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Factors Affecting Coastal Wetland Occupancy for Eastern Musk Turtles (*Sternotherus odoratus*) in Georgian Bay, Lake Huron

Chantel E. Markle[1], Julia M. Rutledge, and Patricia Chow-Fraser

Department of Biology, McMaster University, Hamilton, ON, L8S 4K1, Canada

Abstract: In many jurisdictions, rare species and their habitats can receive protection if species are assessed as being at risk of declining. The assessment process requires data on habitat occupancy as well as identification of threats to a species critical habitat, both of which are difficult to obtain when the species occurs across large spatial scales. Such is the case for Eastern Musk Turtles (*Sternotherus odoratus*), which are obligate coastal wetland species in the Laurentian Great Lakes. We use data collected between 2003 and 2015 to map occupancy and conditional occupancy for musk turtles in coastal wetlands of eastern Georgian Bay (Lake Huron) to identify threats to resident wetland habitat. Data collected from a synoptic survey of 58 coastal wetlands were used to create occupancy models, estimate detection probability, and to conduct a sensitivity analysis to determine model robustness. We had a 64–71% probability of detecting musk turtles, whenever present in the wetland, and an area under curve value of 0.82 confirmed high model accuracy. Coastal wetlands that supported musk turtles were associated with higher proportions of forest cover, lower densities of roads, buildings, and docks within 1 km of the wetland, and more-variable bathymetric slopes. High conditional occupancy across the majority of our study area indicates that, at present, habitat in eastern Georgian Bay is in good condition; however, land-use alterations and development should be limited to ensure the persistence of this population of musk turtles.

Key words: Critical habitat; Detection probability; Georgian Bay; Great Lakes; Kinosternidae; Occupancy modeling; Species at risk

Assessment of the status of species at risk requires key information such as long-term trends detailing the extent of occurrence and area of occupancy of the species as well as identification of habitat requirements and threats to their critical habitat (e.g., Committee on the Status of Endangered Wildlife in Canada [COSEWIC] 2012). Ideally, occupancy information and habitat assessments are collected in the field during targeted species surveys. Often, however, the species in question occurs across a large geographic region in remote areas that are sensitive to human disturbance or budgets may restrict long-term intensive field surveys. Yet lack of targeted survey data should not prevent environmental agencies from the important task of protecting imperiled species and their habitats.

In the case of Eastern Musk Turtles (*Sternotherus odoratus*)—listed as Special Concern under the Ontario Endangered Species Act (Ontario Government 2007) and as Threatened under the federal Species at Risk Act (Government of Canada 2009)—populations were once widespread throughout Ontario, Canada, but have recently declined substantially in the southern part of the province. Currently, only a few areas within the Laurentian Great Lakes still support viable populations (Edmonds and Brooks 1996; Edmonds 1998; COSEWIC 2012), one of which is Georgian Bay; the large eastern arm of Lake Huron. The coastal wetlands of eastern Georgian Bay tend to be small and widely distributed (<2 ha; Midwood et al. 2012; Fracz and Chow-Fraser 2013), many of which are not accessible by road (DeCatanzaro et al. 2009). Difficult terrain and limited access has resulted in lower levels of anthropogenic disturbance compared to other Great Lakes (Campbell 2005), and this is a major factor contributing to high-quality habitat that supports many species of birds, fish, amphibians, and reptiles (Chow-Fraser 2006; Cvetkovic 2008). While the remote location and relatively unique geomorphology (Rokitnicki-Wojcik et al. 2011) keep the wetland habitat in good condition, they also impede field campaigns and limit the ability of managers to conduct targeted surveys at the landscape scale. Consequently, populations of Eastern Musk Turtles are assumed to be stable, even though their abundances and distribution are unknown (COSEWIC 2012), and no data are available to assess the status of their populations or critical habitat.

The primary goal of our study was to investigate landscape-level and site-level characteristics that influence *S. odoratus* occupancy of coastal wetlands. Given the documented sensitivity of this species to anthropogenic disturbance (including shoreline modification) and changes in land cover (DeCatanzaro and Chow-Fraser 2010), we predicted that wetlands with higher density of docks, cottages, and roads would have a lower probability of *S. odoratus* occupancy compared with those with little or no anthropogenic disturbance. Additionally, we predicted that coastal wetlands with a higher proportion of surrounding natural habitats, such as forest cover or additional wetlands, would have a higher probability of *S. odoratus* occupancy. Our second goal was to incorporate detection probability to determine the applicability of occupancy modeling for musk turtles. Lastly, by producing occupancy maps, we aimed to provide insight into the current status and habitats of musk turtles to guide conservation efforts.

