Google Haul Out: Earth Observation Imagery and Digital Aerial Surveys in Coastal Wildlife Management and Abundance Estimation

JERRY H. MOXLEY, ANDREA BOGOMOLNI, MIKE O. HAMMILL, KATHLEEN M.T. MOORE, MICHAEL J. POLITO, LISA SETTE, W. BRIAN SHARP, GORDON T. WARING, JAMES R. GILBERT, PATRICK N. HALPIN, AND DAVID W. JOHNSTON

As the sampling frequency and resolution of Earth observation imagery increase, there are growing opportunities for novel applications in population monitoring. New methods are required to apply established analytical approaches to data collected from new observation platforms (e.g., satellites and unmanned aerial vehicles). Here, we present a method that estimates regional seasonal abundances for an understudied and growing population of gray seals (Halichoerus grypus) in southeastern Massachusetts, using opportunistic observations in Google Earth imagery. Abundance estimates are derived from digital aerial survey counts by adapting established correction-based analyses with telemetry behavioral observation to quantify survey biases. The result is a first regional understanding of gray seal abundance in the northeast US through opportunistic Earth observation imagery and repurposed animal telemetry data. As species observation data from Earth observation imagery become more ubiquitous, such methods provide a robust, adaptable, and cost-effective solution to monitoring animal colonies and understanding species abundances.

Keywords: abundance estimation, gray seals (Halichoerus grypus), Cape Cod, remote sensing, Earth observation

Population monitoring is a key aspect of both wildlife species conservation and resource management (Decker and Purdy 1988, Lancia et al. 2005, Redpath 2013, Kiszka et al. 2015). The critical nature of these data to species management has resulted in the development of a diverse range of analytical methods, data sources, and techniques to account for bias and error. These include targeted surveys, opportunistic sightings, biotelemetry, and harvesting records (Lancia et al. 2005).

Ideally, species-abundance data are produced from targeted surveys specifically designed for optimal and unbiased detection. In the marine environment, many species are less accessible (Harwood 2001, Fuentes et al. 2015) than their terrestrial counterparts and require expensive and laborious at-sea surveys (e.g., line-transect surveys) from aerial- and/or ship-based platforms to produce adequate abundance data. Given these difficulties, the results of such surveys are often imprecise and occur less frequently than necessary (Taylor et al. 2007). For marine animals that periodically return to coastal locations (e.g., pinnipeds and seabirds), surveys can capitalize on predictable aggregations to produce reliable survey counts. In these cases, new remote sensing platforms and novel technological approaches can complement traditional observation platforms (e.g., ships and planes) to produce sufficient data for abundance estimation and reduce the need for costly surveys (McMahon et al. 2014).

Recent advances in remote sensing and networked geospatial data archives represent a growing opportunity for researchers to augment traditional population-assessment programs for some marine species (Laliberte and Ripple 2003, LaRue et al. 2011). Satellite and aerial survey data collected at extremely high resolution for commercial purposes are becoming increasingly accessible to researchers for scientific projects (e.g., Geo-EyE1, WorldView-1, WorldView-2, and QuickBird-2). Earth observation platforms are increasingly capable of resolving species presence and can be incorporated into the field of population monitoring as broad-swath platforms of observation for population assessments (Fretwell et al. 2012, 2014, Lynch and Larue 2014, McMahon et al. 2014). Recent work includes

BioScience 67: 760–768.
doi:10.1093/biosci/bix059 Advance Access publication 14 July 2017

the remote assessment of populations of marine organisms that use terrestrial habitats to rest, molt, or breed (Fretwell and Trathan 2009, Hughes et al. 2011, Platonov et al. 2013). For example, relatively high-resolution data archives have been used to identify, monitor, and even assess a number of marine vertebrate populations in remote locations, including penguins (Fretwell et al. 2012), seals (McMahon et al. 2014), and whales (Fretwell et al. 2014). These remote assessments require careful calibration and/or correction to produce useful estimates of abundance (McMahon et al. 2014). Although abundance estimation has been accomplished for some species of penguins (Fretwell et al. 2012, Lynch and LaRue 2014, Lynch and Schwaller 2014), most marine mammal satellite-based surveys have focused on verifying simple counts (LaRue et al. 2011, Fretwell et al. 2014, McMahon et al. 2014) and have not provided correction factors that scale survey counts to estimates of abundance.

In this study, we survey a coastal marine species from freely available imagery and correct these animal counts with biotelemetry data to produce abundance estimates for a rapidly changing population. In doing so, we highlight the strengths and drawbacks of the approach and provide guidance for the incorporation of Earth observation imagery in established fields of population monitoring.

Gray seals in the northeast United States

Gray seals (*Halichoerus grypus*) are a large phocid seal found only in the waters of the North Atlantic Ocean, from approximately 40.3° N to 71.3° N. They are gregarious animals that seasonally spend time ashore for resting, breeding, and molting. Depleted throughout the northwest Atlantic in the nineteenth and twentieth century by bounty hunting and harvests (Lelli et al. 2009), gray seals have since recovered across their range largely because of exponential growth sustained over decades at the world's largest breeding colony, Sable Island in Nova Scotia, Canada (Bowen et al. 2003, Bowen et al. 2007). Recently, animals have been recolonizing southerly US habitats and have re-established a historic breeding colony at Muskeget Island that is growing rapidly and expanding to nearby sites such as Monomoy Island (Wood 2009, Wood et al. 2011). Pup counts, beach counts, and other population indices indicate apparent growth in the US gray seal population (Wood 2009, Johnston et al. 2015), although little is known about the true abundance of the population (NOAA and NMFS 2016).

Traditionally, gray seal abundance studies use mark-recapture methods or aerial surveys of pups at known breeding sites (Myers et al. 1997, Bowen et al. 2003, Bowen et al. 2007). For the latter, pup counts are incorporated into a population model that takes into account demographic parameters (e.g., reproductive and mortality rates) to estimate total abundance. Although such surveys provide an estimate of the total population at the time of the breeding season, they can be expensive and logistically complex, and they do not capture the significant seasonal movements that can dramatically affect regional abundances of gray seal populations (Breed et al. 2009, Wood et al. 2011). For example, some seals may leave US waters to move into Canada, whereas others may move from Canada into US waters (Mohn and Bowen 1996, Bowen et al. 2007, Breed et al. 2009, Wood et al. 2011). Therefore, to estimate seasonal regional abundances, detailed information about movement, behavior, and local abundances is needed. For example, seasonal estimates of abundance of gray seals in US waters might be combined using counts of animals hauled out, which are then corrected for the proportion of animals at sea at the time the count is made (e.g., Lonergan et al. 2011).

