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Ornithological Methods

Using ringing data to inform geolocator deployment: a case study of the Red-capped Robin-chat *Cossypha natalensis* in East Africa

Uso de datos de anillamiento para informar el despliegue de geolocalizadores: un estudio de caso en *Cossypga natalensis* en Africa oriental.

Raphaël Nussbaumer [1,2,3], *Lennox Kirao* [1], *Felix Liechti* [2] and *Colin Jackson* [1]

ABSTRACT. Thanks to their light weight and low cost relative to GPS trackers, light-level geolocators are uniquely positioned to uncover bird migration patterns across less well-financed and understudied regions of the world. A main drawback of geolocators is the need to recapture equipped birds to retrieve the data. Maximizing the recapture rate is therefore critical to the success of any geolocator study. In this paper, we present a methodology drawing on historical ringing data in order to inform the deployment of geolocators, both in terms of how many birds can be equipped, and when/which birds to equip in order to maximize retrieval. We illustrate this methodology with a geolocator study of Red-capped Robin-chats (*Cossypha natalensis*) on the coast of Kenya and find that it accurately estimates how many geolocators to source. It also provides insights into which classes of birds (based on age, capture history, and timing within the season) are most likely to be recaptured. Finally, the analysis of recapture rates allows minimization of geolocator use and thus potential negative impacts to a population.

RESUMEN. Gracias a su bajo peso y ser de bajo costo relativo a los localizadores de GPS, los geolocalizadores de niveles de luz se encuentran en una posición única para descubrir patrones de migración de aves a través de regiones con poca financiación y poco estudiadas en el mundo. La mayor desventaja de los geolocalizadores es que se requiere la recaptura de las aves equipadas para recuperar los datos. Consecuentemente, es crítico maximizar la tasa de recaptura para el éxito de cualquier estudio que utiliza geolocalizadores. En este documento, presentamos una metodología que utiliza datos históricos de anillamiento con el fin de informar el despliegue de geolocallizadores, en términos de cuantas aves pueden ser equipadas y cuando y cuales individuos se pueden equipar para maximizar la recuperación. Ilustramos esta metodología con un estudio de geolocalización en *Cossypha natalensis* en al costa de Kenia y encontramos que la metodología estima adecuadamente cuantos localizadores se deben utilizar. También provee información sobre cuales clases de aves (basado en edad, historia de captura y fecha en la temporada) que son recapturadas con mayor probabilidad. Finalmente, el análisis sobre las tasas de recaptura permite minimizar el uso de geolocalizadores y por lo tanto los potenciales efectos negativos sobre la población.

Key Words: *data-logger; cost efficiency; optimization; planning; recapture; recovery; survey design*

INTRODUCTION

Light-level geolocators are a well-established technology used to study bird migration. Relying on a simple light sensor and time clock, these devices provide location data based on sunrise and sunset. Thanks to their extremely light weight (0.5 grams), they are currently the main tracking technology available to study migration patterns of very small birds (Bridge et al. 2011, McKinnon and Love 2018). Geolocators have already helped advance our understanding of bird migration on a number of levels: identifying migration routes and non-breeding locations (e.g., Salewski et al. 2013, Smith et al. 2014, Liechti et al. 2015, Kralj et al. 2020), as well as understanding migration strategies (e.g., Adamík et al. 2016, Briedis et al. 2019, Hahn et al. 2020) and migratory connectivity (e.g., Finch et al. 2015, Procházka et al. 2017, McKinnon and Love 2018), among others.

As habitat destruction and climate change accelerate and adversely affect migrant birds, it is urgent to better understand migration patterns to effectively protect migratory bird populations (e.g., Simmons et al. 2004, Sekercioglu 2010, Şekercioğlu et al. 2012, Vickery et al. 2014). Geolocators can be instrumental in helping us understand the routes, timing, triggers, and variability of migration, as well as identify breeding, non-breeding, and stopover sites to protect. This is of particular relevance for long-distance Afro-tropical migrants whose migration patterns still remain largely unknown (e.g., Bennun 2000, Benson 1982, Bussière et al. 2015, Cox et al. 2011, Nwaogu and Cresswell 2016, Osinubi 2018). In addition, thanks to their low-cost relative to GPS solutions (e.g., Bridge et al. 2011), geolocators are particularly well-suited to projects with limited budgets.

Though the material cost for geolocator studies may be low, the fieldwork can be particularly resource-intensive, especially since the birds equipped must be recaptured to retrieve the data. Surveys therefore need to be designed in a way that optimizes both the data collected and the resources used to do so (Hauser and McCarthy 2009, Moore and McCarthy 2016, Smart et al. 2016). The design of efficient and effective survey protocols has received much attention in capture recapture studies (e.g., Devineau et al. 2006, Lindberg 2012). This typically involves varying the levels of effort (survey duration, number of individuals surveyed, etc.) to estimate population level characteristic traits such as survival (e.g., Lieury et al. 2017). Optimizing geolocator surveys, on the other hand,

[1]A Rocha Kenya, [2]Swiss Ornithological Institute, [3]Cornell Lab of Ornithology

generally comes down to maximizing the number of devices retrieved. Indeed, because geolocator studies seek to uncover bird movement information at the individual level, success relies exclusively on capturing enough tracks.

We base our optimization method on the fact that geolocator studies often take place within the context of existing ringing efforts. Indeed, assessing the suitability of the species and the optimal number of individuals to be equipped with logging devices requires basic information on recapture probability. This minimizes not only costs, but also potential negative impacts on a population (Brlík et al. 2020). This initial assessment can be carried out with relatively small datasets with variable effort, or even with data from similar locations or species. Though such historical data could also be leveraged to plan geolocator fieldwork, simple tools and methods to do so are currently lacking.

