Tools and Technology Article

A Sightability Model for Mountain Goats

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ABSTRACT Unbiased estimates of mountain goat (*Oreamnos americanus*) populations are key to meeting diverse harvest management and conservation objectives. We developed logistic regression models of factors influencing sightability of mountain goat groups during helicopter surveys throughout the Cascades and Olympic Ranges in western Washington during summers, 2004–2007. We conducted 205 trials of the ability of aerial survey crews to detect groups of mountain goats whose presence was known based on simultaneous direct observation from the ground ($n = 84$), Global Positioning System (GPS) telemetry ($n = 115$), or both ($n = 6$). Aerial survey crews detected 77% and 79% of all groups known to be present based on ground observers and GPS collars, respectively. The best models indicated that sightability of mountain goat groups was a function of the number of mountain goats in a group, presence of terrain obstruction, and extent of overstory vegetation. Aerial counts of mountain goats within groups did not differ greatly from known group sizes, indicating that under-counting bias within detected groups of mountain goats was small. We applied Horvitz–Thompson-like sightability adjustments to 1,139 groups of mountain goats observed in the Cascade and Olympic ranges, Washington, USA, from 2004 to 2007. Estimated mean sightability of individual animals was 85% but ranged 0.75–0.91 in areas with low and high sightability, respectively. Simulations of mountain goat surveys indicated that precision of population estimates adjusted for sightability biases increased with population size and number of replicate surveys, providing general guidance for the design of future surveys. Because survey conditions, group sizes, and habitat occupied by goats vary among surveys, we recommend using sightability correction methods to decrease bias in population estimates from aerial surveys of mountain goats. (JOURNAL OF WILDLIFE MANAGEMENT 73(3):468–478; 2009)

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Informed management of mountain goats (*Oreamnos americanus*) requires accurate information on the status and trends of local populations. Mountain goats appear to be more sensitive to harvest than most ungulate species due to low rates of natality and recruitment and the likely additive effects of natural and harvest mortality (Hebert and Turnbull 1977, Kuck 1977, Smith 1988, Hamel et al. 2006, Festa-Bianchet and Côté 2008). In Washington State, USA, as throughout much of their range, native mountain goat populations have declined in recent decades and harvest has been suspended or curtailed in many populations (Johnson 1983, Glasgow et al. 2003). Current guidelines in Washington recommend restricting harvest to local populations >50 individuals and to harvest ≤4% of populations, although recent findings suggest more conservative limits may be appropriate (Hamel et al. 2006). Consequently, identifying appropriate harvest levels for mountain goats is dependent on unambiguous estimates of population size.

Mountain goat populations are routinely surveyed from helicopters throughout mountain goats' range due to difficulties obtaining representative sample counts in rugged, high-elevation habitats using other methods (Resources Information Standards Committee 2002, Glasgow et al. 2003, Washington Department of Fish and Wildlife 2003). As with all aerial surveys, helicopter counts of mountain goats are biased by the inability of aerial observers to detect all mountain goats present in a survey area. Previous studies have estimated that helicopter surveys typically detect 60–70% of mountain goats present, based on detection rates for marked mountain goats (Cichowski et al. 1994, Poole et al. 2000, Pauley and Crenshaw 2006, Poole 2007) or by comparing to known populations estimated from other methods (Johnson 1983, Houston et al. 1986, Gonzalez-Voyer et al. 2001). Factors influencing detection biases are incompletely understood, but detection may be influenced by group size, animal activity, and vegetation cover (Poole 2007). Hence, long-term monitoring based on raw count data or one correction term (Houston et al. 1986, Cichowski et al. 1994, Poole et al. 2000, Poole 2007) may be misleading if group sizes or animal distribution vary among surveys, particularly if factors that influence sightability change systemically over time (Gonzalez-Voyer et al. 2001).

We considered several potential methods for obtaining unbiased aerial survey estimates of mountain goat abundance. Mark–resight methods use marked animals (e.g., radiocollared or paint-marked) to estimate abundance based on proportions of marked and unmarked animals resighted during aerial surveys (Cichowski et al. 1994, Pauley and Crenshaw 2006). We judged the method impractical for large-scale application to mountain goat surveys due to costs, safety issues, and wilderness concerns associated with the need to maintain a marked sample in the population for recurring surveys, large sample requirements, and the necessity for replicate surveys to adequately model heterogeneity of resighting probabilities (Pauley and Crenshaw 2006). As an alternative to animal marking studies, double-observer methods use observations from 2 independent observers, either on the same or different sampling plat-

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forms, to sight and resight groups for analysis in classic mark–resight analyses (Smith and Bovee 1984, Conn et al. 2004, Udevitz et al. 2006). We judged double-observer methods employing the same aircraft as unsuitable because of the assumption that observations are independent among the 2 observers, a condition we believed untenable in such highly dissected terrain. Observations of 2 observers from different aircraft are more likely independent but fluidity of group movements in response to aircraft disturbance creates intractable problems in discriminating which groups were sighted by one or both observer teams, as was noted for Dall's sheep (*Ovis dalli*; Udevitz et al. 2006).

Sightability modeling (Samuel et al. 1987) provides an alternative to mark–resight methods. Sightability can be modeled using logistic regression to estimate the probability of sighting groups of animals as functions of covariates hypothesized to influence detection probability. Sightability models can be developed from aerial surveys conducted over groups of animals containing marked individuals or groups that are observed from the ground during the aerial survey and by recording covariates for groups that are both seen and missed by the aerial survey crew. The method was first developed to improve accuracy and reliability of aerial surveys of elk (*Cervus elaphus*) populations in Idaho (Samuel et al. 1987, Steinhorst and Samuel 1989) and has been applied more recently to mule deer (*Odocoileus hemionus*; Ackerman 1988), moose (*Alces alces*; Anderson and Lindzey 1996), mountain sheep (*Ovis dalli*, Udevitz et al. 2006; *O. canadensis*, Bodie et al. 1995), and several other elk populations (Anderson et al. 1998, Cogan and Diefenbach 1998, McCorquodale 2001). No regression-based sightability models have been developed previously for mountain goats, in part due to difficulties associated with obtaining covariates for missed animals in such diverse terrain as mountain goats occupy (Poole 2007).

