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Population size assessment of Adélie penguin (Pygoscelis adeliae) chicks based on vocal activity rate index

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A R T I C L E I N F O

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A B S T R A C T

Passive acoustic monitoring (PAM) is an effective method for bioacoustic researches. With the emergence of autonomous recording units (ARUs) and development of acoustic signal recognizer, PAM has been widely used in researches on conservation and ecology. However, challenges (e.g. extreme weather conditions) still remain in estimating species or population abundance based on acoustic monitoring. Adélie penguin (*Pygoscelis adeliae*) has been regarded as an ecological indicator in the Southern Ocean, and its population dynamics has ecological significance. We assessed the ability of an acoustic index, vocal activity rate (VAR), to estimate population size of Adélie penguin chicks on Inexpressible Island, Ross Sea, using acoustic data collected via ARUs. Linear mixed model analysis showed that VAR had a significant correlation with the abundance of penguin chicks and wind speed (conditional $R^2 = 0.743$). This demonstrated that VAR could be effectively applied in assessing the population size of Adélie penguin chicks with wind speed being considered, affirming the effectiveness of PAM in monitoring the population dynamics of vocal species in extreme-climate regions.

1. Introduction

Population size is one of the most important parameters in ecological researches, with population dynamics a key factor affecting wildlife conservation decisions (Stevenson et al., 2015; Measey et al., 2017). For example, the IUCN (International Union for Conservation of Nature) red list criteria for threatened species depend heavily on population size (IUCN, 2012; Marques et al., 2013). Traditional methods for population survey include distance sampling, territory mapping, mark-recapture methods (Buckland et al., 2000; Williams et al., 2002), and camera traps (Rowcliffe and Carbone, 2008; O'Connell and KU, 2010). In recent years, development of automatic acoustic monitoring technology has been providing new methods for monitoring the population dynamics of vocal wildlife.

Passive acoustic monitoring (PAM) has been widely used in conservation biology (Sugai et al., 2019), with autonomous recording units (ARUs) and automated bioacoustic analyses being powerful tools for monitoring vocal wildlife (Borker et al., 2014). PAM is

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effective in monitoring species distribution and assessing population dynamics (Darras et al., 2018). Compared with traditional field survey, PAM has many advantages: (1) ARUs can be deployed and recovered at any time, making field work more flexible and reducing disturbance to animals (Venier et al., 2012); (2) PAM can achieve long-term and large-scale monitoring, and it is effective even in remote areas or habitats with limited visibility (Alquezar and Machado, 2015); (3) unified quantitative analyses of acoustic recordings can avoid errors caused by subjective factors from different researchers (Venier et al., 2012). In addition, acoustic recordings can be permanently stored, providing important data as background database to support future related researches (Alquezar and Machado, 2015).

One PAM method to estimate population size is the use of vocal activity rate index (VAR) (Borker et al., 2014). VAR is the number of songs/calls per unit time produced by a species (Oppel et al., 2014). It has been confirmed that there is a positive correlation between VAR and population density in amphibians (Nelson and Graves, 2004) and cetaceans (Barlow and Taylor, 2005). In birds, many studies have proven a positive and significant relationship between VAR and population abundance in European bee-eater (*Merops apiaster*) and Dupont's lark (*Chersophilus duponti*) (Pérez-Granados et al., 2019), or a relationship between VAR and colony size in Cory's shearwater (*Calonectris borealis*) (Oppel et al., 2014). Moreover, VAR has been used to estimate nest abundance in Forster's tern (*Sterna forsteri*) (Borker et al., 2014), and to investigate nocturnal burrow-nesting seabird recovery after removal of predator (Buxton and Jones, 2012).

Avian vocal activity differs due to weather conditions, mating status, and breeding seasonality (Farnsworth et al., 2004; Catchpole and Slater, 2008). Hence, no general rule between VAR and avian population size should be expected before researches on specific species under specific conditions. For example, there is no correlation between population size of European nightjar (*Caprimulgus europaeus*) and VAR (Zwart et al., 2014).

