Flashing Large Mammals

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

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13th March 2021

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Chapter 1

Introduction

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

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 (CTs) give us the opportunity to monitor in a quantifiable, somewhat standardised way, that is almost non-invasive. Normally CTs have been using infrared (IR) light to flash animals during the night, as this was believed to be invisible to the animals (which has later been proven wrong). 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 light flashes. CTs comes with either white xenon or white light-emitting diode (LED) technology. Xenon CTs has the disadvantage of a recovery time after each photo. Henrich et al. 2020 experienced a recovery time of at least 22 s, which prevented them from doing meaningful comparisons with black and IR flash. Naturally, a white 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 CTs 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 CTs using white light, whilst the lynx (*Lynx lynx*) is less bothered, when compared to the usage of IR flashes. The wolfs were more shy and aware of all CTs in general, attributed to their higher sense of smell, which is a reminder that each species will perceive CT presence different, and thus behave differently as a respone to the stimuli.

Hypotheses 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 area

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*).

The study area (59.36-60.45° N, 9.31-11.13° E) extends over much of the southeastern parts of Norway in municipalities Flå, Krødsherad, Sigdal, Ringerike, Modum, Hole, Lier, Øvre Eiker, Asker, Oslo, Enebakk, Indre Østfold, Våler, Råde, Moss, Frogn and Vestby in Oslo and Viken counties. The climate has a continental character due to rain shadows of the mountain ridges from the west.

Growing season length was 170 - 190 days (Moen 1999)

2.2 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).

The species I have included in my analyses are roe deer (*Capreolus capreolus*), red fox (*Vulpes vulpes*), badger (*Meles meles*), moose (*Alces alces*), red deer (*Cervus elaphus*), red squirrel (*Sqiurus vulgaris*), hare (*Lepus timidus*), European pine marten (*Martes martes*) and lynx.

2.3 Study design

The Norwegian Institute of Nature Research (NINA) started with CTs to substitute snow track surveys of lynx family groups, after several years of varying snow season length in south eastern Norway (Odden 2015). The surveys are integrated in a coordinated Scandinavian science project on lynx, called Scandlynx.

I was given access to CTs used in the Scandlynx project, and chose the 60 sites closest to Oslo (for logistical reasons) which weren't already equipped with white LED light. Instead, these were equipped with either black or IR flash, but I will refer to them as the IR CTs.

The IR CTs had been installed on trees 1-3 m from wildlife, human or tractor paths, 30-160 cm above ground level, and their distance from houses or roads varied to a large

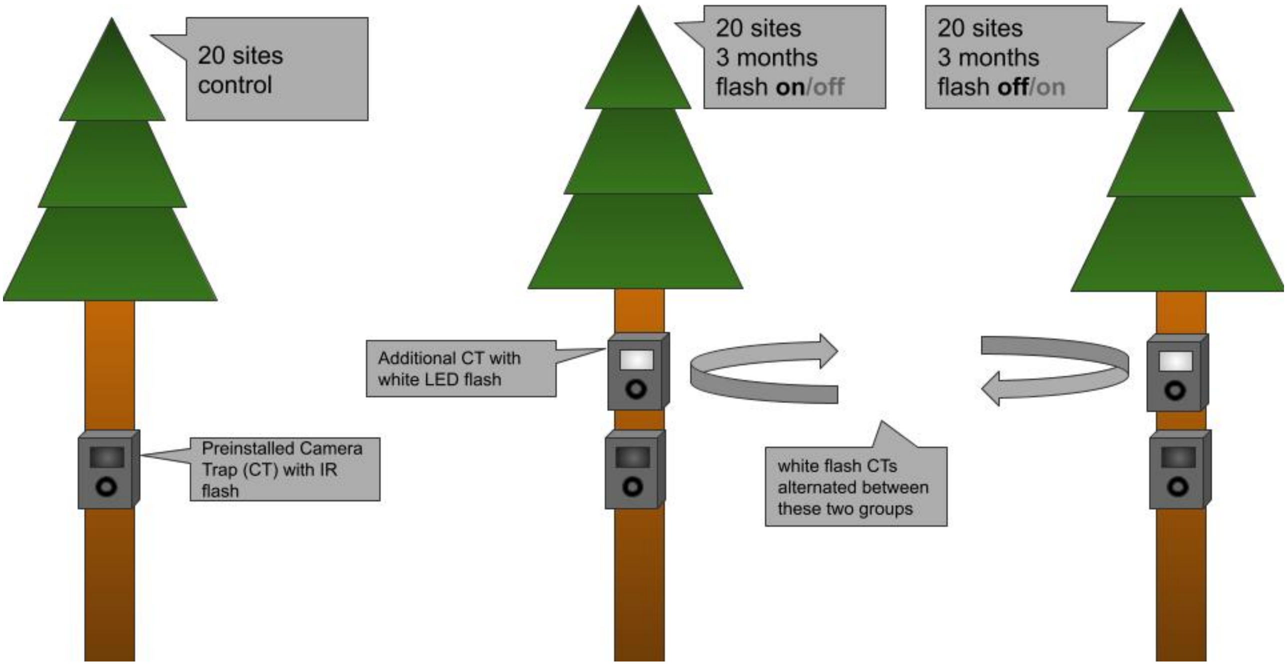

Figure 2.1: Experiment setup
I chose 60 sites with preinstalled Infrared Camera Traps (IR CTs) for my study, and divided them into three groups, where the first group remained unchanged (control group), and the two other alternated on having additional white LED CTs present (treatment groups). Four sites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

extent. They were set up and handled by people from NINA and, at the sites further from Oslo, by local volunteers. 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 occurrence.

I divided the sites randomly into three groups of 20 sites. Cameras in the first group remained unchanged as a control. The remaining two groups (hereby referred to as treatment groups) were equipped with an additional white LED camera (Reconyx PC850; hereby referred to as the LED CTs) in alternating 3 month-periods, as illustrated in figure 2.1.

I set up all LED CTs above the IR CTs already in place (installation examples in figure 2.2). At one site the IR camera had been installed so far above ground level that I chose to position the LED CT below the IR CT.

The camera boxes containing the LED CTs remained at each site untill the end of the experiment. Note that the second treatment group had no extra boxes before the start of their first LED period in May 2019 (i.e. remained identical to the control group untill May).

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

(a) Browning IR installed on fallen tree.

(b) Reconyx IR installed with snow cap.

(c) Reconyx IR 160 cm above the ground. Therefore, I positioned the LED underneath.

(d) Additional CT boxes remained during IR periods.

Figure 2.2: Examples of camera setups
The preinstalled IR cameras varied in the way they were set up. Lower cameras were IR, upper cameras were white LED at all sites except the one in example c.

Table 2.1: Camera models

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

I divided the control group-cameras into four periods of similar lengths to that of the treatment group cameras (see figure 2.3).

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. 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.

As seen in figure **??**, there was a correlation between latitude and camera type.