Drawing on a case study carried out on the Red-capped Robin-chat (*Cossypha natalensis*), an Afro-tropical migrant in Kenya, we demonstrate how performing a pre-deployment analysis using an existing ringing database can improve the planning and implementation of geolocator deployment. In particular, we show how this pre-analysis can inform two questions:

1. How many birds can we expect to equip during a full season for a given ringing schedule? Ordering geolocators requires accurately estimating the number of individuals that can realistically be captured per ringing season. Because geolocators are configured to start collecting data for a specific year when assembled, overestimating the individuals captured would result in wasting devices, while underestimating would lead to missed opportunities and inefficient field work. An accurate estimation of number of birds captured also helps design an optimal ringing effort (in terms of number of sessions, duration of sessions, number of nets, etc.).
2. How can we maximize bird recapture by equipping specific classes of birds (e.g., sex, age) and targeting specific periods of the year? The ringing database provides the recapture rate of a bird as a function of the equipment date but also of its age and weight, allowing the ringer to make an informed decision about whether to equip a given bird. This decision should also account for the number of geolocators available, the number of sessions left, and the specific research question asked.

MATERIALS AND METHODS

Case study species

In this case study, geolocators were placed on Red-capped Robin-chats (RCRC; 16–17 cm; 24–40 g, Collar 2020), a terrestrial thrush living in the forest understory, shrubland, and savannas. It can be found in a variety of forest habitats, and generally occupies low-level shrubs. Because both resident and intra-African migrant populations coexist, the migratory patterns of this species have been difficult to understand (Collar 2020). Further complexity is added by the fact that three sub-species are found in Africa: *larischi* in Western Africa (Nigeria and Angola), *natalensisis* in South Africa, and *intensahas* ranging from N. South Africa to Somalia as well as central Africa.

On the coast of Kenya, RCRC are present from April to October, yet their breeding location and migration routes remain unknown. They are known to hold territory on their non-breeding sites and show site fidelity as demonstrated by the high recapture rate of 42% on the study site, making them an ideal species for a geolocator study.

Capture site and database

The A Rocha Kenya Conservation center is located on the coast of Kenya and in the middle of the Northern Zanzibar-Inhambane Coastal Forest Mosaic ecoregion (3°22′36.3″S 39°59′16.9″E). This region is recognized for its high biodiversity value (Marris 2010) yet faces increasing habitat fragmentation because of the expansion of agriculture and charcoal burning (Burgess and Clarke 2000). The Conservation center is located on a residential coastal scrub/forest that has been protected from limited habitat change over the last 50 years (Alemayehu 2016), in the effort to preserve the ecosystems for tourism. Mist nets are placed in a nature trail that runs through a small patch of forest managed by the Conservation center.

In this study, we use the ringing dataset from capture sessions conducted regularly from 2002 to present. Up to early 2019, the dataset consisted of 3372 entries of 2532 rings covering 96 species collected during 317 sessions. The ringing effort presents some temporal variability, as well as variability in the metadata recorded (see Appendix 1). In general, sessions start at sunrise (Mean [M] = 06.12am; Standard Deviation [SD] =14 minutes) and last until bird activity slows down (session duration M = 4 hours 8 minutes; SD = 1 hour 1 minute; see Fig. A1.2 in Appendix 1). On average, a total of 154 m (SD = 51 m) of nets were used. Descriptive notes on weather conditions were also included and later classified according to their expected influence on the capture rate (none, little, large). We manually checked extreme values in the dataset and removed those that could not be verified.

In addition, we present the ringing data of 2020, when the geolocators were first deployed. We did not include this data in the fitting of the models but rather used it for comparison and discussion purposes.

Predicting the number of birds to be equipped

To address the question of how many birds can be equipped, we first modeled the number of new RCRC captured per session and then computed the total number of RCRC per year given various ringing scenarios. Because an individual RCRC can only be equipped once a year, we must estimate the number of birds that have not yet been captured in the same year (i.e., new bird) rather than the count all RCRC.

In the first step, we modeled this number using a generalized additive model (GAM), assuming the number of captures follows a Poisson distribution. To avoid zero counts from being too frequent, we only fitted the model on the surveys performed between the 10th of April to the 6th of December. The predictor variables tested in the model are (1) year, (2) day-of-year, (3) duration of the session, (4) total length of nets, (5) starting time, (6) weather conditions, and (7) number of unique RCRC previously captured during the year. After testing several parametrizations of the model (see Appendix 2), we retained the capture model that included day-of year as a smooth function,

year as a random fixed effect and total length of nets, total duration, and number of unique RCRC as linear terms:

CountFoY ~ s(Year) + s(DayOfYear) + NetsDuration + NetsLength + CumCountFoY

To overcome the lack of sufficient data for the duration, start time, and length of nets, we used multiple imputation methods (Azur et al. 2011) to generate 30 sets of data without any missing values. For each of these sets, a GAM model was fitted.

In the second step, we predicted the total number of RCRC that can be captured over one year as a function of a ringing scenario. A ringing scenario consists of a schedule of ringing sessions over the year together with specific characteristics (session duration, length of nets, etc.). We estimated the total number as the cumulative sum of the estimated new RCRC of the GAM model fitted above for each successive session. This operation was done iteratively because the GAM model depends on the number of unique RCRC previously captured during the year.

In order to plan an optimal ringing scenario, we evaluated the impact of various components of the ringing effort on the total number of birds captured. The different scenarios tested include the following:

1. default: 4 hr-ringing sessions every 10 days with 156 m of nets
2. 6 hrs: same as default with longer ringing sessions (from 4 to 6 hrs)
3. 200 m: same as default with longer total net length (156 to 200 m)
4. optimized schedule: same as default with weekly ringing sessions from mid-May to early July, bimonthly sessions otherwise

Finally, in order to validate the model, we compared the actual number of RCRC captured in 2020 with the corresponding model prediction using the same schedule, session duration, and length of nets.

