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SHORT COMMUNICATION

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Mind the gap—optimizing satellite tag settings for time series analysis of foraging dives in Cuvier's beaked whales (*Ziphius cavirostris*)

Nicola J. Quick[1*], William R. Cioffi[2], Jeanne Shearer[2] and Andrew J. Read[1]

Abstract

Background: Studies of deep-diving beaked whales using Argos satellite-linked location-depth tags frequently return data with large gaps in the diving record. We document the steps taken to eliminate these data gaps and collect weeks of continuous time series data for a behavioral response study that took place in 2017. We used baseline data collected from 2014 to 2016 to analyze message diagnostics, and assess our current programming schedule using a multiple criteria decision making matrix (MCDM), as a robust way to develop a new sampling regime.

Results: The MCDM approach suggested animal behavior and the quantity of data collected were the main causes of gaps in our baseline tag records. We implemented a new sampling regime to sample only long-duration, presumed foraging dives, simultaneously increasing temporal coverage of each individual message and reducing the number of messages by 50%. The reduction of gaps increased the data available for continuous time series analysis from an average of just over 2 days and 13.5 sequential presumed foraging dives in our baseline tags to just over 19 days and 118 sequential presumed foraging dives in tags deployed during the 2017 behavioral response study.

Conclusions: We demonstrate that a critical approach, based on analysis of baseline data and question-driven weighted criteria, enabled the reduction and even elimination of gaps in the diving records of these tags. This approach enabled us to develop specific settings for our tags to ensure that our data collection was optimized for statistical analysis of the specific hypotheses we were testing.

Keywords: Cuvier's beaked whales, Satellite tags, Argos, Time series, Data gaps, Behavioral response study

Background

Deep-diving odontocete cetaceans provide a unique set of challenges for behavioral research. The inability to directly observe individual animals has led to the development of animal-borne tags to document and study their behavior [1, 2]. Suction cup tags [3] provide high-resolution snapshots of behavior over short temporal scales. However, analysis of time budgets and questions regarding switches between behavioral states require the collection of continuous time series data over longer periods. Longer duration satellite tags, attached trans-dermally [4], provide longer sampling periods, but at the cost of a loss in the resolution of data and reliance on transmission of data in small packages via remote receivers, such as Argos satellites [5]. The availability of Argos satellites varies with latitude, and, although set-up latency for transmission is minimal, it is widely accepted that gaps in the data are inevitable due to a range of factors, including location of study site, animal behavior, environmental conditions and transmitter stability [5, 6].

In cases when estimates of surface position are not regularly spaced in time and have associated errors of varying magnitude, effort has focused on extrapolating between consecutive positions to produce continuous tracks [5, 7, 8]. However, Breed et al. [9] note that variability in temporal resolution of locations through programming schedules and duty cycling strongly affects

*Correspondence: njq@duke.edu
[1] Duke Marine Lab, Division of Marine Science and Conservation, Nicholas School of the Environment, 135 Duke Marine Lab Road, Beaufort, NC 28516, USA
Full list of author information is available at the end of the article

application of time series methods and may reduce the utility of the data, especially when changes in behavior occur on shorter time scales than the duty cycle. For data in the z-dimension, gaps in dive records may result in the loss of dive sequences, surface periods, or even entire foraging bouts. Accounting for these gaps is problematic when the length of the missing records is longer than a single behavioral event (e.g., a foraging dive) as the number of missed events is unknown. This problem is particularly pernicious when research questions are intended to address changes in foraging behavior at the scale of individual dives, over extended temporal scales or in the probability of transitions in behavioral state over time. Statistical approaches for the analysis of foraging behavior have been successfully applied to data from animal-borne tags on deep-diving odontocetes over the scale of hours or days [10, 11]. However, longer duration (i.e., over weeks) continuous time series are lacking for most deep-diving odontocetes, and most studies report the presence of gaps in the behavior record [12, 13].

Changes in diving behavior are considered important effects in behavioral response studies of deep-diving beaked whales [12, 14], due to the possibility of reduced foraging success as a consequence of exposure [15]. In beaked whales, most previous behavioral response studies have documented short-term changes using archival tags with short deployment durations [14, 16, 17]. The use of longer duration tags would enable an assessment of response over greater temporal scales. Nevertheless, in behavioral response studies where exposure to a stimulus is hypothesized to result in a change in behavioral state [12] (i.e., from foraging to traveling), it is necessary to collect relatively complete time series data consisting of entire bouts of behavior. If these time series contain temporal gaps that span periods greater than the duration of the behavioral state in question, accurate analysis of any response and subsequent biological interpretation of behavioral state transitions will be difficult or impossible. All behavioral response studies require implementation of best practices to minimize potential harm and justify identifiable benefits for future conservation and management [18]. In these studies, a primary aim must be to ensure data collection covers the temporal period before, during and following the exposure to allow assessment of any response.

Our objective was to collect behavioral data from Cuvier's beaked whales (*Ziphius cavirostris*) to provide a continuous time series dataset of foraging behavior over a period of weeks. These observations were required to inform the Atlantic Behavioral Response Study (BRS) on the effects of exposure to tactical military sonar that occurred in 2017. Optimizing programming settings for satellite tags is complex, with multiple trade-offs to consider [5, 9]. In the present study, we address an explicit hypothesis to eliminate data gaps within the diving record. We use multiple criteria decision making (MCDM) to evaluate the problem of data gaps within a weighted criteria matrix framework. We inform this matrix with baseline data from this species and the biologically driven question at the core of the 2017 Atlantic BRS.

Methods

Between 2014 and 2016, we deployed eleven SPLASH10-292, Argos satellite-linked location-depth tags (produced by Wildlife Computers, Redmond, Washington) on Cuvier's beaked whales off Cape Hatteras, North Carolina (Table 1). All tags were remotely deployed using a DAN-INJECT JM 25 pneumatic projector (DanWild LLC, Austin, Texas) in the LIMPET configuration [4] from a 9-m rigid-hulled aluminum boat. Tags were attached with two 6.8-cm surgical grade titanium darts with backward-facing petals to a target area in the center or at the base of the dorsal fin. Photographs were taken of all tagged individuals with Canon or Nikon digital SLR cameras equipped with 100- to 400-mm zoom lenses. These photographs were used to identify individuals and compared to an existing photo-identification catalogue (see [19] for full details of deployment methodology). These tags recorded animal position and dive statistics and transmitted data messages via the Argos satellite system. Dive data were collected using the behavior log function that compiles behavior events based on user-defined "dive" and "surface" events. Candidate dives were defined by a conductivity sensor with a preset threshold which detected the beginning and end of submergence. Dive events were retained in the transmitted behavior data log if they were longer than 30 s and deeper than 25 m ($n = 2$) or 50 m ($n = 9$). The intervening time periods that did not meet these criteria were categorized as surface events [12, 13]. Tags were initially programmed to transmit for 20 h per day, with hours specified to take advantage of local satellite coverage and were programmed to duty cycle later in the deployment period [19]. All tag records were checked systematically for data corruption and sensor failure (see [19] for details). Plots of diving data from baseline tags were constructed to examine data gaps, which occur when data messages covering a particular time period are not received by the Argos system. From these baseline data, we explored a range of diagnostic metrics to determine the cause of messages not being received.

