# Wildlife Biology

## **WLB-00726**

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#### A1. Camera deployment and settings

Cameras were programmed to record 3 mega-pixel images (color during daylight and black/white during night), with 3 'rapid-fire' pictures per trigger event and a 2-second delay between subsequent triggers (Table A1-1). Additionally, a set of 3 'rapid-fire' time-lapse pictures were taken twice daily (noon and midnight) to check the functioning of the cameras. Date and time were printed on all the images and recorded in the image metadata.

After selecting all locations and before deploying the cameras, each site was visualized on 2015 aerial photos to help ensure all requirements for deployment were likely met, including an additional requirement that each site was a minimum of 30 m from any non-forested edge, to minimize potential influence due to forest-edge effects (e.g. change in abundance in raccoons: Dijak and Thompson 2000). If a selected site later became unavailable (e.g. site was logged), a new location was chosen as close as possible to the previous site and in a similar forest type when possible.

We attached all cameras to trees using bungee straps, placed the bottom of the camera about 75 cm above the ground, aimed all cameras north (ranging from northeast to northwest) when possible to reduce false triggers and blurred photos from direct sunlight, and removed vegetation in the detection field to minimize false triggers and obstruction. Starting in fall 2016, we added a second strap to the bottom of the camera to reduce alteration of the camera position by bears.

At random-based sites, we collected information on occurrence of and distance to the local features present at the sites. In the final set of locations sampled, feature-based cameras were primarily deployed in close proximity to game trails (64.5%), creeks or other water sources (11.5%) and other landscape features thought to serve as movement 'bottlenecks' (11.5%). We note that a site could have been characterized by more than one feature and that game trails and other local features may have been present at our completely randomly chosen sites; 2 random, lured cameras ended up on small roads, similar to what was described by Cusack and colleagues (2015).

For unlured road-based sites, we allowed flexibility in the final deployment location of cameras due to the need to position the camera on a tree at the desired angle to the road or trail and within sufficient distance of the road to ensure trigger activation by animals; from the original coordinates, operators were allowed a distance of 45 m in either direction down the road or trail to place the

camera. We aimed road cameras at a 45° angle to the main axis of the road to ensure greater opportunity to capture images of faster moving animals. At these sites, we recorded information on use of the road by humans (e.g. recent ATV tracks), road width, and vegetation regrowth along the road. At the final selected locations, width of secondary roads at the camera sites ranged between 1.2 and 8.2 meters (mean +/- SD: 3.3 +/- 1.9); 34% of the forested roads showed signs of frequent use by humans; roads were either free of vegetation (70%), or showed signs of initial (26%) or complete (4%) vegetation regrowth. Access at selected road-based camera sites was classified as being suitable only by all-terrain vehicle (i.e. ATV; 49%) or only by walking (37%).

We did not sample in winter because of the lack or reduced availability of several species (e.g. black bears and striped skunks) to detection, ongoing harvest season for others species, logistical challenges with accessing camera sites in deep snow, and greater risk of camera malfunction or battery depletion due to cold weather.

Table A1-1. Bushnell Trophy Cam HD Aggressor No-Glow (model: 119776) camera setting used during the study.

Parameter	Setting
Mode	Camera
Image size	3M pixel
Image format	Wide screen
Capture number	3
LED control	High
Camera input	Camera number
Video size video	(Not relevant)
Length interval	(Not relevant)
Sensor level NV	2S
Shutter camera	Auto
Mode format	Medium
Time stamp Sset	24 h
Clock	(Not relevant)
Field scan	On
Coordinate	Time at deployment
input video	YES: A 00:00/00:01; B 12:00/12:01; interval 5min
Sound default	Off
Set	(Not relevant)
	(Not relevant)

#### A2. Lorelograms to define independent events

We used lorelograms to define the time interval needed to assure independence among subsequent pictures (Heagerty and Zeger 1998, Iannarilli et al. 2019). The lorelogram quantifies serial correlation in binary data using log-pairwise odds ratios at a set of increasing time (or spatial) lags, quantifying the increase in the odds of detection given the species was detected (versus not detected) at each lag. We used the R-package *lorelogram* (Iannarilli and Fieberg 2019) to construct lorelograms at a series of 1-minute time lags for each combination of species and season, pooling data across years, and defined two subsequent pictures of the same species at the same site as 2 independent events (i.e. sequences) if they were ≥ 30 minutes apart. For most of the species, serial independence was reached at lower values (e.g. < 20 minutes in black bears and wolves); however, we used a more conservative threshold to accommodate species that lingered for a longer time at the site (e.g. raccoons in the fall; Fig. A2-1). We then applied this threshold and extracted the number of independent events within each day using the *camtrapR* R-package (Niedballa et al. 2016).

