior backgrounds were created: the human footprint background and the target-group sample background.

Human footprint background

The first background is a human influence index background, as developed in Kramer-Schadt et al. (2013). The Human Footprint of the Northern Appalachian Acadian Ecoregion (Woolmer et al. 2008) is a measure of human influence on ecosystems using data set on human settlement, access, landscape transformation and electrical power infrastructure. It was resampled to fit our data extent, using the ArcGIS Resample tool.

Target-group sample background

The second background is a grid created due to other species localities, based on Merow et al. (2013). The target-group sample was input into MaxEnt as a single species to predict an estimation of the sampling effort.

The locations used are based on the MBBA data (2006-2010) and the SAR database, assembling data from the Staicer Ornithology team (2006-2013), Alana Westwood's field work (2012-2013) and sightings from the public. In total, 1192 points were available, and after removing points closer than 500 m in order to remove spatial autocorrelation (see section 2.7.2. Reducing spatial autocorrelation), 985 points were left,.
The sampling effort variables, indexed between 0 and 1, are:

- Distance to roads
- Distance to urban areas
- Distance to protected areas
- Topographic roughness[3]

Other ways to correct spatial bias exist and are discussed in the discussion part (see section 4.3.2. Spatial bias correction).

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[3] The topographic roughness were measured using the Relative Topographic Position, defined using DEM (digital elevation model): $\frac{SmoothDEM - MinDEM}{MaxDEM - MinDEM}$, with MinDEM the minimum DEM of the study area, MaxDEM the maximum DEM and SmoothDEM the DEM "smoothed" by the values of the neighborhood around it (Jenness 2002).

2.7. Spatial autocorrelation in the models

2.7.1. Definition and issues

Autocorrelation occurs when two nearby locations exhibit more similar values than two more distant locations, which means that two random points of a same variable, that are a certain distance apart, are more similar than expected (Smith 1994; Wagner and Fortin 2005; Dormann et al. 2007).

Autocorrelation breaks an essential hypothesis of species distribution models: independent observations of the species (Vaughan and Ormerod 2003). It can also cause overprediction, when absences are incorrectly predicted as presences, (Miller et al. 2007; Lobo and Tognelli 2011; Millar and Blouin-Demers 2012) and inflate the importance of some environmental variables (Miller et al. 2010; Kramer-Schadt et al. 2013). Vaughan and Ormerod (2003) therefore recommended to avoid autocorrelation whenever possible, for the benefits of model predictability, model adaptability and biological reality .

2.7.2. Reducing spatial autocorrelation

In order to reduce the spatial autocorrelation that could occur in the dataset, "spatial filtering" technique was used. It implies the imposition of a minimum distance between samples (Vaughan and Ormerod 2003). This technique is widely cited in the literature (Blach-Overgaard et al. 2010; Miller et al. 2010). The best distance would be the bird territory size, but this information is not always available and a territory size may vary between individuals. Millar and Blouin-Demers (2012) suggest at least 1 km between points, Wagner and Fortin (2005) suggest 100 m and Guisan et al. (1998) 200 m. We arbitrarily choose 500 m, which seems a good compromise. Indeed, a bigger distance would eliminate too few occurrences to run the models properly and a smaller distance would probably leave some autocorrelation. This distance is arbitrary and debatable.

Others approaches are to include autocorrelation in the model, as a candidate predictor variable, or to use autoregressive models (Vaughan and Ormerod 2003; Dormann et al. 2007). They allow a better understanding of the patterns in the species distribution. However, it seems that those techniques are not often used with presence-only data. Therefore, and because of a lack of time, they were not explored.

In this way, the duplicates and the points closer than 500 m from each other were removed for each species, using "Remove Duplicates" and "Near" tools of ArcGIS. Sometimes, three points were closer than 500 m from each other. In this case, the point the furthest from the roads were kept, to try to avoid the spatial bias introduced by the road proximity.

2.7.3. Estimation of the spatial autocorrelation

To estimate the autocorrelation of the species' observations, Moran's I test was used. It is widely cited in the literature as an effective test (Dormann et al. 2007; De Marco et al. 2008). It ranges between -1 and 1: values towards -1 indicate a dispersion tendency and values towards 1 indicate clustering tendency. 0 shows a random pattern (ESRI 2010b).

It would be interesting to estimate the spatial autocorrelation in the "raw" and the "corrected" dataset. However, it is difficult to estimate it in the case of presence-only data. Indeed, absence data is needed to explain the spatial autocorrelation. To circumvent this problem, tests were run on the model residuals, defined as the observed value minus the predicted value.

2.8.Other parameters

2.8.1. Number of background points

The number of pseudo-absences created can influence the models. The prevalence is defined as the ratio of presence locations to total data (presences and pseudo-absences) used in the model. A high prevalence (few pseudo-absence points) negatively influences the model because the ecological gradients are not entirely covered (Merow et al. 2013). However, using a lot of pseudo-absence points biases the probability towards the absences. This can be resolved by using a cut-off value to separate potential presences and potential absences.

Lobo and Tognelli (2011) recommend using a large number of pseudo-absences to truly represent unsuitable regions, so that the environmental variables explain most of the distribution and to reduce overprediction. Many studies use the MaxEnt default background number, 10 000 (S. J. Phillips et al. 2009; Blach-Overgaard et al. 2010; Millar and Blouin-Demers 2012; Merow et al. 2013). Preliminary studies were led for one species (Olive-sided Flycatcher) to try to determine the ideal number. Lobo and Tognelli (2011) mentions 100 times the number of presence as a good number of backgrounds. However, no differences were noticed and the standard number of 10 000 pseudo-absence points were chosen.

2.8.2. Training and testing data

MaxEnt splits the data into training and testing data. Training data is used to create the model and the testing data is used to evaluate this model. It is important to have a testing data because without it, MaxEnt will develop and evaluate the model with the same training data. However, the data must be independent, at least spatially, in order to avoid sampling bias (Vaughan and Ormerod 2003; Dudík et al. 2005; S. J. Phillips et al. 2009; Merow et al. 2013). In this study, having enough reliable sighting was a challenge, so we did not possess an independent dataset.

Moreover, another caution arises from literature for the use of testing data. It had been observed that using a testing dataset decreases the model performance when spatial bias is corrected (Lütolf et al. 2006; Syfert et al. 2013). It happens when the testing data has the same sample bias as the training data and is presence-only data. Indeed, without correction, the testing data will respond well to the environmental response curves built with bias. But correcting the bias leads to more realistic environmental response curves, and the testing data will respond worse, because of its inherent bias that is not corrected. Therefore, a presence-absence testing dataset is needed, or at least presence-only unbiased data (Phillips et al. 2009; Syfert et al. 2013). This type of data was not available for this study, so we did not use a testing data set (we set the "random test percentage" to zero) and we based our evaluation of the models only on the training dataset. This might be arguable but it seems the most acceptable way to deal with sample bias issues.

2.8.3. Model replicates

MaxEnt can run several replicates of the same model and then average them. Different techniques were available: crossvalidate, bootstrap and subsample. A total of 40 replicates were run for each model, as in Syfert et al. (2013), so that statistical analyses can be led, and the default crossvalidating method was chosen (data are divided into replicates folds) (Phillips 2005).

2.8.4. Three different types of outputs

Three types of related outputs were available. The raw output gives probabilities such that the sum over all cells used during training is 1 and depends on number of locations, making any kind of comparison challenging. The cumulative output sums up all raw values less than the raw value for a specific location, rescale it between 0 and 100, and assigns it to this location. It can be interpreted as an omission rate (Merow et al. 2013). Finally, the logistic output gives a estimate of the probability of presence. It is the exponential of the entropy of the raw distribution (Phillips and Dudík 2008; Elith et al. 2011). The last type of output was chosen to model the species distribution.

2.8.5. Feature types

Different feature types influence the shape of response curves: linear, quadratic, produce, threshold and hinge features. All the classes can be used together, using the default "Auto features", which allows MaxEnt to model complex responses curves. The default parameter was used for reasons of simplicity (Phillips 2005; Phillips et al. 2006).

2.9. Climate change

2.9.1. Climate change: definition and projections

Climate change refers to a change in the state of the climate that persists for an extended period, typically decades or longer. It may be due to natural internal processes or external forces such as modulations of the solar cycles, volcanic eruptions, and persistent anthropogenic changes in the composition of the atmosphere or in land use (IPCC 2014). Global warming is very likely caused by increasing concentrations of greenhouses gases caused by human activities. (>90% probability; IPCC 2007).

Climate change is difficult to predict and many different scenarios are modeled. However, IPCC predicted increase of global temperature between 1.4 and 5.8 °C, based on several models. Precipitations will also be modified, and sea level will rise (IPCC 2007; Erwin 2009). In general, a decrease in precipitation in the lower latitudes and an increase in the higher latitudes are predicted (Erwin 2009).

IPCC predicts that, in North America, temperature will rise more than 2°C in the 21st century (Romero-Lankao et al. 2014). Precipitation trends are more difficult to anticipate, but it seems that there will be either no change or an increase of 10% to 20%. The pattern across the seasons will be modified: precipitation will be concentrated in the fall, winter and spring, and it will decrease in summer (Johnson et al. 2005). Extreme climate events, such as extreme temperatures, flooding, and drought, are projected to be more common (Romero-Lankao et al. 2014; Nantel et al. 2014).

2.9.2. Climate change in Nova Scotia

Conclusions from studies on climate change in Nova Scotia include the following: (1) Summer rainfall will be reduced and mean temperature increase is predicted in Kejimkujik National Park (Scott and Suffling 2000). (2) Extreme events, for example fire, insect outbreaks and storms, will increase (Drysdale et al. 2008). Forest fire intensity and frequency will increase (Scott and Suffling 2000; Morton et al. 2010). (3) Sea level will rise by 0.5 m around Nova Scotia, causing intercoastal erosion, salt water intrusion and altering marine terrestrial interface (Scott and Suffling 2000). (4) Precipitation will increase in Nova Scotia, between 5-15% before 2100 from current levels (Bourque and Hassan 2008).

Bourque and Hassan (2008) modeled the potential future distribution of 10 tree species and 2 shrub species throughout Nova Scotia, as well as soil water content (SWC), using the "business as usual" greenhouse gas emission scenario (IS92a) and Canadian Coupled Global Climate Model of first generation (CGCM1), for 14 climate stations across Atlantic Canada.

2.9.3. Wetlands as an essential habitat component

CAWA, OFSL and RUBL's habitats are forested wetlands. For CONI and CHSW, wetlands are an essential source of food - abundance of flying insects in these habitats (COSEWIC 2006; 2007a; 2008a).

2.9.3.1. What is a wetland?

Defined by the Environment Act (1994), a wetland is a "*land commonly referred to as marsh, swamp, fen or bog that either periodically or permanently has a water table at, near or above the land's surface or that is saturated with water, and sustains aquatic processes as indicated by the presence of poorly drained soils, hydrophytic vegetation and biological activities adapted to wet conditions*". A wetland has many important functions and services, for example providing critical habitat for rare and endangered species, controlling floods, improving water quality and replenish groundwater.

Nova Scotia counts 5.5 million hectares of wetlands, approximately 6.8% of the total land area. Three quarters of the wetlands are peatlands, 10.1% are shrub swamps and 4.5% are salt marshes (Government of Nova Scotia 2011).

2.9.3.2. Climate change consequence on wetlands

Wetlands are commonly considered to be among the most threatened ecosystems of the planet and are declining at an alarming rate. The causes of the decline are draining for urbanization, agriculture and industrial development, water overuse, pollution and water flow modification with dams (Settele et al. 2014). Up to 70% of wetland have been degraded or destroyed in Canada (Ducks Unlimited Canada 2014).

Moreover, wetlands will be highly affected by climate change, from altered thermal regimes, precipitation and flow regimes, as well as sea level rise for coastal wetlands (Settele et al. 2014). Precipitation modification and temperature rise due to climate change will alter hydrologic regimes in rivers and wetlands and will modify fauna and flora communities (Erwin 2009; Settele et al. 2014). At a global scale, the number of wetlands will most likely decline and geographic location will be modified for some types of wetlands. The changes will be greatly variable across the globe, depending on the ecoregions and the type of wetlands (Erwin 2009).

An extent analysis of the influence of climate change on wetlands was conducted on North American prairie wetlands by Johnson et al. (2005). They created WETSIM, a wetland simulation model, and concluded that any temperature increase will result in decreased water level. Global models assert an additional climate variability of the magnitude. This would greatly affect wetland hydrology and other wetland attributes. They ran three different models. Increasing temperature and decreasing precipitations would have the greatest negative effect on wetlands, with longer and more frequent drought. Increasing temperature alone would lead to a slightly drier climate with modified cover ratios. Increasing both temperature and precipitation would have a counterbalancing effect, with only small change in land cover. A simulation for the prairie wetlands seems to indicate that a 20% increase in precipitation could compensate for a 3°C rise in temperature in general (Johnson et al. 2005).