The location of the tag on each animal was assessed using photo-identification images collected in the field. We measured tag position as a pixel ratio (termed *insertratio*) using ImageJ 1.52a. This ratio was calculated as

Table 1 Summary of satellite tag deployments from 2014–2016 and 2017

Deploy ID	First message date (time)	Last message date (time)	Transmission duration (days)	Number of gaps	Duration of gaps (days)	Percentage of total tag duration as gaps
ZcTag029	13-May-14 (14:48:00)	12-Jul-14 (07:44:30)	59.7	77	41.5	69.5
ZcTag030	16-Sep-14 (17:32:00)	25-Oct-14 (04:29:00)	38.4	53	12.8	33.3
ZcTag038	14-Jun-15 (13:08:00)	09-Aug-15 (21:48.52)	56.3	33	21.9	39.0
ZcTag040	14-Jun-15 (20:00:00)	15-Jun-15 (13:13:02)	0.7	0	0.0	0.0
ZcTag041	15-Oct-15 (13:48:00)	16-Nov-15 (20:49:18)	32.3	28	9.0	27.9
ZcTag042	21-Oct-15 (14:03:00)	08-Nov-15 (00:20:54)	17.4	36	8.1	46.5
ZcTag046	25-May-16 (19:00:00)	04-Jun-16 (18:20:48)	9.9	19	5.9	59.4
ZcTag048	27-May-16 (16:56:00)	27-Jun-16 (00:27:32)	30.3	47	18.4	60.7
ZcTag050	21-Aug-16 (04:06:00)	14-Sep-16 (16:22:32)	24.5	11	22.9	93.4
ZcTag051	22-Aug-16 (07:29:00)	31-Aug-16 (14:46:48)	9.3	11	3.4	36.8
ZcTag054	10-May-17 (16:17:00)	28-May-17 (14:23:00)	17.9	0	0.0	0.0
ZcTag055	10-May-17 (16:37:00)	30-Jun-17 (03:15:26)	50.4	16	35.9	71.3
ZcTag056	10-May-17 (18:59:00)	27-Jun-17 (07:35:10)	47.5	0	0.0	0.0
ZcTag057	16-May-17 (17:50:00)	04-Jul-17 (11:37:18)	48.7	0	0.0	0.0
ZcTag058	16-May-17 (19:48:00)	25-Jun-17 (01:42:36)	39.2	0	0.0	0.0
ZcTag060	17-Aug-17 (17:20:00)	20-Sep-17 (20:37:44)	34.1	7	4.2	12.3
ZcTag061	17-Aug-17 (18:08:00)	30-Sep-17 (05:01:16)	43.5	1	0.3	0.8
ZcTag062	17-Aug-17 (21:31:00)	28-Aug-17 (06:12:20)	10.9	0	0.0	0.0
ZcTag063	20-Aug-17 (16:54:00)	18-Sep-17 (21:39:44)	29.2	9	6.5	22.2
ZcTag064	20-Aug-17 (17:42:00)	23-Sep-17 (21:28:52)	34.2	17	11.1	32.6
ZcTag065	22-Aug-17 (17:09:00)	4-Sep-17 (03:09:48)	12.4	5	1.6	13.0
ZcTag066	04-Sep-17 (14:50:00)	12-Oct-17 (09:13:00)	37.8	3	1.2	3.1
ZcTag067	04-Sep-17 (14:53:00)	16-Oct-17 (08:39:48)	41.7	8	5.1	12.2
ZcTag068	04-Sep-17 (16:16:00)	13-Oct-17 (09:02:56)	38.7	17	8.6	22.1

the number of pixels below or above the perpendicular plane of anterior insertion of the dorsal fin and the number of pixels along the long axis of the tag. We ran a linear regression model to assess the variability for the ratio measure. We then calculated the percentage of gaps in the data record from each whale. The percentage of corrupt messages were determined by loading the tag files into the WC-DAP, Wildlife Computers Data analysis program [20]. The average daily transmissions per tag, from day of deployment, were calculated from the tag status files by dividing the total cumulative transmissions by the duration of the tag record given in the status file. For each behavior log message, we calculated the number of data rows and the proportion of rows that contained a presumed foraging dive, defined as any submergence to greater than 800 m [21]. We also computed distributions for the temporal period each message covers; the count of the number of messages produced each day; and a count of the times each message was successfully received.

We used multiple criteria decision making (MCDM) to evaluate conflicting criteria and determine an optimal solution (see [22] for review) for reducing data gaps in the dive record. MCDM is a decision making framework to structure a question considering multiple criteria that are weighted based on importance. We took six main steps during this decision making process: (1) Identify the problem (too many gaps in the data); (2) Identify four main possible causes of data gaps using the results from our analysis of the baseline data (defined as problems in Table 4); (3) Identify four key criteria to consider in the framework to address each problem in turn (defined as criteria in Table 4). Criteria were chosen based on four areas that we felt were the most important for the success of our study. The first concerned effect on data analysis, the second how easy a solution would be to implement; the third how we might compromise other data streams that would impact the project in general, and the fourth how quickly we could implement the solution. For any MCDM framework, criteria should be measurable and logical with respect to the problem and it should be possible to weight their importance; (4) Assign a weight to each criterion to represent importance by distributing ten points among them. We choose a simple weighting system to distinguish between our criteria, but any weighting method could be used [22]. We considered

