ABSTRACT

MCALISTER, MARK AUSTIN. Resident Canada Goose Abundance and Occurrence at Variable Spatial Extents. (Under the direction of Christopher Moorman and Christopher DePerno).

Since the early 1980's, the Atlantic Flyway resident population of Canada geese (*Branta canadensis*) has increased, but range-wide abundance and distribution estimates are lacking. Efficient methods to precisely estimate resident Canada goose abundance and distribution are needed to help direct adaptive management of the burgeoning population. We compared precision and efficiency between the band return and plot survey methods of goose abundance estimation. Our results indicated the 2 methods produced similar abundance estimates with similar overall costs. However, we suggest the band return method is better for goose abundance estimation because it is more precise and if continued for multiple years will allow calculation of additional population metrics (i.e., survival, recovery rates, and harvest distributions). Also, we investigated the relationship between remotely sensed land cover features (i.e., open water, pasture, forest cover) and goose occurrence. The probability of goose presence increased with increasing open water within the 1-km^2 survey plot and increasing pasture within the 9 km^2 surrounding the survey plot, which provided important cover and food resources, respectively. We suggest our approach of using remote sensing data to predict Canada goose presence across a large spatial extent can be used to determine distributions for other widely distributed species that are easily surveyed.

Resident Canada Goose Abundance and Occurrence at Variable Spatial Extents

by
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DEDICATION

I dedicate my thesis to my grandmother, Dorothy McDowell. Her passion for the outdoors and the love she had for her family had untold impact on my life.

BIOGRAPHY

Mark McAlister was born and raised in Greenwood, South Carolina. His interest in wildlife was developed spending his childhood hunting, fishing, and exploring the woods surrounding his home. After graduating from Ninety Six High School in 2010, he chose to pursue wildlife and wildlife management as a career and attended Clemson University for a B. S. degree in Wildlife and Fisheries Biology. Immediately after graduating from Clemson in May 2014 he began his graduate studies at North Carolina State University.

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Abstract

Since the early 1980's, the Atlantic Flyway resident population of Canada geese (*Branta canadensis*) has increased. Resident Canada geese are a valuable resource for hunting and wildlife viewing, but when in concentrated-large numbers they create negative human-wildlife interactions and pose a risk of zoonotic disease transmission. An efficient method to precisely estimate resident Canada goose abundance at a large spatial extent is needed to help direct adaptive management of the increasing population. Our objective was to compare precision and efficiency between 2 common methods to estimate goose abundance in North Carolina, USA (139,389 km^2). The first method (i.e., band return estimation) used hunter band returns, and the second (i.e., plot survey) used surveys of 1-km^2 plots randomly located across potential goose habitat in the state. To quantify efficiency, we recorded all expenses and time dedicated to goose banding and plot surveys. In June 2014, we banded 2,102 geese at 44 sites. During the 2014-2015 hunting season, we received 173 direct band recoveries. For the band return method, we calculated (using the Lincoln-Peterson formula) an abundance estimate of 153,168 (95% CI= 130,165 – 176,171) and determined it required $72,857.55 and 2,316.5 person-hours to complete. In April 2015, we surveyed 300 1-km^2 plots across North Carolina and observed 449 geese. For the plot survey method, we calculated (by multiplying mean number of geese observed by total available goose habitat plots) an abundance estimate of 155,655 (95% CI= 102,572 – 208,738) and determined it required $80,766.95 and 2,857.3 person-hours to complete. Although results

were similar, we suggest the band return method is better to estimate the resident Canada goose population because it provides a more precise estimate with similar overall costs and if continued for multiple years will allow calculation of additional population metrics including survival, recovery rates, and harvest distributions.

Introduction

At the turn of the 20th Century, population densities of Canada geese (*Branta canadensis*) (from this point forward goose) across North America were severely depleted by overexploitation and the destruction of wetlands (Smith et al. 1999). Since that time, laws governing waterfowl harvest and habitat protection have allowed goose numbers to rebound. This increased protection and restocking efforts by state and federal agencies have led to the establishment of a non-migratory, or resident, geese in the Atlantic Flyway. As of 2015, the flyway population was estimated at around 1 million birds (U.S. Fish and Wildlife Service 2015).

Resident geese are a valuable resource for waterfowl hunters and the general public. Federal harvest estimates indicated that during the September 2014 resident goose season hunters harvested 178,100 birds in the Atlantic Flyway (Roberts et al. 2015). Increased resident Canada goose hunting opportunities potentially have direct economic impacts; according to a 2011 survey, hunters spent an estimated $1.4 billion annually on migratory game bird hunting in the United States (Carver 2015). Additionally, resident geese provide citizens with an opportunity to observe waterfowl. In a public survey regarding geese in Long Island, New York, 78% of respondents said they enjoyed the presence of resident geese (Loker 1996). Resident Canada geese provide increased opportunities for bird watchers in the field, which can have significant economic impacts; according to a 2011 survey, bird watchers spent an estimated $4.1 billion annually on bird watching trips and equipment in the United States (Carver 2013).

When present at high densities, geese can cause negative human-wildlife interactions. Negative human-goose interactions have increased as resident goose densities have risen (Conover and Chasko 1985). Between 1999 and 2010, 59% of the 12,679 complaint calls to the United States Department of Agriculture Wildlife Services regarding geese were related to property damage, including defecating on lawns and sidewalks, which caused lawn damage, excessive cleanup costs, and property being unused by human owners (Smith et al. 1999, Atlantic Flyway Council 2011). One study indicated the cost to repair goose damage (e.g., reestablishing overgrazed lawns, cleaning goose feces from sidewalks) was more than $60 per bird (Allan et al. 1995).

When in close proximity to humans, geese can transmit zoonotic diseases, such as *Escherichia coli*, *Giardia*, and *Campylobacter jejuni*, through fecal matter (Graczyk et al. 1998, Kullas et al. 2002, Rutledge et al. 2013). Also, geese can collide with aircraft and have been identified as the third most hazardous species to aircraft with approximately 1,109 reported goose-aircraft collisions occurring in the United States over an 18-year period from 1990-2007, requiring $47.4 million in repair costs (Dolbeer et al. 2000, Dolbeer and Wright 2008).

The United States Fish and Wildlife Service (USFWS) uses adaptive harvest management (AHM) to set season lengths and bag limits to regulate the resident goose population density at acceptable levels (Williams and Johnson 1995). A key component of

AHM requires that state and federal regulatory agencies monitor goose density trends over time (Nichols et al. 2007). Hence, a precise and efficient method is required to help drive AHM of goose population densities.

Two common methods of estimating goose abundance are the band return and the plot survey methods. The band return method has been used with Arctic-nesting geese (Alisauskas et al. 2009) and mallards (Alisauskas et al. 2013), but typically produces estimates 2 – 4 times greater with larger confidence intervals than count based methods (Alisauskas et al. 2009, Alisauskas et al. 2013). However, abundance estimates are still acceptable to make inferences about long-term trends in the population (Alisauskas et al. 2009). The plot survey method has been used successfully in the northeastern United States since 1989 (Heusmann and Sauer 2000, Heusmann and Sauer 1997) and requires fewer assumptions and correction factors than the band return method. Additionally, plot surveys are conducted during the breeding season and can be used to estimate the number of breeding pairs (Heusmann and Sauer 2000).

Our objectives were to: 1) assess the precision and determine appropriate corrections for the associated biases of the band return and plot survey methods for estimating adult resident goose abundance in North Carolina; and 2) compare direct and indirect costs associated with each method. We predicted the band return method would result in a greater abundance estimate with larger confidence intervals because previous waterfowl studies have shown band return methods result in larger abundance estimates when compared to sight based abundance estimation methods (i.e., plot surveys, transect surveys) (Alisauskas et al. 2009).

Study Area

We conducted band return and plot survey methods across North Carolina, which has a total land area of 139,389 km^2. We used the North American Bird Initiative Bird Conservation Regions to describe North Carolina's 3 physiographic regions. The southeastern Coastal Plain consists primarily of riverine swamps and marshes near the Atlantic Ocean and longleaf (*Pinus palustris*), slash (*Pinus elliottii*), and loblolly pine (*Pinus taeda*) forests further inland. The Piedmont consists of pine and mixed hardwood forests and has the largest amount of urbanization in the state. The Appalachian Mountain consists of oak (*Quercus spp.*) – hickory (*Carya spp.*) forests at lower elevations and hemlock (*Tsuga spp.*) - spruce (*Picea spp.*) forests at higher elevations (North American Bird Initiative 2015).

We set banding quotas for each of the 9 North Carolina Wildlife Resources Commission (NCWRC) Districts (Figure 1, Table 1) using goose observations from breeding bird survey data and a 2009 population estimate completed by North Carolina district biologists (Pardieck et al. 2015). In June 2014, we selected 44 banding sites statewide that had large flocks of molting resident geese (Figure 2). When selecting capture sites, we varied between urban (*i.e.*, golf courses and public parks) and rural (*i.e.*, farm ponds and pastures) sites throughout the state in an attempt capture differences in hunting pressures.

It is likely that Canada goose abundance differs across physiographic regions in North Carolina, but formal studies of goose distribution were lacking, so we elected to use a random sampling approach instead of stratified random sampling. To focus sampling in areas more likely to have geese, we defined available goose habitat as 1-km^2 plots with any open water or less than 80% forest cover. 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, and Albemarle Sound. We used US Geological Survey National Land Cover Database (NLCD) 2011 to determine percent cover of open water and forest cover (Homer et al. 2015). The total number of 1-km^2 plots that met these criteria was 104,001 (Figure 3), with the majority of the plots located in the Piedmont and southeastern Coastal Plain physiographic regions. We assigned plots a unique number and used a random number generator to choose 300 individual plots to survey. Plots were representative of habitat available to geese in North Carolina (Figure 4).

Methods

Goose Capture and Banding

We captured resident geese from June 12-27, 2014 during the flightless period when geese were molting primary feathers. We used a modified version of Cooch's flightless bird roundup technique to herd and manipulate birds to a desired location (Cooch 1953). We coaxed flocks of geese out of water using kayaks, grouped them on land, and slowly surrounded them using mobile ten-foot aluminum panels. After capture, we separated adults and juveniles, divided large groups, and moved the captured geese into shaded areas to reduce risk of overheating and other injury during the banding process. We recorded sex and age (cloacal examination and plumage evaluation) for each bird. Prior to release, each bird received a standard USFWS aluminum leg band (Size 8, U.S. Geological Survey Bird Banding Lab [Laurel, MD]). We submitted the leg band number, sex, age, and location of capture to the U.S. Geological Survey Bird Banding Lab. We monitored direct recoveries of banded geese shot or found dead by hunters from September 2014 – March 2015.

