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Variable area surveys are used in large geographic regions to estimate the density of birds distributed over a region. If some birds go undetected, a measure of the effective area surveyed, the amount of area occupied by the birds detected, is needed. The effective area surveyed is determined by observational, biological, and environmental factors relating to detectability. It has been suggested that density estimates are inaccurate, and that it is risky to compare bird populations intraspecifically over time and space, since factors influencing bird counts will vary.

There have been several controversial studies where variable area survey density estimates were evaluated using density estimates calculated from spot mapping as the standard for comparison. Spot mapping itself is an unproven estimator that the previously mentioned factors also influence. Without a known population density, determining how the different density estimators perform is difficult to access. Variable area surveys of inanimate objects whose densities were known have been conducted under controlled circumstances with results generally supporting the variable area survey method, but time and inability to control for all factors limit the application of this type of study. A simulation program that distributes over a region vegetation and a known density of birds, and then simulates the process of gathering bird detection data is one tool accessible to evaluate variable area density estimates. Within such a simulation study various observational, biological, and environment factors could be introduced.

This thesis introduces such a simulation program, VABS, that was written with the objectives of identifying factors that influence bird counts and determining the limitations of the variable area survey. Within this thesis are discussions concerning the several factors that have been identified as influencing bird counts and the effects that these factors had on the Fourier series, exponential power series, and Cum-D density estimates when these factors were simulated in VABS. Critical assumptions of the variable area survey are identified, and the ability of the variable area survey to estimate density for different detectability curve is examined. Also included are discussions on the topics of pooling data gathered under different detectabilities and monitoring population trends.

Factors Affecting Bird Counts and Their Influence on Density Estimates

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LIST OF SYMBOLS AND VARIABLE NAMES

1. General Symbols

Cum-D	Cum-D estimator (in figures the Cum-D estimator is denoted by C)
FS	FS estimator (in figures the FS estimator is denoted by F)
EPS	EPS estimator (in figures the EPS estimator is denoted by E)
R	target region
A	area of target region
N	number of birds in target region
D	density of birds in target region (D=N/A)
L	total length of transects traversed
α	effective area surveyed
g(y)	detectability curve
f(y)	$\frac{g(y)}{\int g(y)dy}$
F(y)	cumulative distribution function for detected area
cv	coefficient of variation
cov.	coverage of confidence interval
var($\hat{D}$)	variance of the density estimate
se($\hat{D}$)	standard error of the density estimate
CI	confidence interval
dbh	tree diameter at breast height (140cm)
k	the k^{th} ordered detected area used to calculate the slope of F(y)
% visual	percent of detections made solely by visual detection
% audio	percent of birds detected audibly

2. Observations

n	number of birds counted during survey
y	detected area
d	detected distance
x	actual distance between the observer and the bird
$y_{(i)}$	i^{th} ordered detected area
z_i	$y_{(i)}/y_{(n)}$

3. Estimators

$\hat{D}$	bird density
$\hat{D}_I$	population density for a clustered population
$\hat{D}_C$	cluster density
$\hat{\alpha}$	estimate of effective area
$\hat{\alpha}_{CD}$	Cum-D estimate of effective area
$\hat{\alpha}_{FS}$	FS estimate of effective area
$\hat{\alpha}_{EPS}$	EPS estimate of effective area
$\hat{se}(\hat{D})$	estimate of the standard error of the density estimate
$\hat{var}(\hat{D})$	estimate of the variance of the density estimate

4. Notation for program VABS

(obsx,obsy)	(X,Y) coordinates of the observer's location
t_i	time it takes the observer to traverse the i^{th} meter of the transect
(b_{ix},b_{iy})	(X,Y) coordinates of bird i
bht	height above ground level of $bird_i$
S	cluster size of birds
$[c_i,d_i]$	interval on transect where the observer can detect bird i
(h_i,k_i)	(X,Y) coordinates of the center of the i^{th} tree

r_i	radius of i^{th} tree
dbh_i	dbh of i^{th} tree
dbh_c	mean dbh for the c^{th} cluster of trees
sdk_c	standard deviation of dbh_c for the c^{th} cluster of trees

5. Variable names in VABS

W	width of computer generated region
L	length of computer generated region (length of transect)
SLOPE	slope of terrain
NBIRD	bird density
DEN	tree density
DVA	threshold of visual size
DV	threshold of visual distance
PERF	maximum eccentricity of vision
DA	threshold of audio distance
THETA	mean rate of bird vocalizations
TT	mean traversing rate
SDTT	standard deviation of traversing rate
BETA0	β_0 coefficient in LN(visual angle)=$\beta_0+\beta_1\cdot$(eccentricity)
BETA1	β_1 coefficient in LN(visual angle)=$\beta_0+\beta_1\cdot$(eccentricity)
MOVE	distance between the observer and bird where the bird reacts to the observer
RALPHA	γ parameter of log-logistic distribution used to determine the rate of bird movement
RBETA	β parameter of log-logistic distribution used to determine the rate of bird movement
RMOVE	distance a bird moves
RMOVE	angle that a bird moves
XMOVE	distance on the x-axis that a bird moves

RMOVE	distance on the y-axis that a bird moves
LOSE	the maximal distance a bird can move after detection before the observer loses track of the bird
SAT	the maximum number of birds the observer can record during the traversing of 100 meters.
C	proportion of fixed error
BETA	the standard deviation of measurement error
NI	number of intervals transect is split into in order to draw a bootstrap sample of n_i's

FACTORS AFFECTING BIRD COUNTS AND THEIR INFLUENCE ON DENSITY ESTIMATES

1 INTRODUCTION

1.1 Detectability and the Estimation of Density

Growing environmental concerns have increased the need to monitor bird populations over large geographic regions. To monitor populations, information about the bird's population size or density in the targeted region is needed. Since obtaining a census of birds in a large region is generally infeasible, bird counts or measurements of indices are necessary to estimate bird densities or population sizes.

Most methods that use bird counts to estimate density assume a total enumeration of birds in a designated subregion whose area is known. As the distance between a bird and the observer increases, the assumption of a constant probability one of detection becomes unrealistic. If it is presumed that some birds go undetected in the surveyed subregion, some measurement of the area surveyed is required to estimate the population density. Variable area surveys do not assume 100% detectability throughout the subregion surveyed; instead, the amount of area surveyed is estimated.

The area surveyed will vary as detectability varies. Detectability of birds is influenced by observational, biological, and environmental factors. Visual and audio acuity of the observers, conspicuousness of a bird, a bird's behavior, type of habitat, and weather conditions all influence detectability. Dawson (1981) and Verner (1985) are skeptical about the reliability of the variable area density estimate, because of the potential of detectability to vary. Verner (1985) concluded that density estimates, derived using current methodology, are inaccurate, and it is risky to compare bird populations intraspecifically over time and space since detectability will vary. Furthermore, Verner and Milne (1989) advocate that density estimates have limited usefulness for monitoring trends, but simple counts or frequencies will suffice if properly designed to control for factors so that detectability is constant. If a constant area is surveyed for each count, simple counts or frequencies would suffice to monitor populations, but it is very difficult to account and control for all factors influencing bird counts.

Theoretically, the variable area survey can produce two unbiased density estimates for two counts with different detectabilities by adjusting the effective area surveyed for the two counts. If accurate and precise density estimates can be calculated for different detectabilities, then these density estimates can be used to monitor populations. On the other hand, comparisons of simple counts have a much greater potential to lead to false conclusions if detectability differs between counts and the areas are not adjusted.

There have been several studies where variable area survey density estimates were evaluated using density estimates calculated from spot mapping as the standard for comparison (Verner and Ritter 1985, 1988; Emlen 1971, 1977; Franzreb 1976, 1981; Dickson 1978; O'Meara 1981). Spot mapping itself is an unproven estimator that the previously mentioned factors also influence. Without a known population density, determining how the different density estimators perform is difficult. Variable area surveys of inanimate objects whose densities were known have been conducted under controlled circumstances (Burnham et al. 1980) with results generally supporting the variable area survey method, but time and inability to control for all factors limit the application of this type of study.

A simulation program that distributes vegetation and a known density of birds over a region and then simulates the process of gathering bird detection data is one accessible tool to evaluate variable area density estimates. Within such a simulation study, various observational, biological, and environment factors can be introduced. The objective of this study was to create and utilize a simulation program VABS to (1) identify critical assumptions of the variable area survey, (2) determine the ability of the variable area survey to estimate density for different detectabilities, (3) identify factors that influence bird counts, and (4) determine the level of robustness that the variable area survey has to certain observational, biological, and environmental factors.

VABS creates a habitat, places birds within the created habitat, simulates the process of bird detection, and then estimates bird density as well as approximates corresponding confidence intervals. At each step, parameters in VABS allow for the introduction and fluctuation of factors that influence bird counts. When creating the habitat, the dimension of the region can be varied as well as the slope of the terrain. Furthermore, there is an option to create an even or uneven-aged forest whose tree density and mean dbh (diameter 140cm above base) can be varied.

In VABS, a bird's population can be distributed over the region in different ways. Birds can be uniformly distributed over the region or scattered at different levels of underdispersion and overdispersion. Additionally, birds can be restricted to be perched in trees or in clusters. If a clustered population is created, individual bird detections are not independent events, but the detections of individual clusters are independent.

Instead of birds always staying stationary, VABS has options to simulate bird movement. Options include (1) random movement, (2) birds move or hide to avoid the observer, or (3) birds are attracted to the observer. When simulating movement, a bird's speed and the distance between the observer and the bird where the bird moves in response to the observer can be varied.

When simulating the process of detecting birds, detectability in VABS can be varied by fluctuating the observer's audio and visual acuity, the bird's vocalization rate, and the pace at which the transect is being traversed.

Once bird detection data is gathered, VABS estimates density using the exponential power series, Fourier series, and Cum-D; with the option of using covariate adjustments. The standard error of the density estimate is estimated using bootstrap techniques. Confidence intervals are approximated using the normal confidence interval with the bootstrap estimate of standard error, the percentile method, and the two sample bootstrap prepivoting method.

1.2 Format of Thesis

The ensuing chapter presents the standard methodology of the variable area survey and introduces the detectability estimators used in this study. Chapter 3 identifies potential factors influencing bird counts. The basic simulation program VABS is outlined in Chapter 4. Chapter 5 presents results of a simulation study designed to explore the number of independent detections needed to obtain reliable variable area density estimates. The ability of the variable area survey to adjust for different detectabilities is examined in the sixth chapter. Chapter 7 looks into monitoring populations and detecting trends. The variable area survey's robustness to invalid assumptions is examined in Chapter 8 through 11. Chapter 12 outlines what further work needs to be done concerning the variable area survey. A summary of the conclusions reached from the various studies is presented in Chapter 13.

2 VARIABLE AREA SURVEY

2.1 Variable Area Survey

Variable area surveys are typically used to estimate the density D or the total number N of animals distributed over a large region. This thesis is primarily concerned with the estimation of bird densities, although the results do apply to the estimation of other animal densities. If there are N birds in a target region R, density is defined as D=N/A, where A is the area of R. If the area surveyed α is known and all birds within α are detected, then a natural unbiased estimate of density is $\hat{D}=\frac{n}{\alpha}$, where n is the number of birds detected. For an increasing distance between the observer and the detected bird, the assumption of a constant probability one of detection is unrealistic. Therefore, to survey the portion of R needed to obtain satisfactory precision, either several time consuming narrow transects can be surveyed or fewer wider transects traversed with the presumption that some birds will go undetected.

If some birds go undetected, a measure of the area surveyed, the amount of area occupied by the birds detected, is needed. The precise area which makes the ratio an unbiased estimator of population density is defined by Ramsey, Scott, and Clark (1979) as the effective area. The effective area is typically estimated using the detected distances of detected birds. In summary, the number of birds recorded by an observer in a survey is proportional to the effective area surveyed by the observer (Ramsey and Scott 1981b), and the density estimation problem becomes one of using detected distances to estimate the amount of area surveyed.

The line transect survey and the variable circular plot survey are two of the more familiar methods for estimating bird populations. A line transect survey involves traversing T transect lines ($T \geq 1$) each of known length l_j that have been randomly placed in R. For each bird detected, the detection distance d_i, the perpendicular distance between the bird and transect line, is recorded along with other pertinent information.

The variable circular plot survey presented by Reynolds, Scott, and Nussbaum (1980) still uses randomly placed transects in R, but searches are conducted at m_j stations spaced at regular intervals on the transects. Recording of birds and their detection distance only takes place during a predetermined time interval, at the end of which the observer moves to the next station. The detection distance d_i is the distance between the observer and bird. The variable circular plot survey has been shown to be effective in situations where traversing the transect and simultaneously searching for the bird is difficult or dangerous. It is particularly appropriate for use in forested habitats with steep terrain.

Previously, the theories behind the different kinds of variable area surveys have been expressed in terms of detection distance. By transforming the detection distances to detection areas; Ramsey, Wildman, and Engbring (1987b) were able to develop one general theory for variable area surveys. The detection area is defined to be the area interior to a contour of constant probability of detection relative to the observer. Explicitly, the line transect survey assumes the contours of constant probability of detection are parallel and symmetrical to the transect line. The detected area is the area of the rectangle $y_i=2Ld_i$ ($L=l_1+l_2+\ldots+l_T$), where d_i is the perpendicular distance between the transect line and the contour where bird i was detected. Assuming the detection contours are circular for the variable circular plot survey, the detected area for bird i is calculated as $y_i=M\pi d_i^2$ ($M=m_1+m_2+\ldots+m_T$). The detected area was used throughout this study, instead of the detected distance.

2.2 Standard Theory

To develop the standard theory of variable area surveys, the following has been assumed:

(1) N varies stochastically about a mean DA.

(2) Conditional on N, birds are distributed uniformly over the region R, independent of the density D.

(3) The locations of different birds are independent of each other.

(4) Detections of different birds are independent events.

(5) Detection distances are measured without error.

(6) No bird is counted more than once at each station or on each transect.

(7) Birds occupy fixed locations during the survey period.

If the detectability curve g(y) is defined as the conditional probability a bird will be detected given the detected area y, the standard theory assumes:

(8) $g(0)=1$.

(9) $\alpha=\int_0^\infty g(y)dy < \infty$.

The only useful consequence of assumption (2) is that each detected area Y has a uniform distribution. Ramsey (1979) claims that uniformity in Y can be obtained by running the transect in the direction of an anticipated density gradient. This prescription differs from the suggestion by Burnham et al. (1980) that random line placement achieves uniformity. There is general agreement that transect lines that follow railroad tracks, roads, ridge tops, and stream bottoms, as well as animal movement in response to the observer can violate the assumption of uniformity (Buckland 1985, Burnham et al. 1980).

Using the preceding assumptions; Seber (1973), Burnham and Anderson (1976), and Ramsey (1979) showed that, conditional on detection, the detection area of a bird has probability density function $f(y)=g(y)/\alpha$ and that $E(n)=D\alpha$. By evaluating $f(y)$ at $y=0$ an unbiased estimate of density is $\hat{D}=n/\alpha$ where $\alpha=1/f(0)$. Notice that the parameter α is the quantity which the number of detections is divided by to estimate density; it is precisely this interpretation that leads Ramsey et al. (1987) to call α the effective area surveyed. The estimation of α can be accomplished by modeling $g(y)$ and evaluating $f(0)$ (Burnham et al. 1980) or by estimating the slope of the cumulative distribution function of the detection areas at zero (Wildman and Ramsey 1985).

Although several shapes for g(y) have been suggested, this study only concerns itself with the estimators known as the Fourier series estimator, exponential power series estimator, and the Cum-D estimator. These three estimators were selected because they are representative of three unique types of estimators. The exponential power series is considered to be one of the more flexible parametric estimators and is thought to be more robust to movement than other popular estimators. The Cum-D estimator is a nonparametric estimator that examines the cumulative distribution function. The Fourier series estimator has been a popular estimator, even though it can give negative density estimates and is not robust to nonrandom movement. Whereas the exponential power series and Cum-D estimators assume that g(y) is monotonically decreasing, the FS does not make this assumption.

2.3 Estimation of Var($\hat{D}$)

In the estimation formula $\hat{D}=n/\hat{\alpha}$, both n and $\hat{\alpha}$ are subject to sampling variation; therefore, the properties of $\hat{D}$ depend upon the sampling properties of $\hat{\alpha}$ and n. Several methods of estimating var($\hat{D}$) have been proposed; what follows is a brief description of some of the methods.

If there are K replicated lines with corresponding lengths l_j and the sample sizes for each replicate are large enough (80 or more detections, Chapter 5) to accurately and precisely estimate density; then the independent estimates of $\hat{D}_j = n_j/\hat{\alpha}_j$ can be used for a weighted estimate of density,

$$\hat{D}=\frac{\sum_{j=1}^{K} l_j D_j}{L} \qquad (L=\sum_{j=1}^{K} l_j).$$

Furthermore, the weighted sample variance of these independent estimates,

$$\hat{\text{var}}(\hat{D})=\frac{\sum_{j=1}^{K} l_j^2 (D_j-\hat{D})^2}{(K-1)L},$$

may be used to estimate the variance of $\hat{D}$. A serious drawback with this approach is that each of the K replicated lines must have enough detections to obtain the proper estimator for the detection curve.

The delta method approximation

$$\begin{aligned}\text{var}(\hat{D}) &\approx D^2\left[\frac{\text{var}(n)}{(E(n))^2}+\frac{\text{var}(\hat{\alpha})}{(E(\hat{\alpha}))^2}\right] \\ &= D^2[\hat{cv}(n)+\hat{cv}(\hat{\alpha})], \qquad (2.3.1)\end{aligned}$$

(cv($\cdot$) is the coefficient of variation) requires the estimation of the sampling variance of both n and $\hat{\alpha}$. Most of the parametric methods used to estimate α provide formulas to estimate var($\hat{\alpha}$), reducing the problem to one of estimating var(n). If objects are assumed to be randomly distributed, then the counts will be Poisson distributed with var(n)=E(n), and thus $\hat{\text{var}}(n)=n$.

A jackknife estimate of var($\hat{D}$) that requires replicate lines (Burnham et al. 1980) and different bootstrap estimates that use the n detected distances to estimate var($\hat{D}$) (Buckland 1982, Quang 1990) have also been proposed to estimate the var($\hat{D}$).

Confidence intervals on D are generally based on the normal distribution or the t-distribution. Buckland (1982) has suggested a bootstrap procedure based on the percentile method to approximate confidence intervals, and Quang (1990) has proposed a bias reduction method for the Fourier series estimator. Approximate confidence intervals for D are discussed further in Chapter 12.

2.4 Fourier Series Estimator

The Fourier series (FS) estimator developed by Crain et al. (1979) has been a popular estimator of f(0) based upon a Fourier series expansion over a finite interval. For τ defined as the furthest distance a bird can be detected, the FS estimator of effective area is the reciprocal of $\hat{f}(0)$,

$$\hat{\alpha}_{FS}=1/[\tfrac{1}{\tau}+\sum_{k=1}^{m} a_k], \tag{2.4.1}$$

where

$$\hat{a}_k=\frac{2}{n\tau}\sum_{i=1}^{n}\cos\left(\frac{k\pi}{\tau}y_i\right) \quad \text{for } k=1,2,\ldots,m \tag{2.4.2}$$

are the estimated coefficients in the expansion of the finite interval from 0 to τ.

When the FS estimator is used generally 2-3 percent of the data is discarded. Buckland (1987) observed that the FS estimator usually performed poorly if the largest observation was selected as the truncation point of the interval, but a minor truncation of the data often resulted in increased precision of $\hat{D}$.

For a large number of terms in the Fourier series, the FS can give rise to unrealistic shapes for the detection function (Buckland 1985). For ungrouped data, Burnham et al. (1980) suggested selecting m so that

$$m=\min\{k:\tfrac{1}{\tau}\left(\frac{2}{n+1}\right)^{\frac{1}{2}} \geq |\hat{a}_{m+1}|\}. \tag{2.4.3}$$

This selection process is a tradeoff between small bias and large variance. Usually a truncation point of only modest size, such as $m \leq 5$, suffices.

The only assumption needed for the validity of the FS method is the continuity of f(y) at y=0. The FS approximation to f(y) is not a true probability density function (pdf), and it is possible for f(y) to be negative, especially for y near τ. Even with the estimation procedure described above, $\hat{f}(0)$ can take on negative values, and recommendations on how to cope with this possibility need to be sought out.

An estimate for the variance of $\hat{f}(0)$ is:

$$\hat{var}(\hat{f}(0))=\sum_{j=1}^{m}\sum_{k=1}^{m}\hat{cov}(\hat{a}_j,\hat{a}_k),$$

where

$$\hat{var}(\hat{a}_k)=\frac{1}{(n\text{-}1)}\left\{\frac{1}{\tau}(\hat{a}_{2k}+\frac{2}{\tau})\text{-}\hat{a}_k{}^2\right\},\quad k\geq 1,$$

$$\hat{cov}(\hat{a}_k,\hat{a}_j)=\frac{1}{(n\text{-}1)}\left\{\frac{1}{\tau}(\hat{a}_{k+j}+\hat{a}_{k-j})\text{-}(\hat{a}_k,\hat{a}_j)\right\},\quad k>j>1$$

(Burnham et al. 1980).

2.5 Exponential Power Series Estimator

A flexible parametric estimator described by Pollock (1978) and Ramsey (1979) is the exponential power series estimator (EPS). The basic estimator uses the pdf

$$f(y)=\frac{1}{\alpha}\exp\{\text{-}[\Gamma(1+\frac{1}{\gamma})(\frac{y}{\alpha})]^{\gamma}\}\text{ for }y\geq 0,$$

where $\alpha > 0$ is a scale parameter and $\gamma > 0$ is a shape parameter. The estimate of the scale parameter α is the estimate of effective area. The EPS pdf is a monotone decreasing function, with the shape parameter γ influencing the rate of decrease. This flexible family of distributions contains two prominent distributions; when γ=1, the pdf takes on the exponential form, and for γ=2, the pdf takes on the halp-normal form.

For a known shape parameter, the maximum likelihood estimator of α is

$$\hat{\alpha}_{EPS}=\gamma^{\frac{1}{\gamma}}\,\Gamma(1+\frac{1}{\gamma})T\gamma^{\frac{1}{\gamma}}, \tag{2.5.1}$$

with

$$\hat{var}(\hat{\alpha}_{EPS})=\hat{\alpha}^2(\frac{\gamma}{n})^{2/\gamma}\left(\frac{\Gamma(\frac{n}{\gamma}+\frac{2}{\gamma})}{\Gamma(\frac{n}{\gamma})}-\frac{\Gamma^2(\frac{n}{\gamma}+\frac{1}{\gamma})}{\Gamma^2(\frac{n}{\gamma})}\right),$$

where

$$T\gamma=\frac{1}{n}\sum_{j=1}^{n}y_i{}^{\gamma}$$

is the complete minimal sufficient statistic for α. If γ is unknown, it may be estimated by solving iteratively the maximum likelihood equations; however, there is a possibility of obtaining nonconsistent maximum likelihood estimators. Under this situation, Andersen (1973) suggested using the distribution of a maximum invariant statistic under scale changes to estimate the shape parameter γ. Applying this suggestion, Wildman and Ramsey (1985) proposed setting $z_i=y_{(i)}\backslash y_{(n)}$ for i=1,(1),n-1; where $y_{(i)}$ is the i^{th} ordered observed detection area. A maximal invariant statistic under this scale change is $(z_1,z_2,\ldots,z_{n-1})$ whose probability density function is

$$f(z_1,z_2,\ldots z_{n-1})=(\tfrac{n!}{\gamma})\ \Gamma(\tfrac{n}{\gamma})\ \{\Gamma(1+\tfrac{1}{\gamma})\}^{-n}[1+\sum_{i=1}^{n-1} z_i\gamma]^{\frac{n}{\gamma}}.$$

The maximum likelihood estimator of γ for this expression is the solution to

$$\frac{V\gamma}{T\gamma}-(\tfrac{1}{\gamma})[\log(T\gamma)+\psi(1+\tfrac{1}{\gamma})-\psi(\tfrac{n}{\gamma})]+\tfrac{1}{n}=0,$$

where

$$V\gamma=(\tfrac{1}{n})\sum_{i=1}^{n}(y_i)^{\gamma}\log(y_i).$$

This estimate of the shape parameter can be substituted into equation 2.5.1, in order to estimate effective area.

2.6 Cum-D Estimator

The Cum-D estimator was first proposed by Ramsey and Scott (1981a) and further developed by Wildman and Ramsey (1985). Unlike the other estimators mentioned, the Cum-D estimator considers the cumulative distribution function. Since the cumulative distribution function has first derivative $F'(0)=\frac{1}{\alpha}$, the inverse of the slope of F at 0 is an estimate of effective area. The proposed estimator is of the form $F_n(y_k)/y_k$, where y_k is the k^{th} ordered detected area and $F_n(y_k)=k/n$ is the empirical cumulative distribution function. The heart of the problem of estimating the effective area by the Cum-D method is choosing a value of k which is as large as possible while still insuring that there is no significant decrease in the slope between zero and y_k.

If the view is taken that detectability must be monotonically decreasing, Wildman and Ramsey (1985) proposed selecting k by constructing an envelope function for the empirical distribution function as follows. Define $j(0)=y_{j(0)}=0$, and let j(1) be the largest index j such that $d_1=j(1)/y_{j(1)}=\max\{j/y_j:j\geq\sqrt{n}\}$. Continuing for r=2,3,... let j(r) be the largest index for which

$$d_r=\frac{\{j(r)-j(r-1)\}}{\{y_{j(r)}-y_{j(r-1)}\}}=\max\left\{\frac{j-j(r-1)}{y_j-y_{j(r-1)}}:j>j(r-1)\right\}.$$

A convex envelope over F_n, denoted by $\bar{F}_n(a)$, is formed by connecting the points $\{(y_{j(r)},j(r)/n);\ r=0,1,2,\ldots\}$ with straight lines. The slopes d_r of $\bar{F}_n$ describe decreasing average densities of detections over regions increasingly remote from the observer.

The suggested selection rule for k is based on a likelihood ratio test for the null hypothesis of equal slopes between the first region (d_1) and the r^{th} region (d_r). Furthermore, a random distribution of birds, resulting in Poisson counts, is assumed. For

$$u_r=j(1)\log(d_1)+(j(r)-j(r-1))\log(d_r)-(j(r)-j(r-1)+j(1))\log\left(\frac{j(r)-j(r-1)+j(1)}{y_{j(r)}-y_{j(r-1)}+y_{j(1)}}\right),$$

the specific rule is to choose $k=\min\{j(r):u_{r+1}\geq 2\}$. The cutoff value 2 is the normal test approximate 95% critical level. With the selection of k, the effective area estimate is

$$\hat{\alpha}_{CD}=\frac{ny_k}{k}.$$

It has been suggested (Wildman and Ramsey 1985) that the subset of the data on which the estimate $\hat{\alpha}_{cd}$ is based has a minimum sample size of $\sqrt{n}$. This rule will be referred to as the $\sqrt{n}$ rule.

The bootstrap estimate of standard error is suggested for estimation of $var(\hat{\alpha})$ (Wildman and Ramsey 1985).

3 FACTORS AFFECTING BIRD COUNTS

3.1 Factors

The region surveyed while conducting bird counts is determined by factors relating to detectability. Such factors can be any observational, biological, or environmental variable that affects the bird count or the detectability curve. These factors have the potential to influence both the accuracy and precision of the density estimate and may not even be identifiable. In this chapter, variables that have been recognized to influence bird counts are briefly discussed. Further discussions are in the sections examining the factor's influence on bird counts.

Verner (1985) grouped potential factors into five broad categories: (1) observers, (2) habitat, (3) weather, (4) birds, and (5) design factors. A revised list of potential factors are listed under their appropriate category in Table 3.1.

Table 3.1 Factors affecting bird counts.

1. Observers
   - Visual Acuity
   - Aural Acuity
   - Knowledge
   - Experience
   - Distance Judgment
   - Alertness
   - Conduct on Transect
   - Number of Observers
2. Habitat
   - Slope
   - Vegetation Structure
   - Terrain on Transect
   - Period
   - Noise
3. Weather
   - Precipitation
   - Relative Humidity
   - Snow
   - Temperature
   - Wind
   - Cloud Cover
4. Birds
   - Time of Day
   - Season
   - Sex
   - Age
   - Flocking
   - Movement
   - Avoidance/Attraction
   - Density
   - Distribution
5. Design Factors
   - Transect Length
   - Duration of Sampling
   - Speed along Transect
   - Sampling Frequency
   - Timing
   - Distance between Sites
   - Number of Species Recorded

3.2 Observers

Observers are factors in bird counts because of physiological and psychological differences between observers and within observers over time. An observer's visual and audio acuity, skill, and enthusiasm will influence detectability as well as the accuracy of gathered data. Visual, audio, and psychological factors are discussed further in Section 6.1. One factor that is of upmost importance to the outcome of bird counts but will not be discussed further is the ability of observers to detect and discriminate among individuals of several breeding bird species. Much of the ability to discriminate among bird species is related to an observer's knowledge and experience. 'Underqualified' observers in the North American breeding bird survey record consistently lower species totals and are less consistent over time than qualified observers (Faanes and Bystak 1981). Much of this variation can be reduced by careful screening and training of observers. Testing all potential observers on their ability to correctly identify species has been recommended (Kepler and Scott 1981, Cyr 1981).

3.3 Habitat

Vegetative species composition and structure has a significant influence on the behavior and observability of birds (Best 1981). Birds in more open-habitat are more visible than in closed-habitats; visual detection should constitute a smaller percent of all observations in closed-habitats. Vegetation not only obstructs vision but degrades sound (Richards 1981). Additionally, Best (1981) suggests that habitat may influence the function of song and, consequently, persistence of singing. The influence of habitat can change seasonally, especially in mesic ones characterized by lush plant growth during spring.

Terrain will impact bird counts since ambient temperature, plant development, and bird behavior vary with topography. Slagsvold (1973) found a correlation between the time that song thrushes began singing and the leafing of birch trees; there was a delay in song of 2-3 days for every 100m rise in altitude.

Finally, background noise is inclined to affect bird behavior and the observer's aural ability. Otherwise, the presence of active railroads, busy highways, loud rivers and streams, noisy machinery, and days with appreciable rain or wind is likely to hamper detectability. Emlen and DeJong (1981) suggest that background or masking noise is a common and important variable in bird census work that is often uncontrollable except by avoidance.

3.4 Birds

Many attributes of birds affect bird counts, including (1) conspicuousness, (2) behavior, (3) social and breeding system, (4) movement, (5) flocking behavior, (6) seasonal habitats, and (7) density. These attributes contribute to differing detectability curves among birds, both within and among species. Chapters 6, 8, 9, and 10 contain more exhaustive discussions on the influence that the more frequently recognized attributes have on detectability.

There are less distinguishing attributes that influence detectability that are often ignored. For example, the density of birds can be a factor. The detectability of known Red-backed Shrikes in Poland during the prelaying period was significantly higher on a plot with low density than on one with high density (Diehl 1981).

Furthermore, bird behavior is frequently related to environmental conditions. Presumably, an increased number of hops could make a bird more detectable, but it can also move a bird in and out of the outer boundary of the area being surveyed quicker. Interestingly, Ralph (1981) found that the number of hops and flight of the 'Elepaio showed a regular seasonal pattern that could possibly relate to food availability. For species of Hawaiian birds where food resources were quantified, decreased food resulted in more and faster movement.

3.5 Weather

Variation in weather is unavoidable, yet it is known to influence detectability. Weather variables are intercorrelated, making the analysis and control of these factors exceptionally difficult. By traversing all transects within a couple hours and during the same time of day, variation in weather can be controlled to some degree. Several authors (Dawson 1981, Emlen and DeJong 1981, Robbins 1981b, O'Conner and Hicks 1980) recommend that extreme precipitation, relative humidity, temperatures, and winds be avoided.

3.6 Design Factors

Design factors that may influence counts and density estimation include (1) transect length, (2) duration of sampling periods, (3) traversing speed along transect, (4) sampling frequency, (5) timing, and (6) distance between sites. Most design factors can be controlled with well planned surveys.

The total length of the transects covered and sampling frequency should be sufficient to achieve a desired coefficient of variation (Gates 1981). An individual transect length should be short enough that the variation of detectability due to time of day and weather fluctuations are minimal. The speed at which a transect is traversed needs to be slow enough to allow for reasonable detectability but fast enough to prevent double counting and detrimental bird movement.

Duration of sampling periods and distance between counts can bias density estimates. Count periods of different lengths are required for species with dramatically different rates of movement: shorter for more mobile species and longer for sedentary species, particularly if rare or inconspicuous (Scott and Ramsey 1981b).

4 PROGRAM VABS

4.1 VABS

Because of the influence that the previously mentioned factors have on bird conspicuousness, Verner (1985) argues that variable area surveys cannot deliver accurate density estimates in most circumstances. Realistically, examining the effects of all factors affecting bird density estimates out in the field is unattainable, since acquiring actual bird densities for a region and controlling for all factors is impossible. With the complexity of the environment we inhabit, a simulation study contrived to simulate the region being surveyed and the variable area survey process is one tool accessible to address the issues concerning variable area surveys. VABS is a computer simulation program written to address these issues. Simulation studies have been done previously, but detection distances were randomly selected from a known distribution, or when detection was simulated ideal conditions were assumed (Engel-Wilson et al. 1981). This chapter describes the basic setup of VABS.

The objective of VABS is to create a region within which trees and birds are distributed, and then simulate observers traversing a transect and detecting birds while introducing various factors. Once the data is collected, VABS calculates the Cum-D, FS, and EPS density point estimates and corresponding bootstrap estimates of standard error and approximate confidence intervals.

VABS is written in Fortran 77. The Fortran language was selected because of its flexibility, availability, and previous existing related Fortran programs that could be incorporated.

The following sections describe the basic algorithm of VABS. VABS consists of a main program and then numerous subroutines. Within VABS there are various variables that influence bird counts; the levels of these variables are generally specified in the main program of VABS. The additions and alterations to VABS required for the various studies are discussed in the section and corresponding appendices describing that particular study.

Section 4.2 Creating the Region

The first step in creating a region is to define the size of the region R being created. Throughout the various versions of VABS, one unit represents one meter. The transect is located midway along the width of the region and extends the full length of the region. The dimensions of the region should be chosen to ensure that the observer will not detect birds beyond its width. The coordinates of the observer's position on the transect are denoted by (obsx,obsy), where obsx=W/2 and obsy=1,(1),L.

4.3 Distribution of Birds

Before distributing birds over the computer generated region, bird density needs to be specified. There are no restrictions on density; however, the user should specify density to be representative of the species being studied.

One of the standard assumptions of the variable area survey is that birds are distributed uniformly over R, independent of density. This criteria is satisfied by selecting the (X,Y)-coordinates of a bird's location from Uniform[0,W] and Uniform[0,L] distributions, respectively. VABS does have options to depart from a Poisson scattering of birds, either overdispersed or underdispersed. Furthermore, birds may be restricted to be located in clusters or in trees. These distributional options are explained in Chapter 8.

Since no two birds can occupy the same space, birds are required to be at least ten centimeters away from any other bird. The location of bird i is represented by the coordinates (b_{ix},b_{iy}).

4.4 Creating a Forest

The purpose of depicting trees in the computer generated region is to attempt to interject some of the effects that vegetation structure has on bird counts. Two particular concerns are: (1) vegetation impeding on visual detection, and (2) the association between the vegetation structure and the spatial distribution of birds. Although only trees are represented in VABS, results apply to other vegetation structures that influence bird counts in a similar manner.

To simulate a forest, the size and spatial distribution of generated trees needs to be representative of actual tree stands. Essentially, there are considered to be two kinds of tree stands; uneven-aged and even-aged stands. Evidence suggest that uneven-aged stands are more characteristic of mesic forest types, especially those dominated by shade-tolerant species. The even-aged condition is more frequently observed in stands of shade-intolerant species.

The uneven-aged forest dbh (diameter 140cm above base) distribution is characterized by an exponential curve with the proportion of trees in each class remaining relatively constant with time. An exponential curve with irregularities and local peaks is more representative of an even-aged forest; however, even-aged stands can have an exponential dbh distribution if many stands of dissimilar ages are grouped together. A literature search by Lorimer (1980) revealed that for 48 stands of a single tree species 56% were of the irregular exponential type, 25% were of the smooth exponential type, and 19% approached a normal distribution.

Trees distributed uniformly over the stand with trees of every age occurring in every portion of the stand is the theoretical pattern of an uneven-aged forest. In contrast, an even-aged forest is characterized by spatial aggregation of similarly aged stems. Typically, the cluster size of similarly aged stems decreases as the age of the trees increases; older and larger trees have a tendency to be uniformly dispersed. The distribution of dbh for an age class tends to have an approximately normal distribution whose variance increases for older age classes.

Both tree density and the size of the trees limits the observer's field of vision. Trees are represented as circles, with diameter dbh, in VABS. To produce a simulation program that runs in a reasonable amount of time and requires reasonable memory space, a compromise between these two variables is needed. Tree densities are highly variable with recorded densities being as high as 698 trees per hectare (Morrow 1985, Lorimer 1980). Tree density, DEN, is specified in the main program of VABS. For the purpose of this study, tree densities range from 0 to 300 trees per hectare. A density greater than 300 trees per hectare takes VABS an extensive amount of time to depict the reduction in the visual field.

A tree's stem and foliage need to be represented when depicting the reduction in an observer's visual field. Observation and trial computer runs support increasing the diameter of the circle representing a tree to six times the dbh. For example, a tree with dbh equal to 10 centimeters is represented by a circle of diameter 60 centimeters; the area extending 25 centimeters out from the stem represents foliage dense enough to obstruct visual detection.

VABS generates an uneven-aged forest by generating each tree's dbh from an exponential distribution. The VABS user can specify the mean of the exponential variate to represent the species and forest stand of interest. Throughout this study, the mean was fixed at 10 centimeters. The selection of ten centimeters is base on observations of dbh histograms for *Pinus contorta.* The coordinates of the location of the center of a tree, (h,k), are selected from Uniform[0,W] and Uniform[0,L] distributions, respectively. Steps are taken to prevent tree stems from overlapping one another. For the sake of generality, the i^{th} tree is represented on the generated region by a circle with center (h_i,k_i) and radius r_i=dbh/2 ($r_i = 6 \cdot dbh_i/2$, if a tree's foliage is being represented).

An even-aged forest is generated by first selecting a mean dbh (meters), dbh_c, for a cluster of trees. This mean cluster dbh is generated from an exponential distribution equivalent to that used for an uneven-aged forest. The mean cluster size and the standard deviation of dbh of the cluster are calculated by the empirically derived formulas:

$$\text{mean cluster size } \lambda = \begin{cases} -10 \cdot dbh_c + 11 & dbh_c < 1.0 \\ 1.0 & dbh_c \geq 1.0 \end{cases}$$

and

$$sdk_c = \sqrt{.01 \cdot dbh_c^{\,2}} = .1 \cdot dbh_c.$$

The number of trees in a cluster is generated from a Poisson distribution with mean λ. The individual tree diameters are generated $N(dbh_c, sdk_c)$ variates. The coordinates of a center of a cluster, $(\bar{h},\bar{k})$, are generated from Uniform[0,W] and Uniform[0,L] distributions, respectively. Using this center, trees in the same cluster are distributed spatially by generating $h \sim N(\bar{h}, std^2)$ and $k \sim N(\bar{k}, std^2)$

variates. When specifying the value of std, the user should consider that in VABS approximately 95% of the trees in a cluster are within an area of $((4 \cdot \text{std}))^2\text{m}^2$. Morrow (1985) and Bonnicken and Stone (1980) have reported aggregations occupying areas of 300m^2 to 2000m^2.

For both types of forest stands, trees are generated until the specified density is acquired. Figures 4.4.1 to 4.4.4 compare histograms of dbh and spatial distributions of trees from studied (Morrow 1985) and computer generated forest stands. The similarities in the plots suggest that the generated forest stands are representative of actual tree stands.

