Assessment of UAV potential for bioacoustic monitoring of birds and bats: Tests under controlled conditions in Belgium

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Abstract

The importance of biodiversity no longer needs to be demonstrated. The conservation of this heritage requires data whose collection methodology may vary according to the taxon studied and the target habitat. The constant evolution of technology allows new approaches to be developed in order to increase the quantity and/or quality of these data, in particular by studying new species and habitats. For several years, UAVs (unmanned aerial vehicles) have contributed to the enhancement of this database through imagery. To date, very few studies provide information on the effectiveness of UAVs for bioacoustic monitoring. Therefore, this master's thesis aims to evaluate the potential of UAVs for bioacoustic monitoring of birds and bats by means of tests carried out under controlled conditions, i.e. by playing soundtracks of these taxa. The main objective is to compare detection distances and probabilities between UAVs (quadcopter & fixed-wing) and ground recordings. A few tests were also conducted *in vivo* to get a first insight into the effectiveness of this technique compared to standard methods: point counts (birds) and passive ground recordings (bats). All tests were conducted in Wallonia (Belgium).

The songs of 9 bird species and the calls of 5 bat species, corresponding to a representative sample of the sound variability in terms of frequency and intensity, were played through a loudspeaker placed at different distances from the drone. This experiment was repeated at several altitudes.

The effective detection radius (EDR) is lower for UAV-based recordings than ground-based recordings. Bats detectability is sensitive to altitude making the overall EDR twice smaller for a microphone flying at 5 m than for ground recordings. However, for the majority of bird species (5 out of 9), the EDR remains close for both methods (difference ≤ 20%) regardless of altitude. Under *in vivo* conditions, the drone has always detected fewer individuals than standard methods for both taxa.

These initial results lead to the conclusion that UAV-based bioacoustic monitoring underestimate reality and cannot therefore substitute standard monitoring methods in the study area. For avian surveys, this method could be complementary to traditional ones in order to obtain data on the diversity or presence of target species in areas difficult to access for human beings. However, the poor performance of chiropterans tests does not justify such use. Obviously these results are only valid for our equipment, hence the use of quieter drones will clearly improve them.

Extensive testing in less accessible areas such like tropical canopies should therefore be considered to reinforce these conclusions.

Résumé

L’importance de la diversité biologique n’est plus à démontrer. La conservation de ce patrimoine nécessite des données dont la méthodologie de collecte peut varier en fonction du taxon étudié et de l’habitat cible. L’évolution constante de la technologie permet de mettre sur pied de nouvelles approches afin d’augmenter la quantité et/ou la qualité de ces données, notamment par l’étude de nouvelles espèces ou d’habitats. Les drones participent depuis quelques années à enrichir cette base de données par le biais de l’imagerie. À ce jour, très peu d’études renseignent sur l’efficacité des drones pour des inventaires bioacoustiques. Ce travail de fin d’études vise donc à évaluer le potentiel des drones pour des inventaires ornithologiques et chiroptérologiques par bioacoustique grâce à des tests effectués en conditions contrôlées, c’est-à-dire en émettant des enregistrements pour ces taxons. L’objectif principal est de comparer les distances et probabilités de détection entre des enregistrements au sol et des enregistrements avec un quadricoptère et un drone à voilure fixe. Quelques essais ont également été réalisés *in vivo* pour avoir un premier aperçu de l’efficacité de cette technique face aux méthodes traditionnelles : points d’écoute (oiseaux) et enregistrements passifs au sol (chauves-souris). Tous les tests ont été effectués en Wallonie (Belgique).

Les chants de 9 espèces d’oiseau et les cris de 5 espèces chauves-souris, correspondant à un ensemble représentatif de la variabilité sonore en termes de fréquence et d’intensité, ont été émis par un haut-parleur placé à différentes distances du drone. Cette expérience a été répétée à plusieurs altitudes.

Le rayon effectif de détection (RED) s’avère plus faible pour les enregistrements drones que pour ceux exécutés au sol. Pour les chauves-souris, la détectabilité est sensible à l’altitude rendant globalement le RED deux fois plus petit pour un microphone volant à 5 m que pour des enregistrements au sol. Cependant, pour la majorité des espèces d’oiseau (5 sur 9), le RED reste proche pour les deux méthodes (différence ≤ 20%) peu importe l’altitude. Lors des conditions réelles d’inventaire des deux taxons, le drone a toujours détecté moins d’individus que les méthodes traditionnelles.

Ces premiers résultats permettent de conclure que les inventaires acoustiques par drone sous-estiment la réalité et ne peuvent donc pas remplacer les méthodes d’inventaires traditionnelles. Pour les inventaires ornithologiques, cette méthode pourrait être complémentaire aux traditionnelles afin d’obtenir des données de diversité ou de présence d’espèces cibles dans des zones difficiles d’accès pour l’homme. Par contre, les faibles performances obtenues pour les chiroptères ne justifient pas une telle utilisation. Évidemment ces résultats sont valables uniquement pour notre matériel, c’est pourquoi une nette amélioration est envisageable avec un équipement plus silencieux.

Pour renforcer ces conclusions, il faudrait donc envisager des tests approfondis avec un dispositif amélioré dans des zones d’accessibilité restreinte comme la canopée tropicale par exemple.

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List of abbreviations

AC	Alternating Current
ACNI	*Accipiter nisus*
ACSC	*Acrocephalus scirpaceus*
AECA	*Aegithalos caudatus*
ALAE	*Alauda arvensis*
ALAR	*Alopochen aegyptiaca*
ANPL	*Anas platyrhynchos*
APAP	*Apus apus*
BUBU	*Buteo buteo*
CACA	*Carduelis cannabina*
COCO	*Corvus corone*
COMO	*Corvus monedula*
COOE	*Columba oenas*
COPA	*Columba palumbus*
DC	Direct Current
DEMA	*Dendrocopos major*
EDR	Effective Detection Radius
EMCI	*Emberiza citrinella*
ERRU	*Erithacus rubecula*
ESC	Electronic Speed Controller
ESW	Effective Strip Width
FATI	*Falco tinnunculus*
FM	Frequency Modulation
FME	Frequency of Maximum Energy
FRCO	*Fringilla coelebs*
FUAT	*Fulica atra*
GACH	*Gallinula chloropus*
GAGL	*Garrulus glandarius*
HIRU	*Hirundo rustica*
iFM	Initial Frequency Modulation
IPI	Inter-pulse Interval
MOAL	*Motacilla alba*
PACA	*Parus caeruleus*
PAMA	*Parus major*
PD	Pulse Duration
PHCO	*Phasianus colchicus*
PHYCO	*Phylloscopus collybita*
PIPI	*Pica pica*
POCR	*Podiceps cristatus*
POPA	*Poecile palustris*
PRMO	*Prunella modularis*
QCF	Quasi-Constant Frequency
RPAS	Remotely Piloted Aircraft System

SIEU	*Sitta europaea*
SOCWAL	"Surveillance des oiseaux communs en Wallonie" Monitoring program for common breeding birds in Wallonia
SPL	Sound Peak Level
STST	*Sturnus sturnus*
SYAT	*Sylvia atricapilla*
SYBO	*Sylvia borin*
SYCO	*Sylvia communis*
SYCU	*Sylvia curruca*
tFM	Terminal Frequency Modulation
TRTR	*Troglodytes troglodytes*
TUME	*Turdus merula*
UAV	Unmanned Aerial Vehicle

1 Introduction

1.1 Context

Nowadays we are facing an era called the Anthropocene and characterised by a massive biodiversity loss as a result of human activities (McCallum, 2015; Johnson et al., 2017). In fact, the Millennium Ecosystem Assessment reported a current species extinction rate up to 1,000 times higher than background rates and forecasted a future rate 10 times superior to the current one (Millenium Ecosystem Assessment, 2005). Some further evidence of this serious biodiversity loss is the threatened status given to about 30% of the species assessed by the IUCN in the past decade (IUCN, 2017). This losses leads to the alteration of several ecosystem services (Cardinale et al., 2012) and therefore have detrimental impacts on humanity. In this context, it is essential to carry out proper wildlife surveys to highlight any suspicious population decline and to target endangered species in order to plan appropriate conservation measures.

Some taxa have substantial ecological contributions (e.g. pests control, seed dispersal) like both bats and birds (Kasso et al., 2013; Sekercioglu et al., 2004). Their population monitoring is therefore imperative to preserve the benefits of their function within ecosystems. Conventional methodologies to estimate abundance or to determine species richness of these taxa are mainly based on acoustics. Examples include point-count and line-transect sampling which are the most frequently applied for bird census (Gregory et al., 2004; Buckland, 2006; Ralph et al., 1995). More specifically in Wallonia, a monitoring program for common breeding birds (SOCWAL) was set up in 1990 to estimate the population trends of these birds over time. This avian survey technique consists of yearly audial and visual counts on a set of specific points (Aves, 2014). Bats are also monitored through acoustic techniques at a certain time of the year. For instance, censuses by passive and active ultrasonic recordings are often deployed in the context of environmental impact assessments (Simar et al., 2012).

Some innovative techniques could heighten the quantity and/or the quality of the current database. Indeed, the constant evolution of technology allows new approaches to be developed, hence the use of drones—also called unmanned aerial vehicles (UAV) or remotely piloted aircraft systems (RPAS)—could be contemplated carrying out fauna censuses. Wildlife UAV-based survey has already been considered many times through imagery (Lisein et al., 2013) and tested specifically on birds with encouraging results (Han et al., 2017; McClelland et al., 2016). In certain situations, its accuracy might substitute human census (Jarrod C Hodgson et al., 2016; Hodgson et al., 2018). However, drone imagery monitoring is obviously less suitable for non-conspicuous species (e.g. species hidden in trees and shrubs, or small ones). This issue could be solved thanks to bioacoustics for acoustically active species like bats and birds. Audio recording systems offer a wide range of benefits in comparison with picture recording system. They are lighter, more energy efficient and collect data more compactly (Fristrup et al., 2009). Moreover, audio recordings confer additional advantages over active field listening processes such as a multiple listening opportunity (Frommolt et al., 2014; Celis-Murillo et al., 2009), the consultation by numerous skilled analysts (Wilson et al., 2017), a data collection independent on observers expertise level (Klingbeil et al., 2015) and an automatic species identification (Aide et al., 2013; Zakeri, 2017). For example, Celis-Murillo et al., 2012 have shown that acoustic recordings provide higher probability detections for songbird in tropical areas than point counts. Consequently, the combination of a drone and a recorder device seems to be a promising innovative technique to take censuses in less accessible areas like high canopies, large wetlands or cliffs. When the studied area is only walkable (e.g. bogs), drones may be able to travel longer distances faster than a field operator.

1.2 UAV-based acoustic monitoring: current status

1.2.1 Birds

To date, Wilson et al. (2017) have been the only ones to publish in peer-reviewed literature a study which assesses the feasibility of counting songbird using UAVs in the USA. They suspended a ZOOM H1 Handy Recorder 8 metres below a DJI Phantom 2 and tested this equipment under controlled and *in vivo* conditions. With playback of bird recordings, they found no significant influence of UAV flight altitudes (28, 48 and 68m) on detections and detection radii were similar to those of standard point counts. On the field, they found a comparable number of birds per UAV and standard counts. Species richness and abundance were nevertheless underestimates by UAV counts, notably for low-frequency singing species and very abundant species.

They conclude that UAV associated with bioacousitc technologies can become a valuable new surveying tool to study songbirds and even other vocal groups. They also incite further research to improve this counting technique, especially with quieter UAV.

1.2.2 Bats

To date, there is no published research of bats monitoring feasibility using acoustic-mounted UAVs. However, two British friends–Tom August, bat expert & Tom Moore, drone designer, builder and operator–have been exploring the practicability of remotely piloted systems as a survey device for bats since 2014. The purpose of their project called “Project Erebus” is to test whether semi-autonomous vehicles (quadcopter, plane and boat) are able to record proper bat calls. They are currently writing a paper which will be sent for publication this year but all their experimentations are available on their website[1].

They tested several designs to get the best compromise between low noise disturbances, a long flight time and a good flight stability. Their latest results are favourable for the three platforms and can make this approach plausible to bat surveying (Figures 1 & 2).

[1] http://projecterebus.weebly.com/blog

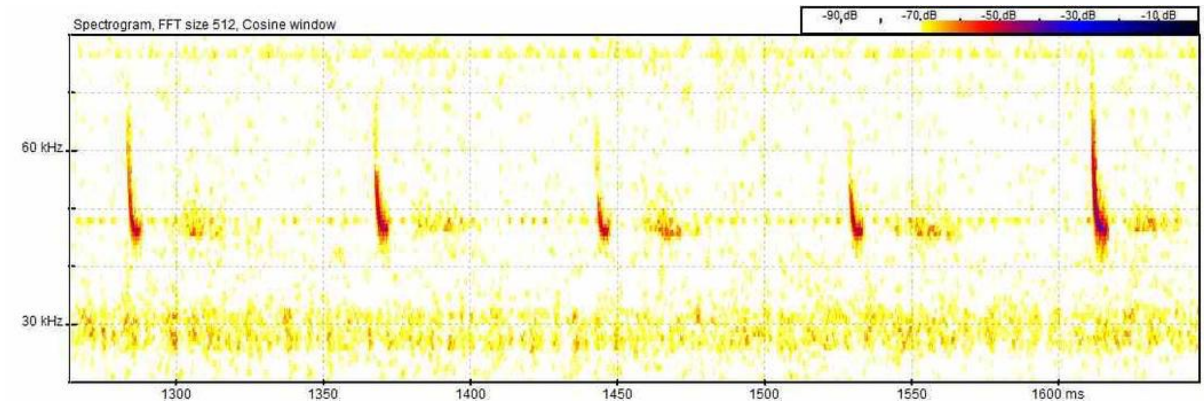

Figure 1. Spectrogram of Common Pipistrelle (*Pipistrellus pipistrellus*) echolocation call recorded with a Peersonic RPA2 detector hanging 4 m below a quadcopter (motors = T-motor MN3510; 360KV; propellers = T-motor 15x5 CF; ESC = X-rotor 15A OPTO; flight controller = 3DR Pixhawk 1; battery = Multistar 4Ah 4S 10C Lipo; frame = 12mm OD 10mm ID woven carbon tubes & 1.5mm 3K carbon plate; LED lights = 5mm red + green 12V). The quadcopter navigated under semi-autonomous flight through the landscape (~200m along tree lines surrounding a field) (Moore et al., 2018).

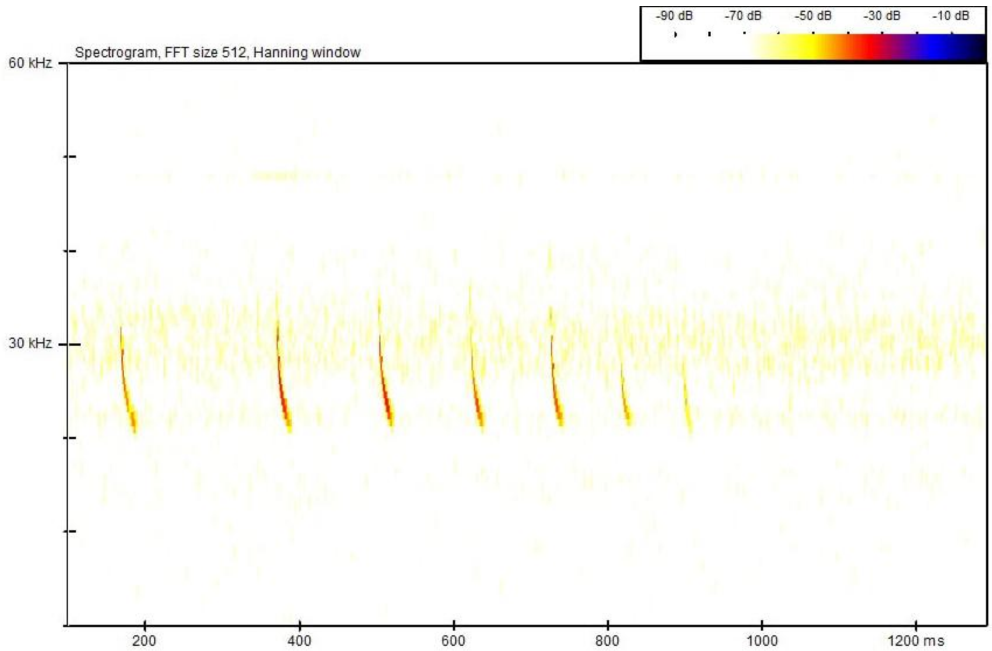

Figure 2. Spectrogram of Myotis bat (*Myotis* sp.) echolocation call recorded with a Peersonic RPA2 detector hanging 4 m below a quadcopter (motors = T-motor MN3510; 360KV; propellers = T-motor 15x5 CF; ESC = X-rotor 15A OPTO; flight controller = 3DR Pixhawk 1; battery = Multistar 4Ah 4S 10C Lipo; frame = 12mm OD 10mm ID woven carbon tubes & 1.5mm 3K carbon plate; LED lights = 5mm red + green 12V). The quadcopter navigated under semi-autonomous flight along waterways, hedge and tree lines (Moore, 2018).

1.3 Objectives

The aim of this master's thesis is to assess the potential of UAVs in bioacoustic surveys for birds and bats, based on Wilson (2017) and Moore (2018) works. The first objective is to give a comparison between detection distances from UAV-based recordings and ground-based recordings under controlled conditions for a sample of species, using two kinds of drones: a quadcopter and a fixed-wing. The second objective is to establish a relation between detection probabilities and song features to make predictions on a wider range of species. Finally, the third objective is to determine the best operating method (UAV device, flight altitude) for field census and to give a quick comparison between the latter and traditional survey methods.

2 Material & Method

2.1 Tests under controlled conditions

Before embarking on any real censuses, tests under controlled conditions are needed to determine the effective detection radius, the link between detection probabilities and song features, and the best operating method for the field.
Globally, these experimentations consist of a drone recorder device (quadcopter or fixed-wing) flying at several altitudes and horizontal distances from a speaker which plays acoustic signals of different species.

2.1.1 Recorders and speakers description

2.1.1.1 Birds

Bird vocalisations are emitted in the audible range (20 Hz to 20 kHz), which allows the use of classical recorder and speaker.

We chose the ZOOM H1 Handy Recorder because it was used by Wilson (2017) for its multiple attributes. Indeed, it is lightweight (88 g, including batteries), compact (44 x 136 x 31mm), low-cost (> 90€) and includes a built-in cardioid microphone, guaranteeing a good sound recording from the ground while minimising drone noise.
For all the tests, the ZOOM H1 Handy Recorder was equipped with its hairy windscreen (WSU-1) and the low-cut filter was switched on, both to reduce wind noise and low frequency whirring sounds from the drone. Files were recorded in 24-bit WAV format with a sampling rate of 44.1 kHz.

Bird songs were broadcast through a JBL Flip 4 wireless loudspeaker (output power = 2 x 8 W; frequency response = 70 Hz to 20 kHz) connected via Bluetooth to a smartphone. The skyward-facing speaker was raised 1.5 m above the ground thanks to a tripod, though bird song post could vary depending on species and environment (Mikkonen, 1985; Polak, 2014; Hulme, 1957; Mathevon et al., 2005; Mathevon et al., 1997). Therefore, this height was chosen as the most representative song perch height of the selected species (see section 2.1.2.1). In any case, no effect of altitude on detectability was expected (Wilson, 2017), hence changing the tripod height for each species did not matter.

2.1.1.2 Bats

Bats produce ultrasonic signals (> 20 kHz); hence the necessity of using a specific recorder and speaker.

AudioMoth is designed as a low-cost open-source environmental acoustic logger for biodiversity and environmental monitoring, which can record both audible range and full spectrum ultrasound[2]. We chose this sensor mainly because it is small (58 x 48 x 15 mm), light (80 g, including batteries) and inexpensive (43€) and thus make it perfect to deploy by drones.

[2] https://www.openacousticdevices.info/audiomoth

Moreover, AudioMoth is also one of the two recorders used for the project Erebus and a first scientific publication brings out the potential of such a device for bioacoustic research (Hill et al., 2018).
For all the experimentations, AudioMoth recording gain and sample rate were customised respectively on medium and 384 kHz via the AudioMoth Configuration Software. The recorder was also covered with a homemade insulation casing for all trials (see section 2.1.4.3; Figure 6).

Bat calls were played by an Avisoft UltraSoundGate Player BL Pro 2 mounted on a one-metre tripod and connected via an USB cable to a laptop. This transmitter is a full-featured ultrasound playback unit for luring bats which comprises a dual speaker system emitting between 1 and 125 kHz[3].
During our trials, the ultrasound playback unit was only powered from the USB interface of the computer, thereby delivering an output power of 1.5 W corresponding to a maximum sound pressure level (SPL) of 100 dB at 10 cm. Volume was configured on the playback software and on the unit itself, so as to maximise the sound level and to avoid clipping (distortion).

2.1.2 Soundtracks

2.1.2.1 Birds

As UAV-based monitoring especially target hard-to-access areas like forest canopies or wetlands, a set of 9 European bird species, which are occurring in wooded or wet environments, was chosen: Eurasian Wren (*Troglodytes troglodytes*), Sedge Warbler (*Acrocephalus schoenobaenus*), Common Reed Bunting (*Emberiza schoeniclus*), Common Blackbird (*Turdus merula*), Eurasian Blackcap (*Sylvia atricapilla*), Common Chaffinch (*Fringilla coelebs*), Song Thrush (*Turdus philomelos*), Goldcrest (*Regulus regulus*) and Common Wood Pigeon (*Columba palumbus*) (DGARNE, 2010). This selection was not based solely on habitat. In fact, these bird species embody a representative sample of the *in vivo* sound variability in terms of frequency and intensity. For instance, the Goldcrest has a weak and high-pitched song, whereas the Common Wood Pigeon's song is very deep.

To be consistent with the vocalisation intensity of each bird species, soundtracks SPL was measured at 1 m with a GRDE sound level meter (frequency range = 31.5 to 8500 Hz; measuring range = 30 to 130 dB; accuracy = ± 1.5 dB) and adjusted avoiding clipping thanks to both Audacity software and speaker volume according to Brackenbury (1979): Eurasian Wren = 90 dB, Sedge Warbler = 80 dB, Common Reed Bunting = 78 dB, Common Blackbird = 87 dB, Eurasian Blackcap = 88 dB, Common Chaffinch = 86 dB, Song Thrush = 100 dB, Goldcrest = 75 dB. Nevertheless, this paper does not mention a SPL for the Common Wood Pigeon which was consequently approximated at 90 dB.

As the propagation of sound depends on meteorological parameters (Van Damme, 2014), the experimentation was repeated 3 times for every species x altitude x distance modality. Repetitions did not occur on the same day to mitigate the impact of the weather. For each

[3] http://www.avisoft.com/usg/usgplayerblpro.htm

repetition, bird sounds (song, call or alarm call) were randomly drawn with replacement out of a pre-selection (Table 1). The latter was formed on the basis of three to five good quality Belgian recordings from xeno-canto: at least 3 songs + 1 or 2 call(s) and/or 1 or alarm call(s) (Appendix 1). This action also allowed to take into account the variability of the different acoustic signals produced by the same species or between individuals (Krebs et al., 1980).

With Audacity 2.2.1.0, all soundtracks were cut to keep a thirty-second duration playback and some were adjusted to mitigate interferences of other species.

Table 1. Xeno-canto codes of the bird soundtracks selection. For each species a preselection of 3 to 5 identifiable sounds (at least 3 songs + 1 or 2 call(s) and/or 1 or 2 alarm call(s)) was made from xeno-canto. For each repetition, the sound was randomly drawn with replacement out of this preselection.

	Quadcopter			Fixed Wing		
Bird Species	**repetition 1**	**repetition 2**	**repetition 3**	**repetition 1**	**repetition 2**	**repetition 3**
Common Blackbird	XC104604	XC104604	XC104604	XC281435	XC281441	XC281435
Common Chaffinch	XC397523	XC397523	XC365672	XC281752	XC397523	XC281752
Common Wood Pigeon	XC394506	XC378844	XC378844	XC380054	XC380054	XC394506
Eurasian Blackcap	XC381478	XC393063	XC393063	XC379971	XC381478	XC379948
Eurasian Wren	XC281371	XC379950	XC281377	XC281377	XC281378	XC379950
Goldcrest	XC281601	XC281601	XC281606	XC281601	XC364246	XC281606
Reed Bunting	XC35208	XC281818	XC281818	XC281817	XC281817	XC35208
Sedge Warbler	XC281519	XC393062	XC281524	XC393062	XC281522	XC281522
Song Thrush	XC281452	XC281452	XC281459	XC348842	XC281452	XC379973

2.1.2.2 Bats

Drone surveys might be useful to record high-flying bat species and/or occurring in forest canopies. In accordance with these criteria, five European bat species were settled on: Noctule (*Nyctalus noctula*), Serotine (*Eptesicus serotinus*), Barbastelle (*Barbastella barbastellus*), Common Pipistrelle (*Pipistrellus pipistrellus*) and Natterer's Bat (*Myotis nattereri*) (Gaillard et al., 2010; DGARNE, 2010; Roemer et al., 2017). The latter are also a representative sample of a wide range of bat signals in terms of pattern, frequency, pulse duration and inter-pulse interval (IPI) (Zoogdiervereniging, n.d.; Laurent et al., 2009). For example, the call of the Natterer's bat is characterised by a steep frequency modulation (FM) with an initial frequency at 15 kHz, a terminal frequency at 135 kHz and a frequency of maximum energy (FME) at 43 kHz, whereas the Noctule emits quasi-constant frequency (QFC) with a FME at 20 kHz (Laurent, 2009; Verkem et al., 2014).

The sound level of some bat calls can reach up to 110-135 dB at 10 cm (Jakobsen et al., 2013; Fenton et al., 2016). Nonetheless, the signal power is variable among species. For instance, the calls of Noctule are loud whereas calls of Natterer's bat are quite weak (Laurent, 2009). Unfortunately, literature does not provide any SPL for the selected species. That's why the output volume of the speaker was maximised while avoiding clipping, in order to emit signals near 100 dB at 10 cm. Moreover, we didn't have any ultrasonic sound level metre to check soundtracks intensity.

Bats emit two kinds of calls: echolocation and social calls. The first ones serve as a representation of the space to move around and to hunt (Laurent, 2009). The second ones serve as intraspecific communication (Barlow et al., 1997; Budenz et al., 2009).
Usually, social calls are emitted at lower frequencies than echolocation calls. Indeed, the condition for a sound wave to cross an obstacle in its path is that the diameter of the obstacle is smaller than the wavelength. That is why the higher the frequency is—and so the shorter the wavelength is— the greater is the probability to hit an obstacle whose dimensions block this sound. In addition, the type of environment, the temperature, the air humidity and the wind influence the sound attenuation proportionally to the frequency. As a result, low frequencies dissipate less quickly and allow communication over a longer distance (Tupinier, 1996).
Common Pipistrelle's and Noctule's social calls are often met on the field and so were added to the playlist to better highlight the potential impact of frequency on detectability.

Like the bird experimentation, there were three repetitions to take into account sound propagation variability because of parameters such as temperature, humidity or atmospheric pressure. Obviously, there are also variations between calls of the same species. Indeed, bats adapt their signals to visualise their environment optimally. In closed habitats, the signal will always move on to an FM and in open habitats, the QFC component increases (Verkem, 2014). The IPI can also be smaller in closed habitats to improve the resolution. However, good quality bat calls are very difficult to obtain, hence the same soundtracks were used for each repetition (Table 2).

