



Research Article

A shot in the dark: White and infrared LED flash camera traps yield similar detection probabilities for common urban mammal species

Daniel J. HERRERA^{1,2,*}, Sophie M. MOORE¹, Valentine HERRMANN³, William J. McSHEA³, Michael V. COVE⁴

¹Humane Rescue Alliance, 71 Oglethorpe Street NW, Washington, D.C. 20011, USA

²Department of Environmental Science and Policy - George Mason University College of Sciences, 4400 University Drive, Fairfax VA 22030, USA

³Smithsonian Conservation Biology Institute, 1500 Remount Road, Front Royal VA 22630, USA

⁴North Carolina Museum of Natural Sciences, 11 W Jones Street, Raleigh NC 27601, USA

Keywords:

camera traps
camera flash
detection probability
urban mammals
LED white-flash
infrared-flash
urban ecology

Article history:

Received: 08 March 2021

Accepted: 10 May 2021

Acknowledgements

We wish to thank Tyler Flockhart, Lauren Lipsey, Erin Robinson, and Sam Decker for their administrative assistance throughout the project, Justin Belsley, Claire Bresnan, Elly Grant, Neha Singh and Sam Newkirk for their assistance in data collection, and Jen Zhao, Haydee Hernandez-Yanez, Helen Bontrager, Ashley Whipple, Johnny Stutzman, Ben Ranelli, Emily Renkey, and Jamie Fetherolf for their assistance with data processing and storage. Major financial support was provided by: PetSmart Charities, American Society for the Prevention of Cruelty to Animals, The Humane Society of the United States, Humane Rescue Alliance, Winn Feline Foundation, Maddie's Fund, Cat Depot and B. Von Gontard.

Abstract

Camera trap surveys use infrared-flash camera traps more frequently than white-flash camera traps due to claims that white-flash cameras impact animal behaviour and reduce capture rates. While several studies have examined the impact of white-flash on individual behaviour, few have assessed the effect of flash type on probability of detection. We used nightly detection histories for seven mammal species common to North American cities using both infrared and white-flash LED camera traps across Washington, D.C., USA, to assess potential differences in the two flash types. Our results revealed that flash type did not affect the detection probabilities for four of these species. Infrared-flash cameras yielded higher probabilities of detection for the remaining three species analysed, but the overlapping confidence intervals of detection probabilities from LED white-flash and infrared-flash cameras suggest that there is little evidence that flash type impacts the inferences drawn from surveys using LED white-flash cameras. Additionally, LED white-flash cameras produce photographs better suited for identification of both species and individuals when unique markings are present. Depending on a study's objectives, a greater capacity for species and individual identification may warrant the moderately lower detection probabilities produced by white-flash camera traps.

Introduction

Camera trap surveys have become an increasingly common sampling method in recent years, owing to their ease of use and passive sampling technique (Rovero and Zimmermann, 2016; McCallum, 2013; Roberts, 2011). Though camera traps were originally available exclusively with white-flash, infrared-flash is more commonly used today (Rovero et al., 2013). This is partially due to the inconspicuous nature of infrared-flash cameras to humans (Glen et al., 2013; Meek and Pittet, 2012) and similar claims for wildlife. Previous research suggests that white-flash cameras disturb nocturnal animals and contribute to camera trap shyness or avoidance (Wearn and Glover-Kapfer, 2017; Glen et al., 2013; Schipper, 2007; Wegge et al., 2004). However, a review of common models of camera traps found that the shutter sound and wavelength of infrared-flash cameras both fall within the range of perception of many mammal species (Meek et al., 2016, 2014), and that some species avoid camera traps altogether due to their human-associated scent (Muñoz et al., 2014). Thus, it is likely that no camera trap goes completely unnoticed by wildlife. Although some studies have investigated the differences in efficacy of white-flash and infrared-flash camera traps, the results are largely inconclusive (e.g., Schipper, 2007; Wegge et al., 2004; for conflicting results, see: Henrich et al., 2020; Taggart et al., 2019). Factors such as paired sampling methods that may inadvertently alert an

animal of the camera's presence prior to being photographed (e.g., impression pads on game trails prior to camera trap; Wegge et al., 2004), small sample sizes (Schipper, 2007), and the confounding effects of the camera's mechanics (Henrich et al., 2020; Glen et al., 2013) further complicate these findings.

