

Incorporating Detection Uncertainty into Presence-Absence Surveys for Marbled Murrelet

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There is a long tradition associated with sample surveys for presence or absence of flora or fauna at sites or stations in sampling units where detectability may be an issue. Species may be present at a sampling unit yet fail to be detected. Historically, the problem with detectability has often been ignored. Recently, attention has been given to the development of survey protocols that increase the likelihood of detection. Often, these protocols call for repeated visits to a sampling unit.

It is a key requirement in the design of an increasing number of surveys that the numbers of visits to sampling unit sites ensure a sufficient level of probability, say 95 percent, that species be detected, either in an individual sampling unit, or in the entire survey region, if they are present. In such instances, the specific objective of the survey is to test the null hypothesis H_0 that species are not present, versus the alternative hypothesis H_A that species are present. The 95 percent probability of at least one detection is the *power* of the survey.

When counts are taken to estimate abundance, various strategies have been developed to address the issue of detectability. Capture-recapture methods allow the estimation of recapture probabilities for both closed and open systems (Otis et al. 1978; Pollock et al. 1990). Distance sampling allows the estimation of a detection function to compensate for the loss

of detectability at increasing distances away from an observer in line transect and point transect surveys (Buckland et al. 1993). An extensive literature exists describing estimators for these methodologies, both capture-recapture (e.g., Jolly 1965, 1982; Cormack 1968, 1979; Nichols et al. 1981; Pollock 1981; Seber 1982, 1986; White et al. 1982; Burnham et al. 1987) and distance sampling (e.g., Burnham et al. 1980). A modified version of Emlen's method also addresses the issue of detectability for count response (Ramsey and Scott 1981; Scott et al. 1986).

For presence-absence surveys, Azuma et al. (1990) addressed some aspects of this problem using spotted owls (*Strix occidentalis*) as an example. They proposed a fixed number of visits to each sampling unit and a bias adjustment to compensate for false negatives when estimating the proportion of occupied sampling units. Link et al. (1994) found that within-site sampling variability is a significant portion of overall variability in breeding bird surveys, particularly for species with low abundance levels. Pendleton (1995) recommended two strategies for addressing the effects of variation in detectability probabilities in bird point count surveys: standardizing surveys, and obtaining separate estimates of detection rates and adjusting for them. Kendall et al. (1992) commented on the problem with detectability in a power analysis study of grizzly bears (*Ursus arctos*), recommending multiple strata and optimal timing of surveys to enhance the

power of the design. Zielinski and Stauffer (1996) were also concerned with detectability probabilities in a power analysis for fisher (*Martes pennanti*) and American marten (*Martes americana*), recommending multiple-station sampling units with repeated visits. Sargent and Johnson (1997) noted the problem of detectability with carnivores due to secretive behavior and low densities.

Predictive accuracy assessment of wildlife habitat relationship models is dependent upon the quality of the response data. Adjustments for the uncertainty of detection with response data must be taken into account. Young and Hutto (Chapter 8) found that problems of detectability can be reduced by using presence-absence responses rather than counts in a survey. They obtained different results in logistic regression and Poisson regression analysis of habitat relationships for Swainson's thrush (*Catharus ustulatus*) over three successive years, partially due to problems with detectability. They collected data on ten-point transects for the three years to mitigate their uncertainty of detection. Karl et al. (Chapter 51) examined the effects of rarity on the predictive accuracy of habitat relationship models. They observed that errors of commission (species predicted but not detected) are either real or apparent. Real errors are caused by species-specific behavior such as the avoidance of humans, cryptic nature, episodic appearance, or temporal and spatial variation. Apparent errors, on the other hand, are caused by inefficient or limited sampling where there is uncertainty of detection. Reed (1996) discussed the influences of detectability in drawing inferences about extinction caused by species density, sampling effort, habitat structure, visibility, observer bias, number of observers, ambient noise, season, and weather. Stauffer (Chapter 3) cautioned against the use of inadequate data in his historical survey of statistical methods applied to wildlife habitat modeling and concluded that simple models, using 0-1 response data, may work best. Authors do not always explicitly address the effect of measurement Type II error caused by problems with detectability (species present but not observed) in their assessments of wildlife habitat relationship model accuracy (e.g., see Conroy and Moore, Chapter 16; Elith and Burgman, Chapter 24; Fielding, Chapter 21; Henebry and Merchant, Chapter 23;

Robertson et al., Chapter 34; Rotenberry et al., Chapter 22).

