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This is an **author produced version** of a paper published in:

Ecological Indicators 107 (2019): 105608

**DOI:** <https://doi.org/10.1016/j.ecolind.2019.105608>

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Effort needed to accurately estimate Vocal Activity Rate index using acoustic monitoring: a case study with a dawn-time singing passerine.

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Declarations of interest: none

**Abstract:**

Indices based on singing activity have often been used in wildlife surveys conducted with passive acoustic monitoring. For instance, the Vocal Activity Rate index (VAR) has been employed to estimate animal populations and detect changes in abundance between years or sites. VAR may differ greatly between days due to environmental and biological factors, therefore leading to inadequate population size estimations and recommendations. However, there is still little information about the minimum number of monitoring days required for estimating a reliable VAR to assess changes over time or sites. We describe, for first time for a terrestrial bird species, the pattern of variation of VAR as a function of the number of monitoring days. Coefficient of variation sharply decreased with the number of monitoring days, and this pattern was similar during the breeding and post-breeding period. Coefficient of variation was close to 100% when a single monitoring day was surveyed, but decreased up to 30% and 20% after six or seven and nine monitoring days, depending on the monitoring period. Mean VAR was significantly related to bird abundance, but no relationship was found between bird abundance and number of days needed to reach a CV lower than 20 %. Our results highlight that prior assessment of effort needed to estimate a reliable VAR should be a prerequisite for future monitoring programmes using singing activity indices. We found large differences in the number of monitoring days needed to obtain a reliable VAR in comparison to prior research on seabirds, suggesting that further research should be developed in different taxa and situations.

**Keywords:** Autonomous recording unit, *Chersophilus duponti*, cue rate, Dupont's lark, population estimates, signal recognition.

## Introduction

The recent development of open source and low-cost Autonomous Recording Units (ARUs hereinafter; Hill et al. 2018) along with advances in automated signal recognition programs, including machine learning processes, have led to an increasing trend in the use of acoustic monitoring for wildlife surveys (see review in Sugai et al. 2019). This technique has served as an alternative to traditional field surveys for describing animal communities, detecting species' presence, or in behavioural studies (Darras et al. 2018). The use of ARUs has a large number of advantages over traditional survey methodologies, since it can be a standardized no-invasive technique able to operate in remote locations or areas with low visual detection. Automated recorders also allow researchers to increase the spatial and temporal scale of studies. However, there are also some disadvantages that cannot be overlooked, among which are the large amount of expert time needed for interpretation of the recordings (Yip et al. 2019) and the difficulty in estimating population densities from sound recordings (but see Hedley et al. 2017, Sebastián-González et al. 2018, Yip et al. 2019). ARUs usually have one, two in best cases, omnidirectional microphone that provides little or no ability to locate the direction of the sound, which makes it difficult to discriminate number of individuals around ARUs (but see Drake et al. 2016 and Hedley et al. 2017).

Vocal Activity Rate index (VAR, hereinafter) is among the few indices used to estimate wildlife population size or assess population changes over time and space with acoustic monitoring. This index, defined as the number of songs detected per unit time (Oppel et al. 2014, Zwart et al. 2014), is expected to increase with increasing population density (density-dependent; Farnsworth et al. 2004). VAR has been used for estimating wildlife abundance in a wide range of taxa, such as anurans (Nelson and Graves 2004), mammals (Barlow and Taylor 2005) or birds (Pérez-Granados et al. 2019a), but also to evaluate wildlife recovery after habitat restoration actions (Buxton and Jones 2012, Buxton et al. 2013). In birds, many studies have described a positive and significant relationship between VAR and bird abundance in different situations, such as nocturnal migration activity (Larkin et al. 2002, Farnsworth et al. 2004), seabirds' colony size (Oppel et al. 2014), and terrestrial bird species (Abrahams 2019, Pérez-Granados et al. 2019a, but see Zwart et al. 2014).

Bird vocal activity differs daily due to weather conditions, mating status and breeding seasonality, among others (Catchpole and Slater 2008). For example, bird singing activity can be affected by raining, mist, temperature, cloud cover (O'Connor

and Hicks 1980), moon phase (York et al. 2014), seasonality (O'Connor and Hicks 1980, Pérez-Granados et al. 2018a), mating status (Kunc et al. 2007) and number of neighbouring males (Olinkiewicz and Osiejuk 2003). Likewise, the effectiveness of ARUs may also differ between days according to environmental conditions (wind speed, rain, etc.) or bird movements. A recent study, using playbacks to simulate a bird calling towards and against different type of recorders showed that tests performed against the recorders detected 50% less calls than those carried out towards the recorder (Pérez-Granados et al. 2019b). Therefore, the influence of all these factors may compromise the use of VAR to estimate bird abundance or assess population changes from sound recordings. Indeed, Abrahams (2019) found a strong and significant relationship between Capercaillie (*Tetrao urogallus*) abundance and VAR when monitoring over an extended survey period (one month), but no relationship was detected over shorter time frames (daily scale) due to considerable daily variation in call activity related to seasonality, adverse impact of weather conditions and large mobility of the Capercaillie around the lek site while displaying (Abrahams 2019).

Programming ARUs to record during a number of monitoring days, as well as using an averaged value of VAR over this period, should decrease the influence of unknown factors. The only known study that assessed number of days needed to estimate a reliable VAR was carried out using seabirds as model species, and concluded that a minimum of 75 monitoring days was needed to reach a stabilised VAR value during the breeding season (Buxton and Jones 2012). However, the authors noted that nocturnal seabird activity is extremely variable from day to day and that seabirds usually leave the colonies for long periods (Buxton and Jones 2012). Therefore, the pattern described in that study may not be representative for terrestrial bird species, for which there is no information available. Moreover, the pattern found by Buxton and Jones (2012) was estimated only during the breeding period, but no information is available about whether the sampling effort should be the same outside the breeding season.

