

22 **Author Contributions**

23 Antoine Morel and Pierre-Paul Bitton together conceived the ideas and designed the methodology.
24 Antoine Morel led the data collection, the analysis and the writing of the manuscript. Pierre-Paul
25 significantly contributed to the analysis and editing the manuscript. All authors contributed to the drafts
26 and gave final approval for publication.

27

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40

41

42 **Abstract**

43 Accurate and extensive data collection is essential for understanding animal sociality, but observing
44 associations between individuals remains challenging. Animals often associate and interact outside of
45 the range of an observer, especially in environments such as underwater or underground. However, the
46 development of proximity loggers using Bluetooth and radio frequency to detect associations allows
47 scientists to access behavioural information that would otherwise be impossible to collect. Here we
48 examined the use of a logger with a proximity feature to capture associations between Atlantic puffin
49 individuals and assessed how it could complement observations in social network studies. To
50 understand the capabilities of the logger, we tested the effect of distance on signal strength and
51 proportion of associations detected, as well as the proportion of contacts recorded by each logger in a
52 dyad, in lab-based and field environments. Thereafter, we tested the loggers on live Atlantic puffins and
53 compared their performance against visual observations. As expected, signal strength decreased with
54 distance, and lab-based values were more consistent than in the field. The proportion of contacts
55 successfully processed decreased with distance, but our experiment in the field was more reliable,
56 probably because we used a lower logger density, limiting opportunities for interference among units.
57 More importantly, the loggers identified more putative associations than detected by observations,
58 including many when and where individuals were not under observation. We further demonstrate that
59 Atlantic puffins that associate frequently on land also associate frequently at sea. Our results bring new
60 insight into the understanding of Atlantic puffin social behaviours, particularly at times and in locations
61 challenging to monitor.

62

63 **Keywords:** Associations, Atlantic puffin, Dyad, Scan sampling, Social behaviour, Social network, Visual
64 observation

65 **Introduction**

66 Social behaviours, defined as interactions between two or more individuals, are likely to be better
67 described in abundant and easy-to-detect species (Webber & Vander Wal, 2019). Furthermore, our
68 understanding of inter-individual relationships is biased by when and where animals are observable,
69 especially for those that spend much time in areas that are challenging to sample (e.g., open sea, dense
70 forest, at night, or during migration). Therefore, it can be difficult to accurately assess social processes
71 without methods that comprehensively sample associations (Farine & Whitehead, 2015; Hoppitt &
72 Farine, 2018). By combining remote sensing with observational data collection, we explored the
73 potential for proximity loggers to replace and/or complement observational data collection in the
74 detection of on-land and at-sea associations in the Atlantic puffin.

75 The quantification of social relationships is often used by researchers to measure sociality
76 between individuals. However, the reliability of this measure is dependent on the accuracy of the data
77 collection (Farine & Whitehead, 2015; Hoppitt & Farine, 2018). Focal and scan observations, involving an
78 observer recording associations or interactions between known individuals, are commonly used in
79 network sampling (Webber & Vander Wal, 2019). To increase the chance of encountering individuals,
80 scientists often target locations where certain species come back regularly, such as breeding sites (e.g.,
81 Nomano et al., 2014) or artificial feeding sites (e.g., Firth et al., 2017, Heinen et al., 2022). While free-
82 range living animals such as birds or mammals are among the most studied taxonomic groups in social
83 networks (Webber & Vander Wal, 2019), they are likely to be challenging to sample when away from
84 their breeding site, and their behaviours may be influenced by human disturbance produced by the
85 presence of the observer. The resulting observational biases can skew data collection toward specific
86 biological mechanisms, periods, and locations (Hoppitt & Farine, 2018). A general example is one of
87 seabird species that migrate broadly and breed on remote protected islands. Targeting individuals at
88 their breeding site is the easiest way to collect social behaviour information. However, sampling on

89 those islands is likely to generate disturbances (Brown et al., 2013) and bias sampling toward specific
90 inland associations. To address these limitations, there is a growing need for new methods that ensure
91 reliable data collection with limited human intervention.

92 Remote technology is gaining popularity in the study of animal behaviour, particularly in
93 collecting associations when and where observations are challenging or not possible (Webber & Vander
94 Wal, 2019; Smith & Pinter-Wollman, 2021). Radiotelemetry and Global Positioning Systems (GPS) have
95 been used in attempts to assess proximity between individuals (Ramsey et al., 2002; Atwood & Weeks,
96 Jr., 2003; Wallace et al., 2022; Davis et al., 2018), but the detection of social relationships often require a
97 high temporal and spatial resolution that these methods lack, particularly when changes in vegetation
98 and topography occur (D'eon & Delparte, 2005; Frair et al., 2010). Miniaturised proximity loggers for
99 association detection on small animals such as birds were initially introduced by Rutz et al. (2015) using
100 radio frequency and later developed with Bluetooth (Kirkpatrick et al., 2021; Huels et al., 2025). These
101 loggers are now often packaged with other functionality, such as GPS and accelerometer and are
102 mounted on a collar, backpack, or leg band. They are powered by batteries, sometimes complemented
103 with solar panels to increase battery life span. While their use remains uncommon (3.6 % of the social
104 network studies reviewed by Webber & Vander Wal (2019) used proximity loggers), they have returned
105 very good results on large and mid-sized mammals such as white-tailed deer (*Odocoileus virginianus*;
106 Walrath et al., 2011), brushtail possums (*Trichosurus vulpecula*; Ji et al., 2005) and domestic cattle (*Bos*
107 *taurus*; Swain & Bishop-Hurley, 2007). Recently, due to the advances in technology, and often at the cost
108 of battery lifespan, miniaturised proximity loggers have been used on birds such as New Caledonian
109 crow (*Corvus moneduloides*; Bettaney et al., 2015), European starlings (*Sturnidae vulgaris*; Kirkpatrick et
110 al., 2021), wire-tailed manakin (*Pipra filicauda*; Ryder et al., 2012) and small mammals such as prairie
111 voles (*Microtus ochrogaster*; Gaidica et al., 2024). However, these systems are limited to a few days in
112 duration, which makes them inconvenient for studying animals over longer periods. Still, proximity

113 loggers with battery life-saving performance and integrated solar panels present a solution for short-
114 term data collection on species that are challenging to observe, and their use on smaller species
115 requiring technology adaptation has received little attention.