Here, we use opportunistic Earth observation imagery data to survey gray seal abundance in the coastal habitats of southeastern Massachusetts. Multiple surveys across multiple years were conducted using single-day synoptic imagery archived and publicly available in Google Earth, tallying the abundance of seals visible on coastal beaches. These raw beach counts were integrated with additional biotelemetry and observational data to estimate the regional abundance of gray seals in southeastern Massachusetts that accounts for two potential sources of error: (1) potential interspecies mixing with sympatric harbor seals (*Phoca vitulina*) at surveyed locations and (2) the proportion of the local population not available to the surveys. We identify the benefits, drawbacks, and additional considerations of using novel Earth observation sources of beach imagery as a population-assessment tool by integrating the novel platform of observation with traditional estimation methods.

Earth observation imagery

We employed current and archived remote sensing imagery of ocean-facing coastlines of southerneastern Massachussetts (figure 1) available in the freely downloadable application Google Earth for all time steps exhibiting adequate ground resolution to distinguish individual seals at known haul outs. This resulted in synoptic beach imagery of the region for 12 March 2012, 16 June 2014, and 24 May 2015. Assessments of known tidally dependent sandbars, water levels, and shadow directions within Chatham Harbor, Cape Cod, were used to estimate the point in the tidal cycle of image capture (table 1).

Digital aerial survey. The coastline of southeastern Massachusetts from 41.15° N to 42.12° N—including the shoreline of Cape Cod, Nantucket, Martha's Vineyard, and smaller islands, sandbars, and shoals—was surveyed from a digital altitude of approximately 200–300 meters (figure 1). For all images, seal haul outs and aggregations were identified visually and individuals counted by loading screen image captures into Logger Pro (Vernier Software and Technology, *www.vernier.com/products/software/lp*; see figure 2 for example image of haul out). Using software capabilities to mark and tally individuals within the image, survey counts were conducted for each image to produce a total number of seals at each haul out. The initial counts of dense haul outs, in which seals were tightly packed, were counted by three separate individuals to assess any observer bias arising from

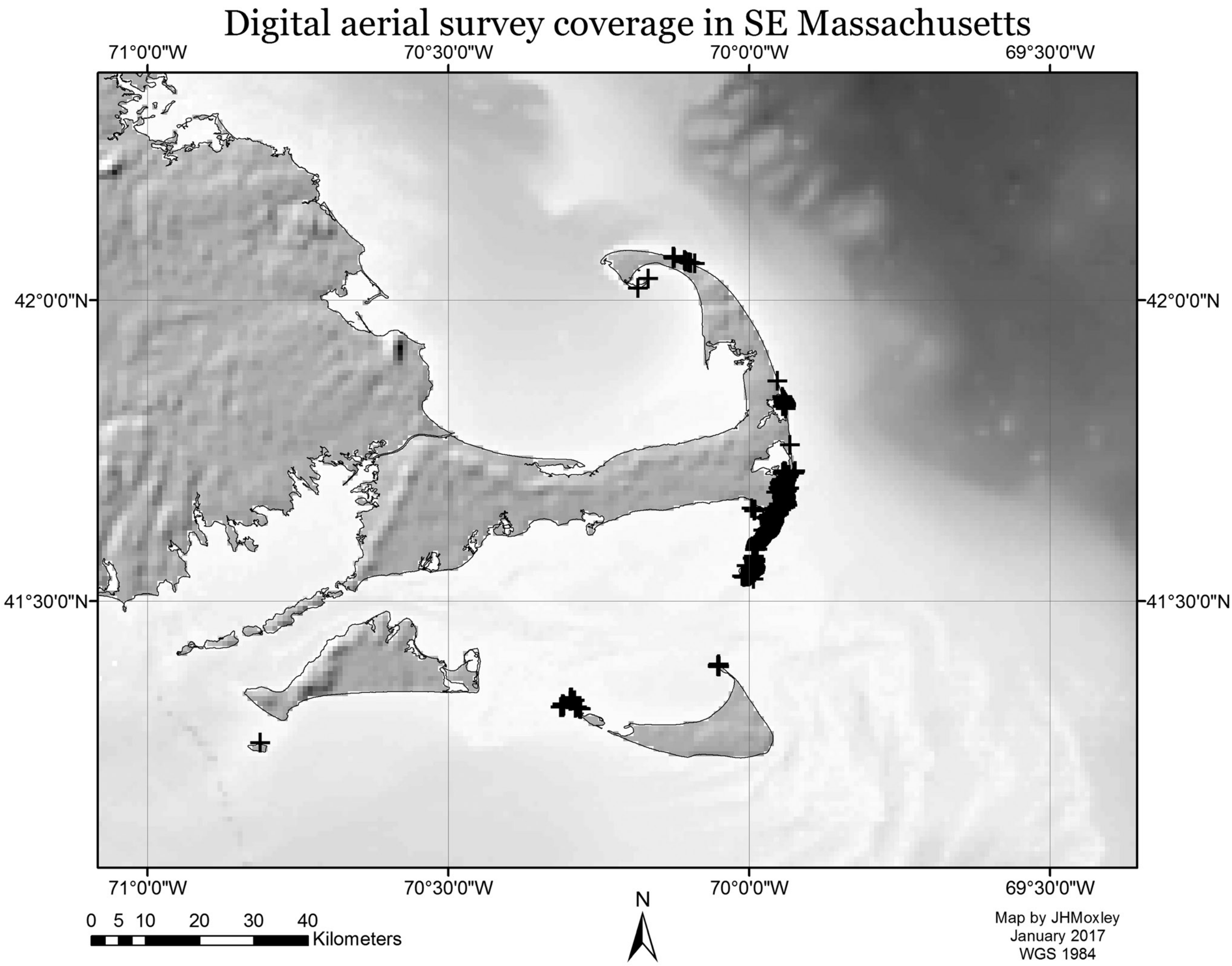

Figure 1. A map of the study area surveyed, with persistent haul outs of seals marked with crosses.

densely packed targets on images. The haul out counts were conducted individually by trained observers after multiple surveys of the same image revealed an acceptably low degree of observer bias ($n = 5$ image comparison, mean count in an image = 435.9, mean $\sigma = 9.4$; median $\sigma = 6.4$).