Materials and Methods

Study Site Selection

A long-term synoptic survey of 89 coastal wetland units of Georgian Bay (Lake Huron) occurred between 2003 and 2015. Although the primary target of these surveys was Great Lakes fish, freshwater turtles were caught incidentally, among which were Eastern Musk Turtles. Because they were not the target species of the sampling effort, we developed a set of criteria to identify comparable sites that would be suitable for development of musk turtle occupancy

[1] Correspondence: e-mail, marklece@mcmaster.ca

models. First, we only included wetlands that were greater than 500 m apart from other sampled wetlands to eliminate the chance of an individual musk turtle being recaptured in multiple wetlands, thus allowing us to treat each site as an independent sampling unit. By separating wetlands at this distance, we assumed turtles caught within the sampled wetland were unlikely to use wetlands beyond the 80-ha unit, a threshold that falls between reported home range sizes of between 6.2 ha (Carrière et al. 2009) and 205 ha (Laverty et al. 2016), with the majority being <50 ha in size (Belleau 2008; Picard et al. 2011). We also restricted our study area to the Parry Sound Ecodistrict to maintain consistency among landscape, habitat, and geological parameters (Crins et al. 2009). Lastly, we excluded years with fewer than 10 sampled wetlands to minimize no-data records. The application of these three criteria led to the exclusion of 31 of the 89 originally sampled sites, and we therefore proceeded with data from 58 coastal wetlands (Fig. 1). The wetlands included in our study spanned the eastern shore of Georgian Bay from the French River (45.9601, –80.8586) to Severn Sound (44.8130, –79.8393) and had been sampled during 7 yr across a 13-yr period (i.e., 2003–2006, 2009, 2014, 2015).

Sampling Methods

Following the protocol established by Seilheimer and Chow-Fraser (2006), we used modified fyke nets to survey wetlands between late May and early September, with the majority of surveys occurring in June, July, and August. As part of this survey protocol, we deployed fyke nets overnight according to a modified technique designed to reduce stress on nontarget species (e.g., turtles). We secured nets in place with metal poles at the 1-m depth contour, with the top of the net extending above the surface of the water, allowing turtles that had been captured to access air. Additionally, we placed floats in the nets to ensure there were air pockets in case unexpected weather events dislodged the nets during the 24-h soak time. In this fashion, we deployed a total of three sets of paired, unbaited fyke nets at each site (Seilheimer and Chow-Fraser 2006). These included two pairs of large nets (13- and 4-mm bar mesh, 4.25 m length, 1 m $\times$ 1.25 m front opening) and one pair of small nets (4-mm bar mesh, 2.1 m length, 0.5 m $\times$ 1 m front opening), which we set parallel to shore in locations where there were a good mix of floating, emergent, and submergent vegetation types. We set fyke nets with pairs facing each other connected by a lead, with 2.5 m wings attached at a 45° angle to the net opening. We immediately identified and released all turtle species captured. Although we originally targeted coastal wetland sites for fish community surveys, previous research has also found that modified fyke nets are an effective trapping method for freshwater turtles (Vogt 1980; Smith et al. 2006; DeCatanzaro and Chow-Fraser 2010).

We wanted to highlight differences between our protocol and that used in commercial fishing in which fyke-nets have been shown to negatively impact freshwater turtle populations (Larocque et al. 2012a,b; Stoot et al. 2013; Midwood et al. 2015). The protocol we used did not pose the same threats to freshwater turtles as do commercial protocols, which require nets to be completely submerged underwater and left to soak for several days, often resulting in high turtle mortality (Midwood et al. 2015).

Model Development and Variables

We used PRESENCE v.6.9 (Proteus Wildlife Research Consultants, Dunedin, New Zealand; Hines 2006) to estimate occupancy (ψ; probability a site is occupied), conditional occupancy ($\psi_{c;}$ probability a site is occupied, given observed detection history), and detectability (p; probability of detecting a species using fyke nets, given it is present) of musk turtles in Georgian Bay coastal wetlands. Including conditional occupancy in our model allowed us to more-accurately identify truly unoccupied sites and allocate conservation resources accordingly. PRESENCE uses detection and nondetection data (i.e., binary data [0,1]) to establish occurrence within a sampling unit, and models are fit with maximum likelihood techniques (MacKenzie et al. 2006). In this study, we defined a sampling unit as a wetland site. The single-season occupancy model accounts for species detection resulting in improved estimates of occupancy. Improved estimates are achieved by including multiple surveys of the same site to more-accurately estimate true and false absences, thus providing a detection history. In our case, wetlands were surveyed across multiple years, which we treated as multiple surveys. If a wetland had not been surveyed every year, we included those years as no-data records. For example, a wetland with a detection history of 00.11 indicated that no musk turtles were caught the first 2 yr, the wetland was not sampled in the third year, and that musk turtles had been caught in the final two sampling years.

We used available geospatial data to develop a set of predictor variables hypothesized to influence musk turtle occupancy of coastal wetlands (Table 1) and quantified all variables in ArcGIS v10.2.2 (ESRI, Redlands, CA). We obtained wetland boundaries from the McMaster Coastal Wetland Inventory (Midwood et al. 2012) and calculated surface area (hectares) of each wetland unit. We used road density, building density, and dock density as proxies for anthropogenic disturbance (e.g., shoreline modification, human population density, traffic volume). In addition, we included the percentage of wetland (including surrounding coastal and upland wetlands) and forest to investigate the relative influence of availability of natural land cover on musk turtle occupancy. To elucidate the effect of spatial scale on turtle occupancy, we calculated density and percent land cover at two buffer sizes (250 m and 1 km) to account for the range of daily movements recorded for Eastern Musk Turtles (0.1–1000 m; Belleau 2008; Laverty et al. 2016). We generated both buffer sizes as circular buffers (radius of 250 m or 1 km) centered on the fyke net location.