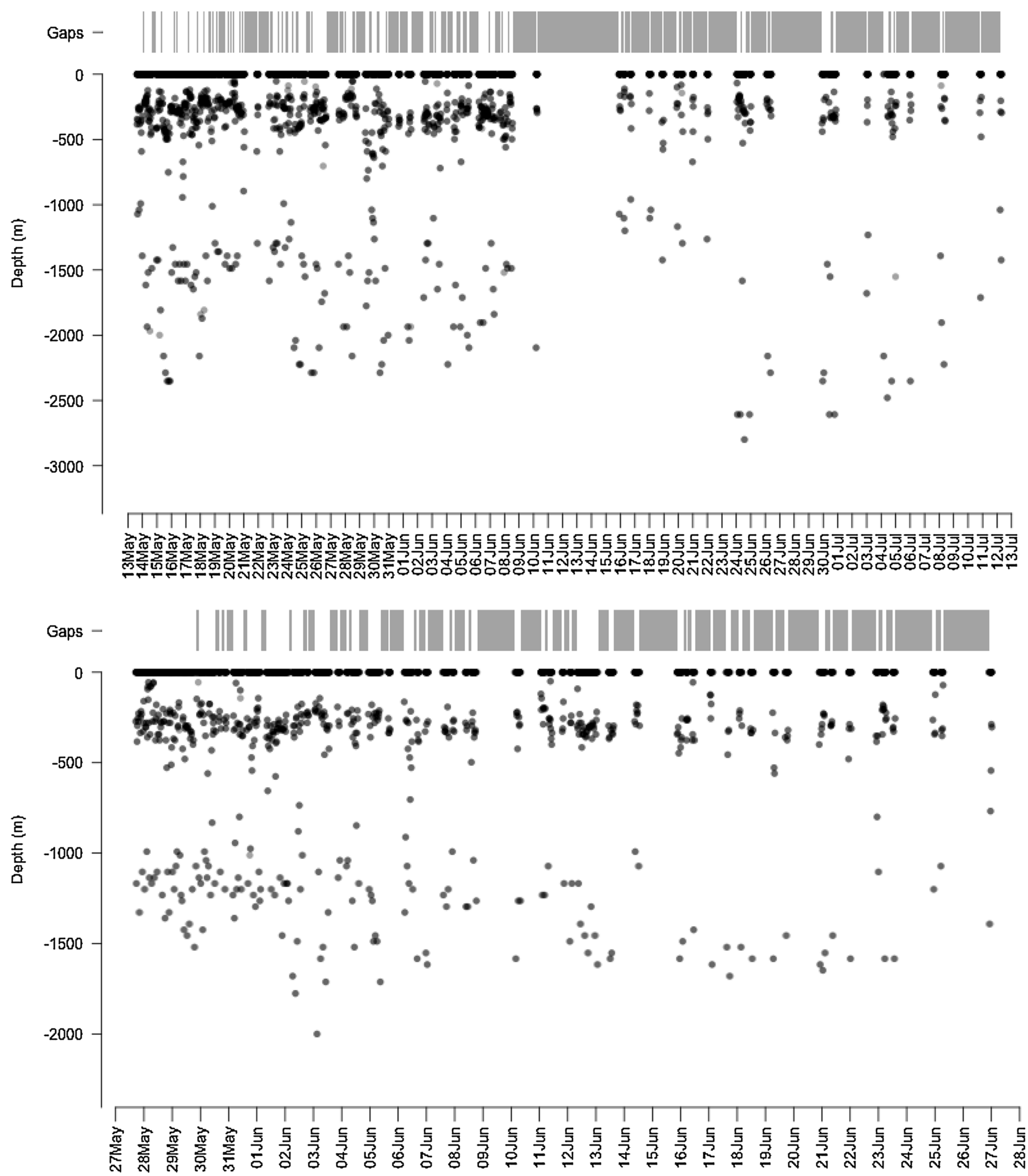

Fig. 1 Plots of entire dive records from two baseline tags ZcTag029 (top) and ZcTag048 (bottom), showing date along the *x*-axis and dive depth on the *y*-axis. Horizontal gray bars show all gaps greater than 1 min duration. Black circles show maximum depths for each dive

an effect on time series foraging analysis as the most important criteria in the context of the response analysis, so we weighted this twice as much as the other criteria (Table 4). We then assigned a weighting scale of high (3), medium (2) and low (1) to evaluate each choice against the criteria; (5) Aggregate our weighting

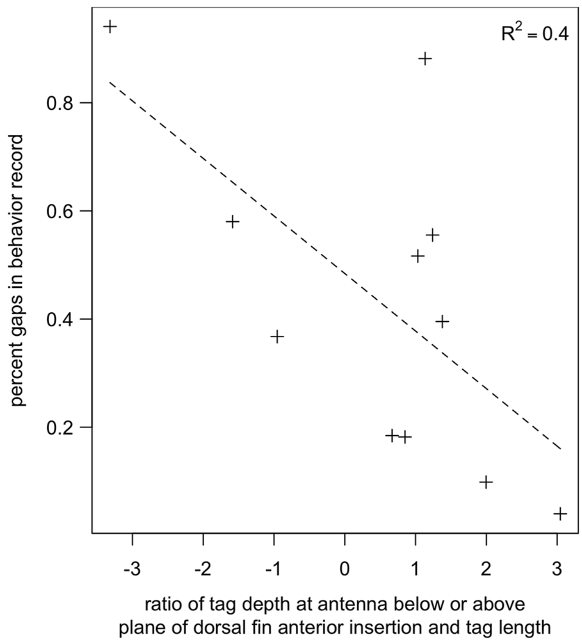

Fig. 2 The percentage of gaps in the behavior record plotted against insert ratio measurements for tag position on the fin. Positive values are above dorsal fin insertion plane, i.e., higher up the fin, and dashed line represents best fit of the general linear model with associated R^2 value

Table 2 The percentage of corrupt messages per baseline tag, the average daily transmissions and the total number of messages received including all message types

Deploy ID	Percentage of corrupt messages	Average daily transmissions	Total number of messages received
ZcTag029	75	374	3916
ZcTag030	54	329	1694
ZcTag038	36	333	2079
ZcTag040	44	358	131
ZcTag041	50	303	1307
ZcTag042	69	349	1444
ZcTag046	78	307	346
ZcTag048	75	337	1087
ZcTag050	92	N/A	271
ZcTag051	81	360	344

N/A shows metric not available for tag

methods by multiplying the criteria weightings by the weighted scale for each individual row and then sum the values across each criteria for each possible cause of data gaps; (6) Make a decision based on the aggregation method in part 5 by selecting the row containing the highest score as the most plausible option for reducing data gaps, but also consider other rows based on their final scores, if final scores were close.

Analysis of the baseline data and information from the MCDM matrix supported the need to streamline data collection on the 2017 tags. In the context of the main objectives of the 2017 Atlantic BRS, we used our results to program tags in 2017. We considered two key aspects. The first was to increase the proportion of each message that contained information on presumed foraging behavior by changing the sampling regime to target deep dives. We determined criteria to define deep dives by plotting depth against duration for all the baseline tags and aligned this with options in the tag programming schedule. The second was to decrease the number of daily messages created, to increase the opportunity for successful message reception.

We deployed an additional fourteen SPLASH10-292, Argos satellite-linked location-depth tags on Cuvier's beaked whales off Cape Hatteras from May to September 2017 (Table 1). All tags were remotely deployed using the system described above. Settings were consistent with the baseline 2014–2016 tag deployments, except for the changes determined by the MCDM and the removal of all duty cycling. We turned off all user-defined functionality for non-behavior log data and adopted a highly selective sampling of dives in the behavior log function. Tags were programmed to sample only long-duration dives, defined as those that exceeded 33 min and 50 m (see below). All other behaviors were combined into the surface category. To validate the outcome of our MCDM matrix, we compared diagnostics between the baseline 2014–2016 tags and the 2017 tags, with respect to gaps in the dive record. We compared the proportion of each behavior message that contained information on presumed foraging dives and compared the proportion of the total tag duration that constituted gaps. We also compared differences in message durations, counts per day and times each message was successfully received by calculating densities using default settings of the density function in the base R stats package. Finally, we compared the longest duration in days of continuous presumed foraging data that could be used for time series analysis across all tags.

