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Estimating *Fringilla coelebs* density using passive acoustic monitoring methods

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Sumário

Nas últimas décadas tem vindo a ser registada uma enorme perda de biodiversidade a uma escala global. Por exemplo, cerca de 48% das espécies de aves existentes encontram-se em declínio e é esperado que este número aumente durante os próximos anos devido a fatores de ameaça, como alterações climáticas e perda de habitat. Tendo isto em conta, é então necessário criar programas e métodos de monitorização eficientes e eficazes para diferentes espécies. As aves são um grupo de animais com uma larga distribuição a nível mundial, que fornecem importantes serviços de ecossistemas. São também consideradas excelentes indicadores da qualidade ambiental devido à sua sensibilidade às alterações dos ecossistemas. Assim é possível monitorizar a qualidade do ecossistema através da monitorização das comunidades de aves que neles habitam.

Na última década os métodos de monitorização acústica passiva (*Passive Acoustic Monitoring* PAM) têm vindo a ganhar uma grande popularidade sendo utilizados para calcular índices gerais de biodiversidade, calcular riquezas especificas e também calcular densidades de animais. Estes métodos baseiam-se em pistas acústicas, por isso podem ser utilizados para monitorizar qualquer grupo de animal que possam ser detetados a partir dos sons que produzem.

Tradicionalmente os métodos de monitorização mais utilizados para o grupo das aves são os pontos-transectos, onde é necessário que um observador registe todos os indivíduos que deteta visual ou auditivamente, e onde é possível fazer o cálculo da densidade de aves através de amostragens nas quais a distância é calculada a partir de um ponto fixo. No entanto, para calcular densidades de animais utilizando PAM é necessário a obtenção de uma estimativa da taxa de produção de sons das espécies em estudo (ou seja, do número médio de vocalizações produzidas por um único individuo durante um certo período de tempo) e conhecer a área de deteção dos gravadores. Tendo estes elementos podemos assim converter a densidade de pistas vocais em densidade de animais.

Há ainda uma grande dificuldade em conseguir estimar densidades de aves através das gravações (Pérez-Granados & Traba 2021) devido a ser um método recente e pouco aplicado em espécies terrestres quando comparado com cetáceos, pois a obtenção dos dados necessários para realizar a estimativa de densidades pode ser trabalhoso no que toca à obtenção de taxas de produção de sons das diferentes espécies.

Assim, o objetivo principal desta dissertação é calcular a densidade de uma espécie de passeriforme através de métodos PAM, sendo esta densidade depois comparada com a densidade obtida através de métodos tradicionais. Para isso será necessário obter a estimativa da *cue rate* da espécie em estudo e a área de deteção dos gravadores utilizados.

Este estudo foi realizado numa área de montado, que ocupam cerca de ¾ da área florestal total da Companhia das Lezírias (CL). Os montados são um sistema silvo-pastoril com elevado valor económico e um dos habitats mais importantes em termos de biodiversidade pois, não só abrigam muitas espécies reprodutoras e invernantes, como também espécies migratórias e com estatuto de conservação. Para este estudo foi escolhido o tentilhão-comum (*Fringilla coelebs*) como espécie-alvo, por ser uma espécie bastante comum em Portugal, nomeadamente em zonas de montado e também por ter um canto muito característico que pode ser facilmente identificado em estudos em que seja necessário usar métodos de monitorização acústica passiva.

As aves produzem dois tipos de vocalizações, os cantos e os chamamentos. Os cantos são geralmente vocalizações mais complexas que são maioritariamente feitas pelos machos para defesa de território, enquanto os chamamentos são vocalizações curtas e simples, utilizadas tanto por machos como

fêmeas para diversas funções como sinais de aviso, perigo, etc. Sendo que, devido ao facto de os cantos serem mais longos e mais facilmente detetados numa área onde outras espécies estejam a vocalizar, faz com que este seja o tipo vocalização a ser utilizada nas amostragens deste estudo.

Neste trabalho foram utilizados aparelhos *AudioMoths* (AM), que foram programados para gravar a uma frequência de 48 kHz, durante as primeiras quatro horas após o nascer do sol, por períodos de uma hora, com 5 segundos de intervalo entre cada gravação.

Para estimar a área de deteção dos gravadores foram realizadas amostragens com aves reais nas quais, quando um indivíduo era observado a cantar e a sua posição era conhecida, o observador ia progressivamente aumentando ou diminuindo a sua distância à ave e registando as diferentes distâncias a que se encontrava usando um *rangefinder*. Cada indivíduo era observado até que por alguma razão se deixasse de ter a certeza que seria o mesmo que continuava a vocalizar ou quando o tempo total de amostragem chegava aos 10 minutos

Para perceber se existe uma diferença nos sons detetados pelos diferentes ângulos do AM, foi construído um suporte com quatro gravadores numerados e virados com o microfone para fora, formando ângulos de 0º, -90º, 90º e 180º em relação ao som emitido. Seguindo o mesmo método utilizado para estimar a área de deteção, quando um tentilhão era detetado e a sua posição conhecida, o observador ia progressivamente aumentando ou diminuindo a distância à ave, desta vez registando qual dos quatro aparelhos estava virado na direção do som.

Para estimar a taxa de produção de sons do tentilhão foram feitas amostragens com um máximo de 10 minutos/indivíduo, nos quais eram registados todos os momentos em que a ave cantava.

Finalmente, para o cálculo da densidade através de métodos tradicionais, foram realizados pontos de escuta com um observador nos mesmos locais de amostragem e ao mesmo tempo que os gravadores, para posterior comparação das estimativas. Durante este trabalho foram realizados 35 pontos de amostragem que abrangiam uma área total de 12,9 km^2 A audição e visualização das gravações de 10 min correspondentes aos censos feitos pelos observadores foi feita no programa *Audacity* de modo a conseguir visualizar os espectrogramas dos cantos produzidos pelas aves e registar os decibéis do pico que existe numa frase dum canto da ave obtendo um total de 3187 cantos.

Para estimar a área de deteção dos nossos gravadores, os dados de decibéis e distâncias registados foram modelados através de um *generalized linear model* (GLM) que resultou numa equação que relaciona os dBs com a distância a que as aves se encontram a cantar. Foi assim possível, a partir deste GLM, atribuir distâncias a uma subamostra dos dados obtidos pelos gravadores. A distância máxima a que os nossos gravadores registaram cantos de tentilhão foi estimada utilizado o programa *DISTANCE*, que permitiu identificar um raio de deteção de 212 metros (uma probabilidade de detetar um indivíduo através deste método de 0.49).

Através da modelação dos dados de decibéis dos quatro ângulos a várias distâncias foi possível perceber que existe uma perda de 10.3 dB entre o angulo 0º e o 180º o que nos indica que pode haver uma sobre-estimativa das aves que não se encontrem a cantar voltadas para o lado em que se encontra o gravador.

Em relação à taxa de produção de sons foi estimado um valor 4.34 pistas/minuto. Finalmente foi estimada a densidade de tentilhões convertendo uma densidade de *cues* em densidade de animais. Para isso foi assim preciso calcular: o número total de cantos obtidos através de PAM, a probabilidade de deteção dos indivíduos, a área de deteção dos gravadores, o tempo em que os censos decorreram (min) e a taxa de produção de sons da espécie. Esta estimativa resultou numa densidade de 3.03 indivíduos/ha,

enquanto através dos métodos tradicionais, utilizando o *DISTANCE* e escolhendo o modelo que mais se ajustava aos dados, a densidade estimada foi de 2.94 indivíduos/ha.

Este estudo permitiu assim perceber que através de métodos PAM é possível obter valores de densidade estimados muito semelhantes aos obtidos através dos métodos tradicionais baseados num observador. No entanto, os intervalos de confiança são bastante diferentes (maiores nos métodos PAM), o que quer dizer que é necessário ajustar as metodologias aplicadas a estes métodos de modo a que estes possam ser aplicados em monitorizações de larga escala.

Palavras-chave: *cue rate*, *AudioMoth*, montados, conservação, aves

Abstract

For the past decades, there has been a globally noticeable decline of Earth’s biodiversity. It has been estimated that around 48% of existing bird species are suffering from population declines. Birds are an important group of animals due to their contribution to our ecosystems and since they are fast to manifest changes in the ecosystems they belong to, ecologists find birds to be excellent indicators their condition. Though the most common standard monitoring methods used are the traditional point-count surveys, dependent on an observer, passive acoustic monitoring (PAM) is a method that has been gaining popularity in the last decade since it offers researchers advantages in comparison to the traditional methods. While using AudioMoth (AM) recorders, the goal of this study is to estimate the density of *Fringilla coelebs* through PAM methods and compare it to the density estimated in the same sampling sites using a traditional method, while also calculating the cue rate of this species, the range of detection of the recorders. This study was conducted in an area of *montado*, which occupies around ¾ of *Companhia das Lezírias*, the largest silvopastoral area in Portugal. Our results show similar density estimates: 2.94 individuals/ha [2.45, 3.47 95% CI] obtained through traditional methods and a density of 3.03 individuals/ha [1.38, 6.63 95% CI] obtained through PAM. We were also able estimate a maximum detection range for these recorders of 212 meters and estimate a cue rate of our species of 3.34 cues/min. Trying to understand the limitations and imperfections that passive acoustic monitoring studies can come across is an important stage to possible be able to use these methods in large scale monitorizations.

Key words: cue rate, AudioMoth, oak woodlands, conservation, birds

TABLE OF CONTENTS

List of tables

List of figures

List of equations

1. Introduction

For the past decades, there has been a globally noticeable decline of Earth's biodiversity. It has been estimated that around 48% of existing bird species are suffering from population declines (Lees *et al*. 2022) and it is expected that these populations will go through considerable changes in the upcoming years, such as species distribution and abundance (Johnston *et al*. 2013; Stowell *et al*. 2018).This is anticipated due to climate change, but birds also face other threats including habitat loss, fragmentation of habitats and invasive alien species (Lees *et al*. 2022), making it essential to conduct suitable wildlife conservation and management actions (Stowell *et al*. 2018; Sebastián-González *et al*. 2018).

To be able to create management conservation actions that are adequate to each species, with techniques and methods that will result in efficient and effective managements, one of the most important steps is having an accurate information of the population size and knowing population tendencies (Sebastián-González *et al*. 2018).

Birds are a group of animals that can be found all over the world, and because of this, researchers have managed to gather a lot of information about their biology, life history and habitat preferences. This also makes them a group that has been easily studied in order to collect information, along the years, about their population sizes and territories (Lees *et al*. 2022). Given their contribution to the ecosystem's services, where they act as seed-dispersers, pollinators and even aid agriculture through pest control, birds end up contributing to support human activities like agriculture (Lees *et al*. 2022; Whelan *et al*. 2015).

Taking these things into account, ecologists find birds to be an excellent indicator of the condition of the ecosystem they belong. Considering the sensitivity birds' manifest when it comes to habitat changes occurring (Lees *et al*. 2022), and since they are vastly spread amongst all types of habitats it can be easier to notice changes in abundance and distribution, so monitoring birds can be used as a tool to address how the ecosystems' health stands.

In the last decade Passive Acoustic Monitoring (PAM) is a method that is increasingly gaining popularity amongst researchers (Abrahams 2018; Darras *et al*. 2018, 2019) due to it being a non-invasive tool that can be used for wildlife monitoring (Pérez-Granados & Traba 2021). With PAM we are not only able to gather recordings of a study site and its wildlife, but most importantly calculate general biodiversity indices, record soundscapes, calculate species richness (Darras *et al*. 2016; Sueur *et al*. 2014) and ultimately calculate animal density. This method is commonly used to survey birds, marine mammals and bats (Darras *et al*. 2016, 2018), but it can also be applied when monitoring amphibians, primates and insects (Darras *et al*. 2016, 2018). Given the fact it relies on acoustic cues, it is utilized to monitor groups of animals that are more easily detected by the sounds they produce than visually (Sebastián-González *et al*. 2018; Stowell *et al*. 2018).

To monitor birds, the standard most used methods are point-counts and transect surveys (Bibby *et al*. 2000; Darras *et al*. 2019), where an observer relies on their visual and aural detection to identify all the species and individuals present (Buckland 2006; Darras *et al*. 2019). With the use of these methods, the density of the birds that exist within an area can be obtained through distance sampling (Buckland 2006). With point-count surveys, an observer will visit each sampling point and on that fixed spot, register all the detected animals, both aurally and visually, and the distance from the point to the animals in their initial locations (Buckland 2006; Ralph *et al*. 1995; Sutherland *et al*. 2004).

However, it faces disadvantages when it comes to areas with difficult access, monitorizations that take long periods of time and it also is dependent on the experience and knowledge of the observers performing it in the field (Alldredge *et al*. 2007), which can lead to not detecting every animal and/or species present, especially the most uncommon ones (Sebastián-González *et al*. 2018).

Whereas with PAM, we can obtain densities of a species through estimating the cue rates of the species (which refers to the mean number of sounds produced by a single individual during a certain period of time), estimating the detection area of the recorders and then we are able to convert this density of cues into animal density (Marques *et al*. 2013).