2.5 Data processing

All SD cards were delivered to NINA for data processing. 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. Consequently, the rate of correctly identified species has gone up as the FRA sometimes detect animals that aren't easily noticed by human sorters (pers.comm. John Odden). The goal is to fully automate this identification 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).

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

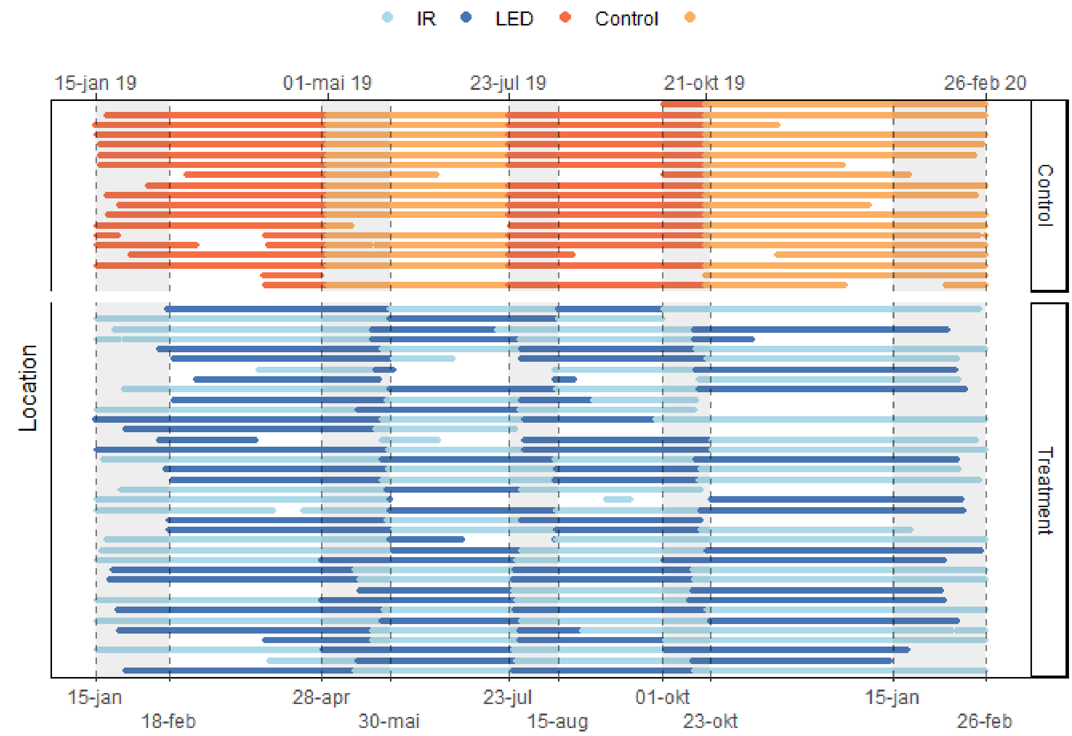

Figure 2.3: Active camera days
Colours indicate the different periods for each camera. Control camera periods were defined in similar lengths to that of the treatment group during analysis. As a result, "day 0" of Control-cameras are often set at dates far from an actual visitation day. Shaded areas represent my field work periods. The first IR period of the second treatment group was defined as "Control" for the analysis, as they remained unchanged untill their first LED period.

output, with a confidence number), verified species (by human sorters), number of animals and distance from camera.

I defined one event as any one species passing with a buffer of 30 minutes untill next detection of the same species, in order to remove autocorrelation in observations, e.g from ruminating individuals. Number of individuals and distance to CT were not taken into account.

4 sites were removed before the analysis due to technical faults, etc. 1 CT from the control group, as it turned out to be a white LED camera.3 CTs from the treatment groups, because of large or frequent gaps due to technical errors, and ineffective placement of the additional white LED camera.

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 (Wickham et al. 2019) and the easystats (**easystats**) frameworks along the way. Complete citation of R packages used are presented in appendix **??**.

GLMM

To test H1 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). I fitted separate models for each species to avoid overly complicated models. The

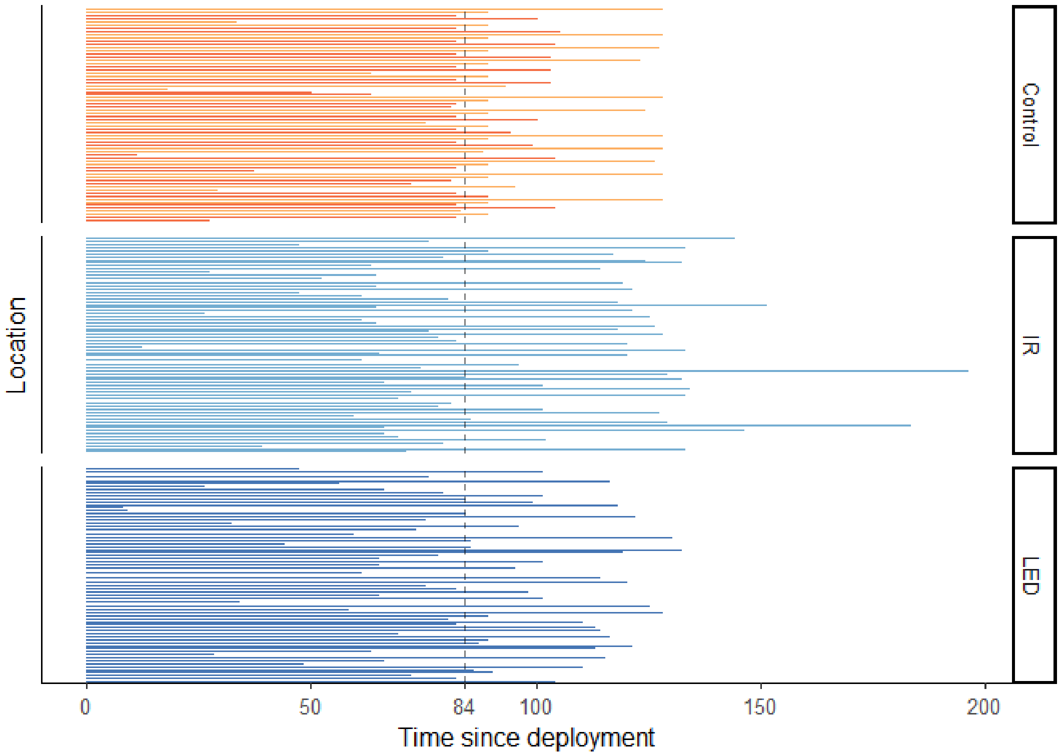

Figure 2.4: Period lengths
Vertical line represents the median IR period length, which was shorter than the median of the other groups. Data superceding the median were trimmed away for the GLMM

dependent variable was count data (number of observations), and I therefore assumed the error term followed a Poisson distribution ($X \sim Pois(\lambda)$).

