

Several methods of measuring changes in the size of animal populations are used in wildlife management and population ecology. Local and large scale (e.g., national and state) surveys are conducted using counts of animals and indirect measurements of abundance such as calls, sightings, tracks, etc. (Artmann 1977, Dolton 1977, Seber 1982, Robbins et al. 1986). Typically surveys are stratified by physiographic regions and political areas. Often primary sampling units (e.g., squares 20 miles on a side) are subsampled with routes along rural roads. Biologists move continuously or stop at specified points along the routes and record the numbers of animals detected under standardized conditions.

The use of these counts as indices of abundance has been criticized because it requires the assumption that animals are equally detectable (Dawson 1981, Wilson and Bart 1985). If the probability of detecting an animal changes, counts are no longer proportional to the number of animals present. For example, the probability of detecting a mourning dove (*Zenaidura macroura*) by its song can change six-fold depending on whether or not the dove has a mate (Sayre et al. 1980). Other methods such as spot mapping and capture-recapture do not require the assumption of equal detectability but are too labor intensive for large surveys (Jarvinen and Vaisanen 1981). If distance measurements are available, line transect methods can be used to estimate abundance without assuming equal detectability (Burnham et al. 1981). Often distance measurements cannot be obtained because the animals might be heard but not seen, or move before being seen.

The bounded count method (Robson and Whitlock 1964, Seber 1982: 58) and the binomial moment method (Caughly and Goddard 1972, Seber 1982: 457) can be used when distance measurements are not available. However, the bounded count method is seriously biased unless the probability of detection is large (Routledge 1982). The binomial moment method requires either binomial distributed counts or two counts with two different probabilities of detection (e.g., aerial observations at different altitudes). The design of many surveys does not allow the observer to control the probability of detection. Usually the probability of detection varies among individual animals, locations, and observers, making the assumption of a binomial distribution questionable (Routledge 1982).

If the probability of detecting an animal can be estimated, the Horvitz-Thompson estimator can be used to estimate animal abundance by dividing the mean number of animals detected by the probability of detection (Horvitz-Thompson 1952, Cochran 1977: 259-261). If individuals are

distinguishable, the probability of detection can be estimated from repeated counts (Hewitt 1967, Seber 1982: 53). Emlen (1971) used the Horvitz-Thompson estimator with estimates of the probability of detection for strips parallel to the transect, assuming all animals were detected on the strip nearest the transect. This method requires a distance measurement to define the strips. In Table 1 we list the probabilities of detecting all animals in the strip nearest the transect. For example, if eight animals are present with a 0.90 detection probability, the probability of detecting all animals is 0.43. With 16 animals that probability is 0.19.

Christman (1984) applied the Horvitz-Thompson estimator to the estimation of the density of territories using spot mapping. Although labor intensive and not applicable to the frequently used roadside counts, this method estimates animal or breeding unit density without assuming equal detectability. We note that the variance of his estimator can be obtained without requiring separate data sets to estimate the mean count and the probability of detection as suggested by Christman (1984), if one uses the bootstrap variance estimator. As Christman notes "the most serious problem with the plot mapping is the potential to overestimate the probability of detection if sparse clusters are not recognized as clusters."

To use plot mapping, all territories must be found in the area used to estimate the probability of detection. One must detect neighboring animals at the same time to separate the territories because one cannot distinguish individuals. If the probability of detection is 0.5 and two animals are present, eight observations are required to achieve a 90% probability of seeing both animals during the same observation (Table 1). If the probability is 0.3, more than 16 observations are required. More individuals will require more observations. If some animals are missed, the probability of detection will be overestimated and the density underestimated. Because of this problem, we do not recommend using Emlen or Christman density estimators unless the probability of detecting the animals in the area used to estimate the probability of detection is high.