3. Results

3.1. Spatial bias correction using three different backgrounds

AUC and COR were compared between 3 types of tests, for each species: without background (nobg), with the target-group sample background (sprbg) and with the human footprint background (hfpbg). A initial selection of suitable environmental variables were adopted in these models. The results with all the species are displayed in Tables 5 and 6 below, and the detailed results for each species are detailed in Appendix 2.

According to the Shapiro-Wilk normality tests, the AUC and COR samples were not normally distributed. So the Wilcoxon test was used. The results were not significant, except for COR between the model without background and the model with the human footprint background, the latter one being less efficient. The means suggested that the model without background was the best regarding the AUC. So, it would seem that the model without background was the most reliable. However, as mentioned in Merow et al. (2013), sample bias should always be taken in account, especially for this study dataset that clearly shows a spatial bias. The target-group sample background was the best background regarding the COR tests. Therefore, this background was used for the following models.

Table 5. Training AUC comparison between backgrounds
nobg: model without background; sprbg: model with the target-group sample background: hfpbg: model with the human footprint background.

Test between variables	Normality test P-value	Wilcoxon test P-value	Mean	
nobg-sprbg	0.184	0.219	**nobg**	0.820
nobg-hfpbg	0.193	0.156	**sprbg**	0.818
sprbg-hfpbg	0.192	1.000	**hfpbg**	0.818

Table 6. COR comparison between backgrounds
nobg: model without background; sprbg: model with the target-group sample background: hfpbg: model with the human footprint background.

Test between variables	Normality test P-value	Wilcoxon test P-value	Mean	
nobg-sprbg	0.514	0. 156	**nobg**	0.136
nobg-hfpbg	0.520	0. 031	**sprbg**	0.182
sprbg-hfpbg	0.653	0.156	**hfpbg**	0.134

3.2.Spatial autocorrelation: Moran's I test results

Moran's I statistic lies between -1 and 1. A positive Moran's I indicates a tendency toward clustering and a negative one toward dispersion. A zero Moran's I value indicates a random spatial pattern. The z-score and p-value were also returned during the tests. They indicate statistical significance. The null hypothesis states that values are randomly distributed across the study area. Therefore, when the p-value is < 0.05, you can reject the null hypothesis and it is very unlikely (at the 5% level) that the feature values are randomly distributed. Z-score are standard deviations. When the p-value is statistically significant (<0.05), and a z-score is positive, it means the feature values are more spatially clustered than random; and a negative z-score means that the values are more spatially dispersed than random (ESRI 2010b).

Moran's I were computed with ArcMap software (ESRI 2010a), for each species and for the raw location data and the spatial filtered data (Table 7).

Table 7. Moran's I test results

Species	CONI	CHSW	OSFL	EAWP	CAWA	RUBL
Raw data						
Number of sightings	210	91	210	103	146	57
Moran's I	0.17	0.15	0.17	0.35	0.35	0.10
Z-score	4.39	3.14	5.41	5.77	7.03	1.74
P-value	0.0000	0.0017	0.0000	0.0000	0.0000	0.0822
Spatially filtered data						
Number of sightings	107	66	185	75	100	50
Moran's I	0.10	0.15	0.06	0.16	0.02	0.09
Z-score	4.59	3.14	5.15	5.26	1.16	2.35
P-value	0.0000	0.0017	0.0000	0.0000	0.2476	0.0188

Except for RUBL raw test and CAWA filtered test, all the p-values were significant, which indicated that the values were not randomly distributed across the landscape. Moreover, the positive Moran's I statistics suggested than the data was spatially clustered. The Moran's I average for all the species was 0.22 for the raw model residuals and was 0.09 for the spatially filtered residuals, which suggested that, even if the location data remained clustered, they were less autocorrelated once spatially filtered.

However, in the case of RUBL, the significant p-value for the raw data and insignificant p-value for the filtered data would indicate that filtering the data would cause spatial clustering, which is unlikely.

3.3.Environmental variables

3.3.1. Preliminary results

Each variable used in MaxEnt was visually analysed to ensure their pertinence. For the distance to burnt areas, only a very few burnt areas were available in the Southwest Nova Scotia landscape. Therefore, the distance to them did not show relevant gradient of burnt areas, and this variable was removed from the models.

The distance to cliffs, dunes and coastal rocks was used in the first-generation Chimney Swift model (Kindree 2014), as a potential habitat for the bird. However, this variable was not relevant to represent only the cliffs, and rather showed the distance to the coast, which was not a relevant predicator. So, this variable was not included in the modeling.

Two models were first established. The first one had all of the variables except the land cover and the type of wetlands, which are two categorical variables; and the second one with the land cover and the type of wetlands but without the redundant distance variables (distance to urban areas, dead trees, wetlands, gravel areas, barrens, agricultural areas for land cover and distance to open, shrubby and treed wetlands for type of wetlands). Indeed, those variables repeated the same information. For each species, the models with gradients always outperformed the models with the land covers. Therefore, land cover and type of wetlands were left aside.

Correlations between the variables were indicated by the Pearson's Correlation Coefficient matrix (details in Appendix 10). The distance to wetlands and to open wetlands were correlated, which is logical, because they are both based partly on the same data (r=0.70). The canopy closure and the first story canopy height were highly correlated (r=0.75). The distance to urban areas, agricultural areas and clearcuts are weakly correlated (r=0.64-0.66).

3.3.2. Results for the second-generation models

3.3.2.1. Results of the estimates

Appendix 11 shows the different steps for the selection of variables for each second-generation model. After selecting the variables for each bird, the best models were finalized. Table 8 summarizes the results for the estimates. The models showed good results for the AUC, which was above 0.75 for all models, indicating good discrimination power of the models, more than 0.80 for 4 models, and even near 0.9 for the EAWP.

Table 8. Results of the estimates for the SDM of each bird

Estimate	CONI	CHSW	OSFL	EAWP	CAWA	RUBL
AUC	0.794	0.850	0.809	0.894	0.782	0.820
COR	0.125	0.122	0.165	0.188	0.104	0.084
Training gain	0.382	0.523	0.487	0.940	0.418	0.517

The COR showed a poorer performance, ranging between 0.08 and 0.19. In Elith et al. (2006), a good model has a COR >0.020. The EAWP model showed the highest COR, and RUBL and CAWA models performed the worst.

Therefore, the models did not show a good calibration ability, which means that the predicted probabilities of presence did not correspond well with the observed distribution of presence, although presence and absence seemed correctly differentiated (high AUC; see 2.3.5. Estimates to compare the models).

3.3.2.2. Results of the environmental variables

Table 9 summarizes the variables chosen for each model. The following paragraphs study the variables for each species, based on the results displayed in the Figures 8 to 13, and detailed results figures are available in Appendices 12 to 17. Wetness and structural variables were important, as well as the urban areas, despite the correction of the sample bias.

Table 9. Final variables chosen for each species distribution models

CONI	CHSW	OSFL	EAWP	CAWA	RUBL
Distance to inland water bodies	Distance to urban areas	Distance to OSFL wetlands	Distance to protected areas	Depth to water table	Depth to water table
Distance to urban areas	Distance to clear cut	Distance to agricultural lands	Distance to low shrub areas	Distance to inland water bodies	Distance to low shrub areas
Distance to shrubby wetlands	First story canopy height	Distance to clear cut	First story canopy height	Distance to uneven aged stands	Distance to agricultural lands
First story canopy height	Distance to inland water bodies	Distance to inland water bodies	Distance to urban areas	Distance to clear cut	Distance to inland water bodies
Distance to low shrub areas	Distance to dead trees	Depth to water table	Depth to water table	Second story canopy height	Distance to clear cut
Distance to clear cut	Distance to open wetlands	Forest type	Distance to inland water bodies	Canopy cover	
	Distance to low shrub areas	Canopy cover	Distance to uneven aged stands		

Common Nighthawk

Six variables were relevant for the CONI model (Figure 8). The most influential was the distance to water bodies (d_wways, 24%). CONI was generally located near lakes and rivers. The second variable indicated that urban areas and areas nearby were favourable to CONI (d_urban, 20%). The third major variable was the distance to shrubby wetlands (d_shrubby_wtl, 17%): the closer a shrubby wetland was, the more likely it was to find a CONI. The first story canopy height pointed out that CONI was usually found in open areas or forests with low trees (less than 5 m) and in tall forests (> 20 m). The distance to clearcuts influenced less the model (d_clearcut, 10%) and its response curve tended to indicate that CONI are found in a close distance from clearcuts (> 2 km), even if the curve pattern showed some leaps.

Chimney Swift

Seven variables stood out in the model (Figure 9). The most important one was the distance to urban areas (d_urban, 38% of contribution). The probability was the highest into urban areas and in areas very close to them (less than 500 m). CHSW were also frequently encountered in areas that were far away from the urban areas (>10 km away). Three other variables were also important to explain the model: the distance to clearcuts (d_clearcut, 16%), the first story height (1story_canopy, 15%) and the distance to waterways (d_wways, 11%). CHSW were usually seen in clearcuts and in areas close to them (0-2.5 km from clearcuts). Tall first story canopy height wes preferred (20-25 m), also CHSW opted for very low first story height as well (0-5 m). CHSW tended to select waterways and areas close by (0-1 km). The distance to dead trees (d_dead, 8%) and to open wetlands (d_open_wtl, 8%) weighted less in the model. The response curves showed that CHSW prefered areas that are at least 1 km away from dead stands and 200 m away from open wetlands.

Olive-sided Flycatcher

Seven variables were important for the OSFL's model (Figure 10). The principal variable was the distance to wetlands except salt marshes and exposed or lichen wetlands (osflwetlanddist, 28%). The closer the wetland was, the more probable OSFL was found. The speciesa was most likely found in areas further than 1 km from agricultural areas, which highly contributed to the model (d_agri, 21%). The probability to find the species was higher within and very close to clearcuts, which was the third variable that explained the model the best (d_clearcut, 19%). Although the curves were not smooth, the distance to water body variable showed that the species was mostly found near lakes and rivers (d_wways, 13%). The three last variables contributed less to the model: depth to water table (depth_wtbl, 8%), forest type (for_typ, 8%) and canopy closure (canopyclosure, 3%). A shallow water table was favorable to the species. OSFL was more likely to be found in a coniferous forest and, to a lesser extent, not forested areas. It was much less frequently found in mixed and hardwood forest. The probability was higher in forested areas with a low first canopy closure.

Eastern Wood-pewee

Seven variables were important to explain EAWP distribution across SWNS (Figure 11). The variable with the major contribution to the model was the distance to protected areas (d_protecteda, 32%), for EAWP were most frequently seen inside and close to protected areas. The distance to blueberry fields was also essential to the model (d_low_shrub, 22%): areas close to blueberry fields (between 2.5 and 10 km) were suitable for EAWP. The next influential variable was the first story canopy height (1story_canopy, 20%). EAWP was most frequently seen in forests with a high canopy (more than 15 m tall). The urban areas can be suitable for EAWP, and largely influenced the model (d_urban, 16%) EAWP is not quite a urban species, as CHSW or CONI, but it can be found near cottages and homes if mature forest is present around. The three last variables had a lesser influence on the model: depth to water table (depth_wtbl, 7%), distance to waterways (d_wways, 3%) and distance to uneven aged stands (d_uneven_age, 1%).

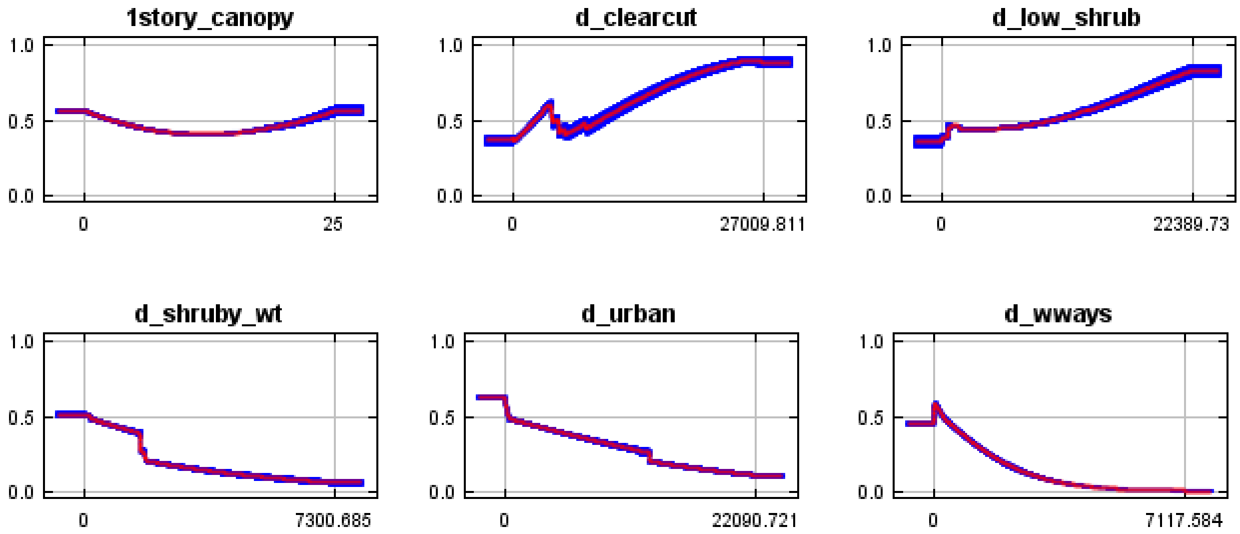

Figure 8. Response curves of habitat suitability for Common Nighthawk
The vertical axis represents the suitability of the habitat (0: unsuitable; 1: most suitable), and the horizontal axis shows each variable's values. Top to bottom, left to right: first story height (1story_canopy), distance to clearcuts (d_clearcut), distance to blueberry fields (d_low_shrub), distance to shrubby wetlands (d_shruby_wt), distance to urban areas (d_urban) and distance to waterways (d_wways).

