Flashing Large Mammals

Quantifying the effect of white LED flash on camera trapping detection rates

Thesis submitted for the degree of Master of science in Bioscience: Ecology and Evolution 60 Credits

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Chapter 1

Introduction

How does the usage of white LED flash affect our data? *** Grove trekk utan kritisk selvblikk:

Scientists often want to estimate how many individuals of certain species are present. When forvalting deer species for hunting, or trying to figure out expected grazing pressure on crops in an area, there is a need to understand how many individuals of different species are present.

So, as mammal species tend to be quite elucive, and mostly night active, it is inherently difficult to count them in a reliable and standardised way. This is especially true for large carnivores, as the Eurasian lynx, and grey wolf. They are both night acitve and highly shy. And in Norway they are forvalta after a precise number of family groups. Hence, there is a dire need to know how many there are of them.

Usually, the lynx has been counted using snow tracks in the winter. However, lately there has been a variable lenght of the snow season, which has made the snow track counts unpredictable and difficult to conduct at a consistent time of year.

Therefore, looking for new methods, NINA has started to use camera traps (CTs). ***

*** Estimating number of animals are central in the bestand ecology, and has always been under development in order to get accurate, reliable ways of conducting surveys.

Counting mammals directly is difficult, as they are shy, elusive, and mainly night active. Some methods involve walking one or several men in a row, scaring up animals, and counting them as they scare away. Still, any such method is prone to undercounting, due to low visibility in dense forests and lack of focus from observers after a while. Other counting methods include counts from vantage points, which is generally considered to be the most accurate (ie. least variable outcome). There are other, indirect methods, like counting and/ or collecting faeces and counting tracks.

In snowy areas, like Norway, counting snowtracks has been a popular method. This method has the advantage of tracks being present for a limited time. Snow track counts also makes it possible to date the activity to the last snowfall, as old tracks are VISKA UT. Tracks are also easily visible.

However, lately there has been a variable lenght of the snow season, which has made the snow track counts unpredictable and difficult to conduct at a consistent time of year.

Therefore, looking for new methods, NINA has started to use camera traps (CTs). CTs have been developing super fast, and have become quite affordable. They offer a consistent, standardised sampling method which also records date, hour and, in some instances, temperature. The impression has long been that it is a non-invasive method, which has been disproven in later years.

CTs normally use infra-red light to photo-capture animals, which is invisible to the human eye, but has been proven to be visible to several other mammals. The photos taken with IR flash are able to tell which species pass, but often lack much detail.

Sometimes scientists want to get photos with better quality in order to answer different questions. For example, in the case of naturally marked species, scientists are able to distinguish individual animals, which makes it easy to estimate densities quite accurately using the well established capture-recapture method. IR CT photos taken during night is in no way detailed enough to provide coat patterns of for example a lynx, which has led to the usage of white light flashes.

However, white light is highly visible to all land dwelling species, and will likely affect the animals to some extent (eg. startle, stress) which in turn could bias the data we collect. Problems related to CT awareness and behavioural changes have already been discussed by many (). Beddari showed that the grey wolf tend to shy away from sites where a white LED CT was used, whilst the lynx seemed less bothered. Heinrich 2020 studied roe deer and red deer's responses to IR flash, black flash and white flash, but used a xenon white flash, which has a long cool down, and hindered any meaningful comparisons with the other flash types.

I will try to quantify whether the detection rate of any common target species are altered when using a white light-emitting diode (LED) flash. The white LED cameras don't have the same cool down period after each triggering, and thus gather more information.

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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 (though this 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 with white light flash 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.

* Null hypothesis (H0): Usage of white LED flash will have no effect on the detection rate of any species.

* Alternative hypothesis (HA): 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.

Chapter 2

Method and materials

2.1 Study area

The mean annual temperatures ranges from 2-6 ℃, precipitation lies between 700-1500mm and growing season length lies between 170 - 190 days (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.

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).

That left nine species, namely 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 60 sites to get a substantial amount of data, while doing a feasible amount of field work besides my master courses at the university. For logistical reasons, I chose the sites closest to Oslo which weren't already equipped with white LED flashes. Instead, these CTs were equipped with infra-red flashes, and I will refer to them as the *IR CTs*.

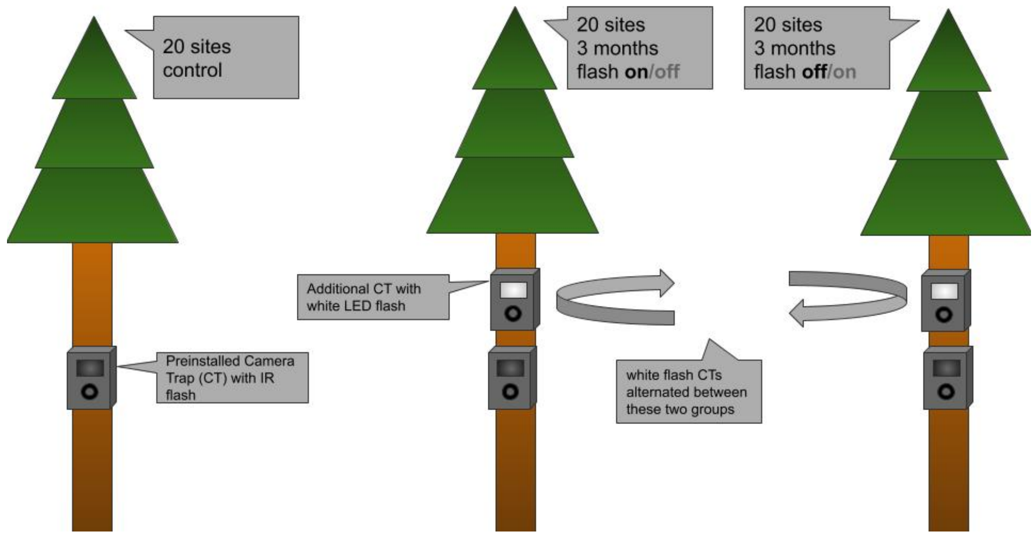

Figure 2.1: Experiment setup I chose 60 sites with preinstalled Infrared Camera Traps (IR CTs) for my study, and divided them into three groups, where the first group remained unchanged (control group), and the two other alternated on having additional white LED CTs present (treatment groups). Four sites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

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 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. The first group remained unchanged as a control, and the remaining two groups (hereby referred to as the *treatment groups*) were equipped with an additional white LED camera (hereby referred to as the *wLED CTs*) in alternating 3 month-periods, as illustrated in figure 2.1. Periods when an additional wLED CT was present, I will refer to as *wLED periods*. Periods when the wLED was absent, I will refer to as *IR periods*. All periods from the control group, I will refer to as *control periods*. Note that control periods also are periods with only IR CTs present, but they differ from the IR periods in that there never was a white LED present at these sites.

