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METHODS FOR ESTIMATING MOUNTAIN GOAT OCCUPANCY AND ABUNDANCE

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METHODS FOR ESTIMATING MOUNTAIN GOAT

OCCUPANCY AND ABUNDANCE

By

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ABSTRACT

Abundance and occupancy are two parameters of central interest to the field of ecology. Furthermore, accurate (both precise and unbiased) estimates are key pieces to the puzzle of effective wildlife management decision-making. While there exist a variety of sampling techniques and statistical models for effectively estimating population parameters for frequently encountered and large mammals, methods for sampling unmarked and rare species are few and far between. The first step to acquiring usable parameter estimates is through the use of sampling theory and incorporation of probabilistic sampling designs to collect count-data and occurrence-data. Often, it is assumed that probabilistic sampling designs will be ineffective in surveying for rare species due to insufficient encounters with the species of interest. However, many of these probabilistic-sampling methods remain untested, both with respect to modern statistical models and in the context of low-density species. The consequences of not incorporating probability-based sampling designs and not meeting field sampling assumptions are not well understood in the field of ecology and can thus provide uncertainty when making management decisions. In this paper, we test disparate field methods and statistical models that apply a complete random sampling design for estimating unbiased occupancy and abundance of mountain goats (*Oreamnos americanus*) – a low-density and difficult-to-study species. In doing so, we developed a novel data analysis approach that directly solves the problem of approximating the closure assumption in addition to successfully producing a method and modelling technique that yields unbiased estimates of mountain goat abundance.

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INTRODUCTION

Ecologists and policymakers need to have a good understanding of the distribution and abundance of the species they study for effective conservation management (Nichols and Williams 2006). Because populations vary through space and time, they require regular and effective monitoring. Recent advances in both the design of monitoring programs and statistical methods have allowed for improved accuracy in estimates of important population parameters (*e.g.,* abundance, occupancy, mortality). However, adoption of some these methods has been slow and inconsistent. In the field of ecology and conservation, we find that this is especially the case with rare and low-density species despite the fact that these species are often most important to monitor given they are of high conservation concern. The lack of effective monitoring techniques for rare species may be due to challenges inherent to the dynamics of low-density species – for example, rare species often occur in complex terrain, making the regular implementation of robust monitoring programs difficult and incredibly resource-intensive. However, rare and low-density species are at the greatest risk of rapid declines due to inappropriate management adaptions and delayed conservation action (Martin et al. 2008). Because of this risk, it is imperative that ecologists and managers work together to obtain accurate estimates of critical population parameters for rare and low-density species populations (Yoccoz et al. 2001).

Convenience sampling and haphazard data collection practices are widespread in ecology and wildlife biology despite a large body of work showing that population estimates derived from these data are biased and uninformative (see Anderson 2001, White 2001). However, ecologists continue to use data collected in this manner to make important management decisions. Fortunately, a number of probability-based sampling schemes that address these problems can be easily incorporated into wildlife field surveys. Probability-based sampling adds a level of randomness to the data collection process and makes data interpretable to the statistical models used in analyses. By incorporating probabilistic sampling designs to the collection of field data, ecologists can effectively estimate unbiased parameters for the population of interest as a whole. However, many of these methods remain untested, both with respect to modern statistical models and in the context of low-density species. In this thesis, we evaluate multiple field methods and statistical models that apply a complete random sampling design to estimate occupancy (distribution) and abundance in an isolated mountain goat (*Oreamnos americanus*) population. Specifically, we test two ground-based and non-invasive survey methods: remotely triggered camera traps and multiple-observer ground surveys.

Furthermore, many wildlife studies fail to fully meet all field sampling and statistical model assumptions. A particularly difficult assumption to meet for large mammal studies is the assumption of geographic closure. The closure assumption is most often approximated as it can be difficult to align sampling unit size and survey period length with wildlife movement (Otto et al. 2013, Rota et al. 2009). Violating closure assumption can result in overestimating population sizes, which can have negative implications for management decisions.

The Rocky Mountain goat is a high alpine-dwelling ungulate that is sparsely distributed throughout the northern Rocky Mountains. Because they occur at low densities and occupy remote habitat, mountain goats are difficult to monitor using traditional survey techniques (mark-recapture methods, line-transect aerial surveys, etc.). While some populations remain stable enough for seasonal harvest, others have shown unexplained population declines (Festa-Bianchet and Cote 2008). Additionally, introduced mountain goat populations have some ecologists concerned about competition with native bighorn sheep. Despite these concerns, irregular population monitoring has resulted in our ignorance of mountain goat population trends across the species' range. The lack of regular mountain goat population monitoring may be a result of the presumed inability to obtain effective mountain goat abundance and occupancy estimates. Here, we focus on overcoming these difficulties using a mountain goat population in the Palisades Mountains in eastern Idaho as a model system. Using statistically rigorous sampling techniques, we test several disparate survey methods in a random sampling framework to build a reliable tool for estimating abundance and occupancy for low-density species. In so doing, we develop a novel analytical approach that solves critical and common model assumption violations, in addition to successfully producing unbiased estimates of mountain goat abundance.

Chapter 1

A Novel Approach to Meeting Closure Assumptions in Estimating Mountain Goat Abundance

INTRODUCTION

Abundance estimation of organisms is of central interest to the field of ecology (Ehrlich and Roughgarden 1987). With the use of effective sampling techniques and appropriate model applications to population count data, ecologists can accurately estimate abundance and track population trends over time (Mackenzie et al. 2005). Across the field of large mammal research, most efforts surrounding population estimation have focused on heavily harvested and common species, such as deer (*Odocoileus* spp.) and elk (*Cervus canadensis*). As a result, population monitoring tools for low-density species remain few and far between (Thompson 2004). Due to inherent qualities of rare and elusive species, obtaining unbiased parameter estimates for these species can be difficult. Furthermore, while accurate estimates of abundance are difficult to procure, they are also imperative to making informed decisions regarding a given species conservation status (White 2001, Yoccoz et al. 2001).

Rocky Mountain Goats (*Oreamnos americanus*) are high alpine-dwelling ungulates that occur in low densities throughout the steep and rocky habitat of the northern Rocky Mountains (Festa-Bianchet and Cote 2008). Because they are found at relatively low densities, exhibit grouping behavior and occupy difficult-to-access terrain, mountain goats have been challenging to monitor. While some populations remain stable for seasonal harvest, others have shown unexplained population declines (Johnson 1983, Glasgow et al. 2004, Festa-Bianchet and Cote

2008). Theories for these declines range from over-harvest to climate change (Festa-Bianchet and Cote 2008, Rice et al. 2009). In an attempt to manage for decreases in population size, wildlife departments introduced mountain goats to a variety of new mountain ranges across the northwestern United States (Cote and Festa-Bianchet 2003). Many of these introductions have been successful, with new mountain goat populations in Wyoming, Colorado, Utah, South Dakota, Nevada, Alaska, Idaho, Montana, and Washington (Hamel et al. 2006). While declining native mountain goat populations remains worrisome, the growth of *introduced* populations have ecologists concerned around disease transition and resource competition with vulnerable native bighorn sheep (Gross 2001, DeVoe et al. 2015, Varley et al. 1994, Houston et al. 1995; Flesch et al. 2016). Regardless, neither population decline nor population growth concerns can be addressed without precise estimation of abundance.

Currently, aerial surveys are the most common tool used for surveying mountain goats. Because aerial surveys are relatively efficient, they are among the most common method for low and high density ungulate population surveys (Rice et al. 2008, Unsworth et al. 1990). Count data from flights can be useful in estimating abundance when tools are available for estimating proportion of unobserved individuals in the population. One way to estimate unobserved individuals from aerial surveys is with sightability models wherein individuals are marked with radio and GPS collars to uniquely identify and track individuals in the population (Unsworth et al. 1990). Alternatively, unobserved individuals can be estimated in unmarked populations when terrain allows for systematic surveying. However, such systematic sampling designs are ineffective in complex terrain (Buckland et al. 2001, Thomas et al. 2010). Therefore, application of these techniques can be reliable when conditions and funding allow for regular flights in homogenous terrain and animals are accessible for capture.

While aerial surveys can be efficient, they are also costly, dangerous, and rarely take into account correcting factors that need to be applied to count data collected during flights (Sasse 2003, Caughley 1977). Additionally, due to the high cost and stress caused to wildlife, biologists have begun to incorporate noninvasive sampling techniques that do not require handling and collaring individuals. While moving away from wildlife collaring has many positive attributes, little effort has been put forth to incorporate alternative means for correcting count data collected from the air. As a result, wildlife biologists commonly use uncorrected counts of unmarked animals gathered from, often haphazardly conducted aerial surveys to inform management decisions (White 2001). It is therefore vital to the field of ecology that we seek a statistically rigorous, safe, and resource-efficient alternative to aerial survey-based wildlife monitoring.

The first step to obtaining informative abundance estimates is to incorporate *effective* sampling designs to the way in which count data are collected (Anderson 2001). An effective sampling design includes a probabilistic sampling component which adds a level of randomness to the way data are collected (*i.e.* complete random sample, stratified random sample, cluster sampling, etc.). Probability-based sampling differs from convenience sampling which involves collecting data from, for example, haphazard aerial surveys or counting animals seen from popular hiking trails. By incorporating probabilistic sampling designs to the collection of count data, ecologists can effectively extrapolate about the population as a whole for an unbiased abundance estimates (Anderson 2001, White 2001).

The second step to improving population estimates is refining our knowledge around if and when we fail to detect individuals in a population. Not accounting for imperfect detection is the most common source of measurement error when estimating species occupancy and abundance (Anderson 2001, Williams, Nichols & Conroy 2002). Imperfect detection can be caused by a variety of factors including animal behavior, weather, vegetation cover, and personnel experience (Burton et al. 2015, White et al. 1982). However, there exist a variety of tools to mitigate and account for the effects of imperfect detection in count data including, but not limited to multiple observer surveys, replication in site surveys and distance sampling (Buckland et al. 2001, Royle 2004). Incorporating detection probability estimation into monitoring techniques allows ecologists to avoid biasing parameter estimates by effectively determining undetected individuals from count data (Mackenzie et al. 2002).

The third step we address in this paper is meeting the critical assumption of demographic and geographic closure pertinent to many population surveys (Otis et al. 1978). As a review, closure is met when the size of the population of interest (or collected count data) is held constant during a period of investigation for a designated area (*i.e.* animals are not moving in and out of designated survey sites during designated sampling periods). If geographic closure is not met, then the area of interest as it relates to abundance or occupancy cannot be defined (White et al. 1982). Despites its importance in wildlife population surveys, the closure assumption is often only approximated rather than met (Kery and Schaub 2012; Kendall 1999; Rota et al. 2009). However, with an appropriate sampling design *and* sampling period, closure can be met and thus produce unbiased parameter estimates (Otis et al. 1978).

In this paper, we use an *N*-mixture model to estimate mountain goat abundance based on count data collected using a complete random sampling design. The *N*-mixture model (also known as binomial mixture model) is a generalized linear mixed-effects model that estimates abundance corrected for imperfect detection from repeat count data (Kery 2010; Royle 2004). *N*-mixture models use a Poisson random variable distributed around mean abundance parameter per site (λ). With a common λ across all sites we can estimate the total number of animals in the population and study area. Total population is calculated by multiplying λ times the number of total sites in the study area. This total population is assumed constant during the designated survey season (Royle 2004). However, while the total number of animals in the study area remains constant, the λ parameter *can* vary by site and site visit based on covariate influences on λ. Therefore, this approach allows flexibility in how count data are collected and analyzed (Joseph et al. 2009, Kery 2010).

As with many population monitoring efforts that leverage variation in count data to estimate detection probability, *N*-mixture models require repeat surveys to estimate detection probability to inform abundance (Royle 2004). Traditionally, survey repetition is met by conducting multiple visits to survey sites within a temporal period that is biologically relevant to assume closure (Kery 2010). However, variation in count data can also be obtained from *spatially* replicated surveys using multiple, independent observations of the same site (Royle 2004). Spatial replication means that multiple observers collect independent count data from spatially disparate vantages of a survey site. With the spatial replication approach, no time exists between surveys since the two surveys are conducted at the same time – therefore meeting the assumption of closure.

We take a novel approach to sampling rare and elusive species that demonstrates the ability to (1) collect informative count data of low-density species using probability-based sampling, (2) estimate detection probability with temporally *or* spatially replicated count data, and (3) analyze count data such that closure assumptions are met. By following these three steps, we directly address issues associated with haphazardly collected data (a result of no probability-based sampling design) and biased parameter estimates (a result of violating field assumptions and ineffectively accounting of imperfect detection). Finally, we determine that by using an N-mixture model with a common λ across all sites, we can effectively estimate a total population of an area while allowing for animal movement among sites between survey occasions, which solves a major problem in sampling large mammals.

METHODS & MODELS

Study Area

In this study, we analyzed data from a single season of independent double-observer ground surveys in a 200 km^2 region of the Palisades Mountains in eastern Idaho. The specific study area (an isolated region within the Palisades Mountains) was selected based on information gathered from decades of aerial mountain goat population surveys conducted by Idaho Department of Fish and Game and Wyoming Department of Game and Fish (Idaho Department of Fish and Game 2015, Fralick 2015). Additionally, GPS collars were fit to 11 mountain goats in 2011 and 2012 as part of an earlier study. GPS collar data assisted in specific study area selection by providing detailed information around mountain goat population distributions and movement throughout the Palisades Mountains (Lowery et al. 2017). The Palisades Mountains sit in the southwestern corner of the Greater Yellowstone Ecosystem (GYE) and border the Teton Range to the north, the Snake River Canyon to the East, and Palisades Reservoir and Snake River to the south and west. The terrain is largely characterized by steep drainages and high peaks. Elevations in the area vary from 1700 to 3100 meters and barely reach above tree line.

Sampling Design and Survey Methods

To delineate survey sites, a 500 x 500 meter grid was overlaid across the Palisades study area. 70 sampling units were selected (for information on sample size, see Appendix VI) using the generalized random-tessellation stratified (GRTS) sampling tool with the R package spsurvey (Kincaid and Olsen 2017, R Core Team 2015). Once sample sites were selected, we used an independent double-observer point count technique (for information on data collection protocol and processes, see Appendix I; for information regarding testing and selection of field methods used in this project see Appendix VII) to survey sites a minimum of 2 times throughout the field season in order to test different periods of sampling closure (July 2, 2019 and August 23, 2019). During each visit, sites were surveyed by two observers who collected independent and simultaneous mountain goat count information from observation points outside of the survey site (between 100 and 2500 meters from the nearest site boundary) (for more information of survey protocol, see Appendix II). Surveys were conducted during daylight hours between 07:00 and 20:00 MST. Independent double-observers surveys account for imperfection detection and estimate detection probability from variation in collected count data – offering both temporal and spatial repeat counts (Royle 2004; Kery 2010; Kery and Schaub 2012). Spatially replicated counts were collected because observers surveyed from different observation points with disparate vantages of survey sites (for detailed field method protocols see Appendix II).