116 This study was conducted on the Atlantic puffin, a central-place forager species that returns to
117 the colony after foraging at sea, offering a good contrast between observable and non-visible
118 associations. We tested the Gipsy 6© (TechnoSmArt Europe, Colleverde, Italy), a miniaturised solar-
119 powered GPS with an embedded proximity logger and evaluated its performance in the detection of
120 associations in Atlantic puffins, at sea and on land. Specifically, we tested its performance and
121 repeatability in lab-based and field environments and compared its detection rate with observational
122 methods to test for detection when and where observations were not possible.

123 **Materials and methods**

124 Study site and species

125 We collected data on Great Island, located in the Witless Bay Ecological Reserve of Newfoundland and
126 Labrador, Canada (47.1855N, 52.8121W). The reserve comprises the largest Atlantic puffin population in
127 North America (~590,000 breeding individuals; Wilhelm, unpublished data, Great Island hosting around
128 350,000; Wilhelm et al., 2015). The Atlantic puffin is a monogamous colonial seabird with a long life span
129 (up to 45 years in the wild; Fransson et al., 2023) that forms densely populated breeding colonies (~1.6
130 burrows/m² in Great Island; Belenguer, 2023). They display daily and seasonal colony attendance cycles
131 with individuals generally gathering more on land in the evening (Calvert & Robertson, 2002). It has also
132 been suggested that individuals on land prefer to be surrounded by conspecifics and will give signs of
133 nervousness in low density (Calvert & Robertson, 2002). Atlantic puffins are highly social and associate
134 more with close nesting conspecifics (Morel et al., 2025). At sea, they often stay in groups (i.e., rafts)
135 that are likely to be used as information centres (Weimerskirch et al., 2010).

136 Data collection

137 Logger testing

138 *Logger description*

139 We used the Gipsy 6© (TechnoSmArt Europe, Colleverde; Figure S1), a remote detection device that
140 combines GPS, accelerometer, and radio frequency to detect proximity between devices. We set the
141 time of activity, signal strength and scanning interval frequency before deployment. The device was
142 shaped to limit frontal surface area and drag (11 x 6 x 4 millimetres), was waterproof to 60 metres and
143 was black to better match the mantle of the puffins. The units were powered by a lithium battery
144 connected to a solar panel, weighed six grams, and were attached using Tesa® tape. The data were

145 downloaded using a base station with a range of 500 metres and a short antenna with a range of 10
146 metres.

147 *Lab-based environment*

148 We evaluated the performance and repeatability of the proximity loggers in optimal conditions by
149 testing them in a lab-based environment. We deployed 12 loggers on an asphalt-shingled rooftop, as it
150 provided a flat high ground away from physical barriers. Each logger had a unique ID and was placed
151 along a circle 0.5 metres away from the centre (Figure S2). The distribution in a circle aimed to
152 reproduce a high-density aggregation of individuals as observed in nature. The scanning interval
153 frequency was set for one minute, and each trial was 20 minutes long, at the end of which loggers were
154 moved an extra 0.5 metres away from the centre. The procedure was repeated until a maximum
155 distance of five metres between the farthest loggers was reached (each 2.5 metres away from the
156 centre).

157 *Field environment*

158 We evaluated the performance and repeatability of proximity loggers under field conditions by
159 deploying them on an established study plot on Great Island, Witless Bay Ecological Reserve. We
160 deployed the same 12 loggers on a 168 square metres (14 x 12 metres) plot. The plot had a consistent
161 40-degree angle slope facing West. Its surface was irregularly covered by tall grass, branches, and
162 shallow, solitary boulders. The density of burrows was estimated at 1.6 burrows/m² (Belenguer, 2023).
163 The loggers were set at 0.5 metres intervals on a diagonal following a 45-degree angle to the bottom
164 ledge (Figure S3). All loggers but the three farthest were programmed to send their signal once every
165 five minutes for 350 minutes. The loggers at distances of 5.5, 5, and 4.5 metres did not implement the
166 new schedule between trials and were scanning every minute.

167 Comparison with observational data

168 To compare the data collected by the loggers with observational data and assess associations potentially
169 missed by scan sampling, we attached proximity loggers to 6 individuals in 2023, as part of a long-term
170 study that included an additional 131 colour-banded individuals (50 in 2021, 74 in 2022, and 13 in 2023).
171 To avoid increasing risks of breeding failure by tagging both parents, we only equipped one individual of
172 any given pair. Because breeding adult seabirds are likely to abandon their nest if disturbed early in the
173 breeding season (Yorio & Boersma, 1994; Rodway et al., 1996; Blackmer et al., 2004), we captured
174 adults only after their chicks had hatched. To evaluate the best capture period, we assessed burrow
175 occupancy regularly and captured birds after 80 % of the eggs had hatched, and we sampled only the
176 burrows in which chicks were present. To maximise the capture rate and minimise disturbance,
177 experienced banders and their assistants operated at night when the birds were usually in the burrow.
178 We trapped the adults in their burrows by hand grubbing before taking them to a banding station set a
179 few metres away. Banders fitted each individual with a unique combination of three Darvic plain colour
180 bands custom-made from *Avian ID* (9.53 mm ID X 7.93 mm HT, Red, White, Green, Black, Grey, Yellow,
181 Light blue and Dark blue), and a Canadian Wildlife Service stainless steel grey band with a unique
182 identifier. Six individuals were tagged with a proximity logger using the methods presented in Wilson
183 and Wilson (1989), with four strips of Tesa® tape and one zip tie. The loggers were set on the lower
184 back, just above the uropygial gland, with an expected retention of 15 days. Each bird was handled for
185 no more than 15 minutes before being released in its original burrow.