I set up all wLED CTs above the IR CTs already in place (installation examples in figure 2.2), using an electric drill. I used short logs to adjust the angle of the wLED CTs, aligning it to the IR CTs field of view. Vegetation obstructing the view of any camera was removed at setup, or when noticed during a later visitation (e.g. tall grass during summer).

At one site the IR camera had been installed so far above ground level that I chose to position the wLED CT below the IR CT.

The camera boxes containing the wLED CTs remained at each site untill the end of the survey. Note that the second treatment group had no extra boxes before the start of their first wLED period in May 2019.

I visited sites of the treatment groups at least once every three months in order to move

(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 wLED 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 had Infra-Red flash, upper cameras had white LED flash.

the wLED 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 local volunteers.

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 and 2.2.

Table 2.1: Camera models included in the survey

Producer	Model name	Flash type
Browning	Spec Ops: Extreme	No-glow IR
	HC500 Semi-Covert IR	Red-glow IR
Reconyx	HC600 High-Output Covert IR	No-glow IR
HyperFire	PC800 Professional Semi-Covert IR	Red-glow IR
Series	PC900 Professional Covert IR	No-glow IR
	PC850 Professional White Flash LED	White LED

Table 2.2: Camera settings and features
All Reconyx-models were part of the HyperFire series and practically identical in all aspects except for type of flash. Camera specifications are gathered from product reviews (www.trailcampro.com).

	Browning	Reconyx
Number of cameras	34(?)	26(?)
Trigger speed	0.43 s	0.28 s
Recovery speed	0.8 s	0.9 s
Photos per trigger	8	3
Detection angle	45.5°	42°
Field of view	40.6°	42°
Quiet period	No delay	No delay
Trigger interval	Rapid fire	Rapid fire
Time lapse	No	Yes

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 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, and the number of active camera days are confounded. 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) was 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). NINA's goal is to fully automate this identification process, which is a request from The Norwegian Data Protection Authority in relation to usage of cameras in densely crowded areas (e.g. parks) (pers.comm. John Odden).

The wLED CTs were considered as external flashes, and so, only the pictures from the preinstalled IR CTs were sorted for species identification. NINA provided me with a data frame containing time stamps for every triggering of each IR CT, including all meta data from the CTs, coupled with predicted species (FRA output, with a confidence number), verified species (by human sorters), number of animals and distance from camera.

Thus, if a moose ruminated in front of a camera for 30 minutes, the data frame would include several detections in sequence. In order to remove autocorrelation in the observations, I defined an event to be any sighting of a species that occured more than 20 minutes after the previous sighting of the same species. Number of individuals was not taken into account. My predictor variable of interest was the three different types of periods, namely IR, wLED and Control periods.

I extracted metadata from all pictures taken by the wLED CTs and used that to define the duration of each wLED period. If a wLED CT stopped working (eg. due to full SD card or empty batteries) before the day I came to move it, the site would have already entered its next IR period. This happened a few times, which can be seen as the times a light blue period starts outside of the shaded areas in figure 2.3. If an IR CT stopped working during a wLED period, that period represented a GAP even though the wLED CT still functioned. Thus, the site, and it's inhabitant animals, would still experience the effect of a white flash up until the start of the IR period. I never experienced that both the IR and the wLED CTs of a site had stopped working at the same time.

When modelling the detection rates 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 IR- and wLED-periods (see figure 2.3).

In total, 4 sites were removed before the analysis due to technical faults, or alike. 1 CT was removed from the control group, as it turned out to be a white LED camera. 3 CTs were removed from the treatment groups, because of large or frequent gaps due to technical errors, and at one site, 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. Locations

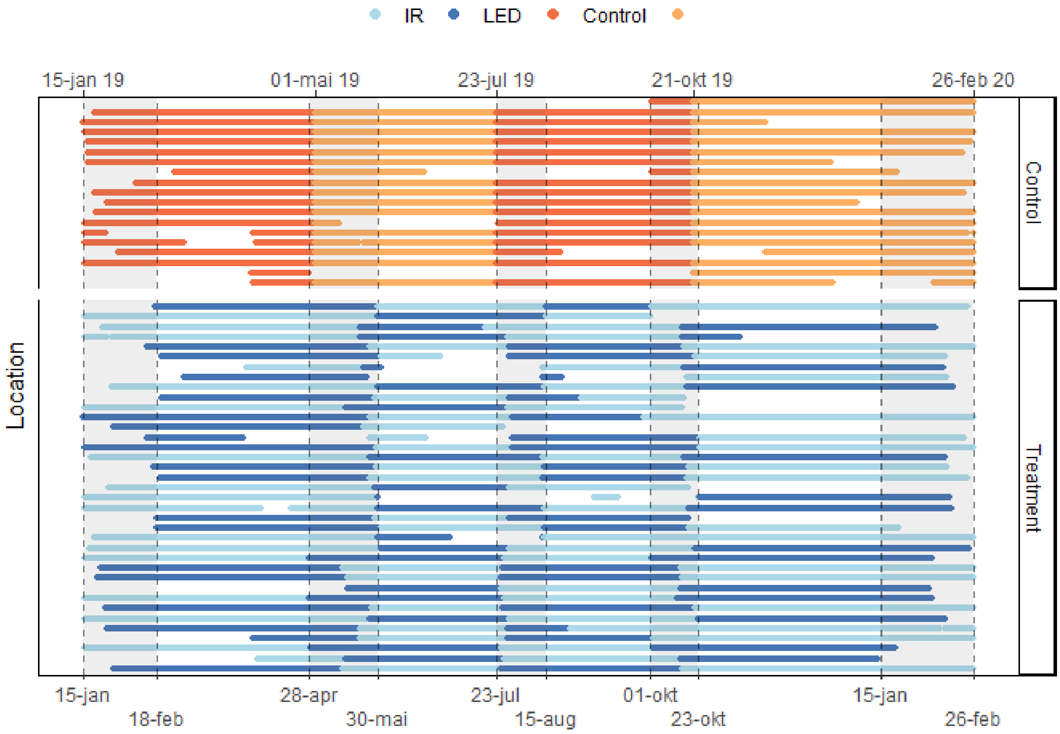

Figure 2.3: Active camera days
Colours indicate the different periods for each site. White spaces indicate gaps where the IR CTs were inactive. Control camera periods were defined in similar lengths to that of the treatment group during analysis. As a result, the first day of control periods are often set at dates far from when I actually visited the site. Shaded areas represent my field work periods.