Our objective was to develop a sightability model applicable to mountain goat surveys in the Cascade and Olympic Mountain Ranges of Washington, so that unbiased population estimates can be derived. Because mountain goats typically move during surveys and are unlikely to be in the same sighting conditions by the end of a survey, we used a combination of ground observers and recent advances in Global Positioning System (GPS) telemetry to obtain covariates for both seen and missed goat groups at the time of over-flight. With the aim of building a broadly applicable model, we examined effects of group size, habitat, and environmental covariates on aerial sightability as well as effects of helicopter type, crew experience, and survey characteristics. Because sightability models assume that all individuals are counted without bias within groups (Cogan and Diefenbach 1998), we also assessed potential biases in determining group size when surveying mountain goats from the air.

STUDY AREA

We conducted sightability trials in mountain goat habitat throughout the Cascade and Olympic ranges in Washington, usually in conjunction with annual population surveys. Survey personnel were typically biologists from state and federal agencies responsible for the area being surveyed and included participants from the Washington Department of Fish and Wildlife, 3 national parks (Olympic, Mt. Rainier, and North Cascades), and 2 Indian tribes (Sauk-Suiattle and Upper Skagit). We divided areas to survey for mountain goats into blocks of contiguous suitable habitat of about 500 ha (Olympics) or a size that we could survey in <30–45 minutes (Cascades). In the Olympics, survey blocks contained all terrain above 1,525 m, whereas in the Cascades, we determined block boundaries on the basis of elevation, habitat maps (Wells 2006), and local expert knowledge. Based on Johnson and O'Neil (2001), surveyed areas were 65% Alpine Grasslands and Shrublands, 22% Montane Mixed Conifer Forest, 8% Subalpine Parklands, 2% Eastside (Interior) Mixed Conifer Forest, and 1% each of Eastside (Interior) Grasslands, Ponderosa Pine and Eastside White Oak Forest and Woodlands, Shrub-Steppe, and Westside Lowland Conifer–Hardwood Forest.

METHODS

Capture and Collaring

We captured 54 mountain goats in representative areas by darting from a helicopter or from the ground (Rice and Hall 2007) or by leg-snaring using a hand-held rope (Stevens 1983, Houston et al. 1994). All captures were in compliance with Washington Department of Fish and Wildlife Policy on Wildlife Restraint or Immobilization (M6003). We fitted captured mountain goats with GPS-equipped collars (Vectronic Plus 4, Berlin, Germany), which were color-coded (black, light blue, red, or yellow) using 3 bands on both sides of the collar. Collars contained a GPS receiver, data storage memory, very high frequency (VHF) beacon, ultra high frequency beacon, accelerometers on the longitudinal and transverse axis of the collar, and radio-modem for data and programming transfer.

Survey Methods

We conducted sightability trials during surveys between 20 June and 24 September, 2004–2007, using 3 helicopter models, Bell Jet Ranger (Bell Helicopter Textron, Inc., Fort Worth, TX), Hughes 500 (MD Helicopters Inc., Mesa, AZ), and Enstrom 480 (Enstrom Helicopter Corporation, Menominee, MI). These helicopters had similar seating configurations and we always positioned crew members with primary observer beside the pilot, secondary observer in the back seat behind the primary observer, and navigator behind the pilot. During surveys, primary and secondary observers were nearly always on the side of the helicopter facing terrain. We conducted surveys under diverse environmental conditions, but we did not fly if cloud cover, fog, or rain obscured a clear view of the ground or if high winds created unsafe flying conditions.

Due to the irregular topography of mountain goat habitat and the diverse terrain and vegetative cover in areas to be surveyed, it was not feasible to adhere to strict flight patterns such as transects. Nor did we judge it economically feasible to maintain a constant flight speed that would be slow enough to survey all terrain effectively. Instead, we standardized survey coverage by specifying that the survey should visually cover the entire block, that flight speed should be maintained between 65 km/hour and 110 km/hour, with multiples passes on contours at 100–300-m intervals.

Prior to the survey, nonsurvey personnel located each GPS-collared mountain goat using standard VHF radiotracking methods. At that time, we reprogrammed each GPS collar remotely to obtain a GPS fix every 10 minutes during days scheduled for surveys in each area. We located radiocollared mountain goats from a fixed-wing airplane flown 300–1,200 m above terrain to minimize disturbance to mountain goats prior to a survey.

We sent ground observers to locate mountain goats within specified survey units and to monitor their movements and group size before, during, and after the survey flight. We instructed ground observers to search for mountain goats within a survey block without disturbing mountain goat activity and movements. If there were many groups available to monitor within a survey unit, we asked ground observers to select a group without collars, where they had opportunity to get a complete count of the group, and a group with low expected sightability (i.e., small Group Size, bedded, presence of Vegetative or Terrain Obstruction). The purpose of this selection was to increase our sample of lower sightability groups. During the survey, at the time of the closest pass of the helicopter to the group, ground observers marked the location of the group on a 1:24,000-scale topographic map and determined the group's coordinates using a transparent overlay grid. Ground observers also judged their estimate of group size as complete, probably complete, or incomplete based on their ability to observe the entire group and surrounding terrain.