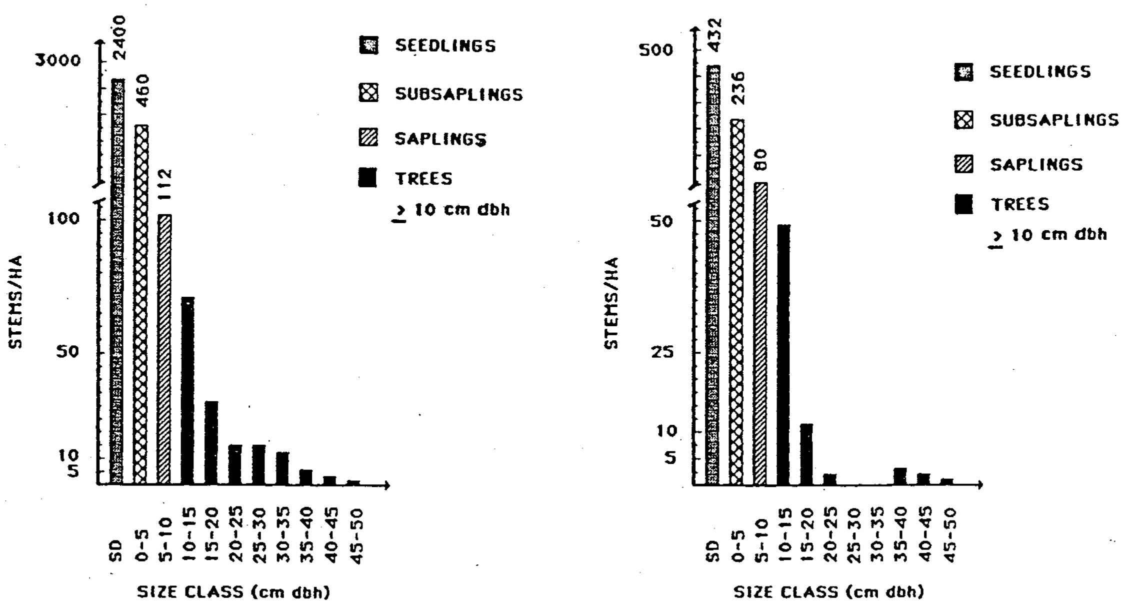


Figure 4.4.1 Size-class distribution of *Pinus contorta* (Morrow 1985). Seedlings (SD) < 144 cm tall, subsaplings ≥ 144 cm tall and ≤ 5.5 cm dbh, saplings > 5.5 cm dbh but < 10 cm dbh (Morrow 1985).

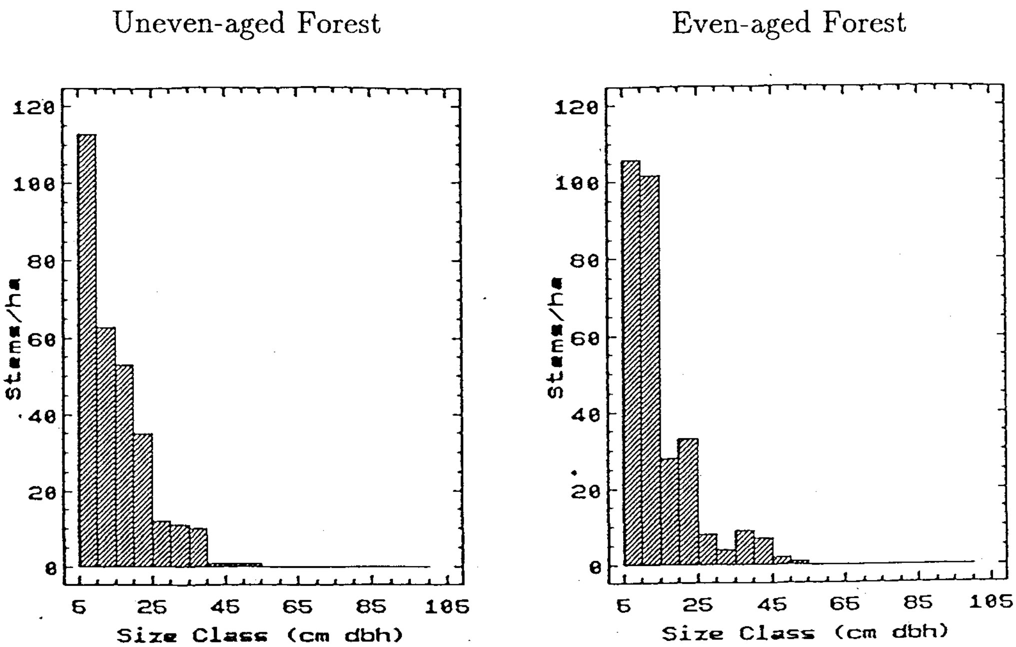


Figure 4.4.2 Size distribution of trees generated by VABS. Trees less than 10 cm tall in VABS are considered too small to influence the visual field and are not generated.

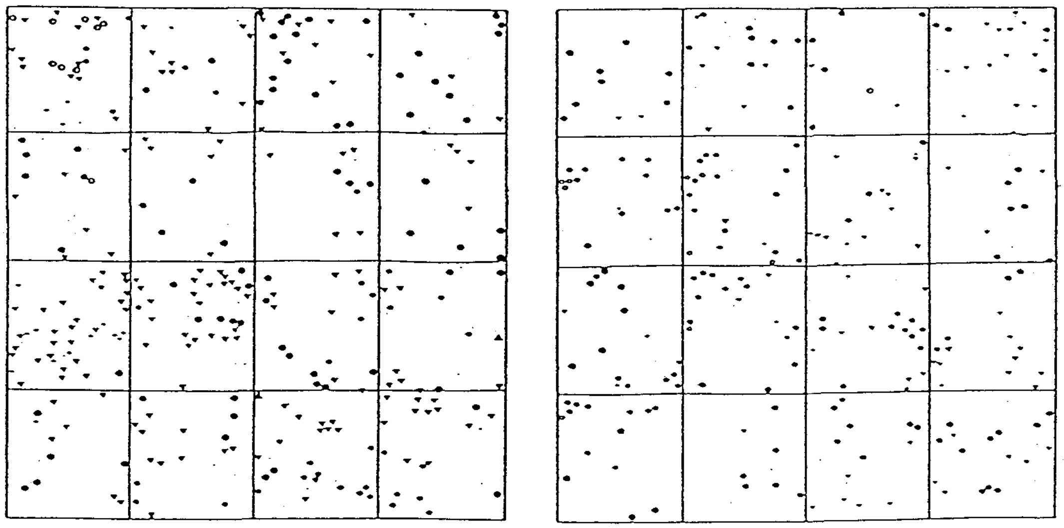


Figure 4.4.3 Spatial distribution of *Pinus ponderosa* and *Pinus contorta* age cohorts on a 1.0 hectare reference stand (Morrow 1985). (•) *Pinus ponderose* > 230 years old, (◦) *Pinus ponderosa* 230-110 years old, (•) *Pinus Ponderose* < 110 years old, (△) *Pinus contorta* 230-110 years old, (△) *Pinus contorta*<110 years old.

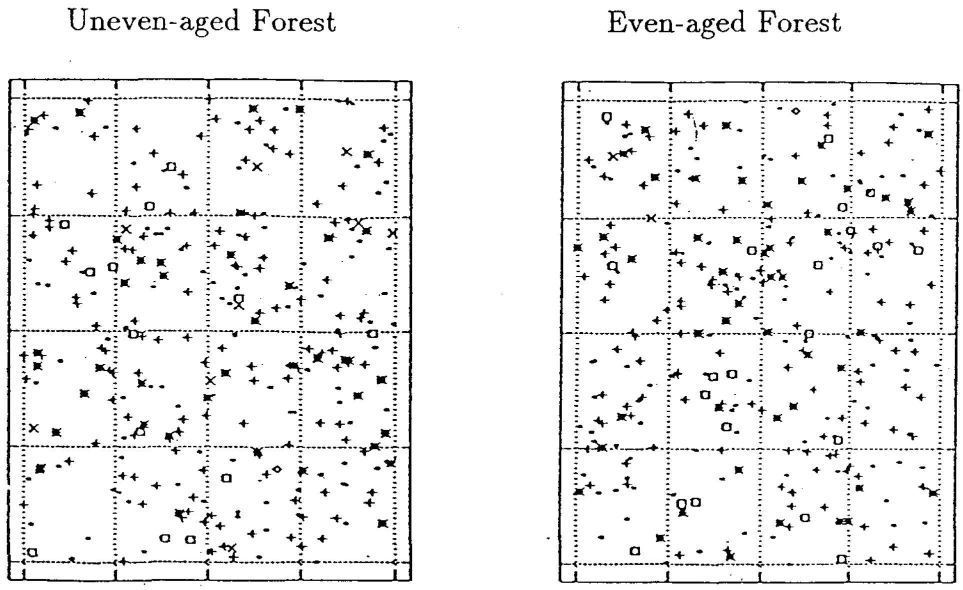


Figure 4.4.4 Spatial distribution of trees generated by VABS on a 1.0 hectare plot. (▫) dbh $\leq$ 10cm, (+) $10 < \text{dbh} \leq 20$, ($*$) $20 < \text{dbh} \leq 30$, (□) $30 < \text{dbh} \leq 40$, (x) $40 < \text{dbh} \leq 50$, ($\triangle$) $50 < \text{dbh} \leq 60$.

4.5 Traversing the Transect

After the study area is created, the process of conducting a variable area survey is simulated. At this time, VABS only simulates the traversing of line transects, but many of the results apply to the variable circular plot survey.

Traversing a transect and searching for birds is a continuous operation; to simulate this on the computer, the process is broken into discrete times. For the purpose of simulating data gathering, determining the probability of detection for each bird every meter appears to be sufficient. The more rigorous interval of 10 centimeters was explored, but trial runs indicated that the significant increase in computer time was unjustified since few bird detections were gained or lost. On the other hand, the interval of 10 meters resulted in a large reduction of bird detections.

When traversing a transect, the observer may need to deviate from the transect line if a tree is located on the transect line. Given a tree is situated on the transect line, the observer will walk around the tree (one meter away from it) in the direction that requires the least amount of deviance from the transect line. If the center of a tree lies on the transect line, the direction is chosen randomly. Specifically, the observer's new position is

$$obsx' = \begin{cases} (h+\sqrt{r^2+(obsy-k)^2}+1) & h < obsx;\ h=obsx \text{ and } R \geq 0.5 \\ (h-\sqrt{r^2+(obsy-k)^2}-1) & h > obsx;\ h=obsx \text{ and } R < 0.5, \end{cases}$$

where R is a random variate between 0 and 1.

Once the observer walks around a tree, the observer is repositioned on the transect line. The perpendicular distance from the transect line is still used to estimate the effective area.

4.6 Audio Detection

While the observer is traversing the transect in VABS, audio and visual detections of birds are simulated. Although visual and audio detection occur simultaneously in the field, except for clustered populations (Section 8.4), VABS first records the birds that are heard and then determines which of the remaining birds are seen. Variables incorporated into VABS that influence audio detection are the time between vocalizations, the observer's traversing pace, and the observer's audio detection threshold.

To detect a bird audibly, a bird must emit at least one audio cue while in the observer's audio field. An observer's audio field is the space that includes all positions of a source whose vocalization can be heard by the observer. Assuming an observer will hear and correctly identify a vocalization emitted within the observer's audio field, for each bird it is only necessary to generate one random variate that represents the time between vocalizations. VABS generates an exponential variate, whose mean is the inverse of the mean frequency of vocalizations, to represent this time. If the time a bird is in the observer's audio field is greater than this variate, VABS identifies this bird as being detected. Past studies have recorded vocalization frequencies ranging from .1 to 42 vocalizations per minute (Kroodsma and Parker 1977, Kiriline 1954, Snow 1961, Nolan 1978).

The pace a transect is traversed will influence bird detection, especially audio detection. For example, if a bird 86.6 meters away from the transect calls at an average rate of .1 calls per minute, and an observer has an audio detection threshold of 100 meters and is walking 5 meters a minute; the observer will hear an average of 2.0 calls from a bird; 10 meters a minute, 1.0 calls; and 20 meters a minute, 0.5 calls. To allow for the variability of the traversing pace, a log-logistic variate is generated to represent the time (minutes), t_j, it takes the observer to traverse the j^{th} meter of the transect. The log-logistic density takes on shapes similar to gamma and log-normal densities. Distributional parameters TT (γ) and SDTT (β), where $E(t_i)=(e^{\gamma}\pi\beta)/\sin(\pi\beta)$ and $E(t_i^2)=(e^{2\gamma}\cdot 2\pi\beta)/\sin(2\pi\beta)$, are specified in the main program. These shapes have been found to be representative of the distribution of time to complete a task (Law and Kelton 1991).

The remaining variable fixed in the main program that influences audio detection is the observer's critical threshold distance (DA), defined as the maximum distance from which a bird's vocal cue can be heard by the observer. Emlen and Dejong (1981) recognized that the detection of a low-intensity or distant sound is an all-or-nothing phenomenon and that all sounds in nature should, at least theoretically, be detected when they are below a critical threshold distance, and go undetected when they are beyond that distance. Theoretically, an observer's audio field is the circular area, with radius DA meters, around the observer. Based on this principal, a bird is detected in VABS if it emits a vocal cue within the observer's audio field.

To determine if the i^{th} bird's vocal cue is detected, VABS first calculates the interval,

$$[c_i = b_{iy} - \sqrt{DA^2 - (obsx - b_{ix})^2},\ d_i = b_{iy} + \sqrt{DA^2 - (obsx - b_{ix})^2}],$$

on the transect where the bird is in the observer's audio field (Figure 4.6.1). The time the observer spends traversing this interval is the sum of the previously generated times it takes the observer to traverse each meter in the interval $(tc_i + tc_{i+1} + \ldots + t_{d_{i-1}} + t_{d_i})$. If the time between the vocalizations for bird i is less than or equal to the time it takes the observer to traverse the interval, the bird's vocal cue is heard and identified, otherwise the bird goes undetected. Each bird is tested for audio detection; if detected, it is not considered for visual detection.

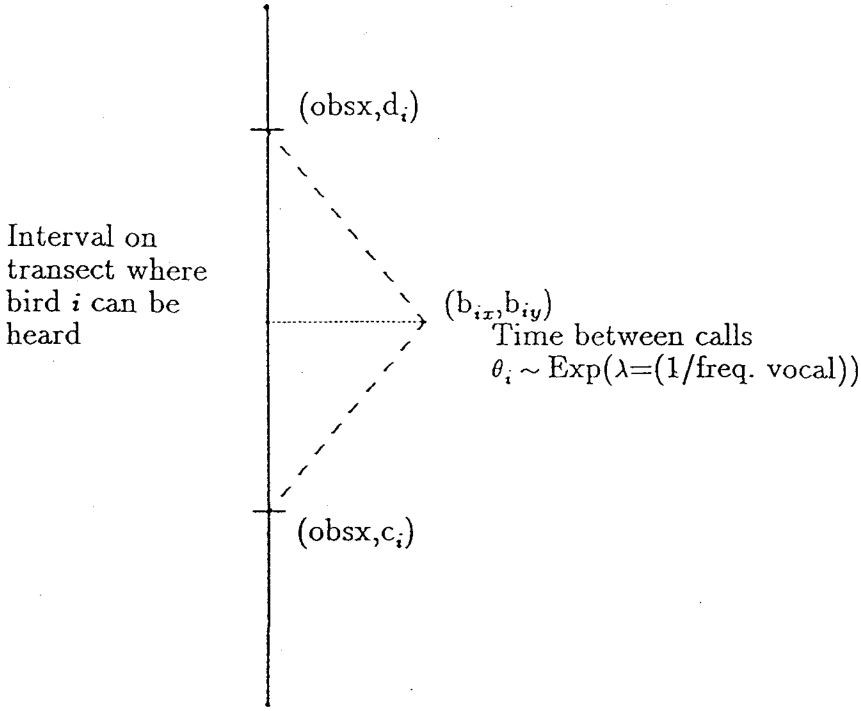


Figure 4.6.1 Interval on transect where audio detection of bird i is possible.

4.7. Visual Detection

After testing for audio detection, VABS simulates the process of visual detection as the observer traverses the transect. For a bird to have a probability greater than zero of being seen, the bird must be in the visual field of the observer at some moment. The visual field is defined by Luckiesh (1944) as the space that includes all positions of a source perceptible to a fixed eye in a head which is stationary. From the line that the fixated eye follows, the visual field extends about 90 degrees on the temporal side of the eye. At the center of the visual field is a small field extending about one degree from the optical axis where we do our accurate seeing of fine detail. The angle between the optical axis and the line joining the fovea (the point where vision is most acute) with the object is known as the eccentricity. As the eccentricity increases visual acuity decreases; at 30 degrees visual acuity is only about one percent of its value in the tiny central one-degree field. In the outer portion of the visual field, we do not see objects of colors with any degree of definiteness, but we see changes in brightness or movements. The least change in the peripheral field initiates a fixation reflex to bring the eye's focus onto the object of attraction.

Visual acuity also decreases as the distance to a bird increases. The maximum distance that critical detail of an object can be made out varies with the size of the object; for this reason, the threshold of vision is in terms of visual size. Visual size is defined as the angle between the two lines extending from the center of the pupil to the outer limit of the object. The threshold of visual size for critical detail ranges from .67 to 4 minutes for persons with normal vision under ideal seeing conditions. If the size of an object is known, a threshold size can be transformed to a distance threshold DV. For the sake of generality, VABS represents a bird with a circle of diameter 10 centimeters; thus

$$DV=\frac{.05}{\tan(\frac{DVA}{2})},$$

where DVA represents the threshold size.

Not surprisingly, as the eccentricity increases the threshold size increases. Table 4.7.1 displays data and corresponding estimated coefficients that demonstrate the relationship between eccentricity and threshold size.

Table 4.7.1 Maximum eccentricity, η, at which a white test of diameter u on a black background is seen (Le Grand 1967).

Maximum Eccentricity

Visual Angle min.	Temporal	η (degrees) Inferior	Nasal	Superior
1.0	10	8	6	4
2.0	21	20	20	18
4.8	36	32	31	29
7.8	60	44	44	40
10.6	62	48	48	42
19.0	85	65	60	56

Least Squares Coefficient
$LN(\text{visual angle})=\beta_0+\beta_1\cdot(\text{eccentricity})$

variable	coefficient	std. error
constant	-4.224	0.196
slope	0.038	0.004

Environmental factors that affect the visual field are brightness-level, brightness-contrast, size of details, backgrounds, surroundings, and color contrasts. Most experiments exploring human vision are in in well lit rooms under controlled lab conditions that maximize vision. Since bird counts generally are not under ideal conditions, the visual field should be smaller than found under laboratory conditions.

The time required to see a bird may only be a few tenths of a second, but additional time is necessary to fixate and identify a bird. For simplicity, it will be assumed that time is not a factor in visual detection but that the observer is traversing the transect at a rate that allows for visual bird identification.

Between bird detections, the observer's optical axis is on the transect line; thus, the angle between the bird and the transect line will be the angle of eccentricity η.

4.7.1 VABS and Visual Detection

Using the relationship between visual size and eccentricity, VABS classifies a bird in the visual field if

(1) $d[(obsx,obsy),(b_{ix},b_{iy})] \leq DV'$ $\quad DV'=DV \cdot e^{-\beta_1 \eta}$

and

(2) $\eta \leq PERF$,

where PERF, the observer's maximum eccentricity, is specified by the user in VABS. The variable β_1 is fixed at .038, the slope of the fitted line in Table 4.7.1. If a bird is located in a blind area created by a tree, it cannot be detected visually (Section 4.8).

To model the decrease of visual acuity due to increasing distance and eccentricity, the conditional probability of visual detection given a bird is in the visual field is model as the monotonic exponential curve,

$$Pr(\text{visual detection}|x,\eta)=e^{\frac{-x}{\lambda \cdot 10}},$$

where x is the Euclidian distance between the observer and bird. For η defined as the angle of eccentricity, λ is calculated as $\lambda=\exp(\beta_0 - \beta_1 \cdot \eta)$, where $\beta_0=\ln(DV*.021715)$. The value of β_0 influences the shape of the exponential curve. To determine the value of β_0, trial runs of VABS were conducted using different values of β_0 until detected area frequency histograms were representative of histograms found in the literature. The value .021715 is the solution to

$$\Pr(\text{visual detection}|x{=}DV){=}\exp(DV/(10e^{\beta_0})){=}.01.$$

At each meter along the transect, the probability of a bird not being detected is calculated. After the transect is traversed, the probability a bird is detected is calculated as

$$\Pr(\text{bird } i \text{ detected}){=}1-\prod_{j=1}^{L}(\text{bird } i \text{ not detected at j}).$$

Once this probability is been determined, a uniform variate between 0 and 1 is selected: a bird is seen and identified if the variate is less than or equal to the probability the bird is detected. In order to estimate effective area, the detection area, calculated using the perpendicular distance between the bird and the transect line, is stored for each bird detected.

4.8. Reduction of the Visual Field Caused by Trees

The area where vision is blocked by a tree and a bird cannot be seen will be defined as a '*blind area*'. Before considering the probability a bird is detected visually, the reduction in the visual field caused by blind areas needs to be calculated. The first step in creating the blind areas is to determine what trees lie in the observer's field of vision for bird detection. Recall that for each previously created tree, the coordinates of a tree's center (h_i,k_i) and radius r_i (includes foliage) have been stored, enabling the recreation of a circle that represents the boundary of the space that the tree occupies. A tree lies in the observer's visual field if the Euclidian distance between the observer and the point of the tree closest to the observer is less than or equal to DV $(d[(h_i,k_i);(obsx,obsy)]-r_i \leq DV)$.

More specifically, the blind area will be defined as the area that lies between the two tangent lines of the circle whose common point is (obsx,obsy) and is above the line l(x) that goes through the two points of tangency (Figure 4.8.1). The next step in creating a blind area is to determine the two points of tangency to the tree. Once these points are determined, the slope (m) and the yintercept (b) of l(x) are calculated. Two angles α_1 and α_2 ($\alpha_1 \leq \alpha_2$) whose sides consist of the transect line and one of the two tangent lines are also calculated at this time. See Figure 4.8.2.

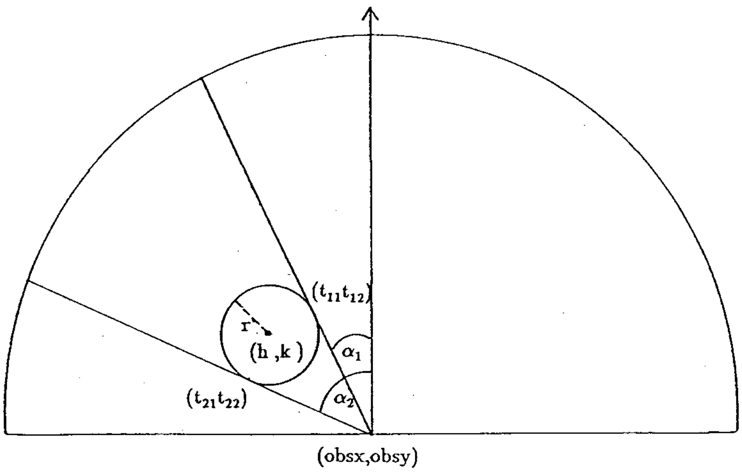


Figure 4.8.1 Blind areas (shaded area) in the observer's visual field caused by the presence of trees.

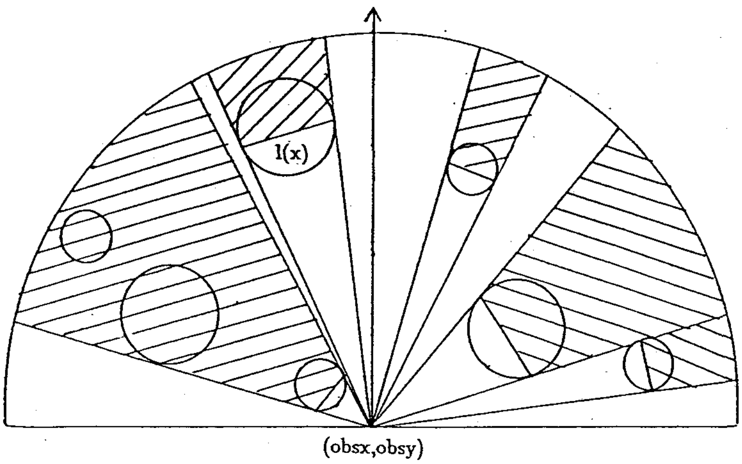


Figure 4.8.2 Tangent lines and corresponding angles used to create a blind area. Lines are tangent to the tree and intersect the observer's location. Angles are measured from the transect line with $\alpha_1 < \alpha_2$.

If T_1 is the point of tangency (t_{11},t_{12}) that creates α_1, and T_2 is the point of tangency (t_{21},t_{22}) that creates α_2, then

$$(t_{11}t_{12})=\begin{cases}(x_L,y_H) & h \geq obsx; k \geq obsy\\ (x_H,y_H) & h \geq obsx; k < obsy\\ (x_L,y_L) & h < obsx; k \geq obsy\\ (x_H,y_L) & h < obsx; k < obsy,\end{cases}$$

$$(t_{21}t_{22})=\begin{cases}(x_H,y_L) & h \geq obsx; k \geq obsy\\ (x_L,y_L) & h \geq obsx; k < obsy\\ (x_H,y_H) & h < obsx; k \geq obsy\\ (x_L,y_H) & h < obsx; k < obsy,\end{cases}$$

where

$$x_L=\frac{-b-\sqrt{b^2-4ac}}{2a}+h,$$

$$x_H=\frac{-b+\sqrt{b^2-4ac}}{2a}+h,$$

$$y_L=-\sqrt{r^2-(x-h)^2}+k,$$

$$y_H=\sqrt{r^2-(x-h)^2}+k$$

for

$$a = (obsx-h)^2+(obsy-k)^2$$
$$b = -2r^2(obsx-h)$$
$$c = r^2(r^2-(obsy-k)^2).$$

From this it follows that

$$\alpha_1=\begin{cases}\tan^{-1}\left(\frac{t_{11}-obsx}{t_{12}-obsy}\right) & t_{12}\neq obsy\\ -\frac{\pi}{2} & t_{12}=obsy,\end{cases}$$

$$\alpha_2=\begin{cases}\tan^{-1}\left(\frac{t_{11}-obsx}{t_{22}-obsy}\right) & t_{12}\neq obsy\\ \frac{\pi}{2} & t_{12}=obsy,\end{cases}$$

$$m=\begin{cases}\frac{t_{22}-t_{12}}{t_{21}-t_{11}} & t_{11}\neq t_{21}\\ -999 & t_{11}=t_{21},\end{cases}$$

and

$$b = \begin{cases} t_{12}-(t_{11}\cdot\frac{t_{22}-t_{12}}{t_{21}-t_{11}}) & t_{11} \neq t_{21} \\ -\frac{b}{2r} & t_{11} = t_{21} \end{cases},$$

where $l(x)=mx+b$ if $t_{11} \neq t_{21}$ and $l(x)=b_y$ if $t_{11} = t_{21}$ (See Appendix A for derivation).

If a tree is totally in a blind area, a blind area is not created for this tree. Each tree that creates an unique blind area has an array stored containing the tree's identity, α_1, α_2, m, and b. Using this array, a blind area can be regenerated and used to check if a bird is located in the blind area and cannot be seen.

A quicker algorithm, if birds are immobile, would be to determine the set of observer locations at which the observer is blinded to the bird.

Section 4.9 Standard Level of Variables

Five hundred simulations were carried out for each configuration of VABS. Each simulation encompassed creating a plot and simulating the gathering of data from which density estimates and corresponding confidence intervals were derived. In order to maintain some consistency between simulation studies, the variables listed in the previous sections were set to the values in Table 4.9.1, unless otherwise noted. The base program VABS is printed out in Appendix C.

Table 4.9.1 Standard values for VABS.

D=10 birds/hectare
W=210 meters
L=1000 meters
DVA=.067° (DV=85.52 meters)
PERF=75°
BETA1=−.038
TT=−3.690 $E(t_i)$=.025 minutes/meter
SDTT=.0272 $E(t_i)$=.00125 minutes/meter
THETA=.3 vocalizations/minute
DA=100 meters

4.10 Estimating Density

Density is calculated as $\hat{D}=n/\hat{\alpha}$, where $\hat{\alpha}$ is the point estimate of effective area. The Cum-D, FS, and EPS estimates of effective area are all calculated in VABS.

Before progressing further, VABS sorts the detected areas in increasing order. The algorithm to estimate the effective area by the Cum-D method follows the approach of developing an envelope function and selecting k, the k^{th} ordered detected area, as described in Section 2.6.

The first step in estimating the FS estimate of effective area is to set τ to the greatest detected area recorded. The data is not truncated as suggested by Burnham et al. (1980) since VABS, in order to be more efficient, limits detection distances to be less than or equal to max(DA,DV), eliminating outliers. To confirm this conjecture, coverage for 95% and 99% nominal confidence intervals for density using the FS with the full data set and the truncated data set (2% data truncated) were compared over 500 simulations. The results showed no evidence of a difference (P=.1025 and P = .4142) between the methods (Table 4.10.1). The coefficients of the FS in VABS are estimated as in equation 2.4.2, using the stopping rule given in equation 2.4.3 with the maximal number of coefficients being set at five. Effective area is calculated as in equation 2.4.1.

Table 4.10.1 Coverage* of nominal confidence intervals (CI) for the FS using the full data set and data with 2% of data truncated: VABS standard settings, density=15 birds/hectare.

	Mean Density Estimate	Mean Bootstrap Estimate of SE	CI 95%	CI 99%
Full data set	15.059	3.1808	.934	.988
2% data truncated	15.084	3.1517	.950	.992

*Critical value for α=.05 is .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
McNemar statistic for nominal 95% CI: 2.67 (P=.10).
McNemar statistic for nominal 99% CI: 0.67 (P=.41).

In order to restrict the EPS model to one where the curve is not unrealistically flat out to the outer detection areas (represents a probability of detection close to one), the shape parameter γ is constrained to the interval

(0,10]. To expedite estimation of γ, the value of the maximal invariant statistic loglikelihood function

$$L(z',\gamma) = \log(\Gamma(\tfrac{n}{\gamma}))\text{-}\log(\gamma)\text{-}n\log(\Gamma(1+\tfrac{1}{\gamma}))+\tfrac{n}{\gamma}\log(1+\sum_{i=1}^{n-1} z_i^{\gamma}),$$

is computed for all values of $\gamma = .25,(.25),10$. See Appendix B for loggamma function approximation. The level of γ that provides the largest value of this loglikelihood function is selected as the scale parameter. Using this estimate of γ, α is estimated using the maximum likelihood equation 2.5.1.

4.11 Estimating Standard Errors and Approximating Confidence Regions

VABS estimates the standard errors for all three density estimates using bootstrap techniques. To estimate the standard errors of $\hat{D}_{CD}$ and $\hat{D}_{FS}$, 100 sets of n samples are selected with replacement from the n detected areas used to estimate effective area. For each bootstrap replication, density is estimated by holding the number of detections fixed at n and using the estimated effective area for the bootstrap sample as the denominator. The sample variance of these estimates is used as the estimate of var($\hat{D}$). VABS approximates confidence intervals for D using the large sample normal approximation,

$$\hat{D} \pm z^{(\gamma)}\hat{se}(\hat{D}),$$

where $z^{(\gamma)}$ is the $100 \cdot \gamma$ percentile point of a standard normal variate.

Recall that both n and $\hat{\alpha}$ are subject to sampling variation; n is held fixed in the previous bootstrap procedure with the suspicion that the variance in $\hat{D}$ due to n is small compared to that due to $\hat{\alpha}$. The Cum-D and FS estimators showed evidence of adequate coverage under this model, but the EPS estimator coverage was low (Table 4.10.2).

Table 4.10.2 Coverage* of nominal CI for density using the Cum-D, FS, and EPS density estimates: Bootstrap estimates of standard error.

	CI	
Density Estimator	95%	99%
Cum-D	.962	.990
FS	.960	.994
EPS	.876	.962

*Critical values for α=.05 are .934 (H_o:p $\geq$ .95) and .982 (H_o:p $\geq$ .99).

To determine if the poor coverage of the EPS model was due to the lack of accounting for the variation in n, n was allowed to vary. Two procedures allowing n to vary were tested: (1) For bootstrap sample i, n_i was generated as a Poisson variate with mean n and then divided by the estimate of effective area for the i^{th} bootstrap sample. (2) The transect was split into r intervals of equal length and the number, n_j, of perpendicular distances intersecting the j^{th} interval was recorded. The numerator of the density estimate of the i^{th} bootstrap sample was the sum of the n_j's chosen in the bootstrap sample of size r of the n_j's. Both of these procedures supplied adequate coverage (Table 4.10.3). The second method was chosen for VABS with the speculation that this method would be less sensitive to the distribution of n. Simulation suggested that r should be chosen so that there are enough intervals to ensure an adequate number of unique bootstrap samples and few intervals with no detections; VABS sets r=10.

Table 4.10.3 EPS coverage* of nominal CI with various bootstrap samples.

Numerator for Bootstrap Replicate Density Estimate	Average $\hat{SE}(\hat{D})$	CI 95%	CI 99%
n fixed	.6446	.728	.822
n ~ Poisson(n)	1.0231	.966	.996
Transect split into 10 intervals	1.0018	.958	.992
Transect split into 50 intervals	1.0287	.966	.998

*Critical values for α=.05 are .934 (H_o:p $\geq$ .95) and .982 (H_o:p $\geq$ .99).

4.12 Random Variate Generation

Throughout VABS there are several occasions where the generation of a psuedorandom variable from a specified distribution is called upon. The necessary Fortran code to generate these psuedorandom variates has been included in VABS as 'function subprograms'. This section briefly describes these subprograms.

4.12.1 Uniform Variates

A uniform variate between (0,1) is not only needed to distribute birds and trees over the created region uniformly but also as a prerequisite to generating random variates from other distributions. To generate pseudorandom numbers in the interval (0,1), the machine independent portable Fortran code proposed by Schrage (1979) is used. Schrage utilizes the multiplicative congruential generator

$$IX(i+1)=A*IX(i)mod(P),$$

where P is the Mersenne prime number $2^{31}-1 = 2{,}147{,}483{,}647$ and $A = 7^5=16807$. All integers that IX produces satisfy $0 < IX < 2^{31}-1$; therefore, $R = IX/2{,}147{,}483{,}647$ generates $R \sim U(0,1)$. This generator is full cycle; otherwise, every integer from 1 to $2^{31}-2$ is generated exactly once in a cycle.

Schrage (1979) claims that this code is machine independent, meaning the generator should produce the same results from machine to machine as long as the input to the program is the same. To maintain machine independence when generating a random integer $K \sim U\ [I,J]$, VABS applies the algorithm

FX = RAND(IX) (RAND function name of random number generator)

$K = (IX\backslash 2{,}147{,}483{,}647\backslash(J-I+1)))+I$

recommended by Schrage (1979). This value of K does not depend upon the manner in which the host machine converts integers to real numbers.

4.12.2 Exponential and Logistic Variates

To generate pseudorandom exponential and logistic variates (Section 9.3) the inverse method is used. The inverse method is based on the property that if X is a random variable with a continuous cumulative distribution function $F_X(x)$, then $X = F_X^{-1}(R)$ for $R \sim U(0,1)$ has the cumulative distribution function $F_X(\cdot)$. Explicitly, $X = -\lambda LN(R)$ generates exponential variates $(F_X(x) = 1-\exp(-x/\lambda),\ \lambda > 0)$, and $X = \alpha+\beta\ln\{R\backslash(1-R)\}$ generates logistic variates $(F_X(x) = [1+e^{-(x-\alpha)\backslash\beta}]^{-1},\ -\infty < \alpha < \infty,\ \beta > 0)$. To acquire a psuedorandom log-logistic variate X (Section 9.3), VABS sets $X = e^Y$ where Y is a logistic variate.

4.12.3 Normal Variates

VABS utilizes the Fortran code supplied by Dagpunar (1988) to generate pseudorandom normal deviates. This algorithm generates a standard random normal deviate using the polar Box-Müller method. The polar Box-Müller method is a modification due to Marsaglia and Bray (1964) of the Box-Müller method which avoids the trigonometric functions and often speeds up the procedure. Dagpunar (1988) claims this generator does not appear to suffer the problems with the tail variates of the Box-Müller method reported by Neave (1973). The generator uses the theory that for two independent random variables $U_1,U_2 \sim U(-1,1)$ if $U_1^2+U_2^2 \leq 1$, then

$$X_1 = \{-2\ln(U_1^2+U_2^2)\}^{\frac{1}{2}}U_1(U_1^2+U_2^2)^{\frac{-1}{2}},$$
$$X_2 = \{-2\ln(U_1^2+U_2^2)\}^{\frac{1}{2}}U_2(U_1^2+U_2^2)^{\frac{-1}{2}}$$

are a pair of standard normal deviates from which only one is used.

4.12.4 Poisson Variates

The Poisson variate ($f(x) = \lambda^x e^{-\lambda}/x!$, $x \geq 0$) is the only discrete variate that VABS calls for. To generate pseudorandom Poisson variates, VABS uses the multiplicative approach where a stream of random numbers $\{R_i\}$ $i = 1,(1),X$ are generated; the Poisson variate X being the largest integer X satisfying

$$\prod_{i=1}^{X} R_i \geq e^{-\lambda}.$$

This method requires a mean of $\lambda+1$ random numbers per variate, thus it is suitable only when λ is small. For $\lambda > 20$, Dagpunar's Fortran code for a modified version of Atkinson's Logistic Envelope Method (Atkinson 1979) is used.

4.12.5 Gamma Variates

The only other random variable to be generated is the gamma variate with pdf

$$f_Z(x) = \frac{\lambda^\gamma x^{\gamma-1} e^{-\lambda x}}{\Gamma(\gamma)} \quad (x \geq 0,\ \gamma > 0,\ \lambda > 0),$$

where γ is the shape parameter and λ^{-1} is the scale parameter. Gamma variates are generated by sampling from a standard gamma distribution ($\lambda = 1$) and setting $Z = X/\lambda$. When only gamma variates for $\gamma > 1$ are needed, such as in VABS, Dagpunar recommends the t-distribution method credited to Best (1978). This method uses envelope rejection, a prospective sample variate is subjected to a random test which results in acceptance or rejection of the sample variate. In this case, the generated prospective variate is $Y=\gamma-1+\beta T$, where T is a Student's t-variate with two degrees of freedom. The term $(\gamma-1)$ relocates the distribution so that the mode is identical to that of the gamma; β is a suitable scaling constant ($\beta=((3\gamma-0.75)/2)^{1/2}$). The acceptance conditions becomes

$$R_2 < (Y/(\gamma-1))^{\gamma-1} e^{-Y+\gamma-1} (4(R_1-R_1^2))^{-3/2}$$

where $R_1, R_2 \sim U(0,1)$. Experiments carried out by Dagpunar (1988) have demonstrated that this method requires virtually no setup time, yet gives competitive performance for most values of γ. Once again, the Fortran code provided by Dagpunar (1988) is employed.

5 SAMPLE SIZE

5.1 Background

This chapter deals with how many independent detections are needed to infer the true underlying detection curve and to estimate density with acceptable accuracy and precision. In the literature, there are conflicting statements concerning sample size. Burnham et al. (1980) states that "As a practical minimum, studies should be designed to assure that at least 40 total objects ($n \geq 40$) are detected; it might be preferable if the total length of the survey is sufficient to allow for the location of at least 60-80 objects." Burnham provides a formula to estimate the length of the transect required to detect the number of birds necessary to obtain the desired precision, but this formula requires a pilot study or advance information on the variability of $\hat{D}$ as a function of line length. Furthermore, this formula does not address the question of how many samples are needed to infer the true underlying detection curve.

Concerning the estimation of the detection curve, Burnham et al. (1980) states that "Even with sample sizes of 100, one has difficulty in inferring the true underlying detection function." This conjuncture agrees with a statement made by Verner and Ritter (1988) who suggest a minimum sample of 100 detections.

5.2 Simulation Study

VABS was used to explore the behavior of the three estimators as the number of independent detections (sample size) increased. To obtain different sample sizes, the density of birds in the study area was varied. All other parameters in VABS were fixed at their standard level (Section 4.9). Throughout this chapter, the standard assumptions of the variable area survey were meet. The percentage of detections made audibly was held as constant as possible so that the shape of the detectability curve was similar between the different sample sizes. The seven densities in Table 5.2.1 were chosen so that approximately 15, 40, 60, 80, 100, 120, and 160 birds were detected.

Table 5.2.1 Mean number of detections and percentage of audible detections for different bird densities.

Density	Mean (se) Number Detected		%Audio	
1.0	15.7	(2.1)	74.5	(11.0)
2.5	39.2	(3.2)	73.6	(7.4)
3.375	59.3	(3.9)	73.8	(5.8)
5.0	78.6	(4.6)	74.8	(5.1)
6.25	98.3	(5.0)	74.9	(4.5)
7.524	118.7	(5.3)	74.6	(4.0)
10.0	157.7	(6.4)	74.7	(3.3)

5.3 Results

Figures 5.3.1 and 5.3.2 indicate that the Cum-D occasionally severely overestimates density. Examination of generated data shows that the Cum-D severely overestimates density when a high proportion of small detection areas are sampled, resulting in a very steep estimate of the slope at F(0). Bootstrap estimates of standard error will overestimate se($\hat{D}$) if just one sample contains an unrepresentative high proportion of small detection areas. Results of the simulations show evidence that odd samples are less likely to occur for larger sample sizes (>60 detections), but they still will occur. A protocol that prevents this situation needs to be developed, if the Cum-D estimator is going to estimate density precisely. One protocol might be to use the 15th percentile detected area to estimate the slope at F(0) if this estimate is significantly smaller than the estimate of slope calculated using the $\sqrt{n}$ rule. The significance level should be chosen so that the 15th percentile is only used when extreme differences occur. Currently, the common bootstrap estimate of standard error does not appear appropriate for the Cum-D density estimate.