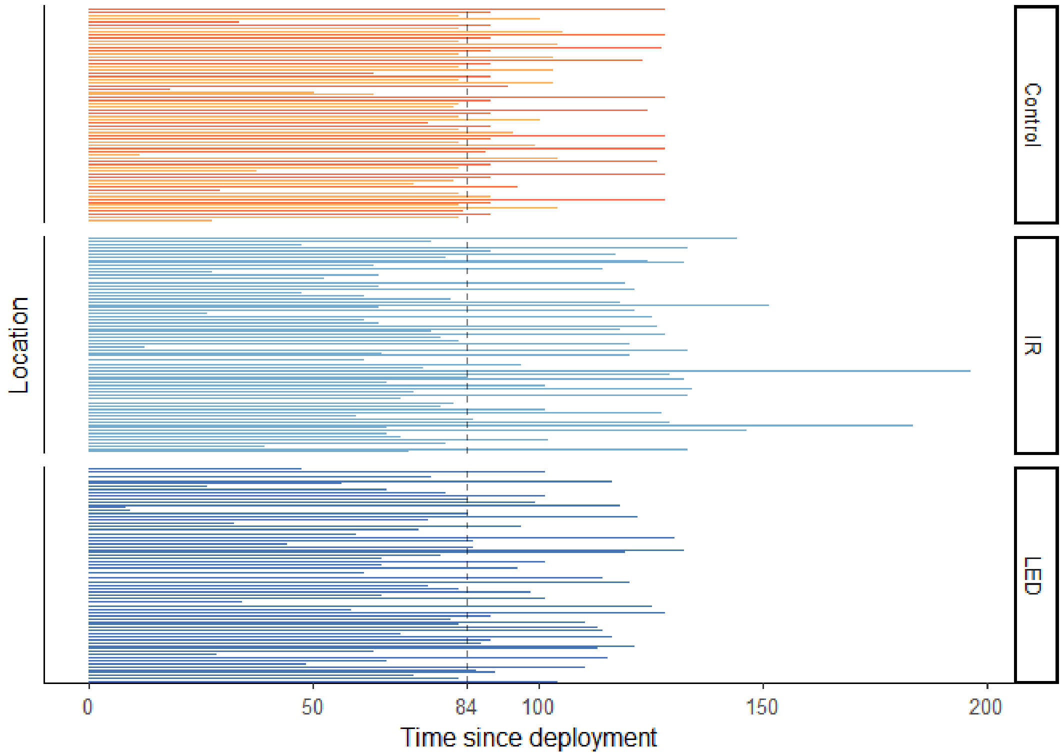

Figure 2.4: Period lengths
Vertical line represents the median IR period length, which was shorter than the median of the other groups. Data superceding the median were trimmed away for the GLMM.

that had 0 observations of the modelled species were filtered out before the modelling, but for all locations that had observed the species, all periods were included. The 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 interacting with type of flash period (formula: n.obs $\sim$ time.deploy $*$ flash). For the sites that were 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 maximum 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 8 corresponds to 80 days.

If there were any effect of the white LED, the IR period should show a regression to the norm, ie. counteracting the trend during the wLED periods. Thus, if the wLED had a negative slope along the time axis, the IR should have a positive slope. Further, the detection rate at the start of each period, should correspond somewhat to the detection rate at the end of the previous period. Still, that pattern could be skewed to some extent due to my visitation of each location at the start of all IR and wLED periods.

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 (www.easystats.github.io/bayestestR/reference/rope_range. accessed 11.3.2021). Hence, I used the default ROPE range which corresponds to a negligible effect size according to Cohen, 1988.

Chapter 3

Results

As the control-group (Intercept in table 3.1) 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).

Table 3.1: 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; periods from sites unchanged through the the whole study period (Intercept), period with only IR camera (IR) and period with additional white LED camera (LED). Random effects are location ID and week of year. 95% Confidence Intervals and p-values were computed using the Wald approximation.