The marbled murrelet (*Brachyramphus marmoratus*) is a particularly important case in point. Federally listed as threatened (USFWS 1997) and listed as endangered in California, the murrelet is difficult to detect on land. This species nests in the canopy of trees in mature and old-growth forests. Each pair spends approximately two months of the April-through-September nesting period incubating and feeding one nestling, and the rest of the year is spent at sea (Ralph et al. 1992). Their flight is rapid and often silent. Furthermore, their detectability is often affected by visibility at survey sites (O'Donnell et al. 1995). Estimates of detectability at survey stations with occupied behavior (see discussion) in six different redwood stand types in California have ranged from 29 to 86 percent, with a mean of 59 percent. In individual stands with 25 or more stations surveyed, estimates of detectability have ranged from 12 to 100 percent (H. B. Stauffer personal observations).

Problems with detectability during repeated presence-absence surveys have lacked a statistical model structure to describe the distribution of the possible survey outcomes for sampling units. It is the objective of this chapter to present such a model and describe its practical application. The theory will be illustrated with its application to marbled murrelet surveys in the Pacific coast forests of North America, to an inland survey for murrelets in low-abundance areas within national forests of California.

Methods

Marbled murrelet terrestrial surveys on the Pacific Coast of North America follow a standardized protocol developed by the Pacific Seabird Group (Ralph and Nelson 1992; Ralph et al. 1994). Sampling units, up to 48.6 hectares (120 acres) in size, are surveyed for two-hour visits at dawn. Each sampling unit is surveyed for presence four times each year for two years—a total of eight visits. The station-visits are distributed over the murrelet nesting season. Observers record murrelet activity consisting of visible and audible detections of varying nesting and non-nesting behaviors.

Murrelets are extremely cryptic and individuals are not easily distinguished. Although identifiable as murrelets as they fly into a stand, detections cannot be readily translated into distinct counts of individuals. We have focused our attention on the *presence* of nesting or non-nesting behaviors as an alternative measure of bird activity.

An Inland Survey for Marbled Murrelets in California

We are using data from extensive surveys for murrelets conducted by the United States Department of Agriculture (USDA) Forest Service, Six Rivers National Forest, in low-abundance inland areas identified as Management Zone 2 in California by the Forest Ecosystem Management Assessment Team (FEMAT) (USDA et al. 1993; Hunter et al. 1998). The primary objective of these surveys has been to determine if murrelets are present in specified regions. They used forest type and geographic location to define habitat strata that were surveyed for presence or absence, using 48.6-hectare sampling-unit locations. These sampling units were visited four times per nesting season in each of two consecutive years following the guidelines of the standardized marbled murrelet protocol (above). It was a critical requirement in the design of the survey that sample sizes be sufficient in each stratum to ensure a 95 percent probability of at least one murrelet detection if they were present in 3 percent of the area. Thus, the objective of this survey was to test, for each stratum, the null hypothesis H_0 that murrelets were not present versus the alternative hypothesis H_A that murrelets were present, with a power of 95 percent. They assumed the *confidence* of the survey was 100 percent; in other words, that there would be no significant Type I error, or false positives.

Incorporating Detectability into the Binomial Model

For presence-absence surveys where there is uncertainty of detection, detectability can be incorporated into the binomial model so that options for power and sample size can be selected for the survey design. It can be incorporated using an adjustment to the probability parameter. The binomial distribution $B(X;P,n)$

(Cochran 1977; Särndal et al. 1992; Thompson 1992) is described by the probability distribution

$$B(X = x; P, n) = \binom{n}{x} \cdot P^x \cdot (1 - P)^{n-x}$$

where x is the number of sampling units where the species is present, P is the probability of presence of the species in a sampling unit, and n is the total number of units sampled. Note that x can vary between 0 and n . The model assumes that the total number of sampling units in the sampling frame is large compared to the number sampled, or that the sampling is performed with replacement. Otherwise, the probability P of presence would not remain constant as the sampling proceeds in a draw-sequential scheme (Särndal et al. 1992). The model also assumes complete certainty of detection, if the species is present in a sampling unit. What happens in surveys where complete certainty of detection is not the case? We need to develop an adjusted model that incorporates uncertainty of detection into its assumptions.

