

Chapter 16: Modeling species assignment in strip transect surveys with uncertain species identification

Final Report to the Department of Energy Wind and Water Power
Technologies Office, 2015

Nathan J. Hostetter¹, Beth Gardner¹, Andrew T. Gilbert², Emily E. Connelly², and
Melissa Duron²

¹North Carolina State University, Department of Forestry and Environmental Resources, Raleigh, NC

²Biodiversity Research Institute, Portland, ME

Project webpage: www.briloon.org/mabs

Suggested citation: Hostetter NJ, Gardner B, Gilbert AT, Connelly EE, Duron M. 2015. Modeling species assignment in strip transect surveys with uncertain species identification. In: Wildlife Densities and Habitat Use Across Temporal and Spatial Scales on the Mid-Atlantic Outer Continental Shelf: Final Report to the Department of Energy EERE Wind & Water Power Technologies Office. Williams KA, Connelly EE, Johnson SM, Stenhouse IJ (eds.) Award Number: DE-EE0005362. Report BRI 2015-11, Biodiversity Research Institute, Portland, Maine. 15 pp.

Acknowledgments: This material is based upon work supported by the Department of Energy under Award Number DE-EE0005362. Additional funding support came from the Maryland Energy Administration and Maryland Department of Natural Resources. HiDef Aerial Surveying, Inc., Dr. Richard Veit (College of Staten Island), and Capt. Brian Patteson made significant contributions towards the completion of this study.

Disclaimers: This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

The statements, findings, conclusions, and recommendations expressed in this report are those of the author(s) and do not necessarily reflect the views of the Maryland Department of Natural Resources or the Maryland Energy Administration. Mention of trade names or commercial products does not constitute their endorsement by the State.

NC STATE
UNIVERSITY



Chapter 16 Highlights

Modeling loon species assignment in digital video aerial surveys with uncertain species identifications

Context¹

High resolution digital video aerial surveys provide numerous advantages to monitoring marine bird abundance and distribution across large spatial areas. In some situations, however, low species identification rates in aerial surveys pose a major challenge when species-specific metrics are of management and conservation interest. While several chapters in Part IV of this report focus on estimating abundance and habitat relationships, this chapter focuses on integrating information from boat-based surveys, with high species identification rates, into a species assignment model to predict species identity in high resolution digital video aerial data.

Common and Red-throated Loons were chosen as the focal species for Chapter 16, due in part to differences in the conservation status of the two species, as well as evidence from Europe of the sensitivity of Red-throated Loons to offshore wind energy development. Loons had low species identification rates in aerial surveys, but high species identification rates in boat surveys. Chapter 19, which focused on combining data from the two survey types, models loons as a genus rather than each species independently, because of the low species identification rate in the aerial data. However, this chapter's results were used to develop species-specific maps of persistent hotspots (see Chapter 17), and it could be used to inform other joint modeling approaches.

Study goal/objectives

Investigate three approaches to modeling species assignment in digital video aerial surveys where species identity was not always completely observed (i.e., some individuals were identified to genus, but not species).

Highlights

- Species identity predictions were qualitatively similar across all three prediction approaches.
- The majority of unidentified loons were assigned as Common Loons, but species assignment varied by survey and with habitat covariates.
- Distance to shore was the strongest habitat predictor of species identity. The probability of assigning an unidentified loon as a Red-throated Loon noticeably decreased with distance from shore.

Implications

Species identification models can assist in prioritizing areas important to specific species of conservation concern, even if current technology cannot identify all observations to the species level. Species-specific conclusions may be of particular interest for Red-throated Loons, which are designated as a species of conservation concern by the U.S. Fish and Wildlife Service.

¹ For more detailed context for this chapter, please see the introduction to Part III of this report.

Abstract

Passive survey techniques (e.g., digital aerial surveys) are increasingly used by ecological monitoring programs. High resolution digital video aerial surveys have tremendous potential to aid in monitoring marine bird abundance and distribution across large spatial areas. Low species identification rates in video aerial surveys, however, pose a major challenge when species-specific metrics are of management and conservation interest. For instance, Red-throated Loons are identified by the US Fish and Wildlife Service as the highest priority open-water species for conservation in the mid-Atlantic US, while global populations of Common Loons are generally considered healthy (see Chapters 2 and 21). Species-specific identification rates of loons in high resolution digital video aerial surveys, however, were low in this study, prohibiting estimates of loon species-specific abundance via this survey method (see Chapter 5). In this chapter, we combine data collected during boat and high resolution digital video aerial surveys to evaluate loon species proportions, important spatial covariate predictors of species proportions, and predicted species assignment of unidentified loons. Boat surveys identified $\geq 95\%$ of individual loons to species (Common Loon or Red-throated Loon) during each survey, and high resolution digital video aerial surveys identified 3% - 63% of individual loons to species during each survey (see Chapters 5 and 8). For each unidentified loon observation in the aerial data, species identity was predicted using three approaches: 1. species proportions from boat data; 2. species proportions from aerial data; and 3. species proportions as a function of spatially varying covariates. Predicted species assignments of unidentified loons in aerial surveys were qualitatively similar across all three prediction approaches, and generally indicated the majority of unidentified loons were Common Loons. However, results provided strong evidence that spatially varying covariates were important predictors of loon species proportions. Distance to shore was correlated with increased Common Loon proportions across all surveys. Sea surface temperature, grain size, and salinity were also important predictors of species proportions, but the nature of these relationships varied by season. Overall, results suggest that joint modeling of boat and aerial data may provide a useful approach to estimate species-specific metrics such as abundance (see Chapters 5, 8, and 12) and the locations of persistent hotspots (see Chapter 17) when species identification rates are low.

Introduction

Passive monitoring techniques (e.g., digital aerial surveys) are rapidly being incorporated in to numerous ecological monitoring and research programs (Buckland et al. 2012, Conn et al. 2014, Johnston et al. 2015). Surveys of marine birds using high resolution digital video aerial surveys (hereafter “digital video aerial surveys”) are increasingly used to monitor species-specific abundance and distribution (Buckland et al. 2012, Johnston et al. 2015). Digital video aerial surveys provide several important advantages compared to boat-based surveys, including increased spatial coverage, reduced survey time, increased safety and reduced disturbance (Buckland et al. 2012). Digital video aerial surveys also have notable weaknesses, however, such as low species identification rates relative to boat surveys (Johnston et al. 2015).