186 To capture associations using proximity detection, we set the loggers to scan every two minutes
187 during periods when birds are the most visible on land (from 5h00 to 22h00 p.m.; Calvert & Robertson,
188 2002). To save battery, we had them turn off from 22h00 to 5h00, when individuals are often found
189 inside their burrow (Calvert & Robertson, 2002). To assess individual presence on the plot, we set one
190 extra logger in the centre of the study area, scanning every two minutes. Data were collected using a

191 long-range base station and, alternatively, a short-range antenna when birds with loggers were
192 observed (Figure S1). The long-range antenna was fixed on the blind used for scan sampling, five metres
193 away and facing the plot.

194 To capture associations based on visual observation, we conducted 210 hours of scan sampling
195 from June 06th to August 07th 2023, on the 137 colour-banded individuals. From a blind facing the plot,
196 we usually conducted two observation sessions of four hours each in a day, regardless of weather
197 conditions. We started the first session at civil twilight and the second session four hours before sunset,
198 the evening session lasting until the visibility was too low to identify colour bands correctly. Each session
199 consisted of two observers equipped with binoculars (Swarovski EL 10x42 WB), observing the plot and
200 the areas peripheral to the limits of the plot, searching for social associations. The observers were
201 trained to accurately assess distance using flags and natural features. To optimise detections, we
202 ensured that the area was scanned from top to bottom, and right to left when the slope was crowded,
203 and we followed specific individuals when in low density. For this study, we defined an association as
204 any known individuals (i.e., identified with colour bands) within a two-metre radius of another.
205 Observers created an event each time a new association occurred or when the association was still
206 ongoing after two minutes. All events were time-stamped and given unique sequential record numbers.

207 Analyses

208 Logger testing

209 For all data management and analyses performed, we used R statistical Software v.4.2.3 (R core Team,
210 2025). To evaluate the performance and repeatability of the loggers in lab-based and field
211 environments, we assessed two metrics: the Received Signal Strength Indicator (RSSI; hereafter signal
212 strength), within and between distances and the proportion of total contacts recorded by each logger in
213 a dyad. Signal strength is expressed in decibel-milliwatts (dBm) and generally ranges between zero and -

214 120 with values close to zero indicating a strong signal. We applied a general linear mixed model to test
215 the significance of the relationships between signal strength and distance between loggers using the
216 glmmTMB package (Brooks et al., 2017). We used strength as the dependent variable and treatment
217 with the logarithmic values of distance as the independent variable. We used logger ID as a random
218 factor, and allowed slopes to vary by Treatment (i.e., Lab-based and Field-based trials as categorical
219 variables). The assumptions were validated by evaluating the analytical plots from the DHARMA package
220 (Hartig & Lohse, 2022), and we found that the t-family error distribution returned the best fitting
221 models. The repeatability of the signal strength was tested using the *rptR* package (Stoffel et al., 2017).
222 We calculated the repeatability estimation using the linear mixed model method by setting signal
223 strength as the response variable and distance as the grouping variable. We obtained the repeatability
224 estimate R, p-value and the confidence interval estimates after bootstrapping the procedure 1000
225 times. We tested the relationship between the proportion of detection, distance and treatment using a
226 generalised linear mixed model. For this model, the square root of distance was used, and logger ID was
227 included as a random factor. Using diagnostic plots, we validated our assumptions and found that the
228 beta-family error distribution was returning the best model fit.

229 To compare the use of loggers against traditional observations, we evaluated three metrics. We
230 1) compared the number of associations concurrently captured by field observations and loggers, 2)
231 assessed the proportion of associations detected by the loggers occurring outside of observation hours,
232 and 3) assessed the proportion of associations detected by the loggers away from the plot. To compare
233 the proportion of associations captured by both methods, we cross-referenced the associations
234 captured during observation from the blind and the data automatically collected from the loggers. We
235 filtered the associations automatically detected in the plot, during observational hours, and for which
236 signal strength was more than -95dBm. The -95dBm threshold was selected as it is the minimum signal
237 strength detected by loggers for which association within two metres distance was visually validated.

238 We excluded associations occurring out of the reach of the visual observation method by including only
239 associations that were also detected by the plot logger. Because loggers can sometimes miss the signals
240 sent every two minutes, we applied a four-minute buffer (i.e., two interval lengths duration). We
241 assumed all individuals on the plot would be detected because they often stay for an extended period
242 on land to rest, which would have been detected by the stationary logger's frequent screening. To select
243 the associations automatically captured at the same time as visual observation, we kept a record of the
244 observation period and selected associations within these time windows. By dividing the number of
245 contacts within the plot but outside of the observation time window, we calculated the proportion of
246 contacts missed by the observation method.

247 To evaluate the pattern of dyadic association on the plot or not (presumably at sea), we first
248 attributed a location to each dyadic association detected by the loggers using the time window built
249 with the stationary logger. Then we represented the distribution of contacts by location and expressed
250 its strength using a Pearson correlation.

