Using Landscape Characteristics to Predict Distribution of Temperate-Breeding Canada Geese

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Abstract - Accurate estimates of species' distributions are needed to ensure that conservation-planning efforts are directed at appropriate areas. Since the early 1980s, temperate-breeding populations of *Branta canadensis* (Canada Goose) have increased, yet reliable estimates of the species' distribution are lacking in many regions. Our objective was to identify the landcover features that best predicted Canada Goose distribution. In April 2015, we surveyed 300 one-km^2 plots across North Carolina and observed 449 Canada Geese. We quantified percent coverage of 7 continuous landcover variables at 5 different spatial extents for each of the 300 plots. We fit logistic regression models using presence and absence at the 300 plots as the dependent variable and percent-cover covariates as independent variables. The best model for predicting Canada Goose presence included percent pasture within the 9 km^2 surrounding the survey plot and percent open water within the 1-km^2 survey plot. The probability of Canada Goose presence increased with increasing percent open water and percent pasture, albeit at different spatial extents, which provided important cover and food resources, respectively. Our approach using remote-sensing data to accurately predict Canada Goose presence across a large spatial extent can be employed to determine distributions for other easily surveyed, widely distributed species.

Introduction

It is essential to accurately estimate species distributions to ensure that conservation-planning efforts are directed to areas where management will be most beneficial (Piorecky and Prescott 2006, Silvy 2012). Typically, accurate distribution determinations are difficult to obtain because animals are dispersed irregularly across the landscape (Caraco 1980, Certain et al. 2007, Silverman et al. 2001) and it is costly and requires many person-hours to collect field data at a large spatial extent (Waddle et al. 2003). However, remote-sensing data can be combined with field observations to reliably estimate distributions for species management (Travaini et al. 2007). This technique of predicting species presence is effective and has been used at several single-geographic extents and with various species, including *Otis tarda* L. (Great Bustard), *Tamia sciurus hudsonicus grahamensis* (J.A. Allen) (Mt. Graham Red Squirrel), *Parnassius mnemosyne* (L.) (Clouded Apollo Butterfly),

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and *Lama guanicoe* (Müller) (Guanaco) (Luoto et al. 2002, Osborne et al. 2001, Pereira and Itami 1991, Travaini et al. 2007). Predicting species presence using 1 spatial extent (e.g., 1 km^2) may be of limited use because landcover variables may influence use at different extents. Testing the effects of landcover at multiple spatial extents is common in studies of wildlife habitat and can provide insight related to the mechanisms underlying habitat associations (Altmoos and Henle 2010, Hall and Mannan 1999, Storch 2002). The multi-extent approach accounts for the influence of spatial variation on species presence and offers more explanatory power than a single-extent approach (Levin 1992, Morris 1987).

Species-distribution data can be used to target areas where actions are most beneficial to achieve management goals. For example, distribution data can identify areas where competition between native and invasive species may occur or areas where habitat improvements will most benefit a species (Piorecky and Prescott 2006, Vicente et al. 2011). Detailed descriptions of species distributions can offer information about the efficacy of hunting for recreation or population management (Robinson et al. 2008, Storm et al. 2007).

Since the early 1980s, the temperate-breeding population of *Branta canadensis* L. (Canada Goose) has increased (Fig. 1; Dolbeer et al. 2014). Temperate-breeding geese provide valuable opportunities for hunting and wildlife viewing, but when present in large numbers or high densities, there is an increased probability of negative human–goose interactions and zoonotic-disease transmission (Graczyk et al. 1998, Kullas et al. 2002, Rutledge et al. 2013). In 2011, because of concern about detrimental impacts, the Atlantic Flyway Council set a goal to lower the temperate-breeding population to 700,000 birds and redistribute geese more evenly across the landscape (Atlantic Flyway Council 2011, Blohm et al. 2006). This goal has