We recorded conditions relating to surveys and potential predictors of sightability at 3 levels: for each flight, for each survey block, and for each group of mountain goats observed. For each flight, we recorded crew members' names and functions (i.e., Pilot, Primary Observer, Secondary Observer, and Navigator) and Aircraft type. When starting to survey a block, we recorded Illumination (i.e., high- or low-contrast lighting), Cloud Cover (to the nearest 10%), Sky Conditions (i.e., clear, mostly clear, mostly cloudy, overcast, or fog), Wind Conditions (i.e., calm, light, moderate, or high), Precipitation (none, mist, or light rain) and ambient Temperature. Usually we recorded Temperature at 1,525 m, but if not, we also recorded the altitude at which we recorded it. For each mountain goat group seen we recorded Time, Group Size, and whether the group contained a collared mountain goat (and the color code of its collar). We also recorded Substrate (majority of animals on rock, snow, herbaceous vegetation, or in forest), Vegetative Obstruction (in 5 classes [%]): 0, 1–25, 26–50, 51–75, or 76–100 of the area encompassing a 10-m buffer around the group capable of obscuring observation of a mountain goat by observers in the helicopter), and whether Terrain Obstruction was present within a 10-m buffer around the group at the moment it was first seen. We defined Terrain Obstruction as any landform (typically fissures, caves, overhanging ledges, and other rock formations) capable of obscuring a mountain goat from the air.

During the survey of each block, the navigator monitored coverage of the block and maintained a GPS track of the helicopter flight path using ArcGIS. When a group of mountain goats was sighted, the navigator used a custom Visual Basic for Applications (VBA) ArcGIS script to plot the location and size of the group.

With the exception of the navigator, the survey crew was not informed of the potential presence of collared mountain goats in survey blocks. Upon completing the survey of all blocks that potentially contained a collared mountain goat, the navigator compared the list of collared mountain goats seen during the survey with those expected on the basis of the presurvey fixed-wing flight. By homing on the VHF beacon, we located any collared mountain goats that were not seen during the survey and recorded Group Size. Because mountain goats are easily disturbed by helicopters (Côté 1996, Goldstein et al. 2005), we did not feel confident using the location of the collared mountain goat after the survey to accurately reflect its location when not seen during the survey. Instead, we downloaded the GPS location history from the collar and, using another VBA script with the helicopter flight track and the mountain goat GPS record, found the mountain goat GPS fix corresponding to the beginning of the 10-minute period during which the helicopter and the mountain goat were closest to each other. We considered this the location of the mountain goat when it was not seen. The navigator directed the helicopter to within 10 m of these coordinates, where we recorded the Substrate, Vegetative Obstruction, and Terrain Obstruction as above.

If ground observers were present, we contacted them by 2-way radio after completing a survey of their block(s) and asked them to provide the coordinates and Group Size of the group they observed during the survey. Using the ArcGIS VBA script, the navigator plotted this location and determined if it corresponded to a group seen during the survey. If we determined it was a group missed during the survey the navigator and ground observer directed the pilot to the location of the group where it was missed during the survey and where we recorded Substrate, Vegetative Obstruction, and Terrain Obstruction. For groups that were not seen during the survey, we took Group Size from the ground observer's record.

Analysis

Variable treatment.—We modified several variables prior to analysis. We transformed the Vegetative Obstruction classes into a continuous variable by assigning each observation the value of the mid-point of its range (i.e., from 0, 1–25, 26–50, 51–75, or 76–100 to 0, 13, 38, 63, or 88). We adjusted Temperatures not recorded at 1,525 m to 1,525 m using the environmental adiabatic rate of 1.83° K/100 m (Leeder and Pérez-Arlucea 2006). We rated survey crew members by experience: 0 = flown <5 survey days for mountain goats or other ungulates, 1 = flown <5 survey days for mountain goats but experienced (rated 2 or 3) in aerial survey for other ungulates, 2 = flown 5–10 survey days for mountain goats, and 3 = flown >10 survey days for mountain goats; where a survey day is equivalent to about 4 hours of survey time. We calculated Crew Experience as the sum of the experience of all 4 crew members and treated it as a continuous variable.

When used as independent variables, ordinal variables such as Pilot Experience must be considered as either categorical or continuous. Because the number of experience levels was small (i.e., 4), we considered them categorical. In situations where values of categorical variables had <10 observations (Hosmer and Lemeshow 2000), we combined that value with an adjacent value (for those that were originally ordinal) or a similar value (for truly categorical variables) such that sample size distribution among values was optimized.

We defined survey Intensity as the number of minutes of flight divided by the area (km^2) of the block. In some cases, the intensive effort required to enumerate groups in high vegetative cover resulted in excessively high and inaccurate estimates of survey Intensity and potential for outliers. Consequently, where Intensity was greater than the third quartile + 1.5 times the interquartile range (Moore and McCabe 2006), we set Intensity to missing.

Model development.—Conceptually, we grouped independent variables into 5 categories. Group Size and survey Intensity were their own categories. Vegetation Obstruction, Terrain Obstruction, and Substrate were in the Location category. Illumination, Cloud Cover, Sky Conditions, Wind Conditions, Precipitation, Temperature, and Time were in the Environment category. Aircraft, Pilot, Primary Observer, Secondary Observer, Navigator, Pilot Experience, Navigator Experience, Primary Observer Experience, Secondary Observer Experience, and Crew Experience were in the Flight category.

To reduce the risk of over-fitting (Harrell 2001) we restricted the selection of independent variables to ≤4 from each variable category, on the basis of likely variable redundancy and our expectation of the variable's effect on sightability. Because of its expected importance on sighting probabilities (e.g., Samuel et al. 1987, Anderson and Lindzey 1996, McCorquodale 2001, Udevitz et al. 2006, Poole 2007), we included Group Size in every candidate model. We constrained candidate models further so that number of parameters did not exceed $n/10$, where n equals the lesser of 1) number of groups seen, and 2) number of groups not seen (Peduzzi et al. 1996, Harrell 2001). Due to our limited sample size, we did not consider any covariate interactions.

Our initial assumption was that Group Size had a significant effect on mountain goat sightability. To check this, we repeated the analysis with models in the confidence set and corresponding models without Group Size. We also determined that if models in the 0.95 confidence set included variables from different categories of covariates, we would assess additional models combining variables from those categories. In addition, we retained a model with only a Group Size effect because it was the only covariate available from historic survey data.