Table 2. Sources of the bat soundtracks selection used for each repetition. All the tracks were adjusted to obtain a five-second duration playback.

Call type	Bat species	Source
Echolocation	Barbastelle	http://www.chauves-souris-passion.be/barbastella_barbastellus_279.htm
	Common Pipistrelle	Plecotus (Natagora)
	Natterer's Bat	http://www.bristol.ac.uk/biology/research/behaviour/batlab/downloads/echolocation/
	Noctule	Plecotus (Natagora)
	Serotine	Plecotus (Natagora)
Social	Common Pipistrelle	Track 6.73 (Middelton et al., 2014)
	Noctule	http://www.batcalls.com

All the soundtracks were amplified (avoiding clipping) and adjusted with Raven Lite 2.0 to obtain a five-second duration playback.

2.1.3 Fixed-wing trials

Basically, these trials tried to emulate traditional transect-line sampling, described by Buckland et al. (1993), under controlled conditions in order to estimate a global effective strip width (ESW) for fixed-wing drones.

The advantage of resorting to remotely piloted planes are multiple against multicopters. Firstly, their ability to soar allows them to have a very much longer flight time. Secondly, they can carry a higher load and thus accurate measuring devices, which are usually heavier. Finally, they would prove quieter as they only include one motor and propeller.

2.1.3.1 UAV description

At first, we started our trials with an entirely homemade plane (Figure 3). It was characterised by a wingspan of 3.20 m (quite big to reduce the flight speed and consequently wind interferences), a payload of 1.5 kg, a battery Lipo 3S-2000mA, an overpowered motor (550 W) to turn a bigger propeller at low speed and so to lessen drone noise, a telemetry module for semi-autonomous flights, and LEDs plus reflective paint for a better visibility in the darkness.

Figure 3.First fixed-wing drone tested.

Unfortunately, this drone crashed fatally due to a technical problem before any data could be collected. Therefore, a substitution plane was used for all the following experimentations explained in this section (Figure 4). The latter was smaller and did not have any ailerons on its wings, making it quicker and less manoeuvrable. The recorder was fixed behind the wings, on the one hand, to move it as far away from the propeller as possible and, on the other hand, not to move the centre of gravity too much.

Figure 4. Second fixed-wing drone tested and equipped with the ZOOM H1 Handy Recorder

2.1.3.2 Study area

Trials were conducted between 1:30 pm and 6:00 pm in mid-April 2018 at the flying site of the "Model Air Club des Ardennes Bertrix" (49°51'25"N, 5°17'24"E). This site provides quite a flat open area of about 7 hectares. Such a wide open space slightly reduces the abundance of competing noises from real birds or anthropogenic ultrasound interferences.
Weather conditions were dry and sunny (temperature around 25 °C, wind speed < 15 km/h).

2.1.3.3 Experimental system

The plane, equipped with the recording device, soared at several altitudes and horizontal distances from the speaker for each call modality played by the latter (Figure 5).

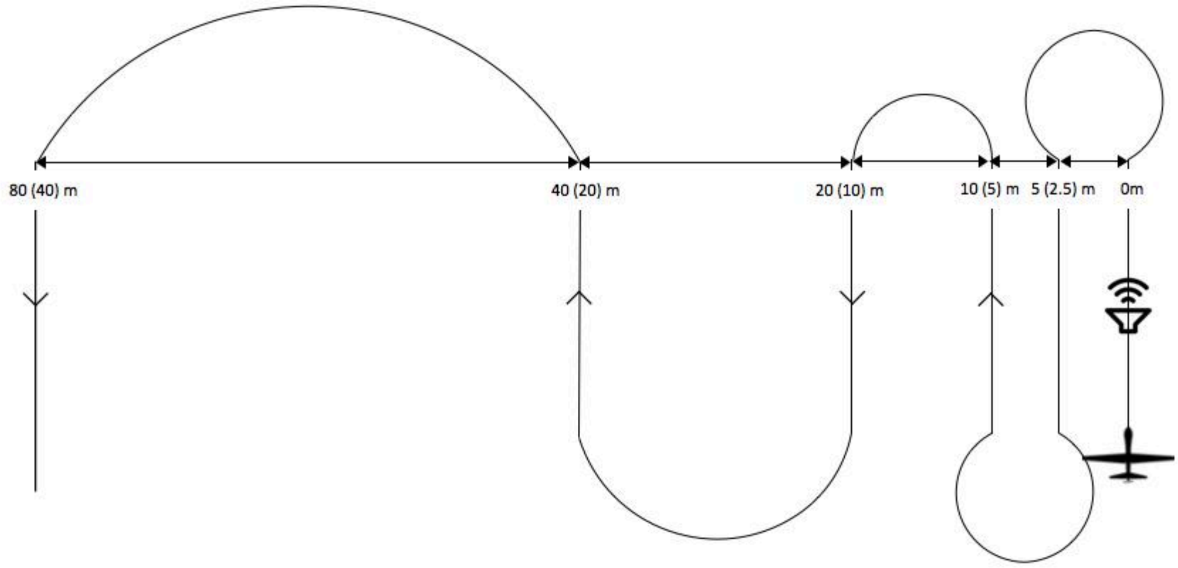

Figure 5. Experimental arrangement for fixed-wing flights under control conditions. The fixed-wing flew at several distances from the speaker. Distances in brackets corresponds to the bat experimentation and the other to the bird experimentation. UAV flight altitudes were 20, 40 & 60m for birds and 10 & 20m for bats. Recordings were also made at ground level as blank samples (altitude 0, without UAV). Bird and bat transect-line lengths were respectively of 420 and 70 m.

The sound level (dB) decreases according to the following equation:

$$dB_{distance\ 2} = dB_{distance\ 1} - 20 * \log\left(\frac{distance\ 2}{distance\ 1}\right)$$

which means that there is an attenuation of 6 dB every time the distance doubles (Tupinier, 1996; Van Damme, 2014). We made the hypothesis that depending on the distance, the detection probability would follow a non-linear reduction too. Therefore, the distance scale for our tests was also non-linear. This choice diminished superfluous distance modalities that we would have had with a constant increment.

Wilson (2017) showed that bird playbacks were not detected beyond 90 m, thus we opted for the following bird distance modalities: 0, 5, 10, 20, 40 and 80 m. The chosen bird flight altitudes were 20, 40 and 60 m like Wilson (2017) trials.

As high-frequency signals do not spread as far as low-frequency ones, we chose smaller distances and altitudes for bats. We went for 0, 2.5, 5, 10, 20 and 40 m for the distance modalities and, 10 and 20 m for the altitude modalities.

With an average flight speed of 45 km/h, the transect-line length was about 420 m for birds in order to play the whole 30-second soundtrack. For bats, seventy metres were enough.

For both taxa, we did blank samples—recordings at ground level without any UAV (altitude 0)—to better understand the effect of the UAV on detectability.

Finally, we had:

- 9 species x 4 altitudes x 6 distances x 3 repetitions for birds (n = 648);
- 7 calls x 3 altitudes x 6 distances x 3 repetitions for bats (n = 378).

As the drone actually used was noisier, faster and less manoeuvrable than the original one the results were not as good as expected. Therefore, after testing the detection of the most audible species (i.e. the best detected by the quadcopter), the fixed-wing part was aborted.

2.1.4 Quadcopter trials

Basically, these tests tried to emulate traditional point-count sampling, described by Buckland (1993), under controlled conditions in order to estimate a global EDR for the quadcopter.
The main advantage of multicopters over remotely piloted planes is its better manoeuvrability and the opportunity to attach the microphone further away from the propellers. Moreover, multicopter recordings are less affected by wind noise than plane recordings thanks to hovering flights.

2.1.4.1 UAV description

The quadcopter used was a DJI Phantom 4 PRO. We had four batteries, each providing a maximum flight time of 30 minutes.
To decrease propellers and motors noise, recorders were hung below the drone thanks to an 8-metre nylon line.

2.1.4.2 Study area

Trials were conducted between 1:30 pm and 6:00 pm mid-April and June 2018 at two different sites: the “Model Air Club des Ardennes Bertrix” (49°51'25"N, 5°17'24"E) and a two-hectare meadow in Henri-Chapelle (50°40'17"N, 5°56'54"E).
Weather conditions were dry and sunny (temperature around 20-25°C, wind speed < 15 km/h).

2.1.4.3 Noise characterisation and mitigation

First, we determined the best nylon line length to minimise the drone noise while keeping a good flight stability. In fact, UAV oscillations due to a suspended recorder follow the physical laws of the moment of a force, which is “a measure of its tendency to cause a body to rotate

about a specific point or axis" (Luebkeman et al., 1995). "The magnitude of the moment of a force acting about a point or axis is directly proportional to the distance of the force from the point or axis" (Luebkeman, 1995). In other words, the longer the nylon line is, the more unstable the drone.
Both bird and bat recorders were mounted on a one-metre tripod while the quadcopter was ascending metre by metre, starting at 1 m from recorders and up to 45 m. Each step was marked with a whistle. We checked all spectrograms to see from which height the drone noise became insignificant in terms of audible and/or ultrasonic sound level, we chose a line length for bird and bat experimentations (both 8 m, see section 3.2.1) and empirically tested flight stability with some conventional manoeuvres.

The Erebus project showed that drones emit ultrasounds. They noticed that microphone insulation with foam mitigated these interferences. Consequently, the aforementioned trials were both done with and without acoustic foam for the AudioMoth device to justify. We built an insulation casing for the latter with a 26 kg/m^3 density pyramid foam (casing = 6 x 8 x 7 cm; top = 13 x 15 cm) (Figure 6). The microphone was oriented downward.

Figure 6. AudioMoth insulation casing with a 26 kg/m^3 density pyramid foam (casing = 6x8x7 cm; top = 13x15 cm)

2.1.4.4 Experimental system

The quadcopter—equipped with the recording device suspended 8 m below with a nylon line—hoovered at several altitudes from the speaker, which was moved to multiple horizontal distances from the hoovering point, and thus for each call modality played (Figure 7).

Distance and altitude modalities were exactly the same as the plane trials (see section 2.1.3.3), except for 2 extra bat altitudes (5 and 15 m) added for purposes of improving the potential effect of altitudes. In fact, quadcopters are easier to operate than fixed-wing drones: flying 5 m above the ground is too risky for fixed-wing drones. It has to be noted that all altitudes for the quadcopter correspond to the height of the recorder and therefore it is necessary to add the length of the nylon line (8 m) to know the real hoovering altitude of the UAV.

Finally, we had:

- 9 species x 4 altitudes x 6 distances x 3 repetitions for birds (n = 648);
- 7 calls x 5 altitudes x 6 distances x 3 repetitions for bats (n = 630).

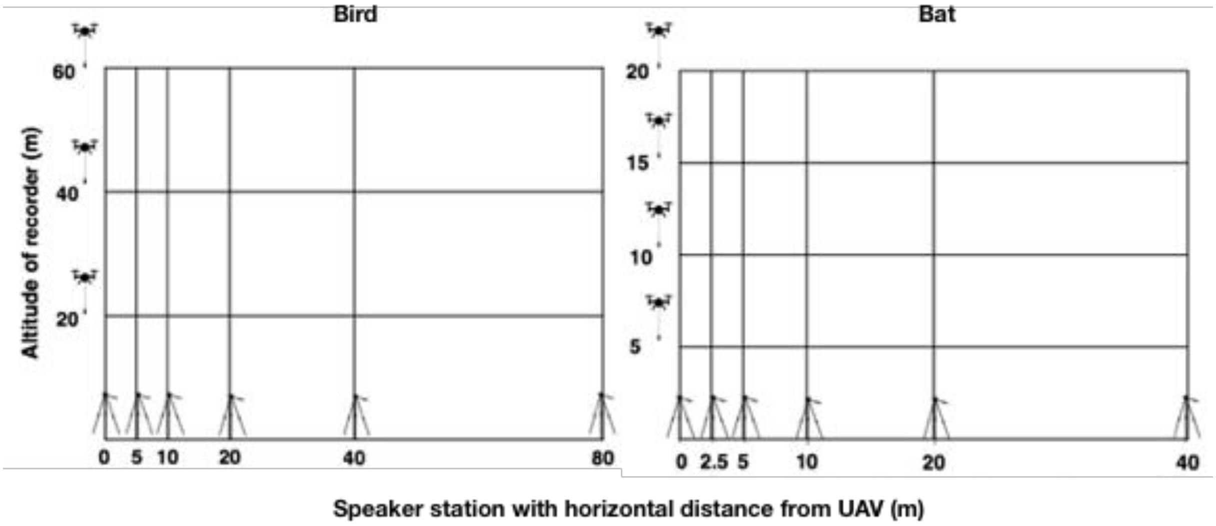

Figure 7. Experimental arrangements for quadcopter flights under control conditions according to the studied taxa. The speaker was placed at several distances from the quadcopter hoovering point. The latter hoovered at multiple altitudes. Recordings were also done at ground level as blank samples (altitude 0, without UAV).

2.1.5 Data analysis

2.1.5.1 Birds

At first, the recordings were filtered to attenuate drone noise by means of the "noise reduction" effect on Audacity software (noise reduction dB = 16; sensitivity = 13; frequency smoothing = 8). This operation guaranteed a better listening comfort, while preserving unaltered birdsongs.

Then, they were randomly numbered on Excel to be analysed by two experienced birdwatchers. Employing external stakeholders and randomly numbering tracks avoided any bias knowing the selected species, altitudes and distances in advance. We chose two experts rather than one because bird songs recognition depends on personal skills.

They listened to each recording and associated them with one or several species (sometimes there were real bird interferences) and an audibility level code for every species recognised: 0 = inaudible, 1 = difficult to hear, 2 = audible, 3 = well audible and clear. The species and the approximate position of the real birds who interfered with the soundtracks were noted down. When the real bird was a different species from the soundtrack, there was no problem since the experts gave a code for each species heard. Fortunately, we never had a singing bird of the same species as the soundtrack that was being played. In this case we would have these experts' outputs.

Afterwards, we checked if the identified species were correct. For non-correct identification, the code 1, 2 or 3 was changed into 0, unless the wrong species identification was the same every time (e.g. identifying all Sedge Warbler recordings as Reed Warbler). This kind of error was linked to the analyst skills and not to the song sequence quality. Then, we classified these results into two distinct groups of detectability: codes 2 and 3 as "detected" and code 0 as "non-detected".

For the statistical analysis, we first checked if there were variations of detectability depending on expert and altitude using chi-square tests and logistic regressions. On the basis of those results, ESW and EDR were calculated using two methods: the “Distance” package in R, based on two candidate models of detection curves, Half-normal and Uniform (Miller et al., 2016), and through a regression of the real detection probability (proportion of recordings detected) regarding the distance, still with R. The ESW/EDR is the distance from the transect/point-count station for which the number of individuals missed within it is equal to the number of individuals detected beyond it (Buckland, 1993), and is obtained according to the following formula:

$$ESW = p * w \quad \text{and} \quad EDR = w * \sqrt{p}$$

where *w* is the maximum distance of detection and *p* the detection probability (Guélin et al., 2017). Its calculation is as follows:

$$p = \int_0^w g(x)[x]dx$$

where *g(x)* is the detection probability function. For line transects, $[x] = \frac{1}{w}$ and for point counts, $[x] = \frac{2x}{w^2}$ (Kéry et al., 2015).

We rejected the two other frequently used candidate models: Hazard Rate and Negative Exponential (Miller, 2016; Guélin, 2017). The first was dismissed because, with our small number of detections, it provided an aberrant detection function or was not able to fit one. The second was dismissed because the shape of a negative exponential (dramatic decline over short distances) does not fit with point-count detection curve (upholding of a probability close to 1 until sound level attenuated by distance approaches the hearing threshold) (Guélin, 2017). We exclusively selected the model using the Akaike’s Information Criterion (AIC). Normally, models should first be checked using the Goodness of fit (Miller, 2016; Guélin, 2017). However, we found that models with greater Cramer-von Mises p-value and AIC underestimated the EDR.

Finally, we checked in R if there was a relation between the song features (frequency and intensity) and the detection probability.

2.1.5.2 Bats

Primarily, song sequences were randomly numbered on Excel to remove the possibility to be influenced by the knowledge of distance, altitude and species/call patterns. Subsequently, they were directly classified by ourselves as “detected” (identifiable tracks) or “not detected” (non-identifiable tracks) on the basis of the spectrograms. We did not involve external experts as identification thanks to spectrograms was based on objective criteria (signal shape, PD, IPI, FME, minimum and maximum frequencies), using the same principle as the identification tree of some bat call analysis software[4]. Recordings of Natterer’s bat which were not identifiable

[4] https://www.ecoobs.com/cnt-batIdent.html

to the species level were classified as “*Myotis* sp.”. The *Myotis* classification thus grouped together all the identifiable Natterer’s bat recordings at the species level or only to the genus level. Finally, all the recordings were treated with Kaleidoscope Viewer 4.5.4 to see the number of tracks that would have been classified as noise if we had done a semi-automatic identification.

Statistical analysis followed the same outline as the bird part (see section 2.1.5.1).

2.2 Tests under real conditions

To get a first insight into the effectiveness of quadcopter-based acoustic monitoring, we did a few comparative trials on the field with conventional survey methods. We used the same equipment as the under control trials.

2.2.1 Birds

We compared quadcopter-based counts with the SOCWAL approach (five-minute point counts). UAV flights were done by a drone operator while traditional point counts were done by an experienced birdwatcher. The equipment was the same as the tests under control.

2.2.1.1 Study area

We conducted our trials on 17 June 2018 between 6:00 and 9:30 am in Gembloux, at eight stations separated at least by 200 m and far from habitation (Table 3). Half of them took place in a wooded area and the other half in an open area (mainly agricultural). Wooded areas consisted of patches of deciduous trees (oaks, hornbeams, etc.) and open areas were mainly crops of cereals, beets and legumes or sometimes grasslands (Figure 8). Weather conditions were dry and sunny (wind speed < 15 km/h).

Table 3. Location and environment type of the bird point count stations.

	GPS location	**Environment**
Station 1	50°34'10.88"N, 4°42'13.86"E	wooded
Station 2	50°34'16.63"N, 4°42'20.19"E	open
Station 3	50°34'12.48"N, 4°42'29.49"E	open
Station 4	50°34'2.44"N, 4°42'29.56"E	open
Station 5	50°35'10.06"N, 4°47'15.69"E	wooded
Station 6	50°35'30.17"N, 4°47'31.10"E	open
Station 7	50°35'38.72"N, 4°47'13.45"E	wooded
Station 8	50°35'37.76"N, 4°46'58.15"E	wooded

Figure 8. Map of bird point count stations at Gembloux, Wallonia, Belgium. Orthophotos from SPW (2015).

2.2.1.2 Experimental setup

UAV-based point counts consisted of a take-off 100 m from the point of interest to avoid any behavioural modifications (escape or song cessation) of the most easily disrupted species (Jarrod C. Hodgson et al., 2016). The quadcopter ascended to the desired altitude and reached the station by horizontal transposition. The chosen altitude was 48 m from the ground (40m for the recorder) because we showed that flight height had no influence on detectability (see section 3.2.3). Forty-eight metres were acceptable for our point-count samples. In fact, the recorder was far over the tree canopy and balancing equipment safety against the drone flying autonomy, there was no need to fly higher. Moreover, it was proved that there were no disturbance effects on waterbirds for multicopter flying above 40 m (McEvoy et al., 2016). Some were approached without any behavioural response to within 4 m (Vas et al., 2015).However, this altitude should be revised for other areas. For instance, we can exceptionally find trees measuring up to 60 m high in Wallonia (Dedry et al., 2015). The drone device hoovered and recorded for five minutes at the station. All the recordings were then listened to by the birdwatcher who noted every bird detection and allocated them to a species identification.

For standard point counts, all bird detections were written down as visual or audial into an orthonormal system where the intersection of the two axes represented the centre of the station.

Two counts in wooded areas as well as two in open areas were started by the standard approach and directly followed by the RPAS recording. And vice versa for the other four counts. The aim is to compensate potential bird disturbance biases caused by the drone and/or by the birdwatcher's movements towards the station.
For the stations started by standard count, the bird expert realised his five-minute data collection while the drone operator remained at the launch point 100 m away. As soon as the classical count was complete, the UAV was sent to the hoovering point. During this five-minute recording, the expert stayed in place and was noting bird detections again. The expert's ability to listen to birds was obviously distorted by the drone noise. However, this bias was also present on the recorded soundtracks and the individuals on site were exactly the same for both techniques, offering a good comparison.
There was no simultaneous listening for the point counts started with the UAV. The expert and the drone operator stayed 100 m away while the drone was recording at the station. The birdwatcher went to the station after the drone returned to his task.

We compared the mean detections per point for each species between UAV-based point counts and standard point counts conducted before/after UAV-based point counts, and also between UAV-based point counts and standard point counts conducted during UAV-based point counts.

2.2.2 Bats experimental protocol

Aside from testing the quadcopter to know if successful recordings could have been made under controlled conditions, we were also interested in whether the recorder on the quadcopter would have recorded bat calls that were not detectable on the ground. For instance, masts from 20 to 25 metres are sometimes deployed in Wallonia to record high-flying species, thus UAV might be an alternative method.

2.2.2.1 Study area

Our testing was carried out on 15 June 2018 between 10:30 and 11:59 pm in the Grünhaut forest. Two stations were chosen, one open habitat and one closed habitat: the pond (50°38'47.34"N, 5°55'6.17"E) and the forest (50°39'6.88"N, 5°55'47.21"E). Weather conditions were suitable for bats to hunt: no precipitation, temperature around 15 °C and wind speed under 10 km/h.

2.2.2.2 Experimental setup

DJI Phantom quadcopters are already lit thanks to their LED system but to improve the night visibility with the suspended recorder (8 m below), we added red LED lights on the top and bottom of the insulation casing. The top one allowed the recorder to be seen from the on-board camera of the UAV, while the bottom one allowed visibility from the ground.

For both stations, a ground recorder (also an AudioMoth) was attached 3 metres above the ground on a tree trunk. The UAV hoovered at two different altitudes—21 and 31 m (hence 13 and 23 m for the drone recorder)—exactly above the ground recorder for five minutes for each. They were thereby 10 and 20 m between the two recorders which were recording simultaneously.
Recordings were sorted as bat signal or as noise by Kaleidoscope Viewer. Then, we checked and identified the bat signal outputs, calculated the detection percentage for all modalities and compared subjectively the spectrograms quality between UAV and ground recordings.

3 Results & Discussion

3.1 Fixed-wing trials under controlled conditions

These tests did not provide any exploitable results. For instance, even the loudest songbirds like the Common Blackbird, which was detected up to 80 m radially with the quadcopter, were not audible by flying at 20 m high (the lowest altitude) just over the speaker (the smallest horizontal distance). Indeed, only the propeller and wind noises were heard.
Our propeller was located in the front of the drone in opposition with the fixed-wing drone of the Erebus project (the Talon) which was at the rear. To reduce drone noise, they decided to fix the recorder at the front, which increases considerably wind interferences by aerodynamics. Therefore, our design should have been with fewer interferences. However, in our experimentation the recorder was likely too close to the propeller to allow proper bird and bat recordings.

These unsuccessful results combined with manoeuvrability difficulties (crashes) urged us not to achieve all the planned modalities and therefore we abandoned this part to focus on the multicopter.

3.2 Quadcopter trials under controlled conditions

3.2.1 Noise characterisation

The UAV emitted mainly low-frequency noise whose sound level decreased with distance to stabilise around 55 dB from 7 m (Figure 9). This sound level is quite close to the one in an outdoor environment without particular noise (around 45 dB).

Significant ultrasounds—also decreasing with distance—were delivered by the drone too (Figures 10 to 13). They are characterised by a maximal frequency of about 45 kHz and a minimal frequency of about 35 kHz, with transmission of three pulsations per second. Without acoustic insulation on the microphone, noise volumes at 5 m were respectively of 85, 70 and 85 for low, medium and high frequencies (Figure 10). With acoustic insulation, we got the same results at 1 m (Figure 12). These results therefore justified the use of our foam casing by showing a significant reduction in nylon line length. However, these signals only disappeared from 25 m without insulation and from 15 m with insulation (Figures 11 & 13), which means that even with acoustic foam we were not able to get totally suppress interferences.

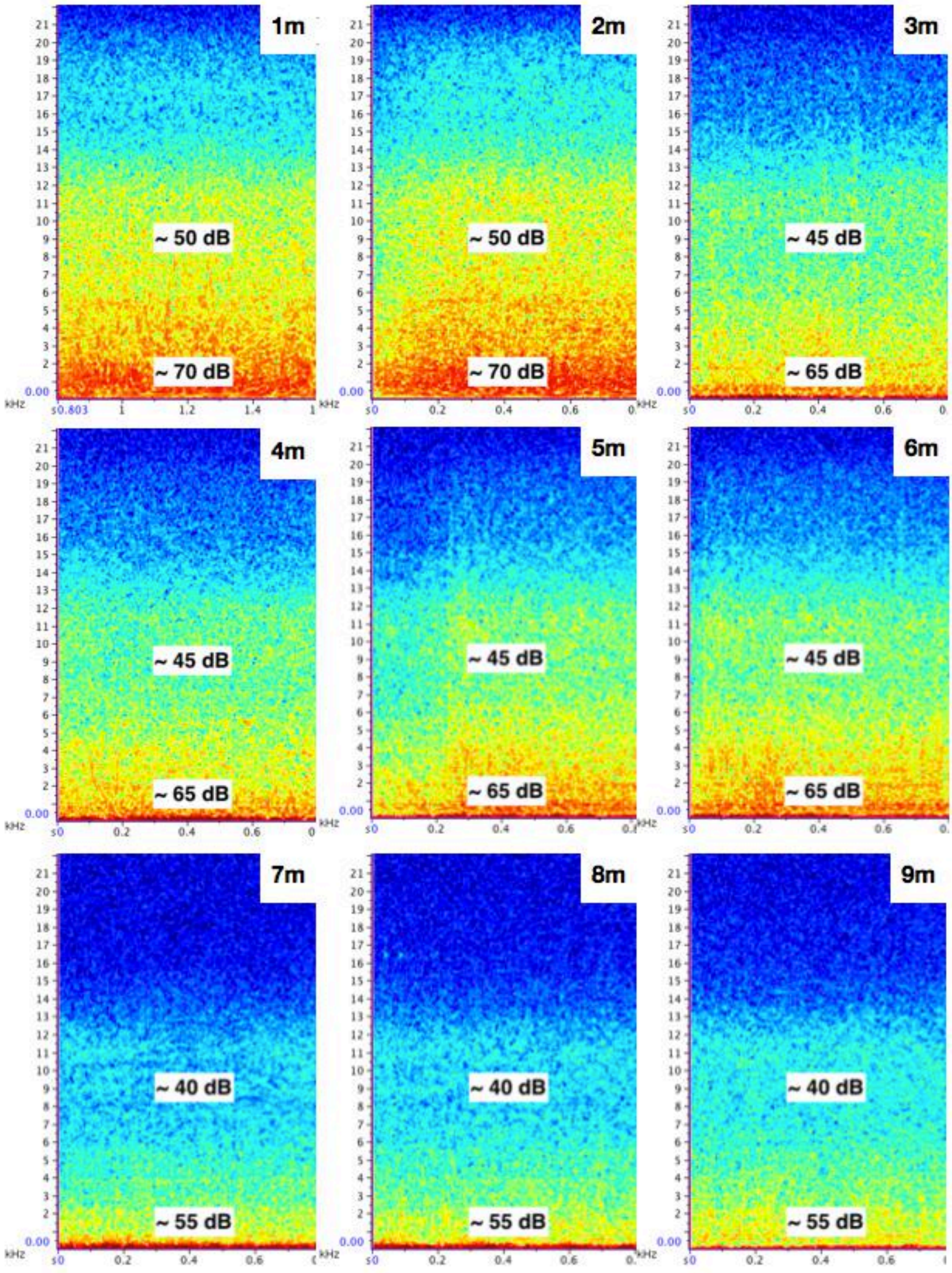

Figure 9. Spectrograms of quadcopter audible noises at several vertical distances, recorded by the ZOOM H1 Handy Recorder. The recorder was mounted on a one-metre tripod with the microphone oriented downward and the drone ascended over it metre by metre. Software used: Raven Lite 2.0.