Sources of biases and correction factors. We developed correction methods to account for two primary sources of bias: (1) the unobserved proportion of the gray seal population away at sea during the survey and (2) the potential for species misidentification due to sympatric harbor seals. Although the interspecies-mixing bias is expected to be minimal because of the region's growing rarity of mixed haul outs and declining and/or displacing harbor seal populations (Johnston et al. 2015, Waring et al. 2015), applying this latter correction ensures a conservative estimate that is justified by the method's novelty.

To account for the unobserved individuals at sea during the survey, we built on published methods for using telemetry data to estimate the probability an individual is exhibiting haul out behavior, whereby they exit the water and rest on sandy habitat above the waterline (i.e., observable) during a low-tide survey (Lonergan et al. 2011). Haul out data were collected from eight GSM or GPRS telemetry tags (Sea Mammal Research Unit, St. Andrews, Scotland) deployed on gray seals ($n = 4$ males, including 1 juvenile; $n = 4$ females, including 1 juvenile) caught in June 2013 at a local haul out near Chatham, Massachusetts, and attached with quick-setting two-part epoxy (note that one tag was deployed opportunistically on a juvenile in September 2012). In addition to monitoring movement, behavior, and local water conditions for the tag duration (range: 2–9 months), telemetry devices recorded haul out events as periods when the tag was continuously dry for more than 10 minutes until the tag was resubmerged for 40 seconds. A total of 8155.4 hours of relevant haul out behavior were examined, excluding any records occurring at sea or away from land.

Correction factors for the unobserved proportion are calculated following standard pinniped survey techniques (i.e., monitor beach behavior at low tide when the maximum beach—and therefore haul out habitat—is exposed)

Table 1. Survey details for Google Earth imagery with adequate ground resolution to resolve individual seals (see figure 2 for example image).

			Approximate		Beach Counts	
Year	Survey date	Low tide (EST)	TOD	Tidal cycle	Total seals	Estimated gray seals
2012	3/11/12	11:18	Late AM	Near Slack	15331	12725
2014	6/16/14	10:43	Early AM	Falling	3816	3167
2015	5/23/15	13:10	Late AM	Falling	20554	17060

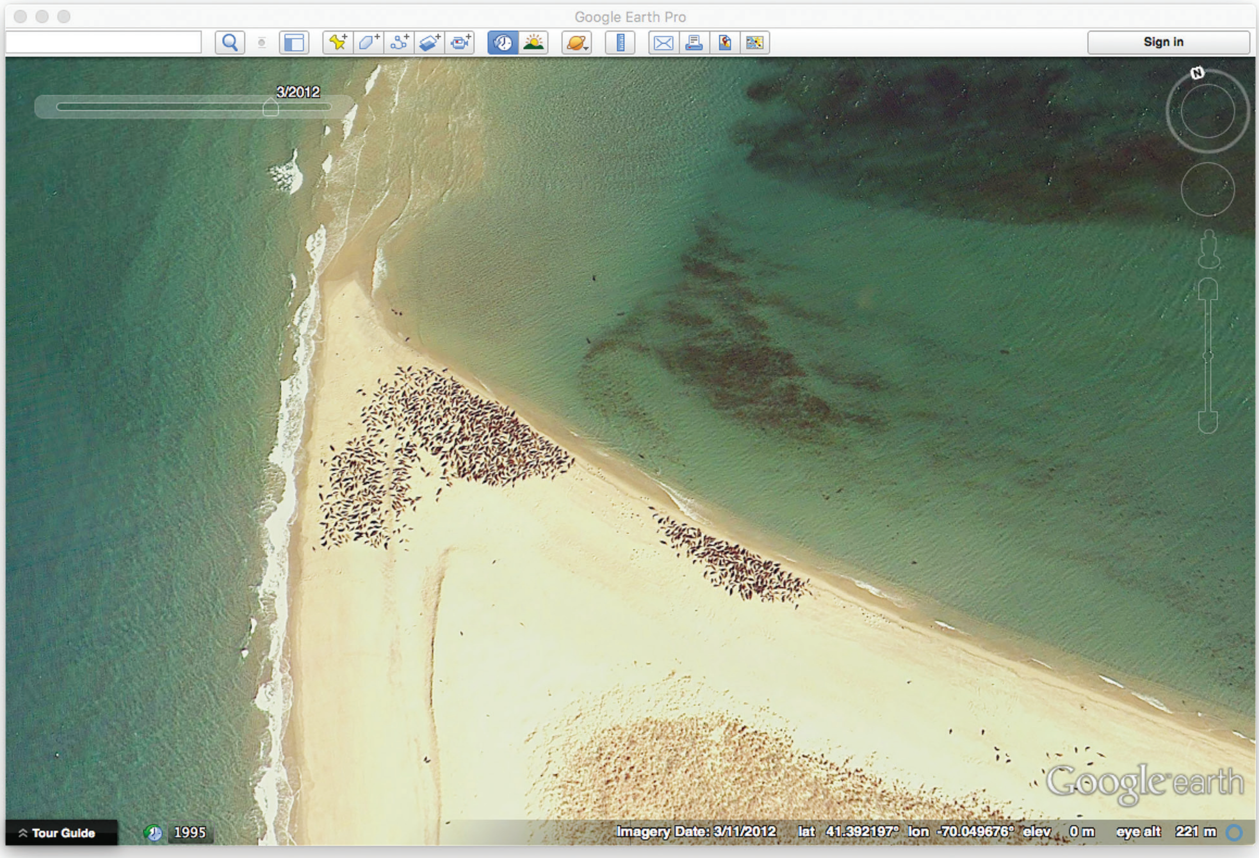

Figure 2. A screenshot from Google Earth (version 7.1.2.2041). This image shows two large groupings of seals hauled out at Great Point on Nantucket Island, Massachusetts. The image was acquired on 11 March 2012 and is viewed at a virtual height of 220 meters (720 feet).