Thus, a good abundance estimator is lacking for situations where (a) distance measurements cannot be obtained, (b) individuals are indistinguishable, and (c) the probability of detection is low. Many species such as woodcock (*Scolopax minor*) and numerous raptors occur in that situation. We investigated methods of improving roadside counts and other abundance indicators by estimating the probability of detection and then applying the Horvitz-Thompson estimator.

We considered two situations where detection probabilities can be estimated.

First, one can estimate the proportion of an area that is occupied by a species. A point is said to be occupied if the species occurs within the observer's detection radius of the point during the animals' normal activity. The biologist makes repeated observations at each point, recording whether or not one or more animals is detected. The observations must be separated by enough time so they are independent. The proportion of detections after the first detection estimates the probability of detection given that the point is occupied. The Horvitz-Thompson estimate of the proportion of the points that are occupied also estimates the proportion of the area that is occupied, provided that the detection radius does not change. If animal spacing is constant, changes in the proportion of area occupied can be used to monitor changes in abundance. For some species, the probability of detecting more than one individual or pair at a point is negligible and the proportion of area occupied is equivalent to relative density.

In the second situation, one can estimate relative abundance. A biologist records the number of animals detected at each point. After completing the observation period, he remains at the point and records whether or not individual animals are detected during a number of subsequent observation periods to estimate the probability of detecting individuals given that they are present. The detection probability during the later periods must be independent of detection during the first period or any dependence must be modeled to avoid biasing the detection probability.

Estimation of the proportion of an area occupied by a species will be developed in this paper but similar methods can be applied to individuals to estimate relative abundance. Resource managers are often oriented to an area or subdivision of land with relevance to certain objectives such as timber harvest, recreational use, stand improvement, or erosion control. The density of animals, per se, may be of little concern to them. Rather, they need to know if certain areas and associated habitats do or do not support species of concern. They may need to know when the species begins to disappear, or reappear, in areas under their management. For resource managers, occupancy is a parameter of interest.

#### ESTIMATION

The data are repeated presence/absence observations at  $n$  points. There are  $m_i$  observations at point  $i$ . The unconditional probability  $d_i'$  of detecting one or more animals at point  $i$  is estimated by the proportion of observations that results in a detection. The conditional detection probability  $d_i$  given that the point is occupied is estimated as the proportion of the observations after the first detection that results in a detection.

$$\hat{d}_i' = \frac{\sum_{t=1}^{m_i} x_{it}}{m_i} \text{ and}$$

$$\hat{d}_i = \left( \sum_{t=1}^{m_i} y_{it} \right) / \left( \sum_{t=1}^{m_i} z_{it} \right),$$

where

$x_{it} = 1$  if one or more animals are detected at point  $i$  and time  $t$ ,

$= 0$  otherwise,

$y_{it} = 1$  if  $x_{it}=1$  and  $x_{it'}=1$  for some  $t' < t$ , that is when one or more animals are detected at a point known to be occupied (i.e., at a point where an animal has previously been detected),

$= 0$  otherwise, and

$z_{it} = 1$  if  $x_{it'}=1$  for some  $t' < t$ , indicating an observation at a point known to be occupied,

$= 0$  otherwise.

While the probability of detection  $\hat{d}_i$  could be estimated for each individual point, a more stable estimate can be obtained by using the mean  $\bar{d}$  over similar points. The mean, a separate ratio estimator, is used because the  $d_i$ 's are expected to differ among points. A combined ratio estimator

$$\left( \sum_{i=1}^n \sum_{t=1}^{m_i} y_{it} \right) / \left( \sum_{i=1}^n \sum_{t=1}^{m_i} z_{it} \right)$$

is not suggested because points with small  $d_i$ 's would be under-represented, biasing the estimator, because fewer observations would be available after the first detection.

