Monitoring Populations of Brown Bears (*Ursus arctos*) within the Arctic Network Park Units: *An Evaluation of Occupancy Models*

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Background

Monitoring populations of rare and elusive wildlife species is necessary for effective management, but a monitoring program may require specific designs and analyses to suit the species of interest in the area of interest (Thompson 2004). More commonly used and conventional designs do not always provide an adequate sample of relatively uncommon and wide ranging species and the type of data that are collected for these species may not meet the assumptions of an analytical technique (Thompson et al. 1998, Thompson 2004). Therefore, in recent years, development of sampling and analytical tools for less common species or species that are difficult to sample has been an active area of work (Thompson 2004, MacKenzie et al. 2006).

Solitary carnivores, and more specifically bears, are one group of animals that are frequently difficult to sample and monitor. They occur over wide areas, they are frequently solitary, and they may occur in habitats where they are not easily visible. As a result, sampling designs and analytical tools for monitoring abundance of bears have often been tailored to the specific species of bear and the area that they occupy (Miller et al. 1997, Quang and Becker 1996).

Two techniques have been predominantly used for monitoring bears in Alaska. The first approach uses capture-mark-recapture (CMR) techniques to estimate abundance and density of bears (Miller et al. 1997). This CMR approach has been used widely across Alaska and has been used for both black (*Ursus americanus*) and brown bears (*U. arctos*). The analytical techniques used for estimation are based on well developed theory (Pollock et al. 1990). A potential logistical and financial limitation of this approach is that a radio marked sample of bears must be established and maintained to estimate probability of detecting bears, to monitor movements of bears between the marking and observation period, and ultimately to estimate abundance and density of bears. Therefore, this technique may be of limited application for large study areas where annual monitoring is of interest.

Distance sampling with line transects is the second most common and rigorous method used to estimate bear density (Quang and Becker 1996). During line transect sampling, a transect is traversed and animals are observed at varying distances. The observation distances are used to model the probability of detecting animals at varying distances from the transect (detection function) with the assumption that detection of individuals on the line is perfect. This detection function is in turn used to correct raw counts of animals for detection probability and to estimate density. The assumption of perfect detection on the line has been relaxed for aerial surveys (Quang and Lanctot 1991) because individuals can not be observed directly beneath the aircraft (i.e., on the transect). Aerial line transect methods have been further modified for bear surveys to allow the use of covariates (e.g., habitat type) related to sightability of individual animals (Quang and Becker 1996), application in mountainous terrain where distance from lines varies with relief (Quang and Becker 1999), and the use of ancillary data (double count data from 2 observers) to further relax the assumption of perfect detection on the transect. Like CMR techniques, line-transects have been successfully applied for bear surveys in several areas around Alaska (Becker 2003) and the sampling and analytical components of this

approach are based on sound theory (Borchers et al. 2002). However, sample size needs may not be met in areas with low densities of bears and independence among observers using the double count procedure has been questioned. Therefore, an alternative technique may be needed to monitor bear populations in some areas of Alaska.

In this report, we consider the viability of using occupancy sampling and modeling (MacKenzie et al. 2006) for monitoring brown bears in and around the Bering Land Bridge National Preserve (Fig. 1). Occupancy models are used to estimate the probability of occupancy of sampling units within the larger study area. These models were selected for this species and area because the previously mentioned techniques were likely not viable due to logistical, financial, or statistical restrictions. Occupancy sampling is conducted by visiting a sample of sites within a larger study area and observing or capturing individual animals, or finding animal sign that confirms presence (e.g., tracks). Sites with no evidence of presence are also recorded. Sampled sites are visited at least twice by independent observers usually within a time period short enough to restrict the probability of births, deaths, immigration, and emigration in sites during the sampling period. From these data, models are used to estimate the probability of detecting presence given a site is occupied and detection probability is used to correct raw observations of presence to estimate occupancy probability; the proportion of sites within the larger study area that are occupied (MacKenzie et al. 2006), thus avoiding bias caused by false absences. More complex models can be used to model community dynamics and presence or absence of multiple species, but for this report we restrict our attention to occupancy of a single species at a single time (year).

Although the concept of presence/absence sampling has been around for some time, occupancy or presence/absence modeling has gained attention in recent years because some species in some situations can not easily be sampled and modeled using techniques commonly used for more abundant or easily observed species. More importantly, recent developments have provided a more rigorous framework for modeling occupancy and avoiding simplified and unrealistic assumptions about perfect detection of presence (MacKenzie et al. 2006). Occupancy may be considered a surrogate of abundance, particularly for territorial species where the size of the sampling unit is roughly equivalent to the territory size. Others view occupancy probability as the appropriate parameter for monitoring programs (Manley et al. 2004) and occupancy modeling is currently being used for monitoring avian, mammalian, and amphibian species (MacKenzie et al. 2006).