The use of camera traps in estimates of occupancy or population size (e.g. capture-recapture) are more common than their use in behavioural studies (McCallum, 2013). However, previous research on white-flash/infrared-flash differences focuses mainly on the individual behavioural responses to flash type (e.g., Henrich et al., 2020; Taggart et al., 2019; Glen et al., 2013). An individual's behavioural response to a flash stimulus likely affects the individual's future detection, and thus detection probability, throughout the remainder of the sampling period (Meek et al., 2016). While previous studies have investigated individual behavioural responses to white-flash cameras (e.g., Taggart et al., 2019), the direct effect of LED white-flash on species detection probability has rarely been explicitly examined (Meek et al., 2015; McCallum, 2013; Cove et al., 2012). We address this gap by using nighttime animal observations from the DC Cat Count (Herrera et al., 2021) to assess the impact of flash type on detection probabilities of seven urban mammal species within Washington, D.C., USA, while simultaneously accounting for seasonality and the degree of nearby urbanisation (Henrich et al., 2020). Furthermore, we investigate the impact of flash type on rates of species and individual identification, as well as non-capture rates (e.g., empty photos).

*Corresponding author

Email address: herrerawildlife@gmail.com (Daniel J. HERRERA)

Materials and Methods

We deployed passive infrared sensor camera traps (Reconyx HyperFire 2 Professional White Flash Camera and Reconyx HyperFire 2 Covert IR Camera, Reconyx Inc., 3828 Creekside Ln, Ste 2, Holmen, WI 54636) without bait in public greenspaces and residential properties across Washington, D.C., USA, from August to November of 2018, and April 2019 to January 2020 as part of the DC Cat Count (Herrera et al., 2021). Both infrared-flash (940 nm; $n=310$) and light-emitting diode (LED) white-flash (5500 K; $n=210$) cameras were deployed independent of each other at a height of <0.5 m, and were aimed at probable corridors of animal movement (e.g. game trails, fence lines, etc.). Technicians noted if the camera was aimed at a human trail (e.g., driveway, forested walking path, etc.) at the time of deployment. Cameras were active for a sampling period of 15 consecutive nights and captured five consecutive photographs at each trigger without a delay period between triggers. The five consecutive photographs were considered a single observation and were only considered “empty” if all five photographs did not contain an animal. Further study details are available in Herrera et al. (2021).

Photographs underwent a two-stage review process and were uploaded to eMammal (McShea et al., 2016; see also: <http://emammal.si.edu>). A subset of photographs of domestic cats (*Felis catus*) underwent additional review in which individuals were identified based on the color and pattern of their fur. Cats that could not be individually identified (e.g., solid black cats, blurry photographs, etc.) were categorized as unidentifiable. For all species, only observations that occurred between the average sunset and sunrise of the 15-night sampling period were considered. Sunset and sunrise data were obtained via NOAA (2020). Nightly detection histories for each camera site were created for seven nocturnal or crepuscular urban mammal species using CamtrapR (Niedballa et al., 2016): brown rat (*Rattus norvegicus*; $n=4228$), common raccoon (*Procyon lotor*; $n=4346$), domestic cat (*Felis catus*; $n=3127$), eastern cottontail (*Sylvilagus floridanus*; $n=318$), red fox (*Vulpes vulpes*; $n=1169$), Virginia opossum (*Didelphis virginiana*; $n=902$), and white-tailed deer (*Odocoileus virginianus*; $n=2326$).

We accounted for seasonality by categorising deployments occurring between December and February as winter deployments, March-May as spring deployments, June-August as summer deployments, and September-November as fall deployments. We created buffers around each camera based on each species’ average home range size as reported by Jones et al. (2009) using ArcMap 10.8 (ESRI, 380 New York Street, Redlands, CA 92373). Home range buffers were used in place of a standard buffer to achieve a biologically relevant measure of urbanisation based on each species’ mobility, (Magle et al., 2017; Jackson and Fahrig, 2012) and can be found in Table 1. We used the United States National Landcover Database (Wickham et al., 2014) to calculate the proportion of developed space (e.g., developed; low-high intensity) within each buffer, and categorised each camera as urban ($>50\%$ development), residential (25–50% development), or semi-natural (0–24% development) relative to each species (*sensu* UWIN, 2021).