Band Return Abundance Estimation

We used a less biased form of Lincoln's Estimator (Lincoln 1930) for population estimation proposed by Chapman (1951):

$$\widehat{N^*} = \left(\frac{(n_1 + 1)(n_{2,i} + 1)}{(m_2 + 1)} - 1\right) * \hat{p}$$

This formula used the total number of birds banded for the first sample (n_1), North Carolina harvest estimates from the NCWRC state estimate ($n_{2,1}$) and USFWS federal estimate ($n_{2,2}$) for the second sample, and the number of direct band recoveries by hunters as the number occurring in both samples (m_2). We used state and federal harvest estimates because they often result in different estimates during the same year. We compared abundance estimates derived using these harvest estimates to determine which was more reliable. Because waterfowl band return rates often are less than 100%, we used results from a reward band study as a correction factor ($\hat{p}$). The study determined reporting rates for geese across the United States and concluded the mean reporting probability of a standard band to be 0.73 (95% CI= 0.69-.077) (Zimmerman et al. 2009b). We assumed no temporal difference between our reporting rate and those reported by Zimmerman et al. (2009b) because studies with other waterfowl species documented no significant difference in reporting rates between years (Conroy and Blandin 1984). Additionally, we assumed the band return rate of 0.73 to remain constant for all individual geese in the population because this is unlikely to change for monomorphic species like Canada geese (Nichols et al. 1995).

The Lincoln-Peterson estimator, as described above, must meet 4 key assumptions (Alisauskas et al. 2009).

I. *The population is closed so that $\widehat{N}$ is constant*.

Mortality losses are acceptable within this assumption as long as marked and unmarked members of the population are subject to equal mortality probability (Robson 1969). We assumed for our study that mortality differences between leg-banded geese and non-banded geese were negligible (Alisauskas et al. 2009). Additionally, we assumed population increases due to breeding were minimal because banding took place after the primary resident goose breeding season (Alisauskas et al. 2009).

II. *Probabilities of animals appearing in a sample may differ between the first and second sampling periods but should be equal for animals within each period.*

We assumed every resident goose across North Carolina had an equal probability of being selected in the first sample (application of a leg band). Decreased hunting pressure within municipal boundaries can affect the probability of a bird appearing in the second sample, but because we selected banding areas with varying degrees of municipal impact, we believe any influence to overall hunting pressure would be negligible. Additionally, the percentage of bands returned from birds banded within municipal boundaries (6.79%) was similar to those banded outside of municipal boundaries (8.9%) (Table 2).

III. *Animals do not lose their mark in the time between the 2 samples.*

We assumed band loss between the summer banding period and the following hunting season to be negligible, because Zimmerman et al. (2009a) determined the retention probability for standard aluminum leg band was high (0.9995) and constant over a 40-month period.

IV. *Geographic area of band recoveries corresponds to geographic area of harvest estimates.*

When harvest estimates are received from the state and the federal governments, they include non-local residents, Atlantic population (AP), Southern James Bay population (SJBP), and Mississippi Valley population (MVP) migratory geese. We used the harvest derivation technique, a method developed by the USFWS, which uses banding totals and direct band recoveries within the state to estimate the proportion of migrant and non-local residents within harvest estimates (Klimstra and Padding 2012).

a. Migrant Populations Correction Factor

There were no direct recoveries by hunters from the migrant populations during our study period, so we calculated the average proportion of migrant geese harvested 2001 – 2015 and obtained MVP and SJBP population estimates from professionals at the Ministry of Natural Resources in Canada (S. Hagey, Ministry of Natural Resources and Forestry Wildlife Research and Monitoring Section Trent University, personal communication).

b. Non-local Resident Population Correction Factor

To account for non-local residents (e.g., birds banded in Maryland and southern Ontario), we obtained population estimates and banding totals from the Atlantic Flyway harvest and population survey data book (Roberts et al. 2015), and Ontario's temperate-breeding goose estimates (C. Davies, Ontario Ministry of Natural Resources & Forestry, personal communication).

We adjusted the harvest estimate to include only adult birds so that final population estimates would be comparable for the band return and plot survey methods. We used the federal hunter parts collection data of the Harvest Information Program (HIP) to estimate the proportion of juvenile birds in the harvest. Also, we applied a correction factor of 0.61 (95% CI = 0.59 – 0.64) to the federal harvest estimate to correct for a consistent overestimation of goose harvest by HIP-based surveys (Padding and Royle 2012).

As a means of estimating the precision of our band return estimate, we calculated the variance of our estimate ($Var(\widehat{N})$) using a formula for variance of a product described below:

$$Var(\widehat{N}) = Var(\widehat{N^*} * \hat{p}) = Var(\widehat{N^*})[\hat{p}]^2 + Var(\hat{p})[\widehat{N^*}]^2 + Var(\widehat{N^*})Var(\hat{p})$$

$$Var(\widehat{N^*}) = \frac{(n_1+1)(n_2+1)(n_1-m_2)(n_2-m_2)}{(m_2+1)^2(m_2+2)}$$

$$Var(\hat{p}) = variance\ obtained\ from\ Zimmerman\ et\ al.(2009b)$$

In this formula $Var(\widehat{N^*})$ describes the standard variance calculation for the estimate of abundance and $Var(\hat{p})$ is the variance for the correction factor of unreturned bands reported by Zimmerman et al. (2009b). We calculated a 95% confidence interval for the band return abundance estimate to make a practical comparison of precision between the 2 abundance estimates. We calculated the 95% confidence interval as follows:

$$95\%\ CI = \widehat{N} \pm 1.96\sqrt{Var(\widehat{N})}$$

Plot Survey Protocol

We based the plot survey protocol on an ongoing breeding waterfowl population survey in the northeastern United States (Heusmann and Sauer 1997, Heusmann and Sauer 2000). We surveyed from April 1 - April 30, 2015 to coincide with peak breeding activity of geese in North Carolina. We completed a single observer survey of each plot in its entirety using a variety of methods (i.e., boats, trucks, foot) and recorded any geese observed (Heusmann and Sauer 1997, Heusmann and Sauer 2000, Dunn et al. 2009).

We did not limit time of day the plot surveys were completed, because visibility of geese is similar throughout the day (Heusmann and Sauer 2000). Similarly, Rutledge et al. (2015) showed that satellite-tagged geese had relatively constant movement probabilities during daylight hours during the breeding/nesting period.

We separated goose observations into 4 categories depending on behavioral characteristics. Confirmed pairs were 2 geese sighted together, exhibiting paired behavior (i.e., nesting, defending a territory). We split lone birds into 2 categories, lone males were any solitary bird sited off of a nest and an incubating female was any bird that was solitary and on a nest. We considered groups to be any flocks consisting of ≥ 3 geese (Heusmann and Sauer 2000, Dunn et al. 2009). All birds we encountered during the plot survey, excluding goslings, were totaled to yield an overall count at each plot (Heusmann and Sauer 2000, Dunn et al. 2009). For final abundance estimate calculation we assumed that lone males and incubating females had a paired mate and added an additional bird for each solitary goose, resulting in an assumed total count at each plot.

Plot Survey Detection and Abundance Estimation

We surveyed 27 plots 2 additional times within 5 days of the initial survey to calculate a probability of detection (Mackenzie and Royle 2005). We used the unmarked package in program R (Fiske and Chandler 2011) to calculate detection probability of the 27 plots, which we used to gauge the reliability of estimates at all sites.

We calculated the mean number of geese on each plot and extrapolated those numbers out to the plots containing goose habitat statewide. We calculated the mean number of geese on each plot using the following formula:

$$\bar{y} = \frac{\sum_1^n y_i}{n}$$

In this formula, $\bar{y}$ describes the sample mean number of geese observed, y_i describes the number of geese observed at the i^{th} plot, and n describes the total number of sample plots (300). We multiplied the resulting sample mean by the total number of available plots in the population (*N*)(104,001) to determine a statewide resident goose abundance estimate ($\hat{\tau}$) (Chochran 1977).

$$\hat{\tau} = N\bar{y} = 104{,}001 * \bar{y}$$

As a means of estimating the precision of our plot survey estimate, we calculated the standard error of our sample plots (s^2) and variance of our abundance estimate ($\widehat{Var}(\hat{\tau})$) using the following formulas:

$$s^2 = \frac{\sum_1^n (y_i - \bar{y})^2}{n-1}$$

$$\widehat{Var}(\hat{\tau}) = N(N-n)\frac{s^2}{n}$$

We calculated a 95% confidence interval for our plot survey abundance estimate to make a practical comparison of precision between both methods of abundance estimation. The 95% confidence interval was calculated as:

$$95\%\ CI = \hat{\tau} \pm 1.96 * \sqrt{\widehat{Var}(\hat{\tau})}$$

Cost Comparison

We used a unique project code to document all NCWRC employee time directed at training and the completion of each of the abundance estimation techniques. Employees used the same code when making purchases of equipment and fuel. At the conclusion of the project, we compiled all expenses from the discrete project code, which resulted in a side-by-side comparison of person-hours and money spent to complete the 2 methods.

Results

Band Return Estimate

We banded 2,102 after hatch year (AHY) geese in June 2014 and received 173 (8.2%) AHY direct band recoveries from the 2014 – 2015 waterfowl hunting season. Before applying correction factors, the initial USFWS harvest estimate was 37,267 (Raftovich et al. 2015) and the initial NCWRC harvest estimate was 56,182 (95% CI = 41,443 – 70,921) (North Carolina Wildlife Resources Commission 2015). We removed 38 birds from the NCWRC and USFWS harvest estimates to account for migratory geese included in the estimates (Southern James Bay Population = 26, Mississippi Valley Population = 12, Atlantic Population = 0). We removed 858 birds from both harvest estimates to account for 8 North Carolina band returns from geese banded in Maryland and Ontario, Canada. Additionally, we removed 21.26% of the birds (USFWS = 7,923 and NCWRC = 12,078) in each of the overall estimates to only account for after hatch year birds. Using the suggested correction factor of Padding and Royle (2012), we reduced the federal harvest estimate by an additional 14,534 birds to correct the overestimate of the federal Canada goose harvest. The final harvest estimate from the USFWS was 17,194 and the final harvest estimate from the NCWRC was

43,532. The band return abundance estimate using the USFWS harvest estimate was 153,168 (95% CI = 130,165 – 176,171), and the abundance estimate using the NCWRC harvest estimate was 387,773 (95% CI = 329,374 – 446,171).

Plot Survey Estimate

We had 449 assumed observations, geese observed or assumed to be paired to a solitary goose, at 300 plot survey locations. Geese were observed at 67 (22.33%) survey plots. Observations were consistent with prior assumptions that goose densities differed across physiographic strata with 14 observations (3.12%) occurring in the Appalachian Mountains, 250 observations (55.68%) occurring in the Piedmont, and 185 observations (41.2%) occurring in the southeastern Coastal Plain. Detection probability was 95.2% at the 27 repeat sample plots. The plot survey abundance estimate was 155,655 (95% CI = 102,572 – 208,738).