Adélie penguins (*Pygoscelis adeliae*) are the only one of all 18 penguin species that breed exclusively on the Antarctic continent (Ancel et al., 2013). They have been regarded as an ecological indicator in the Southern Ocean (Taylor and Wilson, 1990). Both parents of Adélie penguins raise their offspring, with one parent caring their chicks near the nest for the first three weeks (Yeates, 1971). Afterwards, the two parents go to the sea simultaneously to forage, meanwhile the chicks from different nests usually gather into groups called crèches (Williams, 1984), which are guarded by several adult penguins. During the brooding period, the location of most crèches is fixed and the number of individuals within them remains stable for a certain period, which is convenient for the collection of penguins' recording and photo data.

We used VAR to assess population size of Adélie penguin crèches in an extreme-climate region on Inexpressible Island, Ross Sea. Compared with adults, the abundance of Adélie penguin chicks in crèches is more stable because adults need to leave the crèches frequently for foraging, so we focused on chicks when assessing population size of Adélie penguin crèches. The study area is located at

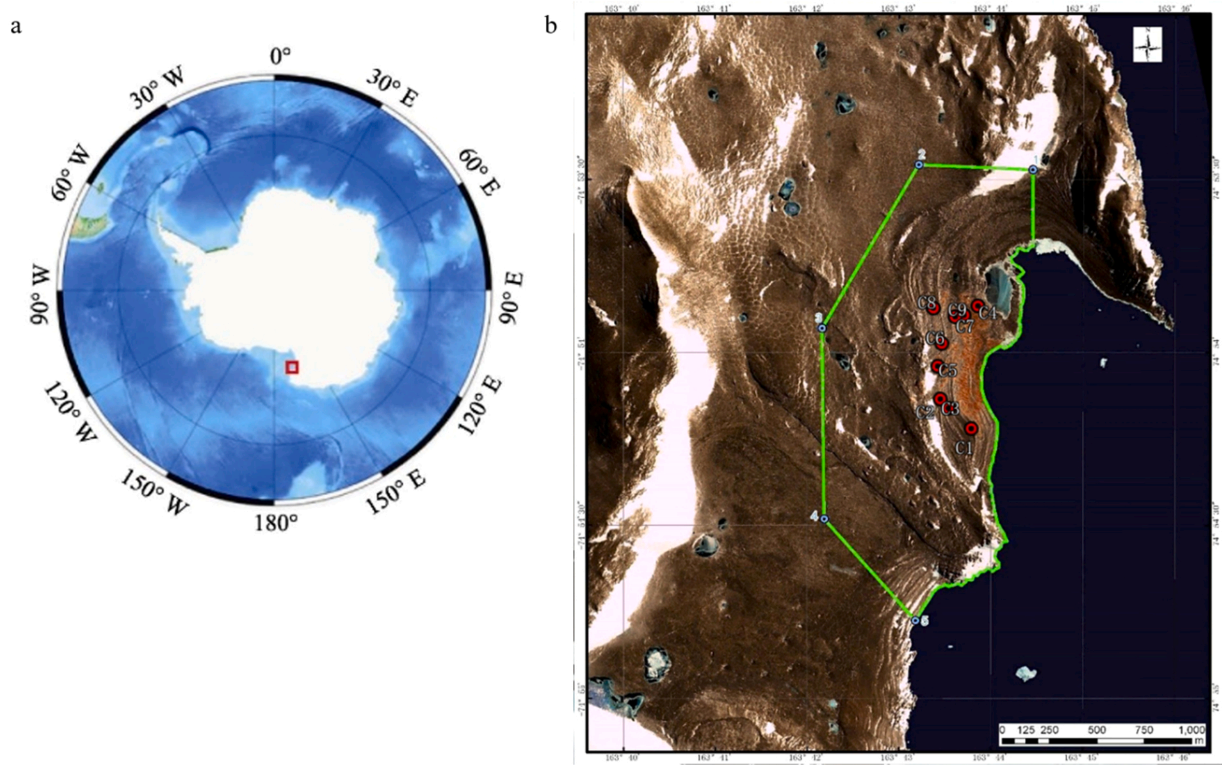

Fig. 1. Satellite map of the study area. a, location of the study area in the Antarctic; b, locations of the nine ARUs in the study area, shown in red dots.

high latitudes, where Adélie penguins are exposed to strong katabatic winds during their breeding seasons. Considering that calling behavior is generally affected by environmental factors (Chen et al., 2020), we also incorporated several meteorological factors into the analyses to improve the ability of VAR to predict chick abundance, and to achieve effective monitoring of population dynamics of Adélie penguin chicks using call recordings.