Two competing occupancy models were used to determine the daily detection probability (p) for each species (MacKenzie et al., 2017). Both models accounted for known predictive variables of wildlife occupancy (ψ) and detection probability (p) and were identical apart from the addition of flash type on p for one model. Degree of urbanisation within the home range buffer was the only variable considered for ψ . Both models considered season and presence of a human trail on p . Models were ranked based on their AICc weights. The unmarked package (Fiske and Chandler, 2011) in R (R Core Team, 2020; RStudio, 2019) was used to develop these models.

We performed two logistic regression analyses to assess the potential influence of flash type on empty triggers (e.g., animal leaves the field of view of the camera trap detection range regardless of flash type: 30 m; infrared illumination range: 45 m; white-flash illumination range: 30 m before being photographed) and our ability to identify species in the photographs (e.g., unable to identify species due to blurry photographs). The counts of empty triggers and unknown animals from each deployment were regressed as response variables

Table 1 – Size of home range buffers based on Jones et al. (2009).

Species	Area of Home range buffer (km ²)
Brown Rat	0.0025
Eastern Cottontail	0.01
Virginia Opossum	0.51
Domestic Cat	1.52
White-tailed Deer	2.29
Red Fox	3.51
Raccoon	4.90

against flash type and compared to a null (constant) model within a generalised linear model (GLM, Poisson distribution) framework using the total number of triggers per deployment as an offset term (Knudsen, 1992). Further, we investigated the impact of flash type on our ability to identify individual animals based on their unique markings. We subsampled domestic cat observations to exclude individuals without distinguishable patterns or features (e.g., solid black cats). The remaining observations contained cats with unique patterns, making individual identification possible in each photo, provided that the photo was not blurry. A third regression analysis was performed regressing the number of observations in which individual cats could not be identified against flash type (GLM, Poisson distribution), and included the number of nocturnal cat observations at each deployment as an offset term. For all regression analyses, effects were considered strong if 95% confidence intervals of the parameter estimates excluded 0.

Results

We used data from 520 camera traps across Washington, D.C. during the summer and fall of 2018, and spring-winter of 2019. The survey resulted in 6,998 trap nights and yielded 28,084 observations of 14 nocturnal or crepuscular mammal species and 5 primarily diurnal mammal species active outside of their typical diel period. Flash-type was included in the top model for only three species: red foxes, eastern cottontails, and brown rats. The detection probability of the remaining species was better estimated when flash was not considered (Tab.2). Infrared-flash cameras yielded higher detection probabilities than did white-flash cameras for species whose top model included flash type (Fig. 1). However, the 95% confidence intervals of each flash type overlapped for both eastern cottontails ($p_{IR}=0.24\pm 0.05$ SE; $p_{flash}=0.17\pm 0.04$ SE) and red foxes

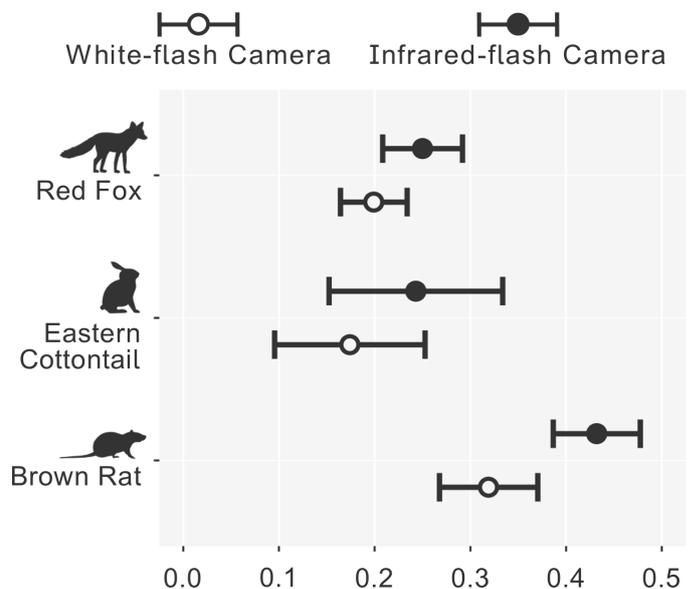


Figure 1 – Estimated detection probabilities and corresponding 95% confidence intervals for species whose top model included flash. Values are shown for the summer season not on a human path.

Table 2 – Model selection results including $\Delta AICc$ values for candidate occupancy models across all species. Model notation uses ψ to denote occupancy probability, and p to denote detection probability.