Cost Comparison

The cost of conducting the band return method was $72,857.55, with $64,179.08 for mileage and salaries, $3,531.30 for training, and $5,147.55 for equipment. The cost of conducting the plot survey method was $80,766.95, with $57,930.32 for mileage and salaries, $19,321.97 for training, and $3,514.66 for equipment (Table 3). The band return method required 2,316.5 person-hours, with 104.5 hours spent on training and 2,212 hours spent on field work. The plot survey method required 2,857.3 person-hours, with 651 hours spent on training and 2,206.3 hours spent on field work (Table 4).

Discussion

Although the 2 methods resulted in incredibly similar statewide abundance estimates, the plot survey 95% confidence interval was larger than the band return confidence interval using the federal harvest estimate. We believe increasing the number of plot surveys and stratifying sample plots by physiographic region are viable options for improving precision. A power analysis of our 2015 data indicated that approximately 1,500 plots should be surveyed to generate the same level of precision as the band return method using the federal harvest estimate. However, increasing survey sample size would result in an increase in survey costs (e.g., person-hours, money). Hence, a better approach for increasing precision may be stratification. Given the heterogeneity of goose distributions across the state, considering each physiographic region as a separate population and combining population estimates from each strata to calculate overall state abundance likely would increase precision to a similar level of the band return using the federal harvest estimate (Chochran 1977). This sort of stratification has been used in surveys of other waterfowl species and caribou (Siniff and Skoog 1964, Heusmann and Sauer 1997).

The band return abundance estimates using the state and federal harvest estimates were considerably different, which is directly related to inclusion of the Padding and Royle (2012) harvest correction factor. Exclusion of the harvest correction factor resulted in an inflated population estimate consistent with previous studies (Otis 2006, Alisauskas et al. 2009). In fact, use of the bias corrected federal harvest estimate resulted in an abundance estimate almost identical to the estimate from the plot survey method. These results highlight the importance of including appropriate bias correction factors in the band return model.

Imperfect detection can bias count-based wildlife studies, but detection probability in our study was high (Arroita et al. 2010). Mackenzie and Royle (2005) recommended that sampling units should be surveyed a minimum of 3 times to calculate a reliable detection probability. However, probability of detecting geese at a plot if geese were present was 95.2% in this study. Hence, we suggest making multiple visits to survey plots to estimate detection is unnecessary because it will result in a minimal gain in accuracy with an increase in project cost (approximately 3 times the amount of person-hours and other expenses).

Monetary cost for completing the band return estimation was less than the plot survey estimation and required less person-hours. However, these overall costs do not represent the continued use of these abundance estimate techniques on an annual basis because this was the initial year of implementation for both methods. Future use of these methods, if continued annually, will require less money for purchasing equipment and less person-hours as only new employees will need to receive training for survey techniques and methods. Considering the first year costs are inflated because of initial training and equipment costs, a more realistic estimate would exclude those costs. After making these exclusions, the methods required similar overall costs and person-hours.

We recommend that managers use the band return method with federal harvest estimates for estimating adult resident goose abundance because it resulted in a more precise estimate with costs similar to the plot survey method. Additionally, the band return method encourages positive agency and public interactions because a large portion of banding occurs in areas where the public can observe and interact with agency employees and many hunters covet the opportunity to shoot banded birds. Finally, we suggest the band return method because when performed over an extended time period it can provide additional population information crucial to the appropriate management of the species, including survival, recovery rates, and harvest distributions (Brownie et al. 1985, Greene and Krementz 2008).

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References

Allan, J. R., J. S. Kirby, and C. J. Feare. 1995. The biology of Canada geese *Branta canadensis* in relation to the management of feral populations. Wildlife Biology 1:129–43.

Alisauskas, R. T., K. L. Drake, and J. D. Nichols. 2009. Filling a void: abundance estimation of North American populations of arctic geese using hunter recoveries In D. L. Thomson, E. G. Cooch, and M. J. Conroy, editors. Modeling demographic processes in marked populations. Environmental and Ecological Statistics 3:463–489.

Alisauskas, R.T., T. W. Arnold, J. O. Leafloor, D. L. Otis, and J. S. Sedinger. 2013. Lincoln estimates of mallard (*Anas platyrhynchos*) abundance in North America. Ecology and Evolution 4:132–143.

Arroita, G. G., M. S. Ridout, and B. J. T. Morgan. 2010. Design of occupancy studies with imperfect detection. Methods in Ecology and Evolution 1:131-139.

Atlantic Flyway Council. 2011. Atlantic flyway resident Canada goose management plan.

Brownie, C., D. R. Anderson, K. P. Burnham, and D. S. Robson. 1985. Statistical inference from band recovery data: a handbook. U.S. Fish and Wildlife Service Resource Publication 131. Washington, D.C.

Carver, E. 2013. Birding in the United States: a demographic and economic analysis. U.S. Fish and Wildlife Service Report 2011: 1.

Carver, E. 2015. Economic impact of waterfowl hunting in the United States. U.S. Fish and Wildlife Service Report 2011: 6.

Chapman, D. G. 1951. Some properties of the hypergeometric distribution with applications to zoological sample censuses. University of California Publication Stat. 1: 131-160.

Cochran, W. G. 1977. Sampling Techniques. 3rd edition, John Wiley and Sons, New York.

Conover, M. R., and G. G. Chasko. 1985. Nuisance Canada goose problems in the eastern United States. Wildlife Society Bulletin 13:228-233.

Conroy, M. J. and W. W. Blandin. 1984. Geographic and temporal differences in band reporting rates for American black ducks. Journal of Wildlife Management 48:23-37.

Cooch, F. G. 1953. Techniques for mass capture of flightless blue and snow geese. Journal of Wildlife Management 17:460-465.

Dolbeer, R. A., S. E. Wright, and E. C. Cleary. 2000. Ranking the hazard level of wildlife species to aviation. Wildlife Society Bulletin 28:372–378.

Dolbeer, R. A. and S. E. Wright. 2008. Wildlife strikes to civil aircraft in the United States, 1990–2007. U.S. Department of Transportation, Federal Aviation Administration, Office of Airport Safety and Standards, Serial Report 14, Washington, D.C., USA.

Dunn, J., H. W. Heusmann, T. Nichols, B. Raftovich, B. Swift, and T. Watts. 2009. Atlantic flyway breeding waterfowl survey training manual.

Fiske, I. and R. Chandler. 2011. Unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance. Journal of Statistical Software 43:1-23.

Graczyk, T. K., R. Fayer, J. M. Trout, E. J. Lewis, C. A. Farley, I. Sulaiman, and A. A. Lal. 1998. *Giardia sp.* cysts and infectious *Cryptosporidium parvum* oocysts in the feces of migratory Canada geese (*Branta canadensis*). Applied Environmental Microbiology 64: 2736-2738.

Greene, A. W., and D. G. Krementz. 2008. Mallard harvest distributions in the Mississippi and Central Flyways. Journal of Wildlife Management 72: 1328–1334.

Heusmann, H. W. and J. R. Sauer. 1997. A survey for mallard pairs in the Atlantic Flyway. Journal of Wildlife Management 61:1191-1198.

Heusmann, H. W. and J. R. Sauer. 2000. The northeastern states' waterfowl breeding population survey. Wildlife Society Bulletin 28: 355–364.

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

Klimstra, J. D. and P.I. Padding. 2012. Harvest distribution and derivation of Atlantic Flyway Canada geese. Journal of Fish and Wildlife Management 31:43-55.

Kullas, H., M. Coles, J. Rhyan, and L. Clark. 2002. Prevalence of *Escherichia coli* serogroups and human virulence factors in feces of urban Canada geese (*Branta canadensis*). International Journal of Environmental Health Research 12:153–162.

Lincoln, F. C. 1930. Calculating waterfowl abundance on the basis of banding returns. Circular U.S. Department of Agriculture No.118:1-4.

Loker, C. A. 1996. Human dimensions of suburban wildlife management: insights from three areas of New York State. M.S. Thesis, Cornell Univ., Ithaca, N.Y.

Mackenzie, D. I. and J. A. Royle. 2005. Designing occupancy studies: general advice and allocating survey effort. Journal of Applied Ecology 42:1105-1114.

Nichols, J. D., R. E. Reynolds, R. J. Blohm, R. E. Trost, J. E. Hines, and J. P. Bladen. 1995. Geographic variation in band reporting rates for mallards based on reward banding. Journal of Wildlife Management 59:697-708.

Nichols, J. D., M. C. Runge, F. A. Johnson, and B. K. Williams. 2007. Adaptive harvest management of North American waterfowl populations: a brief history and future prospects. Journal of Ornithology 148:343–S349.

North American Bird Conservation Initiative [NABCI]. 2015. NABCI homepage. < http://www.nabci-us.org/>. Accessed 3 Nov 2015.

North Carolina Wildlife Resources Commission [NCWRC]. 2015. Hunting Estimates Report

2014-2015 Hunter Harvest Survey. < http://www.ncwildlife.org/Portals/0/Hunting/Documents/2013-14-Hunter-Harvest-Survey-Report.pdf>. Accessed 27 October 2015.

Otis, D. 2006. Mourning dove hunting regulation strategy based on annual harvest statistics and banding data. Journal of Wildlife Management 70:1302-1307.

Padding, P. I. and J. A. Royle. 2012. Assessment of bias in US waterfowl harvest estimates. Wildlife Research 39:336–342.

Pardieck, K.L., D.J. Ziolkowski Jr., M.A.R. Hudson. 2015. North American breeding bird survey dataset 1966 - 2014, version 2014.0. U.S. Geological Survey, Patuxent Wildlife Research Center.

Raftovich, R.V., S. C. Chandler, and K.A. Wilkins. 2015. Migratory bird hunting activity and harvest during the 2013-14 and 2014-15 hunting seasons. U.S. Fish and Wildlife Service, Laurel, Maryland, USA.

Roberts, A.J. et al. 2015. Atlantic Flyway harvest and population survey data book. U.S. Fish and Wildlife Service, Laurel, MD.

Robson, D. S. 1969. Mark-recapture methods of population estimation. Pages 120-140 *in* N. L. Johnson and H. Smith, Jr., editors. New developments in survey sampling. John Wiley-and Sons, New York, N.Y.

Rutledge, M. E., R. M. Siletzky, W. Gu, L. A. Degernes, C. E. Moorman, C. S. DePerno, and S. Kathariou. 2013. Characterization of *Campylobacter* from resident Canada geese in an urban environment. Journal of Wildlife Diseases 49:1–9.

Rutledge, M. E., R. Sollmann, B. E. Washburn, C. E. Moorman, and C. S. DePerno. 2015. Using novel spatial mark-resight techniques to monitor resident Canada geese in a suburban environment. Wildlife Research 41:447-453.