Objectives

1. Use data collect in 2006 to estimates probability of occupancy and abundance of brown bears in the surveyed area.

2. Conduct simulations to develop optimal designs for modeling brown bear occupancy in future surveys.

3. Make recommendations for survey design based on results from objective 2.

Estimates from 2006 Surveys

Data. Pilot data for occupancy modeling were collected 4-9 June 2006 in and around Bering Land Bridge National Preserve. A grid of 118 potential survey sites (S) were established on the northern Seward Pennisula; an area that extended from Cape Wales to approximately 162 degrees East Longitude. Each site (s) was 9 minutes of latitude wide and 15 minutes of longitude long (Fig. 1). Area of sites varied from about 190 to 206 square kilometers. The amount of terrestrial habitat and usable bear habitat varied among sites. Sites were stratified by physiography using a GIS as predominantly coastal, mountains, hills, and valleys.

A stratified, random sample (s) of 11 sites was surveyed in 2006, including sites 3, 22, 23, 34, 40, 47, 51, 93, 96, 102, and 107. Each site was surveyed by 2 independent teams that included a pilot and single observer. Both the pilot and observer looked for bears or bear tracks. All sites were surveyed at different times on the same day by the 2 different teams except site 3, which was surveyed first on 4 June and then again by a different team on 8 June. Survey crews recorded all bear observations by categories: single, sow with cub(s)-of-year, sow with yearling(s), and sow with cub(s)≥ 2 years old. Observations of bear tracks and their condition were also noted. Flight time for surveys ranged from 38 to 204 minutes per site (mean = 121 minutes).

Occupancy Models. We analyzed the 2006 data using occupancy models in program MARK (White and Burnham 1999). We estimated detection probability (p) and the probability that a site is occupied (ψ) using 2 data groupings: direct observations of bears and observations of either bears or their tracks. We used all observations of bear tracks for the second analysis regardless of condition of tracks or where it was observed (e.g., snow or mud). For each analysis, we considered 3 models:

1. a model with no time-specific variation in detection probability between surveys ($\psi(.)p(.)$),
2. a model with pilot-specific detection probability ($\psi(.)p(\text{obs})$), and
3. a model with detection probability as a function of search time ($\psi(.)p(\text{hours})$).

For all models, we maintained a constant occupancy probability. For the pilot-specific model, we arranged the data so p during the first observation occasion represented the p for planes piloted by Hamilton or Shults and the p for the second observation occasion was for planes piloted by Greenblatt because Greenblatt surveyed all the sites. Therefore, variation in p between sampling occasions was the result of differences between observers not time-specific variation. We selected among the 3 competing models using Akaike's information criteria corrected for sample size (AIC_c) and AIC_c weights (W), which can be roughly viewed as the probability that a model in a model set is the most likely given the data (Burnham and Anderson 2002).

Occupancy Model Results. In the analysis that only included direct observations of bears, a model with a constant detection probability (W = 0.83) was favored over the other 2 models. The occupancy probability was 0.48 (SE = 0.17) and p was 0.75 (SE = 0.17). The model with pilot-specific p received limited support (W = 0.12), indicated no