2. Materials and methods

2.1. Study area

Field work was carried out by the ornithology research team of Beijing Normal University on Inexpressible Island, from January 16 to February 3 in local time (GMT +13), 2020. Inexpressible Island (74°54′ S, 163°39′ E) is located in Terra Nova Bay, Victoria Land, Ross Sea, Antarctica (Fig. 1a). Strong katabatic winds from Nansen Ice Shelf open a large polynya in the eastern waters off the Island. According to Manuela Automatic Weather Station (74.946° S, 163.687° E, 78 m above sea level), from 1988 to 2012, the average annual temperature on Inexpressible Island was − 18.5 ℃; the annual average wind speed was 12.0 $m{\cdot}s^{-1}$; and the wind direction was mainly WNW (Zhao et al., 2015).

The Adélie penguin colony on Inexpressible Island is one of the most long-term monitored Adélie penguin populations in the Ross Sea region (Woehler and Croxall, 1997). This colony has the longest continuous occupation history, which is longer than 7000 years (Shepherd et al., 2005; Emslie et al., 2007). The penguins inhabit and breed in an ice-free land with well-defined raised beaches, marine sediments, and wave-cut terraces in every summer (Baroni and Hall, 2004). The breeding colony covers an area of more than 2500 km^2 just next to the Terra Nova polynya, which facilitates foraging for Adélie penguins during the breeding seasons.

2.2. Acoustic data processing

From January 16 to February 3, 2020, we set nine ARUs (Song Meter SM4, Wildlife Acoustics, USA) at nine selected crèches, with one ARU per crèche (Fig. 1b, see Table 1 for detailed coordinates of the ARUs). The maximum effective recording distance of the ARUs is about 70 m (Cole et al., 2022), and the selected crèches inhabit in near ellipse shape areas with major axes < 30 m, so the ARU could effectively cover the relevant crèche. In order to reduce interference from adjacent crèches during recording, the selected crèches were located on the edge of Adélie penguin colony (Fig. 1b) and > 20 m away from their nearest crèches (mean±sd = 39 ± 15 m, Table 1). Considering that the influence of wind on recording is prominent in the open habitat and the upwind ARUs lose the most sound signal (Priyadarshani et al., 2018), we set ARUs at the upwind of the prevailing wind for further reducing the influence from other crèches.

The ARUs were programmed to record continuously in all days (in stereo and.wav format), configured with sampling rate of 22,050 Hz and resolution of 16 bits. The ARUs continued working until February 3, with batteries and SD cards replaced on January 22. We took high-definition photos of the selected crèches every time we checked the ARUs (January 16, January 21, and February 3), which were used to visually count the abundance of Adélie penguin chicks in each crèche.

Adélie penguin chicks did not have significant peaks in their daily vocal activity (Fig. 2), unlike penguins breeding in lower latitudes (Favaro et al., 2021). Thus, we selected the first 10 min in each one-hour recording for subsequent analyses. Recordings on the first and last days (January 16 and February 3) were excluded because they did not cover 24 h of continuous registry. Overall, the data sampling left us with a total of 3672 10-minute recordings.

The sampled recordings were scanned with Kaleidoscope Pro 5.1.8 (Wildlife Acoustics, UAS), searching for candidate sounds matching the signal parameters. Specifically, we measured Adélie penguin chick call parameters within five randomly selected 10-minute recordings using Avisoft SASLab Pro (Avisoft Bioacoustics, Germany) (Xiao et al., 2008). Based on the call parameters, we introduced the following signal parameters into Kaleidoscope and then scanned the sampled recordings automatically: frequency range = 2.5–5.0 kHz; length of detection = 0.1–0.4 s; maximum inter-syllable gap = 0.1 s; maximum distance from the cluster center = 1.5. Kaleidoscope recognizer detected sounds in the recordings that matched the signal parameters.