N-mixture Abundance Model

We used an *N*-mixture model in a Bayesian framework to estimate mountain goat abundance (Royle 2004). *N*-mixture models estimate abundance using information gathered from repeat counts (Royle 2004). *N*-mixture models estimate total population abundance by calculating a mean abundance per site (λ). *N*-mixture models estimate abundance from a two-part process: the biological process which estimates true abundance (at site i, for occasion k) as a random draw from a Poisson distribution centered around λ and an observation process which leverages count data (and variation between repeat counts) as a random draw from a binomial distribution centered around true abundance (N_{ik}) with a probability of success (p_{ijk}) (from site *i*, for observer *j*, during occasion *k*) (see Equation 1). *N*-mixture model estimate total population abundance by multiplying λ by the total number of sites in the study area. The model can use both spatially or temporally replicated counts (Royle 2004, Kery and Schaub, 2012). Here, we use three disparate approaches to analyze count data collected.

Equation 1:

$$N_{ik} \sim Poisson(\lambda)$$

$$y_{ijk} \sim Binomial\ (N_{ik}\ ,\ p_{ijk})$$

Analysis

(1) Season Abundance model – Assumes closure during July-August field season

The first approach analyzes mountain goat count data using the most traditional *N*-mixture model. This approach uses information from temporally replicated counts to obtain an abundance estimate that is adjusted based on variation in counts between visits. This model assumes closure between repeat surveys and therefore, produces a single abundance estimate for the field season.

(2) Occasion Abundance Model– Assumes closure within occasion

The second approach analyzes mountain goat count data using a modified *N*-mixture model to estimate abundance. This approach uses information from temporally and spatially replicated counts to obtain an abundance estimate that is adjusted based on variation in counts *between* observers and *within* survey occasion. This model assumes closure within a survey occasion and therefore, produces four abundance estimate (four is the maximum number of visits a site received). From the four abundance estimates, we can calculate a mean abundance for the total population throughout the field season.

(3) Daily Abundance Model– Assumes closure within survey-day

The third approach analyzes mountain goat count data using the same modified *N*-mixture model to estimate abundance as the Occasion Abundance Model. Again, this approach uses information from temporally and spatially replicated counts to obtain an abundance estimate that is adjusted based on variation in counts between observers within survey occasion. A survey occasion is defined as a single day for the Daily Abundance Model. This model assumes closure within a survey-day and therefore, produces 29 daily abundance estimates (we completed 29 survey-days throughout the field season). From the 29 abundance estimates, we can calculate a mean abundance for the total population throughout the field season.

RESULTS

During the 2019 field season, 70 randomly selected sampling units were surveyed between two and four times from July 2 and August 23, 2019 – totaling 29 survey-days. In this paper a survey-day consisted of surveys conducted by a minimum of one survey team (two observers) and a maximum of 3 survey teams (six observers). Therefore, a survey-day was defined as a day that more than one site was surveyed by a minimum of two observers. Observers recorded mountain goats detected inside or outside of sites. As a result, crews recorded nine separate mountain goat detections within sites – totaling 26 individuals counted within survey sites. From the 9 separate detections, two were repeat detections in sites. For more information on goat detections inside and outside of sites, see Appendix II and Appendix V.

By using a GRTS sample, we derived an exact proportion of the study area surveyed. The sampling fraction survey was 70/574 = 0.12 of the study area. This proportion was included in each *N*-mixture model to estimate total population abundance.

Analysis

<u>(1) Season Abundance model – Assumes closure during July-August field season</u>

In the first approach to analyzing abundance, we used a standard *N*-mixture modelling technique. This approach estimated the Palisades mountain goat abundance at 435 with a 95 % credible interval of between 113 and 721 mountain goats (Figure 1). These data were analyzed using a traditional encounter history format where each site was visited between two and four times. In the likelihood, when modelling the observation process, observations were drawn from a binomial distribution of imputed abundance at site (*i*) with a probability of success being the estimated detection probability of observer *j*. Here, the estimated abundance is based on the maximum observed counts across all occasions – requiring the population is closed at the site level from July 2 to August 23. Because few repeat visits produced similar counts from occasion to occasion, this approach estimated a low detection probability of 0.14 and a 95% credible interval of between 0.08 and 0.22.

Occasion Abundance Model (2) – Assumes closure within occasion

In the second approach to analyzing and modelling abundance, we made a slight alteration to the *N*-mixture model's observation process in which abundance was estimated for each of the four survey occasions (producing 4 abundance estimates). This approach estimated the total mountain goat abundance at 104 with a 95 % credible interval of between 78 and 144. Abundance estimates vary from occasion to occasion with the first occasion estimating a 239 mountain goats with a 95 % credible interval of between 213 and 287; the second estimating a 32 mountain goats with a 95 % credible interval of between 8 and 73; the third estimating a 43 mountain goats with a 95 % credible interval of between 16 and 90; and the fourth estimating a 103 mountain goats with a 95 % credible interval of between 41 and 180.

These data were analyzed using a traditional encounter history format where each site was visited between two and four times (Figure 2). In the likelihood, when modelling the observation process, we added a second level of indexing such that abundance estimates were drawn from site *i* by observer *j* at occasion *k*. Here, the estimated abundance was based on the observed counts *within* each occasions – requiring the population is closed at the site level *within* a cycle of site surveys (typical length of time to conduct a complete survey cycle was 2 – 3 weeks). Replication for this approach was acquire from the independent double-observers surveying from spatially distinct vantage points. Because site-level populations were closed *within* repeat visits, the true population size within each site is no longer assumed constant between visits. However, this model likely violated the closure assumption due to the length of assumed closure period. Finally, since most mountain goat detections between observer pairs produced similar counts, we estimated a higher detection probability of 0.53 and a 95% credible interval of between 0.38 and 0.69 with this approach (Figure 4).

Daily Abundance Model (3) – Assumes closure within survey-day

In the third approach to analyzing and modelling abundance, we used the same model as the second approach to the *N*-mixture model's observation process. However instead of estimating abundance on an occasion basis, we rearranged the data such that data were analyzed on a *daily* basis (Figure 3). This approach estimated the mean total mountain goat abundance at 104 with a 95 % credible interval of between 68 and 153. Since these data were analyzed by 29 survey-days (between 3 and 14 sites were surveyed during a survey-day), we obtained 29 abundance estimates. The 29 mean estimates varied from 88 to 166 mountain goats. Data were analyzed using the same model as the second approach, where occasions are equivalent to 29 survey-days rather than 4 survey occasions. Thus, estimated abundance was based on the observed counts *within* each survey day. Replication for this approach was acquired from the independent double-observers surveying from spatially distinct vantage points. Because populations at the site level were closed *within* each survey-day, variation in counts from day to day were no longer related. Finally, since most mountain goat detections between observer pairs produced similar counts, we estimated a higher detection probability of 0.54 and a 95% credible interval of between 0.38 and 0.68 with this approach (Figure 4).

DISCUSSION

In this paper, we present a novel approach to sampling rare and elusive species. This approach demonstrates that low-density species abundance can be estimated by (1) collecting informative count data using probability-based sampling, (2) estimating detection probability from temporally *or* spatially replicated count data, and (3) analyzing of count data such that closure assumptions can be tested and met. By following the steps outlined in this paper, we collected data in a systematic way that produce an unbiased population estimate by directly address the problem with haphazardly collected data (no probability-based sampling design) and biased parameter estimates (a result of violating field assumptions and ineffectively accounting of imperfect detection).

Here, we evaluated three disparate mountain goat abundance estimates from *N*-mixture models. Each model analyzed the *same* count data while assuming *different* periods of geographic closure. From model results, we examined the varying levels of impact that violating closure assumptions has on parameter estimates. The first model evaluated count data that assumed closure within the field season (Season Abundance Model, Figure 1). The second model evaluated count data that assumed closure within survey occasions (Occasion Abundance Model, Figure 2). The third model assumed closure within a single survey-day (The Daily Abundance Model, Figure 3).

In the Season Abundance Model, abundance estimates were far greater than those estimated in the Occasion Abundance Model and Daily Abundance Model. An overestimated abundance (N = 435) is likely explained by the largely *underestimated* detection probability (Figure 1). Underestimation of detection probability is an expected result of violating the closure assumption in the Season Abundance Model. Therefore, overestimation of the abundance parameter is supported by the results of this model. Conversely, both the Daily Abundance Model and the Occasion Abundance Model estimated similar mean total abundances of 104 individuals – note that mean total abundance was calculated from multiplying λ (mean abundance per site) by the total number of sites in the study area. Because λ was estimated similarly from both models (Occasion Abundance Model and Daily Abundance Model), total abundance was also similar in both models. Variability among Occasion Abundance Model estimates (Figure 2) indicates the closure assumption was likely not met for this model as well. This makes sense biologically as mountain goats can move between sites within the period of assumed closure used in the Occasion Abundance model (survey occasion). However, the consistency and statistically equivalent estimates produced from the Daily Abundance Model

(Figure 3) demonstrate that this model most accurately estimates abundance. We know that closure was met (producing an unbiased estimate) since field assumptions incorporated count data that were collected within a time period that matches mountain goats movement. Therefore demonstrating that the Daily Abundance Model the most effective model for estimating mountain goat abundance.

To sufficiently apply the Daily Abundance Model and effectively estimate mountain goat abundance, we suggest that ecologists follow the three steps discussed in this paper. Our first step to obtaining an unbiased abundance estimate was to incorporate a probability-base sampling scheme. The Daily Abundance Model's statistically equivalent abundance estimates are a due, in part to application of a complete random sample survey design. Random sampling worked in this study because we chose a grid cell size based on area that would be both small enough to effectively survey and big enough that mountain goats would likely not move in or out of sites during surveys. Additionally, we found that when we analyzed temporal and spatial covariate influence on *occupancy* (distribution), we were unable to gather enough information to define disparate strata and therefore rejected use of a stratified sampling design (see Chapter 2). In conclusion, we show that a complete random sample sufficiently surveyed mountain goats while also demonstrating that simplified sampling efforts can be effective for low-density species abundance estimation.

The second step to estimating unbiased abundance was the use of spatial replication as a replacement to repeated site visits. Spatial replication allowed the Daily Abundance Model to estimate detection probability while meeting closure assumptions. Estimation of detection probability is a key process to correctly modelling for abundance (Royle 2004, Mackenzie and Royle 2005). *N*-mixture models require that repeated and variable counts be gathered in order to estimate abundance (Royle 2004, Kery 2010). We demonstrate that with spatial repeat surveys we meet this requirement of the *N*-mixture model. Ideally, we could investigate the influence of site- and observer-level covariates on detection probability. However, applying covariates to estimating detection probability required that we had more detections of mountains goats in sites. To make up for this, we assumed a constant detection probability between observers and estimated overall a precise detection probability (Figure 4).

The third step to obtaining unbiased abundance estimates was defining a study area that was biologically relevant such that the closure assumption could be met at the *study area* level. Furthermore, survey occasions were defined biologically to match animal movement in and out of sites meeting the closure assumption at the *site* level. Additionally, since sites were surveyed simultaneously from spatially unique vantage points, the survey replication requirement – that assumes variation in count data to estimate detection probability – was also met. With the Daily Abundance Model, we define our survey occasion as a single survey-day. Within a survey-day and during survey periods of 20 minutes, mountain goats did not move between sites, again, resulting in meeting the closure assumption. Finally, we demonstrate the efficacy of the Daily Abundance Model from its consistent and statistically equivalent estimates of each daily abundance.

An advantage of the Daily Abundance Model is its ability to leverage λ - the mean abundance estimate across all sites. A mean abundance estimate (λ) fits well here because it allows goats to rearrange between survey occasions (in this case, rearrange each day). Additionally, λ allows for flexibility when accounting for mountain goat distribution across sites (*i.e.* it does not matter whether all of the goats are in one site versus some sites) while assuming a constant *total* population size. With *N*-mixture models, true abundance is a function of a random draw from a Poisson distribution that has a mean around λ. Because true abundance (N_{ik}) of site *i* for occasion (or day) *k* is a function of a Poisson random variable, N_{ik} can vary within sites from survey-day to survey-day, all the while λ remains constant.

N-mixture models have three important assumptions (1) the population is closed at the site level during survey period; (2) independent and identical detection probability for all individuals within a site (detection probability can vary between sites if defined by site-level covariates); and (3) absence of double counting individuals/or other false positive errors (Kery 2010, Royle 2004). Until now, many research projects when applying count data to *N*-mixture models found the closure assumption difficult to meet (Kery 2010, Joseph 2009). To date, one way that ecologists approach closure assumption violations in *N*-mixture models is through the development of a generalized *N*-mixture model (Dail and Madsen 2011). This approach aims to address the closure assumption by removing it and making the generalized *N*-mixture model applicable to open populations. While this increasing generalizability can be advantageous, it adds a level of complexity to the model itself. With our Daily Abundance Model, we solve the assumed closure violation at the site level with a simple rearrangement of the repeat count data.

During the 2018 and 2019 field seasons, Idaho Department of Fish and Game conducted aerial counts as a part of their current mountain goat monitoring efforts. These flights include minimum count surveys and have served as the primary tool for mountain goat population counts. We compared our abundance estimates to the aerial surveys and found that, in both years, we estimated higher abundance than aerial surveys counted. The 2018 flight counted 101 mountain goats in this study area while the 2019 flight counted 48 mountain goats. These flight counts can be helpful as a means to ensure that our abundance models produce an estimate that is at least greater than the aerial survey counts. As a result, variability in minimum counts suggests that aerial surveys are not only unreliable, but also do not offer any measure certainty around aerial counts.

While estimating abundance of wildlife populations can be difficult, it is imperative to conservation and management of future ecosystems. Challenges that exist around obtaining useful abundance estimates are further increased when access to the population of interest is limited. In this paper, we present a tool that directly addresses that challenge. The field of ecology has often relied on minimum counts or indexes of relative abundance to inform management decisions around low-density species populations. We provide a solution to sampling and parameter estimation that directly address the need to rely on relative abundance and minimum counts to make management decisions. By following the steps outlined in this paper, ecologists can finally begin to obtain unbiased estimates and begin to improve precision around abundances estimates of rare and elusive species – a goal that was, until now, thought difficult to achieve.

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FIGURES

Figure 1: The Season Abundance Model abundance estimate. The Season Abundance Model assumes closure within sample sites for the 8-week season. The blue vertical line represents the mean total abundance calculated from the estimated from the Daily Abundance Model.