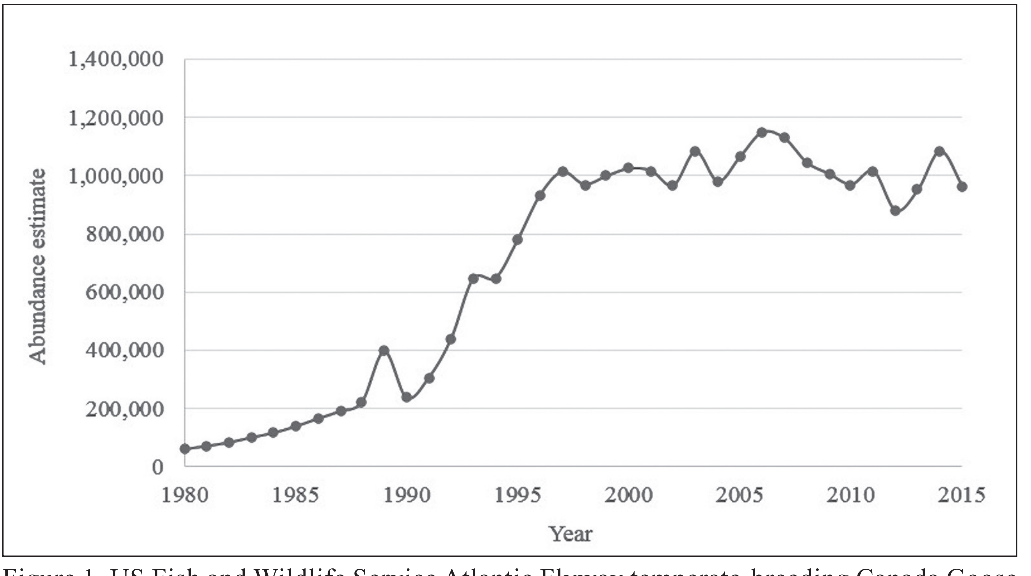

Figure 1. US Fish and Wildlife Service Atlantic Flyway temperate-breeding Canada Goose abundance estimates from 1980 to 2015 (Dolbeer et al. 2014, US Fish and Wildlife Service 2015).

not been achieved to date (Fig. 1). As of 2015, the Flyway population was stable at around 1 million birds (USFWS 2015), and landowner requests for assistance with goose-caused property damage remain relatively constant in areas with high goose-densities (Atlantic Flyway Council 2011).

Canada Geese are known to select specific habitat types seasonally (Bellrose 1980, Kear 2005). Migratory goose populations display notable shifts in seasonal habitat usage, spending winter and early spring foraging in agricultural fields and pastures and roosting in nearby wetland areas, and the summer months feeding on natural forage and roosting on mud-flats near pond margins (Carriere et al. 1999, Manley et al. 2004). Ray (2011) observed that temperate-breeding Canada Geese use sites with different water-body sizes and land-use types depending on season, and Bellrose (1980) noted that Canada Geese used post-harvest grain fields in the fall and early winter for forage. Single-extent habitat relationships have commonly been used to model goose distributions at a landscape level (Donovan et al. 2004, Naugle et al. 1997, Reiter et al. 2013). Rarely have studies on Canada Geese addressed the varying spatial extents at which their habitat relationships occur (but see Conkin and Alisauskas 2013); thus, further research on this topic may offer a better explanation of Canada Goose distribution.

Our objective was to identify landcover features and spatial extents that influence Canada Goose occurrence on the landscape. We predicted that developed open space (e.g., golf courses, cemeteries, and other manicured lawns that provide grazing areas) and open water would increase the probability of Canada Goose presence, but that the spatial extent of the relationships might differ (Smith et al. 1999).