For all sample sizes, all three estimators showed evidence of coverage equal or greater than the nominal size of the confidence interval for density (Table 5.3.1). When sample sizes were large ($n > 80$), the Cochran's Q statistics suggested that there was no difference between the three levels of coverage obtained using the Cum-D, FS, and EPS estimates of density.

The density estimate's coefficient of variation settled down between 60-80 samples for all three estimators (The large mean .4102 of the coefficient of variation for the FS estimate at 5.0 birds per hectare was due to one odd case).

The FS was less bias than the Cum-D and EPS for small samples, but precision was poor. The EPS overestimated density for small samples and underestimated density for large samples. However, starting with about 40 samples, the EPS consistently had the smallest coefficient of variation between the three estimators.

5.4 Conclusions

To achieve reasonable precision and to infer the proper underlying detectability curve, 80-100 detections is minimal to estimate density. The sample size of 40 seems plausible, but there is a noticeable increase in precision between 40 and 80 detections. By adjusting the total length of transects covered, one should be able to acquire the desired number of detections needed to estimate density. Since population density varies during the seasons, transect lengths may need to be adjusted if a sufficient number of detections are to be gathered throughout the year. With the methodology presented in Section 11.3, data sets with different detectability curves can be adjusted and pooled to acquire a larger data set from which to estimate density.

The EPS density estimate appears to be more precise than the FS and Cum-D estimates when samples sizes are above 40, but there is a tendency for the EPS to overestimate area for the curves generated in this study.

Throughout the simulations, the shape of the detectability curve was essentially held constant. Further work should compare the performance of the three estimators between different sample sizes for different shapes of the detectability curve.

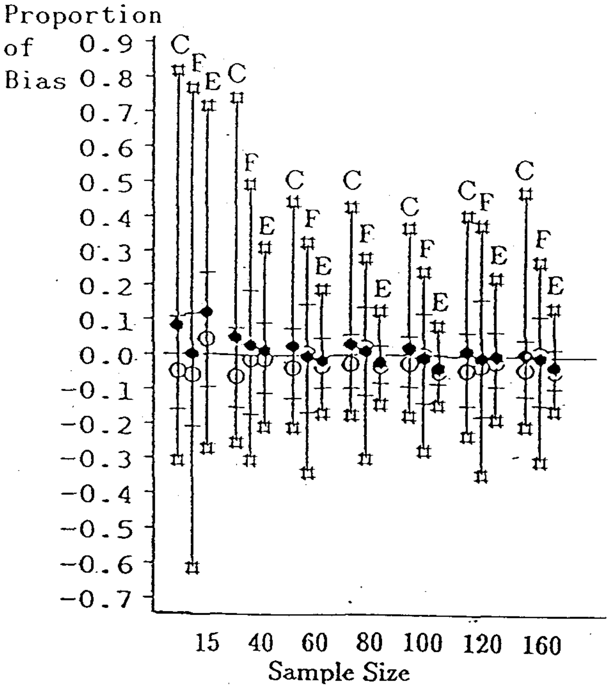


Figure 5.3.1 Bias of density estimates for different sample sizes. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (o) median, (-) 1st & 3rd quartile, (#) 5th & 95th percentile.

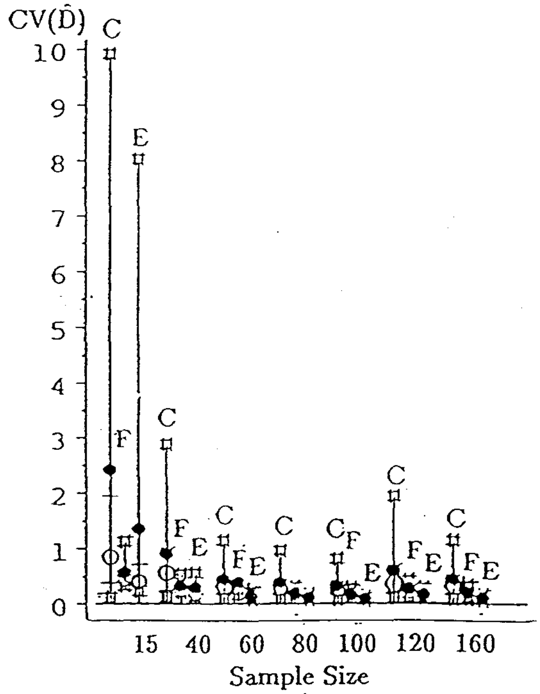


Figure 5.3.2 Coefficient of variation of density estimates for different sample sizes. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (o) median, (-) 1st & 3rd quartile, (#) 5th & 95th percentile.

Table 5.3.1 Coverage* of nominal confidence intervals for different sample sizes.

Sample Size	Cum-D	FS	EPS	Cochran's Q	P-value
95% CI					
15	.966	.984	.998	21.44	.00
40	.982	.986	.994	3.11	.21
60	.982	.982	.982	.00	1.00
80	.966	.978	.984	4.20	.12
100	.972	.972	.970	.59	.74
120	.984	.966	.978	3.71	.17
160	.974	.960	.954	3.59	.17
99% CI					
15	.982	.996	1.000	14.89	.00
40	.988	.998	1.000	8.86	.01
60	.988	.996	.996	4.57	.10
80	.994	.994	.998	1.14	.56
100	.988	.996	.996	3.56	.17
120	.992	.992	.996	.80	.67
160	.996	.994	.988	2.36	.31

*Critical values for $\alpha = .05$ are .934 (H_0:p $\leq$ .95) and .982 (H_0:p $\leq$ .99).

6 ABILITY OF THE VARIABLE AREA SURVEY TO ADJUST FOR DIFFERENT DETECTABILITY

6.1 Motivation

The area surveyed is determined by factors relating to detectability. These factors can vary between years, seasons, days, and hours. Dawson (1981) claims that some workers have treated seasonal changes in counts as if they might be due to changes in density alone and have only acknowledge that the effective area surveyed may have changed when their results made no sense. If the objective of the counts is to detect trends, factors influencing detectability must be controlled or counts must be adjusted for detectability. It is very difficult, if not impossible, to control for all factors influencing detectability. Theoretically, the variable area survey can produce two unbiased density estimates for two counts with different detectabilities by adjusting the effective area surveyed for the two counts. The objective of the simulation studies presented in this chapter was to examine the ability of the variable area survey to adjust for different detectability.

The surveyor should be aware of the numerous factors that affect detectability. To begin with, the observer is a major source of variation in detectability (Verner and Milne 1989); even experienced birders vary considerably in their abilities (Kepler and Scott 1981). Detectability curves between different observers are inclined to differ, since physiological factors influencing visual acuity, color sensitivity, peripheral vision, aural acuity, threshold of audibility, and frequency discrimination will vary among individuals. Corrective devices are available to compensate for some physiological shortcomings, but it is hard to control for all factors brought forth by physiological differences between observers.

Faanes and Bystrak (1981) note that visual factors are certainly encountered but do not appear to be as prevalent nor as important as aural factors. Hearing tests of 274 people among active birders attending a symposium (Ramsey and Scott 1981b) indicated large differences in hearing ability and confirmed that as age of an observer increases hearing ability declines; higher frequencies are lost faster with age than lower ones. Concluding that differences in hearing ability can result in differences as large as an order of magnitude in areas effectively surveyed, Ramsey and Scott (1981b) recommend eliminating all potential observers with uncorrectable hearing thresholds of 20dB or greater in the frequencies emitted by the species of interest.

Psychological factors such as an observer's concentration, motivation, attention span, alertness, endurance, and willingness can all critically influence counts (Kepler and Scott 1981). These psychological factors may vary from day to day or hour to hour in an individual but can be reduced or eliminated with well planned and executed surveys.

Attributes of birds can account for changes in the effective area surveyed. Male birds are typically more detectable than females owing to the females lack of song, usually drab coloration, and larger proportion of the maternal duties requiring secrecy, such as incubation (Franzreb 1981). Age may also influence detectability. For example, known juvenile Willow Tits in Sweden were detected significantly more often than known adult Willow Tits. This discrepancy was attributed to differences in foraging heights among the age and sex classes (Ekman 1981).

Changes in the frequency, clarity, and loudness of songs can account for changes in the effective area surveyed. Variation in bird songs are diurnal and seasonal (Shields 1977, Holmes and Sturger 1975, Ramsey et al. 1987). Song initiation is stimulated by increasing light intensity at dawn with territorial diurnal birds singing most profusely shortly before and after sunrise throughout the breeding season (Best 1981). Skirvin (1981) observed that total detections and total singing bird detections in the morning hours decreased from the first hour to the fourth hour. There are several studies that indicate that singing frequency changes within the breeding season, but how it fluctuates varies between species depending upon the function(s) of song. For species where song is primarily for mate attraction, singing frequency declines dramatically after pair formation. There is evidence that dramatic declines in singing frequency of males once they have paired may result in unmated males being more easily observed (Sayre et al. 1978, Slagsvold 1973). Best (1981) illustrates the effects that stage of the breeding cycle can have on bird detection with count data collected from the Field Sparrow. Singing observations constituted 92% of all observations made of unmated males, whereas only 13% of the observations made of pairs during other stages of the breeding cycle were singing males.

When song is primarily for territorial advertisement, singing may be much more consistent throughout the breeding season (Smith 1959). Territorial diurnal birds sing most profusely shortly before and after sunrise throughout the breeding season (Bull 1981).

Owing to the fact that bird behavior changes during the nesting stages, the variability in nesting success will affect predictability of seasonal changes of detectability for species capable of multiple nestings (Haukioja 1968, Slagsvold 1973).

Because of the preceding evidence, many field studies restrict breeding bird surveys to morning hours during the 'peak' of the breeding period when detections are regarded as highest and populations presumably stable. This period is difficult to obtain when sampling several species simultaneously, since species differ in their breeding schedules.

Observation has implicated precipitation, relative humidity, snow, temperature, and wind as factors in bird counts. These factors can be controlled to some degree by avoiding weather known to have a determinative influence on bird counts.

Weather has a decided influence on bird song. Cool or hot weather, rain, or wind will depress the amount of singing in most species. The number of phases sung per minute by Pied-Flycatchers is directly proportional to air temperature (Curio 1959). There is evidence that the duration of singing in the morning hours is influenced by the rise in daytime temperatures (Robbins and Van Velzen 1970). Studies on the European Blackbird (Colquhoun 1939) show a negative correlation between vocalization and wind. The Bobwhite calling rate is influenced by time of year, time of day, wind velocity, temperature, and relative humidity (Robel, Dick, and Krause 1969). Laperriere and Haugen (1972) report higher levels of cooing in Mourning Doves when more than one bird calls and different levels of calling activity associated with weather conditions.

Birds may restrict their activity and become less conspicuous in severe weather. Robbins (1981b) claims that a steady hard rain probably has a greater effect on bird counts than any other weather condition. Counts on large soaring birds, such as vultures and hawk,s where most detections are visual are hindered in weather that prevents thermals. During cool, rainy weather when flying insects are unavailable for food, fasting adult swifts become torpid (Koskimies 1950). Poor-wills, hummingbirds, doves, swallows, colies, and sunbirds have been observed torpid or at least partially dormant (Welty 1982).

Fog, precipitation, and snow will reduce an observer's vision. Absorption of sound will vary with humidity and air temperatures reducing the intensity of a sound at a given distance. Hot calm air causes sound to be diverted upward away from the observer reducing the number of distant birds detected. Robbins (1981b) claims that birds detected primarily by sight (hawks, swifts, swallows, blackbirds) are found in smaller numbers on foggy mornings, where as fringillids and some of the other passerines with loud songs are found in larger numbers. Fog improves the ability to hear distant birds, and in addition, when observers cannot see distant birds they naturally devote more attention to detecting auditory cues.

Basically, the preceding mentioned factors influence the observer's visual and audio acuity and the conspicuousness of the bird. The effects of these factors can be simulated in VABS by varying the variables related to the bird's conspicuousness and the observer's visual and audio acuity. The next four sections review simulation studies that varied these variables.

In this chapter, only the FS density estimates were calculated throughout: the FS being a popular yet questionable estimator. The Cum-D density estimates were calculated for the first two studies in order to examine the behavior of this less well known nonparametric estimator. Time limited the examination of other estimators; however, the general results should apply to the EPS and other flexible estimators that are robust to the shapes of the different detectability curves generated.

6.2 Visual Detectability

6.2.1 Background

The potential factors that affect visual detectability are numerous. Most commonly mentioned are:

(1) Visual acuity, color sensitivity, peripheral vision, knowledge, and experience of the individual observers.

(2) Physiological state of the observer over time.

(3) Vegetation within the region.

(3) Factors within or between bird species that influence conspicuousness such as: seasonal differences in bird behavior, sex, age, coloring, size, and reproduction status.

(3) Weather: rain, snow, or fog will reduce the visual field and alter bird behavior.

Theoretically, as visual acuity decreases the estimate of effective area should decrease. However, at some point, the standard theory should fail because the assumption g(0)=1 comes into question as visual acuity degrades. This critical assumption is the topic of Section 9.2. The objective of this study was to determine if the variable area survey accurately estimates the decreased area surveyed as visual acuity degrades.

6.2.2 Simulation Study

To achieve the objectives of examining various levels of visual acuity, the two variables DVA (threshold size) and PERF (maximum eccentricity) in VABS were varied (Section 4.7). Since the influence of vegetation on the visual field was not being examined, there were no trees introduced into the plot. The density of birds was fixed at 10 birds per hectare.

Two simulations of observers traversing identical transect lines at various levels of visual acuity were run. The first run covered a range of good to poor visual acuity (Table 6.2.1). The second run filled in the gaps in visual acuity that occurred in the first run, using a factorial design with DVA fixed at .05, .075, .1, .125, and .15 and PERF fixed at 30°, 45°, 60°, 75°, and 90°; respectively. Separate simulation runs of 500 replications were executed for the FS and Cum-D estimators.

Table 6.2.1 Levels of DVA and PERF for the first simulation run concerning visual acuity.

Level	DVA	(DV)	PERF
1	.05	(114.6m)	90°
2	.10	(57.3m)	80°
3	.15	(38.2m)	70°
4	.20	(28.6m)	60°
5	.25	(22.9m)	50°
6	.30	(19.1m)	40°
7	.35	(16.4m)	30°
8	.40	(14.3m)	20°

6.2.3 Results

The minimal number of birds detected over all replications and levels was 113 birds for the FS study and 115 birds for the Cum-D study. Tables 6.2.2 and 6.2.3 report the means for various statistics as well as the coverage of nominal 95% and 99% confidence intervals for density.

Table 6.2.2 Results of visual factors for the FS estimator.

			Means (se)					
Sample Size	DVA	PERF	%Visual	$\hat{\alpha}$	$\hat{D}$	$\hat{SE}(\hat{D})$	Coverage* 95%	99%
199.5	.05	90	31.3	20.2	10.1	1.5	.968	.994
199.7	.05	90	31.3	20.4	10.0	1.6	.958	.998
187.2	.05	75	26.7	19.1	10.0	1.6	.974	.994
174.3	.05	60	21.4	17.7	10.1	1.6	.974	.996
165.6	.075	90	17.2	17.0	10.0	1.7	.968	.996
163.4	.05	45	16.1	16.7	10.0	1.7	.968	.996
162.0	.075	75	15.3	16.5	10.1	1.7	.966	.996
157.4	.075	60	12.7	16.1	10.1	1.7	.964	.992
156.1	.1	90	12.2	15.9	10.1	1.7	.954	.992
154.5	.1	80	11.3	15.7	10.1	1.7	.958	.992
154.2	.05	30	11.0	15.7	10.1	1.7	.952	.990
153.8	.1	75	10.8	15.5	10.1	1.8	.954	.992
152.6	.075	45	10.1	15.4	10.1	1.7	.956	.986
151.3	.125	90	9.3	15.3	10.1	1.8	.960	.984
151.1	.1	60	9.2	15.3	10.1	1.7	.944	.986
149.7	.125	75	8.3	15.3	10.1	1.8	.950	.984
148.4	.15	90	7.5	15.2	10.0	1.8	.944	.980
147.9	.1	45	7.2	15.3	10.0	1.7	.940	.980
148.4	.125	60	7.1	15.2	9.9	1.8	.932	.980
147.5	.075	30	7.0	15.2	9.9	1.7	.932	.974
147.1	.15	75	6.7	15.2	9.9	1.8	.930	.982
146.2	.15	70	6.3	15.4	9.7	1.8	.934	.968
145.4	.15	60	5.7	15.4	9.7	1.8	.920	.980
145.4	.125	45	5.6	15.4	9.7	1.8	.912	.974
144.6	.1	30	5.1	15.5	9.6	1.8	.904	.960
143.7	.15	45	4.4	15.7	9.4	1.7	.880	.952
142.8	.125	30	3.9	15.8	9.3	1.8	.872	.934
142.6	.20	60	3.9	16.0	9.1	1.7	.882	.938
141.6	.15	30	3.1	16.2	9.0	1.7	.824	.922
140.5	.25	50	2.5	16.6	8.7	1.7	.814	.920
139.2	.30	40	1.6	17.0	8.4	1.6	.734	.840
138.3	.35	30	0.9	17.3	8.2	1.5	.674	.812
137.8	.40	20	0.5	17.5	8.1	1.5	.640	.788

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

Table 6.2.3 Results of visual factors for the Cum-D estimator.

Sample Size	DVA	PERF	%Visual	Means (se) $\hat{\alpha}$	$\hat{D}$	$\hat{SE}(\hat{D})$	Coverage* 95%	99%
199.4	.05	90	31.3	19.7	10.4	2.9	.982	.994
199.5	.05	90	31.1	19.7	10.3	2.9	1.000	1.000
187.0	.05	75	26.5	18.6	10.3	3.0	.996	.996
174.1	.05	60	21.0	17.5	10.2	3.1	1.000	1.000
165.6	.075	90	17.0	16.6	10.3	3.2	.998	.998
163.4	.05	45	15.9	16.5	10.3	3.3	1.000	1.000
161.8	.075	75	15.0	16.3	10.3	3.3	.998	.998
157.4	.075	60	12.7	16.0	10.2	3.5	1.000	1.000
156.2	.1	90	12.0	15.9	10.2	3.4	.998	.998
154.4	.1	80	11.3	16.0	10.0	3.5	.966	.990
154.1	.05	30	10.9	15.9	10.1	3.5	1.000	1.000
153.8	.1	75	10.7	15.9	10.1	3.4	1.000	1.000
152.4	.075	45	9.8	15.8	10.1	3.4	.998	.998
151.4	.125	90	9.2	15.7	10.1	3.6	1.000	1.000
151.0	.1	60	9.0	15.8	10.0	3.6	1.000	1.000
149.7	.125	75	8.2	15.7	10.0	3.6	1.000	1.000
148.3	.15	90	7.4	16.1	10.0	3.6	1.000	1.000
147.8	.1	45	7.0	15.7	9.9	3.7	1.000	1.000
147.5	.125	60	6.9	15.7	9.9	3.7	1.000	1.000
147.5	.075	30	6.8	15.6	9.9	3.8	.998	1.000
147.1	.15	75	6.7	15.8	9.9	3.7	1.000	1.000
146.3	.15	70	6.4	15.8	9.7	3.7	.956	.980
145.4	.15	60	5.5	15.7	9.8	3.8	1.000	1.000
145.3	.125	45	5.4	15.8	9.8	3.8	.996	.996
144.5	.1	30	4.9	15.7	9.8	3.8	1.000	1.000
143.6	.15	45	4.3	15.7	9.7	3.9	1.000	1.000
142.6	.20	60	3.9	16.0	9.4	4.0	.926	.966
142.7	.125	30	3.8	15.9	9.6	3.9	1.000	1.000
141.6	.15	30	2.9	15.7	9.4	4.0	.998	1.000
140.6	.25	50	2.5	16.2	9.2	4.0	.902	.948
139.2	.30	40	1.6	16.6	8.9	4.0	.884	.932
138.3	.35	30	1.0	17.0	8.6	3.9	.845	.904
137.7	.40	20	.6	17.3	8.3	3.6	.814	.886

*Critical values for $\alpha = .05$ is .934 (H_0: $p \geq .95$) and .982 (H_0: $p \geq .99$).

Note that the percentage of detections made visually reflects the level of visual acuity; the ratio decreases as visual acuity decreases. The means of the density estimates were within ± 1 bird per hectare of the true density of 10 birds per hectare until the percentage of detections made visually was around 3% for the FS estimator and 1.6% for the Cum-D estimator (Figures 6.2.1 and 6.2.2). As visual acuity declined, estimates of effective area declined and the estimate of the standard error of $\hat{D}$ increased, as expected, until the percentage of detections made solely by visual means was around 6% (FS) and 4% (Cum-D). At this point, the estimates of effective area started to increase and the estimates of the standard error of $\hat{D}$ started to declined. This change in the pattern suggests that the standard theory was beginning to fail or the estimators were no longer fitting the detectability curve.

As visibility decreases, the shoulder of the detectability curve becomes less distinct (narrower). Burnham et al. (1980) identified a detectability curve as having a shoulder if $g'(0)=0$. In this paper, a shoulder will be referred to as distinct if the detectability curve is relatively flat close to zero ($g'(0+\epsilon)=0$ for $\epsilon \doteq 0$) and not distinct if the curve declines rapidly near zero ($g'(0+\epsilon) \neq 0$ for $\epsilon \doteq 0$). It appears that if the shoulder is not distinct the FS and Cum-D estimators overestimate area, the FS being the least robust.

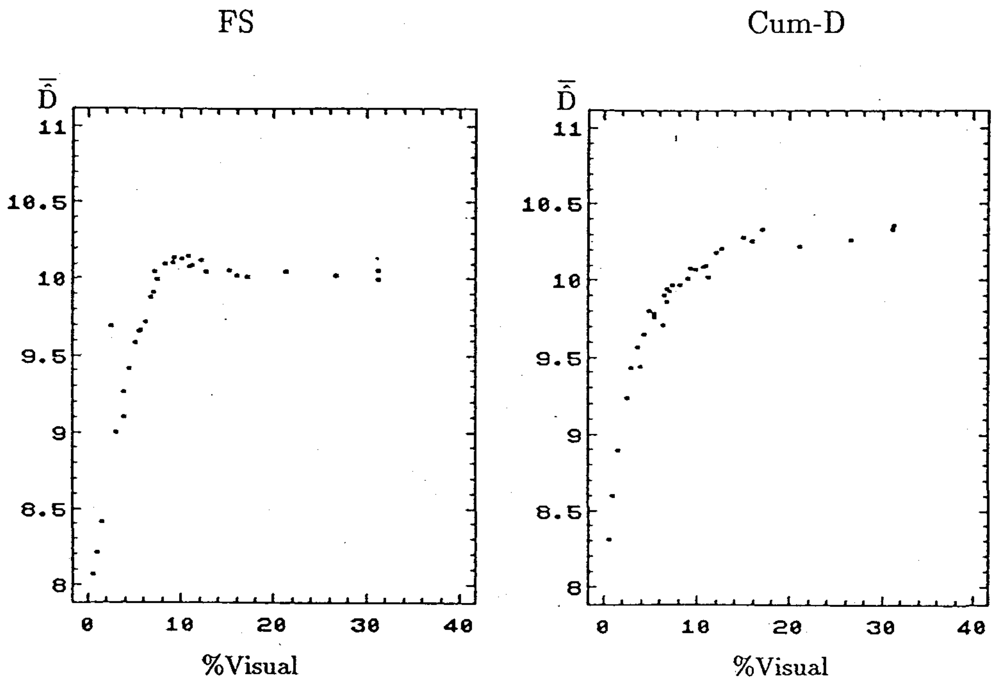


Figure 6.2.1 Mean density estimates versus the mean percentage of detections made visually for different levels of visual acuity.

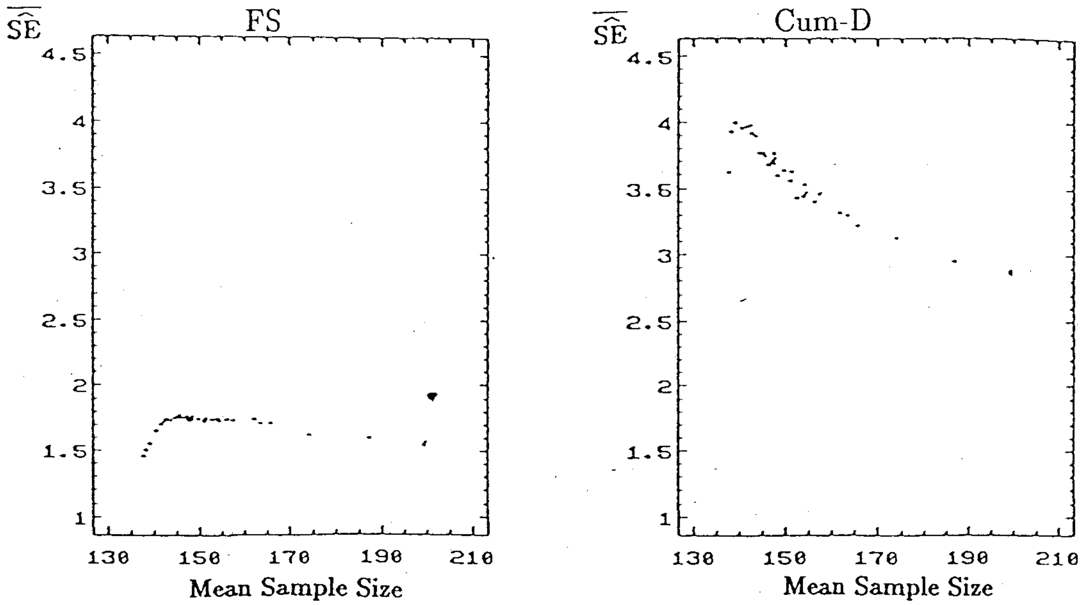


Figure 6.2.2 Mean estimate of standard error versus the mean sample size for different levels of visual acuity.

6.2.4 Conclusions

The FS and Cum-D estimators adjust for the different levels of detectability, until visual acuity is so poor that birds very close to the transect line have a very low probability of detection. At this point, the assumption that $g(0) = 1$ should be questioned. This critical point comes when poor visibility reduces the percentage of detections made solely by visually means to about 6%. This critical point will vary as the probability of audio detection varies. However, assured visual detection on the transect line is necessary unless audio detection insures 100% detectability on the transect.

6.3 Audio Detectability

6.3.1 Background

For a bird or some other animal whose vocalization can be heard and identified by an observer, it is possible to detect the animal's presence and location by audio means. Frequently in bird surveys, the majority of detections are made by sound, and factors that influence audio detection are of concern. The potential factors affecting audio detection fall into two categories: (1) factors hampering the observer's ability to hear a bird's vocalization, and (2) factors influencing the bird's vocalization frequency.

Some of the factors affecting an observer's ability to detect the bird by audio means are the observer's hearing ability, knowledge, experience, and alertness; noises besides those coming from the object of the study; weather; and vegetation. Even if observers without adequate hearing and knowledge are eliminated there will still exist variation among observers. Some known factors that influence a bird's vocalization rate are the sex and age of the bird, season of the year, and time of the day. Note that there is variation between and within observers as well as between and within bird species.

Variable area survey techniques theoretically adjust raw counts so that counts from two observers with different hearing abilities can still produce two unbiased density estimates. Not surprisingly, Ramsey and Scott (1981b) noticed that the precision of the density estimate was greater for the observer with the larger surveyed area, i.e better audio acuity. The objective of this simulation study was to examine if the FS and the Cum-D adjust for the various levels of hearing ability.

6.3.2 Simulation Study

Audio acuity was varied by altering the variable DA, the observer's audio detection threshold. To cover a wide range of audio acuity, DA was fixed at 8 levels: 120m, 110m, 100m, 90m, 80m, 70m, 60m, 50m. The traversing of the same transect was simulated at each level of DA. Separate runs were done for the FS and the Cum-D.

6.3.3 Results

Coverage of the confidence intervals for density is comparable over the various levels of audio detectability (Tables 6.3.1 and 6.3.2). However, as detectability declines so does the number of detections, losing precision (Tables 6.3.3 and 6.3.4). Observers with better audio and visual acuity will increase the number of detections and the precision of the estimates. As the audio detection threshold decreases, the estimate of effective area decreases, adjusting for the declining area being surveyed.

Figure 6.3.1 shows the mean, median, 1^{st} and 3^{rd} quartile, and 5^{th} and 95^{th} percentile of the density estimate bias $(\hat{D} - D)$ for the 500 estimates at each level of DA. As audio detectability decreases, the length of the interval between the 5^{th} and 95^{th} percentile increases. This pattern is reflected in the increasing mean of $\hat{se}(\hat{D})$.

The median bias less than zero reflects the tendency of the Cum-D and FS to overestimate density when the shoulder of the detection curve is not distinct.

Table 6.3.1 Coverage* of nominal CI for different audio detection thresholds: FS estimator.

	DA							
	120m	110m	100m	90m	80m	70m	60m	50m
95% CI	.974	.964	.954	.974	.964	.968	.950	.964
99% CI	.996	.992	.992	.998	.996	.992	.990	.992

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
Cochran's Q statistic 95% C.I.=9.48 (P=.15).
Cochran's Q statistic 99% C.I.=4.91 (P=.56).

Table 6.3.2 Coverage* of nominal CI for different audio detection thresholds: Cum-D estimator.

	DA							
	120m	110m	100m	90m	80m	70m	60m	50m
95% CI	.980	.988	.980	.990	.988	.984	.984	.982
99% CI	.998	.994	.994	.998	.992	.992	.990	.994

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
Cochran's Q statistic 95% C.I.=6.43 (P=.49).
Cochran's Q statistic 99% C.I.=8.52 (P=.29).

Table 6.3.3 Results of different audio detection levels: FS estimator.

	Mean (se)							
DA	120m	110m	100m	90m	80m	70m	60m	50m
Number Detected	199.6 (6.3)	182.0 (7.2)	160.1 (7.6)	151.4 (8.0)	139.1 (7.8)	130.8 (8.3)	125.6 (7.8)	123.2 (8.7)
% Audio	89.4 (2.0)	86.3 (2.7)	82.3 (3.1)	76.9 (3.3)	69.7 (3.8)	60.1 (4.2)	48.8 (4.2)	36.8 (4.7)
$\hat{\alpha}$	20.2 (2.9)	18.5 (2.9)	17.0 (2.7)	15.6 (2.9)	14.4 (2.9)	13.6 (2.7)	13.3 (2.9)	13.0 (2.9)
$\hat{D}$	10.1 (1.4)	10.1 (1.5)	10.0 (1.6)	10.0 (1.7)	10.0 (1.8)	9.9 (1.9)	9.9 (1.9)	9.9 (1.9)
$\hat{SE}(\hat{D})$	1.60 (.38)	1.66 (.36)	1.72 (.40)	1.79 (.45)	1.81 (.47)	1.92 (.40)	1.99 (.38)	2.03 (.40)

Table 6.3.4 Results for different audio detection levels: Cum-D estimator.

	Mean (se)							
DA	120m	110m	100m	90m	80m	70m	60m	50m
Number Detected	199.8 (6.3)	182.7 (6.9)	166.6 (7.6)	151.9 (7.8)	139.2 (8.0)	131.0 (8.0)	125.7 (8.0)	123.3 (8.0)
% Audio	89.1 (2.2)	86.5 (2.7)	82.5 (2.9)	77.1 (3.3)	70.1 (3.8)	60.5 (4.5)	48.9 (4.5)	36.7 (4.5)
$\hat{\alpha}$	20.3 (2.5)	18.4 (2.2)	16.7 (2.2)	15.3 (2.2)	13.9 (1.8)	13.0 (1.8)	12.5 (1.6)	12.3 (1.8)
$\hat{D}$	10.0 (1.6)	10.1 (1.9)	10.2 (2.1)	10.2 (2.1)	10.3 (2.4)	10.4 (2.4)	10.3 (2.4)	10.3 (2.5)
$\hat{SE}(\hat{D})$	3.0 (2.2)	3.3 (2.6)	3.3 (2.6)	3.5 (2.9)	3.7 (3.3)	3.8 (3.6)	3.9 (3.5)	3.9 (3.5)

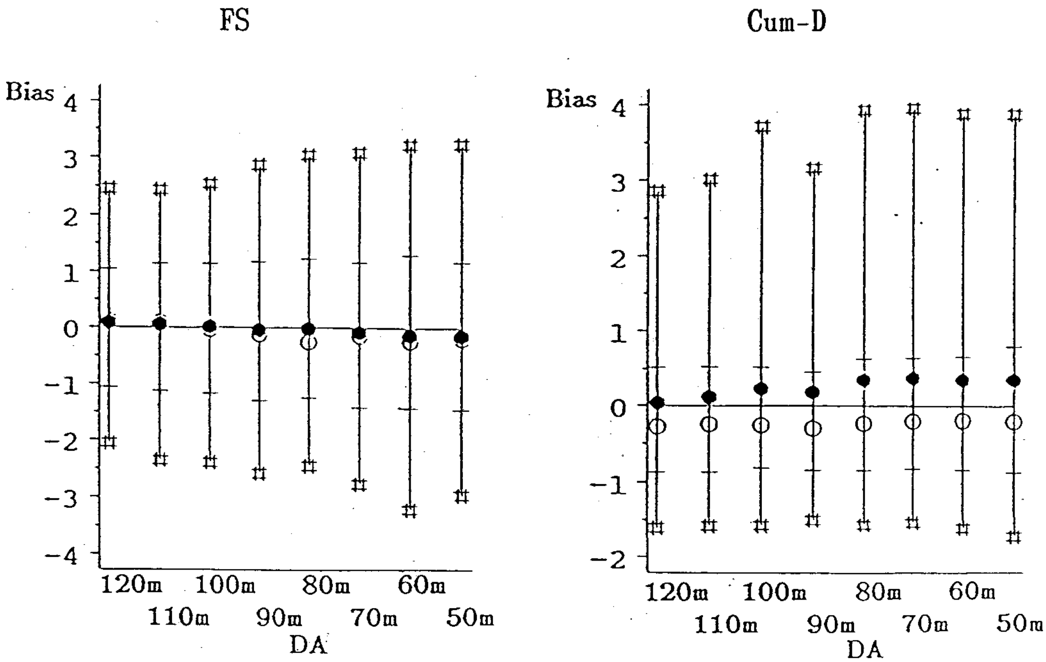


Figure 6.3.1 Bias of density estimates for different audio detection levels. Symbols: (•) mean, (∘) median, (−) 1^{st} & 3^{rd} quartiles, (#) 5^{th} & 95^{th} percentile.

6.3.4 Conclusions

When audio detectability varies, density estimates are successful in adjusting raw counts by the area surveyed. Observers with better audio acuity generally detect more birds, gaining higher precision.

These results support the recommendation that all potential observers be tested for hearing acuity and ability to correctly identify species (Ramsey and Scott 1981). Ramsey and Scott (1981) suggest that one possible way for standardizing experienced observers with their hearing problems would be to have them wear hearing aids which have been individually calibrated to a hearing threshold, say 10dB, within the frequencies emitted by the birds being counted.

6.4 Vocalization Frequency

6.4.1 Background

Vocalization frequencies of bird cues vary between bird species, time of day, season, and sex. Ramsey et al. (1987b) stated that if the decline in bird counts is related to song frequency, and if this is not taken into account in the estimation of detectability, the densities will inevitably be estimated to be lower at those stations surveyed later in the morning than at those surveyed earlier.

The objective of this simulation study was to explore if the variable area survey estimation for density adjusts the area surveyed for different vocalization frequency.

6.4.2 Simulation Study

To achieve this objective, all variables in VABS were held constant, except for the variable that represents the frequency of vocalization, THETA. Note that the traversing pace of the observer and the audio detection threshold interact with vocalization frequency to determine audio detectability. The purpose of this particular simulation study was to examine the effect that various vocalization frequencies have on the density estimate; therefore, only THETA was altered. THETA (calls per minute) was set at eight levels: .001, .05,.1,.15, .225, .3, .5, 1.0. For each replication the same transect was traversed for all eight levels of THETA.

6.4.3 Results

Higher vocalization frequencies allowed for more audio detections, resulting in higher precision (Table 6.4.1). Figure 6.4.1 shows that the accuracy of the FS was greater for the higher vocalization rates; the FS tended to overestimate area for low vocalization frequencies. As the vocalization frequency decreased, the shoulder of the detectability curve became less distinct. For all vocalization rates, there was no supporting evidence that coverage was less than the nominal level of 95% or 99% (Table 6.4.2). Although the Cochran's Q statistic indicated a difference between coverage, this was more than likely due to the increase in sample size.

Table 6.4.1 Results for different vocalization frequencies: FS estimator.

	Mean (se)							
Rate	.001	.05	.1	.15	.225	.3	.5	1.0
Number Detected	126.1 (7.3)	137.1 (6.9)	145.3 (6.8)	152.4 (6.7)	160.7 (6.2)	167.2 (6.0)	179.1 (5.1)	192.3 (5.0)
% Audio	1.7 (1.1)	32.9 (4.0)	49.3 (4.2)	61.6 (4.0)	73.8 (3.1)	82.1 (2.9)	93.2 (2.0)	99.3 (0.7)
$\hat{D}$	9.8 (1.9)	9.9 (1.8)	9.8 (1.7)	9.9 (1.7)	9.9 (1.6)	9.9 (1.5)	10.0 (1.4)	10.0 (1.2)
$\hat{SE}(\hat{D})$	1.97 (.40)	1.89 (.33)	1.86 (.33)	1.80 (.33)	1.75 (.38)	1.69 (.38)	1.57 (.38)	1.49 (.38)

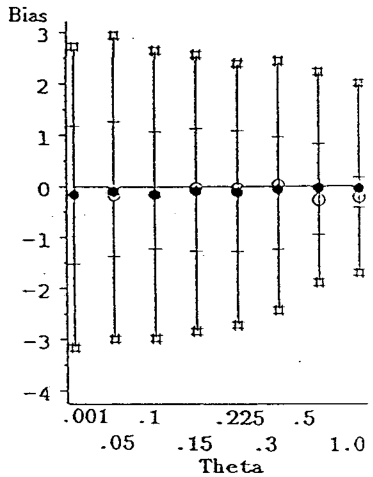


Figure 6.4.1 Bias of FS density estimates for different vocalization frequencies.

Table 6.4.2 Coverage* of nominal CI for different vocalization frequencies: FS estimator.

Rate	.001	.05	.1	.15	.225	.3	.5	1.0
95% CI	.944	.950	.962	.964	.950	.966	.982	.990
99% CI	.992	.992	.990	.988	.990	.992	1.000	1.000

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
Cochran's Q statistic 95% C.I.=38.02 (P = .00).
Cochran's Q statistic 99% C.I.=13.44 (P=.06).

6.4.4 Conclusions

The FS is adjusting for the various levels of vocalization frequency. A survey should be conducted during the time of the day when the frequency of vocalizations is greatest, allowing for a greater surveyed area and thus greater precision and accuracy.

6.5 Traversing Rate

6.5.1 Background

According to Reynolds et al. (1980), rates of travel along a transect vary with terrain, complexity of vegetation, and number of birds seen. The final variable incorporated into VABS that affects audio detection is the observer's traversing rate. As an observer's traversing rate changes so does his probability of hearing a bird. The objective of this section is to examine how the variable area density estimate performs under various traversing rates.

6.5.2 Simulation Study

Recall that in VABS, the time it takes an observer to traverse one meter is a log-logistic variate whose mean and variance are specified in the main program. This study varied the average traversing rate from a very fast rate to a slow rate. Since the variance of traversing rate was fixed at a very low value (Table 6.5.1), the observer maintained a fairly constant pace. Once again, VABS simulated the detection of birds on the same transect line for each of the traversing rates.

Table 6.5.1 Parameter levels for log-logistic distribution for different traversing rates.

Observer	TT	SDTT	Mean time to traverse 1000 meters (minutes)	Standard deviation to traverse 1000 meters
1	-4.613	.0689	10	1.25
2	-4.203	.0459	15	1.25
3	-3.914	.0345	20	1.25
4	-3.690	.0276	25	1.25
5	-3.507	.0230	30	1.25
6	-3.353	.0197	35	1.25
7	-3.219	.0172	40	1.25

6.5.3 Results

When observers walk at different speeds, the slower observer should survey a greater area than the observer who walks more rapidly, because of the slower observer's greater probability of hearing distant bird cues. The mean estimate of effective area surveyed by the FS estimator reflects this logic (Table 6.5.2). Again, the number of detections increases as the effective area increases, resulting in greater precision of the density estimate. The mean and median of bias less than zero for faster traversing rates (Figure 6.5.1) indicate a tendency for the FS to overestimate density when audio detections are less prevalent (less distinct shoulder). These results correspond to previous results. There is no evidence of lower coverage than nominal levels or of any difference in coverage between different levels of traversing rate (Table 6.5.3).

Table 6.5.2 Results of different traversing rates: FS estimator.