I included location ID and week of the year as random effects to account for consistent differences between camera sites and seasonal changes during the year of study. 95% Confidence Intervals (CIs) and p-values were computed using the Wald approximation. I used standardized parameters (mean = 0, SD = 1) to enable comparison of effect sizes.

The main term of interest was time since deployment in days interacting with flash type (formula: n.obs $\sim$ time.deploy $*$ flash). 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 at points reflecting the onset of field work each time, in order to obtain periods of similar lengths to that of the white LED-locations.

I trimmed the period lengths down to a reduced length, based on the median length of the IR and white LED periods, to enhance meaningful comparison. Thus, any period exceeding the shortest median length, was trimmed down, as visualized in figure 2.4. Finally, due to large eigenvalues in the fixed effects, 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 ().

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 0.90.

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 (*https://easystats.github.io/bayestestR/reference* accessed 11.3.2021). 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.

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.

Therefore I set up a new column in my dataset, that told if the flash went off in synchrony with the IR camera or not (category yes/no). 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 (Terry M. Therneau and Patricia M. Grambsch 2000).

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 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 category for verified flash (yes/no). 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. Rather than saying that the species never reappeared (ie. time to event $= \infty$), the model assumes that had the study gone on longer there would eventually be an event. Conversely, in a cancer study, were death is the event, the survival of a patient during the study period wouldn't signify immortality, but rather that the study was ended too soon to record the event.

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.

Chapter 3

Results

3.1 GLMM

3.1.1 All species

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 ≈ 0 in table 3.1). Any fluctuations in detection rates due to weekly (and ultimately seasonal) changes should be controlled for by the random effect-term for week of the year, leaving the control group as a representation of the baseline detection rate. This held true for all the species in my analysis.

In general, the control-group had lower detection rates than the two treatment groups for all species (see table 3.1). However, for most species, the slopes of IR and LED are completely covered by the Control-group's confidence interval (CI), meaning that the differences are non-significant.

If there were any effect of the LED, the IR period should show a regression to the norm, ie. counteracting the effect of the LED. Thus, if the LED had a negative slope along the time axis, the IR should have a positive slope. Further, their respective main effects (ie. when time since deployment = 0) should correspond somewhat to the other factor's simple effect of when time since deployment is at maximum value (84 days). Still, as time since deployment = 0 corresponds to the day of my visitation, my presence could skew that pattern to some extent.

The main effect of LED was positive for most species, although none responded significantly (table 3.1).

Species	Parameter	Coefficient	SE	95% CI	z	p
Roe deer	(Intercept)	-3.47	0.43	(-4.31, -2.62)	-8.05	< .001
	TimeDeploy	-0.03	0.02	(-0.07, 0.00)	-2.22	0.026
	IR	0.08	0.51	(-0.92, 1.08)	0.16	0.876
	LED	0.20	0.51	(-0.79, 1.20)	0.40	0.688
	TimeDeploy * IR	0.01	0.02	(-0.03, 0.05)	0.69	0.489
	TimeDeploy * LED	2.01e-03	0.02	(-0.04, 0.04)	0.11	0.915
Red fox	(Intercept)	-3.44	0.26	(-3.94, -2.94)	-13.41	< .001
	TimeDeploy	-3.82e-04	0.02	(-0.04, 0.04)	-0.02	0.985
	IR	0.03	0.32	(-0.59, 0.65)	0.09	0.926
	LED	0.18	0.31	(-0.44, 0.79)	0.56	0.574
	TimeDeploy * IR	-1.69e-03	0.03	(-0.05, 0.05)	-0.06	0.949
	TimeDeploy * LED	-7.82e-03	0.03	(-0.06, 0.04)	-0.30	0.763
Badger	(Intercept)	-4.79	0.39	(-5.56, -4.02)	-12.15	< .001
	TimeDeploy	0.05	0.02	(0.00, 0.09)	1.90	0.058
	IR	0.27	0.42	(-0.55, 1.09)	0.64	0.523
	LED	0.34	0.42	(-0.48, 1.15)	0.81	0.421
	TimeDeploy * IR	4.96e-03	0.03	(-0.05, 0.06)	0.17	0.865
	TimeDeploy * LED	2.75e-03	0.03	(-0.05, 0.06)	0.10	0.922
Moose	(Intercept)	-4.75	0.38	(-5.50, -4.01)	-12.58	< .001
	TimeDeploy	6.76e-03	0.03	(-0.05, 0.07)	0.21	0.830
	IR	-0.04	0.44	(-0.90, 0.82)	-0.09	0.927
	LED	0.34	0.43	(-0.51, 1.19)	0.78	0.434
	TimeDeploy * IR	0.03	0.04	(-0.05, 0.11)	0.78	0.433
	TimeDeploy * LED	-7.57e-03	0.04	(-0.09, 0.07)	-0.19	0.848
Red deer	(Intercept)	-5.99	0.71	(-7.39, -4.59)	-8.39	< .001
	TimeDeploy	-0.07	0.04	(-0.15, 0.02)	-1.56	0.119
	IR	0.07	0.81	(-1.51, 1.65)	0.09	0.930
	LED	-0.60	0.82	(-2.21, 1.02)	-0.72	0.469
	TimeDeploy * IR	0.04	0.06	(-0.07, 0.16)	0.80	0.424
	TimeDeploy * LED	0.16	0.06	(0.05, 0.27)	2.81	0.005
Lynx	(Intercept)	-6.38	0.71	(-7.77, -5.00)	-9.03	< .001
	TimeDeploy	-0.15	0.10	(-0.34, 0.04)	-1.52	0.128
	IR	-0.49	0.83	(-2.11, 1.14)	-0.59	0.558
	LED	-0.14	0.83	(-1.76, 1.48)	-0.17	0.867
	TimeDeploy * IR	0.17	0.11	(-0.06, 0.39)	1.48	0.140
	TimeDeploy * LED	0.18	0.11	(-0.05, 0.40)	1.54	0.124
Hare	(Intercept)	-4.29	0.43	(-5.13, -3.45)	-10.05	< .001
	TimeDeploy	0.03	0.02	(-0.02, 0.07)	1.13	0.258
	IR	0.24	0.50	(-0.75, 1.23)	0.47	0.637
	LED	0.11	0.51	(-0.89, 1.10)	0.21	0.836
	TimeDeploy * IR	-0.04	0.03	(-0.09, 0.02)	-1.28	0.200
	TimeDeploy * LED	6.42e-04	0.03	(-0.06, 0.06)	0.02	0.982
European Pine Marten	(Intercept)	-6.38	0.57	(-7.50, -5.27)	-11.21	< .001
	TimeDeploy	0.07	0.07	(-0.06, 0.20)	1.01	0.314
	IR	1.67	0.61	(0.47, 2.87)	2.73	0.006
	LED	0.76	0.64	(-0.49, 2.01)	1.20	0.232
	TimeDeploy * IR	-0.08	0.07	(-0.22, 0.06)	-1.08	0.280
	TimeDeploy * LED	0.02	0.08	(-0.13, 0.16)	0.22	0.828
Red squirrel	(Intercept)	-5.72	6.21e-04	(-5.72, -5.72)	-9211.24	< .001
	TimeDeploy	0.06	6.21e-04	(0.06, 0.06)	92.41	< .001
	IR	0.83	6.21e-04	(0.83, 0.83)	1334.42	< .001
	LED	0.51	6.21e-04	(0.51, 0.51)	818.90	< .001
	TimeDeploy * IR	-0.12	6.21e-04	(-0.13, -0.12)	-200.50	< .001
	TimeDeploy * LED	-0.01	6.41e-04	(-0.01, -0.01)	-18.07	< .001

Table 3.1: Standardised model parameters
Results of generalised linear mixed effect models on detection rate of species at 56 different locations in south-eastern Norway, with three different treatment levels; period with only IR camera (flash[IR]), period with additional white LED camera (flash[LED]) 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.