Species-specific marine bird abundances are increasingly important due to interest in renewable energy development in nearshore and offshore waters of the United States (Winiarski et al. 2014). Common

Loons (*Gavia immer*) and Red-throated Loons (*Gavia stellata*) are two species of particular interest due to their known or suspected sensitivity to displacement from offshore wind energy development (Halley and Hopshaug 2007, Petersen et al. 2006, Furness et al. 2013, Langston 2013). Currently, Red-throated Loons are known to be sensitive to displacement from areas around offshore wind energy developments, but there is limited species-specific information on Common Loons (Petersen et al. 2006, Furness et al. 2013). Additionally, conservation status varies between Common Loons and Red-throated Loons. The U.S. Fish and Wildlife Service designated Red-throated Loons as a “species of conservation concern” on their wintering grounds along the New England and Mid-Atlantic Coast (USFWS 2008). Common Loon populations, however, are seen as stable, and the species is no longer on the national list of Birds of Conservation Concern (Chapters 2 and 21; Evers 2004, USFWS 2008, Evers 2010). Common Loons and Red-throated Loons wintering in the mid-Atlantic United States have wide overlap in body size (Barr et al. 2000, Gray et al. 2014), which may reduce species identification rates in digital video aerial surveys. Aerial survey observations of loons identified to genus (*Gavia* spp.) but not to species provide valuable information on loon abundance and distribution, but pose a major challenge when estimating species-level hotspots (see Chapter 17) or abundance (Johnston et al. 2015).

In this study, we investigate three approaches to model species identity assignment in surveys with uncertain species identification. Our case study focuses on Common Loons and Red-throated Loons during the winter and spring of 2012 and 2013. Loons provided a unique opportunity to investigate uncertain species identification in digital video aerial surveys due to low species identification rates in aerial surveys (see Chapter 5), but high species identification rates in corresponding boat surveys (see Chapter 8). Boat and digital video aerial surveys were conducted during each season and provided information on species- and genus-level observations within the surveyed area. We hypothesized that boat surveys would provide important information to predict species identification in aerial surveys, which often suffered from low species identification rates. Investigation of methods that use both datasets are important first steps in developing broader approaches to estimate species-specific abundance from surveys with uncertain species identification.

Methods

Boat and aerial surveys were conducted off the coast of Delaware, Maryland, and Virginia (Figure 16-1) from March 2012 to May 2014. During each boat survey, observers recorded data on species identification, number of individuals observed, and locations of observations (see Chapter 7 for details). Digital video aerial surveys recorded similar metrics, but were completed using four high resolution digital video cameras, each surveying a 50 m strip width (total strip width = 200 m). Video data were manually reviewed to record species identification, number of individuals observed, and locations (see Chapter 3 and Chapter 4 for details). For analysis, each transect was divided into 4-km segments and the number of observed loons in a segment was summed by species identification (Common Loon, Red-throated Loon, or unidentified loon). Boat and aerial data collected during similar times of year were compared to reduce possible differences across seasons. Specifically, we paired boat and aerial surveys that occurred during April-May 2012, December 2012, March 2013, and December 2013 (Table 16-1). April-May 2012 surveys included two months, but boat and aerial surveys were separated by <2 weeks (boat and aerial surveys occurred on 25-29 April and 6-7 May, respectively).

Analysis was conducted in two principal stages: estimation of observed species proportions, and prediction of species identity. Spatially referenced boat and aerial data allowed investigation of three approaches to predict species identity, including: 1. species proportions from boat data; 2. species proportions from aerial data; and 3. species proportions as a function of spatially varying covariates.

Species proportions

During boat surveys, $\geq 95\%$ of all observed loons were identified to species and the remaining $\leq 5\%$ were excluded from analysis (following the protocol of Johnston et al. 2015). Digital video aerial surveys, however, had lower species identification rates generally and were thus comprised of a large number of unidentified loons, which were retained for analysis (Table 16-1, Figure 16-2).

Survey and segment specific proportions of Common Loons and Red-throated Loons were modeled using generalized linear models with a binomial distribution. For Models 1 and 2, which estimated the species proportions based on boat and aerial data, the counts of Common Loons at segment i , y_i , was defined such that:

$$y_i \sim \text{Binomial}(p, N_i)$$

where N_i is the total number of identified Loons (Common Loons and Red-throated Loons) in segment i , and p is the probability that the observation in segment i was a Common Loon. Analyses were conducted separately for each survey date and type (boat and aerial). For each analysis, the estimates of species proportions were assumed to be constant within a survey.

Next, we fit a series of models that allowed species proportions to vary as a function of spatial covariates. We used six covariates in our analyses: three static (distance to shore [DTS], slope, and grain size), and three dynamic (sea surface temperature [SST], salinity [Sal], and chlorophyll-a [Chlor]). The full model for spatially varying species proportions included all six covariates:

$$y_i \sim \text{Binomial}(p_i, N_i)$$

$$\text{logit}(p_i) = \beta_0 + \beta_1 \text{DTS}_i + \beta_2 \text{SST}_i + \beta_3 \text{Chlor}_i + \beta_4 \text{Sal}_i + \beta_5 \text{Slope}_i + \beta_6 \text{Grain}_i$$

For the static covariates, we calculated distance to shore (m) within ArcGIS (ESRI, Redlands, CA) and extracted slope (% rise, 370-m resolution) and grain size ($\phi = -\log_2[\text{mean grain diameter in mm}]$, 370-m resolution) from the data layer derived by NOAA/NOS National Centers for Coastal Ocean Science (Kinlan et al. 2013). For the dynamic covariates, we used Marine Geospatial Ecology Tools in ArcGIS (Roberts et al. 2010) to download remotely-sensed data at the highest resolution available for all segments. We compiled daily values for sea surface temperature ($^{\circ}\text{C}$, 1-km GHRSSST L4) and salinity (Practical Salinity Units, 9-km HYCOM GLBa0.08 Equatorial 4D). Due to missing data along the shoreline at higher resolutions, we used monthly composites of chlorophyll concentration (mg/cubic m, 4-km NASA Ocean Color L3 SMI Aqua). Observations without complete covariate information were excluded from analysis. For each of the four paired surveys, we compared all possible subsets of the full model using AIC_c (Burnham and Anderson 2002). Results are presented as model-averaged parameter estimates as each survey included multiple competing models (Burnham and Anderson 2002).