An adjusted binomial model $B_d(X;P,n,p,m)$ generalizes the binomial model $B(X;P,n)$ to incorporate detectability, using four parameters: P = the probability of presence; n = the number of units sampled; p = the conditional probability of detection, if present, with one visit to a sampling unit; and m = the number of visits to the units sampled. The model is described by the probability distribution

$$B_d(X = x; P, n, p, m) = \sum_{j=x}^n \binom{n}{j} \cdot P^j \cdot (1 - P)^{n-j} \cdot \binom{j}{x} \cdot p^{rx} \cdot (1 - p')^{j-x}$$

where $p' = 1 - (1 - p)^m$ describes the conditional probability of at least one detection, with m visits to a sampling unit, if the species is present. This distribution describes the probability of x , the number of sampling units where the species was present and detected, as the sum of the following probabilities: (1) the probability of sampling x units with the species present, successfully detecting it all x times (of n total sampling units); plus (2) the probability of sampling $(x + 1)$ units with the species present, successfully detecting it x times and failing to detect it once; plus (3) the probability of sampling $(x + 2)$ units with the species present, successfully detecting it x times and failing to

detect it twice; . . . ; plus (4) the probability of sampling n units with the species present, successfully detecting it x times and failing to detect it $(n-x)$ times. The binomial coefficients count the number of combinations of such possibilities. Again, note that x can vary between 0 and n .

The B_d model incorporates detectability into the binomial model. It assumes that the sampling units and visits are independent Bernoulli events. It also assumes that the parameters P and p are fixed throughout the population. The B_d model is actually a special case of a compound binomial-binomial distribution (Johnson and Kotz 1969:194, eq. 36). It can be shown directly from basic assumptions of the B_d model, or with algebraic simplification (J. A. Baldwin personal communication), that $B_d(X;P,n,p,m) = B(X;Pp',n)$.

Power for a Sampling Unit: $Power_{unit}$

The power of a survey at a single sampling unit, $power_{unit}$, the probability of successfully obtaining at least one detection with repeated visits to a sampling unit, is given by the formula

$$power_{unit} = p' = 1 - (1 - p)^m$$

where p is the conditional probability of detection, with one visit, if the species is present, and m is the number of visits to the sampling unit. We assume the visits are independent and the conditional probability p is constant.

One can calculate $power_{unit}$ by using estimates of detectability p , based upon previous surveys, in the formula. Alternatively, if estimates are not available, one can substitute low values for p and obtain approximate lower bounds on $power_{unit}$.

Conversely, one can calculate the number of visits necessary to ensure desired levels of $power_{unit}$ by substituting the prescribed $power_{unit}$ and lower bounds on p and solving for m in the equation as follows:

$$m = \log(1 - power_{unit}) / \log(1 - p).$$

Power for a Regional Survey: $Power_{region}$

The power for a target population in an entire survey region, $power_{region}$, can be calculated as the comple-

ment of the probability of zero detections in a survey of the region, $1 - B_d(0;P,n,p,m)$, using the B_d model:

$$power_{region} = 1 - \{1 - P[1 - (1 - p)^m]\}^n = 1 - \{1 - Pp'\}^n.$$

We are referring here to the presence or absence of a target population in a geographical region consisting of multiple sampling units, such as a ranger district, multiple river drainages, or a national forest, typically 10,000 hectares or larger. Conversely, sample size n can be calculated, if the desired $power_{region}$ and number of visits m are specified along with lower bound estimates of P and p :

$$n = \log(1 - power_{region}) / \log(1 - P(1 - (1 - p)^m)) = \log(1 - power_{region}) / \log(1 - Pp').$$

Results

Below, we summarize our results in three parts: (1) incorporating detectability into the binomial model; (2) power for a sampling unit; and (3) power for a regional survey.

Incorporating Detectability into the Binomial Model

Figure 29.1 shows the probabilities for the B_d model $B_d(X;P,n,p,m)$, contrasted with those of the binomial model $B(X;P,n)$, for the case where a small survey of ten sampling units (i.e., $n = 10$) is conducted in a region where the species is present in 30 percent of the area ($P = 30$ percent). For the B_d model, we consider the case where the conditional probability of detection with one visit is $p = 30$ percent, and there are $m = 2, 4,$ and 6 visits to sampling units.