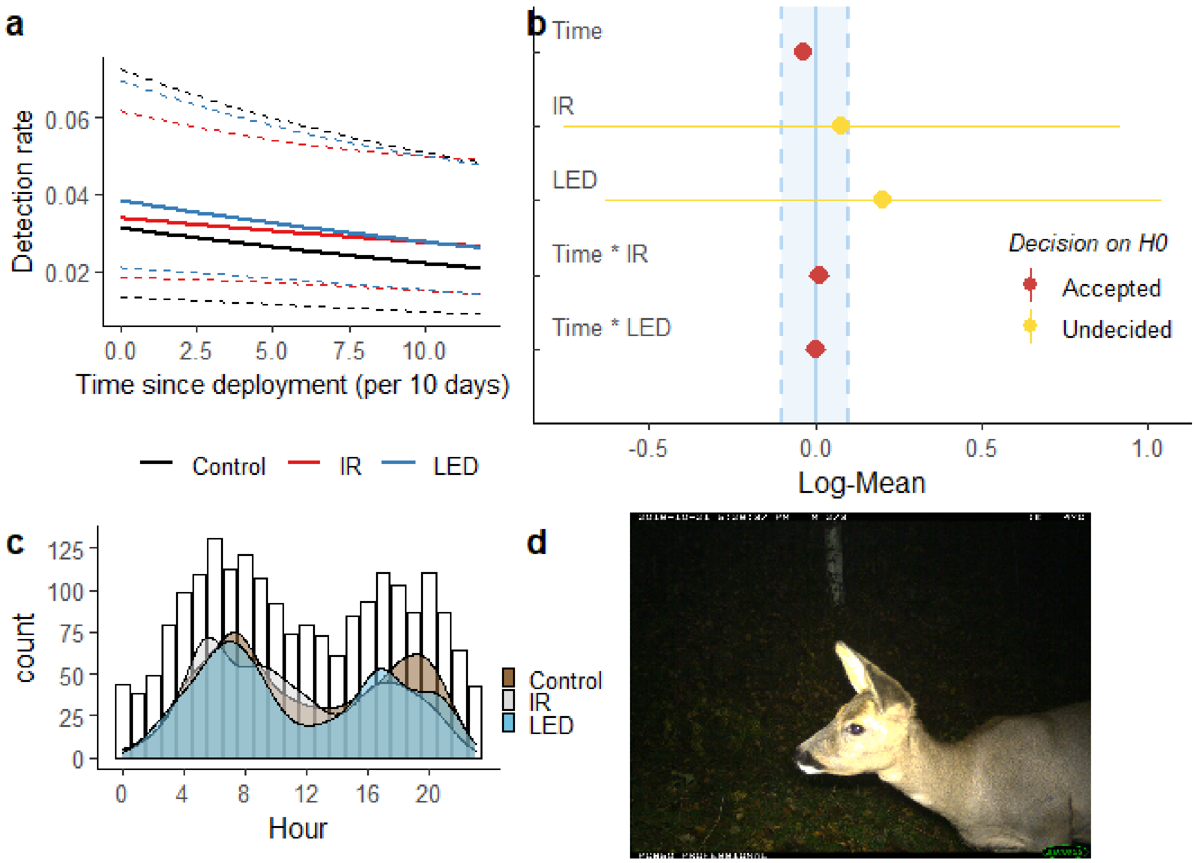

Figure 3.1: Roe deer
a) The predicted detection rate of roe deer for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total roe deer detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a roe deer. The deer passed the camera repeatedly and often stopped in front of the flashing light

3.1.2 Roe deer

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 0.002. 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.

The main effect of the white LED periods were non-significantly positive (flash[LED] in table 3.1) compared to the control-group (Intercept). The same is true for the IR periods, although to a slightly lower extent. However, along the time since deployment-axis (time.deploy $*$ flash [LED]) there was a negative effect, to the extent that after two months the mean detection rate sank below that of the IR periods (see figure 3.1a). Nevertheless, the confidence intervals (CI) of both white LED and IR periods almost completely overlap, and hence, are not significantly different.

When a parameter is within the ROPE in an equivalence test, it signifies that the difference from the Log-mean, and the variance of the parameter, is low enough that we can accept H0, rather than just fail to reject it.

According to this test, white LED is different enough that we cannot conclude on it's main effect, but it's trend over time (Time * LED) 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.