We evaluated the performance of the recognizer by measuring the true-positive rate and recall rate, which are typical metrics for assessing recognizer performance (Knight et al., 2017). True-positive rate is the correct rate of automatically detected target sounds (i.e. Adélie penguin chick calls in this study), and recall rate is defined as the proportion of target sounds that are automatically detected. To calculate the recall rate, we divided the total number of true-positives detected by Kaleidoscope in 18 randomly selected 10-minute

Table 1
Coordinates of the nine ARUs on Inexpressible Island.

Crèche ID	Latitude	Longitude	Distance to the nearest crèche (m)
C1	74°54'13.51" S	163°43'48.62" E	30
C2	74°54'9.93" S	163°43'33.20" E	60
C3	74°54'8.32" S	163°43'27.79" E	30
C4	74°53'51.98" S	163°43'53.08" E	20
C5	74°54'2.56" S	163°43'26.03" E	50
C6	74°53'58.57" S	163°43'28.78" E	30
C7	74°53'53.89" S	163°43'37.78" E	50
C8	74°53'52.36" S	163°43'23.13" E	60
C9	74°53'53.61" S	163°43'43.74" E	20

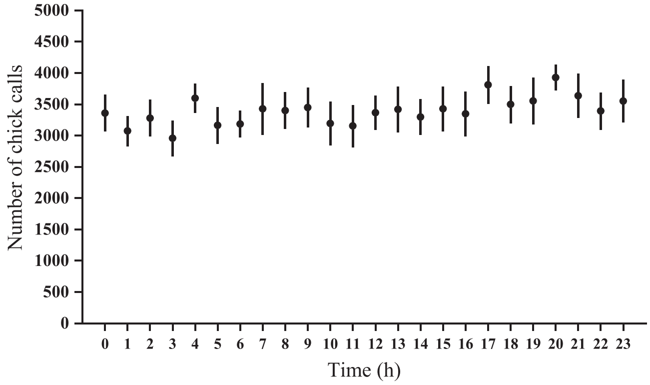

Fig. 2. Daily rhythm of Adélie penguin chick calls. Shown in mean ± se; counted from the sampled 17-day recordings of nine ARUs.

recordings (two recordings per crèche), by the total number of chick calls in these recordings, which was manually counted by an experienced observer through visually and acoustically checking.

2.3. Meteorological data collection

Meteorological data were obtained from our weather station (HOBO U30, Onset, USA) installed in the study area (Fig. 3). We collected the following meteorological factors: air temperature (°C), wind speed (m/s), gust velocity (m/s), solar radiation (W/m^2) and relative air humidity (%). These factors were generated every minute by the weather station. Daily meteorological data were arithmetically averaged to obtain daily value for the five meteorological factors during the study period.

2.4. Statistical analyses

To calculate VAR, we divided the total number of penguin chick calls automatically detected by recording duration (240 min), for each day and crèche respectively. We fitted linear mixed model (LME) to analyze the effects of chick abundance and meteorological factors on VAR of the Adélie penguin chicks. VAR was treated as response variable, while abundance and meteorological factors were included in the models as fixed effects. Considering that the nine crèches were sampled repeatedly during the study period, we set crèche ID and date as random effects to control non-independence among the data (Harrison et al., 2018).

Two steps were applied to obtain possible prediction models. Firstly, variance inflation factor (VIF) was used to detect multicollinearity between fixed effects: the square root of VIF represents the extent to which the confidence interval of regression parameters of variables can be inflated into prediction variables irrelevant to the model (Thompson et al., 2017). Secondly, the final fixed effects were selected using all-subsets selection (Harrison et al., 2018). In order to obtain the best prediction model, we evaluated the predicton models based on Akaike information criterion (AIC) (Burnham and Anderson, 2004). We performed variance partitioning analysis (VPA) (Legendre and Gauthier, 2014) to determine the proportion of the total variance of VAR explained by each fixed effect in the final model.

All statistical analyses were performed in R 4.0.0 (R Development Core Team, 2020). We hypothesize that the VAR index is positively correlated with the size of penguin crèches, and even accurately reflects the number of chicks of crèches; the VAR index might be affected by weather factors (e.g. air temperature, wind speed).