Siniff, D. B. and R. O. Skoog. 1964. Aerial censusing of caribou using stratified random sampling. The Journal of Wildlife Management 28:391-401.

Smith, A. E., S. R. Craven, and P. D. Curtis. 1999. Managing Canada geese in urban environments. Jack Berryman Institute Publication 16, and Cornell University Cooperative Extension, Ithaca, New York, USA.

U.S. Fish and Wildlife Service. 2015. Waterfowl Population Status, 2015.

Williams, B. K., and F. A. Johnson. 1995. Adaptive management and the regulation of waterfowl harvests. Wildlife Society Bulletin 23:430–436.

Zimmerman, G. S., W. L. Kendall, T. J. Moser, G. C. White, and P. F. Doherty, Jr. 2009a. Temporal patterns of apparent leg band retention in North American geese. Journal of Wildlife Management 73: 82–88.

Zimmerman, G. S., T. J. Moser, W. L. Kendall, P. F. Doherty Jr, G. C. White, D. F. Caswell. 2009b. Factors influencing reporting and harvest probabilities in North American Geese. Journal of Wildlife Management 73:710–719.

Table 1. North Carolina Wildlife Resources Commission District banding goals set by state waterfowl biologists and the total number of Canada geese banded in each district, North Carolina (2014).

NCWRC District	**Banding Objective**	**Number Banded**
District 1	188	188
District 2	163	184
District 3	330	350
District 4	158	293
District 5	435	458
District 6	144	231
District 7	260	246
District 8	190	248
District 9	133	198
Total	2001	2396

Table 2. A comparison of after hatch year Canada geese banded within and outside of municipal boundaries and the number of direct leg band recoveries from the same areas, North Carolina (2014).

Banding Location	After Hatch Years Banded	Direct Band Recoveries	Percent Recovered
Within Municipal Boundaries	663	45	6.79%
Outside Municipal Boundaries	1439	128	8.90%

Table 3. Comparison of costs for band return and plot survey methods of Canada goose abundance estimation, North Carolina (2014 – 2015).

	Band Return Estimation	**Plot Survey Estimation**
Mileage/Salaries	$ 64,179.08	$ 57,930.32
Training	$ 3,531.30	$ 19,321.97
Equipment	$ 5,147.17	$ 3,514.66
Total	$ 72,857.55	$ 80,766.95

Table 4. Comparison of person hours for band return and plot survey methods of Canada goose abundance estimation, North Carolina (2014 – 2015).

	Band Return Estimation	**Plot Survey Estimation**
Training	104.5	651
Field Work	2212	2206.3
Total	2316.5	2857.3

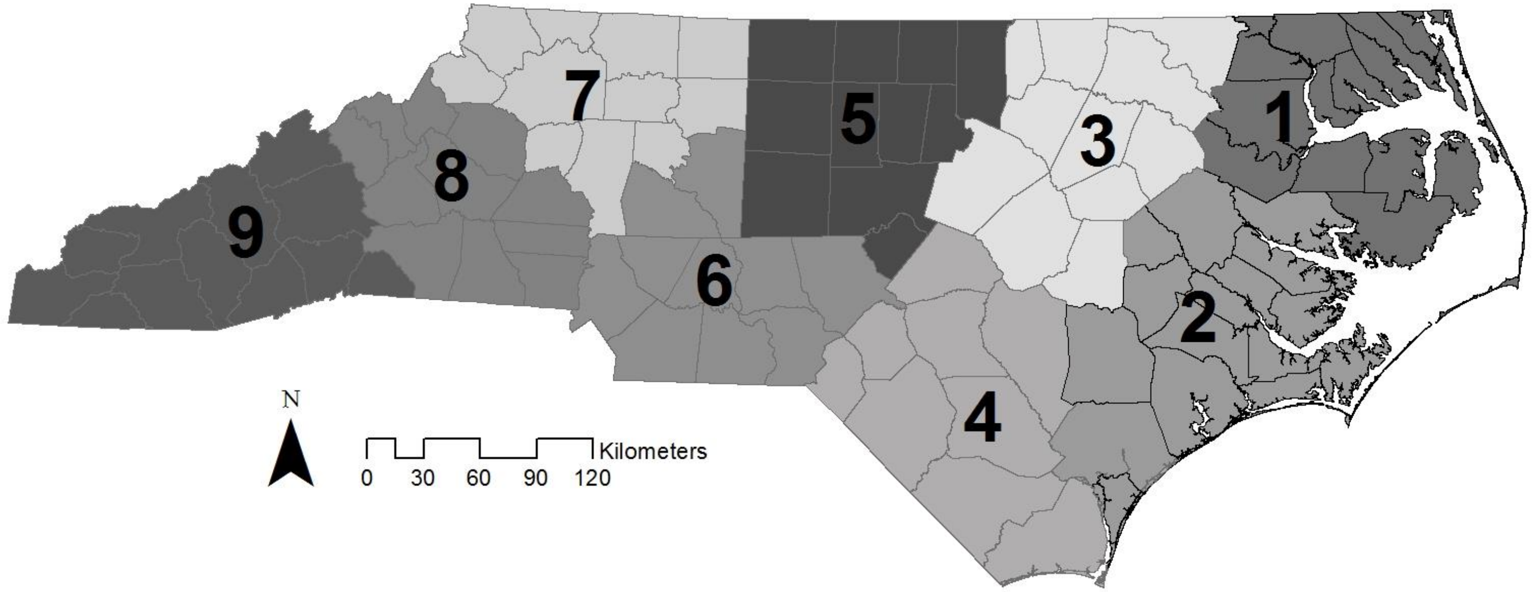

Figure 1. North Carolina Wildlife Resources Commission Districts used for regulatory and management purposes and for setting resident Canada goose banding goals across, North Carolina (2014).

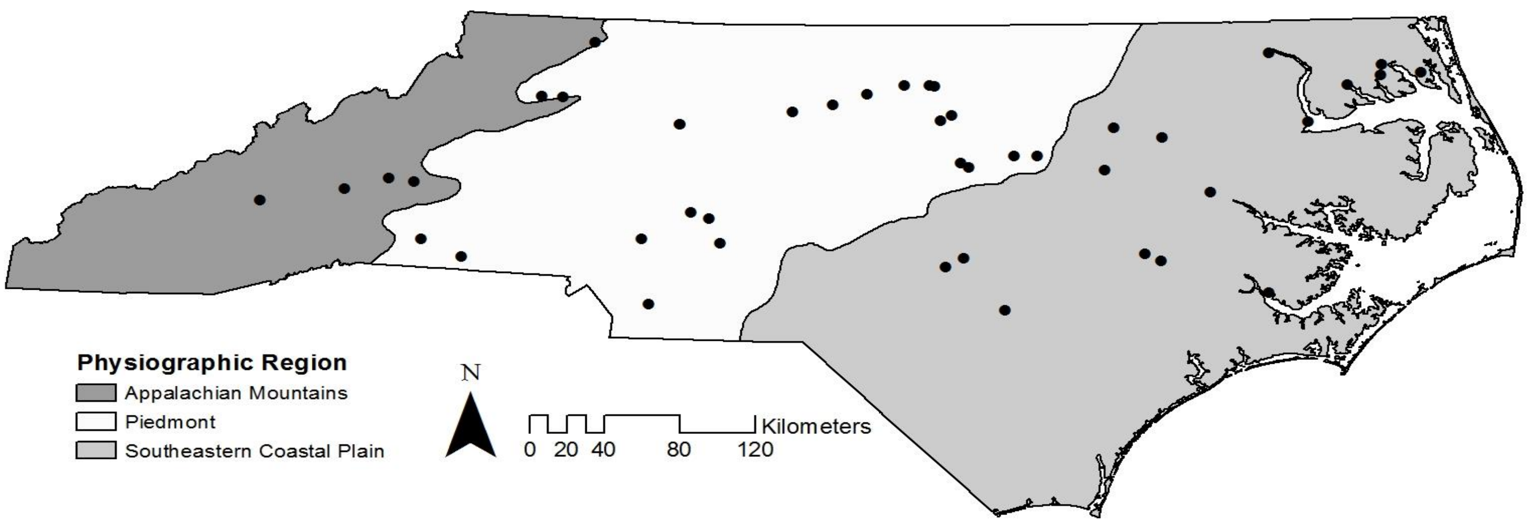

Figure 2. Physiographic regions and locations of 40 sites where Canada geese were banded during the June flightless period, North Carolina (2014).

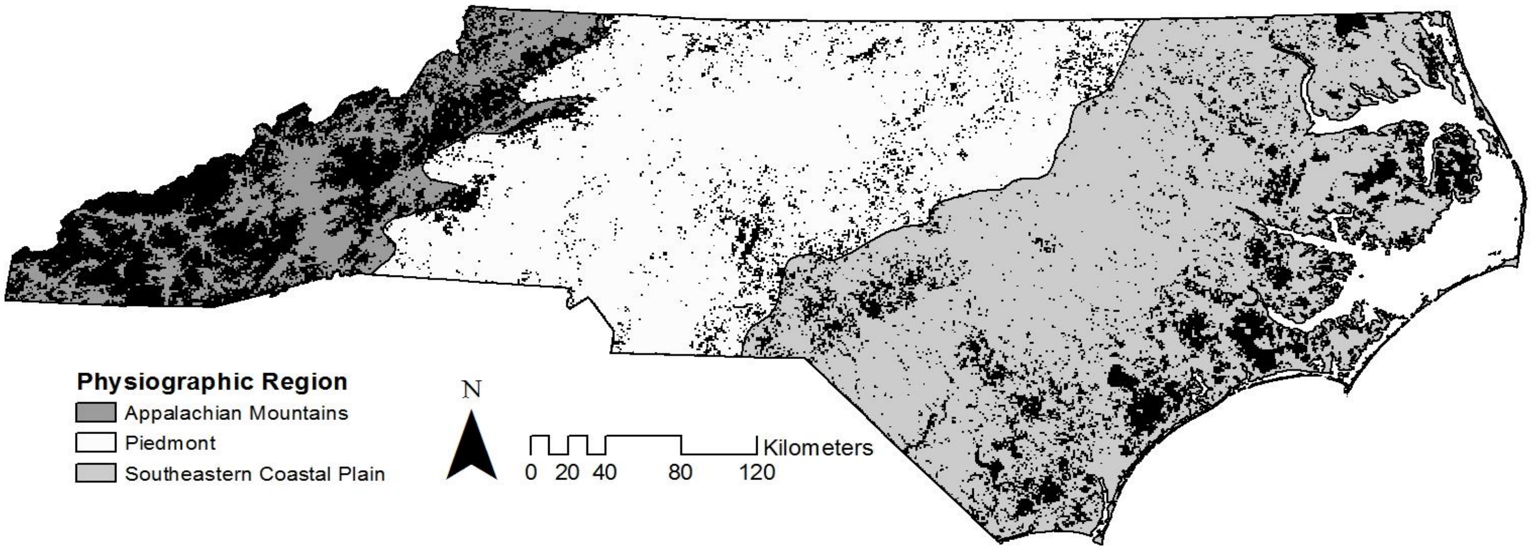

Figure 3. Physiographic regions and potential habitat for Canada goose developed before the random selection of 300 plot survey locations, North Carolina (2015).