The conditional probability  $e_i$  of detecting an animal during any of the  $m_i$  observations at point  $i$  given that the point is occupied is

$$\hat{e}_i = 1 - (1 - \bar{d})^{m_i}.$$

We investigated three estimators of the proportion of an area occupied by a species. The first two,  $\hat{p}_1$  and  $\hat{p}_2$ , use the ratio of the number of points known to be occupied to the total number of points, expanding the count of occupied points to allow for occupied points where no animals were detected. Consider the estimator

$$\hat{p}_* = \sum_{i=1}^n (w_i / e_i) / n$$

where

$w_i = 1$  if  $x_{it}=1$  for any  $t$ , that is when an animal is detected at point  $i$ ,

$= 0$  otherwise.

The unconditional detection probability is  $\text{prob}(\text{detect and occupied}) =$

$\text{prob}(\text{occupied}) \text{prob}(\text{detect} | \text{occupied}),$

$= pe,$

noting that an animal cannot be detected unless the point is occupied. Here the same number of observations are made at each point, resulting in the conditional probability of detection being the same for all points ( $e=e_i$ ). The number of points where animals are detected  $w. = \sum w_i$  is binomially distributed with mean and variance

$$E(w.) = npe$$

$$V(w.) = npe(1-pe).$$

The mean and variance of the estimator  $\hat{p}_*$  are

$$E(\hat{p}_*) = E(w./en) = p$$

$$V(\hat{p}_*) = V(w./en) = p(1-pe)/en.$$

Thus,  $\hat{p}_*$  is an unbiased estimator of  $p$ , the proportion of points that are occupied.

We use bootstrap estimates (Efron 1982) to avoid the assumption of a binomial distribution which is not appropriate if detection probability varies among points. Bootstrap estimates reduce the bias of the ratio estimator and provide a nonparametric variance estimate. A bootstrap distribution is formed by taking a large number (201) of bootstrap samples of  $n$  points with replacement from the actual sample of  $n$  points and calculating the estimates from each bootstrap sample. Symmetric errors in  $\hat{d}$  become asymmetric in  $\hat{p}_*$  because  $\hat{p}_*$  is a non-linear expression in  $\hat{d}$ . This asymmetry suggests using the median instead of the mean of the bootstrap distribution for the point estimate because the median is a better measure of the central tendency of a asymmetric distribution. We take the first estimator  $\hat{p}_1$  to be the median and the second estimator  $\hat{p}_2$  to be the mean of the bootstrap distribution of  $\hat{p}_*$ . The standard deviation of the bootstrap distribution  $\hat{s}$  is the estimate of the standard error of both  $\hat{p}_1$  and  $\hat{p}_2$ .

The third estimator uses the relationship  $\text{prob}(\text{occupied}) = \text{prob}(\text{detect}) / \text{prob}(\text{detect} | \text{occupied})$ . This estimator is

$$\hat{p}_3 = \text{mean}(\hat{d}') / \text{mean}(\hat{d}_i).$$

The following simple artificial example illustrates the estimation of detection probability and area occupied:

i	t	$x_{it}$	$y_{it}$	$z_{it}$	$m_i$	$\hat{d}_i$	$\hat{d}'_i$	$\bar{d}$	$w_i$	$\hat{e}_i$
1	1	0	0	0	5	1/3	2/5	0.417	1	0.933
1	2	1	0	0						
1	3	0	0	1						
1	4	1	1	1						
1	5	0	0	1						

