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JASA ARTICLE

Effects of duty cycle on passive acoustic monitoring metrics: The case of blue whale songs

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ABSTRACT:
Long-term fixed passive acoustic monitoring of cetacean populations is a logistical and technological challenge, often limited by the battery capacity of the autonomous recorders. Depending on the research scope and target species, temporal subsampling of the data may become necessary to extend the deployment period. This study explores the effects of different duty cycles on metrics that describe patterns of seasonal presence, call type richness, and daily call rate of three blue whale acoustics populations in the Southern Indian Ocean. Detections of blue whale calls from continuous acoustic data were subsampled with three different duty cycles of 50%, 33%, and 25% within listening periods ranging from 1 min to 6 h. Results show that reducing the percentage of recording time reduces the accuracy of the observed seasonal patterns as well as the estimation of daily call rate and call type richness. For a specific duty cycle, short listening periods (5–30 min) are preferred to longer listening periods (1–6 h). The effects of subsampling are greater the lower the species' vocal activity or the shorter their periods of presence. These results emphasize the importance of selecting a subsampling scheme adapted to the target species.
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I. INTRODUCTION

Passive acoustic monitoring (PAM) is commonly used to study the seasonal and spatial distribution and acoustic behaviour of cetaceans (e.g., Mellinger *et al.*, 2007; Van Parijs *et al.*, 2009). PAM is a tool of choice for collecting long-term data in remote areas such as the Southern Indian Ocean (e.g., Samaran *et al.*, 2010; Leroy *et al.*, 2016; Torterotot *et al.*, 2020). Unlike visual methods, it offers the possibility of collecting data during day and night, in bad-weather conditions, or when individuals are under the water's surface (Stanistreet *et al.*, 2016).

Blue whales are ideal candidates for such monitoring because of their long (longer than 15 s), frequently repeated loud (more than 180 dB re 1 μPa at 1 m), and low frequency (20–100 Hz) calls (Cummings and Thompson, 1971). The Southern Indian Ocean is inhabited by at least two subspecies of blue whales: the Antarctic blue whale (*Balaenoptera musculus intermedia*) and several populations of pygmy blue whales (*Balaenoptera musculus brevicauda*). Their distinct acoustic repertoire allows distinguishing different acoustic populations (Ichihara, 1966; LeDuc *et al.*, 2003; McDonald *et al.*, 2006; Stafford *et al.*, 2001). Due to the sparse distribution, low density, and wide extent of habitat of these acoustic populations, establishing their migration patterns in a remote area poses a real challenge that can be partly overcome by deploying wide arrays of autonomous recorders (Samaran *et al.*, 2010; Royer 2009).

Long-term PAM of cetacean's species is generally achieved by deploying autonomous recorders, which are anchored to the seabed, that archive data until their recovery after which data can be retrieved and processed on land. Thus, battery capacity generally limits the recording duration of instruments (see review by Sousa-Lima, 2013). Logistics and maintenance costs for redeploying recorders for a long monitoring period must also be optimized. Hence, the choices are either to reduce the frequential sampling rate or recording schedule through temporal subsampling (e.g., Au *et al.*, 2013). Decreasing the sampling rate will impact the recorded frequency band and may restrict the recording of some species. Temporal subsampling involves setting a duty cycle in which the recorder only collects data for a limited fixed time on a repeated basis (Rand *et al.*, 2022). For example, a duty cycle or listening proportion of 0.5 can be set by recording 30 min of data every hour. By adjusting the listening proportion and recording duration, different subsampling schedules can be designed.

However, a subsampling schedule can affect the ecological conclusions drawn from PAM studies (e.g., Thomisch *et al.*, 2015). For instance, inappropriate duty cycles may bias passive acoustic detections (Rand *et al.*, 2022; Riera *et al.*, 2013). Thus, the choice of an adequate subsampling scheme is paramount, must be made according to the research scope and prior knowledge of the acoustic

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behaviour and detectability of the target species, and then according to the available power and deployment plan of the recorders (Rand *et al.*, 2022; Sousa-Lima, 2013). Fortunately, the introduction of low-power, high-capacity storage has significantly reduced storage limitations in recorders.

Previous studies on the effects of PAM subsampling focused on species' daily presence, daily calling rates (Thomisch *et al.*, 2015; Stanistreet *et al.*, 2016), or the detectability of vocalizations (Rand *et al.*, 2022). Here, we analyse the effects of duty cycles on the detection of stereotyped and non-stereotyped vocalizations from three acoustic populations of blue whales at three locations in the Southern Indian Ocean with two main objectives: first, to assess the effects on long-term monitoring of seasonal patterns; and second, to evaluate the effects on daily call rates and the conclusions that can be inferred from them about the presence of several species of large blue whales at the same site.

II. MATERIAL AND METHODS

A. Data acquisition

Acoustic data used in this study were acquired by the OHASISBIO (Observatoire Hydro-Acoustique de la Sismicite et de la Biodiversité; Royer 2009) network of autonomous hydrophones, located in the Southwestern Indian Ocean, spanning from 24°S to 56°S in latitude and from 52°E to 83°E in longitude. Among the nine sites deployed, three sites were selected based on the consistent presence of three different blue whale acoustic populations. These instruments were located west of Kerguelen Island (WKER) and northeast of St. Paul and Amsterdam Islands (NEAMS) from 2010 to 2019 and south of the Southeast Indian Ridge (SSEIR) from 2014 to 2018 (Fig. 1).

At least two subspecies of blue whales live in this area: the Antarctic blue whale (*B. m. intermedia*), hereafter referred to as ANT BW, and the pygmy blue whale (*B. m. brevicauda*), of which two populations were clearly identified in acoustic recordings: Southwestern Indian Ocean (SWIO PBW) and Southeastern Indian Ocean (SEIO PBW) pygmy blue whales. Each of these subspecies emits a distinctive, stereotyped song phrase, as well as possibly common, non-stereotyped *D*-calls (Fig. 2; Torterotot *et al.*, 2019).

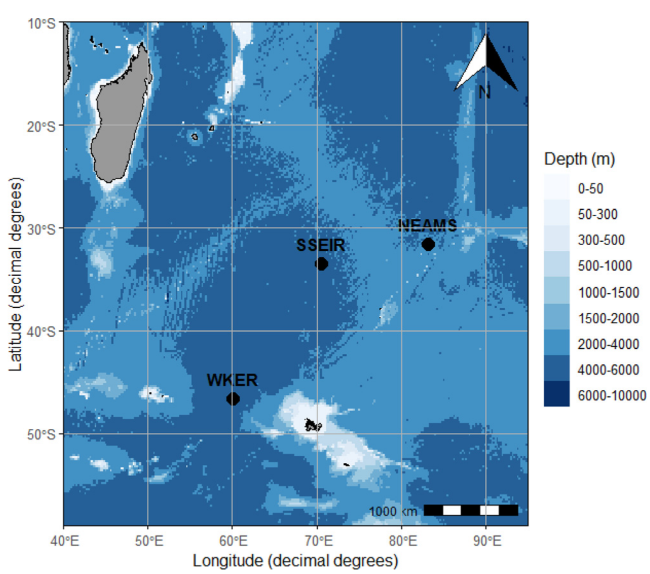

FIG. 1. (Color online) Mooring sites of the OHASISBIO hydrophone network used in this paper.