	Brown Rat	Raccoon	Domestic Cat	Eastern Cottontail	Red Fox	Virginia Opossum	White-tailed Deer
Base model: $\psi(\text{urban}), p(\text{season} + \text{human trail})$	12.88	0	0	0.14	6.38	0	0
Flash model: $\psi(\text{urban}), p(\text{season} + \text{human trail} + \text{flash})$	0	0.45	1.94	0	0	2	0.96

($p_{IR}=0.26\pm 0.02$ SE; $p_{flash}=0.20\pm 0.02$ SE). Brown rats were the only species in which 95% confidence intervals did not overlap between flash types ($p_{IR}=0.43\pm 0.03$ SE; $p_{flash}=0.32\pm 0.03$ SE). In general, detection probabilities displayed a negative relationship with urbanisation. Detection probabilities for species whose top model included flash type saw increased detection probabilities when the camera was set on a human trail, whereas human trails negatively affected the detection probabilities of species not impacted by flash type. Detection probability was generally greater in warmer seasons, however variation occurred between species. These relationships are beyond the scope of the present analyses and were not investigated further.

Infrared-flash was positively associated with instances of unknown species detections ($\beta=0.29\pm 0.10$ SE), empty triggers ($\beta=0.19\pm 0.04$ SE), and instances in which individual cat identification was not possible ($\beta=2.83\pm 0.22$ SE). Counts of empty triggers, unknown animal observations, and instances where individuals could not be identified can be found in Tab. 3.

Discussion

Before the development of infrared-flash, camera traps were only available with xenon white-flash (Rovero et al., 2013). Today, LED infrared-flash, LED white-flash, and xenon white-flash cameras are available. However, white-flash has lost popularity in recent years due to its high visibility to both humans (Glen et al., 2013; Meek and Pittet, 2012) and wildlife (Glen et al., 2013; Schipper, 2007; Wegge et al., 2004). Yet, research has found the mechanical limitations of white-flash cameras to be of greater concern than the flash’s impact on individual behaviour. Henrich et al. (2020) report that the time required for xenon white-flash cameras to recharge between flashes precluded the rapid succession of camera triggers to the extent that the authors were not able to collect adequate data from these cameras. Conversely, infrared-flash cameras only recorded 11% of Australian mammal visits captured by xenon white-flash cameras in a study by (Dixon et al., 2009). However, in the aforementioned study, a passive infrared sensor camera with infrared-flash and active infrared sensor camera with xenon white-flash were compared, and the authors noted the hesitation of individuals to cross the active infrared beam Dixon et al. (2009). Thus, it is possible

Table 3 – Counts of nighttime observations by flash type used in each regression analysis, with associated p where applicable. IR: Infrared-flash cameras; LED: LED white-flash cameras; NA: not applicable.

Analysis of empty photographs	Type of flash		p -value
	IR	LED	
n cameras deployed	310	210	NA
n total camera triggers	15412	10672	NA
n cameras with empty photographs	234	151	NA
n triggers with empty photographs	1866	1 061	<0.001
Analysis of unidentifiable species			
n cameras with unidentifiable species	110	56	NA
n observations of unidentifiable species	204	120	<0.01
Analysis of unidentifiable individuals			
n cameras reviewed for individual cats	77	21	NA
n observations of cats with unique markings	973	440	NA
n cases of unidentifiable individuals due to quality of photo	148	23	<0.001

that these results are an artifact of the cameras’ detection systems rather than flash types. In studies with comparable detection sensors, differences in detection probabilities are minor (for both xenon and LED white-flash see Taggart et al., 2019; for exclusively LED white-flash see Cove et al., 2012; for conflicting results see Cove and Jackson, 2011).

Our analyses accounted for urbanisation, season, and presence of a human trail — all of which are known to have an impact on the occupancy and detection probability of mammals (Herrera et al., 2021; Kolowski and Forrester, 2017; Cusack et al., 2015; Magle et al., 2017). We found that the addition of LED flash type on detection probability increased $\Delta AICc$ in four of the seven species examined, indicating that flash type does not significantly affect detection probabilities for these species. However, the addition of flash type on detection probability improved the model for red foxes, eastern cottontails, and brown rats. For these three species, infrared-flash cameras produced higher daily detection probabilities than did white-flash cameras. However, the 95% confidence intervals for each flash type overlapped for both cottontails and foxes, suggesting a nonsignificant difference between the two flash types. Confidence intervals did not overlap for brown rats, indicating a significant response to flash type.