We calculated road density as road length (kilometer [km]) per buffer area (km^2) using the 2014 road network file from the National Topographic Database (National Resources Canada; http://www.nrcan.gc.ca/earth-sciences/geography/topographic-information/download-directory-documentation/17215). The number of cottages and docks were digitized and enumerated from a combination of IKONOS satellite photos (2002–2008; IKONOS, Geoeye, Dulles, VA), spring orthophotos from the 2013 South Central Ontario Orthophotography Project, and Google Earth image data (Digital Globe in 2015). We calculated all density variables as the number of docks or buildings per buffer area (km^2). Publicly available bathymetric data were obtained from the National Oceanic and Atmospheric

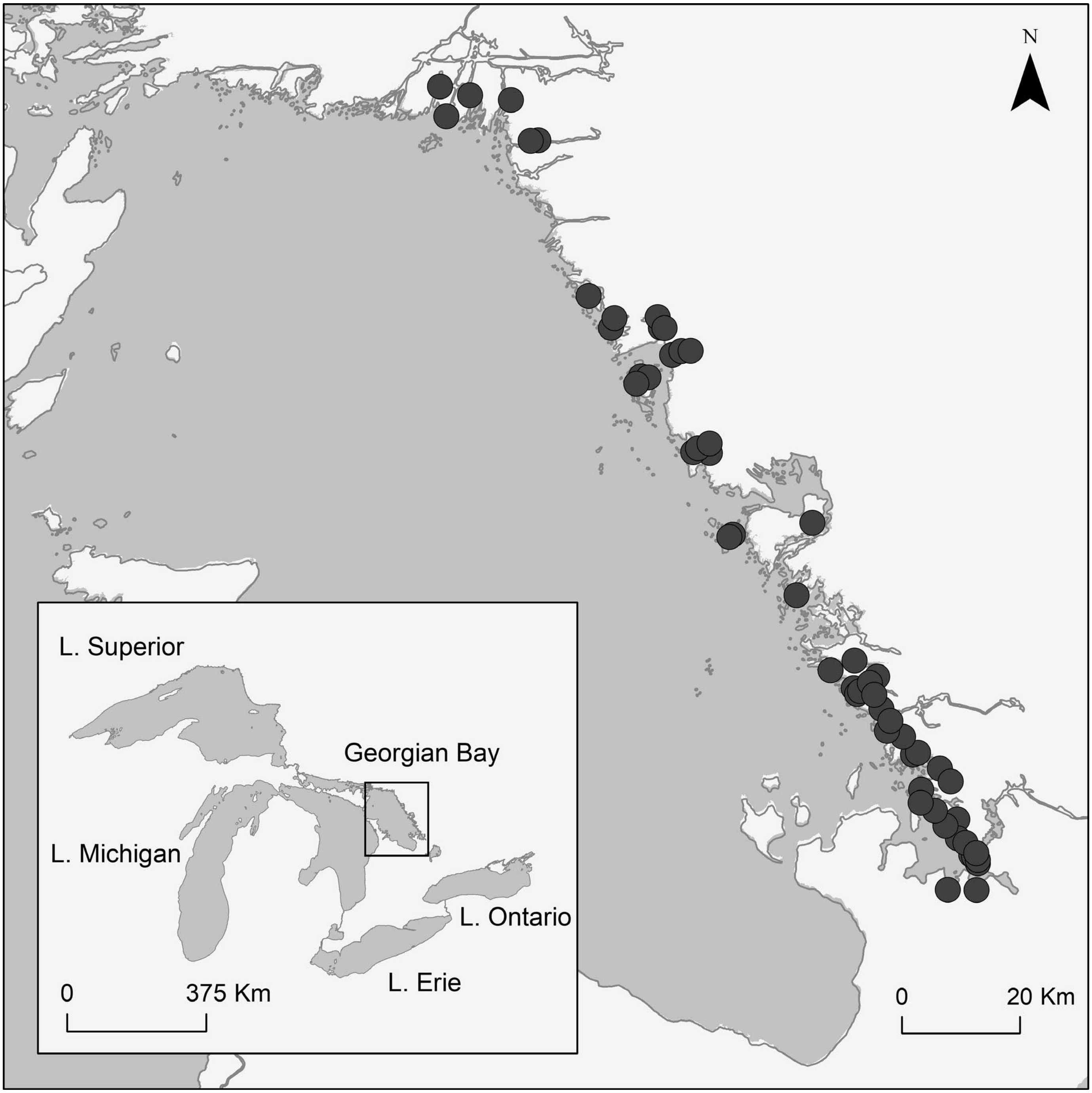

FIG. 1.—Distribution of the 58 coastal wetlands surveyed along eastern Georgian Bay, Lake Huron, and included in the development of occupancy models for Eastern Musk Turtles (*Sternotherus odoratus*).

TABLE 1.—Description of predictor variables considered during development of occupancy models for Eastern Musk Turtles (*Sternotherus odoratus*) in coastal wetlands of Georgian Bay, Lake Huron.