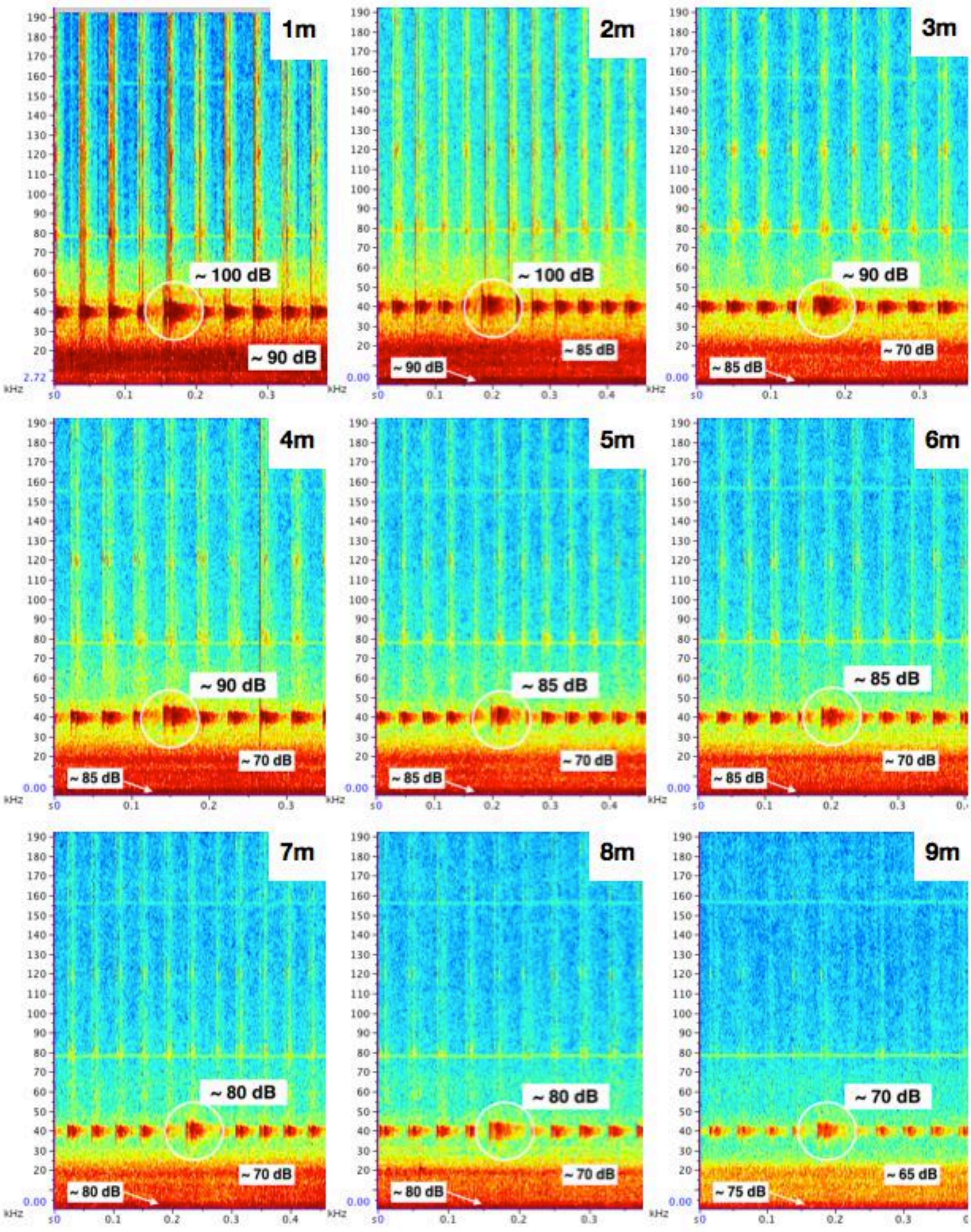

Figure 10. Spectrograms of quadcopter ultrasonic noises at several vertical distances (1 to 9m), recorded by the AudioMoth without the insulation casing. The recorder was mounted on a one-metre tripod with the microphone oriented downward and the drone ascended over it. Software used: Raven Lite 2.0.

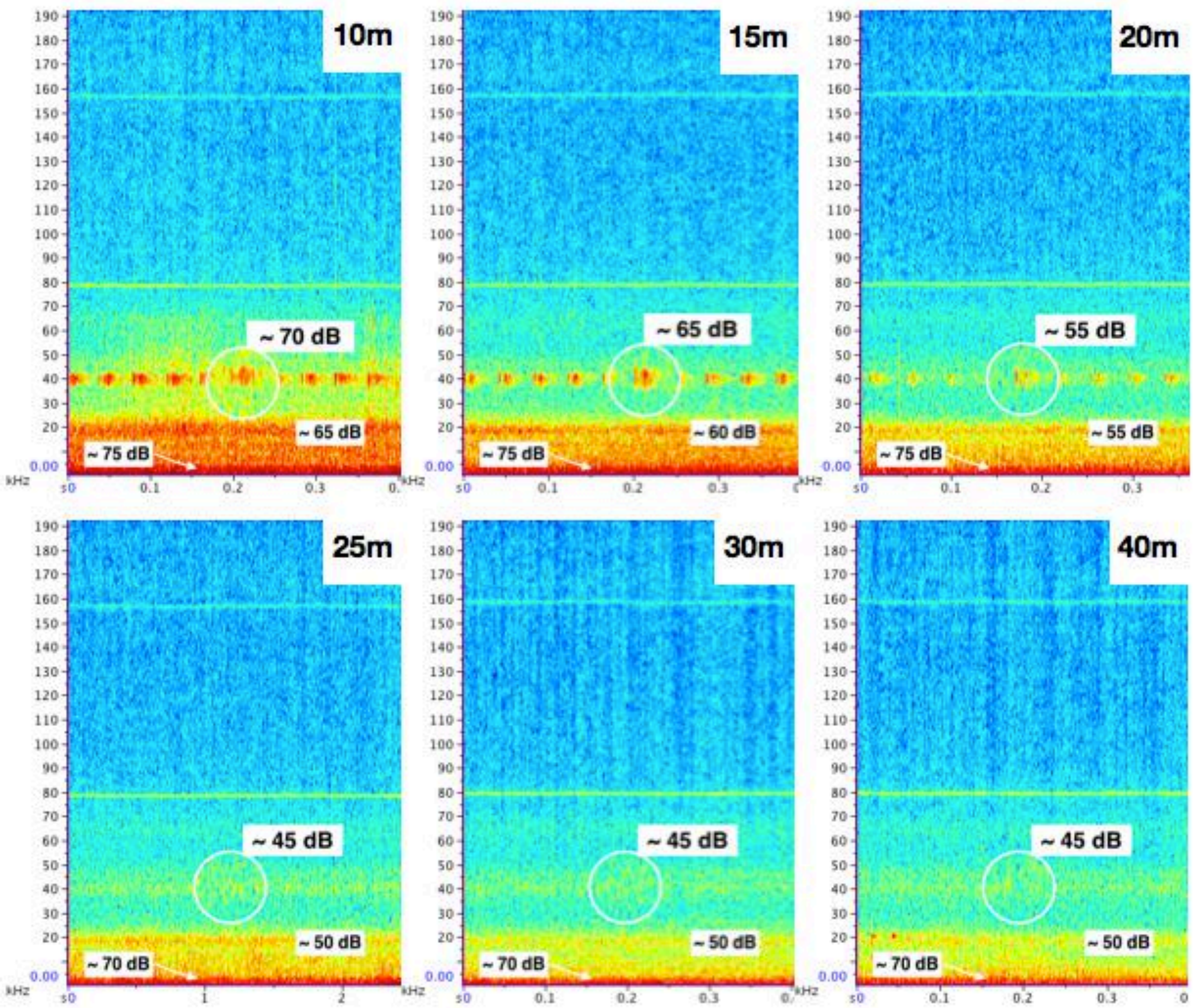

Figure 11. Spectrograms of quadcopter ultrasonic noises at several vertical distances (10 to 40m), recorded by the AudioMoth without the insulation casing. The recorder was mounted on a one-metre tripod with the microphone oriented downward and the drone ascended over it. Software used: Raven Lite 2.0.

Finally, we chose an eight-metre nylon line for both taxa. We could have taken a seven-metre line for the birds because there was no sound level difference between 7 and 8 m (Figure 9). However, there was a slight difference for ultrasound in favour of a length of 8 m (Figure 12), and thus for an ease of use we opted for a constant length for each experiment especially since the drone was still stable with an eight-metre nylon line.
As high frequencies dissipate over a shorter distance (Tupinier, 1996), we could have expected a shorter length to mitigate the UAV ultrasonic noise, but our results still concurred with other references that recommend a microphone at least 3 m away from the quadcopter to reduce ultrasonic interferences efficiently and 8 m away for audible interferences (Moore, 2018; Wilson, 2017).

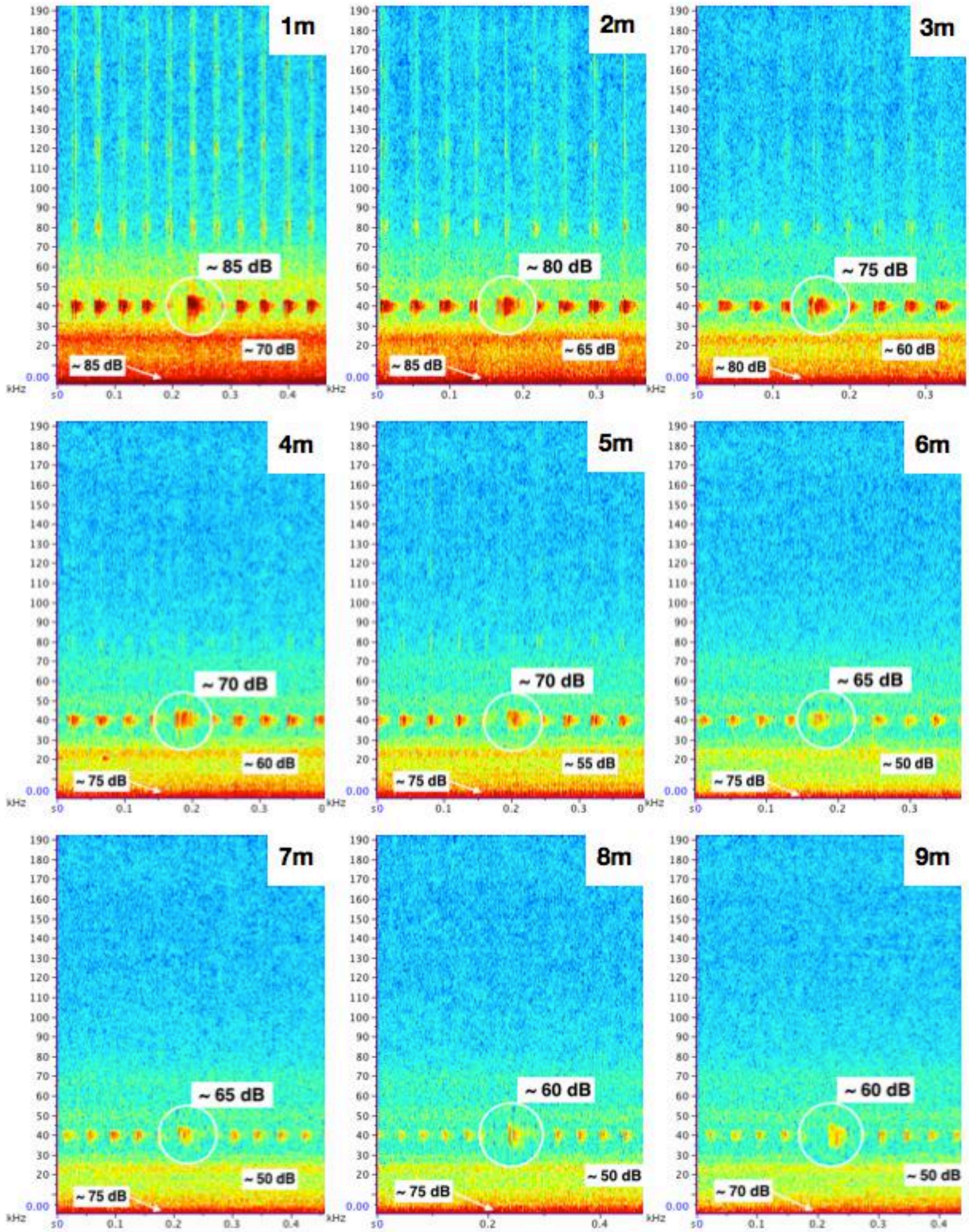

Figure 12. Spectrograms of quadcopter ultrasonic noises at several vertical distances (1 to 9m), recorded by the AudioMoth with the insulation casing. The recorder was mounted on a one-metre tripod with the microphone oriented downward and the drone ascended over it. Software used: Raven Lite 2.0.

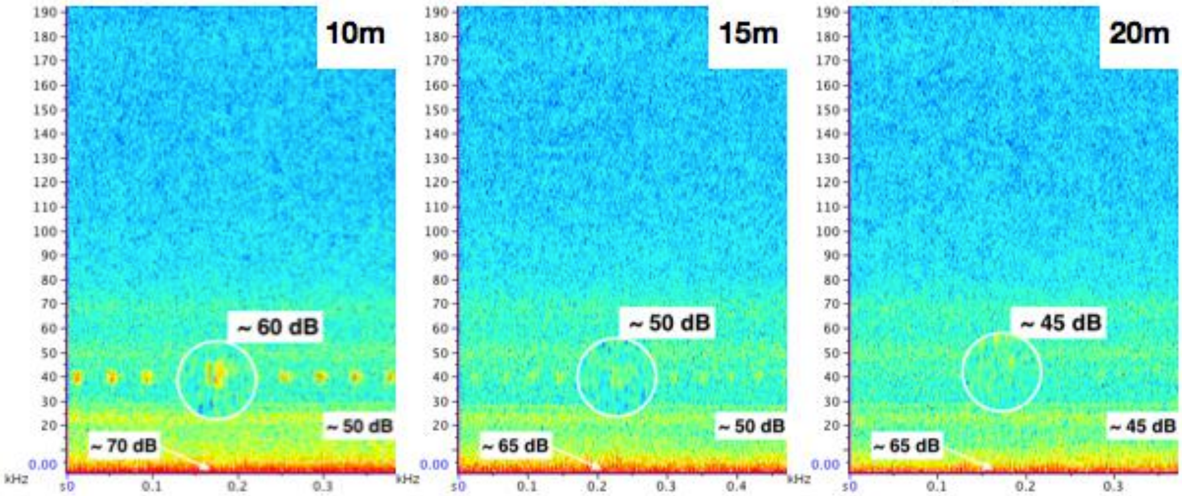

Figure 13. Spectrograms of quadcopter ultrasonic noises at several vertical distances (10 to 20m), recorded by the AudioMoth with the insulation casing. The recorder was mounted on a one-metre tripod with the microphone oriented downward and the drone ascended over it. Software used: Raven Lite 2.0.

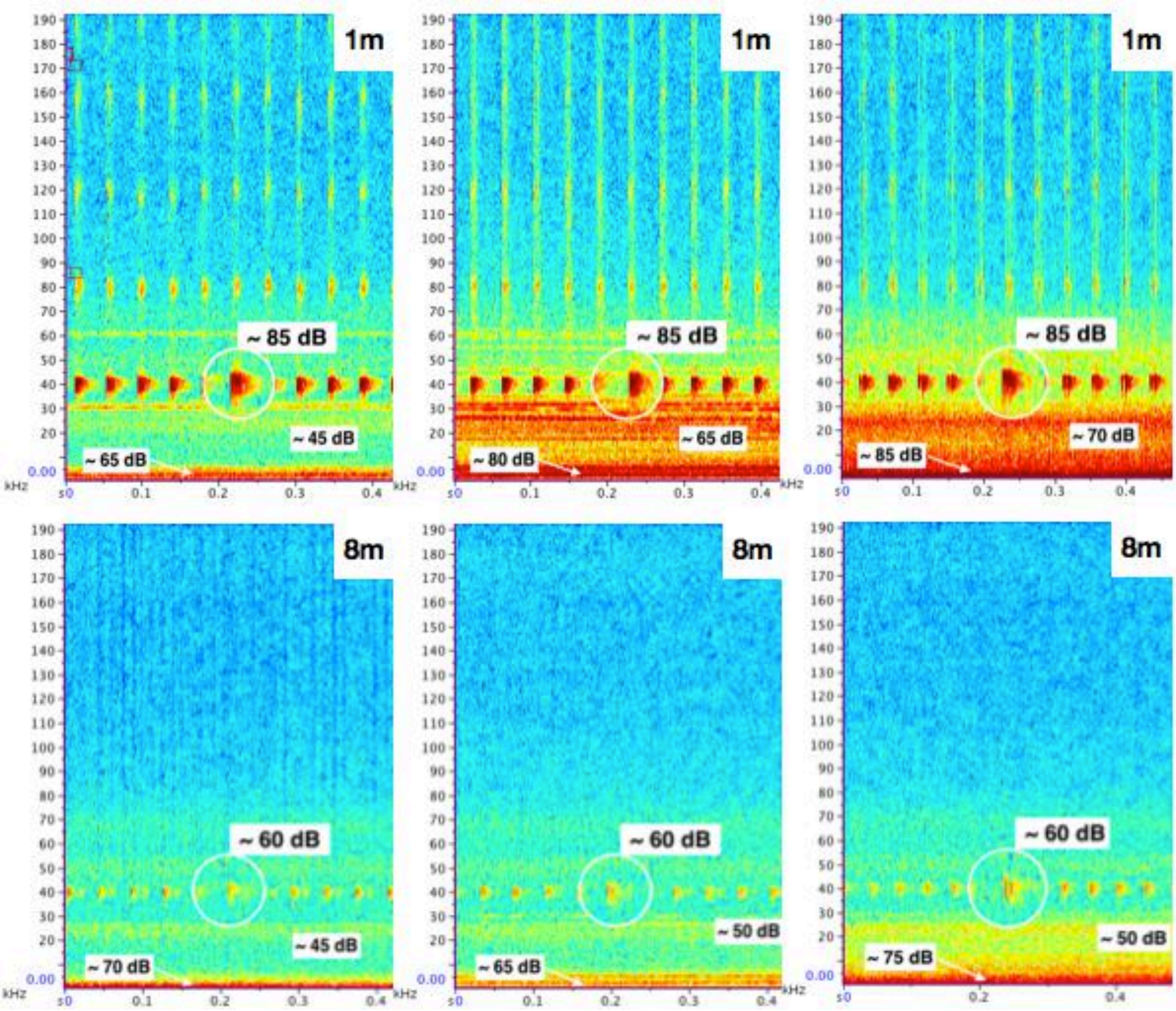

Figure 14. Spectrograms of quadcopter ultrasonic noises at 1 metre and 8 metres (corresponding to the nylon line length), recorded by the AudioMoth with the insulation casing. Left side = UAV on and motors switched off, middle = motors running without propellers, right side = motors running with propellers. The recorder was mounted on a one-metre tripod with the microphone oriented downward and the drone ascended over it. Software used: Raven Lite 2.0.

These ultrasounds did not come from the motors and/or the propellers because they were already emitted when the UAV was powered up without starting the motors (Figure 14). Their sound level as well as their pattern did not change when the motors were running, but the sound level was around 85 dB at 1 m and decreased to 60 dB at 8 m. Consequently, the nylon line length had a great impact on this specific interference.

The main components of a quadcopter are:

- one radio receiver which relays the operator instructions to the flight controller;
- one flight controller which is the "brain" of the drone;
- four ESCs which relay rotation speed instructions from the flight controller to its motor;
- four motors which are brushless in our case;
- four propellers;
- and one battery (Leclercq, 2018).

We made the hypothesis that these ultrasonic signals come from the ESCs. In fact, "brushless DC motor accomplishes commutation electronically" (Zhao et al., 2011). "Commutation is the process of switching the current applied to the motor's phases in a sequence that will generate motion" (Schimdt, 2017). "Usually the high-side switches are controlled using pulse-width modulation (PWM), which converts a DC voltage into a modulated voltage" (Zhao, 2011). This generation of an AC voltage controlled by the ESC might be the origin of this noise.

Motors and ESCs generate the most of the noise at a short distance (1m), but when this distance increases (8 m, like for our bat recordings) propellers have a more significant influence on noise than motors, especially under 10 kHz (+10 dB) (Figure 14). That's why other propeller designs might reduce these acoustic interferences.

These highlighted noises could mask the acoustic signals of certain species (Figures 15 & 16). Wilson (2017) showed that bird species with a low-frequency song could be heavily masked by the UAV noise. The Common Wood Pigeon, which has a very low-frequency song, was no exception to this rule but UAV noise had less effect on alteration of acoustic signals for the other selected species (Figure 15).
For bats, three of the selected species (Barbastelle, Serotine and Natterer's Bat) emitted calls whose frequency range partially passes through the ESC noise band (Figure 16). This was a real issue for the Barbastelle whose typical 35-41 kHz alternating signals in steep FM was completely melted into the ESC noise. Nevertheless, Serotine's flat FM signals combined with a FME around 25-27 kHz and the very wide range of frequencies of Natterer's bat calls allowed the identification of these two species. We also note that no call (echolocation and social) of the various bat species was strongly impacted by motors and propellers noise (Figure 16).

Figure 15. Synthetic graph of the singing ranges in terms of frequency of the selected bird species compared with the sounds emitted by the different UAV components. The intensity of the red colour is proportional to the amplitude of the noise.

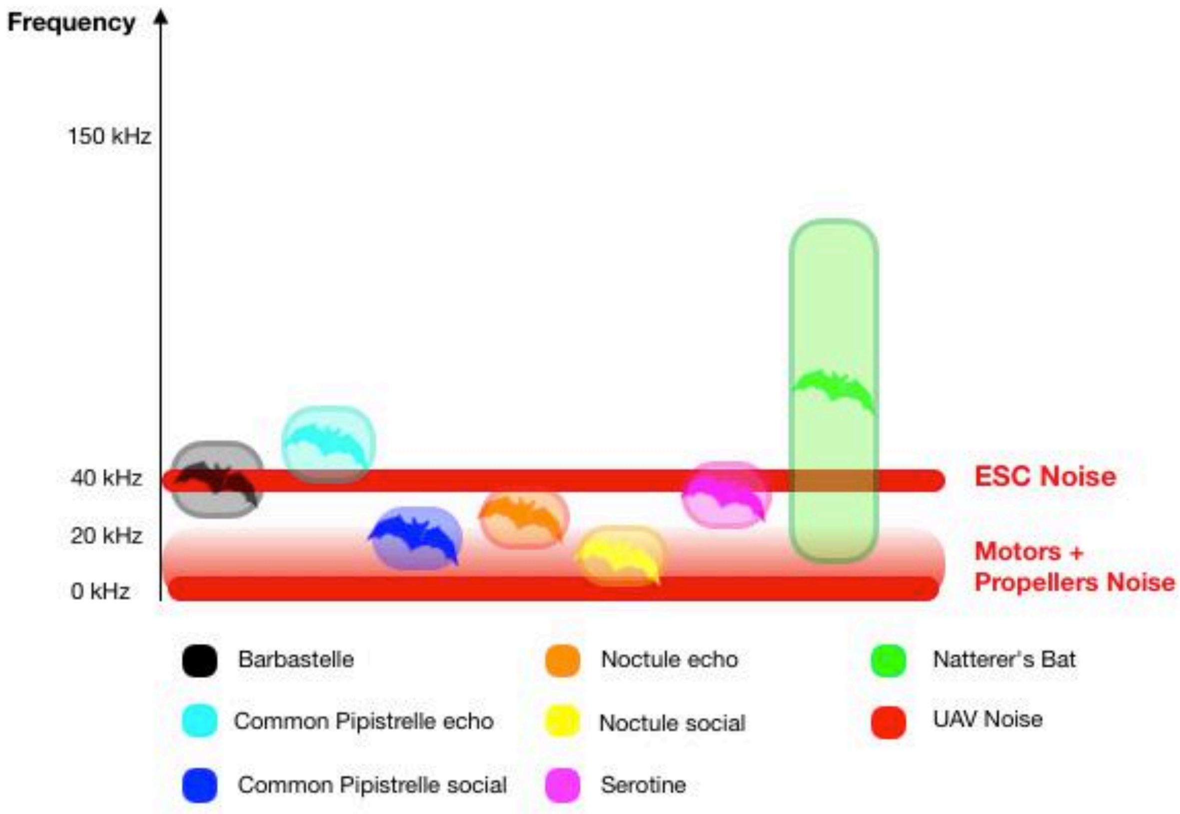

Figure 16. Synthetic graph of the emission (echolocation) ranges in terms of frequency of the selected bat species compared with the sounds emitted by the different UAV components. The intensity of the red colour is proportional to the amplitude of the noise.

3.2.2 Birds

3.2.2.1 Expert and altitude effects

We found a very highly significant difference in overall detection rate between our two bird experts (p-value < 0.01; Table 4), meaning that detectability is definitely subjective for each expert and depends particularly on their skills. We thus decided to keep the data of the two experts in two separate groups for all the following calculations.

Table 4. Chi-square Test of Independence for difference in detection between the two experts.

n	X-squared	df	p-value
1296	29.8164	1	**4.75e-08*** **

Logistic regression curves showed for both experts a stable detectability (all species) between the three UAV altitudes, whereas it was rather decreasing when altitude 0 is included (Figure 17).