251 Ethical Note

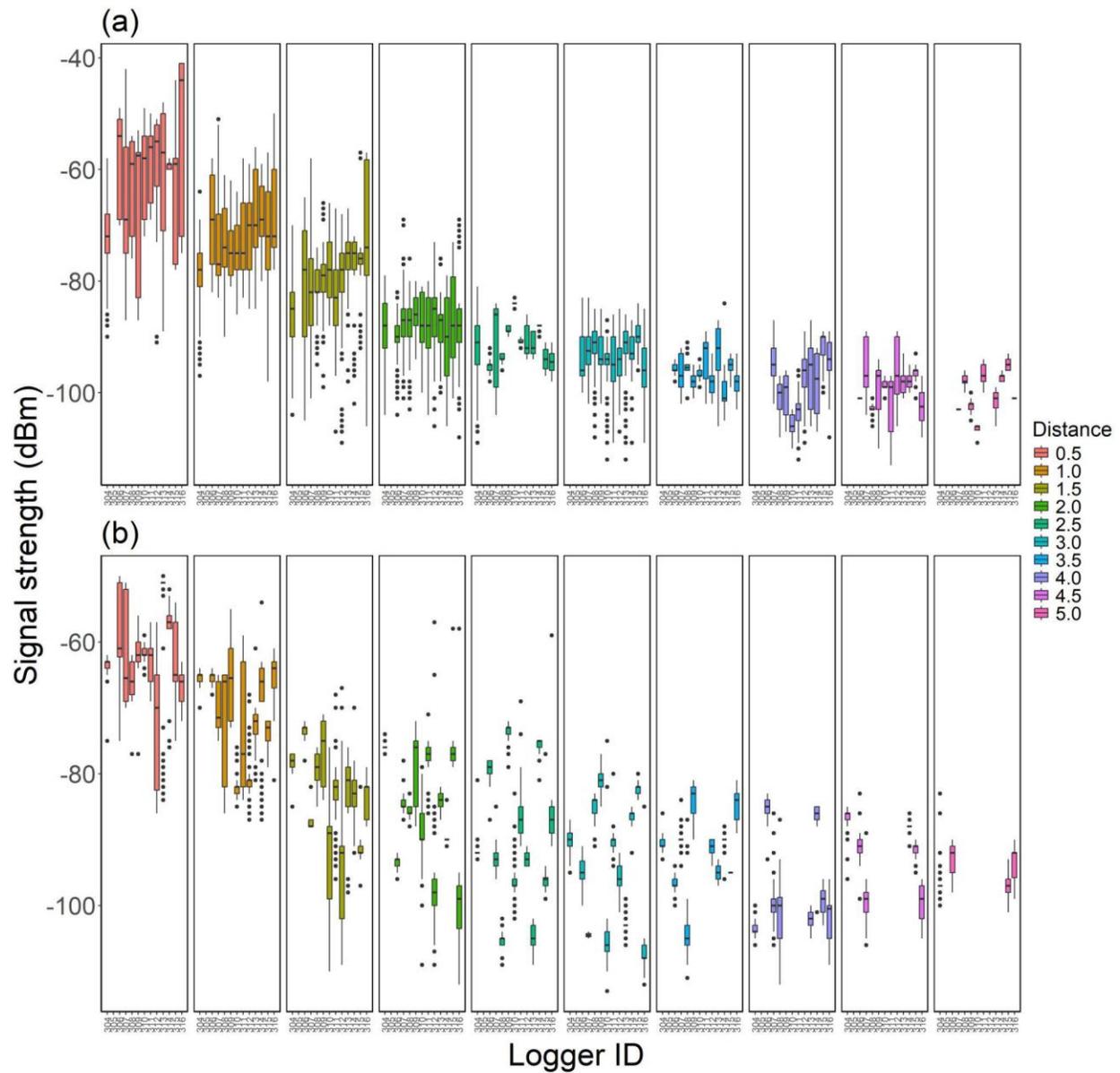
252 This study was performed on a protected Atlantic puffin colony within the natural reserve of Witless Bay
253 Ecological Reserve. Animal ethics were covered by an Animal Use Permit (23-01-PB) issued by the
254 Memorial University of Newfoundland University Animal Care Committee. All research activities,
255 including trapping, banding and the construction of a non-permanent structure, were allowed under a
256 Province of Newfoundland and Labrador scientific research permit (wepr2021-23atpucolouration), a
257 Banding permit (10926) and a Migratory Bird Research permit (SC4061) issued by Environment and
258 Climate Change Canada.

259 Results

260 Logger function in lab-based and field environments

261 In this study, we tested 12 loggers in lab-based and field environments to determine whether signal
262 detection warranted deployment on live animals. When testing the effects of distance and
263 environmental conditions on strength and proportion of contact we found that signal strength
264 decreased with distance ($\chi^2 = 71054.809$, $df = 1$, $p < .001$; Figures 1 and 2), and decreased more in the
265 lab-based environment than in the field setting (coefficient estimate lab-based environment = 18.1402,
266 field setting = 16.1834; $\chi^2 = 23.089$, $df = 1$, $p < .001$). Most of the variance was explained by the logger ID
267 (R^2 conditional = 0.963, R^2 marginal = 0.846). We also found that signal strength was moderately
268 repeatable among distances ($R = 0.661$). Similarly, we found a significant effect of distance on the
269 proportion of contact ($\chi^2 = 58.297$, $df = 1$, $p < .001$; Figure 3), with a difference between treatments (χ^2
270 = 228.532, $df = 1$, $p < .001$). The loggers performed better in the field environment (coefficient estimate
271 lab-based environment = -1.5858, field setting = -0.0954). Additionally, we found a difference in the
272 proportion of contacts recorded by each logger in a dyad (Figure 4). Particularly, for both environments,
273 more than 50 % of the dyads did not record equal logs. (i.e., an equal number of contacts received by a
274 logger and detected by the emitting logger).