Field-site Description

We conducted Canada Goose surveys across North Carolina, which has a total land area of 139,389 km^2. We used the North American Bird Conservation Initiative's bird conservation regions to describe North Carolina's 3 physiographic regions. The southeastern Coastal Plain consisted primarily of riverine swamps and brackish marshes near the Atlantic Ocean and *Pinus palustris* Mill. (Longleaf Pine), *Pinus elliottii* Engelm. (Slash Pine), and *Pinus taeda* L. (Loblolly Pine) forests further inland. The Piedmont was comprised of pine and mixed-hardwood forests interspersed with areas of rapid urbanization. The Appalachian Mountain region consisted of oak–hickory forests at lower elevations and hemlock–spruce forests at higher elevations (North American Bird Conservation Initiative 2015).

We used the US Geological Survey National Land Cover Database (NLCD 2011; Homer et al. 2015) to identify available Canada Goose habitat, which we defined as 1-km^2 plots with any open water or less than 80% forest cover. This initial process of excluding non-goose habitat allowed us to: (1) concentrate limited resources in areas that potentially could have geese present, and (2) better identify predictors of goose presence (Bellrose 1980, Carbaugh et al. 2010, Conover 2011, Homer et al. 2015, Kear 2005). We excluded any plots that were 100% open water and fell outside of a 1-km buffer of the shorelines of the Atlantic Ocean, Pamlico Sound, Currituck Sound, Roanoke Sound, and Albemarle Sound. We identified 104,001 one-km^2 plots that met these criteria (Fig. 2), the majority of which were within the Piedmont and southeastern Coastal Plain. We assigned each plot a number and selected 300 survey plots from those available using a random-number generator (Fig. 3).

Methods

Plot-survey protocol

We based our survey protocol on a breeding-waterfowl population survey used in the northeastern US (Heusmann and Sauer 1997, 2000). We surveyed the 300 plots between 1 April and 30 April 2015 to coincide with peak breeding activity (e.g., nest building, laying, incubation) of Canada Geese in North Carolina. We

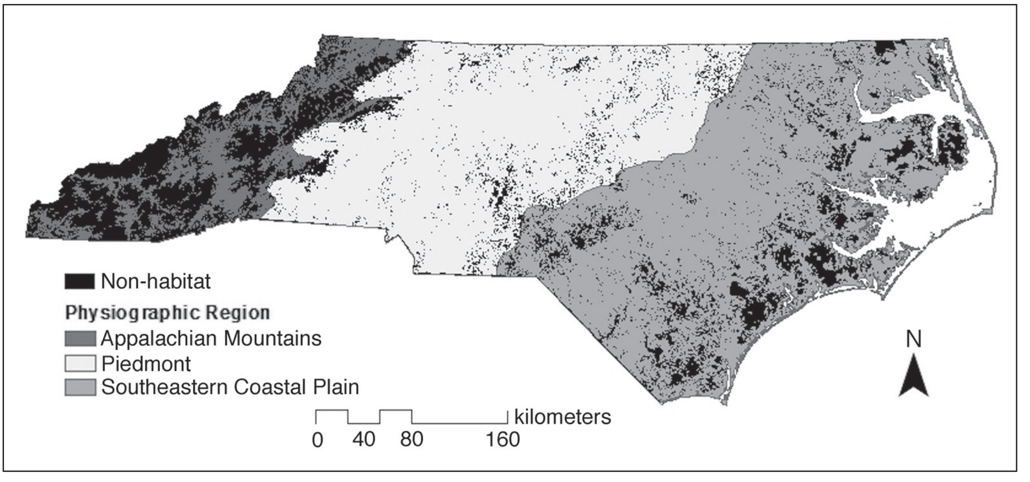

Figure 2. Non-habitat and potential habitat by physiographic region for Canada Goose developed before the random-plot selection, North Carolina (2014).