Variable	Description	Buffer radius
Dock density (number/km^2)	Density of docks within the specified buffer area	250 m, 1 km
Road density (km/km^2)	Density of roads within the specified buffer area	250 m, 1 km
Building density (number/km^2)	Density of buildings within the specified buffer area	250 m, 1 km
Forest (%)	Percent of buffer area classified as deciduous, coniferous, or mixed forest	250 m, 1 km
Wetland (%)	Percent of buffer area classified as wetland	250 m, 1 km
Maximum slope	Maximum slope within the wetland unit determined from bathymetry	n/a
Slope range	Range of slopes within the wetland unit determined from bathymetry	n/a
Wetland area	The total surface area of the wetland unit (ha)	n/a

Administration with a spatial resolution of 5 m (contour spacing) and 1–2 m in some nearshore areas. We used these merged data to calculate maximum wetland slope and range in slopes to assess the effect of wetland morphology on occupancy.

To remove multicollinearity and reduce redundancy among model variables, we performed a principal component analysis (PCA) using all 13 variables in JMP 12 statistical software (SAS Institute Inc., Cary, NC). Prior to running the PCA, all data were *z*-transformed to standardize variables to a mean of zero. The PCA is an ordination technique that extracts eigenvalues and eigenvectors from the original set of variables. It produces as many principal components (PCs) as there are variables, which are weighted linear combinations of the original set of variables (Singh et al. 2004). Therefore, by using the first several PC axes as variables (Table S1), we reduced model redundancy while accounting for a high amount of variability without losing important information. The resulting PC scores were used as variables in our models.

Model Selection

We ran all combinations of candidate models using the single-season model in PRESENCE 6.9 and assumed that detection was constant for all wetland sites. Constant detection means that there is equal likelihood that a turtle would be detected if it was present in a wetland and a fyke net had been used as the sampling technique. Additionally, for the single-season model, we set our biologically relevant time period to the average life span of musk turtles (14–20 yr; COSEWIC 2012). This sampling scope is appropriate given the long generation time for this species. We ranked models using the corrected Akaike's information criterion (AICc) and considered models with a ΔAICc $\leq$ 2 as parsimonious, with no single model outperforming another (Burnham and Anderson 2002). In situations where multiple models were considered equivalent, we calculated average occupancy for each wetland site using the following equation:

$$\text{Average } \psi(\text{site}_i) = \psi(\text{model}_1) * \text{AIC}\omega_1 + \psi(\text{model}_2) * \text{AIC}\omega_2 + \ldots \quad \text{[Eq.1]}$$

where average ψ (site$_i$) is the average occupancy for a wetland site when considering all parsimonious models. We calculated average occupancy using the occupancy estimate from the first parsimonious model (model$_1$), multiplied by the corresponding AICc weight (AICω_1), which was subsequently added to the product of the remaining parsimonious models.

Model Validation

We randomly selected 25% of our wetland sites to be held back for model validation and used the remainder to develop the model (Figure S1). To ensure our resulting model was robust and not dependent upon sites used for model development, we randomly selected three different sets of development and validation datasets (herein referred to as Selection 1, 2, and 3). This allowed us to conduct a sensitivity analysis to compare the model outputs resulting from the three different datasets. If our models were robust, the results would remain consistent across the three trials and give us confidence regarding model results.

We used R v.3.2.1 (R Core Team 2015) to assess model performance by plotting the receiver operating characteristic curve (ROC) to illustrate the performance of our model as the threshold is varied (Pearce and Ferrier 2000). The ROC plot examines the tradeoff between the true positive rate (sensitivity) and true negative rate (specificity), where a 45° diagonal line provides a visual representation of model accuracy. Smaller distances between the ROC curve and the diagonal line indicate that the model follows a random pattern whereas greater distances indicate that the model is better at describing the observed phenomenon. We calculated the area under the curve (AUC) as a measure of model accuracy; an AUC value of 0.5 indicates a model that makes predictions randomly (correct 50% of the time) whereas a value of 1.0 indicates that the model makes predictions that agree completely with observations (correct 100% of the time; Fielding and Bell 1997). From the ROC plot, we estimated the optimal cutoff value by selecting the threshold value that balanced the true positive rate with the true negative rate.

To provide an additional measure of model performance, we estimated overall raw accuracy by dividing the total number of correct classifications by the total number of sites. We used the derived threshold value to determine the cutoff value for estimating presence or absence. In other words, if the occupancy rate was greater than the threshold value, the site was classified as occupied. Alternatively, if the occupancy rate was lower than the threshold value, the site would be classified as unoccupied. These predictions were then compared to the observed survey data to determine total number of correct classifications.

Results

Our 58 wetland sites were sampled up to four times during the 13-yr sampling period (2003–2015). Overall, raw occupancy ranged between 59–64% among the three model selections. Of the 29 wetlands with positive survey results, there were only six wetlands where sites were sampled in multiple years and musk turtles were always captured. The majority of the wetlands sampled had mixed survey results (combination of detections and no detections). In general, we had a 64–71% chance of detecting musk turtles in a coastal wetland using the modified fyke net protocol.