Maximizing geolocator retrieval

In this study we focus on two parameters to maximize bird retrieval: the time of year and the age class (adult or juvenile). Bird sex was not used because it is not possible to determine the sex of a bird in hand. The retrieval probability is estimated by modeling the binomial response of whether a captured bird is retrieved in the following years: we considered that an individual is retrieved if the bird has been recaptured at least once in any of the following years, and this is independent from whether it was already captured in the past. We modeled the count of adults and juveniles per session separately to reveal the influence of age on recapture rates. The weight of the bird was left out of the model because it showed little to no effect on the recapture rate (see Fig. A3.1 in Appendix 3). Additionally, we also compared the recapture rate for RCRC captured for the first time and those that had already been equipped.

All analyses were performed on R (R Core Team 2013), using the MCGV package (Wood 2017) for GAM, and the Mice Package (van Buuren and Groothuis-Oudshoorn 2011) for the imputation. We used and alpha value of 10% for significance.

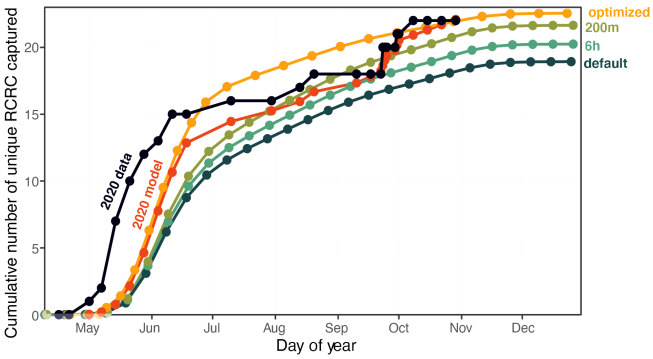
RESULTS

Predicting the number of birds to be equipped

As any typical migrant, the number of RCRC captured per session shows a strong dependence with the day of year ($P < 0.001$), with a bi-modal shape including a peak passage in early June with almost three RCRC per session and a second smaller peak in mid-September with two birds per session on average (Appendix 2). The number of new captures per session was found to be dependent with year ($P < 0.001$), length of the nets ($P < 0.001$), duration of sessions ($P < 0.01$), and number of previously captured RCRC ($P < 0.1$).

Starting time was found to be not significant ($P < 1$) and was therefore excluded from the final model because RCRC are generally active and caught equally throughout the morning and no session was held later in the morning or afternoon. Weather category was also found to be not significant ($P < 1$) and consequently excluded. Five different ringing scenarios were used to (1) estimate the total number of unique RCRC that can be captured in a year and (2) compare different ringing strategies and define an optimal scenario (Fig. 1).

Fig. 1. Model predictions of the total unique Red-capped Robin-chats (*Cossypha natalensis*; RCRC) caught along a year following different scenarios. The default scenario consists of 4 hr capture sessions using 156 m of nets every 10 days. "6 h" and "200 m" are modifications of the default scenario, and "optimized" increases the number of sessions (to every week) during the peak passage (mid-May – July) and decreases them (to every 2 weeks) during the rest of the year. Finally, using the exact date, duration, and net length used in 2020, the model prediction "2020 model" can be compared to the actual data ("2020 data").



Compared with the total number of birds caught with the default scenario (19 birds), increasing the duration of capture sessions by two hours ("6 hr") or adding 44 m of additional nets ("200 m") results in, respectively, 1 and 2 more birds caught. This is likely because RCRC are mostly active in the early hours of the day and additional nets are placed in sub-optimal habitats. However, the optimized scenario yields many more birds, with a total of 23 birds captured in fewer sessions (31 instead of 37 sessions).

In 2020, 27 capture sessions were held with 156 m of nets and an average duration of 3 hours 45 minutes (SD: 0:59). As of 1 November, a total of 30 RCRC were captured from 22 unique individuals. For the exact same information, the model predicted

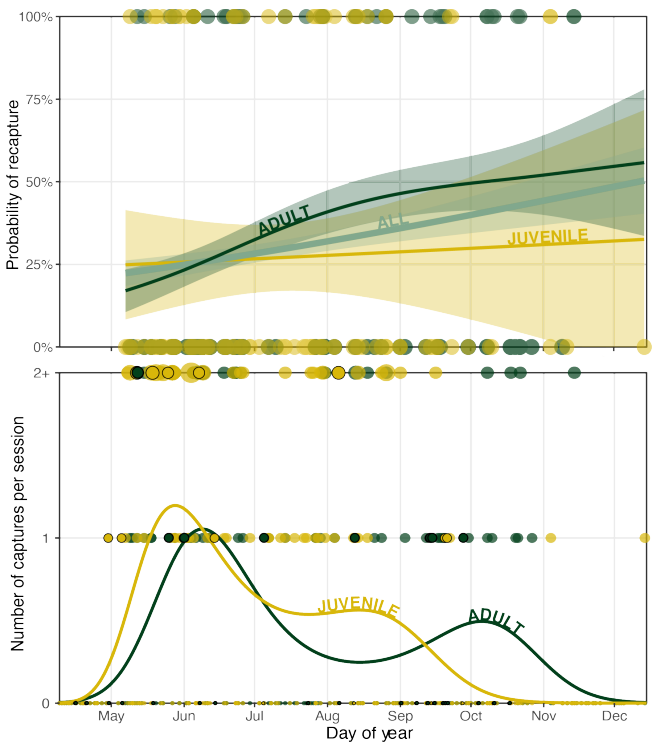
an expected total of 22 unique RCRC. The arrival date proved to be earlier than the average and the numbers appeared to be higher than average at the beginning of the season. This could be due to a particularly good breeding season as attested by the high number of juveniles caught during this period.