The main goal of this paper is to describe the decreasing pattern of variation (Coefficient of Variation, CV) for measuring VAR of a terrestrial bird as a function of the number of monitoring days. We hypothesised that CV is strongly affected by the number of monitoring days. Thus, we expected that CV would decrease as the number of monitoring days increases. We also aimed to explore whether the sampling effort (i.e. the number of monitoring days) needed to estimate a reliable VAR differs between the

breeding and the post-breeding period. We expect that VAR will be lower during the post-breeding period, due to singing relaxation after breeding. On the contrary, a similar number of monitoring days would be needed if the species had a constant singing activity during this period. We believe that our results may encourage researchers to estimate the deployment duration time required to estimate a reliable VAR in further research. Calculate minimum number of monitoring days is desirable for long-term monitoring programmes based on acoustic monitoring, for which the development of effective and standardised monitoring protocols could lead to greater time and economic efficiency.

## **Methods**

### **Study species**

We selected the Dupont's lark (*Chersophilus duponti*) as a study model because it is a threatened passerine (Gómez-Catasús et al. 2018a) for which acoustic monitoring has proven to be an effective tool (Pérez-Granados et al. 2018b, 2018c). It is a highly territorial species that typically sings at high rates from the same location during dawn choruses (Pérez-Granados et al. 2018a). The vocal activity of the species is maximum during the breeding period (March-June, Herranz et al. 1994, Pérez-Granados et al. 2017), when males engage in countersinging disputes (Laiolo et al. 2008). There is also a second peak of vocal activity during the post-breeding period (September-November, Laiolo and Tella 2008, Laiolo et al. 2008).

### **Study area**

The study area was located within the Important Bird Area “*Altos de Barahona*” (Soria province, central Spain, 41°20' N 2°41' W), which harbours one of the largest Dupont's lark populations in Spain (594 males, Gómez-Catasús et al. 2018b). In this area we located five acoustic monitoring stations aiming to conduct a long-term monitoring of the presence and abundance of the Dupont's lark during the following years. Four of the acoustic monitoring stations (Stations A-D) were located in potential areas for the species where habitat reforestation actions were carried out. The remaining station (Station E) was placed within a high-quality habitat and known to have a basis of the vocal behaviour of the species. All sites were flat areas dominated by small and sparse shrub communities (*Thymus* spp. and *Genista* spp.) and a high proportion of bare ground cover.

### **Acoustic monitoring**

In each acoustic monitoring station, we placed one ARU. ARUs consisted of a USB Voice Recorder SK-001 with one integrated and single-channel microphone. Recorders were powered by a 12V/8.0 mAh battery (> 300 hour-autonomy), connected to a digital timer to record at selected times. Devices were protected from weather by small and cryptic plastic boxes (see Appendix Figure A1). Stations A-D were monitored during 14 consecutive working days throughout the breeding season in 2018 (20 March - 30 April) while station E was monitored during the same number of days between 4 April – 17 April 2019. Additionally, two of the stations located in the managed area were also monitored 14 days during the post-breeding period in 2018 (18 September – 2 October).

In all sites recorders were programmed to record from one hour before sunrise to sunrise following the protocol described for monitoring the species (Pérez-Granados et al. 2018b). We selected this recording time to reduce variation in VAR (Oppel et al. 2014), as it coincides with the maximum daily singing activity period of the species (Pérez-Granados et al. 2018b, 2018c). Acoustic stations were separated by more than 500 m to avoid recording the same individual from two adjacent acoustic monitoring stations, since the recorder used have proven to be efficient at detecting Dupont's lark presence at distances up to 256 m (Pérez-Granados et al. 2019b).

### **Bird data**

We carried out Dupont's lark censuses during the breeding period to estimate the number of males within a 200 m buffer around each ARU. Although the recorder is able to detect the species at a distance of 256 m we used the 200 m buffer since the probability of detecting the species beyond that distance, under favourable singing conditions, is always lower than 15% (Pérez-Granados et al. 2019b). Censuses were carried out on dry and windless days within the two following days after recorders were retrieved in order to avoid modifying the natural singing behaviour of the species during acoustic monitoring period. We performed a line transect crossing the location of the stations and using a 500-m maximum detection band on each side of the observer, within which we assumed a detection probability equal to 1 for singing males (Pérez-Granados and López-Iborra 2017). Censuses were carried out during the last hour before sunrise and locations of all singing males detected was estimated acoustically and recorded by GPS. Finally, we estimated the number of males detected within the 200-m buffer around ARUs as an index of abundance.

### **Audio analyses**

Audio recordings were automatically scanned using Song Scope 4.1.5 (Wildlife Acoustics 2011). This software creates a target signal from the feature characteristics of the example songs used for training, which can then be used as a recognizer to determine if a sound within a recording matches these characteristics (Wildlife Acoustics 2011). We built the recognizer by using songs of the species recorded in different populations and considering only the final sequence of the song as a target signal, since it is quite constant and should be easily detected by Song Scope (see Appendix Figure A2 to see the final sequence of the song of the species and Appendix Table A1 for settings employed to built the recognizer). Recordings were always scanned using the algorithm 2.0 and selecting these results with a score > 40% and quality above 20 (Pérez-Granados et al. 2019a, 2019b). All possible events identified by Song Scope were visual and/or acoustically checked by the same observer (CPG) in order to remove false positives from further analyses. A prior assessment using Dupont's lark recordings collected in the same area demonstrated that the recognizer used in this study is able to detect 63.0% of the Dupont's lark songs within a recording (Pérez-Granados et al. 2019a). We estimated VAR per each recording by dividing the total number of true positives automatically detected by Song Scope by recording length (Oppel et al. 2014, Pérez-Granados et al. 2019). We also estimated mean VAR for each site as the mean value obtained throughout the study period (14 days).

