Flashing Large Mammals

Does usage of white LED affect the detection rates of target species?

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Chapter 1

Introduction

How does the usage of white LED flash affect our data?

Litt om estimeringsmetoder og problemer - og at det er særlig vanskelig for nattaktive og sky arter. Litt om bruk av kamerafeller og metodikk som er i enorm utvikling. Binde opp til NINA arbeid og samarbeid i Skandinavia

Capture Recapture models only available for naturally marked species (e.g. tigers *Panthera tigris*, leopards *Panthera pardus*). "Nevertheless, the majority of wildlife species are not easily individually identifiable from photos, rendering CR approaches difficult and leading to widespread interest in alternate analytical approaches for 'unmarked' species" Burton et al. 2015

Camera traps give us the opportunity to monitor in a quantifiable, somewhat standardised way, that is almost non-invasive. Normally the cameras have been using infrared light to flash animals during the night, as this was believed to be invisible to the animals (although - unfortunately for us - it is not). However, the lack of sharpness and detail in these photos limit the information we can retrieve from them (e.g. individual variation in coloration), which has brought us to the usage of white LED flashes. Naturally, the white LED flash is highly visible for any surface dwelling mammal, which begs the question to what extent it impacts the animals. Or rather, to which *additional* extent it impacts the animals, and therefore, how it affects our data. Animal sightings by camera traps can be used to measure species density, and any deviation from the norm in probability of sighting, will skew the precision of the estimate. Beddari 2019 showed that wolfs (*Canis lupus*) tend to shy away from camera traps using white LED flash, whilst the lynx (*Lynx lynx*) is less bothered, compared to the usage of infrared flashes. The wolfs were more shy and aware of all cameras in general, attributed to their higher sense of smell, which is a reminder that each species will perceive the camera presence different, and thus behave differently as a respone to the stimuli.

Ledestjerne In this study, I will attempt to quantify how the usage of white LED flash affects the detection rate of *the most common large mammal species in the area* and whether this effect correlates with other factors as urbanisation.

* Hypothesis 0: Usage of white LED flash will have no effect on the detection rate of any species.

* Hypothesis 1: Usage of white LED flash will stress one or more species in general, and therefore lower the detection rate of the stressed species. The effect will likely vary in extent between species.

* Hypothesis 2: The effect of the white LED will correlate with urbanisation-factors, as individuals that live closer to urban areas are habituated to Artificial Light At Night (ALAN), and thus will have a weaker response to the white LED

Chapter 2

Method and materials

2.1 Study species

The species I'll focus on in this thesis are the species that most frequently was observed *(>50 events)*, excluding farmed animals (e.g. cattle), humans and dogs, and grouped categories of animals (e.g. birds). Given that the decisions on camera placement (height and angle) were made with the aim on photo capturing lynx(), I have also excluded smaller species from the analysis. This includes three species, squirrel(), hare() and European pine marten*(Martes martes)*. Though they showed up frequently on many locations, there are inevitably some cameras that are too biased towards larger animals, resulting in an inconsistency of their detection rates. In turn, it is difficult to distinguish whether the species was affected by the white LED or not, as they could have triggered the camera, but already escaped the frame.

In the end, the species I have used in my analyses are roe deer*()*, red fox*()*, badger*(Meles meles)*, moose*()*, red deer*(Cervus elaphus)* and lynx.

2.2 Study area

The study area (59.36-60.47° N, 9.43-10.91° E) extends over much of the southeastern parts of Norway in counties Flå, Krødsherad, Sigdal, Ringerike, Modum, Hole, Lier, Øvre Eiker, Asker, Oslo, Enebakk, Indre Østfold, Våler, Råde, Moss, Frogn and Vestby. The climate has a continental character due to rain shadows of the mountain ridges from the west.

The mean annual temperatures ranges from 2-6℃and precipitation lies between 700-1500mm (Moen 1999). Topography is predominantly flat towards the south, and more rugged and elevated towards the north. The landscape is a mosaic of forest and agricultural areas, divided with a wide network of gravel roads. The area is situated in the southern boreal and the boreonemoral zones.

Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) make up the dominating boreal coniferous forests, with frequent presence of silver birch (*Betula pendula*) and downy birch (*Betula pubescens*), then aspen (*Populous tremula*), alder (*Alnus incana*) and black alder (*Alnus glutinosa*).