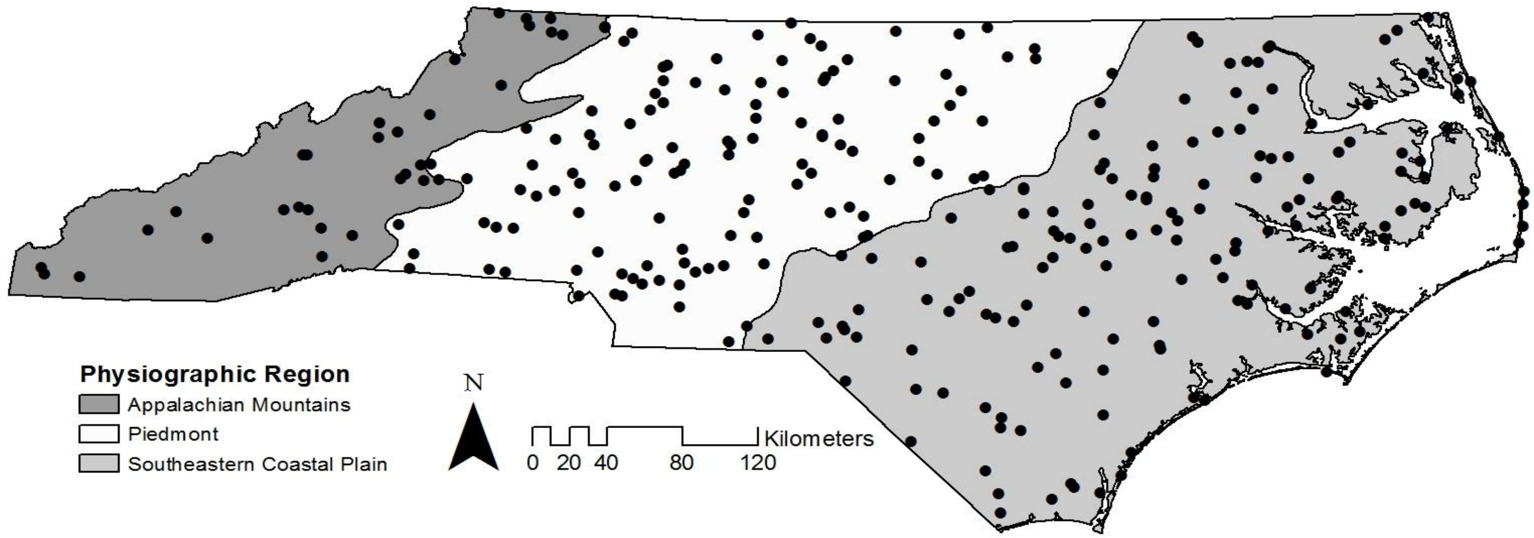

Figure 4. Physiographic regions and location of the 300 1-km^2 plots surveyed for Canada geese, North Carolina April (2015).

CHAPTER 2

Using Landscape Characteristics to Predict Distribution of Resident Canada Geese

Abstract

Quality estimates of species' distributions are needed to ensure that conservation planning efforts are directed in appropriate areas. Since the early 1980's, the Atlantic Flyway resident population (AFRP) of Canada geese (*Branta canadensis*) has increased, yet reliable estimates of goose distribution are lacking in many regions. Our objective was to identify the land cover features that best predicted goose distribution. In April 2015, we surveyed 300 1-km^2 plots across North Carolina and observed 449 geese. We quantified percent coverage of 7 continuous land cover 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 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 used to determine distributions for other widely distributed species that can be surveyed easily.

Introduction

It is essential to generate quality estimates of species distributions to ensure conservation planning efforts are directed in appropriate areas (Piorecky and Prescott 2006, Silvy 2012). Yet, accurate distributions typically are difficult to obtain because animals are dispersed irregularly across the landscape (Caraco 1980, Silverman et al. 2001, Certain et al. 2007). Additionally, collection of field data at a large spatial extent is expensive and requires substantial manpower (Waddle et al. 2003). However, remote sensing and field data can be used to reliably estimate distributions for species management purposes (Travaini et al. 2007).

Species distribution data can be used to target areas where actions are most beneficial to achieve management goals. For example, distribution data can direct actions to 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). Additionally, detailed species distributions can offer information about the efficacy of hunting populations for recreation or population management (Storm et al. 2007, Robinson et al. 2008). Combining remote sensing and field data can be used to determine the effects of land cover on the distribution of a species across a large geographic extent. This technique of predicting species presence is effective and has been used at varying geographic extents and with various species including great bustards (*Otis tarda*), Mt. Graham red squirrel (*Tamia sciurus hudsonicus grahamensis*), clouded Apollo butterfly (*Parnassius mnemosyne*), and guanaco (*Lama guanicoe*) (Pereira and Itami 1991, Osborne et al. 2001, Luoto et al. 2002, Travaini et al. 2007).

Predicting species presence using 1 spatial extent (e.g., 1 km^2) may be of limited use because land cover variables may influence use at different extents. Testing the effects of land cover at multiple spatial extents is a common practice in studies of wildlife habitat and can provide insight related to the mechanisms underlying habitat associations (Hall and Mannan 1999, Storch 2002, Altmoos and Henle 2010). The multi-extent approach takes into account the influence of spatial variation on species presence and offers more explanatory power than a single-extent approach (Morris 1987, Levin 1992).

Since the early 1980's, the Atlantic Flyway resident population (AFRP) of Canada geese (*Branta canadensis*) (hereafter referred to as goose) has increased (Dolber et al. 2014). Resident geese provide valuable opportunities for hunting and wildlife viewing, but when present in concentrated-large numbers they create negative human wildlife interactions and pose a risk of zoonotic disease transmission (Graczyk et al. 1998, Kullas et al. 2002, Rutledge et al. 2013). In 2011, because of concern about detrimental impacts of an elevated goose population, the Atlantic Flyway Council set a goal to lower the AFRP to 700,000 birds and redistribute geese more evenly across the landscape using adaptive harvest management (AHM) (Blohm et al. 2006, Atlantic Flyway Council 2011). Yet, this strategy has not reduced the goose population (Figure 1); as of 2015, the Flyway population was stable at around 1 million birds (U.S. Fish and Wildlife Service 2015). Additionally, 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 associate with 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 while 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 resident Canada geese use sites with different water body size and land use type dependent 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 commonly have been used to model goose distributions at a landscape level (Naugle et al. 1997, Donovan et al. 2004, Reiter et al. 2013). However, habitat relationships may occur at varying spatial extents and extent rarely has been addressed when researching Canada goose habitat associations (Conkin and Alisauskas 2013). Further research on habitat associations at different spatial extents may offer a better explanation of goose distribution.

Our objective was to identify land cover features and spatial extents that influence goose occurrence on the landscape. We predicted that developed open space (e.g., golf courses, cemeteries, and other manicured lawns) and open water at smaller spatial extents would have significant effects on goose usage. We identified developed open space and open water as attractants for geese (Smith et al. 1999). We postulated land cover features at varied spatial extents would have different impacts on goose occurrence across the landscape (Conkin and Alisauskas 2013).

Study Area

We conducted goose surveys across North Carolina, which has a total land area of 139,389 km^2. We used the North American Bird Initiative Bird Conservation Regions to describe North Carolina's 3 physiographic regions. The southeastern Coastal Plain consists primarily of riverine swamps and marshes near the Atlantic Ocean and longleaf (*Pinus palustris*), slash (*Pinus elliottii*), and loblolly pine (*Pinus taeda*) forests further inland. The Piedmont consists of pine and mixed hardwood forests and has the largest amount of urbanization in the state. The Appalachian Mountain region consists of oak (*Quercus spp.*) – hickory (*Carya spp.*) forests at lower elevations and hemlock (*Tsuga spp.*) - spruce (*Picea spp.*) forests at higher elevations (North American Bird Initiative 2015).

To focus sampling in areas more likely to have geese, we defined available goose habitat as 1-km^2 plots with any open water or less than 80% forest cover. 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, and Albemarle Sound. The number of 1-km^2 plots that met these criteria was 104,001 (Figure 2), with the majority of the plots located in the Piedmont and southeastern Coastal Plain. We assigned each plot a number and then used a random number generator to choose 300 plots from those available (Figure 3).

Methods

Plot Survey Protocol

We based our survey protocol on a breeding waterfowl population survey used in the northeastern United States (Heusmann and Sauer 1997, Heusmann and Sauer 2000). We surveyed from April 1 - April 30, 2015 to coincide with peek breeding activity of geese in North Carolina. We completed a single observer survey of each plot in its entirety using a variety of methods (e.g., boats, trucks, foot), recording the number of geese observed (Heusmann and Sauer 1997, Heusmann and Sauer 2000, Dunn et al. 2009). We surveyed 27 plots 2 additional times within 5 days of the initial survey to calculate a probability of detection (Mackenzie and Royle 2005). We used the unmarked package in program R (Fiske and Chandler 2011) to calculate detection probability across the 27 plots, which we used to gauge the reliability of estimates at all sites.

GIS Coverage and Covariate Selection

We used ArcGIS 10.2.2 (ESRI, Redlands, California, USA) to quantify percent coverage of 7 variables deemed important for 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 would encompass an array of landscape level effects on the probability of goose presence. We used US Geological Survey National Land Cover Database (NLCD) 2011 to determine percent cover of developed open space, open water, forest cover, pasture/hay, and cultivated crops (Homer et al. 2015). 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 (North Carolina Department of Transportation 2015) to determine percent coverage of municipal boundary (North Carolina Department of Transportation 2015).

We used Analysis of Variance (ANOVA) to test for non-stationarity between survey plots located in different physiographic regions in North Carolina. We used JMP (JMP®, Cary, North Carolina, USA) to determine if there was a difference in the mean number of goose observations among physiographic region.

We tested for collinearity in the 7 habitat variables at all 5 spatial extents using the multivariate methods function in JMP (JMP®, Cary, North Carolina, USA) to calculate

Pearson Correlation Coefficients (PCC). We described covariates to be collinear when $|r| \geq 0.6$, because Dorman et al. (2007) suggested when $|r| > 0.7$ collinearity began to distort model estimation and prediction.