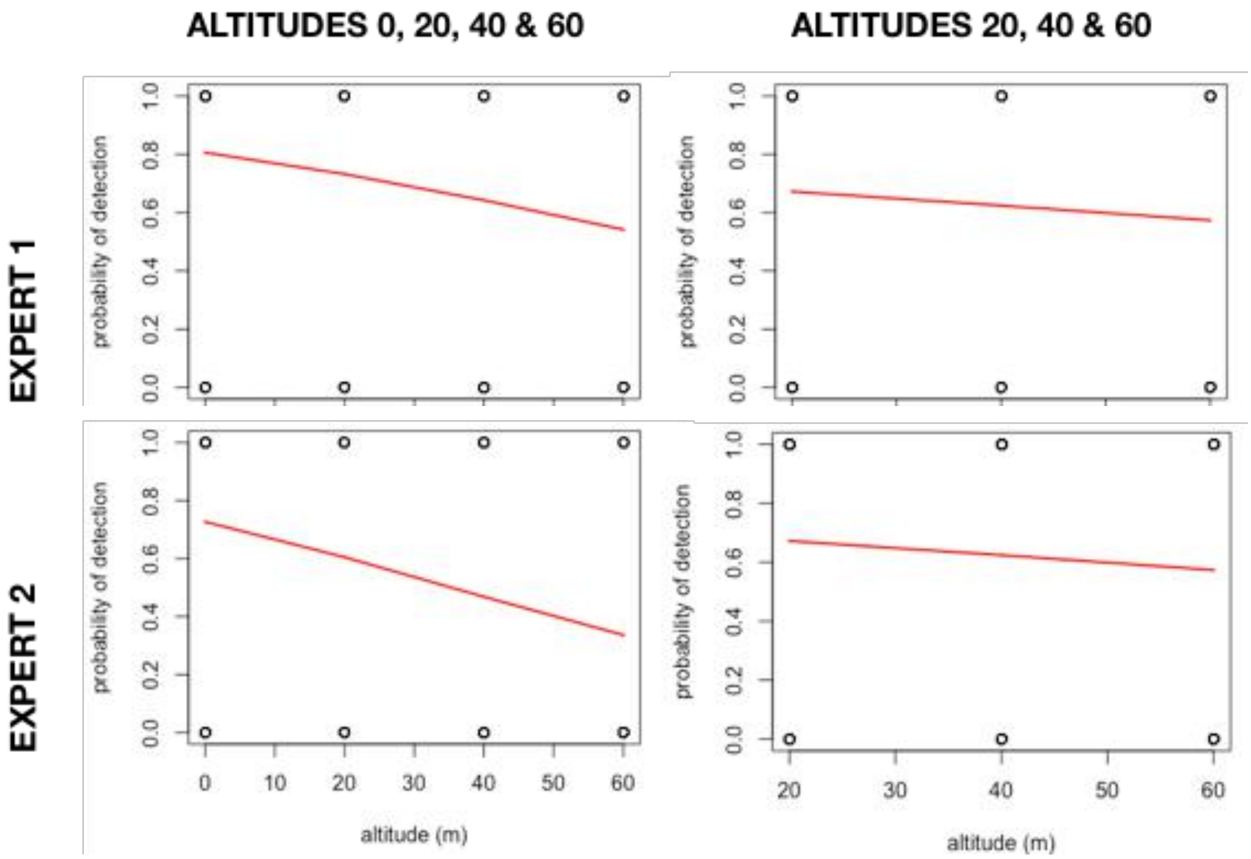

Figure 17. Logistic regression curves for the effect of altitude on overall bird species detectability. Calculated with and without blank sample altitude (= altitude 0) and for both bird experts.

There were significant differences in detectability for some species between the blank sample (altitude 0) and UAV altitudes, especially for expert 2 (Table 5). When we only considered the different UAV altitudes without the control altitude, there was no more significant difference

in detectability (chi-square test for altitudes 20, 40 & 60; Table 5). Thereby, UAV-based recordings do not provide the same detection rate than ground-based recordings.
Table 5 results confirmed and detailed the ones from figure 16. In fact, some species like the Common Wood Pigeon seemed to be more affected by the drone noise.
On this basis we decided to make two groups out of these altitudes for EDR calculation: "Control" for altitude 0 and "UAV" for altitudes 20, 40 and 60.

Table 5. Chi-square Tests of Independence (p-value) for difference in detection between several UAV altitudes, and thus for each expert.

	Chi-square test for altitudes 0, 20, 40, 60		Chi-square test for altitudes 20, 40, 60	
Bird species	**p-value expert 1 (n = 72)**	**p-value expert 2 (n = 72)**	**p-value expert 1 (n = 54)**	**p-value expert 2 (n = 54)**
Common Blackbird	0.6279	0.3035	0.5698	0.5698
Common Chaffinch	0.3497	0.2026	0.7251	0.492
Common Reed Bunting	0.3335	**0.002408****	0.5664	0.09275
Common Wood Pigeon	**3.231e-06*****	**5.133e-05***	0.1054	0.4235
Eurasian Blackcap	0.1718	0.2741	0.3926	0.9285
Eurasian Wren	0.3535	**0.02517***	0.348	0.09558
Goldcrest	0.6471	**0.04819***	0.7227	0.05697.
Sedge Warbler	**0.009072****	**7.7e-06*****	0.595	0.358
Song Thrush	0.3497	**0.01959****	0.7251	0.2212

3.2.2.2 Effective Detection Radius

As we knew exactly the number of detected and undetected audio recordings for each species, we were able to build detection probability functions on the basis of the real probabilities of detection[5] alongside distance sampling detection curves which only used detected species. We found important differences between our two EDR calculation methods (Figure 18; a table with exact values is available Appendix 2). There are two possible reasons for this discrepancy. First, distance sampling only considered detected individuals to build its detection curve. As our tests under controlled conditions used a non-linear distance scale, number of detections under 20 metres is excessively higher than the number of detections over 20 metres. It led to a detection function which underestimated the real detection probability (Figure 19).
Secondly, the first assumption of distance sampling theory, which is "objects on the line or point are detected with certain" or g(0) = 1 (Buckland, 1993), is sometimes violated (Detection probability < 1 at 0 m; Figures 21 & 24 to 27). Thus, outliers occured.
Hence, we decided to focus on regression EDR for the interpretation.

We note that overall EDR were lower for UAV-based recordings than ground-based recordings, but Common Blackbird, Common Chaffinch, Common Reed Bunting, Eurasian Blackcap and Goldcrest EDR were at most 20% smaller for at least one of the two experts (Figure 18). The vocalisations of Common Wood Pigeon, Eurasian Wren, Sedge Warbler and Song

[5] Real detection probability = detected /(detected + undetected)

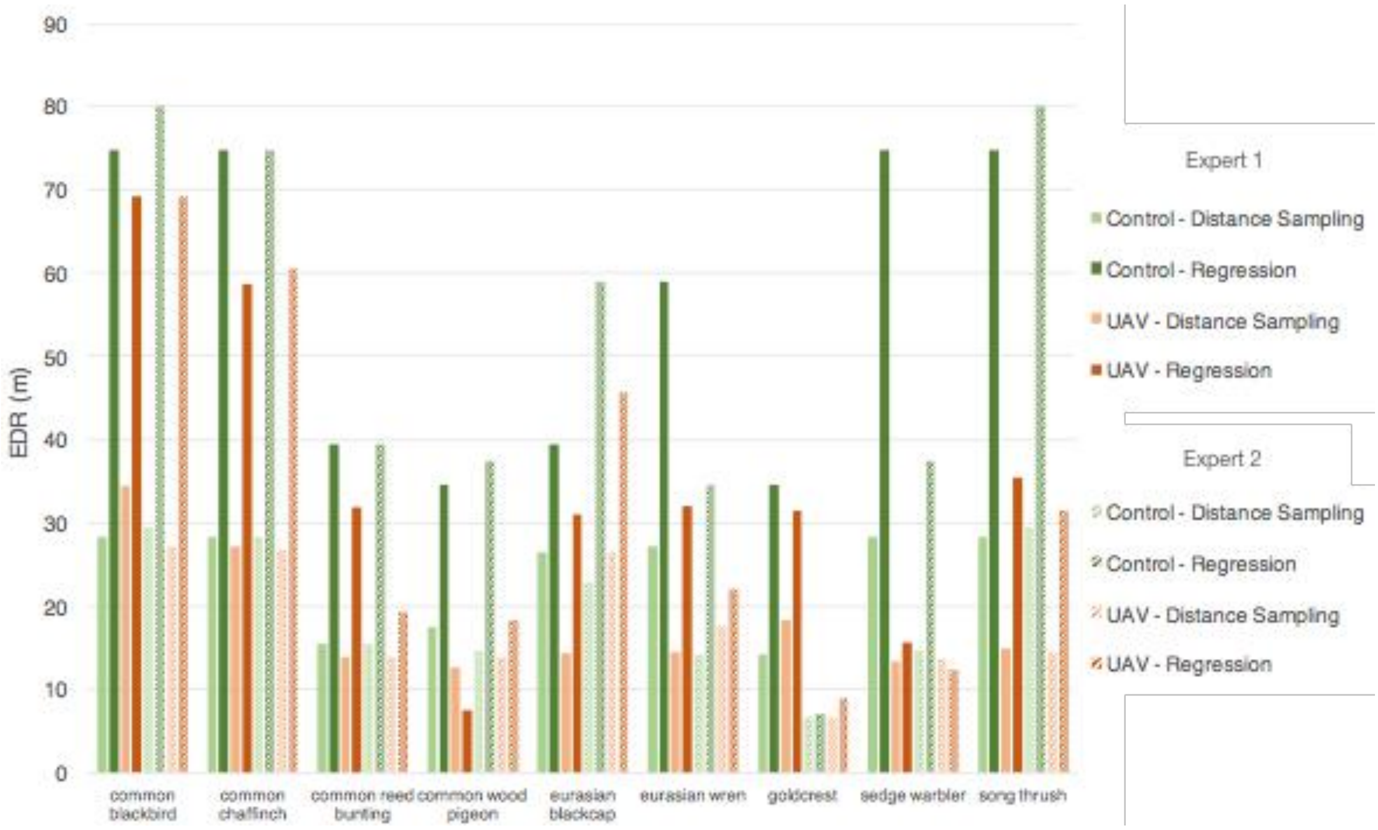

Figure 18. Effective Detection Radius depending on bird species, expert and calculation method.

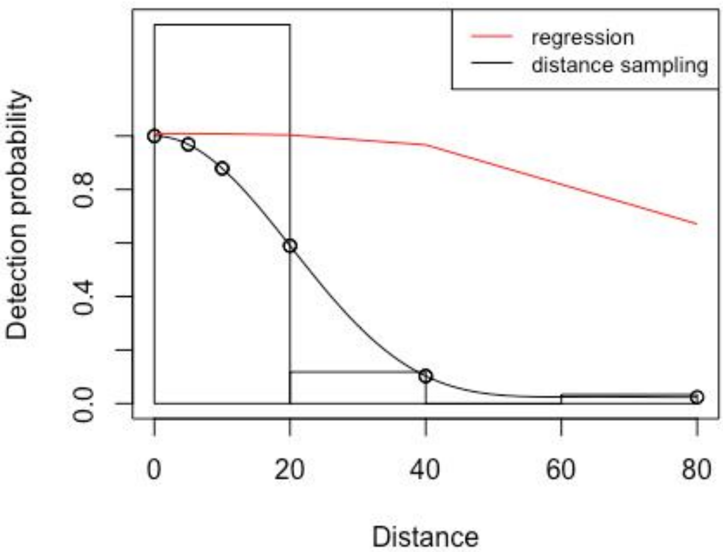

Figure 19. Comparison of detection probability function determined by the distance sampling method and by regression for the Common Chaffinch (Control, Expert 2).

Thrush are thus more affected by drone interferences. For instance, Sedge Warbler EDR fell sharply by 59.1 m (-79%) when we used the UAV device.
Song Thrush and Eurasian Wren were the loudest species in our selection (respectively 100 and 90 dB), which made the interpretation of these results complicated in terms of song features. In fact, we would have expected a much lower sensitivity to UAV noise for high-volume songs. Moreover, these cases cannot be generalised to all noisy species since the Common Blackbird has acoustic features very close to the Song Thrush (Figure 15) and was not really affected by UAV noise. However, identification of bird songs is not exclusively based on pitch and volume; musicality, trills, nasality, voice breaks, polyphony are other important criteria to take into account (Weber, 2014). Some specific song patterns were surely more distorted by the UAV noise, making the EDR species dependant. Obviously, we note that the highest ground-based EDR were mostly from loud species.
For both experts, control EDR of the Common Wood Pigeon was twice as large as the UAV one. We expected that the Common Wood Pigeon songs recorded with our UAV device would not be detected properly because of drone noise. However even the EDR from ground recordings was low compared to the other loud species, especially since low frequencies have to travel greater distances. We attribute these small EDR to the quality of the played soundtracks—Common Wood Pigeons are mistrustful and often high perched resulting in remote recordings)—and to the low cut filter on the microphone, which might make its vocalisations less perceptible.

EDR differences were also found between experts as the chi-square test suggested. For certain species, this difference was important.
Goldcrest's EDR was 3 times smaller for expert 2 than for expert 1 (expert 1 regression > 30 m; expert 2 regression < 10 m; Table 6). This gap is linked to the ability to hear the high-frequency song of this species which declines with age (Tucker et al., 2014). In fact, expert 1 is in his twenties rather than expert 2 is over 55 years old.
Playing calls or alarm calls for species like the Sedge Warbler could also be a reason of this divergence. In fact, calls are often less specific than songs and thus need advanced skills to be identified.

EDR gave us a global idea of the distance where individuals are the most likely to be detected, but not the possible maximal distances of detection. This information was provided by regressions which modelled detection probability functions on the basis of the proportion of detected and undetected recordings (Figures 20 to 27). The assumptions of all these regressions were checked in Appendix 3.
Control regression curves were all built on the basis of a 100 percent detection rate at 0 m and were mainly non-linear (power equation 3) as we predicted (Figures 20 to 23). Common Blackbird, Common Chaffinch and Song Thrush could have been detected beyond experimental distances by both experts from ground recordings (> 100 m; Figures 20 to 23).
UAV regression curves were rarely built on the basis of a 100 percent detection rate at 0 m and were mainly linear, contrary to our expectations that agreed with the theoretical law of sound attenuation in the air (Figures 24 to 27). Common Blackbird, Common Chaffinch were the only songbirds which were sometimes detected at 80 m by both experts from UAV-based recordings and could have been detected beyond this (Figures 24 & 26).

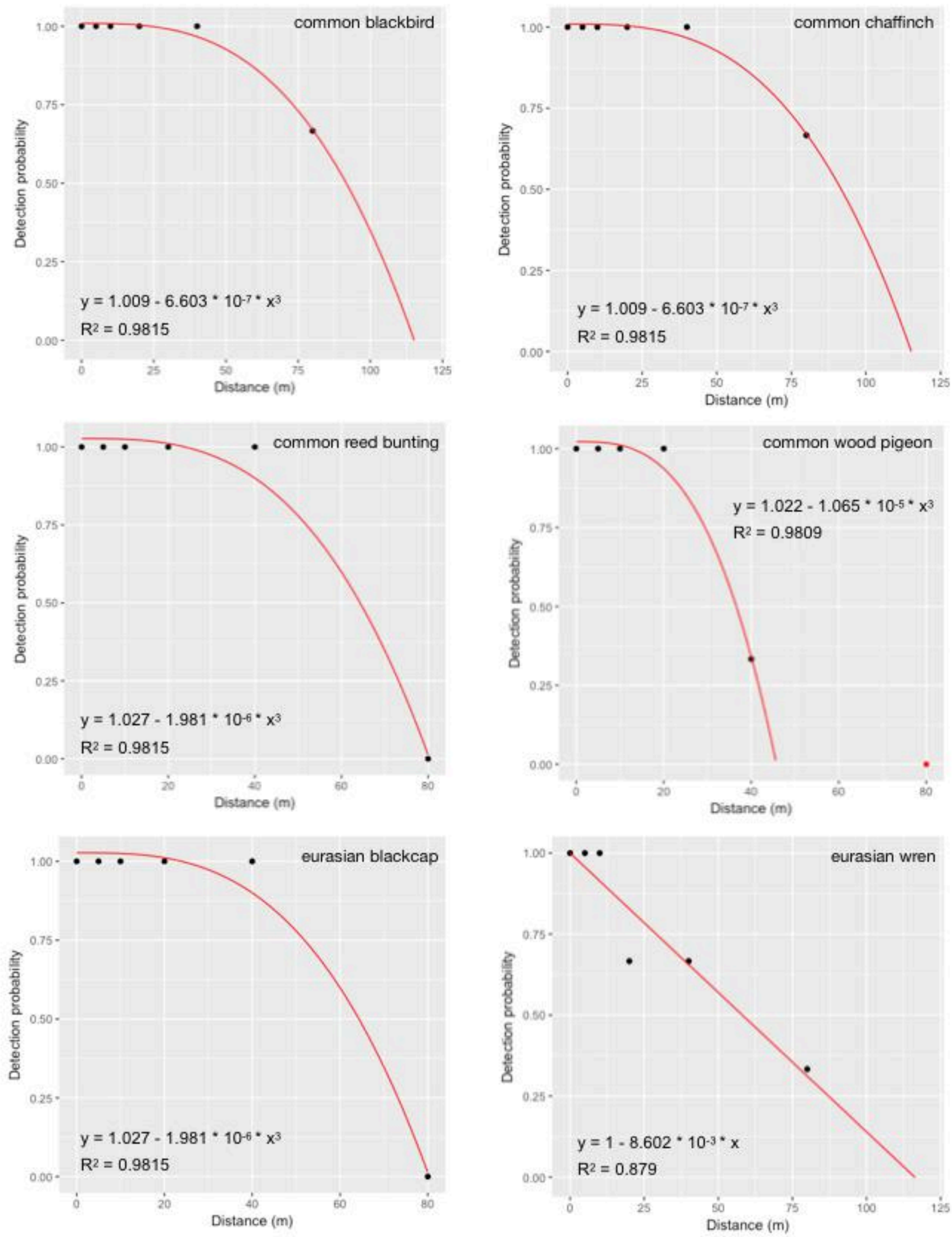

Figure 20. Detection probability functions of Common Blackbird, Common Chaffinch, Common Reed Bunting, Common Wood Pigeon, Eurasian Blackcap and Eurasian Wren for expert 1 on the basis of ground recordings (control). Red points were not used to build the regression model.

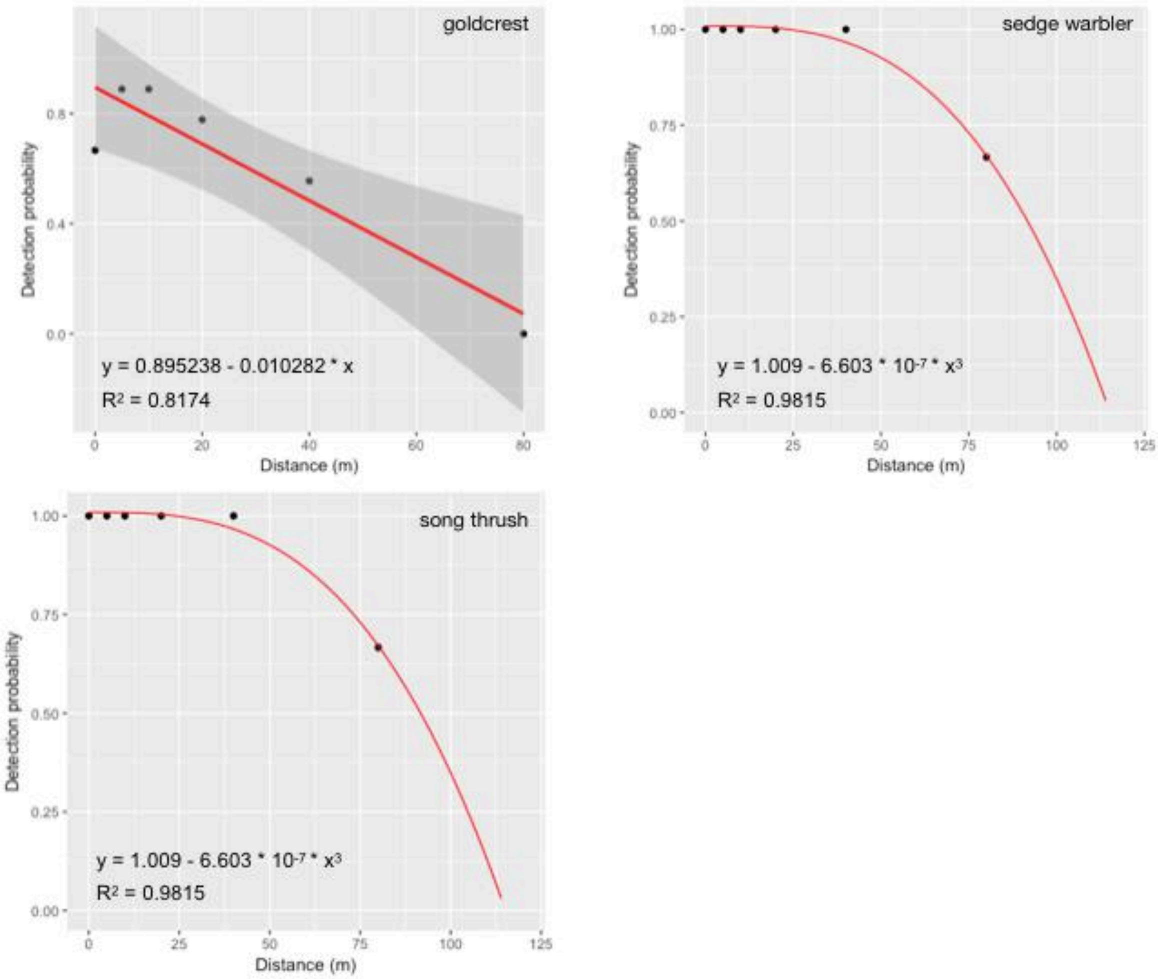

Figure 21. Detection probability functions of Goldcrest, Sedge Warbler and Song Thrush for expert 1 on the basis of ground recordings (control).

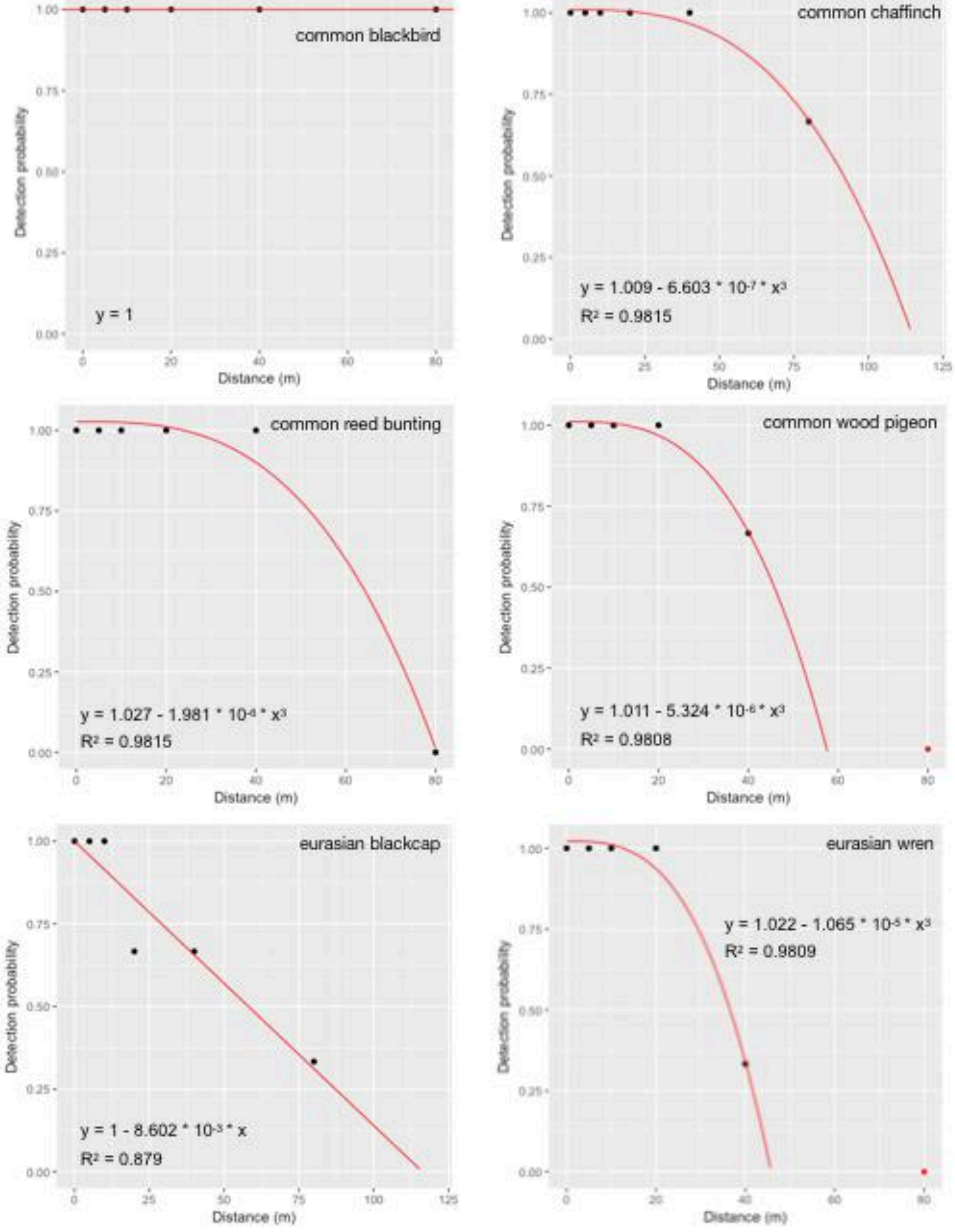

Figure 22. Detection probability functions of Common Blackbird, Common Chaffinch, Common Reed Bunting, Common Wood Pigeon, Eurasian Blackcap and Eurasian Wren for expert 2 on the basis of ground recordings (control). Red points were not used to build the regression model.

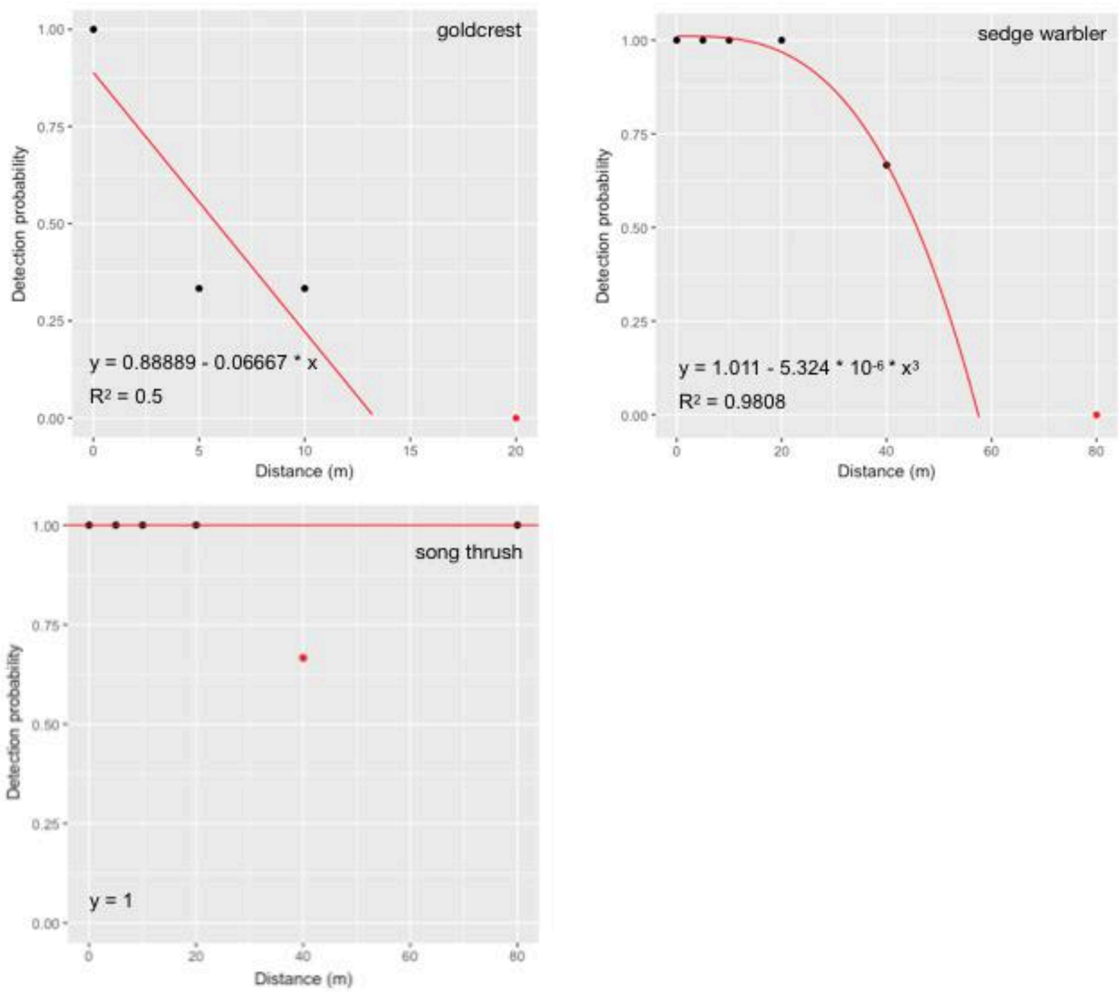

Figure 23. Detection probability functions of Goldcrest, Sedge Warbler and Song Thrush for expert 1 on the basis of ground recordings (control). Red points were not used to build the regression model.