Results

Data from ten of the eleven tags deployed during 2014–2016 were used in the analysis. One tag experienced a severe sensor failure and was not considered further, while four others had spurious data removed before analysis [19]. The duration of data records ranged from 0.7 to 59.7 days with a median of 27.4 days (Table 1). The number of gaps in the diving record ranged from zero to 77, with a mean gap duration across all tags of 14.4 days, ± 12.3 days (Table 1). The percentage of the

Table 3 Total number of messages and presumed foraging dives per tag and the proportion of each message that constituted information on presumed foraging behavior

Deploy ID	Total messages from behavior log	Median rows of data per message (min–max)	Total foraging dives	Median rows of data per message that are foraging dives (min–max)	Proportion of message containing data on foraging	Longest duration time series in days (no. foraging dives)
ZcTag029	163	10 (9–10)	165	1.0 (0–2)	0.10	0.90 (6)
ZcTag030	242	10 (9–10)	260	1.0 (0–3)	0.10	2.30 (22)
ZcTag038	307	9 (9–10)	327	1.0 (1–3)	0.10	9.80 (98)
ZcTag040	6	10 (10–10)	9	1.5 (1–2)	0.15	0.70 (9)
ZcTag041	197	10 (9–10)	275	1.0 (0–3)	0.10	2.90 (32)
ZcTag042	86	10 (9–10)	97	1.0 (0–3)	0.10	0.95 (12)
ZcTag046	40	10 (9–10)	58	1.0 (1–3)	0.10	0.70 (11)
ZcTag048	117	10 (9–10)	140	1.0 (0–2)	0.10	2.20 (26)
ZcTag050	13	10 (9–10)	23	2.0 (1–4)	0.20	0.20 (2)
ZcTag051	31	9 (8–10)	66	2.0 (1–4)	0.20	1.40 (15)
ZcTag054	48	8 (8–9)	193	4.0 (4–5)	0.50	17.9 (193)
ZcTag055	40	8 (8–9)	161	4.0 (4–5)	0.50	6.3 (64)
ZcTag056	130	8 (8–9)	524	4.0 (4–5)	0.50	47.5 (524)
ZcTag057	75	8 (8–9)	303	4.0 (4–5)	0.50	48.7 (303)
ZcTag058	88	8 (8–9)	352	4.0 (4–4)	0.50	39.2 (352)
ZcTag060	69	8 (8–9)	278	4.0 (4–5)	0.50	9.7 (81)
ZcTag061	112	8 (8–9)	450	4.0 (4–5)	0.50	37.6 (386)
ZcTag062	22	8 (8–8)	88	4.0 (4–4)	0.50	10.9 (88)
ZcTag063	56	8 (8–9)	227	4.0 (4–5)	0.50	5.0 (41)
ZcTag064	59	8 (8–9)	238	4.0 (4–5)	0.50	9.4 (97)
ZcTag065	38	8 (8–9)	154	4.0 (4–5)	0.50	5.9 (82)
ZcTag066	97	8 (8–9)	393	4.0 (4–5)	0.50	16.9 (172)
ZcTag067	93	8 (8–9)	379	4.0 (4–5)	0.50	10.4 (122)
ZcTag068	85	8 (8–9)	343	4.0 (4–5)	0.50	6.0 (113)

Final column gives the longest duration period of continuous time series data per tag in days with the number of presumed foraging dives within this period. Tags 029–051 were deployed in 2014–2016 and tags from 054–068 were deployed in 2017

total tag duration consisting of gaps ranged from zero to 93.4% with a mean of 46.7%, ± 25.7% (Table 1). Only one tag (ZcTag040) contained a complete diving record, but this tag record was of the shortest duration, lasting only 0.7 days (Table 1). Plots of the diving records from these tags showed gaps of variable lengths in the time series across the entire record (Fig. 1). The measurements of tag position (*insertratio)* suggested a general trend of reduced gaps in the diving record when the tag was placed higher on the dorsal fin and the results of the general linear model returned an R^2 value of 0.4 (Fig. 2).

The percentage of corrupt messages per tag ranged from 36 to 92% with a mean across tags of 65.4%, ± 18.2% (Table 2). For all tags, the average number of transmissions per day was lower than the maximum programmed attempts of 450 (Table 2). The total number of messages from the behavior log, per tag, ranged between 6 and 307 with a mean of 120.2, ± 104.1, but the median rows of data per messages were extremely consistent at 9 or 10 across all tags (Table 3). The number of presumed foraging dives returned for each tag varied greatly, due to tag duration, and ranged between 9 and 327, but the median number of rows of data per message providing data on presumed foraging dives was low, at 2 or less, across tags (Table 3). Across all tags the proportion of data on presumed foraging dives per message was consistently low at 0.2 or less (mean 0.12, ± 0.04) (Table 3). The distributions of message duration across tags were variable with a median of 1.5 h (Fig. 3). The number of messages produced each day was also considerably variable across tags with a median count of 5, and the number of times each message was received was low with a median of 2 (Fig. 3).

The MCDM analysis produced the highest score for gaps resulting from too much data collected for reception (Table 4). Across each of the weighted criteria, this problem scored high on the weighting scale. The next highest score was associated with animal behavior affecting reception rate. Tag position on the animal

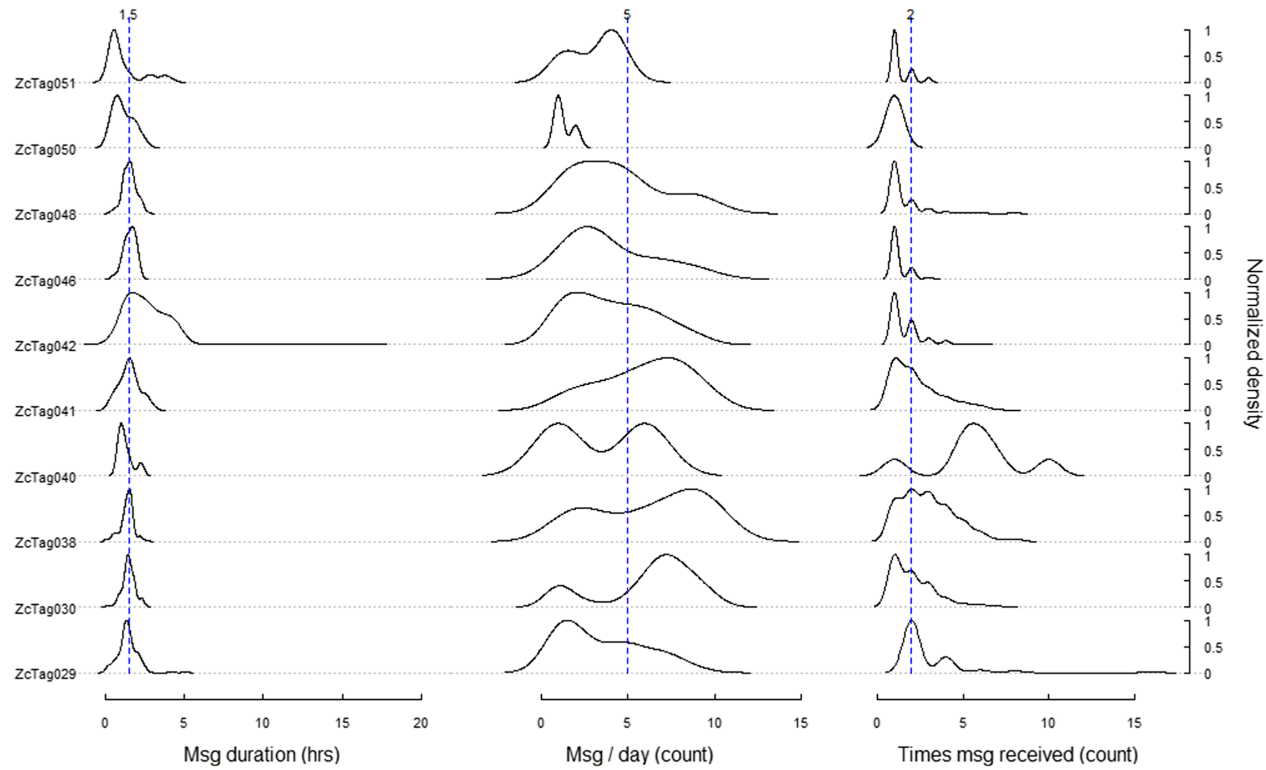

Fig. 3 Normalized density plots of individual message length in hours (left panel), the number of messages created each day (middle panel) and the number of times each message was successfully received by Argos satellite (right panel) for all baseline (2014–2016) tags. Plots are normalized so the magnitude of the peaks is not comparable between animals but the location of the peaks are. Dashed line shows median value