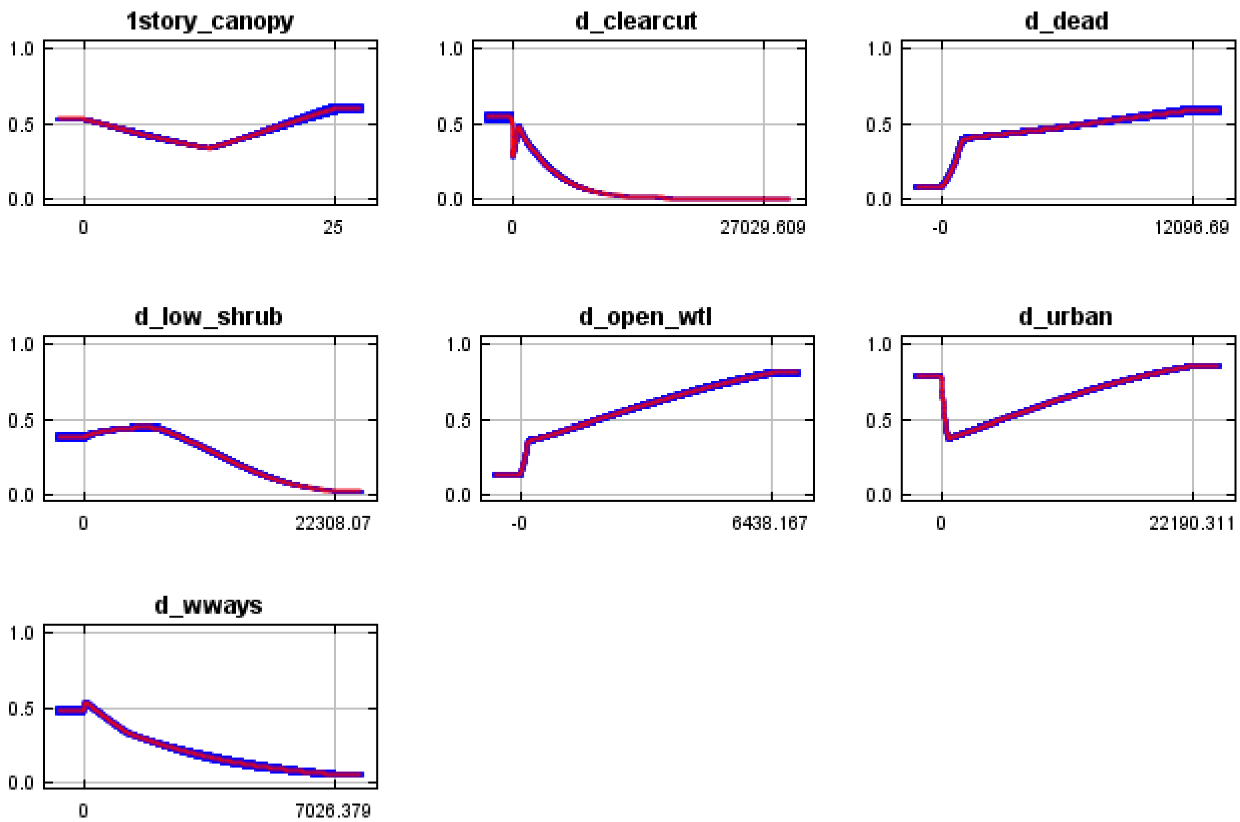

Figure 9. Response curves of habitat suitability for Chimney Swift
The vertical axis represents the suitability of the habitat (0: unsuitable; 1: most suitable), and the horizontal axis shows each variable's values. Top to bottom, left to right: first story height (1story_canopy), distance to clearcuts (d_clearcut), distance to dead trees (d_dead), distance to blueberry fields (d_low_shrub), distance to open wetlands (d_open_wtl), distance to urban areas (d_urban) and distance to waterways (d_wways).

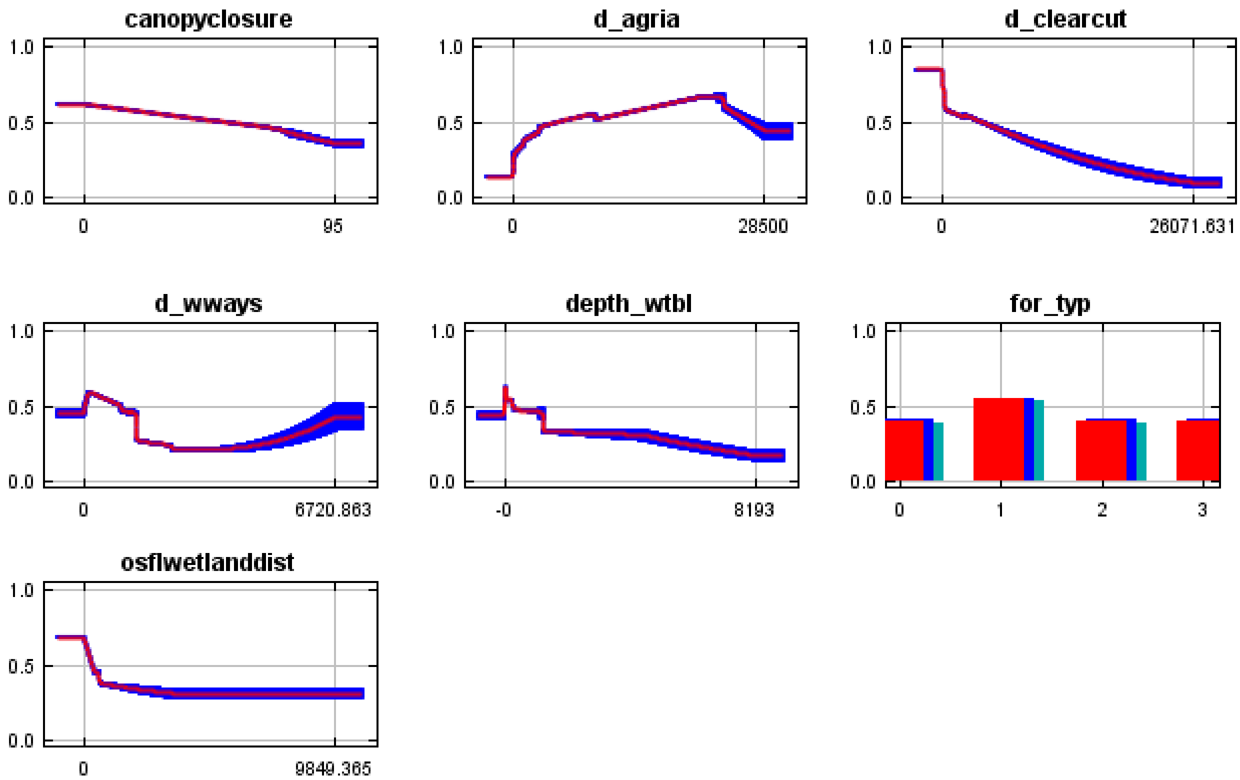

Figure 10. Response curves of habitat suitability for Olive-sided Flycatcher

The vertical axis represents the suitability of the habitat (0: unsuitable; 1: most suitable), and the horizontal axis shows each variable's values. Top to bottom, left to right: canopy closure (canopyclosure), distance to agricultural areas (d_agri), distance to clearcuts (d_clearcut), distance to waterways (d_wways), depth to water table (depth_wtbl), forest type (for_typ) and distance to OSFL's suitable wetlands.

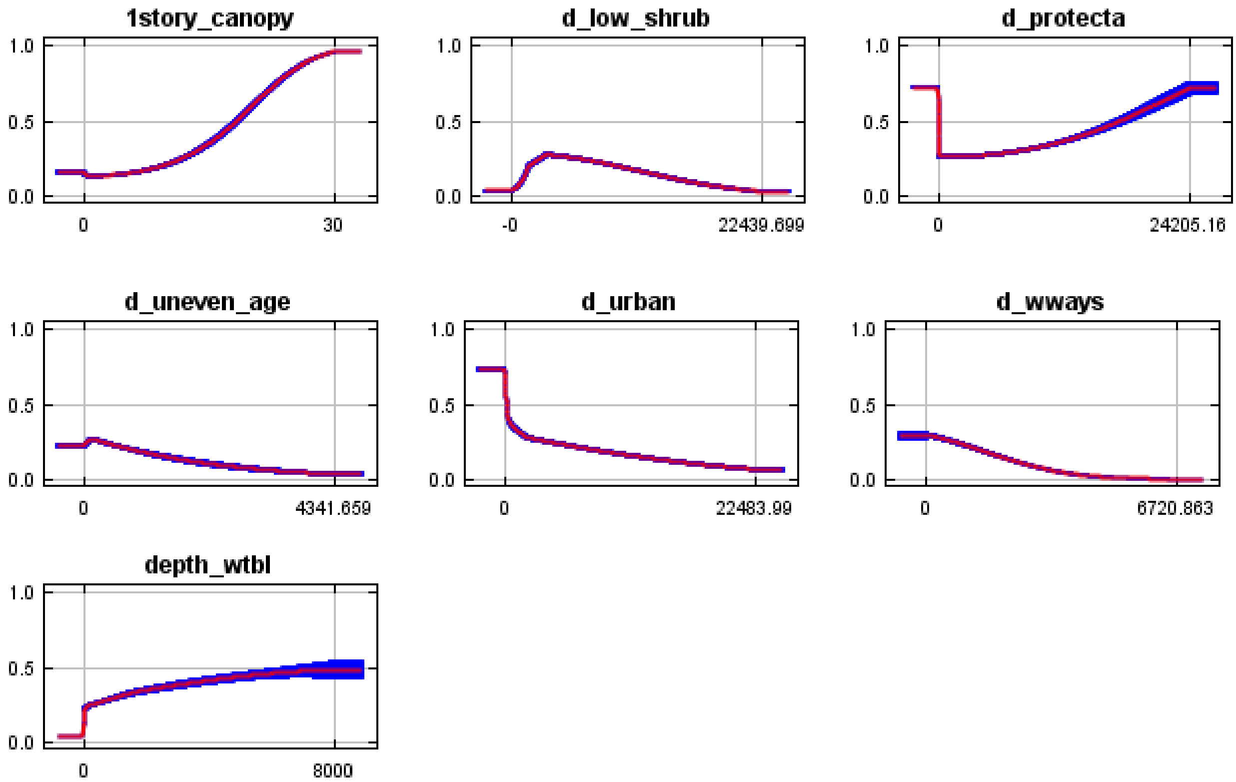

Figure 11. Response curves of habitat suitability for Eastern Wood-pewee

The vertical axis represents the suitability of the habitat (0: unsuitable; 1: most suitable), and the horizontal axis shows each variable's values. Top to bottom, left to right: first story height (1story_canopy), distance to blueberry fields (d_low_shrub), distance to protected areas (d_protecta), distance to uneven aged stands (d_uneven_age), distance to urban areas (d_urban), distance to waterways (d_wways) and depth to water table (depth_wtbl).