Maximizing geolocator retrieval

Over the 161 unique RCRC individuals captured in the dataset, 67 (42%) were recaptured at least once (including recapture the same year). When considering the 301 capture events (including same individuals), the general recapture rate increases to 47%. However, looking at recapture in any subsequent year, the recapture rate is 30%. In this study, we consider the retrieval rate as a recapture any subsequent years (latter definition), similar to the procedure employed with geolocators.

In general, adults show a slightly higher retrieval rate (34%; n = 127) than juveniles (27%; n = 174), but statistically not significant (test of proportions, $P < 0.1$). When modeled over the day of year (Fig. 2a), the retrieval rate in subsequent years shows that birds equipped later in the year are twice as likely to be recaptured, with a retrieval rate increasing from 25% to almost 50%. Separating adults from juveniles allows us to identify further trends. The increase in juveniles' retrieval rate is not significant. By contrast, adults show a clear increase from May to August, before stabilizing from September to October, indicative of birds establishing and maintaining territory. Modeling the number of captures of adults and juveniles (Fig. 2b), we observe an earlier arrival of juveniles (late May vs early June for adults) and earlier departure in August, while adults show a second peak early October.

Fig. 2. Comparison of adult (green) and juvenile (yellow) trends in (a) recapture rate in subsequent years and (b) number of captures per session throughout the year.



Finally, a RCRC that has already been captured in the past has a higher recapture rate (36%) compared to a bird without a ring (24%). We did not find a significant effect of weight on retrieval rate (see Fig. A3.1 in Appendix 3), which is known to usually impact survival rate (e.g., Saether 1989).

Informing geolocator deployment

We illustrate how the results above have informed the practical deployment of geolocators on RCRC in 2020 and following years. In light of the results, rather than increasing session duration or net length, we favored increasing the frequency of ringing sessions when numbers are highest (mid-May to early July).

Results show that while waiting for July/August seemed preferable to increase the retrieval rate, the number of birds captured decreases strongly in this period. We thus sought to find a trade-off between deploying all the devices and equipping as many as possible later in the year by releasing some birds captured earlier in the year without a device. In order to test the hypothesis of variable departure/arrival dates based on age, we wanted to equip both juveniles and adults. We therefore only equipped six RCRC (of a total of 15 geolocators) before mid-June, when juveniles were more common to keep enough geolocators for July and August, when adults were more common.

DISCUSSION

The new method presented in this study leverages ringing datasets to enable fact-based planning of geolocator studies. The main objective is to support cost-effective planning of fieldwork and to determine the optimal number of logging devices, taking into account the specific research question. This relatively simple method does not replace or compete with the various more complex existing capture-recapture models (McCrea and Morgan 2014).

Predicting the number of birds to be equipped

Varying the different components of the survey design can greatly affect the number of captures, and in turn the cost-efficiency of a study (e.g., Lieury et al. 2017). Our method allows to test the effect of each effort component on the total number of captures, thus enabling researchers to refine the survey design in view of optimizing number of captures. In the RCRC case study, we found that increasing net length or session duration carried limited added-value compared to increasing the frequency of ringing sessions when bird numbers are highest (mid-May to early July). The pre-analysis presented here is particularly useful in contexts where the ringing database is limited, or past ringing effort has been variable (e.g., Ruiz-Gutiérrez et al. 2012).

Maximizing geolocator retrieval

For the geolocator study to be successful, not only do we need to maximize the number of birds equipped (with minimal ringing effort), but we also need to optimize the device retrieval rate. Modeling the geolocator retrieval probability does not need to separate the survival, recapture, and emigration rates. Therefore, a complex capture recapture model (McCrea and Morgan 2014) was not required. Instead, we used a simple approach able to identify the time of year and class of bird that yield the highest geolocator retrieval rates. In the case of the Red-capped Robin-chats, retrieval is highest among adults, which is typically the case for birds (e.g., Gardali et al. 2003), and among birds who have already been ringed in the past. The results provided useful

conclusions to adjust the timing and intensity of the fieldwork, almost doubling the expected logger retrieval rate.

The approach followed in this paper contains some limitations. First, a bird was considered retrieved if it was captured again in any year following the initial capture. However, for a geolocator study, the retrieval needs to happen within the duration of the study. The retrieval rate of the full dataset (30%) reduces to 19% when restricting to retrievals taking place the following year, 26% for the following two years, and 28% for the following three years. This suggests that ringing should continue for at least two years following equipment to benefit from maximal geolocator data. Second, by using retrieval data from the ringing database as a proxy for retrievals involving geolocators, we ignore the effect geolocators may have on survival compared to ringed birds (e.g., Streby et al. 2015, Weiser et al. 2016, Brlík et al. 2020). Therefore, it does not replace the need for a control group. The potential weight-dependent impact of geolocators on bird survival (e.g., Brlík et al. 2020) is not accounted for in this analysis.

Finally, equipping specific classes of birds needs to be carefully considered in light of the research question. Geolocator studies are inherently biased in that we only learn about birds that (1) have initially been captured in the mist net, (2) have survived until the subsequent year, and (3) have come back to the exact same area. Our approach relies on the fact that individual birds respond differently to these effects based on their age, sex, or weight. Targeting specific classes can only accentuate the biases inherent to geolocator studies. This should be duly acknowledged in the study and accounted for in the analysis.

Outlook

Although the model and results of this study are tailored to the specific case of the RCRC on coastal Kenya, the application of this methodology can be extended to other situations where some historical ringing data is available for a given study site and species. In general, our methodology is only applicable for cases where the deployment of geolocators is performed with a similar protocol (e.g., mist net, nest trap, spring nest trap) and context (e.g., place, time, general ringing effort) as the ringing database. In this study, we carried out analyses comparing only adults and juveniles because it is not possible to determine the sex of a bird in hand. The same analysis can be performed on any class of bird identifiable in hand (sex, molt stage, breeding status, subspecies). The approach presented can be applied to any study relying on the recapture of specific individuals (e.g., archival GPS; Hallworth and Marra 2015).