and exceeding daily transmission schedule returned the lowest scores (Table 4). The MCDM matrix suggested a primary solution that demonstrated a high effect on the time series analysis, had high ease and speed to solve, and also had a high effect on the other data streams. The secondary solution produced high or medium effects on each of the criteria and hence should also be considered in concert with the primary solution. To implement the two outcomes from the MCDM matrix, we considered each criterion in turn. To reduce the number of messages created per day we needed to reduce the total amount of data collected. To do this efficiently, we needed to be more selective about which data we required. To minimize loss of data across all data streams we also needed to be more selective about which data we needed. Each behavior message contained, on average, only 12% of data on presumed foraging dives, with the other 88% containing information on presumed non-foraging dives and surface behavior (Table 3). Therefore, to reduce the amount of data collected, and to focus on presumed foraging behavior, we decided to sample only long-duration dives. The plot of dive depth against duration showed a strongly bimodal pattern in diving behavior, with deep presumed foraging dives exceeding 800 m (Fig. 4). Tag programming did not allow a depth cutoff greater than 75 m, so we computed a duration that incorporated 99.4% of all deep dives (Fig. 4) and programmed the tags to record only dives greater than 33 min duration.

Data from all fourteen tags deployed during 2017 were used in the comparison between the baseline 2014–2016 tags and 2017 tags. Transmission duration for the 2017 tags ranged from 10.9 to 50.4 days with a median of 34.7 days (Table 1). The number of gaps in the diving record ranged from zero to 17, with an average gap duration across all tags of 5.3 days, ± 9.5 days (Table 1). The percentage of the total tag duration consisting of gaps ranged from zero to 71.3% with an average of 13.5%, ± 19.7% (Table 1). Five tags contained complete diving records, ranging from 10.9 to 48.7 days (Table 1). We compared counts of the total number of messages from the behavior log and the total number of presumed foraging dives per individual (Fig. 5). In 2017, the total number of messages from the behavior log ranged from 22 to 130 with a mean of 72.3, ± 30.6 (Fig. 5). This was a 40% reduction in message number compared to the 2014-2016 tags (Table 3). The number of presumed foraging dives ranged from 88 to 524 with a mean of

Table 4 Multiple criteria decision making matrix showing the four weighted criteria against the four main problems identified from the baseline data

Problem	Criteria				
	Effect on time series foraging analysis for BRS	**Ease to solve**	**Effect on other tag functions**	**Speed to solve**	
	4	**2**	**2**	**2**	
Gaps due to tag position preventing transmissions	Low: experienced tagger ensured good tag placement	Low: tags are attached remotely	Medium: all data streams are compromised if tag is poorly positioned	Low: limited number of deployments each season	
	$4 \times 1 = 4$	$2 \times 1 = 2$	$2 \times 2 = 4$	$2 \times 1 = 2$	12
Gaps due to too much data recorded to receive	High: current programming schedule is collecting more daily messages than can be received	High: change programming schedule to reduce data amount	High: loss of data across all data streams	High: tags can be programmed before next deployment	
	$4 \times 3 = 12$	$2 \times 3 = 6$	$2 \times 3 = 6$	$2 \times 3 = 6$	30
Gaps due to not enough transmissions per day	Low: daily transmission limit was not reached in baseline tags	Low: daily transmission limit was not reached in baseline tags	Medium: changing transmission number will impact battery life	Low: no other options to receive data	
	$4 \times 1 = 4$	$2 \times 1 = 2$	$2 \times 2 = 4$	$2 \times 1 = 2$	12
Gaps due to animal surfacing behavior affecting reception rate	High: behavior affects message number	Medium: no way to control animal behavior, but can change programming schedule	Medium: behavior effects how all data streams are received	Medium: no way to control animal behavior, but can change programming schedule	
	$4 \times 3 = 12$	$2 \times 2 = 4$	$2 \times 2 = 4$	$2 \times 2 = 4$	24

Criteria numbers are weighted to a maximum of ten based on relative importance. Allocations in the matrix are based on a rating of high, medium and low allocating 3, 2, and 1 points, respectively

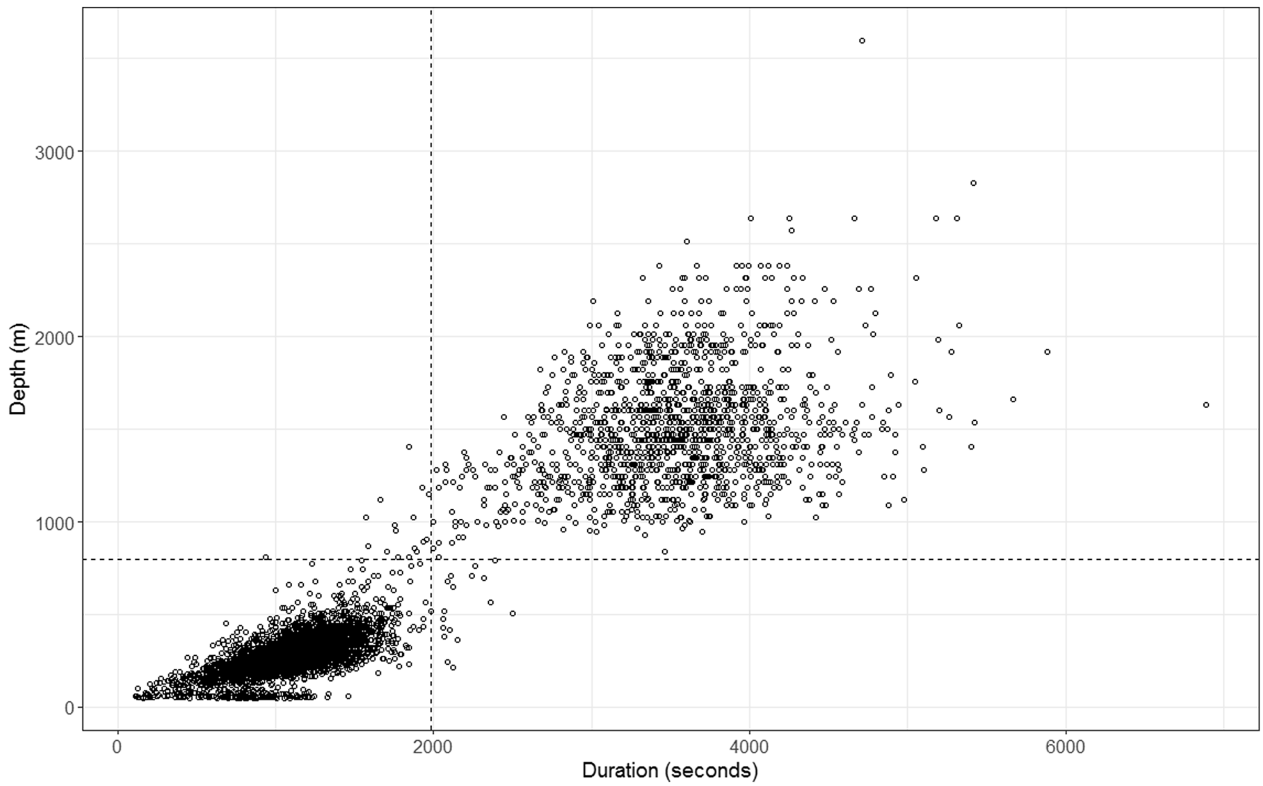

Fig. 4 Dive depth plotted against dive duration of all dives from the baseline tags. Horizontal dashed line is placed at 800 m, the vertical dashed line is at 1980s, equivalent to 33 min and shows the time duration cutoff used to sample presumed deep foraging dives