Furthermore, PAM methods bring advantages when compared to traditional methods such as: researchers are able to place recorders over multiple sample sites at the same time, allowing unattended recordings to happen over long periods of time which makes it easier to have a wider temporal and spatial sampling areas in monitoring programs. Using recorders also makes it easier to gather data about species that inhabit areas with difficult access or even remote locations and since there are no researchers present when the data is being collected the method becomes less invasive and disruptive to the animals in the area. With the recorders, data can be collected at any given time of the day no matter the weather conditions and monitorizations using PAM can lead to big amounts of data being collected that can be reexamined at any given time (Abrahams 2018; Marques *et al*. 2013; Pérez-Granados & Traba 2021; Sebastián-González *et al*. 2018; Sugai *et al*. 2019).

However, regarding density estimations, it isn’t yet confirmed if the use of these methods can fully replace the use of traditional methods which are dependent on observers (Darras *et al*. 2019) given that it is a relatively recent applied method (Marques *et al*. 2013) and mostly in cetaceans.

Therefore, the main objective of this study is to calculate the density of a passerine species, the common chaffinch *Fringilla coelebs*, using passive acoustic monitoring methods, and to analyze the performance of these results obtained through PAM methods by comparing it with density results obtained from traditional observer point-count surveys. For these the specific objectives are estimating the cue rate of *Fringilla coelebs* (Marques *et al*. 2013), estimating the range of the recorders that are being used, given that they are recent (Hill *et al*. 2018) and not many studies have been done with them, and also to understand if there is a noticeable difference in the detection of sounds from a source produced in the various angles in relation to the recorder.

2. Methods

2.1. Study site

The study was carried out in Charneca do Infantado, a property which belongs to Companhia das Lezírias, in Santarém, Portugal, which hosts the largest silvopastoral and forest area in the country. This forest area covers around 11 thousand hectares of diverse types of trees like *Eucalyptus sp*. (560 ha), *Pinus pinea* (680 ha), *Pinus pinaster* (1040 ha), and *Quercus suber* (6570 ha). Cork oak woodlands are therefore the most common habitat present in Companhia das Lezírias, making up to 75% of the total forest area (Companhia das Lezírias 2016).

Oak woodlands (*Quercus suber* and *Quercus rotundifolia*) managed as silvopastoral systems, also denominated as *montados* in Portuguese and *dehesas* in Spain, are very common habitats amongst Mediterranean countries (Pinto-Correia *et al*. 2011), in which activities like: livestock rearing, honey production and extraction of cork from the bark of the trees take place (Leal *et al*. 2011).

Even though *montados* are a human managed silvopastoral ecosystem, the trees present don't have a uniform pattern, which results in different tree densities depending on the region, with a low density of shrubs (Pereira & Fonseca 2003), therefore we get a woodland with open areas and an heterogenous landscape (Godinho & Rabaça 2011).

Montados are a very important type of habitat with a big amount of breeding and wintering bird's species that depend on it and migratory species (Almeida & Granadeiro 2000; Díaz *et al*. 1997; Tellería 2001) which makes it the habitat with the highest species richness in the Iberian Peninsula (Tellería 2001), creating a type of habitat that is worth keeping protected due to them being a hotspot for biodiversity (Myers *et al*. 2000).

This study is part of an ongoing PORBIOTA project, which aims to contribute to gathering and sharing data collected of monitorizations of biodiversity at a national level.

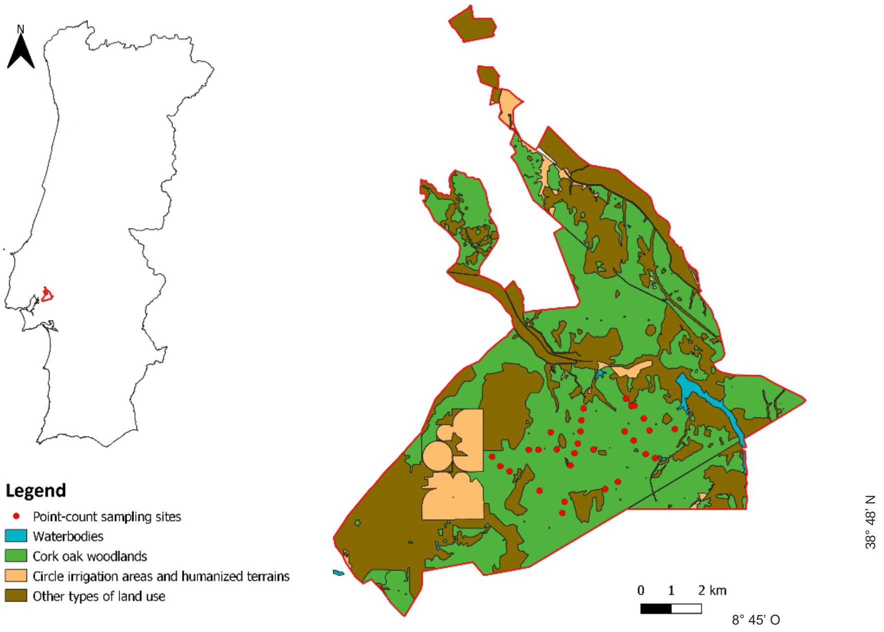

Figure 2.1: Location and map of the study area, showing the difference soil usage within *Companhia das Lezírias* and the red dots representing the point-count sampling sites where both the acoustic and traditional monitoring occurred.

2.2. Chosen species

One of the most common species that we are able to find in a *montado* area is the common chaffinch (Figure 2.2 A), which is a resident species and one of the most common passerines in Portugal that can be found all over the country (Catry *et al*. 2010).

This species is commonly found in all kinds of wooded areas, like riverside woods, orchards and even trees along roadsides, even though they are more frequently found in agricultural habitats (Catry *et al*. 2010). The breeding season of this species in Portugal is still unknown, but it is known that they start to vocalize/sing around February till the beginning of the summer (Catry *et al*. 2010).

Given their distinct and characteristic song (Figure 2.2 B), compared to other species, it makes it easier to identify *Fringilla coelebs* individuals in studies where we have to apply acoustic monitoring methods.

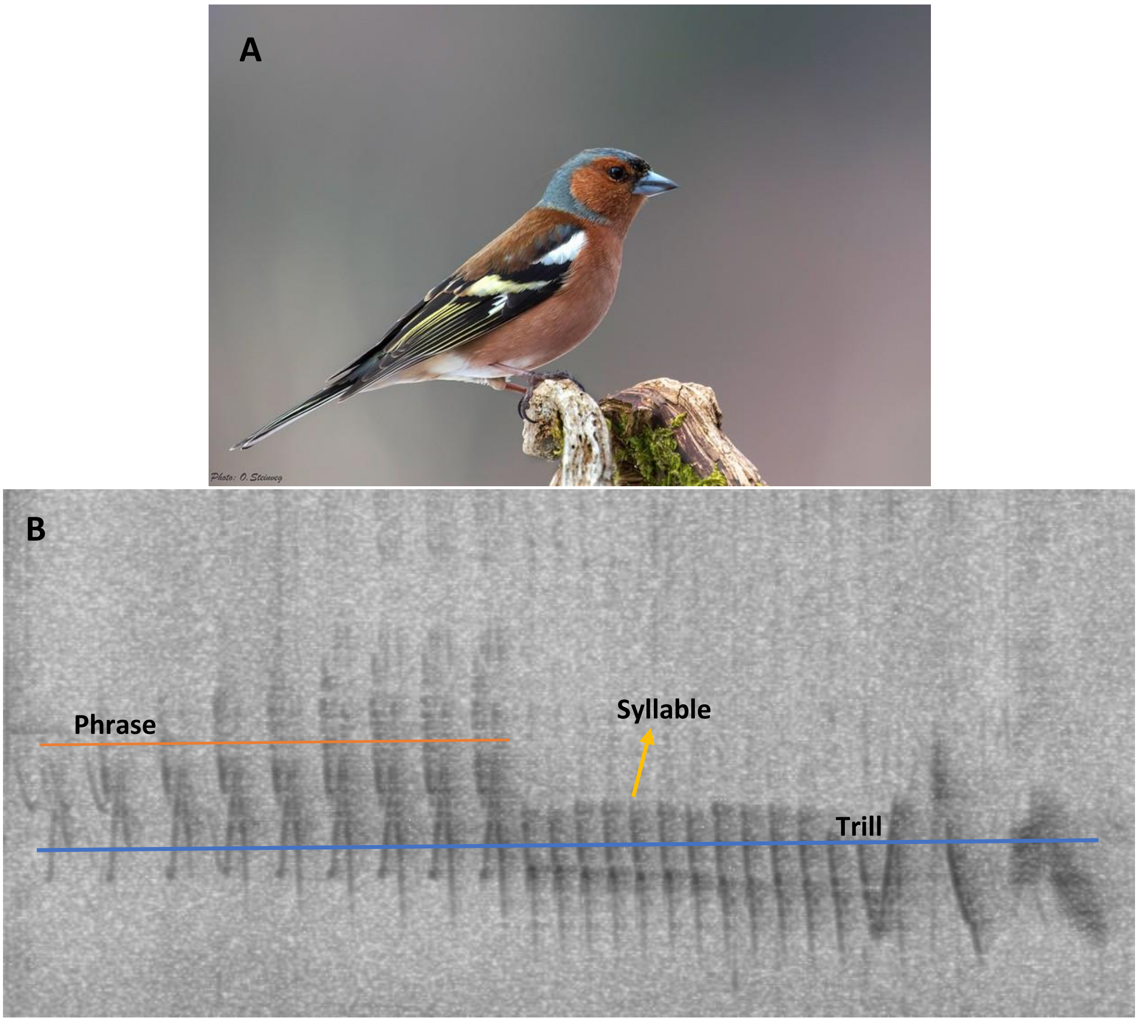

Figure 2.2: **A** – Photo of a male *Fringilla coelebs* (@Odd Steinveg). **B** – Spectrogram obtained through Audacity® of a song a male *Fringilla coelebs* produces in which is represented a trill (blue), a phrase (orange) and a syllable (yellow).

2.3. Data collection using recorders

The fieldwork occurred between March and May of 2022, and data was collected using automatic sound recorders called AudioMoth (AM). During this period of time, we selected days where the meteorological conditions were appropriate for better recordings quality, as days where there was no wind or rain.

AudioMoths are small, in terms of size and weight, affordable recorders with an inbuilt microphone that can be programmed to record within specific filters and schedules (i.e., frequencies up to 348 kHz and recording throughout 24h with 5s intervals between each recording), can store data through an SD card and runs on batteries (Hill *et al*. 2018, 2019).

For this study, AudioMoths were programmed to record at a 48 kHz, which is the fittest frequency given that our subject group is birds, and they were set to start recording the first 4 hours after sunrise, for periods of 1 hour with a 5 seconds interval between each recording.

Birds produce two main types of vocalizations: songs and calls. Songs are usually loud and often long, more complex vocalizations that are mostly used by males to defend their territory, and they are formed by syllables (basic units), phrases (repeated syllables) and trills (rapid repetitions of 3 or more simple syllables) (Gill 2007). Calls, on the other hand, are short and simple vocalizations, that are used by both males and females that can be warning calls, distress calls, flight calls, nest calls and flock calls. (Gill 2007).

In this study, we are going to be using songs as our vocalization-type focus, given the fact that it will be a longer vocalization and easier to detect in an area with other vocalizing species.

2.3.1. Range of detection using an AudioMoth

Given that AudioMoths are relatively new devices, there isn't a lot of research done about their range of detection of bird vocalizations. However, to calculate animal density we need to better understand the area of detection of these recorders.

So to estimate this, we first conducted a field test to analyze how the audibility of bird sounds received by the recorders varies at different distances and how this might affect the spectrograms shown in the program that will be used to visualize sounds. So, we started by using recordings of different species of birds played through a phone at different distances from the recorders (see Appendix A and Appendix B), in a volume that the observers considered a "normal" volume that would be heard if these species were to be vocalizing in a tree right above them. For each species, an observer would reproduce its song at progressively greater distances from the recorder registered using a rangefinder.

After these experiments, we proceeded to use a similar process with real *Fringilla coelebs* individuals. The observer walked slowly in the woodlands and once a bird was spotted singing, an observer would progressively increase or decrease their distance to the singing bird and registered its distance using a rangefinder. We had to make sure that the individual stayed in the same place and that we were always capturing the same individual, for a period of 10 minutes maximum for each bird, once the bird would fly away, or we couldn't be sure it was the same individual we could no longer continue to collect the data from that individual.

2.3.2. Differences in the sounds detected from different angles of an AudioMoth

Since our AudioMoths recorders only have 1 inbuilt microphone (Hill *et al*. 2018), we need to understand if the position in which the recorder receives the sound coming from a bird (i.e., in front of the microphone, on each side or at the back) is going to influence the detection of the same sound emitted by the same bird at the same time. Therefore, by building an attachment that consisted of a long squared wooden stick that could hold 4 numbered AMs, each one in each side of the stick, with their microphone facing outwards (Appendix C), we were able to have all 4 directions like a compass (0º, -90º, 90º, 180º).