Responses to this article can be read online at:
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Data Availability:

The data and code that support the findings of this study are openly available in [Github] at https://github.com/A-Rocha-Kenya/MaximizingRecapture.

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Appendix 1

Data extent

The capture sessions are relatively well-spread throughout the year (y-axis in Figure A1.), although with a slightly higher intensity in March-April than June-July or December-January. The distribution is more heterogenous when comparing different years (x-axis in Figure A1.1): there is very good coverage between 2003 and 2007, variable from 2008 to 2012, and relatively stable since then.

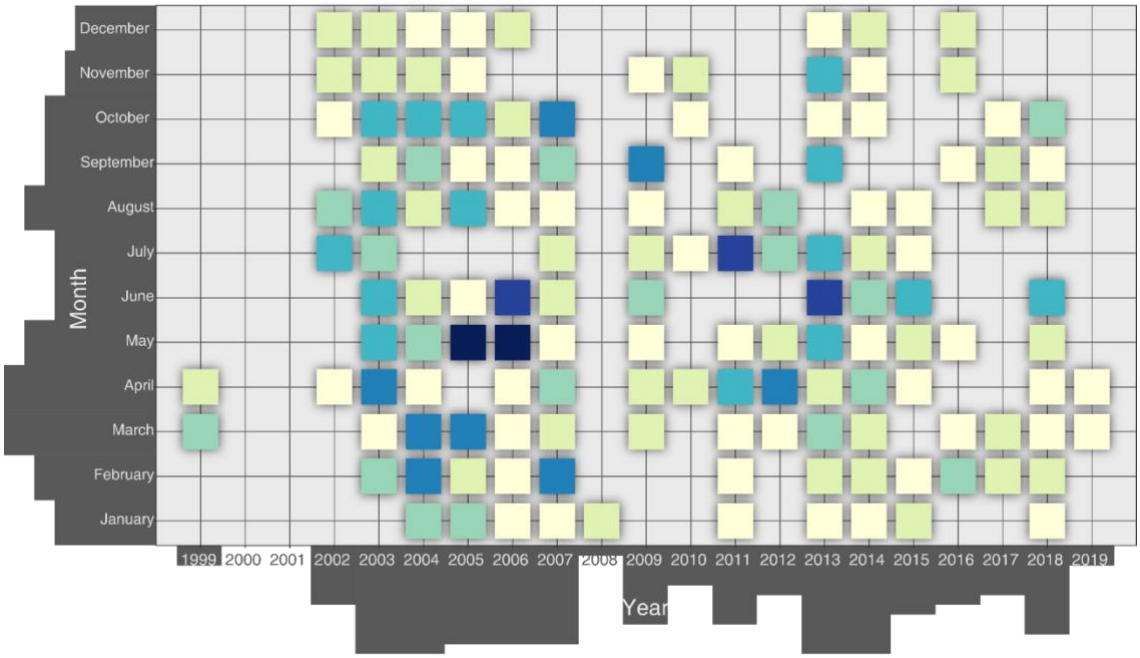

Figure A1.1: Distribution of the capture sessions according to year and month. Colour scale indicates the number of capture sessions.

Additional information was available for some sessions: start time (data available for 74% of the sessions), closing time (39%), sum of net lengths (23%), weather conditions (45%).

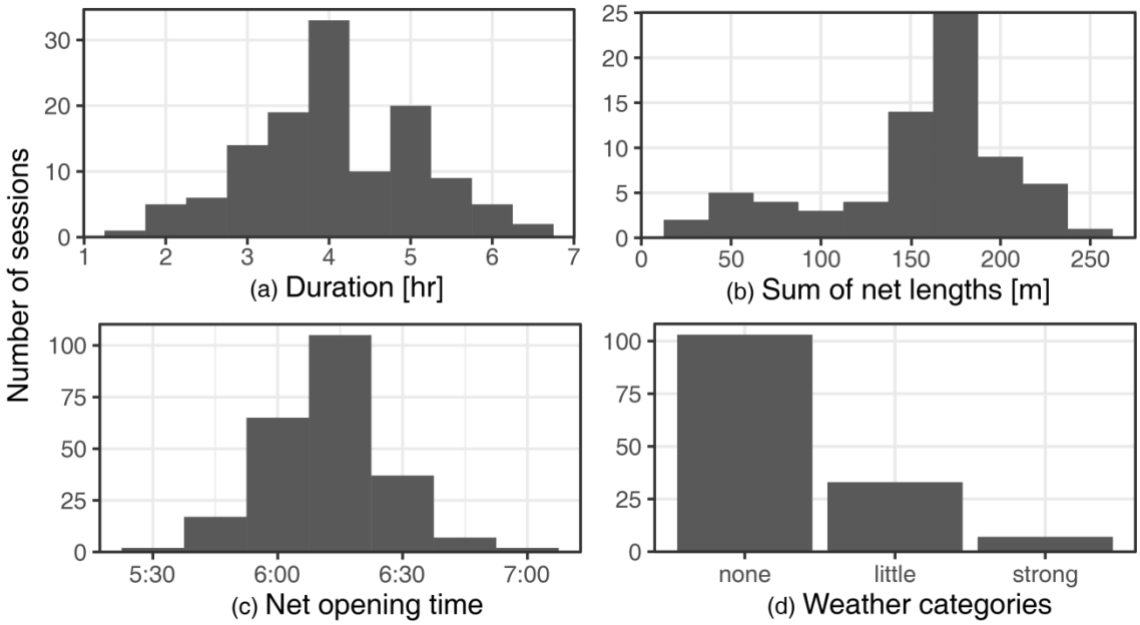

Figure A1.2: Histograms of the metadata recorded for each capture session (N=317) of (a) total length of nets (N=73), (b) duration of capture session (N=124), (c) weather category (N=143) and (d) time of session start (N=235).