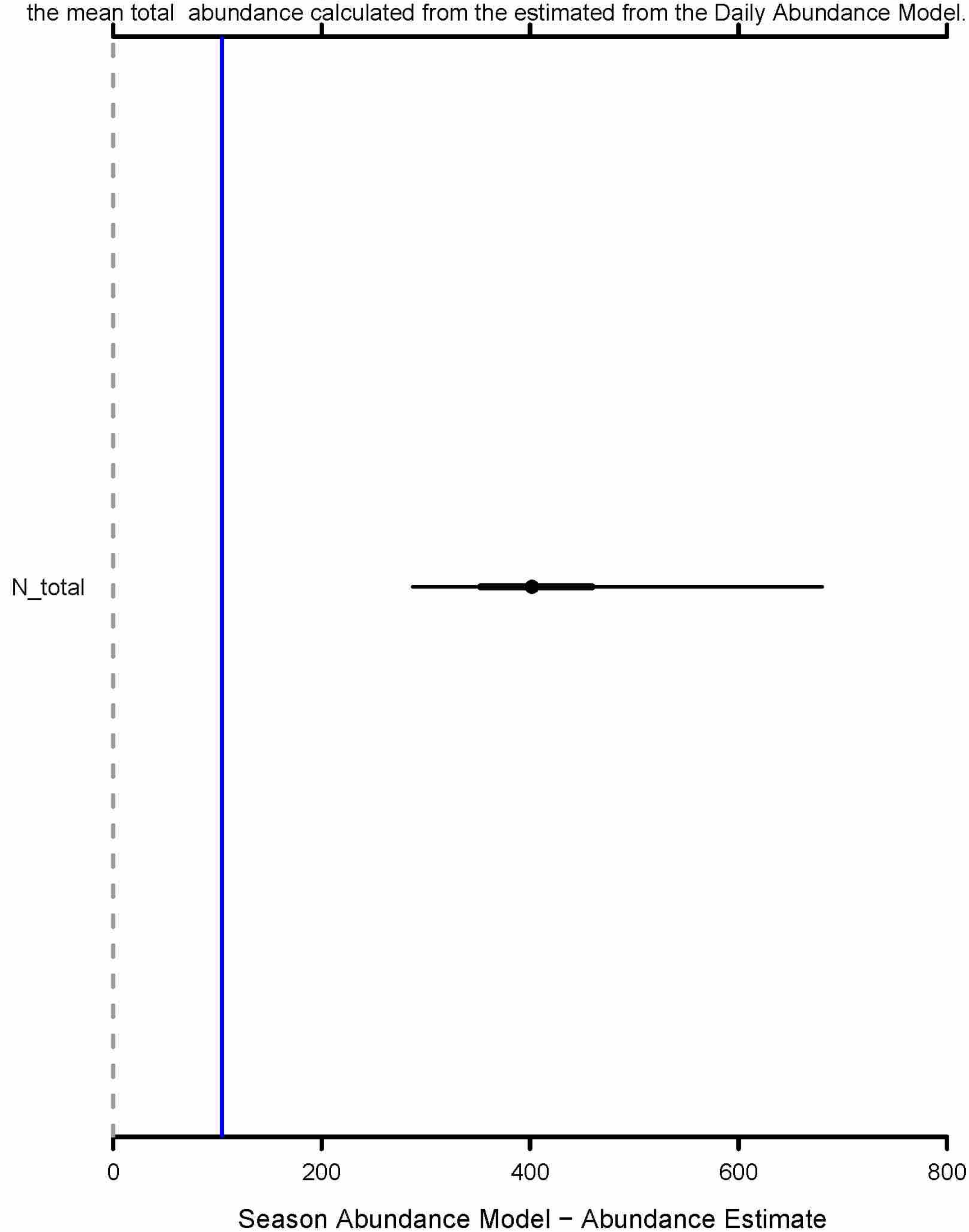


Figure 2: The Occasion Abundance Model abundance estimates. The Occasion Abundance Model assumes closure within sample sites for each survey-occasion. The blue vertical line represents the mean total abundance calculated from the Daily Abundance Model.

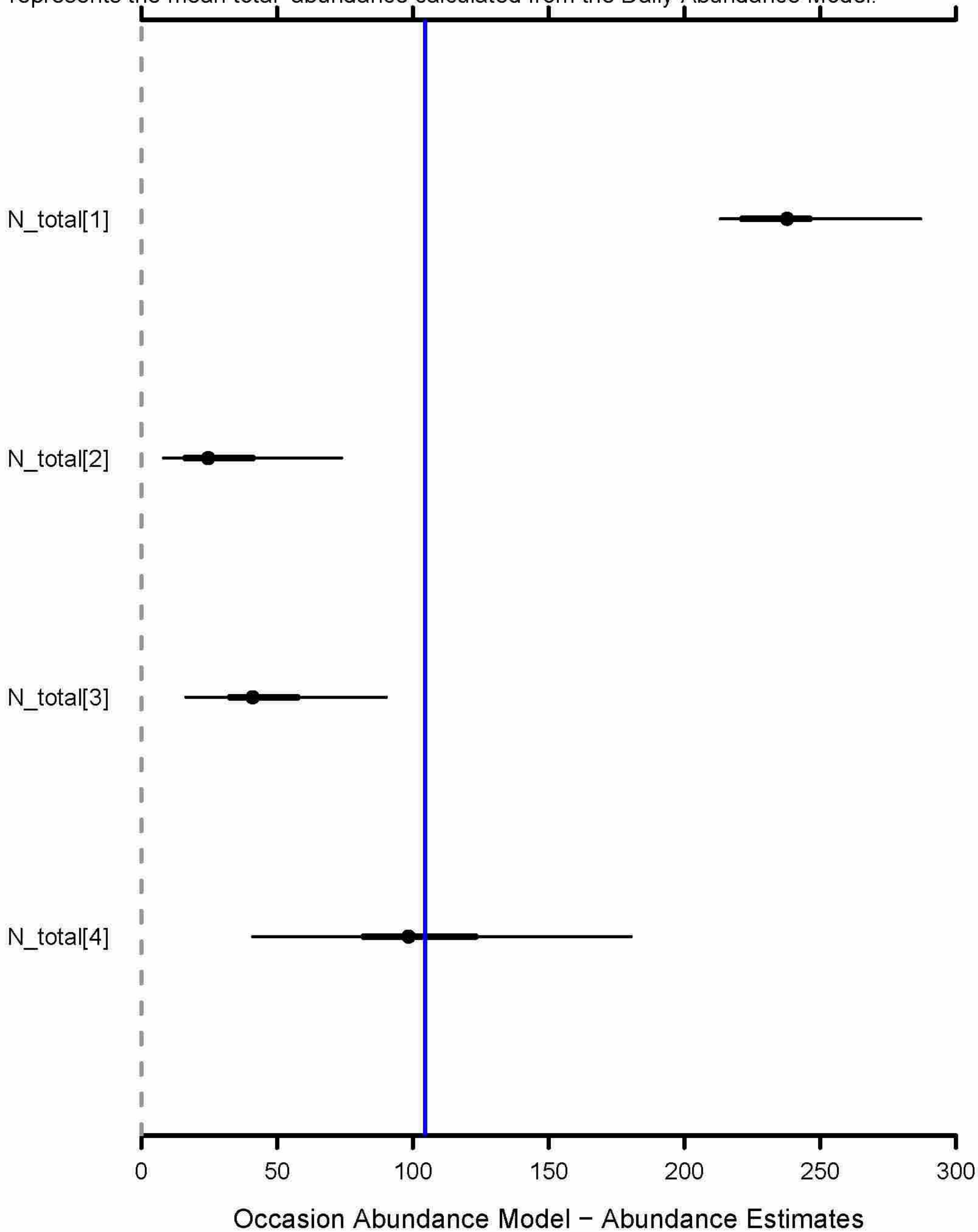


Figure 3: The Daily Abundance Model abundance estimates. The Daily Abundance Model assumes closure within sample sites for each survey-day. The blue vertical line represents the mean total abundance calculated from the Daily Abundance Model.

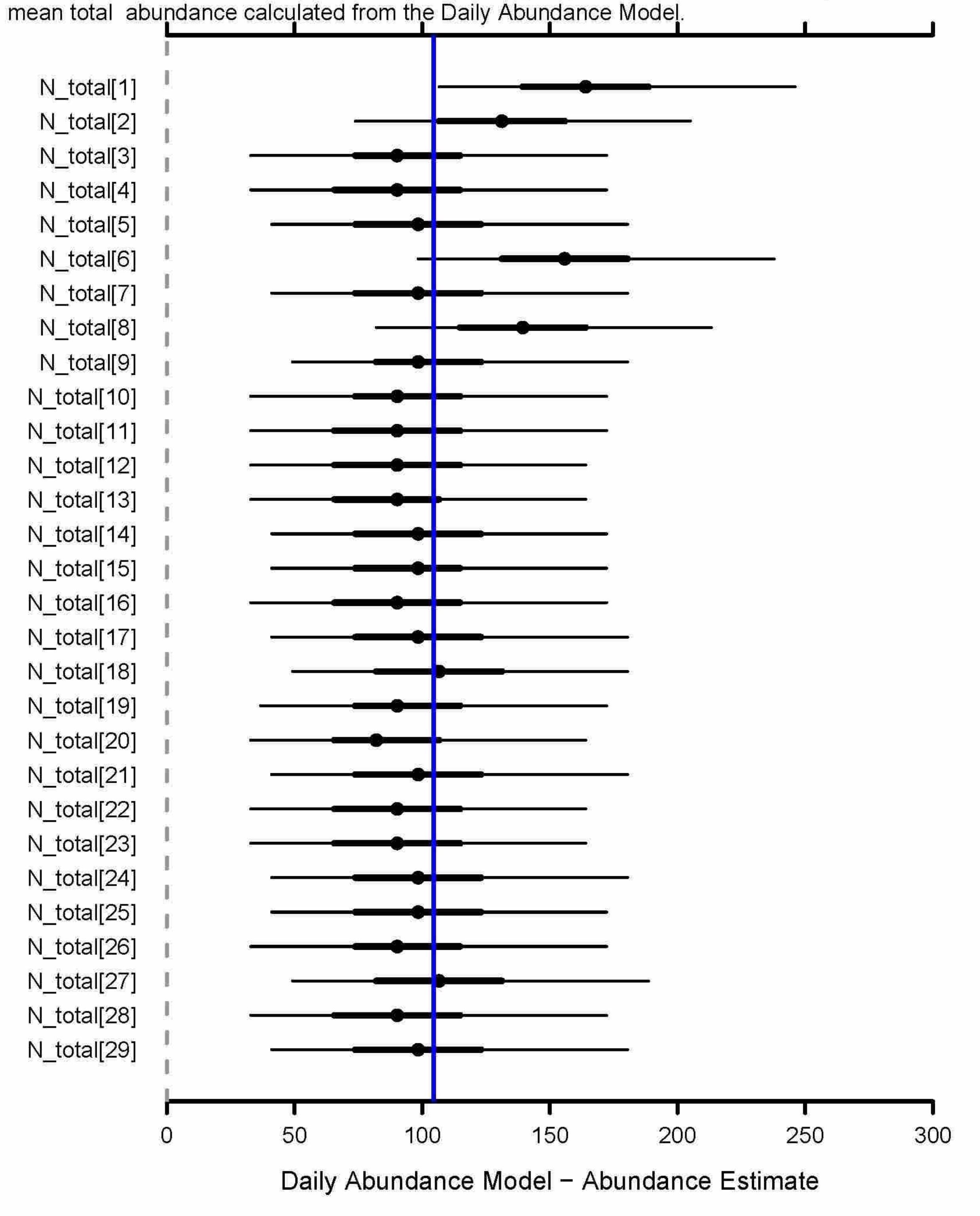
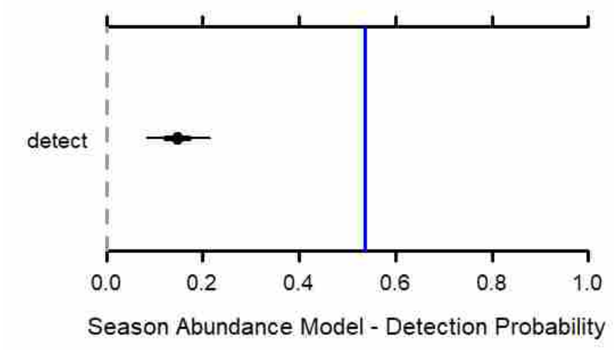
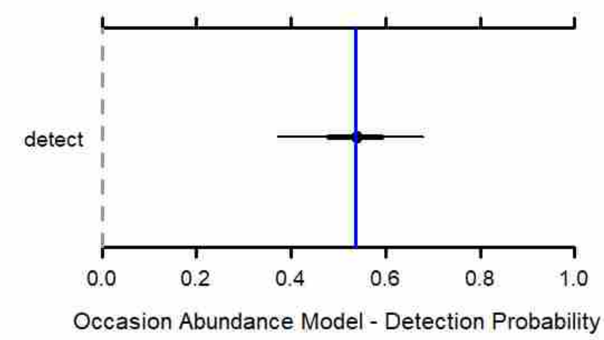
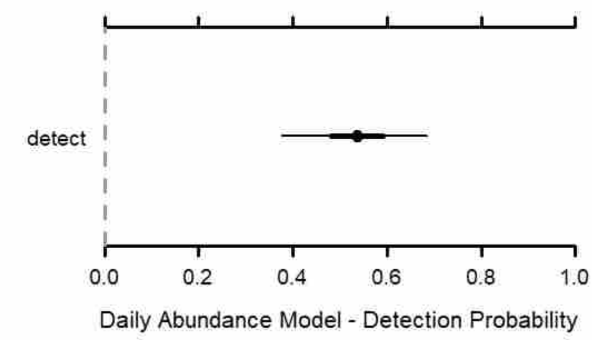


Figure 4: Estimated detection probability (detect) from the Season Abundance Model, Occasion Abundance Model & Daily Abundance Model. The blue vertical line in the Season Abundance Model plot and Occasion Abundance Model plot represents the mean detection probability estimated from the Daily Abundance Model. Note that we set the two observers' probability of detection equal to one another, thus producing a since estimate of detection probability.







Chapter 2

Understanding Mountain Goat Occupancy Patterns to Improve Abundance Estimation

INTRODUCTION

In the field of ecology, occupancy, or the presence-absence matrix of a species, has been described as a fundamental unit of analysis (Gotelli 2001, McCoy and Heck 1987). Occupancy, as a tool, serves to measure species occurrences, species ranges and species distribution through estimating the probability that a sampling unit is occupied by a species of interest (Mackenzie et al. 2006, Kery 2010). Additionally, occupancy is a parameter that can be effectively estimated for a variety of taxa (Mackenzie and Royle 2005). Because of its flexibility, occupancy can be a more efficient parameter to estimate for species that span a variety of densities and habitat types. Occupancy, can therefore offer additive information or supplementary information to species abundance estimates by describing where and when species are detected across the landscape.

Occupancy is further defined as the assessment of species presence/absence on a sampling unit. Specific habitat characteristic can often help define the probability that a unit contains the species of interest (Thompson 2004, Mackenzie et al. 2006). Additionally, estimating the probability of occupancy on a sampling unit requires identifying if and when we fail to detect individuals in a sampling unit (otherwise thought of as false negatives) (Tyre et al. 2003). Accounting for imperfect detection can be accomplished by estimating a probability of detection for the species of interest. Incorporating detection probability into occupancy estimation allows ecologists to avoid biasing parameter estimates by effectively determining undetected individuals from occurrence data (Mackenzie et al. 2006).

Variation in estimates of detection probability and occupancy can be caused by a variety of factors including animal behavior, geographic landscape, vegetation cover, and personnel experience (White et al. 1982). Once identified, factors driving estimates of species occupancy and detection probability can help more precisely model parameters of interest with the use of stratifying sampling efforts (*e.g.* Scott et al. 2002). Occupancy can therefore be a tool to guide appropriate sampling designs. Selecting an appropriate sampling design is of particular importance for low-density species as unbiased occupancy estimates can be difficult to come by with decreased encounters (Thompson 2004, Engler, Guisan & Rechsteiner 2004).