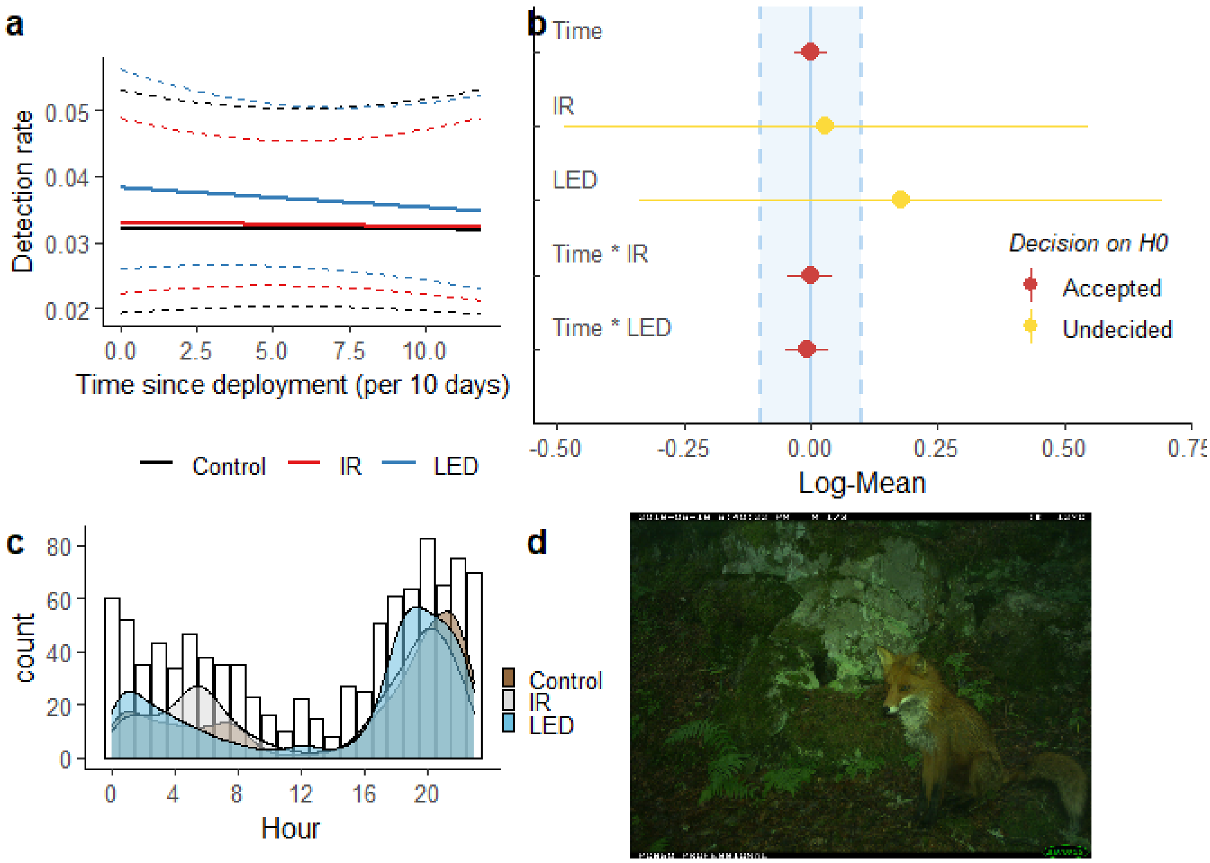

Figure 3.2: Red fox
a) The predicted detection rate of red foxes for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total fox detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a red fox. The fox stopped in front of the flashing camera and waited for a following individual before they continued.

3.1.3 Red fox

For red fox, the model explaining variation in detection rate has a moderate explanatory power (conditional R2 = 0.19), and the part related to the fixed effects alone (marginal R2) is just 0.001.

The main effect of the white LED periods were non-significantly positive (flash[LED] in table 3.1) compared to the IR- and control-periods (flash[IR];Intercept) . However, along the time since deployment-axis (time.deploy $*$ flash [LED]) there was a negative effect, to the extent that after two months the mean detection rate sank below that of the IR periods (see figure 3.1a). Nevertheless, the confidence intervals (CI) of both white LED and IR periods almost completely overlap, and hence, are not significantly different.

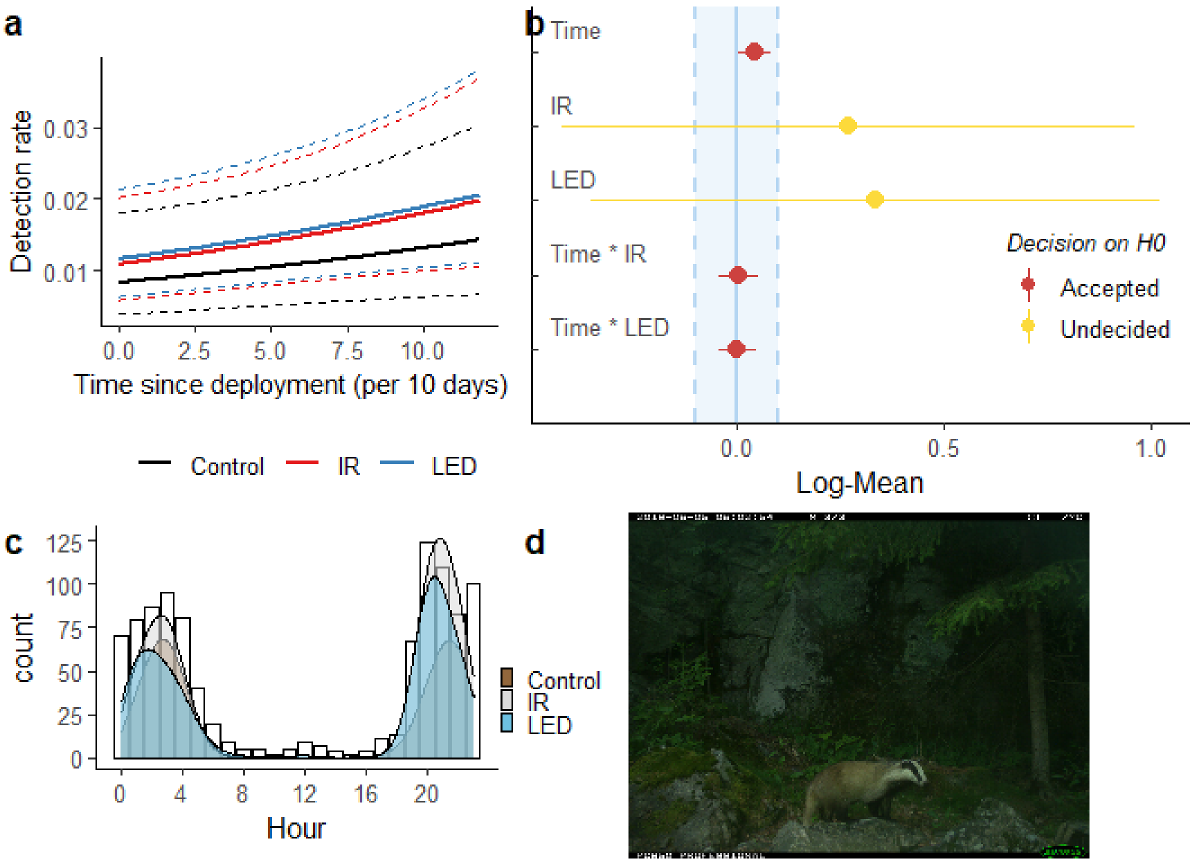

Figure 3.3: Badger
a) The predicted detection rate of badgers for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total badger detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a badger. DESCRIPT

3.1.4 Badger

For badger, the model explaining variation in detection rate has a substantial explanatory power (conditional R2 = 0.42), but the part related to the fixed effects alone (marginal R2) is just 0.006.