Predicting species identity

For digital video aerial surveys, where it was not possible to always identify observations to species, unidentified loons were assigned a species (Common Loon or Red-throated Loon) based on the previously estimated species proportions. This resulted in three estimates of predicted species assignment based on: 1. species proportions from boat data (approach 1); 2. species proportions from aerial data (approach 2); and 3. species proportions using spatial covariates (approach 3). Spatial covariate predictions were derived from model-averaged parameter estimates and predicted to covariate values located at the midpoint of each aerial transect segment. The observational nature of this study did not allow for validation of prediction approaches. Results for all three prediction approaches are therefore presented and compared. All analyses were conducted in R version 3.0 (R Development Core Team 2013).

Results

Species proportions

The total number of observed loons varied by survey, ranging from 320 individuals to >1,300 individuals (Table 16-1, Figure 16-2). Total loon counts were higher in winter surveys (December) compared to spring surveys (March and April; Figure 16-2). Species identification rates were always $\geq 95\%$ in boat surveys, but varied from 3% – 63% in aerial surveys (Table 16-1, Figure 16-2). Species proportions also varied by survey (Figure 16-3). For instance, Common Loons comprised >90% of identified loon species in both boat and aerial surveys during December 2013 (Figure 16-3). In March 2013, however, Common Loon proportions were much lower in boat surveys (~40%) as compared to aerial surveys (>70%; Figure 16-3).

Species proportions also varied across the surveyed area (Figure 16-4). Model-averaged parameter estimates provided strong evidence that species proportions of Common Loons and Red-throated Loons varied as a function of spatial covariates (Table 16-2). Distance to shore was the strongest spatial predictor of species proportions, and indicated proportions of Common Loons increased as distance to shore increased (Table 16-2, Figure 16-4). Sea surface temperature was also a significant predictor of species proportions, but results were season-specific (Table 16-2). In spring surveys, proportions of Common Loons increased as sea surface temperature increased, but during winter surveys Common Loon proportions decreased as sea surface temperature increased (Table 16-2). Grain size and salinity were also significantly correlated with species proportions during at least two surveys (Table 16-2). Similar to sea surface temperature, however, relationships were opposite during spring (negative) and winter (positive) surveys (Table 16-2). Effects of chlorophyll a and slope varied across surveys, but model-averaged parameter estimates for these covariates often overlapped zero (Table 16-2).

Predicting species identity

Overall predictions of species identity by survey were qualitatively similar across all three prediction approaches (Figure 16-5). All three prediction approaches (aerial proportions, boat proportions, and spatial covariate relationships) assigned the majority of unidentified loons as Common Loons (Table 16-3, Figure 16-5). March 2013 was the lone exception, where boat proportions and spatial covariate approaches predicted more Red-throated Loons than Common Loons, while aerial proportions predicted

more Common Loons (Table 16-3, Figure 16-5). Differences in predicted species identity during March 2013 surveys reflected differences in observed proportions during boat and aerial surveys (Figure 16-3) and low numbers of identified loons during aerial surveys ($n = 14$ loons identified to species during aerial surveys; Table 16-1).

Predicted numbers of individual Common Loons and Red-throated Loons within each transect were generally much greater than the observed numbers, due to assignment of unidentified loons to a species (Table 16-3). Increased species-specific numbers were most dramatic in December 2012, March 2013, and December 2013, due to low rates of species identification and high numbers of observed loons in aerial surveys (Table 16-3). For instance, 84 Common Loons were identified in December 2012 (Table 16-3), while 556 were classified as unidentified loons during that same survey. Species predictions for those unidentified loons resulted in predictions ranging from 402 Common Loons (95% CI 357-445) using aerial proportion predictions to 519 (95% CI 461-562). Common Loons using spatial covariate predictions (Table 16-3). Conversely, in April 2012, there were 45 individuals identified to Red-throated Loon, and the mean predicted number of Red-throated Loons was 46 – 71. Thus the predicted value was similar to the observed, i.e., only 1 – 26 individuals more than the number actually identified during aerial surveys (Table 16-3).

Discussion

Uncertain species identification, currently common in digital aerial surveys, presents a major challenge when estimating species-specific abundance (Conn et al. 2013, Johnston et al. 2015). In some situations, technological solutions to improve species identification (such as higher camera resolution or other equipment modifications) may be available to improve species identification rates. In other these situations, model-based approaches that account for species uncertainty may be more efficient and feasible approaches to estimate species-specific abundances (Johnston et al. 2015).

The approaches we used to assign species identity included relative species proportions from boat and aerial surveys and spatial covariates. These approaches were rather simplistic given the numerous sources of uncertainty that may arise from these types of surveys. For instance, false identification rates were assumed to be zero. False identification rates in either survey, however, would inflate identification rates and bias results to an unknown degree. Further, detection and availability probabilities were assumed to be similar across species. High altitude digital aerial surveys may reduce disturbances that may alter species behavior, but species-specific detection remains confounded with actual species proportions. For boat surveys, distance sampling is often used to account for imperfect detection probability (Buckland et al. 2001). Recently, integrated modeling of line and strip transect surveys have begun to address uncertain species identification (Conn et al. 2013; Johnston et al. 2015). A particular advantage of these recent approaches is their ability to propagate uncertainty at each level, resulting in final estimates of density that account for each source of uncertainty (Johnston et al. 2015). Joint modeling approaches that directly account for uncertain species identification improve our ability to utilize multiple sources of information, and ultimately identify important drivers of species abundance and distribution.