Appendix 2

Capture model

Before fitting the GAM modelling the count of new RCRC captured per session, we explored the response of each of the variables separately with a GAM or GLM (Figure A2.1).

a) **Year** (Figure A2.1a). A general decline in the overall number of birds is observed over the 20 years of the dataset. However, this trend was not estimated to be realistic but possibly due to change in survey effort or net location. Year was included as a random fixed effect.
b) **Day-of-year** (Figure A2.1b). Day-of-year has a strong influence on the number of captures and varies non-linearly. This variable is thus included in the model as a smoothing term.
c) **Duration** (Figure A2.1c). The duration of the session computed as the difference between closing time and opening time shows a positive correlation with the number of captures. It is thus included in the model as a linear term.
d) **Net opening time** (Figure A2.1d). The fit of the opening time seems to indicate a higher capture rate for sessions starting later. This relationship is contrary to common knowledge and considered non-meaningful. It is thus not retained for the model.
e) **Sum of net lengths** (Figure A2.1e). Between 50 and 200m, the fit shows an increase of captures as the total length of the nets increases. Yet, above 200m, the fit shows a stabilisation of the count. This is explained by the fact that the nets added above 200m are located in habitats which are not ideal for RCRC and thus do not contribute to an increase in capture. This term is included as a smoothing term.
f) **Weather categories** (Figure A2.1f). The weather categories do not show a clear pattern and are thus not included in the model.

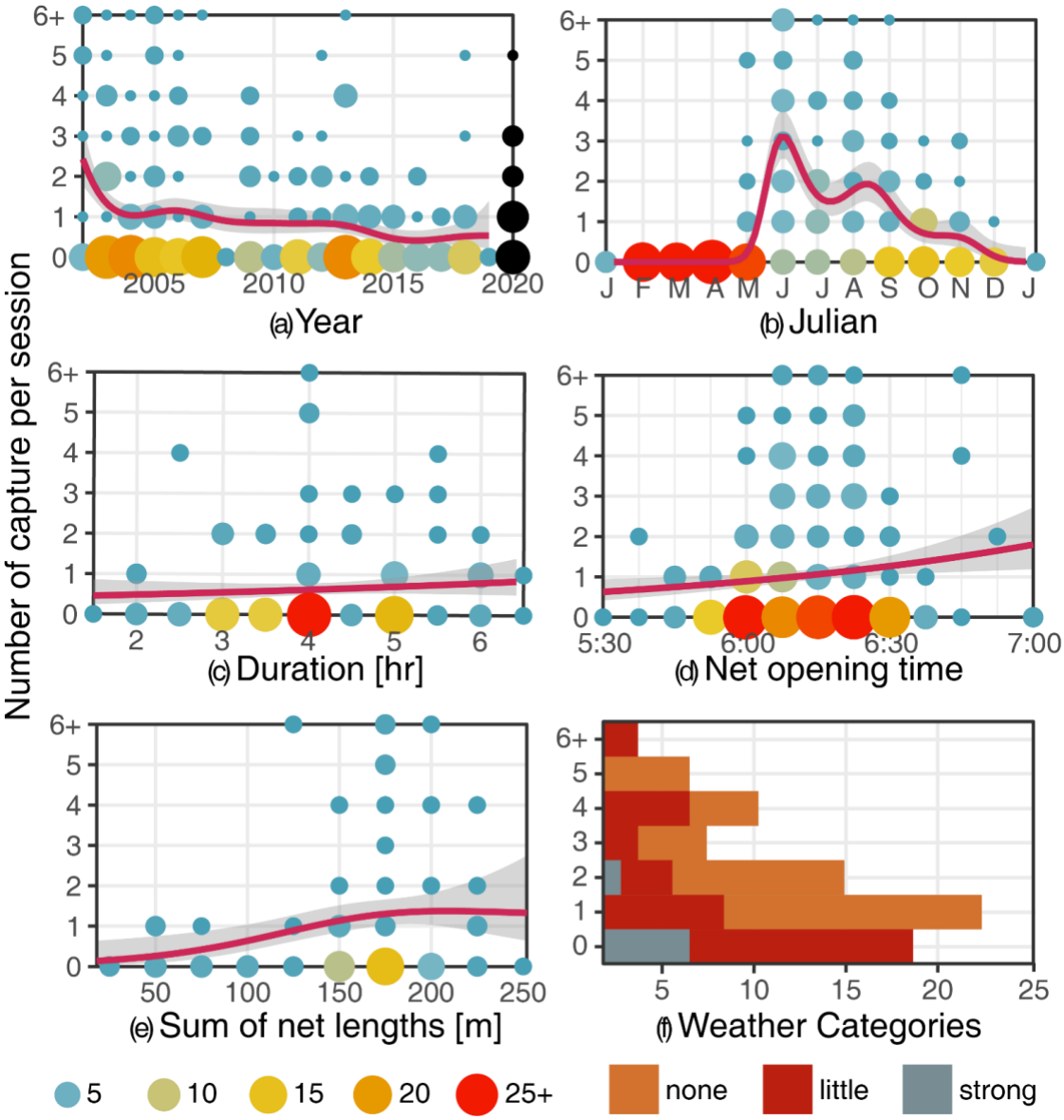

Figure A2.1: Number of RCRC captured by session as a function of (a) total length of nets, (b) duration of capture session, (c) weather category and (d) time of session start. The red line with shaded area is a smoothed curved fitted on the data (GAM or GLM)

We provide the model fit summary for the final model (Box A2-1) and the model including all variables possible (Box A2-2)