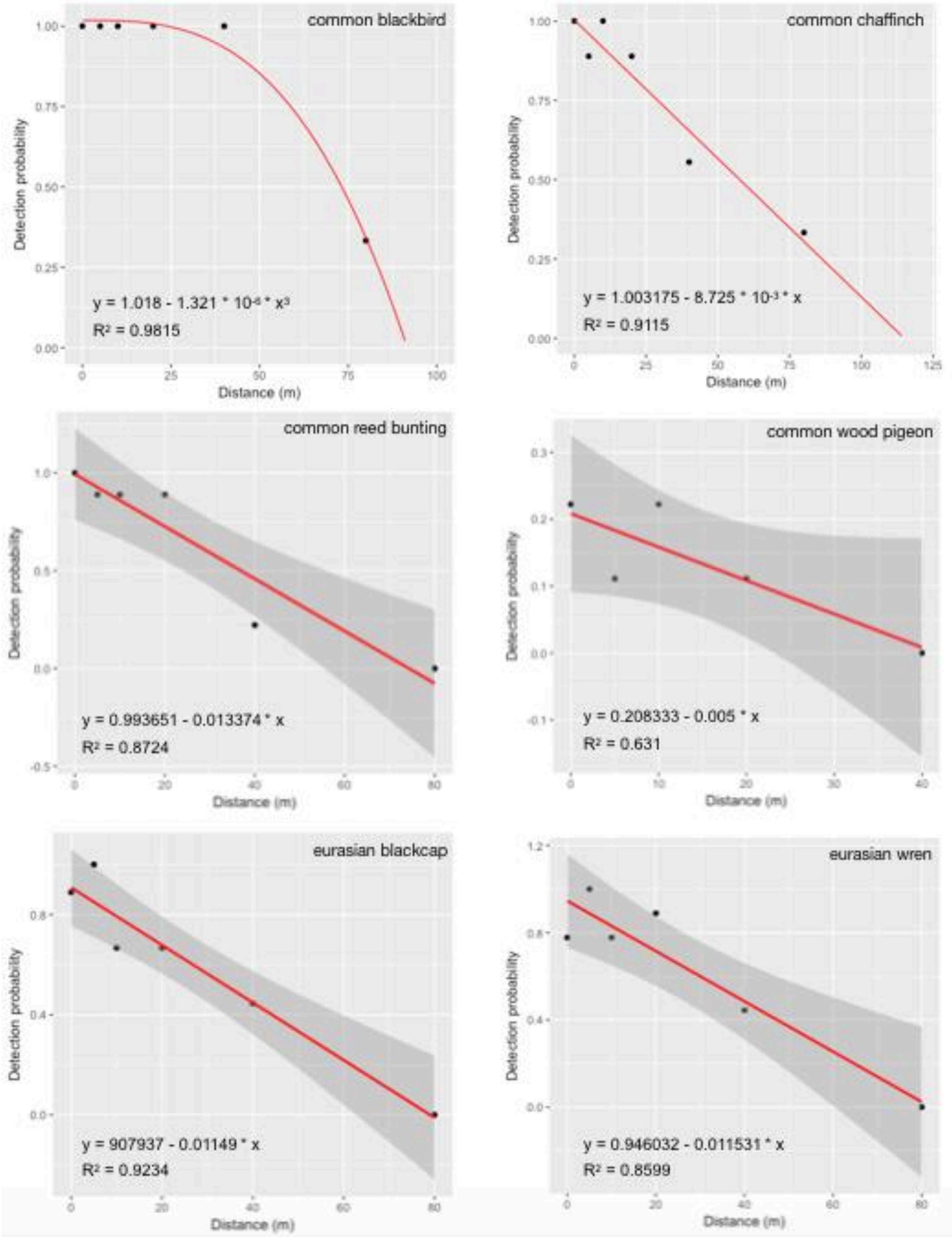

Figure 24. Detection probability functions of Common Blackbird, Common Chaffinch, Common Reed Bunting, Common Wood Pigeon, Eurasian Blackcap and Eurasian Wren for expert 1 on the basis of UAV recordings.

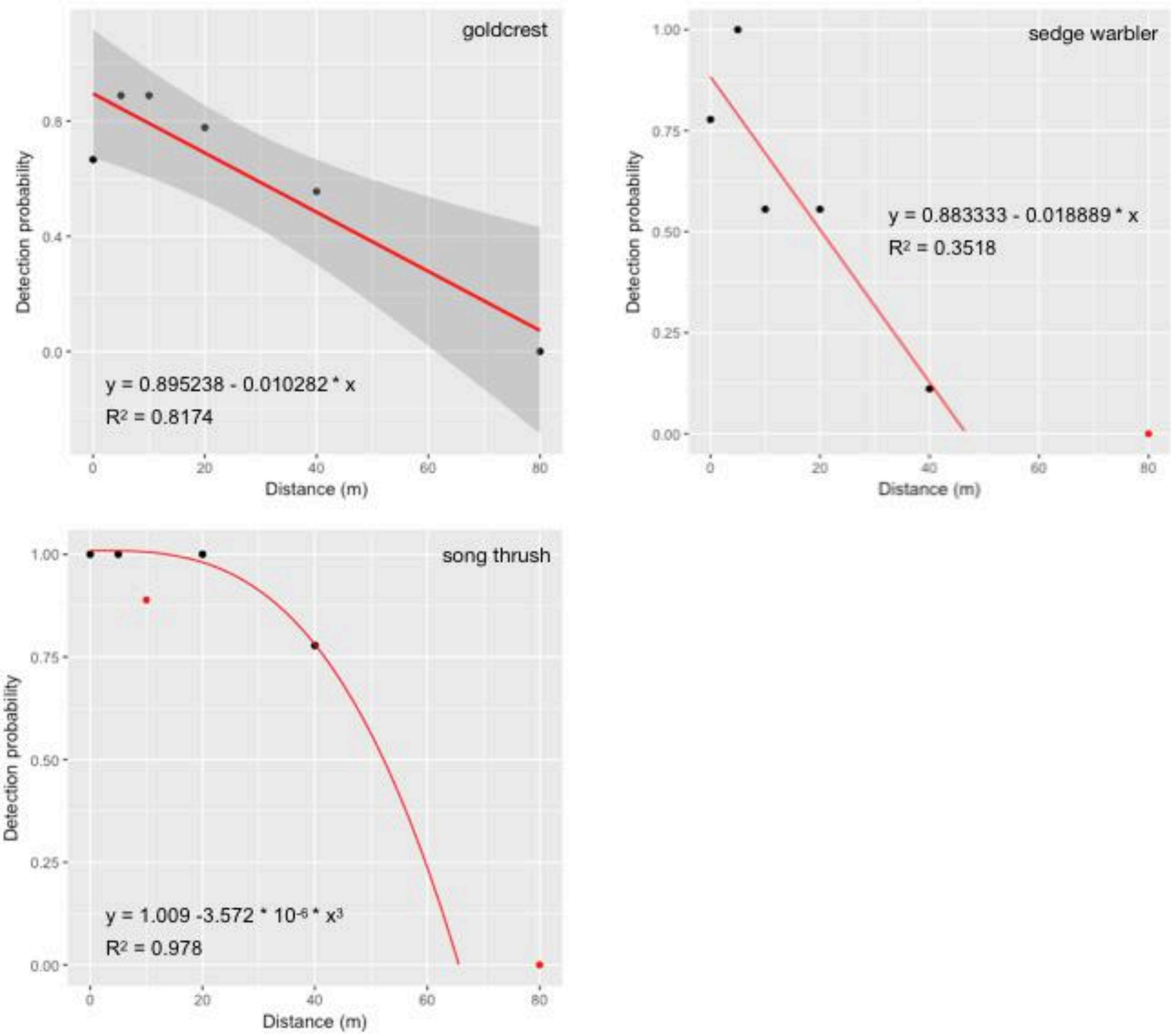

Figure 25. Detection probability functions of Goldcrest, Sedge Warbler and Song Thrush for expert 1 on the basis of UAV recordings. Red points were not used to build the regression model.

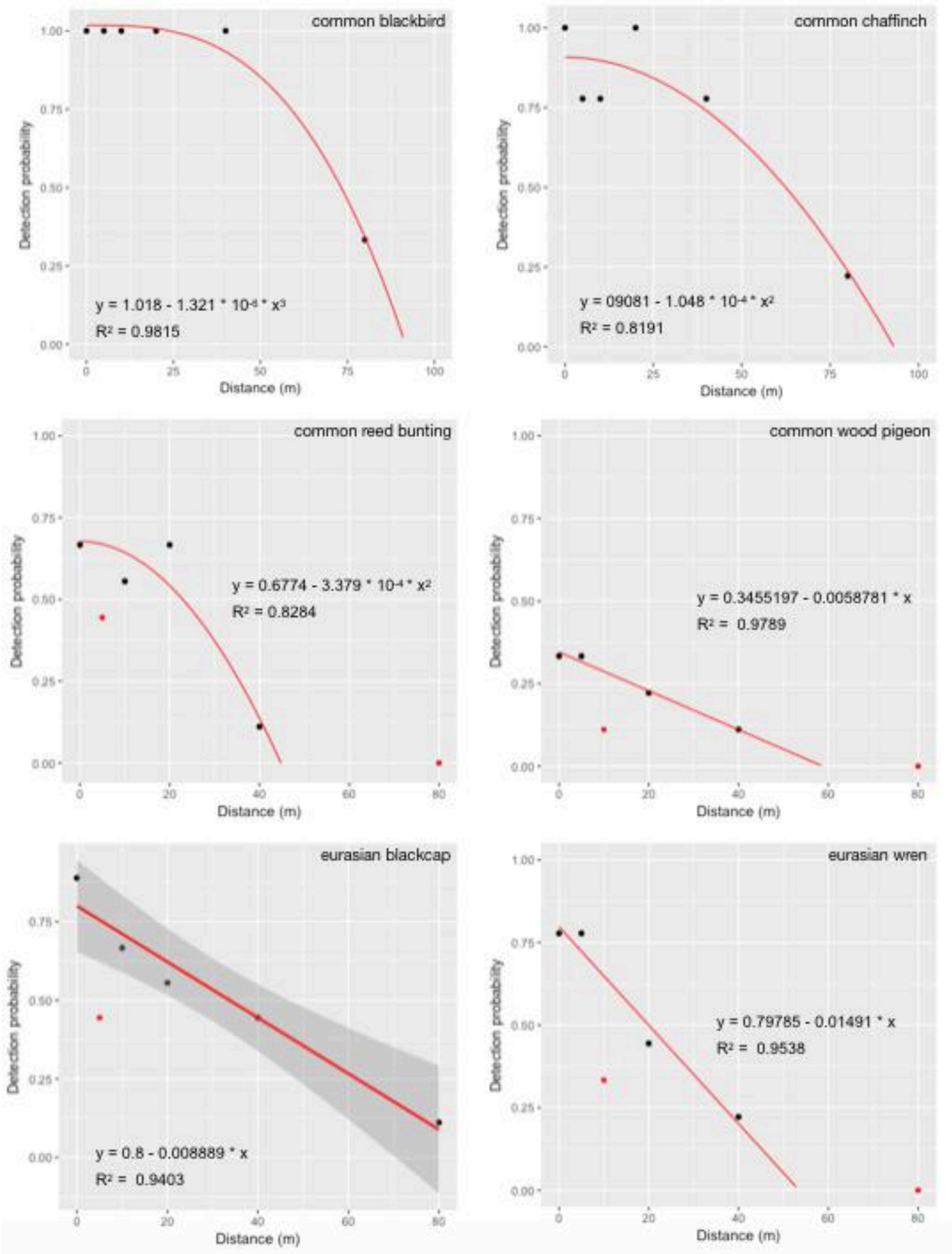

Figure 26. Detection probability functions of Common Blackbird, Common Chaffinch, Common Reed Bunting, Common Wood Pigeon, Eurasian Blackcap and Eurasian Wren for expert 2 on the basis of UAV recordings. Red points were not used to build the regression model.

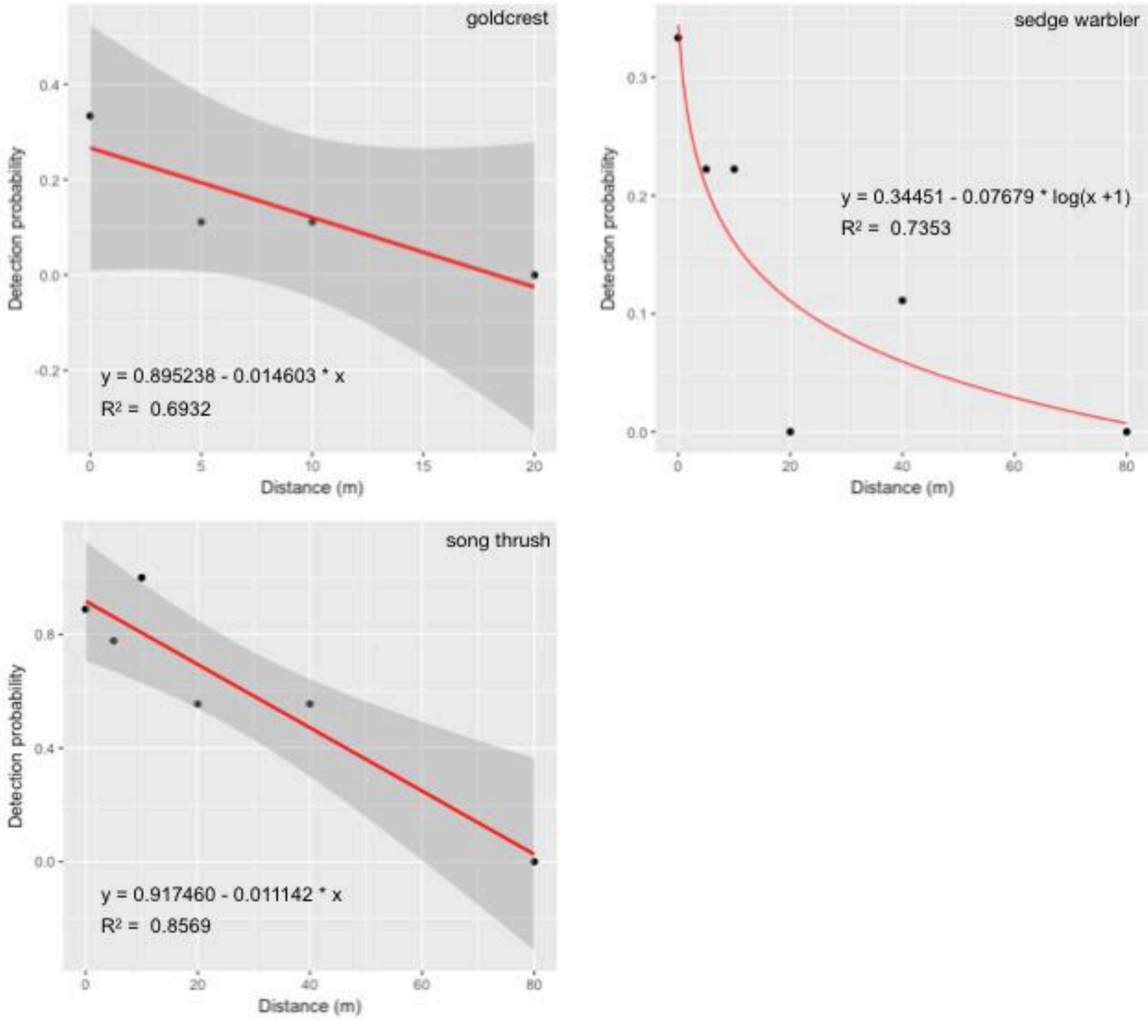

Figure 27. Detection probability functions of Goldcrest, Sedge Warbler and Song Thrush for expert 2 on the basis of UAV recordings.

To conclude, we demonstrated that detection rate and EDR of ground-based and UAV-based recordings were quite similar, nevertheless it does not necessarily mean than UAV-based recordings will detect the same number of individuals or amount of species than fieldworkers. Literature proved several times better results with bioacoustics recorders than with operators on the field (Acevedo et al., 2006; Zwart et al., 2014). However, our less sensitive recorder could show otherwise for our survey experimentations (Wilson, 2017). In fact, some bird species can be detected over 250 m during point-count surveys (Guélin, 2017).

3.2.2.3 Song features regressions

Graphic illustrations of detection probability depending on song features such as sound level, minimal, maximal and mean frequencies did not show any clear relation between these variables (Appendix 4). In fact, no trend line could be plotted. Consequently, experts were not significantly affected by song features either from of ground recordings or UAV recordings. These results justify our previous hypothesis made in section 3.2.2.1.

3.2.3 Bats

3.2.3.1 Altitude effect

Logistic regression curves showed a declining detectability (all species) for an increasing altitude, with or without the altitude 0 in the model (Figure 28). Therefore, we demonstrated that bat call detection was affected by small variations in flight altitude. This result is in conformity with the findings of the project Erebus: detection of broadcast ultrasounds at 10 m and no more at 20 m. For bats, the combination of the drone noise and the flight altitude distorted detectability.

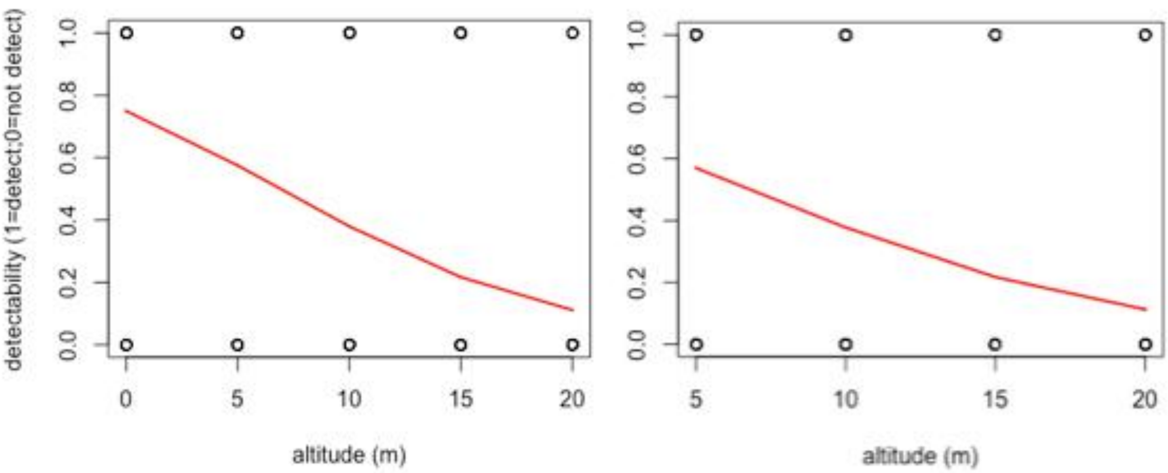

Figure 28. Logistic regression curves for the effect of altitude on overall bat species detectability. Calculated with and without blank sample altitude (= altitude 0).

Detectability depended significantly on flight altitude for all bat species, even without blank sample recordings (p-value < 0.05; Table 6). The situation remained the same for low-frequency echolocation calls (Noctule) or social calls whose propagation distance was higher. Thereby, the choice of the UAV flight altitude during monitoring will be a determining factor to detect bats effectively. For example, an effective vertical detection of less than 10 m underneath the forest canopy should be considered if the recorder is suspended just above treetops (detectability > 0.5; Figure 28). Especially since the experimental tests were carried out in open areas and the foliage may attenuate the bat calls (Martens et al., 1981).

This dependency was certainly due to the propagation properties of ultrasound but also to the orientation of the loudspeaker. Indeed, the cylindrical shape of the bird loudspeaker made the emission of bird songs more omnidirectional and therefore able to propagate better vertically. The beam width of calls transmitted by the ultrasonic speaker was much limited (horizontal emissions). Nevertheless, this hypothesis should not be interpreted as a bias of our experimental setup since sonar calls of bat can be highly directional on the field, especially when either frequency or emitter size is high (Surlykke et al., 2012; Jakobsen, 2013).

Table 6. Chi-square Tests of Independence (p-value) for difference in detection between several UAV altitudes. NA means that there was no detection at all.

		Chi-square test for altitudes 0, 5, 10, 15, 20	Chi-square test for altitudes 5, 10, 15, 20
Call type	**Bat species**	**p-value (n = 90)**	**p-value (n = 72)**
Echolocation	Barbastelle	3.398e-10 ***	NA
	Common Pipistrelle	4.427e-06 ***	0.00084 ***
	Natterer's Bat (Myotis)	3.195e-06 ***	NA (0.0005318 ***)
	Noctule	6.927e-05 ***	0.000501 ***
	Serotine	2.838e-05 ***	0.0002368 ***
Social	Common Pipistrelle	1.612e-05 ***	0.00034 ***
	Noctule	0.0001306 ***	0.00648 ***

On the basis of these observations we decided to compare statistically means of detections in response to the UAV altitudes thanks to a one-way ANOVA (Assumptions checked in Appendix 5). The idea was to make groups of altitudes for EDR calculation, keeping our blank sample altitude apart.

The ANOVA showed a significant effect of altitude on detectability (p-value < 0.05; Table 7). Detectabilities of altitudes 5 and 20 m were significantly different and it was almost true for altitudes 5 and 15 m (Table 8). Pairwise comparisons gave us thereby three distinct groups: altitude 5, altitudes 10 & 15 and altitude 20 (Table 9). Finally, we had four groups for EDR calculation by adding the blank sample altitude.

Table 7. Analysis of variance of the means of bat detections in response to UAV altitudes (without altitude 0).

	Analysis of Variance Table				
	Df	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
altitude	3	7586.1	2528.69	3.391	0.03169 *
Residuals	28	20880.1	745.72		

Table 8. Multiple comparisons of bat detectability means regarding altitude using Tukey's method.

	Multiple Comparisons of Means: Tukey Contrasts			
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
10 - 5 = 0	-11.81	13.65	-0.865	0.8226
15 - 5 = 0	-33.33	13.65	-2.441	0.0923 .
20 - 5 = 0	-37.48	13.65	-2.745	0.0483 *
15 - 10 = 0	-21.51	13.65	-1.576	0.4083
20 - 10 =0	-25.66	13.65	-1.879	0.2595
20 - 15 = 0	-4.15	13.65	-0.304	0.9900

Table 9. Groups of altitude with the same bat detection rate, determined by the comparison of means.

Altitude	Group
5	b
10	ab
15	ab
20	a

3.2.3.2 Effective Detection Radius

We also found important differences for bats between our two EDR calculation methods (Table 10), hence we decided to focus on regressions to interpret EDR for the same reasons as discussed in section 3.2.2.2.

We note that overall EDR were strongly lower for UAV-based recordings than ground-based recordings. Globally, EDR was halved between altitude 0 and altitude 5, except for the Serotine whose EDR only declined from 18.3 to 17.3 m (Table 10). This drop is even more marked at higher altitudes. The Barbastelle (as we have anticipated, see section 3.2.1) and the Natterer's bat were no longer identifiable when the drone was recording at any flight altitude. The latter was still effectively detectable as *Myotis* species but only up to 5 metres high. In fact, steep FM which are characteristic of the genus were still observable, but very high frequencies were quickly and strongly attenuated, thereby reducing the very wide bandwidth typical of *Myotis nattereri*.

Social calls were effectively detected at further distances than echolocation calls, with or without using the drone: +5.4 m for the Noctule and +22.5 m for the Common Pipistrelle at ground level (altitude 0; Table 10). We demonstrated thus that low-frequency ultrasonic signals, like Noctule's echolocation and social calls, or Common Pipistrelle social calls had a greater detection range than high-frequency ultrasonic signals.

In general, EDR were smaller than expected. As an illustration, calls of Noctule can bring to nearly 150 m (Laurent, 2009) but our maximum EDR for this species was only around 35-40 m (altitude 0; Table 10). We could not expect to detect its echolocation calls over 45 m (Figure 29). Another example is the Common Pipistrelle echolocation calls which were recorded at 10-15 m from UAV device during the project Erebus tests. For our experimental tests, they were detected within this range without using the drone (Figure 30), but when we hoovered the quadcopter at the lowest altitude (5 m), EDR was 2.5 m (Table 10) and maximum detection distance was 5 m (Figure 30).
Consequently, we made the hypothesis that our EDR were underestimated. First of all, our experimentations were biased by the speaker power which limited call intensity. Transmitted soundtracks never exceeded a sound level of 100 dB at 10 cm, thus limiting the effective detection radius of certain loud species such as the Noctule. Nevertheless, we did not have a specific sound level for each species and therefore we cannot affirm that species emitting weak calls, such as the Natterer's bat, were subjected to an EDR underestimation.

Table 10. Comparison of manual detection percentage, semi-automatic detection efficiency and EDR for bats, between altitudes. Semi-automatic efficiency corresponds to false noise within manual detection classified as noise by Kaleidoscope Viewer software. EDR values with a star could not be calculated by regression. They correspond thus to the furthest distance with the highest probability of detection. EDR were not calculated for manual detection under 15%. We attributed a slash to EDR for which there were not enough detections to calculate them.

