Predator Management Plan
Fiscal Year 2020 Appendix

Annual Predator Management Project Reporting From

Please fill out this form to the best of your ability. If you have questions please contact Predator Management Staff Specialist Pat Jackson at Pjackson@ndow.org or 775-688-1676. If necessary please use additional pages in your responses.

1. Fiscal Year Reporting:
2. Date Report Submitted:
3. Name of Contractor (include name of submitter if different):
4. Address of Contractor:
5. Phone Number of Contractor:
6. Email of Contractor:
7. Contract Number:
8. Dates of Contract:
9. Dates Worked:
10. Assessment of Habitat Conditions of Project Area (if applicable):
11. Briefly describe work conducted:
12. List number and species of predators removed.
13. Provide an overall assessment of project. In your opinion should the project continue?

State: Nevada
Organization: Nevada Department of Wildlife
Grant Opportunity: Black Bear Surveying
Contact: Pat Jackson – pjackson@ndow.org

TITLE: Using non-invasive techniques to estimate the abundance and occurrence of black bears (*Ursus americanus*) in Nevada

DETAILED STUDY DESIGN

Nevada's black bears occupy parts of the Sierra Nevada, Sweetwater, Pine Nut, Wassuk, and White mountain ranges on the western edge of the state near Lake Tahoe (Beckmann 2002). More specifically, black bears select conifer forests within these mountain ranges, while the sage-brush valley bottoms are readily traversable but not highly suited to the establishment of home ranges (Beckmann and Lackey 2004). In addition to these more rural areas, black bears will also use urban environments in western Nevada (Beckmann 2002). Black bears in these urban areas tend to be larger in body size, occur at higher densities, and generally have smaller home ranges than more rural black bears. These differences are attributable to the relative abundance of anthropogenic food sources near towns and cities (Beckmann 2002).

We have centered our sampling efforts on the current range of black bears. NDOW maintains a shapefile depicting this extent (http://gis.ndow.nv.gov/ndowdata/). Sampling schemes are typically devised with a resolution determined by some proportion to the overall

home range size of the target species. Within this context, there are a variety of sampling schemes that could be implemented including array sampling, stratified random sampling, clustered sampling, or temporal sequence sampling (Sun et al. 2014). Here we have implemented a consistent grid sampling approach (i.e., regular sampling) throughout the current range of black bears. We selected this approach given that; *i*) NDOW's scope of work is to develop *"(1) a statewide population estimate on black bear with statistical confidence intervals, (2) an estimate on how densities vary throughout inhabited portions of Nevada, and (3) an optimal sampling framework that may be used to develop population estimates*," 2) the most recent sampling for black bear home range size and distribution in Nevada occurred in 2002, and 3) this effort identified highly variable home range sizes. For instance, the home range size for black bears inhabiting more rural areas was estimated to be 172.8 - 519.6 km^2 for female and male bears respectively (Beckmann 2002). The home range sizes were smaller and much more consistent in the urban areas. These ranged from 52.9 - 55.2 km^2 (Beckmann 2002).

As NDOW is interested in the application of passive survey techniques for population and distribution estimation of black bears, sampling across the range of the species distribution in the state is necessary. Thus, a grid sampling approach provides the most reliable means to precisely measure the abundance and distribution of black bears in the state. This approach is consistent with a growing appreciation among researchers and wildlife managers that unbiased sampling designs are more appropriate measures for depicting animal occurrence (Tobler and Powell 2013; Swanson et al. 2015). With a grid sampling scheme selected, the next decision was the resolution that most appropriate to assess the research objectives.

The spacing of sampling efforts is fundamental to the quantification of accurate population and distribution estimates (Sun et al. 2014). If traps are too far apart, animals of interest may only be detected at a single trap and the resultant models will not converge. If the traps do not span an adequate amount of the state space, then all animals across that range will not have a non-zero probability of detection, and density will be under estimated (Sollmann et al. 2012). Further, trap placement that is too close together can be cost-prohibitive when