	Mean (se)						
Traversing rates	10	15	20	25	30	35	40
Number Detected	128.7 (7.4)	132.8 (7.4)	136.5 (7.8)	139.6 (7.4)	142.8 (7.2)	145.8 (7.6)	148.7 (7.4)
% Audio	31.2 (4.0)	38.8 (4.2)	45.5 (4.2)	51.7 (4.2)	56.9 (4.0)	61.4 (3.8)	65.4 (3.8)
$\hat{\alpha}$	13.6 (3.1)	14.0 (3.1)	14.3 (2.9)	14.5 (2.9)	14.9 (3.1)	15.3 (3.6)	15.5 (3.1)
$\hat{D}$	9.9 (1.9)	9.9 (1.9)	9.9 (1.8)	9.9 (1.8)	9.9 (1.8)	9.9 (1.8)	9.9 (1.8)
$\hat{SE}(\hat{D})$	1.93 (.40)	1.92 (.40)	1.91 (.38)	1.89 (.40)	1.88 (.40)	1.85 (.40)	1.85 (.40)

Table 6.5.3 Coverage* of nominal CI for different average traversing rates: FS estimator.

Study I	Traversing Rates 10	15	20	25	30	35	40
95% CI	.966	.960	.972	.960	.976	.956	.968
99% CI	.994	.986	.994	.986	.986	.992	.990

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
95% Cochran's Q statistic=10.77 (P=.10).
99% Cochran's Q statistic=11.53 (P=.07).

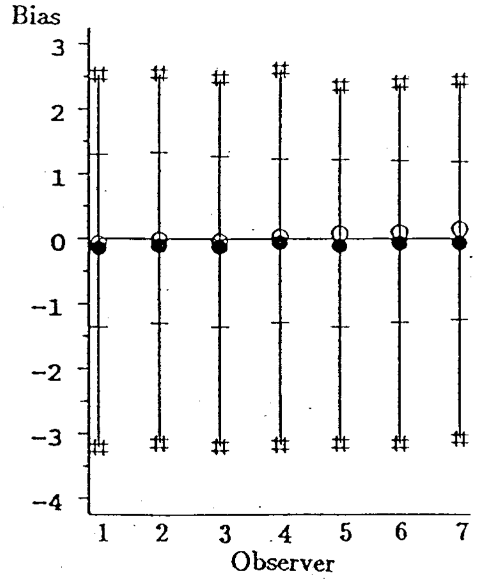


Figure 6.5.1 Bias of density estimates for various average traversing rates. Symbols: (•) mean, (∘) median, (−) 1^{st} and 3^{rd} quartiles, (#) 5^{th} and 95^{th} percentile.

6.5.4 Conclusions

Once again, the variable area survey has the capacity to adjust raw counts by the area surveyed. To gain higher precision, transects should be traversed at a rate slow enough to maximize the area surveyed but fast enough to prevent movement, time of day, and other factors from becoming detrimental.

6.6 Overall Conclusions

The variable area survey has the ability to produce accurate density estimates for counts with different detectabilities. When the proper estimator is used to fit the detectability curve, there is no reason why moderate differences in detectability cannot be tolerated. The principal reason for avoiding extremes in hearing and visual conditions (excluding condition where g(0)=1 is invalid) is sample size, not bias. There are conditions that are conducive to biased density estimates, but generally these situations can be avoided with well designed surveys and proper data analysis.

The results in this chapter supported the following suggested guidelines in planning a survey:

(1) Extreme levels of factors, such as extreme weather, should be avoided.

(2) Observers should be trained and tested for visual and audio acuity in order to maximize the area surveyed and gain higher precision.

(3) Surveys should be conducted during the time of day and season when the bird under study is most conspicuous, both in terms of visual and audio detectability.

(4) Factors that influence detectability should be controlled, if possible, in order to prevent extreme differences in the shape of the detectability curve.

The general results of this chapter should apply to other estimators, unless at some level, the estimator is not robust to the shape of the detectability curve. When selecting what estimator to use to estimate density, the shape of the detectability curve must be considered. Before choosing an estimator, VABS can be used to explore how the estimator behaves over the various levels of the factors of concern. Throughout this chapter, there was evidence that the FS is not robust to a narrow shoulder. If one is calculating densities for counts obtained with different detectabilities, the selection of the estimator should be done separately for each count. Different estimators can be used for different counts.

7 MONITORING AND DETECTION OF POPULATION TRENDS

Bird counts are often used to monitor and detect population trends. Population trends that may be of interest are: (1) annual population trends in a species' population, (2) seasonal population trends, and (3) successional trends used to measure habitat suitability or preference. To detect trends simple counts may be used, but a constant area must be surveyed if meaningful comparisons are to be made. Otherwise, to compare simple counts, detectability must be constant between observers, years, seasons, and habitats. Verner and Milne (1989) advocate the use of simple counts or frequencies for the detection of trends, provided that observer variability is reduced by testing and training observers, and the study is designed to control or measure those factors that influence bird counts.

Although there is a general consensus that a multitude of factors affect bird counts, recognition and the control of all these factors is unlikely. It was shown in the previous chapter that variable area survey density estimates may be used to monitor and detect trends without the assumption of a constant area surveyed. Verner and Milne (1989) recommended against the use of density estimates from variable area surveys for monitoring trends in bird populations because:

(1) Trends can be adequately indicated by measures of relative abundance, such as total counts or frequencies, and density estimates go beyond what is needed.

(2) Variable area density estimates require sufficient effort to obtain counts of 100 or more for all species of interest and are basically unobtainable for uncommon species.

In rebuttal, simple counts and frequencies are indisputably affected by many factors, and it seems unlikely that all of them can be recognized and controlled. If the area surveyed is not constant, comparisons of simple counts will be misleading. As will be seen in Section 11.3, the methodology exists, by means of covariate adjustments, where one can pool adjusted data from species of similar detectabilities to examine detectability and then derive adjusted density estimates for the uncommon species.

In Chapter 6, the influences of an observer's audio ability, the traversing rate, and a bird's vocalization frequency on bird counts were examined. This data is further analyzed in this chapter in order to compare the ability of simple counts and variable area density estimates to monitor population trends when detectability is not constant.

7.1 Testing for Trends

To test for trends, it is assumed that N_i and N_j, the number of birds in the region at time i and j, are independent and Poisson distributed with means $D_i\alpha_i$ and $D_j\alpha_j$, respectively. Under these conditions, the conditional distribution of N_i given the value of N_i+N_j is

$$\text{Binomial}\left(\frac{\alpha_i D_i}{\alpha_i D_i+\alpha_j D_j},\ n_i+n_j\right).$$

Under the null hypothesis of no trend, $D_j/D_i=1$, the parameters of this distribution are $\theta=\alpha_i/(\alpha_i+\alpha_j)$ and n_i+n_j. Using the normal approximation to the binomial distribution with a significance level of .05, the test for a trend reduces to

$$|\, n_i-(n_i+n_j)\,\hat{\theta}| > 1.96\sqrt{\hat{\theta}(1-\hat{\theta})(n_i+n_j)},$$

where $\hat{\theta}=\hat{\alpha}_i/(\hat{\alpha}_i+\hat{\alpha}_j)$. (The null hypothesis of no trend is accepted if the above equation is false.) For counts it is further assumed that $\alpha_i=\alpha_j$, reducing the test to

$$|\, n_i-((n_i+n_j)/2)| > 1.96\sqrt{14(n_i+n_j)}.$$

A population trend between the various factor levels of audio, vocalization frequency, and average traversing rate was tested for using simple counts and density estimates for all 500 simulations. Recall that density was held fixed at 10 birds per hectare. With the significance level fixed at .05, the test for no trend would be expected to falsely reject the null hypothesis 5% of the time.

7.2 Results of Testing for Trends

Tables 7.2.1 to 7.2.3 report the percentage of times a trend was falsely detected out of the 500 simulations. There is strong evidence that the test using simple counts is not achieving the nominal significance level. When simple counts were used an unexpectable low number of trends were falsely detected when the difference in detectability was small. However, when the difference in detectability was high, an unexpectable high number of trends were detected. *The test for simple counts is not robust to unequal surveyed areas.*

The number of rejections were much closer to the expected number for the variable area survey. The number of rejections of no trend increased as the differences in detectability increased, but not as flagrantly as with simple counts. The increase in the Type I error may be attributed to the tendency of the FS to overestimate area when the shoulder of the detectability curve is narrow.

Table 7.2.1 Percent of times test falsely rejected (α=.05) the null hypothesis of no trend using simple counts and FS density estimates for different audio levels. Critical values are 5.0% $\pm$ 2.0% for H_o: α=5.0% at a .05 significance level.

		Audio Levels (Mean Number Detect)						
		110m	100m	90m	80m	70m	60m	50m
Rate	Test	182.0	160.1	151.4	139.1	130.8	125.8	123.2
120m	counts	0.0	24.4	95.0	100.0	100.0	100.0	100.0
	densities	4.6	4.6	9.6	11.2	10.2	10.4	12.0
110m	counts		0.0	19.4	89.4	99.4	100.0	100.0
	densities		3.6	7.8	10.4	8.0	9.2	8.6
100m	counts			0.0	9.2	60.8	86.2	91.6
	densities			5.6	7.4	6.2	8.4	6.6
90m	counts				0.0	1.2	12.0	23.2
	densities				6.2	5.4	6.6	6.6
80m	counts					0.0	0.0	0.2
	densities					4.4	6.8	6.2
70m	counts						0.0	2.0
	densities						4.4	3.2
60m	counts							0.2
	densities							3.2

Table 7.2.2 Percent of times test falsely rejected (α=.05) the null hypothesis of no trend using simple counts and FS density estimates for different average traversing rates. Critical values are 5.0% $\pm$ 2.0% for H_o:α=.05 at a .05 significance level.

		Traversing Rate (Mean Number Detected)					
		2	3	4	5	6	7
Rate	Test	133	137	140	143	146	149
1	counts	0.0	0.0	0.0	0.0	0.4	1.8
	densities	1.6	2.2	2.2	3.4	3.2	2.8
2	counts		0.0	0.0	0.0	0.0	0.4
	densities		3.0	2.0	2.2	2.0	1.6
3	counts			0.0	0.0	0.0	0.0
	densities			1.8	2.6	3.8	3.0
4	counts				0.0	0.0	0.0
	densities				1.8	2.2	1.8
5	counts					0.0	0.0
	densities					2.0	2.2
6	counts						0.0
	densities						2.2

7.3 Conclusions on How to Test for Trends

These results support the use of variable area survey density estimates, not simple counts, to monitor population trends when constant detectability cannot be assured. Steps should be taken to reduce differences in detectabilities, such as avoiding bad weather, training and testing observers, and sampling in a consistent manner. Before testing for trends, it is essential to estimate the effective area surveyed accurately. Estimators robust to the shape of the detectability curve need to be selected; otherwise, the FS should not be used when there is a narrow shoulder. If bird behavior is such that variable area surveys provide poor density estimates, then other methodology needs to be sought out to monitor for population trends.

Table 7.2.3 Percent of times test falsely rejected (α=.05) the null hypothesis of no trend using simple counts and FS density estimates for different vocalization frequencies. Critical values are 5.0% ± 2.0% for H_o:α=5.0% at a .05 significance level.

		Vocalization Frequency (Mean Number Detected)						
		.05	.1	.15	.225	.3	.5	1.0
Rate	Test	137	145	152	161	167	179	192
.001	counts	0.4	3.0	17.0	57.6	87.0	99.8	100.0
	densities	4.4	5.0	6.0	5.0	7.2	10.4	12.6
.05	counts		0.0	0.2	6.2	28.6	83.8	100.0
	densities		2.6	4.6	4.2	4.4	8.4	12.6
.1	counts			0.0	0.2	2.4	42.0	95.6
	densities			3.2	4.4	5.6	9.6	11.2
.15	counts				0.0	0.0	7.8	70.2
	densities				2.0	3.4	6.8	10.2
.225	counts					0.0	0.0	16.8
	densities					3.6	8.8	11.2
.3	counts						0.0	1.6
	densities						4.0	10.4
.5	counts							0.0
	densities							5.2

8 NON-CRITICAL ASSUMPTIONS

8.1 Motivation

In Section 2.2, a list of standard assumptions for the variable area survey is given. Bird behavior frequently violates these assumptions. For example, one would not expect birds to be uniformly distributed over a large region, because the distribution of birds is dependent on habitat, terrain, and season. Flocking is a common behavior, and when flocking occurs, detections of different birds are apt to be dependent events. Furthermore, logic indicates that the larger a flock is the greater the chance of detection. Consequently, a member of a large flock should have a greater chance of being detected than a member of a small flock.

Some of these assumptions are critical, others are not. Using VABS, a group of simulation studies were conducted in order to determine what assumptions are critical. This chapter discusses those assumptions that were found not necessary.

8.2 Bird Distribution

8.2.1 Background

A Poisson scattering of birds is generally assumed, although this general assumption is not necessary. Seasonal departures from Poisson scattering is common; many species cluster in flocks (overdispersion) during the non-breeding season, while many scatter at more regular intervals (underdispersion) during the breeding season because of territorial defense (Ramsey et al. 1979).

8.2.2 Simulation Study

The objective of this study was to examine how the three density estimators perform when overdispersion and underdispersion of a bird's population occurs. Overdispersion is when the variance of N is greater than would be expected for a Poisson scattering of birds; underdispersion is when the variance is less than expected. Three studies were carried out using VABS that simulated an overdispersed, Poisson, and underdispersed scattering of birds.

To model underdispersion, the study plot was split into square hectare plates, and on each plate ten birds were randomly located. A model of Poisson scattering was created by selecting the number of birds on plate i, N_i, as a Poisson variate with a mean of ten birds per plate. These N_i birds were then randomly located on the plate. To achieve an overdispersed model, a compound Poisson distribution was used. Basically, for each plate, a $\lambda \sim \text{Gamma}(\theta,\beta)$ ($E[\lambda]=\theta/\beta$, $Var[\lambda]=\theta/(\beta^2)$) variate was generated and then the $N_i \sim \text{Poisson}(\lambda)$ variate. Under this formula, $E_\lambda\{E(N|\lambda)\}=10$ and $E(N|\lambda)=\lambda$. The variance of λ was set at five levels: 1,10,20,30, and 40. The detection of birds was simulated in the usual manner of VABS; thus, the detection of different birds were independent events. See Appendix D for programming information.

After the first simulation run of the overdispersed models, it was noticed that the coverage of the confidence interval for density was low for the Cum-D and FS, compared to the EPS (Table 8.2.1). Recall that the EPS bootstrap procedure accounts for the variation in n. The bootstrap procedure used for the EPS was then tried for the FS and Cum-D for $Var[\lambda]$=20, 30, and 40.

8.2.3 Results

The mean biases (Table 8.2.1) for all dispersion models and estimates are smaller than $\pm .4$; however, the coverage (Table 8.2.2) of the confidence intervals for density decline as the population becomes more overdispersed (λ increases). The confidence interval plots in Figures 8.2.1 to 8.2.3 show the 500 density estimates with their corresponding 95% confidence limits (values are shifted to the left by subtracting the true density). For each plot, coverage of the confidence interval for density is shown. The curve representing the bias of the density estimates appear to keep basically the same shape, but the range of the curve expands as λ increases. Both the EPS and the Cum-D show a tendency to underestimate density. Furthermore, the Cum-D appears skewed to the right.

Although the primary concern was to test if at least the nominal level of coverage was obtained, the coverage for the confidence interval of the underdispersed model appeared high. Otherwise, $se(\hat{D})$ may have been overestimated.

Table 8.2.1 Results for various bird distributions.

	Poisson Scattering	Under-Dispersion	Mean(se) Overdispersion 1	10	20	30	40
Bias							
Cum-D	0.2	0.1	0.3	0.2	0.2	0.4	0.4
	(2.0)	(2.0)	(2.1)	(2.2)	(2.1)	(2.5)	(2.8)
F.S.	0.1	-0.1	-0.0	-0.1	-0.0	0.2	-0.0
	(1.7)	(1.5)	(1.7)	(1.8)	(2.1)	(2.2)	(2.4)
EPS	-0.33	-0.42	-0.39	-0.34	-0.19	-0.03	0.01
	(0.76)	(0.40)	(0.78)	(0.98)	(1.27)	(1.50)	(1.70)
$\hat{SE}(\hat{D})$							
Cum-D	3.4	3.6	3.6	3.3	3.7	3.5	3.7
	(2.7)	(3.1)	(3.2)	(2.7)	(3.0)	(2.3)	(2.6)
FS	1.75	1.75	1.75	1.74	2.10	2.12	2.27
	(.40)	(.36)	(.40)	(.45)	(.51)	(.58)	(.63)
EPS	.91	.66	.93	1.12	1.28	1.39	1.56
	(.25)	(.18)	(.25)	(.31)	(.38)	(.49)	(.56)

*For var(λ) = 20,30,40; n was allowed to vary in bootstrap density estimates.

Table 8.2.2 Coverage* of nominal CI for various bird distributions.

	Cum-D		FS		EPS
95% CI	n varies	n fixed	n varies	n fixed	
$N_i \sim$ Poisson(10)		.982		.964	.946
N_i=10		1.000		.978	.978
Var(λ)=1		.982		.950	.935
Var(λ)=10		.960		.928	.936
Var(λ)=20	.976	.940	.952	.862	.930
Var(λ)=30	.968	.904	.924	.824	.914
Var(λ)=40	.970	.898	.904	.808	.908
99% CI					
$N_i \sim$ Poisson(10)		.990		.996	.978
N_i=10		1.000		.998	1.000
Var(λ)=1		.994		.994	.976
Var(λ)=10		.986		.978	.974
Var(λ)=20	.992	.956	.994	.952	.972
Var(λ)=30	.988	.934	.978	.924	.956
Var(λ)=40	.986	.952	.976	.906	.964

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

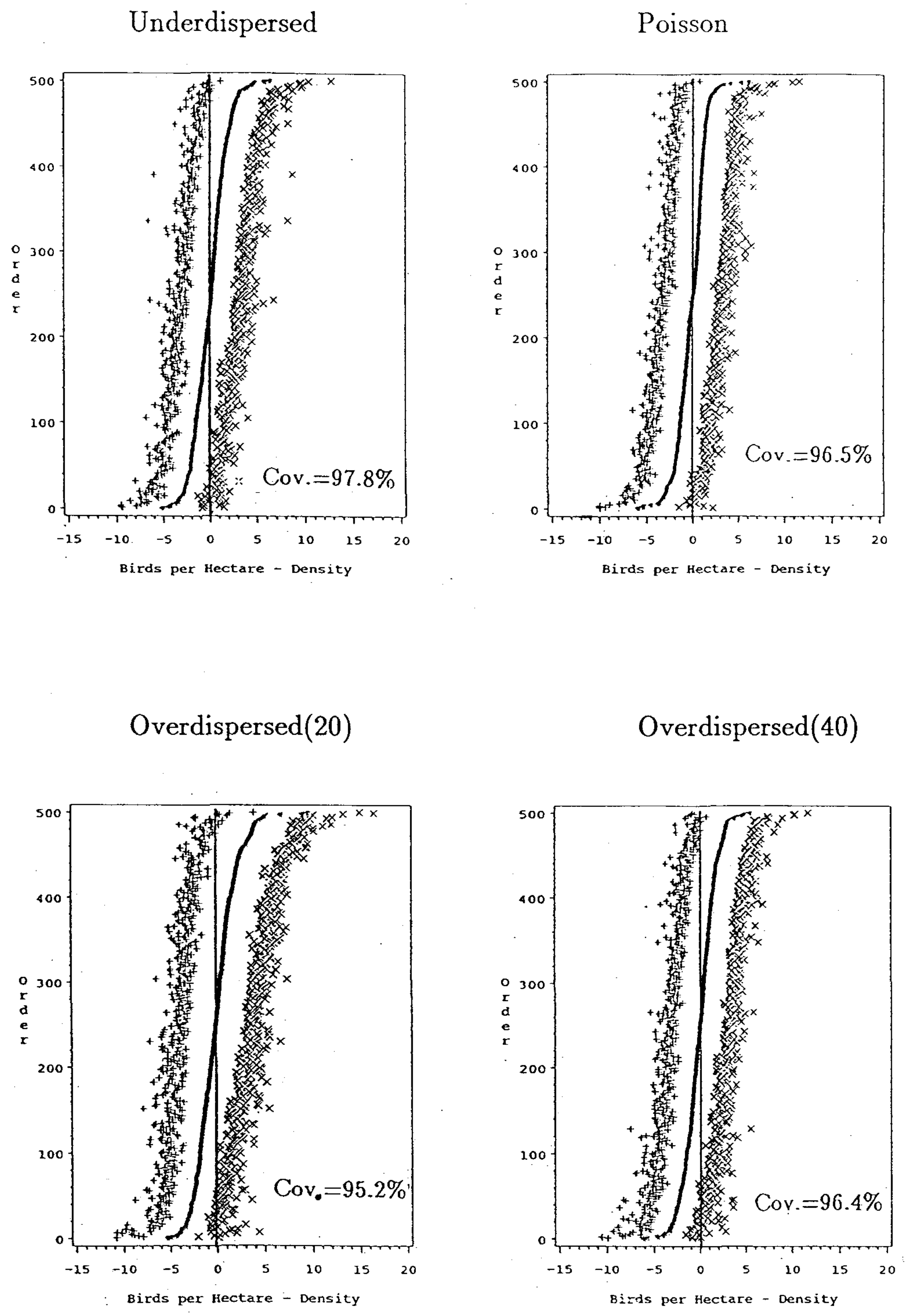


Figure 8.2.1 Ordered FS density estimates and corresponding 95% confidence limits minus the true density for over and under-dispersed bird populations (Cov.=coverage).

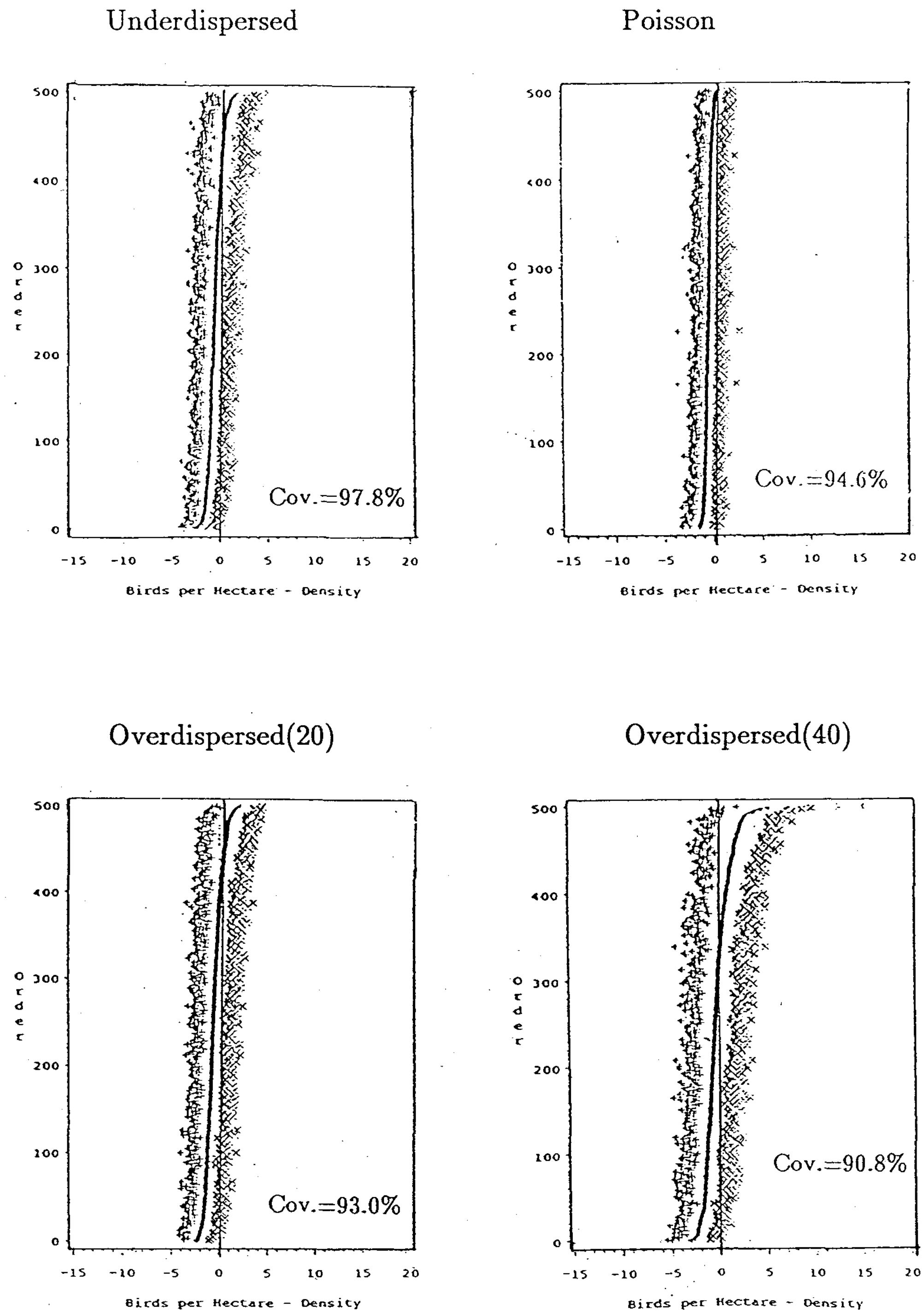


Figure 8.2.2 Ordered EPS density estimates and corresponding 95% confidence limits minus the true density for over and under-dispersed bird populations (Cov.=coverage).

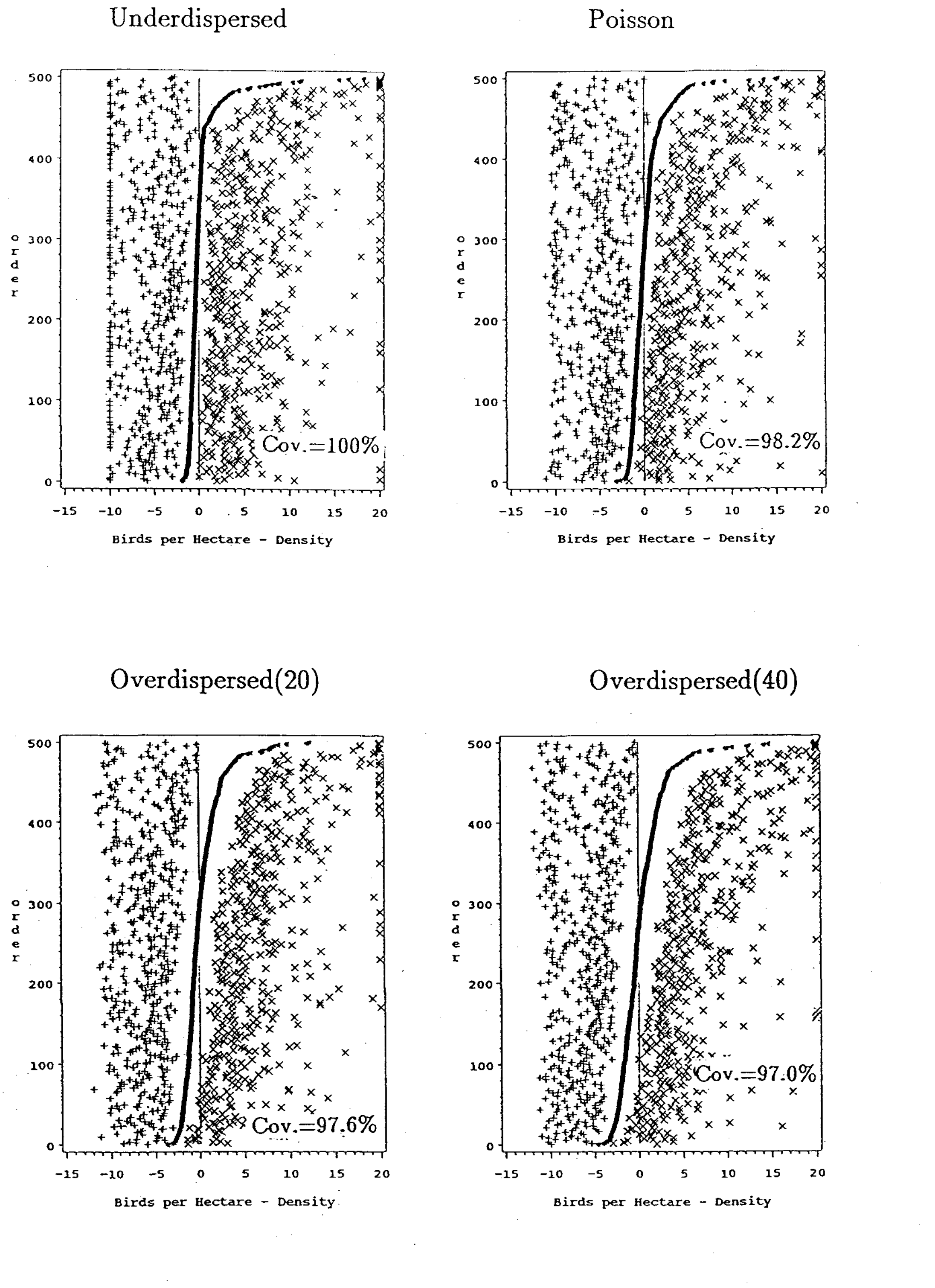


Figure 8.2.3 Ordered Cum-D density estimates and corresponding 95% confidence limits minus the true density for over and under-dispersed bird populations (Cov.=coverage). Points on the right boundary fall outside the graph's range.

8.2.4 Conclusions

The variable area survey is robust to under and over-dispersion of a bird's population; however, the estimate of var($\hat{D}$) must account for the variation in n. Further work is necessary to determine if inappropriate confidence intervals or poor estimates of area are causing the low coverage found in extreme overdispersion. Evidence suggests that the EPS and the Cum-D density estimates may not be normally distributed about the true density, indicating normal confidence intervals are inappropriate.

8.3 Bird Distribution Dependent on Vegetation

8.3.1 Background

Because of the shelter trees provide to birds, some species of birds will almost always be found perched in trees when they are not in flight. If visibility is not a problem and trees are abundant and randomly distributed, there should be no cause for concern. What happens to the variable area density estimate when trees are scarce and found in clusters? This study addressed the question of what happens when birds are perched in trees.

8.3.2 Simulation Study

For this particular study, all the birds were perched in trees. VABS was altered such that the tree a bird was located in and where it was perched on the tree were randomly selected (See Appendix E). Audio and visual detection of birds was simulated in the standard manner of VABS, accounting for blind areas. Since the influence of the distribution of birds in vegetation was being examined and not the reduction of the visual field, foliage was not taken into account. Tree densities were fixed at 10, 100, and 300 trees per hectare for both types of forest stands. Bird density was fixed at 20 birds per hectare.

8.3.3 Results

Unlike the other two estimators, the coverage of the nominal confidence intervals for the EPS was low for both 100 and 300 trees per hectare. The EPS tended to underestimate density for both kinds of forest stands (Figures 8.3.1

and 8.3.2). This tendency increased as tree density increased, thus the reduction in the visual field due to vegetation appears as the predominate factor in the bias estimates. The results in Section 9.2 support this acquisition.

Coverage of the FS and Cum-D confidence intervals were low when there were only 10 trees per hectare (Table 8.2.1). Having few trees per hectare with all birds perched in the trees would result in a clustering of birds. In Section 8.1, it was concluded that when overdispersion occurred it is necessary to take into account the variation in n to obtain proper coverage. Note: the EPS bootstrap estimate of standard error accounts for the variation in n, and it had sufficient coverage.

The Cum-D not only tended to overestimate density, but it had a suspiciously wide range of density estimates and wide confidence intervals (Figures 8.3.1 and 8.3.3). The FS density estimates were more symmetrical around the true density, with confidence intervals that did not include the true density occurring in both tails (Figure 8.2.4).

Table 8.3.1 Coverage* of nominal CI for birds perched in trees

	Stand	Density	Cum-D	FS	EPS
95% CI					
	Even	10	.902	.858	.968
		100	.992	.958	.924
		300	.978	.942	.870
	Uneven	10	.884	.848	.954
		100	.958	.948	.924
		300	.958	.964	.838
99% CI					
	Even	10	.964	.966	.992
		100	.996	.992	.970
		300	.990	.980	.958
	Uneven	10	.938	.950	.984
		100	.986	.988	.978
		300	.986	.990	.942

*Critical values for for α=.05 are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

8.3.4 Conclusions

The EPS model shows difficulty in fitting the detection curve when visual detection is hampered. When vegetation is scarce and birds are distributed in the vegetation, the appropriate estimation of se($\hat{D}$) and approximation of the confidence intervals for density need to be determined. Further studies should apply the bootstrap procedure used with the EPS to the FS and Cum-D to test if this methodology of estimating se($\hat{D}$) is appropriate.

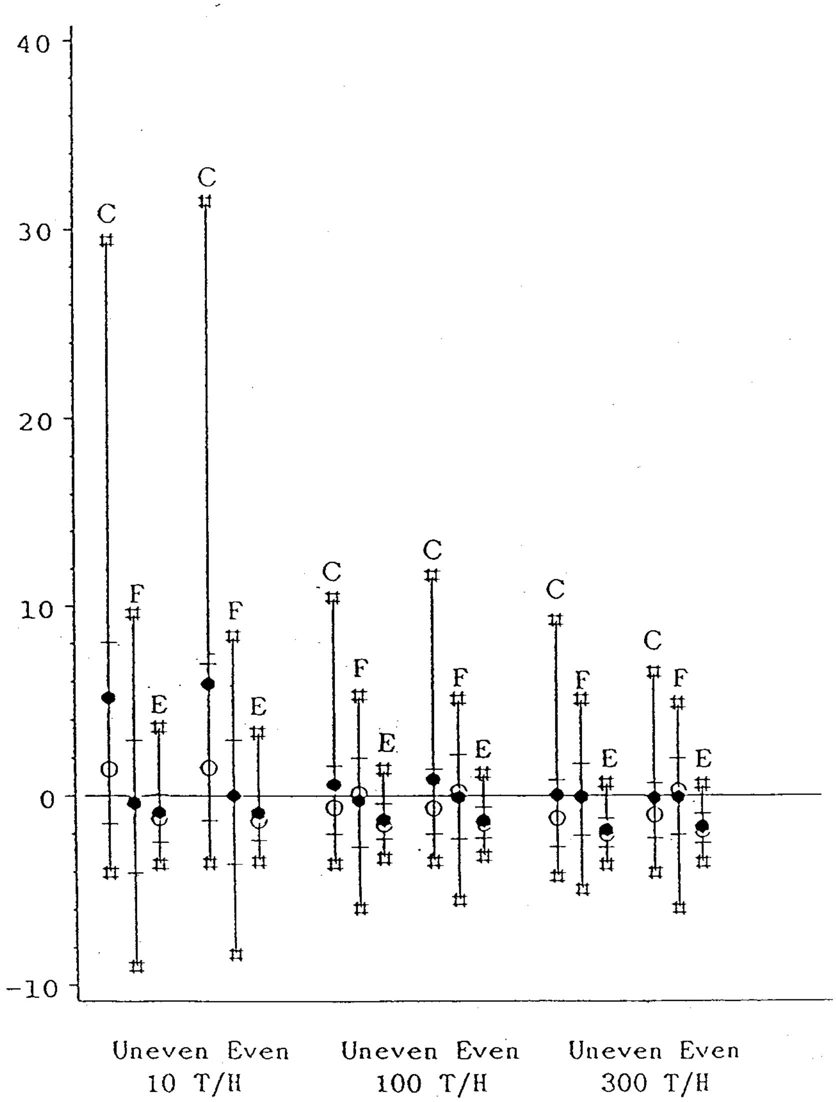


Figure 8.3.1 Bias of density estimates for different levels of tree density when birds were detected perched in trees. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} and 95^{th} percentile.

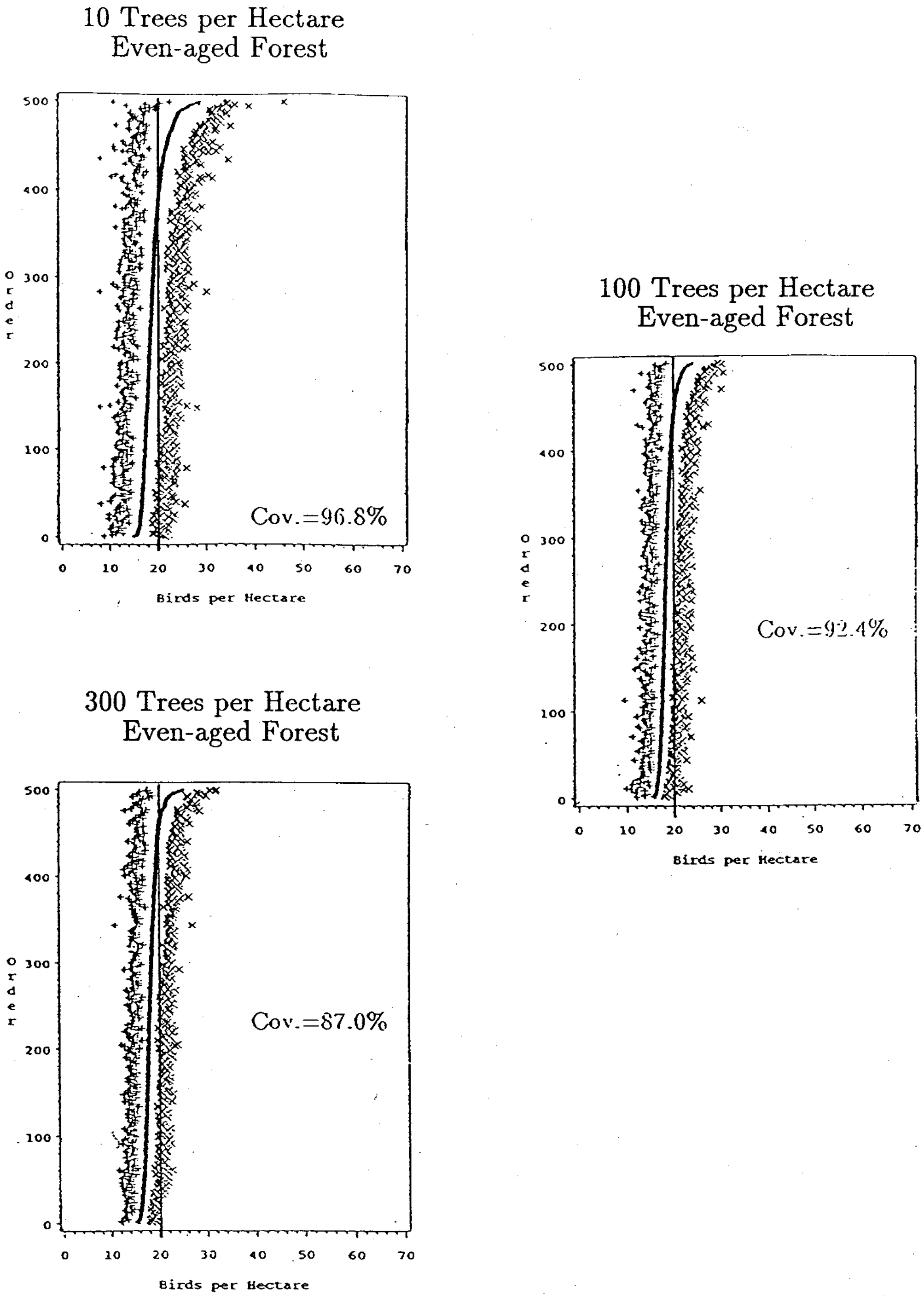
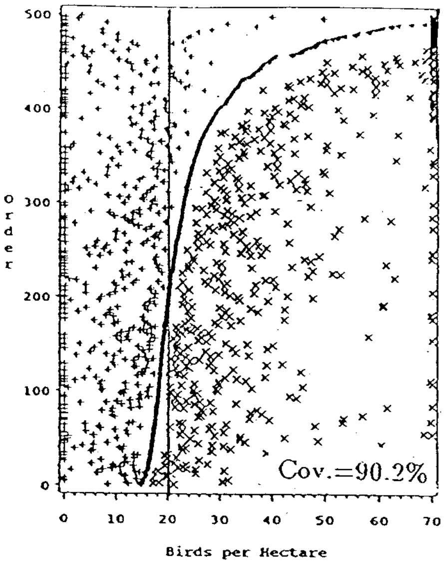
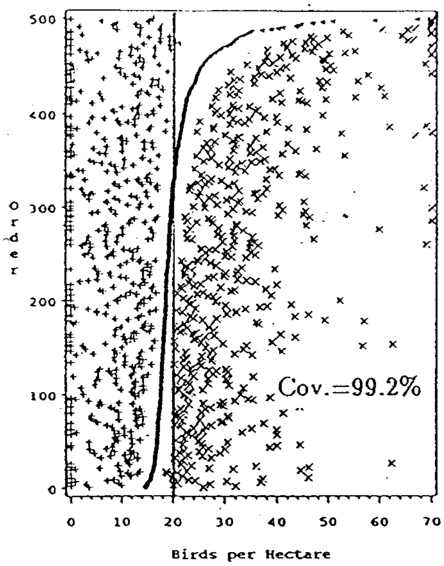


Figure 8.3.2 Ordered EPS density estimates and corresponding 95% confidence limits for different tree densities when birds were perched in trees (Cov.=coverage).