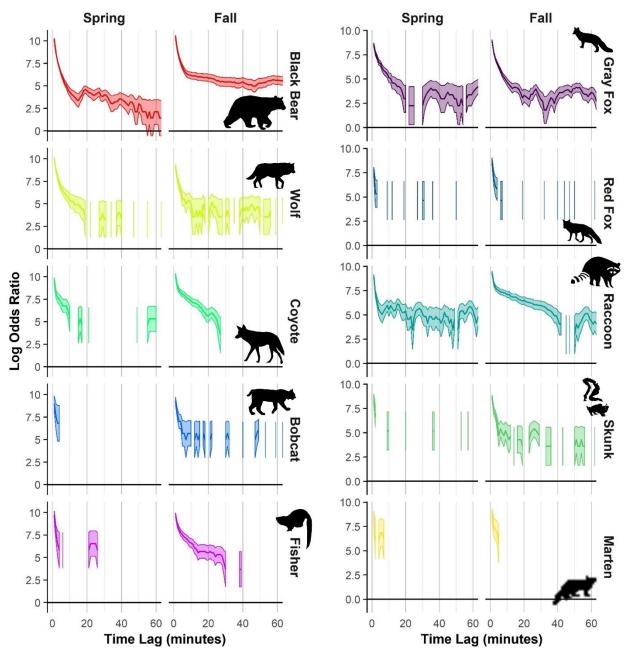


Figure A2-1. Lorelograms at the minute scale estimated by species and season. Pairwise log odds ratios (y-axis) level off at lags (x-axis) between 10 and 30 minutes, which we used to define an approximate time lag for determining independence among subsequent pictures. Gaps in the curves represent time intervals for which we did not record detection events (i.e. no pictures x minutes apart).

### A3. Modelling year effects

As a form of sensitivity analysis, for each species we ran an additional model to test for annual variation in encounter frequencies by adding a parameter to account for the *Year* effect to the model presented in the manuscript (see section 'Statistical analysis'):

$$\log(\mu_{ijtk}) = \alpha_{\omega(ijk)} + \beta_1 * Season_k + \beta_2 * Day_t + \beta_3 * Season_k * Day_t + \beta_4 * Year + \varphi_j + \gamma_{ij}$$

Encounter frequencies for black bears and wolves exhibit an increasing trend over time, whereas expected numbers of independent encounters per day were similar across years for all other species (Fig. A3-1).

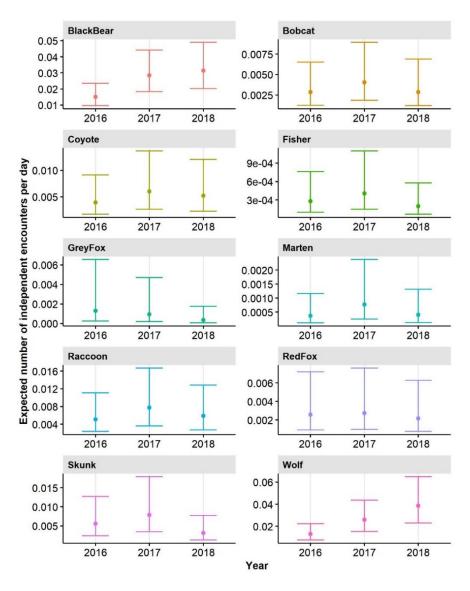


Figure A3-1. Expected number of independent events per day by species and year. Values were calculated using the function *ggpredict* in the ggeffects package (Lüdecke 2018) and keeping random effects equal to zero and values for variables other than *Year* constant to a certain value: *Treatment* = unlured, road-based camera; *Season* = spring; *Day* = 1.17, that is equivalent to 35 days since deployment.

#### References

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