Incorporating spatial covariates allowed species assignments to be informed by underlying habitat characteristics. In this study, distance to shore, sea surface temperature, grain size, and salinity were strong predictors of loon species proportions. These relationships suggested that assignment of unidentified loons may be improved if observation locations (and associated covariate values) are known. Relationships between species proportions and spatial covariates often changed in strength and direction between seasons. The lack of consistent relationships implies that joint models should be cautious about integrating data collected during different temporal periods. Most boat and aerial surveys in this study were separated by <2 weeks, which based on temporal variability of environmental covariates used in our models was likely adequate to meet these assumptions. Coordinated efforts to overlap surveys in both space and time may provide several benefits, including reduced differences in dynamic covariates between surveys (e.g., sea surface temperature) and direct comparisons of survey-specific results.

Uncertain species identification in digital video aerial surveys was evident across several species in this study (e.g., gulls, terns, scoters; see Chapter 5). Loon species identification rates in digital video aerial surveys, however, were some of the lowest for any avian taxon (see Chapter 14). As a result, loons provided a unique opportunity to investigate uncertain species identification in digital video aerial surveys due to the low species identification rates in digital video aerial surveys, but high species identification rates in corresponding boat surveys (Figure 16-2).

Ecological studies are increasingly using passive monitoring techniques, which provide numerous advantages, but often suffer from low species identification rates (Conn et al. 2013; Johnston et al. 2015). Joint models that integrate multiple sources of data may provide useful model-based methods to estimate species-specific abundance and distribution. Future studies should consider expanding these methods to address >2 species (e.g., gulls and terns), uncertain species identification in both boat and aerial surveys (e.g., scoters), and methods to validate model results.

Ongoing applications

We have integrated approaches developed in this chapter with lease block hotspot mapping (see Chapter 17), allowing us to identify species-specific hotspots even when aerial surveys cannot perfectly assign species. Species assignment approaches were investigated for other species (e.g., scoters), but will require more complex approaches due to imperfect species identification in both video aerial and boat surveys. Exploration of methods to incorporate uncertain species identification in integrated boat and aerial models (Chapter 19) is a possible topic for future research, especially as digital video aerial surveys increase in application.

Literature cited

- Barr, J.F., Eberl, C., & McIntyre, J.W. 2000. Red-throated Loon (*Gavia stellata*). No. 513 in The Birds of North America Online (A. Poole, Ed.). Cornell Lab of Ornithology, Ithaca, NY. Retrieved from the Birds of North America Online, 16 January 2015: <http://bna.birds.cornell.edu/bna/species/513>.
- Buckland, S.T. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press.
- Buckland, S.T., Burt, M.L., Rexstad, E.A., Mellor, M., Williams, A.E., & Woodward, R. 2012. Aerial surveys of seabirds: the advent of digital methods. *Journal of Applied Ecology* 49: 960–967.
- Burnham, K.P., & Anderson, D.R. 2002. Model selection and inference - a practical information-theoretic approach., Second edition. ed. Springer-Verlag, New York, New York.
- Conn, P.B., McClintock, B.T., Cameron, M.F., Johnson, D.S., Moreland, E.E., & Boveng, P.L. 2013. Accommodating species identification errors in transect surveys. *Ecology* 94: 2607–2618.
- Conn, P.B., Ver Hoef, J.M., McClintock, B.T., Moreland, E.E., London, J.M., Cameron, M.F., Dahle, S.P., & Boveng, P.L. 2014. Estimating multispecies abundance using automated detection systems: ice-associated seals in the Bering Sea. *Methods in Ecology and Evolution* 5: 1280–1293.
- Evers, D.C. 2004. Status assessment and conservation plan for the Common Loon (*Gavia immer*) in North America. U.S. Fish and Wildlife Service, Hadley, MA.
- Evers D.C., Paruk J.D., McIntyre J.W., & Barr J.F. (2010) Common Loon (*Gavia immer*). In: Poole A (ed.) Birds of North America Online. Cornell Lab of Ornithology, Ithaca, NY.
- Furness, R.W., Wade, H.M., & Masden, E.A. 2013. Assessing vulnerability of marine bird populations to offshore wind farms. *Journal of Environmental Management* 119: 56–66.
- Gray, C.E., Paruk, J.D., DeSorbo, C.R., Savoy, L.J., Yates, D.E., Chickering, M.D., Gray, R.B., Taylor, K.M., Long, D., Schoch, N., Hanson, W., Cooley, J., & Evers, D.C. 2014. Body Mass in Common Loons (*Gavia immer*) strongly associated with migration distance. *Waterbirds* 37: 64–75.
- Halley, D.J., & Hopshaug, P. 2007. Breeding and overland flight of Red-throated divers *Gavia stellata* at Smøla, Norway, in relation to the Smøla wind farm. NINA Report 297. 32 pp.
- Johnston, A., Thaxter, C.B., Austin, G.E., Cook, A.S.C.P., Humphreys, E.M., Still, D.A., Mackay, A., Irvine, R., Webb, A., & Burton, N.H.K. 2015. Modelling the abundance and distribution of marine birds accounting for uncertain species identification. *Journal of Applied Ecology* 52: 150–160.
- Kinlan, B. P., Poti, M., Drohan, A., Packer, D.B., Nizinski, M., Dorfman, D., & Caldow, C. 2013. Digital data: Predictive models of deep-sea coral habitat suitability in the U.S. Northeast Atlantic and Mid-Atlantic regions. Downloadable digital data package. Department of Commerce (DOC), National Oceanic and Atmospheric Administration (NOAA), National Ocean Service (NOS), National Centers for Coastal Ocean Science (NCCOS), Center for Coastal Monitoring and Assessment (CCMA), Biogeography Branch. Released August 2013. Available at: <http://coastalscience.noaa.gov/projects/detail?key=35>

- Langston, R.H.W. 2013. Birds and wind projects across the pond: A UK perspective. *Wildlife Society Bulletin* 37: 5–18.
- Petersen, I. K., Christensen, T.K. , Kahlert, J., Desholm, M., & Fox, A. D. 2006. Final results of bird studies at the offshore wind farms at Nysted and Horns Rev, Denmark. Technical report published by the National Environmental Research Institute, Ministry of the Environment, Denmark.
- R Core Team. 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org/>.
- Roberts, J., Best, B., Dunn, D., Treml, E., & Halpin, P. 2010. Marine Geospatial Ecology Tools: An integrated framework for ecological geoprocessing with ArcGIS, Python, R, MATLAB, and C++. <http://mgel.env.duke.edu/mget>
- U.S. Fish and Wildlife Service. 2008. Birds of Conservation Concern 2008. United States Department of Interior, Fish and Wildlife Service, Division of Migratory Bird Management, Arlington, Virginia.
- Winiarski, K.J., Burt, M.L., Rexstad, E., Miller, D.L., Trocki, C.L., Paton, P.W.C., & McWilliams, S.R. 2014. Integrating aerial and ship surveys of marine birds into a combined density surface model: A case study of wintering Common Loons. *The Condor* 116: 149–161.