Growing season length 170 - 190 days (Moen, 1999, map 6, s.21) Snow cover length

Most cameras were set in forest areas, usually by a tractor path or human trail, sometimes by animal paths. Their distance from houses or roads varied to a large extent, and some areas were logged (ved Vansjø) and even greatly changed under development of new infrastructure (toglinje på nordligste kamera 1255)

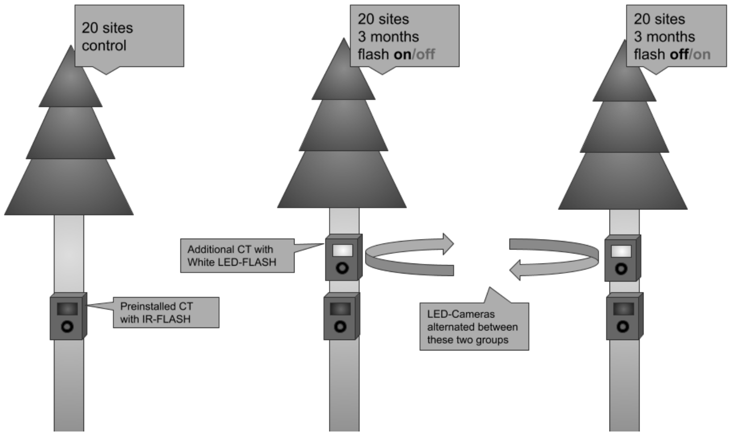


Figure 2.1: Experiment setup
I chose 60 sites with preinstalled IR Camera Traps (CTs) for my study, and divided them into three groups, where the first group remained unchanged as a control, and the two other alternated on having an additional white LED camera present. In the end, seven CTs were removed from the analysis due to large gaps in the data, etc.

2.3 Study design

For the study I chose 60 already established camera sites with infrared light(Reconyx and Browning models). The cameras had been installed on trees 1-3 meters from human or tractor paths, 40-120 cm above ground level, with the original aim to photo capture lynx (Odden 2015). I divided the sites randomly into three groups of 20 cameras. Cameras in group A remained unchanged, whilst group B and C were equipped with an additional white LED camera (Reconyx PC850) in alternating 3 month-periods, as shown in figure 2.1.

The preinstalled cameras were set up and handled by people from the Norwegian Institute of Nature Research (NINA) and — at the sites further from Oslo — by members of the Norwegian Hunters and Fishers Society (NJFF). The installation of the cameras did not follow a strict protocol, nor were their locations chosen randomly. The overall placement was systematic as decided by NINA, then there was a deliberately-biased placement of the CTs put up in areas where the individual handler deemed it most likely to photograph lynx, and hence, based on a combination of site accessibility and expectations of animal occurence

As shown in figure 2.1, I set up all white LED cameras above the cameras already in place. However, at the particular site shown in figure 2.2c on page 9 the infrared camera had been installed so far above ground level that I chose to position the white LED camera below the camera already in place. For the periods without white flash treatment, I moved the cameras to their next site. However, the boxes installed on the trees remained (see figure 2.2d). First, I equipped Group B with an additional white LED as seen in 2.2 on page 9. After approximately three months, I moved the white LED cameras to group C. These two periods were both marked as period 1-1, as seen in **??**. The camera boxes remained at each site untill the end of the experiment. Note that group C had no extra boxes before the start of their first period in May 2019 (i.e. remained identical to the control group A untill May).

I visited sites of group B and C at least once every three months in order to move the LED cameras. For logistical reasons I visited sites of group A less often. However, as the cameras were part of other, ongoing projects, they were occasionally visited by other workers from NINA to retreive the Secure Digital memory cards (hereby SD Cards) for

Table 2.1: Camera models

Producent	Model name	Flash type	Trigger speed	photos/trigger	N
Reconyx HyperFire Series	HC500 Semi-Covert IR	IR	0.2s	3	?
	HC600 High-Output Covert IR	Black	0.2s	3	?
	PC800 Profoessional Semi-Covert IR	IR	0.2s	3	?
	PC900 Professional Covert IR	Black	0.2s	3	?
	PC850 Professional White Flash LED	White	0.2s	8	20
Browning	Spec Ops: Extreme	IR	0.7s	24	

data. This was mostly the case for sites close to, and south of, Oslo, or rather, the cameras not normally operated by members of the NJFF.