Following the same method that we had for the detection range, once we spotted an individual of *Fringilla coelebs* singing we would register the distance to the AM with a rangefinder saying loudly to the recorder which AM (number) was facing the bird. Then the observer would try to increase and decrease the distance to the singing bird making sure we were always capturing the same individual.

2.3.3. Cue rate of *Fringilla coelebs*

The cue rate of a species is the average number of vocalizations that one single individual produces per period of time. So, in this case, it's the number of times the same *Fringilla coelebs* individual is registered singing over a period of time.

To estimate the cue rate, we spotted an individual, in which, we registered every time the individual would sing during a maximum of 10 minutes. During data collection, if by any chance we would lose track of the individual we were following, we would stop the timer and stop registering data for that individual.

We managed to register the cue rates of 46 individuals, making sure that after each bird we would change location to try to avoid capturing the same individuals.

2.3.4. Using automated recorders to calculate density estimates

To ensure that there is no overlapping in the area of detection of the multiple recorders, and therefore reduce the chances of capturing the same animals, each recorder was placed always with a minimum distance of 300 m between each other. The recorders were also placed, 2 m above ground level, attached to tree's trunks with smaller widths to try not to block sounds from reaching the microphone, which also involved making sure that there were no branches or any other trees right in front of the recorder once it was placed.

We placed 10 recorders in different suitable *montado* locations on the April 28th till the May 3rd, 2022, and each day we would move them to other locations after the monitoring through point-count with an observer once the survey on the site was completed.

We ended up having a total of 35 sample sites covering a sampled area of approximately 12,9 km^2 (Figure 2.1). The total sampled area ensures that we have a polygon that contains all the sample sites where the density estimates census were performed, including a 100 m buffer on the outline of the polygon to safeguard the detection of birds throughout the point-count census (Appendix D).

2.4. Data collection by an observer

2.4.1. Point-counts with an observer to calculate density estimates

The observer point-counts were done at the same time and sampling site where the AudioMoths were recording to allow later comparison of the results. The point-counts (Ralph *et al*. 1995; Sutherland *et al*. 2004) had a 10 minutes duration, during which, the observer registered any individual of *Fringilla coelebs* seen or heard and estimated their distance to the observer in 20 m distance bands up to 100 m.

Counting's were always done within the first 4 hours after sunrise, making sure to catch the peak hours of activity of birds (Ralph *et al*. 1995) and the sampling period also occurred from April 28th till the May 3rd, 2022.

To allow comparison with data from the recordings, before the start of each monitoring, a signal was spoken loudly to be able to know the exact moment the sampling was starting.

2.5. Data and statistical analysis

We started by selecting the recordings that were obtained at the same time as the observer point-counts, and within those recordings we only analyzed the 10-minute window correspondent to it, registering every song detected produced by an individual of our species of interest. For this, the program Audacity® (Audacity Team 2021) was used to be able to visualize the spectrograms of the songs produced by birds and thus register the dBs and Hz of the peak that we can see in a trill of a singing bird (Figure 2.2 B).

In order to estimate the range of detection of our recorders, we modelled the dBs of a real singing bird and their correspondent distances, in meters, through a generalized linear model (GLM) of the gamma family and with a log link, which gave us the model that correlates the power of the sound (dB) and the distances of singing birds.

To try to understand if the direction of the sound source, in comparison to the front of the AM (therefore facing the microphone), holds any significant changes in the power of the sounds (dB) that are captured, a linear mixed-effect model was implemented. The power of the sound (dB) and the four angles were used as fixed effects and we added a random intercept to account for individual differences between the animals that were being studied.

In order to calculate the cue rate of our species we simply had to calculate the mean of the number of times each of the 46 individuals sang over the correspondent total period of time that they were being surveyed.

We needed to subset the data gathered from the surveys obtained from the data collected by the recorders, the same surveys that were conducted at the same time as the point-counts. This was done by going through all the recordings obtained and through a systematic selection, choosing the first song that was heard at every minute of the 10 minutes recordings, where we were able to register their dBs but not their distances since it was gathered by the recorders. With this data, we were able to use our GLM obtained through modelling the data collected with real birds and predict the distances of each vocalization (Figure 2.3).

Adding these new predicted distances subset data, we were able to use the DISTANCE package (Miller *et al*. 2019) in RStudio (RStudio Team 2022) which has a function that fits detection functions to line or point-transect data and allows the calculation of abundances and densities, while also showing us the probability of detecting an animal. From we were able to retrieve the probability of detecting an animal and the maximum distance that was registered through the recorders (according to the modelled dBs and their correspondent predicted distances) by modelling the data and seeing which model was best. The best model was selected based on observing the goodness of fit results through the Cramer-von Mises test and the model with the lowest AIC (Akaike information criterion) value (Table 3.1).

When it comes to estimating density through cue counting, we can do it by using the following formula (Marques *et al*. 2013),

$$\widehat{D} = \frac{n(1-\hat{f})}{\hat{p}a\hat{r}}$$

Equation 2.1: General formula to estimate animal density.

in which we can convert the number of times that an animal produces sounds (in our case, the number of times a bird sings), to animal density. $\widehat{D}$ is the estimated animal density through cue counting, n is the number of vocalizations that were identified, $\hat{f}$ corresponds to the false positives (which are sounds not of our interest), $\hat{p}$ is the probability of the recorders detecting the vocalizations, a is the covered area by the recorders, and $\hat{r}$ are the multipliers that are what turns sound density to animal density (Marques *et al*. 2013).

Since in this study we are working with cue counts, we can then use the following formula,

$$\widehat{D} = \frac{n(1-\hat{f})}{\hat{p}aT\hat{r}}$$

Equation 2.2: Formula to estimate animal density using cue counts.

where, n is the number of vocalizations identified during T time units, $\hat{f}$ corresponds to the false positives proportion, $\hat{p}$ is the probability of the recorders detecting a vocalization within the area (a) range of said recorders and $\hat{r}$ is the estimated cue rate, which corresponds to the mean number of vocalizations per individual per time unit (Marques *et al*. 2013). Making it possible for us to turn our total number of vocalizations registered throughout all our data gathered with the recordings into a density estimate.

There is no analytical closed form expression for an estimator of the variance of the density estimates obtained in this equation that we achieved, but this can be obtained in two ways: using a non-parametric bootstrap or using a delta method approximation (Powell 2007). Here we chose to consider the later, as suggested in Marques *et al*. (2013, cf. equation 6). For that we just require estimates of the variances of each of the random components involved in the estimator, which in our case, equates to the variances of the encounter rate, the detection probability and the cue rate components. From these we can easily obtain confidence intervals for density considering a log-normal approximation to the distribution for the density of animals (Marques *et al*. 2013, cf. equations 7-9).

As suggested in Marques *et al*. (2013) equation 6, we can adjust this equation by simplifying it into:

$$var(D) = \hat{D}^2 * \left[\frac{\frac{SD}{\sqrt{n}}}{p} + \frac{\frac{SD}{\sqrt{n}}}{r} + \frac{\frac{SD}{\sqrt{n}}}{n} \right]$$

Equation 2.3: Formula to estimate the variance of the density, using a delta method approximation, having equation 6 in Marques *et al*. (2013) as base, given that our random components are the detection probability (p), the cue rate (r) and the encounter rate (n).

in which, every $\frac{SD}{\sqrt{n}}$ corresponds to the error of each one of our random components, and to estimate their variances (SD) we must $\frac{error}{value\ of\ our\ component}$.

To estimate *Fringilla coelebs* density values using observer point-counts, we used the same DISTANCE package (Miller *et al*. 2019) in RStudio (RStudio Team 2022) using the data collected in the surveys by the observers, which has a function that fits detection functions to line or point-transect data and can allows the calculation of abundances and densities. The truncation in the models being tested was set to 5%, to remove the observations most distant from the points, as detections at these distances contain little information about the shape of the fitted probability density function. The best model was selected based on observing the goodness of fit results through the Cramer-von Mises test and the model with the lowest AIC (Akaike information criterion) value (Table 3.3). As a result, the selected model to estimate densities through point-counts done by observers was a model with a key function uniform with cosine adjustment term of order 1.

3. Results

Analyzing the 35 recordings of 10 minutes each, corresponding to the data recorded by the AudioMoths while the observers were performing the point-counts methods, resulted in a total of 3187 songs registered.

3.1. Range of detection of an AudioMoth

With recordings of known dBs and distances of singing birds, we were able model our data to a generalized linear model (GLM) of the gamma family and with a log link, correlating the power of the sound (dB) and the distance of the singing bird in meters, that allowed us to predict the distances according to their dBs (Figure 3.1).

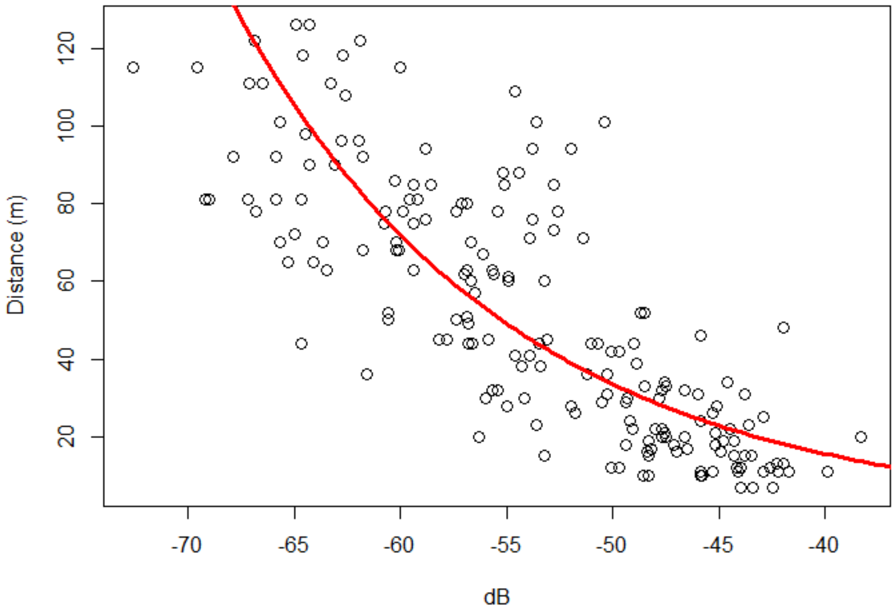

Figure 3.1: Generalized linear model (GLM) of the modelled dBs of a real singing bird and their correspondent distances to the recorder (in meters), which correlates the power of the sound (dBs) and the distances of singing birds, where the regression line of the model is shown (red).

Afterwards, using a subsample of data collected with the recorders we were able to estimate with DISTANCE, the probability of detecting an animal ($\hat{P}_a$ = 0.49) (Table 3.1) and the maximum detection range of the recorders which was 212 meters.

Table 3.1 - Model selection summary of data obtained through recorders with Cramer-von Mises test p-value, probability of detecting an individual, the standard error (SE) and the difference between the AICs of the 2 tested models.

Model key function	C-vM p-value	$\hat{P}_a$	SE($\hat{P}_a$)	ΔAIC
Hazard-rate	0.291	0.492	0.026	0.000
Half-normal	0.001	0.337	0.027	27.435

3.2. Differences in the sounds detected from different angles of an AudioMoth

Our results from data collected for the different angles show that there is a significant statistically difference when comparing 0º with 180º. It is also possible to see that -90º has a difference of 6.7 dB (p-value = 2.888x10^{-3}, p < 0.05), 90º a difference of 8.4 dB (p-value = 1.704x10^{-4}, p-value < 0.1) and 0º a difference of 10.3 dB (p-value = 4.592x10^{-6}, p-value < 0.001). Therefore, 180º is the angle that affects the sounds detected between the different angles of our recorders the most (p-value = 4.012x10^{-122}, p-value < 0.001) (Table 3.2).

Table 3.2 – Summary of the linear mixed-effect model results regarding the changes in the dBs of the vocalizations between the different angles when compared to the sound emitter.

	Value	Std. Error	t-value	p-value
(Intercept)	-57.324	1.698	-33.764	$4.012\text{x}10^{-122}$
-90º angle	6.657	2.221	2.997	$2.888\text{x}10^{-3}$
90º angle	8.426	2.221	3.793	$1.704\text{x}10^{-4}$
0º angle	10.313	2.221	4.642	$4.592\text{x}10^{-6}$

3.3. Cue rate of *Fringilla coelebs*

The cue rate for our species was estimated to be 4.34 cues/minute.

3.4. Density estimate using data from the recordings

Using Equation 2.2 to calculate animal density from cue counts, and using data collected by the recorders, we are able to estimate the density of *Fringilla coelebs*. We can change our values considering:

- the total vocalizations obtained from the recorders of 3187 (n = 3187),
- false positives proportion to be null ($\hat{f}$ = 0),
- probability of detecting an animal to be 0.49 ($\hat{p}$ = 0.49),
- our area to be the circular area with the maximum distance range of the AudioMoths as our radius and given that the data was retrieved from 35 sampling sites we have to account for the total area (a = $35 * \pi * 212^2$), in a total of 10 minutes per survey (T = 10) and
- our cue rate as 4.34 cues/min ($\hat{r}$ = 4.34).