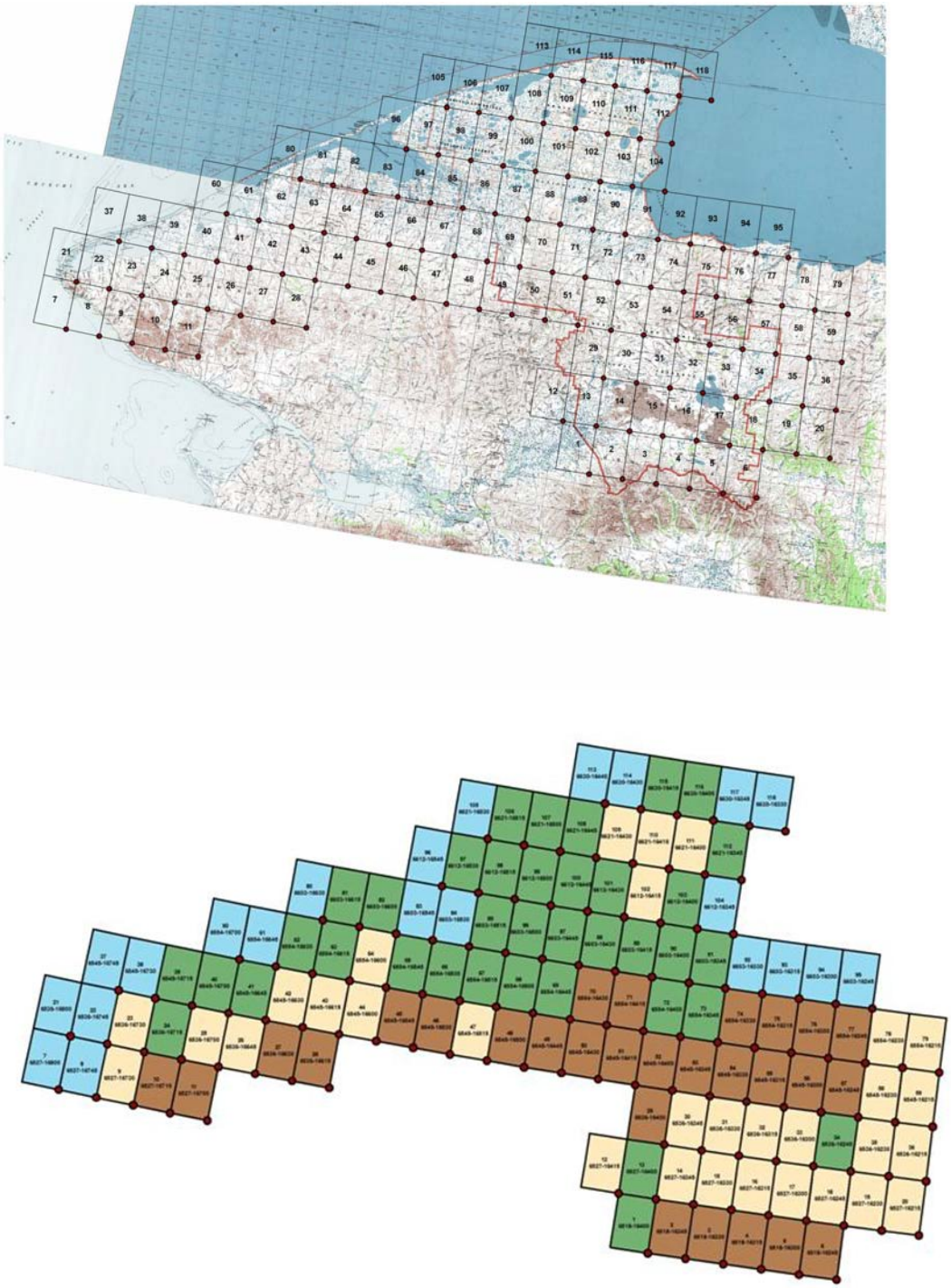

Figure 1. Location of study area with grid of 118 potential sampling sites (top) and strata (below).

difference in p (0.75, SE = 0.22) between observer teams, and produced an identical estimate of ψ as the first model. Therefore the extra model parameter for the pilot-specific model was not warranted. The model with p as a function of search time would not optimize, likely because few sightings were included in the data. This model received the least support (W = 0.05).

The model with constant p was also the most supported in the analysis that included observations of either bears or tracks (W = 0.78). The probability of detecting a bear or track ($\hat{p}$ = 0.71, SE = 0.14) was slightly lower than p for bears only and the estimate was more precise because more bears and tracks were seen than just bears. The probability of occupancy for bears or tracks ($\hat{\psi}$ = 0.89, SE = 0.15) was higher than ψ for bears only and again the precision of the estimate for bears and tracks was improved because of more data. The model with pilot-specific p received some support (W = 0.18), but the difference in p between Hamilton/Shults ($\hat{p}$ = 0.63, SE = 0.17) and Greenblatt ($\hat{p}$ = 0.83, SE = 0.15) was not large enough to justify the extra model structure. A model with p as a function of search hours received the least support (W = 0.04); however, estimates from this model indicated that the relationship between detection and search time was positive ($\hat{\beta}$ = 0.76, SE = 0.58, slope for logit linear model) and with additional data this model may be a parsimonious description of the data (see *Survey Recommendations* below). We explored other models with an interaction between observer and search time effects on p because p varied between observers. This model was poorly supported (W < 0.01) because this much model structure (5 parameters) could not be supported by the data.

Census Estimates. We can obtain an estimate of abundance by treating the data collected in 2006 as census; i.e., assuming that detection probability for bears is 1.0 for the combined surveys. From the occupancy modeling, we estimated that the probability of detecting a bear on an occupied site during a single survey is 0.75, so the probability of detecting at least one bear on an occupied site during at least 1 of the 2 surveys is 0.9375 ($\hat{p}^* = 1.0-(1.0-0.75)^2$). However, because some sites included more than a single bear and some sightings were not independent (e.g., sows with cubs), detection probability for a single bear is <0.9375, but by an unknown amount. Therefore, estimates of abundance under the assumption of a census are negatively biased low by at least 6.25% and this bias may vary in space and time. We also assumed for this analysis that no bears were counted more than once.

We estimated total abundance of bears for the study area ($\hat{A}$) as $S \cdot \overline{A}$ (see Scheaffer et al. 1996), where $\overline{A}$ is the mean abundance of bears in the surveyed sites. When bears were observed during both surveys for a site and different counts were obtained, we used the higher of the 2 counts. The mean number of bears counted on the 11 surveyed sites was 1.73 and estimated abundance for the 122 sites in the study area was 143 bears. The standard error of this estimate ($SE(\hat{A})$) was 116.5:

$$\hat{S}E(\hat{A}) = \sqrt{S^2(\mathrm{var}(\overline{A}))(1 - s/S)};$$

where, var($\overline{A}$) is the sampling variance of the mean abundance. This equation for $\hat{S}E$ ($\hat{A}$) included a finite population correction (fpc) factor and therefore reduced variance by a factor of 1-11/122 (1-s/S). Even with this fpc the coefficient of variation for this estimates was 81% (116.5/143).

Simulations with Occupancy Models

Simulations. Simulations were performed to determine the optimal design for the desired level of precision for estimates of occupancy. We considered 2 main design features that could be controlled by the observers: 1) intensity of surveys within sites and 2) number of sites surveyed (extent). Several aspects of survey design could affect intensity; including time spent surveying each site, size of sites, number of repeat surveys per site (K), and observer abilities. These design aspects affect either detection probability (e.g., survey time) or probability of occupancy (e.g., size of site) and we considered their collective effects on design by changing p and ψ and examining how this affected the optimum number of sites that should be surveyed.