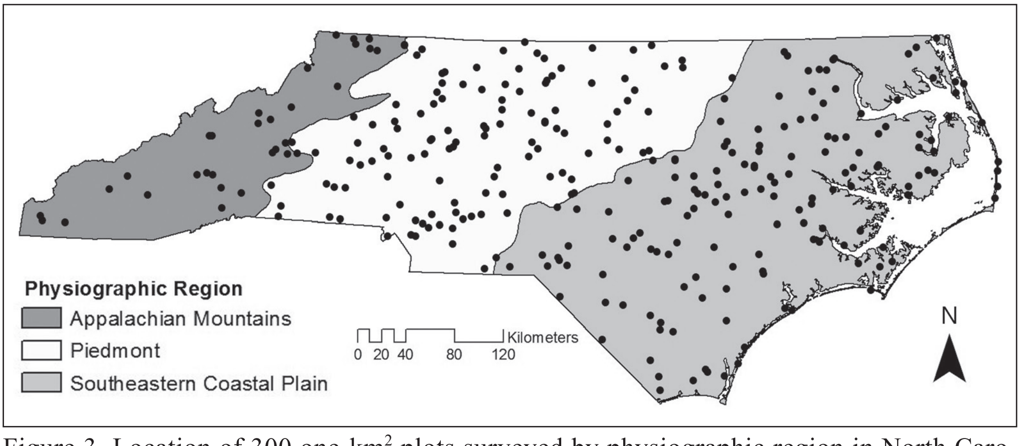

Figure 3. Location of 300 one-km^2 plots surveyed by physiographic region in North Carolina (April 2015).

completed a single-observer survey of each plot in its entirety using a variety of methods (e.g., boats, trucks, foot), and recorded the presence or absence of geese (Dunn et al. 2009; Heusmann and Sauer 1997, 2000). We did not limit the time of day that the plot surveys were conducted because visibility of Canada Geese has been shown to be similar throughout the day (Heusmann and Sauer 2000). Moreover, Rutledge et al. (2015a) showed that satellite-tagged geese in central North Carolina had constant-movement probabilities in daylight hours during the breeding/nesting period.

Landcover variables

We used ArcGIS 10.2.2 (ESRI, Redlands, CA) to quantify percent coverage of 7 variables deemed important for Canada Goose usage at 5 different spatial extents: 1 km^2, 9 km^2, 25 km^2, 49 km^2, and 81 km^2. We chose these spatial extents because they represented 4 consecutive 1-km buffers around each 1-km^2 survey plot, and the increasing area encompassed an array of landscape-level effects on the probability of Canada Goose presence. These 5 spatial extents encompassed the home-range sizes documented in 2 studies of temperate-breeding geese in North Carolina and Nebraska (Groepper et al. 2015; Rutledge et al. 2015a, 2015b). We used the NLCD 2011 to determine percent cover of developed open space, open water, forest cover, pasture/hay, and cultivated crops (Homer et al. 2015). The NLCD 2011 data was the most fine-grained (i.e., 30 m x 30 m) and most comprehensive available. Using this comprehensive dataset allowed seamless modeling of the landcover variables. We used the national impervious surface datasets to determine percent coverage of impervious surfaces (Xian et al. 2011). We used the municipal boundaries dataset provided by the North Carolina Department of Transportation to determine percent coverage of municipal boundary (North Carolina Department of Transportation 2015).

We employed analysis of variance (ANOVA) to test for spatial non-stationarity between the mean number of Canada Goose observations in survey plots located in different physiographic regions in North Carolina. We tested for collinearity in the 7 habitat variables at all 5 spatial extents using the multivariate-methods function in JMP (JMP®, Cary, NC) to calculate Pearson correlation coefficients (PCC). We described covariates as collinear when $|r| \geq 0.6$ because Dormann et al. (2007) suggested that when $|r| > 0.7$, collinearity began to distort model estimation and prediction.