The three pairs of contrasting bar graphs (Fig. 29.1) illustrate that for low values of X , the probabilities that X sampling units, out of the ten sampled, would have detections is greater when detectability is uncertain. For example, note in the figure that the probability of detections at zero of the sampling units ($X = 0$) for the binomial model (white bar) is approximately 3 percent (i.e., $power_{region} = 97$ percent), whereas the probabilities of $X = 0$ for the B_d model are approximately 19, 8, and 5 percent (i.e., $power_{region} = 81, 92,$ and 95 percent) with $m = 2, 4,$ and 6 visits, respectively (black bars). With small

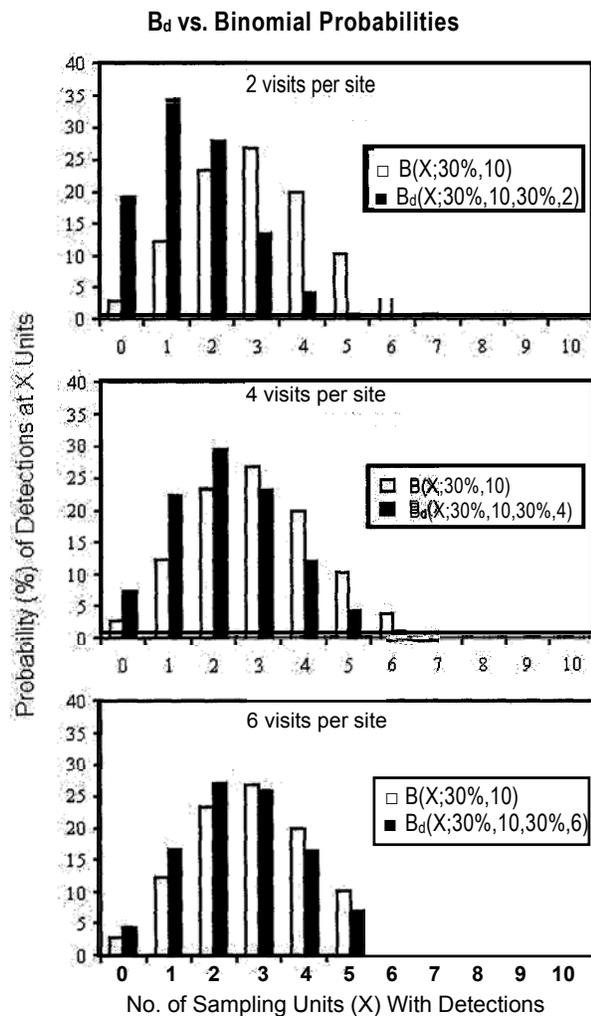


Figure 29.1. Comparison of the B_d model $B_d(X;P,n,p,m)$ with the binomial model $B(X;P,n)$ where X is number of sampling units with detections. We surveyed $n = 10$ sampling units, each with a probability of presence $P = 30\%$, conditional probability of detection with one visit $p = 30\%$, and $m = 2, 4,$ and 6 numbers of visits to sampling units. The bars show the probability of X sampling units having detections out of ten surveyed. For example, with $m = 2$ visits (top graph), the probability of $X = 0$ sampling units with detections with the B_d model is 19 percent (i.e., $\text{power}_{\text{region}} = 81\%$) (black bar) in contrast to 3 percent (i.e., $\text{power}_{\text{region}} = 97\%$) for the binomial model with complete certainty of detection (white bar). Additional visits to the sampling units decreases the probability of zero detections to 8 percent and 5 percent (i.e., $\text{power}_{\text{region}} = 92\%$ and 95%), respectively, for $m = 4$ and 6 visits (black bars) (middle and bottom graphs). The probability of $X = 1$ sampling units with detections is 34 percent, 22 percent, and 17 percent with $m = 2, 4,$ and 6 visits, respectively, for the B_d model in contrast with 12 percent for the binomial model.

numbers of visits (e.g., $m = 2$), the B_d model probabilities (black) are much higher for lower X values, in contrast to the binomial model probabilities (white). With fewer numbers of visits, sampling units having the species present will be more likely to have zero detections; the probability of Type II error of false negatives will be greater. As the number of visits increases, the probabilities in the B_d distribution approach those of the binomial model that has complete certainty of detection.