When doing the analyses I needed periods of similar lengths to each other. Therefore, I divided the control group-cameras into four periods of similar lengths to that of the cameras with white LED periods (see figure **??** on the previous page).

2.4 Data Collection

Five different models of RECONYX™ (address: 3828 Creekside Ln, Ste 2, Holmen, WI 54636, USA, www.reconyx.com) cameras were used, and one model of BROWNING™ (address: One Browning Place, Morgan, UT 84050, USA, www.browningtrailcameras.com), details in table 2.1.

Reconyx-cameras have been reported of having an average trigger speed of 0.2 seconds, whereas the Browning model was reported an average of 0.7 seconds (Trigger speed shootout, Trailcampro 2014).

Cameras were operating 24 hours per day. The RECONYX™ cameras were set to take one time lapse photo per day in order to verify that the cameras had been operational. They were set to take 3 pictures per series, as fast as possible using *rapidfire*, and retrigger immediately using *no delay*.

The BROWNING™ cameras were also set to rapidfire, but to 8 photos per trigger, which unfortunately made the memory cards more vulnerable to filling up before being collected. This happened in some areas with sheep and/or cattle, and sometimes due to triggering by vegetation.

Therefore, the BROWNING™ cameras tended to have more gaps of inoperable days. As seen in figure **??**, there was a correlation between latitude and camera type. In addition, there were a correlation between camera type and which trail type the cameras were put up in. BROWNING™ cameras were more frequently set up in trail types easily accessible by man, which in turn lead to more pictures of humans and vehicles on the browning cameras.

These differences should all be kept in mind when interpreting the models.

Whenever I noticed vegetation blocking the view of the camera, or excessively triggering it, I removed the vegetation.

2.5 Data processing

All SD cards were delivered to NINA for data collection. Firstly, a facial recognition algorithm (FRA) is used to sort all the pictures. Afterwards, a human sorter checks the softwares' output, confirming all the correct decisions (i.e. species detections) and correcting all the wrong ones. The goal is to fully automate this process, which is a request from The Norwegian Data Protection Authority (DPA) in relation to usage of cameras in densely crowded areas (e.g. parks). As per the four eyes principle, the detection rate of photographed species has gone up as a result of the FRA (pers.comm. John Odden).

(a) Browning infrared,
installed on a fallen tree

(b) Reconyx infrared,
installed with a snow cap

(c) Reconyx infrared above,
installed 160 cm above ground level

(d) Browning infrared,
white LED flash has just been removed

Figure 2.2: The preinstalled cameras varied in the way they were set up. Lower cameras with infrared, upper cameras with white LED (except in example c)

The output I got as a result, was a data frame containing a time stamp for every shutter activity, including all meta data from the camera, coupled with predicted species (FRA output, with a confidence number), verified species (by human sorters), number of animals and distance from camera. The time stamps from the white flash cameras were used to verify whether an animal was in fact flashed or not, which I then used as my main predictor in the modelling.

I defined one event as any 1 species passing with a buffer time of 5 min before or after

The true number of active camera days are confounded by the lack of time lapse photos from the Browning cameras. To approach the true number of active days, I assumed all Browning cameras to be functional every day, unless the camera was inactive when I visited it. In that case, I considered the camera inactive since the day of its last photo.

2.6 Statistical analysis

To test for effects of the white LED flash I used the R programming language (R Core Team 2020), in the RStudio IDE (RStudio Team 2020), adopting large parts of the tidyverse framework along the way (Wickham et al. 2019). Session info in appendix **??**.

GLMM

To test H_1 I looked for differences in detection rate per day, using Generalised Linear Mixed Models (GLMM) with the glmer function from the R package lme4 (Bates et al. 2015).

Generalised Linear Model, because my dependent variable was count data, which I assume follows a Poisson distribution ($X \sim Pois(\lambda)$). Mixed effects to include location ID and week of the year as random effects, accounting for differences between camera sites, and seasonal changes during the year of study.

Accordingly, I fitted a poisson mixed model (estimated using Maximum Likelihood and Nelder-Mead optimizer) on a subset of each species, to predict number of observations, with time since deployment in days interacting with flash type (formula: n.obs   time.deploy * flash).