Temperate-breeding Canada Goose distribution

We conducted binary logistic regression to model the conditional probability of a goose encounter relative to landcover covariates using the glm function in R (Keating and Cherry 2004, R Core Team 2014). To further explore data prior to building models, we tested whether habitat covariates at each of the 5 spatial extents significantly affected Canada Goose presence ($P \leq 0.05$). If a habitat covariate did not affect goose presence at a specific spatial extent, we excluded it from the creation of final model sets for model simplicity. We used Shapiro-Wilk tests to test for non-normality and transformed covariates appropriately. To select the combination of habitat covariates and spatial extents that had the greatest effect on Canada Goose presence, we ran all possible model combinations of significant habitat and spatial-extent covariates without including interaction terms in JMP (JMP®, Cary, NC), resulting in a total of 60 candidate models. We evaluated support for the models using Akaike's information criterion corrected for small sample-size (AIC_c; Burnham and Anderson 2002). We determined top models for predicting Canada Goose presence by selecting models within 2 ΔAIC_c of the highest-ranked model.

Prior to fitting the logistic regression model, we tested for spatial autocorrelation within Canada Goose presence–absence data with the model-standardized Pearson residuals using the Moran's I tool in ArcGIS 10.2.2 (ESRI, Redlands, CA; Carl and Kuhn 2007). The Moran's I test resulted in a *P*-value of 0.869, indicating there was no spatial autocorrelation in the data. Therefore, we did not incorporate any correction for spatial autocorrelation.

After selecting the best model of the 60 candidate models, we tested the strength of the model to predict Canada Goose presence by calculating area-under-the-curve (AUC) using receiver-operating-characteristic curve (ROC) (JMP®, Cary, NC). The AUC value is equal to the probability that the 2 random samples from different cases (i.e., presence and absence) will be ranked in the correct order (Deleo 1993). We used JMP to select a discrimination value that minimized omission and commission rates, thereby increasing the estimate accuracy of the AUC for the model of goose presence and absence (Hartley et al. 2006). We randomly allocated 70% of the 300 plot-survey data points as a training-data set for the model, and used the remaining 30% for model validation. We considered AUC values between 0.7 and 0.8 acceptable for discrimination, between 0.8 and 0.9 excellent for discrimination, and greater than 0.9 outstanding for discrimination (Hosmer and Lemeshow 2000).

To create a map of predicted Canada Goose presence, we applied the parameter estimates from the top model to landcover variables in the GIS. We used the map-calculator function in ArcGIS Spatial Analyst to solve for the dependent variable y, log odds of goose presence, across all goose habitat in North Carolina (ESRI, Redlands, CA). We then applied the logistic transformation, $\exp(y) / (1 + \exp[y])$, to obtain a probability-of-goose encounter within each 1-km^2 plot.

Results

We counted 449 Canada Geese during visits to the 300 plot locations. We observed geese at 67 (22.33%) survey plots. There were 4 occupied plots in the Appalachian Mountains, 34 occupied plots in the Piedmont, and 29 occupied plots in the southeastern Coastal Plain.

We detected collinearity ($|r| \geq 0.6$) between 3 habitat covariates (i.e., percent impervious surface, percent developed open space, and percent municipal boundary) at all 5 spatial extents. We elected to include only percent developed open space in final models because it provided the best explanation of goose presence out of the 3 collinear habitat-covariates. We did not detect a difference ($P < 0.05$) in the mean number of goose observations per physiographic region using ANOVA. Hence, it was not necessary to account for non-stationarity between survey plots located in different physiographic regions of North Carolina. The Moran's I test resulted in a P-value of 0.869, indicating there was no spatial autocorrelation in the data. Therefore, we did not incorporate any correction for spatial autocorrelation.

The best model for determining presence of Canada Geese included percent pasture within the 9 km^2 surrounding the survey plot and percent open water within the 1-km^2 survey plot (Table 1):

$$Log\ Odds\ (presence) = -1.44 + (0.31)\ (\%\ \text{open water at}\ 1\ \text{km}^2) + (0.4)(\%\ \text{pasture at}\ 9\ \text{km}^2)$$

No other models were within 2 ΔAIC_c. Increases in percent open water and percent pasture increased the probability of goose presence. The ROC area under the curve was 0.73, which indicated that the binary model correctly ranked random sites with Canada Goose presence higher than sites without geese 73% of the time (Fig. 4). The probability of goose presence within the 104,001 plots varied from 0.0097 to

Table 1. The number of parameters (K), AIC_c, ΔAIC_c, and model weight (ω) for models with significant covariate combinations for the top 10 models and null model of Canada Goose presence, North Carolina (2015).