In summary, when detection is uncertain, calculations of power based upon the binomial model will be misleadingly high. This could result in a greater likelihood of false negatives (i.e., undetected presence).

Power for a Sampling Unit: $\text{Power}_{\text{unit}}$

We calculated the power for a sampling unit, $\text{power}_{\text{unit}}$, of a detection during at least one visit, with increasing numbers of visits m to a sampling unit (Table 29.1). Table 29.1 presents a range of levels of conditional probability p of detection with one visit: 10, 30, 50, 70, and 90 percent. Fewer numbers of visits are necessary to realize a 95 percent power for a sampling unit as the conditional probability of detection increases. For example, with a 10 percent conditional probability of detecting the birds in one visit, twenty-nine visits are necessary for a 95 percent probability of at least one detection at a sampling unit. With a 90 percent conditional probability of detection, on the other hand, only two visits are required for a 95 percent power of successfully detecting presence.

With a 30 percent conditional probability of detection with one visit, eight visits will ensure an approximate 95 percent power of at least one detection. The current marbled murrelet survey protocol, based upon eight visits to sampling units (Ralph and Nelson 1992; Ralph et al. 1994), ensures an approximate 95 percent power for values of p as low as 30 percent. The Pacific Seabird Group is currently revisiting the protocol to consider revising the number of visits, since some estimates for p , particularly in low-abundance areas, have been falling below the 30 percent threshold. A study is in progress to determine if it will be necessary to revise the protocol, at least for sampling unit locations in some regions.

TABLE 29.1.

Power at a sampling unit ($power_{unit}$) for presence-absence surveys.

p^a (%)	m^b	$Power_{unit}^c$ (%)
10	2	19.00
10	4	34.39
10	6	46.86
10	8	56.95
10	10	65.13
10	12	71.76
10	14	77.12
10	16	81.47
10	18	84.99
10	20	87.84
10	22	90.15
10	24	92.02
10	26	93.45
10	28	94.77
10	30	95.76
30	2	51.00
30	4	75.99
30	6	88.24
30	8	94.24
30	10	97.18
50	2	75.00
50	4	93.75
50	6	98.44
70	1	70.00
70	2	91.00
70	3	97.30
90	1	90.00
90	2	99.00

^a p = conditional probability of detection at the sampling unit, with one visit.

^b m = number of visits to the sampling unit.

^c $power_{unit}$ = probability of detecting presence at the sampling unit, with m visits (= p^b).

Power for a Regional Survey: $Power_{region}$

We calculated sample sizes required to realize specified levels of $power_{region}$ (95, 90, and 80 percent), for varying levels of the probability of presence P (1, 3, 5, and 10 percent), and varying levels of detectability p (10, 25, and 50 percent) (Table 29.2). In these calculations,

TABLE 29.2.

Sample sizes (n) for target populations in a region for presence-absence surveys.

p^a (%)	p^b (%)	m^c	$Power_{region}^d$ (%)	n
1	10	8	95	525
1	10	8	90	404
1	10	8	80	282
1	25	8	95	332
1	25	8	90	255
1	25	8	80	179
1	50	8	95	300
1	50	8	90	231
1	50	8	80	161
3	10	8	95	174
3	10	8	90	134
3	10	8	80	94
3	25	8	95	110
3	25	8	90	85
3	25	8	80	59
3	50	8	95	99
3	50	8	90	76
3	50	8	80	54
5	10	8	95	104
5	10	8	90	80
5	10	8	80	56
5	25	8	95	66
5	25	8	90	51
5	25	8	80	35
5	50	8	95	59
5	50	8	90	46
5	50	8	80	32
10	10	8	95	52
10	10	8	90	40
10	10	8	80	28
10	25	8	95	32
10	25	8	90	25
10	25	8	80	18
10	50	8	95	29
10	50	8	90	22
10	50	8	80	16

^a p = probability of presence.

^b p = conditional probability of detection at a sampling unit, with one visit.

^c m = number of visits to a sampling unit.

^d $power_{region}$ = probability of at least one detection in a region.

we assumed eight visits per sampling unit, corresponding to the marbled murrelet protocol. With $P = 1$ percent and $p = 10$ percent, 525 sampling units are neces-

sary to realize a 95 percent power for a target population in an entire region. At the other extreme, with the more optimistic levels $P = 10$ percent and $p = 50$ percent, only twenty-nine sampling units are required for 95 percent power.