10 Trees per Hectare
Even-aged Forest



100 Trees per Hectare
Even-aged Forest



300 Trees per Hectare
Even-aged Forest

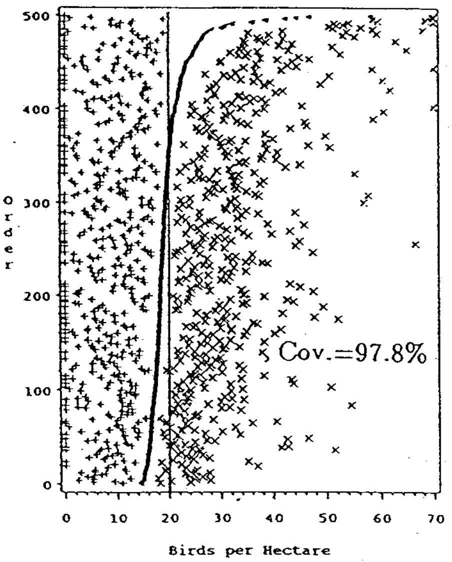
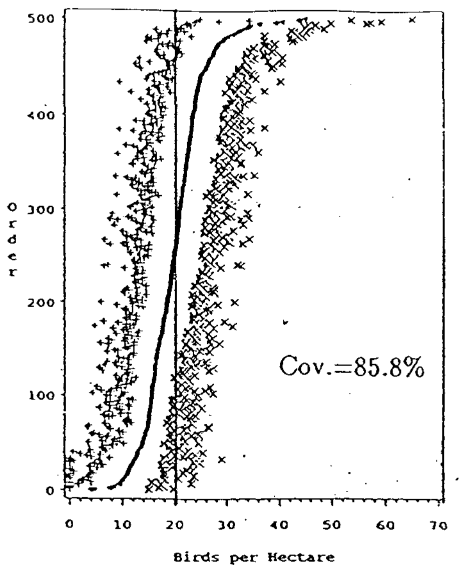
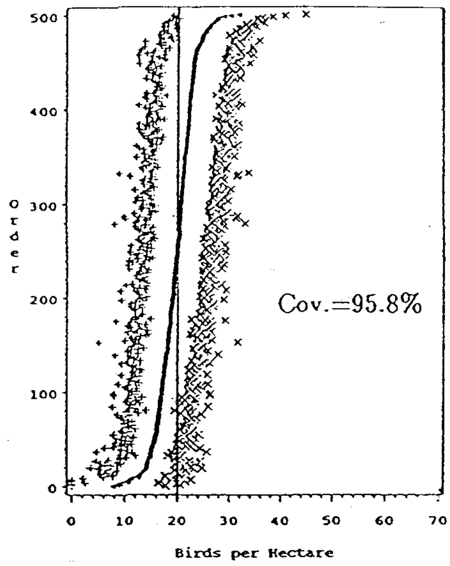


Figure 8.3.3 Ordered Cum-D density estimates and corresponding 95% confidence limits for different tree densities when birds were perched in trees (Cov.=coverage). Points on the right boundary fall outside the graph's range.

10 Trees per Hectare
Even-aged Forest



100 Trees per Hectare
Even-aged Forest



300 Trees per Hectare
Even-aged Forest

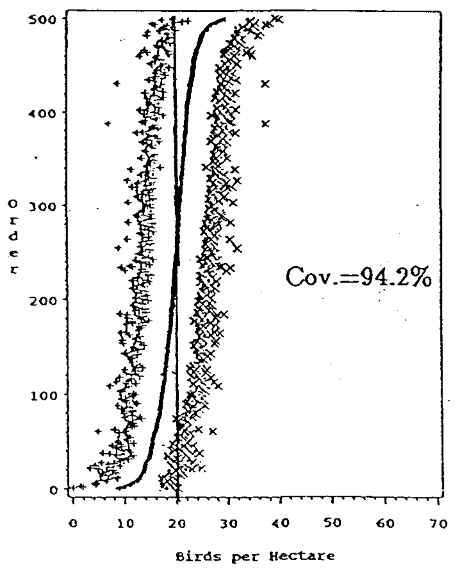


Figure 8.3.4 Ordered FS density estimates and corresponding 95% confidence limits for different tree densities when birds were perched in trees (Cov.=coverage).

8.4. Clustered Populations

8.4.1 Background

In biological populations, it is quite common for animals to aggregate into tight groups (flocks, herds, pods, etc.), referred to as clusters. With clustered populations it is necessary to distinguish the density of clusters from the density of individual birds, since the lack of independence in the detection of birds within a cluster will result in an underestimate of the true variance.

In variable area surveys, each cluster is generally treated as the primary object whose detections are assumed to be independent events. The standard theory of variable area survey enables estimation of the cluster density. To estimate the population density of the individuals, information about cluster size is needed.

Burnham et al. (1980) claim that estimation of the average cluster size and the density of individuals is complicated only if the detection probability is related to cluster size. The general consensus is that the detection probability is related to cluster size. Buckland (1985) states that a large cluster is more likely to be detected than a small one, likely resulting in overestimates of average cluster size and hence animal density. Quinn (1981) comments that it is intuitive that the probability of sighting a school of porpoises, whose school sizes range from ten to thousands, should increase as school size increases. In this chapter, the estimation of the density of clusters and of the population density are examined for clustered populations.

8.4.2 Creating and Detecting Clusters

To determine cluster size, S_i, four models were used: (1) $S \sim$ Uniform(10,50), (2) $S \sim$ Poisson(λ=10) exclusive of zero, (3) $S \sim$ Poisson(λ=4) exclusive of zero, and (4) S is the number of individuals in a cluster of families (extended family). The intent of the extended family was to represent more than one family grouped together. First, the number of families in a group was selected from a truncated Poisson distribution with a mean of two. The family size was then selected such that a family of size 1, 2, 3, 4, 5, or 6 had the probability of .1, .4, .15, .15, .15, and .05 of being selected, respectively. The number of birds in the cluster was the sum of the family sizes.

A central point (μ_x,μ_y) for each cluster was selected randomly such that no cluster was within 10 meters of another cluster's central point. Each bird within a cluster was then placed on the plot (L=10,000, W=300) by generating $N(\mu_x,4)$ and $N(\mu_y,4)$ variates to represent the x and y coordinates of the bird's location.

To represent the dependence of detecting birds, the observer's eyes no longer focused on the transect line between each detection but focused on the location of the last bird detected. At each meter, every bird was checked for audio detection (THETA=.1). The bird that vocalized first was marked as being detected, and the observer's visual focus was changed to be on that bird. All birds were again checked for visual detection. If the bird did not belong to the cluster, the probability the bird was originally detected at meter i was calculated as

$$gv_i \prod_{j=1}^{i-1} (1-gv_i), \text{ where } gv_i=\exp(\frac{-y_i}{10 \cdot \lambda})$$

(λ calculated as in Section 4.7). If it is thought that birds are in clusters and a bird is detected, the observer will naturally concentrate his attention to the area close to the bird detected in order to detect the other birds belonging to the cluster. To incorporate dependence, the probability of visual detection of a bird belonging to the cluster of the last bird seen was increased and considered independent of what happened before. Visual detection of a bird in a detected cluster was still modeled as an exponential curve, but the probability of detection was increased. The probability,

$$gv_i=\exp(\frac{-y_i}{100\lambda}),$$

was used after trial runs of VABS supported this choice.

Probabilities were ordered and tested for visual detection. When a bird was visually detected, the observer focused on the location of the bird, and the probabilities of visual detection were recalculated for all birds not previously detected. These birds were then tested again for detection. If no birds were detected visually, audio detection was checked again. See Appendix F.

8.4.3 Measuring Detected Area

The first question addressed was what point of the cluster should be used to measure the perpendicular distance between the transect line and the cluster? Burnham et al. (1980) suggested the geometric center (centroid) of the cluster. If using the centroid, clusters 1 and 2 (Figure 8.4.1) have equal detected areas; however, it seems that cluster 2 has a higher probability of detection than cluster 1, since the boundary of cluster 2 comes closer to the transect line. For this simulation study, the detected area (Section 2.1) for the cluster was calculated using the perpendicular distance between the transect line and (1) the first bird detected in the cluster, (2) the nearest bird in the cluster to the transect line, and (3) the geometric center of the cluster.

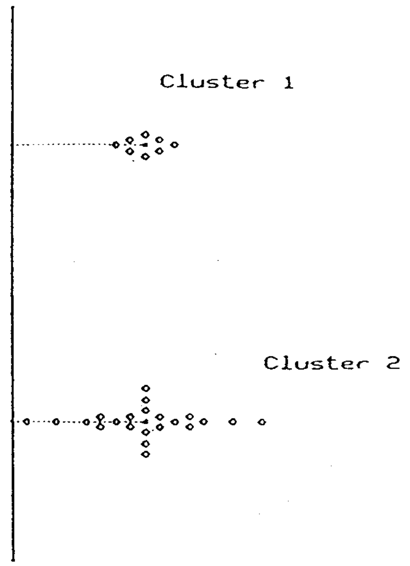


Figure 8.4.1 Detection distances for clustered populations when the cluster's centroid is used. Cluster 1 and cluster 2 have equal detection area, yet it appears as if cluster 2 should have a higher probability of being detected. Symbols: ( ) birds in cluster, (·) cluster's centroid.

The detected areas based on the nearest bird was inclined to overestimate density, regardless of the estimator used (Figure 8.4.2). The density estimates based on the first bird and the centroid were less bias, but they had a tendency to underestimate density.

Figures 8.4.3 to 8.4.5 are histograms of detected areas from a computer generated data set in VABS. Included are the FS, EPS, and Cum-D fitted curves. These plots aid in viewing the distribution of detected area and the fit of different estimators.

The detected areas based on the nearest bird detected appear to be more erratic, high number of detections followed by a low then high number of detections.

At this point, a comparison of this data set with similar ones gathered using the variable area survey on a clustered population is needed to support VABS and the conclusions drawn here.

On the side, there is little difference between the estimates of cluster density for unadjusted and adjusted (for cluster size) detected areas. But, if cluster size has a greater influence on detectability than programmed, results in Chapter 7 would suggest a larger difference in estimates, with the adjusted data providing less bias estimates.

Since using the centroid of the cluster assumes all birds are detected in the cluster, the first bird detected is used in VABS when estimating densities of clustered populations.

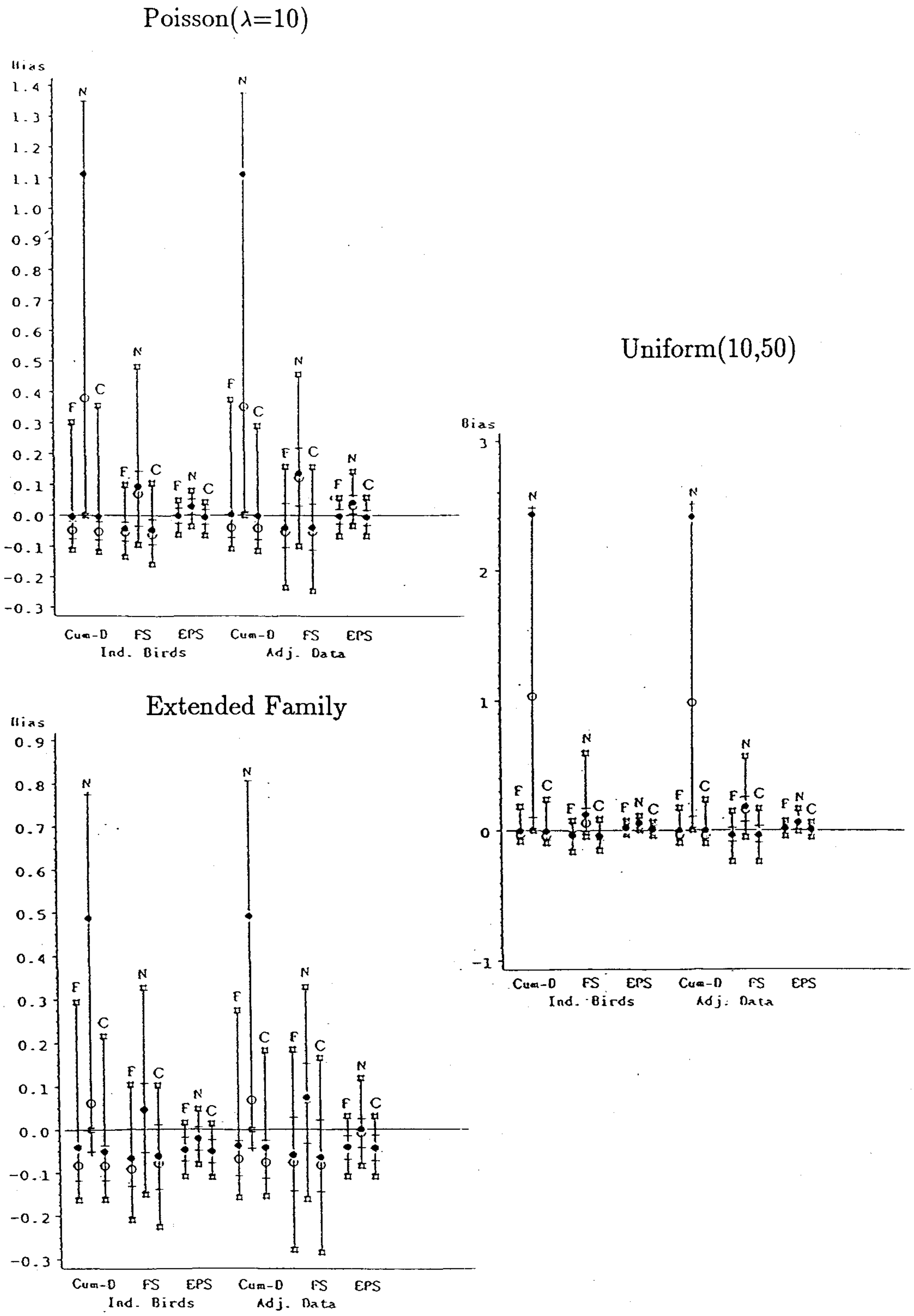


Figure 8.4.2 Bias of estimates of cluster density for clustered populations for different measured detected areas: first bird detected (F), nearest bird to the transect line (N), and the centroid of the cluster (C). Symbols: (•) mean, (∘) median, (−) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile. Note that the 5^{th} and 95^{th} percentiles were at times extreme for the nearest bird and are not shown.

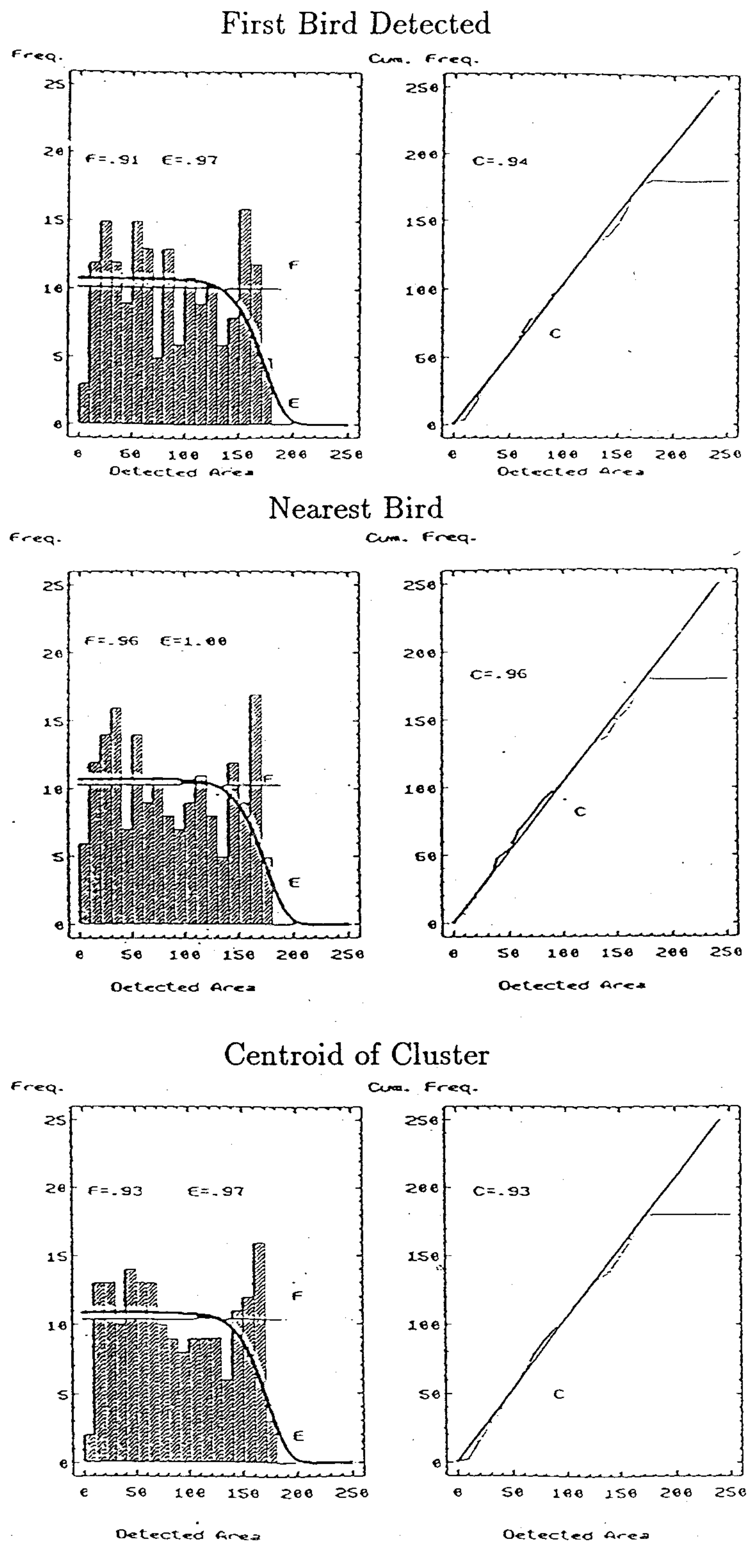


Figure 8.4.3 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates for different measures of detected areas, adjusted for cluster size, when cluster sizes were truncated Poisson(λ=10) variates (Cov.=coverage). Data set is from one simulation of VABS.

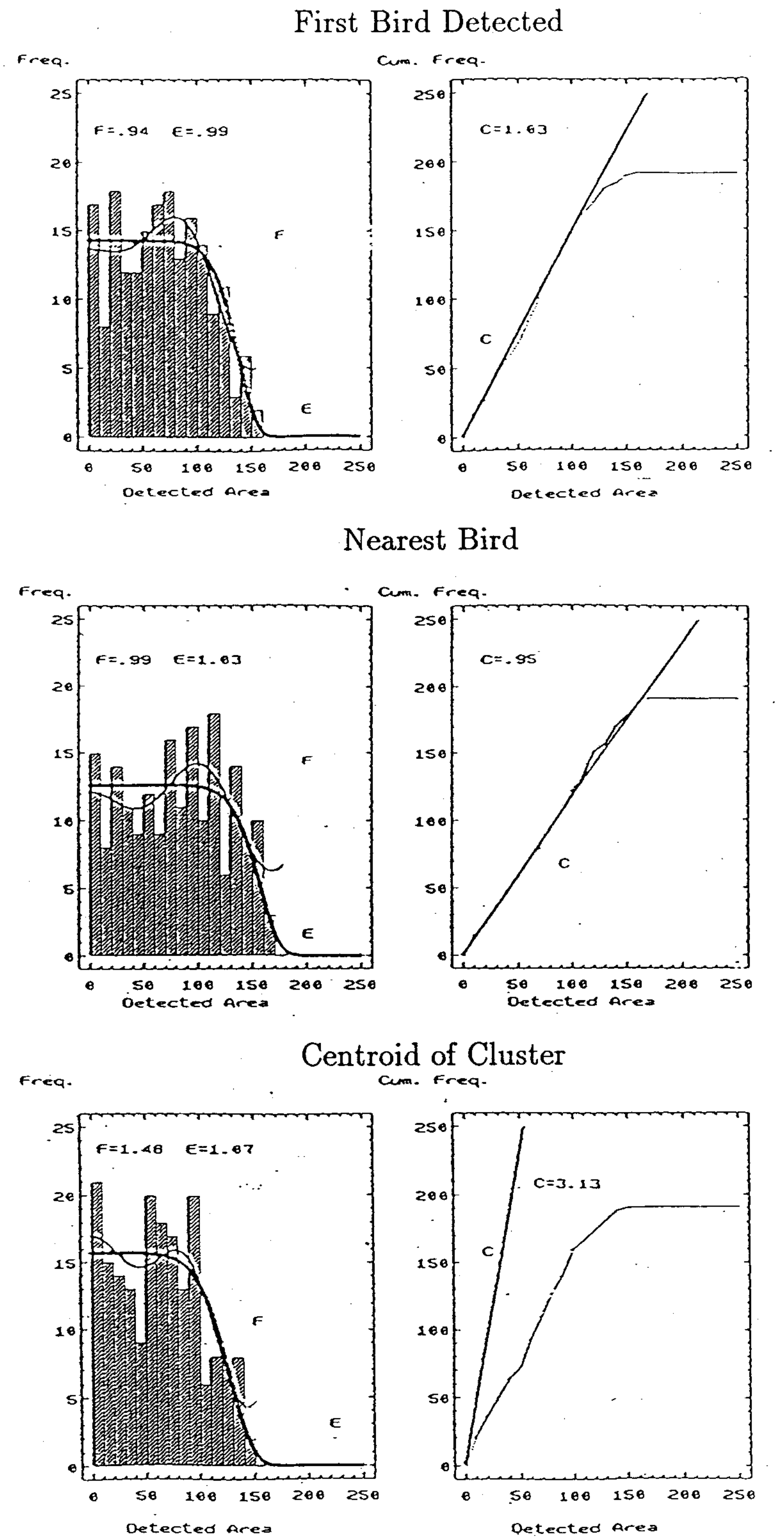


Figure 8.4.4 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates for different measures of detected areas, adjusted for cluster size, when cluster sizes were Uniform(10,50) variates (Cov.=coverage). Data set is from one simulation of VABS.

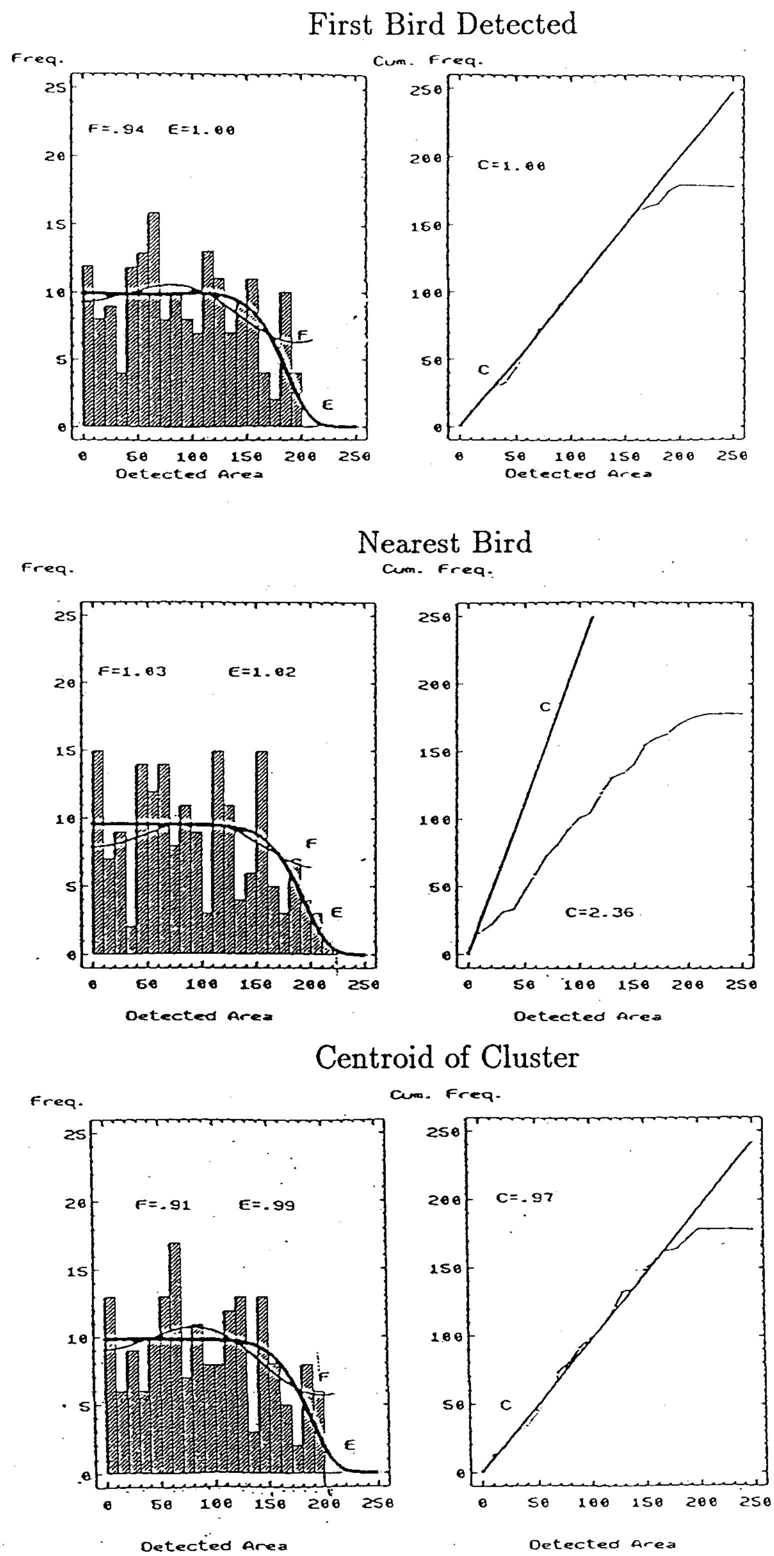


Figure 8.4.5 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates for different measures of detected areas, adjusted for cluster size, when cluster sizes were distributed as an extended family (Cov.=coverage). Data set is from one simulation of VABS.

8.4.4 Estimating Population Density

This section deals with different proposed methods for estimating the population density of individuals from clustered populations. For S=cluster size and N_S=number of clusters of size S, the methods that VABS used to calculate the population density were:

(1) Calculate density using individual bird detections ignoring clustering.

(2) Estimate the density of clusters and multiply this estimate by the average detected cluster size, $\hat{D}_I=\bar{S}\hat{D}_C$ (Burnham et al. 1980).

(3) Estimate the density of clusters and multiply by a log-weighted mean of cluster size: $\hat{D}_I=\bar{S}_1\hat{D}_C$, where

$$\bar{S}_1=[\sum_{S=1}^{\infty} N_S S/\ln(S)]/[\sum_{S=1}^{\infty} N_S/\ln(S)].$$

This method assumes that α is proportional to ln(S) (Quinn 1981).

(4a) Treat size as a covariate where $\ln(\alpha_i)=\beta_0+\beta_1(S_i-1)$, and proceed as in Chapter 7. Estimate density by

$$\hat{D}_I=\sum_{S=1}^{\infty} S \frac{N_S}{\hat{\alpha}_0 \cdot \exp\{\beta_1(S\text{-}1)\}}$$

(Ramsey et al. 1987). Estimates of standard error were calculated using a bootstrap sample of the raw data.

(4b) Use the maximum likelihood estimate of β_1 (epmle) in the link function of Ramsey et al. (1987).

(5a) Treat size again like a covariate, but this time assume $\alpha_i=\alpha_0 S_i^{\lambda}$, and calculate density as

$$\hat{D}_I=\sum\left(\frac{S_i}{\hat{\alpha}_0 S_i^{\lambda}}\right).$$

The least squares estimate for λ_1 where $\ln y_i=\lambda_0+\lambda_1\ln(S_i)$ was used (Drummer and McDonald 1987).

(5b) Use the maximum likelihood estimate of λ_1 in the link function of Drummer and McDonald (1987).

(6) Use a bivariate detection function based on the Fourier series (Quang 1991).

8.4.5 Results

Tables 8.4.1 to 8.4.4 and Figures 8.4.6 to 8.4.9 show that:

(1) The standard error of $\hat{D}$ was underestimated if clusters and the variation in $\hat{D}$ due to the variation in n were ignored. On the other hand, the EPS did take into account the variation in n, and se($\hat{D}$) was overestimated.

(2) When cluster sizes were correctly counted and the mean cluster size was multiplied by the cluster density, the density estimates tended to overestimate density, in accordance with Buckland's statement. However, density estimates were underestimated when cluster sizes were not counted correctly.

(3) Using a log-weighted mean does not appear appropriate when a cluster size of 1 is possible, but for the situation where cluster size is consistently large it does appear to be a reasonable estimator of population density.

(4) When covariate adjustments were used, the coverage for the EPS confidence intervals of density decreased as the average cluster size increased. The least square estimates for the adjustment parameters provided less biased density estimates than the maximum likelihood estimates, assuming the EPS. The method used to select the shape parameter (Section 4.10) could have led to these results, since the true mle of these parameters were not being calculated. Regardless, these results support the use of the least square estimates, which are more versatile, than the maximum likelihood estimates, which are dependent on the estimate being used to estimate area.

(5) The bivariate function proposed by Quang is not recommended, since it consistently had lower coverage than the confidence interval's nominal level.

Table 8.4.1 Results when cluster sizes were truncated Poisson(λ=4) deviates.

Estimate	Method	Nominal Level* 95%	99%	Mean(se) Bias		$\hat{SE}(\hat{D})$	
Ind. birds	Cum-D	.732	.826	0.62	(1.10)	0.72	(0.66)
	FS	.652	.790	0.02	(0.89)	0.45	(0.17)
	EPS	1.000	1.000	-0.04	(0.28)	2.89	(0.79)
Mean·Cluster	Cum-D	.956	.980	0.22	(0.85)	1.26	(1.27)
	FS	.948	.976	0.09	(0.58)	0.65	(0.28)
	EPS	1.000	1.000	0.10	(0.24)	1.37	(0.43)
Logwt.Cluster	Cum-D	.016	.030	-3.05	(0.23)	0.31	(0.32)
	FS	.000	.000	-3.08	(0.18)	0.16	(0.11)
	EPS	.000	.006	-3.08	(0.12)	0.33	(0.43)
Cov. adj all	Cum-D	.962	.980	0.80	(1.10)	1.18	(1.20)
	FS	.916	.974	-0.01	(0.65)	0.70	(0.23)
	EPS	.912	.962	0.08	(0.31)	0.28	(0.13)
epmle	Cum-D	.776	.872	0.22	(0.28)	0.20	(0.07)
Drum-Cov.	Cum-D	.956	.980	0.74	(1.13)	1.21	(1.26)
	FS	.918	.982	-0.10	(0.65)	0.70	(0.20)
	EPS	.892	.948	0.11	(0.37)	0.37	(0.33)
epmle	EPS	.804	.960	0.09	(0.25)	0.18	(0.06)
Quang		.512	.646	-0.23	(0.62)	0.26	(0.69)

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99)
Mean number of birds=1219.2 Detected mean cluster size=3.8
Mean number detect=667.9 True mean cluster size=4.2
Number of clusters detected=174.12

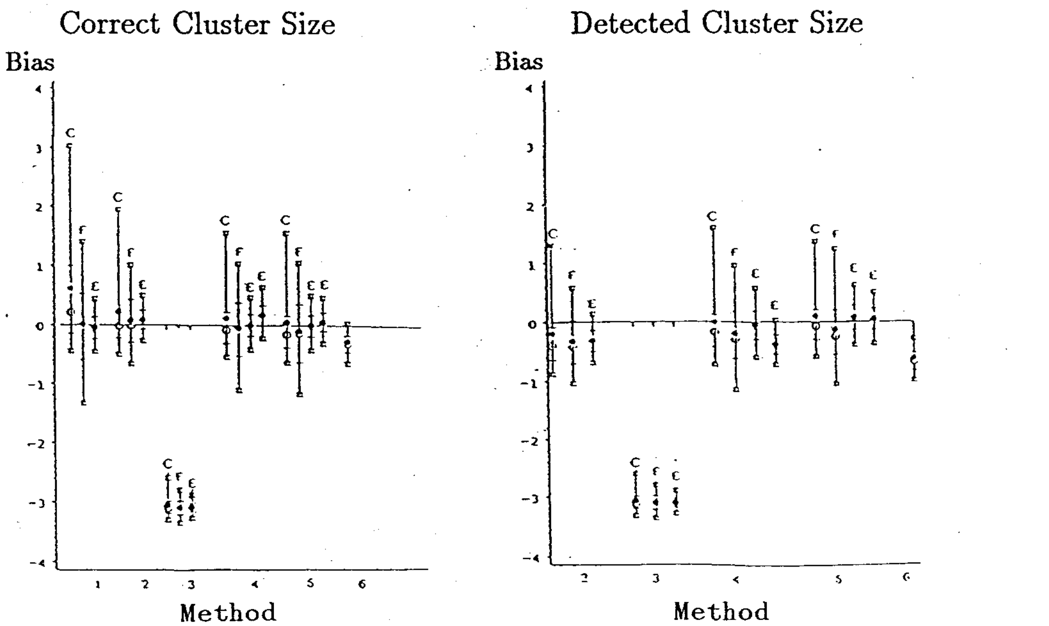


Figure 8.4.6 Bias of different population density estimates using correct and detected cluster sizes when cluster sizes were truncated Poisson(λ=4) variates. Symbols: (C) Cum-D, (F) FS, (E) EPS, ($\bullet$) mean, ($\circ$) median, ($-$) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

Table 8.4.2 Results when cluster sizes were truncated Poisson(λ=10) deviates.

		Nominal Level*		Mean(se)			
Estimate	Method	95%	99%	Bias		$\hat{SE}(\hat{D})$	
Ind. birds	Cum-D	.526	.526	1.74	(2.58)	1.15	(1.19)
	FS	.484	.588	0.05	(2.19)	0.76	(0.33)
	EPS	1.000	1.000	0.30	(0.55)	8.25	(2.22)
Mean·Cluster	Cum-D	.960	.978	0.62	(2.07)	2.55	(2.84)
	FS	.980	.996	0.10	(1.02)	1.40	(0.88)
	EPS	1.000	1.000	-0.64	(0.47)	2.59	(0.79)
Logwt·Cluster	Cum-D	.886	.850	-0.39	(2.75)	2.54	(2.71)
	FS	.920	.972	-0.86	(2.10)	1.47	(0.88)
	EPS	.972	.996	-0.37	(2.02)	2.55	(0.88)
Cov. adj all	Cum-D	.964	.992	-0.42	(1.81)	2.55	(2.74)
	FS	.956	.988	-0.03	(1.52)	1.62	(0.54)
	EPS	.818	.902	0.44	(0.57)	0.53	(0.26)
epmle	EPS	.584	.760	0.90	(0.66)	0.52	(2.14)
Drum-Cov.	Cum-D	.952	.986	0.28	(1.96)	2.59	(2.77)
	FS	.916	.968	-0.27	(1.73)	1.68	(0.48)
	EPS	.808	.898	0.38	(0.65)	0.58	(0.55)
epmle	EPS	.446	.612	0.62	(0.47)	0.29	(0.09)
Quang		.752	.858	-0.11	(0.69)	0.04	(1.20)

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
Mean number of birds=2985.8 Detected mean cluster size=8.9
Mean number detect=1560.7 True mean cluster size=10.1
Number of clusters detected= 194.1

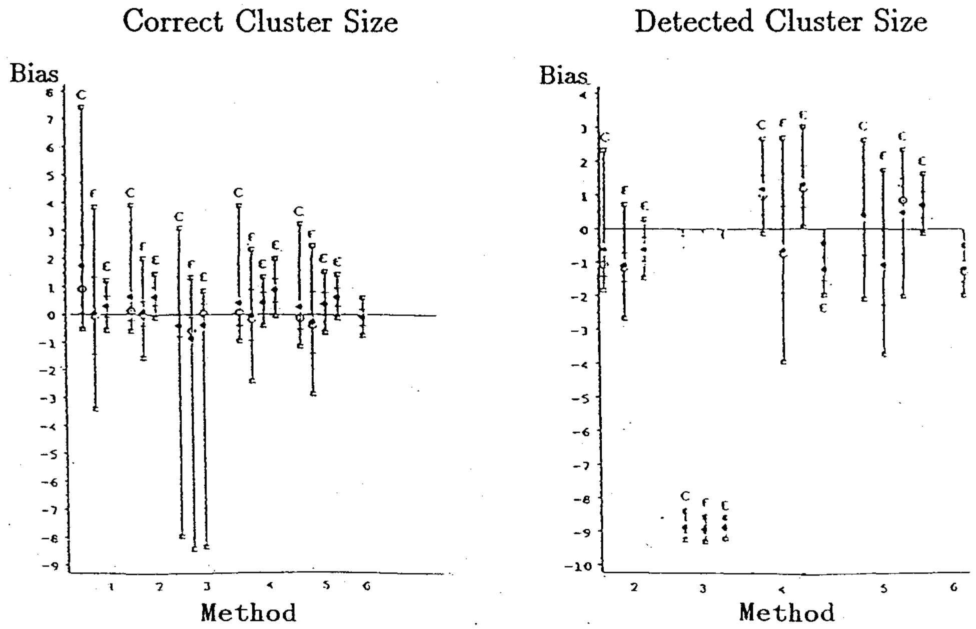


Figure 8.4.7 Bias of different population density estimates using correct and detected cluster sizes when cluster sizes were truncated Poisson(λ=10) variates. Symbols: (C) Cum-D, (F) FS, (E) EPS, ($\bullet$) mean, ($\circ$) median, ($-$) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

Table 8.4.3 Results when cluster sizes were Uniform(10,50) deviates.

Estimate	Method	Nominal Level* 95%	99%	Mean(se) Bias		$\hat{SE}(\hat{D})$	
Ind. birds	Cum-D	.338	.402	6.2	(7.8)	2.39	(2.53)
	FS	.340	.416	0.4	(6.6)	1.38	(0.76)
	EPS	1.00	1.000	1.2	(1.7)	25.25	(6.92)
Mean·Cluster	Cum-D	.958	.982	2.0	(4.7)	8.15	(8.32)
	FS	.974	.986	0.5	(3.5)	4.35	(1.89)
	FS	.992	1.000	2.3	(1.4)	3.69	(1.31)
Logwt·Cluster	Cum-D	.938	.974	0.3	(4.5)	7.74	(7.86)
	FS	.952	.978	-1.1	(3.3)	4.13	(1.78)
	EPS	1.000	1.000	0.6	(1.3)	3.51	(1.23)
Cov. adj all	Cum-D	.970	.990	1.8	(5.3)	7.95	(7.90)
	FS	.956	.986	0.3	(4.3)	4.76	(1.52)
	EPS	.750	.876	1.1	(1.7)	1.60	(0.65)
epmle	EPS	.538	.726	2.8	(1.9)	1.55	(0.46)
Drum-Cov.	Cum-D	.942	.972	0.9	(5.7)	7.91	(7.90)
	FS	.926	.978	-1.3	(5.0)	4.99	(1.45)
	EPS	.910	.966	0.7	(1.7)	1.70	(1.16)
epmle	EPS	.786	.908	2.3	(1.4)	1.00	(0.25)
Quang		.820	.924	0.7	(2.2)	1.28	(2.87)

*Critical values for $\alpha = .05$ are .934 (H_0:p$\geq$.95) and .982 (H_0:p$\geq$.99)

Mean number of birds=8815.5 — Detected mean cluster size=25.7

Mean number detect=4693.7 — True mean cluster size=29.7

Number of clusters detected=201.0

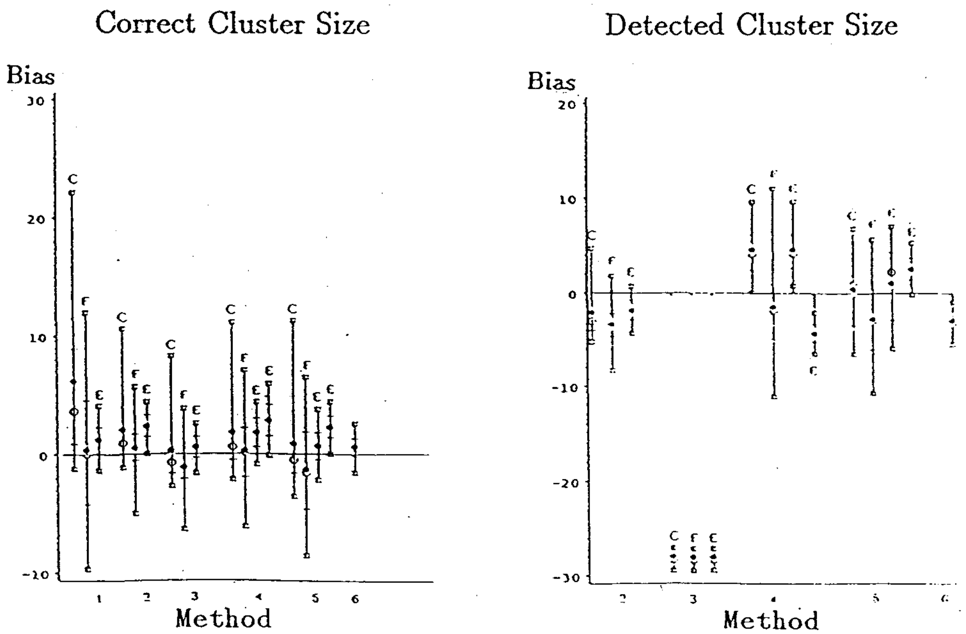


Figure 8.4.8 Bias of different population density estimates using correct and detected cluster sizes when cluster sizes were Uniform(10,50) variates. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

Table 8.4.4 Results when cluster sizes were representative of an extended family.