and published analytical methods (Lonergan et al. 2011). Specifically, beach-count results were converted into population estimates by dividing raw counts (adjusted for interspecies mixing) by the estimated proportion of the population observable during the low-tide survey window (2 hours before and after the daytime low tide recorded in the National Oceanic and Atmospheric Administration, NOAA, tidal record, *tidesandcurrents.noaa.gov*, Station no. 8447435; see Ries et al. 1998, Jeffries et al. 2003, Gilbert et al. 2005). This probability is calculated from the proportion of survey time tagged individuals exhibit haul out behavior (i.e., "observable") to the amount of time surveyed (i.e., the sum of each tag's entire 4-hour survey window due to continuous behavioral monitoring by a telemetry device). The probabilities were summed daily and used to calculate that day's correction factor and abundance estimate so that uncertainty is propagated completely through to the monthly and seasonal (warm: June–October; cold: November–March, excluding January during postbreeding recovery) summaries. Further emphasizing our conservative approach and accounting for low tag numbers (n = 3–8 depending on the month; table 2), the probabilities for days without tagged individuals observed hauling out were neglected and instead imputed from a random normal centered on that month's mean and

Table 2. Tag cohort details by warm (June–October) and cold (November–December; February–March) for haul out analysis.

				Haul out events		
Sex	Tag no.	Duration	Season	Total	LT survey	Percentage detected
M	12358	39	warm	40	13	0.325
		132	cold	42	22	0.524
F	12373	47	warm	87	56	0.644
		0	cold	NA	NA	NA
M	12397	137	warm	280	137	0.489
		96	cold	67	25	0.373
M	12646	31	warm	68	37	0.544
		0	cold	NA	NA	NA
F	12652	139	warm	447	167	0.374
		54	cold	42	22	0.524
M	12654	138	warm	242	120	0.496
		114	cold	30	13	0.433
F	12658	138	warm	143	100	0.699
		116	cold	27	20	0.741
F	12709	138	warm	475	97	0.204
		123	cold	44	26	0.591

Note: The duration is the number of days in each season the tag was active and recording data. The total number of haul out events observed, as well as the number during the low-tide survey window and therefore the percentage detected, are also listed.

standard deviation. To account for individual variability, we used a bootstrapping procedure (5000 replicates) with individual animals as the resampling unit to account for unsampled individual variation from the interindividual variability within the tag data set.

To correct for potential tallying of harbor seals, a regional mixing rate of 0.83 was estimated from direct haul out observations reported in 5 surveys between 1986 and 2011 (R. DiGiovanni, Riverhead Foundation, Riverhead NY, personal communication, 1 December 2011) and is applied conservatively to all beach counts in order to avoid potential overestimation. Associations between harbor and gray seals at haul outs are dynamic in space and time and would be best captured via hierarchical frameworks that ensure adequate alignment between the parameter and survey counts (Kéry and Royle 2015). However, data availability (e.g., only 2 surveys occur during years of gray seal abundance in the region) and quality (e.g., coarse spatial and temporal coverage within the region) were insufficient at this time to support the development of a such a model without tenuous assumptions about the shape of the sampling distribution. As data concerns diminish because of ongoing monitoring efforts at sufficient spatial and temporal coverage, we suggest that future applications directly assess this distribution and potential spatiotemporal patterns in species-mixing estimates.

We expect this bias is not limiting in our estimation because of diverging trends in the region's seal populations and reductions in mixed haul outs. Within this study system, gray and harbor seal population trends are observed to be diverging (Johnston et al. 2015, Waring et al. 2015), and increasingly, haul out aggregations within the region are exclusively composed of gray seals. Given the limited prior survey data, the application of a fixed mixing correction ensures a conservative abundance estimate while still acknowledging the low possibility of species-identification errors (Fuentes et al. 2015). In future applications, researchers should structure adequate quantitative and increasingly hierarchical approaches when possible. This will allow researchers to capatitalize on available data while harnessing the advantages of untargeted Earth observation imagery in generating knowledge for environmental monitoring and wildlife censusing.

Digital survey results

Over 4 years, Google Earth imagery of adequate resolution was available for surveys on three dates, all at least 1 year apart. The data from these surveys are presented in table 1, including the date of image capture, the approximate time of day and tidal cycle, the total number of seals counted, and the estimated number of gray seals corrected for interspecific mixing. The survey counts show a range of pinniped abundances (table 1), with two surveys (2012 and 2015 counts of 15,331 and 20,554 total seals, respectively) falling within the range of two maximum counts reported officially by the NOAA and National Marine Fisheries Service (NMFS): a March 2011 single-day maximum count of 15,756 gray seals (NOAA and NMFS 2016) and the most recent April 2016 molting survey of nearly 25,000 gray seals (NOAA and NMFS 2016). Raw survey counts and corrected

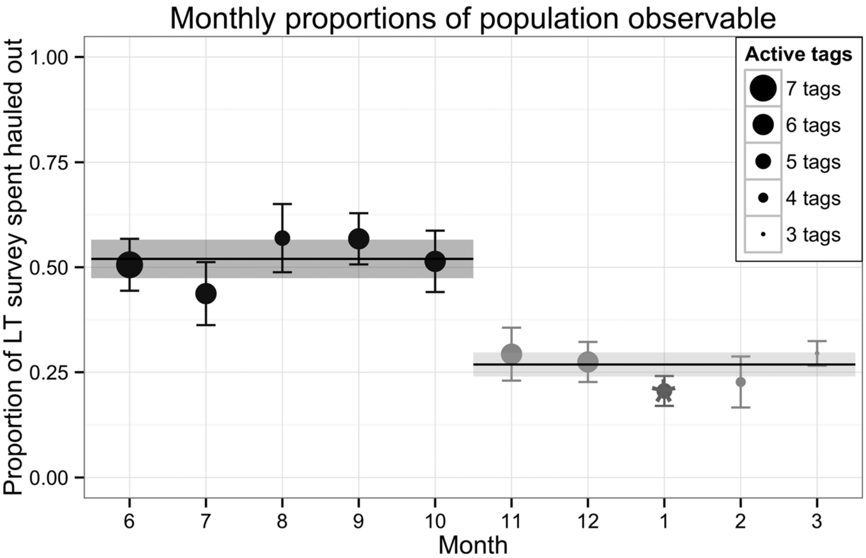

Figure 3. The observable proportion of the gray seal population during low-tide surveys exhibits a seasonal pattern. Here, the estimated monthly mean proportion is presented with 95% confidence intervals (CI) that overlap with seasonal estimates (warm months, dark shading; cold months, light shading). The postbreeding period during the month of January, when animals recover from an energetically expensive fast, is denoted with the asterick.