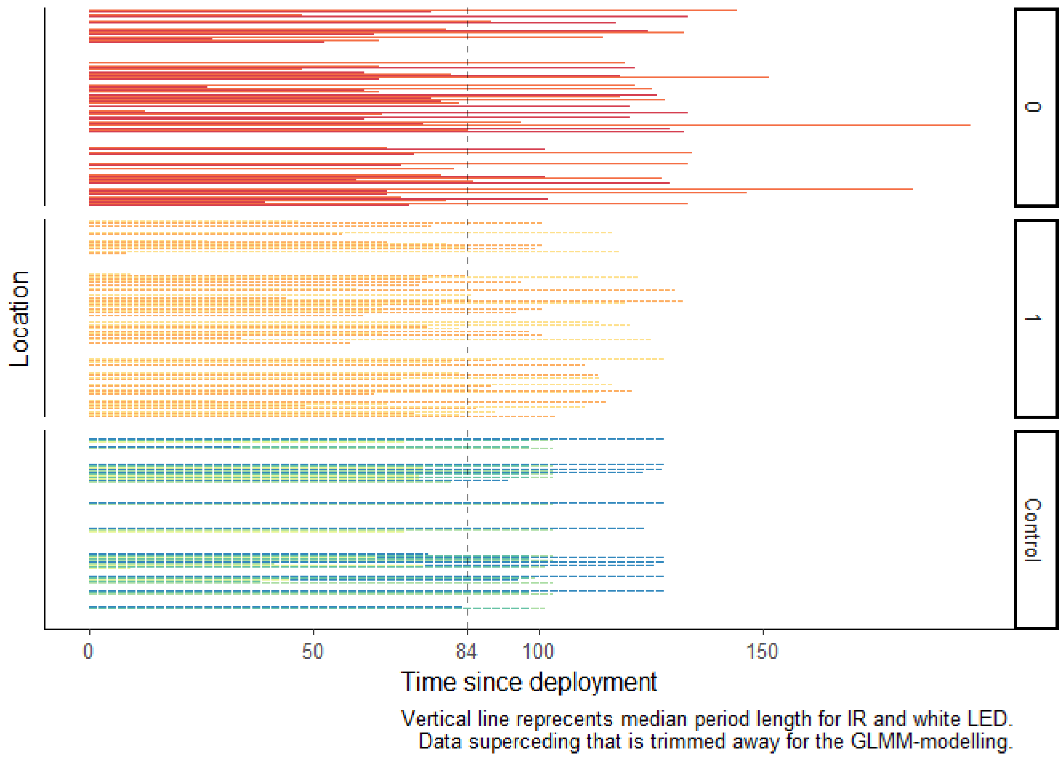
Standardized parameters were obtained by fitting the models on standardized versions of the data subset. 95% Confidence Intervals (CIs) and p-values were computed using the Wald approximation.

The flash type-variable corresponds to white LED present/absent or control group. For the cameras that was equipped with an additional white LED camera, time since deployment starts from the day I visited the camera, and set up/ took down the white LED. The control group's "day 0" of time since deployment were set by me when doing the analysis, at points reflecting my weeks of field work, in order to obtain periods of similar lengths to that of the white LED-locations. See Further, I also trimmed the period lengths down to a reduced length, based on the median length of the IR and white LED periods. Thus, any period exceeding the shortest median length, was trimmed down, as visualized in 2.3. Finally, due to large eigenvalues, the model failed to converge, and an error message prompted me to rescale variables. Therefore I divided the time since deployment-variable by ten, which solved the error. Consequently, the time axis is shown in days/10, which means that 7.5 corresponds to 75 days.

2.6.1 Equivalence test

I used the standard significance level of $\alpha = .05$, and performed an equivalence test on my model outputs, using the function equivalence-test from the R package parameters ().

Figure 2.3: Period lengths



In an equivalence test, model parameters are tested against a Region of Practical Equivalence (ROPE) as opposed to merely one single mean value, thus accounting for the *effect size* of each parameter. If the parameters estimate and CI falls outside the ROPE, their null hypothesis is rejected. However, if the CI is inside the ROPE, H0 is accepted, no matter if a standard Null Hypothesis Significance Test (NHST) would have deemed it significant.

Inside the function equivalence-test I used the Two One-Sided Tests (TOST) rule, where the confidence interval (CI) is set to $1 - 2 \times \alpha$. In my case that gave a narrow CI of .90,

For models from count data, the residual variance is often used to define the ROPE range. However, the description of the rope-range function from the package bayestestR () states this threshold as "rather experimental" and that the range is probably often similar to the default [-0.1, 0.1] of a standardized parameter. Hence, I used the default ROPE range which corresponds to a negligible effect size according to Cohen, 1988.