		Altitude 0m (Control)			
Call type	**Bat species**	**Manual detection (%)**	**Semi-automatic efficiency (%)**	**EDR Distance Sampling (m)**	**EDR Regression (m)**
Echolocation	Barbastelle	61.1	36.4	4.8	9.3
	Common Pipistrelle	61.1	9.1	4.8	9.3
	Natterer's Bat (Myotis)	60.0 (66.7)	0.0 (16.7)	4.2 (6.9)	5.0 (16.0)
	Noctule	88.9	0.0	13.6	34.6
	Serotine	72.2	23.1	7.3	18.3
Social	Common Pipistrelle	77.8	14.3	13.6	31.8
	Noctule	100.0	5.6	14.7	40.0

		Altitude 5m			
Call type	**Bat species**	**Manual detection (%)**	**Semi-automatic efficiency (%)**	**EDR Distance Sampling (m)**	**EDR Regression (m)**
Echolocation	Barbastelle	0.0	/	/	/
	Common Pipistrelle	38.9	85.7	3.8	2.5*
	Natterer's Bat (Myotis)	0.0 (44.4)	/ (75.0)	/ (4.6)	/ (5*)
	Noctule	83.3	40.0	7.7	19.8
	Serotine	66.7	75.0	6.9	16.0
Social	Common Pipistrelle	72.2	61.5	7.1	17.3
	Noctule	83.3	26.7	7.7	19.8

		Altitudes 10 & 15m			
Call type	**Bat species**	**Manual detection (%)**	**Semi-automatic efficiency (%)**	**EDR Distance Sampling (m)**	**EDR Regression (m)**
Echolocation	Barbastelle	0.0	/	/	/
	Common Pipistrelle	5.6	100.0	/	/
	Natterer's Bat (Myotis)	0.0 (11.1)	/ (100.0)	/	/
	Noctule	63.9	82.6	7.3	16.8
	Serotine	33.3	100.0	8.1	10*
Social	Common Pipistrelle	27.8	90.0	6.6	5*
	Noctule	66.7	83.3	7.2	5*

		Altitude 20m			
Call type	**Bat species**	**Manual detection (%)**	**Semi-automatic efficiency (%)**	**EDR Distance Sampling (m)**	**EDR Regression (m)**
Echolocation	Barbastelle	0.0	/	/	/
	Common Pipistrelle	0.0	/	/	/
	Natterer's Bat (Myotis)	0.0 (0.0)	/	/	/
	Noctule	27.8	100.0	6.5	5*
	Serotine	5.6	100.0	/	/
Social	Common Pipistrelle	16.7	100.0	/	10*
	Noctule	38.9	100.0	7.0	10*

Secondly, trials were conducted during the daytime to avoid real bat interferences. “Daytime vertical temperature profiles typically create refractive regimes that impose more severe limits on maximum range of detection” (Fristrup, 2009). Moreover, the relative humidity in the air is also higher at night and as sound attenuation decreases when moisture increases, sounds propagate further and faster during nighttime (Van Damme, 2014).
It should therefore be appropriated to retry the same tests with a more powerful speaker, measurement and adjustment of call sound levels in conjunction with reality and even higher quality soundtracks (as sound level is directly dependent to soundtrack quality) to confirm this underestimation assumption.

Manual detection percentages illustrated the effect of altitude on detectability: call detection was over 60% at ground level and dramatically fell between 0 to 38.9% at 20 metres high (Table 10). Altitude also affected the ability of our bat call analysis software to detect calls properly. Indeed, the software assigned a false noise classification from 0 to 36.4% of manual detections according to species, with the recordings from ground level, and thus was efficient (Table 10). However, it already assigned a false noise classification from 26.7 to 85.7% of manual detections according to species, with the five-metre high UAV recordings, and thus was not efficient anymore (Table 10). These percentages still increased when the altitude increased: no more calls were detected semi-automatously at 20 metres.
Such results mean that the aptitude of UAV noise to drown out bat signals was significant for our bat call analysis software. This efficiency assessment is a real issue to consider UAV-based bioacoustic monitoring for bats because manual analysis of a large number of recordings is extremely time-consuming since bats emit several calls per second. Thereby the requirement to analyse data entirely manually is a very limiting factor of this new technique.

Regression curves of detection probability depending on distance—whose assumptions of were checked in Appendix 6—were all non-linear (power equation 2 or 3) but rarely built on the basis of a 100 percent detection rate at 0 m for UAV-based recordings (Figures 29 to 33). This was probably due to the directionality of the ultrasound transmitted by the speaker (cone shape) combined with to sound level which made better detection rates at small distances over 0 m (2.5 and 5 m). Indeed, a certain distance was needed for the acoustic signals to reach the microphone efficiently overhead. The ground-based recordings were obviously not affected by this phenomenon because for any horizontal distance the microphone was always in the trajectory of the transmitted signal.

Finally, our EDR results highlighted deficiencies and pitfalls of bat UAV-based recordings like the restricted detection range, the sensitivity to call frequencies, the inability to detect all species like the Barbastelle and the inefficiency of bat call analysis softwares. However, it still does not totally reject the use of this technique because the difference between UAV-based and ground-based recordings was due to the combination of the drone noise and the altitude difference. In fact, we did not compare recordings with and without drone use at the same vertical distance from the speaker. It could therefore be possible that UAV device detect more individuals than ground recorder for some high-flying species. The tests under real conditions will allow us to answer this question.

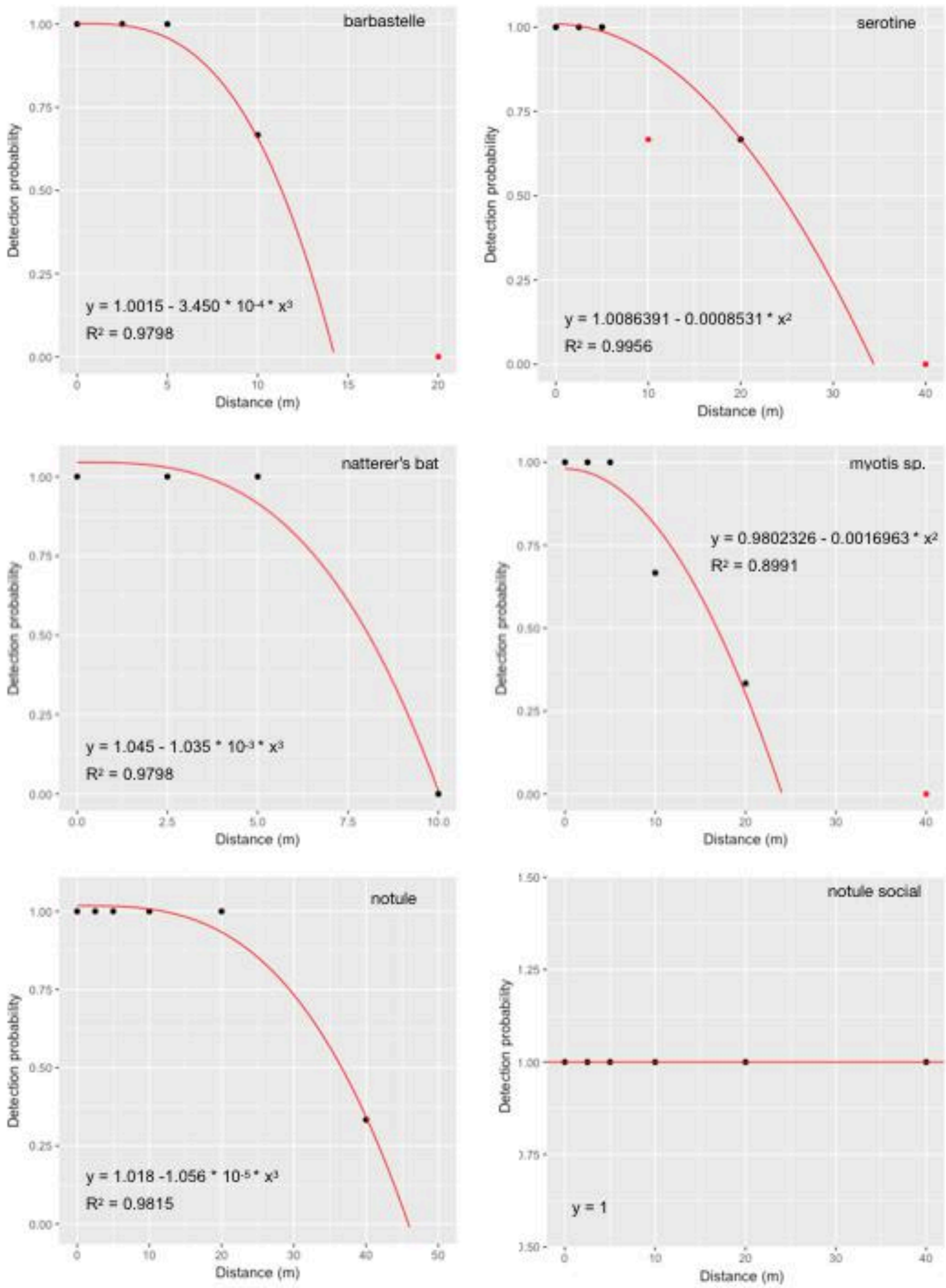

Figure 29. Detection probability functions of Barbastelle, Serotine, Natterer's bat, Myotis sp. and Noctule (echolocation & social calls) on the basis of ground recordings (altitude 0). Red points were not used to build the regression model.

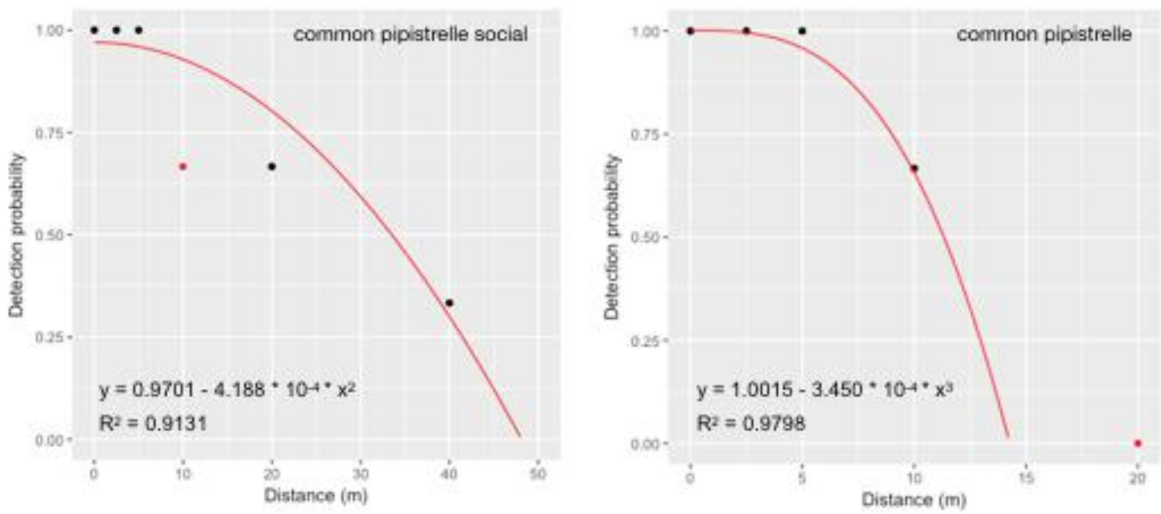

Figure 30. Detection probability functions of Common Pipistrelle (echolocation & social calls) on the basis of ground recordings (altitude 0). Red points were not used to build the regression model.

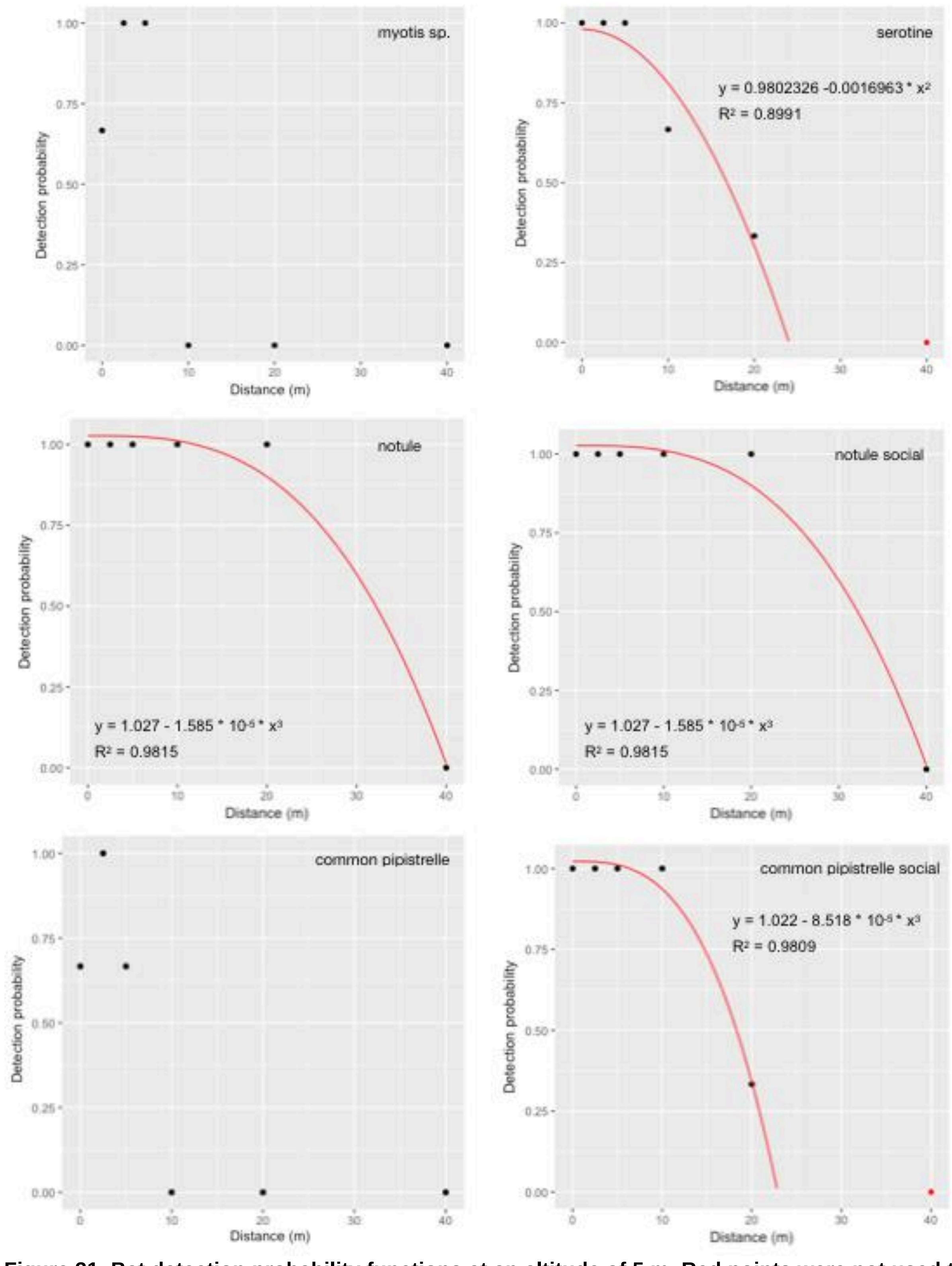

Figure 31. Bat detection probability functions at an altitude of 5 m. Red points were not used to build the regression model. Species not included were never detected.

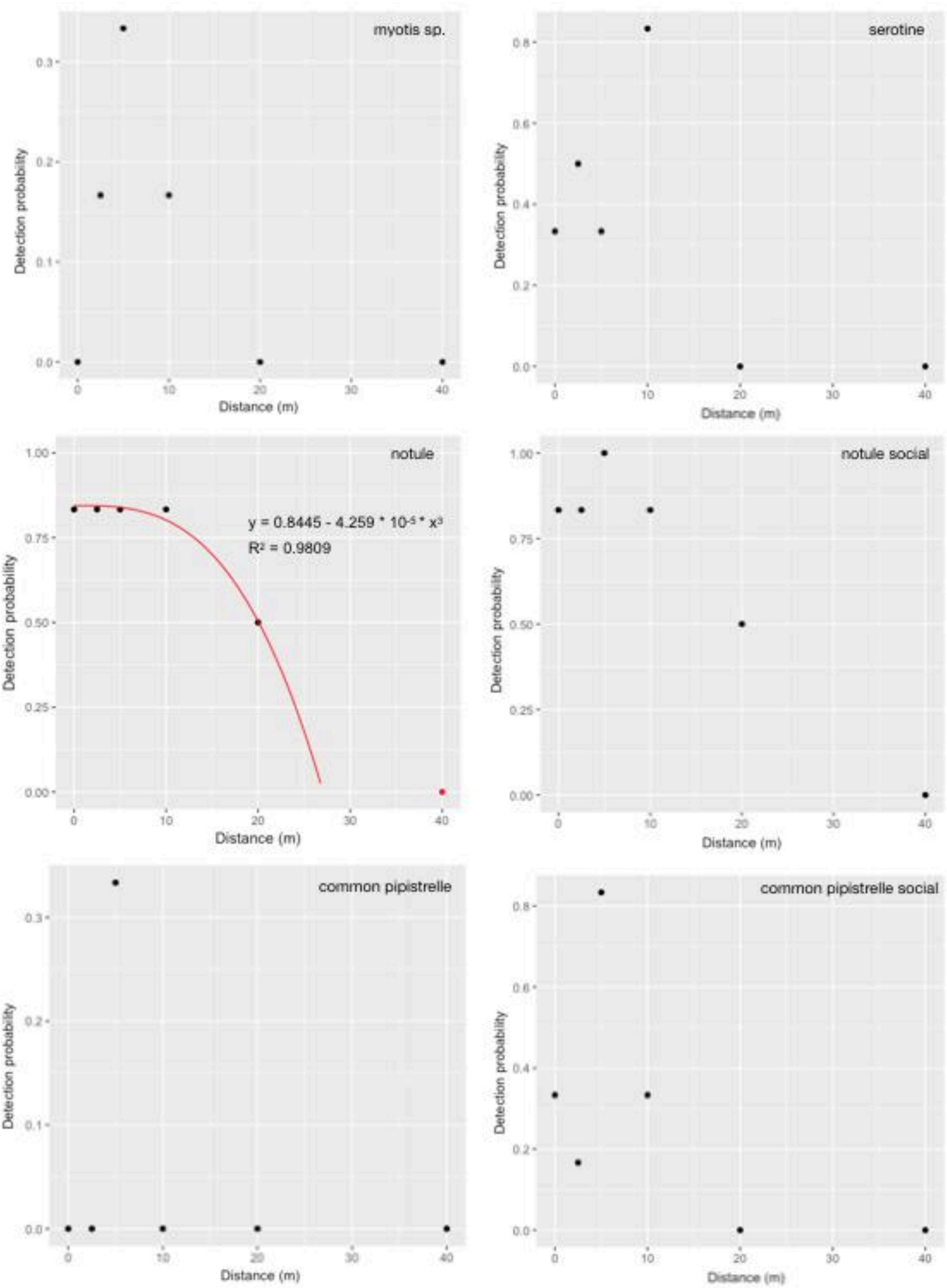

Figure 32. Bat detection probability functions at altitudes of 10 and 15 m. Red points were not used to build the regression model. Species not included were never detected.

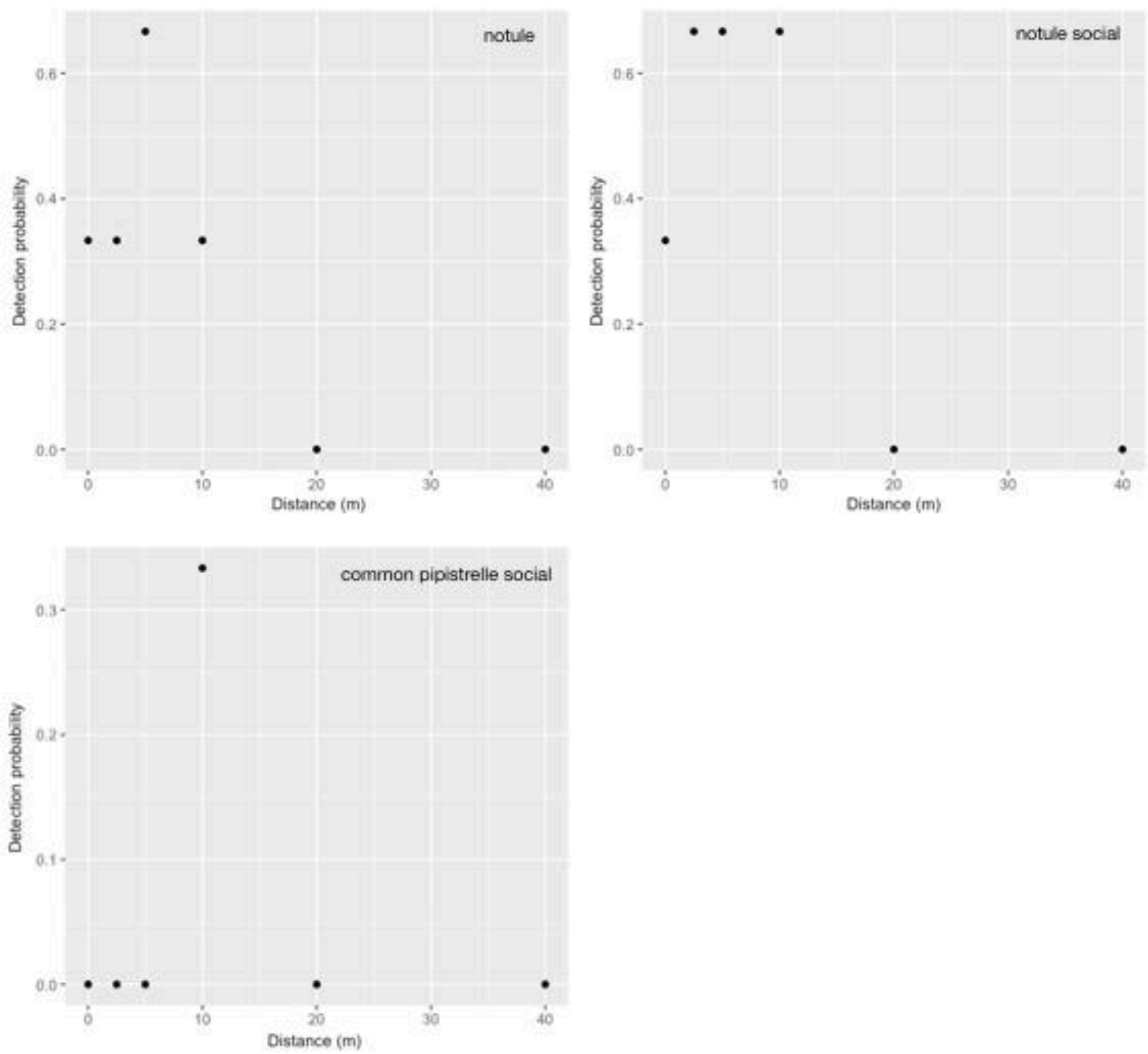

Figure 33. Bat detection probability functions at an altitude of 20 m.

3.2.3.3 Song feature regressions

We previously found that low-frequency signals like social calls were better detected. However, graphs of detection probability depending on song features such as minimal, maximal, mean and peak frequencies did not show any clear relation between these variables (Appendix 7). Indeed, no regression model could be built. Nevertheless, we observed a greater tendency of high detection probabilities to coincide with lower frequency parameters (min, max, mean and peak) for an altitude higher than 10 metres. Thus, frequency features in combination with altitude had an effect on detectability even if it could not be modelled.

3.3 Tests under real conditions

3.3.1 Birds

A total of 39 bird species were identified during our field session: ACNI, ACSC, AECA, ALAE, ALAR, ANPL, APAP, BUBU, CACA, COCO, COMO, COOE, COPA, DEMA, EMCI, ERRU, FATI, FRCO, FUAT, GACH, GAGL, HIRU, MOAL, PACA, PAMA, PHCO, PHYCO, PIPI, POCR, POPA, PRMO, SIEU, STST, SYAT, SYBO, SYCO, SYCU, TRTR, TUME.
All of them were detected on standard point counts (26 in open areas, 26 in wooded areas), but only 12 species were detected on UAV point counts (7 in open areas, 9 in wooded areas).

Visual detections were also taken into account during standard point counts, thus some species escaped from the UAV census. For instance, raptors (BUBU, FATI) were detected only visually but this cannot be seen on the graphs in Figures 34 & 35 as their observation was rather rare making their average number per point very low. One of the reasons for the three times lower total specific richness for UAV-based monitoring is therefore the absence of visual detection for the latter. However, in terms of abundance for the most detected species, the means of audial detections and all detections (audial & visual) per point did not really differ (Figures 34 and 35). In fact, we only observed a difference for certain species such as the Common Wood Pigeon (COPA) or the Skylark (ALAE) whose abundance were increased by visual detections (flying flocks).
The difference in overall effectiveness of the two counting methods can be seen in Figure 34, i.e. it gives an efficiency trend rather than an exact comparison since the UAV and birdwatcher data were not collected at the same time (at least 5-minute interval). As a reminder, performing standard point counts sometimes before and sometimes after the UAV point counts allowed to take into account and to counterbalance the potential escape effects resulting from the operating procedure of two techniques. Then, figure 35 makes a comparison of the two techniques at the same time with a common UAV noise bias, thus the specific richness and abundance are supposed to be identical (points on the equivalency line), at least for audial detections, whether the two approaches are equivalent. We found an overall tendency of UAV point counts to underestimate all species abundance, especially for very common species like the Eurasian Wren (TRTR), the Common Chaffinch (FRCO) and the Eurasian Blackcap (SYAT) (Chart B; Figures 34). These underestimations were less important for the exact comparison (Figure 35). The Carrion Crow (COCO), the Common Pheasant (PHCO) and the Western Jackdaw (COMO) were even better detected with the drone recordings than by the field operator (audial detection only) (Chart B; Figure 35). However, it cannot be concluded that these species will be better detected by drones than by birdwatchers without the presence of the UAV since the real detection ability of our field operator was impaired by the sound of the quadcopter hovering overhead. If it was the case, charts A would show higher means of detections for these species per UAV point than per standard point.
Since altitude had no effect on detectability, the higher mean detections per standard point count on charts B are explained primarily by a smaller impact of drone noise (i.e. masking capability of bird songs) on the operator's detection ability in the field than on his detection ability when listening to recordings, except for low-frequency songs (e.g. COMO, COCO). Secondly, the operator's audibility distance in the field had a greater range than the recording distance.

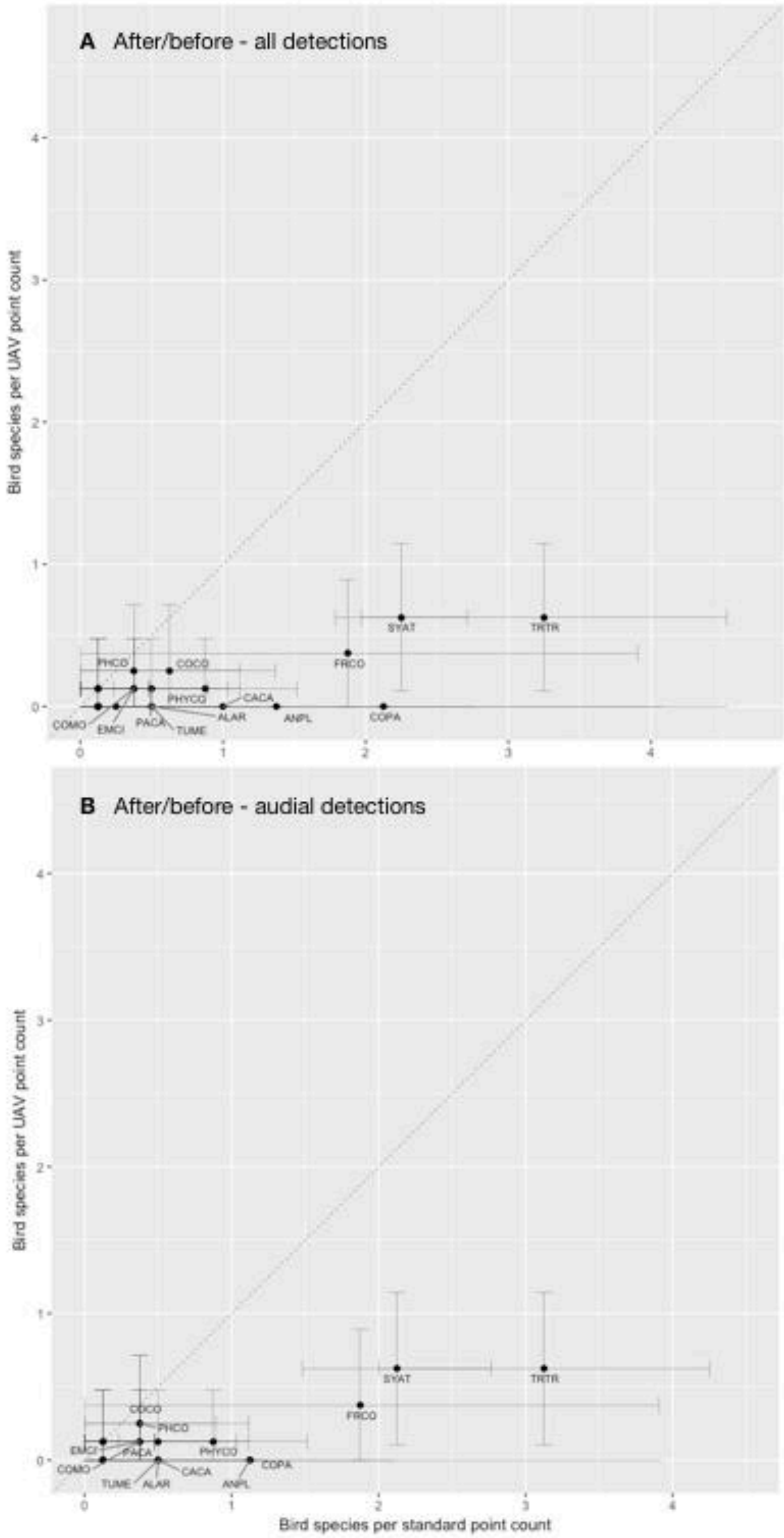

Figure 34. Species mean detections per point for UAV and standard point counts plotted against an equivalency line. "After/before" modality: standard point counts conducted just after or before the UAV ones. (A) Audial & visual detections; (B) Audial detections.