Box A2-1: Model fit summary including all variables

```
Family: poisson
Link function: log

Formula:
CountFoY ~ s(Year, bs = "re") + s(DayOfYear) + NetsDuration + NetsLength + CumCountFoY
```

```
Parametric coefficients:
                    Estimate Std.   Error        z value     Pr(>|z|)
(Intercept)         -1.045689       0.486146    -2.151      0.03148  *
NetsDuration        -0.187815       0.067547    -2.780      0.00543  **
NetsLength          0.008530        0.001586    5.378       7.54e-08 ***
CumCountFoY         -0.032821       0.016956    -1.936      0.05291 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                    edf             Ref.df      Chi.sq      p-value
s(Year)             11.398          17.000      59.11        <2e-16 ***
s(DayOfYear)        7.683           8.483       49.79       <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.506   Deviance explained = 55.3%
UBRE = 0.1729  Scale est. = 1         n = 218
```

Box A2-2: Model fit summary including all variables

```
Family: poisson
Link function: log

Formula:
CountFoY ~ s(Year, bs = "re") + s(DayOfYear) + NetsDuration +  NetsLength + CumCountFoY + WeatherCat +
NetsOpen

Parametric coefficients:
                    Estimate        Std. Error  z value     Pr(>|z|)
(Intercept)         2.189854        2.625865    0.834       0.40431
NetsDuration        -0.207513       0.069385    -2.991      0.00278 **
NetsLength          0.009492        0.001698    5.589       2.29e-08 ***
CumCountFoY         -0.036019       0.017505    -2.058      0.03962 *
WeatherCatlittle    0.322829        0.175153    1.843       0.06531 .
WeatherCatstrong    0.022859        0.323731    0.071       0.94371
NetsOpen            -0.561870       0.436665    -1.287      0.19819
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                    edf             Ref.df      Chi.sq      p-value
s(Year)             11.868          17.000      59.46       <2e-16 ***
s(DayOfYear)        8.002           8.673       43.16       <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.529   Deviance explained =   57%
UBRE = 0.17087  Scale est. = 1         n = 218
```

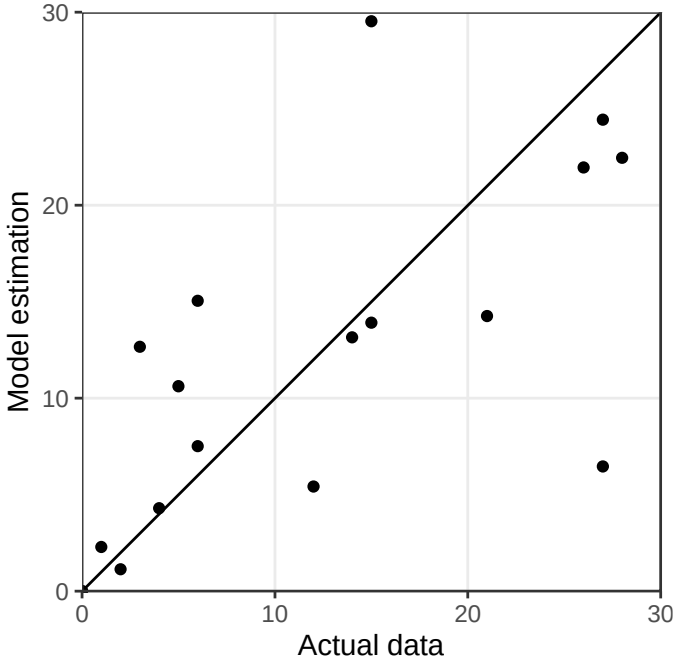

Figure A2.1: Comparison of the total number of new Red-capped Robin Chat caught per year between the model estimation and the data.

Appendix 3

Recapture model

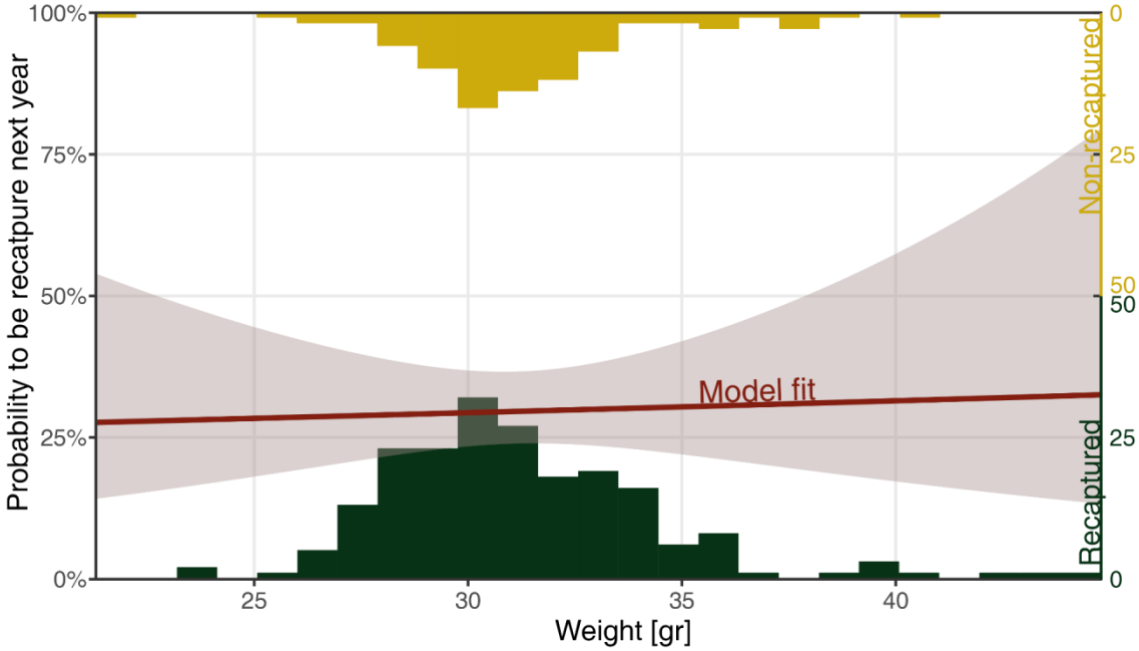

Figure A3.1: Histograms of the weight of RCRC recaptured in a following year and those not recaptured, together with the model fit. The uncertainty of the model shows that weight has an unclear influence on the recatpure rate.