For continuous covariates in candidate models, we checked for linear effects under a logit model by dividing each variable into 4–6 groups and examining the plot of the log-odds for each group against the median value in each group (Elswick et al. 1997, Hosmer and Lemeshow 2000). We also checked for association between all variables occurring in the same model and excluded models in which related variables occurred. For comparisons of continuous covariate pairs we used a criteria of $r \geq 0.50$, for continuous–categorical comparisons we considered pairs in an analysis of variance with $R^2 \geq 0.25$ to be related, and for categorical–categorical comparisons, we examined contingency tables to evaluate association.

Imputation of missing values.—Missing values occurred in the collected data (see Results). In performing model selection by information-theoretic methods, available case analysis (Harrell 2001, Horton and Kleinman 2007) is unsuitable because the data set changes among models (Burnham and Anderson 2002). Complete case analysis yields estimates of lower precision and biased parameters estimates unless missing values occur completely at random (Harrell 2001, Schafer and Graham 2002, Horton and Kleinman 2007). Using multiple imputation, multiple analysis on imputed data sets can be combined to create an inference that reflects sampling variability due to the missing values (Schafer 1997, Horton and Kleinman 2007). For these reasons, we used multiple imputation in our analysis.

We used the R program (R Foundation for Statistical Computing, Vienna, Austria) package MICE (van Buuren and Oudshoorn 1999, 2000) to generate multiple imputed data sets. The R package MICE uses the approach of multiple imputation by chained equations, employing a Gibbs sampler to impute missing values from a specified model matrix. Following the advice of van Buuren and Oudshoorn (1999), we specified the imputation model matrix by considering all variables that had a reasonable expectation of being related due to either our expectations about mountain goat behavior or operational relationships. For instance, mountain goat groups are typically smaller in forested terrain, so we included Group Size in the imputation model for Vegetative Obstruction and vice versa. Similarly, time and temperature would be expected to increase together, and should reference each other in the imputation model matrix. On the other hand, we excluded spurious relationships such as Group Size and Pilot Experience. For each covariate, we specified the imputation method according to its type (i.e., continuous variables using Bayesian linear regression, categorical with 2 categories using logistic regression, and categorical with >2 categories using polytomous logistic regression) with the exception of continuous covariates that were bounded (Group Size and

Vegetative Obstruction) where we used predictive mean matching (van Buuren and Oudshoorn 2000).

In multiple imputation, each parameter β is estimated as the mean of the estimated parameter values across imputations (Harrell 2001, Horton and Kleinman 2007). The corresponding variance T of β is calculated as

$$T = (1 - m^{-1})B + \overline{U}$$

where

B is the between-imputation variance,

$$(m-1)^{-1}\sum_{j=1}^{m}\left(\hat{\beta}_j - \overline{\beta}\right)^2,$$

$\overline{U}$ is the average within-imputation variance of β,

$$(m)^{-1}\sum_{j=1}^{m}\hat{U}_j,$$

and m is the number of imputations (Harrell 2001, Kenward and Carpenter 2007).

To evaluate the relationship between number of imputations and the variance of parameter estimates, we examined plots of T as a function of m to evaluate the number of imputations sufficient to produce a stable estimate of parameter variance (T).

As with other parameter estimates, we then averaged Akaike's Information Criterion (AIC_c) for each model across imputations and calculated the difference between these means and their minimum among models as $\Delta\overline{AIC}_c$ and used this for model selection and model weighting.

Model selection.—Although weighted model-averaging can be performed across all candidate models (Burnham and Anderson 2002), there are disadvantages to doing so. Not only are estimation equations more complex than necessary, there is little reason for aerial survey crews to continue to collect data for covariates that have negligible effects on estimation. Consequently, we determined a 95% confidence set of models where, when ordered by $\Delta\overline{AIC}_c$, model weights accumulated to $\geq$0.95 (Burnham and Anderson 2002), and we model-averaged using weights recalculated within the confidence set. To assess goodness-of-fit of the averaged model, we performed the Hosmer–Lemeshow test (Hosmer and Lemeshow 2000) using all observations with no missing values for covariates in the confidence set.

Over- and under-counting.—Sightability models assume that a group, if seen, is enumerated correctly (Cogan and Diefenbach 1998). This may not be the case, especially if terrain or vegetation obscures some animals completely. It is also possible for some animals to be counted twice when enumerating a large group as it fractures with subgroups moving in different directions, as often happens with mountain goats. Thus over-counting and under-counting are both possible.

To test for bias resulting from counting error, we compared Group Size determined by the survey crew (GS_S) with that of Group Size determined by ground observers (GS_G). Because GS_S was occasionally much larger than GS_G, we eliminated from these comparisons all GS_G rated as incomplete, those rated as probably complete where GS_S was $\geq$50% larger than GSG, and those rated as complete where GS_S was $\geq$100% larger than GS_G. For the latter 2 conditions, we judged that the count difference was more likely to have resulted from differences in group delineation (survey and ground crews combined or separated scattered animals into different group designations) than from differences in enumeration of the same actual group of mountain goats.

We then tested whether the slope of the regression of GS_S against GS_G (no intercept) differed from one, after log-transforming both to give a more even distribution of observations across the scale of the comparison. Second, we used a *t*-test (Zar 1996) to test the null hypothesis of $\overline{GS_S - GS_B} = 0$.

Simulations.—We conducted simulations to assess the magnitude of the effect of counting bias on population estimates, to evaluate overall sightability for our mountain goat surveys, and to estimate expected precision of resulting estimates. For these simulations, we used survey records from 127 blocks in 19 areas (i.e., geographic collections of blocks) surveyed in 2004–2007, which consisted of 1,139 groups (205 of which were sightability trials) and 4,799 individuals.

