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; 1) 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 underestimated (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;

\[ y_{ijk} \sim \text{Poisson}(\lambda_{ij}) \]

where \( y_{ijk} \) is the number of detections for animal \( i \), at trap \( j \) in occasion \( k \) while \( \lambda_{ij} \) 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;

\[ \lambda_{ij} = \lambda_0 e^{\frac{||x_j - s_i||^2}{2\sigma^2}} \]

where \( \lambda_{ij} \) is the probability animal \( i \) is detected at trap \( j \), \( \lambda_0 \) is the probability an animal is detected at a trap given that it occupied that area, \( \sigma \) is the scale parameter (i.e., how detection probability decreases with distance), \( x_j \) is the location of trap \( j \), \( s_i \) is the unobserved location of the activity center of animal \( i \), and \( ||x_j - s_i|| \) 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.](image)
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 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 \( y_{ijk} \) over all detected animals, such that \( n_{jk} = \sum y_{ijk} \). The number of detections \( n_{jk} \) are then assumed to be Poisson distributed with probability \( \Lambda_j \) such that

\[
 n_{jk} \sim \text{Poisson}(\Lambda_j)
\]

where,

\[
\Lambda_j = \lambda_0 \sum_i e^{-2\sigma^2 \| x_j - s_i \|^2}
\]

\( \lambda_0 \) is the rate at which an animal is detected at a trap given the animal encountered the trap, \( x_j \) is the location of trap \( j \), \( s_i \) is the unobserved location of the center of activity for animal \( i \), \( \sigma \) is the scale parameter, relating how detection probability decreases with distance and \( \| x_j - s_i \| \) 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 \( \lambda_0 \) and equivalent scale parameters \( \sigma \). 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 \( \psi \), 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 \( \psi \) 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 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:

\[
\text{logit}(\psi_i) = \alpha + \alpha_1 \text{habitat}_1 + \cdots + \alpha_n \text{habitat}_n,
\]

where \( \psi_i \) is the occupancy probability at the \( i \)th camera-trap site, the intercept \( \alpha \) 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 (\( \mu \)) 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., \( \exp(\alpha)/(\exp(\alpha) + 1) \)) to back-transform the response variable such that it was scaled from 0 to 1 (i.e., estimated probability of occupancy, \( \psi \)) 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
California Department of Fish and Game. 2011. Bear hunting: draft environmental document. California Department of Fish and Game. Sacramento, CA, USA.
Nevada Department of Wildlife.


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


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).