counts accounting for the mixing of harbor and gray seals are presented in table 1.

The estimates of the mean proportion of a daytime, low-tide survey window that animals spend hauled out followed an apparent seasonal pattern that adjusts the correction factor for the proportion of the population unobserved. Figure 3 shows monthly rates (mean ± 95% confidence intervals) of haul out behavior around low tides. During warm months (June–October), haul out behavior is nearly daily and occurs regularly for nearly 50% of survey windows. Beginning in November, haul outs become more infrequent, and the time between consecutive haul out periods lengthens. Haul out behavior is infrequent in the month of January, during a postbreeding period after adult animals emerge from fasting and presumably increase foraging effort to recover body mass and energy stores lost during reproduction. Given the stark differences between the months of different seasons (e.g., warm, June–October; cold, November–March, excluding postbreeding behavior in January; ANOVA with Tukey multiple comparisons: $F = 18.87$, $p < .01$), haul out behavior was also summarized in seasonal metrics (see shaded boxes, figure 3, constituting 95% SE around the mean).

The estimates from 2012 and 2015 surveys that fall within the range of published maximum counts suggest a range of gray seals between 30,000 and 50,000 animals when using monthly correction factors (table 3). Seasonal correction factors aggregate more individuals over a greater period of time and therefore reflect a more variable range of possible abundance estimates because of a greater variability in the correction factors and underlying behavior. Molting behavior, observed in northwest Atlantic gray seals around late March and April, affects haul out probability and therefore likely the 2012 survey counts, but it is not captured by telemetry methods because of tag detachment during the shedding of fur. 2014 survey counts fall well below all other survey counts, as well as official reports of maximum beach counts in 2012 and 2016 (NOAA and NMFS 2015, 2016).

The utility, challenge, and potential of Earth observation imagery in abundance estimation

In this study, we demonstrate how digital aerial surveys can harness data available in Earth observation imagery and produce regional abundance estimates by integrating surveys with correction factors obtained from biotelemetry devices. Survey data from commercial Earth observation imagery sources (including satellite and aerial platforms) are now used as corroborative or supplementary sources to traditional surveys (Fretwell and Trathan 2009, Larue et al. 2011, Fretwell et al. 2012, McMahon et al. 2014) but rarely as the primary source of abundance information. Here, we extend this approach by incorporating telemetry data to produce corrected regional abundance estimates of an increasing coastal wildlife population. As a first demonstration of concept for marine mammals (see Lynch and Larue 2014 for an example with seabirds), this study highlights new considerations for technological approaches to population monitoring and management funding priorities.

First, the growing ubiquity and expansion of Earth imagery must be embraced by wildlife ecologists as a legitimate data source that can supplement and even supplant traditional methods (Laliberte and Ripple 2003, Horning et al. 2010, Linchant et al. 2015). Earth imagery is being collected globally, frequently, and at increasingly relevant resolution by third-party operators (e.g., Planet Labs, DigitalGlobe, Skybox Imaging, Urthecast, and Land Info Worldwide Mapping; for an example workflow of identifying and acquiring relevant imagery, see Fretwell et al. 2014). Pricing will vary between vendors and depend on satellite platform (e.g., WorldView-1, WorldView-2, WorldView-3, QuickBird, Geoeye-1, Ikonos, and Pleiades), resolution, spectral bands, as well as additional processing, but example pricing is available on many vendors websites (see *www.landinfo.com/satellite-imagery-pricing.html*). Most vendors allow clients to preview imagery at moderate resolutions (e.g., QuickView features available from DigitalGlobe; see Fretwell et al. 2014) and will closely work with researchers to ensure the purchase of adequate and properly georeferenced imagery

Table 3. Total and adjusted counts, correction factors, and estimated abundance for the three surveys conducted with Google Earth imagery of Cape Cod, Massachusetts, and the surrounding islands and shoals.

Survey		Counts			Correction Factor		Abundance estimate					
							All seals			Gray seals		
Year	Date	All seals	Gray seals	Scale	Mean	Standard Deviation	Mean	Lower CI	Upper CI	Mean	Lower CI	Upper CI
				Month	4.324	1.963	54980	49450	60530	45640	41040	50240
2012	3/12/13	15,330	12,730	Season	6.387	8.763	97760	73410	122130	81150	60930	101370
				Bootstrap	5.519	3.481	84610	32180	NA	70230	26710	NA
				Month	2.106	0.563	8040	6930	9150	6670	5750	7590
2014	6/15/15	3,820	3,170	Season	2.865	4.998	10945	6650	15240	9080	5520	12650
				Bootstrap	1.972	5.286	7520	6430	9030	6240	5330	7500
				Month	2.106	0.563	43290	37300	49270	35930	30960	40900
2015	5/23/15	20,550	17,060	Season	2.865	4.998	58950	35800	82100	48930	29720	68150
				Bootstrap	1.972	5.286	40530	34610	48660	33640	28730	40390

Note: The correction factors listed represent the most appropriate monthly, seasonal, and bootstrapped estimates of haul out behavior for that year's survey (e.g., a March 2012 survey uses March monthly factors, as well as raw and bootstrapped cold-season factors). Abbreviation: CI, 95% confidence intervals.

for the study question. By capitalizing on these commercial services, further work can identify adequate imagery for other regional populations of gray seals in Maine and eastern Canada.