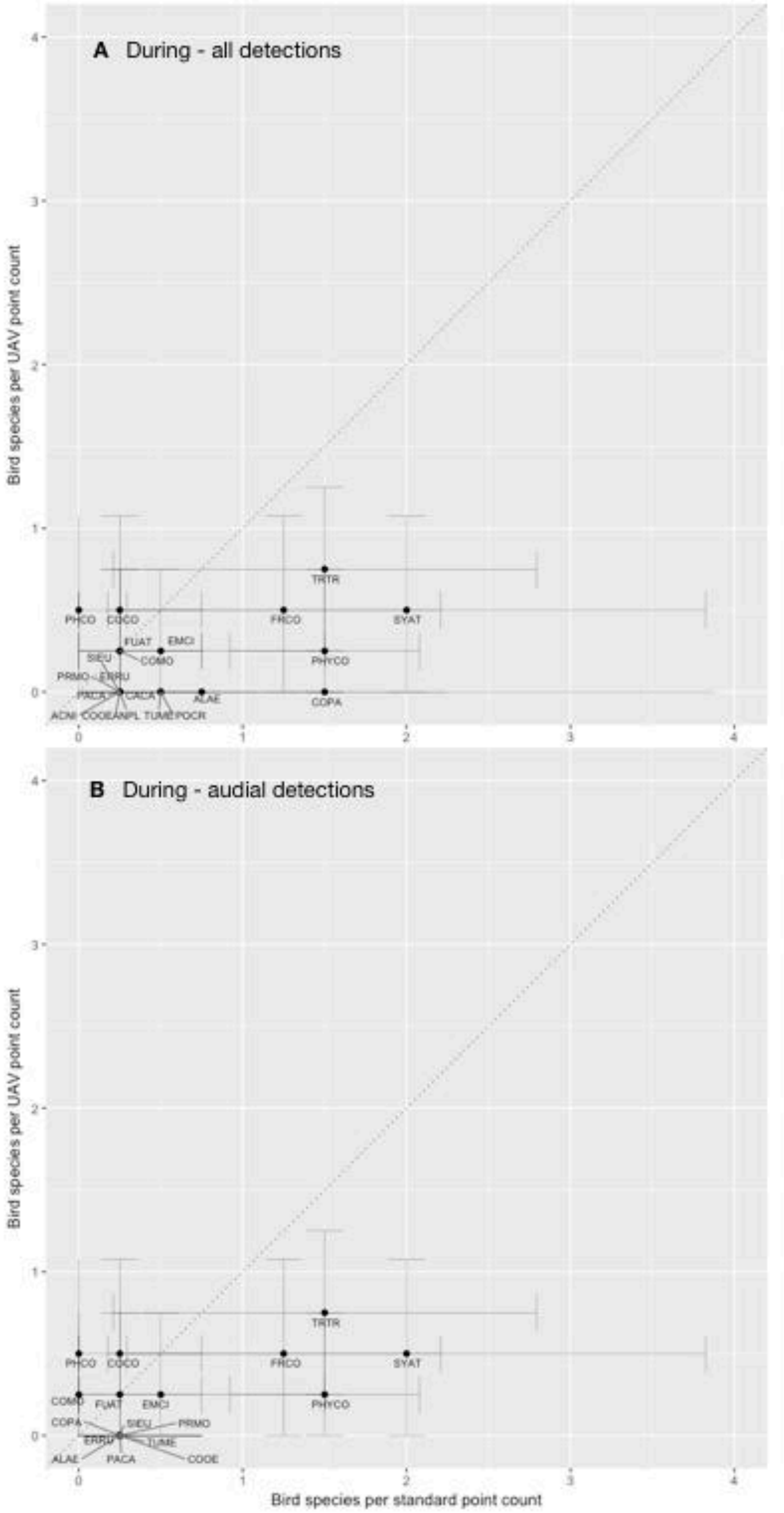

Figure 35. Species mean detections per point for UAV and standard point counts plotted against an equivalency line. "During" modality: standard point counts conducted at the same time as UAV ones. (A) Audial & visual detections; (B) Audial detections.

Means of species richness (number of species) and of abundance (number of individuals regardless the species) per point, considering only audial detections, were always lower for UAV-based monitoring than for traditional monitoring (Table 11).
Paired t-tests for difference between these means gave p-values of respectively 0.0003 and 0.0001 for species richness and abundance of “after/before” modality. The ones of the “during” modality were respectively 0.039 and 0.0039. Thus, neither species richness nor abundance were equal from a statistical point of view, confirming the lower performances of UAV-based method for our study area.

Table 11. Comparison of species richness (number of species) and abundance (number of individuals) per point count between standard and UAV methods. Standard method only included audial detection.

		Species richness per point		Abundance per point	
Point-count method	**Period**	**Mean**	**SE**	**Mean**	**SE**
Standard (audial detection)	Before/After	9.4	3.0	15.6	5.9
	During	3.0	3.3	4.6	5.3
UAV	Before/After	3.0	1.9	3.0	1.9
	During	1.9	2.4	1.9	2.4

To conclude, these results did not claim to advocate or exclude the use of UAVs for acoustic bird surveys on the basis of powerful statistical tests, in view of the small number of stations carried out. The aim was to give a first glimpse of UAV potential for this kind of monitoring and thus further field tests should be undertaken. Despite this, we highlighted some deficiencies of this new approach in comparison to traditional techniques.
Losses of information and accuracy are the main problems and are caused by the absence of visual detections, a low-quality soundscape and a limited scope of the microphone. The latter two factors, which are due to drone noise and microphone sensitivity, prevent to locate and identify each individual properly. In fact, multidirectional audible perspective delivered by stereophonic recordings is not comparable with the human ear's perception of the soundscape directly in the field (except for high quality recorders). Thus abundance may be wrong, especially when individuals of a same species are found in high densities (Wilson, 2017).
With our equipment, species richness and abundance were underestimated. Fortunately, it is possible to improve soundscape quality and recorder range, and consequently bird detections, using a quieter quadcopter like the new DJ Phantom 4 PRO V2.0 whose noise reduction is about 4 dB[6] and a more sensitive (but heavier) recorder like the ZOOM H5 Handy Recorder[7].

[6] https://www.dji.com/phantom-4-pro-v2
[7] https://www.zoom-na.com/products/field-video-recording/field-recording/zoom-h5-handy-recorder

3.3.2 Bats

Almost all of the individuals detected were Common Pipistrelles. We had mostly echolocation calls but some social calls were recorded too. We also caught a few *Myotis* calls (probably *Myotis daubentonii*).
All bat signals detected by both devices (UAV and ground) were better detected qualitatively by the ground recorder than by the UAV-based recorder. A representative sample of spectrograms which shows the quality of the recorded bat calls for each modality is given in figures 36 to 39. We notice that for UAV recordings the noises of the drone reduced the visibility of Common Pipistrelle's signals because of their intensity which lessened the size of the pulses and not by overlapping. This was perhaps amplified by bat flights further away from the drone recorder than from the ground recorder. The ESC interference bands can also be observed around 35 kHz on UAV spectrograms, distorting the ability to identify the species.
Quantitatively, one 10-second bat call recording out of 116 was detected by the drone device and not by the ground recorder (Table 12, Figure 36). Table 12 details the different detection percentages of each recorder and shared by the two recorders according to the two habitat and altitude modes. Total percentages of detections shared by the two recorders were 44.4 or 52.5% depending on the kind of environment. The UAV detected 0% of additional bat signals for the pond and 5.6% for the forest, therefore the percentage of exclusive ground detections was 50.0% for the pond and 47.5% for the forest.

There was no tendency for the drone to detect more signals than the recorder at ground level, even for the highest flight altitude (23 m). For example, ninety percent of the detections were shared by both recorders with no additional detection for the UAV recorder at 13 m at the pond station whereas shared detections were 15% with still no additional detection for the UAV recorder at 23 m (Table 12). We can therefore imagine that for our recording session, bats tended to fly close to the ground because their calls were all detected by the ground recorder, with the exception of one recording. A bat flying at an altitude of more than 20 metres would certainly have escaped the ground detector range when it would probably have been properly recorded by the microphone suspended at an altitude of 23 metres. However, it is also possible that some individuals flew higher than 23 metres, thus above the microphone of the drone. They may have escaped the recorder detection range because the vertical distance to the ground recorder would have been too important and the downward orientation plus the insulation of the drone microphone would have prevented its calls from being detected.
Our controlled condition tests showed a decrease in detectability with increasing altitude. For instance, the analysis software hardly detected any signals above 5 metres. The high percentage of detections shared by the two detectors for the flights at 13 metres near the pond (90%) showed that 10 metres (i.e. distance between the two microphones) was the maximum vertical detection distance of the UAV microphone.
We can therefore conclude that the bats detected for the 23-metre altitude modality were flying at an altitude of about 15 metres.

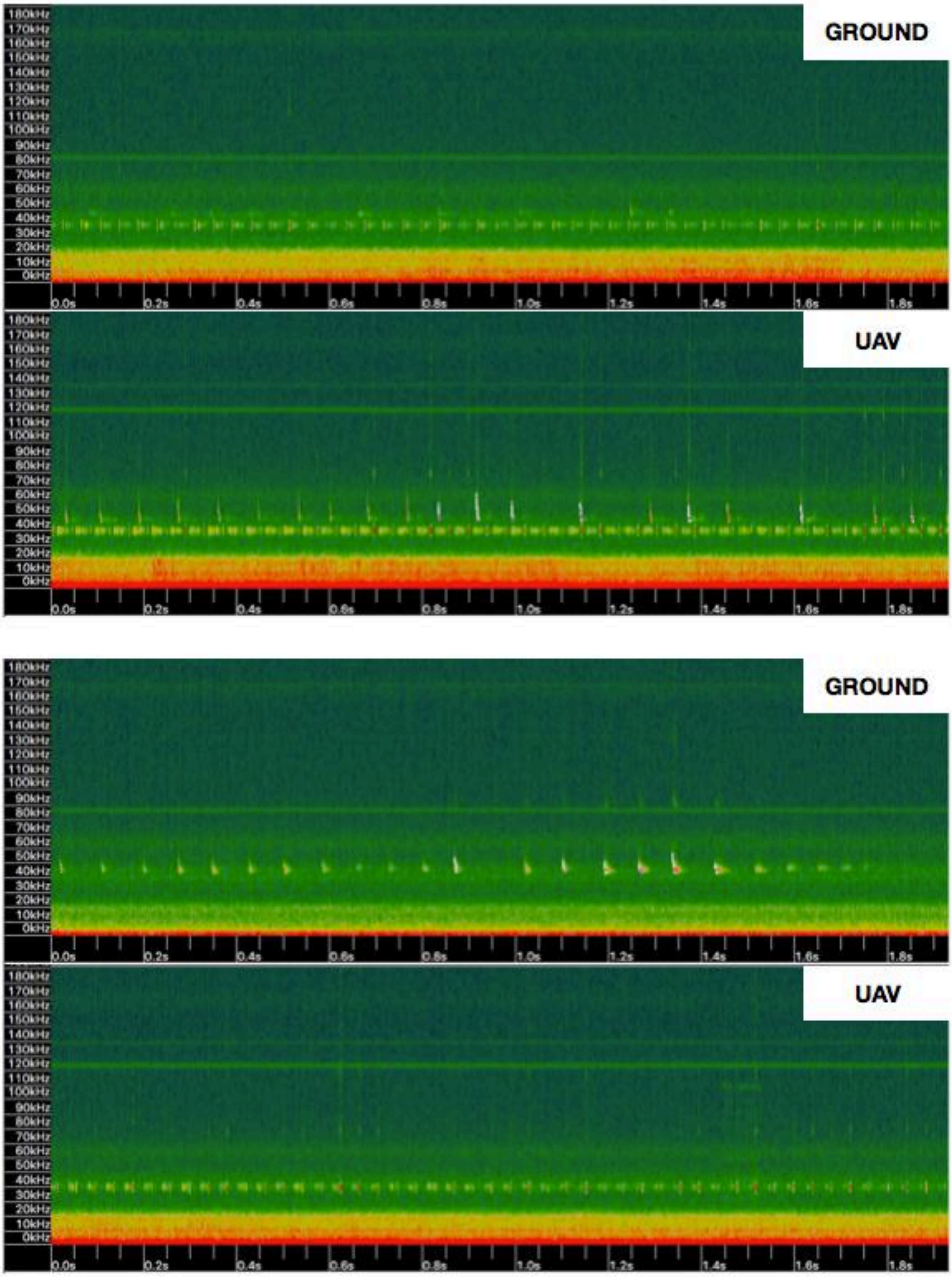

Figure 36. Examples of bat calls spectrograms obtained at the same time by the ground recorder and the UAV recorder hoovering at 13 m in the forest.

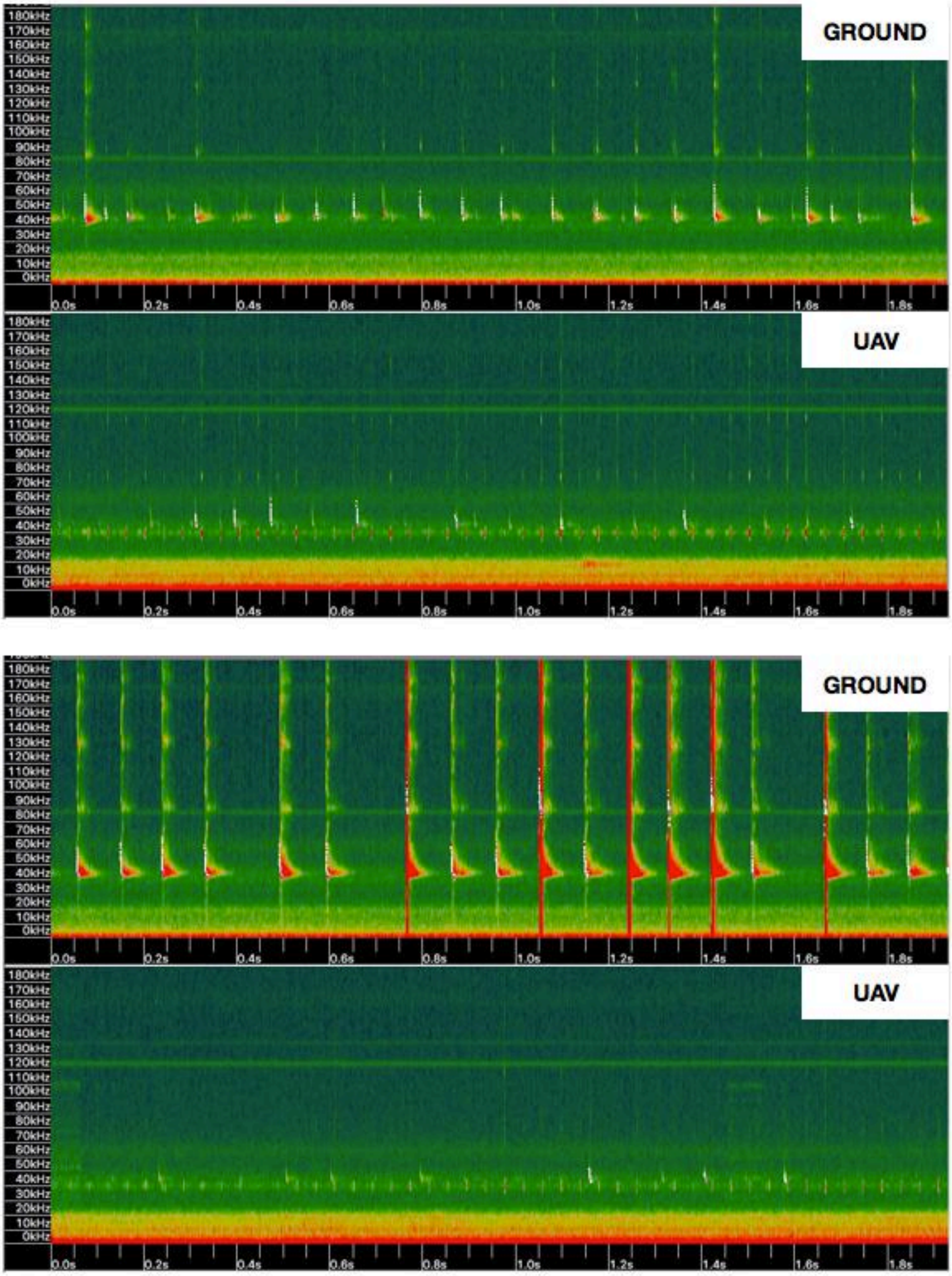

Figure 37. Examples of bat calls spectrograms obtained at the same time by the ground recorder and the UAV recorder hoovering at 23 m in the forest.

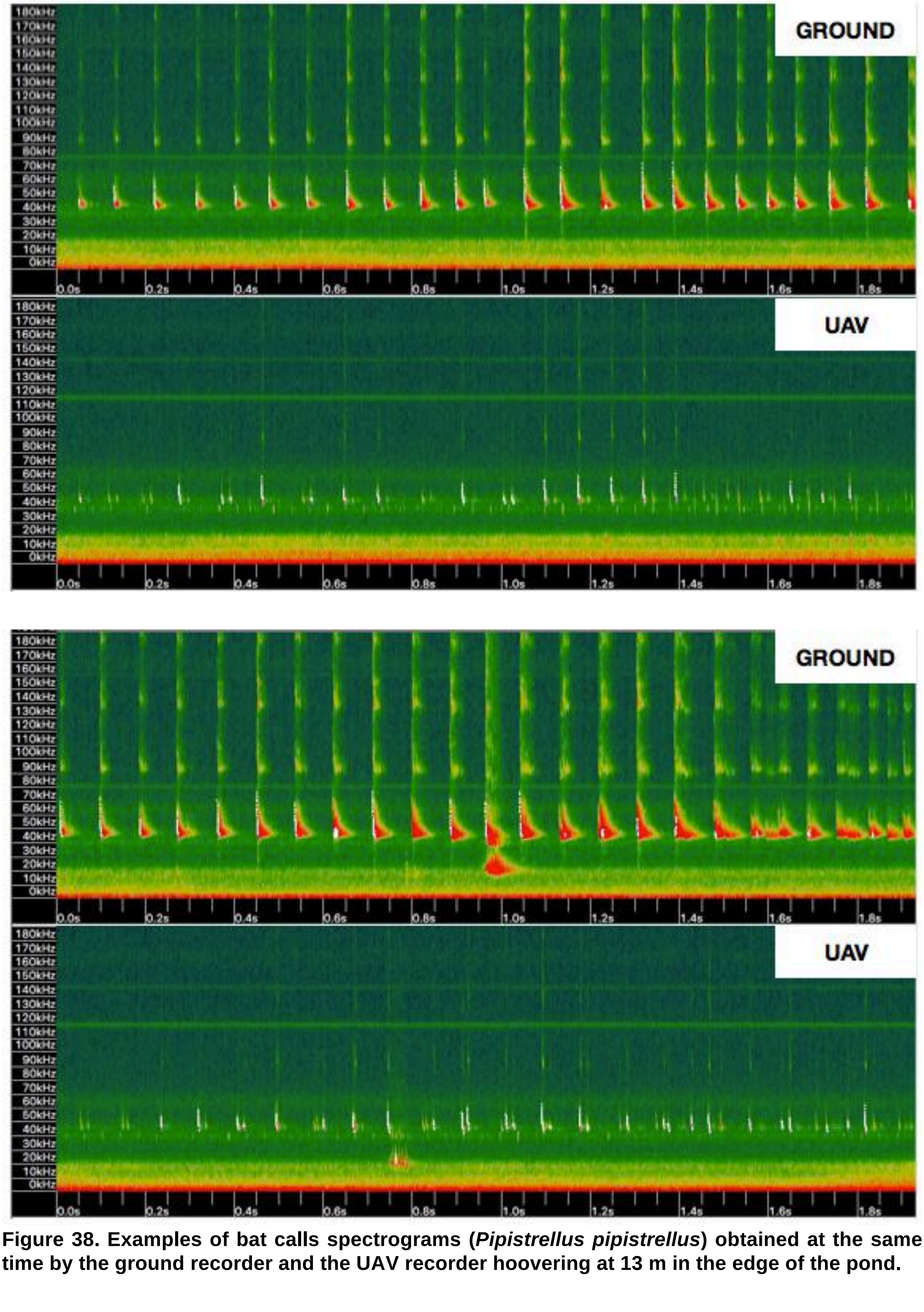

Figure 38. Examples of bat calls spectrograms (*Pipistrellus pipistrellus*) obtained at the same time by the ground recorder and the UAV recorder hoovering at 13 m in the edge of the pond.

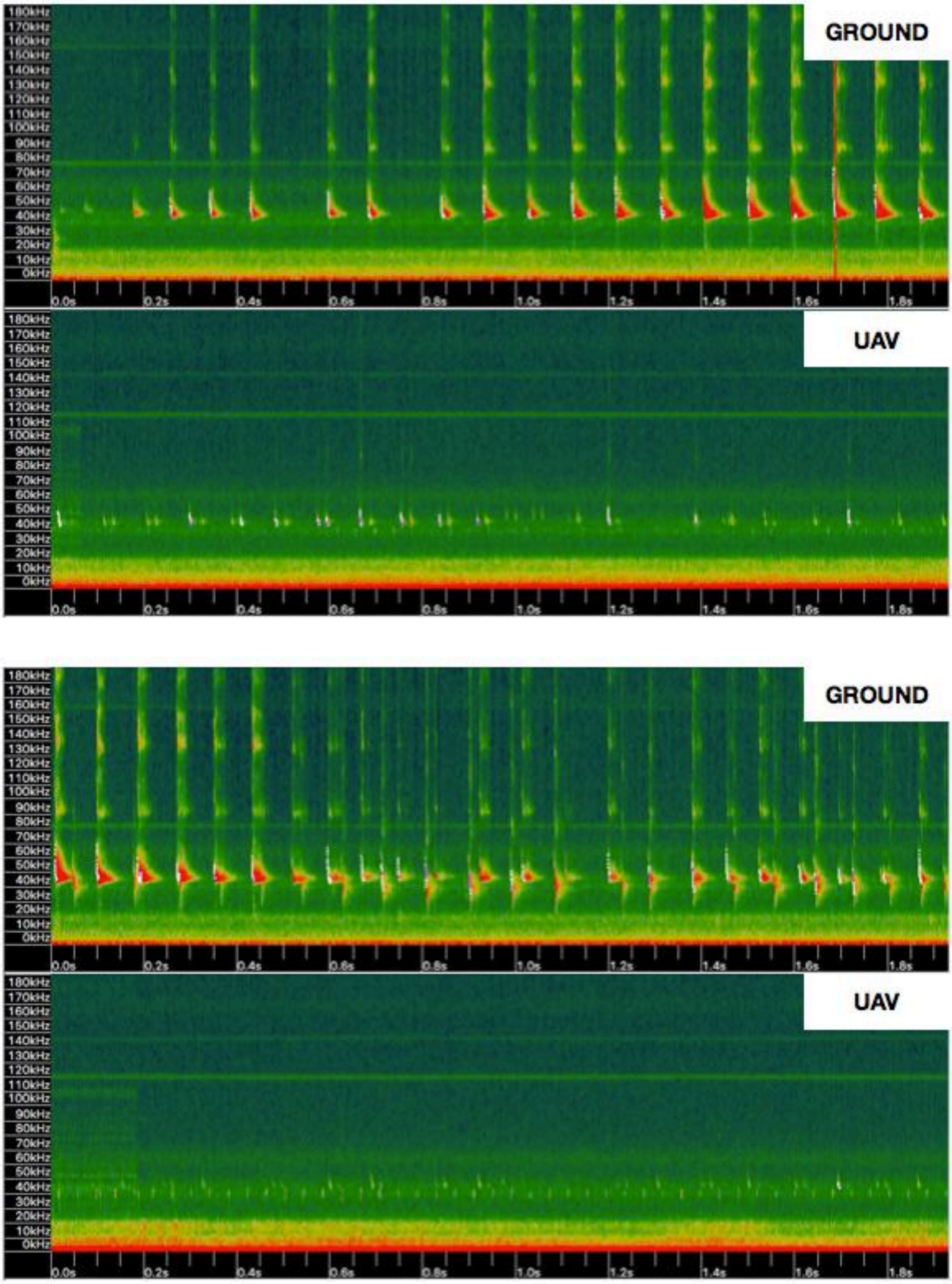

Figure 39. Examples of bat calls spectrograms obtained at the same time by the ground recorder and the UAV recorder hoovering at 23 m in the edge of the pond.

Table 12. Comparison of bat calls detection percentages between ground recorder and UAV recorder hoovering at 13 and 23 m for two kinds of habitats (forest and pond).

	UAV Recorder Altitude 13m		UAV Recorder Altitude 23m		Total	
	Forest (n=2)	Pond (n=20)	Forest (n=16)	Pond (n=20)	Forest (n=18)	Pond (n=40)
Ground detections (%)	50.0	100.0	100.0	100.0	94.4	100.0
UAV detections (%)	50.0	90.0	50.0	15.0	50.0	52.5
Detected by Ground & not by UAV (%)	50.0	10.0	50.0	85.0	50.0	47.5
Detected by UAV & not by Ground (%)	50.0	0.0	0.0	0.0	5.6	0.0
Detected by Ground & UAV (%)	0.0	90.0	50.0	15.0	44.4	52.5

Strangely the only drone detection missed by the ground recorder took place in the forest at an altitude of 13 metres and not at 23 metres. This was probably due to the fact that the bat passed behind the ground microphone. Indeed, the ground recorder was attached to a tree and thus its microphone was oriented parallel to the ground and not skyward or downward. Consequently, its range corresponded to a cone directed only forwards making any detection behind it (i.e. behind the tree trunk) impossible. The microphone on the drone received signals within a circle whose centre was the ground recorder position and thus could have detected a bat flying at least 3 metres high in the back of the ground microphone.