3. Results

3.1. Detection of penguin chick calls

Kaleidoscope automatically detected a total of 732,955 Adélie penguin chick calls from the sampled 17-day recordings of the nine crèches. According to manual checking of the 18 randomly selected 10-minute recordings, true-positive rate of Kaleidoscope detecting penguin chick calls was 96.89% (coefficient of variation, CV = 3.40%), and the recall rate was 89.14% (CV = 8.36%) (Table 2). We calculated VAR for each day and crèche respectively using these detected calls, resulting in 147 VAR values (17 days × 9 crèches, with 6 missing values because of the prematurely shut down of C6). The changing trend of VAR is shown in Fig. 4.

3.2. Abundance change of Adélie penguin chicks

We measured the abundance of Adélie penguin chicks of the nine crèches by visually counting of the crèche photos (Table 3), and chick abundance did not show a significance difference among the three days ($p > 0.05$, paired-samples t-test, Table 4). Therefore, we used the average number of penguin chicks in the three days to represent the chick abundance during the study period, for each crèche respectively.

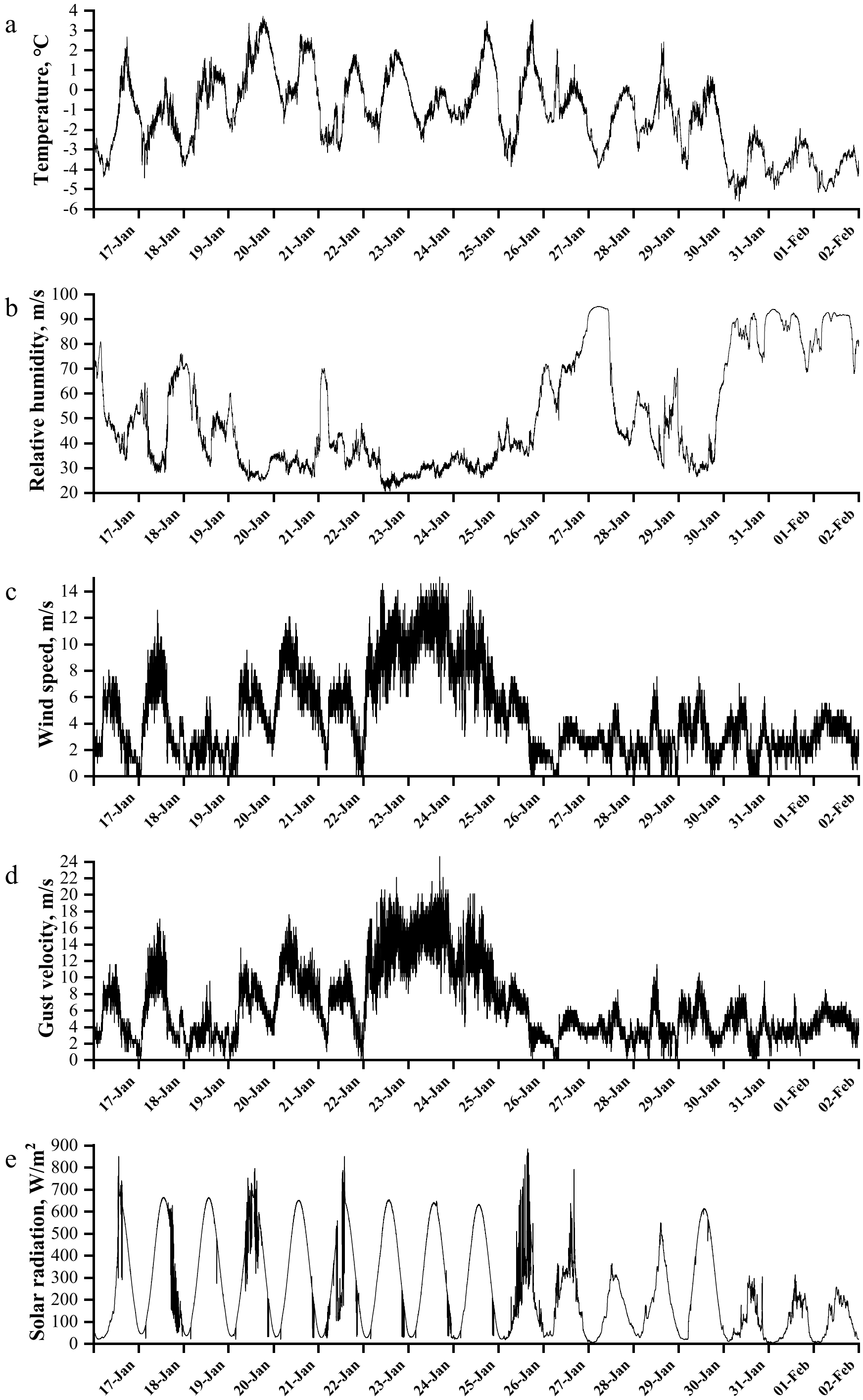

Fig. 3. Fluctuations of the five meteorological factors during the study period. a, air temperature; b, relative air humidity; c, wind speed; d, gust velocity; e, solar radiation.

3.3. LME modeling

We performed LME modeling with VAR as response variable, chick abundance and five meteorological factors as fixed effects, crèches ID and date as random effects. Based on collinearity diagnosis, we removed two fixed effects which contributed to multi-collinearity: gust velocity and relative air humidity. Due to the high correlation between air temperature and solar radiation (spearman correlation coefficient = 0.778), we excluded models containing these two fixed effects at the same time when running all-subsets

Table 2
The true-positive rate and recall rate of Adélie penguin chick calls automatically detected by Kaleidoscope software in the 18 recordings (selected 2 in each crèche randomly).

Recording File	Manual Count Number	Automatically Detected Number	False-positive Number	True-positive Rate	Recall Rate
S4A01579_20200107_185658.wav	230	220	4	98.18%	93.91%
S4A01579_20200129_100510.wav	60	60	2	96.67%	96.67%