Species	Parameter	Coefficient	SE	95% CI	z	p
Roe deer	(Intercept)	-3.47	0.43	(-4.31, -2.62)	-8.06	< .001
	TimeDeploy	-0.05	0.02	(-0.09, -0.01)	-2.22	0.026
	IR	0.08	0.51	(-0.92, 1.08)	0.16	0.875
	LED	0.20	0.51	(-0.79, 1.20)	0.40	0.688
	TimeDeploy * IR	0.02	0.03	(-0.04, 0.08)	0.69	0.489
	TimeDeploy * LED	2.86e-03	0.03	(-0.05, 0.06)	0.11	0.916
Red fox	(Intercept)	-3.44	0.26	(-3.94, -2.94)	-13.40	< .001
	TimeDeploy	-5.47e-04	0.03	(-0.06, 0.05)	-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	-2.41e-03	0.04	(-0.08, 0.07)	-0.06	0.949
	TimeDeploy * LED	-0.01	0.04	(-0.08, 0.06)	-0.30	0.763
Badger	(Intercept)	-4.79	0.39	(-5.56, -4.02)	-12.15	< .001
	TimeDeploy	0.07	0.03	(0.00, 0.13)	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	7.08e-03	0.04	(-0.07, 0.09)	0.17	0.865
	TimeDeploy * LED	3.93e-03	0.04	(-0.07, 0.08)	0.10	0.922
Moose	(Intercept)	-4.75	0.38	(-5.49, -4.01)	-12.58	< .001
	TimeDeploy	9.66e-03	0.05	(-0.08, 0.10)	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	0.05	0.06	(-0.07, 0.16)	0.78	0.433
	TimeDeploy * LED	-0.01	0.06	(-0.12, 0.10)	-0.19	0.849
Red deer	(Intercept)	-5.99	0.71	(-7.39, -4.59)	-8.38	< .001
	TimeDeploy	-0.10	0.06	(-0.21, 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	0.06	0.08	(-0.09, 0.22)	0.80	0.424
	TimeDeploy * LED	0.23	0.08	(0.07, 0.39)	2.81	0.005
Lynx	(Intercept)	-6.38	0.71	(-7.77, -5.00)	-9.03	< .001
	TimeDeploy	-0.21	0.14	(-0.48, 0.06)	-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	0.24	0.16	(-0.08, 0.56)	1.48	0.140
	TimeDeploy * LED	0.25	0.16	(-0.07, 0.57)	1.54	0.124
Hare	(Intercept)	-4.29	0.43	(-5.13, -3.45)	-10.05	< .001
	TimeDeploy	0.04	0.03	(-0.03, 0.10)	1.13	0.258
	IR	0.24	0.50	(-0.75, 1.23)	0.47	0.636
	LED	0.11	0.51	(-0.89, 1.10)	0.21	0.835
	TimeDeploy * IR	-0.05	0.04	(-0.13, 0.03)	-1.28	0.199
	TimeDeploy * LED	8.95e-04	0.04	(-0.08, 0.08)	0.02	0.983
European Pine Marten	(Intercept)	-6.38	0.57	(-7.50, -5.27)	-11.20	< .001
	TimeDeploy	0.10	0.09	(-0.09, 0.28)	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	-0.11	0.11	(-0.32, 0.09)	-1.08	0.280
	TimeDeploy * LED	0.02	0.11	(-0.19, 0.24)	0.22	0.828
Red squirrel	(Intercept)	-5.72	6.21e-04	(-5.72, -5.72)	-9211.38	< .001
	TimeDeploy	0.08	6.21e-04	(0.08, 0.08)	132.04	< .001
	IR	0.83	6.21e-04	(0.83, 0.83)	1334.43	< .001
	LED	0.51	6.21e-04	(0.51, 0.51)	818.92	< .001
	TimeDeploy * IR	-0.18	6.21e-04	(-0.18, -0.18)	-286.42	< .001
	TimeDeploy * LED	-0.02	6.21e-04	(-0.02, -0.02)	-26.66	< .001

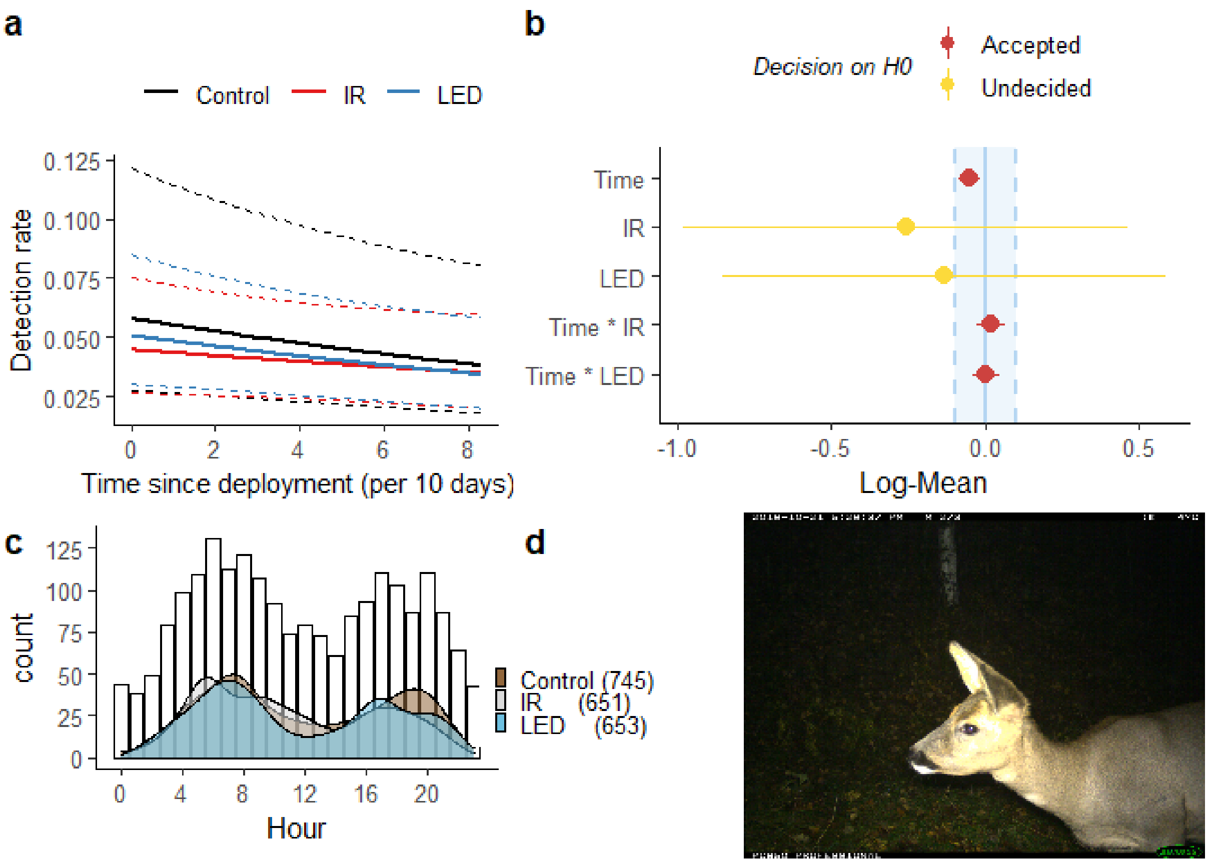

Figure 3.1: Roe deer a) The predicted detection rate of roe deer for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ±0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count 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 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 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.