Model Variables

The first three axes of the PCA explained 67% of the total variation in the data (Table 2); PC1 reflected the degree of anthropogenic disturbance within 1 km of the wetland, at the landscape-level (27% variation), whereas PC2 was most associated with characteristics within 250 m of the wetland, or site-level characteristics (23% variation), and PC3 corresponded to differences in wetland morphology (16% variation). Accordingly, sites with positive PC1 scores corresponded to those associated with higher densities of roads, buildings, and docks within 1 km of a wetland (0.85, 0.74, 0.58, respectively; Table 2). In addition, the size of the wetland (0.58), building density, and percent of wetland within 250 m of the wetland were also correlated with PC1 (0.54 and 0.65, respectively). Sites with positive PC2 scores

TABLE 2.—The first three principal components (PC; explaining 67% of the variation in the dataset) used as predictor variables to develop occupancy models for Eastern Musk Turtles (*Sternotherus odoratus*) in coastal wetlands of Georgian Bay, Lake Huron. Variables with a loading value higher than 0.54 are included; all variables included in the PCA were standardized.

PC axis	Variance explained (%)	Variable	Loading
		Road density (1 km)	0.85
		Building density (1 km)	0.74
		Wetland % (250 m)	0.65
		Wetland area	0.58
		Dock density (1 km)	0.58
PC1 landscape-level	27.3	Building density (250 m)	0.54
		Forest % (250 m)	0.54
		Building density (250 m)	0.68
		Dock density (250 m)	0.71
		Wetland % (1 km)	−0.66
		Wetland % (250 m)	−0.60
PC2 site-level	23.3	Wetland area	−0.60
		Maximum slope	0.94
PC3 morphology	16.3	Slope range	0.94

corresponded to sites impacted by site-level variables, and were associated with higher densities of docks and buildings within 250 m of the wetland (0.71 and 0.68, respectively), in addition to higher forest cover (0.54). Sites with negative PC2 scores were associated with larger wetlands and higher amounts of wetland in 250 m and 1 km buffers (–0.60, –0.60, and –0.66, respectively). Finally, sites with positive PC3 scores reflected wetland morphology and were associated with coastal wetlands that have a larger maximum slope and provide a range of bathymetric slopes (0.94 and 0.94, respectively).

Model Selection and Sensitivity Analysis

We ran all combinations of reduced variables (e.g., PC1, PC2, PC3) to produce seven occupancy models per selection round. Models with a ΔAICc $\leq$ 2 were considered parsimonious and therefore were not eliminated (Table 3). In total, four models were considered equivalent (models A, B, C, and D; Table 3). Our sensitivity analysis revealed that occupancy estimates from each of the three development datasets were comparable (ANOVA, $F_{2,129} = 0.07$, $P = 0.93$), where probabilities only varied by an average ($\pm$1 SE) of 7 $\pm$ 0.8% for an individual coastal wetland. Similarly, estimates for conditional occupancy were comparable among the three models (Wilcoxon χ^2 = 1.13, df = 2, P = 0.57) and only varied by 3 $\pm$ 1.4% for an individual coastal wetland. Because estimates were consistent across the three models, we calculated means of the three datasets to derive an averaged model of turtle occupancy.

In the final averaged model (Table 4), site-level characteristics were an important predictor of occupancy (PC2); as proportion of forest cover within 250 m of the coastal wetland increased, so did occupancy. Wetland size and percent of wetland in the landscape did not increase the probability of occupancy. Although human modifications such as docks and buildings within 250 m of a wetland appeared to increase the probability of occupancy, modifications within 1 km of a wetland decreased the probability of musk turtle occupancy in coastal wetlands (PC1). Lastly, a larger range of bathymetric slopes and wetlands with a greater maximum slope were associated with a higher probability of musk turtle occupancy (PC3).

Model Validation and Predictive Mapping

Area under the receiver operating characteristic curve (AUC) was 0.83 (lower 95% CI = 0.66, upper 95% CI = 0.92), which indicates that the averaged model was a better predictor of occupancy than was the null model (AUC = 0.5; Fig. 2). The detection–nondetection cutoff or threshold value of 0.52 resulted in a raw accuracy (total number of sites correctly predicted/total sites) of 74%. Specifically, the model's ability to correctly predict when a wetland was occupied (sensitivity) was 80% and its ability to correctly predict when a wetland was unoccupied (specificity) was 71%.

We mapped average occupancy and conditional occupancy estimates of predicted musk turtle occurrences within our study area (Fig. 3). Musk turtles were more likely to occupy coastal wetlands associated with higher surrounding forest cover (at the site-level), lower densities of docks, cottages, and roads (at the landscape-level), and more-variable bathymetric slopes (Fig. 3a). When detection history was accounted for, predicted occupancy generally increased across the study area (conditional occupancy; Fig. 3b). A few clusters of coastal wetlands were predicted to have lower conditional occupancies (Fig. 3b); these sites tended to be associated with lower forest cover, higher levels of anthropogenic disturbances, and very shallow or very steep slopes (reduced slope range). Therefore, our model predicted the majority of the coastal wetlands in the Parry Sound ecodistrict to be currently occupied by musk turtles.