S4A01586_20200117_190942.wav	414	320	8	97.50%	75.36%
S4A01586_20200129_165052.wav	59	57	3	94.74%	91.53%
S4A02761_20200117_234248.wav	123	107	2	98.13%	85.37%
S4A02761_20200122_221429.wav	690	679	2	99.71%	98.12%
S4A05342_20200117_021011.wav	221	211	2	99.05%	94.57%
S4A05342_20200128_034123.wav	296	291	3	98.97%	97.30%
S4A05356_20200118_021944.wav	380	346	3	99.13%	90.26%
S4A05356_20200202_014132.wav	424	376	1	99.73%	88.44%
S4A05628_20200107_232355.wav	64	60	4	93.33%	87.50%
S4A05628_20200130_040255.wav	55	50	7	86.00%	78.18%
S4A05631_20200107_065616.wav	60	62	5	96.77%	95.00%
S4A05631_20200117_200206.wav	436	368	19	94.84%	80.05%
S4A05660_20200120_055821.wav	307	236	2	99.15%	76.22%
S4A05660_20200121_085806.wav	67	70	5	95.71%	97.01%
S4A05943_20200117_090551.wav	248	233	6	97.42%	91.53%
S4A05943_20200128_085809.wav	306	271	3	98.89%	87.58%

selection. All-subsets selection listed all possible LME models and ranked them according to AICc values and model weights (Table 5). Model 1, VAR ~ abundance + wind speed + (1| crèche ID) + (1|date) (conditional $R^2 = 0.743$) performed best based on AICc values. In addition, Model 1 required fewer fixed effects, which meant less difficulty to obtain raw data and higher application value. Finally, we chose Model 1 as the final prediction model. The Model 1 showed that penguin abundance and wind speed had high interpretation of VAR; VAR was positively correlated with the abundance, and negatively correlated with the wind speed.

We performed VPA in order to determine the proportion of the total variance of VAR explained by wind speed and abundance in Model 1 (Fig. 5). VPA result showed that wind speed is more explanatory to VAR than abundance, and there was no collinearity in the interpretation of VAR variance between the two fixed effects (shared explanatory degree < 0).

4. Discussion

We monitored populations of Adélie penguin chicks on Inexpressible Island using PAM, specifically established the positive correlation between VAR and penguin chick abundance. This kind of correlation (i.e. between VAR and population abundance/size) has been established based on multiple populations in some sea birds, such as Cory's shearwater (*Calonectris borealis*) (Oppel et al., 2014; Borker et al., 2014), and terrestrial birds, such as European bee-eater and Dupont's lark (Pérez-Granados et al., 2019).