In terms of horizontal detection distance, it was impossible to say with any certainty if our EDR or maximum detection distances under controlled conditions such as 5 metres for Common Pipistrelle's echolocation calls at a vertical distance of 5 metres from the UAV microphone were higher under *in vivo* conditions. On the basis of our field observations, we estimated this maximum detection distance below 15 metres with the UAV device.

Apart from these small vertical and horizontal detection ranges, there is currently another limiting factor in Belgium for the implementation of such an inventory technique: the legislation on night flights. Indeed, UAV flights during the night require a costly derogation (196 €) whose validity is limited (maximum 6 months) (SPF Mobilité et Transports, 2015).
However, legislation varies greatly from one country to another. An overview of this variability is provided by the Global Drone Regulations Database website[8]. For example, flying at night is allowed in the UK for drone operators who passed an additional training course and updated their operations manual (Moore, 2018).
Note that the reduced visibility of obstacles caused by night flights is not a real problem since tracking flights can take place during the day. Resultant waypoints can then be used for an automatic and safe UAV flight.

To conclude, our results of this first field approach are not encouraging, as were those of the tests under controlled conditions. In fact, the performances of the UAV were qualitatively and quantitatively under standard recordings. There was a lot of information loss with very little additional input for the drone approach. However, this experiment cannot assert that the drone does not have the potential to significantly collect additional information from the ground recordings. Repetitions to record more high-flying bat passages would be necessary

[8] https://www.droneregulations.info/index.html

to demonstrate the potential of UAVs in targeted surveys of certain species (except the Barbastelle) in canopies or at high altitudes. However, our experimentation pointed out that compared to a recorder fastened on a mast at the same height as a recorder suspended on a drone, recordings of the latter would display a number of signals detected much lower and often unusable for precise identification. Therefore, the presence and activity level of bats in the study area would be underestimated.
The main factors dissuading from the use of this technique are therefore the limited detection range and the second-rate recordings making data analysis complicated. The legislation related to the study area may also constitute an obstacle to the implementation of this technique.

3.3.3 UAV disturbance on wildlife

It is important to consider and to know the possible impacts that UAV surveys could have on the monitored fauna. This theme is therefore discussed by taxon in this section.

3.3.3.1 Birds

Birds are more sensitive to UAV than terrestrial mammals (carnivores, pinnipeds, primates and ungulates) (Mulero-Pázmány et al., 2017). We previously mentioned some references such as Vas (2015) which demonstrated that there is no disturbance of waterbirds by UAV if some criteria, like the flight altitude, are respected. This cannot be generalised to all bird species because reactions depend on intrinsic characteristics of animals like life-history stage or aggregation level (Mulero-Pázmány, 2017). Large birds (body size > 70 cm and weight > 1 kg) and gregarious species are more prone to react to UAV flights (Mulero-Pázmány, 2017). Acoustic monitoring by UAV will mainly focus on small species found in low density, i.e. those less sensitive to the presence of UAVs.
During our experiments, we did not notice any disturbance, i.e. song cessation, flight path change, escape, attack or mobbing, for the following species during our experimental flights: *Hirundo rustica, Delichon urbicum, Apus apus, Passer domesticus, Buteo buteo, Milvus milvus, Falco tinnunculus, Accipiter nisus, Coruvs corone, Fringilla coelebs*.
This new kind of anthropogenic disturbance is consequently not significant enough to discriminate birds monitoring with UAV.

3.3.3.2 Bats

As UAVs have never been used to monitor bats, there is no study documenting the risks of UAV disturbance on this taxon yet. Drones transmit ultrasounds which surely affect bat behaviour. Changes in bat signals may occur if frequencies of drone noise are overlapping echolocation calls. This new anthropogenic noise can also act either as an attractive or repulsive stimulus. The attraction of bats could lead to lethal injuries if individuals fly too close to the propellers. The repulsion of bats could produce biases in data collection (e.g. false absence of sensitive species) and have negative consequences on bats fitness by temporarily reducing hunting and breeding areas. Repulsion is the most likely behavioural response since it has already been proven that anthropogenic noises reduce foraging efficiency or activity level depending on the species (Luo et al., 2015; Bunkley et al., 2015).

Note that we observed Common Pipistrelles flying at least of 10 metres from the UAV. However, we cannot make any hypothesis on the kind of stimulus for this species. In fact, our observations could just turn out to be a few curious or less disturbed individuals.
Therefore, research on UAV disturbance on bats must be conducted before any UAV monitoring is conducted.

3.4 General discussion

Fixed-wing drones cannot be completely excluded from acoustic monitoring. Indeed, if the tests were carried out with the drone initially provided, the results would undoubtedly have been better considering its enhancement to reduce the noises of the drone and the wind.
The Erebus project team was able to record simulated bat calls with their fixed-wing drone flying at an altitude of 10 metres, but the microphone used was not the same as ours. They showed through noise recording tests that their microphone, the Peersonic RPA2, was strongly less sensitive to sound interference. In fact, intense noise was only observed around 30 kHz with the Peersonic while very intense noise covered the whole spectrogram. Moreover, they modify the Talon with an extension at the front to move away the microphone from the source of interference. We could therefore imagine for both birds and bats to fix a better microphone (exclusive to ultrasound for bats) on an extension at the back of the drone that would move the microphone further away from the propeller.
However, the recordings will always be of lesser quality for fixed-wing drones than for quadcopters because the latter is not in motion (or at least at lower speed) and thus the wind impact is considerably reduced. The distance between the microphone and the drone is also much longer for quadcopters.

Depending on the species, bird effective detection radii under controlled conditions were between 40 and 70 m for Wilson (2017) and roughly between 10 et 70 m for our trials. We see that the maxima are equivalent but some of our species are not detected as well. The gap between these minima can be partially explained by the relative difference between the sound level of the American birds' vocalisations and the sound level of our birds. Indeed, the SPL of our loudest bird was 15 dB higher than the SPL of the quietest bird. For Wilson (2017), this difference was only 6 dB.
Our comparison of standard and UAV point-count methods is on the opposite less in favour of UAVs compared to Wilson (2017) which show less severe underestimations for UAVs. Several reasons may explain this discrepancy. First, the methodologies were not exactly identical. In fact, our drone made its recordings either directly before or directly after a traditional point count. For Wilson (2017), the two types of survey for a same station were always 20 min to 2 hours apart. Secondly, our small number of stations, all conducted on the same day, may have disadvantaged the UAV means of detections. In fact, the microphone could be more sensitive than the human ear to weather variations and consequently to variations in sound propagation. Additional repetitions could potentially reduce the underestimation of the drone. Finally, as already mentioned above, the skills of one birdwatcher to another can be very variable. Obviously, our two field operators were not the same and so were their ability to detect birds in the field (i.e. the distance within which they are able to spot them). However, the recording range of the drone microphone was the same in both cases. This factor is therefore potentially a source of this difference.

Our quadcopter noise characterisation tests showed a pronounced overlapping of bat calls to ESC noise. We could therefore consider developing a sound insulation system for this component of the drone to improve our recording quality as well as the number of detectable species such as the Barbastelle. However, propeller and motor noises are not negligible for both birds and bats. This is why the continuous development of quieter drones like the Phantom PRO 4 V2.0 promotes the use of this technology to carry out bioacoustic surveys in the near future. Drones based on a balloon such as the Spacial Halo[9] could be the type of drone suitable for acoustic monitoring. These are drones that maintain their flight altitude by means of a helium balloon and are navigable by using a remote controller system. This device therefore emits very little noise and may also carry out transects by minimising the impact of the wind thanks to its very slow flight speed (~15 km/h) (Juang, 2017). Its flight autonomy is probably superior to conventional multicopters. In addition, Fristrup et al. (2009) showed that the use of a drifting balloon system combined with a microphone allows songbirds monitoring. However, a shortcoming in their system was the absence of control of the position and flight path of the balloon. Consequently, this new type of drone—originally developed for indoor cinematography—has a real potential for the implementation of bioacoustic monitoring with UAVs.

[9] https://spacialdrone.com/halo-/

4 Conclusion

Our tests under controlled conditions excluded the possibility of using fixed-wing drones for bioacoustic surveys because this type of device was too noisy and therefore did not provide any usable recordings. However, this conclusion is only valid for our equipment. A device with a microphone further from the propeller and/or better insulated from it, a more sensitive microphone, a quieter motor and propeller and a larger wingspan should be tested. The quadcopter had rather promising results depending on the taxon.

For bats, the purpose of the quadcopters was to provide additional data for targeted surveys (e.g. forest canopy). But our tests showed very limited horizontal and vertical detection distances, making the input of data very restricted. Then, the poor performance of ultrasound analysis software in detecting bat signals from UAV recordings further reduced the potential to collect additional data. Finally, the implementation of this technique was definitively ruled out by the low-quality recordings obtained which made the identification of certain species very complicated or even impossible. Indeed, chiropterologists often have difficulty identifying some good quality records with certainty. Thus the risk that the data provided by the drone are useless is high and makes this new technique of little relevance. Especially since some species are not detectable, such as the Barbastelle which is a rare species and classified in the "near threatened" category of the IUCN Red List.

Overall bird effective detection radii were slightly lower for UAV recordings than ground recordings during our tests under controlled conditions. However, the absence of visual detections, the low-quality soundscape and the limited scope of the microphone provided lower means of detections per UAV-based point count per than standard point count. Therefore, tis technique cannot replace a birdwatcher under penalty of underestimating the abundance and the species richness of the studied area by missing low-frequency species or visible non-singing ones. However, it can still be considered as a complementary method to standard point counts where access is compromised for birdwatchers (i.e. canopies of tropical forests), especially if quieter quadcopters and more sensitive microphone are used.
The combination of the lower performances of the UAV against the effectiveness of the SOCWAL programme and the small portion of areas difficult to access (e.g. bogs), this new approach cannot be considered in Wallonia even in a complementary manner.

However, further research and practical implementations are possible for both taxa in study areas other than Wallonia. Indeed, the development of an ESC acoustic insulation system would allow more bat species to be detected. Moreover, the use of remotely controlled balloon whose noise emission is practically non-existent, combined with high quality microphones could be very promising for acoustic monitoring of birds and bats in impracticable areas for ground operators.

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6 Appendix

Appendix 1. Selection of high quality bird recordings from xeno-canto.

Number	Code	Species	Song type	URL
1	XC281374	eurasian wren	song	https://www.xeno-canto.org/281374
2	XC379950	eurasian wren	song	https://www.xeno-canto.org/379950
3	XC281371	eurasian wren	song	https://www.xeno-canto.org/281371
4	XC281377	eurasian wren	alarm call	https://www.xeno-canto.org/281377
5	XC281378	eurasian wren	alarm call	https://www.xeno-canto.org/281378
6	XC281519	sedge warbler	song	https://www.xeno-canto.org/281519
7	XC281522	sedge warbler	song	https://www.xeno-canto.org/281522
8	XC393062	sedge warbler	song	https://www.xeno-canto.org/393062
9	XC281524	sedge warbler	alarm call	https://www.xeno-canto.org/281524
10	XC353680	reed bunting	song	https://www.xeno-canto.org/353680
11	XC281817	reed bunting	song	https://www.xeno-canto.org/281817
12	XC281818	reed bunting	song	https://www.xeno-canto.org/281818
13	XC35208	reed bunting	call	https://www.xeno-canto.org/35208
14	XC281435	common blackbird	song	https://www.xeno-canto.org/281435
15	XC281434	common blackbird	song	https://www.xeno-canto.org/281434
16	XC104604	common blackbird	song	https://www.xeno-canto.org/104604
17	XC281441	common blackbird	call	https://www.xeno-canto.org/281441
18	XC281439	common blackbird	alarm call	https://www.xeno-canto.org/281439
19	XC393063	eurasian blackcap	song	https://www.xeno-canto.org/393063
20	XC379971	eurasian blackcap	song	https://www.xeno-canto.org/379971
21	XC379948	eurasian blackcap	song	https://www.xeno-canto.org/379948
22	XC381478	eurasian blackcap	call	https://www.xeno-canto.org/381478
23	XC397523	common chaffinch	song	https://www.xeno-canto.org/397523
24	XC379968	common chaffinch	song	https://www.xeno-canto.org/379968
25	XC281752	common chaffinch	song	https://www.xeno-canto.org/281752
26	XC365672	common chaffinch	call	https://www.xeno-canto.org/365672
27	XC281758	common chaffinch	call	https://www.xeno-canto.org/281758
28	XC379973	song thrush	song	https://www.xeno-canto.org/379973
29	XC281459	song thrush	song	https://www.xeno-canto.org/281459
30	XC281452	song thrush	song	https://www.xeno-canto.org/281452
31	XC348842	song thrush	call	https://www.xeno-canto.org/348842
32	XC345608	song thrush	alarm call	https://www.xeno-canto.org/345608
33	XC353829	goldcrest	song	https://www.xeno-canto.org/353829
34	XC364246	goldcrest	song	https://www.xeno-canto.org/364246
35	XC281601	goldcrest	song	https://www.xeno-canto.org/281601
36	XC281606	goldcrest	call	https://www.xeno-canto.org/281606
37	XC380054	common wood pigeon	song	https://www.xeno-canto.org/380054
38	XC394506	common wood pigeon	song	https://www.xeno-canto.org/394506
39	XC378844	common wood pigeon	song	https://www.xeno-canto.org/378844

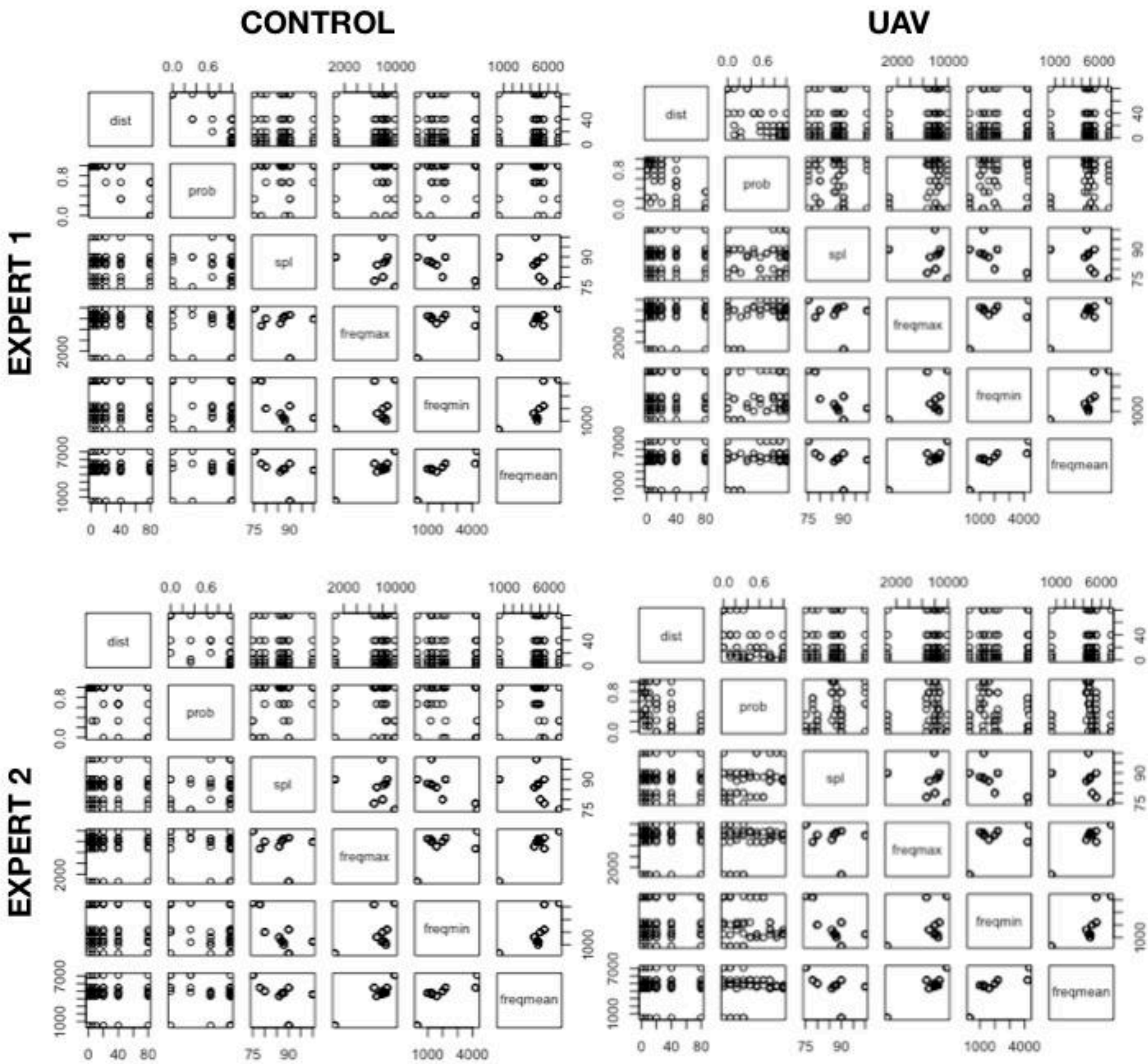
Appendix 2. Multiple comparison of bird EDR: between experts, between ground-based recordings (control) and UAV-based recordings, between calculation methods (distance sampling and regression).

	Effective Detection Radius of expert 1				Effective Detection Radius of expert 2			
	EDR Control (m)		EDR UAV (m)		EDR Control (m)		EDR UAV (m)	
Bird species	Distance Sampling	Regression	Distance Sampling	Regression	Distance Sampling	Regression	Distance Sampling	Regression
Common Blackbird	28.3	74.8	34.4	69.2	29.5	80.0	27.2	69.2
Common Chaffinch	28.3	74.8	27.2	58.7	28.3	74.8	26.8	60.5
Common Reed Bunting	15.5	39.5	13.9	31.9	15.5	39.5	14.0	19.4
Common Wood Pigeon	17.5	34.6	12.6	7.5	14.7	37.4	14.0	18.3
Eurasian Blackcap	26.5	39.5	14.3	31.0	22.9	58.9	26.5	45.7
Eurasian Wren	27.2	58.9	14.5	32.0	14.2	34.6	17.6	22.1
Goldcrest	14.2	34.6	18.4	31.5	6.7	7.1	6.7	8.9
Sedge Warbler	28.3	74.8	13.3	15.7	14.7	37.4	13.7	12.4
Song Thrush	28.3	74.8	15.0	35.0	29.4	80.0	14.5	31.5

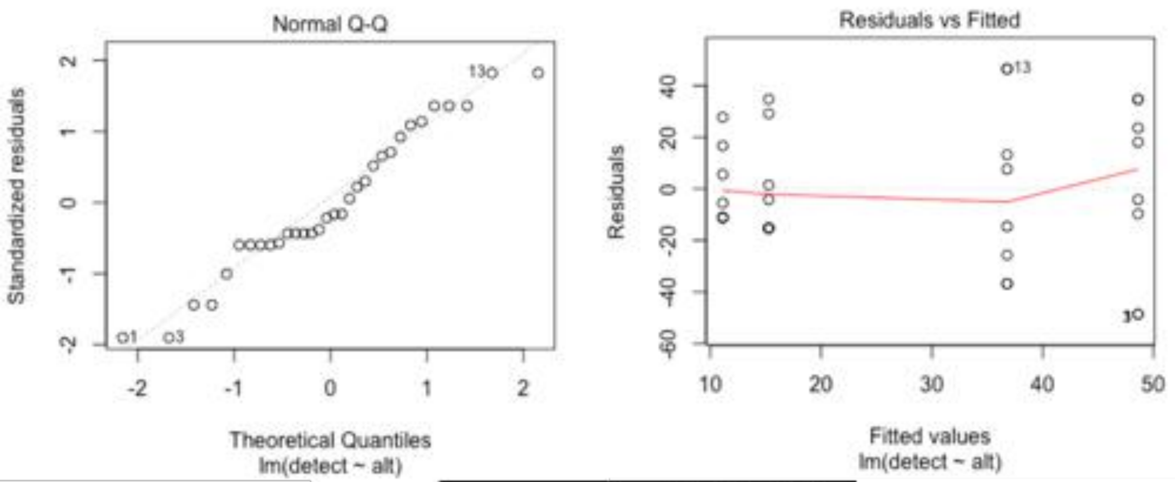
Appendix 3. Assumptions verification of regression models (p-value) for detection probability function of bird species. Normality of residuals checked with Shapiro-Wilk and/or Kolmogorov-Smirnov tests and Homoscedasticity (variance homogeneity of model residuals) checked with Breusch-Pagan test.

	Shapiro-Wilk normality test				One-sample Kolmogorov-Smirnov test				studentized Breusch-Pagan test			
	Expert 1		Expert 2		Expert 1		Expert 2		Expert 1		Expert 2	
Bird species	Control	UAV	Control	UAV	Control	UAV	Control	UAV	Control	UAV	Control	UAV
Common Blackbird	**0.0006802**	**0.0006802**	NA	**0.0006802**	0.06881	0.07215	NA	0.07215	0.7707	0.7707	NA	0.7707
Common Chaffinch	**0.0006802**	0.6582	**0.0006802**	0.5021	0.06881	0.1019	0.06881	0.1267	0.7707	0.8035	0.7707	0.07219
Common Reed Bunting	**0.0006802**	0.6079	**0.0006802**	0.5293	0.07563	0.1498	0.07563	0.2567	0.7707	0.5078	0.7707	0.5649
Common Wood Pigeon	**0.01073**	0.8064	0.01073	0.6967	0.1243	0.1498	0.118	0.1956	0.635	0.3031	0.635	0.1198
Eurasian Blackcap	**0.0006802**	0.3362	0.0989	0.8327	0.07563	0.1258	0.1029	0.1516	0.7707	0.2406	0.6541	0.1078
Eurasian Wren	0.0989	0.6811	**0.01073**	0.9351	0.1029	0.1537	0.1243	0.2276	0.6541	0.1631	0.635	0.6508
Goldcrest	0.06461	0.06461	**< 2.2e-16**	0.8957	0.1085	0.1085	0.4433	0.2378	0.2953	0.2953	1	0.1632
Sedge Warbler	**0.0006802**	0.655	**0.01073**	0.3162	0.06881	0.2045	0.118	0.09098	0.7707	0.1726	0.635	0.5899
Song Thrush	**0.0006802**	0.07425	NA	0.6782	0.06881	0.1934	NA	0.1338	0.7707	0.4275	NA	0.3968

Appendix 4. Graphs of bird detection probability (all species) depending on different song features (SPL, maximum frequency, minimum frequency, mean frequency) for each combination of expert and recording type.



Appendix 5. Assumptions verification for analysis of variance (graphic and statistic) between bat detectability and altitude.



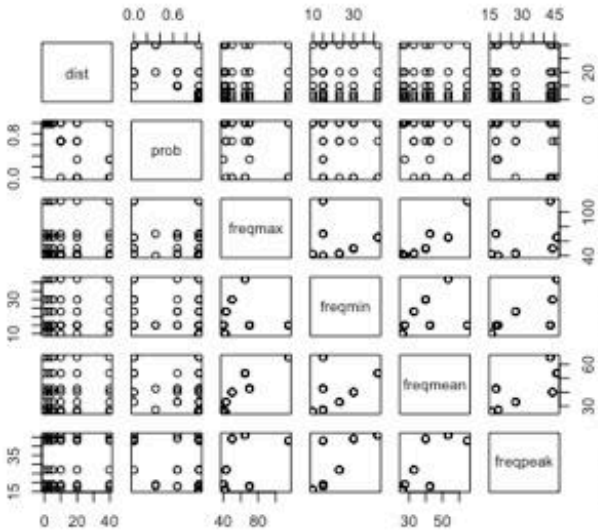
	Shapiro-Wilk normality test	Bartlett test of homogeneity of variances
p-value	0.2575	0.1344

Appendix 6. Assumptions verification of regression models (p-value) for detection probability function of bat species. Normality of residuals checked with Shapiro-Wilk and/or Kolmogorov-Smirnov tests and Homoscedasticity (variance homogeneity of model residuals) checked with Breusch-Pagan test.

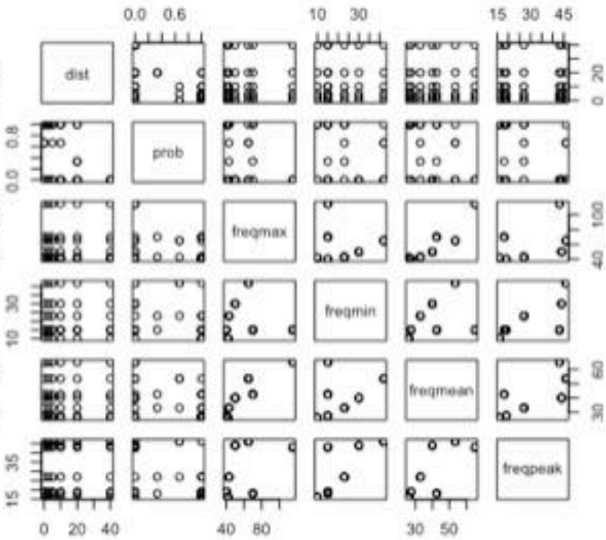
		Shapiro-Wilk normality test			Kolmogorov-Smirnov test			studentized Breusch-Pagan test		
Call type	**Bat species**	**Altitude 0**	**Altitude 5**	**Altitudes 10-15**	**Altitude 0**	**Altitude 5**	**Altitudes 10-15**	**Altitude 0**	**Altitude 5**	**Altitudes 10-15**
Echolocation	Barbastelle	0.1993	NA	NA	0.1976	NA	NA	0.4095	NA	NA
	Common Pipistrelle	0.1993	NA	NA	0.1976	NA	NA	0.4095	NA	NA
	Natterer's Bat	0.1993	NA	NA	0.2201	NA	NA	0.4095	NA	NA
	Myotis sp.	**0.01804**	NA	NA	0.1487	NA	NA	0.914	NA	NA
	Noctule	**0.0006802**	**0.0006802**	0.118	0.07215	0.07563	0.08936	0.7707	0.7707	0.635
	Serotine	0.5414	**0.01804**	NA	0.1932	0.1487	NA	0.3012	0.914	NA
Social	Common Pipistrelle	**0.0006453**	**0.01073**	NA	0.1349	0.1243	NA	0.983	0.635	NA
	Noctule	NA	**0.0006802**	NA	NA	0.07563	NA	NA	0.7707	NA

Appendix 7. Graphs of bat detection probability (all species) depending on different song features (maximum frequency, minimum frequency, mean frequency, FME) for each group of altitude.

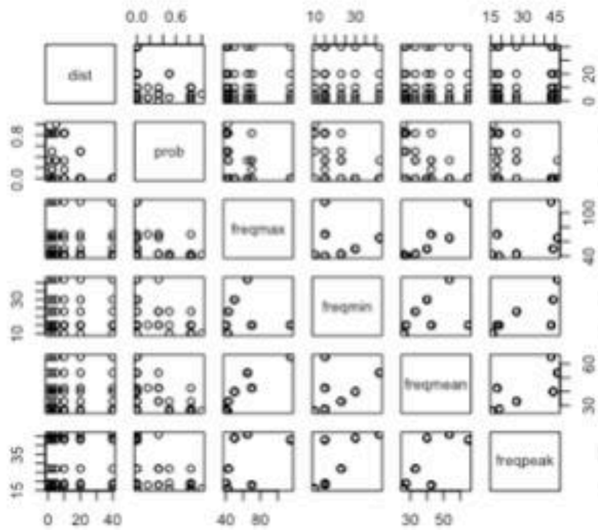
Control (Alt 0m)



Altitude 5m



Altitudes 10-15m



Altitude 20m