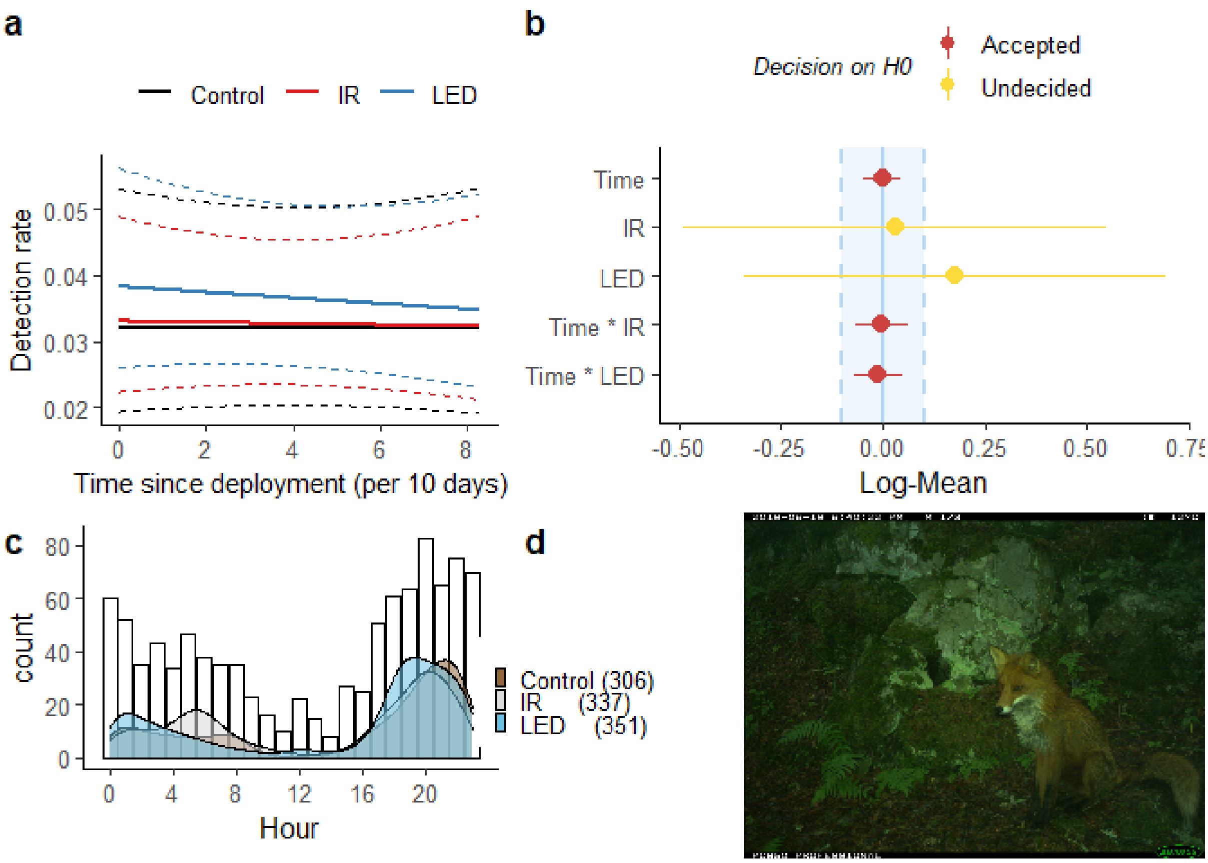

Figure 3.2: Red fox
a) The predicted detection rate of red foxes for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ±0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count 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.

3.2 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, CI of both white LED and IR periods almost completely overlap, and hence, are not significantly different.

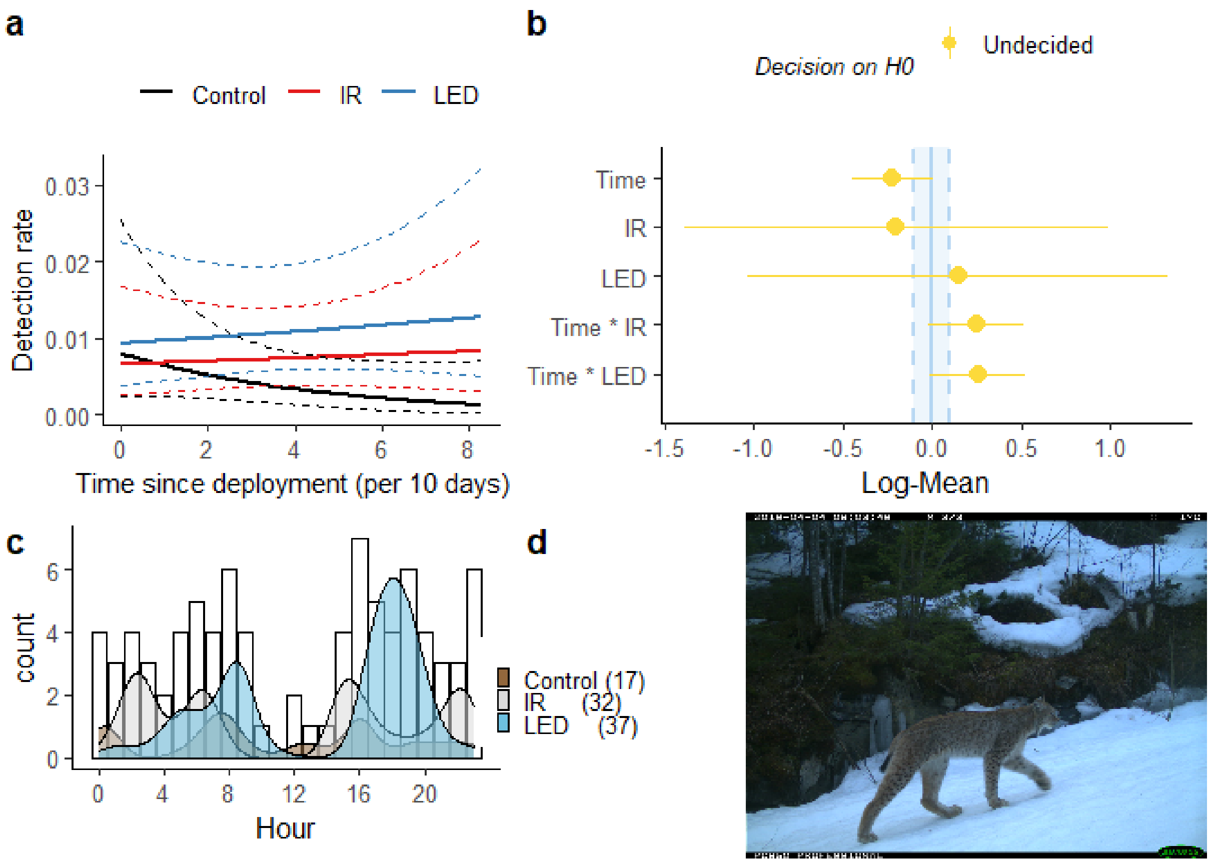

Figure 3.3: Lynx
a) The predicted detection rate of lynx for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total 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