Each autonomous mooring consisted of an anchor, an acoustic release, an adjustable line, and a submerged buoy hosting the recording system. Instruments were moored between 1000 and 1300 m below sea-surface and recorded continuously at a sampling rate of 240 Hz (see Torterotot *et al.*, 2020, for more details).

B. Call automated detections

The study uses the detections from Torterotot *et al.* (2020), who applied an automatic detection algorithm based on dictionary learning and sparse representation of blue whale calls (Socheleau and Samaran, 2017; Torterotot *et al.*, 2020). The algorithm scanned the acoustic data with a sliding window of duration, t, and tried to reconstruct the observed signal with a combination of calls composing the dictionary: for SEIO PBW, only the second unit of the song phrase was targeted, $t = 25$ s; for SWIO PBW, only the first unit of the song phrase was targeted, $t = 20$ s; for ANT BW, the all song phrase was targeted, $t = 18$ s; and for D-calls, the whole call was targeted, $t = 8$ s (Torterotot *et al.*, 2019). Each part of the song phrase defined above will be named "call" in the rest of the paper. The data analysed herein consists of the call detections from the three acoustic populations described above, which have already been processed at the three sites over a period of 9 or 4 yr. The detection data included the recording site, the detected acoustic population, as well as the start date and time of each detected call.

C. Subsampling analysis

1. Subsampling schemes

Subsampling schemes are defined by a listening period, L (in minutes), and a cycle period, Tc (in minutes); the ratio L/Tc defines the duty cycle, D (in percent), and N is the number of cycles per day (Thomisch *et al.*, 2015). Note that a given duty cycle, D, can be designed with different subsampling strategies, e.g., a single long listening period per day or several short windows evenly distributed over the day but amounting to the same listening period in a day.

The continuous data containing call detections were subsampled according to 23 temporal subsampling schemes with listening periods from 1 min to 6 h and duty cycles, D, of 50%, 33%, and 25%. Potential effects of these subsampling schemes were explored by varying the listening period, L (hence, the number of cycles per day, N), and the duty cycle, D (Table I).

Because a listening period can start anytime within a cycle period, Tc (6 h every 12 h can be either the first 6 h or the last 6 h), different listening phases, r (without overlap), must be considered. For statistical analyses of the effects of subsampling data, each possible realization r ($r = 2$ for

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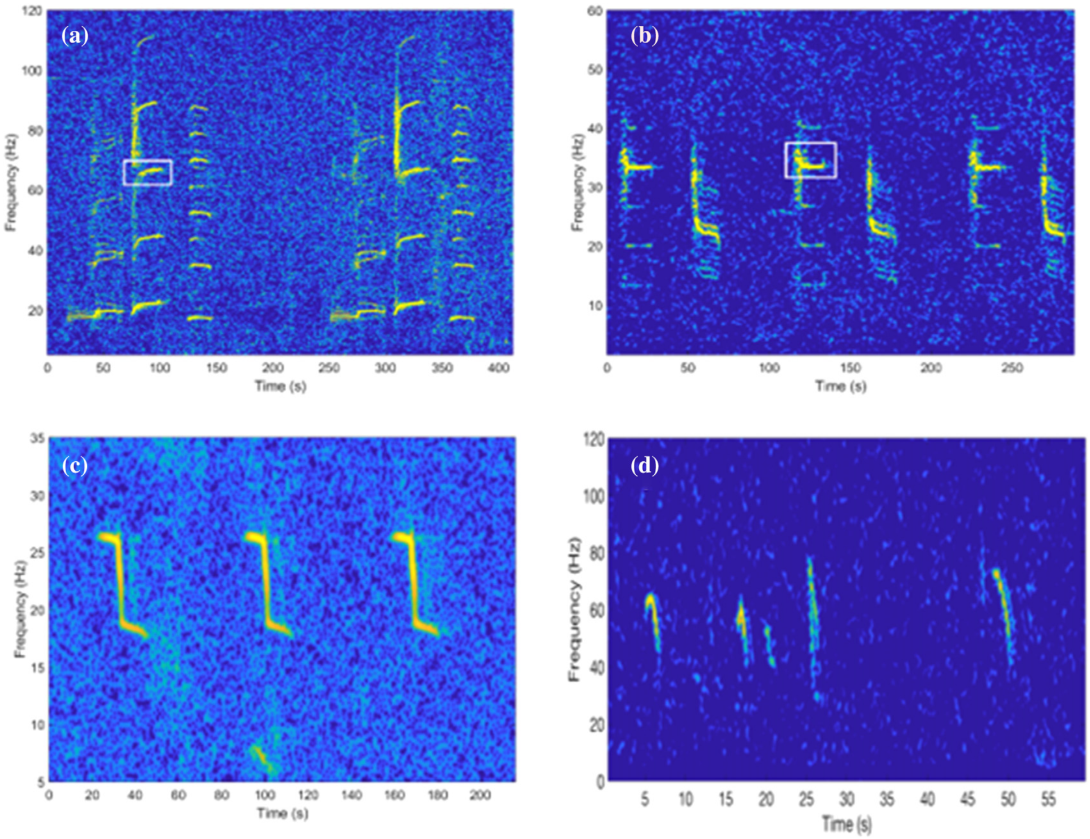

FIG. 2. (Color online) Typical spectrograms of three stereotyped song phrase of (a) a Southeastern Indian Ocean pygmy blue whale (SEIO PBW), (b) a Southwestern Indian Ocean pygmy blue whale (SWIO PBW), (c) an Antarctic blue whale (ANT BW), and (d) a series of five non-stereotyped *D*-calls, all recorded in the Southern Indian Ocean by the OHASISBIO network.

$D = 50\%$, $r = 3$ for $D = 33\%$, and $r = 4$ for $D = 25\%$) of each listening period for all cycles, N, and each duty cycle, D, were processed and averaged.

If the detection of a blue whale call in continuous data occurred during the listening period for a determined duty cycle, it was included in the subsampled data set for this duty cycle. To account for long calls that might only be partially captured by subsampled data, detections must have 100% of the call duration falling within the listening period to be included in the set. This choice was justified to agree with the automatic detector used by Torterotot *et al.* (2020), which operates from the calls described in Sec. II B. The average percentage of excluded calls for each subsampled dataset is presented in Table II.