Estimate	Method	Nominal Level* 95%	99%	Bias	Mean(se)	$\hat{SE}(\hat{D})$	
Ind. birds	Cum-D	.524	.632	1.33	(2.04)	0.97	(1.00)
	FS	.494	.624	0.06	(1.72)	0.63	(0.27)
	EPS	1.000	1.000	0.14	(0.50)	5.31	(1.48)
Mean·Cluster	Cum-D	.970	.986	-0.52	(1.63)	2.12	(2.24)
	FS	.962	.992	0.31	(0.94)	1.10	(0.49)
	EPS	1.000	1.000	0.39	(0.40)	2.05	(0.69)
Logwt·Cluster	Cum-D	.058	.126	-5.76	(0.73)	0.96	(1.39)
	FS	.014	.078	-5.79	(0.74)	0.70	(0.85)
	EPS	.048	.118	-5.78	(0.73)	0.83	(0.87)
Cov. adj all	Cum-D	.960	.984	0.27	(1.52)	2.05	(2.42)
	FS	.946	.982	0.01	(1.16)	1.22	(0.42)
	EPS	.916	.968	0.14	(0.55)	0.55	(0.33)
epmle	EPS	.674	.830	0.57	(0.44)	0.40	(0.12)
Drum-Cov.	Cum-D	.942	.972	0.04	(1.41)	1.99	(2.00)
	FS	.926	.978	-0.17	(1.22)	1.23	(0.37)
	EPS	.910	.966	0.00	(0.48)	0.53	(0.35)
epmle	EPS	.786	.908	0.32	(0.40)	0.35	(0.11)
Quang		.858	.932	-0.15	(1.17)	0.47	(1.21)

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99)

Mean number of birds=2072.6 — Detected mean cluster size=6.4

Mean number detect=1175.0 — True mean cluster size=7.3

Number of clusters detected= 182.5

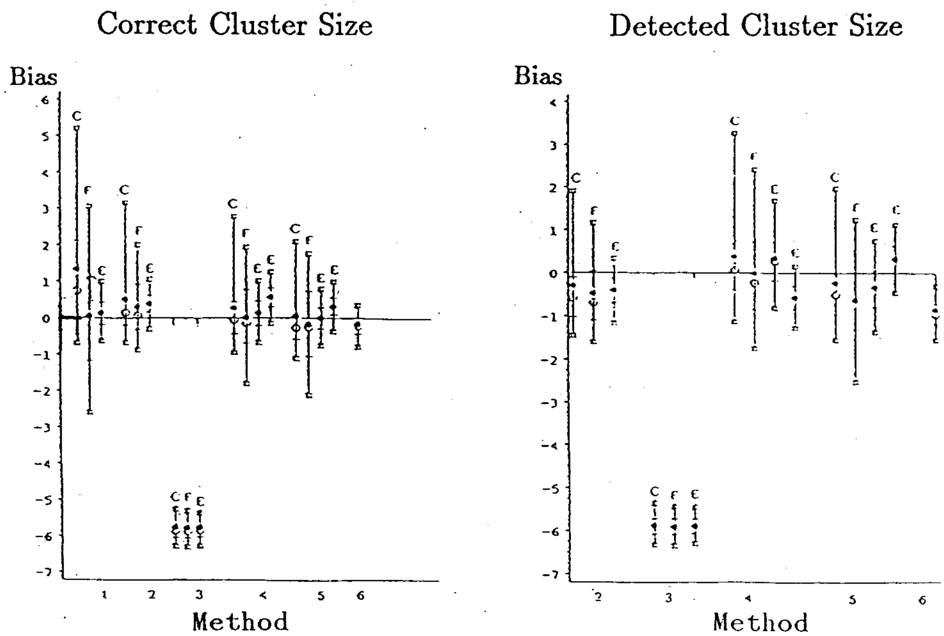


Figure 8.4.9 Bias of different population density estimates using correct and detected cluster sizes when cluster sizes were extended family variates. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

8.4.6 Conclusions

If cluster size does affect detectability, covariate adjustments for cluster size are recommended when the cluster or population density is being estimated. Coverage of the confidence intervals derived using the adjusted Cum-D and FS estimates is sufficient when the clusters are distributed uniformly over the plot. If clusters are overdispersed, the results in Section 8.2 suggest a bootstrap technique that accounts for the variation in the number of clusters. The question of how to account for this variation was not addressed in this study, but the results in Section 11.3 should apply.

If cluster sizes are not counted accurately, other estimators should be used than those evaluated here. One possibility would be to estimate the mean cluster size by some method, separate of the variable area survey count, that would ensure a less bias estimate of mean cluster size.

8.5 Overall Conclusions

The results of the studies discussed in this chapter support the claim that the assumptions

(1) birds are distributed uniformly over the region,

(2) the location of different birds are independent events,

(3) detection of different birds are independent event

are not necessary to estimate density via the variable area survey. Generally, if the above assumptions are invalid, the point estimates of density will not be affected, but the estimate of se($\hat{D}$) will be biased if the variation in n is not properly accounted for.

If detections of different birds are dependent events it may be necessary to define the primary unit as the unit whose detections are independent events, i.e. clusters. If clusters are the primary unit, population density can be calculated only if cluster sizes are counted without error.

The shape of the detection curve was not varied within a study so the performance of the three different estimators under different shapes of the detectability curve cannot be compared. However, there is evidence that $\hat{D}$ may not be normally distributed about the true density, especially for the Cum-D and EPS. Research on how to estimate se($\hat{D}$) and approximate confidence intervals of density needs to be done.

9 BIRD MOVEMENT AND THE ESTIMATION OF AREA

9.1 Motivation

Many of the problems encountered during surveys are associated with mobile populations, particularly when the animal moves in response to the observer. One of the assumptions of the variable area survey is that the population is immobile before detection. If an animal hides or moves and then is detected, the assumption of immobility is invalid. It is thought that movement has no detrimental effect on the density estimate, unless it is in response to the approaching observer and before animals are detected (Burnham et al. 1980). Short lateral movements caused by the observer's approach have been observed or suspected in numerous studies (Eberhardt 1978, Hirst 1969, Dassmann and Mossman 1962).

If movement is in response to the observer, area measurements may be less accurate (Burnham et al. 1980); furthermore, the distribution of detection areas will not be uniform, and the variable area density estimates will be biased (Engeman and Bromaghin 1990). Some estimators are more robust to movement than others. Engeman and Bromaghin (1990) have examined the performance of the EPS when animal movement occurs and concluded that the EPS shows promise for estimating density in the presence of movement. Wildman and Ramsey (1985) state that if birds hide or move, the probability of detection on the transect line can be zero, but one can still read effective areas from cumulative distribution functions.

The kind of survey being conducted can influence movement. On Nihoa Island, Hawaii, Millerbirds seemed to be attracted to a moving observer, perhaps to forage on insects; finches appeared to be attracted to a stationary observer in order to feed on seabird eggs temporarily abandoned during the count (Conant, Collins, and Ralph 1981).

The topic of animal movement has been the subject of several papers where basically four forms of mobility have been examined:

(1) The animals move randomly with respect to the observer before detection.

(2) The animals avoid detection by moving away from the observer.

(3) The animal hides before detection.

(4) The animals are attracted to the observer before detection. (Burnham et al. 1980; Engeman and Bromaghin 1990; Wildman and Ramsey 1985, Scott and Ramsey 1981b, Schweder 1977). This chapter examines the robustness of the Cum-D, FS, and EPS to these four forms of movement.

9.2 Simulating Movement

To simulate bird movement, the distance a bird moved during the time the observer took to traverse one meter was generated as

$$\text{RMOVE} = z*t_{obsy},$$

where z was a log-logistic variate, whose parameters were RALPHA (γ) and RBETA (β). More details about the direction of movement are given in the sections discussing random movement, avoidance, and attraction.

The subroutine DETECT was altered so that at each meter, bird movement was simulated before testing for visual and audio detection. First, it was determined whether the bird was going to move. If the bird was going to move, the bird was moved RMOVE meters. The probability of visual detection was calculated using the location of the bird at its new location: testing for visual detection was carried out as before.

The next step determined if the bird was in the observer's audio field. If the bird was in audio range, the cumulative time it took the observer to traverse the last meter was added to the time the bird had been in the observer's audio range. If the cumulative time exceeded or equaled the time between the bird's vocalizations, the bird was detected audibly. If the bird had been in the observer's audio field but had just moved out, the cumulative time was set to zero, and a new Poisson variate was selected to represent the time between vocalizations. The rational for this is that the algorithm for audio detection uses the 'time between vocalizations' as the amount of time before the next vocalization after the observer comes within hearing range of the bird. See Appendix G.

9.3 Random Movement

9.3.1 Background

If animals move randomly with respect to the observer, then overestimates of density may occur. Turnock and Quinn (1991) and Schweder (1977) stated that the level of bias in the density estimate depends on the speed of the animal with respect to the speed of the observer: animals that move slowly and randomly with respect to the observer may cause insignificant levels of bias. If the subject of the study is a highly mobile animal (passerine bird), Burnham et al. (1980) claim that serious problems due to movement can arise, often to the extent of rendering line transect sampling useless for such species. Scott and Ramsey (1981b) warn that birds, usually being very mobile, may seriously bias variable circular plot density estimates derived from counts of longer duration. This section discusses the results of a simulation study that examined the effects of random movement and the speed of that movement with respect to the observer.

9.3.2 Simulation Study

The parameters in VABS determining the observer's pace were held fixed at their standard values, but the parameters determining the bird's speed of movement were varied. The speed of bird movement ranged from a very slow to a very fast pace, relative to the observer (Table 9.3.1). The bird was allowed to move randomly around the plot, but the plot was considered a closed system with a width of 610 meters – the width was increased to 610 meters to allow birds to move in and out of the observer's detection range. It was felt that 610 meters was wide enough to capture the impact of random movement. The distance the bird moved (RMOVE) was generated as previously discussed. The direction (AMOVE) of the bird movement was a Uniform(0,2π) generated variate. To determine the direction of movement in terms of the x (XMOVE) and y (YMOVE) axis, the following equations were used:

$$XMOVE=RMOVE*\cos(AMOVE)$$
$$YMOVE=RMOVE*\sin(AMOVE).$$

Once the animal was moved, it was tested for detection based on its new location as previously discussed.

Table 9.3.1 Levels of bird speed for random movement. (Observer's average speed was 40 meters/minute)

γ	β	E(X)(meters/minute)	SD(X)
-7.0360	.2757	.04	.03
-0.8215	.2757	20	11.96
-0.1283	.2757	40	23.93
0.5648	.2757	80	47.86
0.9703	.2757	120	71.78
1.2580	.2757	160	95.71
1.4810	.2757	200	119.64
2.1740	.2757	400	239.20
2.5800	.2757	600	359.00

9.3.3 Results

Bird movement at a rate slower than three times the observer's traversing rate had little influence on the density estimates (Figure 9.3.1). Beyond this rate, there was a pattern of increasing positive-bias in the density estimate accompanied with decreasing precision and coverage (Table 9.3.2).

It appears that as the rate of movement increased, the number of detections and the proportion of them close to the observer increased (Figure 9.3.2). The fitted curves do not appear to fit poorly. Otherwise, the fitted curves can appear to fit the histogram of observed detected areas but underestimate area!

The observed detected areas were calculated using the location where the observer detected the bird, not the bird's location when the survey began. These original locations were needed to determine detectability. Basically what happened was that birds originally outside the detection field were moving into the detection field, but these outer distances were not recorded as such. The consequence, the tail of the fitted curve was to short. Furthermore, birds who were not close to the transect line, where the probability of detection was high, when the survey began moved closer and were detected. Consequently, a substantial fraction of observed detections close to the transect was comprised of birds whose original locations were intermediate values. The result, detected area was underestimated.

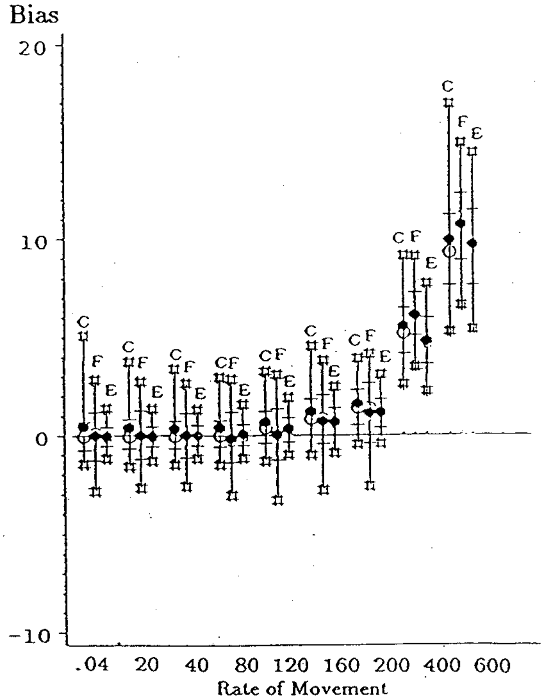


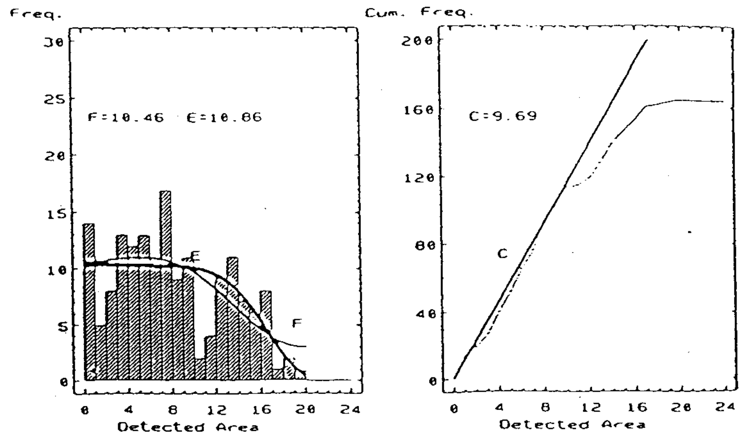
Figure 9.3.1 Bias of density estimates for random movement at different speeds. Symbols: (F) FS, (E) EPS, (C) Cum-D, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

Table 9.3.2 Coverage* of nominal CI for random movement.

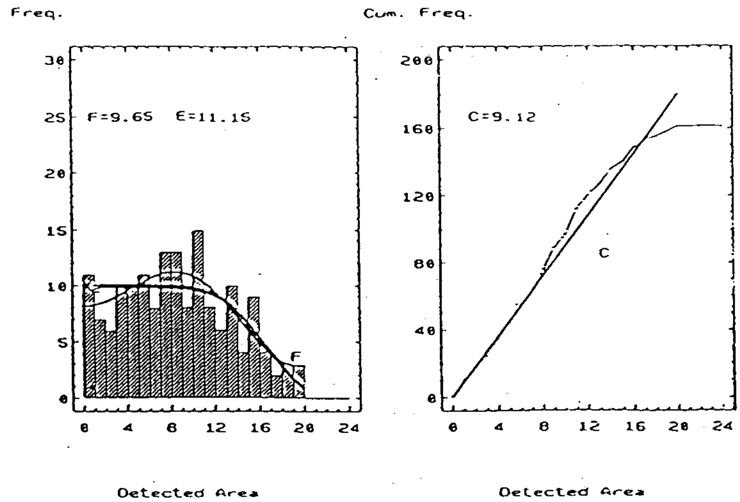
	Rate	Cum-D	FS	EPS
95% CI	.04	.968	.952	.972
	20	.962	.948	.956
	40	.966	.952	.954
	80	.984	.938	.964
	120	.968	.944	.962
	160	.950	.942	.942
	200	.928	.892	.910
	400	.696	.136	.294
	600	.544	.010	.026
99% CI	.04	.990	.990	.992
	20	.986	.986	.994
	40	.994	.994	.988
	80	.998	.986	.992
	120	.990	.980	.988
	160	.980	.980	.982
	200	.972	.976	.976
	400	.824	.352	.644
	600	.704	.038	.164

* Critical values for α=.05 are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

Speed 40 meters/minute



Speed 120 meters/minute



Speed 200 meters/minute

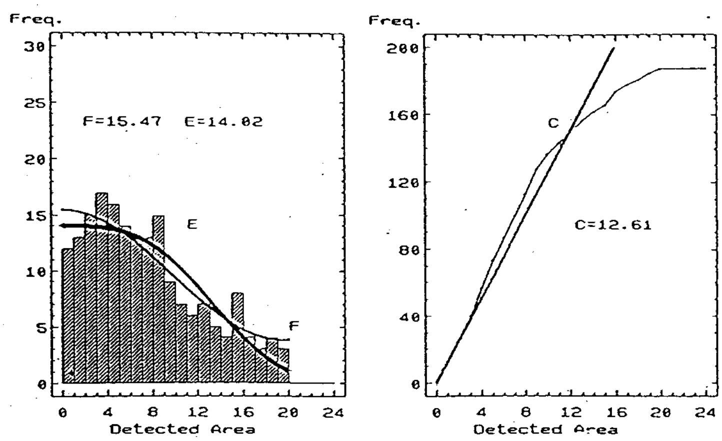


Figure 9.3.2 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates for random movement of birds at different mean speeds.

9.3.4 Conclusions

These results stress the importance of maintaining a rapid pace while traversing a transect if the population is mobile. If the animal is very mobile and the observer cannot achieve a traversing pace close to that of the animal of interest, the variable area survey should not be used to measure animal abundance. All observers should understand that stopping or slowing down significantly when traversing a transect to observe birds can bias density estimates. VABS, for this study, selected the random direction of a bird's movement every time the observer traversed one meter. Otherwise, a bird was constantly shifting directions but was flying around its original location: characteristic of phoebes and swallows. As the random direction changes less often, the robustness of the variable area survey to movement should decrease. Studies (Turnock and Quinn 1991, Schweder 1977) where animals continuously move in one direction suggest that animal movement faster than the observer is detrimental.

9.4 Avoidance

9.4.1 Background

Burnham et al. (1980) stated that nonrandom movement in response to the observer before detection probably is the most realistic situation concerning animal movement. Animal movement away from the line (avoidance) has been recognized as a potential problem by Eberhardt (1968) and Emlen (1971). The avoidance response of the animal only causes problems if the animal moves before being detected and its original location is unknown, or not all animals originally on the transect line are detected. Avoidance will cause the estimate of density to be biased negatively, because the effective area surveyed will be exaggerated (Burnham et al. 1980; Turnock 1991; Engeman and Bromaghin 1990). It has been recognized that observer avoidance is the principal cause of a donut shaped observed detectability curve.

The term 'donut shaped' refers to a curve that is concaved downward with local maximum to the right of the transect line – the term was originally used to describe detectability curves from variable circular plots. The 'observed' detectability curve refers to the curve of detected areas from recorded observed locations, not necessarily original locations.

9.4.2 Simulation Study

The objective of the simulation study in this section was to examine the robustness of the FS, EPS, and Cum-D estimators to avoidance. Two studies were undertaken, where animals within a certain distance of the observer had a fixed probability of avoiding the observer. In the first study, the probability was fixed at 1.0; whereas, in the second study, the probability was fixed at .4.

To create avoidance, a variable MOVE was introduced into the program. If at any time the distance between the bird and the observer was less than MOVE meters, the bird had the potential of moving away from the observer. The bird avoided the observer if a generated random number between 0 and 1 was less than or equal to the probability the bird avoided the observer. The plot was considered a close system.

For both studies, MOVE was set at ten levels. The parameters concerned with bird speed were fixed at RALPHA=2.174 and RBETA=.2757 (400 meters a minute), and the observer's speed was fixed at its standard value (40 meters a minute). The variable AMOVE was a generated Uniform($-\pi/2,\pi/2$) variate. Additional lines of code were added to DETECT to insure that a bird moved to the right of the x-axis if the observer was on the left of the animal and vice-versa.

9.4.3 Results

The minimum number of detections over all trials was 115 birds for the first study and 137 birds for the second. All three density estimators became more negatively biased as the variable MOVE increased (Figures 9.4.1 and 9.4.2). As this variable increased, the donut shape became more prevalent. The FS was very sensitive to the higher frequency of observations in the middle of the detection range (Figures 9.4.3 and 9.4.4); frequently giving negative estimates of density.

The EPS and Cum-D were less sensitive to this donut shape, providing reasonably accurate density estimates, until the donut shape was extreme and few birds, if any, were detected on the transect line. With a smaller proportion of fewer detections close to the transect line, the Cum-D bootstrap estimates of the standard error did not have the same problems previously mentioned. In fact, the width of the estimated confidence intervals appears too narrow (Table 9.4.1).

The results of the second study, approximately 40% of birds within MOVE meters moved, were less dramatic with the negative bias estimates occurring at higher values of MOVE (Tables 9.4.2 and Figure 9.4.2). In this study, the donut shape was less prevalent and there were more detections closer to the transect line. The FS was still the most negatively-biased.

9.4.4 Conclusions

In conclusion, the EPS and Cum-D are robust to avoidance, until it becomes extreme and birds on the transect line have a very low probability of being detected before avoiding the observer. In more detail, the variable area survey, with the appropriate estimator, can be used when avoidance is present, until birds that are further than 50% of the maximal detection distance from the observer move very quickly (10 times faster than the observer) to avoid the observer. If some birds hesitate before movement or not all birds move, the variable area survey is even more robust to avoidance. Frequently, birds will become quit after they have moved to avoid the observer. Further runs of VABS are needed to simulate this situation, but it is expected that the estimators will be less robust to this type of avoidance.

With avoidance, many of the birds detected further out were originally located close to the transect: it is this original location of the bird that is needed to calculate detected area. Recall that the EPS and Cum-D functions are monotonically decreasing. Since the curve cannot increase, the fitted curve behaves as if some of the observed detected areas to the left of the local maximum are detections from distances close to the observer. On the other hand, the FS behaves as if the observed detected areas were the original detection areas. Hence, the FS in not robust to avoidance.

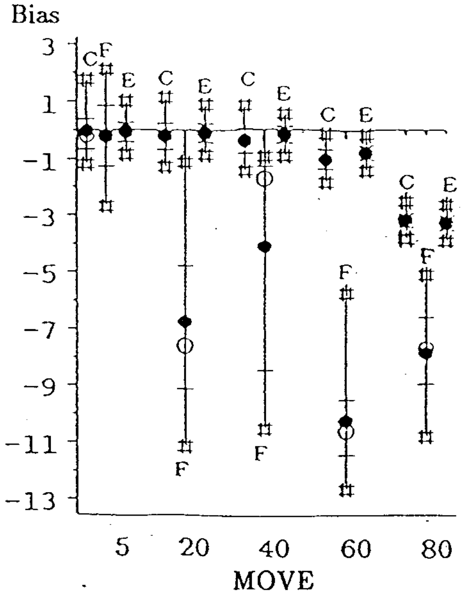


Figure 9.4.1 Bias of density estimates when all birds within MOVE meters of the observer avoided the observer. Symbols: (F) FS, (E) EPS, (C) Cum-D, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

Table 9.4.1 Coverage* of nominal CI when all birds within MOVE meters of the observer avoided the observer.

	MOVE	Cum-D	FS	EPS
95% CI	1	.986	.970	.994
	5	.970	.970	.992
	10	.958	.912	.992
	20	.936	.322	.992
	30	.908	.604	.992
	40	.838	.714	.996
	50	.676	.042	.974
	60	.292	.046	.862
	70	.018	.038	.186
	80	.000	.002	.000
99% CI	1	.994	.994	1.000
	5	.992	.992	1.000
	10	.978	.986	.998
	20	.972	.740	.998
	30	.958	.862	.998
	40	.918	.844	1.000
	50	.828	.084	.992
	60	.438	.058	.956
	70	.002	.076	.470
	80	.000	.002	.000

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

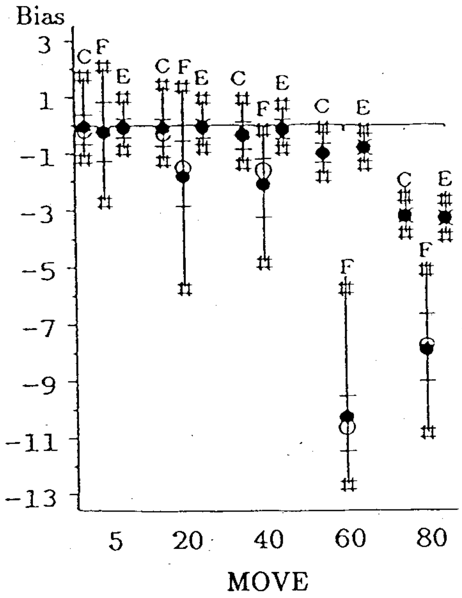


Figure 9.4.2 Bias of density estimates when birds within MOVE meters of the observer had a probability of .4 of avoiding the observer. Symbols: (F) FS, (E) EPS, (C) Cum-D, (•) mean, (∘) median, (–) 1st & 3rd quartile, (#) 5th & 95th percentile.

Table 9.4.2 Coverage* of nominal CI when birds within MOVE meters of the observer had a probability of .4 of avoiding the observer.

		Mean (se)		
	MOVE	Cum-D	FS	EPS
95% CI	1	.988	.984	.996
	5	.982	.960	.986
	10	.962	.958	.996
	20	.966	.890	.992
	30	.952	.686	.996
	40	.932	.770	.988
	50	.920	.912	.988
	60	.804	.744	.960
	70	.610	.468	.814
	80	.592	.332	.210
99% CI	1	1.000	.996	1.000
	5	.994	.990	.998
	10	.988	.992	1.000
	20	.990	.974	.998
	30	.988	.936	1.000
	40	.972	.930	.996
	50	.962	.970	.996
	60	.862	.890	.990
	70	.682	.714	.942
	80	.666	.580	.464

*Critical value for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

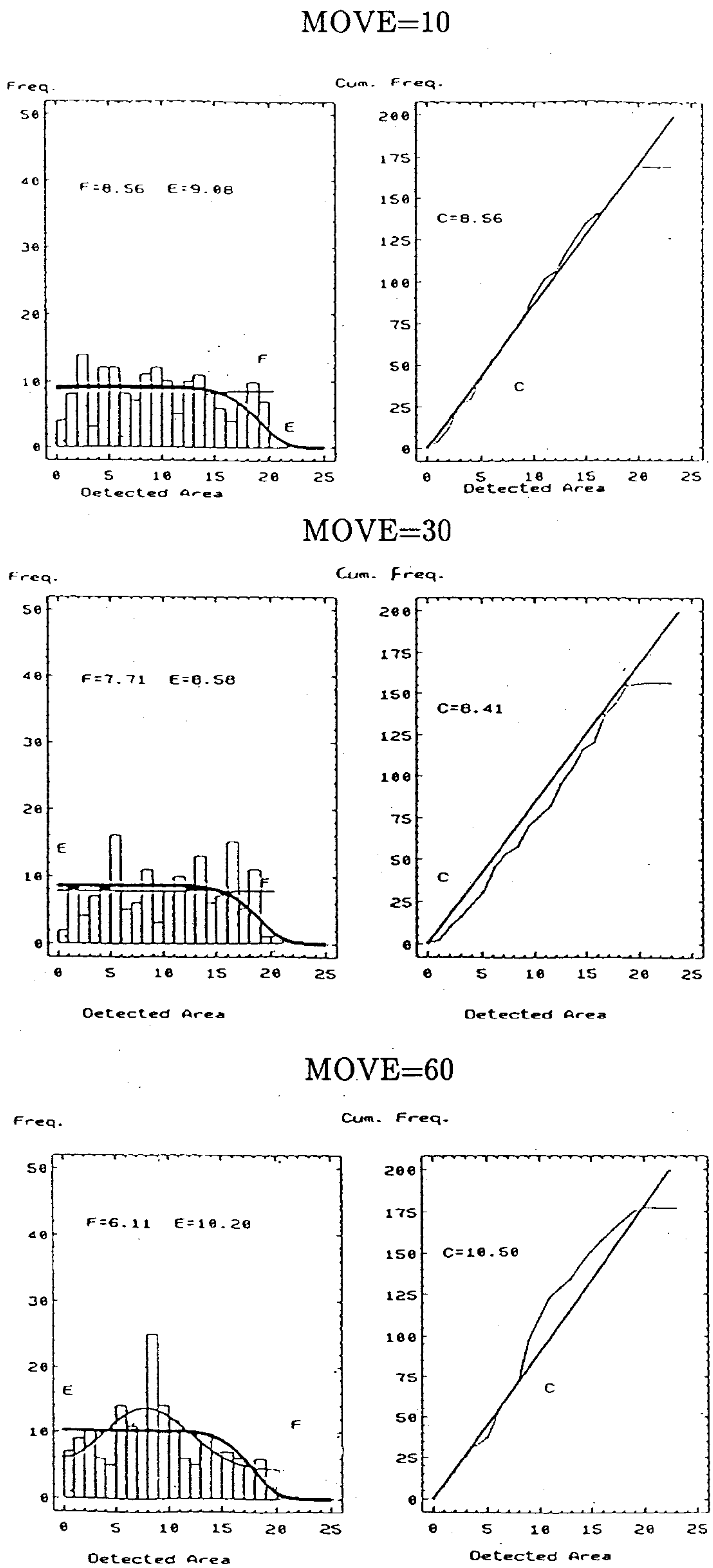


Figure 9.4.3 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates when all birds within MOVE meters of the observer avoided the observer.

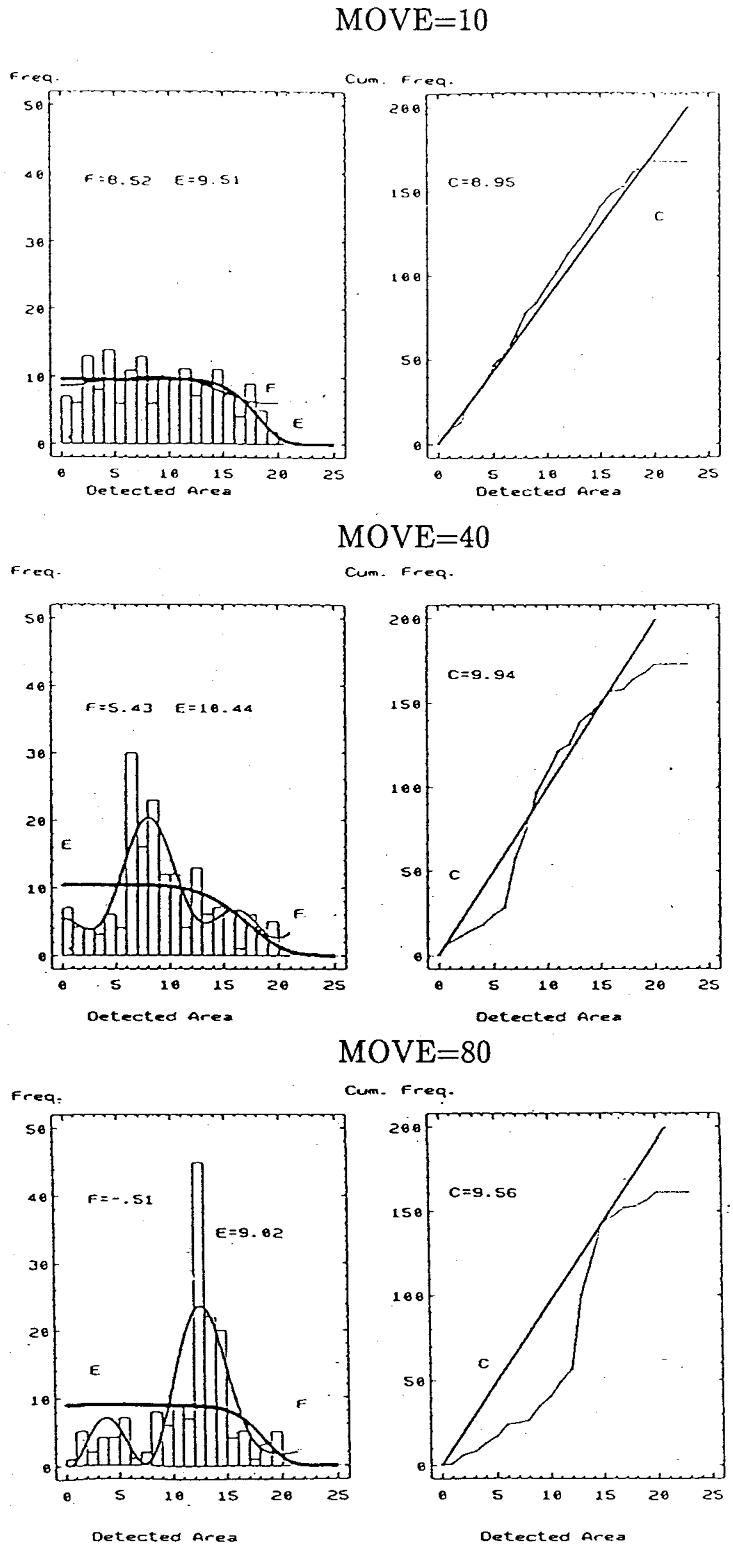


Figure 9.4.4 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates when birds within MOVE meters of the observer had a probability of .4 of avoiding the observer.

9.5 Concealment

9.5.1 Background

Birds near the observer may move away from the path of the observer or they may conceal themselves completely from detection (Wildman and Ramsey 1985). Ramsey et al. (1979) observed that a bird that does not move but alters its vocal pattern or hides in the foliage in responds to the observer is changing its detectability.

9.5.2 Simulation Study

The objective of this study was to determine how robust the three estimators are to concealment. To achieve this objective, the subroutine DETECT was altered. If the distance between bird i and the observer was less than or equal to MOVE, the bird hid and became quiet, otherwise the bird was undetectable. VABS was run for four levels of MOVE: 1m, 5m, 10m, 20m. Two simulation studies were carried out: the first study had all birds within MOVE meters of the observer hiding, whereas the second had birds within MOVE meters hiding with a probability of .4.

9.5.3 Results

For all replications, the minimum number of birds detected was 124 birds. The characteristic of hiding in VABS created a donut shape detection curve (Figures 9.5.1 and 9.5.2), typically resulting in negative-biased density estimates. All three estimators performed poorly when there was a sharp increase in detections at first followed by a gradual decline. Not surprisingly, as the value of MOVE increased, the bias increased (Figures 9.5.3 and 9.5.4) and coverage of the confidence interval decreased (Table 9.5.1 and 9.5.2).

There were times that the fitted curve appeared to fit, but the density was underestimated. Birds on the transect line were not always being detected before they hid, especially for the greater values of MOVE. Theoretically, if $g(0) \neq 1$, density will be underestimated, explaining the increasing negative-bias. The FS was clearly the least robust of the three estimators. The EPS is more robust than the other two estimators, although it was not clearly superior to the Cum-D. In the second simulation study, the estimators were more tolerant of hiding, since there were several detections near zero and the donut shape was not as extreme.

Table 9.5.1 Coverage* of nominal CI when all birds within MOVE meters of the observer hid from the observer.

	MOVE	Cum-D	Mean (se) FS	EPS
95% CI	1	.982	.940	.990
	5	.868	.840	.964
	10	.596	.700	.826
	20	.224	.668	.300
99% CI	1	.998	.980	.998
	5	.948	.950	.992
	10	.724	.880	.946
	20	.318	.788	.570

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

Table 9.5.2 Coverage* of nominal CI when a bird within MOVE meters of the observer had a .4 probability of hiding.

	MOVE	Cum-D	FS	EPS
95% CI	1	.976	.948	.992
	5	.970	.944	.996
	10	.942	.876	.972
	20	.872	.814	.894
99% CI	1	.996	.990	.998
	5	.988	.986	1.000
	10	.962	.976	.996
	20	.916	.960	.962

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

9.5.4 Conclusions

In general, hiding appears to be a more critical problem then avoidance. When birds within 10 or more meters of the observer conceal themselves, the standard variable area survey should not be used. Since all three estimates are less robust to birds hiding than birds moving to avoid the observer, the researcher should attempt to determine the nature of the disturbance. Concealment of birds jeopardizes the assumption that birds on the transect line are detected.

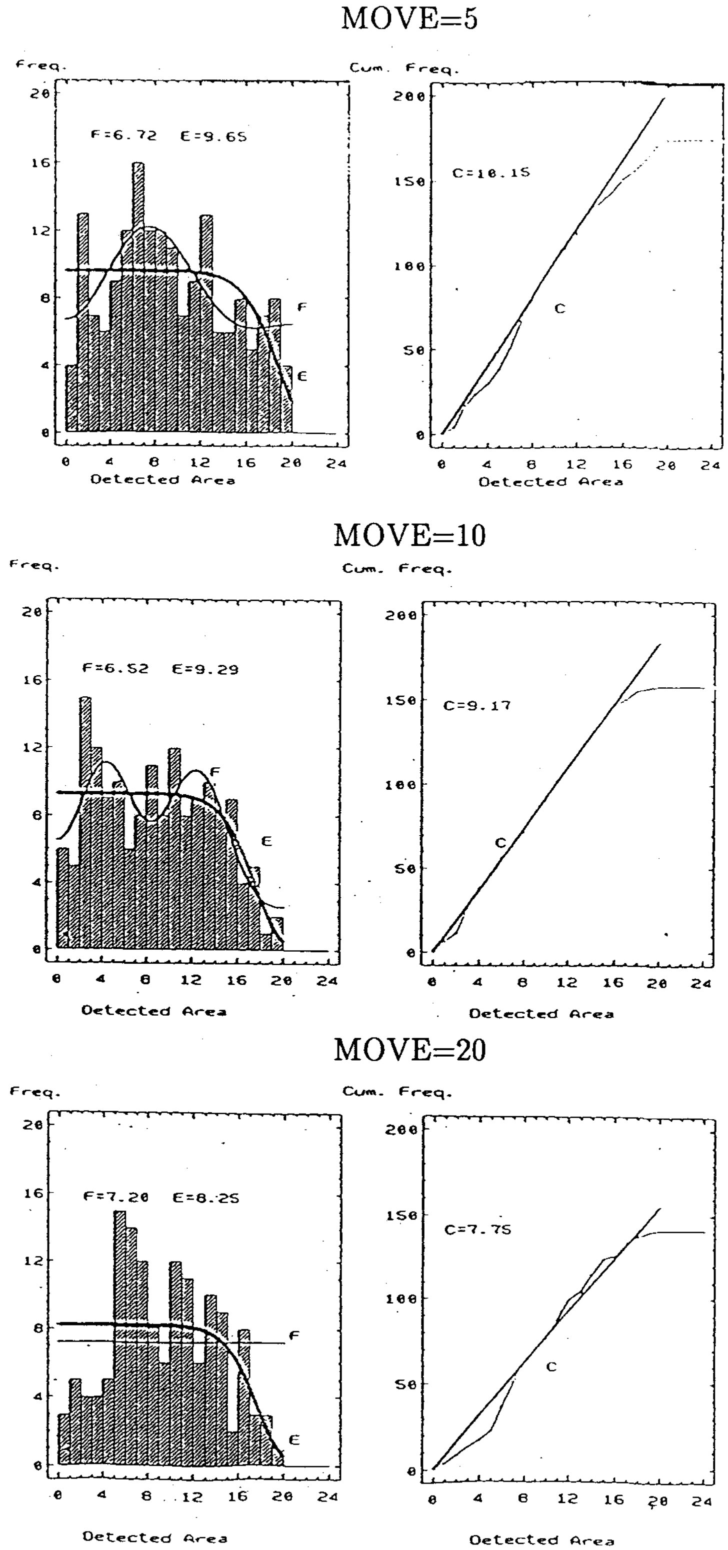


Figure 9.5.1 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates when all birds within MOVE meters of the observer hid from the observer.