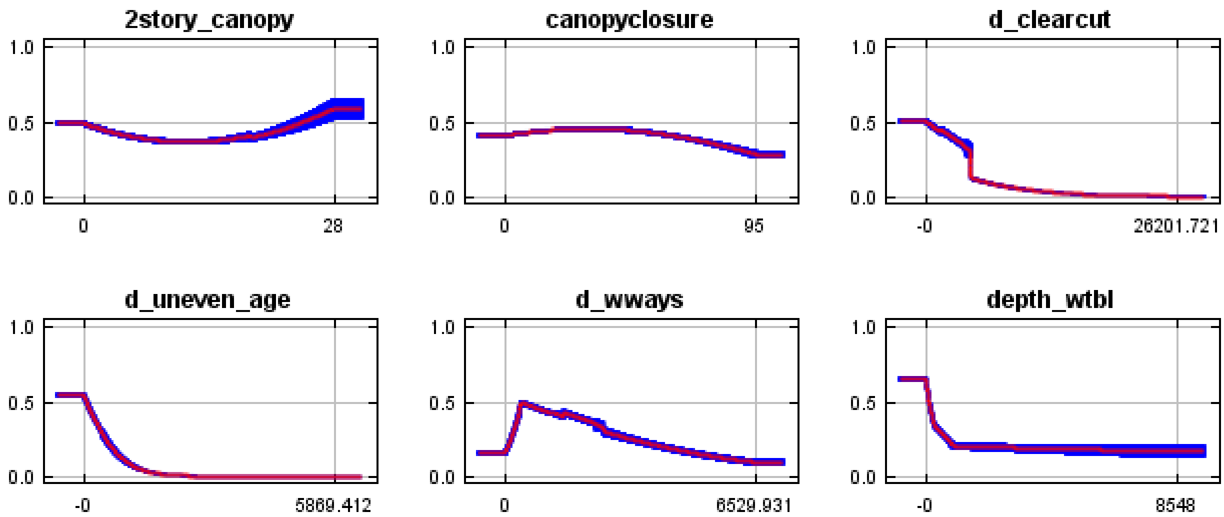

Figure 12. Response curves of habitat suitability for Canada Warbler
The vertical axis represents the suitability of the habitat (0: unsuitable; 1: most suitable), and the horizontal axis shows each variable's values. Top to bottom, left to right: Second story canopy height (2story_canopy), canopy closure (canopyclosure), distance to clearcut (d_clearcut), distance to uneven aged stands (d_uneven_age), distance to waterways (d_wways) and depth to water table (depth_wtbl).

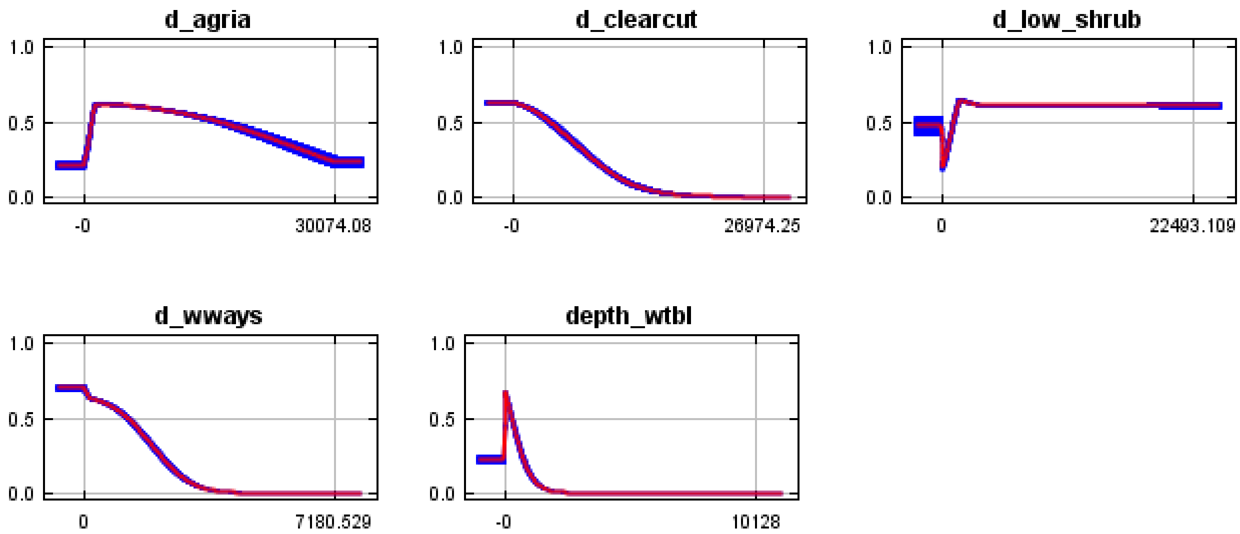

Figure 13. Response curves of habitat suitability for Rusty Blackbird
The vertical axis represents the suitability of the habitat (0: unsuitable; 1: most suitable), and the horizontal axis shows each variable's values. Top to bottom, left to right: distance to agricultural areas (d_agri), distance to clearcuts (d_clearcut), distance to blueberry fields (d_low_shrub), distance to waterways (d_wways) and depth to water table (depth_wtbl).

Canada Warbler

Six variables stood out in CAWA MaxEnt model (Figure 12). The variable that explained the most of the model was the depth to water table (depth_wtbl, 37% of contribution). CAWA prefered shallow depth (0-1 m). The next three variables that explained the model well were the distance to waterways (d_wways, 22% of contribution), uneven aged stands (d_uneven_age, 18%) and clearcuts (d_clearcut, 17%). The probability of presence was higher within 500 m and 2.5 km of waterways. CAWA prefered uneven aged stands, since its probability decreased the farther it got from this type of forest, and became null further than 2 km away. CAWA showed a clear preference to areas < 5 km away from clearcuts. The last two variables were the second story height (2story_canopy, 4%) and the canopy closure (canopyclosure, 2%). CAWA seemed to prefer very low second story (0-5 m) and very tall second story (> 25m). This trend was only visible in the marginal response curve, and not in the model created using only the second story height. This indicated that the variable interacted with the other variables used to build the model. Canopy closure was optimal at 40%, with a high probability of presence between 0% and 60%.

Rusty Blackbird

Because of the relatively low number of sightings for RUBL (51), only 5 variables were selected, despite the fact than more variables could have improved the AUC (Figure 13). Indeed, risk of overfitting may arise when number of sightings is less than 10 times the number of variables (Vaughan and Ormerod 2003; Lobo and Tognelli 2011; Kramer-Schadt et al. 2013; see 2.5.2. Selection of the variables in MaxEnt models). The leading variable was the depth to water table (depth_wtbl, 43%). Although a water table at the surface did not show a high probability of presence, areas with shallow water tables were more suitable for RUBL. The species was most likely found in areas farther than 1 km from blueberries areas, which highly contributed to the model (d_low_shrub, 23%). Agricultural area was the next most important variable (d_agri, 19%); its influence on RUBL distribution was the same as low shrub areas. The two last variables were less influential on the RUBL distribution: distance to waterways (d_wways, 9%) and distance to clearcuts (d_clearcut, 6%). The closer a water body or a clearcut, the higher the probability to find a RUBL.

3.3.3. Results and comparison with the former models

According to the Table 10, representing the mean of the estimates for the first-generation (without background) and second-generation models (with target-group sample background), AUC was better for the second-generation models, except for CONI and EAWP, whose tests were not statistically significant. COR showed more mixed results: CONI, OSFL, CAWA, and RUBL had a higher COR for the second-generation models, but CHSW and EAWP's first-generation models had a higher COR. Removing the distance to burnt areas from the CONI first-generation model (which is not a relevant variable) did not change the results of the COR and AUC. Considering only the mean of the AUC and COR for all the models together, the models with a background showed better performances.

However, when the first-generation models were run again with the target-group sample background and compared with the second-generation models (which also have this background), all AUC and COR were higher in the new models (Table 10). So the second-generation models showed better results in general, according to both AUC and COR.

Table 10. Mean of AUC and COR for the first-generation models without background or with target-group sample background (P*) and second-generation models, with target-group sample background (N*)

Statistic	First-generation models without background						First-generation models with target-group sample background		
	CONI	CHSW	OSFL	EAWP	CAWA	RUBL	OSFL	CAWA	RUBL
COR P*	0.124	0.125	0.114	0.235	0.063	0.058	0.108	0.063	0.057
COR N*	0.125	0.122	0.165	0.188	0.104	0.084	0.165	0.104	0.084
AUC P*	0.794*	0.841	0.725	0.895*	0.684	0.738	0.724	0.684	0.730
AUC N*	0.794*	0.850	0.809	0.894*	0.782	0.820	0.809	0.782	0.820

* Wilcoxon test was statistically significant.

3.4. Including 2014 field work in the models

The field surveys done during the spring and summer 2014 were used in the models, as well as new data collected from E-bird (2006-2013) and from the Breeding Bird Survey (2010-2014). 110 sites were visited during the field surveys, and 52 birds were found, mostly EAWP. 60 new sightings were received from the public, mainly throughout the e-mail address landbirdSAR@merseytobeatic.ca. Appendix 19 shows the details for each species and the Figure 14 shows the locations of the new sightings.

Statistical tests were conducted between models used for variable selection (V*) and models with added data from 2014 (N*; Table 11). All the Wilcoxon tests, that compare the models by pair, were statistically significant and the Table 11 shows the mean for AUC and COR. AUC was lower for most models with 2014 data, only EAWP and CHSW new models were better. However, COR showed better results for 4 models, and CAWA and RUBL had close COR between models without 2014 data and models including 2014 data.

Table 11. Mean of AUC and COR for the variable selection models (V*) and the 2014 added data (N*)
All the Wilcoxon test were significant.

	CONI	CHSW	OSFL	EAWP	CAWA	RUBL
COR N*	0.135	0.187	0.168	0.253	0.102	0.082
COR V*	0.125	0.122	0.165	0.188	0.104	0.084
AUC N*	0.789	0.893	0.807	0.915	0.769	0.811
AUC V*	0.794	0.850	0.809	0.894	0.782	0.820

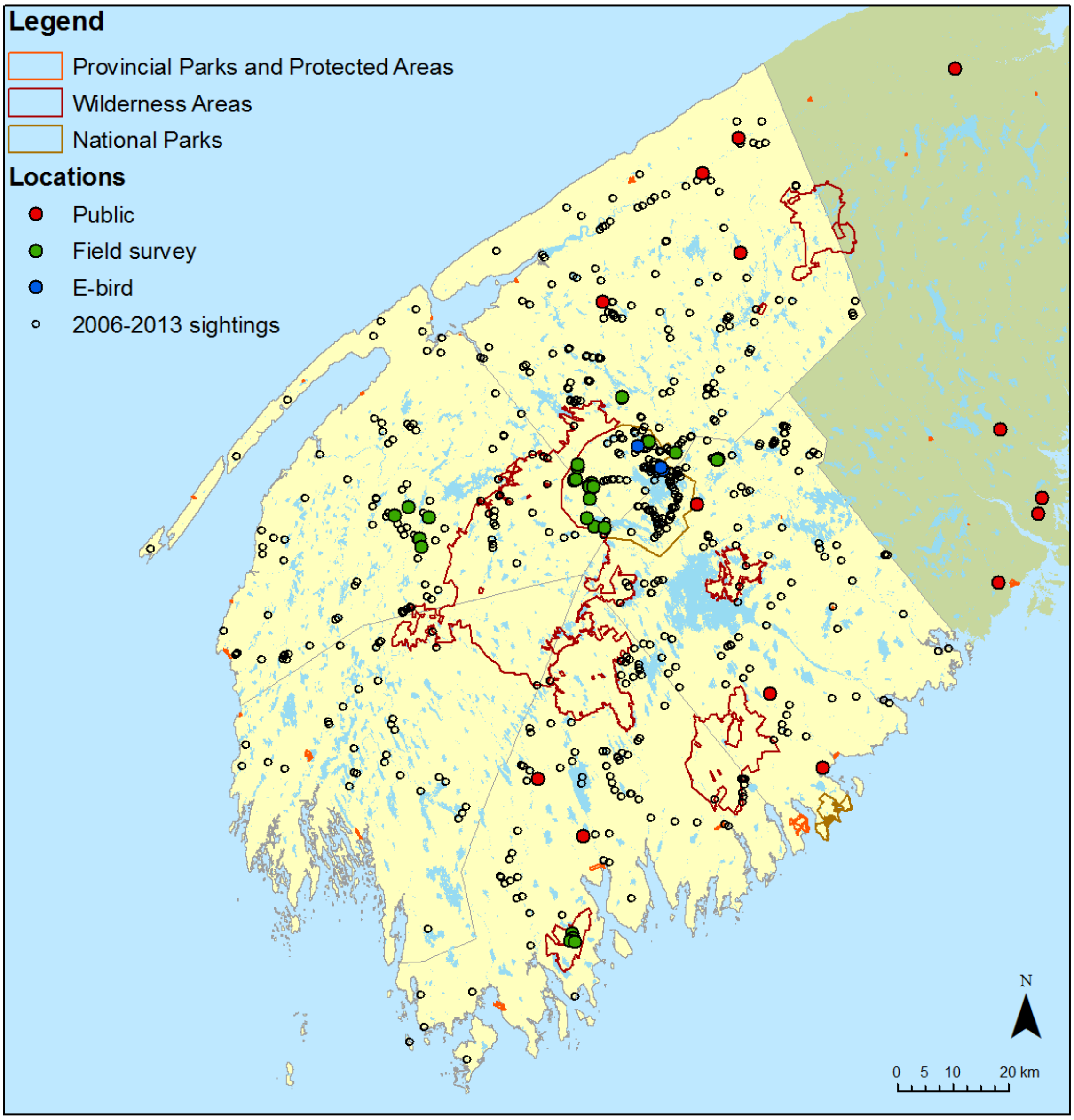

Figure 14. SAR sightings in southwestern Nova Scotia, including those added in 2014 from field survey, public participation and eBird Canada

3.5.Spatial distribution of the species

The predicted distribution of suitable habitat were displayed, based on the models with the best set of variables, the sample prior background and the latest location data available (Figures 15 to 20).