Cost-effective savings in image acquisition can save management resources (both in terms of funding and effort), as has been seen in growing applications of unmanned aircraft systems to acquire high-resolution landscape imagery (Linchant 2015). Data acquired from wildlife telemetry are capable of supporting a broad range of management objectives beyond correcting survey counts for detectability, including habitat requirements, space use, and behavioral patterns (Hart and Hyrenbach 2009, McIntyre 2014). In designing future studies, telemetry programs should look to deploy a larger numer of tags with enough spatial and temporal coverage to generate an estimate applicable for the region of interest during the appropriate timeframe. For example, a comprehensive abundance estimate of the British gray seal population used targeted aerial imagery acquired annually in August and employed telemetry data from 107 animals deployed over 13 years within 5 different population centers (Lonergan et al. 2011).

To be an effective and comparable method to traditional approaches, survey designs that harness data from Earth observation imagery and accompanying methodologies must be able to account for sources of bias, error, and uncertainty. As far as available data allow, hierarchical models are adaptive quantitative techniques highly capable of accounting for these various effects at multiple spatiotemporal scales (Kéry and Royle 2015, Hefley and Hooten 2016). In our study, opportunistic imagery permits no control of the season or the time of day of the imagery, thereby affecting surveys that use aspects of species biology (e.g., aggregations due to behaviors such as breeding and molting) or habitat changes (e.g., maximization of survey-capable habitat at low tide or at times of the year with high background contrast or low obstruction from vegetation or clouds) to improve survey counts and minimize estimation errors. Comparisons between opportunistic and any existing targeted imagery can identify the quality and reliability of opportunistic imagery as a source of survey data. In our case, we employed a purposefully conservative modeling approach to insulate estimates from potential errors until such comparative analyses with targeted imagery could be made. Future applications, however, can capitalize on commercial databases that feature greater sampling frequency and more temporal targeting of imagery to ensure surveys match sensible time frames, preferred survey seasons, and environmental conditions that affect detectability (Simpkins et al. 2003, McMahon et al. 2014). For additional costs, opportunities to schedule commercial imagery acquisition further strengthens this method to develop robust and precise population estimates (McMahon et al. 2014). Decisions about prioritizing species for commercial image acquisition should be guided by the species of interest, its management status, and requirements of precision and accuracy (e.g., highly endangered species and commercial resources). For the abundant and growing gray seal population along the northeastern US coastline, opportunistic imagery combined with telemetry-enabled corrections provides crucial seasonal benchmarks in abundance, particularly during warm months not captured by wintertime breeding and springtime molting surveys.

Broad knowledge gaps exist in the ecological understanding of recovering gray seals along the northeast US coast, including a lack of abundance estimates. Such gaps limit the evaluation and mitigation of conflicts and concerns over fishery interactions, space-use conflicts, and the impacts of the growing pinniped population on other protected species (Bogomolni et al. 2010, O'Boyle and Sinclair 2012, Rafferty et al. 2012, Nichols et al. 2014, Johnston et al. 2015). Two (survey years 2012 and 2015) of this study's three digital aerial surveys produced abundance indices within the bounds of official reports of maximum beach counts (NOAA and NMFS 2015, 2016). Markedly lower 2014 survey counts were considered unreliable because of their large deviation from all other reported abundance indices and neglected because of poor temporal alignment in the imagery with low tide (table 1) and likely subsequent suboptimal survey conditions (e.g., unfavorable tidal phase, unobserved, disturbances, and other unaccounted factors).

Our study also provides insights about the utility of untargeted surveys when combined with telemetry-enabled behavioral observation. Wintertime aggregations (e.g., breeding and molting) targeted by traditional survey designs are associated with larger uncertainty because of stark seasonal changes in haul out behavior shown in the telemetry record, as well as increased individual and sexual variability during cold months (Breed et al. 2009) and reduced sample size due to tag detattachment near molting. Instead, behavioral similarity, sample size, and ultimately certainty in correction factors are maximized during warm summer months (June–October), providing crucial indices of abundance during seasons less targeted by population biologists. Further work must connect and compare traditional sources and estimation approaches of abundance data with this ancillary source of untargeted abundance data. In our case, demographic-modeling approaches may maximize understanding of the population changes in manners unaffected by survey design, interspecies mixing, and age and sex effects in haul out behavior, whereas Earth observation imagery can track intraannual fluctuations in abundance.

Conclusions

The recovery of gray seals along the eastern US coastline has been remarkable but not well monitored because of alternate funding priorities and federal research interests. We outline a technological approach that produces the first abundance estimates of a marine mammal from publicly available remote sensing imagery and wildlife telemetry data. The growing ubiquity of high-quality imagery sources for Earth observation indicates that our approach can serve an important role in monitoring and estimating abundance for a wide variety of other species that are not the focus of funding or devoted survey efforts. As researchers embrace new sources of imagery, cost-effective savings can be redirected to other methods, such as telemetry, that can produce correction factors for abundance estimates, monitor a range of behaviors, and supplement numerous research questions with ancillary data streams. As has been demonstrated by the variability in the counts and resulting estimates, this method is not yet a complete substitute for traditional population monitoring efforts, particularly for species of concern for which precision is a high priority. However, it does expand the opportunities for high-quality abundance monitoring and population trajectories to more species outside direct management focus. Furthermore, it outlines a technological solution to a common management problem (i.e., population monitoring) in a cost-effective manner that supplements traditional approaches while preserving valuable funding for other research priorities that supplement a range of scientific questions.

Acknowledgments

We would like to thank generous support from International Fund for Animal Welfare, the Bureau of Ocean Energy, and the Oak Foundation for funding support for the telemetry devices. In addition, we thank the National Marine Fisheries Service and the Bureau of Ocean Management for support to conduct live captures and health assessments of gray seals on Cape Cod. Digital aerial surveys were completed with the generous help of Abigail Machernis, Sean Stanton, Lydia Utley, Logan Pallin, Susan Heaslip, and Heather Heenehan. The manuscript was also much improved with helpful reviews from Michael Moore and Elizabeth Josephson. Finally, we would like to acknowledge the insightful review and helpful comments from Dr. Michael Lonergan and an anonymous reviewer that greatly improved this article.