This gives us an estimated density of 3.03 individuals/ha.

Estimating the variance of the density using a delta method approximation (Powell 2007) we estimated the variances of each of the random components involved in the density estimation which in our case is: the variances of the encounter rate, which equals to the variance of the total of vocalizations obtained from the recorders; the variance of the detection probability; and the variance of the cue rate.

By using Equation 2.3, we then estimated this variance:

$$var(D) = 3.03^2 * \left[\frac{0.026^2}{0.49} + \frac{2.53}{4.16} + \frac{254.14}{3187}\right]$$

$$var(D) = 9.18 * [0.0014 + 0.0921 + 0.080]$$

$$var(D) = 1.59$$

Equation 3.1: Solving the formula to estimate the variance of the density, using a delta method approximation (Powell 2007), having equation 6 in Marques *et al.* (2013) as base.

3.5. Density estimate using observer point-counts

With a total of 142 observations, both aurally and visually, in a total of 35 sampling sites, and a total covered area of approximately 12.9 km^2, we were able to estimate the number of individuals within the covered area (n = 323), using the model with a key function uniform with cosine adjustment term of order 1, a probability of detecting an animal to be 0.44 and the density of *Fringilla coelebs* to be 2.94 individuals/ha.

Table 3.3 - Model selection summary of point-count data with Cramer-von Mises test p-value, probability of detecting an individual, the standard error (SE) and the difference between the AICs of the 3 tested models.

Model key function	C-vM p-value	$\hat{P}_a$	SE($\hat{P}_a$)	ΔAIC
Uniform w/ cosine adjustment term of order 1	0.217	0.439	0.039	0.000
Hazard-rate	0.236	0.498	0.084	1.379
Half-normal	0.193	0.469	0.051	2.015

3.6. Differences in the density of *Fringilla coelebs* using recorders vs point-counts

We calculated a final density of *Fringilla coelebs* (Figure 3.2) of 2.94 individuals/ha [2.45, 3.47 95% CI] obtained through traditional methods done by an observer while a density of 3.03 individuals/ha [1.38, 6.63 95% CI] obtained through passive acoustic monitoring methods.

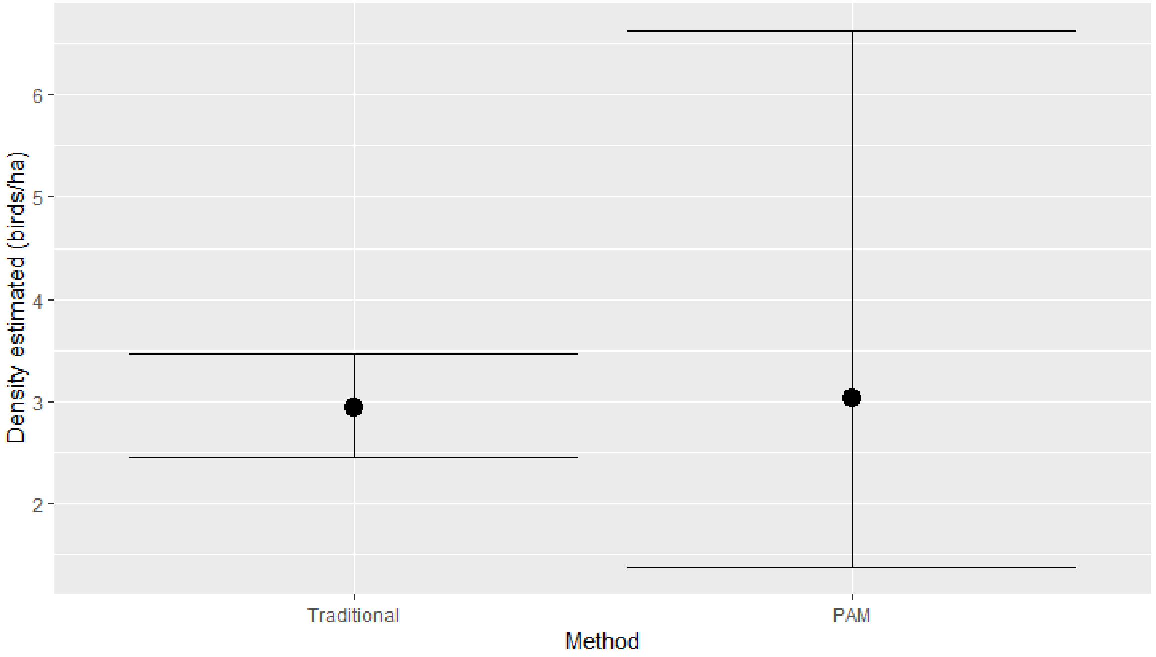

Figure 3.2: Density (birds/ha) estimated for both methods, traditional and PAM, showing their confidence intervals at 95%.

4. Discussion

In this study we estimated the density of *Fringilla coelebs* by using passive acoustic monitoring methods with AudioMoth recorders and we then compare it with a density estimated using a traditional point-count method based on human observations performed at the same time in the same sampling sites.

Additionally, we estimated the cue rate of our chosen species and we tried to understand what is the range of these recorders since it hasn't been yet specified, as well as see what is the difference in the sounds detected by a recorder that only has one inbuilt microphone.

4.1. Range of detection of an AudioMoth

With known distances to birds and dBs of sounds produced by singing individuals, we were able to model and correlate the power of the sounds (dB) emitted with their distance (Figure 3.1).

This correlation shows us a big variance between dBs values registered at the same distance. We expect that calls emitted closer to the recorders will have a higher sound power (dB) than calls emitted from afar, which does not always happen, we often see different sound power (dB) for the same distance. One of the reasons for this to happen may be the fact that when we are recording a singing bird, we don't know if the animal is facing the direction of the microphone or if it's facing any other direction. These differences in the direction of the sound emitted by singing the bird may change the vocalization parameters and makes the same distances have such a high variance in power sounds (Patricelli *et al*. 2008, Sebastian-González *et al*. 2018).

The produced model allowed us then to predict distances from a subset of the data collected with the recordings at the same time as the observers were doing the point-count surveys, for which we didn't know the distances to the singing birds. Given the high variance of dBs obtained for each distance, this may lead into bias so a bigger sample is needed to shorten the variance. Moreover, the range of detection distance of recorders most likely varies with species and habitat (Darras *et al*. 2018). After modelling this subset of data, we were able to estimate the probability of detecting an animal to be 0.49 (Table 3.1) and the associated maximum range of detection of the recorders to be 212 meters.

4.2. Differences in the sounds detected from different angles of an AudioMoth

When it comes to the differences in the sounds detected from different angles of an AudioMoth, our results show us that there is indeed a difference between the sounds detected between the four different angles. In fact, we registered a 6.7 dB difference between sounds detected at 180º and -90º, 8.4 dB difference between 180º and 90º and 10.3 dB difference between 180º and 0º (Table 3.2). This makes it obvious that, in this case, there is a considerable loss of power of sound from a recorder that is facing away from the sound source, and that there is already a loss of this power of sound from the side angles (-90º, 90º) even though this value should be more similar. Darras *et al*. (2018) states that "microphones that have an omni-directional polar patten have a loss of sensitivity towards the back of the microphone", which is what we see happening with our recorders. Knowing this effect can be very relevant because these differences can ultimately be affecting the estimated distances when we use only one recorder in the field and the sound source isn't directly facing the way of the microphone.

Besides the position of the bird singing (e.g. if the bird is vocalizing in the same direction facing the recorder or not) that can lead into a change in the sounds detected, the habitat of where the monitorization is happening can also affect aural detections. This is due to the influence that habitat structure has on sound attenuation and the ambient sounds level it holds (Darras *et al*. 2016, 2018; Yip *et al*. 2017) affecting the quality of the recordings and therefore the detectability of sounds of interest.

Sound attenuation is usually different in open areas and forests, as it results from the dissipation of the sounds, deflection of the sound waves, ground attenuation and the dispersion of the sound wave (Wiley & Richards 1978) so it is affected by the density of vegetation present, forest structure and microclimate (Richards & Wiley 1980). Meanwhile ambient sounds are sounds from sources such as anthropogenic (originated from human activities), biophonic (e.g. rustling leaves noises), geophonic (e.g. wind noises) and all the noises produced by animals such as birds (Darras *et al*. 2018), which makes distant sounds more difficult to be able to detect if we are in a noisy habitat than a more quieter one (Darras *et al*. 2016) and animal vocalizations emitted in areas with dense vegetations will degrade more rapidly than in open areas (Forrest 1994).

4.3. Cue rate of *Fringilla coelebs*

After registering the cue rates of 46 individuals, we were able to get a mean cue rate for *Fringilla coelebs* of 4.34 cues per minute, noting that the data collected for this study was focused on the four hours after sunrise, corresponding to the peak of vocal activity of birds (Ralph *et al*. 1995) and during breeding season. Since singing rates can vary among individuals, depending on the season and other factors (e.g. pairing status) (Gibbs & Wenny 1993; Wilson & Bart 1985) this has to be taken into account when calculating cue rate values.

While we were collecting data in the field, we noticed that this species appears to have periods of singing time (in which the birds sings with short intervals between signals) and a period of time in which the individual is silent. This means that, when we are registering cue rates, we might not identify the bird until it starts singing because it was in a “silent period”, since many times it is easier for the observer to detect a bird by sound then by sight (especially in more closed environments, like forests). Moreover, when we lost track of the bird or couldn’t confirm it was the same individual because it stopped vocalizing, we would cancel the registers. However, the bird could also be in a “silent period”, and that can cause an overestimation on the cue rate of the species and consequently lead to an underestimation of the density.

Although in this study we did not take these patterns into account to estimate our density, having a better understanding of how these singing and silent periods can affect the cue rate of our species and therefore the estimated density is something to be explored.

4.4. Density estimate using data from the recordings

After estimating the range of detection of the recorders, which through our results it estimated to be 212 meters and estimating the cue rate of our focal species, we had everything we needed to be able to perform a density estimation using cue counts. So with data collected from the 35 recordings (n = 3187 vocalizations) of 10 minutes surveys, we were able to estimate the density from the recording to be 3.03 individuals/ha (Marques *et al*. 2013).

We estimated the variance of our density by estimating the variance of the encounter rate, detection probability and cue rate (using a delta method approximation Powell 2007). Our calculated variance was 1.59. If we look at Equation 2.3 and Equation 3.1 it's possible to understand that the variance of the detection probability (p) is our random component that has a small interference in the variance value; while both the variances of our cue rate and the variance of our encounter rate (n) is what is significantly increasing the estimated variance. So, in order to reduce the variance of our estimated density, we need to reduce the variance on our cue rate, which can possibly be achieved by accomplishing a bigger sample of cue rates and reduce the variance on our encounter rate by increasing the number of sampling sites.

4.5. Density estimate using observer point-counts

Using traditional observer point-count methods, we obtained an estimated density of 2.94 individuals/ha. These methods have different associated errors since they rely on the observers' experience on detecting the animals and their capacity to correctly estimate the distance to the singing bird in the surveys (Alldrege *et al*. 2007). Moreover, as they are based on both aural and visual identifications (Buckland 2006; Darras *et al*. 2019) nonvocalizing birds can be detected which doesn't happen when we are just working with PAM.

All in all, through our results we achieved a density of 3.03 individuals/ha estimated through passive acoustic methods and a density of 2.94 individuals/ha through traditional point-count methods performed by observers.

Sebastian-González *et al*. (2018), while studying a Hawaiian forest bird species *Chlorodrepanis virens*, found their density estimates to be higher when they were based on traditional methods compared to PAM, 10.50 individuals/ha and 6.02 individuals/ha, respectively.

However, comparing our final density estimates of *Fringilla coelebs* of 2.94 individuals/ha through traditional observer methods and a density of 3.03 individuals/ha through PAM methods shows us we can obtain similar densities estimates through both methods. Although we had very different confidence intervals using the two methods (Figure 3.2). This may be due to many different factors. For example, with traditional methods we are relying on an observer to estimate density by detecting individuals aurally and visually in a 100 meters radius, leaving less parameters to induce errors. However, with PAM, density was estimated through having the range of the recorders calculated through a model (which gave us more than double the radius of what we had with traditional methods -100 and 212 meters, respectively-) and through estimating cue rates (which we noticed that could be affected by *Fringilla coelebs* "silent and singing periods"). That may induce errors in the estimated cue rate, and consequently predicted values of density, especially because the variance of the cue rate component was the random component that was used to estimate the variance that had the largest value associated with it.

4.6. Final remarks

To create management conservation actions that are adequate, with techniques and methods that will result in efficient and effective measures, one of the most important steps is having accurate information of the population size and knowing their population tendencies (Sebastián-González *et al*. 2018), because biased density estimates can lead to unsuitable conservation strategies (Marques *et al*. 2017).

This study shows that, although it may not be an easy process, after all density estimates through passive acoustic monitoring can be achieved and have similar values to those obtained by traditional methods.