275

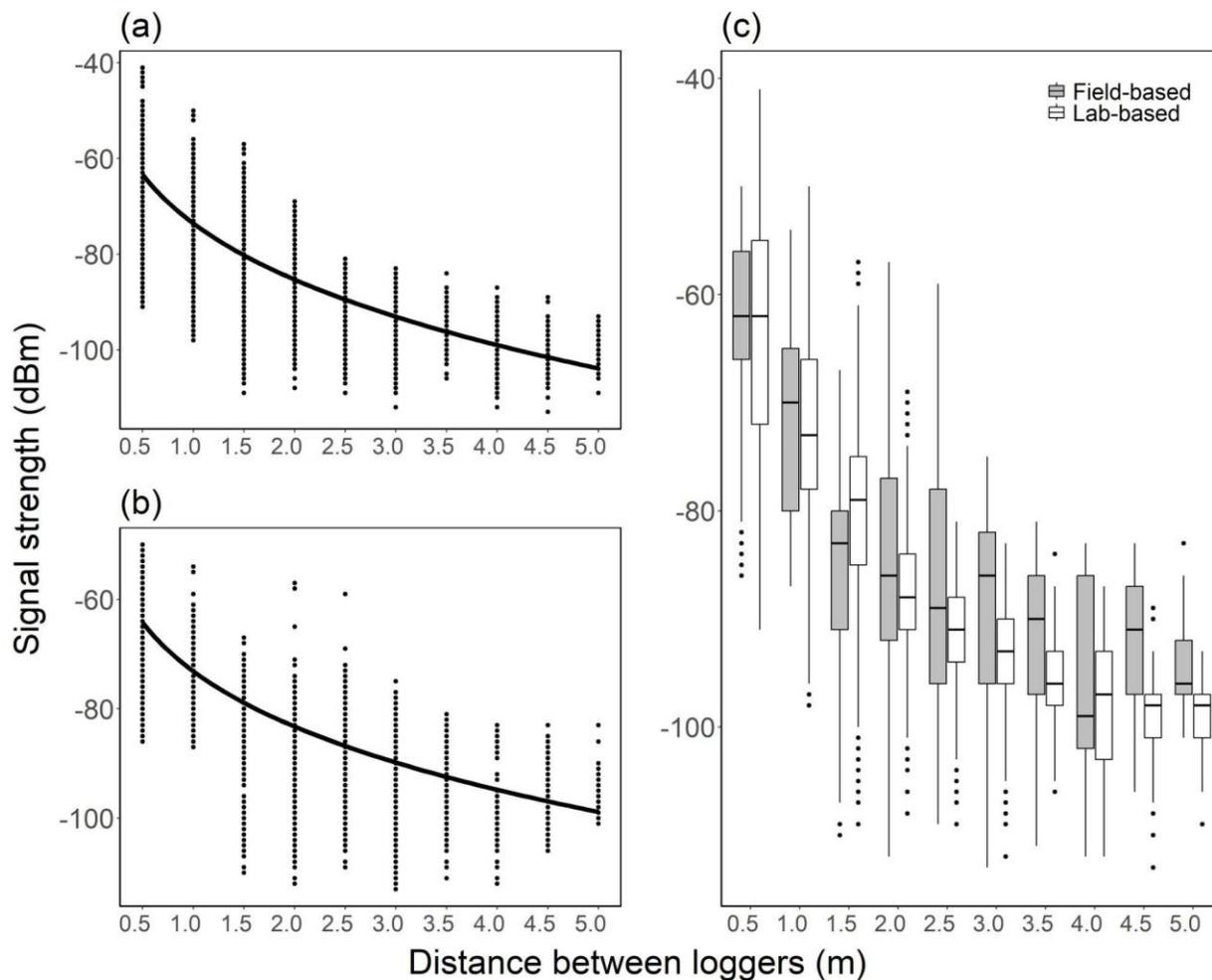


276

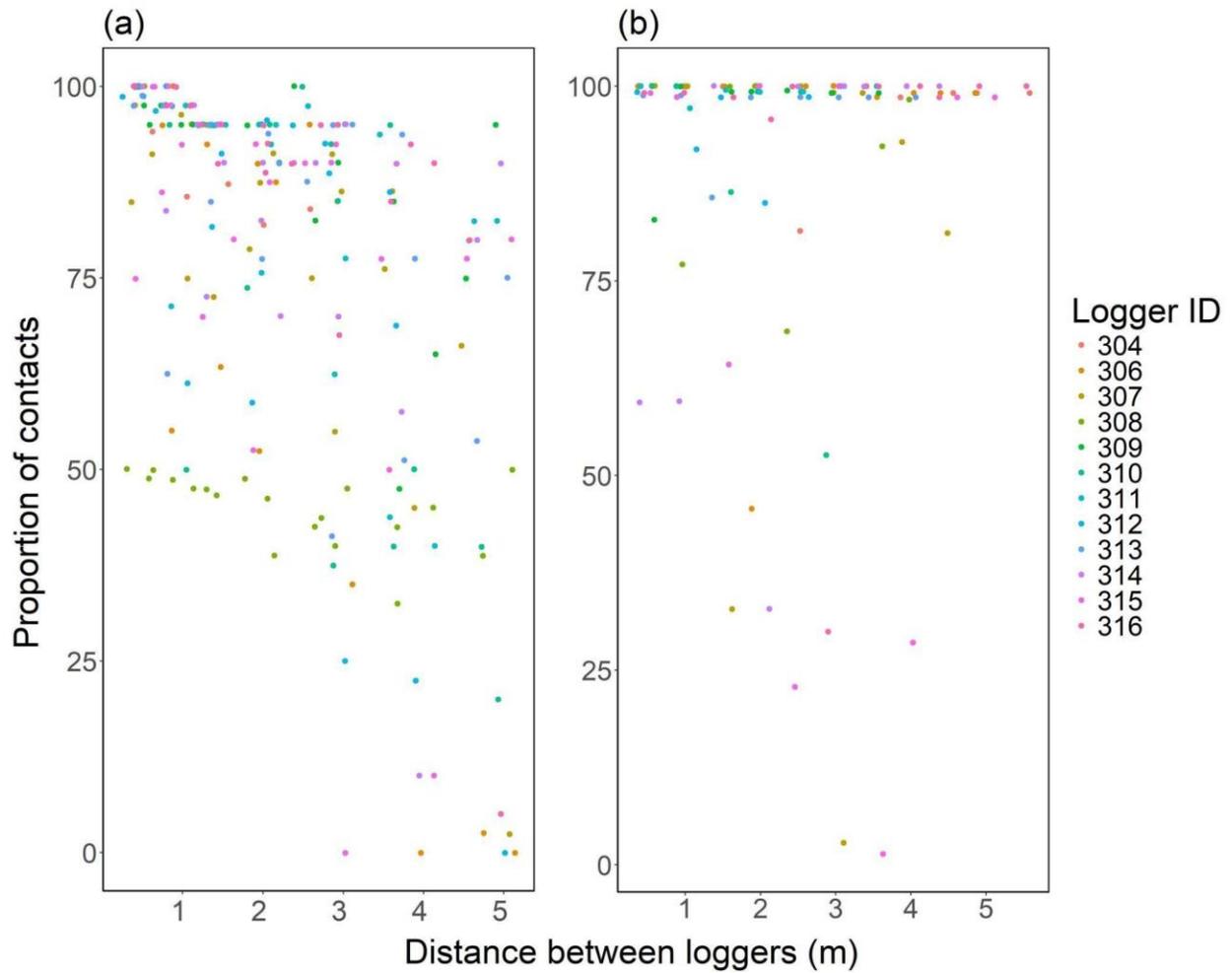
277 *Figure 1. Among- and within-logger variation in signal strength in relation to distance between units.*