An example of a low-density species that is difficult to obtain precise parameter estimates for is the Rocky Mountain Goat (mountain goats). Mountain goats are high alpine-dwelling ungulates that occur in low densities throughout the steep and rocky habitat of the northern Rocky Mountains (Festa-Bianchet and Cote 2008). Because they are found at relatively low densities, exhibit grouping behavior and occupy difficult-to-access terrain, mountain goats have been challenging to monitor. While some populations remain stable for seasonal harvest, others have shown unexplained population declines (Glasgow et al. 2004, Festa-Bianchet and Cote 2008). Theories for these declines range from over-harvest to climate change (Festa-Bianchet and Cote 2008, Rice et al. 2009). In an attempt to manage for decreases in population size, wildlife departments introduced mountain goats to a variety of new mountain ranges across the northwestern United States (Cote and Festa-Bianchet 2003). Many of these introductions have been successful, with new mountain goat populations in Wyoming, Colorado, Utah, South Dakota, Nevada, Alaska, Idaho, Montana, and Washington (Hamel et al. 2006). While declining native mountain goat populations remain worrisome, the growth of *introduced* population distributions have ecologists concerned about disease transmission and resource competition with vulnerable native bighorn sheep (Gross 2001, DeVoe et al. 2015, Varley et al. 1994, Houston et al. 1995; Flesch et al. 2016). Therefore, there is a need to better understand shrinking and expanding mountain goat population ranges. Such questions around population distributions can be directly addressed from obtaining unbiased estimates of occupancy.

Incorporation of a probabilistic sampling design is essential to obtaining an informative occupancy estimate (Anderson 2001, Mackenzie et al. 2006). In the case of this paper, an effective sampling design means applying a completely random sample of all possible survey sites to effectively identify if and how mountain goat occupancy might vary across spatial and temporal covariates. Probability-based sampling is different from convenience sampling which involves collecting data from, for example, hiking trails or heavily populated areas where people are more likely to encounter the species of interest (*i.e.* disease prevalence and occurrence) (Nusser et al. 2008). By incorporating random sampling to the collection of occurrence data, ecologists can effectively extrapolate about the population as whole for an unbiased occupancy estimate – even for low-density species like mountain goats (Mackenzie and Royle 2005, Thompson 2004).

Random sampling is the most basic form of theoretically driven sampling. Results from random samples can often guide sampling designs for further and more involved sampling efforts (Lohr 2010). Complete random sampling designs are often used to evaluate overall spatial and temporal covariate effects on occupancy and detection probability estimation. By answering the question of what type of habitat variables define occupied sites and what temporal frames optimize species detection, ecologists can better define sampling designs for future *abundance* surveys (as in Chapter 1). Identifying covariate correlation with mountain goat occurrence, allows ecologists to determine how best to stratify sampling designs. Stratified sampling designs are appealing as they can increase precision of estimators (Lohr 2010). It is critical, however, that *correct* supplementary knowledge on species distribution is gathered prior to implementing stratified sampling scheme (Cochran 1977, Lohr 2010).

A wildlife monitoring tool that has been largely utilized in recent years is the remotely-triggered camera trap (camera trap). Camera traps offer a promising solution for population monitoring as rapid technological advances and decreasing prices have made camera traps a cost effective, efficient, non-invasive tool for estimating species occupancy and abundance (O'Connell et al. 2011). Recent advancements in statistical models applied to camera trap data have further enhanced the versatility of remotely-triggered cameras. Again, with application of camera traps to probability based sampling schemes, ecologists have begun to see improvements in parameter estimates (O'Connell et al. 2011). Since camera traps are widely applicable and significant model advancements have been made, we sought to test their efficacy as an efficient tool for determining unbiased occupancy estimates of a low-density species in rugged terrain.

Because abundance is often of more interest to wildlife managers, few studies have thoroughly estimated mountain goat occupancy (DeVoe et al. 2015, Lowrey et al. 2017, O'Reilly et al. 2012). DeVoe at al. (2015) conducted independent double-observer surveys over three field seasons (June – October) to estimate occupancy in the northern Absaroka and Gallatin Ranges of Wyoming and Montana. While this technique proved successful and informative, it also excluded mid-elevation and below treeline habitat resulting in potential bias and required extensive and prolonged field efforts making this technique quite expensive.

Here, we test an alternative technique that aims to reduce field sampling effort in addition to leveraging a completely random sample sampling design to include *all* potential mountain goat habitat.

Based on mountain goat habitat selection criteria from Lowrey et al. (2017) and occupancy estimation from DeVoe et al. (2015), we selected four covariates to evaluate with mountain goat occupancy: variation in elevation (elev), mean slope angle (slope), mean aspect (aspect) and mean forest cover (cover) (DeVoe et al. 2015, Gross et al. 2002, Poole and Heard 2003). The covariates we chose to evaluate were selected based on habitat characteristics that were predicted to correlate with mountain goat occurrence. Because mountain goats are typically found at high elevations and on steep slopes, we predicted a positive relationship between mountain goat occupancy and covariates of elevation and slope angle. Additionally, we predict that high temperatures in the summer would suggest mountain goats, a cold-adapted species, seek cooler temperatures on northern aspects. Therefore, predicting that mountain goat occupancy have a positive relationship with north-facing aspects. Finally, we chose to evaluate cover as we predicted that mountain goats would seek habitat near and above treeline, suggesting a negative relationship between mountain goat occupancy and cover. Again, evaluation of these various models aims to guide future abundance and distribution survey efforts.

In this paper, we used camera traps with a completely random sampling design to estimate unbiased mountain goat occupancy (presence/absence) as a proxy to measure mountain goat distribution. We were interested in variation across mountain goat distributions for both spatial and temporal covariates. We address whether camera traps could be at tool for estimating spatial variation by measuring elevation, slope angle, aspect and cover influence on mountain goat occupancy estimates. In addition to assessing whether camera traps function as a tool to assess *where* mountain goats were encountered we sought to examine if we could detect *when* mountain goats were encountered (*i.e.* does occupancy vary by disparate time periods within the survey season). Obtaining an accurate and firm grasp of how mountain goat encounters vary temporally and spatially could inform further population monitoring efforts and guide future sampling designs for increased parameter precision.

METHODS & MODELS

Study Area

We conducted a single season of camera trap surveys during the summer of 2019 in a 200 km^2 region of the Palisades Mountains in eastern Idaho. The study area selection was based on decades of mountain goat population surveys conducted by Idaho Department of Fish and Game and Wyoming Department of Game and Fish (Idaho Department of Fish and Game 2015, Fralick 2015). Additionally, GPS collars were fit to 11 mountain goats in 2011 and 2012 as part of an earlier study. GPS collar data provided detailed information for specific study area selection and population distributions (Lowery et al. 2017) (Appendix I). The Palisades Mountains sit in the southwestern corner of the Greater Yellowstone Ecosystem (GYE) and border the Teton Range to the north, the Snake River Canyon to the East, and Palisades Reservoir and Snake River to the south and west. The terrain is largely characterized by steep drainages and high peaks. Elevations in the area vary from 1700 to 3100 meters and barely reach above tree line.

Sampling Design and Survey Methods

To delineate survey sites, a 500 x 500 meter grid was overlaid across the Palisades study area. 70 sampling units were selected using the generalized random-tessellation stratified (GRTS) sampling tool with the R package spsurvey (Kincaid and Olsen 2017, R Core Team 2015). Camera traps were placed in all physically accessible sites (*i.e.* no cliffs or hazardous terrain such that technicians could access sites safely), totaling 61 survey sites. Once sample sites were selected, we placed a camera trap in each site such that photos captured the maximum amount of space in an image. For further camera placement information and protocol, see Appendix III. All cameras were placed on the landscape between the dates of July 19, 2019 and August 12, 2019. Each camera was placed on a time-lapse setting such that a photo was taken every 15 minutes between the hours of 0530 and 2130 each day. A time-lapse setting was selected in order to maximize capturing photos of mountain goats in a mostly open landscape. This technique allowed us to evaluate camera traps as a tool for unbiased occupancy estimates.

Analysis

Prior to camera trap data analysis, images were scored using the program Timelapse (Greenberg et al. 2019). Timelapse allows the viewer to count the total number of individuals captured per image. Additionally, the program allows image viewers to track individual animal species, sex and age. However, most images captured mountain goats at a distance such that sex and age were undetectable. For a full description of camera trap viewing protocol, see Appendix IV.

A site-occupancy model was used in a Bayesian framework to measure mountain goat distribution across sampling units (Mackenzie et al. 2006). In this model, the true state of each site (z_i) is a random draw from a Bernoulli governed by the occupancy parameter ψ. We can identify the probability of detecting the species of interest through modelling the observation process of site i during survey j (y_{ij}), which is the result of a random draw from a Bernoulli distribution around true occupancy per site (z_i) multiplied by the probability of detection (p_{ij}). In this model, both ψ and p were separately estimated by repeated site visits (Kery 2010). Additionally, given occurrence data are available, the model can estimate the influence of covariates on both parameters.

$$z_i \sim Bernoulli\ (\psi)$$

$$y_{ij} \sim Bernoulli\ (z_i\ ,\ p_{ij})$$

In order to account for repeat visits with camera traps (a technique that has the ability to survey continuously), we selected arbitrary time frames with which to define a survey occasion. Here, a survey occasion was defined as 4 days. By defining this time frame, we determined if a goat was detected in a photo within each 4-day period. Within the field season, this amounted to six four-day occasions – or 6 visits per site.

Spatial and Temporal Analyses

In total, we ran 11 occupancy models: a constant model, 2 periods of occupancy models, 3 periods of occupancy, a time-varying model and 4 spatial covariate models. To test for influence of temporal variation in mountain goat occupancy, we analyzed data in three different time intervals: (1) full field season (6 occasions in July 18 – August 11); (2) two periods of 12 days (3 occasions per period in July 18 – July 30 and July 31 – August 11); and (3) three periods of 8 days (2 occasions per period in July 18 – July 26, July 27 – August 3, August 4 – August 11). Additionally, we ran a time-varying model to evaluate variation in detection probability in the constant model.

To evaluate spatial covariate influence on mountain goat occupancy estimates, a summary value was calculated for each survey site. Covariates measured were: variation in elevation (elev), mean slope angle (slope), mean aspect (aspect) and mean forest cover (cover). For elevation and slope, we compared the variable mean to variable standard deviation (a measure of covariate variation). Using DIC and model convergence, we determined that standard deviation was more effective for measuring elevation influence on occupancy and mean was more effective for measuring slope influence on mountain goat occupancy.

In order to assess influence of variables on mountain goat occupancy, we used model selection criteria (DIC), coefficient parameter values, MCMC model outputs and $\hat{R}$ values.

RESULTS

We ran the constant occupancy model on each of the three temporal models (the single-period model, 2-period model, and 3-period model). We found that the occurrence data collected from camera traps did not have sufficient encounters to determine variation in occupancy across disparate temporal periods as models failed beyond a single period (Table 1, Figure 4). After identifying a single temporal period for which to analyze occurrence data, we ran a time-varying model to identify if detection probability could be modeled as varying across time in the constant model (Table 2). Because the time-varying model did not fully converge, we did not further evaluate temporal variation across the spatial covariate models (Figure 2, Table 2).

The constant model did successfully converge (Table 3), suggesting it an effective model in estimating overall occupancy. For the constant model, our mean occupancy estimate was 0.157 per cell with a 95% credible interval between 0.064 and 0.294 (Figure 1a). Mean detection probability from the constant model was estimated 0.304 with a 95% credible interval of 0.084 and 0.475 (Figure 1b).

All four spatial model results (variation in elevation, mean slope, mean cover and mean aspect) suggested no influence on mountain goat occupancy as our 95% credible intervals all straddled 0 (Figure 3). Therefore, we found neither weak nor strong correlation between covariates and mountain goat occupancy. Upon careful evaluation of convergence statistics such as $\hat{R}$ (a value less than 1.1 is one evaluation technique for model convergence) and MCMC model outputs, we found that most spatial covariate models meet convergence requirements (Table 4, Table 5, Table 6, Table 7). However, MCMC trace plots and density plots along with the MCMC effect size from the slope model and aspect model suggest the models did not converge. In addition to model convergence evaluation, we used model selection criteria (DIC) to further confirm that the constant model was clearly rated our top model (Table 3).

DISCUSSION

In this paper, we estimate overall mountain goat occupancy (ψ) and probability of detection (p) using camera trap data in a Bayesian occupancy model with a complete random sample survey design. While we did estimate overall occupancy, we did not find any correlation between spatial or temporal covariates and occupancy (Figure 3, Table 1). Contrary to assumptions that mountain goat occupancy is influenced by covariates such as elevation and slope angle (DeVoe et al. 2015, Lowrey et al. 2017), we found that the constant model was our top model for occupancy estimation. Likely explanations for these results are: (1) mountain goats are widely distributed throughout the study area and mountain goats *do* occur beyond high elevations and steep slopes; (2) the size of our survey sites was large enough that sites contained varying covariate values; (3) or we did not have enough mountain goat encounters in our camera trap data to confidently detect covariate influences on occupancy estimates. While these results do not help define strata that would allow increased precision in future study design efforts, we were able to examine the efficacy of camera trap surveys and random sampling for estimating mountain occupancy across temporal and spatial variations. By using a random sample, we avoided biasing our estimates from incorrect assumptions about goat distribution.

One explanation for the lack of support for spatial covariate correlation with mountain goat distribution is that mountain goats are widely distributed across geographical areas. Previous research suggests that mountain goat surveys have underrepresented non-alpine habitat characteristics (DeVoe et al. 2015, Varley et al. 1997, Lowrey et al. 2017). The underrepresentation of non-alpine habitat variables is largely due to the assumption that mountain goats occupy only high elevation and steep terrain. However, from GPS collar data (Lowrey et al. 2017) and camera trap data analysis, we know that mountain goat ranges expand beyond the alpine. The hypothesis that mountain goat distribution varies more widely than ecologists assume has been the driving force behind selection of a completely random sample for the study design behind this paper. While further investigation could provide more information on habitat characteristics that define mountain goat distribution, our results suggest that this population of mountain goats cannot be defined by the spatial covariates that we evaluated in this paper. Therefore, our results support the hypothesis that mountain goat distribution is not highly correlated with spatial covariates and suggests that mountain goat distribution varies throughout this study area. These results are further supported by the fact that goats occupy habitat in the Black Hills of South Dakota and at sea level in Alaska (Hamel et al. 2006).

Another factor for explaining the lack of support for spatial covariate correlation with mountain goat distribution is the synthesis of complex terrain to a single value per sampling unit. Here, we used camera traps to survey 500 x 500 meter grid cells (our sampling unit) for which to estimate presence and absence of mountain goats. In the Palisades study area, a 500 meter grid cells included significant variation across covariate values. Variation in covariates that fit into a single sampling unit include, but are not limited to: (1) entire mountain-tops that include all slope aspects; (2) large cliffs in which 500 horizontal meters include 1000 meters in elevation change; and (3) steep drainages with flat valleys which offer 0 degrees up to 90 degree slope angles. In conclusion, due to variation of spatial covariates across complex terrain, synthesis of habitat characteristics to a single value per sampling unit should be viewed with caution.