PAM is an emergent method used in ecological research (Sugai *et al*. 2019) and brings advantages over traditional methods, such as the fact that the use of PAM can be more efficient and effective than using traditional methods from a financial and logistical perspective, given that they can be placed and programmed to survey for longer periods of time, generating recordings that can be reanalyzed as many times needed. PAM can also aid with detecting species that are not so easily detected in point-counts (Celis-Murillo *et al*. 2009; Holmes *et al*. 2014) such as rare or discrete species. So, trying to understand the limitations and imperfections that studies involving passive acoustic monitoring come across, as animal density estimation, is a big steppingstone to be able to apply these methods in large scale monitorizations.

5. References

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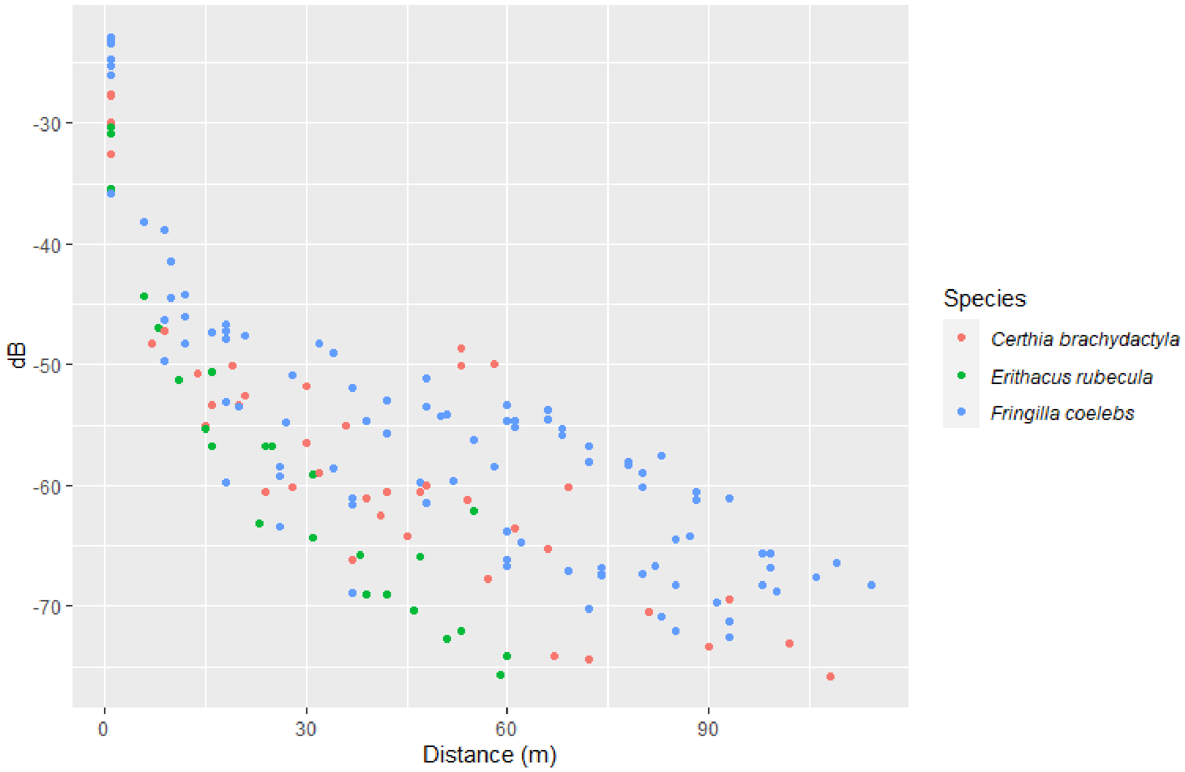
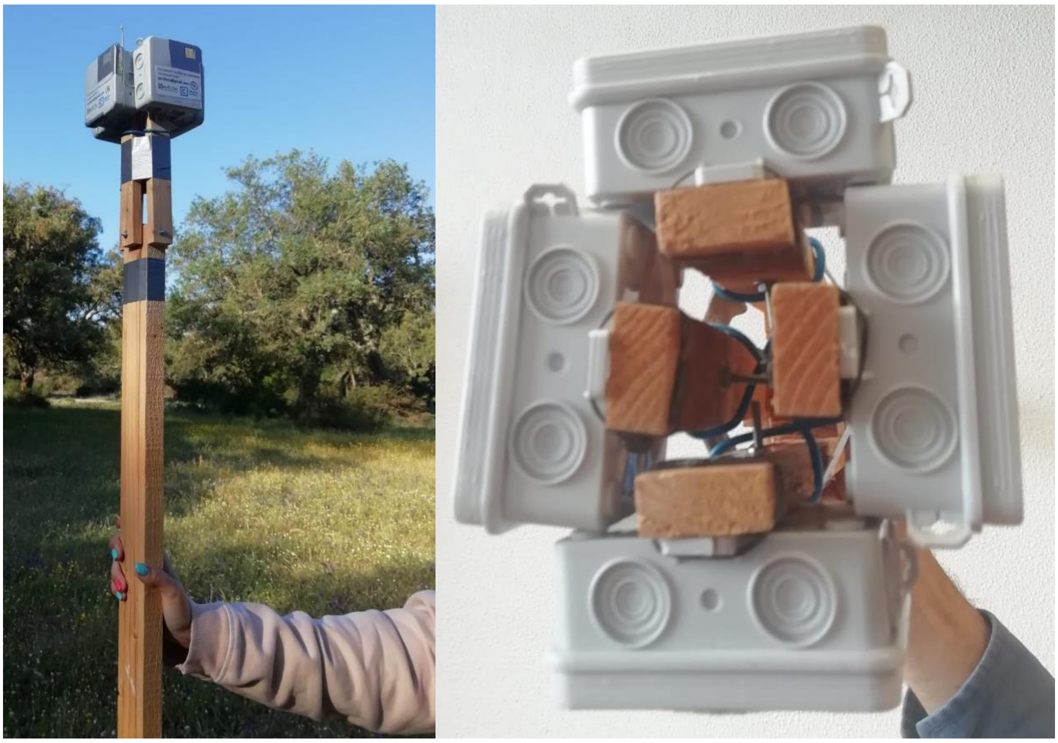
6. Appendix



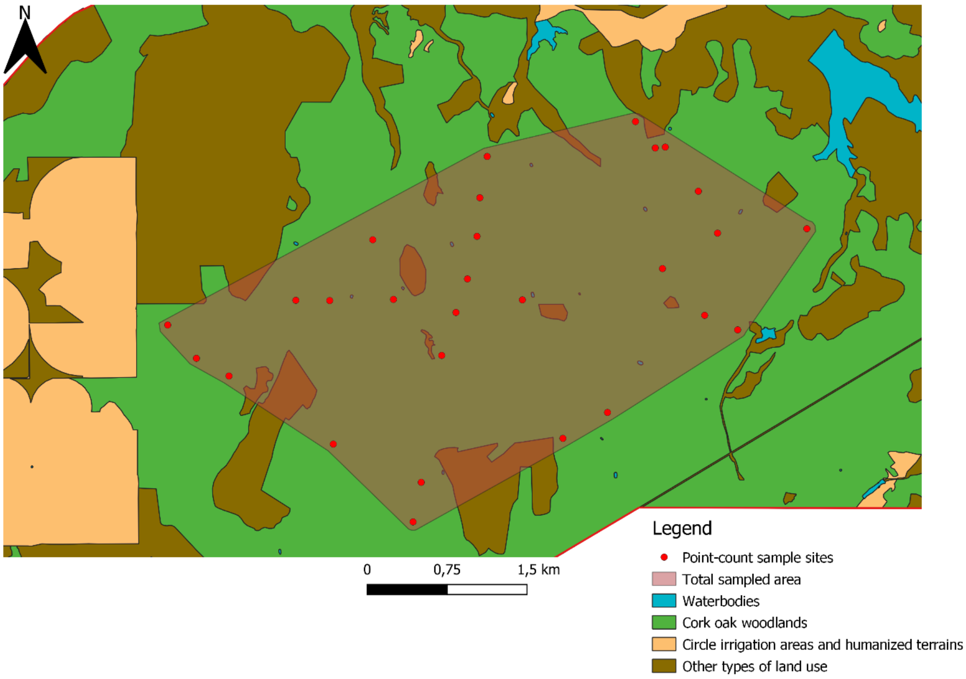
Appendix A – Graph showing variation of dBs at different distances (m) for three species of Passeriformes: the red dots representing the short-toed treecreeper (*Certhia brachydactyla*), the green dots representing the European robin (*Erithacus rubecula*) and the blue dots representing the common-chaffinch (*Fringilla coelebs*). Using recordings of these 3 species of birds played through a phone at different distances from the recorders, in a volume that the observers considered a "normal" volume that would be heard if these species were to be vocalizing in a tree right above them. For each species, an observer would reproduce its song at progressively greater distances from the recorder registered using a rangefinder.

Appendix B – Table of the recordings used for the experiments, with their respective codes and author's names, all available in http://www.xeno-canto.org.

Species	Recording number	Author's name
Fringilla coelebs	XC606979	Jaime Pires
Erithacus rubecula	XC516408	Xavier Riera
Certhia brachydactyla	XC416607	Peter Boesman



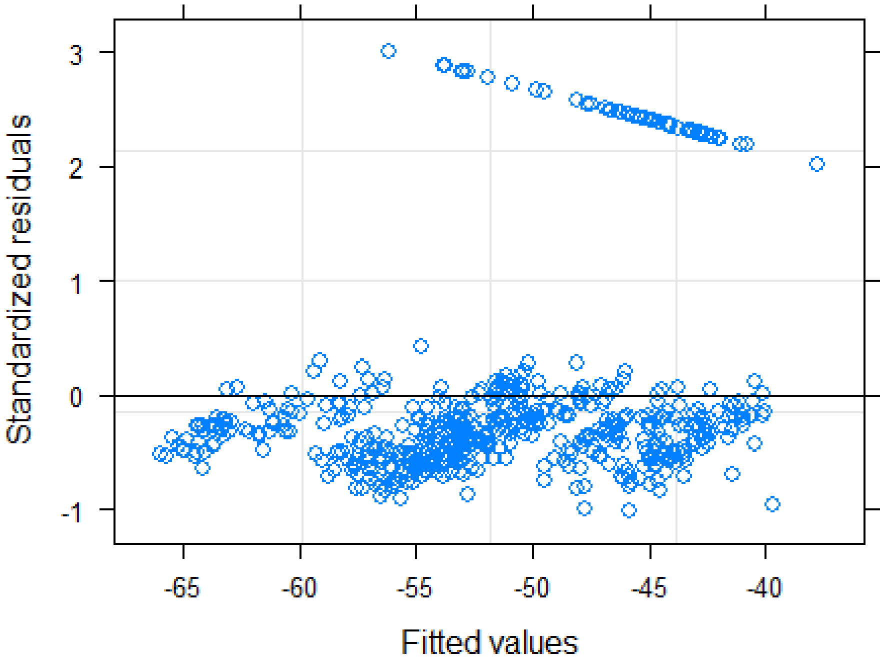
Appendix C – Pictures of the attachment that consisted of a long squared wooden stick that could hold four numbered AMs, each one attached to one side of the stick.



Appendix D - Map of the study area in *Companhia das Lezírias* zoomed in, with the point-count sampling sites (in red) and the polygon (as a 100 m buffer) which represents the total area of 12.9 km^2 sampled within *Companhia das Lezírias*.

Appendix E – Data analysis performed in RStdudio for the differences of sounds detected in the different angles.