Different subsampling schemes were applied on each day of each year of the recording period at three sites and over 9 yr. Prior to averaging data across years, an analysis of variance (ANOVA) was performed; this preliminary analysis was used to check that the results did not vary statistically significantly across years for the different metrics: seasonality, daily call rate estimates, and call type richness. These different metrics will be described in Secs. II C 2–II C 4. All statistical analyses and subsampling schemes were implemented in *R* (R Core Team, 2021).

TABLE I. Different subsampling designs used for blue whale detections. The duty cycle, D, (%) is the ratio between the listening period, L, and the cycle period, Tc, repeated throughout a day.

	$D = 50\%$		$D = 33\%$		$D = 25\%$	
	$r = 2$		$r = 3$		$r = 4$	
Listening period Lp	Cycle period Tc	Cycles per day N	Cycle period Tc	Cycles per day N	Cycle period Tc	Cycles per day N
1 min	2 min	720	3 min	480	4 min	360
5 min	10 min	144	15 min	96	20 min	72
15min	30 min	48	45 min	32	1 h	24
30 min	1 h	24	1 h30 min	16	2 h	12
1 h	2 h	12	3 h	8	4 h	6
3 h	6 h	4	9 h	2.66	12 h	2
6 h	12 h	2	18 h	1.33	24 h	1

TABLE II. Average percentage and relative standard deviation of excluded calls from subsampled datasets for each type of call described in Fig. 2, based on each duty cycle, D, and listening period., Lp. This is an average across all possible realizations, r.

Duty cycle, D	Listening period, Lp	SWIO PBW Mean of excluded calls (%)	SEIO PBW Mean of excluded calls (%)	ANT BW Mean of excluded calls (%)	*D*-calls Mean of excluded calls (%)
50%	1 min	66.6 ± 0,4	70.8 ± 0.3	65.0 ± 0.4	56.6 ± 0.2
	5 min	53.3 ± 0.3	54.0 ± 0.2	53.0 ± 0.5	51.3 ± 1.1
	15 min	51.1 ± 0.4	51.4 ± 0.8	51.0 ± 0.1	50.5 ± 0.2
	30 min	50.6 ± 0.9	50.7 ± 0.1	50.5 ± 0.5	50.2 ± 0.8
	1 h	50.3 ± 0.9	50.3 ± 1	50.3 ± 0	50.1 ± 0.3
	3 h	50.3 ± 0.7	50.3 ± 1.7	50.3 ± 1.5	50.1 ± 2.3
	6 h	50.3 ± 0.6	50.3 ± 1.6	50.3 ± 2.1	50.1 ± 4
33%	1 min	77.7 ± 0.9	80.5 ± 0.7	76.7 ± 0.2	71.0 ± 0.9
	5 min	68.9 ± 0.3	69.3 ± 0.8	68.7 ± 0.1	67.5 ± 1.1
	15min	68.9 ± 0.5	69.3 ± 0.8	68.7 ± 0.2	67.5 ± 1.6
	30 min	67.1 ± 0.1	67.1 ± 1.5	67.0 ± 0.3	66.8 ± 3.2
	1 h	66.9 ± 0.4	66.9 ± 1.6	66.8 ± 0.6	66.7 ± 3.4
	3 h	66.9 ± 0.5	66.9 ± 1	66.8 ± 0.1	66.7 ± 2.7
	6 h	66.9 ± 2.3	66.9 ± 0.7	66.8 ± 0.8	66.7 ± 1.9
25%	1 min	83.3 ± 0.4	85.4 ± 0.3	82.5 ± 0.4	78.3 ± 0.5
	5 min	76.7 ± 0.9	77.0 ± 0.4	76.5 ± 0.5	75.7 ± 2.2
	15 min	76.7 ± 0.9	77.0 ± 0.8	76.5 ± 0.5	75.7 ± 1.2
	30 min	75.3 ± 1	75.3 ± 1.8	75.3 ± 0.5	75.1 ± 1.7
	1 h	75.2 ± 1.6	75.2 ± 1.4	75.1 ± 0.5	75.1 ± 1
	3 h	75.2 ± 1.7	75.2 ± 2.1	75.1 ± 3.6	75.1 ± 5.2
	6 h	75.2 ± 1.1	75.2 ± 4.7	75.1 ± 4.4	75.1 ± 11.2

2. Seasonal patterns

To explore the effect of duty cycles on the seasonality, we examined the seasonal patterns described in Torterotot *et al.* (2020). Continuous data were subsampled according to the different patterns presented in Table I. Seasonal patterns were here represented based on the absolute number of detections per day for the calls as described in Sec. II B of the three acoustic populations of interest, as well as for the *D*-calls. Four types of seasonal patterns were identified and used to compare the effect of subsampling (Fig. 3): (i) a strong seasonal pattern with a high number of detections (SEIO PBW at the NEAMS site), (ii) a strong seasonal pattern with a low number of detections (SWIO PBW at the NEAMS site), (iii) a no clear seasonal pattern with a high number of detections (ANT BW at the WKER site), and (iv) a no clear seasonal pattern with a low number of detections (SEIO PBW at the SSEIR site).

To assess the accuracy of the seasonality implied by the subsampled data, the ratio of sum of squares of residuals to total sum of squares was calculated between all different types of subsampling and continuous data. Given the objective of obtaining a more precise depiction of the seasonality in continuous data, the regression coefficient was determined as follows:

$$R^2 = \left(1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}\right), \qquad (1)$$

where n is the number of measurements, y_i is the value of ith measurement, $\hat{y}_i$ is corresponding predicted value, and $\overline{y}$ is the mean of measurements.

A regression coefficient result close to one indicates a good fit of the model and, thus, a good representation of the seasonality from the subsampled data (three examples of linear regression for three listening periods with a duty cycle, $D = 50\%$; Fig. 4).

Furthermore, an ANOVA test was conducted for each distinct dataset (site and vocalization type) to validate differences in R^2 values between each listening period of each duty cycle. Subsequently, pairwise comparison tests were performed for datasets in which the ANOVA p-value was significant, between each listening period and the subsequent period, to compare the mean R^2 values pairwise using the Tukey test to adjust the p-values.

3. Daily call rate estimation

The daily call rate or average number of calls detected over a day was computed with the formula used in Thomisch *et al.* (2015):

$$\overline{\gamma_{r,J}} = \frac{1}{N}\sum_{j=1}^{N}\gamma_{r,j}, \qquad (2)$$

where $\overline{\gamma_{r,J}}$ was the daily call rate estimated from call rates, $\gamma_{r,j}$, of the rth realization in all N cycles of the jth day. This estimation was accomplished for all possible independent realizations, r, of listening periods for all cycles, N, and each duty cycle, D.