Resident Canada Goose Distribution

We conducted binary logistic regression to model the spatial distribution of geese relative to land cover covariates using the glm function in R to predict conditional probability of encounter (Keating and Cherry 2004, R, version 3.2.1, cran.r-project.org, accessed 12 February 2015). Prior to building models, we tested whether habitat covariates at each of the 5 spatial extents significantly affected goose presence ($p \leq 0.05$). If a habitat covariate did not significantly affect goose presence at a specific spatial extent, it was excluded from the creation of final model sets for model simplicity. To select the combination of habitat covariates and spatial extents that had the greatest effect on goose presence, we ran all possible model combinations of significant habitat and spatial extent covariates without including interaction terms in JMP® (JMP®, Cary, North Carolina, USA). We evaluated support for the models using Akaike's Information Criterion corrected for small sample size (AICc) (Burnham and Anderson 2002). We determined the top model for goose presence by selecting models that had similar ΔAICc values using the MuMIn package and the model > 2 ΔAICc of competing candidate models was considered the top model (Barton 2013).

Prior to fitting the logistic regression model, we tested for spatial autocorrelation within our goose presence and absence data with the model standardized Pearson residuals using the Moran's I tool in ArcGIS 10.2.2 (Carl and Kuhn 2007, ESRI, Redlands, California, USA). 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, we tested the strength of the model to predict goose presence by calculating area-under-the-curve (AUC) using receiver operating characteristic curve (ROC) (JMP®, Cary, North Carolina, USA). The AUC value is equal to the probability 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 the remaining 30% was used 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). We used the best logistic regression model and field calculator in ArcGIS 10.2.2 (ESRI, Redlands, California, USA) to calculate probability of goose presence at each 1-km^2 plot within North Carolina. We used the resulting probabilities to create a predictive map to show where geese were most likely to occur in North Carolina.

Results

We counted 449 geese during initial visits to the 300 plot locations. Geese were observed at 67 (22.33%) survey plots. Goose distribution differed across physiographic strata with 4 occupied plots (6% of plots with observed geese) in the Appalachian Mountains, 34 occupied plots (50.7% of plots with observed geese) in the Piedmont, and 29 occupied plots

(43.3% of plots with observed geese) in the southeastern Coastal Plain. Estimated detection probability was 95.2% at the 27 repeat sample plots.

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. As a result, it was not necessary to account for non-stationarity between survey plots located in different physiographic regions of North Carolina.

The best model for determining presence of 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). Increase in percent open water and percent pasture both increased probability of goose presence (Table 2). The AUC was 0.73, meaning the spatial model correctly predicted goose presence 73% of the time (Figure 4).

Probability of goose presence within the 104,001 plots ranged from 0.0097 – 0.7511, and 4,425 plots had a probability of presence greater than 0.5. High probabilities of goose presence were situated around large water bodies, particularly in areas with pasture (Figure 5). Yet, the predictive map indicated low probability of goose presence in urbanized areas in the Piedmont, where geese are known to be present in high densities.

Discussion

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

However, the distribution model did not perform well in urban areas in the Piedmont, where goose density is known to be high (Heusmann and Sauer 2000). The NLCD often failed to identify the areas of open water in urban areas used as nesting sites by geese (i.e., retention ponds and ditches) (Smith et al. 1999). This likely was because the NLCD uses a 30x30 meter resolution that is not fine grain enough to detect the smaller water bodies common in new development (Chamberlain and Tighe 2009). Also, the random selection of survey plots resulted in proportionally less survey plots (10%) in urban areas than available (17%), which may have reduced capacity to predict urban goose presence. 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, but detection probability in our study was high (Arroita et al. 2010). Mackenzie and Royle (2005) recommended that sampling units should be surveyed a minimum of 3 times to calculate a reliable detection probability. However, the probability of detecting geese at a plot if geese were present was 95.2% in our study. Hence, we suggest making multiple visits to survey plots to estimate detection is unnecessary because it will result in a minimal gain in accuracy with a significant increase in project cost.

The land cover variables that best predicted goose distribution provided 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 geese (Bellrose 1980, Kear 2005). Pasture provides forage during early brood rearing and adult molt as well as additional forage outside of the brood rearing area after birds obtain flight capability (Hanson and Eberhardt 1971). Conversely, developed open space and percent cropland cover had no effect on goose distribution likely because they are less important during the breeding season. Smith et al. (1999) identified developed open space as an attractant for geese, but geese may forage less in these areas during the breeding and brood-rearing season as they spend more time near open water (Hanson and Eberhardt 1971). Agricultural crops are important foraging areas for geese (Bellrose 1980), but agricultural crops are not available during the nesting/brood rearing season in North Carolina as they tend to be warm-season (e.g., corn, soybeans) and have not emerged or are being planted.

The 2 most important land cover predictors were at very different spatial extents. Water was important at the smallest spatial extent because geese were nesting near water sources (Bellrose 1980). Conversely, pasture was important at the larger 9-km^2 spatial extent because adult geese use areas further away from water for foraging. This pairs well with previous research by Rutledge et al. (2013) that documented an average home-range of 9.92 km^2 in central North Carolina, which matched closely the 9-km^2 extent for pasture.

Management Implications

Although the study was conducted during the nesting/brood rearing season, we believe results can be used to concentrate AHM techniques in areas with greater probabilities of goose presence during the Canada goose hunting season. Although Rutledge et al. (2015) showed that home range size of telemetered geese varied seasonally, the mean annual home-range was 9.92 km^2. Hence, resident geese likely would remain in the local area where they were observed year round. Our approach to combine surveys for geese with remote sensing data at multiple spatial extents accurately predicted probability of presence across a large spatial extent and easily could be implemented for resident Canada geese in other regions. Several northeastern US states conduct yearly breeding waterfowl surveys that can be used with these methods to predict goose distributions at a large geographic extent (Heusmann and Sauer 2000). Additionally, we suggest the approach could be used for other game species for which occurrence data is available (e.g., wood duck [*Aix sponsa*], coyotes [*Canis latrans*], and wild turkey [*Meleagris gallopavo*]).

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References

Altmoos, M. and K. Henle. 2010. Relevance of multiple spatial scales in habitat models: a case study with amphibians and grasshoppers. Acta Oecologica 36:548-560.

Arroita, G. G., M. S. Ridout, and B. J. T. Morgan. 2010. Design of occupancy studies with imperfect detection. Methods in Ecology and Evolution 1:131-139.

Atlantic Flyway Council. 2011. Atlantic flyway resident Canada goose management plan.

Barton, K. 2013. MuMIn: multi-model inference, R package version 1.9.13.

Bellrose, F.C. 1980. Ducks, geese, and swans of North America. Third edition. Stackpole Books, Harrisburg, Pennsylvania, USA.

Blohm, R. J., D. E. Sharp, P. I. Padding, R. W. Kokel, K. D. Richkus KD. 2006. Pages 199 – 203 *in* G. C. Boere, C. A. Galbraith, D. A. Stroud, editors. Waterbirds around the World. The Stationary Office, Edinburgh, United Kingdom.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer-Verlag, Berlin, Germany.

Caraco, T. 1980. Stochastic dynamics of avian foraging flocks. American Naturalist 115:262–275.

Carl, G. and I. Kuhn. 2007. Analyzing spatial autocorrelation in species distributions using Gaussian and logit models. Ecological Modelling 207:159-170.

Carriere, S., R. G. Bromley, and G. Gauthier. 1999. Comparative spring habitat and food use by two arctic nesting geese. The Wilson Bulletin 111:166-180.

Certain, G., E. Bellier, B. Planque, and V. Bretagnolle. 2007. Characterizing the temporal variability of the spatial distribution of animals: an application to seabirds at sea. Ecography 30:695–708.

Chamberlain, D. and M. L. Tighe. 2009. Land cover classification: a comparison between U.S. national land cover dataset (NLCD) and Intermap's NEXTMap USA derived land cover maps. Proceedings of ASPRS/MAPPS Fall Conference. San Antonio, Texas, USA.

Cochran, W. G. 1977. Sampling Techniques. 3rd edition, John Wiley and Sons, New York.

Conkin, J. A. and R. T. Alisauskas. 2013. Modeling probability of waterfowl encounters from satellite imagery of habitat in the central Canadian arctic. Journal of Wildlife Management 77:931-946.

Deleo, J. M. 1993. Receiver operating characteristic laboratory (ROCLAB): software for developing decision strategies that account for uncertainty. Pages 318-325 *in* B. M. Ayyub, editor. Proceeding of the second international symposium on uncertainty modelling and analysis. IEEE Computer Society Press, College Park, Maryland, USA.

Dolbeer, R. A., J. L. Seubert, and M. J. Begier. 2014. Population trends of resident and migratory Canada geese in relation to strikes with civil aircraft. Human-Wildlife Interactions 8:88–99.

Donovan, M. L., G. M. Nesslage, J. J. Skillen, and B. A. Maurer. 2004. The Michigan GAP analysis project. Wildlife Division, Michigan Department of Natural Resources, Lansing.

Dormann, C.F., J.M. McPherson, M.B. Araujo, R. Bivand, J. Bolliger, G. Carl, R.G. Davies, A. Hirzel, W. Jetz, W.D. Kissling, I. Kuehn, R. Ohlemueller, P.R. Peres-Neto, B. Reineking, B. Schroeder, F.M. Schurr, and R. Wilson. 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography 30:609–628.

Dunn, J., H. W. Heusmann, T. Nichols, B. Raftovich, B. Swift, and T. Watts. 2009. Atlantic flyway breeding waterfowl survey training manual.

Fiske, I. and R. Chandler. 2011. Unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance. Journal of Statistical Software 43:1-23.

Graczyk, T. K., R. Fayer, J. M. Trout, E. J. Lewis, C. A. Farley, I. Sulaiman, and A. A. Lal. 1998. *Giardia sp.* cysts and infectious *Cryptosporidium parvum* oocysts in the feces of migratory Canada geese (*Branta canadensis*). Applied Environmental Microbiology 64: 2736-2738.

Hall, L. S. and R. E. Mannan. 1999. Multiscaled habitat selection by elegant trogons in Southeastern Arizona. Journal of Wildlife Management 63:451-461.

Hanson, H. C. and L. E. Eberhardt. 1971. A Columbia River Canada goose population. Wildlife Monographs 82.

Hartley, S., R. Harris, and P. J. Lester. 2006. Quantifying uncertainty in the potential distribution of an invasive species: climate and the Argentine ant. Ecology Letters 9: 1068-1079.

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

Hosmer, D.W. and S. Lemeshow. 2000. Applied Logistic Regression, 2nd Edition. John Wiley & Sons Incorporated Publication, New York, New York, USA.

Heusmann, H. W. and J. R. Sauer. 1997. A survey for mallard pairs in the Atlantic Flyway. Journal of Wildlife Management 61:1191-1198.

Heusmann, H. W. and J. R. Sauer. 2000. The northeastern states' waterfowl breeding population survey. Wildlife Society Bulletin 28: 355–364.

Kear, J., editor. 2005. Ducks, geese, and swans. Volume 1. Oxford University Press, New York, New York, USA.