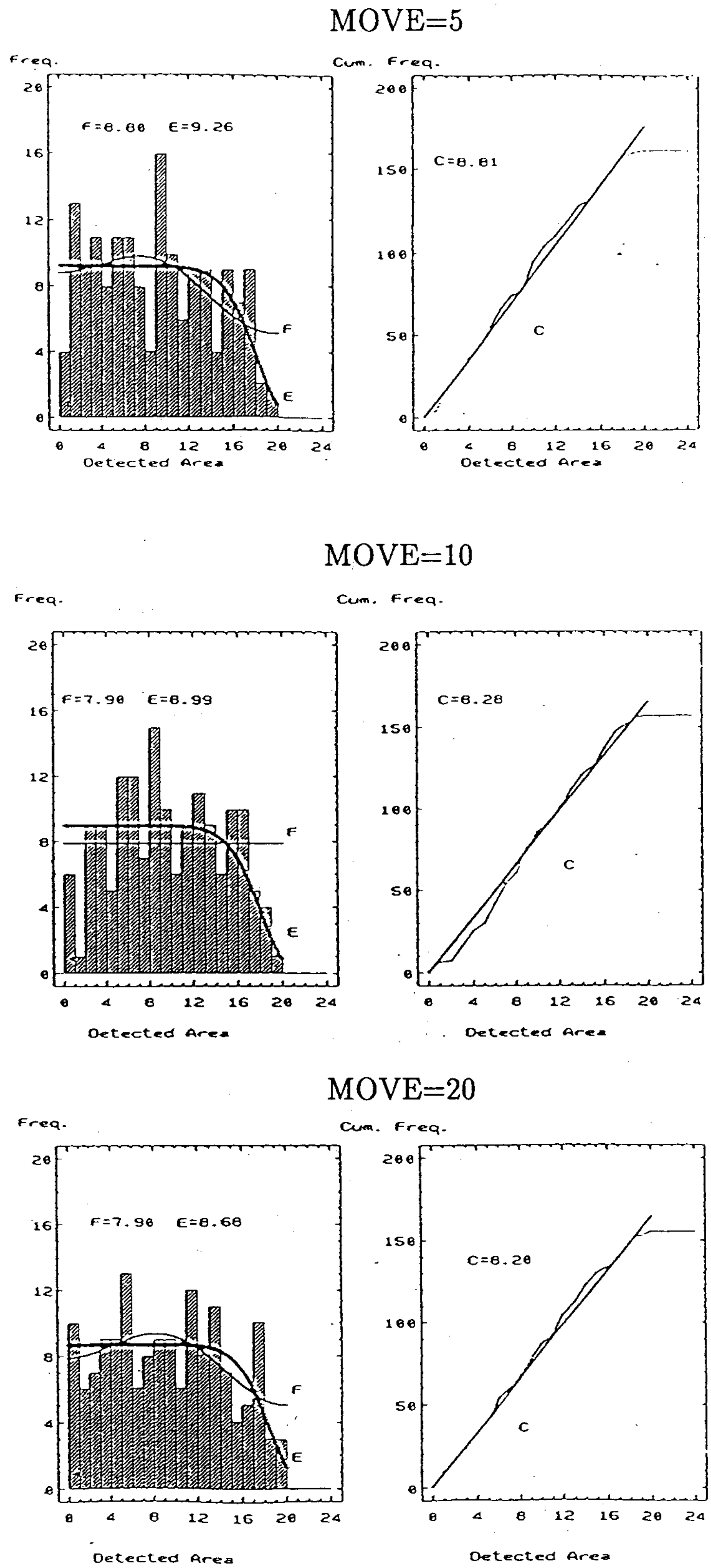


Figure 9.5.2 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates when a bird within MOVE meters of the observer had a .4 probability of hiding from the observer.

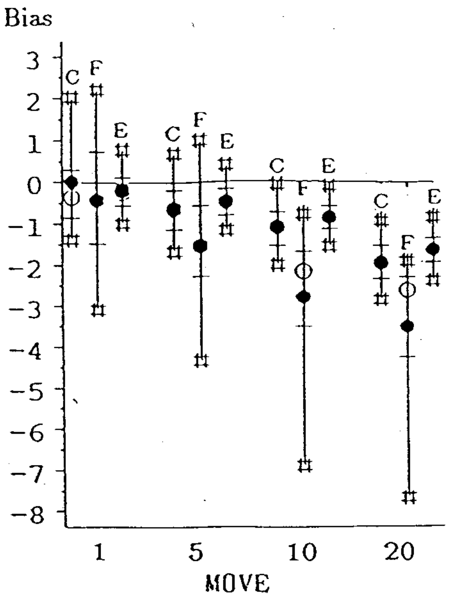


Figure 9.5.3 Bias of density estimates when all birds within MOVE meters of the observer hid from the observer. Symbols: (F) FS, (E) EPS, (C) Cum-D, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

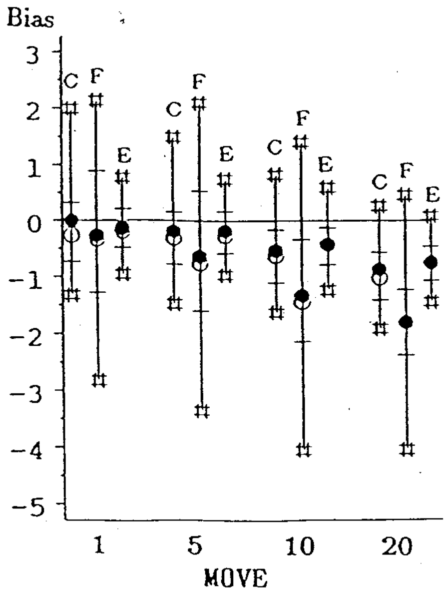


Figure 9.5.4 Bias of density estimates when a bird within MOVE meters of the observer had a .4 probability of hiding from the observer. Symbols: (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

9.6 Attraction

9.6.1 Background

Movement of an animal in response to the observer is usually avoidance, but animals are sometimes attracted to the observer. If movement toward the transect line occurs before the animals are observed, positive bias is thought to occur, because of the observed higher density of animals close to the transect line (Turnock 1991). Attraction can result in the first bar of the histogram being high enough that none of the estimators provide a good fit (Buckland 1985). Note that this pattern can also occur if transects follow roads, railroads, pathways, etc.; and the animals are attracted to these objects.

The objective of this study was to determine the robustness of the three estimators to attraction. To achieve this objective, the subroutine DETECT was altered so that MOVE acted as a critical value from which to judge if an animal moved towards the observer. Three different simulation studies were conducted to represent different patterns of attraction.

9.6.2 Simulation Study I: Birds within MOVE Meters were Attracted to the Observer.

The first simulation study had birds moving if they were within MOVE meters of the observer. The variable MOVE was fixed at four levels: 10,20,30, and 40 meters. The bird's mean rate of movement was fixed at 200 meters per minute. If a bird moved, the variables XMOVE and YMOVE were determined as before, except the bird would move closer to the transect line. The birds could cross the transect line, but whichever direction it moved the distance between it and the observer decreased. This kind of movement resulted in a hat shape curve of observed detectability (Figure 9.6.1) – the term 'hat-shaped' refers to a curve that is first concaved downward and then upward.

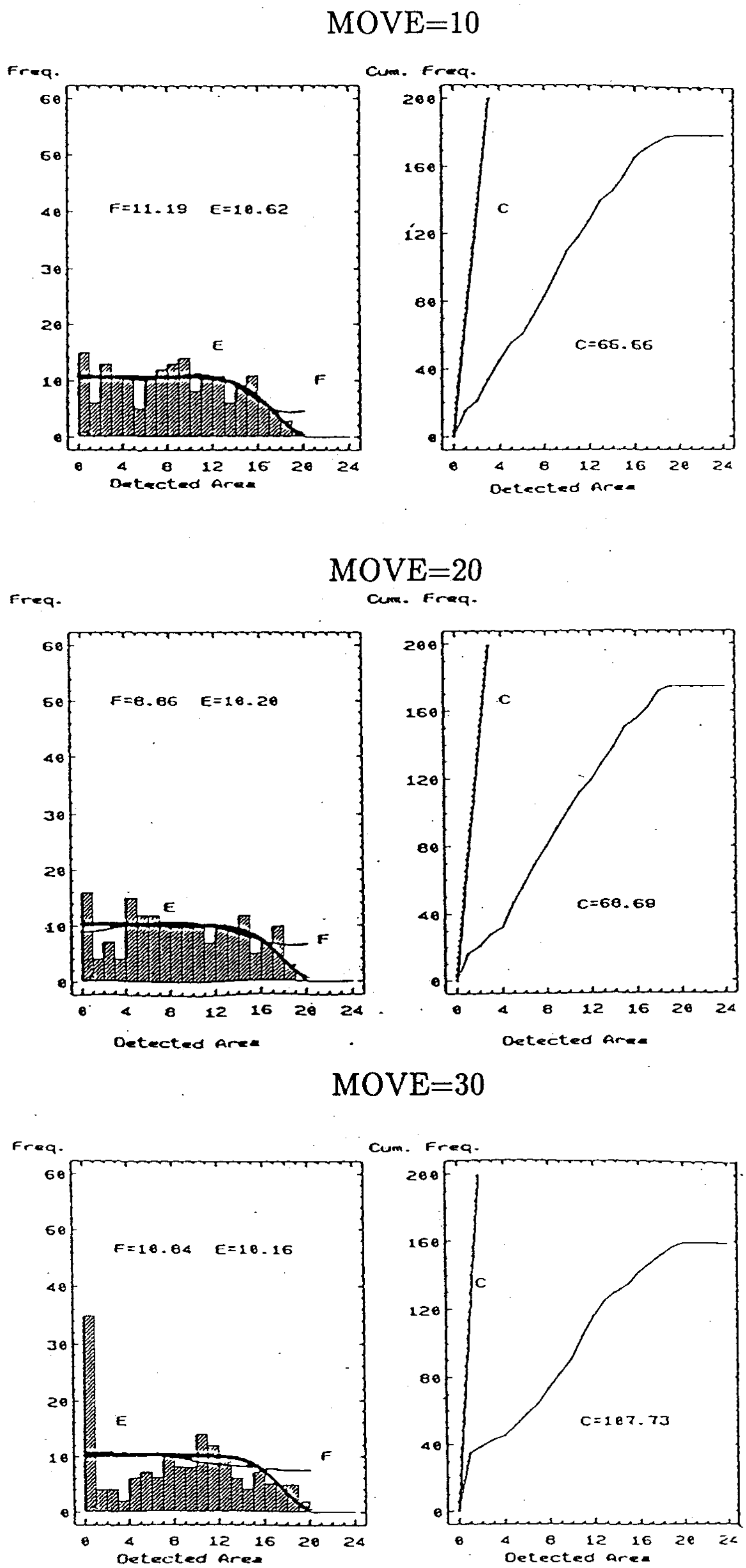
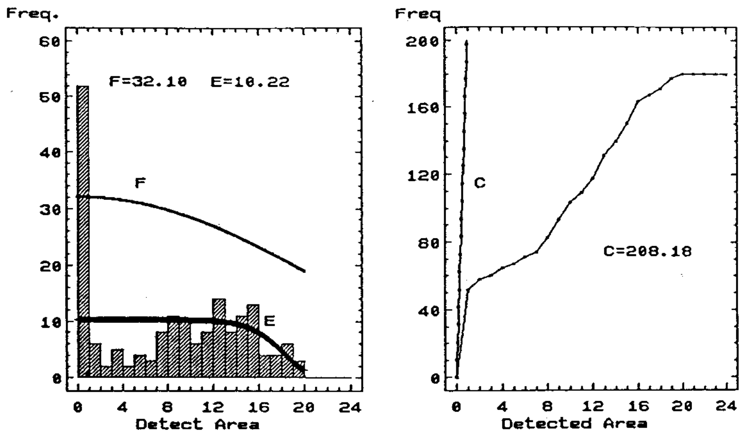


Figure 9.6.1 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding histograms, and density estimates when a bird within MOVE meters of the observer moved closer to the observer.

Figure 9.6.1 (continued)

MOVE=40



9.6.3 Study I Results

The positive bias of the density estimate increased as MOVE increased (Table 9.6.1). The Cum-D had serious problems quickly as it was fooled by the large percentage of detections close to the observer. The EPS performed noticeably better than the other two estimators, but in the extreme case, it also underestimated the area surveyed and had insufficient coverage (Table 9.6.2). As more birds were attracted to the observer, a large fraction of observed detections close to the transect were in fact detections from intermediate areas. An estimator that treats a fraction of the detected areas as if they were from intermediate areas – between the transect and the first local maximum away from the transect – should be more robust to this kind of attraction.

Table 9.6.1 Results when a bird within MOVE meters of the observer was attracted to the observer.

		Mean (se)				
MOVE	Cum-D		FS		EPS	
$\hat{D}$						
10	33	(27)	10.2	(1.7)	9.94	(.62)
20	109	(48)	12.3	(3.1)	9.95	(.63)
30	181	(61)	16.6	(7.1)	12.1	(30.6)
40	272	(90)	30.7	(6.8)	245.0	(263.4)
$\hat{SE}(\hat{D})$						
10	31	(18)	1.83	(0.46)	.88	( )
20	57	(34)	3.27	(1.15)	2.3	(9.4)
30	88	(51)	6.76	(1.46)	52.0	(64.2)
40	123	(74)	6.50	(2.19)	206.4	(64.7)

Table 9.6.2 Coverage* of nominal CI when a bird within MOVE meters of the observer was attracted to the observer.

MOVE	Cum-D	FS	EPS
95% CI			
10	.968	.964	.984
20	.542	.904	.988
30	.396	.730	1.000
40	.310	.146	.724
99% CI			
10	.996	.994	.998
20	.788	.990	.996
30	.632	.946	1.000
40	.540	.326	.876

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

9.6.4 Study I Conclusion

Estimators that are monotonically decreasing and are less sensitive to values near the transect line will be more robust to birds near the observer being attracted to the observer.

For situations similar to what was simulated, the variable area survey should not be used to estimate density when birds within 25% (25 meters in study) or more of the maximum detection distance (100 meters in study) are attracted to the observer at a rate 5 times faster than the observer's traversing rate.

9.6.5 Simulation Study II: Birds MOVE Meters Away were Attracted to the Observer.

The next simulation study had the birds being attracted to the observer if the distance between them and the observer was greater than MOVE meters. The speed of the birds was fixed at 10 meters per minute. This pattern of movement could represent curious animals who approach the observer with caution. Typically in this situation, a high percentage of birds are detected close to the transect, resulting in an initial rapid decline in detectability (narrow shoulder) followed by a gradual decrease in detectability (Figure 9.6.2).

9.6.6 Study II Results

Once again, the Cum-D was the least robust and the EPS was the most robust (Table 9.6.3 and Figure 9.6.3) estimator of area. As MOVE decreased, the positive-bias of the density estimates increased. When MOVE=80, there was evidence that the EPS had insufficient coverage for a 95% nominal confidence interval (Table 9.6.4).

This time, detections out towards the tail area of the curve were recorded as being closer to the transect, because the animal was attracted to the observer before being detected. Although the FS appears to fit the curve for MOVE=70 (Figure 9.6.2), density was overestimated because not all birds detected on or near the transect line were originally located there. The EPS fitted curve displays a long shoulder but underestimated the tail values, thus, underestimating area.

9.6.7 Study II Conclusions

In this study, birds were moving at a rate four times slower than the observers traversing rate; as the bird's speed increases, the robustness of the EPS should decrease. For a slow rate of movement, the EPS can be used to estimate density until birds 75% (75 meters in study) or less of the maximum detection distance (100 meters in study) away from the observer are being attracted to the observer.

To estimate density when this kind of attraction occurs, what is needed is an estimator that behaves like the EPS, but whose curve does not have the tendency to quickly drop-off to zero near the maximal observed detected area.

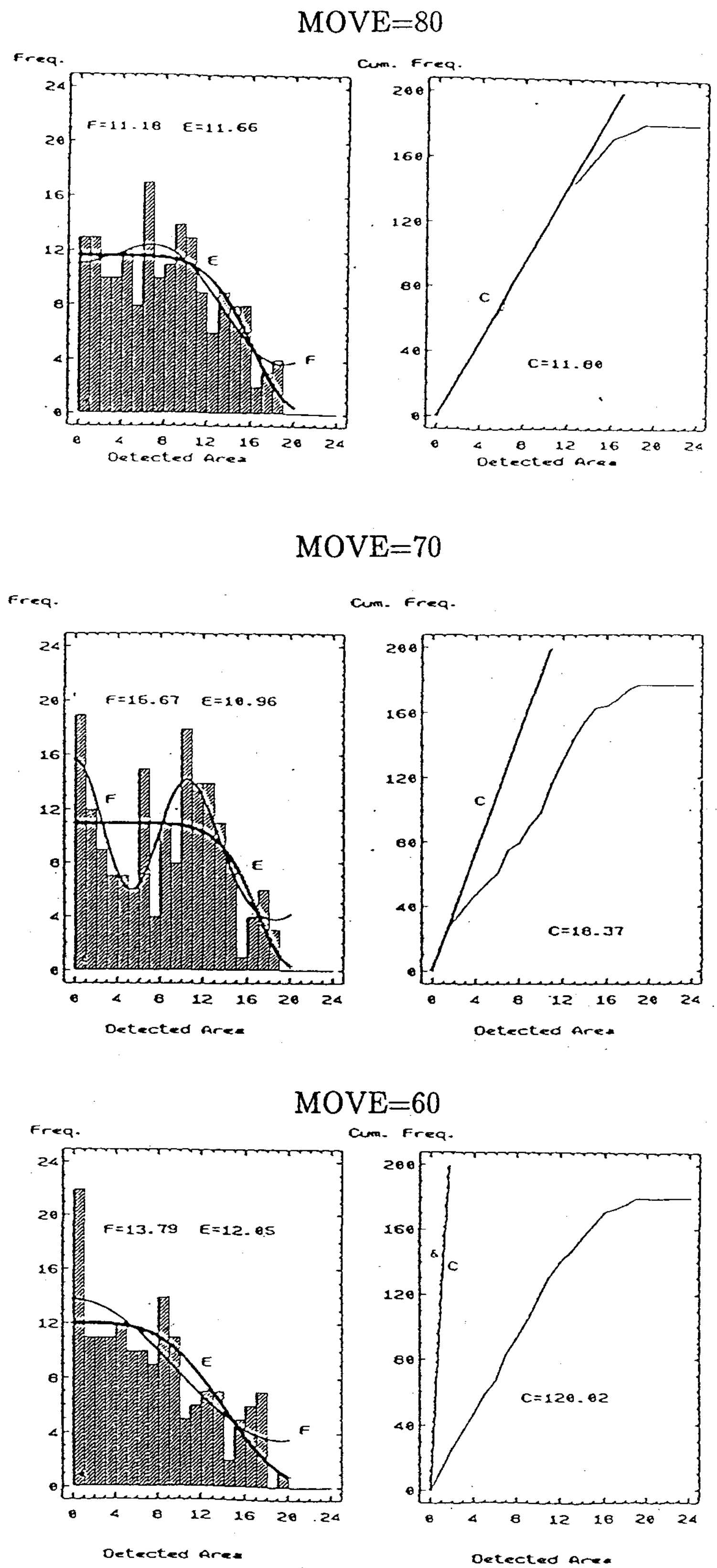


Figure 9.6.2 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates when birds MOVE meters away from the observer were attracted to the observer.

Table 9.6.3 Results when birds MOVE meters away were attracted to the observer.

MOVE	Cum-D		FS		EPS	
			Mean (se)			
$\hat{D}$						
95	11.4	(3.8)	10.5	(1.6)	10.15	(.48)
90	13.6	(7.3)	11.2	(1.7)	10.36	(.49)
85	19	(20)	11.8	(1.9)	10.70	(.52)
80	31	(42)	12.4	(1.9)	11.02	(.62)
75	47	(69)	13.0	(2.0)	11.37	(.65)
70	91	(108)	14.0	(2.5)	11.79	(.70)
60	211	(160)	15.0	(3.0)	12.59	(1.05)
$\hat{SE}(\hat{D})$						
95	7	(10)	1.78	(.41)	.87	(.21)
90	17	(28)	1.92	(.53)	.87	(.21)
85	35	(42)	2.11	(.60)	.91	(.26)
80	64	(58)	2.21	(.63)	.97	(.38)
75	94	(79)	2.31	(.69)	1.02	(.44)
70	134	(82)	2.64	(.75)	1.34	(3.60)
60	190	(93)	3.16	(1.03)	2.52	(8.56)

Table 9.6.4 Coverage* of nominal CI when birds MOVE meters away were attracted to the observer.

MOVE	Cum-D	FS	EPS
95% CI			
95	.994	.982	1.000
90	.998	.966	.992
85	.992	.922	.982
80	.996	.890	.930
75	1.000	.788	.856
70	.972	.664	.732
60	.906	.676	.608
99% CI			
95	.998	1.000	1.000
90	1.000	.990	1.000
85	.998	.988	1.000
80	1.000	.966	.988
75	1.000	.936	.974
70	.996	.870	.930
60	.974	.834	.856

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

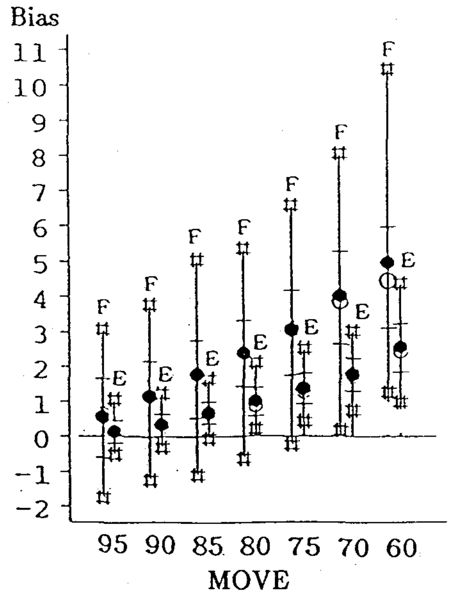


Figure 9.6.3 Bias of density estimates when a bird MOVE meters away from the observer was attracted to the observer. Symbols: (F) FS, (E) EPS, (C) Cum-D, (•) mean, (∘) median, (−) 1st & 3rd quartile, (#) 5th & 95th percentile.

9.6.8 Simulation Study III: Birds were Attracted to an Area Away from the Observer

The third simulation study had the birds moving closer to the observer if the distance between the bird and the observer was greater than MOVE meters and moving away from the observer if the distance between the bird and the observer was less than MOVE/2 meters. Otherwise, there was a strip of area, MOVE/2 meters away from the observer and MOVE/2 meters wide, where birds gathered. The speed of the bird movement was 10 meters per minute. The variable MOVE was fixed at six levels, representing a very narrow band to a wide band. This scenario is probably more characteristic of mammals who are observing the observer.

9.6.9 Study III Results

As the band width increased and was located further out, the detection curve changed from one with a short steep initial decline, to one with a long shoulder, and finally to a donut shape (Figure 9.6.4). The performance of the estimators changed as the observed detectability curve changed (Table 9.6.5 and 9.6.6 and Figure 9.6.5). The FS had problems both with a narrow shoulder (overestimates density) and the donut shape (underestimates density). The Cum-D method had problems with a narrow shoulder (overestimates density) but did well otherwise. The EPS density estimates were the most stable, although overestimates and poor coverage occurred if the initial decline was steep.

Table 9.6.5 Results when birds were attracted to an area away from the observer.

		Mean (se)					
	MOVE	Cum-D		FS		EPS	
$\hat{D}$	45	73	(91)	16.2	(2.3)	14.07	(1.7)
	55	18	(17)	13.5	(2.1)	12.98	(1.2)
	65	12.1	(1.6)	10.8	(2.1)	12.15	(.79)
	75	11.14	(.67)	8.7	(1.9)	11.35	(.60)
	85	10.47	(.74)	7.1	(2.0)	10.68	(.48)
	95	10.02	(.70)	7.2	(2.1)	10.09	(.44)
$\hat{SE}(\hat{D})$							
	45	117	(83)	2.53	(.78)	2.03	(.85)
	55	34	(44)	2.20	(.41)	1.39	(.32)
	65	6	(14)	2.17	(.39)	1.13	(.23)
	75	2.6	(6.8)	2.12	(.44)	.97	(.20)
	85	1.2	(2.1)	2.14	(.49)	.85	(.19)
	95	.9	(1.4)	2.19	(.51)	.81	(.19)

Table 9.6.6 Coverage* for nominal CI when birds were attracted to an area away form the observer.

MOVE	Cum-D	FS	EPS
95% CI			
45	.988	.240	.450
55	.956	.594	.396
65	.796	.922	.560
75	.792	.950	.814
85	.910	.730	.958
95	.912	.690	1.000
99% CI			
45	.994	.594	.396
55	.976	.810	.736
65	.890	.980	.828
75	.910	.996	.950
85	.968	.962	.998
95	.962	.940	1.000

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

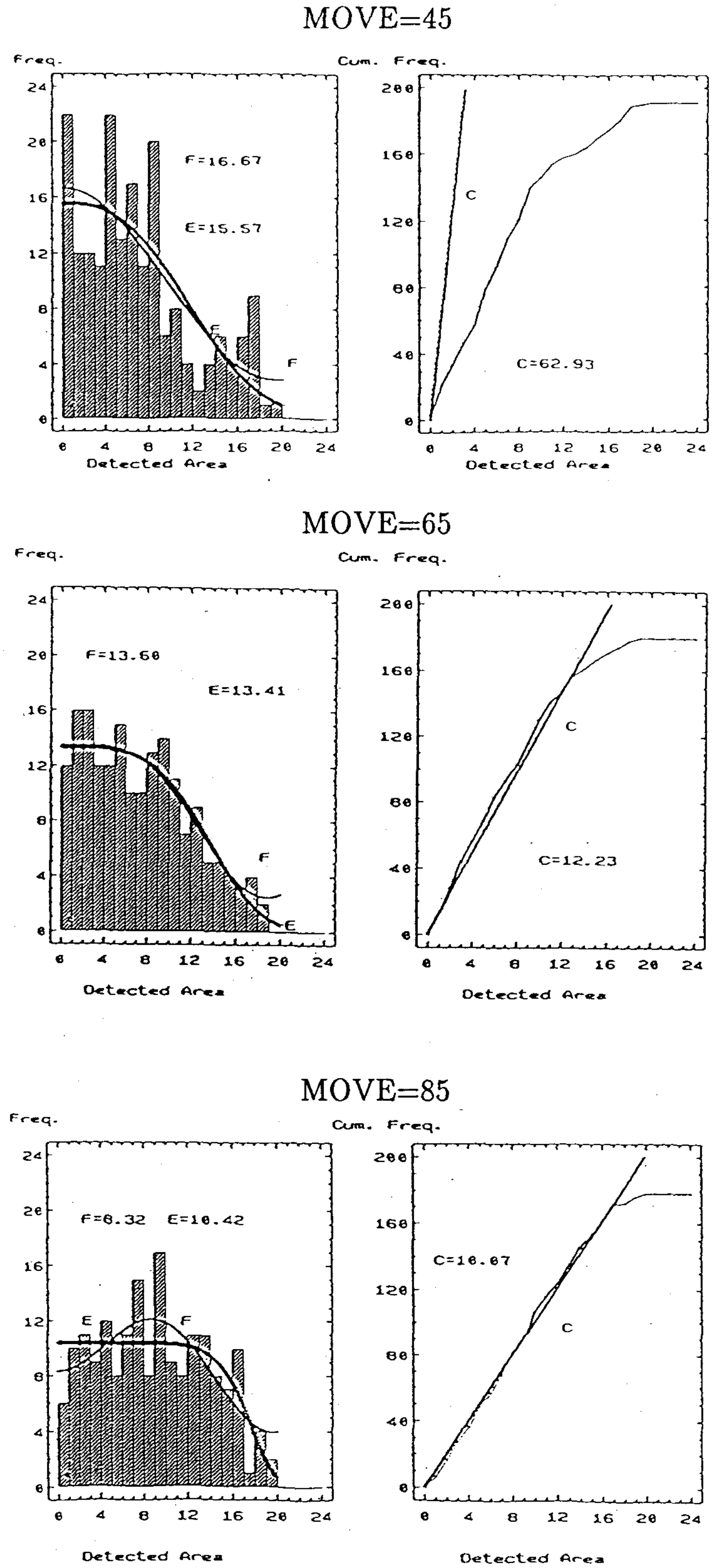


Figure 9.6.4 Examples of fitted FS (F), EPS (E), Cum-D (C) curves, corresponding frequency histograms, and density estimates when a bird is attracted to an area away from the observer.

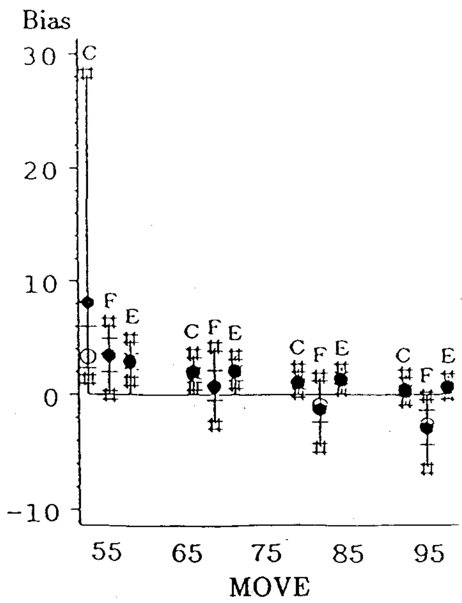


Figure 9.6.5 Bias of density estimates when a bird was attracted to an area away from the observer.

9.6.10 Study III Conclusions

Estimators are less robust to birds being attracted to a very small area versus a large area. This is because the observed detected areas are grouped closely together and are not representative of the true detected areas. Even when the estimator appears to fit the curve defined by the observed detected area, the estimate of area can be bias, because the observed detected areas are not equivalent to the true detected areas.

9.7 Overall Conclusions on Movement

These results demonstrate that estimators whose detectability functions are not monotonically decreasing (FS) are not robust to movement. Estimators that are based on monotonically decreasing functions are more robust to movement, particularly if they are sensitive to intermediate values. The Cum-D method is robust to movement, except when attraction is the problem and there is a steep decline in detectability initially. In this case, further investigation on the selection of k, as mentioned previously, may resolve the problem. Buckland

(1985) mentions that extreme movement may sometimes be evident in a histogram of the data. It is important to produce and examine histograms before selecting an estimator. Beware, different kinds of movement can result in similar histograms, but the level of robustness to the different kinds of movement can be dramatically different. For example, avoidance and concealment both result in 'donut shaped' histograms, but the variable area survey is more robust to avoidance. Hence, the pattern of movement should be determined.

When movement is a factor, the fit of the curve defined by the observed detected areas can be misleading. What is important is how the curve fits the true detected areas. Since original bird locations are unknown, it is important to choose functions that are restricted to realistic curves, such as monotonically decreasing functions.

Movement can be brought on by conduct on the transect, thus all efforts must be taken by the observers to reduce the risk of movement. If movement is suspected before surveys are carried out, the survey methodology taken should take movement into account. Burnham et al. (1980) suggest grouping distances to reduce the effect of movement, if movement is not too extreme . If variable circular plots are used, count periods can be shorten to reduce the probability of movement; however, if several species are being observed, count periods of different lengths are required for species with dramatically different rates of movement (Scott and Ramsey 1981b). For line transect sampling, the traversing speed should be chosen to minimize the effect of movement but still allow for a sufficient number of detections. Buckland and Turnock (1992) have proposed field methodology and analysis methods whose estimates are robust to movement and that do not require all animals on the trackline be detected. This approach is applicable only to surveys in which two observation platforms are available, with effort concentrated close to the observer carried out from one platform and a wider area scanned from the second. Turnock (1991) discussed a correction factor method that estimates the bias caused by movement and applies it to the f(0) value (see Buckland and Turnock 1992).

10 CRITICAL ASSUMPTIONS

10.1 Motivation

The assumptions (1) g(0)=1, (2) no bird is counted more than once, (3) all detected birds are recorded, and (4) detection distances are measured without error have been considered basic to any accurate determination of effective area. However, there are situations when these assumptions are invalid. For example:

(1) Vegetation is dense enough that birds on the transect line may go undetected because they are hidden in the foliage.

(2) Movement of birds may result in a bird being recounted further down the transect line.

(3) A high density of birds may prevent the observer from distinguishing and recording all birds seen.

(4) If detected distances are being estimated, it is unlikely that distances will be error free.

(5) The area measured in the field does not correspond to the area that density refers to (Section 10.5).

This chapter examines these critical assumptions and what happens when they are invalid.

10.2 Vegetation Impeding Visual Detection and the Assumption g(0)=1.

10.2.1 Background

The assumption that g(0)=1 implies that all birds on the transect line are detected. Dense vegetation will threaten this assumption, because birds on the transect line can be hidden in the foliage. Theoretically, if there is not 100% detection on the transect line, density will be underestimated. However, if g(y) is known for some y, then the standard theory of the variable area survey can be easily modified to derive an accurate estimate of density.

In Section 6.2, there is evidence that if visibility is poor enough that g(0)=1 is in question, then the standard methodology for line transect surveys should not be used. Visibility in this case is reduced by increasing the visual threshold size and decreasing the maximum eccentricity; therefore, poor visibility is consistent throughout the transect. With vegetation there can be clear spots that allow for higher visual detectability. The objective of the simulation study reported in this section was to explore how a reduced visual field caused by vegetation affects birds counts and the variable area density estimates.

10.2.2 Simulation Study

To introduce vegetation on the created region, trees with foliage were distributed over the study area as described in Section 4.4. Trees and birds were distributed independently of each other. Tree density for an even-aged forest was fixed at 10, 100, and 300 trees per hectare. For comparative purposes, an uneven-aged forest was generated with density fixed at 100 trees per hectare. Bird density was fixed at 15 birds per hectare. The vocalization frequency (THETA) was reduced to .1, in order to emphasize what happens when vegetation prevents birds on and near (1 cm) the transect line from being detected. In denser vegetation, more emphasis is naturally placed on auditory detections. As vocalization frequency increases, more birds on the transect line will be detected, but unless bird vocalization is frequent enough to ensure 100% detectability on the transect, the assumption $g(0)=1$ is still invalid.

10.2.3 Results

The density estimates had adequate coverage with reasonably accurate density estimates for 10 and 100 trees per hectare (Figures 10.2.1 to 10.2.3). At 300 trees per hectare, all three models had a tendency to overestimate the effective area (underestimate density), particularly the exponential power series. Furthermore, the confidence intervals that did not include the true value of density predominantly corresponded to the negative-biased density estimates.

At 300 trees per hectare, the detection curve (Figures 10.2.4) appears to have a wide shoulder followed by a sharp decline and then a flat tail, a situation that all three estimators had difficulties fitting. Even when the estimator appeared to fit (top histogram), density was still underestimated, indicating the assumption $g(0)=1$ had been violated.

The EPS confidence intervals (Figures 10.2.2) appear to become wider as the estimate of density increases. This pattern is more noticeable for an uneven-aged forest. The fitted EPS curve is sensitive to a tail. If these tails are not included in a bootstrap sample, the EPS curve would be incline to differ. The tail values are less common and are more likely not to be represented in a bootstrap sample; therefore, the se($\hat{D}$) should be larger for curves with longer tails. Furthermore, an uneven-aged forest should be more prone to tails: trees are uniformly distributed and breaks in the forest, where distant detections can be made, are less common. Using the preceding arguments, one could hypothesize that the EPS is incline to underestimate density when there is no tail and overestimate density and have greater variance when there is a long tail.

10.2.4 Conclusions

The assumption g(0)=1 (or g(y) is known for some y) is critical. Line transects should not be used to estimate density when vegetation is dense enough that birds on the transect line can go undetected. Reynolds et al. (1980) have suggested the use of the variable circular survey when vegetation is dense. Since the observer stays at one point for a given amount of time, the vegetation can be examined more carefully. If g(y) is unknown for all y, methods using two platforms have been proposed as a way to estimate g(0) and density (Butterworth, Best, and Basson 1982; Buckland 1987; Hiby and Hammond 1989).

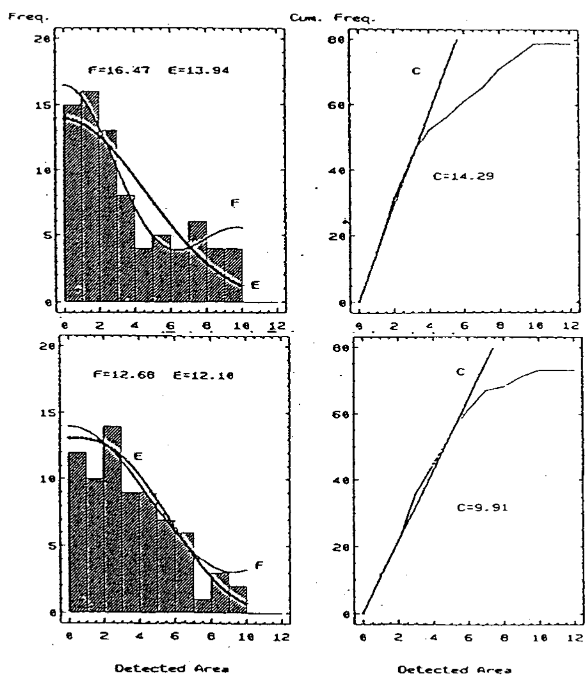


Figure 10.2.4 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding histograms, and density estimates for 300 trees per hectare impeding vision.

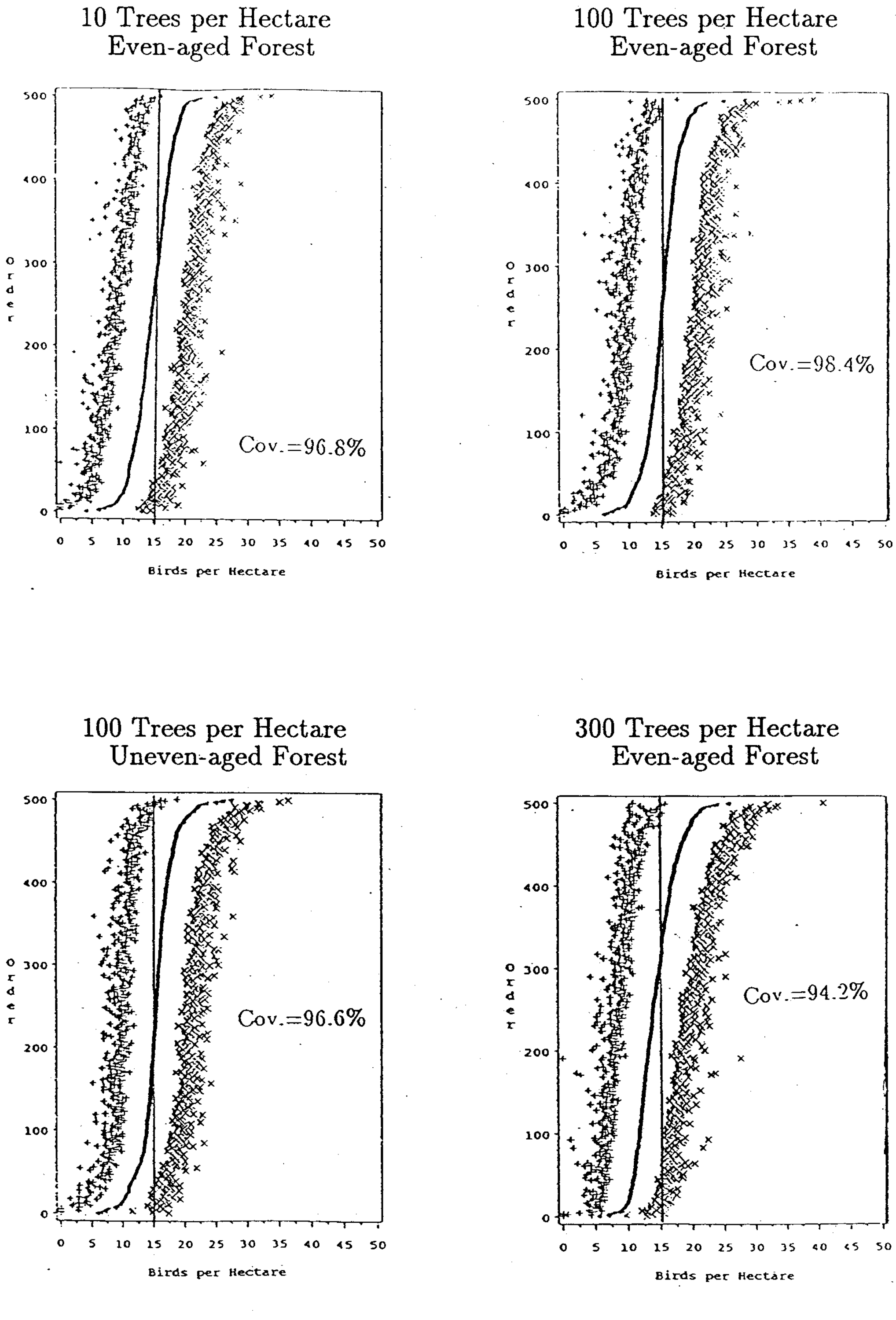


Figure 10.2.1 Ordered FS density estimates and corresponding 95% confidence limits for various levels of tree density impeding vision (Cov.=coverage).