2	1	1	0	0	3	1/2	2/3	0.417	1	0.802
2	2	0	0	1						
2	3	1	1	1						

3	1	0	0	0	2	.	0/2	0.417	0	0.660
3	2	0	0	0						

$i = 1, 2, \dots, n$  points,  
 $t = 1, 2, \dots, m_i$  times (observations),  
 $x_{it} = 1$  if animal detected,  
 $= 0$  otherwise,  
 $y_{it} = 1$  if animal detected at point known to be occupied,  
 $= 0$  otherwise,  
 $z_{it} = 1$  if point known to be occupied,  
 $= 0$  otherwise,  
 $\hat{d}_i = \text{prob}(\text{detect} | \text{occupied})$ ,  
 $= (\sum_{t=1}^{m_i} y_{it}) / (\sum_{t=1}^{m_i} z_{it})$ ,  
 $\hat{d}'_i = \text{prob}(\text{detect}) = \sum_{t=1}^{m_i} x_{it} / m_i$ ,  
 $\bar{d} = \text{mean}(\hat{d}_i) = (1/3 + 1/2) / 2 = 0.417$ ,  
 $w_i = 1$  if animal detected at point during any observation,  
 $= 0$  otherwise,  
 $\hat{e}_i = 1 - (1 - \bar{d})^{m_i} = \text{conditional}$

probability of detecting an animal during any observations given that the point is occupied,  
 $p =$  proportion of points that are occupied,

$$\hat{p}_* = \sum_{i=1}^n w_i / e_i n$$

$$= (1/0.993 + 1/0.802 + 0/0.660) / 3$$

$$= 0.751$$

$$\hat{p}_3 = \text{mean}(\hat{d}') / \text{mean}(\hat{d}_i)$$

$$= [(2/5 + 2/3 + 0/2) / 3] / [(1/3 + 1/2) / 2]$$

$$= 0.853$$

Taking five bootstrap samples for illustration with  $b =$  bootstrap sample and  $i =$  actual sample:

b	i	$\hat{d}_i$	$\bar{d}$	$m_i$	$\hat{w}_i / \hat{e}_i$	$\hat{p}_*$
1	1	0.333	0.444	5	1.056	1.157
1	2	0.500		3	1.208	
1	2	0.500		3	1.208	
<hr/>						
2	1	0.333	0.417	5	1.072	0.773
2	3	.		2	0.000	
2	2	0.500		3	1.247	
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3	1	0.333	0.333	5	1.152	0.768
3	1	0.333		5	1.152	
3	3	.		2	0.000	
<hr/>						
4	3	.	0.500	2	0.000	0.381
4	3	.		2	0.000	
4	2	0.500		3	1.143	
<hr/>						
5	2	0.500	0.444	3	1.208	1.157
5	1	0.333		5	1.056	
5	2	0.500		3	1.208	

$\hat{p}_1 = \text{median } \hat{p}_* = 0.773$   
 $\hat{p}_2 = \text{mean } \hat{p}_* = 0.847$   
 $\hat{s} = \text{standard deviation of } \hat{p}_* = 0.324$

#### SIMULATION

A computer simulation was used to compare and evaluate the estimators  $\hat{p}_1$ ,  $\hat{p}_2$ , and  $\hat{p}_3$ . Forty cases, each with 250 surveys, were simulated. Surveys consisted of  $n'$  points that were observed on  $m$  occasions and  $n''$  points that were observed once. Each point had a probability  $p$  of being occupied. Each occupied point was assigned a probability of detecting one or more animals during an observation. These probabilities were drawn from a normal distribution with mean  $d$  and variance  $s^2$ . Observations on the  $n'$  multiple observations points had a probability  $r$  of being missing; none of the  $n''$  single observation points had missing observations. The means and standard errors of  $\hat{p}_1$ ,  $\text{se}(\hat{p}_1)$ ,  $\hat{p}_2$ ,  $\hat{p}_3$ ,  $\text{se}(\hat{p}_3)$ ,  $\bar{d}$ , and  $\text{se}(\bar{d})$  were estimated from the results of the 250 simulated surveys for each case, where  $\text{se}()$  indicates a standard error estimate. The proportion of estimated 95% and 90% confidence intervals that enclosed the true value were recorded. Those proportions will be referred to as the observed confidence.