Common Nighthawk (Figure 15) suitable habitat was relatively high is southwestern Nova Scotia, except in the center of the area. Very good habitats were located in Kejimkujik National Park, and around Rossignol, Ponhook and Molega lakes. Good habitat seemed also located along the roads and urban areas.

Chimney Swift (Figure 16) showed few suitable habitats across Nova Scotia, especially within remote areas such as the Tobeatic Wilderness Area. Good habitats were predicted near the urban areas and the edges of the lakes, particularly near Brigdetown (north), Yarmouth (west) and around Lake Rossignol (south-east).

The Olive-sided Flycatcher suitable habitats (Figure 17) seemed evenly spread across all southwestern Nova Scotia and were located along the edges of the water bodies, especially between the Tidney and the Tobeatic Wilderness Areas. The northern region was not suitable: around Annapolis Royal and Bridgetown, higher urbanized areas, as well as the remote part of the Tobeatic Wilderness Area.

Predicted suitable habitats for the Eastern Wood-Pewee (Figure 18) were located in protected areas, such as Kejimkujik National Park, north and southeastern of the Tobeatic Wilderness Area, and in Lake Rossignol and Cloud Lake Wilderness Areas. Shelburne and Yarmouth counties (south and southeastern) had a very low suitability for the pewee.

The Canada Warbler predicted habitat (Figure 19) was low in the western part of Kejimkujik National Park and in the Tobeatic and Tidney River Wilderness Areas. High-suitability areas were scattered in all Nova Scotia, particularly around Lake Rossignol.

For the Rusty Blackbird (Figure 20), predicted habitats were lowest in the western side of Kejimkujik National Park, the Tobeatic Wilderness areas and in the south of the study area. High-suitability habitats occurred around Lake Rossignol areas and in the north of the region.


Kejimkujik National Park © Clara Ferrari

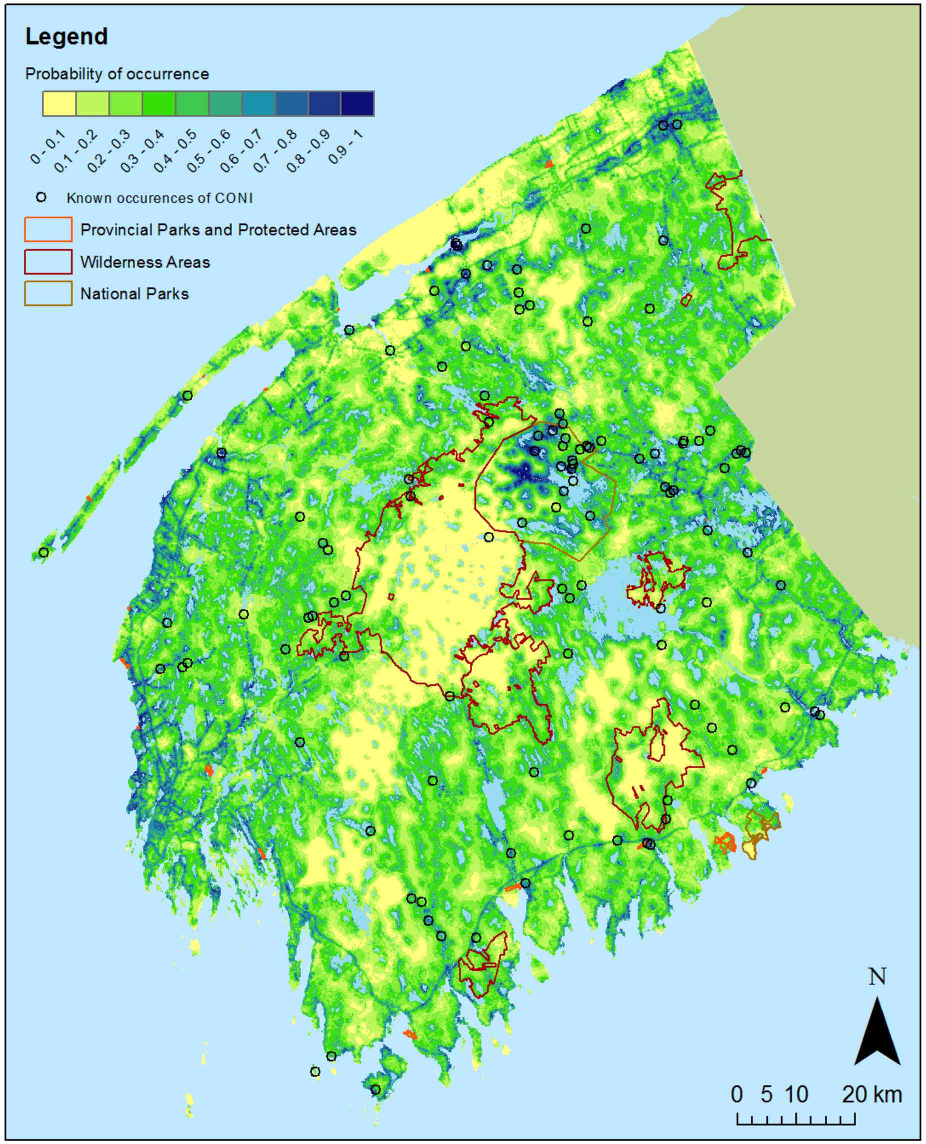

Figure 15. Habitat suitability for Common Nighthawk in southwestern Nova Scotia, modeled by MaxEnt

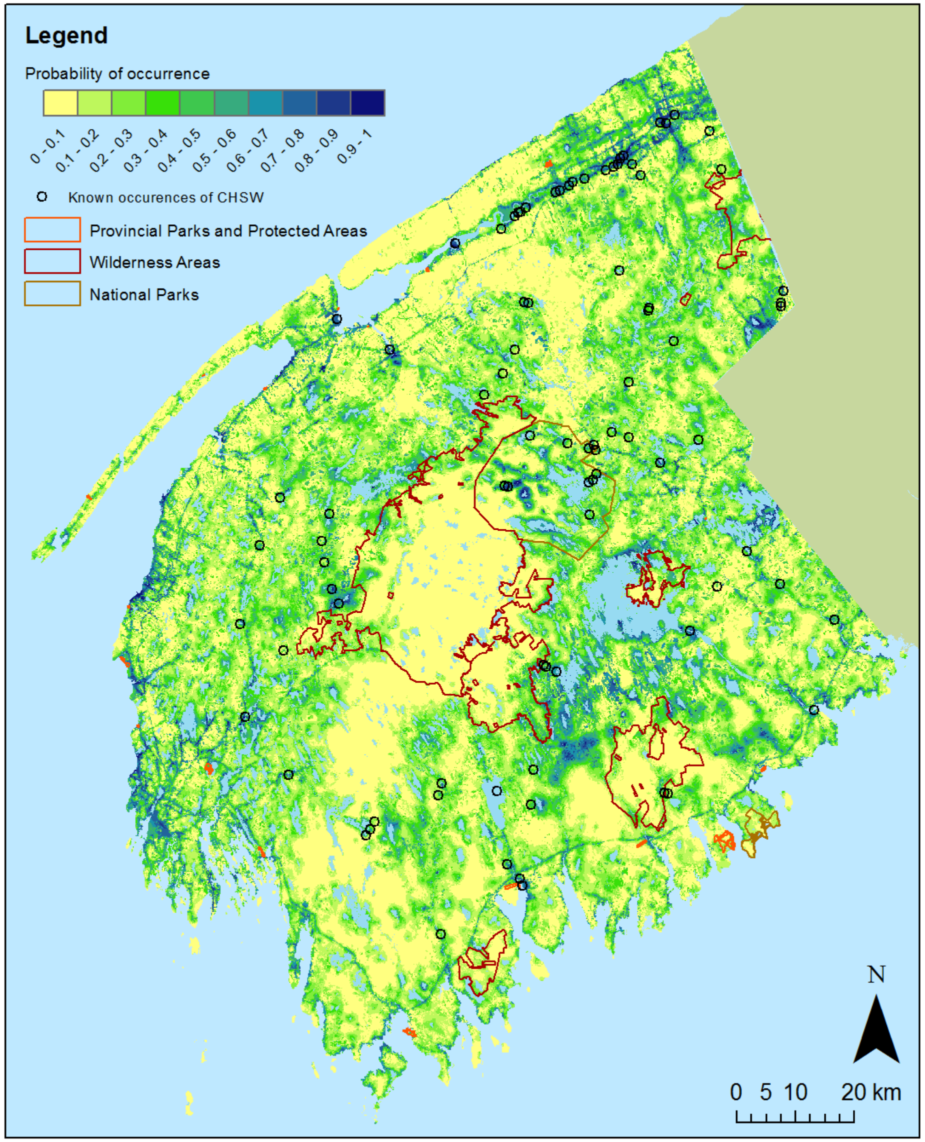

Figure 16. Habitat suitability for Chimney Swift in southwestern Nova Scotia, modeled by MaxEnt

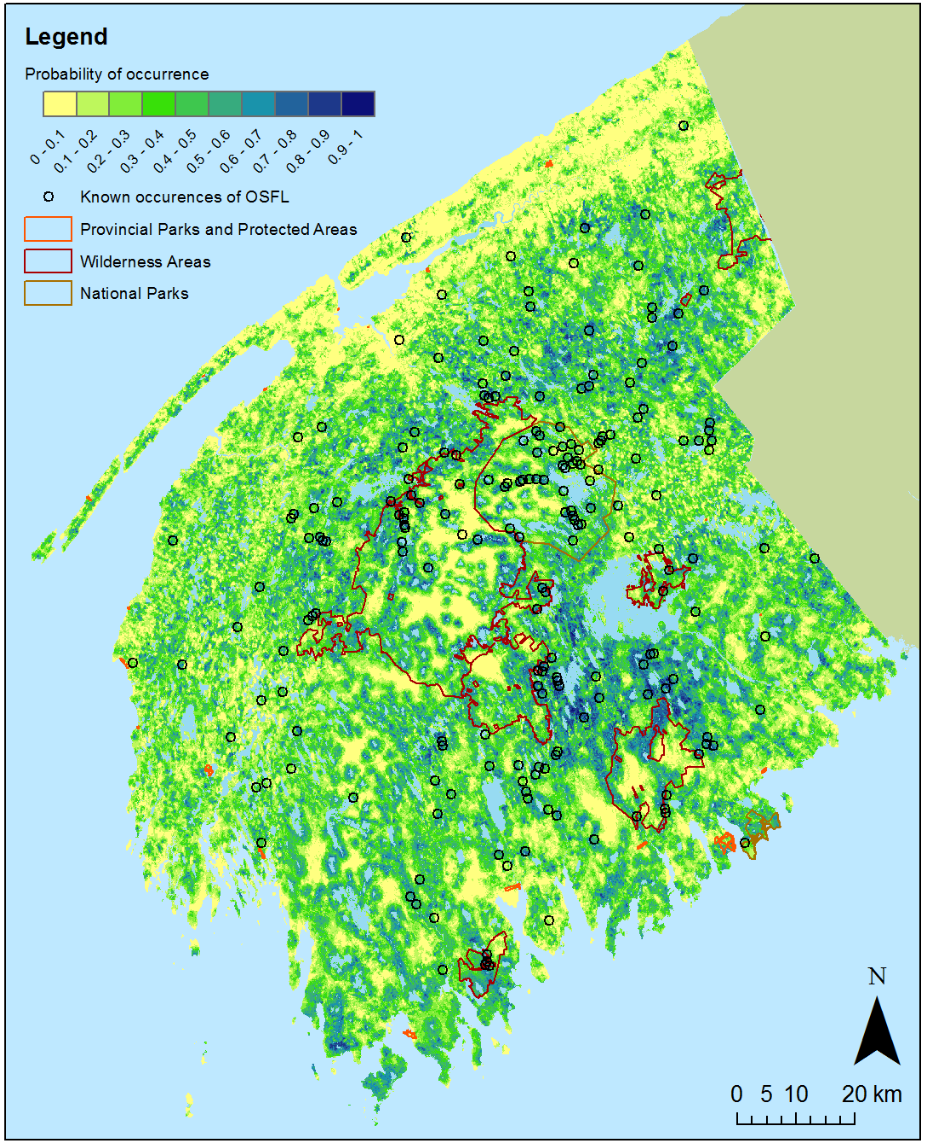

Figure 17. Habitat suitability for Olive-sided Flycatcher in southwestern Nova Scotia, modeled by MaxEnt