Counting bias modeled by regressing aerial count on ground count in the log scale assumes that bias relative to group size increases with group size and errors were log-normal, implying variability in bias increases with group size. For count bias simulations, we took survey groups as the true group size and drew groups from survey records to simulate surveys of populations of 50 and 100 mountain goats. To compensate for low representation of groups with low sightability in survey records, we weighted drawing by the inverse of the model-averaged detection probability (θ; Steinhorst and Samuel 1989) for each group. For each mountain goat group in each population, we assigned a true sightability based on the group's covariate values and a multivariate normal draw (R package MASS) from the parameter distributions for the averaged model (see Results). We then scored each group in the population as seen if its true sightability was greater than a random uniform (0,1) variable. We then simulated biased aerial survey count for each group 50 times, based on the *t*-distribution of the estimated mean log aerial count for that group size from the bias regression model. Finally, we estimated the population by applying the averaged model to the seen groups for both unbiased and biased group counts and estimated percent bias as $\frac{\overline{biased} - \overline{unbiased}}{\overline{unbiased}}100$ and did this 250 times.

For sightability simulations, we partitioned survey records into groups of low, medium, and high sightability (π groups) because sightability varies geographically with conditions in different parts of mountain goat range. We partitioned survey records by minimizing the sum of squared errors of expected sightability (π) within π groups to form 3 groups while keeping all records from each area together (platform Partition in JMP, v7.0; SAS Institute, Cary, NC). For each

Table 1. Values of continuous covariates in 205 observations of mountain goat sightability in Washington, USA (2004–2007).

Variable	$\bar{x}$	Median	Range	*n* missing
Group Size	8.2	4	1–53	6
Vegetative Obstruction (%)[a]	18.8	13	0–88	7
Temp (° C)	12.1	11	0.8–23.9	6
Time	0848	0805	0600–1600	10
Crew Experience	7.5	8	2–12	0
Intensity (min/km^2)	3.7	3.3	0.7–8.1	8[b]

[a] After transformation to midpoint of class.
[b] Calculated values that qualified as outliers.

Table 2. Observed values of categorical covariates in 205 observations of mountain goat sightability in Washington, USA (2004–2007).

Variable	Values	*n*	%[a]	*n* missing
Terrain	Yes	84	43	9
Obstruction	No	112	57	
Substrate	Snow	9	5	10
	Herbaceous	29	15	
	Forest	33	17	
	Rock	124	64	
Illumination	High	163	82	6
	Low	36	18	
Primary	1	40	20	0
Observer	2	57	28	
Experience[b]	3	108	53	
Pilot	0	42	20	0
Experience	2	14	7	
	3	149	73	
Aircraft	Enstrom 480	25	12	0
	Hughes 500	55	27	
	Jet Ranger	125	61	

[a] % of nonmissing values.
[b] As a consequence of low sample size in one category, we combined the Primary Observer Experience of 0 ($n = 4$) with that of 1 ($n = 36$).

π group and for all surveys, we estimated typical sightability for groups and individuals by averaging expected sightability and dividing the total number of animals seen by the sightability-adjusted estimate.

To assess expected precision of sightability-adjusted estimates we simulated populations to be surveyed for each π group by drawing from the collection of survey records as we did for bias simulations. For each π group, we simulated populations of 25, 50, 100, 250, and 500 mountain goats by drawing from the survey records in that π group, repeating this 350 times for 1–6 replicate surveys. We calculated variance of the estimates using the formulas of Steinhorst and Samuel (1989) and for the average estimate over replicated surveys we added an additional variance term because of the correlation among replicates, which will be the subject of another report. As a measure of precision, we used a confidence interval coefficient of variation (CICV), defined as half the 95% confidence interval divided by the estimate. We calculated the mean CICV for each population size, π group, and number of replicates among the 350 simulations. We also estimated the probability of the point estimate deviating from the population size by $>\pm 25\%$.

RESULTS

We acquired 205 observations for sightability evaluation of which 161 (79%) were of groups seen during surveys. Of 205 observations, 115 were of groups with a collared mountain goat, 84 were of groups watched by ground observers, and 6 were both. Collar and ground observer groups were seen at similar rates (79% and 77%, respectively). The values of covariates recorded during sightability surveys covered a range of values (Tables 1 and 2).

Only Environment and Flight covariate categories had >4 variables. Of the Environment variables, we discarded Cloud Cover and Sky Conditions as redundant with Illumination. Only 4 observations had Precipitation other than none, so we discarded it. Of the remaining, we judged Wind Conditions least likely to affect sightability, leaving Illumination, Temperature, and Time for candidate model development. For the Flight category, we chose Aircraft, Primary Observer Experience, Pilot Experience, and Crew Experience. We did not attempt to test for individual crew member effects. Altogether, 42 individuals participated as crew members.

Of continuous covariates (i.e., Group Size, Vegetative Obstruction, Temperature, Time, and Intensity) only Intensity appeared nonlinear in the logit. Log-odds were lower for the lowest and highest Intensity groups than for intermediate levels. Although we found lack of independence among some pairs of covariates, none of these pairs occurred in our candidates, resulting in 17 candidate models (Table 3).

Among covariates, the rate of missing values ranged 0–5% (Tables 1 and 2). We considered all missing values to be missing at random (Schafer and Graham 2002). Substrate, Time, Terrain Obstruction, Vegetative Obstruction, Illumination, and Temperature were missing when the Secondary Observer neglected to record them. Group Size was missing when groups that were not seen were in thick vegetation and no animals could be located after the survey. Within the set of group sizes that occur under these conditions, we judged there was no relationship between the size of the group and the fact that its size was missing.

We found that variance estimates for parameters stabilized after 10 imputations. This is similar to that found in other multiple imputation implementations (Schafer 1999, Kenward and Carpenter 2007).

The best models among our candidates were Group Size + Vegetative Obstruction + Terrain Obstruction, followed by Group Size + Terrain Obstruction. These 2 models constituted the 0.95 confidence set (Table 3). Within this confidence set, recalculated Akaike model weights were 0.765 and 0.235 for the 2 models, respectively. Other models were not plausible, given our data ($\Delta\overline{AIC_c} > 4$; Table 3). Parameter estimates indicated that sightability increased with group size and decreased with Vegetative Obstruction and Terrain Obstruction (Tables 4 and 5; Fig. 1). The Hosmer–Lemeshow goodness-of-fit test of the averaged model for available cases indicated close agreement between observed and predicted sighting probability within each

Table 3. Candidate models for mountain goat sightability (Washington, USA, 2004–2007) considered a priori with number of parameters (K), covariate category, $\Delta\overline{AIC_c}$,[a] and model weight (w_i).