### **Statistical analyses**

To assess the minimum number of monitoring days needed to obtain a reliable VAR we created curves of CV (%) as a function of accumulated monitoring days. First, we quantified the mean and standard deviation (SD) of VAR estimated for all possible combinations from one to 13 monitoring days and then calculated CV by dividing SD by the mean VAR estimated for each combination of monitoring days (Reed et al. 2002). For each site, we excluded the combination for 14 monitoring days because it reports a unique value with no SD, and therefore CV cannot be computed (see Appendix Table A2). In two of the seven acoustic monitoring stations we did not analyse recordings for three or four monitoring days due to strong raining, and in these cases we excluded the combination for eleven and ten monitoring days, respectively (see Appendix Table A2). Although raining activity could fit within the natural variation of bird singing activity due to environmental predictors (O'Connor and Hicks 1980) we opted for not including these days in posterior analyses since we consider that this factor can be easily controlled for researchers (e.g. when selecting sampling dates



or analyzing the recordings). Therefore, hereinafter we will use the term monitoring days referring to “effective monitoring days” (with no rain). Finally, we also assessed the relationship between the number of breeding territorial males around ARUs and number of days required per site to reach a CV lower than 20% in order to evaluate whether the effort needed depends on bird abundance. Additionally we also tested the relationship between VAR and number of breeding males around ARUs. Data collected during the post-breeding period was excluded from these analyses since no field censuses were performed during this period. Data analyses were conducted in R 3.4.1 (R Core Team 2016). We used the *combinations* function in the R ‘*gtools*’ Package (Warnes et al. 2018) to obtain the possible combinations from one to ten, 11 or 13 monitoring days (see script used in Appendix script A1).

## Results

Bird abundance around ARUs varied between one and four males and mean VAR per acoustic monitoring station ranged between 12.4 and 102.8 (see Appendix Table A3). In all stations CV sharply decreased with the number of monitoring days (Figure 1). We found slight differences in the CV between sites, but the pattern of decrease was relatively similar between sites (Figure 1) and between periods (Table 1). However, during the post-breeding this pattern was even clearer and a lower number of days were needed to reach a similar CV (Table 1). When considering only one day for estimating VAR in all data together, the CV was very high and showed a mean value higher than 99% (Table 1 and see Appendix Table A3 for results per site). We estimated that a mean number of seven and nine monitoring days were needed during the breeding period to obtain a VAR with a CV lower than 30% and 20%, respectively (Table 1), while these values decreased to six and nine monitoring days during the post-breeding period (Table 1). We found a positive and significant relationship between VAR and Dupont’s lark abundance around ARU ( $R^2 = 0.84$ ,  $p = 0.028$ , Figure 2), but no relationship was found between bird abundance and number of days needed to reach a CV lower than 20 % ( $R^2 = 0.08$ ,  $p = 0.645$ , Figure 2). When comparing data collected at the same location, VAR obtained after 14 monitoring days during the post-breeding period was between 26-29% higher than during the breeding period (Appendix Table A3).

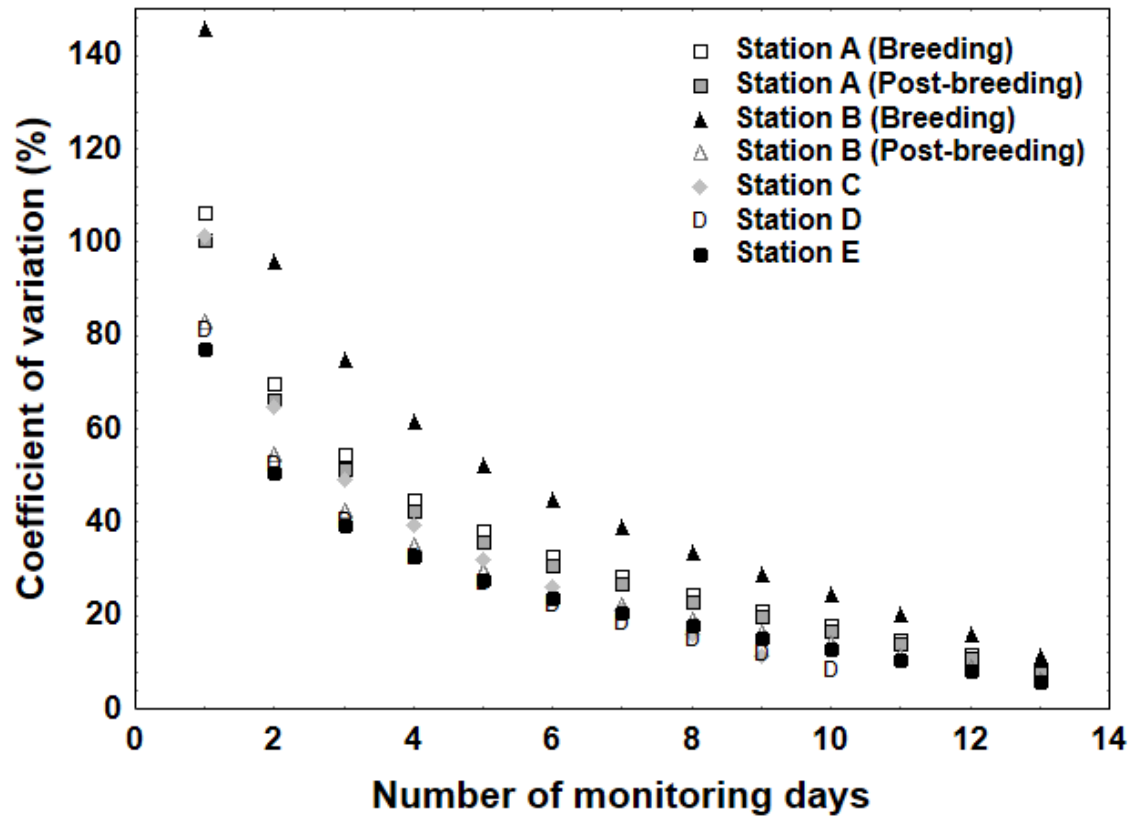


Figure 1. Coefficient of variation (%) of the Vocal Activity Rate index of the Dupont's lark estimated as a function of monitoring days. Coefficient of variation was calculated by dividing standard deviation by mean of the vocal activity rate obtained for each possible combination from one to thirteen monitoring days. Values obtained for each monitored site are expressed with different markers.

Table 1. Mean ( $\pm$ SE) coefficient of variation (CV, %) of the Vocal Activity Rate index of the Dupont's lark as a function of monitoring days. Mean values are expressed for the breeding period (5 stations monitored), post-breeding period (2 stations) and all data together.