Four different survey designs were simulated. The base design had a total of 250 observations, a constant probability of

detection given occupancy  $d$ , no single observation points, and no missing observations. Different combinations of number of observations per point ( $m=5, 10$ ), occupancy probability ( $p=0.3, 0.5, 0.7$ ), and detection probability given occupancy ( $d=0.3, 0.5, 0.7$ ) were used. The number of points changed so that the total number of observations and thus the cost of the survey was constant. The next design included 50 points with single observations. The third "design" allowed  $d$  to vary among points ( $s^2=0.05$ ) and allowed observations to be missing with probability 0.10, simulating some field conditions. The last design increased the total number of observations to 1000.

All three estimators were found to be biased (Table 3): bias( $\hat{p}_1$ )=0.0043 [ $\pm 0.0016$  (std. err.),  $P=0.0129$  ( $t$ -test),  $n=40$  cases]; bias( $\hat{p}_2$ )=0.0106 ( $\pm 0.0032$ ,  $P=0.0021$ ); and bias( $\hat{p}_3$ )=0.0146 ( $\pm 0.0035$ ,  $P=0.0002$ ). The least biased estimator is  $\hat{p}_1$  ( $\hat{p}_1$  less biased than  $\hat{p}_2$  or  $\hat{p}_3$   $P<0.01$ ,  $\hat{p}_2$  less biased than  $\hat{p}_3$   $P<0.05$ , paired  $t$ -tests  $n=40$  cases).  $\hat{p}_1$  was found to have a smaller standard error than  $\hat{p}_3$  ( $P=0.0001$ , paired  $t$ -test,  $\hat{p}_1$  and  $\hat{p}_2$  have the same standard error estimate). The mean observed confidence of estimated 95% and 90% confidence intervals were 94.4% ( $\pm 0.3\%$ ,  $P=0.021$ ) and 89.5% ( $\pm 1.6\%$ ,  $P=0.269$ ) respectively, suggesting that the confidence of estimated 95% confidence intervals may be too low.

From these results, we concluded that  $\hat{p}_1$  is the best estimator. Although  $\hat{p}_1$  was shown to be biased, the bias (0.0043) was much less than the standard error (0.0899). Therefore, bias is unimportant.

An analysis of variance of the simulation results for  $\hat{p}_1$  was conducted with main effects for survey design,  $p$ ,  $d$ ,  $m$ , and their two-way interactions (Table 2). The effect of survey design was divided into three contrasts that compared each design to the base design. The positive bias was increased by small  $d$  ( $P<0.001$ ) and the use of single observation points ( $P=0.008$ ). A constant  $d$  was associated with positive bias and a variable  $d$  with negative bias ( $P=0.017$ ). The standard error was increased by small  $d$  ( $P<0.001$ ), using points with single observations ( $P<0.001$ ), and fewer total observations ( $P<0.001$ ). The effect of small  $d$  in increasing the standard error was larger when single observation points were used ( $P<0.001$ ), when there were fewer total observations ( $P=0.007$ ), and when there were fewer observations per point ( $P<0.001$ ). There was evidence for an interaction between  $m$  and  $d$  on the observed confidence of estimated 95% confidence intervals. The effect of  $d$  was greater for small  $m$  ( $P=0.030$ ). The confidence of estimated 90% confidence intervals was larger than 90% for small  $d$  and smaller than 90% for large  $d$  ( $P<0.001$ ), and this effect was greater with fewer total observations ( $P=0.030$ ).

Use of points with single observations increased both the bias and standard error. The effect of using single observation points

was to decrease the information available for estimating  $d$  and increasing information for  $p$ . The simulation has shown, at least under these conditions, that good estimates of  $d$  are crucial. Therefore, all points should have multiple observations. With small  $d$ , ten observations per point gave the smallest standard error, but for large  $d$ , five observations per point gave the smallest standard error. This suggests using more observations per point when the probability of detection is low.