278 *Data were collected on 12 loggers in a (a) lab-based environment and (b) field environment. Values of*

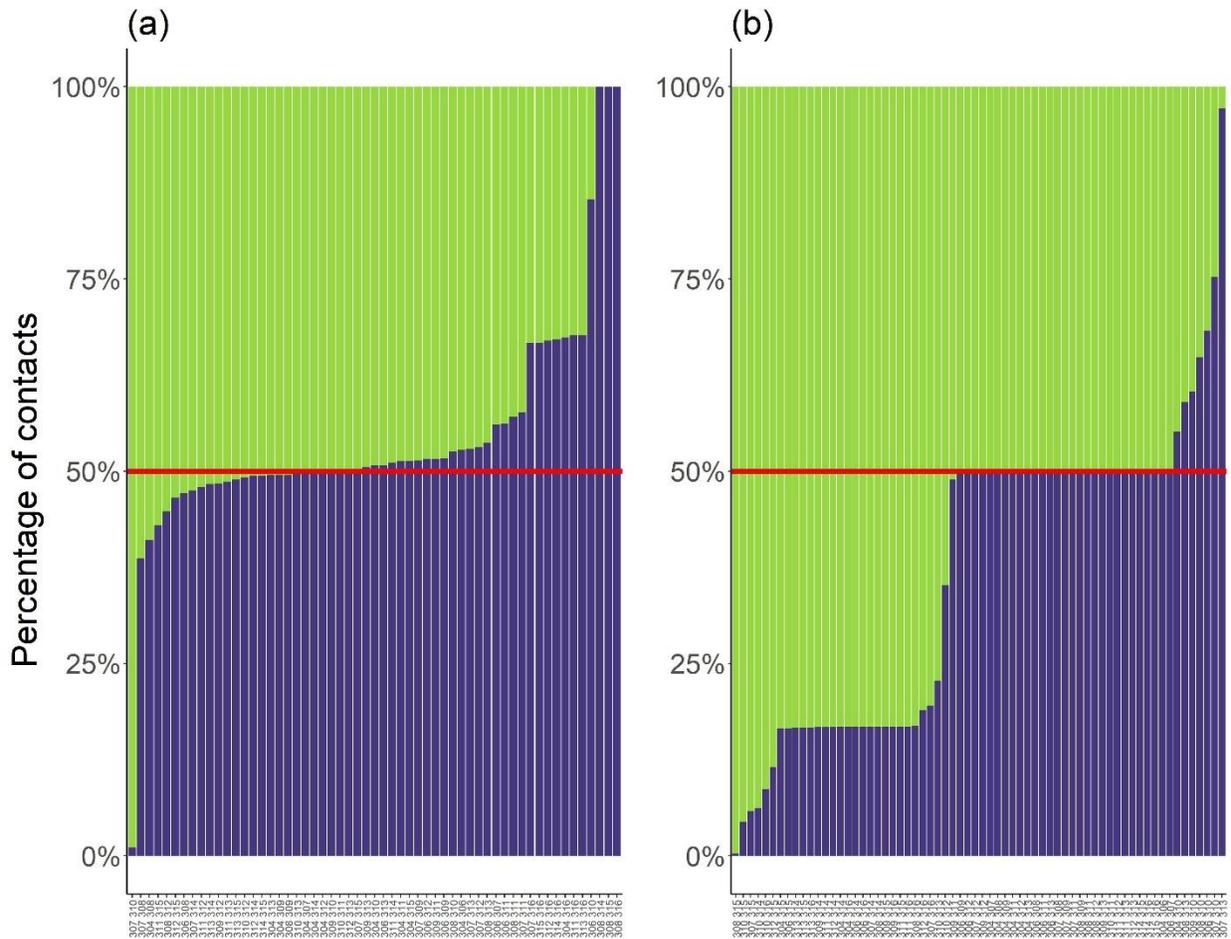
279 *signal strength (in decibel-milliwatts) closer to zero indicate a strong signal strength.*



281
 282 *Figure 2. Relationship between logger signal strength and distance for 12 loggers tested in (a, c) a lab-*
 283 *based environment and (b, c) in a field-based environment. The trendlines represent the exponential*
 284 *decay equation of the line of best fit.*



285
 286 *Figure 3. Relationship between the proportion of expected contacts correctly processed and distance for*
 287 *12 loggers tested in (a) a lab-based environment and in (b) a field environment. The values are jittered on*
 288 *the x-axis for better representation.*