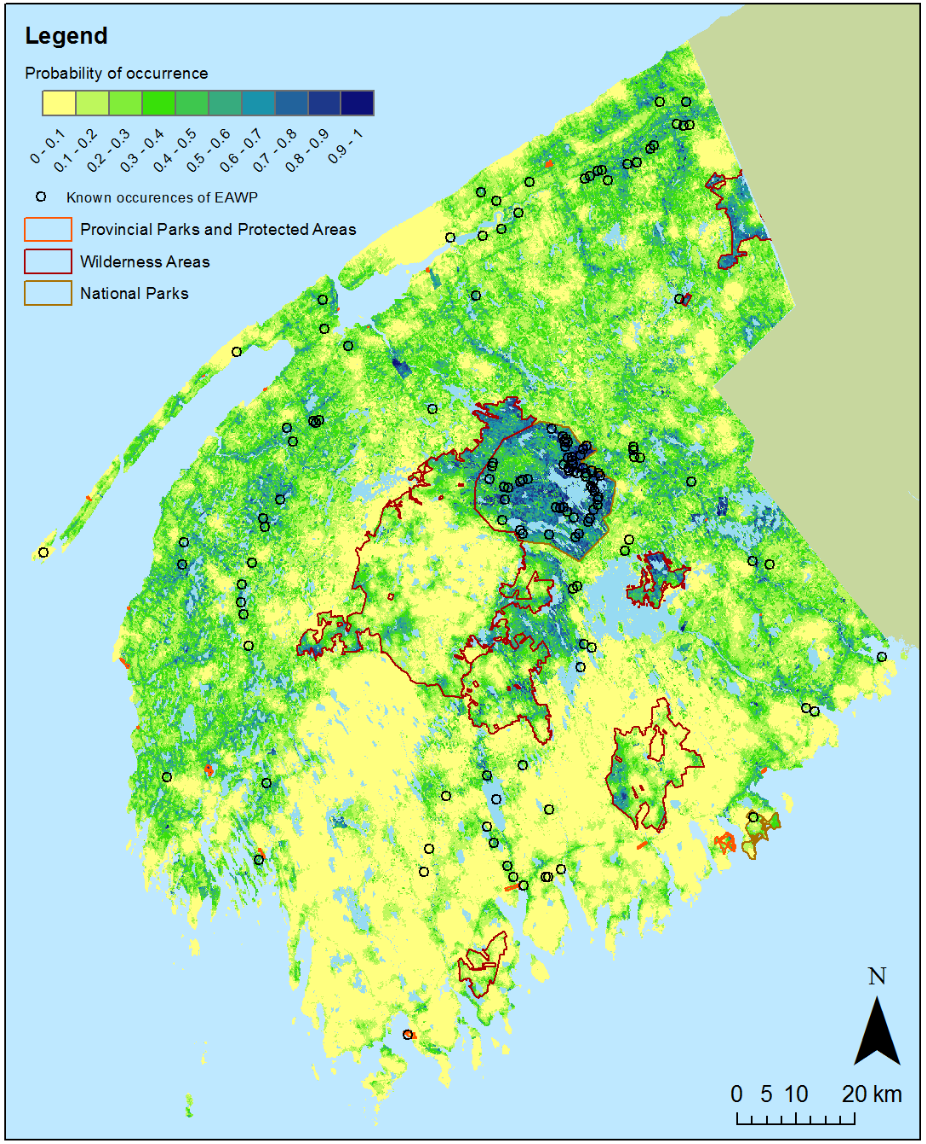

Figure 18. Habitat suitability for Eastern Wood-pewee in southwestern Nova Scotia, modeled by MaxEnt

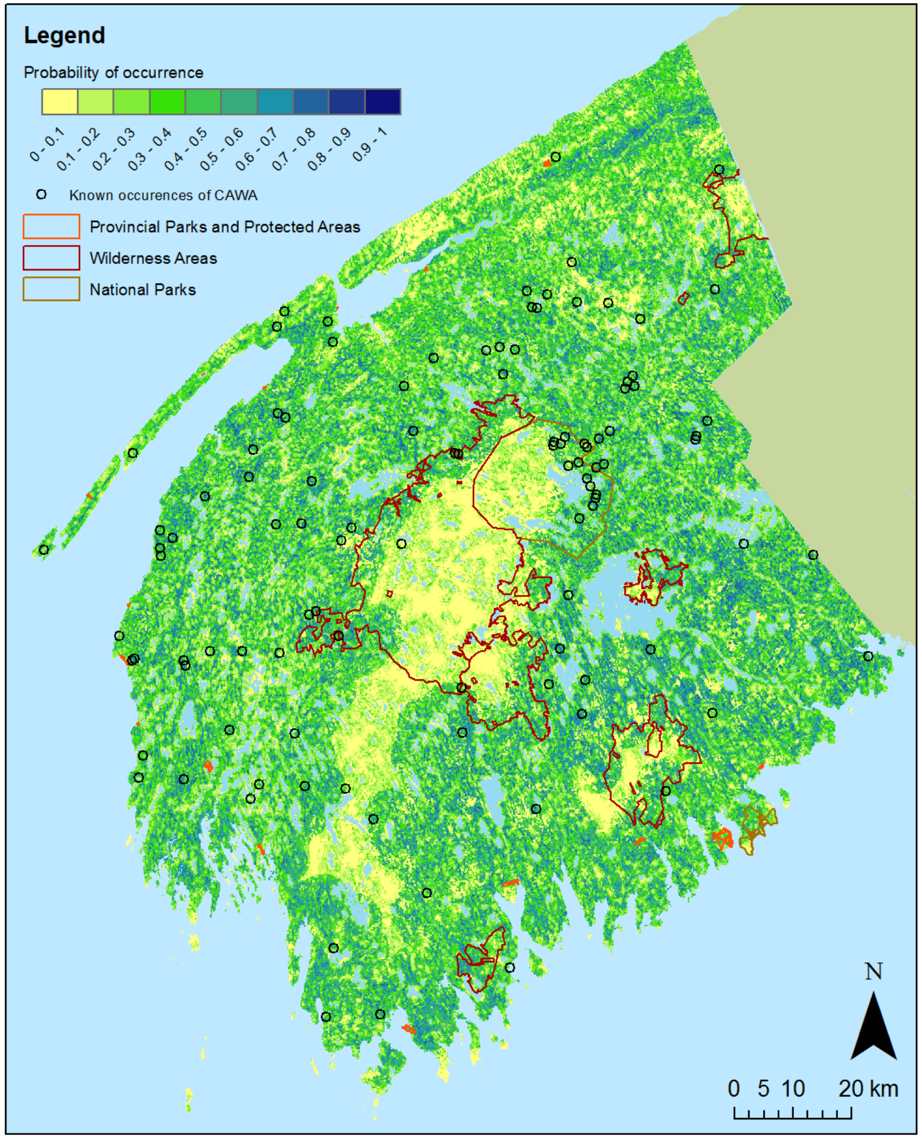

Figure 19. Habitat suitability for Canada Warbler in southwestern Nova Scotia, modeled by MaxEnt

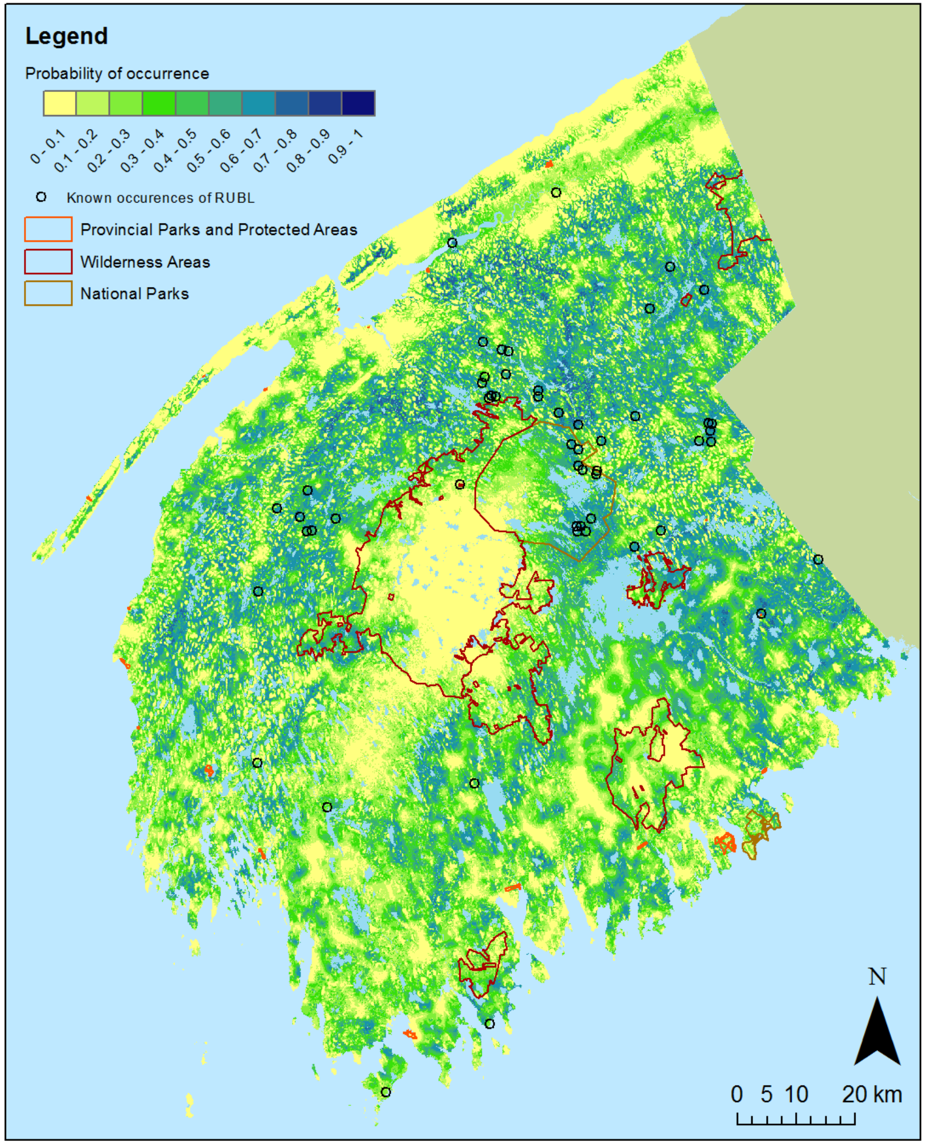

Figure 20. Habitat suitability for Rusty Blackbird in southwestern Nova Scotia, modeled by MaxEnt

4. Discussion

4.1. Analysis of the results

4.1.1. Interpretation of the environmental variables

Common Nighthawk

The typical CONI's habitat is an open area with dry bare ground or rock, with water bodies nearby to feed (COSEWIC 2008a).

Its feeding habitat was consistent with the main influence of the distance to waterways in the model, as well as the lesser influence of the distance to shrubby wetlands. Urban gravel rooftops or gravel roads can be a good nesting habitat, which explained the positive influence of the distance to urban areas (COSEWIC 2008a). The habitat's openness credited the positive impact of clearcuts and shrubby areas, where bare ground or rock patches can appear. This was also coherent with the positive influence of a very low first story canopy height. However, we could have expected that the blueberry fields would have a positive influence on CONI's distribution, but we observed the opposite: the further a blueberry field was, the more common CONI were seen. A possible explanation was that a low shrub area is not suitable for CONI if there is not bare ground, which is seldom the case in blueberry production fields.

Based on the different contribution of the variables, CONI's habitat was well defined by both its water bodies and its open structure (shrubby wetlands, clearcut, urban areas).

Chimney Swift

Chimney Swift has two different types of nesting habitat. The first one is its natural habitat, old forest with large hollow trees or dead branches for nesting. But because of the logging of most of its natural nesting and roosting sites, much CHSW current habitat is man-made structures such as chimneys or barns. Water bodiesa also an important feature of its habitat for foraging (COSEWIC 2007a).

This double habitat was well modeled since the dominant variable was the distance to urban areas. Moreover, CHSW was found in urban areas (its "urban" habitat) and well-away from urban areas, which can be interpreted as its natural habitat, less affected by forestry. Its preference for a tall first story canopy was also coherent with its natural habitat, since a tree height can be related with tree age.