For the marbled murrelet Zone 2 inland survey in California, lower bound estimates of $P = 3$ percent and $p = 10$ percent were assumed and a sample size of 174 was necessary to attain a 95 percent power for each forest habitat stratum (Hunter et al. 1998).

Discussion

In the marbled murrelet protocol, observers note, murrelet activity, recording visible and audible detections with behaviors assigned to one of three categories: (1) occupancy: present and exhibiting nesting behavior; (2) presence: present but not exhibiting nesting behavior; and (3) absence. Although we have referred solely to "presence" or "absence" of species, for the murrelet, "occupancy" may be substituted for "presence" for the B_d model, if appropriate to the requirements of a particular survey.

Maximum Likelihood Estimators

In this chapter, we have focused on the assumptions of the B_d model and its probability distribution. We have presented formulas for the calculation of power—for sampling units and for target populations in entire regions—for presence-absence surveys satisfying the assumptions of this model. Such information is useful in the determination of sampling design for such surveys.

For the analysis of data collected from presence-absence surveys, T. A. Max, J. A. Baldwin, and H. T. Schreuder (personal communication) have developed closed-form maximum likelihood estimators for P and p within a probability parameter space, for marbled murrelet and spotted owl survey protocols in the Pacific Northwest. Their owl estimators assume a protocol whereby the number of visits to sampling units is modeled by a negative binomial model: the visits to sampling units are ceased once the behavior (i.e., presence) has been observed, or a specified maximum number of visits has been achieved. Their murrelet estimators alternatively use the assumptions of the B_d

model, prescribing a fixed number of visits to each sampling unit. Their estimators assume fixed P and p for a region.

More general maximum likelihood estimators need to be developed, allowing varying P and p for multiple regions, years, and seasons. One approach might use computer optimization routines to approximate maximum likelihood solutions. This context would be analogous to capture-recapture estimators, with capture-recapture heterogeneity corresponding to varying B_d regional P and p , and varying recapture and survival estimators corresponding to varying year and season P and p .

Repeated Visits to Sampling Units—Its Effect on Power for Regional Surveys

Presence-absence surveys have historically focused on locations where species are present at relatively high abundance, to determine behavioral and habitat characteristics. Protocols for such surveys have emphasized repeated visits to sampling units to ensure a high degree of power to detect presence in each sampling unit. Without repeated visits, the conditional probability of detection at specific locations may be low and the probability of not detecting the species unacceptably high.

In surveys, however, where the primary objective is to sample a rare species to determine whether it is present in a region, a more efficient sampling design may be quite different. With this objective, it can be shown that the power of the survey will be effectively increased by sampling additional sampling units rather than by repeatedly revisiting sampling units that have already been sampled, if conditions are reasonably approximated by the assumptions of the B_d model. That is, increasing n is more efficient and cost effective than increasing m . This observation may be surprising at first to surveyors accustomed to existing protocols that have emphasized repeated visits to sampling units.

The reason for this is that the first visit to a sampling unit will provide a maximum amount of "information"—more than a second visit. The amount of information then decreases with each successive visit. Revisiting a sampling unit will indeed increase the probability of detection of the species if it is present,

but moving on to new sampling units will increase the probability even more for detection of the species in the entire region. If a sampling unit has been visited once and the species was not detected, a second visit to that sampling unit will have probability $P(1 - p)p$ of detecting the species. A visit to a new sampling unit, however, will have probability Pp of detecting the species. Since $P(1 - p)p \leq Pp$, it is thus the better strategy from a statistical point of view to move on to new sampling units rather than to revisit old ones.

We illustrate this effect with an example. If $n = 50$ units are sampled in a population with $P = 1$ percent, an increase in sampling intensity from $m = 4$ to 8 visits to each sampling unit will raise the power from 37.6 to 39.4 percent. However, if the sample size is raised to $n = 100$ with $m = 4$ visits, resulting in an equal number of total sampling unit-visits, the power of the survey will be increased to 61.0 percent. Costs will likely be higher for the latter alternative, to move to new sampling units, but even if $n = 75$ sampling units are surveyed with $m = 4$ visits, the power is raised to 50.7 percent. These comparative differences will remain generally true for other cases although the contrasts will be less extreme where the levels of P are higher.