Model	K	AIC_c	ΔAIC_c	ω
Water1 + Pasture9	2	285.4	0.00	0.93
Water1 + Pasture81	2	290.9	5.56	0.05
Water9 + Pasture9	2	295.3	9.97	0.01
Water1 + Pasture1	2	295.8	10.44	0.01
Water9 + Pasture9	2	301.7	16.35	0.00
Water9 + Pasture81	2	302.2	16.86	0.00
Water81 + Pasture9	2	308.0	22.64	0.00
Water81 + Pasture81	2	308.3	22.92	0.00
Water9 + Pasture1	2	309.0	23.62	0.00
Pasture9	1	314.9	29.51	0.00
Null	0	323.1	37.78	0.00

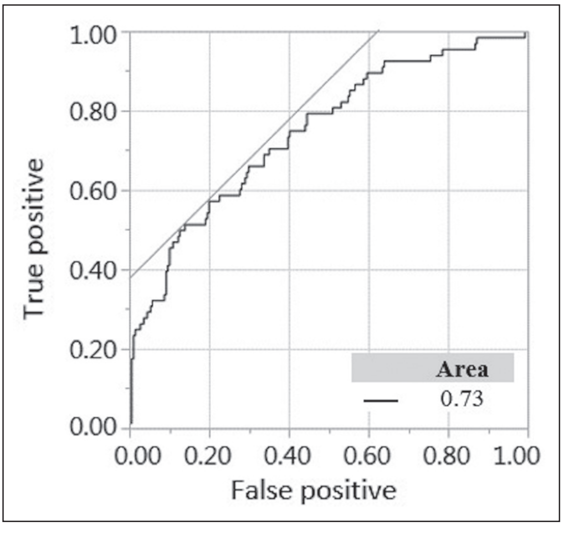

Figure 4. Receiver operating-characteristic (ROC) curve testing the strength of the best model to predict Canada Goose presence in North Carolina (2015).

0.7511, and 4425 plots had a probability of presence greater than 0.5. Plots with high probabilities of goose presence were situated around large water bodies, particularly in areas where pasture was also present (Fig. 5).

Discussion

We combined field observations with remote-sensing data to accurately predict probability of Canada Goose presence across a large spatial extent. The best predicting model performed well, and the AUC value was comparable to those reported in similar studies (Conkin and Alisauskas 2013, Nielsen et al. 2010, Parris and Schneider 2009, Tuanmu et al. 2011). The inclusion of multiple spatial extents in the model allowed us to account for the influence of spatial variation on Canada Goose presence and increased the model's explanatory power (Levin 1992, Morris 1987).

However, the distribution model did not perform well in urban areas in the Piedmont. The predictive map indicated a low probability of Canada Goose presence in urbanized areas in the Piedmont, but geese are observed there more frequently than other physiographic regions during annual breeding bird surveys (Pardieck et al. 2016). Although relatively fine-grained, the NLCD 2011 failed to identify the areas of open water in urban areas used as nesting sites by geese (e.g., retention ponds and ditches) (Chamberlain and Tighe 2009, Smith et al. 1999). Also, the random selection of survey plots resulted in proportionally fewer survey plots (10%) in urban areas than available (17%), which may have reduced our capacity to predict Canada Goose presence in urban areas. Increasing the number of survey plots or stratifying urban and rural sampling areas when selecting survey plots could make sampling more representative of the available goose habitat (Cochran 1977).