Number of monitoring days	Breeding period	Post-breeding period	TOTAL
1	102.4 $\pm$ 12.2	91.7 $\pm$ 8.7	99.3 $\pm$ 8.9
2	66.8 $\pm$ 8.1	60.3 $\pm$ 5.7	64.9 $\pm$ 5.9
3	51.6 $\pm$ 6.4	46.9 $\pm$ 4.4	50.2 $\pm$ 4.6
4	42.2 $\pm$ 5.4	38.7 $\pm$ 3.7	41.2 $\pm$ 3.8
5	35.4 $\pm$ 4.6	32.8 $\pm$ 3.1	34.7 $\pm$ 3.3
6	30.0 $\pm$ 4.1	28.3 $\pm$ 2.7	29.5 $\pm$ 2.9
7	25.5 $\pm$ 3.7	24.5 $\pm$ 2.3	25.2 $\pm$ 2.6
8	21.5 $\pm$ 3.4	21.2 $\pm$ 2.0	21.4 $\pm$ 2.4
9	17.7 $\pm$ 3.3	18.2 $\pm$ 1.7	17.8 $\pm$ 2.3
10	15.9 $\pm$ 3.5	15.5 $\pm$ 1.4	15.8 $\pm$ 2.2
11	15.3 $\pm$ 2.7	12.8 $\pm$ 1.2	14.3 $\pm$ 1.6
12	12.0 $\pm$ 2.1	10.0 $\pm$ 0.9	11.2 $\pm$ 1.3
13	8.4 $\pm$ 1.5	7.0 $\pm$ 0.6	7.8 $\pm$ 0.9

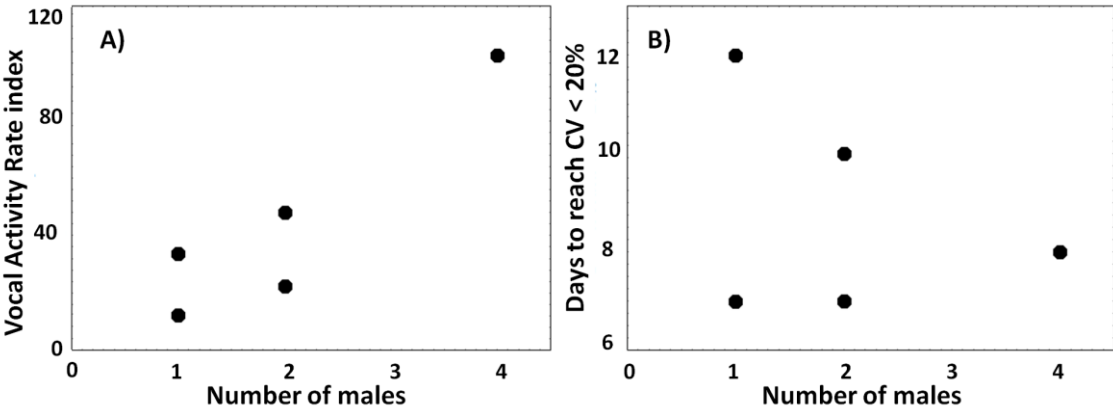


Figure 2. Relationship between breeding Dupont's lark abundance around recorders and: A) Vocal Activity Rate index, and B) Number of days required to reach a CV lower than 20%.

## Discussion

In this work we describe, for first time for a terrestrial bird species, the pattern between CV and VAR as a function of accumulated monitoring days. According to our prediction, CV decreased when a larger number of monitoring days was surveyed and highlight the need to extend the monitoring period to more than one week to obtain a reliable VAR. VAR index has been used to evaluate the response of birds to habitat management actions (Buxton and Jones 2012, Buxton et al. 2013), as well as to estimate wildlife populations of a wide range of taxa e.g. Nelson and Graves 2004, Barlow and Taylor 2005). The annual change in calling activity is also the most important conservation information for practitioners for some monitoring programmes (Digby et al. 2013). In all these cases, scientists and managers require low-error estimates, with statistical power, to infer population abundances and to detect changes in abundance between years or sites. Otherwise, incorrect results may arise and inadequate recommendations may be proposed.

Surprisingly, we found a higher VAR during the post-breeding period than during the breeding one, even though we would have expected a lower vocal output outside the breeding season. This result could be related to a greater number of individuals around recorders during the post-breeding period due to the presence of both resident males and a large number of singing juveniles looking for territory (Laiolo and Tella 2008, Laiolo et al. 2008). However, as we did not perform field censuses during the post-breeding period we cannot conclude whether or not the higher VAR detected during the post-breeding period was related to larger bird abundance. We also found that number of days needed to reach a similar CV value was slightly lower during the post-breeding period than during the breeding one. Although that difference was very low, and regardless we have no bird data during the post-breeding period, it highlights that vocal activity of the species was more constant during the post-breeding period than during the breeding season.

We found a strong and significant relationship between VAR and Dupont's lark abundance, which is in agreement with prior results found in a large number of bird species (Borker et al. 2014, Oppel et al. 2014, Abrahams 2019, Pérez-Granados et al. 2019a). Surprisingly, the same  $R^2$  was found when analyzing the relationship between VAR and Dupont's lark abundance at a larger spatial scale ( $N = 27$  sites, Pérez-Granados et al. 2019a). However, we did not find any relationship between bird abundance and number of days required to reach a CV lower than 20%, which could be

explained by the fact that bird vocal activity changes accordingly to bird abundance, and therefore no relationship might be found. However, we cannot rule out the possibility of finding a concrete pattern between bird abundance and days needed to reach a low CV due to reduced number of sites monitored in our study.

Little is known about how CV differs between species and sites due to the low number of studies that has evaluated this topic. A common feature, however, is that large differences arise between studies. Buxton and Jones (2012) stated that a minimum number between 75 and 200 monitoring days were needed to reach a stabilising value of the VAR uttered by different seabird species during the breeding period. However, according to our results, the number of monitoring days needed to reliably monitor the singing activity of the Dupont's lark, both during the breeding and the post-breeding period, were much lower. We estimated that nine monitoring days was the minimum effort needed to obtain a VAR with a CV smaller than 20%, though this value could be lowered by up to 10% after 13 monitoring days. It is important to keep in mind that our results are based on "effective monitoring days" (after excluding days with raining activity), and therefore ARUs should be left at the field during a larger number of days in order to ensure that minimum number of effective monitoring days is reached. Afterwards those days with raining presence could be easily excluded from posterior analyses. On the other hand, differences between studies seem to be mainly related to different behaviour of monitored species. Buxton and Jones (2012) monitored nocturnal singing activity of different seabirds, which are known to greatly differ in their singing activity between days, sometimes disappearing from their colonies during long periods. In this study we monitored the nocturnal singing activity of a resident and territorial passerine that performs long dawn choruses (Pérez-Granados et al. 2018a) and with very limited displacement movements (100 m between years, Laiolo et al. 2007), which may explain why the VAR showed constant values and therefore the less number of days required to reach a low CV.