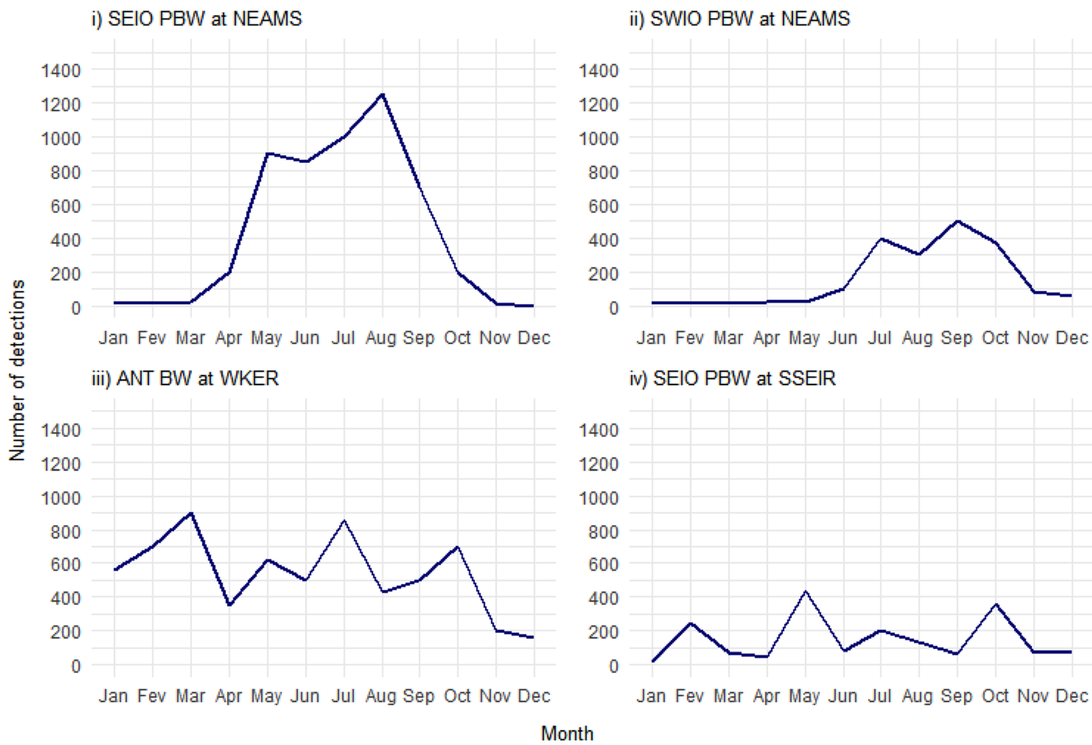

FIG. 3. (Color online) Schematic seasonal patterns, showing (i) and (ii) strong seasonal patterns with high and low numbers of detections by month, respectively; (iii) and (iv) no clear seasonal patterns with high and low numbers of detections by month, respectively. See Fig. 4 of Torterotot *et al*. (2020) for an actual example of such seasonal distributions.

To assess the variability of estimated call rates according to the type of subsampling, the ratio of call rate of subsampled data to call rate of continuous data was calculated for each $\overline{\gamma}_{r,j}$:

$$\text{ratio}_{r,j} = \frac{\overline{\gamma_{r,J}} - \gamma_{\text{true}j}}{\gamma_{\text{true}j}}. \tag{3}$$

The continuous data were subsampled according to different schemes in Table I. This procedure was repeated for all D percentages for each day to provide a mean and standard deviation of call rate estimates according to defined subsampling scheme.

4. Call type richness

Call type richness is a measure of the number of acoustic populations present in a habitat at a given time. In this study, only specific calls of three blue whale acoustic populations were used, as D-calls cannot be unambiguously

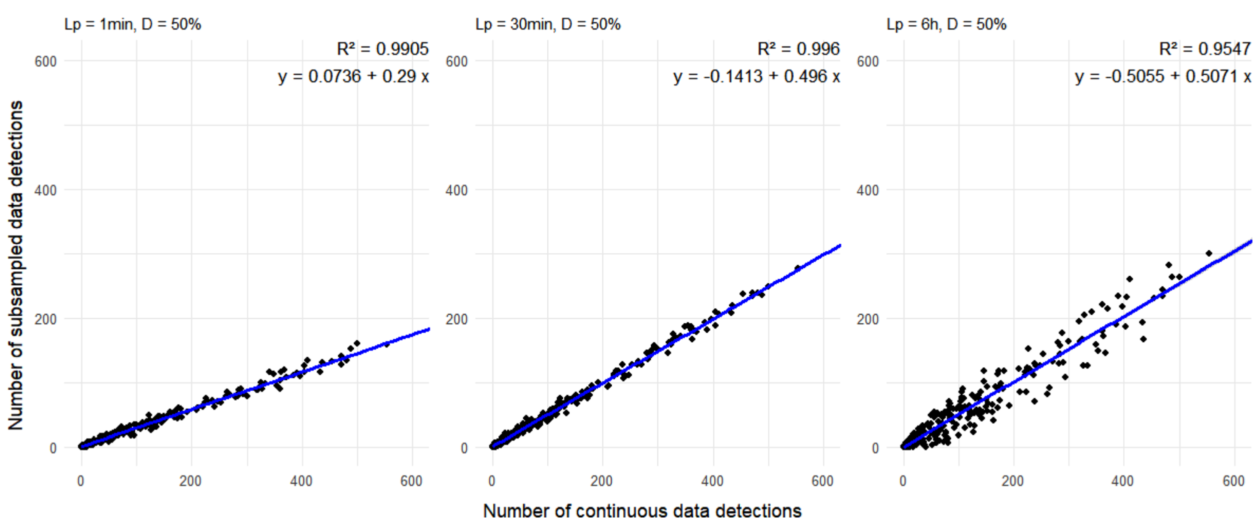

FIG. 4. (Color online) Relationship between the number of continuous data detections and the number of subsampled data detections for SWIO PBW call type at NEAMS site across three listening periods (1 min, 30 min, and 6 h) with a duty cycle, $D = 50\%$. The data points (black circles) are fitted to a linear regression model (blue line). X axis represents the number of detections per day for continuous data, and Y axis represents the number of detections per day for subsampled data.

linked to any specific acoustic populations. For continuous data, an acoustic population was considered present if there was at least one call detected during the day. In the subsampled data, an acoustic population was considered present acoustically if there was a detection in any of the N cycles of the day. Call type richness at a site for continuous and subsampled data was, therefore, calculated by counting the number of acoustic populations present at the site per day (maximum call type richness = 3).