Figures and tables

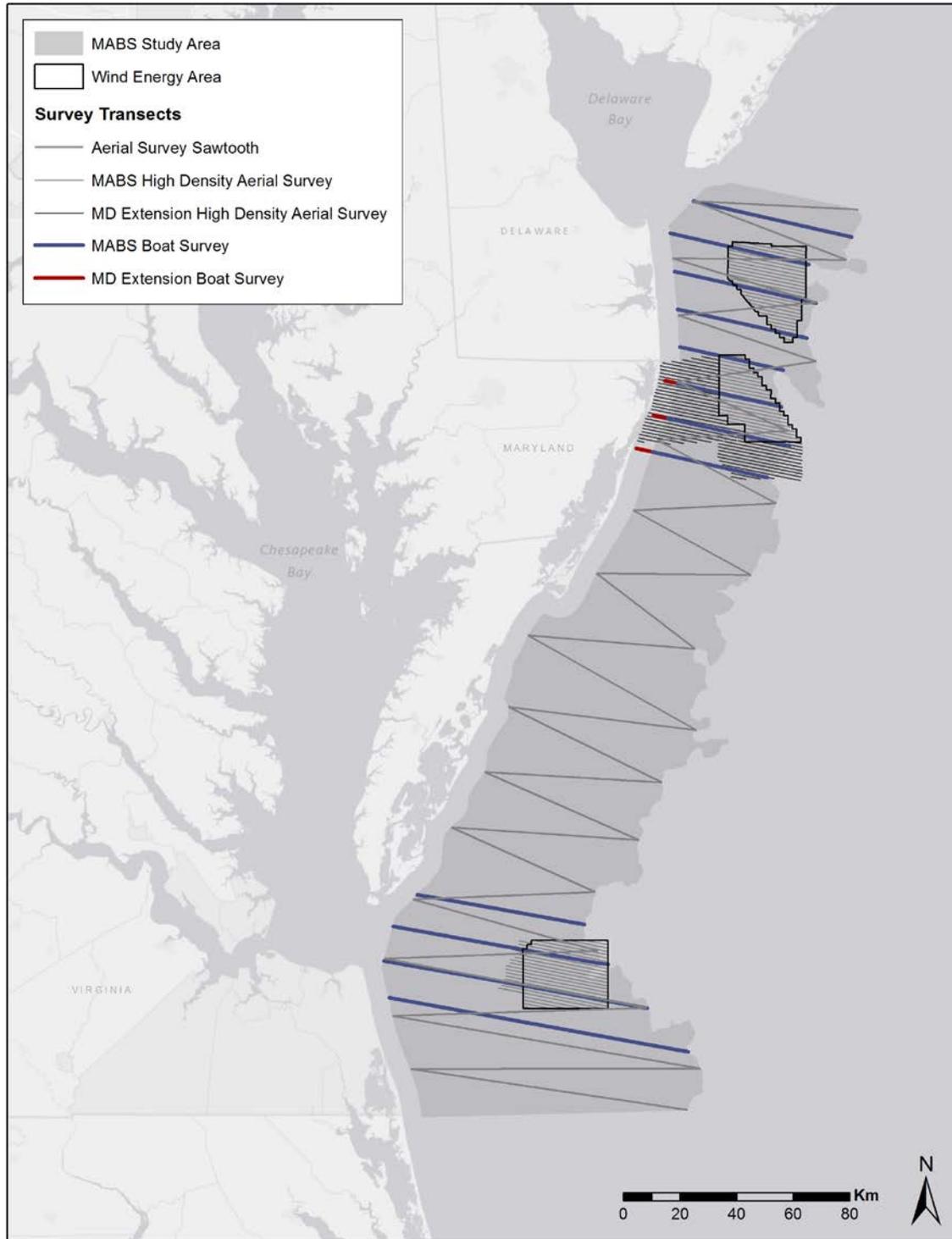


Figure 16-1. Study area. Boat transects are shown in blue and red and aerial transects in light and dark grey; Maryland extension transects (funded by the state of Maryland and conducted only in the second year of surveys) are shown in red and dark grey. Department of Energy (DOE)-funded high-density aerial surveys were located within federally designated wind energy areas (WEAs).