Model	K	Category	$\Delta\overline{AIC_c}$	w_i
Group Size + Vegetative Obstruction + Terrain Obstruction	4	Location	0.0	0.733
Group Size + Terrain Obstruction	3	Location	2.4	0.225
Group Size + Vegetative Obstruction	3	Location	6.2	0.033
Group Size	2	Group Size	12.2	0.002
Group Size + Pilot Experience	4	Flight	12.4	0.002
Group Size + Substrate	5	Location	13.3	0.001
Group Size + Time	3	Environment	13.9	<0.001
Group Size + Temperature	3	Environment	14.0	<0.001
Group Size + Illumination	3	Environment	14.2	<0.001
Group Size + Crew Experience	3	Flight	14.2	<0.001
Group Size + Intensity	3	Intensity	14.2	<0.001
Group Size + Intensity + Intensity^2	4	Intensity	15.0	<0.001
Group Size + Primary Observer Experience	4	Flight	15.6	<0.001
Group Size + Temperature + Time	4	Environment	15.7	<0.001
Group Size + Aircraft	4	Flight	15.8	<0.001
Group Size + Illumination + Time	4	Environment	15.9	<0.001
Group Size + Illumination + Temperature	4	Environment	16.0	<0.001

[a] Difference between averaged Akaike's Information Criterion for each model across imputations and their minimum among models.

decile of covariate pattern (Table 6) and overall, $\chi^2_8 = 3.961$, $P = 0.861$, $n = 191$.

In post hoc model comparisons, models without Group Size had considerably higher $\Delta\overline{AIC_c}$ than those that included Group Size. For the Terrain Obstruction model, $\Delta\overline{AIC_c}$ was 18.4 and for Vegetative Obstruction + Terrain Obstruction it was 15.8. Relative importance of Group Size, Vegetative Obstruction, and Terrain Obstruction in determining sightability can be assessed by the $\Delta\overline{AIC_c}$ of the model lacking each term but including the other terms in the most parsimonious model (i.e., Group Size $\Delta\overline{AIC_c} = 15.8$, Terrain Obstruction $\Delta\overline{AIC_c} = 6.2$, and Vegetative Obstruction $\Delta\overline{AIC_c} = 2.4$; Table 3; Fig. 1).

All covariates in our model confidence set were from the same variable category (Location). Consequently, we developed no additional post hoc models on the basis of competitive models including variables from different categories.

Table 4. Parameter estimates for mountain goat sightability models in the 0.95 confidence set and model-averaged parameters (Washington, USA, 2004–2007).

Model and variable	Estimate	SE	95% CI
Group Size + Vegetative Obstruction + Terrain Obstruction			
Intercept	1.447	0.390	0.681–2.212
Group Size	0.157	0.060	0.039–0.275
Terrain Obstruction	−1.101	0.399	−1.883 to −0.318
Vegetative Obstruction	−0.015	0.007	−0.030 to −0.001
Group Size + Terrain Obstruction			
Intercept	1.184	0.368	0.463–1.906
Group Size	0.161	0.062	0.039–0.284
Terrain Obstruction	−1.261	0.388	−2.021 to −0.501
Model-averaged			
Intercept	1.385	0.401	0.599–2.171
Group Size	0.158	0.061	0.039–0.277
Terrain Obstruction	−1.138	0.402	−1.927 to −0.350
Vegetative Obstruction	−0.012	0.009	−0.029–0.006

Table 5. Covariance matrix for mountain goat sightability model parameters after model-averaging in the confidence set (Washington, USA, 2004–2007).

Parameter	Intercept	Group Size	Terrain Obstruction	Vegetative Obstruction
Intercept	0.161	−0.013	−0.090	−0.001
Group Size	−0.013	0.004	−0.001	0.000
Terrain Obstruction	−0.090	−0.001	0.162	−0.000
Vegetative Obstruction	−0.001	0.000	−0.000	0.000

For the model with only a Group Size effect, the coefficient for the intercept was 0.482 (SE = 0.270, 95% CI = −0.047–1.010) and that for Group Size was 0.167 (SE = 0.060, 95% CI = −0.049–0.285). Covariance of intercept and Group Size was −0.012.

In the comparison of group size counts between ground and aerial survey observations, we deleted 4 observations on the basis of our criteria. The resulting data had $n = 66$ pairs. The slope of the regression of log-transformed GS_S against GS_G ($\beta = 0.962$, SE = 0.013) was different from one ($t_{65} = -3.017$, $P = 0.004$). We used Cook's distance (>1) to identify one influential observation, which was suspect because it represented an unlikely degree of under-counting ($GS_G = 18$, $GS_S = 6$). With this influential observation removed, the slope changed to 0.977 (SE = 0.009, $t_{64} = -2.515$, $P = 0.014$). For $\alpha = 0.05$, mean difference between GS_S and GS_G was not different from zero ($\bar{x} = -0.455$, SE = 0.257, $t_{65} = -1.772$, $P = 0.081$).

Simulations of counting bias for populations of 50 and 100 mountain goats yielded a mean estimated bias of −3.64% for 50 (min. = −2.21%, max. = −4.99%) and −4.57% for 100 (min. = −3.71%, max. = −5.66%). With the questionable data point excluded, estimated bias was reduced to −1.96% for 50 (min. = −1.04%, max. = −2.66%) and −2.56% for 100 (min. = −1.88%, max. = −3.51%).