If the call types richness between subsampled and continuous data contained the same number of acoustic populations, then the decision was correct ($d = 1$) otherwise it was incorrect ($d = 0$). To compute an average proportion of days p_d for which call type richness was correctly assessed using each subsampling programme, d was determined for each day, j, and for each duty cycle, D, and then averaged over all, i, listening period phases. This allowed establishing an average proportion of days in which call type richness was well determined for each subsampling scheme such that

$$\overline{p_d} = \frac{1}{nr}\sum_{i=1}^{r}\sum_{j=1}^{n} d_{ij}, \tag{4}$$

where n is the number of days with detections, r is the number of listening phases, and d_{ij} is the value of d for phase i on day j.

To compare the results of different duty cycles, comparison of means was performed. As the data were not normally distributed, a nonparametric Wilcoxon test was applied for each site.

III. RESULTS

A. Seasonal patterns

Effects of subsampling strategies were first evaluated on seasonal patterns in the occurrence of three blue whale acoustic populations and D-calls at three selected sites by calculating R^2, which is the regression coefficient. Results for different duty cycles of 50%, 33%, and 25% are presented in Fig. 5.

For all acoustic populations and at all sites, the highest duty cycle (largest proportion of listening, 50%) gave the highest value of the regression coefficient, indicating a better accuracy of seasonal model. Unsurprisingly, a 33% duty cycle gave better estimates than a 25% duty cycle.

Within each duty cycle, short listening periods of 5–30 min improved the accuracy of the seasonal model compared to longer listening periods of 1–6 h. Indeed, in many cases, a significant difference was found between $Lp = 1$ h and $Lp = 3$ h (Fig. 5), indicating that from $Lp = 3$ h onward, significantly lower mean regression coefficient values were measured.

However, a listening period that was too short also had a negative impact on the seasonal occurrence pattern. Significant differences primarily occurred between 1-min ($Lp = 1$ min) and 5-min ($Lp = 5$ min) listening periods, resulting in lower mean regression coefficient values compared to other Lp durations, especially for long calls from the SEIO PBW acoustic population [Figs. 5(d)–5(f)].

The best fit between subsampled and continuous data was achieved for acoustic populations with a strong seasonal pattern and many detections. This was the case for the SEIO PBW at NEAMS site, where regression coefficient was approximately 0.95 for a cycle period 5 min and a duty cycle of 50% [Fig. 5(d)]. Additionally, this dataset is the only one in which there is no significant difference between successive Lp (p-value > 0.05). High regression coefficient was also measured when an acoustic population had a no clear seasonal pattern with many detections, such as the ANT BW at the WKER site, where the regression coefficient was always higher than 0.9 for a duty cycle of 50% and listening time of 5 min [Fig. 5(i)]. Moreover, a significant difference between successive Lp was observed only from $Lp = 1$ h onward.

In contrast, the regression coefficient was lower for datasets with few detections and a no clear seasonal pattern [e.g., SEIO PBW at SSEIR, regression coefficient for 30 min at 50% ≈ 0.7; Fig. 5(e)] or few detections and a strong seasonal model [SWIO PBW at NEAMS, regression coefficient for 5 min at 50% ≈ 0.75; Fig. 5(a)]. Notably, on the WKER site, differences in mean regression coefficient values emerged earlier, between 30 min and 1 h of listening period [Figs. 5(c), 5(f), 5(i), and 5(l)]. Conversely, for D-calls, significant p-values between consecutive listening periods varied across sites: for the SSEIR site [Fig. 5(k)], significant differences were observed between $Lp = 5$ min and $Lp = 15$min as well as between $Lp = 15$ min and $Lp = 30$ min. However, for the WKER site [Fig. 5(l)], the first significant differences between two listening periods occurred between $Lp = 30$ min and $Lp = 1$ h.

B. Daily call rate estimates

The call rate of the subsampled data were very sensitive to the duty cycle D and the listening period L (Fig. 6). The average value of the ratio of subsampled to continuous data were consistently below 0 for all listening durations, indicating a subsampled data underestimation of the daily call rate for different listening durations. This underestimation was most pronounced for the 1-min listening duration, which deviated significantly from the expected value of 0 for longer duration calls [Figs. 6(a)–6(c)]. This deviation from expected values was also observed for all listening periods for usage cycles of 33% and 25%.

In general, the ratio variability [as defined in Eq. (3)] increased as the listening period increased for a given duty cycle percentage and increased as the duty cycle percentage decreased. For a given duty cycle, its variability was greater for the longest listening times (1–6 h).

The subsampled data underestimation and variability were most significant for the SEIO PBW, which had the longest call duration [25 s; Fig. 6(b)]. In contrast, the subsampled data underestimation of the daily call rate was lower for D-calls, which were the shortest calls [8 s; Fig. 6(d)]. Note that for this particular type of call, variability