CV must be estimated for each case using appropriate validation studies (Reed et al. 2002), since there is no consensus on the optimal value of CV as it depends on the context (Reed et al. 2002). Different authors consider CVs smaller than 20% to be acceptable, while values higher than 30% should be discarded due to high variability (Patel et al. 2001, Gordón-Mendoza and Camargo-Buitrago 2015). Future studies should evaluate which threshold of the CV should be considered as adequate to detect significant changes over years and sites, since up to date the selection of a CV (e.g. 20

as we did) is arbitrary. In any case, we encourage researchers developing monitoring programmes based on acoustic monitoring to estimate the number of days needed to reach a mean VAR, with a reduced CV. This consideration should be useful in current and future monitoring programmes using acoustic monitoring to evaluate long-term changes in biodiversity (e.g. Ecoregion Biodiversity Monitoring project, Furnas and Callas 2015). For that, we provide an R-code in order to follow our approach (Appendix script A1).

Relationship found between VAR and bird abundance in our study and the one carried out by Oppel et al. (2014) using the averaged VAR of the Cory's shearwater (*Calonectris borealis*) obtained over the breeding season (three months) were almost identical. Concretely, Oppel et al. (2014) found a  $R^2$  of 0.86 while ours was of 0.84, despite different vocal behaviour between the Dupont's lark (constant vocal behaviour) and the Cory's shearwater (high daily variations in vocal behaviour, Oppel et al. 2014). Similarly, Borker et al. (2014) found, after a mean number of 86 monitoring days per year, that mean active nests abundance of Forster's terns (*Sterna forsteri*) were highly correlated ( $R^2 = 0.88$ ) with the variation of VAR between years. Therefore, similar relationship among these studies besides large different species' behaviour might be related to the use of a VAR with low CV in all cases, which highlights the importance of estimating low-error VAR to get accurate results. However, prior studies have also found strong and significant relationships between VAR and bird abundance even when recording only one monitoring day (Pérez-Granados et al. 2019a), which suggests that relationship between VAR and bird abundance would greatly differ between monitored species.

Acoustic monitoring and the use of vocal activity rates have proven to be robust tools for monitoring changes in wildlife over time and space. Our results suggest that more attention should be paid to estimating the minimum number of monitoring days for effective monitoring protocols. It is even more important to be evaluated in those long-term monitoring programmes aimed to detect change over time. If not, incorrect findings could lead to misguided decisions. We are aware that our study focussed on a single bird species inhabiting in low densities and that number of monitoring days required to reach a low CV probably is species-specific. Therefore, further research should evaluate the variation of VAR as a function of accumulated monitoring days in a large number of species and taxa, but also at different population densities, since it is

expected that a species' singing behaviour may differ in different contexts and situations.

### **Ethics Statement**

The study was performed under proper legislation of the Spanish law.

### **Acknowledgements**

We wish to thank Javier Seoane for his valuable comments at the beginning of the study, to Josep Albarracín for technical advice and support in the design and use of ARUs, and Gerard Bota and David Giralt for their close collaboration in conception and development. We thank Sarah Young for help with the written English. We are also grateful to two anonymous reviewers whose comments helped to improve the manuscript.

### **Funding**

This is a contribution to the LIFE Ricoti (LIFE15-NAT-ES-000802), supported by the European Commission, the "BBVA-Dron Ricoti", funded by the BBVA Foundation and the Excellence Network Remedinal 3CM (S2013/MAE2719), supported by Comunidad de Madrid.

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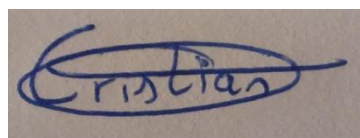
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## AUTHOR DECLARATION TEMPLATE

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property. We further confirm that any aspect of the work covered in this manuscript that has involved either experimental animals or human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

We understand that the Corresponding Author is the sole contact for the editorial process (including Editorial Manager and direct communications with the office). He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author and which has been configured to accept email from (cristian.perez@ua.es).

I, Dr. Cristian Pérez-Granados sign this document on behalf of all authors.

A handwritten signature in blue ink, reading "Cristian", is enclosed within a blue oval. The signature is written on a light-colored, textured surface.

Madrid, June, 2019.

588    Appendix Table A1: Settings used for recognizer creation in Song Scope.

589

590    **Display**

591    Brightness: 0

592    Contrast: 0

593    Inverse video: No

594    Hue: 0

595    Saturation: 255

596    Luminosity: 128

597    **Mixer**

598    Sample rate: 10.000 Hz

599    Playback speed: Normal

600    Max sample delay: 64

601    First channel Gain (dB): 0

602    First channel delay (1/32,000 s): 0

603    **Spectrogram**

604    FFT Size: 256

605    FFT Overlap:  $\frac{1}{2}$

606    Frequency minimum: 46 (1,796 Hz)

607    Frequency range: 75 (4,726 Hz)

608    Amplitude Gain (Db): 0

609    Background filter: 1 s

610    **Detector**

611    Max syllable (ms): 600

612    Max syllable gap (ms): 600

613    Max song (ms): 500

614    Dinamic range: 20

615    Algorithm: 2.0  
616    **Recognizers**  
617    Minimum quality: 20  
618    Minimum score: 50  
619    Show top: 1 match  
620  
621  
622  
623  
624  
625  
626  
627  
628  
629  
630  
631  
632  
633  
634  
635  
636  
637  
638

Appendix Table A2: Total number of possible combination of monitoring days per acoustic monitoring station. Number of days monitored in each station are not the same since some days were excluded from audio analyses due to strong raining activity (see statistical analyses section). \*Stations A and B were monitored during the same number of days during the breeding and post-breeding period.