Penguins might stop calling and snuggle together to keep warm under extreme weather conditions such as strong winds. Thus, meteorological factors might also be the key factor affecting VAR. Therefore, VAR might better reflect the abundance of Adelie penguin chicks when meteorological factors (e.g. wind speed) are included in the prediction model, which was confirmed by our LME modeling results.

PAM of target species using ARUs has advantages of effort saving, simple operation, low interference, and more objective results of population monitoring (Marques et al., 2013). However, recording quality and recording range of ARUs are easily affected by meteorological and geographical conditions (Shonfield and Bayne, 2017). Studies have shown that vocal production, and even vocal pattern, were affected by environmental factors, such as the change of moon light and air temperature (Perez-Granados et al., 2021), or rain and dry seasons (Szymanski et al., 2021).

The results of LME modeling and VPA showed that among all meteorological factors, wind speed had the greatest impact on

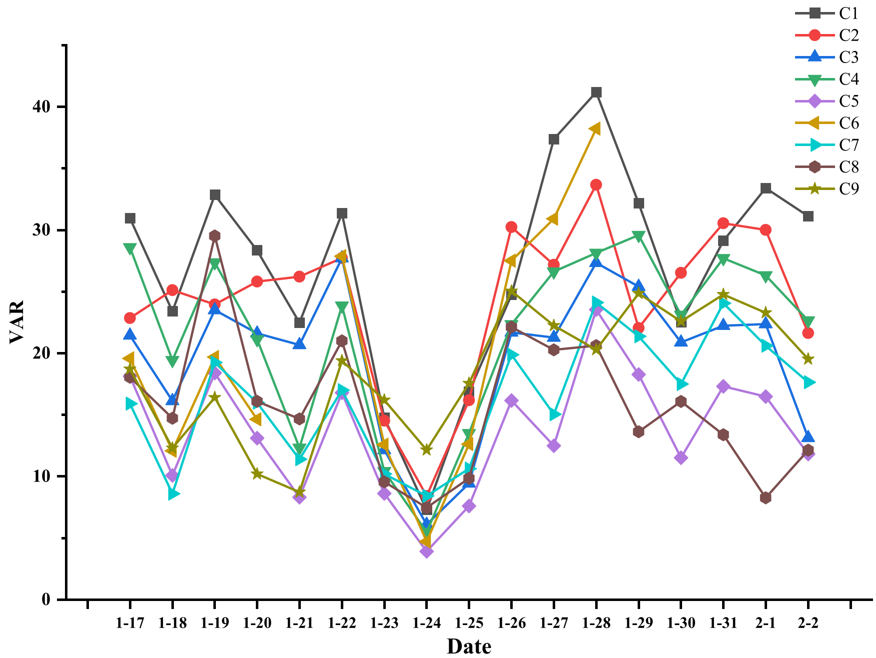

Fig. 4. The changing trend of VAR of Adélie penguin chicks in the nine selected crèches. C1–C9, ID of the nine crèches.

Table 3
Change of abundance of Adélie penguin chicks in the nine crèches.

Crèche ID	1–16	1–21	2–3	Mean ± sd
C1	90	93	86	89.67 ± 2.87
C2	34	46	47	42.33 ± 5.91
C3	34	41	32	35.67 ± 3.86
C4	110	113	100	107.67 ± 5.56
C5	16	16	15	15.67 ± 0.47
C6	91	113	116	106.67 ± 11.15
C7	35	34	34	34.33 ± 0.47
C8	20	20	16	18.67 ± 1.89
C9	67	65	59	63.67 ± 3.40

Table 4
Results of paired samples t-test on Adélie penguin chick abundance among the three counting days.