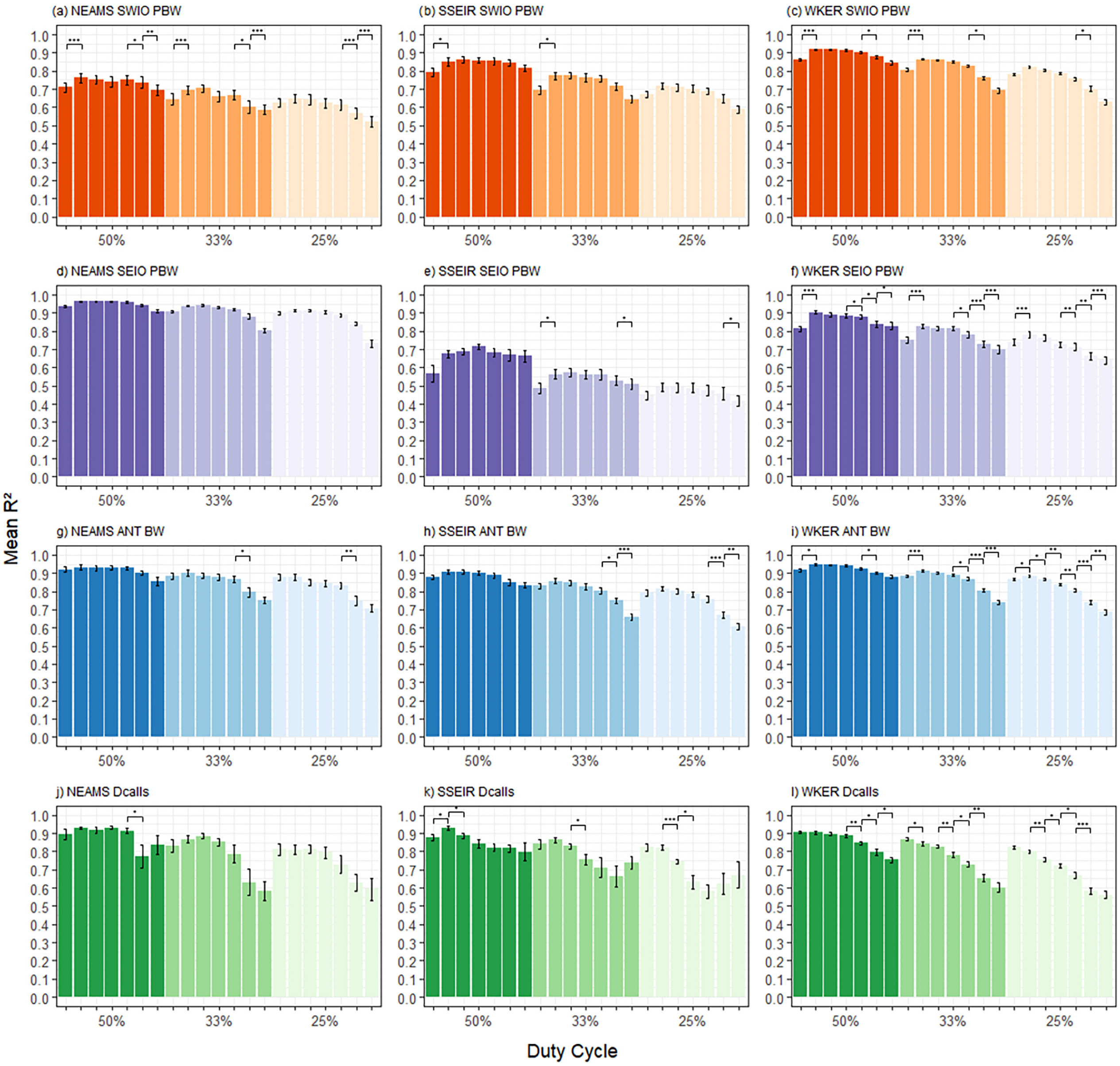

FIG. 5. (Color online) Comparison of different subsampling schemas in which each column represents a site (from left to right, NEAMS, SSEIR, and WKER) and each row represents a call (from top to bottom, SWIO PBW, SEIO PBW, ANT BW, and *D*-calls). Each shade of colour corresponds to a given duty cycle, *D* (from left to right, 50%, 33%, and 25%), and bar plots represent different listening periods, *L*, for a given duty cycle (from left to right, 1 min, 5 min, 15 min, 30 min, 1 h, 3 h, and 6 h, respectively). Vertical black lines are the standard deviations of the regression coefficient. The four types of seasonal patterns described in Sec. II C 2 are represented here as (a) SWIO PBW to NEAMS with a strong seasonal pattern and few detections, (d) SEIO PBW to NEAMS with a strong seasonal pattern and many detections, (e) SEIO PBW to SSEIR with a no clear seasonal pattern and few detections, and (i) ANT BW to WKER with a no clear seasonal pattern and many detections. Horizontal bars marked with "*," "**," and "***" show domains where Tukey tests yielded $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

was most pronounced for each listening period, likely stemming from the irregularity in its occurrence.

C. Call type richness

The proportion of days in which call type richness was correctly assessed according to different subsampling schemes also depends on the selected duty cycle, *D*, and duration of listening period, *L* (Fig. 7). Highest proportions of days with correctly assessed call type richness was observed for duty cycles of 50%, then 33%, and finally 25% for each of the three sites. Results of Wilcoxon tests between different duty cycles for each site show significant *p*-values ($p < 0.0001$), indicating that the average number of days with a correct estimate of the call type richness differs according to the subsampling scheme. For each duty cycle, a 1-min listening period was less likely to correctly capture call type richness than longer listening periods. Short periods (between 5 and 30 min) gave a higher average proportion of days with correctly assessed call type richness than longer listening period (more than 1 h). WKER site had more days correctly evaluated compared to the other two

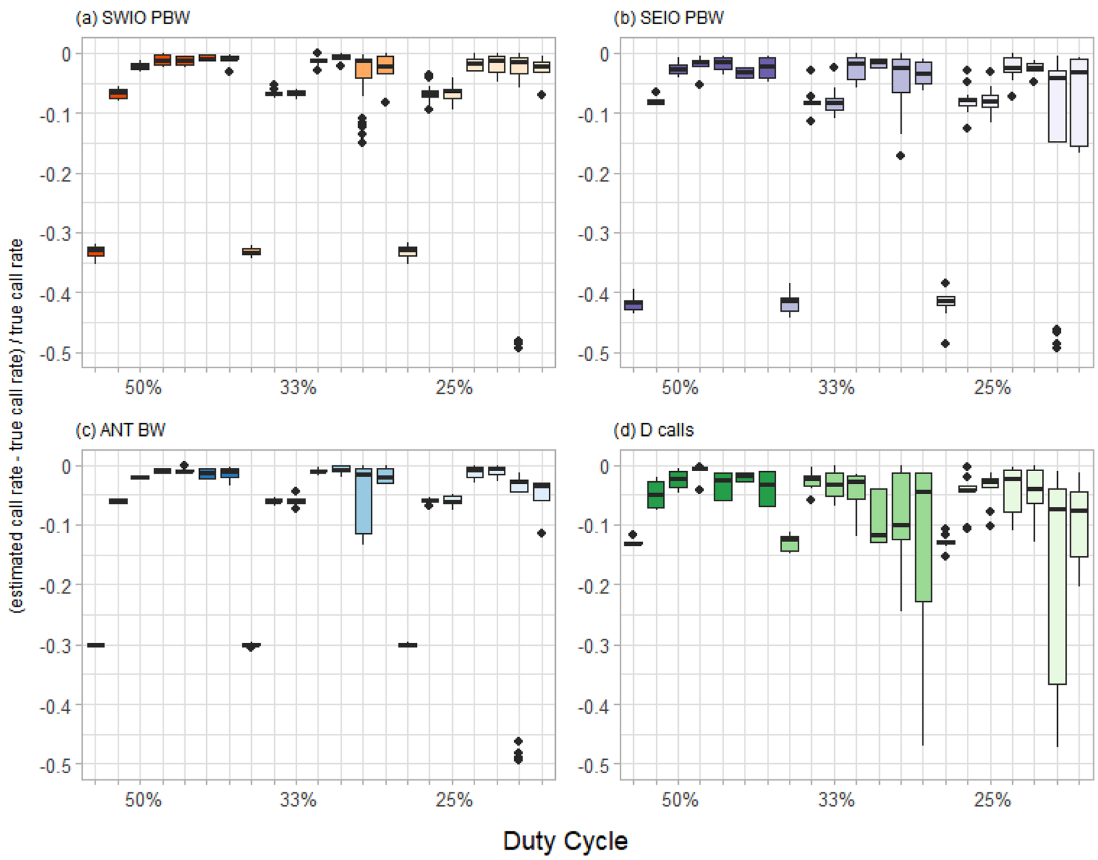

FIG. 6. (Color online) Comparison of different subsampling patterns on the ratios between estimated and actual daily call rates for different duty cycles and acoustic populations: a) SWIO PBW, b) SEIO PBW, c) ANT BW, d) D-calls. For each duty cycle, boxplots represent different listening periods L (from left to right: 1 min, 5 min, 15 min, 30 min, 1 h, 3 h, 6 h respectively).