DISCUSSION

Consistent with our expectations, we identified land cover as an important predictor of coastal wetland occupancy. Specifically, coastal wetlands with the lowest densities of buildings, docks, and roads (our proxy for anthropogenic disturbance) within 1 km, and the highest proportions of forest cover within 250 m, had the highest probability of occupancy. We also found that musk turtles were associated with wetlands providing a range of bathymetric slopes. Coastal wetlands with more-variable bathymetric slopes typically support a more diverse plant community because steeper slopes (3–7°) support a more diverse community of canopy submerged aquatic vegetation (SAV), which occupy the water column, whereas shallower slopes (<3°) promote a higher density of substrate-covering SAV (Duarte and Kalff 1986; Leblanc 2015). Eastern Musk Turtles are a highly aquatic species and thus rely heavily on wetland vegetation, particularly SAV, for shelter, foraging, and aquatic basking (Ernst 1986; Ford and Moll 2004). Typically, coastal wetlands surrounded by undisturbed land (i.e., forest) have been shown to have reduced nutrient and sediment runoff and therefore a higher diversity and areal cover of SAV (Dillon and Kirchner 1975; Beaulac and Reckhow 1982; Mohammad and Adam 2010). On the other hand, anthropogenically disturbed coastal wetlands are more likely to be characterized by high nutrient concentrations and suspended solids, which decreases light penetration and, therefore, are habitats expected to have lower diversity of SAV (Lougheed et al. 2001).

Table 3.—Results of AICc-based model selection to determine models with a ΔAICc $\leq$ 2 for occupancy of coastal wetlands by Eastern Musk Turtles (*Sternotherus odoratus*) in Georgian Bay, Lake Huron. Change in AICc (ΔAICc) and AICc weights (AICω) are shown for each of the three randomly selected development datasets. The weights resulting from the three development datasets were averaged to produce AIC$\bar{\omega}$.

Model	Predictor variables	ΔAICc	AICω
		$\Delta AICc_1$	$AIC\omega_1$
A	PC2, PC3	0.00	0.38
B	PC2	0.92	0.24
		$\Delta AICc_2$	$AIC\omega_2$
B	PC2	0.00	0.47
		$\Delta AICc_3$	$AIC\omega_3$
B	PC2	0.00	0.37
C	PC1, PC2	1.63	0.16
D	PC1	1.78	0.15
			$AIC\bar{\omega}$
A	PC2, PC3		0.38
B	PC2		0.36
C	PC1, PC2		0.16
D	PC1		0.15

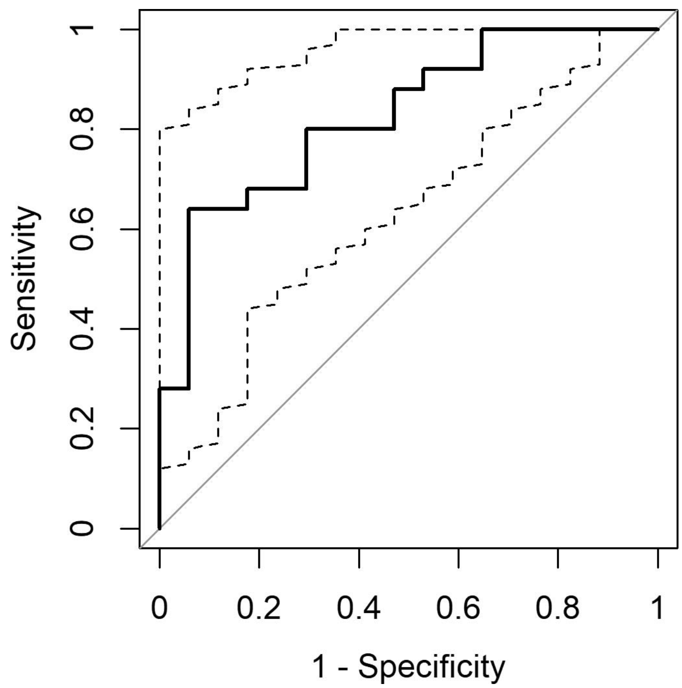

Fig. 2.—The receiver operating characteristic (ROC) curve generated using survey data from coastal wetland validation sites in Georgian Bay, Lake Huron, across the three randomly selected model development groups. The dashed lines indicate the 95% confidence intervals. The area under the curve for the occupancy model is 0.82, indicating good model fit.

Contrary to our predictions, we found an inverse relationship between occupancy and proportion of surrounding wetland habitat. We had expected turtles to use other wetlands in the surrounding landscape, but this might not be applicable to wetlands in Georgian Bay. Highly variable topography (Kor et al. 1991; Campbell 2005) might prohibit upland movements among distinct wetlands, especially because musk turtles do not tend to move great distances on land (Ernst 1986; Buhlmann and Gibbons 2001). Longer-distance movements tend to occur within water (e.g., Laverty et al. 2016). Buildings and docks within 250 m of a coastal wetland were also not significant predictors of occupancy (PC2). We did not want to over-interpret this, however, because it might be an artifact of the low number of docks in our dataset (i.e., <1 dock/km^2 within the 250-m buffer). To test the effect of dock density at this scale would require a dataset with a range of dock densities, and such conditions are not realistic in our study area, nor desirable. It was not until the 1-km buffer size that densities of anthropogenic disturbance varied among wetlands. The more-important site characteristic driving PC2 is likely the amount of forest cover within 250 m of the coastal wetland, which did have a significant effect on turtle occupancy (Tables 2 and 4). On average, wetlands that supported musk turtles had 70% forest cover within a 250-m buffer whereas wetlands without musk turtles had a lower cover of 53%.