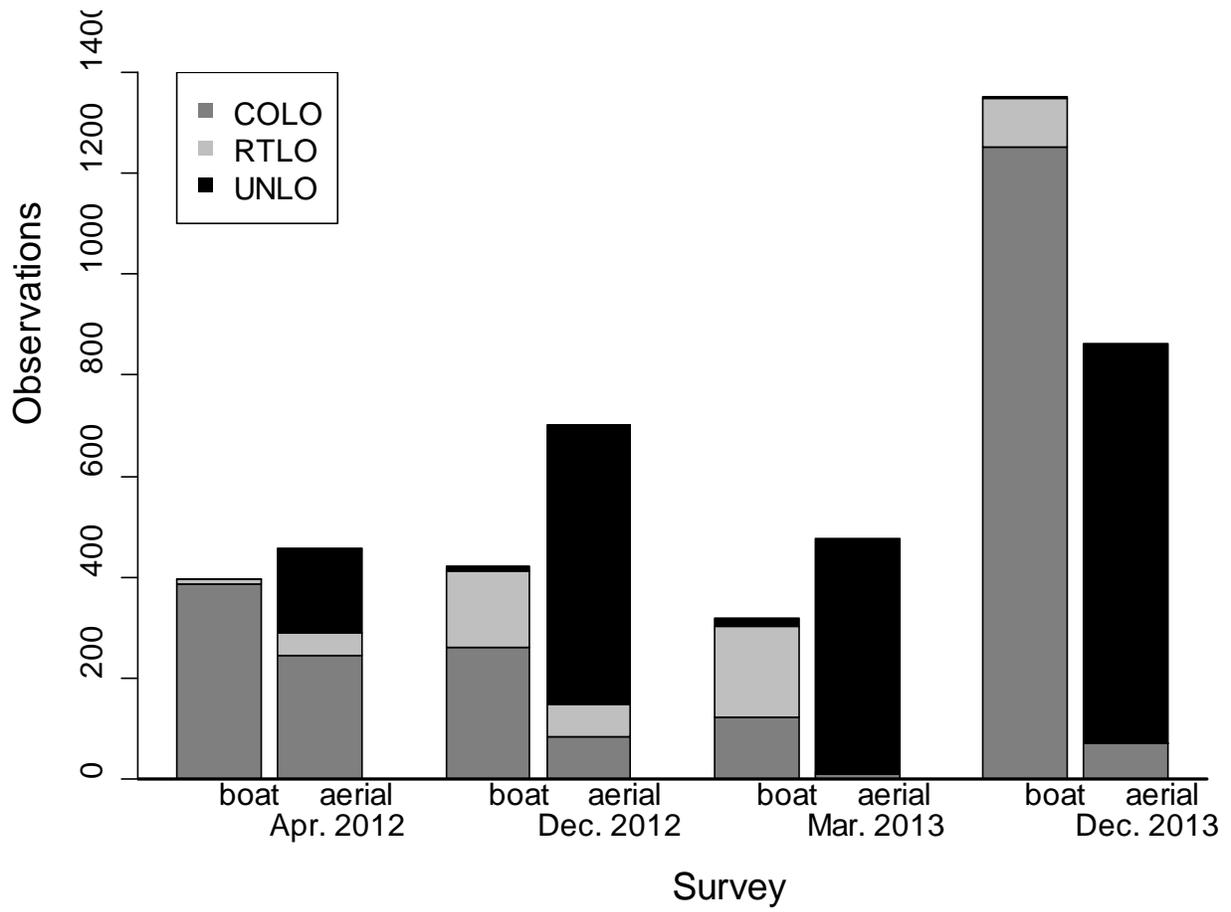


Figure 16-2. Numbers of individual Common Loons (COLO), Red-throated Loons (RTLO), and unidentified loons (UNLO) observed during corresponding boat and aerial surveys.

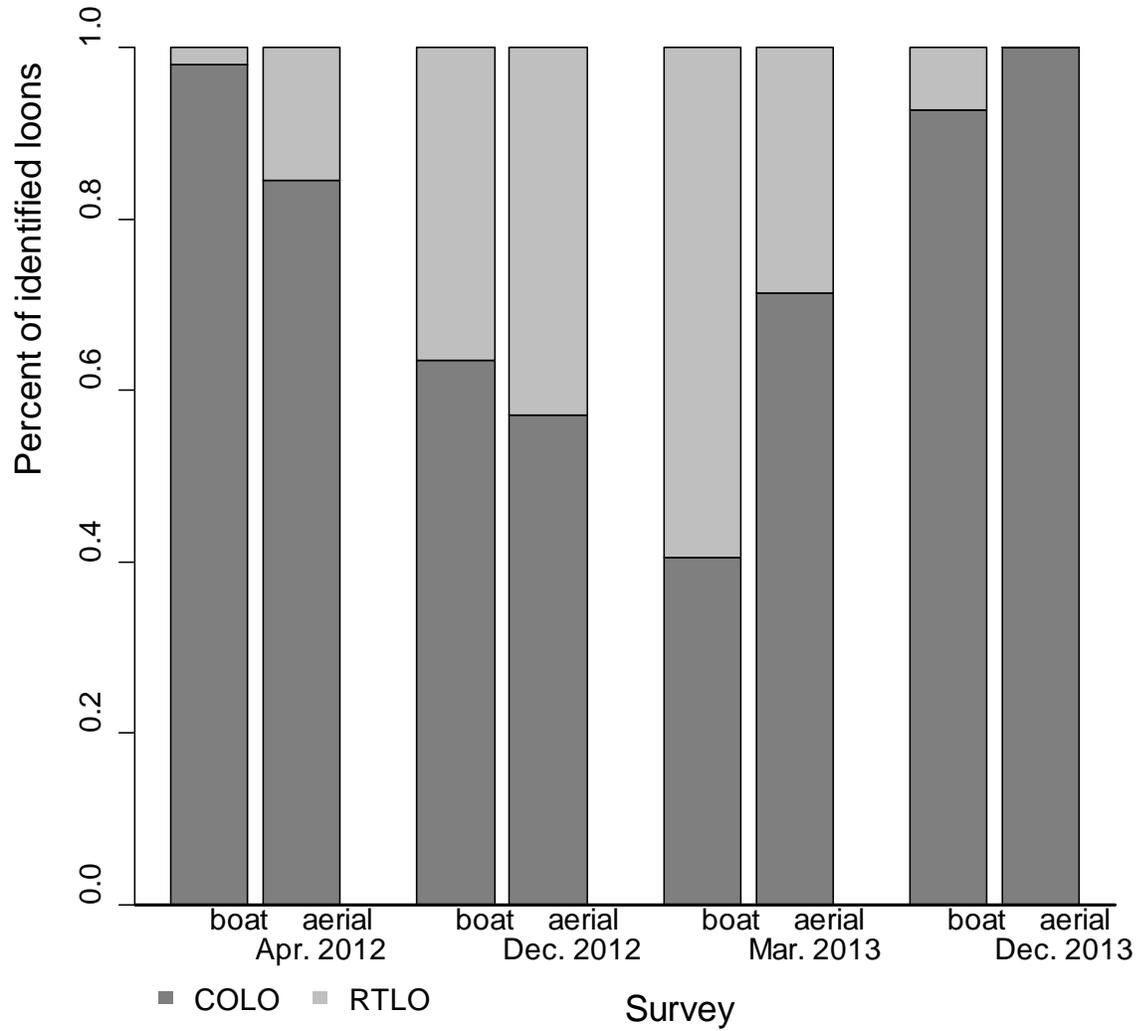


Figure 16-3. Percent of loons identified to species that were Common Loons (COLO) or Red-throated Loons (RTLO) during corresponding boat and aerial surveys.