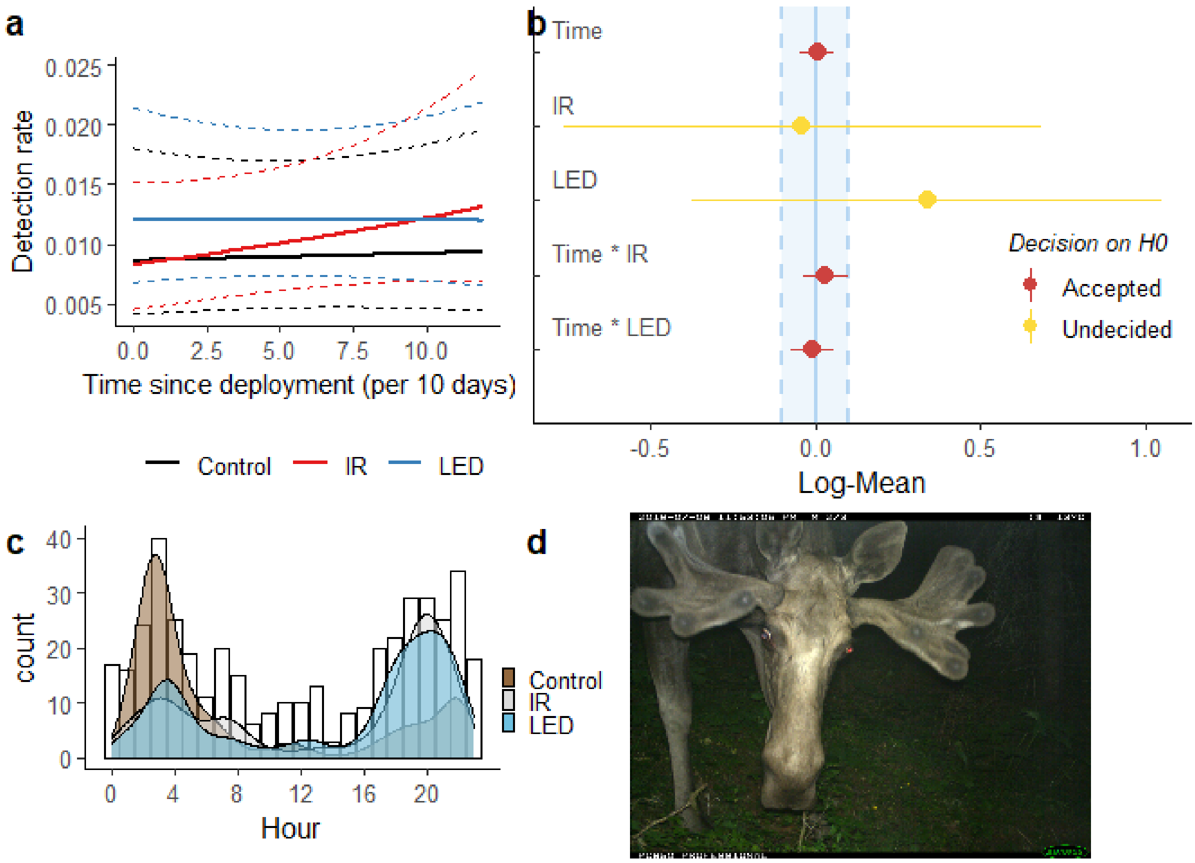

Figure 3.4: Moose
a) The predicted detection rate of moose for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total detections per hour of the day, and density curves show the overall pattern for each group
d) LED-CT photograph of a Moose. DESCRIPT

3.1.5 Moose

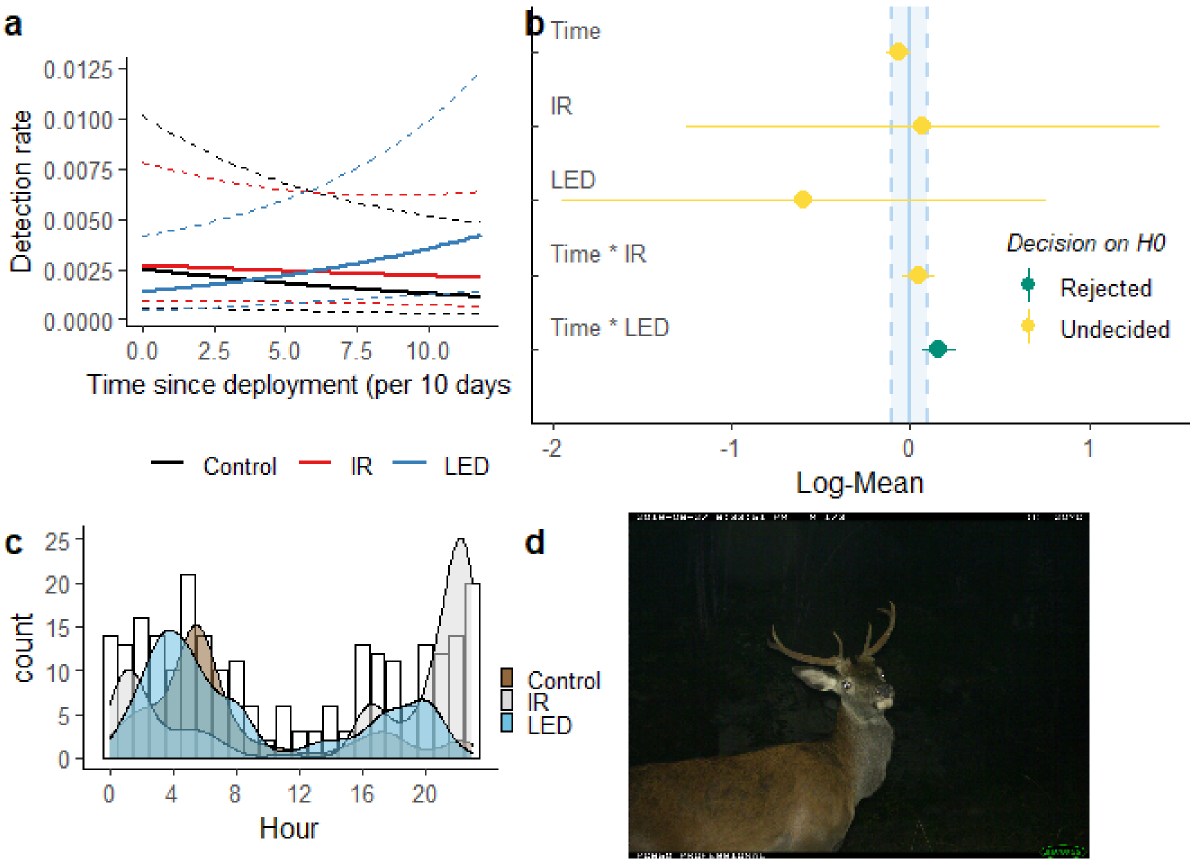

Figure 3.5: Red deer
a) The predicted detection rate of red deer for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total Red deer detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a red deer. DESCRIPT