–	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 1 1-16 & 1-21	-4.889	7.785	2.595	-10.873	1.095	-1.88	8	0.096
Pair 2 1-16 & 2-3	-0.889	11.118	3.706	-9.435	7.657	-0.24	8	0.816
Pair 3 1-21 & 2-3	4	5.22	1.74	-0.013	8.013	2.299	8	0.051

sd, standard deviation.

penguin call, which even had a greater contribution to VAR than penguin abundance. In Inexpressible Island region, strong katabatic winds from Nansen Ice Shelf even open a large polynya in the eastern waters off the Adélie penguin nesting area. The area is open terrain and has no vegetation as shelter, and strong winds affected the recording quality of target animals: sounds of the winds masked distant target sounds, reducing the effective recording range; the ice slag, sand, and gravel hit the ARUs, overloading the recording. During the strong wind, the chicks in a crèches gathered around, turned their backs out and reduced calling on the basis of field observation.

In order to reduce the influence of wind and other noise produced factors on PAM, researches have provided some reliable methods

Table 5
Fitting results of the LME model based on all-subsets selection.

Model ID	(Intercept)	fixed effects				AICc	ΔAICc	weight
		abundance	air temperature	solar radiation	wind speed			
1	24.07	0.07661			-1.914	861.4	0	0.403
2	24.91	0.07638	0.3527		-2.003	862.8	1.46	0.194
3	25.03	0.07686		-0.00629	-1.793	862.8	1.48	0.192
4	28.42				-1.911	864	2.65	0.107
5	29.27		0.3617		-2.002	865.4	4.05	0.053
6	29.37			-0.00615	-1.793	865.5	4.14	0.051
7	24.16	0.07615		-0.03643		884.4	23.03	0
8	28.46			-0.03629		886.8	25.45	0
9	15.4	0.07576				889.4	28.01	0
10	13.87	0.07596	-1.249			889.5	28.16	0
11	19.71					891.7	30.35	0
12	18.21		-1.24			891.9	30.52	0

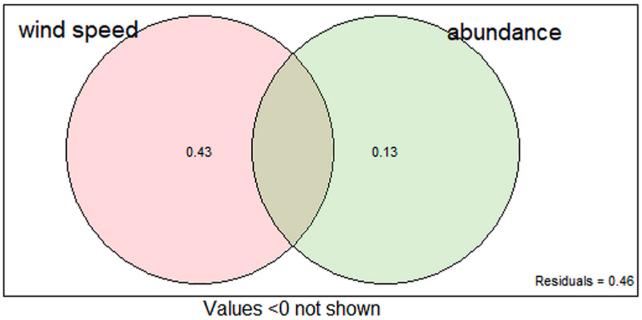

Fig. 5. VPA result for the fix effects in Model 1, and the fractions of variation displayed in the Venn diagram were computed from adjusted R^2.

to preprocess acoustic signals. For example, using minimum-mean square error short-time spectral amplitude estimator (MMSE STSA) as a stationary noise filter (Brown et al., 2018); using an estimator which can transient noise level to a wavelet packet representation and then combine with log-spectral subtraction to stabilize the background level (Juodakis and Marsland, 2022). We should pay more attention to the impact of environmental factors on recordings, and to develop a protocol to preprocess or discard the low-quality recordings in future PAM research.

The Kaleidoscope acoustic recognizer had a high true-positive rate in detecting Adélie penguin chick calls, reaching 96.89% in total and being higher than 86.00% in any of the sampled recordings. On the other side, the recall rate (89.14%) was relatively lower, varing greatly among different sampled recordings. A recent study used monitoR to build an acoustic recognizer for night parrot (*Pezoporus occidentalis*) (Leseberg et al., 2020). After introducing intrinsic and environmental variables of the recognizer into the training model to improve the performance of the recognizer, higher true-positive rate was achieved than the pre-training recognizer (Leseberg et al., 2020). Similarly, we could try to incorporate environmental variables into the training model of the Kaleidoscope recognizer to optimize its performance on detecting the sounds of the target species in the future.

VAR is a fast and convenient method for monitoring the abundance and dynamics of a vocal species/population. With the development in low-cost automated recording unit technology (Hill et al., 2018), continuous optimization of signal recognizers (Leseberg et al., 2020), and the establishment of new reliable relationships between VAR and population dynamics, more opportunities would be provided for PAM on vocal wildlife, further contributing to conservation, ecology, and ethology.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Ethics

The experiments reported here comply with the current laws of China. The animal use protocol in the experiment has been reviewed and approved by the Ethic and Animal Welfare Committee (EAWC, No. CLS-EAW-2018–012).

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