	Stations A*, B* and E	Station C	Station D
Nº monitoring days	14	10	11
<b>Possible combinations</b>			
One day	14	10	11
Two days	91	45	55
Three days	364	120	165
Four days	1001	210	330
Five days	2002	252	462
Six days	3003	210	462
Seven days	3432	120	330
Eight days	3003	45	165
Nine days	2002	10	55
Ten days	1001	1	11
Eleven days	364	-	1
Twelve days	91	-	-
Thirteen days	14	-	-
Fourteen days	1	-	-
<b>TOTAL</b>	<b>16383</b>	<b>1023</b>	<b>2047</b>

651 Appendix Table A3: Coefficient of variation (CV, %) of the Vocal Activity Rate index of the Dupont's Lark obtained by using acoustic  
652 monitoring during a successive number of days. Results are shown separately for each acoustic monitoring station. Number of males detected  
653 within the 256-m buffer around each station and the mean Vocal Activity Rate (VAR) registered, is shown.

Number of monitoring days	Station A (Breeding)	Station A (Post-breeding)	Station B (Breeding)	Station B (Post-breeding)	Station C	Station D	Station E
1	106.3	100.4	145.9	82.9	101.5	81.1	77.1
2	69.9	66.1	96.0	54.5	64.9	52.3	50.7
3	54.4	51.4	74.8	42.4	49.2	40.0	39.5
4	44.9	42.4	61.7	35.0	39.4	32.4	32.6
5	38.1	36.0	52.3	29.7	32.1	26.8	27.6
6	32.8	31.0	45.0	25.5	26.2	22.3	23.8
7	28.4	26.8	39.0	22.1	21.1	18.5	20.6
8	24.6	23.2	33.7	19.1	16.2	15.0	17.8
9	21.1	20.0	29.0	16.5	11.2	11.6	15.3
10	17.9	16.9	24.6	14.0	-	8.1	13.0
11	14.8	14.0	20.4	11.5	-	-	10.7
12	11.6	11.0	16.0	9.0	-	-	8.4
13	8.1	7.7	11.2	6.3	-	-	5.9
<b>Number of males</b>	<b>2</b>		<b>1</b>		<b>2</b>	<b>1</b>	<b>4</b>
<b>Mean VAR</b>	<b>48.1</b>	<b>64.8</b>	<b>12.4</b>	<b>17.4</b>	<b>22.5</b>	<b>33.7</b>	<b>102.8</b>

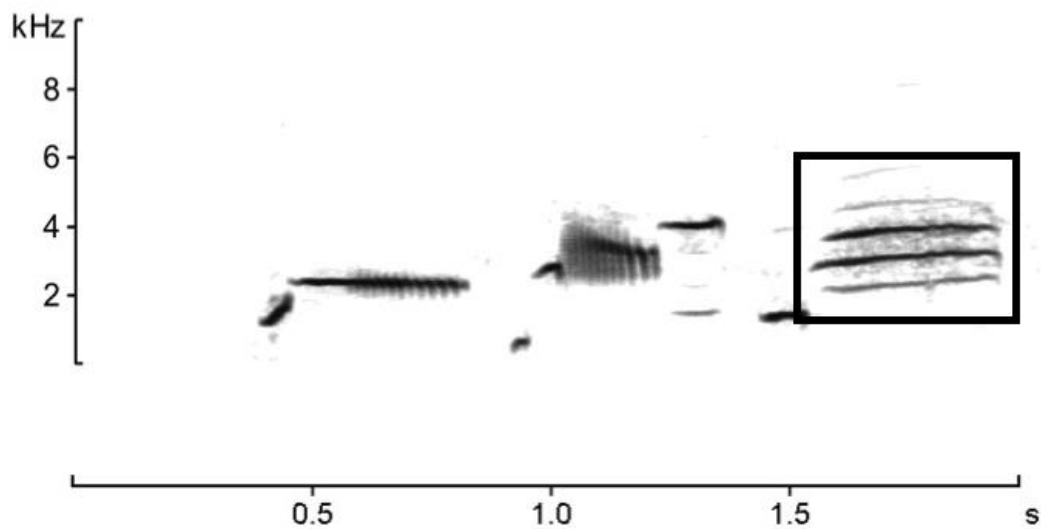
654



Appendix Figure A1: Series of pictures showing the Autonomous Recorder Unit used in this study (RECoTi). The recorder (black USB) and the long-lived battery can be seen at top left picture. The weatherproof box with the microphone outdoors can be seen at top right picture. All items are connected into an internal circuit while digital timer (with up to 16 different programmes) is accessible from the exterior panel.



Appendix Figure A2: Sonogram of a typical Dupont's Lark song. Rectangle shows the final song of the species, which was used for building the recognizer, due to its very particular, recognizable and consistent characteristics.



```

693 Appendix script A1:
694
695 # The present Script can be used to:
696 # 1. Create all possible combinations of VAR from 1 up to I monitoring days
697 # 2. Estimate the Coefficient of Variation in the VAR index for each set of monitoring
698 days
699 # 3. Estimate the number of monitoring days required to reach a Coefficient of
700 Variation lower than a specific threshold (e.g. 20%)
701
702 ##### INDEX #####
703 # *1* Load the Data
704 # *2* Estimate the Coefficient of Variation
705 # *3* Understanding the output
706 # *4* Export your Results
707 # *5* Plotting results
708 # *6* Estimate the minimum number of monitoring days to reach a Coefficient of
709 Variation lower than a specific threshold
710 # *7* Presenting results in tables
711
712 # Load the needed libraries:
713 library(readxl) # to load the excel file with the data
714 library(gtools) # to generate all possible combinations of VAR values
715
716 #####
717 #####
718 ### *1* LOAD THE DATA
719
720 # Use example: Excel File named 'Recordings.xlsx' available at:
721 https://figshare.com/articles/Database\_for\_estimating\_CV\_of\_VAR/8118290/1
722
723 # This file must contain the same structure than our excel file named "Recordings.xlsx":
724 ##### Columns: Monitoring Days
725 ##### Rows: Recordings
726 ##### First Row: Monitoring days (i.e. Day1, Day2, Day3)