While infrared-flash cameras yield slightly higher detection probabilities than LED white-flash cameras, the relatively low energy provided by the infrared-flash necessitates a longer exposure time and often produces blurry photographs of mobile animals (Glen et al., 2013; Meek and Pittet, 2012). Blurred and greyscale photographs can hinder the differentiation of sympatric species (Meek and Pittet, 2012) or identification of individuals (Rovero et al., 2013; Taggart et al., 2019). Identifying species using infrared-flash cameras is especially difficult for small-bodied (<200 g) species. Palmeirim et al. (2019) reported that 25% of observations collected in an infrared-flash camera trap survey of small mammals were unidentifiable to species or genus due to poor image quality. In contrast, white-flash cameras capitalise on their high-energy flash by using a shorter exposure time (Meek and Pittet, 2012). This leads to crisp and coloured photographs that better facilitate accurate photo review, especially among novice photo reviewers (Burns, et al., 2017). Our analyses support these claims and found that both empty photographs and detections of unidentifiable species are more likely to occur when using infrared-flash cameras. It is possible that the higher rate of empty photographs yielded by infrared-flash cameras are not a product of true absence, but rather contain an animal at the edge of the camera’s illumination range. The combination of low light at that distance and greyscale may cause the animal to be indistinguishable from the background, whereas the contrast between the animal and background is more apparent when viewed in color. Furthermore, urban environments contain few putative species pairs (e.g., red fox and grey fox [*Urocyon cinereoargenteus*]), which likely contributed to this study’s scant observations of unidentifiable species. These results could vary substantially in more diverse mammal communities (e.g., tropical forest).

Similarly, we found that individual identification of cats was greater when using white-flash cameras. Because our analyses only used photographs of cats with unique markings, this finding further speaks to the advantage of the full-color and crisp photographs produced by white-flash cameras. Studies using individual capture-recapture methods will benefit from the use of white-flash cameras, as accurate individual detection histories are more easily attained (Meek et al., 2015). However, this difference is moot for studies in which detection of species is valued over detection of individuals, provided full-colour is not necessary to differentiate sympatric species. Though our analysis is limited to

free-roaming domestic cats, we believe our findings are generalizable to other terrestrial mammal species which bear unique markings (e.g., bobcats [*Lynx rufus*] or white-tailed deer fawns [Heilbrun et al., 2003; Jacobs et al., 2021]).

Camera traps are a common method for surveying mammal communities, but they are not without their limitations (McCallum, 2013; Rovero et al., 2013). Care must be taken when designing a study to maximize survey efficiency and reliability, including careful equipment and site selection (Kays et al., 2020; Kolowski and Forrester, 2017). Our analyses suggest that while infrared-flash camera traps produce nominally higher detection probabilities than LED white-flash cameras, LED white-flash cameras better facilitate the identification of both species and individuals. Researchers should consider their study objective, environment, and species of interest before selecting a flash type. Because our study occurred in a metropolitan area, it is possible that resident wildlife are accustomed to artificial lights and may be less sensitive to these disturbances than individuals in less-developed areas. Future studies would benefit from a replication of these methods along the entire urban-rural gradient. Future studies would further benefit from a comparison of both LED white-flash and xenon white-flash cameras to see if these results are generalizable across light sources. ☞