For the initial simulations, we fixed the desired level of precision to a coefficient of variation (CV = $\hat{\psi} / SE(\hat{\psi})$) of 25% on estimates of probability of occupancy, as was described to us as the target level of precision. We also initially made the simplifying assumption of K=2 because a priori >2 surveys per site was not considered efficient. We considered a range of values for ψ and p based on results of analysis of the data collected in 2006. Specifically for CV=25% and K=2 we determined s for p between 0.4-0.9 and ψ between 0.3-0.9 using equation 6.3 in MacKenzie et al. (2006):

$$s = \frac{\psi}{\mathrm{var}(\psi)}\left[(1-\psi) + \frac{(1-p^*)}{p^* - Kp(1-p)^{K-1}}\right].$$

Below we report on the results from the conditions we used for our simulations; however, results could be obtained for any user specified conditions using a program, which we developed for this work (calculates estimated sample R; attached), for use in program R (R Development Core Team 2006). Program R is a freeware that can be downloaded from a number of mirror sites <http://www.r-project.org/>.

Based on 2006 estimates of p (0.75) and ψ (0.48) for the bear sighting models, observers would have needed to sample 22 sites to obtain a CV of 25% on estimates of ψ. As expected, the desired s declined as ψ increased (Fig. 2). To obtain a CV of 25% on estimates of ψ, s ranged from about 45 to 5 sites over the range of values for ψ (0.3-0.9) and p=0.7. Detection probability had more of an effect on s than ψ, as the range of s was greater when p was changed than when ψ was changed (Figs. 2 and 3). For ψ = 0.5, s ranged from about 88 when p = 0.4 to 16 when p = 0.9 (Fig. 3). This differentially important effect of p on precision of estimates of ψ is further illustrated in simulations where we simultaneously changed p and ψ over a wide range of values and observed the effects of these changes on estimates of SE of ψ (Fig. 4). The steep response of SE to changes in p clearly indicates the sensitivity of precision to p. In fact, for values of

$p<0.6$, and regardless of values for ψ, the SE exceeded a CV of 25% and increased rapidly for $p<0.6$. The rapid increase in the SE for $p<0.6$ was also consistent across a range of values of s (Fig. 5). In contrast, SEs were similar for all values of ψ when $p>0.6$ and the difference in precision among values of ψ were small for $p<0.6$ (Fig. 3).

Number of surveys per site. At least 2 surveys per site are needed to estimate p and ψ. We assumed a priori that >2 surveys would not be logistically feasible. Nonetheless, we explored if increasing K to 3 may be an efficient way to increase precision of occupancy estimates.

The optimal number of surveys increases as p declines, but the effects of K on precision are minimized when $p>0.6$, and in this case, when $\psi=0.5$ and s=10 (Fig. 6). Therefore, for the p observed in the preliminary data analysis (0.75), K=2 appears to be the optimal number of surveys because the data provided by the additional survey does not compensate for the loss of precision in estimates of ψ caused by the increase in parameters that have to be estimated (e.g., p for the third survey). This conclusion is reinforced by resulted presented in MacKenzie and Royle (2005) and summarized in Table 6.1 of MacKenzie et al.(2006). From these analyses, MacKenzie et al. (2006) concluded that $K\geq3$ would be optimum when $\psi=0.5$ and $p<0.61$.