Cox Proportional Hazards

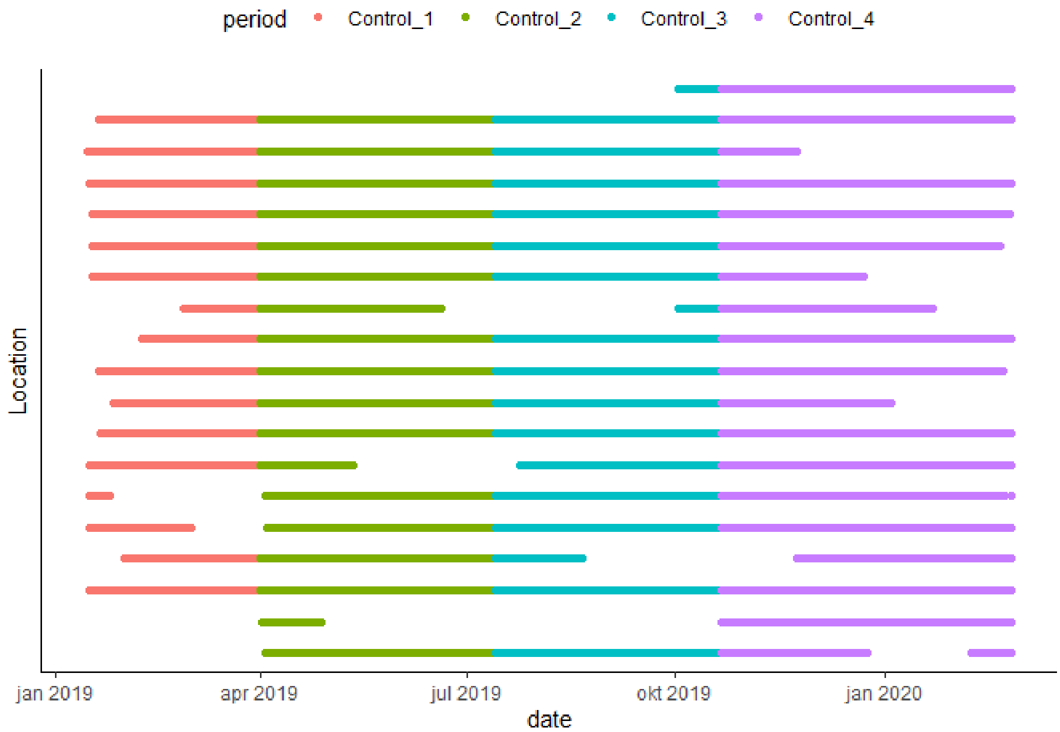
However, the way I set up the GLMMs, it only takes into account whether a flash was present or not. It can't tell if the flash actually went off, or how many times it did.

Therefore I set up a new column in my dataset called flashed, that told if the flash went off in synchrony with the IR camera. I then used the flashed-column to set up a time to event-analysis.

Also called Survival analysis, time to event-analyses compares groups' risk of experiencing an event, and was first developed for use in medicinal studies (e.g. cancer risk studies).

The difference between the groups is called the hazard *ratio*, and is *assumed to be proportional* over time. That is, if after 2 days, the hazard of detecting a fox (i.e. experiencing an event) for the IR-group is twice as large compared to the white LED-group, it should

(a) Cameras with white LED periods



(b) Control cameras'
period breaks were set during the analysis.

Figure 2.4: Colours indicate the different periods for each camera. Control camera periods were defined in similar lengths to that of the cameras that had periods with an additional white LED CT. Thus, "day 0" of Control-cameras are often set at dates far from an actual visitation day.

remain twice as large after 25 days as well. Or in other words, the IR-group should detect twice as many foxes as the white LED-group in general.

The Cox proportional hazards regression model (CPH model) (Cox, 1972), is a popular development of the time to event-analysis because it allows for more than one predictor. I used the R package Survival (Therneau 2020a) and the function coxme from the R package coxme Therneau 2020b to perform a CPH with mixed effects (fixed and random effects).

Again, location ID and week of the year were used as random effects to account for differences between the camera sites and seasonal changes during the study period.

As fixed effect I used the flashed-column. If a species was flashed, it went into the "flashed"-group, and time to next detection was recorded. If the species didn't reappear it was "censored" from the model.