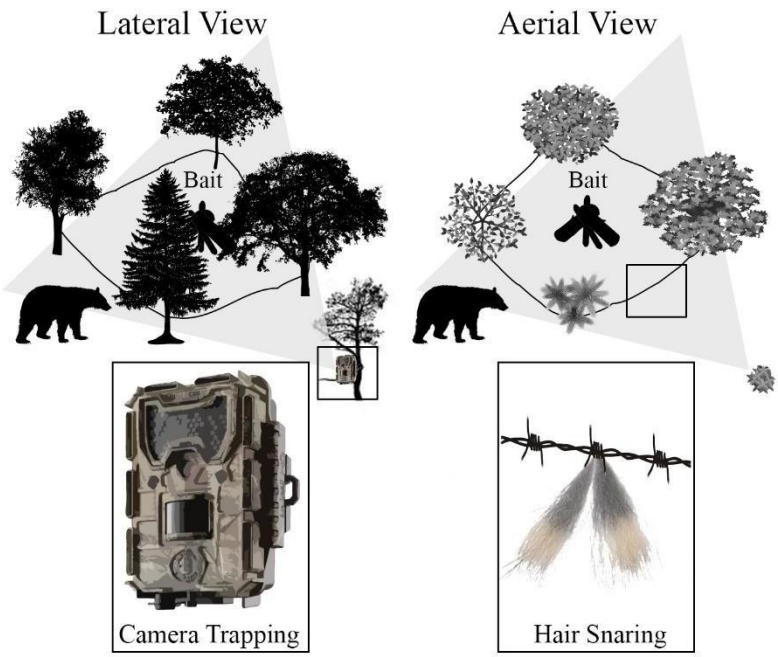
implemented across a species population range. There were several factors that we considered herein;

1) Resolutions for hair snaring and camera trapping of black bears in the published literature vary from 2.6 km^2 to 157.1 km^2 (see Kelly and Holub 2008; Gardner et al. 2010; Wilton et al. 2014).

2) Resolution should be, at a minimum, the size of one animal's home range (Tobler and Powell 2013) and a resolution of two traps per home range is advised (Dillon and Kelly 2007).

3) Given this evidence and the fact that home ranges for black bears in Nevada vary from 52.9 and 519.6 km^2 (Beckmann 2002), we selected a resolution of 49 km^2 or 1- 10 traps per Nevada black bear home range. The other advantage of this resolution is that it was effectively applied in another published study for black bear density (Stetz et al. 2013).

Data Collection System Our data collection system includes; 1) DNA mark-recapture estimation using SCR techniques from hair snaring of black bears and 2) density estimation and probability of occurrence mapping from concurrent camera trapping (Fig. 1). At each site we have deployed barbed wire hair snares and Bushnell Trophy Cam HD Aggressor – No Glow, Model 119776C camera-traps (Lepard et al. in review; Fig. 1). These passive, non-invasive technologies enable us to pursue our research objectives in this study.



Evaluating Objective 1 - Abundance Estimation via SCR and Hair Snaring We are in the process of collecting black bear hair samples using barbed wire snares (Woods et al. 1999; Wilton et al. 2014, 2016).

These snares consist of 16-gauge barbed wire oriented 50 cm above ground and wrapped around nearby trees forming a perimeter around the site (Fig. 1; Stetz et al. 2013). In the center of each site we are depositing an attractant including raspberry oil (Mother Murphy's Laboratories, Inc., Greensboro, NC), fish oil, anise oil (Minnesota Snareline Products, Pennock, MN), and Ultimate Bear Lure (Wildlife Research Center, Ramsey, MN; see Wilton et al. 2014). Hair snares are being checked weekly. This time period coincides with the summer season when bears are losing hair on their coats. During each visit, we check the length of the barbed wire for hair and package each individual hair sample into coin envelopes using gloved hands. The samples are then be air dried and prepared for processing.