#### EXAMPLE

Data on the presence or absence of red-shouldered hawks (*Buteo lineatus*) detected by playing conspecific calls were collected by J. A. Mosher, M. R. Fuller, and M. Kopeny (Table 3). Animals were detected at 80% of the points in the first study area, which had an estimated probability ( $\hat{d}$ ) of detecting animals with a single observation of  $0.198 \pm 0.040$  (std. err.), whereas animals were detected on 60% of the points on the second study area where  $\hat{d}$  was  $0.230 \pm 0.080$ . There was a 89.0% probability of detecting animals that were present on the first study area at least once with ten observations ( $e$ ) and a 87.6% probability on the second area with eight observations. Using these estimates to account for occupied points where birds were not observed, we estimated that  $90.9\% \pm 16.5\%$  of the first study area was occupied by red-shouldered hawks and that  $72.9\% \pm 26.5\%$  of the second was occupied.

For comparison, we applied the bounded count and the binomial moment methods using the count of the points where birds were observed for each observation. The bounded count estimate of the number of occupied points is 2 (largest count) - (next largest count). These estimates are  $2(3)-3=3$  (30%) and  $2(3)-2=4$  (40%) for the first and second area respectively. The binomial moment estimate is  $m^2/(m-v)$  where  $m$  and  $v$  are the mean and variance of the observed counts. These estimates are  $(1.80)^2/(1.80-0.84)=3.4$  (34%) and  $(1.50)^2/(1.50-.57)=2.4$  (24%). All are substantial underestimates because we know that birds have been observed at 8 points (80%) on the first study area and at 6 points (60%) on the second.

#### CONCLUSIONS

Our estimator of the area occupied by a species provides a method for monitoring populations for those situations where distance measurements cannot be obtained, individuals are indistinguishable, and the probability of detection is small. For monitoring populations, the use of area occupied requires either that animal spacing does not change or that the probability of detecting more than one individual (or pair) is negligible. Estimates of area occupied also may be of interest in other situations

where the objective is not to monitor population abundance. The use of presence/absence data allows the estimation of detectability without knowledge of the true number of individuals present. For other situations where a relative abundance estimator is required, the same methods can be applied to individuals to estimate relative abundance.

We have shown that the proposed estimator performs well in the simulated situations. Although it is biased, the bias is much less than the standard errors. Thus, bias is unimportant. Good estimates of the probability of detecting one or more animals was shown to be crucial to good estimates of the proportion of area occupied. This suggests that observers should make multiple observations at each point. More observations should be taken at a point when the probability of detection is low.

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Table 1. Probability p of detecting all animals that are present during the same observation if a animals are present, m observations are made and the probability of detecting each animal during an observation is q. Assuming independence  $p = [1 - (1 - q^a)^m]$ . This is the probability of knowing the true number of animals present when one cannot distinguish individual animals.

Anim.	Obs.	Prob. q of detecting each animal					
a	m	0.10	0.30	0.50	0.70	0.90	
1	2	0.19	0.51	0.75	0.91	0.99	
1	4	0.34	0.76	0.94	0.99	1.00	
1	8	0.57	0.94	1.00	1.00	1.00	
1	16	0.81	1.00	1.00	1.00	1.00	
1	32	0.97	1.00	1.00	1.00	1.00	
1	64	1.00	1.00	1.00	1.00	1.00	
2	1	0.01	0.09	0.25	0.49	0.81	
2	2	0.02	0.17	0.44	0.74	0.96	
2	4	0.04	0.31	0.68	0.93	1.00	
2	8	0.08	0.53	0.90	1.00	1.00	
2	16	0.15	0.78	0.99	1.00	1.00	

Table 1. Continued.