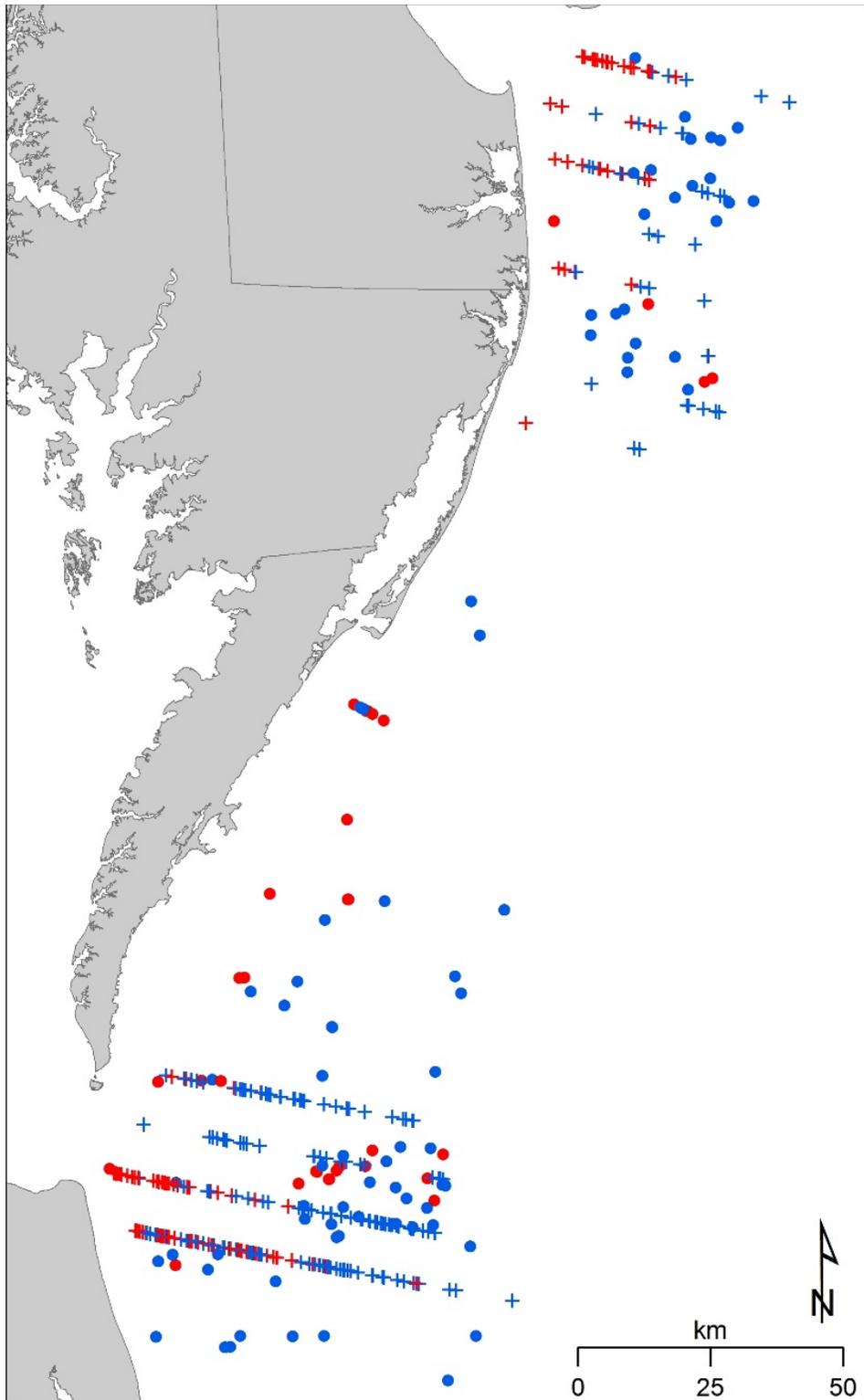


Figure 16-4. Locations of identified Common Loons (blue) and Red-throated Loons (red) during boat surveys (crosses) and aerial surveys (dots) in December 2012.