Via genetic sequencing analysis, each bear in our study will be marked and potentially recaptured at later time periods. We will then implement SCR techniques to develop the population estimate (Efford and Fewster 2013; Royle et al. 2014). The SCR model uses the spatial correlation of recaptures of bears over a sampling grid to estimate the location of individual centers of activity of both marked and unmarked animal subjects. This approach models the spatial correlation in animal detections as a natural process (Royle et al. 2014). Within this modeling framework, the capture histories (i.e., number of times each bear was detected) are assumed to derive from a Poisson distribution;

$$y_{ijk} \sim Poisson(\lambda_{ij})$$

where y_{ijk} is the number of detections for animal *i*, at trap *j* in occasion *k* while λ_{ij} is the probability of detecting animal *i* at location *j*. The spatial pattern of detections from an individual animal is used to estimate the parameters of the chosen detection model, including the unobserved location of the animal's activity center and the scale parameter (Royle et al. 2014P. 128). The detection model quantifies an intuitive concept; that an individual is more likely to be detected at traps closer to the center of that individual's core activity. This part of the model takes the form;

$$\lambda_{ij} = \lambda_0 e^{\frac{\|\boldsymbol{x}_j - \boldsymbol{s}_i\|^2}{2\sigma^2}}$$

where λ_{ij} is the probability animal *i* is detected at trap *j*, λ_0 is the probability an animal is detected at a trap given that it occupied that area, σ is the scale parameter (i.e., how detection probability decreases with distance), x_j is the location of trap *j*, $\boldsymbol{s}_i$ is the unobserved location of the activity center of animal *i*, and $\|\boldsymbol{x}_j - \boldsymbol{s}_i\|$ is the Euclidean distance between trap *j* and unobserved activity center location *i*. The output of this technique will be an estimate, with associated confidence intervals, of the number of black bears in Nevada. Furthermore, this estimate divided by the effort across the sampling area will provide an estimate of the density (#Bears / km^2; Fig. 2).

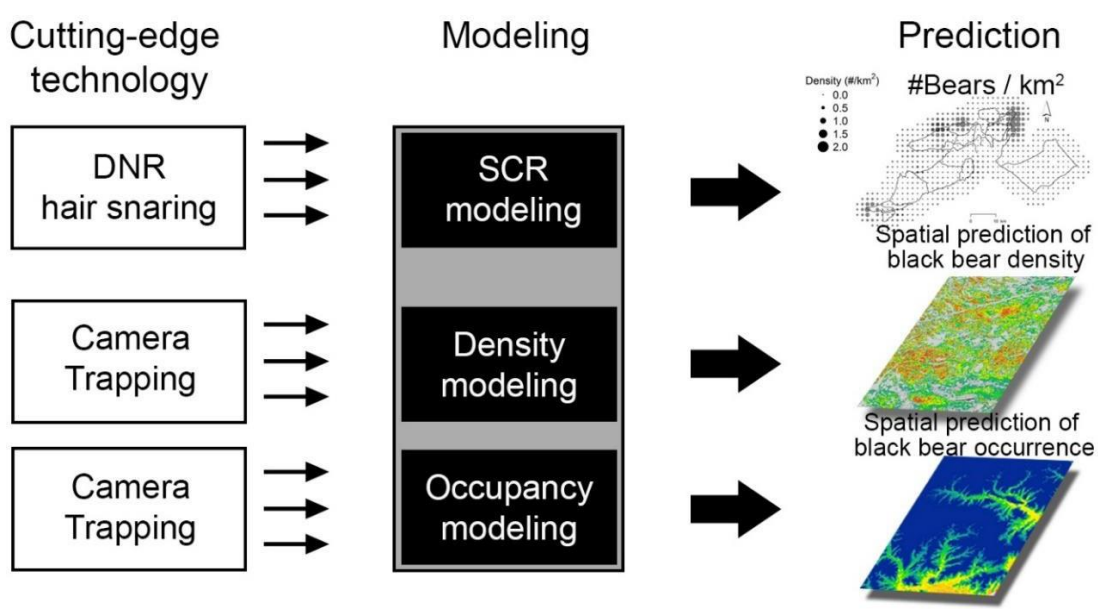


Fig. 2. The passive non-invasive technology and the modeling techniques that will be used to predict black bear abundance, density, and occurrence in the state of Nevada.