Similar to our findings, Eastern Musk Turtles were associated with forest cover in the Thousand Islands ecosystem in southeastern Ontario (Quesnelle et al. 2013). Because musk turtles rely on surrounding upland habitat for oviposition, turtles usually nest within 50 m of a water body (Steen et al. 2012). Furthermore, we presume high dock densities are associated with increased motorboat traffic, which has been shown to contribute to mortality of musk turtles (Bennett and Litzgus 2014). These results are consistent with turtles' requirement for undisturbed wetlands with low nutrients and suspended solids (DeCatanzaro and Chow-Fraser 2010; Wieten et al. 2012) and confirm the negative impacts of land conversion and shoreline modification. Although Laverty et al. (2016) found that low-impact recreational activities (e.g., campsites) do not severely impact musk turtles, our results indicate the wetland occupancy by musk turtles appears to be negatively affected by higher numbers of human structures such as roads, docks, and buildings.

Table 4.—Untransformed estimates of regression coefficients for predictor variables included in occupancy models for Eastern Musk Turtles (*Sternotherus odoratus*) in coastal wetlands of Georgian Bay, Lake Huron. Models A, B, C, and D are the occupancy models selected as parsimonious based on their AICc values. Regression coefficient estimates ($\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$) are provided for each of the three randomly selected model development groups. $\hat{\bar{\beta}}$ denotes the average of the three regression coefficient estimates and the values used to produce the final occupancy estimates and occupancy maps.

Model	Variable	$\hat{\beta}_1$	SE_1	$\hat{\beta}_2$	SE_2	$\hat{\beta}_3$	SE_3	$\hat{\bar{\beta}}$	$\overline{SE}$
	PC2	0.47	0.23	0.39	0.22	0.38	0.24	0.41	0.22
A	PC3	0.48	0.29	0.10	0.24	0.02	0.23	0.20	0.23
B	PC2	0.46	0.23	0.40	0.22	0.38	0.24	0.41	0.23
	PC1	−0.03	0.21	−0.04	0.20	−0.18	0.21	−0.08	0.21
C	PC2	0.45	0.23	0.40	0.22	0.36	0.24	0.40	0.23
D	PC1	−0.05	0.19	0.05	0.18	−0.21	0.21	−0.07	0.19