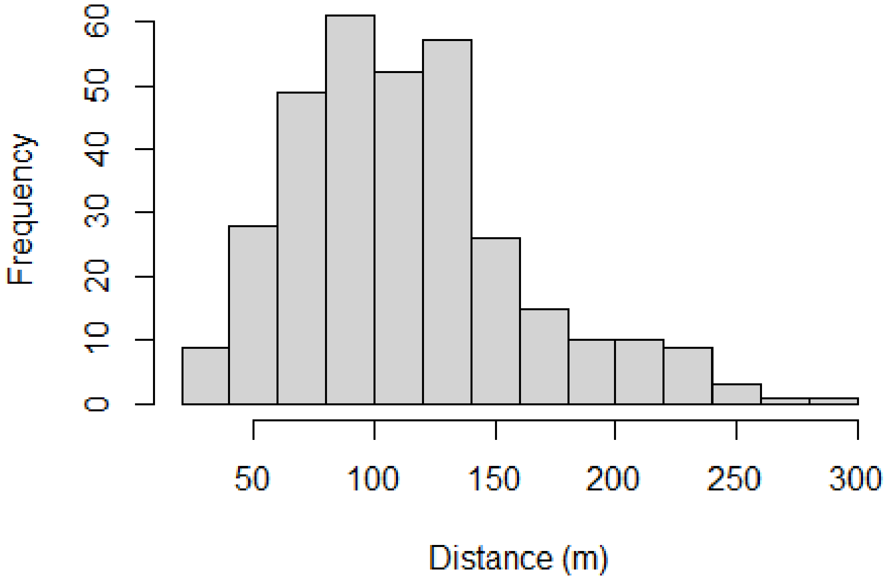
```
# lmm with the data of the 4 angles referent to the source of the sound in directi
on of the microphone

library(readxl)

library(nlme)
library(ggplot2)

library(dplyr)

library(lme4)

X4angles <- read_excel("4angles.xlsx")
#View(X4angles)

str(X4angles)

## tibble [568 x 4] (S3: tbl_df/tbl/data.frame)
##  $ ID      : num [1:568] 1 1 1 1 2 2 2 2 3 3 ...
##  $ distance: num [1:568] 18 18 18 18 22 22 22 22 22 22 ...
##  $ dB      : num [1:568] 0 -52 -55.4 -53.4 0 -53.9 -59.5 -52.9 0 -52.6 ...
##  $ angle   : num [1:568] 0 90 180 -90 0 90 180 -90 0 90 ...

head(X4angles)

## # A tibble: 6 x 4
##      ID distance    dB angle
##   <dbl>    <dbl> <dbl> <dbl>
## 1     1       18   0       0
## 2     1       18 -52      90
## 3     1       18 -55.4   180
## 4     1       18 -53.4   -90
## 5     2       22   0       0
## 6     2       22 -53.9    90

X4angles$angle <-factor(X4angles$angle, levels= c("180", "-90", "90", "0"))

lme1 <- lme(dB ~ as.factor(angle), random = ~1 | ID, data = X4angles)

lme1

## Linear mixed-effects model fit by REML
##   Data: X4angles
##   Log-restricted-likelihood: -2498.692
##   Fixed: dB ~ as.factor(angle)
##         (Intercept) as.factor(angle)-90  as.factor(angle)90   as.factor(angle)0
##          -57.323944            6.657042            8.426056           10.313380
##
## Random effects:
##  Formula: ~1 | ID
##         (Intercept) Residual
## StdDev:    7.678685 18.71735
##
## Number of Observations: 568
## Number of Groups: 142

plot(lme1)
```



```
tut <- summary(lme1)


tabl <- tut$tTable

tabl

##                             Value  Std.Error  DF     t-value       p-value
## (Intercept)            -57.323944  1.697764 423 -33.764372 4.012327e-122
## as.factor(angle)-90      6.657042  2.221340 423   2.996858  2.888390e-03
## as.factor(angle)90       8.426056  2.221340 423   3.793230  1.703635e-04
## as.factor(angle)0       10.313380  2.221340 423   4.642863  4.592434e-06
```

Appendix F – Data analysis performed in RStdudio for the subsamble of data from PAM methods to estimate the range of the recorders and the probability of detecting an animal.

```
hist(censosAM_distance$distance, xlab= "Distance (m)", main= "Data obtained throug
h a subsample of data from recorders")
```



```
## making the model of the data
fring.hn <- ds(data=censosAM_distance, key="hn", adjustment=NULL,
              transect="point", truncation="5%")

## Fitting half-normal key function

## Key only model: not constraining for monotonicity.

## AIC= 3233.109

##summary of the model
summary(fring.hn)

## 
## Summary for distance analysis 
## Number of observations :  314 
## Distance range         :  0  -  212 
## 
## Model : Half-normal key function 
## AIC   : 3233.109 
## 
## Detection function parameters
## Scale coefficient(s):  
##             estimate         se
## (Intercept) 4.498095 0.04817531
## 
##                         Estimate          SE         CV
## Average p              0.3370151  0.02651715 0.07868236
## N in covered region 931.7089000 84.89463724 0.09111713
##
```

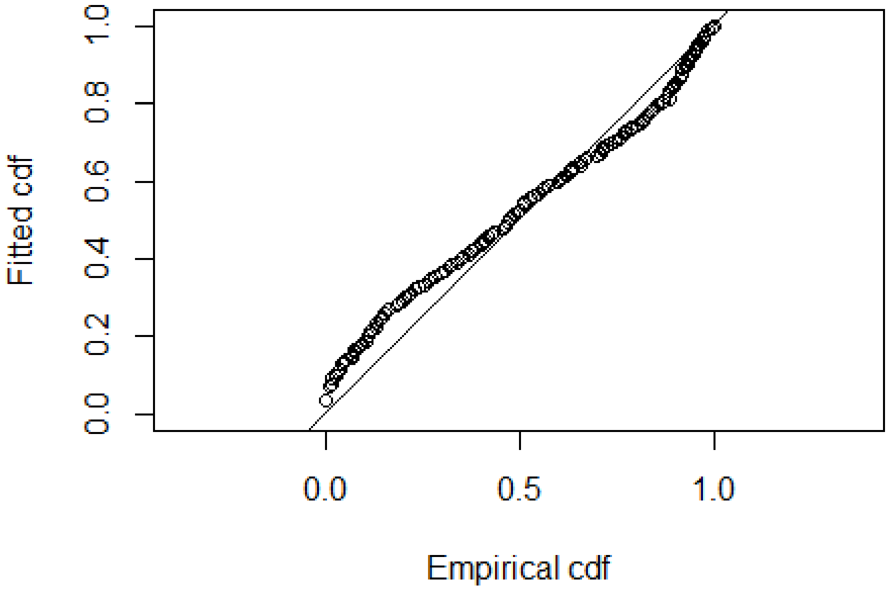
```
## Summary statistics:
##   Region     Area CoveredArea Effort   n  k       ER     se.ER      cv.ER
## 1     CL 12883000     4941851     35 314 35 8.971429 0.3417349 0.03809147
##
## Abundance:
##   Label Estimate       se         cv      lcl      ucl       df
## 1 Total 2428.889 212.3281 0.08741781 2045.757 2883.773 316.7415
##
## Density:
##   Label     Estimate           se         cv          lcl          ucl       df
## 1 Total 0.0001885344 1.648126e-05 0.08741781 0.0001587951 0.0002238433 316.7415

## compare between hn poly and cos and try the goodness of fit of the model to the data to see if the model is good

fring.hr.poly <- ds(data=censosAM_distance, key="hr", adjustment="poly",
              transect="point", truncation="5%")

## Starting AIC adjustment term selection.

## Fitting hazard-rate key function

## AIC= 3205.673

## Fitting hazard-rate key function with simple polynomial(4) adjustments

## AIC= 3207.673

##
## Hazard-rate key function selected.

summary(fring.hr.poly)

##
## Summary for distance analysis
## Number of observations :  314
## Distance range         :  0  -  212
##
## Model : Hazard-rate key function
## AIC   : 3205.673
##
## Detection function parameters
## Scale coefficient(s):
##             estimate         se
## (Intercept) 4.880398 0.03862108
##
## Shape coefficient(s):
##             estimate        se
## (Intercept) 1.808329 0.1273415
##
##                        Estimate          SE         CV
## Average p             0.4922964  0.02598306 0.05277931
## N in covered region 637.8271246 42.32090364 0.06635168
##
## Summary statistics:
##   Region     Area CoveredArea Effort   n  k       ER     se.ER      cv.ER
## 1     CL 12883000     4941851     35 314 35 8.971429 0.3417349 0.03809147
##
## Abundance:
##   Label Estimate       se         cv      lcl      ucl       df
## 1 Total 1662.763 108.2281 0.06508929 1462.713 1890.174 206.8049
```

```
##
## Density:
##   Label     Estimate           se         cv          lcl          ucl       df
## 1 Total 0.0001290664 8.400843e-06 0.06508929 0.0001135382 0.0001467184 206.8049
```

```
##check all AICs of the 3 models to compare

AIC(fring.hn, fring.hr.poly)
```

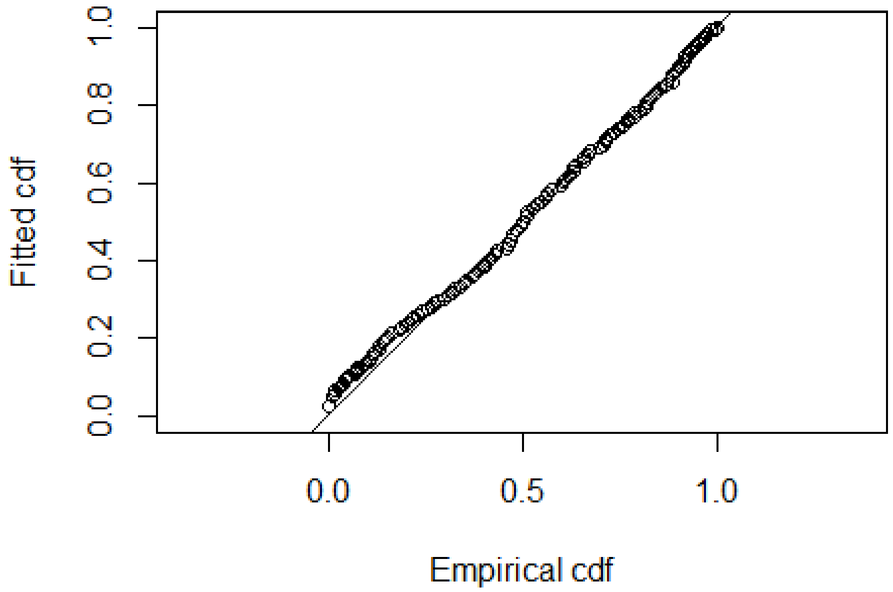
```
##                df      AIC
## fring.hn        1 3233.109
## fring.hr.poly   2 3205.673
```

```
gof_ds(fring.hn)
```



```
##
## Goodness of fit results for ddf object
##
## Distance sampling Cramer-von Mises test (unweighted)
## Test statistic = 1.10613 p-value = 0.00139079
```

```
gof_ds(fring.hr.poly)
```



```
##
## Goodness of fit results for ddf object
##
## Distance sampling Cramer-von Mises test (unweighted)
## Test statistic = 0.188263 p-value = 0.291409
```

```
## combine both the AICs values and the gof_ds to summarize which is the better mo
del
## Table: Model selection summary of our data

knitr::kable(summarize_ds_models(fring.hn, fring.hr.poly),digits=3,
             caption="Model selection summary of Fringilla coelebs data obtained t
hrough recorders.")
```

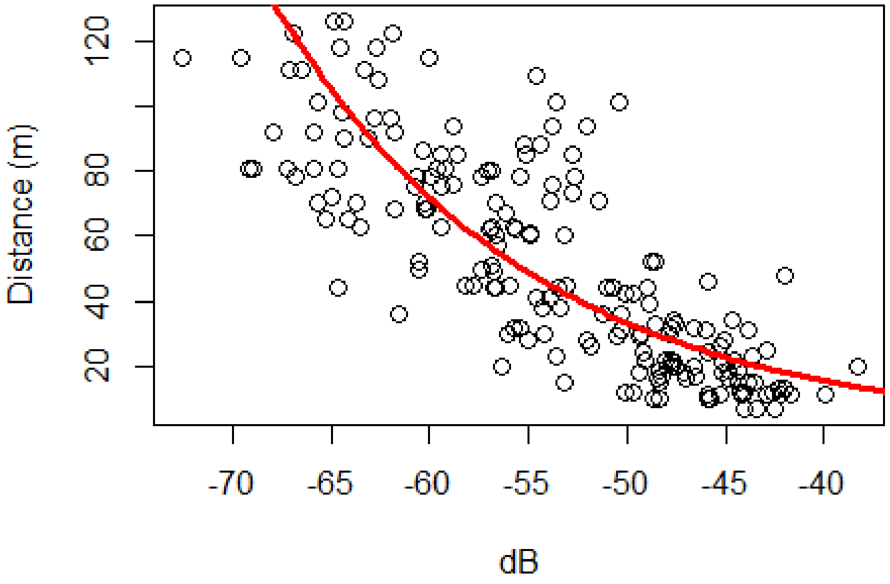
Model selection summary of Fringilla coelebs data obtained through recorders.