3.3 Badger

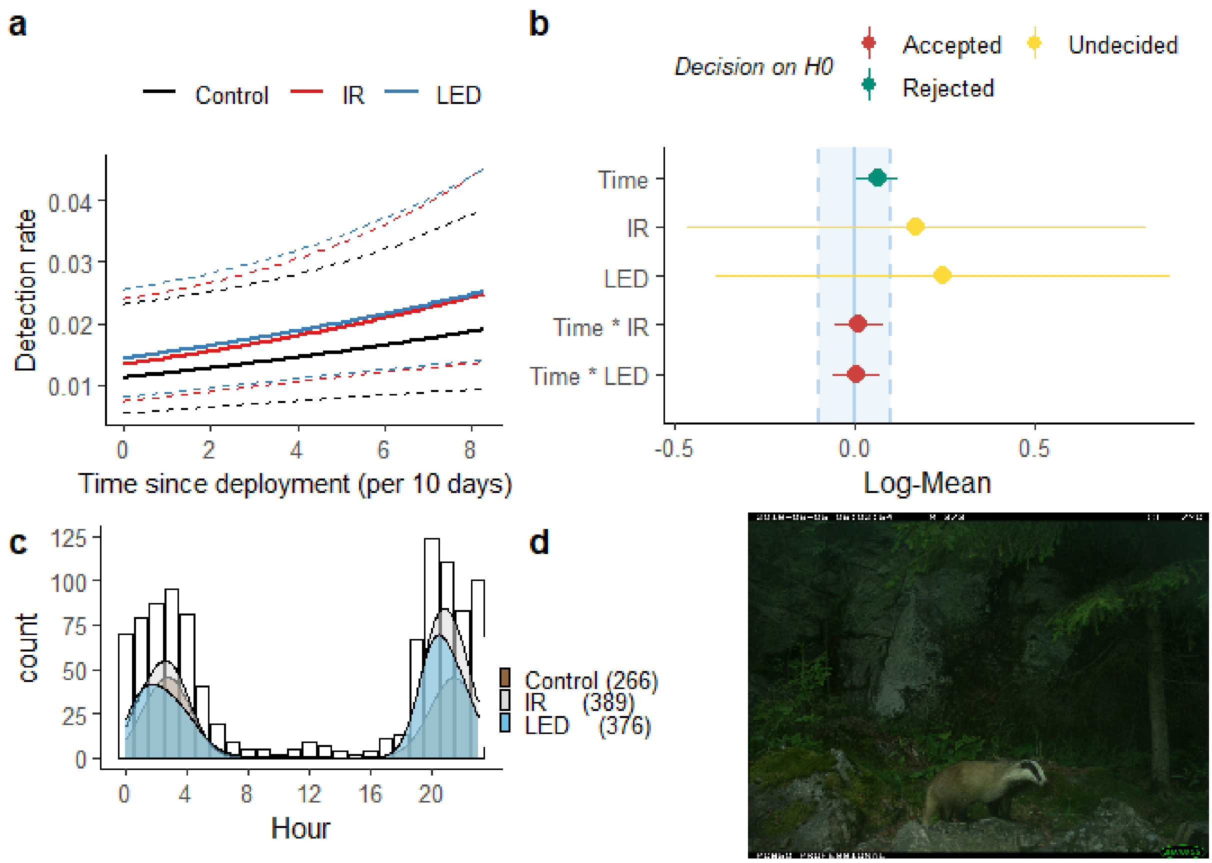

Figure 3.4: Badger
a) The predicted detection rate of badgers for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ±0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of 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

3.4 Hare

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.