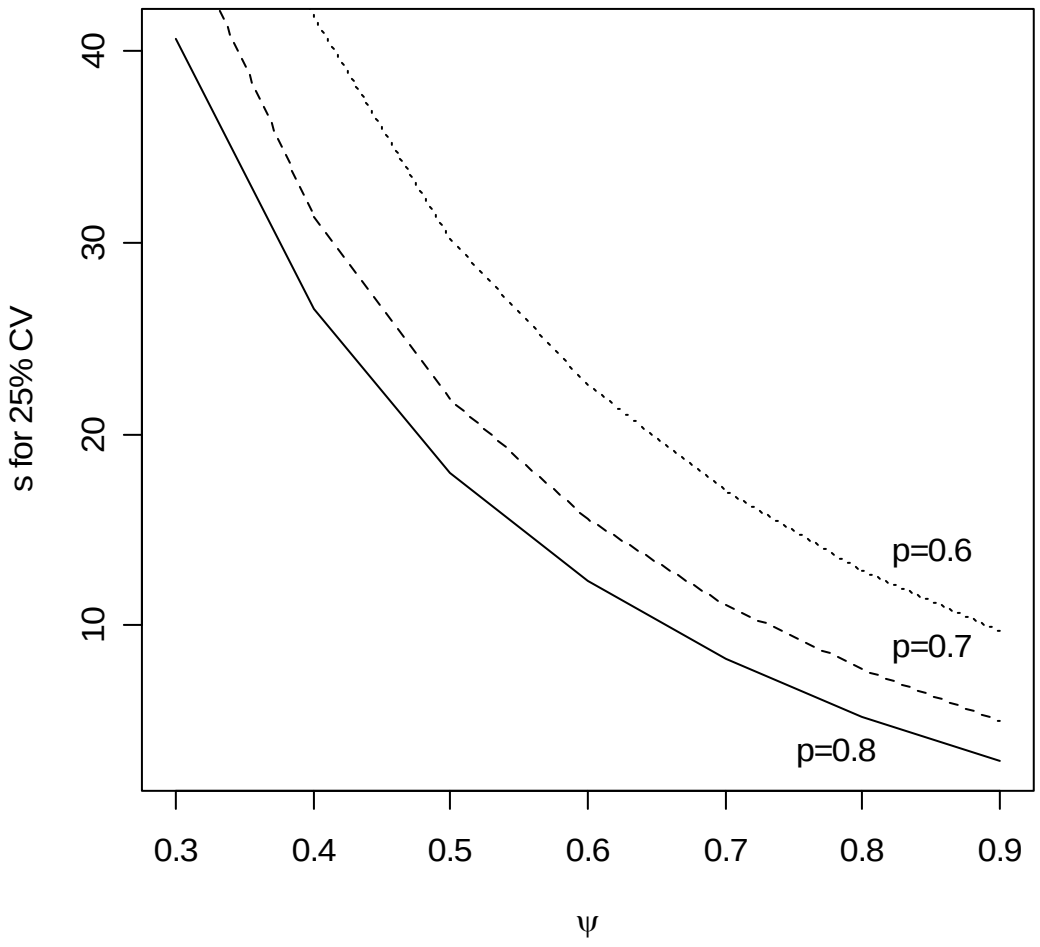

Figure 2. Relationship between number of surveyed sites (s) needed for a CV of 25% for estimates of occupancy (ψ) and probability of occupancy when surveys per site (K) is 2 and detection probability (p) is 0.6, 0.7, and 0.8.

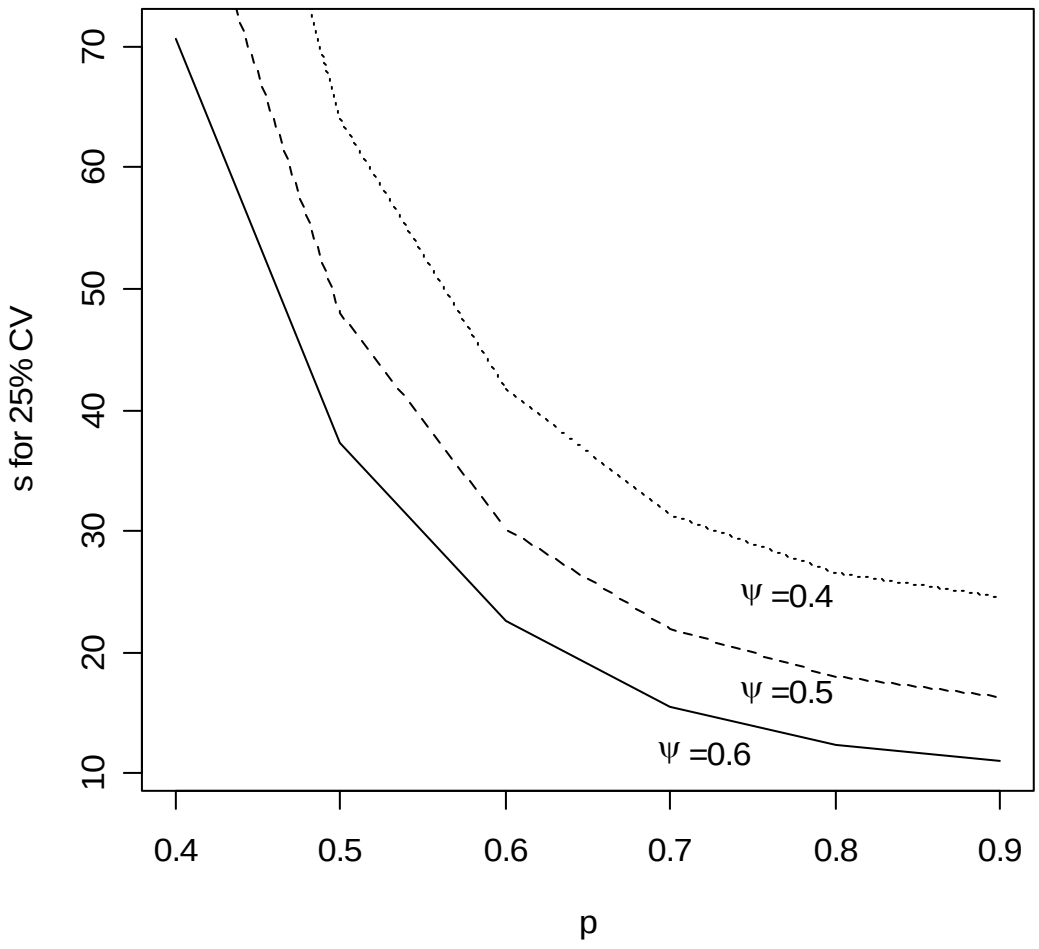

Figure 3. Relationship between number of surveyed sites needed for a CV of 25% for estimates of occupancy (ψ) and detection probability (p) when surveys per site (K) is 2 and probability of occupancy (ψ) is 0.4, 0.5, and 0.6.