During mountain goat surveys in 2004–2007 in the Cascade and Olympic Ranges, mean group sightability ranged 0.708–0.819 among π groups, whereas individual

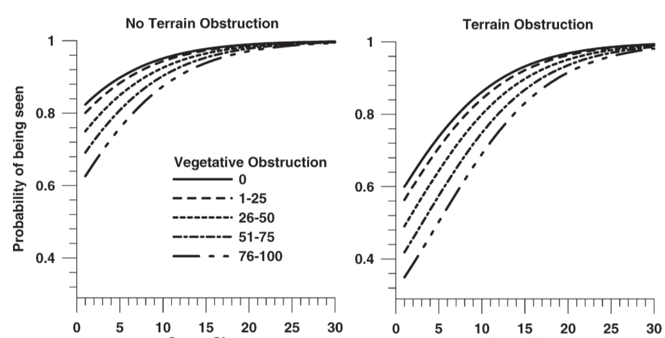

Figure 1. Probability of a mountain goat group being seen as a function of Group Size, Vegetative Obstruction, and Terrain Obstruction estimated by model-averaged parameters from the confidence set based on 205 observations in Washington, USA, 2004–2007.

Table 6. Hosmer–Lemeshow goodness-of-fit for the Akaike's Information Criterion (AIC) weight-averaged model of mountain goat sightability (Washington, USA, 2004–2007).

Decile mean						
Group Size	Vegetative Obstruction	Terrain Obstruction	Detection probability	Proportion seen	n	Contribution to the χ^2 score
1.74	53.79	1.00	0.474	0.526	19	0.207
2.00	16.18	1.00	0.592	0.682	22	0.728
3.58	23.32	0.84	0.672	0.632	19	0.142
2.95	22.59	0.32	0.772	0.727	22	0.249
2.74	9.37	0.16	0.822	0.842	19	0.055
4.10	3.67	0.19	0.855	0.905	21	0.426
6.00	12.11	0.06	0.892	0.833	18	0.651
11.28	12.78	0.17	0.943	1.000	18	1.095
19.16	18.74	0.16	0.980	1.000	19	0.392
39.07	9.14	0.14	0.999	1.000	14	0.016

sightability ranged 0.746–0.912 (Table 7). Among the 17 survey areas with >10 groups recorded, these ranges were 0.639–0.846 and 0.646–0.948, respectively.

Within each π group, the CICV declined with population size and number of replicate surveys (Table 8). In assessing substantial deviations (±25%) of the estimate from the population size, probability of a survey estimate being <75% of the population size (–25% error) was >0.05 for populations of 25 for all π groups when the number of replicates was <3 and for populations of 50 when the number of replicates was <2. Probability of a survey estimate being <75% of the population size was >0.10 only for populations of 25 for Low and Medium π groups when the number of replicates was <2. Probability of a survey estimate being >125% of the population size (+25% error) was >0.05 for populations of 25 for Low and Medium π groups when the number of replicates was <2. This probability was <0.10 for all populations and π groups.

DISCUSSION

Mountain goat sightability during helicopter surveys was determined primarily by Group Size, Terrain Obstruction, and Vegetative Obstruction. Counting bias may occur, but its effects on using a sightability model for mountain goat population estimation are probably minor. Because of variation in terrain mountain goats occupy, sightability varies geographically. Hence, the degree of adjustment to the survey for population estimation and the precision of the estimate will also vary among survey areas.

Table 7. Number of groups counted, total mountain goats counted, average estimated sightability for groups ($\overline{\pi}$), sightability-adjusted estimate, and individual mountain goat sightability by survey areas divided into π groups of low, medium, and high sightability from all mountain goat survey records in the Cascade and Olympic ranges in Washington, USA, 2004–2007.

π group	Groups	Total	$\overline{\pi}$	Estimate	Individual sightability
Low	383	1,062	0.708	1,423	0.746
Medium	402	1,410	0.770	1,699	0.830
High	354	2,327	0.819	2,550	0.912
All	1,139	4,799	0.764	5,672	0.846

We evaluated and estimated sightability bias associated with helicopter surveys of mountain goats as they are practiced throughout Washington and many adjoining regions. Unlike some other survey evaluations (Samuel et al. 1987, Poole et al. 2000, Gonzalez-Voyer et al. 2001, Udevitz et al. 2006, Poole 2007), we used many personnel and 3 helicopter types. This may have increased variability in our assessment but should make application of our model suitable to a wide variety of circumstances. Because we found no significant effect of helicopters, survey crew experience, or survey intensity, it seems likely that our model will be applicable in other parts of the mountain goat's range. Nevertheless, we caution against uncritical application of our sightability models to other regions.

Group Size was the key factor affecting sightability of mountain goats during aerial surveys, similar to effects documented for mountain goats and other species (e.g., Samuel et al. 1987, Anderson and Lindzey 1996, McCorquodale 2001, Udevitz et al. 2006, Poole 2007). Vegetative Obstruction was in only 1 of the 2 models in the confidence

Table 8. Confidence interval coefficient of variation (CICV, i.e., half the 95% CI divided by the population estimate) for mountain goat surveys of areas with low, medium, and high sightability (π group) by the number of survey replicates and population size (Washington, USA, 2004–2007).

		Population size				
π group	Replicate surveys	25	50	100	250	500
Low	1	0.45	0.32	0.24	0.18	0.15
	2	0.33	0.24	0.18	0.14	0.12
	3	0.27	0.20	0.15	0.12	0.10
	4	0.23	0.17	0.13	0.10	0.09
	5	0.21	0.16	0.12	0.09	0.08
Medium	1	0.38	0.27	0.19	0.13	0.10
	2	0.28	0.20	0.14	0.10	0.08
	3	0.23	0.16	0.12	0.08	0.07
	4	0.20	0.14	0.10	0.07	0.06
	5	0.18	0.13	0.09	0.06	0.05
High	1	0.34	0.22	0.15	0.10	0.07
	2	0.25	0.16	0.11	0.07	0.05
	3	0.21	0.13	0.09	0.06	0.04
	4	0.18	0.12	0.08	0.05	0.04
	5	0.16	0.10	0.07	0.05	0.03

set and may be of lesser importance for mountain goats than other species because mountain goats are usually surveyed in areas with low or sparse vegetation. Terrain Obstruction was second in importance to Group Size in determining sightability. Terrain Obstruction in the form of fissures, crevasses, caves, overhanging ledges, and other rock formations is an important feature of mountain goat habitats, and we occasionally observed mountain goats seeking topographic cover in response to survey disturbance. We described Terrain Obstruction as presence or absence, but given the importance of such terrain both to mountain goats and sightability, it may be useful to develop a more fine-scaled metric of terrain in future efforts to model sightability.