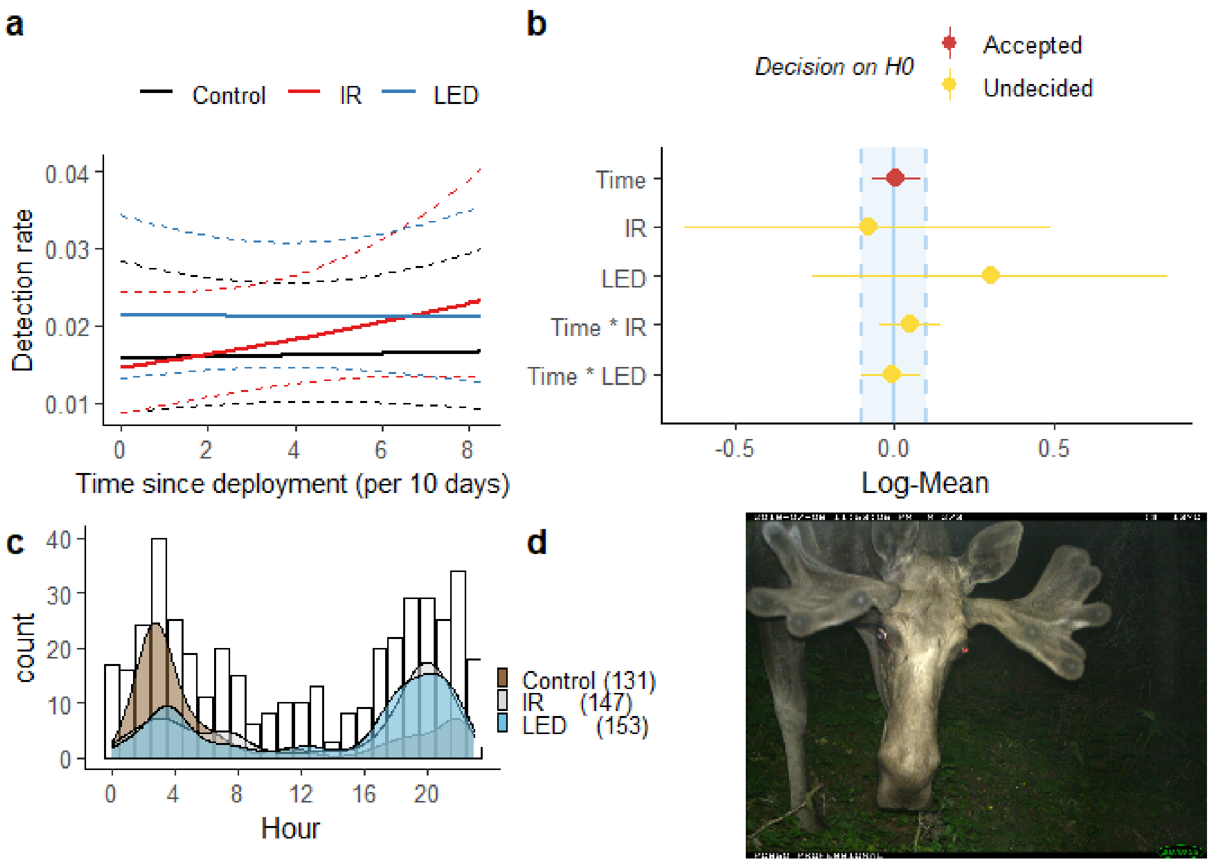

Figure 3.5: Moose
a) The predicted detection rate of moose for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total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

3.5 Red squirrel

3.6 Moose

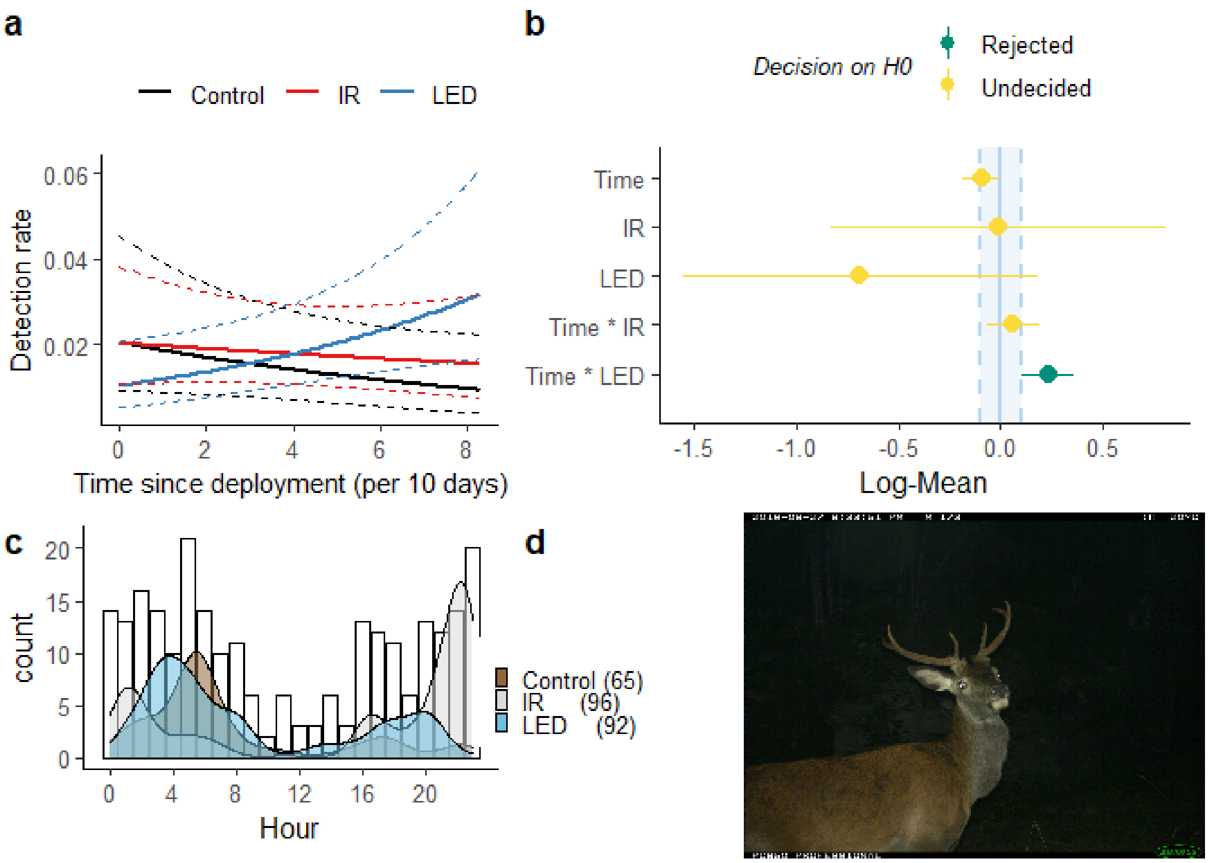

Figure 3.6: Red deer
a) The predicted detection rate of red deer for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ±0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count 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