The third explanation for no correlation between spatial covariates and mountain goat occupancy is insufficient numbers of mountain goat encounters. While camera traps offer a tool for continuous monitoring (especially when applying a time-lapse setting), mountain goats remain a low-density species. With low-density species, we should expect infrequent species encounters when obtaining unbiased estimates from a complete random sampling design (Mackenzie and Royle 2005). As a result, of 24 total survey-days with photos taken every 15 minutes, we encountered mountain goats in 7 of the 53 usable camera-sites and 5 sites containing repeat encounters between survey occasions. While these data provide enough information for overall parameter estimation, it is insufficient to extrapolate beyond overall occupancy. Ways to address this issue in the future are to increase the length of survey time or increase the number of cameras deployed.

While these results do not suggest strata definition or inform future study design efforts, we were able to examine the efficacy of camera trap surveys and random sampling for estimating mountain goat occupancy across temporal and spatial variations. Recently, camera traps have showed significant promise as a useful tool for gathering population monitoring data (O'Connell et al. 2011). They offer the opportunity to collect continuous information on spatial use by a variety of taxa, especially when using time-lapse photos and the potential for capturing close images of the species of interest are available. We found that although camera traps have proved useful for estimating species occupancy for a variety of taxa, that they do not offer an effective tool for measuring temporal period or spatial covariate effects on mountain goat occupancy or detection probability in this study area. Because we did not find any support for stratifying future sampling designs to estimate occupancy *or* abundance of mountain goats, we can feel confident in the results we obtained from Chapter 1 – a study where we successfully estimated abundance using a complete random sample.

For effective implementation of stratified sampling, multiple variables must be taken into account. First, ecologists must have sufficient information about the population of interest in the sampling frame in order to guide strata definitions. Second, ideally ecologists have information about how many and what proportion of the population belong to each strata. Third, individuals within the population cannot move between strata. Finally, stratification is most effective when mean covariate values vary widely between each strata (Cochran 1977, Lohr 2010). Consequences of *incorrectly* defining strata in stratified sampling designs result in heavily biasing estimates in addition to adding complexity. Cochran (1977) describes the effects of errors in defining strata within a sampling design as: (1) producing biased estimates, and (2) nullifying the precision gained from stratifying because of introduced bias that cannot be made up for by increasing sample size within a strata. Therefore, the consequences of wrongly stratifying do not out-weigh the low encounter rates obtained from a complete random sample.

We demonstrate that while it is often assumed that only occupancy can be estimated for low-density and rare species, this is not always true. In Chapter 1, we show that abundance can be estimated for a low-density and difficult-to-monitor species using non-invasive, ground-based sampling. Here, in Chapter 2, we show that we can also use non-invasive, ground-based sampling to estimate overall occupancy. We found that with double-observer ground surveys (methods from Chapter 1), mountain goats were detected in 10% of our sites (see Appendix V) while occupancy estimates suggest that mountain goats occur in 15% of our sites. We find that mean detection probability was slightly higher in our *N*-mixture models (0.54) than our occupancy models (0.30). However, because the 95% credible intervals from both studies' detection probability estimates overlap, we can infer that two estimates are statistically equal (see results from Chapter 1). Therefore, we show that for near equal personnel effort and less cost (no cameras or batteries), we can estimate the abundance of mountain goats (Chapter 1) with better results than occupancy (Chapter 2).

In this paper, we present the value of random sampling when surveying for low-density species distributions. Application of smart sampling designs avoid limiting information gain during the initial stages of species population parameter estimation. When surveying for a rarely-encountered species, a common goal is to identify when and where those species occur. Random sampling can be a useful tool in ensuring information gain is not limited to specific habitat characteristics that may be misguided, leading to biased parameter estimates. When effectively estimated, occupancy can help fill in information regarding how species are distributed across the landscape. Because we did not find any support for stratification by temporal or spatial variables, we show that for this study, a random sample was a good fit for estimating occupancy.

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FIGURES

Figure 1: Estimates of occupancy and detection probability from the constant model. The black line denotes the mean estimated value for each parameter.

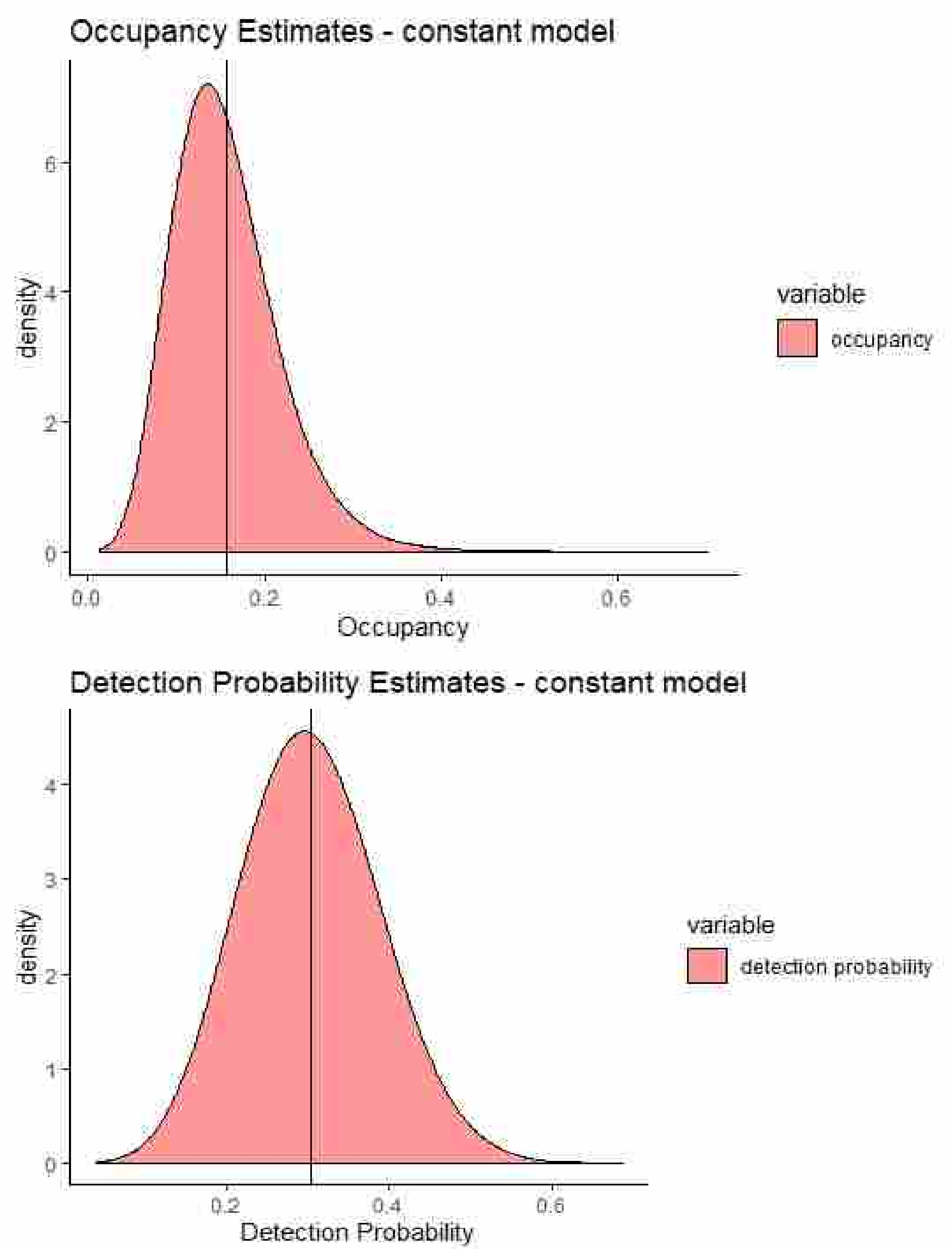


Figure 2: Estimates of occupancy and detection probability from the time-varying model. The black line denotes the mean estimated value for each parameter from the *constant* model. Time-varying models estimate a probability of detection for each survey occasion and results suggests high levels variation in probability of detection. Note that during the sixth occasion, the model fails as there were not enough mountain goat encounters.

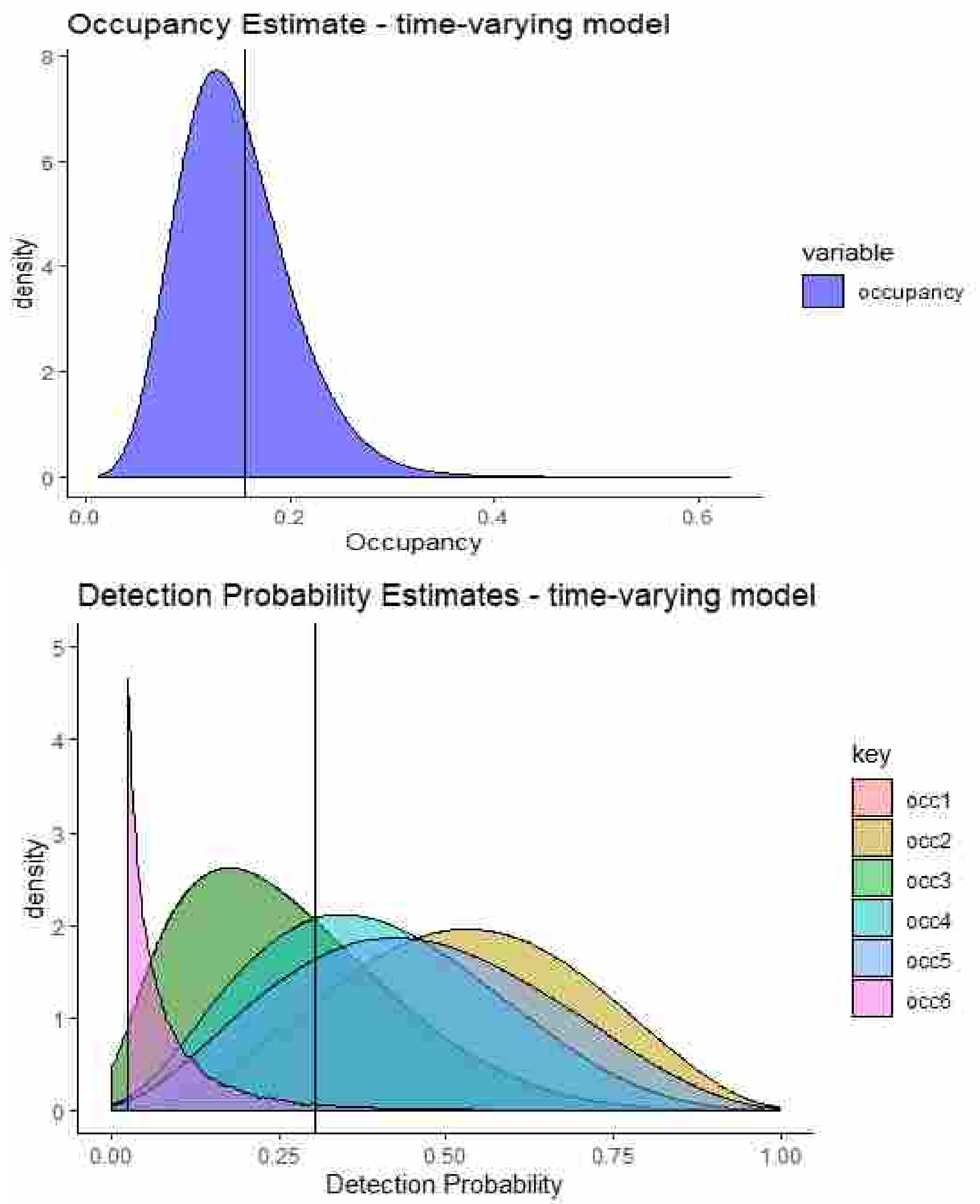
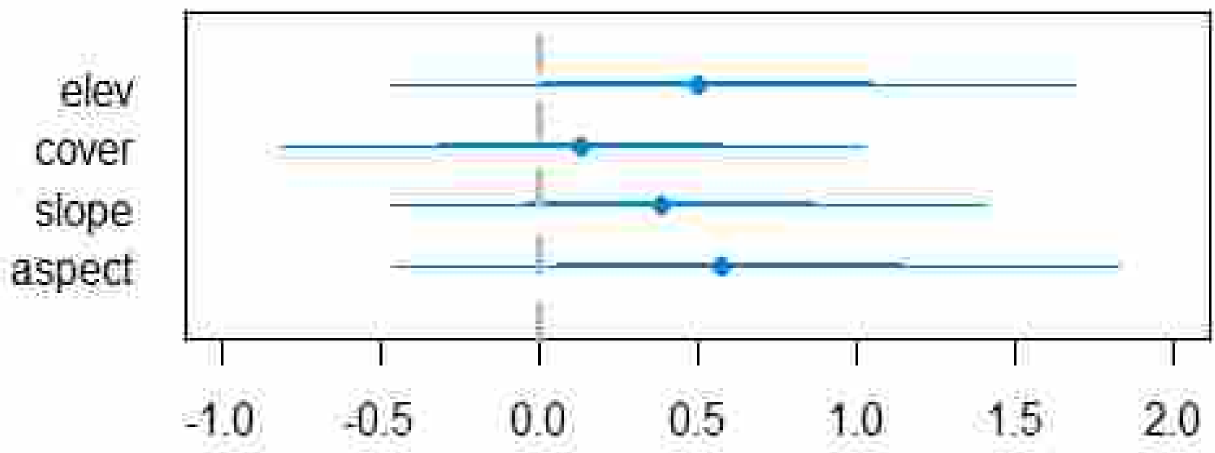


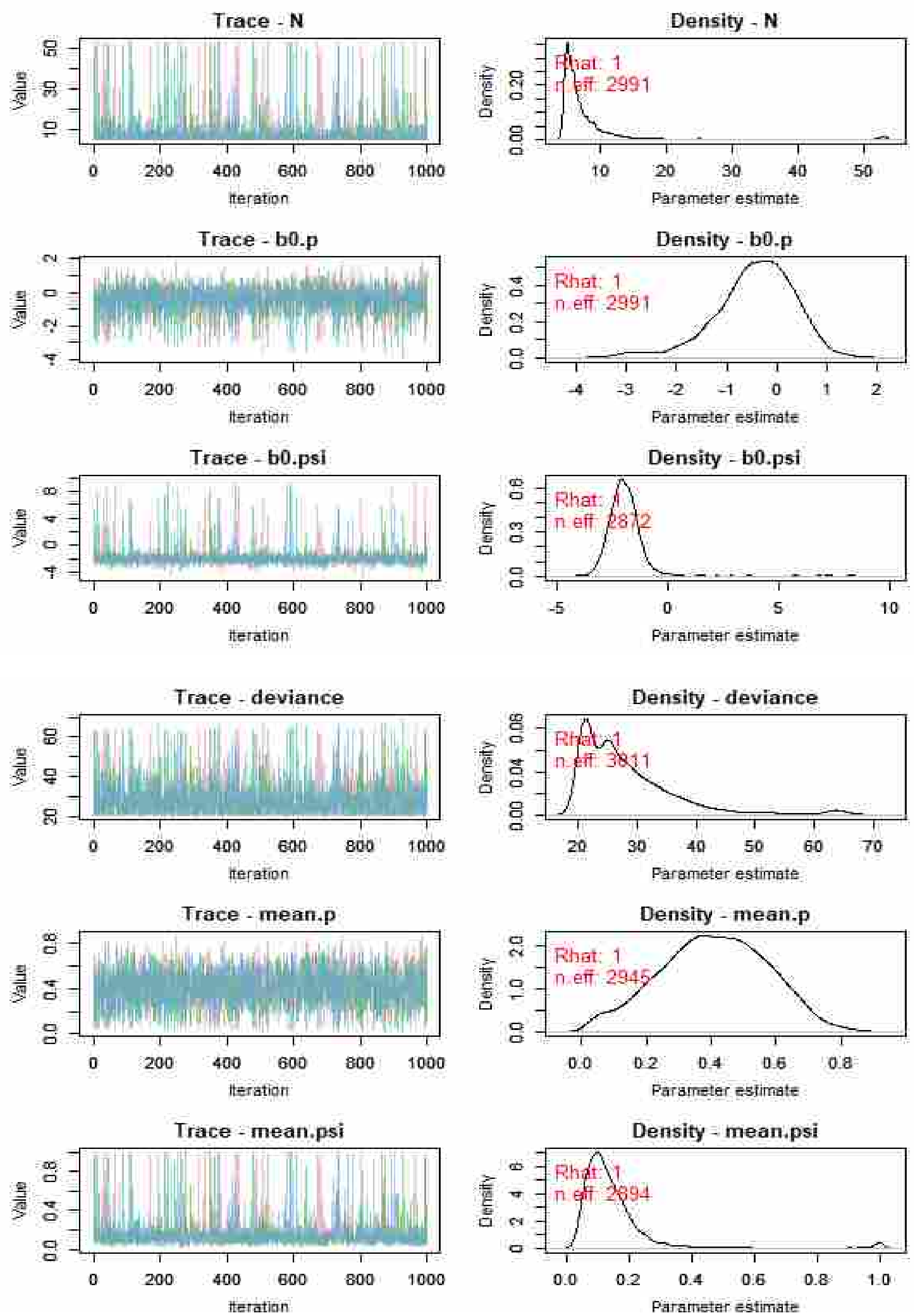
Figure 3: Parameter estimates for spatial covariates in blue (elevation, cover, slope & aspect). The x-axis shows values for various spatial covariates. The dashed gray line denotes zero intercepting the x-axis and demonstrates little to no correlation between occupancy and spatial covariates.