3.1.6 Red deer

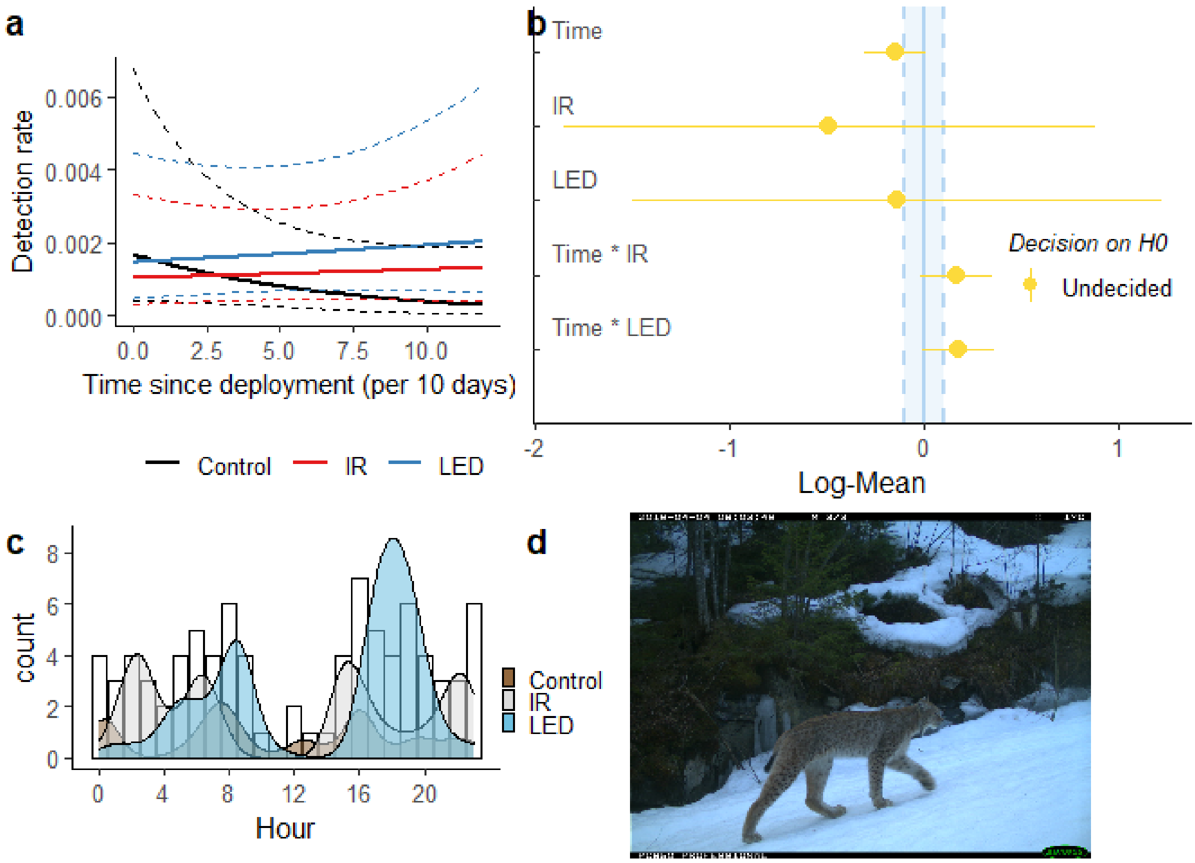

Figure 3.6: Lynx
a) The predicted detection rate of lynx for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total lynx detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a lynx. DESCRIPT

3.1.7 Lynx

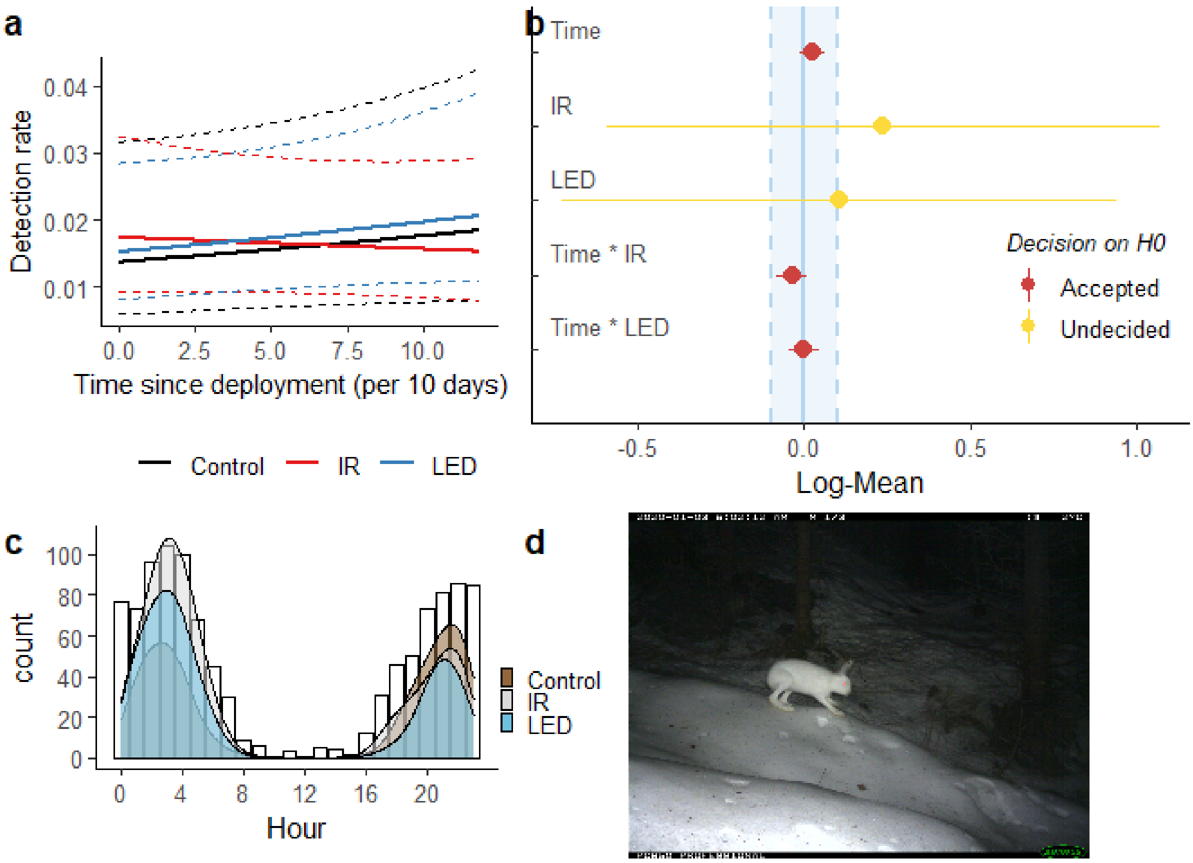

Figure 3.7: Hare
a) The predicted detection rate of hares for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total hare detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a hare. DESCRIPT

