Catchy title

Quantifying the effect of a common olfactory lure on urban dwelling mammals

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# Introduction

Humans have trapped furbearing animals for millennia. While the motivations for mammal trapping are varied, our predecessor’s trials and tribulations have distilled much wisdom to beguile wildlife into snares, leg-hold traps, or cages. One suggested technique to bolster trap efficacy is the use lures or bait. The motivation for such an approach stems from the notion that lures or bait will engage a species sense of smell, sight or hearing and therefore increase the chance a target species investigates a trap (as reviewed by Schlexer 2008). Indeed, the overall success of a trapping operation may well depend on the type of lures or baits used, and a plethora of commercially available lures and baits exist for live-trapping purposes (Schemnitz 2005, Schlexer 2008).

For research purposes, motion-triggered camera traps (hereafter camera traps) have become an important alternative to livetrapping (refs). Camera traps allow researchers to passively sample multiple locations simultaneously and do not require the physical restraint of an organism, thereby eliminating the chances of trap-mortality or injury. Further, camera traps can be used to answer many ecological questions about the distribution and abundance of wildlife (refs). Yet, for an animal to be caught (i.e., photographed) it must move in front of a deployed camera trap, and camera trapping surveys must therefore look for ways to increase the detectability of species via study design (O’Connel et al. 2011, Hofmeester et al. 2019). As a result, both lures and bait have been suggested as ways to increase the likelihood of detecting species that occupy an area of interest (refs). However, the reasoning behind the use of lures or bait is mostly grounded in custom rather than quantifiable effectiveness (refs).

Studies that have quantified the effect of lure

Of studies that do quantify the effects of lure, we discuss here why they may (at times) be inadequate. Compare the effects of lured / non-lured locations where the occupancy or abundance of an organism may be different. Lure may also influence the detectability of an organism in a variety of ways, which to date has not been addressed. For example, lure could increase the number of days a species is detected over a survey, could reduce the amount of time it takes to detect a species, or simply increase the amount of time an organism spends in front of a camera trap thereby increasing the number of photos.

It is important to quantify the effect of lures as they may have varying effects on a given wildlife community.

In this paper we quantify the effect of a commonly used olfactory lure on a suite of furbearing species in natural areas throughout Chicago, Illinois, USA. Our study design differs from others in that we deploy two camera traps per sampling unit, spaced apart by 100 m, over a 28 period to experimentally assess if lure can modify the detectability of a species both within and between sites. To do so, we changed lure treatments every 7 days by placing either a lure or a no lure control in view of each camera following a full factorial design. This arrangement allows us to quantify if lure increases the chances of detecting a species as they may be drawn more often to a camera that has lure relative to a nearby camera that does not. We predicted that the use of lures would increase the detectability of mesocarnivores. Conversely, we predicted that prey species would have lower detection rates in the presence of lures.

# Methods

## Study area and site selection

For Gabby

## Experimental design

For Gabby

## Statistical analysis

We fit three separate hierarchical occupancy models to all species with sufficient data. For simplicity, we explain these models for a single species. In the 3 models, we assume the occupancy status of a species does not change over the 28-day sampling period and that the probability of occupancy does not vary between sites. Thus, the probability of occupancy, *ψ*, at *s* in 1,…,*S* sites is the following Bernoulli process

where *zs* is a random binary variable that represents the occupancy status of a species. If the species is present *zs* takes the value of 1 and is otherwise 0. Such a model is no different than the latent state of an intercept-only occupancy model, which we assume is adequate given the proximity of and similarity between natural areas sampled in this study.

### Observation model 1: Does lure increase the number of days a species is detected?

Our first model assumes that days within a sampling week are repeat surveys in which a species may be detected given its presence. This is the most traditional formulation of a hierarchical occupancy model (ref). For each of the two cameras, *c*, deployed at a site and *k* in 1,…,4 weeks of sampling we can model the effect of lure as the following Binomial process:

Where *ys,k,c* are the number of days a species was detected at site *s* on week *k* at camera *c*, *js,k*are the number of days sampled at site *s* on week *k*, and *ps,k,c* is the probability of detecting a species given their presence (i.e., *zs* = 1). We can incorporate the presence of lure on *ps,k,c* via the logit-link function such that

Here, is the log odds a species is detected without lure, is the log odds difference in detection given the presence of lure, is an indicator variable which takes the value 1 when lure is present at a camera, and is a site-level random effect to account for variability that may exist between sampling locations not attributed to lure.

### Observation model 2: Does lure decrease the amount of time to first detection?

Instead of increasing the number of days a species investigates a camera, lure may decrease the amount of time it takes to detect them for the first time (Bischof et al. 2014). To quantify this effect, we instead treat data collection as a continuous time process. Thus, let the response variable of this model, , be the continuous number of days to first detection (i.e., the amount of time it takes to collect the first image of a species per camera). However, if a species is present at a site but not detected after 7 days when treatments are changed there is uncertainty about how long it would take for the species to be photographed. To account for this, we model as a censored exponential random variable. Let *Tmax* represent the maximum amount of time a lure treatment is placed in front of a functioning camera station (i.e., *Tmax* = 7 days). Following Kery and Royle (2016), the continuous time-to-detection observation model is

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Here, is an indicator function which takes the value 1 if a species was not detected in a given week at a camera trap. Thus, equals 1 if a species is present but went undetected or if they were not present (i.e., *zs* = 0). When this occurs, . Otherwise, equals 0 and we sample from the Exponential distribution to estimate the inverse scale parameter from the right-censored data. To estimate the effect of lure on this rate we employ the log link function

We use a similar parameterization to the linear in model 1 (Eq. X), except the coefficients in this model are on the log-scale. Further, these coefficients estimate the expected time between detection events in the presence or absence of a lure, all while controlling for variability between sites not attributed to lure via the site-level random effect .