This may seem to contradict its preference for areas near clearcuts, but an open area can be a good foraging habitat, with the abundance of insects. The importance of water bodies and low shrub areas were also consistent with its foraging habitat, as well as its preference for areas with a low story canopy height. We could have expected to find CHSW in areas in or near dead stands, since it prefers old forest with large snags, but the model showed the exact opposite: CHSW seemed to avoid dead stands areas. It was the same puzzling result for the open wetlands: CHSW prefered areas far away from those wetlands, though they can be a good foraging habitat.

Olive-sided Flycatcher

OSFL is found in coniferous or coniferous dominated forest. It also needs forest edges or openings and snags to perch. Open wetlands or any areas with abundance of insects are good foraging habitat for OSFL (COSEWIC 2007b).

The species preference for wetlands, clearcut areas, a sparse canopy closure and, to a lesser extent, non-forested areas were consistent with its foraging habitat, as well as the higher probability of presence near water bodies and where the water table was shallow, two variables that matched its habitat's wetness. The distance to agricultural lands was strongly correlated to the distance to urban areas (correlation=0.87, see Appendix 10). Therefore, it seemed logical that OSFL were more frequently encountered in more natural environment rather than agricultural or urban areas. A possible explanation was that poor and wet soil, that are suitable of OSFL, are not good soil for farming and are left aside. The higher probability in coniferous forest can clearly be attributed to the preference of the OSFL for this type of forest.

According to the different contribution of the variables, OSFL habitat was less defined by the type of the forest and more by the wetness (distance to OSFL wetlands and to water bodies and depth to water table) and the structure of the environment (distance to agricultural areas, distance to clearcut and canopy closure).

Eastern Wood-pewee

EAWP breeds in almost any type of wooded habitat (except boreal forest), with a slight preference for deciduous and riparian forests. It is more frequently encountered in mature forests and stands of intermediate age. It also likes forest gaps, medium canopy edges and mid-canopy branches to perch and wait for prey (COSEWIC 2012; Darlington-Moore 2014).

The positive influence of a tall first canopy height was attributed to its forested habitat. Its "sit-and-wait" predatory behavior was shown throughout the impact of uneven aged stands (with mid-size trees) and of areas near blueberry fields, which can be forest edges. The negative influence of the depth to water table can be explained by the fact that this species, unlike some of the other studied landbirds, does not breed in wetland area; it prefers upland forests. This statement was quite in contradiction with the positive influence of areas near water bodies on the model. Another explanation was that these areas are well-provided in insects for the EAWP. However, EAWP are commonly present where pines grow near water, thanks to rocky or sandy soil (Cindy Staicer, pers. com.). The probability of finding an EAWP was much greater inside protected areas. This was either due to a bias in the sample, because protected areas were more surveyed than the rest of the lands; or it was due to a more intact habitat for the EAWP: indeed, intermediate and mature stands tend to be cut down outside protected areas. Finally, the positive influence of the urban areas was harder to explain. EAWP should be more commonly found far away from the cities, where its habitat is more suitable. It could be due to sample bias.

Canada Warbler
Canada Warbler's habitat is either a forested wetland or a riparian forest (COSEWIC 2008b). The large influence of the depth to water table and the distance to waterways was consistent with the wetness of their habitat. Also the very edge of a waterway did not make a suitable habitat for the CAWA, according to the low probability of presence between 0 and 500 m from a waterway.

Another important feature for CAWA was the structure of their habitat. They prefer a complex forest floor, with a dense layer of tall shrubs and a high volume of understory foliage, along with a semi-open canopy and some emergent trees, in order to perform their specific behaviour: they sing at mid-canopy and nest near the ground, hidden by shrubs and ferns (COSEWIC 2008b). This was well-modeled by the weight of the uneven aged stands, as well as the predilection for open canopy. A low second story height matched a dense shrub layer. A possible explanation for the preference for areas near clearcuts was that the opening created by clearcuts enhanced the growth of the understory vegetation, such as tall shrubs and ferns.

The percent contribution showed clearly that the wetness variables (depth to water table and distance to waterways) explained more than the structure variables (second story height, canopy closure and distance to clearcuts and uneven aged stands).

Rusty Blackbird
Rusty Blackbird is found in any type of forest, as long as coniferous saplings are present for nesting. They forage in shallow water, in wooded wetlands, beaver ponds or stream and lake edges (COSEWIC 2006).

Their foraging habitat was consistent with the waterways and depth to water table influence on the model. Coniferous saplings grow in open areas such as clearcuts and areas close by; therefore the clearcut areas influence on the model was in accordance with RUBL nesting habitat. This feature of its habitat can also explain that the RUBL opted for areas near agricultural lands and low shrub areas, which can correspond to areas of agricultural abandonment and forest edges.

The contribution of each variable showed that the wetness variables (depth to water table and distance to waterways) explained most part of the habitat, before the structure variables (distance to low shrubs, agricultural areas and clearcuts).

4.1.2. Comparison of the models and choice of the environmental variables

The comparison between the first-generation models, built by Dalhousie students, and the second-generation ones, built in this study, showed overall better results for the latest ones, with better AUC and most of the time better COR (except for CONI and EAWP). Therefore, those models seemed the best option to study the habitat distribution of the species, even if they included weaknesses as well.

Comparing the second-generation models with and without the 2014 data showed that adding data improves COR, and therefore the calibration of the models, which means that the predicted probabilities of presence and the actual distribution of presence in the landscape showed a better agreement. However, the AUC was mainly lower. A possible explanation is that the selection of environmental variables was calibrated for these specific sets of locations data, and maybe choosing a different set of variables would have shown better results.

Indeed, difficulties arose about choosing the optimum set of variables. In this study, MaxEnt results were directly used to select the best variables, but it might not be the best way to do it. Indeed, MaxEnt does not provide statistical tests to distinguish the best variables, which is the case in GLM (generalized linear models; Elith et al. 2010). Correspondence analysis (CA) is a multivariate statistical technique that could have been used to analyse the weight of the variables in the species distribution, but it needs presence-absence data (Benzécri and Bellier 1976).

4.2. Influence of climate change on a potential future distribution of the landbirds in Southwestern Nova Scotia

4.2.1. Potential wetlands modification due to climate

Wetlands are very vulnerable to water losses by evapotranspiration, due to their large wet areas and shallow depths. Therefore, unless increase in precipitation offsets increase in evaporation, wetlands will face increasing stress due to lack of water supply (Environment Canada 2004).

Figure 21 shows the results of soil water content (SWC) for current and future climate conditions by Bourque and Hassan (2008): in southwestern Nova Scotia, decrease of SWC is predicted in a few areas, for each tri-decade, and in other areas it will remain similar. SWC is the quantity of water contained in the soil and can be related to the depth to the water table. Indeed, if the SWC increases, depth to water table can be expected to decrease. Thus, depth to water table should experience a rather small decrease in some areas of Nova Scotia.

Therefore, according to Bourque and Hassan (2008), a relatively low decline of the wetlands should be expected in Nova Scotia. However, field observations in Kejimkujik National Park and around its surroundings tend to show that wet patches of forests have been drying out at least since 1996, when the first bird studies were done by Cindy Staicer (pers. com.). So it is difficult to identify an accurate trend for the wetlands. Nevertheless, any change in the distribution of wetlands, and especially drought, could have important negative effects on the landbird population, since wetlands are an essential feature of their habitat, for nesting and foraging.

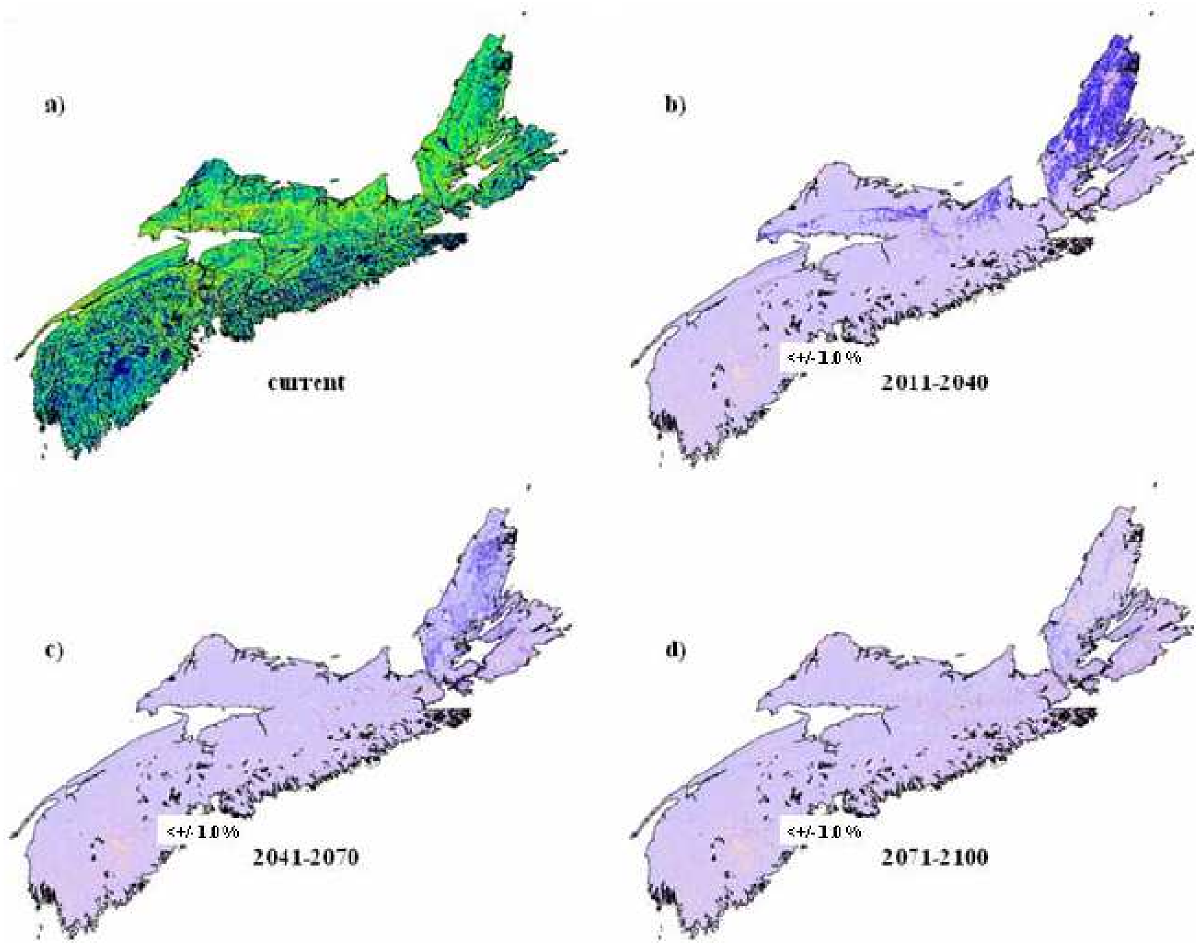

Figure 21. Soil water content (SWC) for current and future conditions, derived from the Landscape Distribution of Soil moisture, Energy, and Temperature model (LanDSET) (from Bourque et Hassan, 2008)

(a) current SWC and (b-d) SWC percentage difference maps between previous and future tri-decade, calculated from average temperature increases, precipitation (with an increase of 5% from 2011-2040, 10% for 2041-2070 and 15% for 2071-2100). Pink colors represent a net decrease of SWC (i.e. drying) and blue represent a net increase (i.e. wetting). Black areas indicate exposed bedrock and null SWC. Source: (Bourque and Hassan 2008).

4.2.2. Potential modification in the tree species distribution

Bourque and Hassan (2008) also studied the future distribution of five deciduous tree species, five coniferous tree species and two shrub species for 2011-2040, 2041-2070 and 2071-2100. The coniferous species were expected to decline and be restrained to cooler areas, near the Bay of Fundy and Atlantic Ocean. Balsam fir (*Abies balsamea* (L.) Mill.), black spruce (*Picea mariana* (Mill.) B.S.P.) and red pine (*Pinus resinosa* Ait.) would be disappearing from most part of southwestern Nova Scotia, and red spruce (*Picea rubens* Sarg.) and white pine (*Pinus strobus* L.) would be favored in 2011-2040 and then would decline in most part of the area.

The hardwood species would mostly benefit from the climate change, and expand in 2011-2040 and 2041-2070 and slightly decrease in 2071-2100. Trembling aspen (*Populus tremuloides* Michx.) would decline in Nova Scotia but red oak (*Quercus rubra* L.), black cherry (*Prunus serotina* Ehrh.), yellow birch (*Betula alleghaniensis* Britton) and American beech (*Fagus grandifolia* Ehrh.) would generally have an improved distribution in the future. Different species of shrub would have different trend: lambkill (*Kalmia angustifolia*) would decline and witch hazel (*Hamamelis viginiana*) would expand.