291.6, ± 123.3 for the 2017 tags compared to 142, ± 112.1 for 2014–2016 (Table 3, Fig. 5). The average proportion of each behavior log message that constituted a presumed foraging dive increased dramatically from 0.12 (± 0.04) in 2016–2017 to 0.5 (± 0) in 2017 (Table 3). The distributions of message length increased across all 2017 tags with a median of 9.3 h (Fig. 6). The median number of messages produced each day was reduced by 50% to a median value of 2 compared to 4 from the 2014–2016 tags. Conversely, the median number of times each message was received was doubled from 2 on the 2014–2016 tags to 4 for the 2017 tags (Fig. 6). The longest duration of continuous presumed foraging data was 9.8 days (mean 2.2 days ± 2.8 days) for the 2014–2016 tags (Table 3, Fig. 7). Within these time series, the range of presumed foraging dives available for analysis ranged from 2 to 98, median 13.5. In 2017, the longest duration of continuous presumed foraging data available for time series analysis was 48.7 days (mean 19.4 days ± 16.3 days) (Table 3, Fig. 7). Within these time series, the range of presumed foraging dives available for analysis ranged from 41 to 524, median 118 (Table 3, Fig. 7).

Discussion

Our results show that it is possible to optimize settings on SPLASH10-292, Argos satellite-linked location-depth tags to collect continuous time series data for beaked whales off Cape Hatteras, North Carolina, USA. A critical approach based on analysis of existing data, and employing question-driven weighted criteria, enabled us to considerably reduce and even eliminate gaps in the diving records from our tags. This reduction of gaps increased the data available for continuous time series analysis from on average just over 2 days and 13.5 sequential presumed foraging dives to just over 19 days and 118 sequential presumed foraging dives. In turn, this afforded us the ability to conduct continuous time series analysis of foraging behavior of Cuvier's beaked whales for an extended period and to capture all phases of the controlled exposure experiment, including the hour of exposure and the preceding and subsequent hours and days.

Our assessment of baseline data suggested a significant possibility of data gaps occurring either during the exposure period of the 2017 Atlantic BRS or for the hours and days directly before or after it. These gaps were consistent with other studies of Cuvier's beaked whales, in which

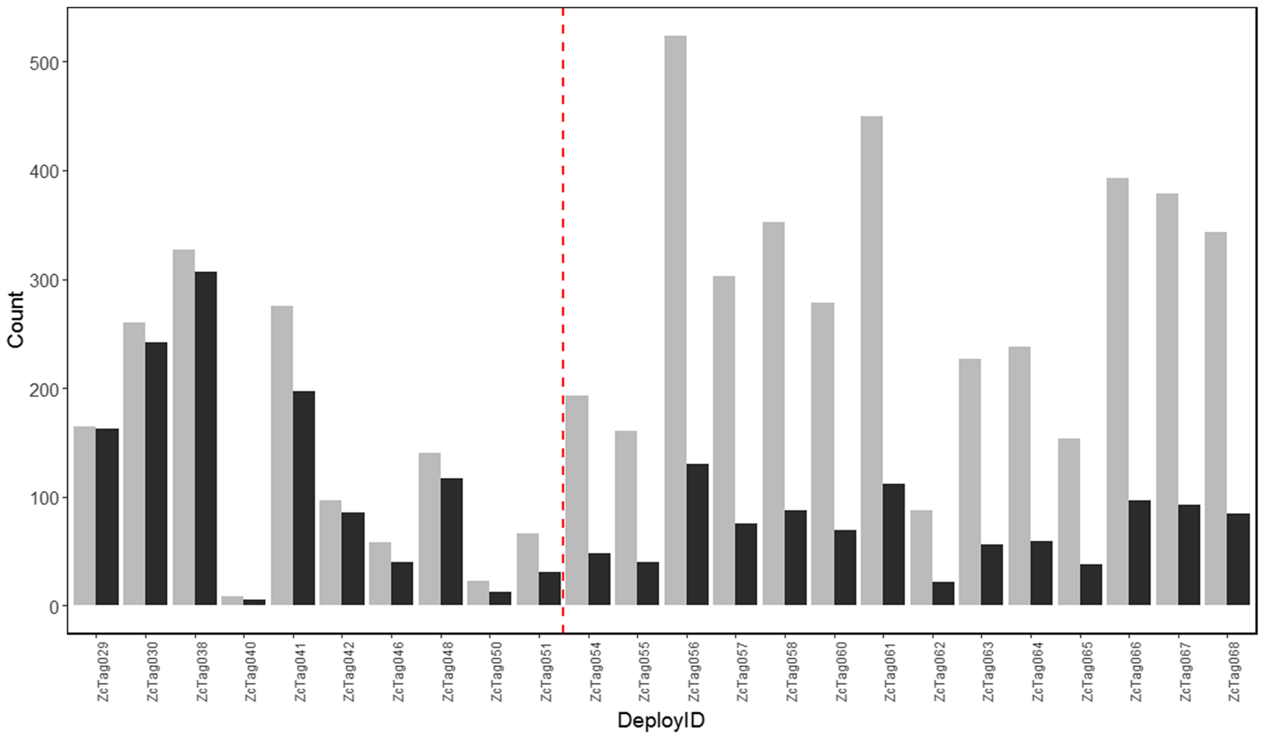

Fig. 5 Count of the total messages (black bars) received from the behavior log data file and the total number of foraging dives (gray bars) for each tag. Tags to the left of the red dashed line are baseline tags from 2014 to 2016. Tags to the right of the dashed line are 2017 tags with the updated settings

authors often report tag deployment durations in days, but behavior log data (i.e., diving records) in cumulative hours [12, 13] suggesting considerable gaps in the diving data. In general, gaps in satellite tag data are inevitable, especially with variation in the availability of overhead satellites in different latitudes [5]. Thus, researchers face a programming dilemma driven by considerations of the trade-offs in programming schedules against attempts to maximize richness of data, reduce power consumption and extend tag life through duty cycling [9]. Duty cycling is especially common for studies focused on long-term movements in which the longest period of data collection is desired. Most previous studies of long-term movements of beaked whales, for which limited information exists about most aspects of their ecology and behavior, have attempted to optimize multiple data streams and extend temporal sampling to help collect general information on their biology [12, 13, 21]. Our 2017 study focused on behavioral response, which required us to collect position estimates to understand horizontal avoidance, but also data on diving behavior to address questions of short- (hours) to medium (days)-term response in deep-diving (and presumed foraging) behavior. Our temporal scale of interest was well below the median tag duration of 27.4 days previously recorded for tags in our study area. This presented a scenario where the common limitation of managing power consumption to extend tag life was not the main constraint.