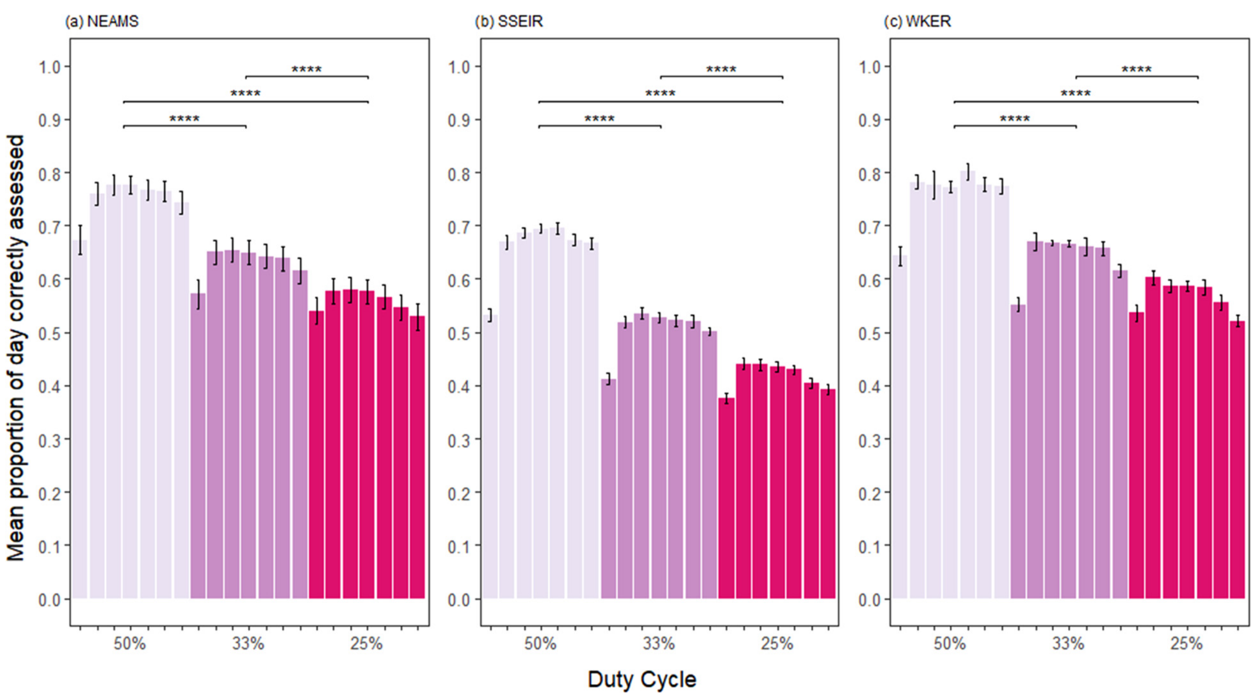

FIG. 7. (Color online) Comparison of proportion of days with a correct assessment of site call type richness with its standard deviation according to different subsampling schemes, showing (a) NEAMS, (b) SSEIR, and (c) WKER. Each shade of colour matches a different duty cycle, D (from left to right, 50%, 33%, and 25%). For each duty cycle, barplots represent different listening periods, L (from left to right, 1 min, 5 min, 15 min, 30 min, 1 h, 3 h, and 6 h respectively). Vertical black lines are the standard deviations. Horizontal bars with "****" show domains where Wilcoxon tests yielded $p < 0.0001$.

sites [Fig. 7(c)]. For example, call type richness was correctly assessed at WKER site, with an average probability of 75% for $D = 50\%$ with probabilities decreasing with smaller D (approximately 55% for $D = 25\%$).

IV. DISCUSSION

The aim of this study was to evaluate how temporal subsampling schemes can potentially bias metrics commonly used in passive acoustic studies to assess the occurrence of acoustic populations of blue whales in the Southern Indian Ocean based on call detections. Effects of subsampling are not the same, depending on the selected metric and chosen subsampling strategy.

It is important to note that the results of this study are specific to how calls were processed and detected. Here, the detection algorithm was based on dictionary learning and sparse representation of blue whale calls within specified time windows. Other algorithms, for instance, based on call rhythm or chorus intensity (e.g., Leroy *et al.*, 2018), will not be affected in the same way as in this study.

A. Effect of temporal subsampling on seasonal patterns

High duty cycles had higher regression coefficient, indicating that the seasonality was best represented with high duty cycles (or, conversely, poorly represented with low duty cycles). The best results were obtained when a species had a very marked seasonality with a high number of detections in few months. At NEAMS site, SEIO PBW has a very marked seasonality (April–July) with a minimum of 200 detections per week when the species was present and stable over the years (Torterotot *et al.*, 2020). In such a case, real and estimated seasonal patterns match even with a duty cycle of 25% [$R^2 > 0.9$; Fig. 5(d)].

High regression coefficient was also obtained for the ANT BW species. Number of detections of this species was high at the 3 selected sites (> 500 per week). However, unlike the SEIO PBW at NEAMS, its peaks of presence were less marked: significant emissions are observed over a more spread-out number of months. This result suggests that areas where vocalizations are numerous and constant over time provide a good representation of seasonal patterns.

In contrast, SWIO PBW calls at NEAMS site were only present occasionally between April and May. Its seasonal pattern was, therefore, more difficult to represent when data were subsampled, even for a high duty cycle ($R^2 < 0.75$ for 50%). Similarly, SEIO PBW calls at SSEIR site have a low coefficient of regression, suggesting a less accurate representation of seasonal patterns for this acoustic population ($R^2 < 0.6$ for 50%). These results are explained by its low acoustic activity (<90 calls per week) with calls, therefore, less likely to be captured in subsampled data.

Even though D-calls are shorter in duration and, thus, a smaller percentage of calls are removed by subsampling, the results show that they exhibit similar patterns to the signals emitted by the three studied acoustic populations. This suggests that irregularly emitted vocalizations, despite being shorter, should also be considered when choosing the duty cycle.

High acoustic activity with a high number of detections is the most important input for accurately representing the patterns of species presence from subsampled data. Conversely, continuous data collection seems unavoidable to monitor species that frequent an area irregularly or are present without acoustic activity or with a sparse acoustic activity.