While SCR modeling is a robust technique for developing a population estimate of the number of bears with an associated confidence interval, mapping the spatial variation in density is most suited to occupancy mapping where habitat and multi-species effects can be readily incorporated (Kelly and Holub 2008; Royle et al. 2009; Tobler and Powell 2013; Swanson et al. 2015). The spatial variation in black bear density and occurrence is particularly useful information for understanding how increasing black bear abundance may lead to conflict with human communities (Lackey et al. 2004). Given NDOW's stated desire to identify "*an optimal sampling framework that may be used to develop population estimates*" we have elected to also consider the role that camera trapping may play in examining spatial variable in black bear density/occurrence and how these variation may correlate with human activity in Nevada. Camera trapping is a flexible tool which can produce maps depicting spatial variation in black bear density and occurrence (Kays and Slauson 2008; Kelly and Holub 2008; Gardner et al. 2010). These predictive maps can be developed by season and can be compared with known patterns of human activity to identify where conflict hotspots may occur even before conflict incidences are reported. Thus, camera trapping provides a useful framework for the optimization of future research efforts and the prioritization of potential mitigation work conducted by NDOW.

Evaluating Objective 2 - Density Estimation and Probability of Occurrence Mapping from Camera Trapping While mark-recapture studies are a traditional means to derive abundance estimates of wildlife, emerging techniques, such as camera trapping, demonstrate that density estimates can be calculated from unmarked individuals (Chandler et al. 2013; Denes et al.

2015; Chauvenet et al. 2017). Thus, in addition to the hair snaring, we are also mapping black bear density (Royle et al. 2009) and the probability of black bear occurrence (Kelly and Holub 2008) from camera trap data. At each site we have deployed a Bushnell Trophy Cam camera trap. As with the barbed wire, we have positioned each camera 50 cm above the ground. However, in this case, the camera is affixed to a tree outside of the hair snare site (Fig. 1). The camera traps are positioned in a northerly direction directed across the viewshed of the hair snare (Fig. 1). The northerly direction is a proven technique to decrease false triggers caused by sunrise and sunset (Kays and Slauson 2008; Newey et al. 2015). We have programmed these camera traps to take three images per trigger via these settings (LED control = high, time interval = 10 seconds, sensor level = auto, and night vision shutter = high; Lepard et al. in review). Furthermore, we have set a time interval between triggers of 5 minutes. Our previous research has shown that this time interval does not compromise detections of conspicuous species, such as black bears, but can drastically extend battery life and memory (Lepard et al. in review). We chose these settings (LED, sensor, and shutter) following a series of pilot deployments that suggested these settings simultaneously maximized the sensitivity of camera-trap detection and the clarity of wildlife photographed.

The camera trapping effort will be able to provide robust density estimates and predict the probability of black bear occurrence across seasons. This is important, given that black bear conflict with humans has been shown to exhibit seasonal variability (Baruch-Mordo et al. 2014; Obbard et al. 2014). All data will be processed (i.e., animals on the images identified) by undergraduate student employees in the PI's laboratory at Michigan State University.

Density Estimation - Encounter histories from camera traps will be analyzed using a spatial capture modeling for unmarked populations (Royle et al. 2014 p. 473). Note: we will also consider time-to-event (TTE) approaches to estimate abundance via the interpretation of unmarked animal trapping rates (see Moeller 2017). From trapping rate and encounter data (i.e, interpretation of camera trap photographs) black bears will not be individually identifiable, as they are in our hair snare encounter models. The hair snare encounter data consist of counts (y_{ijk}) of detection for specific animals (i) at a particular trap (j) on a given occasion (k). The

camera encounter histories will simply be the total number of detections (n_{jk}) at a particular trap (j) on a given occasion (k). The observed encounter histories from the camera (n_{jk}) can be thought of as the sum of unobserved individual encounter histories ($\acute{y}_{ijk}$) over all detected animals, such that $n_{jk} = \sum_i \acute{y}_{ijk}$. The number of detections (n_{jk}) are then assumed to be Poisson distributed with probability Λ_j such that

$$n_{jk} \sim Poisson(\Lambda_j)$$

where ,

$$\Lambda_j = \lambda_0 \sum_i e^{\left(\frac{\|\boldsymbol{x}_j - \boldsymbol{s}_i\|^2}{2\sigma^2}\right)}$$

λ_0 is the rate at which an animal is detected at a trap given the animal encountered the trap,
$\boldsymbol{x}_j$ is the location of trap *j*,
$\boldsymbol{s}_i$ is the unobserved location of the center of activity for animal *i*,
σ is the scale parameter, relating how detection probability decreases with distance and
$\|\boldsymbol{x}_j - \boldsymbol{s}_i\|$ is the Euclidean distance between trap *j* and unobserved activity center location *i*.