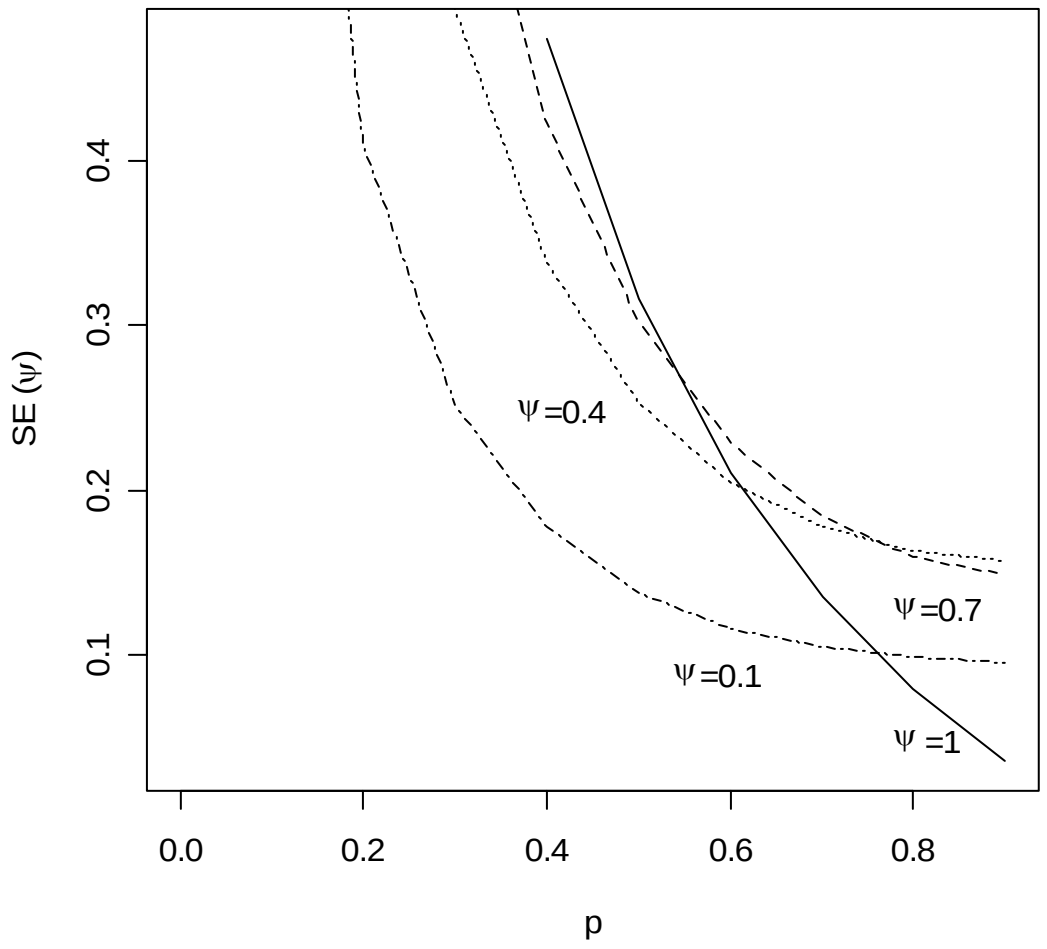

Figure 4. Relationship between precision (SE) of occupancy (ψ) estimates and changes in detection probability (p) and occupancy for surveys per site (K) equals 2 and surveyed sites(s) equals 10.