Imperfect detection can bias count-based wildlife studies (Arroita et al. 2010), but detection probability in our study was high. Mackenzie and Royle (2005) recommended that sampling units should be surveyed a minimum of 3 times to

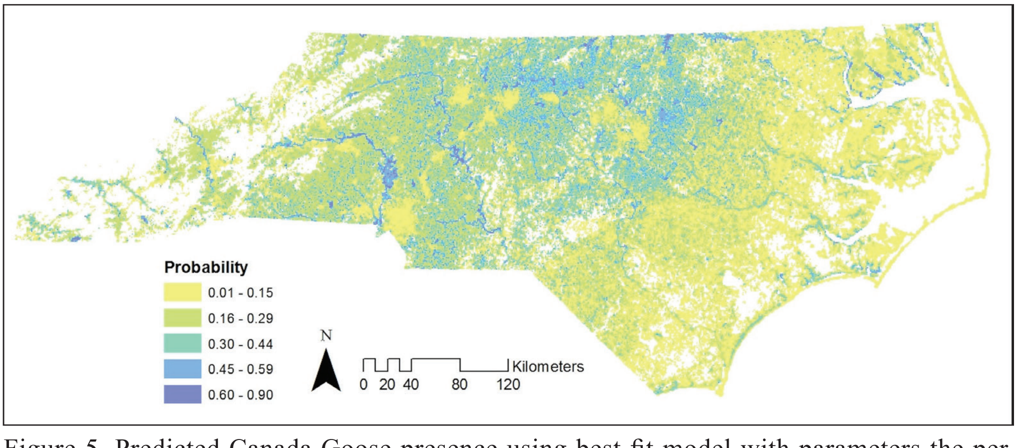

Figure 5. Predicted Canada Goose presence using best-fit model with parameters the percent pasture within the 9 km^2 surrounding the survey plot and percent open water within the 1-km^2 survey plots in North Carolina (April 2015). The white area was removed a priori with the assumption that no geese were present in non-goose habitat.

calculate a reliable detection probability. However, in our study, the probability of detecting Canada Geese at a plot if geese were present on our single visit was 95.2% (McAlister 2016). Hence, we suggest making multiple visits to survey plots to determine whether the data they generate significantly improve model accuracy or simply increase project cost.

The land-cover variables that best predicted Canada Goose distribution represented key cover and food resources. Geese were more likely present in areas with open water. Open-water sources provide safe roosting sites for adults and a refuge from predation for flightless goslings and molting adult temperate-breeding Canada Geese (Carbaugh et al. 2010, Conover 2011). Pasture provides forage during early brood-rearing and adult molt as well as additional forage outside of the brood-rearing period after birds attain flight capability (Hanson and Eberhardt 1971). Conversely, developed open space and percent cropland cover had no effect on Canada Goose distribution, likely because these resources are less important during the breeding season. Smith et al. (1999) identified developed open space as an attractant for the species, but geese may forage less in these areas during the breeding and brood-rearing season because they spend more time near open water during this period (Carbaugh et al. 2010, Conover 2011, Hanson and Eberhardt 1971). Agricultural crops are important foraging areas for Canada Geese (Ankney 1996), but they tend to contain warm-season crops (e.g., corn, soybeans) in North Carolina that have not emerged or are being planted during the nesting/brood-rearing season.

The 2 most-important landcover predictors were at different spatial extents. Water was important at the smallest spatial extent because Canada Geese were nesting near water sources. Conversely, pasture was important at the larger 9-km^2 spatial extent because adult geese use areas further away from water for foraging, but still within their average home-range of 9.92 km^2, as documented by Rutledge et al. (2015a) in central North Carolina.

Although we conducted our study during the nesting/brood-rearing season, we believe our results can be used to help focus management actions throughout the year in areas with greater probabilities of Canada Goose presence. Rutledge et al. (2015a) showed that space use of telemetered geese varied seasonally, but the mean annual home-range was only 9.92 km^2, and individuals tended to use the same water bodies throughout the year and from one year to the next. Hence, most temperate-breeding Canada Geese likely remain year round in the local area where they were observed. Our approach to combine surveys for Canada Geese with remote-sensing data at multiple spatial extents accurately predicted probability of goose presence across a large spatial extent and could be implemented for temperate-breeding Canada Geese in other southeastern US states.

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