Additionally, the same assumptions of the marked model are made in the unmarked model with respect to the chosen distance function and spatial distribution (see equations from previous section). Given that camera detections will be unable to distinguish between male and female bears, this model will require the additional assumption that male and female bears have equal baseline encounter rates (λ_0) and equivalent scale parameters (σ). The density estimates from the camera data will undoubtedly be less precise given the reduced amount of information (Royle et al. 2014 p. 486). Though the hair snare data and camera data will not be independent, we feel there is value in comparing these two estimates of black bear density to determine the best technique for NDOW to use to map black bear density in future.

Occupancy Estimation - To estimate detection and occupancy (hereafter synonymous with *p* and *ψ*, respectively), we will use a hierarchical Bayesian framework to fit occupancy models to detection/non-detection histories of black bears. Here, *p* refers to the probability of detecting black bears at a site during a single survey replicate (i.e., one week), given that it is occupied by that species (Mackenzie et al. 2002), and *ψ* refers to the probability that the site was used by the species during the study (Kendall and White 2009). We will bin black bear detections into one-week survey replicates using the camtrapR package (Niedballa et al. 2016). We will select one-week intervals to reflect common practice among mammalian camera-trap studies (e.g., Kilshaw et al. 2015; Moll et al. 2016) and to help ensure our models meet the closure assumption of single-season occupancy models (Kendall and White 2009).

We will include a random intercept by site to account for potential spatial autocorrelation among model residuals (Rhodes et al. 2009; Moll et al. 2016). This model will take the form:

$$\text{logit}(\psi_i) = \alpha_r + \alpha_1 * \text{habitat}_i \ldots + \alpha_2 * \text{habitat}_n,$$

where ψ_i is the occupancy probability at the *i*th camera-trap site, the intercept *α* is a normally distributed random variable whose mean and variance are hyperparameters, and a series of habitat covariates that describe each of the *i*th sites. Habitat covariates will be developed as part of a Geographic Information System (GIS) that we will develop to describe the study area. This GIS database will be built using data housed in the NDOW and Nevada state geospatial libraries.

Finally, we will develop a predictive black bear occupancy map for each season by multiplying the vector of coefficients from the occupancy model (detailed above), composed of the posterior mean of the random intercept (*μ*) and model-averaged posterior means of habitat

coefficients, with values of rasters for each habitat covariate across the full extent of the black bear range in Nevada. To develop these predictions, we will use the inverse logit function (i.e., exp(**α**)/(exp(**α**) +1)) to back-transform the response variable such that it was scaled from 0 to 1 (i.e., estimated probability of occupancy, ψ) on our predictive maps.

Model Prediction, Evaluation, and Assessment In all cases, models will be implemented using appropriate software (STAN, BUGS, glmmADMB, see, e.g., Fournier et al. 2012; Skaug et al. 2015; Hooten and Hobbs 2015), or depending on the computational complexity (e.g., if spatio-temporal residual dependence structures are necessary to meet model assumptions) we will write our own software. We will conduct extensive exploratory data analysis (EDA) using R (R Core Team 2016) and thoroughly assess key model assumptions (test for multicollinearity among the predictor variables excluding those with high correlations or use a variable selection model, e.g., Bayesian lasso), assess the appropriateness of the posited error sub-models, and diagnose and treat issues e.g., via spatio-temporal random effects, departures from independent and identically distributed residuals.

The analytical frameworks will include an integrated approach for assessing model performance and comparing different models using replicated datasets. A replicated dataset refers to the dataset that the model would have predicted using the value of the model parameters estimated from the observations. Here, each replicated data point can be regarded as the "model-predicted" value for the corresponding observation. The posterior distribution for the replicated observation is precisely the posterior predictive distribution (e.g., Gelman et al. 2013; see also Banerjee et al. 2014, for spatial models specifically) but evaluated at the observed space-time coordinates. Given field observations, we will confirm if a posited model sufficiently explains data variability (i.e., whether the model is consistent with the data). This is called model adequacy and is assessed by how well the replicated data emulates the observed data. More precisely, we will use some omnibus test measure and compute a Bayesian p-value (see e.g., Gelman et al. 2013).