Keating, K. A. and S. Cherry. 2004. Use and interpretation of logistic regression in habitat-selection studies. Journal of Wildlife Management 68:774-789.

Kullas, H., M. Coles, J. Rhyan, and L. Clark. 2002. Prevalence of Escherichia coli serogroups and human virulence factors in feces of urban Canada geese (*Branta canadensis*). International Journal of Environmental Health Research 12:153–162.

Levin, S. A. 1992. The problem of pattern and scale in ecology. Ecology 73:1943-1967.

Luoto, M., M. Kuussaari, and T. Toivonen. 2002. Modeling butterfly distribution based on remote sensing data. Journal of Biogeography 29:1027-1037.

Mackenzie, D. I. and J. A. Royle. 2005. Designing occupancy studies: general advice and allocating survey effort. Journal of Applied Ecology 42:1105-1114.

Manley, S. W., R. M. Kaminski, K. J. Reinecke, and P. D. Gerard. 2004. Water bird foods in winter-managed rice fields in Mississippi. Journal of Wildlife Management 68:74-83.

Morris, D. W. 1987. Ecological scale and habitat use. Ecology 68:362-369.

Naugle, D. E., J. S. Gleason, J. A. Jenks, K. F. Higgins, P. W. Mammenga, and S. M. Nusser. 1997. Factors influencing wetland use by Canada geese. Wetlands 17:552-558.

Nielsen, S. E., G. McDermid, G. B. Stenhouse, and M. S. Boyce. 2010. Dynamic wildlife habitat models: seasonal foods and mortality risk predict occupancy-abundance and habitat selection in grizzly bears. Biological Conservation 143:1623-1634.

North American Bird Conservation Initiative [NABCI]. 2015. NABCI homepage. < http://www.nabci-us.org/>. Accessed 3 Nov 2015.

North Carolina Department of Transportation. 2015. Municipal Boundaries [Polygon Layer]. <http://dotw-xfer01.dot.state.nc.us/GISdot/DistDOTData-Current/State/shpe/MunicipalBoundaries.zip>. Accessed 13 August 2015.

Osborne, P. E., J. C. Alonso, and R. R. Bryant. 2001. Modeling landscape scale habitat use using GIS and remote sensing: a case study with great bustards. Journal of Applied Ecology 38:458-471.

Parris, K. M. and A. Schneider. 2009. Impacts of traffic noise and traffic volume on birds of roadside habitats. Ecology and Society 14:29-52.

Pereira, M. C. and R. M. Itami. 1991. GIS-based habitat modeling using logistic multiple regression: a study of the Mt. Graham red squirrel. Photogrammetric Engineering and Remote Sensing 57:1475-1485.

Piorecky, M. D. and D. R. C. Prescott. 2006. Multiple spatial scale logistic and autologistic habitat selection models for northern pygmy owls, along the eastern slopes of Alberta's Rocky Mountains. Biological Conservation 129:360-371.

Ray, E. 2011. Population Dynamics and Habitat Selection of Resident Urban Canada Geese (*Branta canadensis*) Scottsdale, Arizona. Thesis, Arizona State University, Arizona, USA.

Reiter, M. E., D. E. Anderson, A. H. Raedeke, and D. D. Humburg. 2013. Species associations and habitat influence the range-wide distribution of breeding Canada geese (*Branta canadensis*) on western Hudson Bay. Waterbirds 36:20-33.

Robinson, H. S., R. B. Wielgus, H. S. Cooley, S. W. Cooley. 2008. Sink populations in carnivore management: cougar demography and immigration in hunted population. Ecological Applicatons 18:1028-1037.

Rutledge, M. E., R. M. Siletzky, W. Gu, L. A. Degernes, C. E. Moorman, C. S. DePerno, and S. Kathariou. 2013. Characterization of *Campylobacter* from resident Canada geese in an urban environment. Journal of Wildlife Diseases 49:1–9.

Rutledge, M. E., R. Sollmann, B. E. Washburn, C. E. Moorman, and C. S. DePerno. 2015. Using novel spatial mark-resight techniques to monitor resident Canada geese in a suburban environment. Wildlife Research 41:447-453.

Silverman, E. D., M. Kot and E. Thompson. 2001. Testing a simple stochastic model for the dynamics of waterfowl aggregations. Oecologia 128:608-617.

Silvy, N. J. editor. 2012. The wildlife techniques manual. Seventh edition. The Johns Hopkins University Press, Baltimore, Maryland, USA.

Smith, A. E., S. R. Craven, and P. D. Curtis. 1999. Managing Canada geese in urban environments. Jack Berryman Institute Publication 16, and Cornell University Cooperative Extension, Ithaca, New York, USA.

Storch, I. 2002. Linking a multi-scale habitat concept to species conservation. Pages 303-320 *in* J. Bissonette and I. Storch, editors. Landscape Ecology and Resource Managemtn Linking Theory with Practice. Island Press, Washington, D.C., USA.

Storm, D. J., C. K. Nielsen, E. M. Schauber, and A. Woolf. 2007. Deer-human conflict and hunter access in an exurban landscape. Human-Wildlife Conflicts 1:53-59.

Travaini, A., J. Bustamante, A. Rodriguez, S. Zapta, D. Procopio, J. Pedrana, R. M. and Peck. 2007. An integrated framework to map animal distributions in large remote regions. Diversity and Distributions 13:289-298.

Tuanmu, M. N., A. Vina, G. J. Rologg, W. Liu, Z. Ouyang, H. Zhang, and J. Liu. 2011. Temporal transferability of wildlife habitat models: implications for habitat monitoring. Journal of Biogeography 38:1510-1523.

U.S. Fish and Wildlife Service. 2015. Waterfowl Population Status, 2015.

Vicente, J., C. F. Randin, J. Goncalves, M. J. Metzger, A. Lomba, J. Honrado, and A. Guisan. 2011. Where will conflicts between alien and rare species occur after climate and land-use change? A test with a novel combined modeling approach. Biological Invasions 13:1209-1227.

Waddle, J. H., K. G. Rice, and H. F. Percival. 2003. Using personal digital assistants for collection of wildlife field data. Wildlife Society Bulletin 31:306-308.

Xian, G., C. Homer, J. Dewitz, J. Fry, N. Hossain, and J. Wickham. 2011. The change of impervious surface area between 2001 and 2006 in the conterminous United States. Photogrammetric Engineering and Remote Sensing 77:758-762.

Table 1. The number of parameters (K), AICc, ΔAICc, and model weight (ω) for models with significant covariate combinations of percent open water (spatial extents: 1 km^2, 9 km^2, 81 km^2) and percent pasture (spatial extents: 1 km^2, 9 km^2, 81 km^2) for the top 10 models and null model of Canada goose presence, North Carolina (2015).

Model	K	AICc	ΔAICc	ω
Water1 + Pasture9	2	285.4	0	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
Water9 + Pasture81	2	302.2	16.86	0
Water81 + Pasture9	2	308	22.64	0
Water81 + Pasture81	2	308.3	22.92	0
Water9 + Pasture1	2	309	23.62	0
Pasture9	1	314.9	29.51	0
Null	0	323.1	37.78	0

Table 2. Posterior means and 95% credible intervals of parameter estimates (on log scale) for the top-ranked model of Canada geese presence, North Carolina (2015).

Parameter	Mean	2.50%	97.50%
Percent Water 1km	0.31	0.2	0.43
Percent Pasture 9km	0.4	0.23	0.59

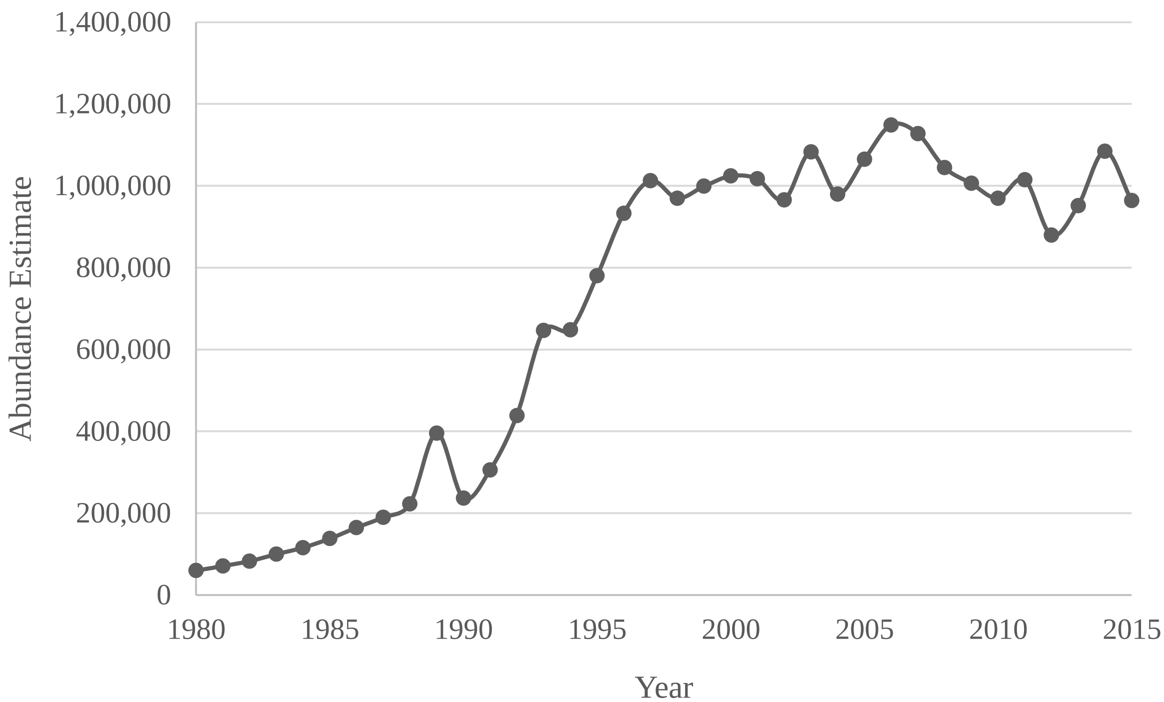

Figure 1. US Fish and Wildlife Service Atlantic flyway resident Canada goose abundance estimates from 1980 – 2015 (Dolber et al. 2014, U.S. Fish and Wildlife Service 2015).