All loggers pairs

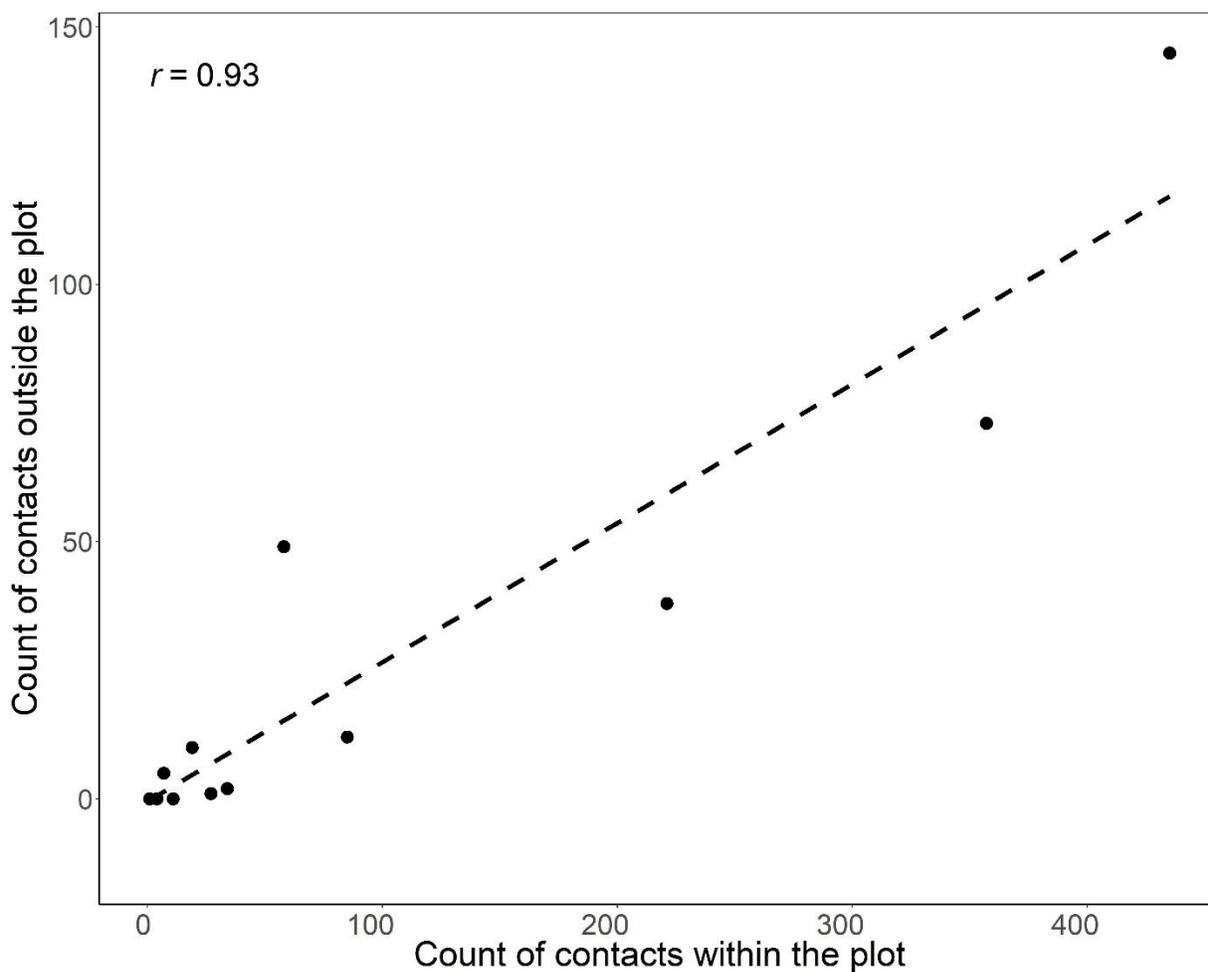
289
 290 *Figure 4. Percentage of contacts recorded by loggers for each dyad formed by 12 loggers tested in (a) a*
 291 *lab-based environment and in (b) a field environment. The horizontal red line represents an equal*
 292 *proportion of contacts received within the dyad.*

293 Logger function on live animals

294 To determine if the use of the Gipsy 6© proximity feature could be used instead of scan observations,
 295 we tested six devices on live animals and evaluated whether they were detected at the same time by
 296 visual observations and their proximity loggers. We found that all six visual occurrences of associations
 297 between logger carrying birds made by an observer were confirmed at the same time by contact
 298 detection. However, only 6.5 % of the associations captured by loggers were confirmed by visual
 299 observation. By looking at the contact detection outside of the plot and between observation periods,
 300 we found that 20.26 % of loggers' contacts occurred outside the plot (number of contacts outside the

301 plot = 338, number of contacts within the plot = 1330) and 19.92 % of loggers' contacts within the plot
302 happened outside of observation hours (number of contacts outside hours = 265, number of contacts
303 within hours = 1065 contacts).

304 To test whether individuals associated with the same conspecific on land and at sea, we
305 compared the count of association in and outside of the plot, for each dyad (Figure 5). We found that
306 the counts of association on land and outside the plot (presumably at sea) were strongly correlated
307 ($r(17) = 0.93, p < 0.01$).



308
309 *Figure 5. Relationship between the count of contacts within and outside of the plot for 13 dyadic*
310 *combinations formed by six individuals. Each dot represents a dyad, and the dashed black line represents*
311 *the trend.*

312 Discussion

313 Remote sensing data collection has become increasingly popular to gather information when and where
314 in-person observations are constrained. However, the use of proximity loggers for the collection of
315 association data in small species is fairly limited. In this study, we tested Gipsy 6© loggers, a device with
316 proximity functions, in a lab-based and field environment to evaluate their performance in contexts
317 similar to our deployment condition, and on live animals to test their potential to replace human
318 observers, particularly when individuals are not visible.

319 When testing the loggers in lab-based and field environments, we found a loss in signal strength
320 with distance. We also found that signal strength was only moderately repeatable and that the identity
321 of the logger was responsible for most of the variance in the model. Existing literature suggests three
322 main explanations for the loss in signal strength in these types of devices. The dilution of the signal with
323 distance (Ripperger et al., 2016; Kirkpatrick et al., 2021; Huels et al., 2025), the technical differences
324 between devices as well as their settings (Prange et al., 2006; Huels et al., 2025) and the natural
325 obstacles such as tall grass or reflecting materials disturbing the signal (Rutz et al., 2015; Triguero-Ocaña
326 et al., 2019; Kirkpatrick et al., 2021). Our results align with those statements, and as expected, we
327 reason that signal strength was affected by all three factors. As a consequence, signal strength should be
328 used cautiously when attempting to evaluate the distance between individuals. In the context of social
329 network analysis, they would be best used to assess group membership in flocking/herding species, or
330 as in this study, to evaluate if conspecifics that nest near one another also travel or forage together.
331 Nonetheless, using arbitrary thresholds of detections with minimum signal strength could be used to
332 approximate the distance between individuals, which could still be sufficiently precise for studies that
333 are interested in near-contact occurrence (Hamede et al., 2009).