JHM, PH, JG, and DWJ conceived the survey and analysis. JHM, AB, MH, MP, LS, BS, GW, and DWJ conducted animal captures and device deployment. JHM completed the analysis and modeling. JHM, AB, MH, KM, MP, LS, BS, GW, JG, PH, and DWJ wrote the manuscript.

References cited

Bogomolni A, Early G, Matassa K, Nichols O, Sette L. 2010. Gulf of Maine Seals: Populations, Problems and Priorities. Woods Hole Oceanographic Institution. Technical Report no. 2010-04.

Bowen W, McMillan J. 2007. Reduced population growth of gray seals at Sable Island: Evidence from pup production and age of primiparity. Marine Mammal Science 23: 48–64.

Breed GA, Jonsen ID, Myers RA, Bowen WD, Leonard ML. 2009. Sex-specific, seasonal foraging tactics of adult grey seals (*Halichoerus grypus*) revealed by state-space analysis. Ecology 90: 3209–3221.

Decker DJ, Purdy KG. 1988. Toward a concept of wildlife acceptance capacity in wildlife management. Wildlife Society Bulletin 16: 53–57.

Fretwell PT, Trathan PN. 2009. Penguins from space: Faecal stains reveal the location of emperor penguin colonies. Global Ecology and Biogeography 18: 543–552. (2 May 2017; *http://doi.org/10.1111/j.1466-8238.2009.00467.x*)

Fretwell PT, LaRue MA, Morin P, Kooyman GL, Wienecke B, Ratcliffe N., Ratcliffe N, Fox AJ, Fleming AH, Porter C, Trathan PN. 2012. An emperor penguin population estimate: The first global, synoptic survey of a species from space. PLOS ONE 7 (art. e33751). (2 May 2017; *http://doi.org/10.1371/journal.pone.0033751*)

Fretwell PT, Staniland IJ, Forcada J. 2014. Whales from space: Counting southern right whales by satellite. PLOS ONE 9 (art. e88655). (2 May 2017; *http://doi.org/10.1371/journal.pone.0088655*)

Fuentes MMPB, Bell I, Hagihara R, Hamann M, Hazel J, Huth A, Seminoff JA, Sobtzick S, Marsh H. 2014. Improving in-water estimates of marine turtle abundance by adjusting aerial survey counts for perception and availability biases. Journal of Experimental Marine Biology and Ecology 471: 77–83. (2 May 2017; *http://doi.org/10.1016/j.jembe.2015.05.003*)

Gilbert J, Waring G, Wynne K. 2005. Changes in abundance of harbor seals in Maine, 1981–2001. Marine Mammal Science 21: 519–535.

Hart K, Hyrenbach K. 2009. Satellite telemetry of marine megavertebrates: The coming of age of an experimental science. Endangered Species Research 10: 9–20.

Harwood J. 2001. Marine mammals and their environment in the twenty-first century. Journal of Mammalogy 82: 630–640.

Hefley TJ, Hooten MB. 2016. Hierarchical species distribution models. Current Landscape Ecology Reports 1: 87–97.

Horning N, Robinson JA, Sterling EJ. 2010. Remote Sensing for Ecology and Conservation. Oxford University Press.

Hughes KA, Fretwell P, Rae J, Holmes K, Fleming A. 2011. Untouched Antarctica: Mapping a finite and diminishing environmental resource. Antarctic Science 23: 537–548. (2 May 2017; *http://doi.org/10.1017/S095410201100037X*)

Jeffries SJ, Brown RF. 1993. Techniques for capturing, handling and marking harbour seals. Aquatic Mammals 19: 21–25.

Johnston DW, Frungillo J, Smith A, Moore K, Sharp B, Schuh J, Read AJ. 2015. Trends in stranding and by-catch rates of gray and harbor seals along the northeastern coast of the United States: Evidence of divergence in the abundance of two sympatric phocid species? PLOS ONE 10 (art. e0131660). (2 May 2017; *http://doi.org/10.1371/journal.pone.0131660*)

Kery M, Royle JA. 2015. Prelude and Static Models. Applied Hierarchical Modeling in Ecology: Analysis of Distribution, Abundance, and Species Richness in R and BUGS, vol. 1. Academic Press.

Kiszka J, Heithaus M, Wirsing A. 2015. Behavioural drivers of the ecological roles and importance of marine mammals. Marine Ecology Progress Series 523: 267–281.

Laliberte AS, Ripple WJ. 2003. Automated wildlife counts from remotely sensed imagery. Wildlife Society Bulletin 31: 362–371.

Lancia RA, Kendall WL, Pollock KH, Nichols JD. 2005. Estimating the number of animals in wildlife populations. Techniques for Wildlife Investigations and Management: 106–153.

LaRue MA, Rotella JJ, Garrott RA, Siniff DB, Ainley DG, Stauffer GE, Porter CC, Morin PJ. 2011. Satellite imagery can be used to detect variation in abundance of Weddell seals (*Leptonychotes weddellii*) in Erebus Bay, Antarctica. Polar Biology 34 (art. 1727). (2 May 2017; *http://doi.org/10.1007/s00300-011-1023-0*)

Lelli B, Harris DE, Aboueissa A-M. 2009. Seal bounties in Maine and Massachusetts, 1888 to 1962. Northeastern Naturalist 16: 239–254.

Linchant J, Lisein J, Semeki J, Lejeune P, Vermeulen C. 2015. Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. Mammal Review 45: 239–252. (2 May 2017; *http://doi.org/10.1111/mam.12046*)

Lonergan M, Duck C, Thompson D. 2011. British grey seal (*Halichoerus grypus*) abundance in 2008: An assessment based on aerial counts and satellite telemetry. ICES Journal of Marine Science 68: 2201–2209.