In survival-analyses the time-variable is part of the outcome of the model. Event (i.e. detection) and time is joined as a Surv-object by the Surv function from the Survival package.

Both these models told me something about the fallacy of H_0, whether I could reject it, or fail to reject it. If the null hypothesis was rejected for a species, I considered H_1 to be true. Then I went on to test H_2

P-tests and assumptions

For both the GLMM and the CPH mixed effect model, I used the Wald test as significance test, with xyz distribution over df degrees of freedom. osvosv.

The R package performance (cite) was used to check assumptions for GLMM, and ggeffects (cite) was used to visualize the results.

R package Survminer was used to visualize the results of the time to event analyses. The Schoenfeld test was used to check for the CPH's assumption of proportional hazards.

Chapter 3

Results

3.1 GLMM

For roe deer, the model explaining variation in detection rate has a substantial explanatory power (conditional $R2 = 0.45$), but the part related to the fixed effects alone (marginal R2) is just 0.01.

In other words, most of the explained variation in detection rate is due to seasonal changes and variation between the different camera sites captured in the random terms. Neither the intercept value, nor the interaction term with time were deemed significant for the white LED periods (flash[1]).

The white LED periods had a non-significant positive effect in the beginning (flash[1] in table 3.1) compared to the IR periods (Intercept). However, along the time since deployment-axis (time.deploy $*$ flash [1]) there was a negative effect, to the extent that after two months the mean detection rate was lower for white LED periods, than for IR (flash [0]; figure 3.1a). However, the confidence interval (CI) of both white LED and IR periods almost completely overlaps, and hence, are not significantly different.

As the control-group stayed unchanged through the whole study period, and was visited less than the other cameras, I expected there to be no trend over time (i.e. time.deploy $*$ flash [Control] ≈ 0). Any fluctuations in detection rates due to weekly (and ultimately seasonal) changes should be controlled for by the random effect-argument for week of the year.

3.1.1 Equivalence test

As all the parameters in the roe deer GLMM were considered non-significant, it is interesting to evaluate them against a Region of Practical Equivalence (ROPE) in an equivalence test. When a parameter is within the ROPE in an equivalence test, it signifies that the difference from the mean, and the variance of the parameter, is low enough that we can accept H0 (that using white LED has no effect on the detection rate), rather than just fail to reject it.

According to this test, white LED is different enough that we cannot conclude on it's immediate effect (intercept value), but it's trend over time (interaction with time since deployment) is practically equivalent to H0. In other words, the equivalence test suggests that there is no significant difference in the long run, but there might be an increase in detections right after the day of deployment. However, the increase could also result from inhereting a slightly higher detection rate from the IR periods *if* there truly is a negative effect of the white LED over long periods of time.