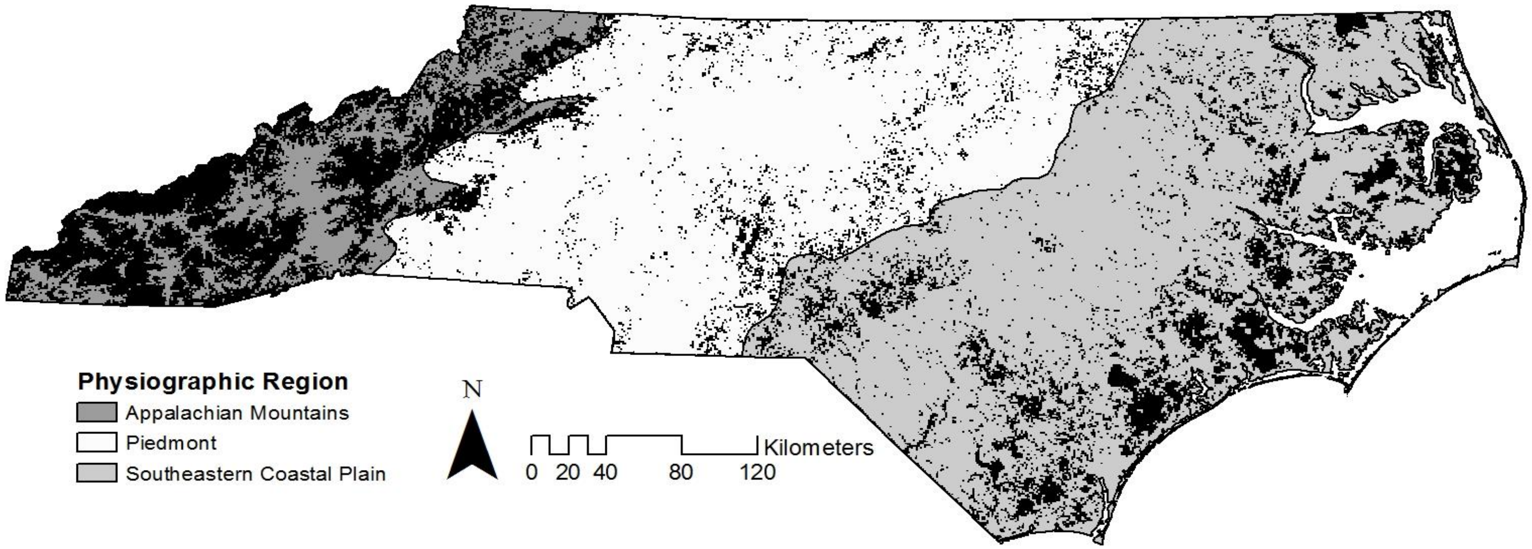

Figure 2. Physiographic region and non-habitat and potential habitat for Canada goose developed before the random plot selection, North Carolina (2015).

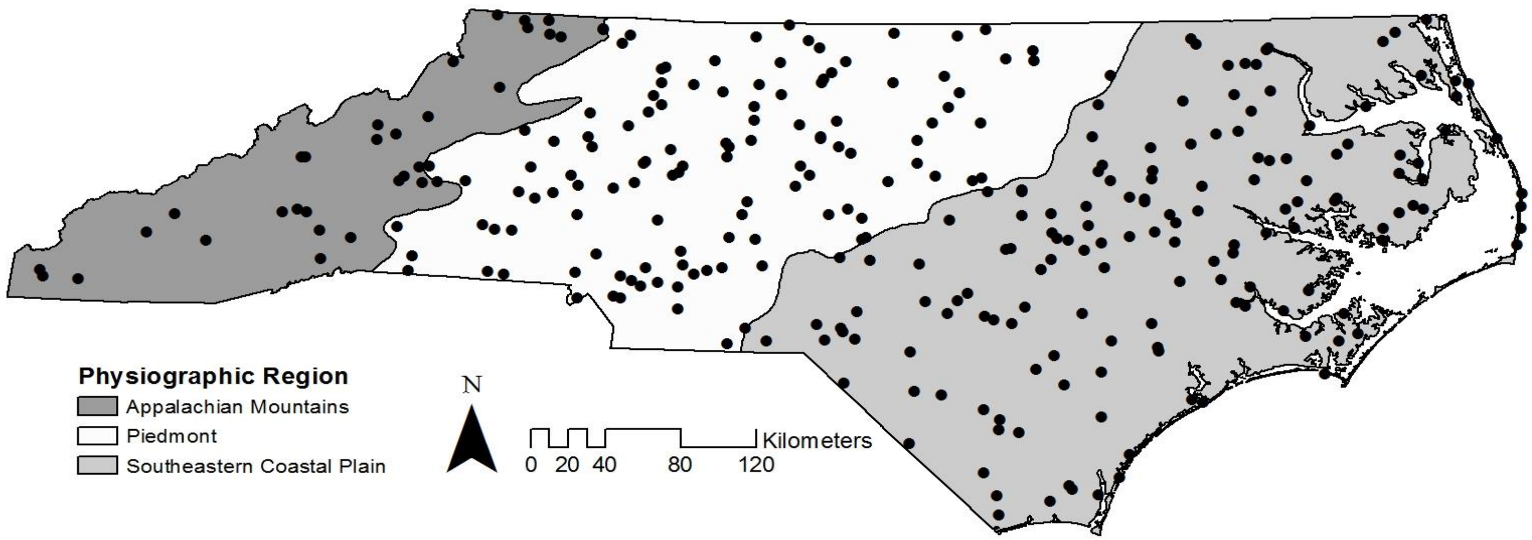

Figure 3. Physiographic regions and location of 300 1-km^2 plots surveyed, North Carolina April (2015).

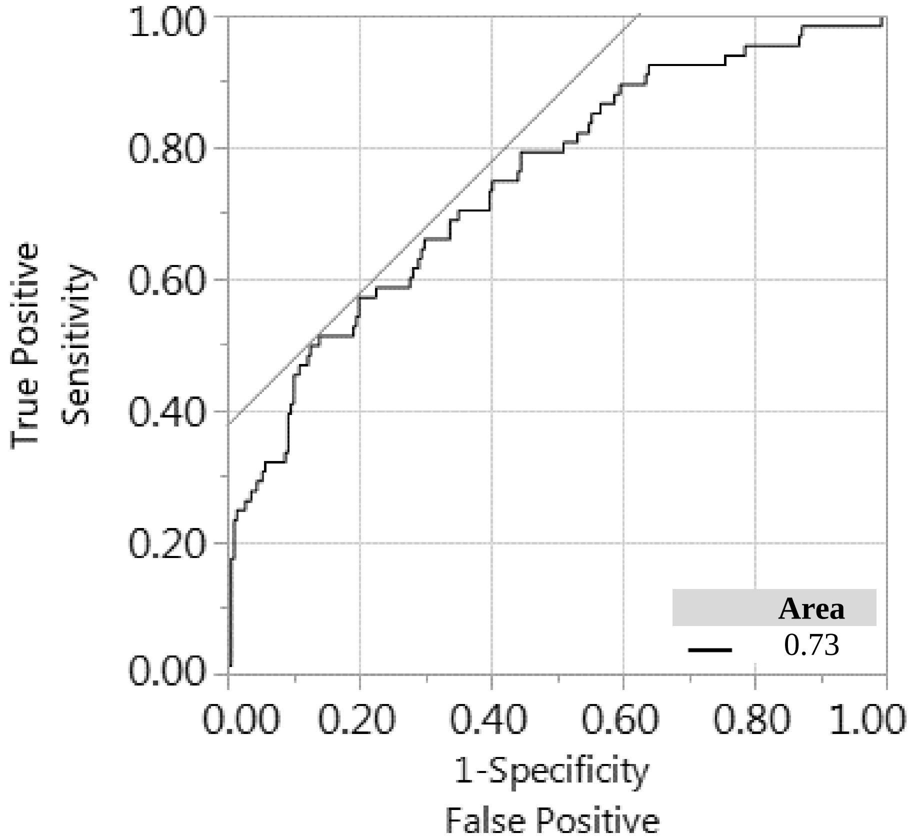

Figure 4. Receiver operating characteristic (ROC) curve testing the strength of the best model to predict goose presence, North Carolina (2015).

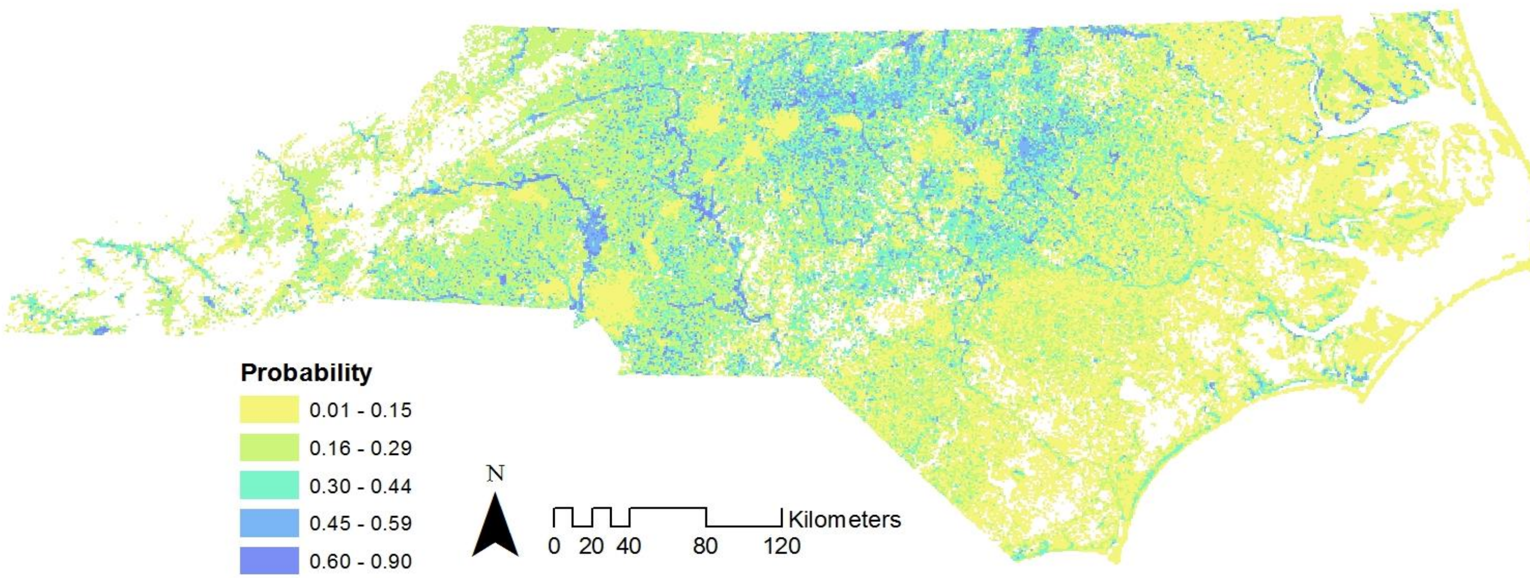

Figure 5. Predictive map of Canada goose presence using best fit model with parameters percent pasture within the 9 km^2 surrounding the survey plot and percent open water within the 1-km^2 survey plot. White area removed *a priori* assuming no geese present in non-goose habitat, North Carolina April (2015).