Variation in P and p and Its Effects on Power_{region}

It is disconcerting that in practical application it may not be realistic to make the assumption that P and p are fixed, as in the B_d model. How might variation in the probability of presence P and the conditional probability of detection p affect the B_d model and its power? Species such as the fisher and the American marten (Zielinski and Stauffer 1996) may very well be opportunistic and the probabilities p may increase, or decrease, with time due to the capabilities of the species to adapt their behavior to visiting baited sign detection stations. For murrelets, the effective survey area of a morning's visit to a 48.6-hectare sampling unit is estimated to be approximately 12.2 hectares (30 acres). This reflects an observer's ability to hear and see murrelet behavior that often includes circling in and around the nest area. Therefore, the sampling unit cannot be completely surveyed in a morning's visit and must be surveyed with repeated visits spread over the April-August nesting season and between

years. It is certainly likely in these cases that P and p may vary, geographically, seasonally, and annually.

Feller (1968:230-231) proves the surprising result that the variability of the probability of presence P in the binomial model actually decreases the variance of its estimator. For the conditional probability of detection p , it can be shown, with some elementary probability calculations for the B_d model, that if p varies in a survey at or above a minimal (assumed) fixed value, say p_f , then the power of the survey will be at least as large as that calculated for the fixed p_f . In fact, if p varies symmetrically around a fixed p_f , then the power of the survey can be shown to be at least as large as that calculated for the fixed p_f . These results suggest that the power of the survey will not be reduced by p varying above, or symmetrically around, an assumed fixed average p_f for a survey; in other words, power calculations for regional surveys using the B_d model are robust to those types of variation in p .

Matsumoto (1999) has conducted a sensitivity analysis of power estimates for the murrelet protocol, applied to regions with low species abundance. Her study determined that power estimates are quite robust to varying parameter probabilities P and p within the investigated ranges. She examined varying P and p , assuming low average abundance levels of $P = 1, 3, 5,$ and 10 percent, and average levels of conditional probability of detection $p = 10, 25,$ and 50 percent. Her simulation study examined the effects of varying P and p on estimates of power_{region}, based upon the B_d model assumptions of fixed P and p . She allowed P and p in her simulation to vary, using beta distributions with mean values equal to the assumed fixed values and with varying standard deviations. Her study indicated that power estimates are quite robust to varying parameter probabilities for P and p within those ranges and beta distributed around assumed fixed averages.

Biological and Sampling Components Affecting Presence and Detectability

Errors of commission (species predicted but not observed) in wildlife habitat relationship modeling, both real and apparent, affect the predictive accuracy of wildlife habitat relationship models. We have focused on the statistical aspects of power and sample size se-

lection for presence-absence surveys for a species characterized by an uncertainty of detection. A number of biological components affect both detectability p and presence P . Real errors are caused by species-specific behavior, such as avoidance of humans, cryptic nature, episodic appearance, or temporal and spatial variation. Such behavior occurring globally throughout the survey region affects P , the probability of presence of the species. Apparent errors, on the other hand, are caused by similar behavior occurring dynamically within sampling units. This affects p , the conditional probability of detection of the species, if present. Other influences on apparent error, such as species density, sampling effort, habitat structure, visibility, observer bias, number of observers, ambient noise, season, and weather affect the detectability p . It has been beyond the scope of this study to investigate the contribution of each of these biological and sampling components to P and p . Future investigators are well advised to examine the relative effects of each of these contributors to detectability in their species surveys.

Conclusions

By incorporating uncertainty of detection into survey design and analysis, the predictive accuracy of wildlife habitat relationship models can be improved. The adjusted binomial B_d model provides a method for incorporating uncertainty of detection into presence-absence surveys. The B_d model is useful for both the

design and analysis of the survey. For the design, it allows the calculation of the number of visits necessary at sampling units to ensure a prescribed power, or probability of detection, when the species is present. It also allows the calculation of sample sizes and power for regional surveys. For the analysis, it provides a model for estimating the parameters P , the probability of presence, and p , the conditional probability of detection if the species is present, based upon presence-absence data from a survey; using maximum likelihood. Moreover, although its application has been illustrated here for a particularly challenging species, the marbled murrelet, it is sufficiently general to be applicable to presence-absence surveys of other species in sampling units or regions, wherever detectability is of concern.

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and Scale*

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