3.7 Red deer

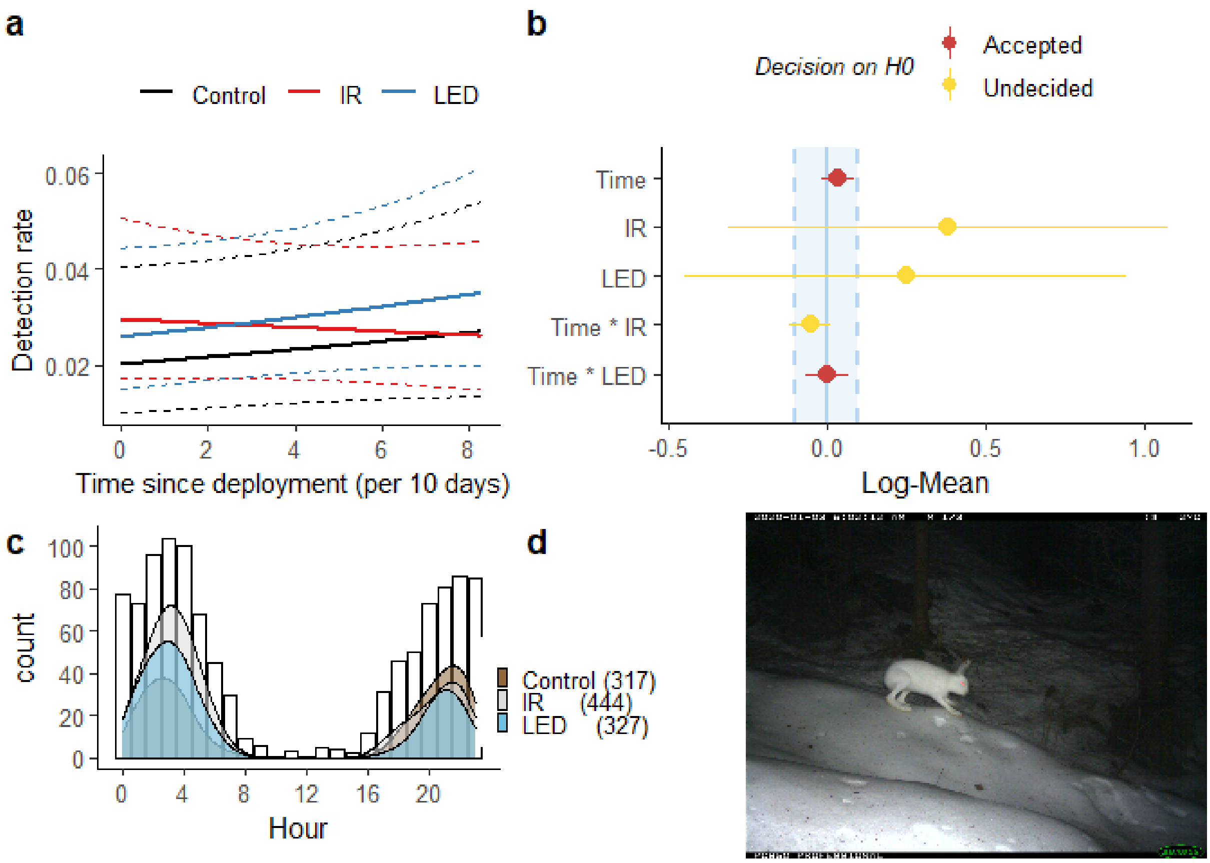

Figure 3.7: Hare
a) The predicted detection rate of hares for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ± 0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw count of total 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

3.8 Pine marten

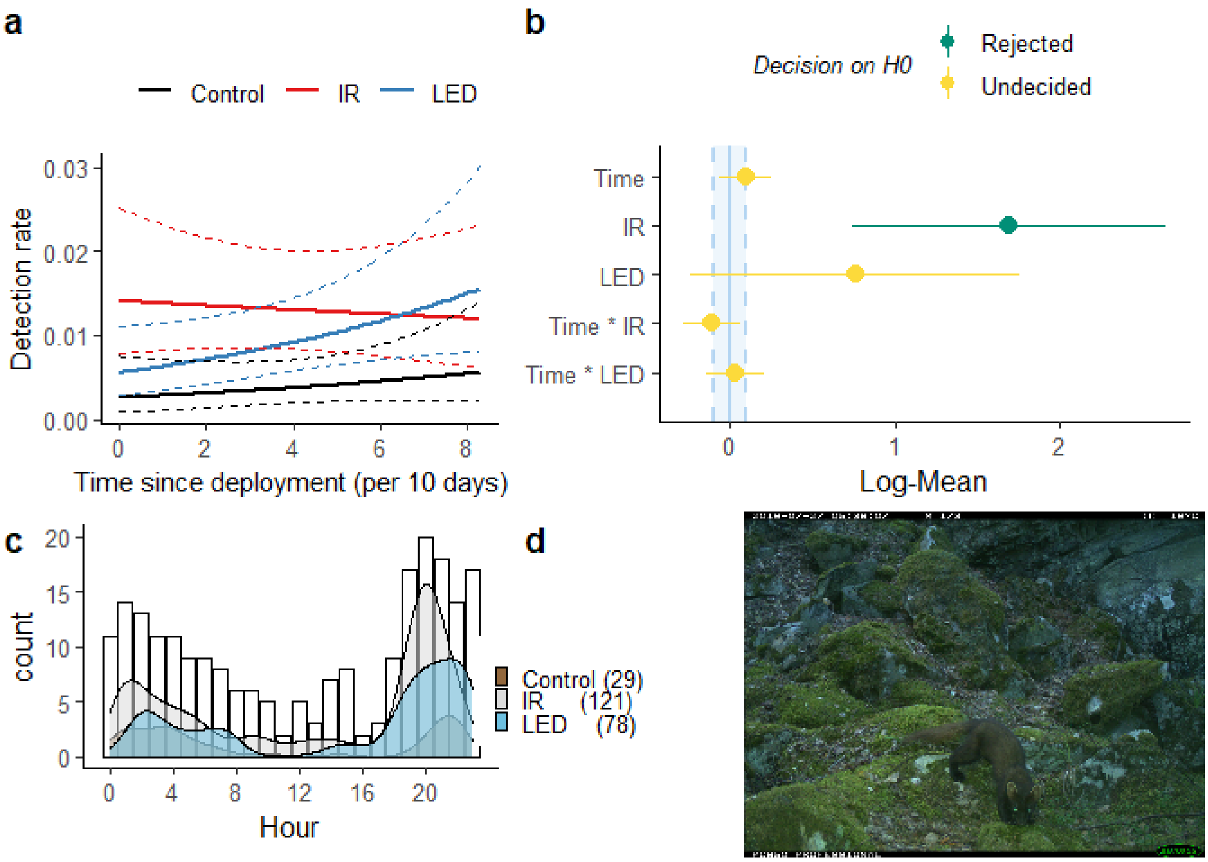

Figure 3.8: Pine marten
a) The predicted detection rate of pine martens for each level of the flash-variable. Confidence intervals (CI) represented by dotted lines.
b) Model parameters presented in an equivalence test. ROPE is set to ±0.1 Log-Mean, $CI = 1 - 2 \times \alpha$.
c) Bars represent the raw 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

3.9 Lynx

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