Our goal was to assess changes in foraging behavior of Cuvier's beaked whales over a temporal scale centered on an hour-long controlled exposure to tactical sonar. The exposure of marine mammals to potentially harmful stimuli during controlled exposure experiments requires researchers to design experiments with great care and to reduce uncertainty [18]. In addition, the use of transdermal satellite tags poses an additional risk of physical injury due to tag attachment [23, 24]. Thus, we considered the existence of data gaps in any exposure period to be unacceptable, and initiated a multiple criteria decision making matrix to find the optimal results. Our decision matrix required an initial evaluation of the extent of potential causes of the data gaps. We identified four most likely causes of these data gaps for our study site. There may be other causes of data gaps that we did not consider here, and it is likely that different problems, such as differences in satellite overpass availability in other locations, or areas with variable sea states, contribute to gaps for other species that exhibit different patterns of diving behavior.

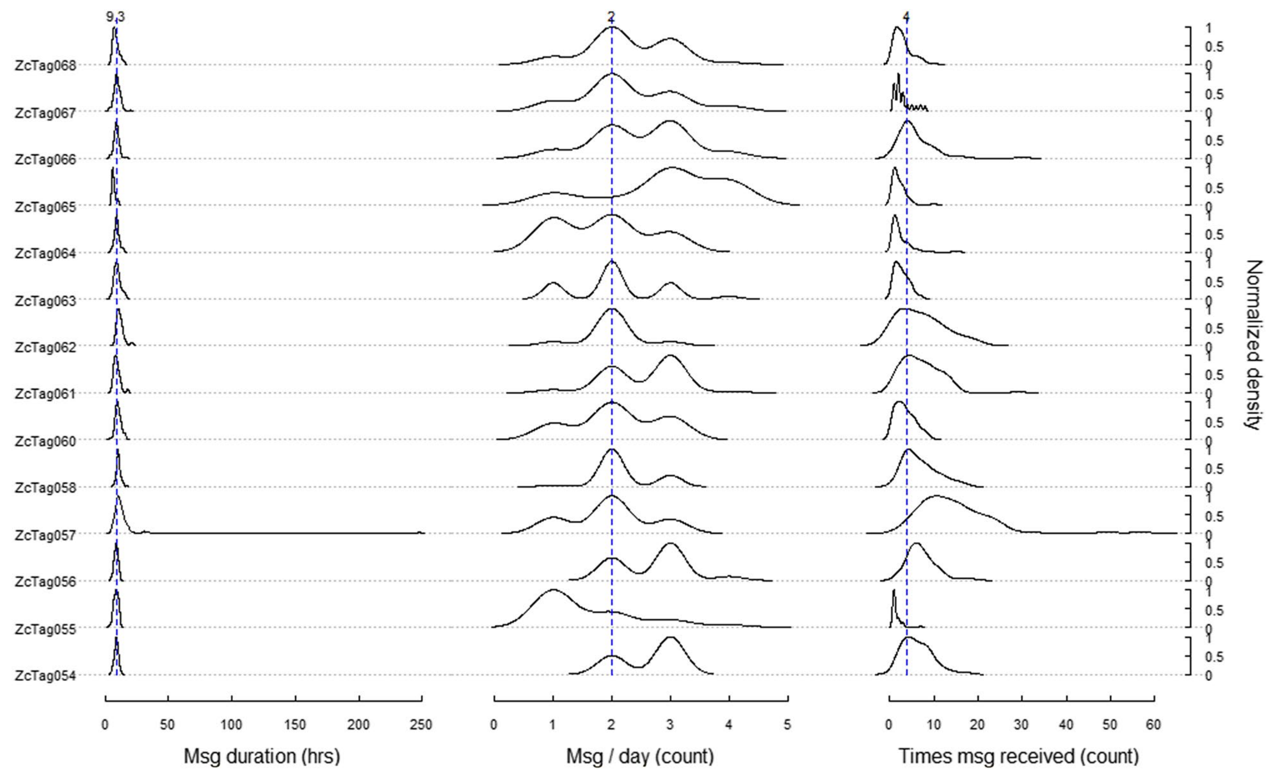

Fig. 6 Normalized density plots of individual message length in hours (left panel), the number of messages created each day (middle panel) and the number of times each message was successfully received by Argos satellites (right panel) for all 2017 tags. Plots are normalized so the magnitude of the peaks is not comparable between animals but the location of the peaks are. Dashed line shows median value

Beaked whales are extreme divers and spend little time at the surface [21, 25]. Previous studies of Cuvier's beaked whales in our area demonstrated median surface durations of 2.2 min [19]. These short surface durations provide very limited time for successful reception of Argos messages. The number of corrupt messages received from our baseline tags was very high (65%) suggesting that some transmitters may have been submerged mid-message. There was also a general trend of more gaps in our baseline records when tags were placed lower on the animal. We thus identified tag placement as an important metric for minimizing data gaps. We did see a relationship between our tag placement metric and the number of gaps, suggesting that, as long as the tag was placed relatively high on the fin, successful receptions were possible. With remotely deployed tags, we are not able to precisely determine where a tag is placed, so the MCDM matrix did not give strong support to changing our current method of tag placement as a solution to reducing the data gaps. Neither did the MCDM matrix strongly support the concept that gaps were caused because not enough transmissions occurred each day. Our analysis of average daily transmissions from the baseline tags showed we were not reaching our daily transmission limit, suggesting that animals were not engaged in extended surface behavior that would quickly exhaust the daily transmission budget. Therefore, it was clear that we did not need to increase our daily transmission allowance. We decided to maintain the transmission allowance at 450, as battery life was not a main constraint in our study and we did not want to introduce more gaps by limiting transmission options [9].

Another option to enhance data recovery is the use of extra receivers such as the ground-based listening and data relay stations; Motes (Wildlife Computers™) [26], or the Argos Goniometer (CLS America, Inc). These systems have been shown to greatly increase the number of messages received from tagged animals within range [26]. In general, the use of these systems has been restricted to terrestrial areas of high elevation, but we are currently employing a vessel based system due to the absence of elevated land masses near our study site. Implementation of such systems could provide significant advantages to reducing data gaps in future.