We will also implement statistical sensitivity analysis for the models. This is relevant because we must acknowledge the possibility of more than one reasonable model to provide an adequate fit to the dataset under investigation. In some cases, we anticipate enhancing and extending a model to address specific aspects of the data, e.g., spatial and/or temporal autocorrelation of depredation. There, we want to assess how much the posterior inferences change when other probability models are used in place of the present model. Finally, model selection techniques will be used to assess the impact of predictor variable and model choice among a set of competing models (e.g., Hooten and Hobbs 2015).

All data, code, results, and predictions will be provided to NDOW. The objective is to use the information derived from this study to optimize future efforts to map the population density and occurrence of Nevada black bears using non-invasive techniques that are robust.

PROJECT INVESTIGATORS

Dr. Montgomery (PI) is a professor of carnivore ecology in the Department of Fisheries and Wildlife at Michigan State University (MSU) the first Land Grant University (see attached Biographical Sketch below for more information). At MSU, he is the Director of the Research on the Ecology of Carnivores and their Prey (RECaP) Laboratory. The research conducted in the RECaP Laboratory is both spatially and taxonomically diverse. However, it consistently involves the application and development of techniques to map the abundance, distribution, and occurrence of large carnivores.

Dr. Millspaugh (PI) is the Boone and Crockett Professor of Wildlife Conservation at the University of Montana (see attached Biographical Sketch below for more information). His

research addresses animal space use, habitat interactions, and population dynamics. Dr. Millspaugh has worked throughout the Midwest and Western states on a diversity of species and systems with a common theme of collaborative research that is applied and intended to address relevant questions to wildlife managers.

REFERENCES

Baruch-Mordo, S., Wilson, K.R., Lewis, D.L., Broderick, J., Mao, J.S. and Breck, S.W., 2014. Stochasticity in natural forage production affects use of urban areas by black bears: implications to management of human-bear conflicts. PloS one, 9(1), p.e85122.

Beckmann, J.P. and Berger, J., 2003a. Rapid ecological and behavioural changes in carnivores: the responses of black bears (Ursus americanus) to altered food. Journal of Zoology, 261(2), pp.207-212.

Beckmann, J.P. and Berger, J., 2003b. Using black bears to test ideal-free distribution models experimentally. Journal of Mammalogy, 84(2), pp.594-606.

Beckmann, J.P., 2002. Changing Dynamics of a Population of Black Bears (Ursus americanus): Causes and Consequences. University of Nevada, Reno, Reno Nevada.

Beckmann, J.P., and Lackey, C., 2004. Are desert basins effective barriers to movements of relocated black bears (Ursis Americanus)? Western North American Naturalist 64:269-272.

California Department of Fish and Game. 2011. Bear hunting: draft environmental document. California Department of Fish and Game. Sacramento, CA, USA.

Chandler, R.B. and Royle, J.A., 2013. Spatially explicit models for inference about density in unmarked or partially marked populations. The Annals of Applied Statistics, 7(2), pp.936-954.

Chauvenet, A.L., Gill, R.M., Smith, G.C., Ward, A.I. and Massei, G., 2017. Quantifying the bias in density estimated from distance sampling and camera trapping of unmarked individuals. Ecological Modelling, 350, pp.79-86.

Denes, F.V., Silveira, L.F. and Beissinger, S.R., 2015. Estimating abundance of unmarked animal populations: accounting for imperfect detection and other sources of zero inflation. Methods in Ecology and Evolution, 6(5), pp.543-556.

Don Carlos, A.W., Bright, A.D., Teel, T.L. and Vaske, J.J., 2009. Human–black bear conflict in urban areas: an integrated approach to management response. Human Dimensions of Wildlife, 14(3), pp.174-184.

Efford, M. G., and Fewster. R.M., 2013. Estimating population size by spatially explicit capture–recapture. Oikos 122:918-928.

Gardner, B., Reppucci, J., Lucherini, M. and Royle, J.A., 2010. Spatially explicit inference for open populations: estimating demographic parameters from camera-trap studies. Ecology, 91(11), pp.3376-3383.