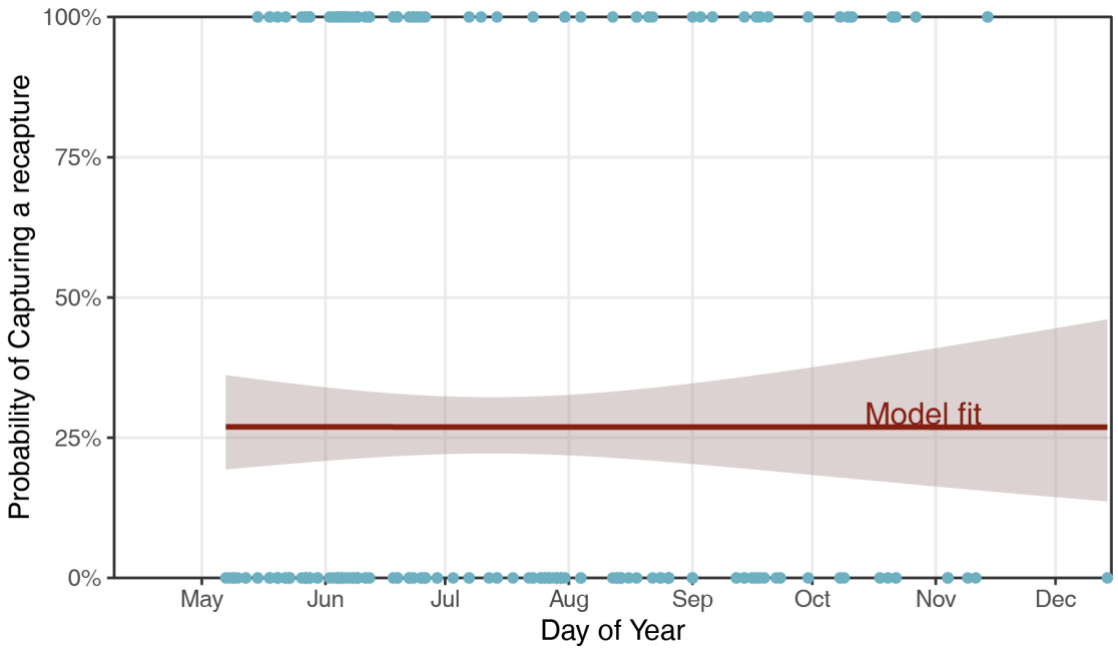

Figure A3.2: Variation throughout the year of the probability that a bird captured is a bird that has been captured in previous years. Blue dots denote the data for each capture of the database and the red line represents the GLM fit of a binomial model. The probability does not change throughout the year, indicating that maximizing the capture of bird capture in previous seasons is the same as maximizing the number of captures.

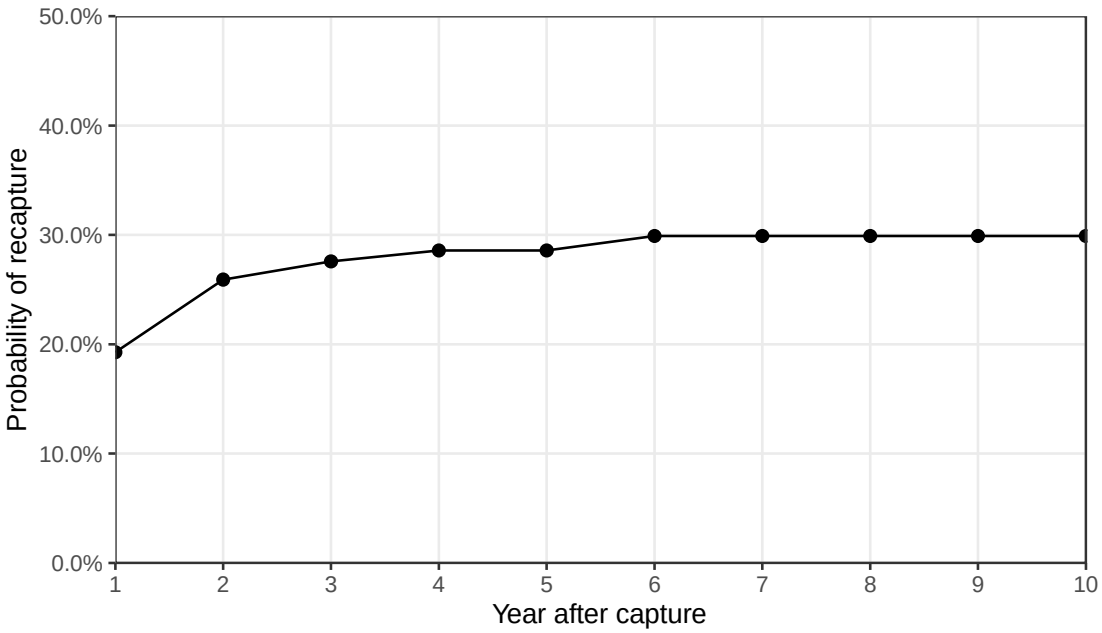

Figure A3.3: Evolution of the probability of recapture as a function of the number of years of capture after the original capture. The probability of recapturing still increases in the second year, so that, it will be worth to still ringing two year after the end of the equipment.