The MCDM matrix defined animal surfacing behavior affecting reception rate as the second most important problem. Beaked whales exhibit long foraging dives followed by a series of shorter duration shallow dives, each

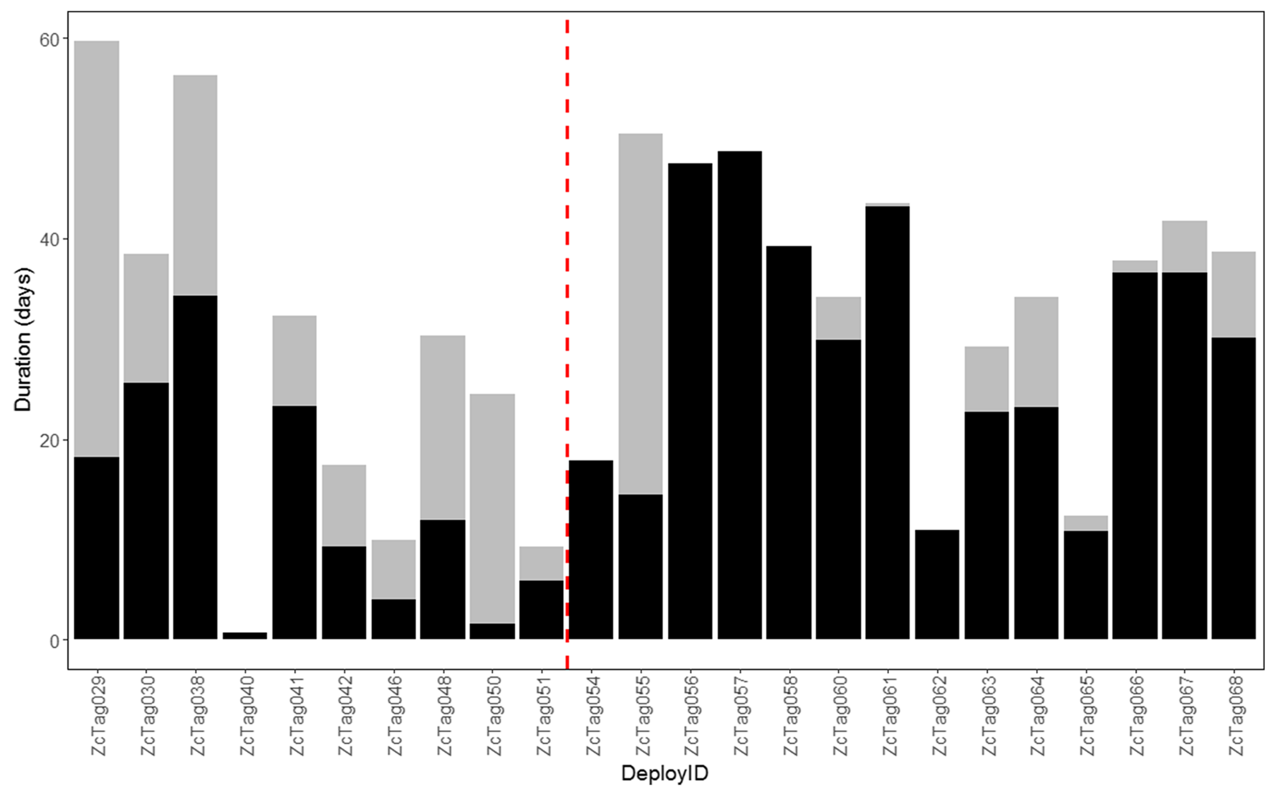

Fig. 7 Duration expressed as the number of days, of gaps (gray bars) and data (black bars) for the total duration of each tag. Tags to the left of the red dashed line are baseline tags from 2014 to 2016. Tags to the right of the dashed line are 2017 tags with the updated settings

with its own surface period [25]. Each shallow dive and inter-shallow dive surface period contribute two rows of data in each behavior log message. By recording all submergences greater than 50 m, as in our baseline beaked whale tags, most of our messages were populated with data from presumed non-foraging dives. In our 2014–2016 tags, only 12% of data per message represented presumed foraging dives. In 2017, 50% of all behavior messages contained data on presumed foraging dives and the other 50% were periods equivalent to inter deep dive intervals (IDDIs) as commonly reported in other studies of beaked whale behavior [12, 13]. This change in message composition meant that we could use all data in the time series analysis of foraging behavior, but we lost resolution in our IDDI data, as we could not differentiate between dives of less than 33 min duration and periods of respiration. We acknowledge that presumed non-foraging periods consist of multiple different behavioral states grouped together, which precludes any differentiation of behavior during these periods. We also acknowledge that whales could be engaged in foraging dives of less than 33 min duration during these periods. Very little is known about behavioral time budgets in Cuvier's beaked whales, but it is widely accepted [25, 27] that they exhibit a bimodal distribution of foraging and non-foraging dives. Our 33-minute duration cutoff may not capture every foraging dive, but we are confident from assessment of our baseline data, and from other studies, that this cutoff is a good proxy for determining non-foraging versus foraging behavior. However, without associated acoustic records, to confirm foraging behavior from detection of echolocation clicks and foraging buzzes, we refer to our long-duration dives as presumed foraging dives.

The change in programming also addressed the other problem outlined by the MCDM matrix—gaps caused by the existence of too much data to receive. Plots of message length, the number of messages produced per day and the number of times each message were received demonstrated that we were producing too much data to receive over the Argos system, given the short surface periods of the animals. Our approach greatly increased the length of time covered by each message, resulting in half as many messages created for transmission and a 50% increase in the number of times each message was successfully received. By coupling solutions from the two primary problems identified during the MCDM approach, we were able to collect more targeted data.

This approach positively impacted the number of times each message was received from the tag, while also generating more data on presumed foraging dives than we had previously recorded. These outcomes culminated in the desired continuous records for the time series analysis required in our 2017 Atlantic BRS.

Our study highlights the benefits of analysis-driven tag programming and supports the conclusions of Breed et al. [9] that tag programming should be carefully tailored to the behavior of each species and each study area. We needed to consider both animal behavior and the limitations of the Argos system to collect data on behavior over sustained periods. We urge researchers to develop regimes for data collection that are driven by research questions, to ensure data collection is optimized for statistical analysis, especially when invasive tags are used [23, 24] in studies that have explicit conservation and/or management implications [2]. We implemented a significant change in data collection that was readily achievable and with little logistical cost. We only identified this change by critically evaluating our current methodology and using the MCDM approach to assess the problem of data gaps. Our approach was successful in collecting presumed foraging data, but we did lose resolution in other behavioral data, underscoring the existence of trade-offs in the use of SPLASH10-292 tags. Ultimately, the behavior of beaked whales and the limitations of the Argos system meant we had to accept the fact that our tags could not collect complete data streams in all behavioral states. Consideration of this fact, in concert with the risk of data gaps during a known and predetermined experimental period, enabled us to be pragmatic in our approach and focused our efforts to ensure robust data collection.

Abbreviation

MCDM: multiple criteria decision making.

Authors' contributions

NQ conceived the idea for the study. NQ and WRC conducted the data processing and analysis. JS prepared all 2014–2016 datasets. NQ prepared the manuscript with assistance from WRC and AR. All authors read and approved the final manuscript.

Author details

[1] Duke Marine Lab, Division of Marine Science and Conservation, Nicholas School of the Environment, 135 Duke Marine Lab Road, Beaufort, NC 28516, USA. [2] University Program in Ecology, Duke Marine Lab, 135 Duke Marine Lab Road, Beaufort, NC 28516, USA.

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Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets used during this study are held on an Open Science Framework portal at Duke University and are available from the corresponding author on reasonable request.

Consent for publication

Not applicable.

Ethics approval and consent to participate

All research activities were carried out under NOAA/NMFS Scientific Research Permits 17086 and 20605 issued to Robin Baird; NOAA/NMFS permit 14809-03, issued to Doug Nowacek; and NOAA General Authorization 16185, issued to Andrew Read, in accordance with the relevant guidelines and regulations on the ethical use of animals as experimental subjects. The research approach was approved by the Institutional Animal Use and Care Committee (IACUC) of Cascadia Research Collective.

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