3.1.8 Hare

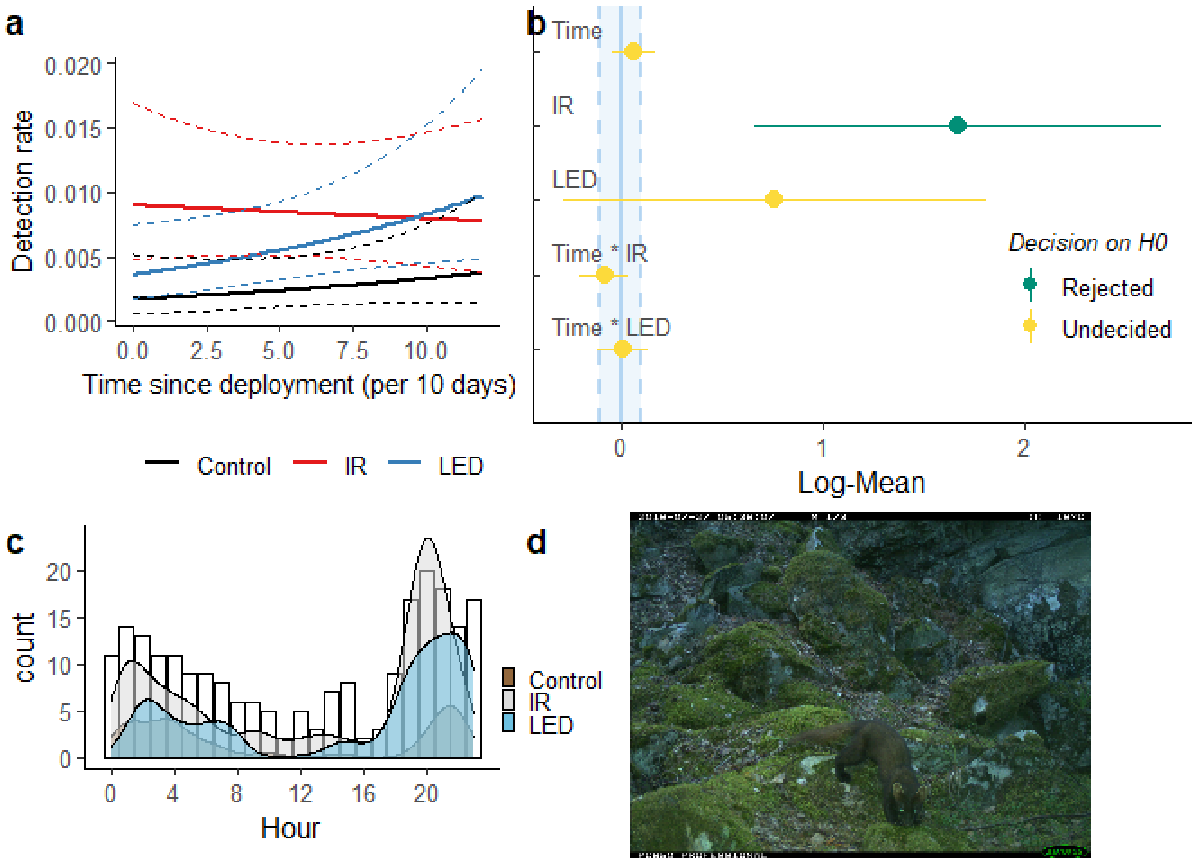

Figure 3.8: Pine marten
a) The predicted detection rate of pine martens for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ±0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total pine marten detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a pine marten. DESCRIPT

3.1.9 Pine marten

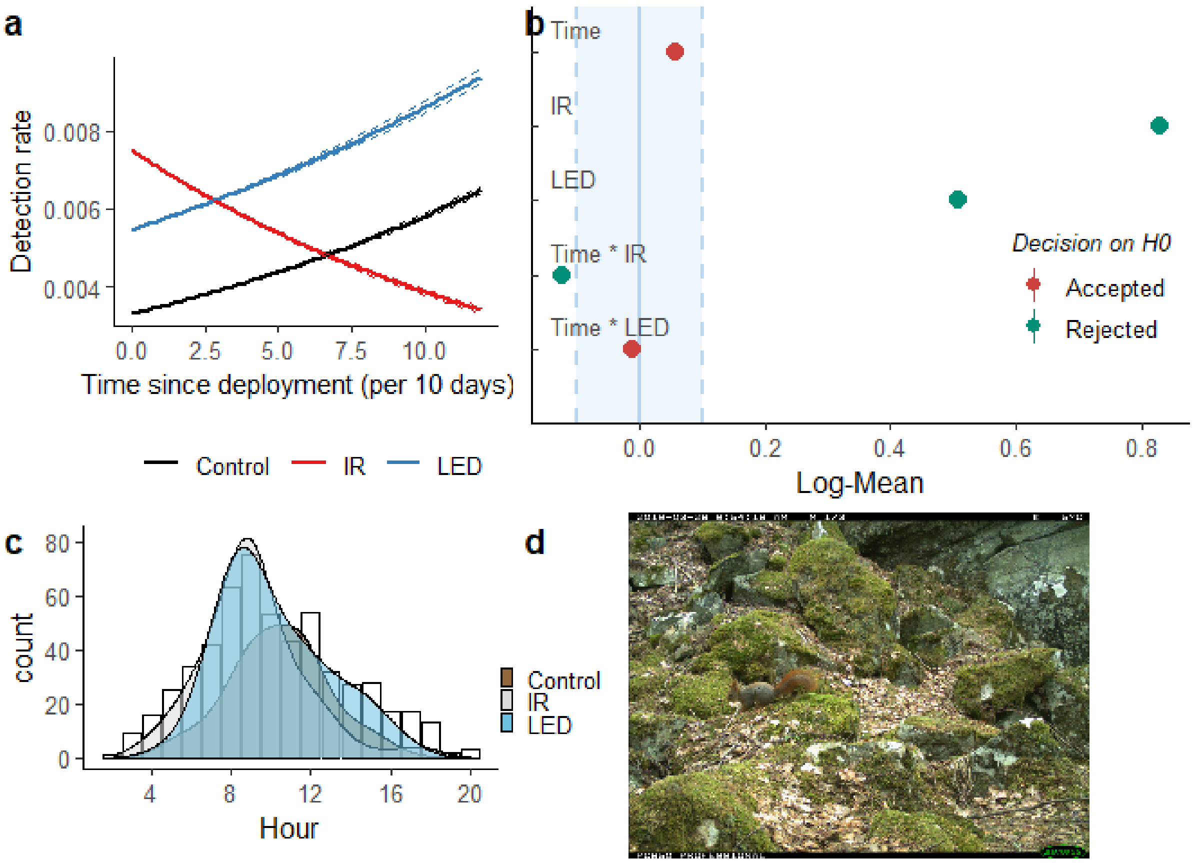

Figure 3.9: Red squirrel
a) The predicted detection rate of squirrels for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total squirrel detections per hour of the day, and density curves show the overall pattern for each group.
d) LED-CT photograph of a squirrel. DESCRIPT

3.1.10 Red squirrel

The model for red squirrel failed to converge, and therefore the p-values should be disregarded.

Still, it is interesting to see the IR and LED-slopes crossing each other. Looking at the density plot, one would not expect that most squirrels were flashed by the white LED particularly often, as most detections are during the day.

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