Garshelis, D.L., 1990. Monitoring effects of harvest on black bear populations in North America: a review and evaluation of techniques. In Proceedings of the Eastern Workshop on Black Bear Research and Management (Vol. 10, pp. 120-144).

Goodrich, J.M., 1990. Ecology, conservation and management of two western Great Basin black bear populations. M.S. Thesis. University of Nevada, Reno.

Goodrich, J.M., 1993. *Nevada Black Bears: Their Ecology, Management, and Conservation*. Nevada Department of Wildlife.

Gore, M.L., Siemer, W.F., Shanahan, J.E., Schuefele, D. and Decker, D.J., 2005. Effects on risk perception of media coverage of a black bear-related human fatality. Wildlife Society Bulletin, 33(2), pp.507-516.

Jonkel, C.J., Cowen, I. 1971. The black bear in the spruce-fir forest. Wildlife monographs, (27), pp.3-57.

Kays, R. W., and Slauson. K. M., 2008. Remote Cameras. Pages 110–140 in R. A. Long, P. MacKay, and J. Ray, editors. Noninvasive Survey Methods for Carnivores. Island Press, Washington, US.

Kelly, M.J. and Holub, E.L., 2008. Camera trapping of carnivores: trap success among camera types and across species, and habitat selection by species, on Salt Pond Mountain, Giles County, Virginia. Northeastern Naturalist, 15(2), pp.249-262.

Kendall, W.L. and White, G.C., 2009. A cautionary note on substituting spatial subunits for repeated temporal sampling in studies of site occupancy. Journal of Applied Ecology, 46(6), pp.1182-1188.

Kilshaw, K., Montgomery, R.A., Campbell, R.D., Hetherington, D.A., Johnson, P.J., Kitchener, A.C., Macdonald, D.W. and Millspaugh, J.J., 2016. Mapping the spatial configuration of hybridization risk for an endangered population of the European wildcat (Felis silvestris silvestris) in Scotland. Mammal Research, 61(1), pp.1-11.

Lackey, C., 2004. Nevada's black bear: Ecology and conservation of a charismatic omnivore. Biological Bulletin No. 15. Nevada Department of Wildlife.

Lackey, C., 2010. Managing bear-human conflicts: A procedural manual for personnel of the Nevada Department of Wildlife. Nevada Department of Wildlife.

Lackey, C.W., Beckmann, J.P. and Sedinger, J., 2013. Bear historical ranges revisited: Documenting the increase of a once-extirpated population in Nevada. The Journal of Wildlife Management, 77(4), pp.812-820.

Lepard, C., Moll, R.J., Cepek, J.D., Dennis, P.M., Robison, T., and Montgomery, R.A., Examining the effect of camera-trap settings on data storage, wildlife detection, and ecological models. Remote Sensing. In review.

MacKenzie, D.I., Nichols, J.D., Lachman, G.B., Droege, S., Andrew Royle, J. and Langtimm, C.A., 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology, 83(8), pp.2248-2255.

Mazur, R.L., 2010. Does aversive conditioning reduce human–black bear conflict?. Journal of Wildlife Management, 74(1), pp.48-54.

Miller, S.M., Miller, S.D. and McCollum, D.W., 1998. Attitudes toward and relative value of Alaskan brown and black bears to resident voters, resident hunters, and nonresident hunters. Ursus, pp.357-376.

Moeller, Anna K., 2017. New methods to estimate abundance from unmarked populations using remote camera trap data. Master of Science Degree, University of Montana.

Moll, R.J., Kilshaw, K., Montgomery, R.A., Abade, L., Campbell, R.D., Harrington, L.A., Millspaugh, J.J., Birks, J.D.S. and Macdonald, D.W., 2016. Clarifying habitat niche width using broad-scale, hierarchical occupancy models: a case study with a recovering mesocarnivore. Journal of Zoology, 300(3), pp.177-185.

Morin, D.J., Fuller, A.K., Royle, J.A. and Sutherland, C., 2017. Model-based estimators of density and connectivity to inform conservation of spatially structured populations. Ecosphere, 8(1).

Nevada Hunting Guide 2016. Nevada Department of Wildlife.