2-Periods Model Results					
param	**mean**	**sd**	**2.5%**	**97.5%**	**Rhat**
July					
N	**8.1691742**	7.3366355	5.0000000	30.2469344	1.001004
b0.p	**-0.4385291**	0.8155084	-2.5182069	0.8889591	1.001775
b0.psi	**-1.8293770**	1.2977347	-3.1598895	0.3273555	1.000554
mean.p	**28.5191418**	8.6407668	20.7381023	55.1184618	1.000811
mean.psi	**0.4090697**	0.1636173	0.0745910	0.7086750	1.001659
deviance	**0.1541625**	0.1459924	0.0407034	0.5811119	1.000553
August					
N	**6.8392060**	8.0003042	4.0000000	40.0000000	1.000998
b0.p	**-0.1694423**	1.0572002	-2.8844126	1.6057116	1.000998
b0.psi	**-2.1186252**	1.4432034	-3.6337679	1.1270177	1.001002
mean.p	**19.7534324**	8.1669209	13.4641749	48.3076174	1.000998
mean.psi	**0.4733264**	0.2060182	0.0529295	0.8328151	1.000998
deviance	**0.1290327**	0.1560697	0.0257366	0.7552881	1.000998

Table 1: Results from occupancy estimates from 2 temporal periods (July and August). Here, we estimated occupancy as it varied temporally. It is clear from Figure 4 that there are various measures of model convergence. In Figure 4, we show trace plot results because the models clearly do not converge suggesting that these results are insufficient in modelling occupancy.

Figure 4: Trace plot and posterior density plot results from occupancy estimates from July only. We estimated occupancy from 2 temporal periods (July and August) to determine if mountain goat occupancy varied temporally. It is clear from Table 1 that there are various measure of model convergence and here we demonstrate that models did not converge despite an acceptable R-hat value. Additionally, we do show trace plot results because they also do not converge.



Time-varying Model Results					
	mean	**sd**	**2.5%**	**97.5%**	**Rhat**
N	**7.7804**	1.2811	7.0000	11.0000	1.001
b0.p[1]	**-1.2199**	0.9367	-3.2386	0.4631	1.001
b0.p[2]	**0.1176**	0.8414	-1.5102	1.8192	1.001
b0.p[3]	**-1.2178**	0.9359	-3.2404	0.4556	1.001
b0.p[4]	**-0.4991**	0.8306	-2.1876	1.0930	1.001
b0.p[5]	**-0.2149**	0.9019	-2.0151	1.5616	1.001
b0.p[6]	**-6.0502**	2.3673	-9.8011	-1.6280	1.001
b0.psi	**-1.8264**	0.4418	-2.7359	-1.0006	1.001
deviance	**53.3419**	6.0921	45.5077	68.2913	1.001
mean.p[1]	**0.2623**	0.1534	0.0377	0.6137	1.001
mean.p[2]	**0.5248**	0.1809	0.1809	0.8605	1.001
mean.p[3]	**0.2626**	0.1532	0.0377	0.6120	1.001
mean.p[4]	**0.3936**	0.1723	0.1009	0.7489	1.001
mean.p[5]	**0.4544**	0.1898	0.1176	0.8266	1.001
mean.p[6]	**0.0202**	0.0479	0.0001	0.1641	1.001
mean.psi	**0.1468**	0.0540	0.0609	0.2688	1.001

Table 2: Time-varying model results demonstrate detection probability as it varies through time. The table shows a disparate detection probability for each sampling of the 6 sampling occasions. Similar to estimates of occupancy as it varies temporally, we find that our time-varying model does not converge when measuring variation in detection probability. The distinct decline in detection probability in the last survey occasion (mean.p[6]) suggests uncertainty in model results. Furthermore, MCMC posterior trace plots and posterior density plots present lack of convergence similar to that of Figure 4.

Constant Model Results

	mean	sd	2.5%	97.5%	Rhat	n.eff
N	**8.3054**	1.8154	7.0000	13.0000	1.001	190000
b0.p	**-0.8633**	0.4173	-1.7485	-0.1055	1.001	110000
b0.psi	**-1.7527**	0.4589	-2.6822	-0.8740	1.001	290000
deviance	**58.0523**	6.3104	51.8014	73.9871	1.001	190000
mean.p	**0.3038**	0.0836	0.1482	0.4737	1.001	110000
mean.psi	**0.1567**	0.0599	0.0640	0.2944	1.001	290000

Table 3: Results from the constant model. This model was evaluated using Rhat, effect size, MCMC model outputs and DIC.

Elevation Model Results

	mean	sd	2.5%	97.5%	Rhat	n.eff
N	**8.485**	2.640	7.000	14.000	1.006	6900
b0.p	**-0.881**	0.435	-1.797	-0.109	1.001	16000
b0.psi	**-1.607**	0.631	-2.631	-0.632	1.044	1900
b1.psi	**0.530**	0.568	-0.466	1.689	1.002	22000
deviance	**58.499**	7.046	51.802	75.369	1.002	16000
mean.p	**0.301**	0.085	0.142	0.473	1.001	13000
mean.psi	**0.178**	0.082	0.067	0.347	1.001	16000

Table 4: Results from the elevation model. This model was evaluated using Rhat, effect size, MCMC model outputs and DIC.

Forest Cover Model Results

	mean	sd	2.5%	97.5%	Rhat	n.eff
N	**8.458**	2.134	7.000	14.000	1.001	29000
b0.p	**-0.883**	0.429	-1.798	-0.111	1.001	130000
b0.psi	**-1.798**	0.493	-2.776	-0.865	1.001	31000
b2.psi	**0.124**	0.470	-0.810	1.026	1.001	160000
deviance	**58.528**	6.796	51.802	75.505	1.001	42000
mean.p	**0.300**	0.085	0.142	0.472	1.001	100000
mean.psi	**0.152**	0.064	0.059	0.296	1.001	50000

Table 5: Results from the forest cover model. This model was evaluated using Rhat, effect size, MCMC model outputs and DIC.

Slope Model Results						
	mean	**sd**	**2.5%**	**97.5%**	**Rhat**	**n.eff**
N	**8.616**	3.509	7.000	14.000	1.017	1800
b0.p	**-0.889**	0.453	-1.840	-0.107	1.003	4800
b0.psi	**-1.617**	0.822	-2.659	-0.644	1.066	990
b3.psi	**0.405**	0.573	-0.471	1.415	1.031	4500
deviance	**58.672**	7.706	51.802	76.544	1.006	3300
mean.p	**0.300**	0.086	0.137	0.473	1.005	3400
mean.psi	**0.174**	0.093	0.065	0.344	1.002	7500

Table 6: Results from the slope model. This model was evaluated using Rhat, effect size, MCMC model outputs and DIC.

Aspect Model Results						
	mean	**sd**	**2.5%**	**97.5%**	**Rhat**	**n.eff**
N	**8.653**	2.924	7.000	15.000	1.002	16000
b0.p	**-0.902**	0.451	-1.886	-0.114	1.001	35000
b0.psi	**-2.057**	0.621	-3.299	-0.965	1.001	12000
b4.psi	**0.617**	0.698	-0.458	1.831	1.005	16000
deviance	**58.939**	7.663	51.802	77.951	1.001	27000
mean.p	**0.297**	0.087	0.132	0.471	1.001	28000
mean.psi	**0.127**	0.071	0.036	0.276	1.001	26000

Table 7: Results from the aspect model. This model was evaluated using Rhat, effect size, MCMC model outputs and DIC.

<u>APPENDIX I</u>: PALISADES STUDY AREA MAP

APPENDIX II: INDEPENDENT DOUBLE-OBSERVER FIELD PROTOCOL

BY: MOLLY MCDEVITT, JUNE 2019

The most common method that Mountain Goat Monitoring Crew will use to survey mountain goats is called the **Independent double-observer method**. The independent component simply implies that each observer will conduct their own survey without communication with your partner. This method is a regularly implemented technique for estimating a variety of species population sizes. In this project, we aim to adapt this method to a system and species in a way that it has not been utilized to estimate population. This is *really* cool! With the development of a method that is novel to mountain goat population surveying, there will be some kinks to work through. With that, I ask for patience and feedback to improve the technique. Thank you!

How it works:

Each observer pair will have a set of grid cells to survey each day (see Palisade Mountain Goat Study Area map p.5). Each cell will have a minimum of 2 observation points (OPs). Surveys of these cells are conducted in teams of 2 an each observer will have their own OP from which they survey from. These OPs will be separated in such a way that each observer obtains a different viewshed of the cell. Observers will need to communicate via radio to determine when each individual has reached their OP as some OPs will take longer to travel to than others. Know the label of each OP regardless of whether you are establishing a new OP or simply revisiting one. Make sure you have thought about your route to each OP ahead of time as terrain can be difficult to navigate and the viewshed can be different than expected. Once an observer has reached an OP, move around to improve viewshed as needed. OP coordinates are reference locations and observers can move up to 50 meters from the reference point. Finally, **survey for a minimum of 20 minutes** per OP.

Make a plan. Be safe. Look for goats.

All survey and observation data will be collected on the Survey123 data collection app (see Data Collection with Survey123 above for more information).

Preparing for a cell survey

1) Know your list of cell OPs to survey for each day (as a team and as an individual observer).
2) Plan route to OPs accordingly.
3) Identify who Observer 1 and Observer 2 is.
4) Communicate with one another to determine when each observer has reached their OP. Length of survey does not need to be equal, this is simply for communication with one another about where you are in the survey process.
5) Upon arrival to an OP, each observer will proceed with one of the following:
    - Establish a new OP *and* Survey a cell

- Establish a new OP if your current OP does not already exist (the same goes for any OP within in a 50 meter radius).

OR

- Survey a cell

Establish a New Observation Point (OP) Form instructions

If an observation point (OP) has not been establish for a cell (*i.e.* we have not surveyed this cell before or we have discovered a new/improved OP), then once you arrive to this *new* OP, you will open Survey123 and select "Establish new OP". At the start of the field season, and any time a cell is surveyed for the first time, a new OP needs to be established. *Make sure to record and label the new point correctly in your GPS.* Once OPs have been established for each cell and we begin to repeat cell surveys, we will no longer need to fill this form out when surveying a cell.

Note that an OP includes the 50 meters within the recorded coordinates.

1) Observer Name: your name – the one filling out this form.
2) Date and start time of survey – This should automatically be filled out in Survey123.
3) Cell ID – For 2019 surveys, 1 – 70 (these will remain constant throughout a season.
4) OP ID – Observation point ID. This identifies which OP with respect to THAT cell you are surveying from: A, B, C, D, E, F (this would be 6 points for a single cell and will vary between cells depending on the complexity of the terrain in THAT cell).
5) GPS ID -- which GPS are you using to record your OPs and observations from (1 – 6)
   a. Datum – Check to make sure that the Datum is set to the appropriate one – WGS84.
   b. Record coordinates in GPS for format 01A or 12B
6) OP latitude – Your OP's latitude
7) OP longitude – Your OP's longitude
8) Do you want to survey a cell now? – Confirm that you want to survey a cell now and the form will appear.

Note: Hard copies of this form are not available as the critical information can be recorded in a GPS (Cell ID, Point ID, GPS ID, Coordinates and Date collected).

Cell Survey Form instructions

9) Observer Name: Your name – the one filling out this form.
10) Date and start time of survey – This should automatically be filled out in Survey123.
11) Observer ID – Are you Observer 1 or Observer 2? This can *vary from cell to cell*, but will be the *same within a cell survey*, no matter the number of OPs a cell has.
12) Cell ID – For 2019 surveys, cell IDs will fall between 01 and 70 (these will remain constant throughout a season).

13) OP ID – Observation point ID. This identifies which OP with respect to THAT cell you are surveying from: A, B, C, D, E, F (this would be 6 points for a single cell and the number will vary between cells depending on the complexity of the terrain in that cell).
14) GPS ID -- which GPS are you using to record your OPs and observations (1 – 6)
    a. Datum – Check to make sure that the Datum is set to the appropriate one – WGS84.
15) Number of groups of goats detected -- Fill out 0 if you do not detect goats during a cell survey.
16) Confirm your information – YES!
17) End of survey time – When did you finish surveying your cell?
18) Notes: Add 'em if you at all think that I cannot read your mind.

Once your survey is complete, check with you partner to determine how much more time, if any, they need to complete their survey.

IF goats are observed during a cell survey by only one observer:

- Once both observers have completed their surveys, ask one another (while you are both still at your respective OPs) if you have goat(s) in view.
- If *one* observer has goats in view and the other does not, have the observer *without* goats join the observer *with* goats. **However! Do not tell them how many**! Just point out the goat(s) general direction.
    - When the observers are together and have goats in view, they will conduct independent counts of the goat(s). **This is key for estimating observer detection probability and estimating misidentification rates of males and female mountain goats*.**
      * Please ask me questions about this if you have them. This is a cool parameter estimation step in this research that is pretty fun to learn about.
    - The observer who did *not* detect goats initially will fill out **Record an observation** form separate from their Cell Survey form. **Please add Notes to describe the situation in both observers' forms**.