Our estimates of sightability (0.75–0.91) were generally higher than those from other studies, which was true for previous estimates in Washington (0.63 and 0.66; Johnson 1983, Houston et al. 1986) and elsewhere (0.59–0.69; Cichowski et al. 1994, Poole et al. 2000, Gonzalez-Voyer et al. 2001, Pauley and Crenshaw 2006, Poole 2007). Notably, previous estimates of detection biases in Washington (Nason Ridge and the Olympics; Johnson 1983 and Houston et al. 1986) were derived predominately in areas we classified as having low sightability (i.e., low π group). Hence, there was less difference between previous estimates of detection bias compared to our estimates of the low π group (0.75) than to our overall estimates (0.75–0.91). Furthermore, we censored 11 trials of sightability bias from our computations because collared goats were outside the sampling frame (blocks) and were not valid trials of sightability. Previous estimates derived from population reconstruction (Houston et al. 1986) or proportional observations of marked animals computed detection bias at the population level rather than for a specific sampling frame. Hence our estimates, although likely representative of true detection biases within the sampled population, may be conservative at the population level if mountain goats occasionally descend to low elevations outside the sampling frame.

The only previous study of covariates affecting aerial sightability of mountain goats indicated that groups size, vegetation, and activity class (i.e., bedded, standing, or moving) all affected sightability (Poole 2007). We recorded activity class during surveys but found no reliable method for assessing activity of animals in missed groups. Mountain goats react to helicopters, especially at distances common during aerial surveys, although such disturbance is typically of short duration (Goldstein et al. 2005). Consequently, there is a high probability of change in activity between over-flight and the end of the survey, and assessing activity of missed groups by documenting it after the survey is likely to be misleading. In our trials, ground observers recorded activity of most mountain goats in a group at the time of the closest pass of the helicopter, but our records for groups seen from both the air and ground showed that ground observers classified a higher proportion of groups as inactive (bedded) compared to aerial observers, calling into question the ground observers' classification of groups that were missed. Also, although we could estimate activity of collared animals on the basis of accelerometers on the collars, these had a resolution to 5 minutes, which was too coarse to assign activity at the time of over-flight.

By all measures, nearly all mountain goats were active during helicopter surveys. In our sightability data 94% of nonmissing values ($n = 188$) were active. In the mountain goat surveys we conducted in 2004–2007, 95% of 1,135 groups were active and 96% of 4,793 mountain goats seen were in active groups. Consequently, any effect of activity on sightability would have little effect on population estimates.

Despite evidence for negative bias in aerial counts of mountain goats within groups, our simulations indicated that the effect of under-counting on population estimation for typical goat populations was expected to be small (−1.96 to −4.57%). The wider range of percent bias from all simulated populations (min. = −1.04%, max. = −5.66%) reflect combined effects of lack of precision in our estimate of counting bias due to problems we encountered with the data set (true group size can be difficult to determine) and influence of the group composition of a given population. We conclude counting bias is low in mountain goat surveys but more data are needed to better estimate the counting error.

Our simulations provide guidance for survey design given confidence criteria, estimates of population size, and expected sightability (Table 8). For example, if it is desired to have the confidence interval of $\leq \pm 10\%$ of the estimate, for a population of 250 in an area with medium expected sightability, 2 replicate surveys are indicated. Likewise, this level of precision cannot be expected for small populations (e.g., 25), even with 5 replicate surveys, regardless of π group. Generally, the decrease in CICV for a given π group and population size was a nearly linear function of *ln*(*n* replicates), so the increase in precision was considerably greater between 1 and 2 replicates than between 2 and 3, et cetera. Due to the lack of precision of estimates for small populations, reliable population estimation and management of small population segments remain a challenge.

Replicate surveys are typically not flown due to cost constraints, and most mountain goat populations are in the 25–100 range. Under these conditions, confidence intervals are likely to be greater than most managers would like to see (±15–45%) and may lead to questions of the utility of the sightability approach to mountain goat population estimation. These confidence intervals are derived from 2 sources of variability associated with sightability (uncertainty of sighting a group) and the logistic model (Steinhorst and Samuel 1989:422). For unreplicated surveys of populations of 25–100 the sightability variance component in our simulations averaged 76–94% of total variance. Thus, variability in the adjusted estimates was primarily derived from whether or not a group was seen (sightability) as opposed to variability from adjusting survey counts for missed groups (model). Consequently, most of the variability is inherent in using helicopters for surveying mountain goat populations and the primary benefit of employing a sightability model may be in providing precision of the estimate compared with providing an adjusted estimate.

MANAGEMENT IMPLICATIONS

Mountain goats are monitored throughout much of their range in support of diverse management objectives that range from establishing acceptable harvest (Washington Department of Fish and Wildlife 2003) to controlling populations considered excessive (Houston et al. 1991). Because survey conditions vary from year to year in terms of group size composition, terrain, and vegetation in which mountain goats are located, a fixed correction factor for mountain goats is likely to result in erratic estimates. Variation due to sampling error is to be expected, especially when surveying small populations, but estimating and correcting for sightability biases should reduce variability among annual estimates by accounting for changing goat population characteristics, distributions, and environments and should improve power to detect trends in population size. Our findings also indicate that fixed correction factors can lead to erroneous estimation if applied outside the area they were developed or to subdivisions of that area. Our simulations suggest that probabilities of deviation from the estimate of $>\pm 25\%$ were not large, even for small populations. Thus, the risk of making management assessments on the basis of highly erroneous estimates is low. We therefore feel that sightability-based estimates, which provide greater consistency, and an estimate of precision of population estimates, should be a valuable contribution to mountain goat population management efforts, whether the goal is harvest management, recovery, or population control.

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