References

- Burns P.A., Parrott M.L., Rowe K.C., Phillips B.L., 2017. Identification of threatened rodent species using infrared and white-flash camera traps. *Aust. Mammal.* 40: 188–197. doi: 10.1071/AM17016
- Cove M.V., Jackson V.L., 2011. Differences in detection probability between camera trap types for surveying bobcats in a fragmented suburban landscape. *Wild Felid Monitor* 4(2): 24.
- Cove M.V., Jones B.M., Bossert A.J., Clever D.R. Jr., Dunwoody R.K., White B.C., Jackson V.L., 2012. Use of camera traps to examine the mesopredator release hypothesis in a fragmented midwestern landscape. *Am. Midl. Nat.* 168(2): 456–465. doi:10.1674/0003-0031-168.2.456
- Cusack J.J., Dickman A.J., Rowcliffe J.M., Carbone C., Macdonald D.W., Coulson T., 2015. Random versus game trail-based camera trap placement strategy for monitoring terrestrial mammal communities. *PLoS ONE* 10(5): e0126373. doi:10.1371/journal.pone.0126373
- Dixon V., Glover H.K., Winnell J., Treloar S.M., Whisson D.A., Weston M.A., 2009. Evaluation of three remote camera systems for detecting mammals and birds. *Ecol. Manag. Restor.* 10(2): 156–157. doi:10.1016/j.1442-8903.2009.00479.x
- Fiske I., Chandler R., 2011. *unmarked*: An R package for fitting hierarchical models of wildlife occurrence and abundance. *J. Stat. Softw.* 43(10): 1–23. <http://www.jstatsoft.org/v43/i10/>
- Glen A.S., Cockburn S., Nichols M., Ekanayake J., Warburton B., 2013. Optimising camera traps for monitoring small mammals. *PLoS ONE* 8(6): e67940. doi:10.1371/journal.pone.0067940
- Heilbrun R.D., Silvy N.J., Tewes M.E., Peterson M.J., 2003. Using automatically triggered cameras to individually identify bobcats. *Wildlife Society Bulletin* 31(3): 748–755.
- Henrich M., Niederlechner S., Kröschel M., Thoma S., Dormann C.F., Hartig F., Heurich M., 2020. The influence of camera trap flash type on the behavioral reactions and trapping rates of red deer and roe deer. *Remote Sens. Ecol. Cons.* 6(3): 399–410. doi:10.1002/rse2.150
- Herrera D.J., Moore S.M., Flockhart D.T.T., McShea W.J., Cove M.V., 2021. Thinking outside the park: Recommendations for camera trapping mammal communities in the urban matrix. *J. Urban Ecol.* 7(1): e1–13. doi:10.1093/jue/juaa036
- Jackson H.B., Fahrig L., 2012. What size is a biologically relevant landscape? *Landscape Ecol.* 27: 929–941. doi:10.1007/s10980-012-9757-9
- Jacobs J.G., Lashley M.A., Cove M.V., 2021. Fawn counts and adult female site use are mismatched indicators of habitat quality in an endangered deer. *Diversity* 13: 92. doi: 10.3390/d13020092
- Jones K.E., Bielby J., Cardillo M., Fritz S.A., O'Dell J., Orme C.D.L., Safi K., Sechrest W., Boakes E.H., Carbone C., Connolly C., Cutts M.J., Foster J.K., Grenyer R., Habib M., Plaster C.A., Price S.A., Rigby E.A., Rist J., Teacher A., Bininda-Emonds O.R.P., Gittleman J.L., Mace G.M., Purvis A., 2009. PanTHERIA: a species-level database of life history, ecology, and geography of extant and recently extinct mammals. *Ecology* 90: 2648. doi:10.1890/08-1494.1
- Kays R., Arbogast B.S., Baker-Whatton M., Beirne C., Boone H.M., Bowler M., Burneo S.F., Cove M.V., Ding P., Espinosa S., Sousa Gonçalves A.L., Hansen C.P., Jansen P.A., Kolowski J.M., Knowles T.W., Moreira Lima M.G., Millsbaugh J., McShea W.J., Pacifici K., Parsons A.W., Pease B.S., Rovero F., Santos F., Schuttler S.G., Sheil D., Si X., Snider M., Spironello W.R., 2020. An empirical evaluation of camera trap study design: How many, how long and when? *Methods in Ecology and Evolution* 11(6): 700–713. doi:10.1111/2041-210X.13370
- Knudsen D.C., 1992. Generalizing poisson regression: Including apriori information using the method of offsets. *Professional Geographer* 44(2): 202–208.
- Kolowski J.M., Forrester T.D., 2017. Camera trap placement and the potential for bias due to trails and other features. *PLoS ONE* 12(10): e0186679. doi:10.1371/journal.pone.0186679
- MacKenzie D.L., Nichols J., Royle J.A., Pollock K.H., Bailey L.L., Hines J.E., 2017. *Occupancy Estimation and Modeling*, 2nd Edition. Academic Press.
- Magle S.B., Lehrer E.W., Fidino M., 2015. Urban mesopredator distribution: examining the relative effects of landscape and socioeconomic factors. *Animal Conservation* 19(2): 1–13. doi:10.1111/acv.12231