The great changes in the hardwood-softwood association could have great impacts on the six studied species. Indeed, the Olive-sided Flycatcher prefers coniferous forests and it could be negatively impacted by the decline of boreal coniferous species. Coniferous saplings would most likely decline as well as grown trees, and the Rusty Blackbird could lose its nesting habitat. General forest dieback could cause massive death of trees, which could led to openings and snags, and favor Common Nighthawk, Olive-sided Flycatcher and Rusty Blackbird. The complex structure of the Canada Warbler habitat with a lot of shrub species would be difficult to model in the future, and the creation of Cinnamon fern future distribution could be interesting to understand its future habitat (COSEWIC 2008b).

4.2.3. Potential analyses of climate change

Time restrictions impeded full study of the influence of climate change on the landbird species at risk, but it would have been interesting to model the future distribution of each bird. Data from Bourque and Hassan (2008) could have been used as environmental variables to input in MaxEnt program. Raster layers from current conditions could be used to build a model, using the current sighting data, and the obtained train model could be "projected" to another set of environmental variables, corresponding to the future conditions for 2011-2040, 2041-2070 and 2071-2100. The "projecting" tool in MaxEnt would be employed to do so (Phillips 2005).

Environmental layers would not be the same as the final models built for current conditions (see 3.3.2.2. Results of the environmental variables), because they are not available for future conditions, but the soil water content, five softwood species (balsam fir, black spruce, red spruce, white pine, and red pine), five hardwood species (red oak, yellow birch, American beech, trembling aspen, and black cherry) and two shrub species distribution (lambkill and witch hazel) from Bourque and Hassan (2008) could be used as proxies for the wetness, the association between deciduous and coniferous species, and shrub distribution. Moreover, the future human footprint, as studied in Trombulak et al. (2008), could be a good indicator of the human impact, and could be used as an environmental feature as well. It would be difficult to obtain data for land cover, so current land cover features could be used, for example distance to burnt areas, dead trees, uneven aged stands or even canopy height, assuming that quite small changes would occur during the 21st century.

4.3. Limits of the study

4.3.1. Location data

Quality of the data is debatable. Indeed, many sources provided the locations (experts, birders and public), and the accuracy of the location was variable: GPS is much more accurate than Google Maps or simple name of a location. However, we assumed that all sightings were correct, which can be arguable.

The birds being at risk in Nova Scotia, it is possible that suitable habitats were no longer used by the species, by lack of individuals. For example, during the 2014 field surveys, good habitats for the Rusty Blackbird and the Canada Warbler were found in Kejimkujik National Park, but no bird were seen (Laura Achenbach, pers. com.). It would be interesting to find a way to use this data in the modeling, even though it would not be right to use them as sightings. They could be used for verification of the models.

Furthermore, the main goal of this internship was to collect more data, especially in remote areas, such as Kejimkujik National Park backcountry (west part of the park) and the Tobeatic Wilderness Area, in order to get a better sample and therefore better potential distribution maps. However, long distance and challenging terrain made it difficult to access such areas. Even if a field survey was conducted during five days in Kejimkujik backcountry, and only few birds were found, it does not mean that this area is not suitable for the species at risk. Indeed, 2014 seemed a poor year for birds, as relatively few birds were found in Nova Scotia (Donna Crossland, Laura Achenbach, pers. com.).

Moreover, sightings of birds are point data in GIS, which is appropriate for birds with a small territory, such as Canada Warbler (COSEWIC 2008b). However, for Common Nighthawk for example, its territory can range to 260 ha (COSEWIC 2008a; Randall 2013). Therefore, using surface data would be better to map their territory than using points.

The geographical extent used in the models was southwestern Nova Scotia. It would have been interesting to map the bird habitat at a finer scale, in Kejimkujik National Park, to have more accurate results and to know which areas within the park it would be useful to monitor. However, sufficiently accurate environmental data were not available for this area.

4.3.2. Spatial bias correction

Among the three set of models run, the models without background performed the best, then the models with the target-group sample background, and the worst models were the one with the human footprint background. The human footprint background is a very thorough-built raster that could be an interesting background, but, as advised in different papers , the "target-group background" approach is said to be the best way to approximate the sampling bias. The models without background performed the best, as in other papers (Lütolf et al. 2006; Millar and Blouin-Demers 2012). However, even if the estimates were higher, the lack of bias correction usually leads to inaccurate predicted distribution, and several papers mention that the sample bias should always be considered, even if the performance of the model decreases (Merow et al. 2013; Syfert et al. 2013).

Moreover, another way to correct the sample bias would have been to directly use locations as pseudo-absences, such as locations of other taxonomically related species or broad biological group of species, which were sampled using the same methods, or even historical localities where the bird were found in the past (Lütolf et al. 2006). But not enough data were available to use as pseudo-absences, and building a "target-group" background seemed the most efficient way to correct sample bias.

A simple glance at the species potential distribution maps (see section 3.5. Spatial distribution of the species and Figures 15 to 20) points out that CONI and CHSW were both highly correlated to the urban areas, especially along the roads, as indicated in the variable selection (see section 3.3.2.2. Results of the environmental variables). This was consistent with their ecology, since they both use human structures to nest (COSEWIC 2007a; 2008a). However, it is not certain that the impact of the distance to urban areas were only due to their ecology and not to spatial bias.

Moreover, all the species showed a low potential distribution in the center of the studied area, especially in the Tobeatic Wilderness Area, particularly for CAWA and RUBL. Nearly no data was available in this area, and it might not mean than the habitats were unsuitable but rather than spatial bias remained. Indeed, this area includes old forests, large undisturbed wetlands and barrens and semi-barrens resulting from human fires, which could be interesting habitats for the birds (Nova Scotia's Protected Areas and Nova Scotia Environment and Labour 2006).

4.3.3. Spatial autocorrelation correction

For almost every model, Moran's I test indicated that spatial clustering was present, even if it seemed to decrease in general. Although filtering out more the data could appear tempting, for example by removing all the data closer than 1 km, too few data would have remained, weakening the analysis (Vaughan and Ormerod 2003).

Due to the lack of time, no further attempts to correct spatial autocorrelation were made. However, autocorrelation can be used as a predictor variable, such as mentioned in Vaughan and Ormerod (2003). Several types of regression exist (autocovariate regression for example), but no real method was found to include it in presence-only modeling. Indeed, including spatial autocorrelation in the models is widely discussed in the literature for presence-absence models, but rarely discussed in presence-only models.

4.3.4. Estimates

AUC may not be a perfect estimate to use in the case of presence-only absence, because AUC is built using presence and absence locations. In MaxEnt, presence and pseudo-absence are used, the latest including presence location and potentially unsampled locations as well. Therefore, AUC theory is violated by using this type of data (Jiménez-Valverde 2012; Merow et al. 2013).

Other potential estimates

The deviance is the square root of the variance, which is the average of the squared differences from the mean. It is used to measure how spread the probabilities are, and a model with a null deviance has a perfect discrimination. It is therefore an interesting estimate, but AUC was chosen to measure the discrimination (Phillips and Elith 2010; Lütolf et al. 2006).

Another estimate that could have been used is the POC plot, or presence-only calibration plot, introduced by Phillips and Elith (2010). It is used to measure how the prevalence (proportion of presence) varies across the study area with the predicted probability of occurrence, or calibration (Syfert et al. 2013). More details are available in Phillips and Elith (2010).

Comparing the threshold of potential presence and absence is used in some papers, such as in Kramer-Schadt et al. (2013), but it is hard to have a meaningful threshold, especially with presence-only data, so this estimate was not used (Merow et al. 2013).

4.3.5. Other modeling algorithms available

MaxEnt is usually recommended for presence-only data, because it is one of the best modeling methods available (Kramer-Schadt et al. 2013; Syfert et al. 2013). However, other presence-only modeling method exist, such as GARP, DOMAIN, BIOCLIM and ENFA (Ecological Niche Factor Analysis), but they seem to perform less well than MaxEnt, according to literature (Phillips et al. 2009; Pearson 2010; Elith et al. 2006).

Another interesting method is the boosted regression trees (BRT). BRT are based on two algorithms, regression trees and boosting. Regression trees are a modeling method that makes a decision tree with binary splits for regression; and boosting is a method that combines many models to give a better prediction performance (Elith et al. 2008). Millar and Blouin-Demers (2012) compared MaxEnt and BRT and according to their results, BRT models were better calibrated and more discriminative. Therefore, it would be interesting to use both techniques and compare the results (Millar and Blouin-Demers 2012). Unfortunately, the lack of time did not allow further analysis.

4.3.6. MaxEnt settings

As mentioned in the Materials and Methods part (2.8. Other parameters), many parameters can be adjusted.

Only training data were used, testing data being put aside so that sample bias could be properly corrected. However, this could be a weakness of the models and further research might be interesting, even if no paper were found in the literature dealing with this problem.

The auto features setting was used, allowing MaxEnt to choose between the feature types that control the shape of the response curves (2.8.5 Feature types). However, the response curves for CONI and OSFL (Figures 10 & 12) show a staircase curve shape, with "steps", which might not actually reflect the real model respond but rather a peculiar distribution of the sightings that influence the feature types and favor the threshold feature type. Therefore, an analysis of the feature type selections could be interesting.

Moreover, regularization coefficient can be modified and optimized, in order to reduce overfitting by making sure that the environmental variables do not fit the presence locations too precisely. To do so, it is widely recommend to explore a range of regularization coefficient (Merow et al. 2013).

4.4. Conservation implications and perceptives

The potential distribution maps are an important tool for conservation. It is important to protect the few remaining suitable habitats for species at risk that face extinction. These six species are declining in their wintering habitat, mainly due to habitat loss and degradation and massive use of pesticides for the insectivorous species (COSEWIC 2006; 2007a; 2007b; 2008a; 2008b; 2012). High-suitability breeding habitat could be identified from the species distribution maps, so that important habitats of the six species could be protected.

Research studies are not effective if they are not applied in management plans. In this way, partnership should be developed between conservation stakeholders, such as the Mersey Tobeatic Research Institute, Parks Canada, Nova Scotia Bird Society, Nova Scotia Nature Trust, etc., as was discussed during the "Landbirds at Risk Partners in Conservation Workshop", which took place in March 2014. Also, the local communities should not be forgotten in the conservation of the species, and their involvement could be an important factor to steward the birds.

Osprey, Kempt © Clara Ferrari

Conclusion

Species distribution models are effective tools to understand the habitat requirements and locations of the populations of species at risk. The maximum entropy modeling method (MaxEnt) enabled modeling elusive, rare species, when only presence data were available. Attempts were made to remove spatial autocorrelation and spatial bias, but the results showed that some remained in the models. Therefore, special care should be taken when using the distribution maps, because they do not reflect the exact distribution of the species, and only give a primary estimation of their distribution across the landscape and the environmental variables that influence their habitat.

MaxEnt does not offer an easy way to select the features to build the models, therefore the chosen variables might not be optimal and further studies would be interesting. However, the models built in this project showed better performance than the first-generation models built by Dalhousie students in the previous year. Therefore, it can be concluded that MaxEnt second-generation models worked well.

The Common Nighthawk had favorable habitats mainly in Kejimkujik and Lake Rossignol areas, as well as urban areas. Indeed, the main environmental features that influenced its distribution were the presence of water bodies and urban areas. The Chimney Swift was affected mainly positively by urban areas, as well as the presence of water bodies, which was visible in the distribution map: the few effective habitats were located in anthropogenic areas and near lakes. The Olive-sided Flycatcher was principally impacted by the wetness of the habitat, as well as the structure and coniferous forests. Suitable habitats were scattered all across southwestern Nova Scotia, with a marked preference for lakes edges. The Eastern Wood-pewee preferred protected areas, such as Kejimkujik National Park and the Tobeatic Wilderness area, as well as mature forest and to a lesser extent wetness features. The Canada Warbler was highly influenced by wetness, and to a lesser extent the complex structure of its habitat (estimated by uneven aged stands, clear cut, second story canopy height and canopy cover). Favorable habitats were scattered all across the region, with a lower suitability in the center of the study area. Finally, the Rusty Blackbird preferred wet areas with openings, and suitable habitats were located around the Lake Rossignol area and the northern portion of the study area, but the center of southwestern Nova Scotia only showed poor habitats for this bird.

Collecting more data is essential to keep improving our knowledge about these birds. Field surveys should be continued into the future. Another way to gather data is involving the local communities, teaching them basic information about the birds and making them aware of the threats and the way to protect those species at risk. Moreover, climate change modeling tends to show that wetlands would be threatened and the associated hardwood-softwood matrix would shift with an increase of deciduous species. This could highly impact the bird species and thus monitoring their distributional changes would be interesting.

Keeping in mind the limitations of the models, species distribution maps can be used in the management plans at local and provincial scales immediately, because the next few years and decades will be decisive for the recovery or extinction of these six species of landbirds at risk. Moreover, global stewardship is important for these migratory birds, so that conservation programmes can be conducted in both breeding and wintering grounds, where threats keep intensifying.

Sandpipers and plovers, Martinique beach © Clara Ferrari