Definitions:
**OP = Observation Point*
***MG = Mountain goat*
****Mountain goat group is >= 2 MG within 100 meters.*
*****Kid is young of the year – born summer of 2019*
******Yearling is a MG born the summer before (summer 2018)*

CELL SURVEY FORM

Cell ID:	Observer Name:	Observer ID:	Date: _____ / _____ / 2019
OP ID: ________	OP Latitude: 43. _______________		OP Longitude: -111. _______________
GPS ID: (*Circle one*) **1 2 3 4 5 6**	Number of mountain goat groups detected: __________		Start time: ____:____:____ End time: ____:____:____
Notes (DID YOU FILL OUT AN OBSERVATION FORM IF NUMBER OF GOAT GROUP IS > 0??):			

Cell ID:	Observer Name:	Observer ID:	Date: _____ / _____ / 2019
OP ID: ________	OP Latitude: 43. _______________		OP Longitude: -111. _______________
GPS ID: (*Circle one*) **1 2 3 4 5 6**	Number of mountain goat groups detected: __________		Start time: ____:____:____ End time: ____:____:____
Notes (DID YOU FILL OUT AN OBSERVATION FORM IF NUMBER OF GOAT GROUPS IS > 0??):			

Cell ID:	Observer Name:	Observer ID:	Date: _____ / _____ / 2019
OP ID: ________	OP Latitude: 43. _______________		OP Longitude: -111. _______________
GPS ID: (*Circle one*) **1 2 3 4 5 6**	Number of mountain goat groups detected: __________		Start time: ____:____:____ End time: ____:____:____
Notes (DID YOU FILL OUT AN OBSERVATION FORM IF NUMBER OF GOAT GROUPS IS > 0??):			

Cell ID:	Observer Name:	Observer ID:	Date: _____ / _____ / 2019
OP ID: ________	OP Latitude: 43. _______________		OP Longitude: -111. _______________
GPS ID: (*Circle one*) **1 2 3 4 5 6**	Number of mountain goat groups detected: __________		Start time: ____:____:____ End time: ____:____:____
Notes (DID YOU FILL OUT AN OBSERVATION FORM IF NUMBER OF GOAT GROUPS IS > 0??):			

Observation Form instructions

- This form is for any observation of an *individual goat* or *group of goats* observed either *inside* or *outside* of a cell.
- Please note that this "Record an observation" form is to be filled out independent of your partner given you detect an individual goat or group of goats during a cell survey.
- <u>Fill in every spot</u> – *Nothing is left blank.* This means that if you see a group of 10 mountain goats (8 nannies and 2 kids), you will fill out: Total group size: 10 // Adult male: 0, Adult female: 8, Neo: 2, Yearling: 0.
- <u>What is a different group?</u> – A group is considered greater than or equal to *1 mountain goat* within 100 meters of one another. This means if there are 2 goats ~ 90 meters apart from one another (you can eye ball this), this is 1 group of goats.

For observations made *within* a cell:

- Please fill out "Survey a cell" form in Survey123 first.
- Within this "Survey a cell" form, you will select the <u>number for groups</u> of goats detected in the cell (regardless of 1 individual or multiple goat groups). This will automatically add space to include separate observations for the number of groups you detect within the cell.

For observations made *outside* a cell:

- Simply fill out "Record an observation" form in Survey123.

1) Observer Name: Your name – the one filling out this form.
2) Date and start time of survey – This should automatically be filled out in Survey123
3) Group in cell? – This is for redundancy in the data.
    a. If "Yes", then there is a "Survey a cell" form filled out with the associated cell containing the goats.
    b. Obviously, if "No", then you are recording an observation and no associated cell data will be collected.
4) Adult female: Individuals > or = 2 years old (born summer 2017 or earlier). Estimate the number of females in the group. 0 if none detected. Nothing is left blank.
5) Adult male: Individuals > or = 2 years old (born summer 2017 or earlier Estimate the number of males in the group. 0 if none detected. Nothing is left blank.
6) Yearlings: Individuals 1 year old (born summer 2018). 0 if none detected. Nothing is left blank.
7) Kids: Individuals 1 year old (born this summer 2019). 0 if none detected. Nothing is left blank.
8) Total group size: Will automatically update when you enter the above values for the number of individuals in the group. Make sure it matches what you see.
9) Observer latitude: Your latitude.

a. If observation is outside of a cell survey, record this point in the GPS as PalNA – no need to record the label of the OP if the observation is in a cell as the associated information is recorded in the Cell and Point ID.

10) Observer longitude: Your longitude.
11) Estimated distance to goat(s): If you have a range finder, use it and take an average of 3 distances. Otherwise, use your GPS or map to estimate straight line distance to the goat(s).
12) Bearing to goat(s): Use compass to get bearing in degrees. Include declination. For Palisades ~ + 11 degrees (+ means to the east).
13) Estimated goat(s) latitude: Use your GPS/map to estimate goat(s) latitude. You do not need to label this location in the GPS.
14) Estimated goat(s) longitude: Use your GPS/map to estimate goat(s) longitude. You do not need to label this location in the GPS.
15) Observation time: What time did you detect the goats?
16) Notes: Add 'em if you at all think that I canNOT read your mind.

MOUNTAIN GOAT OBSERVATION FORM:

Observation Form

Double Observers Team: ______________ , ______________

Observation type: (*Circle one*) **Inside survey cell** **Outside survey cell**	Date: _____/_____/ **2018**	Cell ID: (PAL_NA *if not in cell*) ______	Observer ID: (*Circle one*) **1 2 Other** (Notes)
	Time of detection: _____ : _____	Point ID: (NA *if not in cell*) ______	GPS ID: (*Circle one*) **1 2 3 4 5 6 Other** (Notes)
Total group size:	Goat individuals: (*Unk sex for all neonates/yearlings*) **Adult male** _____ **Adult fem** _____ **Yearling** _____ **Neo** _____		Observation point: (*Lat/Long*) **43.** ____________, **-111.** ____________
General location:	Distance to group: (*meters*) ______	Bearing: (*degrees*) ______	Estimated goat group location: (*Lat/Long*) **43.** ____________, **-111.** ____________
Notes:			

Observation type: (*Circle one*) **Inside survey cell** **Outside survey cell**	Date: _____/_____/ **2018**	Cell ID: (PAL_NA *if not in cell*) ______	Observer ID: (*Circle one*) **1 2 Other** (Notes)
	Time of detection: _____ : _____	Point ID: (NA *if not in cell*) ______	GPS ID: (*Circle one*) **1 2 3 4 5 6 Other** (Notes)
Total group size:	Goat individuals: (*Unk sex for all neonates/yearlings*) **Adult male** _____ **Adult fem** _____ **Yearling** _____ **Neo** _____		Observation point: (*Lat/Long*) **43.** ____________, **-111.** ____________
General location:	Distance to group: (*meters*) ______	Bearing: (*degrees*) ______	Estimated goat group location: (*Lat/Long*) **43.** ____________, **-111.** ____________
Notes:			

Observation type: (*Circle one*) **Inside survey cell** **Outside survey cell**	Date: _____/_____/ **2018**	Cell ID: (PAL_NA *if not in cell*) ______	Observer ID: (*Circle one*) **1 2 Other** (Notes)
	Time of detection: _____ : _____	Point ID: (NA *if not in cell*) ______	GPS ID: (*Circle one*) **1 2 3 4 5 6 Other** (Notes)
Total group size:	Goat individuals: (*Unk sex for all neonates/yearlings*) **Adult male** _____ **Adult fem** _____ **Yearling** _____ **Neo** _____		Observation point: (*Lat/Long*) **43.** ____________, **-111.** ____________
General location:	Distance to group: (*meters*) ______	Bearing: (*degrees*) ______	Estimated goat group location: (*Lat/Long*) **43.** ____________, **-111.** ____________
Notes:			

*** IF ANIMALS OBSERVED, please attach this Observation Form to the appropriate Cell Survey sheet ***

NOTHING IS LEFT BLANK!!!!

APPENDIX III: CAMERA TRAP FIELD PROTOCOL

CAMERA SITE SELECTION – MOUNTAIN GOAT EDITION

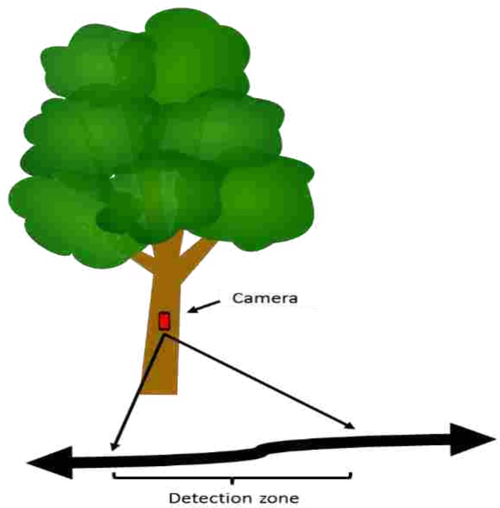
D. Ausband, IDFG, April 17, 2018
Modifications for mountain goat cameras by M. McDevitt June, 2019

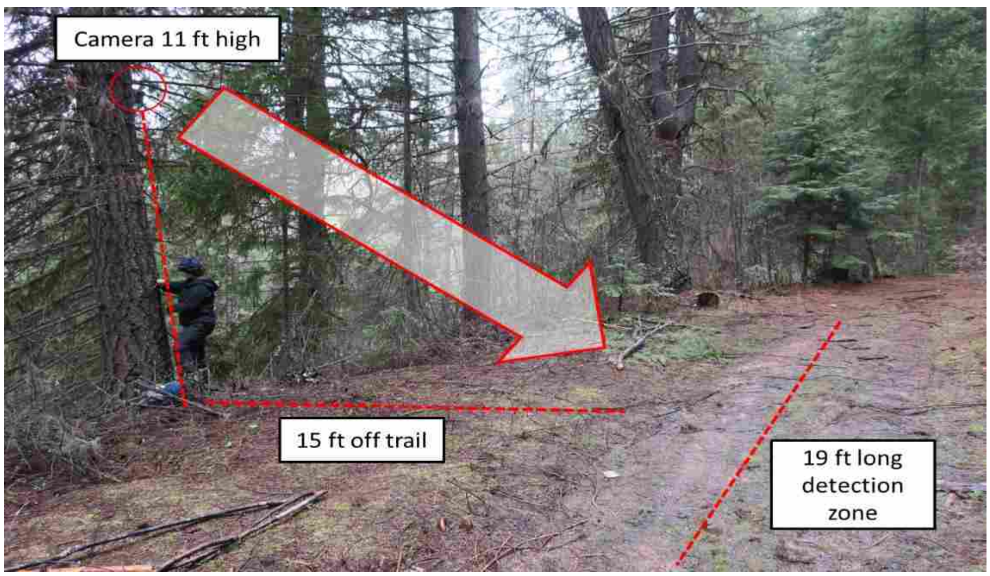
1) You can place the camera anywhere within 500 x 500 meter cell. This provides flexibility for you to use your on-the-ground knowledge to find an ideal location for the camera station. Remember that these mountain goat cameras are set on a *motion sensor and time lapse setting*. This means that cameras must be placed to capture photos of animals both moving in front of the camera AND animals that will not trigger the camera but will still be captured in the photo frame – potentially up to 500 meters away.

2) Ideally, within that 500 x 500 meter cell there will be an open space (meadow, cliff band, open slope, mountain face) OR hiking trail/game trail to use for camera station placement. If open slopes are not available, junctions of trails are good places for camera station deployment provided you capture the junction with the camera's detection zone (the "walk-test" – see below - will let you know if you've adequately covered the area).

3) Any limbs, branches and tall brush that are directly in front of the camera should be cut and removed. Envision wind and the potential for vegetative growth when choosing what to cut. Using the “walk-test” and shaking branches is a good way to test if a branch will yield false detections. Theft has been minimal. Placing cameras high in trees and locking them deters most theft so be liberal about cutting away limbs and branches that may interfere with camera images and flash.

4) Placing the camera several feet off the trail or road yields a larger detection zone. Trees (or fence posts in some Regions) right along the edge of the trail or road will have a smaller detection zone. Place the camera as far off the trail as you can (up to 25 ft) as long as ground vegetation and trees are not obstructing the camera’s detection zone. In most field settings, you should be able to place your camera 10-20 ft off the trail or road yielding a detection zone that is 12-16 ft in length.





An example of a camera station with an adequate detection zone.

Camera station protocol

1) Cameras are deployed on a grid system across the study area beginning June 10, 2019. Cameras are provided by research are programmed with the proper settings and passcode, 2264. Python locks provided by research use a 3918 key. We will install a 32 GB or 64 GB memory card and adjust settings for 3 pictures per trigger event, "Rapidfire", no delay between triggers, high sensitivity, high resolution (3.1 MP), and "balanced" night mode.

2) Cameras are deployed at sites that will maximize ability to capture photos of mountain goats. Cameras should face open slopes, open meadows, or cliffs that could likely host mountain goats – remember that we are also place cameras on a timelapse setting (photos every 15 minutes from 0530 and 2130 to capture images of animals that are too far away to trigger the motion sensor yet still in the photo frame. Second best option will be facing a hiking or game trail to capture animals moving in front of the camera – this applies the motion sensor setting. Both are helpful.

   Note: When placing cameras that face uphill at a cliff or an open mountain slope, the detection zone can be difficult to find. If you cannot perform a "walk test" because the camera if facing uphill in such a way that is too steep, it is OK. Since timelapse photos are ideal for capturing images of mountain goats, the motion sensor trigger (and "walk test" function) can be difficult to capture. Again, this is OK as this camera will be a timelapse camera more than a motion triggered camera.

3) Heavily used trails are not ideal because of false detections (vehicles, people) and increased chance of theft. If this is your only option, be discrete with the camera placement. Use your judgement.

4) When possible, cameras should be deployed at a height >6 feet on a tree that is >6 inches in diameter. Small trees sway in the wind leading to false detections. If you must use a small tree you can cut the top and most branches off the tree to create a "fence post" that will not sway in the wind. Generally, at a height of >6 feet, cameras will need to be angled downward slightly to capture movement on the trail or road below. If facing upslope, the camera will need to be dramatically angled upwards. We provided tree-mounts screw-in that screw into trees for this purpose. Be sure all screws on mounts are tight! If you do not have a mount, placing a stick between the top of the camera and tree will work. If you are in an area without trees, mounting the camera on a fence post or using a t-post is recommended. Sage will sway in the wind and is not an ideal camera mount.

5) If on a trail, cameras should be several feet off of the road or trail. Junctions are best. Vegetation that could interfere with the camera should be removed. We recommend carrying a collapsible saw.

Example photo where obstructing vegetation was not removed and detections at night were diminished.

6) Once camera is affixed and positioned properly, you should test it using the "walk test" in the Reconyx menu. The red light on the front of the camera will flash to let you know where the detection zone is for the current camera position. Crawling or using a very low, stooped walk in front of the camera is recommended for optimal results. Ideally, your detection zone should be 15-20 feet long. Please record the length (meters) of your detection zone on the data form. Once you're satisfied with your detection zone you can simply leave the camera after you have locked the cable. After 2 minutes of no further walk test detections the camera will arm itself automatically.

7) Please let the camera take a photo of you holding a piece of paper (e.g., the back of your data form) that has the cell ID and camera ID number written on it. Ensure you are reasonably close to the camera when doing this (a few feet). This helps ensure data quality when memory cards become separated from cameras.