	Model	Key function	Formula	C-vM p-value	$\widehat{P_a}$	se($\widehat{P_a}$)	ΔAIC
2		Hazard-rate	~1	0.291	0.492	0.026	0.000
1		Half-normal	~1	0.001	0.337	0.027	27.435

Appendix G – Data analysis performed in RStdudio for the subsamble of data from PAM methods to to predict their distance values.

```
mod2 <- glm(distance~dB, family=gaussian(link="log"), data=distAvesReais)

summary(mod2)

##
## Call:
## glm(formula = distance ~ dB, family = gaussian(link = "log"),
##     data = distAvesReais)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -45.263  -14.958   -5.024   10.234   61.823
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.765644   0.224142   3.416 0.000783 ***
## dB          -0.057588   0.003694 -15.589  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 413.6978)
##
##     Null deviance: 195356  on 184  degrees of freedom
## Residual deviance:  75709  on 183  degrees of freedom
## AIC: 1643.7
##
## Number of Fisher Scoring iterations: 6

#fazer GAM

mod3 <- glm(distance~dB, family=Gamma(link="log"), data=distAvesReais)

summary(mod3)

##
## Call:
## glm(formula = distance ~ dB, family = Gamma(link = "log"), data = distAvesReais
)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -0.93421  -0.36567  -0.09357   0.20687   1.30718
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.312758   0.240726  -1.299    0.195
## dB          -0.076453   0.004434 -17.241   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Gamma family taken to be 0.2096602)
##
##     Null deviance: 90.641  on 184  degrees of freedom
## Residual deviance: 35.702  on 183  degrees of freedom
```

```
## AIC: 1601.7
##
## Number of Fisher Scoring iterations: 5

##fazer o predict do modelo para ver os resultados



range(distAvesReais$distance)

## [1]   7 126

xs <- seq(-80, -30, length=200)

novosdados <- data.frame(distAvesReais)

predGam <-predict(mod3, newdata= data.frame(dB=xs),type="response")

range(predGam)

## [1]   7.248667 331.439162

plot(distAvesReais$dB,distAvesReais$distance, xlab= "dB", ylab="Distance (m)", cex
= 1.2)
lines(xs, predGam, col= "red", lwd= 3)
```



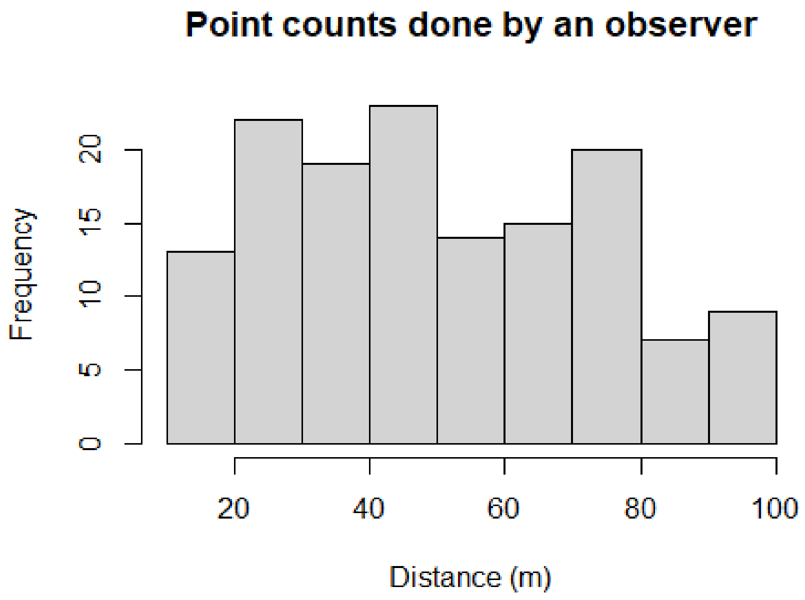
```
# subsample of data with known dB but NO DISTANCE -> predict distances

censosAM <- read_excel("censosAM.xlsx")

predict(mod3, newdata=data.frame(dB=censosAM$dB), type="response")

##         1         2         3         4         5         6         7         8
## 114.52053 149.65579 104.48160  86.96667 138.64066  46.81761  94.59671  99.03707
##         9        10        11        12        13        14        15        16
##  76.95347  58.43832 133.44096 118.07678  81.18396  80.56565  86.30432  86.30432
##        17        18        19        20        21        22        23        24
##  70.20769  70.20769 106.90566 119.89611 144.04297  84.34740  98.28280 156.68062
##        25        26        27        28        29        30        31        32
##  75.78576  65.04019 179.79620  61.65094  54.13707  62.12409 125.52402 114.52053
```

```
##        33        34        35        36        37        38        39        40
## 124.56801 148.51600 229.63064 130.41522 150.80433 171.73498 131.41610 121.74347
##        41        42        43        44        45        46        47        48
## 109.38596  84.99472 111.07138 226.14618 137.58476 106.90566 114.52053 102.11251
##        49        50        51        52        53        54        55        56
##  85.64702 147.38488 115.39942 134.46506  96.79143  86.96667  72.38788  96.79143
##        57        58        59        60        61        62        63        64
## 111.92380  79.95206 132.42466  99.79714  60.25303  87.63410 161.54609 222.71459
##        65        66        67        68        69        70        71        72
## 136.53690  93.87626 118.98297 151.96169 253.62591 207.90554 103.68586  91.74764
##        73        74        75        76        77        78        79        80
##  88.98437 181.17606 160.31573 102.89618 192.60304 150.80433 133.44096 114.52053
##        81        82        83        84        85        86        87        88
## 212.72911  73.50323 123.61929  97.53426  69.14234  78.13916  86.96667  50.15242
##        89        90        91        92        93        94        95        96
##  66.04233  80.56565 149.65579 159.09475  88.30665 127.45809 114.52053  84.99472
##        97        98        99       100       101       102       103       104
## 124.56801 125.52402 138.64066 144.04297 102.89618  39.56971 116.28506 113.64833
##       105       106       107       108       109       110       111       112
## 139.70466 173.05297 151.96169 204.75074 189.68044 233.16879 148.51600 139.70466
##       113       114       115       116       117       118       119       120
## 131.41610  88.98437  83.06749 131.41610 132.42466 125.52402  88.98437  76.36738
##       121       122       123       124       125       126       127       128
##  62.60086  72.38788  23.70846 191.13616 147.38488 189.68044 164.03519  97.53426
##       129       130       131       132       133       134       135       136
## 179.79620 140.77683 109.38596 157.88307  66.54917  97.53426 105.28345 233.16879
##       137       138       139       140       141       142       143       144
## 133.44096 136.53690 121.74347 164.03519 118.98297  52.50657 174.38108 127.45809
##       145       146       147       148       149       150       151       152
## 146.26239 136.53690 117.17749 102.11251 147.38488 109.38596  52.90953 118.07678
##       153       154       155       156       157       158       159       160
## 178.42686 115.39942 132.42466 135.49702  72.94342 118.07678 144.04297 136.53690
##       161       162       163       164       165       166       167       168
##  49.39139  98.28280  96.05426  94.59671  86.96667  70.74650 118.98297  55.81822
##       169       170       171       172       173       174       175       176
## 112.78277  78.13916  53.31559  90.35544  53.72476  60.25303 141.85723  69.14234
##       177       178       179       180       181       182       183       184
## 130.41522  70.20769  46.46104  93.16128 135.49702 113.64833 110.22545  70.74650
##       185       186       187       188       189       190       191       192
## 129.42197  72.94342  92.45176 139.70466 126.48736 222.71459  97.53426  75.20857
##       193       194       195       196       197       198       199       200
## 121.74347 125.52402 192.60304 240.40948 166.56264 219.33508 183.96762 212.72911
##       201       202       203       204       205       206       207       208
##  88.98437 149.65579 110.22545 121.74347 122.67779 151.96169 130.41522  39.56971
##       209       210       211       212       213       214       215       216
## 106.90566  97.53426 127.45809 107.72612  75.78576 255.57238  77.54405  70.20769
##       217       218       219       220       221       222       223       224
##  79.34313  74.06734  93.87626 109.38596 293.27778 236.76146 207.90554 128.43627
##       225       226       227       228       229       230       231       232
##  67.05991  91.04888 127.45809  49.39139  84.34740 126.48736  77.54405 108.55287
##       233       234       235       236       237       238       239       240
## 186.80219  47.90382  82.43484  78.73885  96.05426 111.92380  93.87626  54.55255
##       241       242       243       244       245       246       247       248
## 110.22545  41.74504 132.42466 114.52053  78.13916  43.37169  91.04888  91.04888
##       249       250       251       252       253       254       255       256
##  40.48776  76.95347  56.24660  83.06749  61.65094  47.53898  34.21979  61.18140
##       257       258       259       260       261       262       263       264
## 116.28506 138.64066 111.92380 120.81626  81.80701 139.70466 123.61929 146.26239
##       265       266       267       268       269       270       271       272
```

```
## 103.68586 135.49702 151.96169 148.51600 207.90554 197.07159 171.73498 164.03519
##       273       274       275       276       277       278       279       280
## 125.52402 111.07138  68.61575  83.06749  96.05426 134.46506 207.90554 113.64833
##       281       282       283       284       285       286       287       288
##  70.74650  49.39139  42.71356 204.75074 224.42383 271.69162 249.77734 122.67779
##       289       290       291       292       293       294       295       296
## 177.06794 166.56264 211.10894 121.74347  52.10667 111.07138  46.81761  89.66728
##       297       298       299       300       301       302       303       304
## 114.52053  65.04019  85.64702  81.80701  56.24660  75.78576 198.58402  49.39139
##       305       306       307       308       309       310       311       312
##  68.61575  84.34740  99.03707  81.80701  51.31599  91.74764  75.20857  34.21979
##       313       314       315       316       317       318       319       320
## 104.48160  92.45176  34.48241  35.28243  38.37794 111.92380 170.42703 138.64066
##       321       322       323       324       325       326       327       328
##  81.80701  78.13916  58.43832  79.34313 123.61929 102.11251  79.95206  88.98437
##       329       330       331
##  64.54483  69.67298  72.38788
```

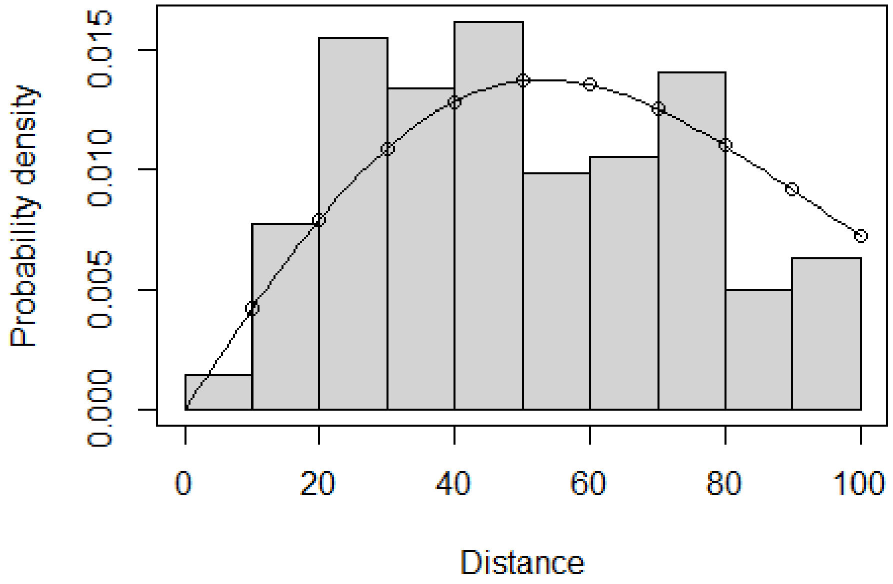
Appendix F – Data analysis performed in RStdudio with DISTANCE package with data from point-count surveys done by observers.

```
library(Distance)

library(mrds)

## example of distance using Point transect density estimation in http://examples.
distancesampling.org/Distance-points/pointtransects-distill.html

## Histo of the frequency of fringilla coelebs we have in the different distances
(m) in the point counts done by an observer

hist(censos_distance$distance, xlab= "Distance (m)", main= "Point counts done by a
n observer")
```



```
# to check on our data
head(censos_distance)

## # A tibble: 6 x 14
##   date                Sample.La~1 specie comp  dista~2 quadr~3 vento neb   visi
b
##   <dttm>              <chr>       <chr>  <chr>   <dbl>   <dbl> <chr> <chr> <chr
>
## 1 2022-04-28 00:00:00 AM39        Fring~ c          30       1 n     s     b
## 2 2022-04-28 00:00:00 AM39        Fring~ c          20       2 n     s     b
## 3 2022-04-28 00:00:00 AM39        Fring~ c          50       2 n     s     b
## 4 2022-04-28 00:00:00 AM40        Fring~ c          40       1 n     s     b
## 5 2022-04-28 00:00:00 AM40        Fring~ c          50       2 n     s     b
## 6 2022-04-28 00:00:00 AM40        Fring~ c          80       2 n     s     b
## # ... with 5 more variables: chuva <chr>, Region.Area <dbl>,
## #   Region.Label <chr>, Effort <dbl>, Area <dbl>, and abbreviated variable
## #   names 1: Sample.Label, 2: distance, 3: quadrante
```

```
##truncation is employed to remove 5% of the observations most distant from the tr
ansects, as detections at these distances contain little information about the sha
pe of the fitted probability density function near the point.

## making the model of the data
fring.hn <- ds(data=censos_distance, key="hn", adjustment=NULL,
              transect="point", truncation="5%")

## Fitting half-normal key function

## Key only model: not constraining for monotonicity.

## AIC= 1278.384

##summary of the model
summary(fring.hn)

##
## Summary for distance analysis
## Number of observations :  142
## Distance range         :  0  -  100
##
## Model : Half-normal key function
## AIC   : 1278.384
##
## Detection function parameters
## Scale coefficient(s):
##              estimate         se
## (Intercept) 3.973579 0.08549091
##
##                         Estimate          SE        CV
## Average p              0.4690201  0.05102139 0.1087830
## N in covered region 302.7588907 37.78186756 0.1247919
##
## Summary statistics:
##   Region     Area CoveredArea Effort   n  k      ER     se.ER      cv.ER
## 1     CL 12883000     1099557     35 142 35 4.057143 0.2205526 0.05436156
##
## Abundance:
##   Label Estimate       se        cv     lcl      ucl       df
## 1 Total 3547.284 431.3841 0.1216097 2792.82 4505.562 174.9657
##
## Density:
##   Label     Estimate           se        cv          lcl          ucl       df
## 1 Total 0.0002753461 3.348475e-05 0.1216097 0.0002167834 0.0003497293 174.9657

cutpoints <- c(0, 10, 20, 30, 40, 50, 60, 70, 80, 90, max(censos_distance$distance
, na.rm= TRUE))
plot(fring.hn, breaks=cutpoints, pdf=TRUE, main="titulo", showpoints=TRUE)
```



```
## compare between hn poly and cos and try the goodness of fit of the model to the
data to see if the model is good

fring.hr.poly <- ds(data=censos_distance, key="hr", adjustment="poly",
                transect="point", truncation="5%")

## Starting AIC adjustment term selection.

## Fitting hazard-rate key function

## AIC= 1277.748

## Fitting hazard-rate key function with simple polynomial(4) adjustments

## AIC= 1279.748

##
## Hazard-rate key function selected.

summary(fring.hr.poly)

##
## Summary for distance analysis
## Number of observations :  142
## Distance range         :  0  -  100
##
## Model : Hazard-rate key function
## AIC   : 1277.748
##
## Detection function parameters
## Scale coefficient(s):
##             estimate        se
## (Intercept)  3.98093 0.1858912
##
## Shape coefficient(s):
##              estimate        se
```

```
## (Intercept) 0.8631472 0.2884251
##
##                         Estimate          SE        CV
## Average p             0.4982373  0.08382371 0.1682405
## N in covered region 285.0047473 50.85431603 0.1784332
##
## Summary statistics:
##   Region      Area CoveredArea Effort   n  k       ER     se.ER      cv.ER
## 1     CL 12883000     1099557     35 142 35 4.057143 0.2205526 0.05436156
##
## Abundance:
##   Label Estimate       se        cv      lcl      ucl       df
## 1 Total 3339.267 590.3996 0.1768051 2361.548 4721.777 163.4244
##
## Density:
##   Label     Estimate          se        cv          lcl          ucl       df
## 1 Total 0.0002591995 4.58278e-05 0.1768051 0.0001833073 0.0003665123 163.4244
```