- McCallum J., 2013. Changing use of camera traps in mammalian field research: habitats, taxa, and study types. *Mammal Rev.* 43(3): 196–206. doi:10.1111/j.1365-2907.2012.00216.x
- McShea W.J., Forrester T., Costello R., He Z., Kays R., 2016. Volunteer-run cameras as distributed sensors for macrosystem mammal research. *Landscape Ecology* 31(1): 55–66. doi:10.1007/s10980-015-0262-9
- Meek P.D., Pittet A., 2012. User-based design specifications for the ultimate camera trap for wildlife research. *Wildlife Res.* 39: 649–660. doi:10.1071/WR12138
- Meek P.D., Ballard G., Fleming P.J.S., 2015. The pitfalls of wildlife camera trapping as a survey tool in Australia. *Aust. Mammal.* 37: 13–22. doi:10.1071/AM14023
- Meek P.D., Ballard G., Fleming P.J.S., Falzon G., 2016. Are we getting the full picture? Animal response to camera traps and implications for predator studies. *Ecol. Evol.* 6(10): 3216–3225. doi:10.1002/ece3.2111
- Meek P.D., Ballard G., Fleming P.J.S., Schaefer M., Williams W., Falzon G., 2014. Camera traps can be seen and heard by animals. *PLoS ONE* 9(10): e110832. doi:10.1371/journal.pone.0110832
- Muñoz D., Kapfer J., Olfenbuttel C., 2014. Do available products to mask human scent influence camera trap survey results? *Wildlife Biology* 20: 246–252. doi:10.2981/wlb.00003
- Niedballa J., Sollmann R., Courtiol A., Wilting A., 2016. *camtrapR*: An R package for efficient camera trap data management. *Methods Ecol. Evol.* 7(12): 1457–1462. doi: 10.1111/2041-210X.12600
- NOAA – National Oceanic and Atmospheric Administration, 2020. NOAA Solar Calculator. Washington (DC): NOAA Earth System Research Laboratory and Global Monitoring Laboratory. <https://www.esrl.noaa.gov/gmd/grad/solcalc/> [Accessed 1 December 2020]
- Palmeirim A.F., Benchimol M., Peres C.A., Vieira M.V., 2019. Moving forward on the sampling efficiency of neotropical small mammals: insights from pitfall and camera trapping over traditional live trapping. *Mammal Res.* 64: 445–454. doi:10.1007/s13364-019-00429-2
- R Core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available at <https://www.R-project.org/>
- RStudio Team, 2019. RStudio: Integrated development for R. RStudio, Inc., Boston, MA. Available at <http://www.rstudio.com/>
- Roberts N.J., 2011. Investigation into survey techniques of large mammals: surveyor competence and camera-trapping vs. transect sampling. *Biosci. Horizons* 4(1): 40–49. doi:10.1093/biohorizons/hzr006
- Rovero F., Zimmermann F., Berzi D., Meek P., 2013. “Which camera trap type and how many do I need?” A review of camera features and study designs for a range of wildlife research applications. *Hystrix* 24(2): 148–156. doi:10.4404/hystrix-24.2-8789
- Rovero F., Zimmermann F., 2016. Chapter 1: Introduction. In: Rovero F., Zimmermann F. (Eds.) *Camera trapping for Wildlife Research*. Pelagic Publishing, Exeter. 1–7.
- Schipper J., 2007. Camera-trap avoidance by kinkajous *Potos flavus*: Rethinking the “non-invasive” paradigm. *S. Carnivore Conserv.* 36: 38–41.
- Taggart P.L., Peacock D.E., Fancourt B.A., 2019. Camera trap flash-type does not influence the behaviour of feral cats (*Felis catus*). *Aust. Mammal.* 42(2): 220–222. doi:10.1071/AM18056
- UWIN – Urban Wildlife Information Network. 2021. UWIN Study Design Overview. Chicago: Lincoln Park Zoo. Available at <https://static1.squarespace.com/static/5c4a26d0b40b9dccb2c8012f/t/5faa9ac60774d073812b6874/1605016264649/Design+Overview.pdf>
- Wearn O.R., Glover-Kapfer P., 2017. Camera-trapping for conservation: a guide to best-practices. *WWF Conservation Technology Series* 1, 1. doi:10.13140/RG.2.2.23409.17767
- Wegge P., Pokheral C.P., Jnawali S.R., 2004. Effects of trapping effort and trap shyness on estimates of tiger abundance from camera trap studies. *Anim. Conserv.* 7(3): 251–256. doi:10.1017/S1367943004001441
- Wickham J., Homer C., Vogelmann J., McKerrow A., Mueller R., Herold N., Coulston J., 2014. The multi-resolution land characteristics (MRLC) consortium — 20 years of development and integration of USA national land cover data. *Remote Sens.* 6: 7424–7441. doi:10.3390/rs6087424