334 The loss of signal strength with distance ultimately leads to a decrease in successful contacts as
335 it becomes harder for a device to capture a weak signal. However, it is not the only reason driving

336 loggers to miss contacts. Here, we found that only 50 % of the devices accurately detected the
337 associations from their dyad both ways, regardless of the environments tested or their distance. Missing
338 contacts have already been observed in other loggers (Drewe et al., 2012; Kirkpatrick et al., 2021; Huels
339 et al., 2025), alongside extended-duration contact interpreted as multiple events (Prange et al., 2006).
340 Missing contact often comes from weak signal strength from loggers at the edge of range detection
341 (Prange et al., 2006), when the battery has diminished power (Drewe et al., 2012) or when the collision
342 rate increases due to a locally saturated device emission environment (Kirkpatrick et al., 2021).
343 Collisions prevent the proper detection of emitted signals and are generated when two or more loggers
344 advertise simultaneously (Ghamari et al., 2018). We suspect that missing contacts in our study were the
345 result of collision, as we deployed the loggers in high density, and with a relatively high sampling rate. As
346 noted elsewhere, relatively high collision rates are one of the main limitations to the use of proximity
347 loggers regardless of their use of Bluetooth signals (Kirkpatrick et al., 2021) or radio frequency signals
348 (Drewe et al., 2012). The collision risk between loggers advertising at the same time is impossible to fully
349 eliminate. However, it can be reduced by limiting the number of devices and the emissions interval to
350 locally reduce congestion. Adding a small interval to gradually trigger the advertisement signal can also
351 reduce collisions (Kirkpatrick et al., 2021). Those issues express the need to carefully review the dataset
352 and apply corrective factors based on false-negative probability if necessary. Data sets with missing
353 observations can, for example, be calibrated using corrective factors such as a simple ratio index or half-
354 weight index (Hoppitt & Farine, 2018). However, adding statistical manipulations might limit the
355 benefits of using proximity loggers compared to traditional methods.

356 By testing the effect of distance with two treatments (field and laboratory), we found that signal
357 strength was more affected by distance in the lab setting than in the field environment. However, the
358 number of contacts in the lab setting was more consistent than in the field. We suggest that these
359 differences are explained by the topography and the deployment setting of the different locations. The

360 loggers in the lab environment were deployed in a circle, only a few centimetres apart from each other,
361 sending a signal every minute. In addition, the loggers were deployed on an asphalt-shingled rooftop
362 with radio frequency reverberation properties different from regular soil (Omusonga et al., 2015). This
363 configuration, in close proximity, with a high signal rate and in a reflective environment, might have
364 increased the collision rate. In contrast, the loggers in the field environment were deployed diagonally,
365 on a heterogeneous landscape with a 40-degree angle slope. Together with a lower frequency of signals,
366 this configuration might have generated fewer signal collisions, but also higher variability in the number
367 of contacts.

368 To investigate the potential of the Gipsy 6© proximity logger in replacing visual observation
369 methods, we tested if observational data matched logger detections. Because loggers were set to turn
370 off at night to save battery life, we did not record nocturnal social activities. Atlantic puffins have limited
371 activity at night, either because they are sleeping in their burrow or resting at sea. Additionally, no pairs
372 have been tagged with loggers and between-mate activity was not recorded. Thus, if some associations
373 may have been missed, mainly individuals rafting at sea, we do not expect those associations to change
374 the nature of their social network. We found that all tagged individuals observed on the plot were also
375 confirmed by a contact made by loggers, but that the loggers detected more potential associations. Only
376 6.5 % of associations captured by loggers were confirmed by visual observation, while all visual
377 observations of birds with loggers were remotely detected. While it is possible that observers missed a
378 large number of associations, it is more likely that the number of associations within two meters
379 detected by loggers was overestimated. As argued above, signal strength cannot be reliably used to
380 estimate distance and many of the contacts identified by loggers could be the result of birds identified
381 by the observer, but not included in an association because they were not close enough. Nonetheless,
382 this finding suggests that, despite the unequal proportion of contacts recorded by each logger within a
383 dyad and the decreasing signal strength with distance, the automatic detection not only matches but

384 has the potential to outperform visual observation. Thorough ground truthing of the loggers in different
385 contexts would be needed every time. Our results are similar to other studies testing observational
386 methods and proximity logger (Drewe et al., 2012; Ripperger et al., 2016; Kirkpatrick et al., 2021; Huels
387 et al., 2025), and can be explained by the limited number of individuals an observer can simultaneously
388 keep track of. However, Drewe et al. (2012) detected decreasing battery and logger performance over
389 time, an aspect that we did not cover due to the low retention time of the device on birds. While we
390 cannot predict with certainty the consequences of low battery level on the Gipsy 6© performance, the
391 presence of a solar panel, little battery consumption and the setting modularity of this model should
392 limit such problems.

393 During the trial on animals, associations were detected by the loggers outside of the observation
394 time (19.92 % of the observations) and plot (20.26 % of the observations). Indeed, those results highlight
395 the benefit of having automatic detection to increase the quantity of data collected, but they also reflect
396 the important proportion of data collected using a traditional scanning method. Knowledge of an
397 animal's behaviour, in this case the aggregation of individuals at higher density at dawn and dusk,
398 optimised the opportunities to observe near-contact between individuals. Of all associations, over 20 %
399 were detected outside of the plot, which would never have been visible to observers. In themselves,
400 these data are useful as they suggest that individuals in the study area probably raft or forage together.
401 Furthermore, by comparing the number of contacts each dyad had on land and at sea, we found that
402 individuals were often associated with the same social partners, suggesting that associations on land are
403 maintained at sea. While leaving the colony (e.g., because of predation), Atlantic puffins take off in
404 groups that circle above the ground or land on the water to form rafts. These aggregations on water are
405 probably complemented by individuals from nearby parts of the colony, which could be expected to
406 randomly mix. However, previous research has found that Atlantic Puffins not only associate on land
407 with close conspecifics but can move to seek potentially familiar individuals (Morel et al., 2025). Because

408 tagged individuals mainly associate away from the colony with the same conspecifics as on land, we
409 suggest that familiar individuals may also seek each other at sea.

410 The development of miniaturised devices encourages the use of remote sensing to replace
411 traditional observation techniques. The overall performance of the Gipsy 6© allowed us to determine
412 that scan observations timed with the highest density of birds on land captured a majority of true
413 associations, but also suggested that associations were likely missed. Furthermore, we were able to
414 confirm that associations in our study area were maintained away from the plot, probably at sea.
415 Broader use of these devices would certainly help answer questions pertaining to the social structure of
416 high-density colonial animals such as seabirds, but only after extensive consideration of the impact of
417 signal collision rates, and in a context where the actual distance between the individuals of interest is
418 not as important as the fact that they are near one another.

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