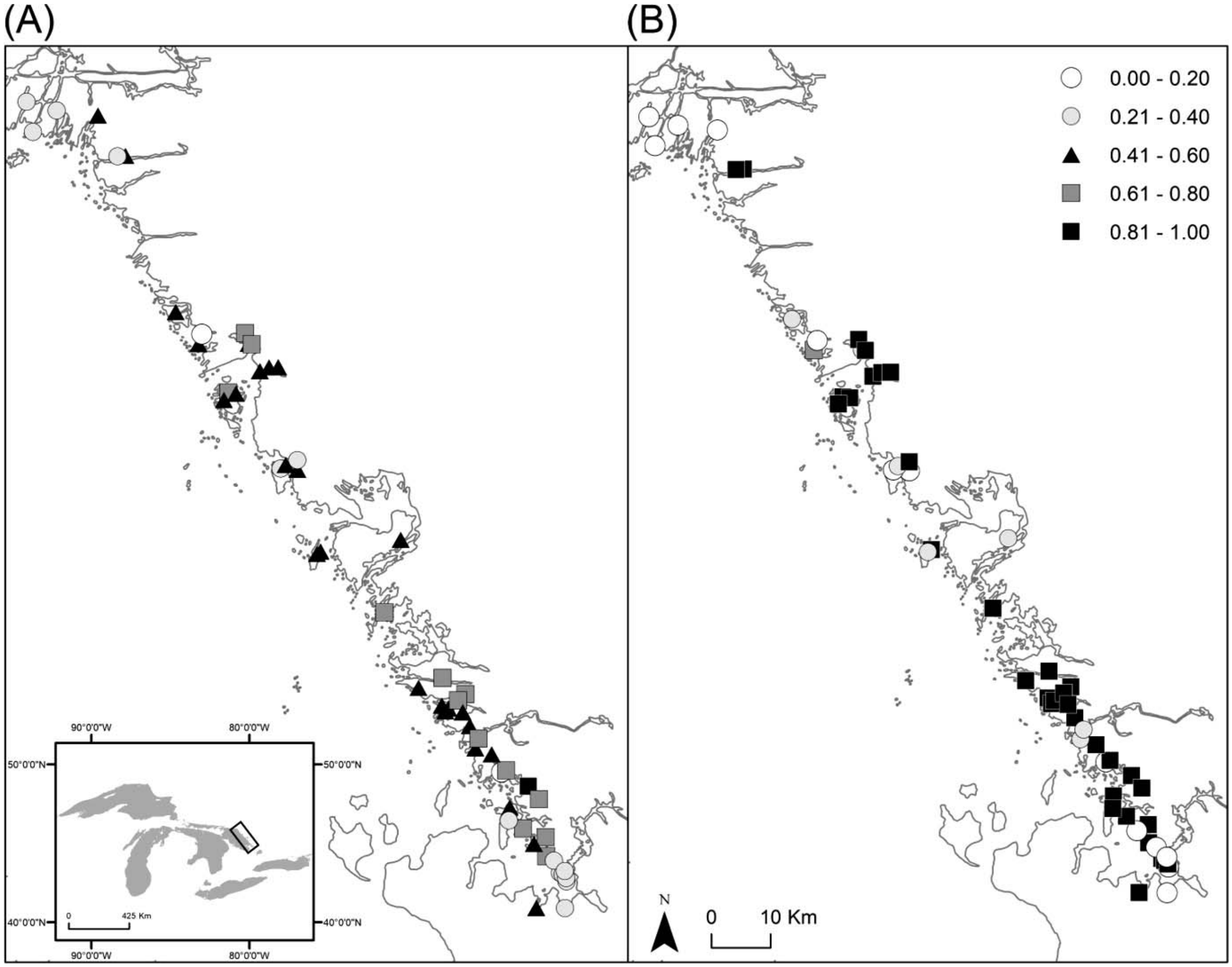

Fig. 3.—Mean probability of (a) occupancy (ψ) and (b) conditional occupancy (ψ_c occupancy given detection) for Eastern Musk Turtles (*Sternotherus odoratus*) in coastal wetlands along eastern Georgian Bay, Lake Huron. A color version of this figure is available online.

Including detection history, or how often a turtle is located, can improve occupancy estimates, determine the number of times a wetland should be sampled before declaring absence, and evaluate effectiveness of a survey method. Furthermore, conditional occupancy results are important for small-bodied, secretive species such as Eastern Musk Turtles that can be difficult to locate (COSEWIC 2012). If detection probabilities are not accounted for when estimating the extent of occupied habitat, underestimates might result. When detection was considered (conditional occupancy), coastal wetlands with a 61–100% probability of occupancy increased from 13 wetlands to 36 wetlands. The increase in number of wetlands that have suspected occupancy is desirable for conservation purposes. This designation is based on the likelihood that a wetland with low anthropogenic disturbance at the landscape-level, higher amounts of forest surrounding the wetland, and more-variable bathymetric slopes would support musk turtles. Conversely, we had eight coastal wetlands with low occupancy estimates (21–40%), which decreased even further when detection was considered (0–20%). Despite the wetlands having land cover covariates that indicate suitable habitat, the wetland had been sampled on multiple occasions without musk turtles being detected, and therefore has a high probability of being truly unoccupied.

We had a 64–71% probability of detecting musk turtles using the modified fyke net protocol—if they were actually present in the coastal wetland. This means if a wetland is surveyed five times using our protocol, musk turtles should be captured during three or four of these surveys, if they were present in the wetland. By creating the model at the landscape level, we have not accounted for other factors that might influence wetland occupancy or the 30% of the sampling effort wherein we did not detect turtles even though they were present. For example, competition for resources (Lindeman 2000; Luiselli 2008), risk of predation (Marchand et al. 2002; Harding and Mifsud 2017), and use of specific microhabitats (Edmonds 1998; Picard et al. 2011) might influence where turtles are found within the wetland or affect their willingness to enter the fyke net. False absences can also be attributed to the fyke net protocol and time of year that nets are set. Because nets used in our study were restricted to the 1-m depth contour, musk turtles were detected only if they were near these areas.

Although our model is limited to the unique landscape of Georgian Bay (featuring granitic bedrock and thin soils), our framework can be adapted and applied to other geographic regions or species. Estimating occupancy at the landscape level allows for a regional approach to conservation decision-making and provides an assessment of habitat quality and insight into the status of a population. Recently, Environment Canada (2016) proposed a recovery strategy for Eastern Musk Turtles, emphasizing land conversion and shoreline alteration as major concerns for the recovery of the species. If eastern Georgian Bay continues to be developed, water quality and wetland habitat will continue to degrade, which might have detrimental effects on musk turtle populations. Based on our results, we recommend that increases in the number of building, docks, and roads within 1 km of coastal wetlands be regulated and that declines in forest cover within 250 m be limited to ensure long-term occupancy and persistence of musk turtles in the coastal wetlands of Georgian Bay. Occupancy modeling is most applicable for species that are long-lived and habitat specialists, and it can be used to assess factors that govern occupancy for sensitive species across large spatial scales. Given that Eastern Musk Turtles are a small-bodied, secretive species, nontarget species data can improve our knowledge of their distribution while limiting resources spent on large-scale targeted surveying efforts and can provide critical information where data gaps exist. Our occupancy maps can be used to guide future surveys for musk turtles and identify coastal wetlands with a high probability of occupancy to ensure site-level protection and population persistence.

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Supplemental Material

Supplemental material associated with this article can be found online at https://doi.org/10.1655/Herpetologica-D-18-00002.SF1; https://doi.org/10.1655/Herpetologica-D-18-00002.ST1.

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