8) Please record information about the camera station location on the data form (attached p. 5).
9) Return after August 15 to retrieve the camera.
10) Please walk through the camera's detection zone when you retrieve the camera. Images taken during retrieval provide assurance that the camera was still working properly.

Thank you for all your efforts!!!

2019 mountain goat camera station data form

Name(s):	GMU: 67
Date deployed:	Grid cell ID number:
Camera ID number:	Memory card ID number:

Camera location (lat/long): 43. ____________, -111. ____________

Camera capture distance (measured from base of tree and estimate farthest point in viewshed) meters:

Length of Detection Zone: feet: inches:

Camera height: feet: inches:

Date camera retrieved:	Camera still functional? Y/N (if no, please comment)

Did you perform a "walk test" after securing the camera? Y/N

Removed obstructing vegetation? Y/N

Did you take a photo of the camera & grid cell number written on paper? Y/N

Site characteristics

Facing hiking trail/game trail Facing cliff band/open slope

Facing meadow Facing forest

Habitat type:

Alpine (at/above treeline) Sup alpine meadow/forest Mtn. forest (Doug fir/pine)

Deciduous forest (aspen/cottonwood Xeric (sage/open)

Additional comments/sketch about camera location that would help someone else find it:

APPENDIX IV: CAMERA TRAP PHOTO ANALYSIS PROTOCOL
BY: KAITLYN STRICKFADEN, JUNE 2019

Getting started with Timelapse2

1) Download the Timelapse2 software from http://saul.cpsc.ucalgary.ca/timelapse/pmwiki.php?n=Main.Download2. Unzip the folder. Click on the "Timelapse2" application to start Timelapse2. It must stay in that folder with the rest of the files in order to work. If you want to make it easier, create a desktop shortcut.

2) **Copy and paste the template document** into a folder containing the images you want to analyze. **Every folder (IDFG2827 – IDFG2916) must have its own copy of the template.**

3) Open Timelapse2. Go to **"File"** and select **"Load template, image, and video files."** Find the folder containing the images you want to analyze and **click on the template file** in that folder.

4) Timelapse2 will read in the images. This may take a while.

5) Once the images have been loaded in, fill in the following three fields:
    a. **"Viewed By"** with your name.
    b. **"Date Processed"** with the date in the format "mm/dd/yyyy" (ex; 01/19/2019 or 10/02/2019)
    c. **"Cell Number"** with the PAL number shown by the technicians setting up the camera. This will probably not be the first photo in the camera, so scroll through photos until you find it. Otherwise, you can find the cell number in a spreadsheet in the Box folder called "9_4_cam_data_backup".

6) Fill in these fields on all photos by right-clicking on the field and selecting either **"Copy forward to end"** or **"Copy to all."**
    a. The "Copy forward" option is helpful for a lot of things. For instance, if you have 1000 pictures in a row of fog, then change the Operating State to "foggy weather" and copy that value forward until the weather clears up. Then change the operating state back to "normal" and copy it forward.

7) When you are done looking through a set of photos, go to "**File"** and select **"Export data for this image set as a .csv file"** to create a CSV containing the data.

8) Go to the folder containing the images you just reviewed and find the CSV file.

9) **Copy the CSV file** and **paste it into the "CSV" folder** in the "2019 MoGo CamTraps" folder.

10) **Rename the CSV** so it matches the name of the camera.

11) Copy a template into a new folder and do it all again!

Camera Operation

12) Fill in the **Operating State** for every photo as follows:
    a. **"maintenance"** when technicians are setting up or taking down the camera (generally right at the beginning and right at the end).
        i. NOTE: you don't have to fill in a "Human" count during maintenance photos.
    b. **"normal"** for normal camera operation.
    c. "malfunction" when there is some kind of electronic error with the camera.
    d. "tilted" when the camera is bumped by something but the original field of view is still mostly there. Use your best discretion when the camera is shaking in the wind; if it's only shaking a little, don't bother to change the operating state.
    e. "misdirected" when the camera is facing down the tree trunk, is on the ground, or has been tilted enough that the original field of view is no longer visible.
    f. "vegetation obstruction" when a tree or leaf has blocked the field of view significantly.
    g. **"sun"** when light conditions are probably impacting your ability to see an animal. **Applies to both sun glares and to complete darkness. Use your best judgment; if you think you could miss a goat because of the light conditions, use this operating state.**
        i. If an animal motion-triggers the camera at night, then any photos of that animal should be marked as "normal" operating state.
    h. "snow on lens" when snow is blocking your field of view.
    i. "foggy lens" when the lens is fogged up.
    j. **"foggy weather"** when there is fog in the air affecting your ability to see.
    k. "poop/slobber" when a bear or other animal has messed with the camera and left something on the lens that blocks your field of view.

13) The cameras have two settings: motion-trigger and timelapse.
    a. **Motion-trigger** photos are marked with a "1/3", "2/3", or "3/3" at the top-center of the image. This denotes that three pictures were taken because the camera detected motion. Sometimes, this occurs because of vegetation moving in the wind, but it generally occurs when an animal walks by the camera.
    b. **Timelapse** photos are taken every 15 minutes whether or not an animal is in the frame.

Recording data

14) Record any animals or people you see in each photo. **You need to fill in the count for every photo in which the animal appears, whether it's the whole body, the hindquarters, the foot, or the tip of an ear**. For instance, if a mule deer buck appears in 8 photos, then all 8 photos should have a "MD Buck" count of 1.

15) There are two ways to **fill in counts**.
    a. click the up/down arrows in the count fields to add or subtract animals from your count.
    b. click on the name of the count field. The circle next to the name of the field will glow blue. Now you can click on the photo to mark the animals and add one count to your total. **Helpful for marking mountain goats so you can find them later if you need to.** If you need to remove a mark, hold your cursor over the mark and right-click.

16) For most animals, there is just a Count field, but for Humans and Others, there is an additional "What" field for being more specific about the activity or species (Human what = hiker, Other

What = coyote). “Other What” also contains an “unknown” option for when you see an animal but can’t confidently identify it.

   a. Feel free to leave **Comments** if you have an idea of what an animal might be (ex. “either a bobcat or a lynx”). Also leave Comments for bird spp. squirrel/chipmunk spp., or weasel spp. if you happen to know what species it is (Red-tailed Hawk, Golden-mantled Ground Squirrel, etc.), but don’t get too caught up in doing this.

17) More specifics about counts;
   a. For **deer, elk, and moose**:
      i. “Antlerless” categories for adult animals without antlers. This may apply to females or to males that do not have antlers or noticeable pedicles.
      ii. “Calf” or “Fawn” categories for young of the year. If you aren’t sure if it’s an adult or an older calf, then call it “antlerless.”
      iii. “Buck” or “Bull” for animals with antlers or noticeable pedicles.
   b. For **predators**:
      i. “Cub”, “Kitten”, or “Pup” for young of the year.
      ii. “Adult” for everything else.
   c. For **humans**:
      i. Fill in “human what” as appropriate.
      ii. Count for every source of disturbance. For instance, three hikers would have a count of 3, but a vehicle driving by would have a count of 1 even if there were three humans in the vehicle.
   d. For **goats**:
      i. “MountGoat” for any age and sex of goat

Other Tips and Tricks

18) Use the wheel on your mouse to scroll out and get a **multi-photo view**. From there, you can use the Ctrl and Shift keys to select several photos. Then you can **fill in fields on several photos at a time**. Ex. For the 8 MD Buck photos from before, rather than have to fill in the MD Buck count on every photo individually, you can go to multi-photo view, select the first photo, hold Shift, click on the last photo to select all 8, then fill in the count of 1.

19) Alternatively, for filling in lots of data at once, you can fill in a count on the first photo, find the last photo, right-click the field, and select **“propagate from last non-empty value to here.”** This tells Timelapse2 to find the last value that isn’t zero and fill in every photo from that one to the one you are currently on with that value. So fill in 1 on the first MD Buck photo, go to the 8th photo, right-click the MD Buck field, and select “propagate from last non-zero value to here, and photos 1-8 will be filled with a count of 1.

20) Timelapse2 has a few options for navigating photos. The arrows below the template allow you to go through photos without having to press the arrow keys (though I like the responsiveness of the arrow keys). A single triangle will go to the next/previous image, the two triangles will slowly cycle through the photos, and the three triangles will quickly cycle through the photos. A triangle with a rectangle next to it will take you to the first or last photo. There’s also a bar above the photos which allows you to scroll through the list of images.

21) A few other fields to know about:

   a. **“Review?”** is for photos that you want someone else to look at
   b. **“Great picture”** is for really cool or funny photos. Also add these photos to either the “Critter pics” or “Goat pics” folders.
   c. **“Unique mark”** is for animals that have collars, ear tags, or some kind of identifiable mark. Check this box for every photo of an animal with a unique mark and write a comment about the mark (“collar”, “ear tag”, “notch in left ear”)

Appendix v: Summary statistics table

2019 Season surveys and observations	Double-observer crew	Camera traps
Total sites surveyed	70	61
Total usable sites for analysis	70	53
Sites with goat detections	7	7
Sites with repeat goat detections	2	5
Max number goats detected in sites	26	23
Number goats detected beyond survey period and survey site*	163	58
Number of survey days	29	24

* For camera traps, this includes photos with goats detected beyond designated survey periods (*e.g.* pictures of goats prior to all camera deployment as analysis only includes photos during which all cameras were on the landscape). For double-observer surveys, this includes goats detected inside and outside of survey sites. Note that no measurable effort can be calculated for goat detections outside of survey sites. Therefore, all goat detections beyond site surveys were collected opportunistically.

Appendix vi: Independent Double-observer Bootstrap Sample Mean and Variance

Sample size	Total abundance mean estimate	Total abundance standard error	Total abundance 95 % credible interval
70	106	12	82 – 130
60	109	18	74 – 144
50	109	28	54 – 164
40	117	46	27 – 207
30	134	77	0 – 285

This table demonstrates the effect of decreasing sample size on abundance estimates and their variance. We used bootstrap sampling to calculate a mean abundance from a subset of samples, using 60, 50, 40, or 30 sites. In addition to calculating a mean abundance estimate per bootstrap sample, we present the bootstrap standard errors and 95% confidence interval around each mean abundance. We truncated confidence intervals that overlapped zero because negative abundances were nonsensical.

APPENDIX VII: FIELD METHODS TESTED AND EXPLANATIONS FOR FIELD METHODS USED FOR MOUNTAIN GOAT ABUNDANCE ESTIMATION

The Mountain Goat Monitoring project proposed a variety of disparate sampling methods that we aimed to test and then compare those that proved effective. First round field tests identified methods that were not feasible given field limitations while other methods proved unsuitable for field sampling and model assumptions. In the end, we identified one method in particular that was logistically feasible in complex and rugged terrain in addition to meeting all field and model assumptions.

The following field methods were tested during the Mountain Goat Monitoring Project:

1) Line-transects through survey sites (both double- and single-observer)
2) Scat collection surveys for DNA analysis and mark-recapture surveys
3) Camera trap surveys
4) Double-observer point count surveys (*observation points outside of survey sites*)
5) Single-observer point count surveys (*observation points outside of survey sites*)

Below we provide a brief description of each method tested and reasons for method selection or removal from the study.

Line-transect surveys

Line-transect surveys were proposed as a usable method because of previous work done by Suryawanshi et al. (2012). Suryawanshi et al. (2012) used line-transects to travel through rugged terrain to estimate mountain ungulate abundance in the Himalaya. Given limited work that aims to estimate abundance of mountain ungulate with non-invasive and ground-based means, we felt that the technique used by Suryawanshi et al. (2012) would be worth testing.

Once in the field and travelling through the Palisades Mountains, it became very clear that line-transects would prove infeasible in complex terrain with the grid-cell size used in this study. Suryawanshi et al. (2012) and the Mountain Goat Monitoring Project also had different sampling designs and in this study, we aimed to survey randomly selected sites rather than travelling through accessible valley drainages – as Suryawanshi et al. (2012) did.

Primary reasons for incompatibility of line-transects and collection of mountain goat count data are as follows:

1) Particularly rugged sites were unnavigable due to terrain hazards (*i.e.* cliffs, rivers, thick underbrush). Because of this, not all sites could be surveyed, thus altering advantages of random site selection.
2) Travel through sites proved extremely time-intensive since observers need to move slowly so as to thoroughly survey the complete site.
3) Travel inside sites often offered less viewshed of a site due to forest cover and cliffs within sites.
4) Increased likelihood of bumping mountain goats from sites due to close proximity to wildlife in 500 meter sites. This alters both detection and violates closure assumptions.

Scat surveys for DNA analysis and mark-recapture surveys

DNA analysis from scat samples was proposed as a joint effort with line-transect surveys through sites. We chose to test this method as Poole et al. (2001) utilized scat surveys for mountain goat abundance estimates and we sought to determine the efficacy to DNA sampling in the our system. The aim with this method was to thoroughly survey each 500 meter grid cell for any mountain goat scat samples. This method proved infeasible for similar reasons as line-transect method *in addition* to high costs of DNA analysis which would prove unsustainable for future monitoring efforts:

Primary reasons for incompatibility of scat surveys to estimate of mountain goat abundance are as follows:

1) Particularly rugged sites were unnavigable due to terrain hazards (*i.e.* cliffs, rivers, thick underbrush).
2) Due to unnavigable areas, there would it exist gaps in survey area, violating a key piece in the efficacy of mark-recapture surveys.
3) Travel through sites proved even more time-intensive than simply collecting count data from inside sites since observers need to move very slowly to thoroughly survey the complete site. Furthermore, recaptures would prove unlikely given the time required to travel to and through each sites.
4) Complete surveys of sites would be very difficult in complex terrain and few sites would provide quality samples for effective individual identification for mark-recapture.

Camera trap surveys

Camera trap surveys were proposed as a method to estimate abundance of mountain goats as a follow up to work done by Moeller et al. (2018). We proposed to use Moeller et al.'s (2018) Space-to-event (STE) model to estimate abundance. This model, while showing lots of potential, did not prove feasible with mountain goats for the following reasons:

1) We are still learning about the assumptions made in the STE model.
2) We found that we did not meet model assumptions in this specific study.

It would be beneficial to revisit this technique in the future as we obtain a better grasp of the model function and field assumptions.

Double-observer point count surveys

We decided to test the independent double-observer point count survey as a useful tool to survey mountain goats because DeVoe et al. (2015) used this field technique to gather population information about mountain goats. In this study, survey sites were a size that allowed us to effectively survey most sites from an average of two observation points. With two observers, the independent double-observer method proved *effective* for the following reasons:

1) With two observers, we found that observations could be more efficient when observers split up and surveyed sites simultaneously from the two observation points.
2) Since the two observation points were spatially distinct, we could obtain survey replication through spatial replication. Spatial replication in surveys was achieved when observer 1's vantage was different than observer 2's with some overlap between the two vantages.
3) Simultaneous and distinct surveys allows the closure assumption be met.

With this approach we were both more efficient with surveys while, more importantly, developing a field method that meets field sampling assumptions.

Single-observer point count surveys

Since we planned to conduct independent double-observer surveys using either line-transects or point count surveys, we wanted to test whether abundance could be estimated in our models with half the field effort using one observer rather than two. Given the most effective method required simultaneous, independent observations from two observers for efficiency and in order to meet closure assumptions, the single-observer method proved ineffective.

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