Anim.	Obs.	Prob. q of detecting each animal				
a	m	0.10	0.30	0.50	0.70	0.90
2	32	0.28	0.95	1.00	1.00	1.00
2	64	0.47	1.00	1.00	1.00	1.00
4	1	0.00	0.01	0.06	0.24	0.66
4	2	0.00	0.02	0.12	0.42	0.88
4	4	0.00	0.03	0.23	0.67	0.99
4	8	0.00	0.06	0.40	0.89	1.00
4	16	0.00	0.12	0.64	0.99	1.00
4	32	0.00	0.23	0.87	1.00	1.00
4	64	0.01	0.41	0.98	1.00	1.00
8	1	0.00	0.00	0.00	0.06	0.43
8	2	0.00	0.00	0.01	0.11	0.68
8	4	0.00	0.00	0.02	0.21	0.89
8	8	0.00	0.00	0.03	0.38	0.99
8	16	0.00	0.00	0.06	0.61	1.00
8	32	0.00	0.00	0.12	0.85	1.00
8	64	0.00	0.00	0.22	0.98	1.00
16	1	0.00	0.00	0.00	0.00	0.19
16	2	0.00	0.00	0.00	0.01	0.34
16	4	0.00	0.00	0.00	0.01	0.56
16	8	0.00	0.00	0.00	0.03	0.81
16	16	0.00	0.00	0.00	0.05	0.96
16	32	0.00	0.00	0.00	0.10	1.00
16	64	0.00	0.00	0.00	0.19	1.00

Table 2. Means of significant effects for  $\hat{p}_1$  in the simulation study.

Effects	Response Variables			
	Bias	Standard error	95 % Conf. inter.	90 % Conf. inter.
	P=0.0001	P=0.0001	P=0.0002	
d= 0.3	0.0111	0.1188	91.28	
d= 0.7	-0.0019	0.0661	87.98	
obs. d	P=0.0084	P=0.0001		
Multiple	0.0050	0.0950		
Single	0.0142	0.1334		
d	P=0.0173			
Constant	0.0050			
Variable	-0.0031			
	P=0.0001			
250 obs.	0.0950			
1000 obs.	0.0434			
obs. d	P=0.0001			
Mult. 0.3	0.1132			
Mult. 0.7	0.0768			
Sing. 0.3	0.1950			
Sing. 0.7	0.0718			

Table 2. Continued.

Effects	Response Variables			
	Bias	Standard error	95 % Conf. inter.	90 % Conf. inter.
obs. d	P=0.0074		P=0.0299	
250 0.3	0.1132		91.60	
250 0.7	0.0768		86.30	
1000 0.3	0.0480		91.10	
1000 0.7	0.0388		90.20	
m d	P=0.0001		P=0.0303	
5 0.3	0.1304		95.60	
5 0.7	0.0566		93.52	
10 0.3	0.1072		94.10	
10 0.7	0.0755		94.60	

Table 3. Presence or absence of red-shouldered hawks.

Point	First Study Area										$\hat{d}$
	Observations										
1	0	0	0	0	0	0	0	0	0	0	.
2	0	0	0	0	1	0	1	0	0	0	.200
3	0	0	0	0	0	0	0	0	0	0	.
4	0	0	0	0	0	1	0	0	0	1	.250
5	0	0	0	0	0	1	0	0	0	1	.250
6	0	1	0	0	0	0	0	0	0	1	.125
7	1	1	0	0	0	0	1	1	0	0	.333
8	0	0	1	1	0	0	0	0	0	0	.142
9	0	0	1	0	0	0	0	0	0	0	.000
10	0	0	1	0	0	1	0	0	1	0	.286
Count	1	2	3	1	1	3	2	1	1	3	

  

Point	Second Study Area										$\hat{d}$
	Observations										
1	1	1	0	0	0	0	0	0	1	.	.286
2	0	0	0	0	1	0	0	0	0	.	.000
3	0	0	1	0	1	1	0	0	.	.	.400
4	0	0	0	0	1	0	0	0	.	.	.000
5	0	0	0	0	0	0	0	0	.	.	.
6	0	0	0	0	0	0	0	0	.	.	.
7	0	0	0	0	0	0	0	0	.	.	.
8	0	1	0	1	0	0	0	0	.	.	.167
9	0	0	0	0	0	0	0	0	.	.	.
10	0	0	0	0	0	1	1	0	.	.	.500
Count	1	2	1	1	3	2	1	1	.	.	