### Observation model 3: Does lure increase the number of photographs of a species?

Finally, lure may increase the number of photographs taken of a species if it increases the amount of time they spend in view of a camera. This may be advantageous if a study species can be identified to an individual level by their markings, such as a leopard’s spots, which is easier to do with multiple images (refs). Here, let be the number of images collected of a species as site *s*, week *k*, and camera *c*. We then model the number of images collected as the following Poisson process

where and are the same as before while is a rate parameter which estimates the average number of photos expected per day given a species presence. Similar to model 2, is used to control for the observational treatment window length. To incorporate the effect of lure we again use the log link:

### Specification of priors and model fitting

For all models, we the probability of occupancy, *ψ*, an uninformative Beta(1,1) prior. For the observational process, the choice of priors depended on the link function used in a given analysis. For model 1, which uses the logit-link, we followed the suggestions of Gelman et al (2008) and gave the intercept, *a0*, a Cauchy(0, 10) prior while the lure effect parameter (*a1*) received a Cauchy(0, 2.5) prior. For models 2 and 3, the log-link intercept and lure effect parameters received uninformative Normal(0, 10000) priors. Finally, random effects from all models were drawn from Normal(0, σ) distributions where σ ~ Gamma(0.001, 0.001).

Models were written and executed in JAGS version 4.3.0 (Plummer 2003) through program R version 3.5.2 (R Core Team 2018) via the runjags package (Denwood 2016). Following a 1,000 step adaptation phase, models had a burn-in period of 50,000 steps. After the burn-in, parameters were sampled a total of 300,000 times across 6 chains. MCMC chains were thinned by 5. Model convergence was assessed by visually inspecting trace plots and ensuring that Gelman-Rubin diagnostics for each parameter were < 1.10 (Gelman et al. 2014). Significance of the estimated regression coefficients was calculated by assessing if 95% credible intervals did not overlap 0.

# Results

Over the course of this study 1,110 functional camera days out of a possible total of 1,120 (28 days \* 40 cameras) were collected. In this period, 6,110 images were taken of 12 species. Eight species had enough data to fit the three occupancy models: coyote (*Canis latrans*), eastern chipmunk (*Tamias striatus*), eastern cottontail rabbit (*Sylvilagus floridanus*), eastern gray squirrel (*Sciurus carolinensis*), fox squirrel (*Sciurus niger*), raccoon (*Procyon lotor*), Virginia opossum (*Didelphis virginiana*, hereafter opossum), and white-tailed deer (*Odocoileus virginianus*). The remaining four species that had insufficient data were the American mink (*Neovison vison*), long-tailed weasel (*Mustela frenata*), southern flying squirrel (*Glaucomys volans*), and striped skunk (*Mephitis mephitis*). Eastern gray squirrel were photographed the most over the survey, totaling 1,917 pictures across all 20 of the sites. Of the species that could be analyzed, eastern cottontail rabbit were detected the least, totaling 72 pictures across 9 of the 20 sampling sites.

## Does lure increase the number of days a species is detected?

Without lure, daily detection probability varied greatly between species (Figure 1). Coyote, for example, had a 5.77% (95% CI = 2.85 – 9.21) probability of being detected each day, which did not increase when lure was placed in front of a camera (Figure 1). Raccoon and gray squirrel had the highest detection probabilities, which were respectively 46.09% (95% CI = 36.69 – 55.00) and 47.89% (95% CI = 36.45 – 58.49) without lure. On average, the presence of lure increased raccoon and gray squirrel detection by roughly 5%, but 95% credible intervals of this effect bounded zero (Figure 1). Overall, the presence of lure significantly increased the number of days two species were detected: opossum and chipmunk. Opossum detection probability increased by 8.20% (95%CI = 3.32 – 13.36) when lure was present up to a total daily detection probability of 25.08% (95% CI = 18.03 – 32.46). Lure had a lesser effect on chipmunk and increased by 4.76% (95% CI = 0.38 – 10.40). There was some indication that the presence of lure decreased the number of days eastern cottontail were detected, but this effect was not significant (Figure 1).

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**Figure 1.** Lure had a marginal, but varying effect on the number of days species were detected. The left plot illustrates the daily probability of detecting a species when no lure was in front of a camera. The right plot illustrates how a species detection probability on the left changes given the presence of lure. Vertical solid lines are median estimates which are plotted over the posterior distribution that fell within the associated 95% credible interval.

## Does lure decrease the amount of time to first detection?

Without lure, the expected number of days to first detection ranged from 2.21 (95% CI = 1.12 – 3.69) for gray squirrel to 20.75 days (95% CI = 9.63 – 45.37) for cottontail rabbit (Figure 2). When lures were placed in view of a camera most species showed a general decrease in the amount of time to first detection (Figure 2). However, credible intervals of this effect bounded zero for all species except the opossum. On average, the expected time to detect opossum decreased by 35.34% (95% CI = 11.13 – 55.83) to 5.57 days (95% CI = 3.73 – 7.81). There was some indication that it took longer to detect both coyote and cottontail rabbits given the presence of lure, but this effect was also not significant (Figure 2).



**Figure 2.** Opossum were the only species to arrive earlier if a lure was placed in front of a camera. The left plot is the expected number of days until the first photograph is taken given a species presence. The right plot is the proportional effect that lure has on the number of days until a photograph is taken, with values < 1 indicating a decrease in the amount of time to first detection. Vertical solid lines are median estimates which are plotted over the posterior distribution that fell within the associated 95% credible interval.

## Does lure increase the number of photographs of a species?

**Discussion**

# References

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