Newey, S., Davidson, P., Nazir, S., Fairhurst, G., Verdicchio, F., Irvine, R.J., and van der Wal, R., 2015. Limitations of recreational camera traps for wildlife management and conservation research: A practitioner’s perspective. Ambio 44:624–635.

Niedballa, J., Sollmann, R., Courtiol, A. and Wilting, A., 2016. camtrapR: an R package for efficient camera trap data management. Methods in Ecology and Evolution, 7(12), pp.1457-1462.

Obbard, M.E., Howe, E.J., Wall, L.L., Allison, B., Black, R., Davis, P., Dix-Gibson, L., Gatt, M. and Hall, M.N., 2014. Relationships among food availability, harvest, and human–bear conflict at landscape scales in Ontario, Canada. Ursus, 25(2), pp.98-110.

Powell, R.A., Zimmerman, J.W., Seaman, D.E. and Gilliam, J.F., 1996. Demographic analyses of a hunted black bear population with access to a refuge. Conservation Biology, 10(1), pp.224-234.

Rhodes, J.R., McAlpine, C.A., Zuur, A.F., Smith, G.M. and Ieno, E.N., 2009. GLMM applied on the spatial distribution of koalas in a fragmented landscape. In Mixed effects models and extensions in ecology with R (pp. 469-492). Springer New York.

Royle, J. A., Chandler, R.B., Sollmann, R. and Gardner, B., 2014. Spatial capture-recapture. Elsevier, Waltham, MA, USA.

Royle, J.A., Nichols, J.D., Karanth, K.U. and Gopalaswamy, A.M., 2009. A hierarchical model for estimating density in camera-trap studies. Journal of Applied Ecology, 46(1), pp.118- 127.

Siemer, W.F., Decker, D.J. and Shanahan, J., 2007. Media frames for black bear management stories during issue emergence in New York. Human Dimensions of Wildlife, 12(2), pp.89-100.

Sollmann, R., B. Gardner, and J. L. Belant., 2012. How Does Spatial Study Design Influence Density Estimates from Spatial Capture-Recapture Models? PLoS ONE 7:e34575.

Spencer, R.D., Beausoleil, R.A. and Martorello, D.A., 2007. How agencies respond to human– black bear conflicts: a survey of wildlife agencies in North America. Ursus, 18(2), pp.217- 229.

Stetz, J.B., Kendall, K.C. and Macleod, A.C., 2014. Black bear density in Glacier National Park, Montana. Wildlife Society Bulletin, 38(1), pp.60-70.

Stowell, L. R., and R. C. Willging. 1992. Bear damage to agriculture in Wisconsin. Proceedings of the Eastern Wildlife Damage Control Conference 5:96-104.

Sun, C.C., Fuller, A.K. and Royle, J.A., 2014. Trap configuration and spacing influences parameter estimates in spatial capture-recapture models. PloS one, 9(2), p.e88025.

Swanson, A., Kosmala, M., Lintott, C., Simpson, R., Smith, A. and Packer, C., 2015. Snapshot Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an African savanna. Scientific data, 2.

Tobler, M.W. and Powell, G.V., 2013. Estimating jaguar densities with camera traps: problems with current designs and recommendations for future studies. Biological conservation, 159, pp.109-118.

Wilton, C.M., Beringer, J., Puckett, E.E., Eggert, L.S. and Belant, J.L., 2015. Spatiotemporal factors affecting detection of black bears during noninvasive capture–recapture surveys. Journal of Mammalogy, 97(1), pp.266-273.

Wilton, C.M., Puckett, E.E., Beringer, J., Gardner, B., Eggert, L.S. and Belant, J.L., 2014. Trap array configuration influences estimates and precision of black bear density and abundance. PloS one, 9(10), p.e111257.

Woods, J.G., Paetkau, D., Lewis, D., McLellan, B.N., Proctor, M. and Strobeck, C., 1999. Genetic tagging of free-ranging black and brown bears. Wildlife Society Bulletin, pp.616- 627.

Zielinski, W.J., Truex, R.L., Schlexer, F.V., Campbell, L.A. and Carroll, C., 2005. Historical and contemporary distributions of carnivores in forests of the Sierra Nevada, California, USA. Journal of Biogeography, 32(8), pp.1385-1407.