For calls from the three acoustic populations and D-calls, long listening periods (≥ 1 h) result in a less accurate representation of continuous data compared to shorter listening periods. Similarly, a 1-min listening period leads to the less accurate results on the representativeness of seasonality in subsampled data. Indeed, many vocalizations will be cut off by an excessively short listening period and, thus, are less likely to be detected. This effect is even greater for acoustic populations with the longest window length used by the automatic detection algorithm (25 s for SEIO PBW). Although short listening periods seem to give better results, it is necessary to consider the duration of call (and/or the function and parameters of the detection algorithm) of the target species as a decisive factor in designing the subsampling scheme. In this regard, listening periods between 5 and 30 min provide similar representations of continuous data by subsampled data and, therefore, seem most suitable for our acoustic populations in the area.

B. Effects of temporal subsampling on daily call rate and call type richness

The accuracy of daily call rate estimates is highly influenced by subsampling designs, as depicted in Fig. 6. There is a notable variation between the estimated call rate and the actual call rate, particularly for extended listening periods ranging from 1 to 6 h. Furthermore, this discrepancy becomes more pronounced as the duty cycle decreases. These findings align with those observed by Thomisch *et al.* (2015). Specifically, a listening period of only 1 min consistently leads to a strong underestimation of the call rate, accompanied by low variability. This suggests that such a short duration is inadequate for our target species, which produces long calls between 18 and 25 s.

This is especially notable for the acoustic population with the longest call duration, SEIO PBW. As partial calls were excluded from the subsampled datasets to retain only complete calls, a substantial proportion was removed (70.8% for $Lp = 1$ min and $D = 50\%$; Table II), resulting in a persistent underestimation regardless of the listening period.

Additionally, the variability is amplified when calls are generated in irregular patterns (such as D-calls, for example) or there are few detections. These findings are consistent with those of Thomisch *et al.* (2015), who observed a greater disparity between call rate estimates and the actual rate for vocalization patterns characterized by low call rates.

Regarding *D*-calls, their irregular emission and shorter duration align with the conclusions of the study by Rand *et al.* (2022) on killer whales (*Orcinus orca*), where the optimal duty cycle has shorter listening lengths than for the stereotyped vocalizations of the acoustic populations studied here. These cycles would facilitate capturing the variation in acoustic behaviour throughout the day.

Regardless of the selected duty cycle (50%, 33%, or 25%), the daily call rates across all listening periods are consistently underestimated. Nevertheless, the 30-min listening period provided the most accurate daily call rate (i.e., the closest to the daily call rate from continuous sampling) and the lowest variability for all four types of calls, as shown in Fig. 6. This suggests that a 30-min listening period may represent the optimal compromise for studying stereotyped vocalizations and irregular *D*-calls. The richness of call types was as underestimated as the percentage of work cycles decreased: a duty cycle of 50% yields more accurate results than a duty cycle of 25%. These findings match the trends observed by Thomisch *et al.* (2015), who showed that a duty cycle of 10% led to a 26% underestimation of the daily presence of North Atlantic right whales (*Eubalaena glacialis*), or those observed by Riera *et al.* (2013), who found that a duty cycle of 25% resulted in a 24% decrease in killer whale (*O. orca*) acoustic encounters compared to continuous recording.

Short listening periods (between 5 and 30 min) increase the likelihood of accurately assessing call type richness regardless of duty cycle. For listening periods of 1 min or longer than 1 h, call type richness is more likely to be underestimated (Fig. 7). These results are consistent with those found for the daily acoustic presence of other marine mammal species such as killer whales (Rand *et al.*, 2022) or beaked whales (Stanistreet *et al.*, 2016).

It is important to note that the studies cited above relate to the daily presence of a single species, whereas this study relates to the call type richness of a site, i.e., the total number of call types present per day. The effect of subsampling is greater on the call type richness metric than on the daily presence metric computed by Thomisch *et al.* (2015): the proportion of days with a correct assessment of call type richness is lower (maximum 77% for a duty cycle of 50%). In comparison, Thomisch *et al.* (2015) found a 100% probability of correctly assessing daily presence of ANT BWs at a site for a duty cycle of 50%.

In sites where multiple acoustic populations of blue whales coexist, with many detections for each (e.g., WKER), number of days with a correctly assessed call type richness is better at a site recording a majority of calls from a single population and few calls from the other acoustic populations (e.g., SSEIR; Fig. 7). Therefore, duty cycle has a significant impact on the estimation of call type richness in the study area. A good knowledge of the use and presence of species in the study area is, thus, critical to choose the most appropriate recording strategy so as not to miss detection of a rare species due to inadequate subsampling.

V. CONCLUSION

This study demonstrates that temporally subsampling acoustic data can have heterogeneous effects on results of long-term monitoring of blue whale acoustic populations as well as the assessment of call type richness daily call rate based on their presence in different geographic areas.

If subsampling is necessary because of technical or logistical constraints, it is preferable to collect data in several short listening periods compatible with the duration of the vocalizations sought. Such a subsampling scheme leads to many cycles per day and allows for a better representation of daily call rate over the course of a day as well as a better representation of seasonal patterns.

The occurrence of different types of seasonal patterns may affect the accuracy with which subsampling patterns represent continuous data. Number of detections is a decisive factor for using a low duty cycle (25%) to obtain good results. This study also showed that when acoustic populations are rare in an area, continuous sampling may be required to not lose too much information in representation of seasonal patterns, the daily call rate, and estimation of call type richness. Indeed, if the objective of a passive acoustics project is to characterize a soundscape and explore its acoustic biodiversity, continuous recordings are necessary to avoid missing rare or transient species over a very short period.

The subsampling strategy must, therefore, be chosen based on biological considerations and a good understanding of the vocal behaviour of the target species. In addition, for long-term and large-scale monitoring studies, selection of the temporal subsampling strategy should also be based on an understanding of the different migration and occurrence patterns of the species in the study area. For a multiyear project, it would be appropriate, for example, to monitor continuously an area during the first year to gain knowledge about the acoustic presence of species, and then adapt the subsampling plan accordingly for the remainder of the monitoring period.

Depending on the automatic detection algorithm, subsampling may affect study results differently. The implementation of subsampling must, therefore, also consider the detector that will be used to process the data. In this study, 100% of the vocalization had to be included in the listening period because the detector used to detect the vocalization worked this way (i.e., a detector cannot detect incomplete calls if they are not sufficiently similar to the calls used to build the learning dictionary; Socheleau and Samaran, 2017). As other detectors exist and may operate differently, it is important to define their operation upstream, which may influence the subsampling strategy.

Embedding acoustic signal processing algorithms in acquisition systems now offers new possibilities for acoustic monitoring. A random subsampling scheme could, for instance, limit the effect of single species dependence by generalizing it to multiple species. However, the effect of such schemes would first need to be evaluated on continuous data. The data in this study focused on low frequency emissions from blue whales. Over a wider frequency range, many other species with their different behaviours might require specific subsampling schemes for each. Optimizing passive acoustic data collection procedures, including the selection of appropriate sampling strategies, is among the issues for future management and conservation studies of underwater biodiversity.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Ethics Approval

No animals were harmed during the project.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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