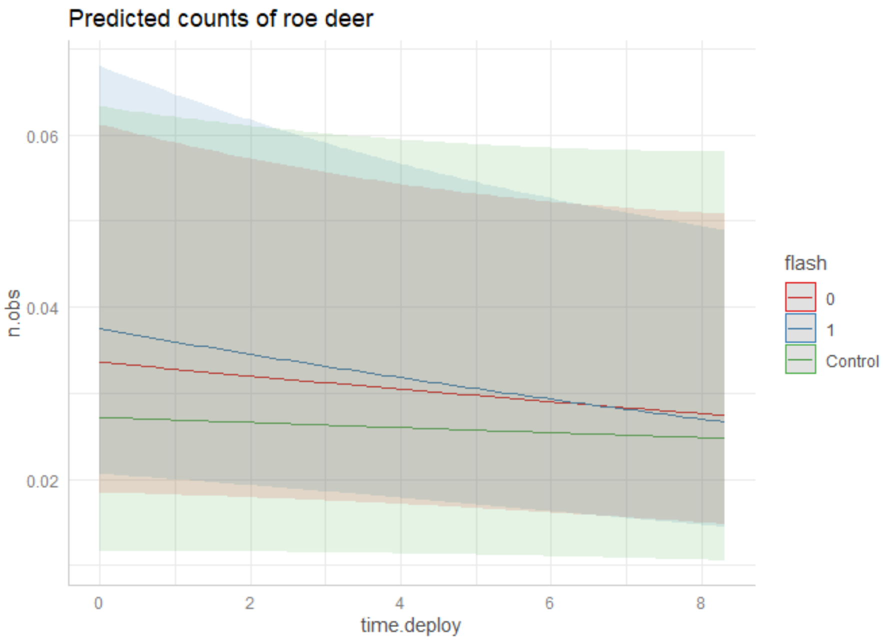


Figure 3.1: Roe deer

	Parameter	Coefficient	SE	95% CI	z	p
1	Roe deer					
2	(Intercept)	-3.49	0.29	(-4.06, -2.91)	-11.84	< .001
3	time.deploy	-0.06	0.06	(-0.17, 0.05)	-1.04	0.297
4	flash [1]	0.05	0.07	(-0.09, 0.18)	0.64	0.522
5	flash [Control]	-0.16	0.50	(-1.14, 0.82)	-0.32	0.748
6	time.deploy * flash [1]	-0.04	0.07	(-0.17, 0.10)	-0.56	0.572
7	time.deploy * flash [Control]	0.03	0.08	(-0.12, 0.18)	0.41	0.681
8	Red fox					
9	(Intercept)	-3.41	0.17	(-3.74, -3.09)	-20.50	< .001
10	time.deploy	-1.87e-03	0.07	(-0.13, 0.13)	-0.03	0.978
11	flash1	0.12	0.09	(-0.05, 0.29)	1.36	0.174
12	flashControl	-0.04	0.28	(-0.59, 0.50)	-0.16	0.872
13	time.deploy:flash1	-0.02	0.09	(-0.19, 0.15)	-0.23	0.815
14	time.deploy:flashControl	-1.21e-03	0.09	(-0.19, 0.18)	-0.01	0.990
15	Badger					
16	(Intercept)	-4.26	0.29	(-4.83, -3.69)	-14.65	< .001
17	time.deploy	0.14	0.08	(-0.01, 0.29)	1.87	0.062
18	flash1	0.06	0.09	(-0.12, 0.24)	0.62	0.534
19	flashControl	-0.35	0.39	(-1.10, 0.41)	-0.89	0.371
20	time.deploy:flash1	-2.65e-03	0.09	(-0.18, 0.18)	-0.03	0.977
21	time.deploy:flashControl	-0.11	0.11	(-0.34, 0.11)	-0.99	0.324
22	Moose					
23	(Intercept)	-4.62	6.93e-04	(-4.62, -4.61)	-6661.58	< .001
24	time.deploy	0.11	6.93e-04	(0.11, 0.11)	155.60	< .001
25	flash1	0.15	6.93e-04	(0.15, 0.15)	219.58	< .001
26	flashControl	-0.19	6.93e-04	(-0.19, -0.19)	-275.38	< .001
27	time.deploy:flash1	-0.14	6.93e-04	(-0.14, -0.14)	-203.48	< .001
28	time.deploy:flashControl	-0.06	6.93e-04	(-0.06, -0.06)	-87.90	< .001
29	Red deer					
30	(Intercept)	-6.06	0.50	(-7.05, -5.07)	-12.04	< .001
31	time.deploy	-0.06	0.14	(-0.33, 0.21)	-0.44	0.658
32	flash1	-0.03	0.18	(-0.39, 0.33)	-0.18	0.859
33	flashControl	-0.32	0.75	(-1.80, 1.16)	-0.43	0.670
34	time.deploy:flash1	0.37	0.19	(0.01, 0.73)	1.99	0.047
35	time.deploy:flashControl	-0.09	0.20	(-0.48, 0.30)	-0.46	0.648
36	Lynx					
37	(Intercept)	-6.75	0.48	(-7.69, -5.82)	-14.16	< .001
38	time.deploy	0.08	0.21	(-0.33, 0.49)	0.38	0.705
39	flash1	0.39	0.29	(-0.19, 0.96)	1.32	0.187
40	flashControl	-0.33	0.65	(-1.59, 0.94)	-0.50	0.614
41	time.deploy:flash1	0.02	0.28	(-0.54, 0.57)	0.06	0.955
42	time.deploy:flashControl	-0.23	0.37	(-0.96, 0.50)	-0.62	0.538

Table 3.1: Standardised model parameters
Results of generalised linear mixed effect models on detection rate of species at 53 different locations in south-eastern Norway, with three different treatment levels; period with only IR camera (flash:0), period with additional white LED camera (flash:1) and site unchanged through the whole study period (flash:Control). Random effects are location ID and week of year. Standardised parameters were obtained by fitting the model on a standardised version of the dataset. 95% Confidence Intervals and p-values were computed using the Wald approximation.

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