Catchy title

Authors: Mason Fidino, Gabby Barnas, Elizabeth Lehrer, Maureen Murray & Seth Magle

# Introduction

Humans have trapped furbearing animals for millennia. While the motivations for 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 that are used, and a plethora of commercially available lures and baits exist for live-trapping purposes (Schemnitz 2005, Schlexer 2008).

Instead of live-trapping, motion-triggered camera traps (hereafter camera traps) have become an important research tool to monitor the occupancy and abundance of wildlife (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. Yet, for an animal to be caught (i.e., photographed) it must still move in front of a deployed camera trap, and camera trapping surveys must therefore look for ways to increase the detectability of species in their study design (refs). 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 experimentally quantify the effect of lure on a suite of mammalian 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. Each week, we placed either lure or no-lure in view of each a camera following a full factorial design. Such a design allow us to more fully 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

## Experimental design

## Statistical analysis

For the species with sufficient, we fit three separate occupancy models to the data, all of which varied in how the detection function estimates the probability of detecting a species given their presence. For all models, we assume that the occupancy status of a species does not change within a single season and that the probability of occupancy does not vary across sites. Thus, we model the probability of occupancy, *ψ*, at *s* in 1,…,*S* sites as the following Bernoulli process

Where *zi* is the occupancy status of a species, which takes the value of 1 if it is present and is otherwise 0. For simplicity, we explain these models for a single species. 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.

### 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 it’s presence, which is the most traditional formulation of an 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, and is a site-level random effect to account for variability that may exist between sampling locations.

### 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

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  |  |
|  |  |  |

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 .

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

Finally, lure may increase the number of photographs taken of a given 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 would be easier 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 a 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 expect in this case there is no right-censoring of data. To incorporate the effect of lure we again use the log link:

### Specification of priors and model run lengths

For all models, we gave ψ, the probability of occupancy, an uninformative Beta(1,1) prior. For the observational process, the choice of priors depended upon 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 intercept and lure effect parameters received a Normal(0, 10000) prior. Finally, all random effect’s 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 2017) with the runjags package (Denwood YEAR). 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 regression coefficients was calculated by assessing if 95% credible intervals did not overlap 0.

**Results**

Over 28 days of trapping, a total of X species were detected. Overall, enough data was collected to fit occupancy models to eight species: coyote, eastern chipmunk, eastern cottontail rabbit, eastern gray squirrel, fox squirrel, raccoon, Virginia opossum, and white-tailed deer. Eastern gray squirrel were detected the most over the survey, totaling X pictures across at Y of the 20 sampling sites. Coyote were detected the least, totaling X pictures at Y of the 20 sampling sites.

**Discussion**