```

```

727 ##### First column: Recording Identifier (i.e. Recording1, Recording2)
728
729 DATA <- read_excel("Recordings.xlsx")
730 Data <- DATA [, 2:dim(DATA)[2]] # Remove the first column for the Recording
731 Identifier ID
732
733 # Convert the Data to a matrix without column names
734 Data <- data.matrix (Data)
735 colnames(Data) <- NULL
736
737 NRecordings <- dim(Data)[1] # Number of recordings
738 Max_MonitoringDays <- dim(Data)[2] # Maximum Number of Monitoring Days for all
739 Recordings
740 MonitoringDays <- lapply (1:NRecordings, function(x) length(Data[x,][!is.na
741 (Data[x,])])) # Number of Monitoring days per recording
742 MonitoringDays[[6]] # Number of Monitoring Days for Recording 6
743
744 #####
745 #####
746 ### *2* ESTIMATE THE COEFFICIENT OF VARIATION
747
748 # Create the needed objects:
749 Results_combinations <- array(list(NULL), dim = NRecordings) # Store Results: all
750 possible combinations from 1 up to I Monitoring Days, for each Recording
751 Results_mean <- matrix (nrow= NRecordings, ncol= Max_MonitoringDays) # Store
752 Results: mean of the VAR estimated for all possible combinations from 1 up to I
753 Monitoring Days, for each Recording
754 Results_sd <- matrix (nrow= NRecordings, ncol= Max_MonitoringDays) # Store
755 Results: standard deviation of the VAR estimated for all possible combinations from 1
756 up to I Monitoring Days, for each Recording
757 Results_CV <- matrix (nrow= NRecordings, ncol= Max_MonitoringDays) # Store
758 Results: Coefficient of Variation for each set of Monitoring Days and each Recording
759
760 # Create all possible combinations of monitoring days (from 1 up to i Monitoring Days)

```

```

761 # Estimate the mean and sd
762 # Estimate the Coefficient of Variation
763
764 for (n in 1:NRecordings){
765     combinations <- array(list (NULL), dim= Max_MonitoringDays) # Array of lists to
766     store all possible combinations for each set of Monitoring days
767     mean_combinations <- array(list (NULL), dim= Max_MonitoringDays) # Array of
768     lists to store the mean VAR value for each combination
769
770     for (i in 1:MonitoringDays[[n]]){
771         combinations[[i]] <- combinations (MonitoringDays[[n]], i, Data[n,], set = FALSE)
772         for (j in 1:dim(combinations[[i]])[1]){
773             mean_combinations [[i]][j] <- sum
774             (combinations[[i]][j,]/length(combinations[[i]][j,]))
775         }
776         Results_combinations[[n]][i] <- combinations[i]
777         Results_mean[n,i] <- sum(mean_combinations[[i]])/length(mean_combinations[[i]])
778         Results_sd[n,i] <- sd(mean_combinations[[i]])
779         Results_CV[n,i] <- (Results_sd[n,i]/Results_mean[n,i])*100
780     }
781 }
782
783 #####
784 #####
785 ### *3* UNDERSTANDING THE OUTPUT
786
787 # Results_combinations[[n]][i] output for all possible combinations from i=1 to i=I
788 Monitoring Days in Recording n
789 # Some examples below:
790 Results_combinations[[1]][1] # Combinations for [1] monitoring day in Recording [[1]]
791 Results_combinations[[2]][3] # Combinations for [3] monitoring days in Recording
792 [[2]]
793 Results_combinations[[3]][5] # Combinations for [5] monitoring days in Recording
794 [[3]]

```

```

795 Results_combinations[[4]][7] # Combinations for [7] monitoring days in Recording
796 [[4]]
797 Results_combinations[[5]][10] # Combinations for [10] monitoring days in Recording
798 [[5]]
799 Results_combinations[[6]][11] # Combinations for [11] monitoring days in Recording
800 [[6]]
801 Results_combinations[[7]][13] # Combinations for [13] monitoring days in Recording
802 [[7]]
803
804 # Results_mean[n,i]: overall mean of the VAR value for all possible combinations of i
805 Monitoring Days in recording n
806 # Some examples below:
807 Results_mean[1,1] # Overall mean for all possible combinations of 1 Monitoring Day in
808 Recording 1
809 Results_mean[3,2] # Overall mean for all possible combinations of 2 Monitoring Days
810 in Recording 3
811 Results_mean[6,5] # Overall mean for all possible combinations of 5 Monitoring Days
812 in Recording 6
813 Results_mean[7,6] # Overall mean for all possible combinations of 6 Monitoring Days
814 in Recording 7
815
816 # Results_sd[n,i]: standard deviation of the VAR value for all possible combinations of
817 i Monitoring Days in recording n
818 # Some examples below:
819 Results_sd[1,1] # Standard deviation for all possible combinations of 1 Monitoring Day
820 in Recording 1
821 Results_sd[3,2] # Standard deviation for all possible combinations of 2 Monitoring
822 Days in Recording 3
823 Results_sd[6,5] # Standard deviation for all possible combinations of 5 Monitoring
824 Days in Recording 6
825 Results_sd[7,6] # Standard deviation for all possible combinations of 6 Monitoring
826 Days in Recording 7
827
828 # Results_CV[n,i]: Coefficient of variation for i Monitoring Days in Recording n