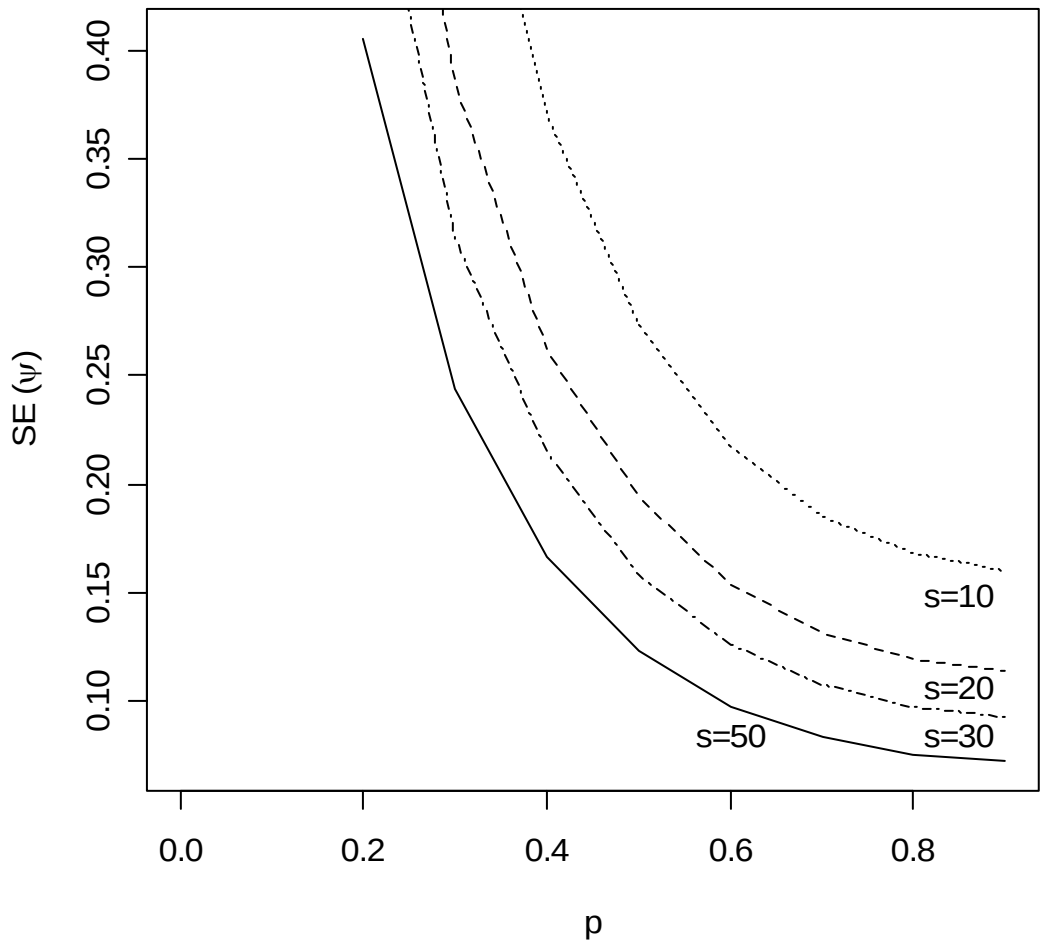

Figure 5. Relationship between precision (SE) of occupancy (ψ) estimates and detection probability (p) for surveyed sites (s) between 10-50 and surveys per site (K) equals 2.

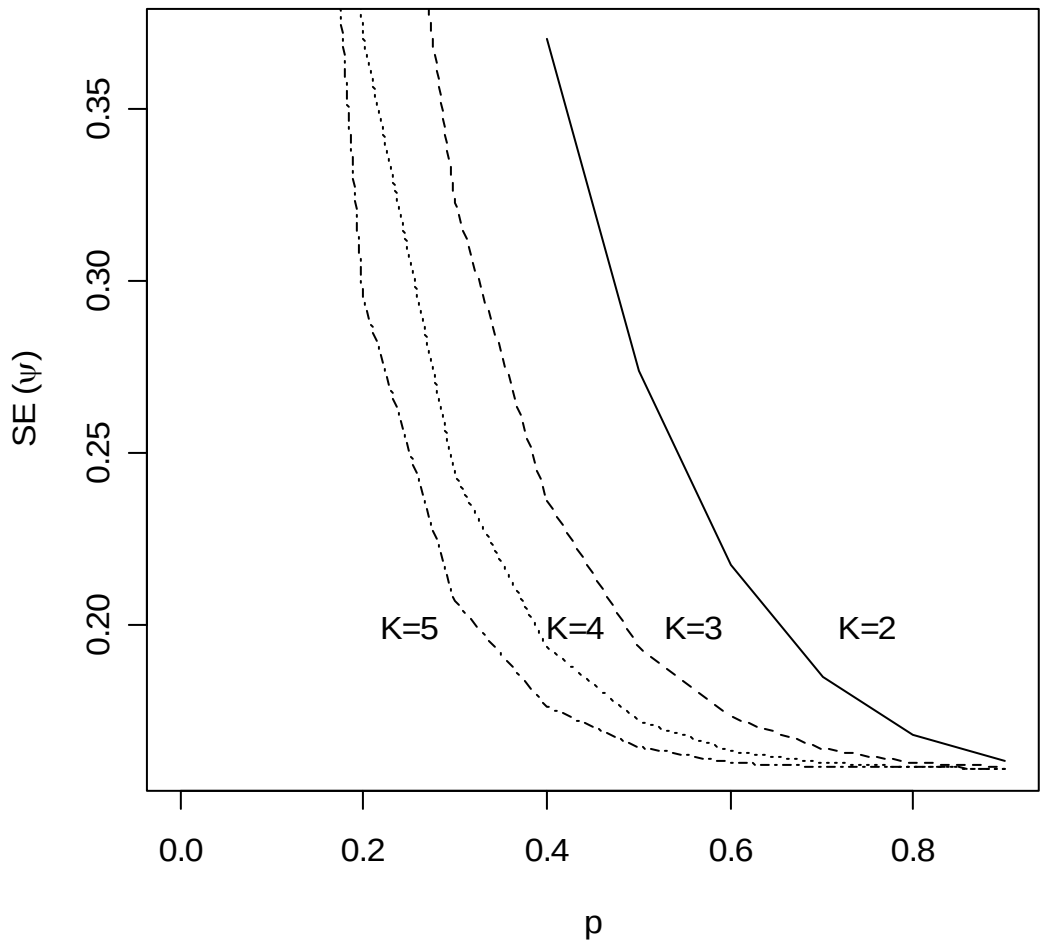

Figure 6. Relationship between precision (SE) of occupancy (ψ) estimates and detection probability (p) for surveys per site (K) between 2-5, ψ=0.5, and surveys sites (s) equals 10.

Survey Recommendations and Discussion

Bear Occupancy Models. Simulations indicate that approximately a doubling of survey effort will be required to obtain estimates for occupancy of bears with the desired level of precision. If condition and abundance are similar in 2007, we recommend 22 sites are sampled for a total of 44 surveys.