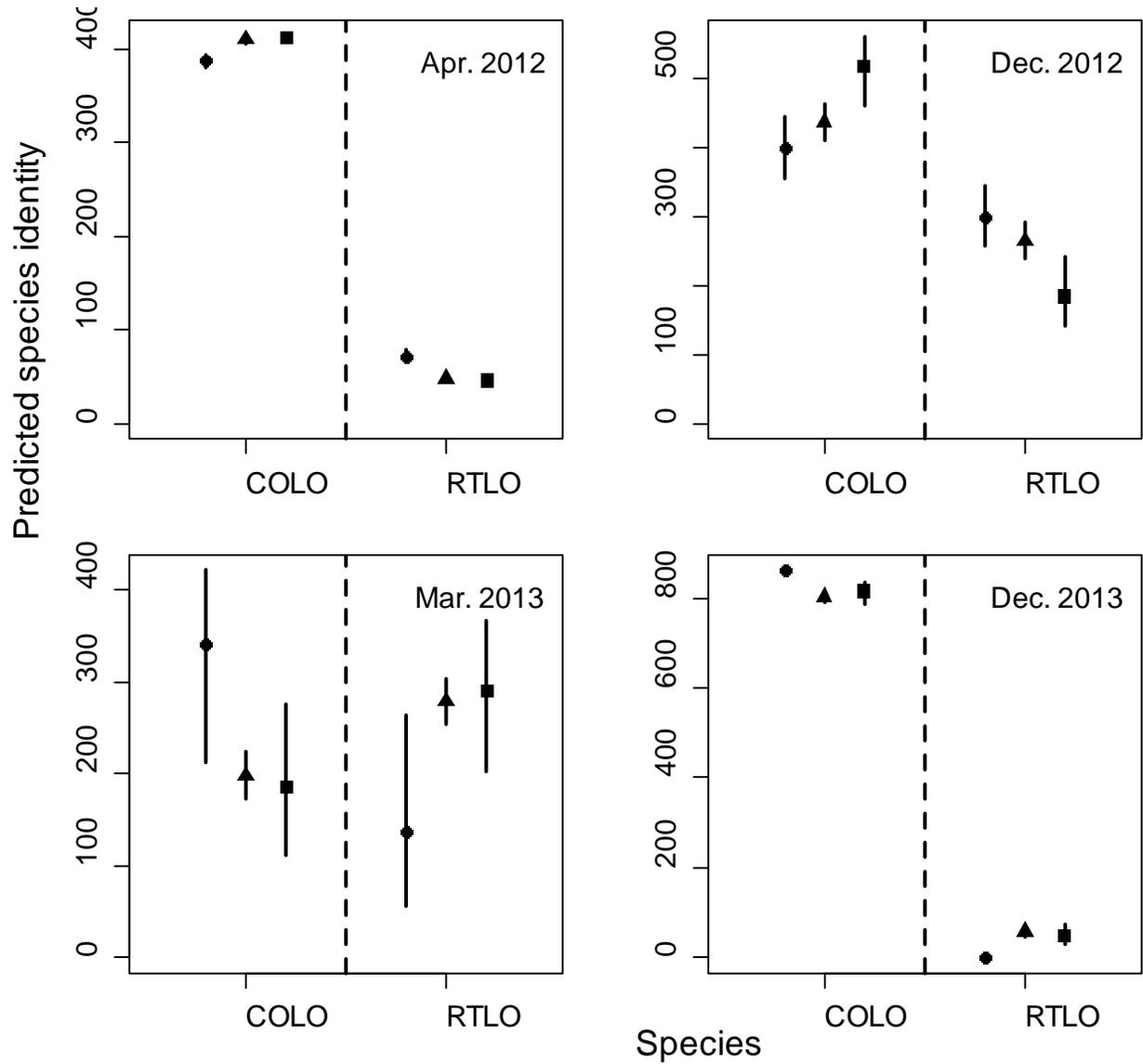


Figure 16-5. Predicted numbers of Common Loons (COLO) and Red-throated Loons (RTLO) in digital video aerial surveys. Unidentified loons (UNLO) observed during aerial surveys were assigned to a species using one of three methods: (i) the proportions of identified loons in the aerial data (circles), (ii) the proportions of identified loons in the boat data (triangles), or (iii) model averaged spatial covariate relationships (squares). Error bars denote 95% confidence intervals. Note survey-specific y-axis.

Table 16-1. Numbers of individual Common Loons (COLO), Red-throated Loons (RTLO), and unidentified loons (UNLO) observed during corresponding boat and aerial surveys.

Survey	Boat			Aerial		
	COLO	RTLO	UNLO	COLO	RTLO	UNLO
April/May 2012	387	8	0	245	45	168
December 2012	262	150	9	84	63	556
March 2013	123	180	17	10	4	463
December 2013	1251	98	3	70	0	792

Table 16-2. Model-averaged logit-scale parameter estimates (95% CI) predicting loon species proportions across 4 boat surveys. Model-averaged parameter estimates that did not overlap zero are bolded.

Parameter	Survey			
	April/May 2012	December 2012	March 2013	December 2013
Int.	7.13 (4.32, 9.93)	1.15 (0.74, 1.57)	-0.37 (-0.67, -0.07)	6.77 (5.49, 8.06)
DTS	4.84 (1.81, 7.87)	1.48 (0.25, 2.71)	0.26 (-0.32, 0.85)	5.47 (3.98, 6.95)
SST	1.44 (0.46, 2.42)	-0.49 (-1.00, 0.02)	1.83 (1.10, 2.56)	-2.96 (-3.91, -2.01)
Grain size	-0.14 (-1.05, 0.77)	0.85 (0.42, 1.27)	-0.39 (-0.76, -0.03)	0.85 (0.36, 1.35)
Salinity	-0.37 (-1.94, 1.20)	0.57 (-0.23, 1.36)	-0.77 (-1.45, -0.08)	1.32 (0.31, 2.32)
Chlor	0.47 (-1.14, 2.07)	-1.70 (-2.66, -0.73)	-0.45 (-0.93, 0.03)	-1.06 (-2.57, 0.45)
Slope	-0.66 (-1.44, 0.13)	-0.34 (-0.75, 0.06)	-0.15 (-0.49, 0.19)	0.50 (-0.25, 1.25)

Table 16-3. Predicted numbers (95% CI) of Common Loons (COLO) and Red-throated Loons (RTLO) in aerial survey transects. Unidentified loons (UNLO) observed during aerial surveys were assigned to a species using one of three methods: (i) proportions of identified loons in the aerial data (aerial), (ii) proportions of identified loons in the boat data (boat), or (iii) model-averaged spatial covariate relationships (spatial).

Survey	Method	COLO	RTLO	UNLO
April/May 2012	Observed	245	45	168
	Aerial	387 (379, 393)	71 (65, 79)	
	Boat	410 (406, 411)	48 (47, 52)	
	Spatial	412 (408, 413)	46 (45, 50)	
December 2012	Observed	84	63	556
	Aerial	402 (357, 445)	301 (258, 346)	
	Boat	438 (411, 463)	265 (240, 292)	
	Spatial	519 (461, 562)	184 (141, 242)	
March 2013	Observed	10	4	463
	Aerial	341 (213, 421)	136 (56, 264)	
	Boat	198 (173, 224)	279 (253, 304)	
	Spatial	186 (111, 275)	291 (202, 366)	
December 2013	Observed	70	0	792
	Aerial ^a	862 (NA)	0 (NA)	
	Boat	804 (792, 815)	58 (47, 70)	
	Spatial	815 (787, 834)	47 (28, 75)	

^a Confidence interval could not be estimated due to zero observations of Red-throated Loons in the aerial data