Lynch HJ, LaRue MA. 2014. First global census of the Adélie Penguin. Auk 131: 457–466. (2 May 2017; *http://doi.org/10.1642/AUK-14-31.1.s1*)

Lynch HJ, Schwaller MR. 2014. Mapping the abundance and distribution of Adélie penguins using Landsat-7: First steps towards an integrated multi-sensor pipeline for tracking populations at the continental scale. PLOS ONE 9 (art. e113301). (2 May 2017; *http://doi.org/10.1371/journal.pone.0113301*)

McIntyre T. 2014. Trends in tagging of marine mammals: A review of marine mammal biologging studies. African Journal of Marine Science 36: 409–422. (2 May 2017; *http://doi.org/10.2989/1814232X.2014.976655*)

McMahon CR, Howe H, van den Hoff J, Alderman R, Brolsma H, Hindell MA. 2014. Satellites, the all-seeing eyes in the sky: Counting elephant seals from space. PLOS ONE 9 (art. e92613). (2 May 2017; *http://doi.org/10.1371/journal.pone.0092613*)

Mohn R, Bowen W. 1996. Grey seal predation on the eastern Scotian Shelf: Modelling the impact on Atlantic cod. Canadian Journal of Fisheries and Aquatic Sciences 53: 2722–2738.

Myers RA, Hammill MO, Stenson GB. 1997. Using mark-recapture to estimate the numbers of a migrating stage-structured population. Canadian Journal of Fisheries and Aquatic Sciences 54: 2097–2104. (2 May 2017; *http://doi.org/10.1139/f97-116*)

Nichols OC, Eldredge E, Cadrin SX. 2014. Gray seal behavior in a fish weir observed using dual-frequency identification sonar. Marine Technology Society Journal 48: 72–78. (2 May 2017; *http://doi.org/10.4031/MTSJ.48.4.2*)

[NOAA] National Oceanic and Atmospheric Administration, [NMFS] National Marine Fisheries Service. 2015. Gray seal (*Halichoerus grypus*) Western North Atlantic Stock Assessment. NOAA, NMFS. (2 May 2017; *www.nefsc.noaa.gov/publications/tm/tm231/169_grayseal_F2014August.pdf*)

———. 2016. Gray seal (*Halichoerus grypus*) Western North Atlantic Stock Assessment. NOAA, NMFS. (2 May 2017; *www.nmfs.noaa.gov/pr/sars/pdf/stocks/atlantic/2015/f2015_grayseal.pdf*)

O'Boyle R, Sinclair M. 2012. Seal–cod interactions on the Eastern Scotian Shelf: Reconsideration of modelling assumptions. Fisheries Research 115–116: 1–13.

Platonov NG, Mordvintsev IN, Rozhnov VV. 2013. The possibility of using high resolution satellite images for detection of marine mammals. Biology Bulletin 40: 197–205. (2 May 2017; *http://doi.org/10.1134/S1062359013020106*)

Rafferty AR, Brazer EO, Reina RD. 2012. Depredation by harbor seal and spiny dogfish in a Georges Bank gillnet fishery. Fisheries Management and Ecology 19: 264–272. (2 May 2017; *http://doi.org/10.1111/j.1365-2400.2011.00837.x*)

Redpath SM, et al. 2013. Understanding and managing conservation conflicts. Trends in Ecology and Evolution 28: 100–109.

Ries EH, Hiby LR, Reijnders PJH. 1998. Maximum likelihood population size estimation of harbour seals in the Dutch Wadden Sea based on a mark-recapture experiment. Journal of Applied Ecology 35: 332–339. (2 May 2017; *http://doi.org/10.1046/j.1365-2664.1998.00305.x*)

Simpkins M, Withrow D, Cesarone J. 2003. Stability in the proportion of harbor seals hauled out under locally ideal conditions. Marine Mammal Science 19: 791–805.

Taylor BL, Martinez M, Gerrodette T, Barlow J, Hrovat YN. 2007. Lessons from monitoring trends in abundance of marine mammals. Marine Mammal Science 23: 157–175. (2 May 2017; *http://doi.org/10.1111/j.1748-7692.2006.00092.x*)

Waring GT, DiGiovanni RA Jr, Josephson E, Wood S, Gilbert JR. 2012. Population Estimate for the Harbor Seal (*Phoca vitulina concolor*) in New England Waters. National Oceanic and Atmospheric Administration. Technical Memorandum no. NMFS-NE-235.

Wood S. 2009. Dynamics of Recolonization: A Study of the Gray Seal (*Halichoerus grypus*) in the Northeast US. PhD dissertation. University of Massachusetts, Boston.

Wood S, Frasier T, McLeod B. 2011. The genetics of recolonization: An analysis of the stock structure of grey seals (*Halichoerus grypus*) in the northwest Atlantic. Canadian Journal of Zoology 89: 490–497.

Jerry H. Moxley completed this work during his dissertation at the Duke University Marine Lab, a division of the Nicholas School of the Environment in Beaufort, NC USA. He is currently a research scientist at the Monterey Bay Aquarium in Monterey, CA USA. Andrea Bogomolni is affiliated with the Woods Hole Oceanographic Institute, in Woods Hole, USA. Mike O. Hammill is affiliated with the Maurice-Lamontagne Institute, in Department of Fisheries and Oceans, in Mont-Joli, Canada. Kathleen M.T. Moore is affiliated with the Marine Mammal Rescue and Research Program, at International Fund for Animal Welfare, in Yarmouth Port, Massachusetts, USA. Michael J. Polito is affiliated with the Department of Oceanography and Coastal Sciences, at Louisiana State University, in Baton Rouge, USA. Lisa Sette is affiliated with the Provincetown Center for Coastal Studies, in Provincetown, USA. W. Brian Sharp is affiliated with the Marine Mammal Rescue and Research Program, at International Fund for Animal Welfare, in Yarmouth Port, Massachusetts, USA. Gordon T. Waring is affiliated with the Protected Species Branch, retired, at Northeast Fisheries Science Center, in Woods Hole, USA. James R. Gilbert is affiliated with the Department of Wildlife, Fisheries, and Conservation Biology, emeritus, at University of Maine, in Orono, USA. Patrick N. Halpin is affiliated with the Marine Geospatial Ecology Lab, at Nicholas School of the Environment, Duke University, in Durham, USA. David W. Johnston is affiliated with the Division of Marine Science and Conservation, at Nicholas School of the Environment, Duke University Marine Lab, in Beaufort, USA.