The size of the sites and the observer effort appear to provide reasonable values of ψ and p. Mackenzie et al. (2006) recommended that site size should be designed to provide estimates of ψ between 0.2-0.8 for optimal estimation. The estimate of ψ from the 2006 data was near the middle of this distribution (0.5). However, a different site size may be desirable if managers want to use occupancy as a surrogate of abundance (see below).

Our simulations and work by others (Mackenzie et al. 2006) clearly shows that $p>0.6$ leads to efficient designs. The observer effort expended in 2006 produced estimates of $p\approx0.75$, indicating that the survey intensity used in 2006 was adequate. Furthermore, variation in detection probability among observers for bears was minimal and should not lead to excessive heterogeneity if this type of survey protocol is followed in the future.

Although a model with p as a function of hours searched was difficult to optimize because of data limitations, our analysis indicated that detection probability was positively related to hours observed. Data were inadequate to consider models with quadratic relationships between hours surveyed and detection, which we suspect exists, and possibly identify optimal levels of survey effort. Therefore, we recommend that survey hours are recorded in future surveys. This ancillary data may improve precision of estimates of p when more sites are surveyed and with additional data quadratic models may converge and allow assessment of optimal survey time.

Our analysis and work by others indicate that 2 surveys per site, as was done in 2006, is optimum for the observed values of ψ and p. Therefore, except for changes in the number of sites sampled, we are not recommending any additional changes for the surveys.

Can occupancy estimates be used as a surrogate of abundance? Occupancy is equivalent to abundance when a single individual or a known, constant number of individuals exists in the occupied site. This may occur in situations where the size of the site is perfectly equivalent to the home range of an individual. This assumption is most likely to be met with animals that are relatively solitary during the survey period (e.g., large carnivores during the non-breeding season). Therefore, bears may provide an opportunity to infer abundance from occupancy.

Bears sightings occurred 16 times during 2006 surveys and bears were sighted in 5 of the 11 sites that were sampled. Number of bears observed per site ranged from 1-21 ($\overline{X}$ = 8.4, sd = 1.6). Some of these counts may represent bears seen during both surveys for a site, nonetheless, occupancy can not be equated to abundance with this level of variation in counts and the actual number of bears at a site is unknown because $p<1.0$. If abundance is a necessary parameter, occupancy models may provide a better measure of

abundance if data are stratified by classes of bears (e.g., single, cub-of-year). This was done in 2006, but data were inadequate to complete an occupancy analysis for each class of bears. Stratification of occupancy models by bear social class will require a large increase in recommended sample size and interpretation of occupancy probability may be more useful and appropriate (Garshelis and McLellan 2006). Changing the size of the site may also provide a higher correlation between occupancy and abundance. However, only one site had an unusually high number of bear sightings (21 compared to <6 for the other sites) and several years of surveys may be required to identify the best site size to match the distribution of bears in this area. We do not recommend stratifying by social class or changing the size of the sample site. Instead, we encourage exploration of models that exploit the positive relationship between occupancy and abundance to estimate abundance (Royle and Nichols 2003, Royle et al. 2005). Additional analysis would be required to determine the viability of the Royle models for estimating brown bear abundance in the area of interest

Spatial Stratification of the Study Area. The study area was stratified into sites primarily composed of valleys, hills, mountains, and coast based on dominate feature in each of the survey sites. Under the assumptions of similar occupancy and detection probability among stratum, we recommend that samples are allocated among stratum proportional to the size (number of sites) of the stratum (Scheaffer et al. 1996). For example, if a stratum includes 40% of the total study area, that stratum should receive 40% of the samples. At minimum, stratification proportional to size, will assure that samples are distributed across the study area. If subsequent surveys and analysis indicate that occupancy and detection probability vary by stratum, we recommend additional analysis to allocate samples accordingly. Stratum that have sites with lower probabilities of occupancy and detection should receive a larger allocation of samples than stratum with a relatively higher occupancy or detection probability, but at this time insufficient data exist for proper allocation.

Bear and Track Occupancy Models. One of the assumptions of occupancy models is that sites are closed during the survey period. That is, bears or tracks observed at one site are not observed at another site during the survey period. We think this assumption was likely met for bears because most sites, except one, were surveyed on the same day. This assumption may be violated for tracks because tracks may persist across several days or even weeks of surveys. Violation of the closure assumption would lead to positive bias in estimates of occupancy. In addition, we found some indication that detection probability differed among observers for tracks. If this source of heterogeneity is not properly modeled, biased estimates of occupancy probability may occur (MacKenzie et al. 2006). Proper modeling of observer-specific detection probability may reduce bias, but the additional parameters needed for these models may reduce precision.

In general, we would discourage use of tracks for occupancy modeling because of the problems with closure and heterogeneity already discussed above and problems with interpreting how occupancy of tracks is related to abundance of bears. The tracks of a single bear could be observed at multiple sites and over multiple surveys. If tracks are to be used size of sites should be enlarged to include at least the home range of a bear and to

meet the closure assumption. Additional training and protocols should be established to aid in detection of tracks and to define criteria for inclusion of tracks of different condition.

Analysis for trends. Additional analysis is needed to provide design recommendations if trends in occupancy probability over time are of interest. Specifically, if occupancy models are considered viable, additional information about desired level of power to detect changes in occupancy would be needed.

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