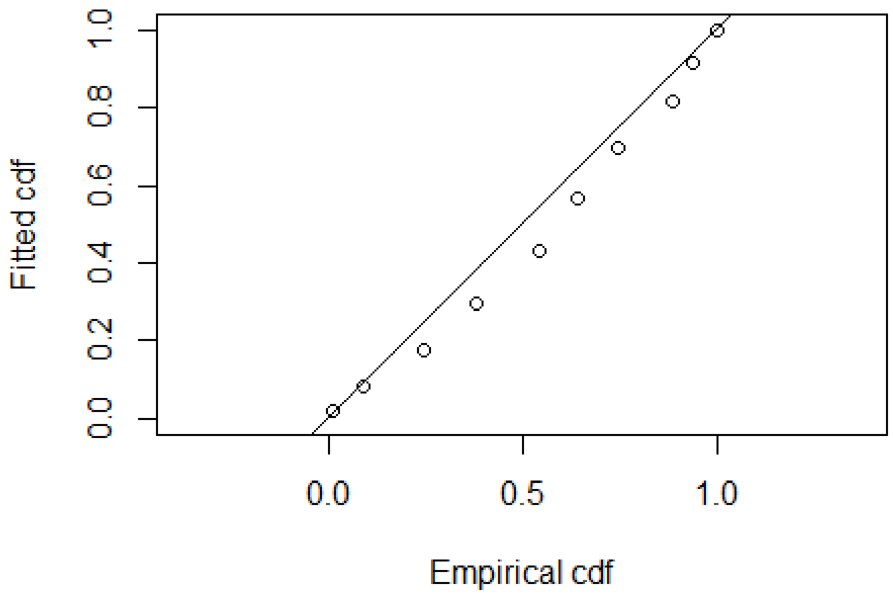
```
fring.unif.cos <- ds(data=censos_distance, key="unif", adjustment="cos",
              transect="point", truncation="5%")
```

```
## Starting AIC adjustment term selection.

## Fitting uniform key function

## AIC= 1310.708

## Fitting uniform key function with cosine(1) adjustments

## AIC= 1276.369

## Fitting uniform key function with cosine(1,2) adjustments

## AIC= 1278.166

##
## Uniform key function with cosine(1) adjustments selected.
```

```
summary(fring.unif.cos)
```

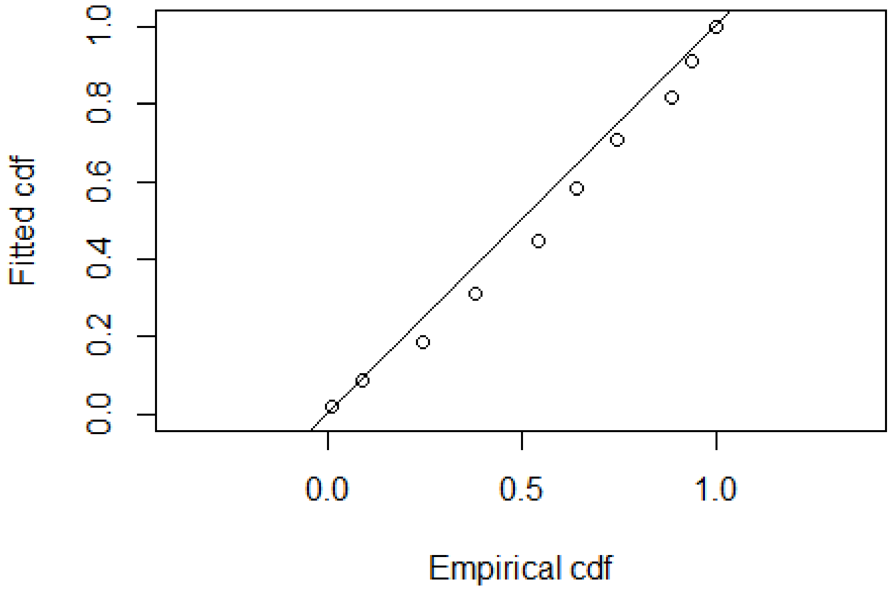
```
##
## Summary for distance analysis
## Number of observations :  142
## Distance range         :  0  -  100
##
## Model : Uniform key function with cosine adjustment term of order 1
##
## Strict monotonicity constraints were enforced.
## AIC   : 1276.369
##
## Detection function parameters
## Scale coefficient(s):
## NULL
##
## Adjustment term coefficient(s):
##               estimate         se
## cos, order 1 0.6649153 0.07678993
##
##                       Estimate          SE         CV
## Average p             0.438773  0.03892999 0.08872466
## N in covered region 323.629729 35.19146712 0.10873991
```

```
##
## Summary statistics:
##   Region     Area CoveredArea Effort   n  k       ER     se.ER      cv.ER
## 1     CL 12883000     1099557     35 142 35 4.057143 0.2205526 0.05436156
##
## Abundance:
##   Label Estimate      se       cv      lcl      ucl      df
## 1 Total 3791.818 394.554 0.104054 3089.408 4653.929 168.347
##
## Density:
##   Label     Estimate           se       cv         lcl          ucl      df
## 1 Total 0.0002943273 3.062594e-05 0.104054 0.000239805 0.0003612457 168.347

##check all AICs of the 3 models to compare

AIC(fring.hn, fring.unif.cos, fring.hr.poly)

##                df      AIC
## fring.hn        1 1278.384
## fring.unif.cos  1 1276.369
## fring.hr.poly   2 1277.748

## In addition to the relative ranking of models provided by AIC, it is also impor
tant to know whether selected model(s) actually fit the data. The model is the bas
is of inference, so it is dangerous to make inference from a model that does not f
it the data.

## gives us a plot of half normal detection function of our data.

gof_ds(fring.hn)
```

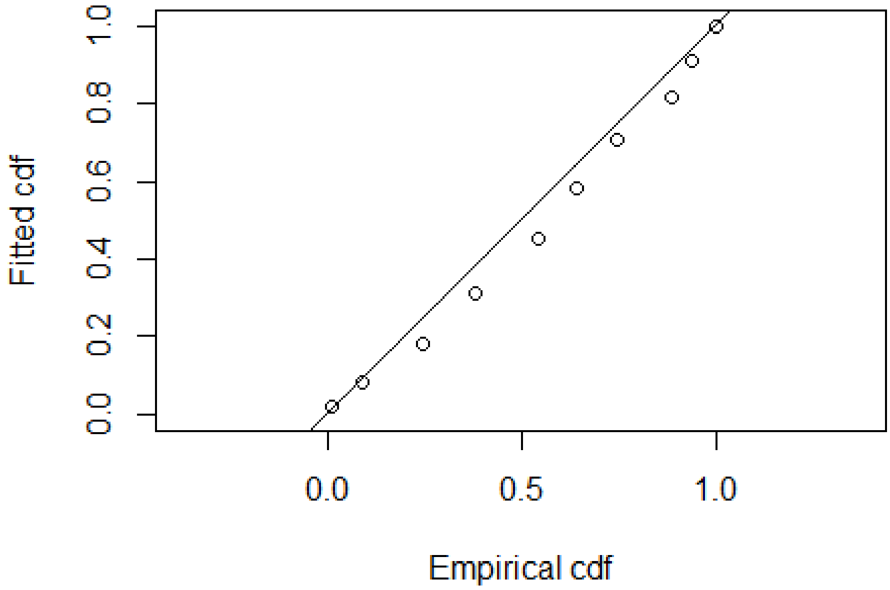


```
##
## Goodness of fit results for ddf object
##
```

```
## Distance sampling Cramer-von Mises test (unweighted)
## Test statistic = 0.246426 p-value = 0.193017

gof_ds(fring.unif.cos)
```



```
##
## Goodness of fit results for ddf object
##
## Distance sampling Cramer-von Mises test (unweighted)
## Test statistic = 0.229657 p-value = 0.216684

gof_ds(fring.hr.poly)
```

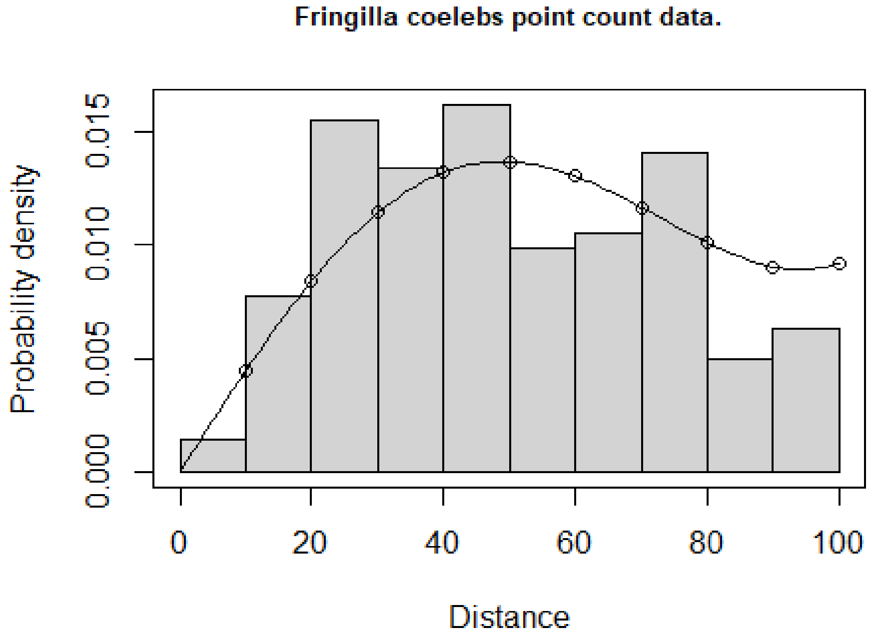


```
##
## Goodness of fit results for ddf object
##
## Distance sampling Cramer-von Mises test (unweighted)
## Test statistic = 0.21743 p-value = 0.236103

## combine both the AICs values and the gof_ds to summarize which is the better mo
del
## Table: Model selection summary of our data

knitr::kable(summarize_ds_models(fring.hn, fring.hr.poly, fring.unif.cos),digits=3
,
             caption="Model selection summary of Fringilla coelebs point count dat
a.")
```

Model selection summary of Fringilla coelebs point count data.

Model	Key function	Formula	C-vM p-value	$\widehat{P_a}$	se($\widehat{P_a}$)	ΔAIC
3	Uniform with cosine adjustment term of order 1	NA	0.217	0.439	0.039	0.000
2	Hazard-rate	~1	0.236	0.498	0.084	1.379
1	Half-normal	~1	0.193	0.469	0.051	2.015

```
#Conclusões:
# fring.unif.cos - Uniform with cosine adjustment term of order 1 - é o melhor mod
elo com um AIC de 1276.369
# ele estima que existam 323.62 individuos na área que foi amostrada, sendo que o
nosso n (numero de individiuos que vimos foi 142)
# probabilidade de detetar um animal é de 0.439
# densidade de 0.0002943273 Fringilla por m2 ou seja 2,94 por km2

cutpoints <- c(0,10,20,30,40,50,60,70,80,90 ,max(censos_distance$distance, na.rm=T
RUE))
plot(fring.unif.cos, breaks=cutpoints, pdf=TRUE, main="Fringilla coelebs point cou
nt data.")
```



```
plot(fring.unif.cos)
```