```

```

829 # Some examples below:
830 Results_CV[1,3] # Coefficient of Variation for 3 Monitoring Days in Recording 1
831 Results_CV[3,2] # Coefficient of Variation for 2 Monitoring Days in Recording 3
832 Results_CV[6,5] # Coefficient of Variation for 5 Monitoring Days in Recording 6
833 Results_CV[7,6] # Coefficient of Variation for 6 Monitoring Days in Recording 7
834
835 #####
836 #####
837 ### *4* EXPORT YOUR RESULTS
838 # Create the data.farme
839 Coefficients_Variation <- as.data.frame(Results_CV)
840 Coefficients_Variation <- data.frame (DATA$Recording, Coefficients_Variation) #
841 Incorporate the Recording identifier
842 colnames(Coefficients_Variation) <- colnames(DATA) # Give names to the columns
843
844 #Save the Coefficient of Variation in your working directory:
845 write.csv(x= Coefficients_Variation, file= "Coefficients_Variation")
846
847 #####
848 #####
849 ### *5* PLOTTING THE RESULTS
850 Results_CV [!is.finite(Results_CV)] <- -100 # Replace NAs with -100 values to avoid
851 Error messages
852 MaxCV <- max(Results_CV)
853 Recordings <- DATA$Recording
854
855 par(mgp=c(2.75,0.75,0), # mgp distance between the axis titles and the axis labels
856     mar=c(5,4,2,2)) # margins
857
858 plot(1,type='n',
859      xlim=c(1,Max_MonitoringDays+1),
860      ylim=c(0,MaxCV+20),
861      xlab='Number of monitoring days', ylab='Coefficient of variation (%)',
862      font = 2, font.lab = 2, # font= 2 bold

```

```

863     cex.axis = 1,
864     cex.lab = 1.5)
865
866 # Coefficient of Variation for each Recording and each set of Monitoring Days
867 for (n in 1:NRecordings){
868     points (1:Max_MonitoringDays, Results_CV[n,], pch = n, cex = 1.5) # pch: symbols;
869     cex: size
870 }
871
872 # Incorporate the legend: Recording Identifier
873 legend(Max_MonitoringDays-4, MaxCV-4, # places a legend at the appropriate place
874     Recordings, # puts text in the legend
875     pch = 1:NRecordings, # gives the legend appropriate symbols (lines)
876     cex = 1, # Size
877     box.lty = 0, # No border for the box
878     text.font = 2,
879     y.intersp = 0.5, # Distance between elements of the legend (vertical)
880     x.intersp = 0.5, # Distance between the symbol and the text (horizontal)
881     bg = "transparent") # Background
882
883 #####
884 #####
885 ### *6* ESTIMATE THE MINIMUM NUMBER OF MONITORING DAYS TO
886 REACH A CV LOWER THAN 20%
887
888 Min_Monitoring_Days <- data.frame (Recording= DATA$Recording,
889 Min_Monitoring_Days= NA)
890
891 # Number of Monitoring days when the Coefficient of Variation is lower than 20%
892 for (n in 1:NRecordings){
893     Min_Monitoring_Days$Min_Monitoring_Days[n] <- which (Results_CV[n,]<20)[1]
894 }
895
896 # Mean Number of Monitoring Days for all Recordings

```



```

897 mean(Min_Monitoring_Days$Min_Monitoring_Days)
898
899 # Export your results
900 write.csv(x= Min_Monitoring_Days, file= "Min_Monitoring_Days")
901
902 #####
903 #####
904 ### *7* PRESENTING RESULTS IN TABLES
905
906 Breeding <- Coefficients_Variation[c(1,3,5:7), 2:15]
907 Breeding_days <- lapply (1:Max_MonitoringDays, function(x)
908 length(Breeding[,x][!is.na (Breeding[,x])])) # Number of Monitoring days per recording
909 Mean_Breeding <- lapply (1:Max_MonitoringDays, function (x)
910 sum(Breeding[,x][!is.na (Breeding[,x])]/Breeding_days[[x]])
911 SE_Breeding <- lapply (1:Max_MonitoringDays, function (x) sd(Breeding[,x][!is.na
912 (Breeding[,x])]/sqrt(length(Breeding[,x][!is.na (Breeding[,x])]))))
913
914 Post_Breeding <- Coefficients_Variation[c(2,4), 2:15]
915 Post_Breeding_days <- lapply (1:Max_MonitoringDays, function(x)
916 length(Post_Breeding[,x][!is.na (Post_Breeding[,x])])) # Number of Monitoring days
917 per recording
918 Mean_Post_Breeding <- lapply (1:Max_MonitoringDays, function (x)
919 sum(Post_Breeding[,x][!is.na (Post_Breeding[,x])]/Post_Breeding_days[[x]])
920 SE_Post_Breeding <- lapply (1:Max_MonitoringDays, function (x)
921 sd(Post_Breeding[,x][!is.na (Post_Breeding[,x])]/sqrt(length(Post_Breeding[,x][!is.na
922 (Post_Breeding[,x])]))))
923
924 TOTAL <- Coefficients_Variation[, 2:15]
925 TOTAL_days <- lapply (1:Max_MonitoringDays, function(x) length(TOTAL[,x][!is.na
926 (TOTAL[,x])])) # Number of Monitoring days per recording
927 Mean_TOTAL <- lapply (1:Max_MonitoringDays, function (x) sum(TOTAL[,x][!is.na
928 (TOTAL[,x])]/TOTAL_days[[x]])
929 SE_TOTAL <- lapply (1:Max_MonitoringDays, function (x) sd(TOTAL[,x][!is.na
930 (TOTAL[,x])]/sqrt(length(TOTAL[,x][!is.na (TOTAL[,x])]))))

```

```

931
932
933 Table1 <- matrix (nrow= Max_MonitoringDays-1, ncol= 6)
934
935 for (i in 1:(Max_MonitoringDays-1)){
936   Table1[i,1] = Mean_Breeding [[i]]
937   Table1[i,2] = SE_Breeding [[i]]
938   Table1[i,3] = Mean_Post_Breeding [[i]]
939   Table1[i,4] = SE_Post_Breeding [[i]]
940   Table1[i,5] = Mean_TOTAL [[i]]
941   Table1[i,6] = SE_TOTAL [[i]]
942 }
943
944 Table1 <- as.data.frame(Table1)
945 colnames(Table1) <- c("Mean_Breeding", "SE_Breeding", "Mean_Post_Breeding",
946 "SE_Post_Breeding", "Mean_TOTAL", "SE_TOTAL")
947 Table1
948
949 ## APPENDIX TABLE A3
950 Coefficients_Variation
951 TableA3 <- t(Coefficients_Variation)
952 Names <- TableA3[1,]
953 TableA3 <- data.frame(TableA3[2:14,])
954 colnames (TableA3) <- Names
955
956 TableA3
957

```