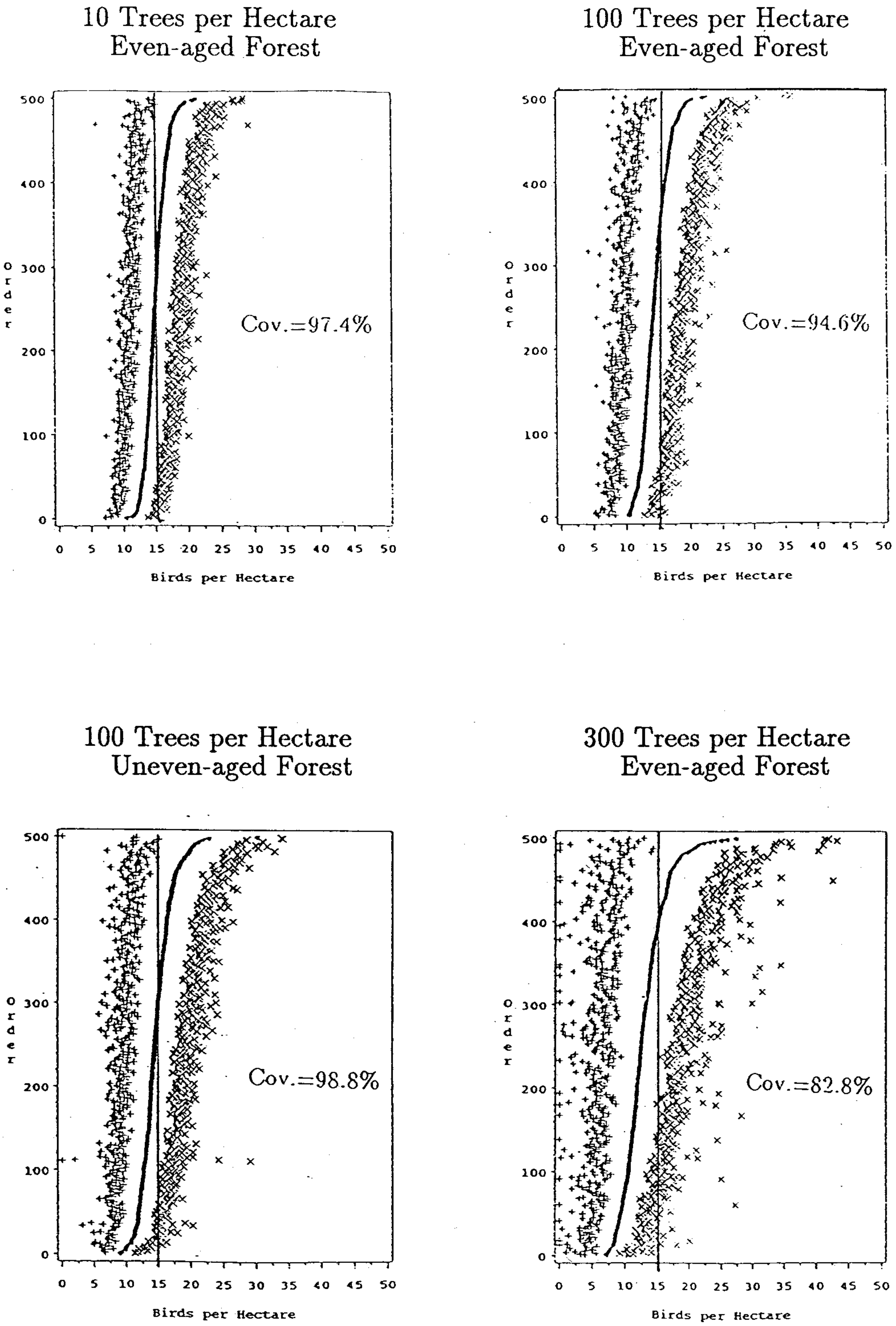


Figure 10.2.2 Ordered EPS density estimates and corresponding 95% confidence limits for various levels of tree density impeding vision (Cov.=coverage) .

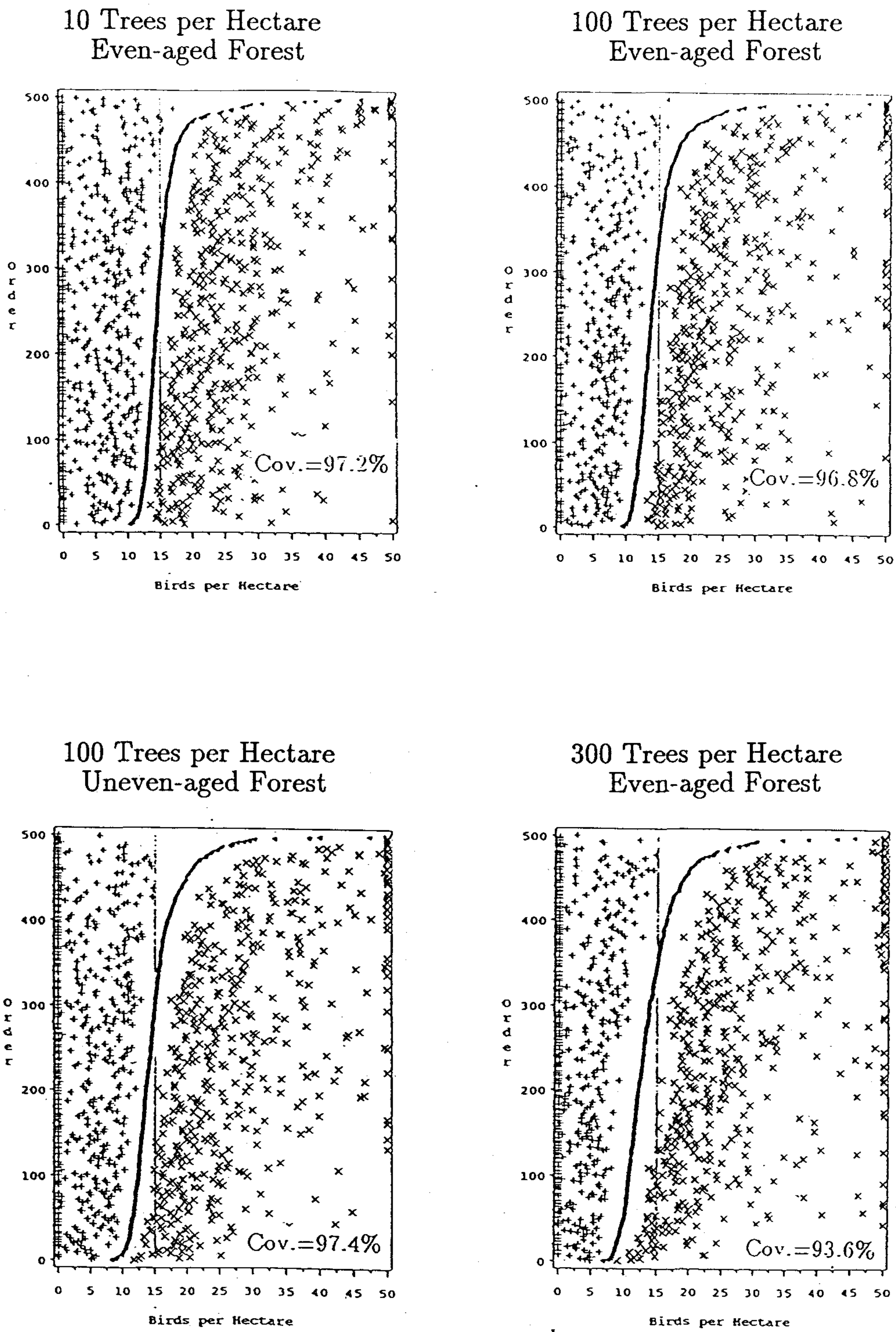


Figure 10.2.3 Ordered Cum-D density estimates and corresponding 95% confidence limits for various levels of tree density impeding vision (Cov.=coverage). Points on the right boundary fall outside the graph's range .

10.3 Counting Error

10.3.1 Background

Movement of birds may lead to violations of standard assumptions, other than birds occupy a fix location. With highly mobile species in regions of high bird density, the chance of recounting some individuals certainly is present (Ramsey et al. 1979). Burnham et al. (1980) recognized that in response to the observer some animals, particularly many songbirds, move ahead of the observer near the line of travel, and unless this can be observed and negated an animal may be recounted later. Duplicate counts of birds should cause $\hat{D}$ to be overestimated.

10.3.2 Simulation Study

The objective of the simulation study reported in this section was to determine the consequence of duplicate counting. To achieve this objective, VABS had birds randomly moving around the study area (see Section 9.2) with the potential of being recounted. To create multiple counts, a new variable LOSE, representing the maximum distance a bird could move before the observer lost track of it, was introduced into VABS. There were two possibilities where birds could be recounted: (1) the bird moved a distance greater than the variable LOSE, and (2) a bird moved in and out of the observer's detection range. The average bird's speed was fixed at 40 meters per minute, equivalent to the observer's traversing speed.

Multiple detections were possible by means of both audio and visual detection. At each meter, audio detection was checked for; if the time the bird was within the observer's audio range was greater then the time between calls, the bird was detected. However, every time the bird moved out of the observer's hearing range, the cumulative time the bird was in the observer's audio range was set to zero, and another Poisson variate representing the time between calls (after observer enters audio field) was generated. The instance a bird moved more than LOSE meters or left the observer's visual field, the bird was tested for visual detection. After being tested for visual detection, the probability the bird had not been detected since the last critical movement was set at 1.0. See Appendix H.

10.3.3 Results

Density estimates and the var($\hat{D}$) increased simultaneously with the number of multiple counts (Figure 10.3.1 and Table 10.3.1). Until around five to ten percent of the bird counts were duplicates, the point estimates and coverage for each estimator were adequate (Table 10.3.2); however, there was a tendency for density to be overestimated when any multiple counting existed. Even when the of number of unique counts was used in the numerator of $\hat{D}$, the estimates still tended to overestimate density (Figure 10.3.2). This underestimation of the effective area surveyed may be attributed to bird movement, but the results in Section 9.2 indicate that movement is not a problem when birds move at the same speed of the observer. Hence, the multiple detected areas recorded for one bird causes effective area to be overestimated.

Table 10.3.1 Statistics on bird detection for counting error.

LOSE	Number Detect		Mean (se) % Audio		Duplicate Counts*	
40	172.6	(50.3)	77.1	(3.6)	.474	(.65)
35	169.5	(11.4)	77.3	(3.1)	.654	(.78)
30	170.1	(11.2)	77.1	(3.3)	1.196	(1.10)
25	171.3	(11.4)	76.3	(3.3)	3.298	(1.94)
20	178.1	(12.2)	75.1	(3.1)	9.968	(3.17)
18.34	184.5	(38.7)	74.5	(3.1)	14.494	(3.80)
16.67	188.6	(13.7)	73.0	(3.1)	19.956	(4.47)
15	197.3	(13.6)	71.8	(3.1)	28.024	(5.37)
10	239.5	(17.8)	67.3	(2.7)	62.802	(7.67)

*This number represents the mean number of counts made that were duplicate counts of a bird already detected.

10.3.4 Conclusions

The assumption that no bird is counted more than once is a critical assumption. Unless one is aware and can negate for multiple counts, the standard area survey methodology will likely provide biased estimates. If multiple counts account for over five percent of total counts, the variable area survey should not be used.

Table 10.3.2 Coverage* of nominal CI for counting error.

	LOSE	Cum-D	FS	EPS
95% CI				
	40	.966	.944	.954
	35	.974	.938	.952
	30	.982	.962	.960
	25	.970	.964	.974
	20	.988	.922	.940
	18.34	.960	.886	.928
	16.67	.940	.838	.798
	15	.900	.754	.616
	10	.576	.370	.042
99% CI				
	40	.988	.994	.988
	35	.994	.988	.980
	30	.994	.998	.988
	25	.992	.998	.994
	20	.996	.982	.984
	18.34	.984	.978	.976
	16.67	.978	.958	.936
	15	.956	.890	.880
	10	.716	.370	.042

*Critical values for α=.05 are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

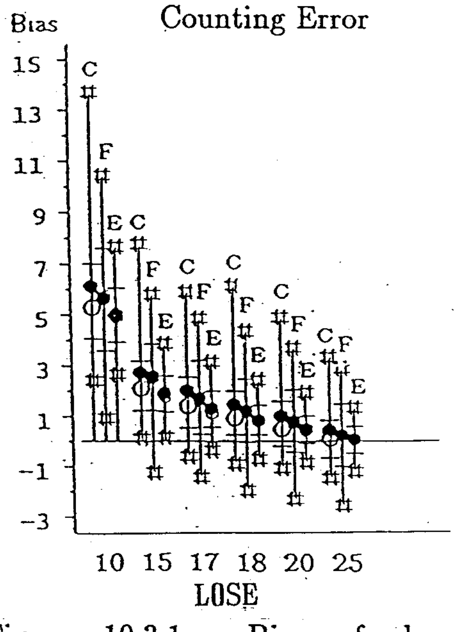


Figure 10.3.1 Bias of density estimates when some birds were counted more than once. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (-) 1st & 3rd quartile, (#) 5th & 95th percentile.

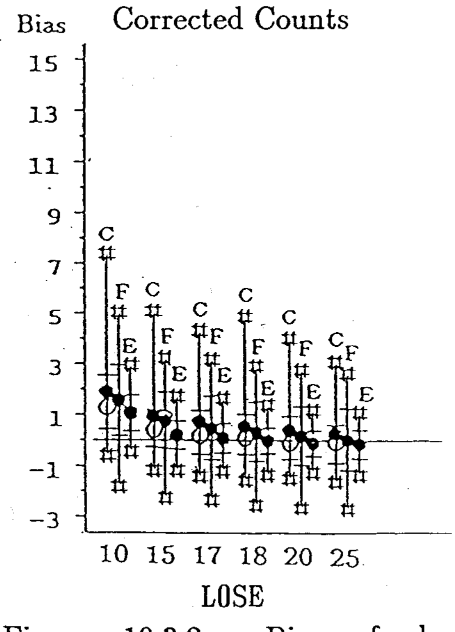


Figure 10.3.2 Bias of density estimates when some birds were counted more than once, but the correct number of unique counts was used in the numerator of $\hat{D}$. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (-) 1st & 3rd quartile, (#) 5th & 95th percentile.

10.4. Saturation

10.4.1 Background

Saturation in this context refers to the inability of a single person to record a large number of birds accurately, because they are unable to sort out individuals or they simply become confused. Saturation can occur when there are too many birds of a single species to record accurately or the numbers recorded are for all species encountered, and the added responsibility of keeping track of a large number of species leads to a loss of information. The ability of a single person to record accurately all individuals and species has been challenged by Carney and Petrides (1957), Scott and Ramsey (1981a), Lack (1976), and Preston (1979).

10.4.2 Simulation Study

The problem of saturation was examined by a simulation study using VABS. To limit the number of detections during a time period, a new variable SAT, representing the maximum number of birds that could be detected within ten meters, was introduced. After VABS completed the detection process, the number of perpendicular distances intersecting exclusive ten meter intervals were summed. If more than SAT detections were in an interval, the detections with the greater detected areas were deleted from the data set until there were only SAT detections per interval. SAT was fixed at eleven levels (Table 10.4.1), with the number detected before and after truncation being recorded. For the levels 2.75, 2.5, 2.25; the third closest bird had a .75, .5, .25 probability of being recorded, respectively. See Appendix I for programming.

10.4.3 Results

The density estimates increasingly underestimated density as the ability of the observer to record all birds detected decreased (Figure 10.4.1). The coverage of the confidence intervals of density showed evidence of less than nominal coverage as soon as 2.5% (FS) and 8% (EPS) of the birds went unrecorded (Tables 10.4.1). Between the three estimators, the EPS displayed the greatest bias. The incorrect count of birds in the numerator of the density estimate explains the underestimation of density, but not why the EPS estimate had greater bias.

When correct counts were used in the numerator of the density estimate, the estimates were still biased (Figure 10.4.2). In this case, the Cum-D and FS overestimated density, as was expected, but the EPS still underestimated density. In Figures 10.4.3 and 10.4.4 there were instances where the curve appears to fit, yet the density estimate was bias. Recall, the detections out in the tail were not always recorded. The EPS appears to be sensitive to these tail values: when they were not present, the EPS had a long shoulder followed by a rapid decline. If these tail values were present, the shape of the curve would likely be different. In conclusion, without the detected areas for all birds detected, the area surveyed cannot be estimated accurately, even if the curve fits the recorded detected areas.

Table 10.4.1 Coverage* of nominal CI for saturation.

			Nominal Levels					
	% of Birds	Number	Cum-D		FS		EPS	
SAT	Recorded	Detect*	95%	99%	95%	99%	95%	99%
80	99.1	163.3	.956	.978	.958	.990	.982	.994
40	97.5	163.8	.968	.984	.932	.996	.984	1.000
20	95.3	163.5	.946	.964	.862	.986	.958	.988
10	92.2	163.6	.952	.980	.778	.996	.910	.992
5	88.7	163.6	.934	.960	.548	.980	.786	.972
4	86.2	163.4	.930	.938	.426	.972	.702	.966
3	81.0	163.5	.830	.908	.258	.852	.468	.912
2.75	77.8	163.6	.748	.848	.210	.902	.390	.862
2.5	74.6	163.7	.696	.842	.205	.900	.272	.812
2.25	71.6	163.3	.548	.754	.108	.838	.234	.714
2	68.2	163.0	.486	.714	.088	.818	.192	.658

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
*This is the number birds seen before data is reduced for saturation.

10.4.4 Conclusions

The recording of each bird detected and its detected area is a critical assumption. If the density of birds is so high that one person cannot accurately record all birds detected, then the work should be partitioned to other observers in some manner. Scott and Ramsey (1981a) recommend that counts of common birds, when several individuals of a species are likely to be recorded in a short period, should be made by dividing responsibilities between observers, with each responsible for a selected number of species whose numbers are comparable. If saturation cannot be avoided and over five percent of the birds seen will not be recorded, then the standard variable area survey should not be implemented.

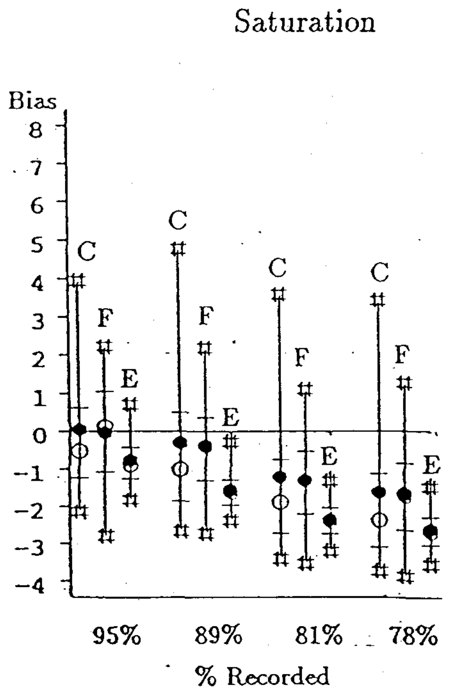


Figure 10.4.1 Bias of density estimates for saturation. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (-) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

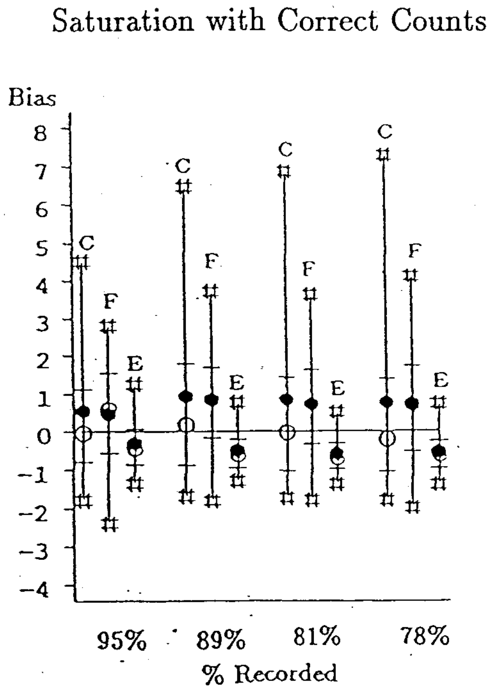


Figure 10.4.2 Bias of density estimates for saturation with correct counts in the numerator of $\hat{D}$. Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (-) 1^{st} & 3^{rd} quartile, (#) 5^{th} & 95^{th} percentile.

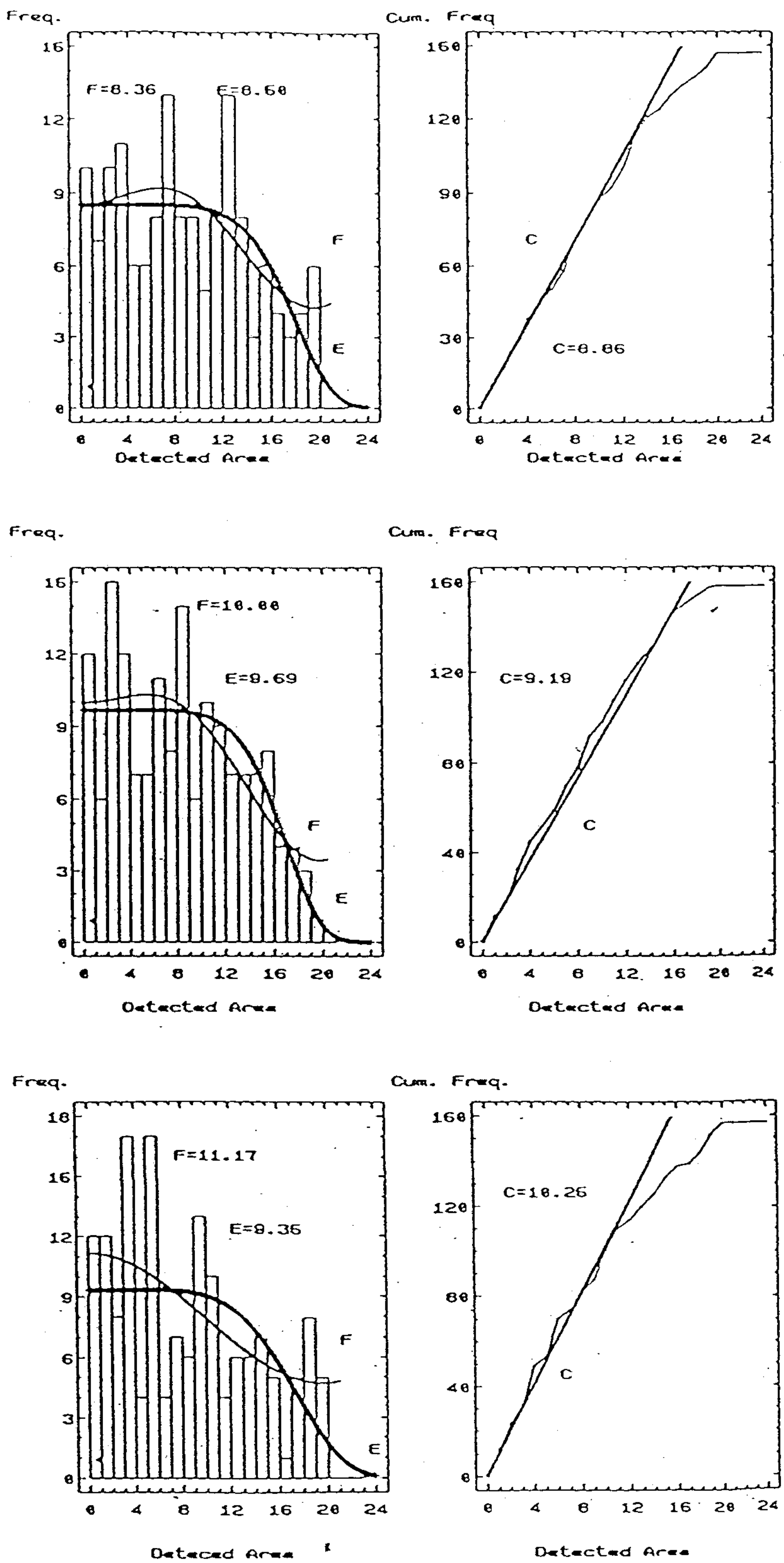


Figure 10.4.3 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding histograms, and density estimates when SAT=20 (95% of birds seen recorded).

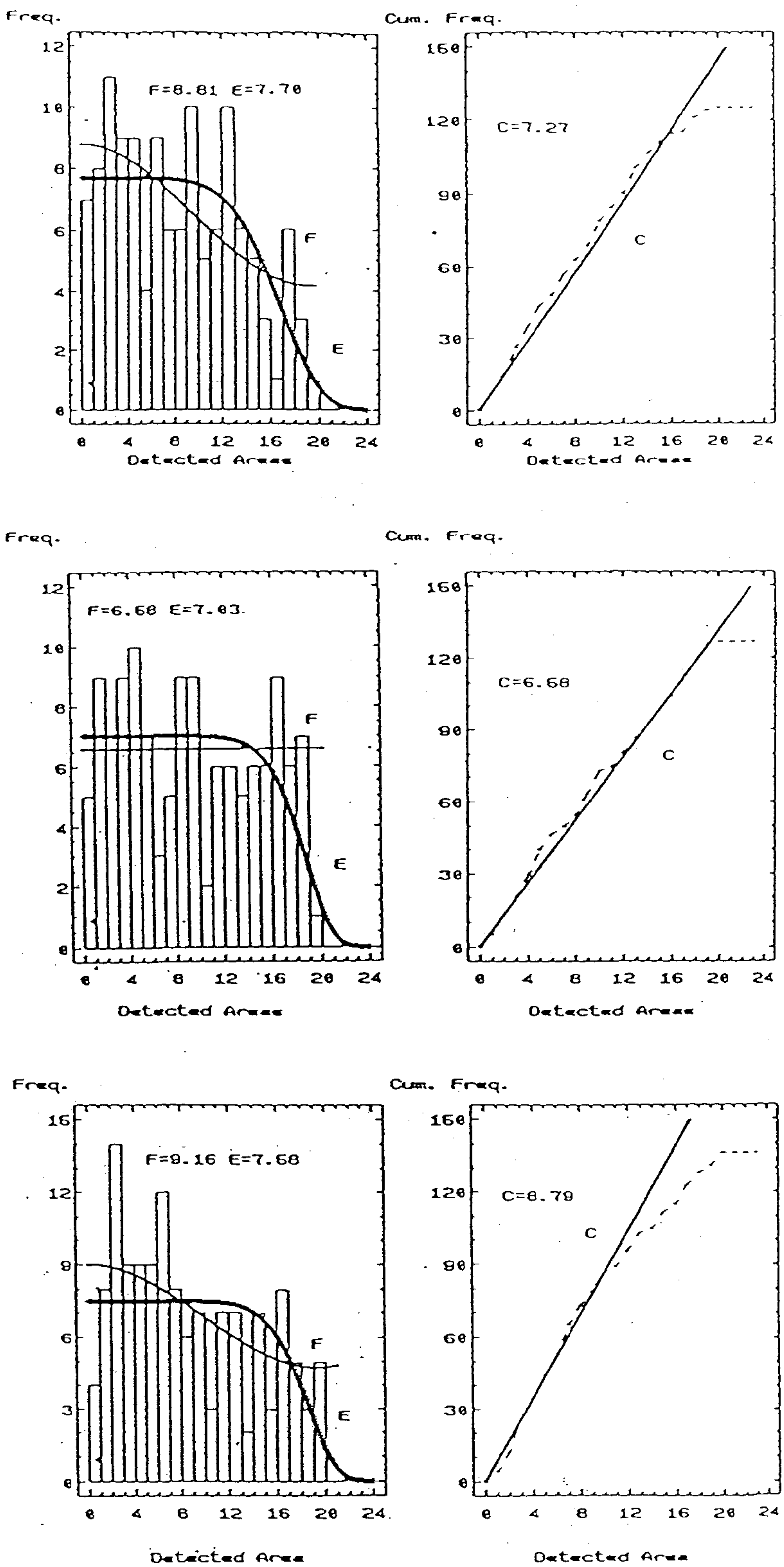


Figure 10.4.4 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding histograms, and density estimates when SAT=3 (81% of birds seen recorded).

10.5 Measurement Error

10.5.1 Background

Burnham et al. (1980), Emlen (1977) and Scott et al. (1981) stress that accurate measurement of distances is essential to any accurate estimate of bird density; Burnham even suggests that tape measure accuracy is the standard of measurement needed. Yet in many surveys, distances are not measured precisely but are estimated at the time of detection (Scott et al. 1986, Sen and Smith 1974). With bird surveys, where a large majority of detections are solely aural, distances to a guessed location must be estimated since physical measurement of the distances become impractical as the number of detections increase. Under such circumstances, one must realistically assume the distances are not error-free (Ramsey and Scott 1979, Wildman and Ramsey 1985). On the whole, observers vary in their ability to estimate distances to objects but are believed to quickly become accurate within ±10-15% when estimating distances to birds that can be seen (Emlen 1977) or heard (Scott and Ramsey 1981) under good field conditions. Variables that decrease the accuracy of distance measurements are: (1) large number of birds detected in a short time (0-20 seconds), (2) only one call or song heard, and (3) bird cues are heard when the observer is looking in a different direction (Scott et al. 1981).

Ramsey and Scott (1985) claim that the effects of low-to-moderate levels of measurement errors are negligible. Only for extreme measurement errors is the negative-bias in the estimators apparent, and the EPS is the estimator most seriously influenced. Burnham et al. (1980) claim that small random errors in measurement will not cause bias, but sampling variance will be increased. Schweder (1977) notes that systematic errors occur in measurements of perpendicular distances; however, it is the accuracy of measurements near the transect line that is crucial. Errors in measurement near the outer region are undesirable but are claimed to have far less effect on the estimate of density, because it is f(0) that must be estimated, not f(w).

There are several possible sources of measurement error: distances can be mismeasured, underestimated, overestimated, or rounded off to convenient figures. Scott et. al. (1981) claim there is some small tendency for observers to overestimate short distances and underestimate longer distance and that the density estimates become more severely biased as the magnitude of the error in distance estimation increases.

10.5.2 Simulation Study

The objective of this study was to introduce measurement error and then to examine how the FS performed. Because of time restrictions, only the FS estimator was investigated. Other estimators should be tested under different kinds of measurement error. Estimators that are sensitive to detections close to the transect (FS, Cum-D) should be compared to those sensitive to detections in the tail of the curve (EPS).

Two studies were undertaken, one where measurement error was proportional to detected area and the other where measurement error was random. Recall that detected area was used in VABS, instead of detected distance (Section 2.1), to estimate area. In the first study, measurement error was a fixed proportion of the true measurement. Otherwise, it simulated observers who always underestimated or overestimated distances. There were nine levels of proportional error; the first level being the correct measurement.

For the second study, measurement errors were random variates selected from either a logistic (symmetric) or log-logistic (skewed) distribution. The means of the logistic and the log-logistic distribution were set to the correct detected area, and the standard deviations were a proportion, c, of this detected area. See Appendix J for programming details.

10.5.3 Results

When the observer underestimated distance, the density was overestimated and vice-versa (Figure 10.5.1). However, when the error is proportional to the detected area, the percent of bias of the estimated area is that proportion (Table 10.5.1). If this proportion was known, density estimates could be adjusted. Nominal confidence levels were not being reached when distances where being underestimate by at least 10-20% or overestimated by at least 5-10% (Table 10.5.2). For the Fourier series, overestimates of distances were more critical than underestimates. The modest fraction of a large number of detections made near the observer but then overestimated may have accounted for a substantial fraction of the detections at intermediate distances.

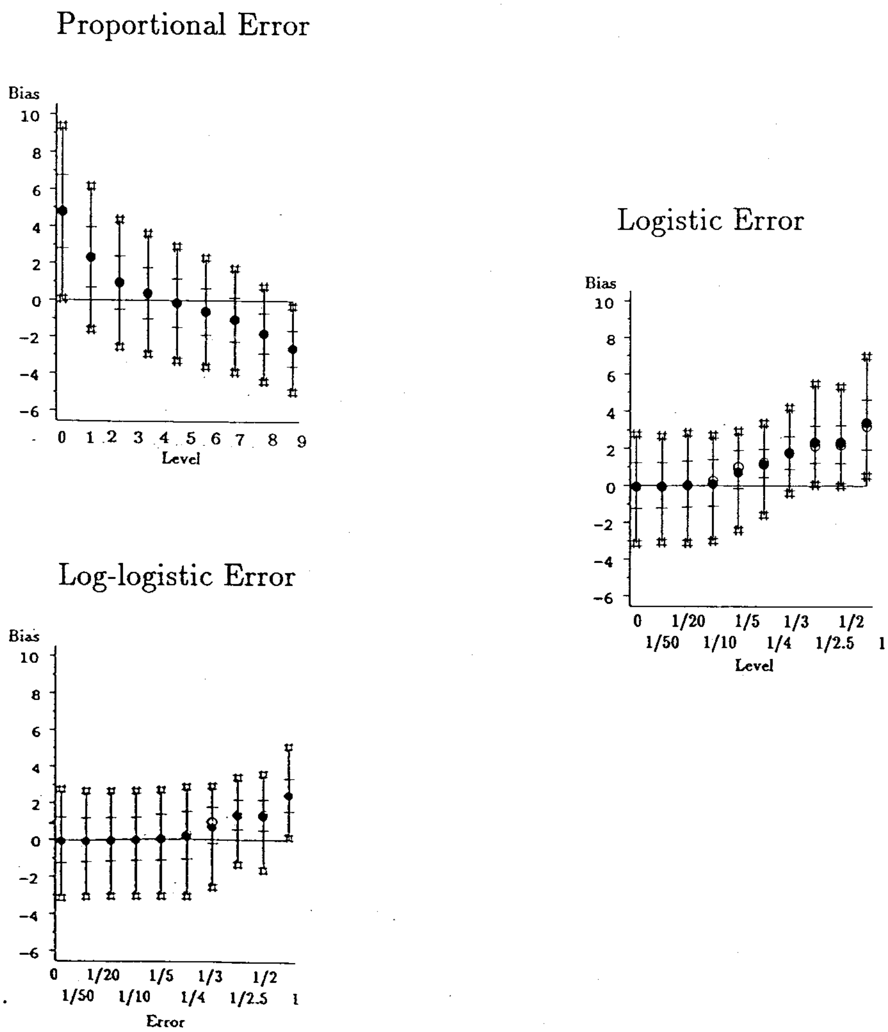


Figure 10.5.1 Bias of density estimates when measurement errors occured. Symbols: (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartiles, (#) 5^{th} & 95^{th} percentiles.

Table 10.5.1 Mean percent bias of effective area for fixed proportional error

%Error	Area	Mean % of bias
0	14.7	
-1/20	13.9	- 5.0
-1/10	13.2	-10.0
-1/5	11.7	-20.0
-1/3	9.8	-33.3
1/20	15.4	5.0
1/10	16.1	10.0
1/5	17.6	20.0
1/3	19.6	33.3

Table 10.5.2 Coverage* of nominal CI for fixed proportion measurement error.

CI	2/3	4/5	9/10	19/20	c* 1	21/20	11/10	6/5	4/3
95%	.596	.808	.938	.962	.956	.938	.912	.776	.536
99%	.778	.944	.982	.994	.994	.984	.972	.918	.754

*Levels of error; perp=c·perp′ (perp′ is the true detected distance)
*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99)

The second study showed that the FS estimate was robust to moderate random error, but as the standard deviation of the error increased, the estimate of effective area and the coverage of nominal confidence intervals decreased (Figure 10.5.1 and Table 10.5.3). In VABS, the larger detected distances succumbed to greater measurement error, changing the detection curve to one with a narrow shoulder and a longer tail (Figure 10.5.2). Not surprisingly, the FS fitted poorly when there was a narrow shoulder. The random logistic errors affected the density estimates sooner than the random log-logistic errors, due to what appears to be a less distinct shoulder.

Table 10.5.3 Coverage* of nominal CI for random measurement error

	No Error	1/50	1/20	1/10	c** 1/5	1/4	1/3	1/2.5	1/2	1
Logistic										
95%	.966	.960	.970	.968	.954	.938	.884	.804	.802	.598
99%	.994	.992	.996	.998	.992	.994	.972	.954	.958	.826
Log-logistic										
95%		.966	.970	.968	.966	.964	.956	.930	.910	.632
99%		.996	.992	.994	.996	.994	.992	.980	.984	.848

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
**Parameters of logistic and log-logistic are such that (μ=perp′,σ=c·perp′).

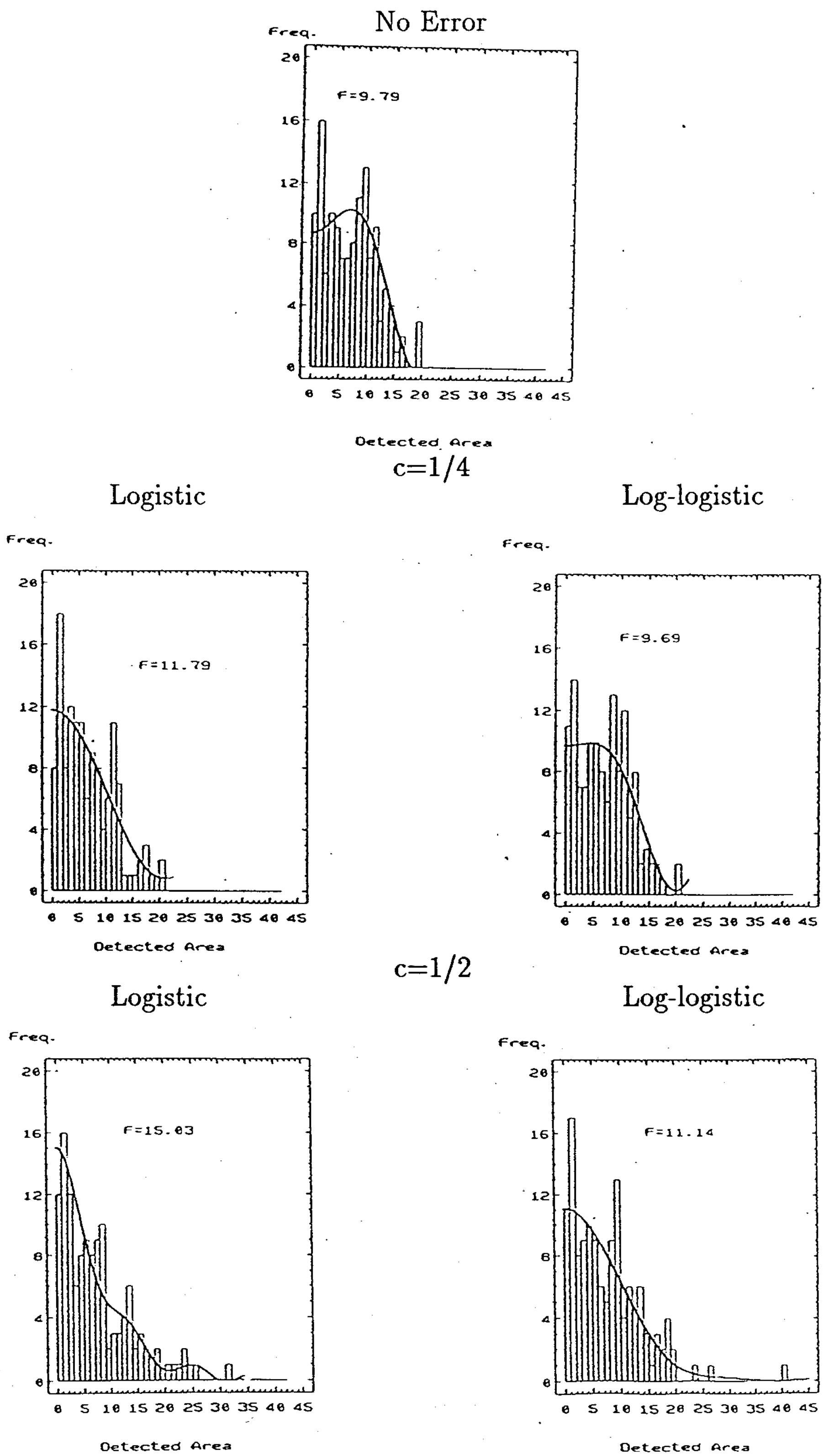


Figure 10.5.2 Examples of fitted FS (F), EPS (E), and Cum-D (C) curves, corresponding frequency histograms, and density estimates when random error occurs.

10.5.4 Conclusions

The FS is robust to moderate random measurement error, but not to fixed error. If distances are overestimated by five percent of the correct distance or underestimated by ten percent, the Fourier series estimator should not be used. However, if an independent estimate of fixed error is used to correct for measurement error, accurate estimates of density can be obtained. When fixed measurement error occurs and is not corrected, the observed detectability curve is different than the true detectabiltiy curve; otherwise, estimators could fit the observed curve but be biased. For this reason, it is unlikely that another estimator would be robust to measurement error; hence, the variable area survey should not be used to estimate density.

The Fourier series is robust to moderate random error. Unless the random error is highly variable (σ=25% of correct value), the variable area survey is appropriate to estimate density.

All efforts should be made to reduce measurement error, because not only does it lead to bias, but it also results in lower precision. The assumption of accurate recording of data is under at least partial control of the investigator; much innovation and improvement is possible in this area. Suggestions for reducing the bias in density estimates resulting from measurement errors include: (1) training observers, (2) flagging known distances, (3) using range finders, (4) explaining to observers the importance of their work, (5) minimizing the responsibilities of observers, (6) using robust methods to analyze data (Scott et al., 1981).

Burnham et al. (1980) believe grouping the data will often achieve a degree of robustness to certain types of measurement errors. Feature runs of VABS should compare the FS with the Cum-D and EPS and look into how grouping data helps ameliorate biases created by measurement error. Another study could model the overestimation of short distances and underestimation of larger distances.

10.6 Terrain

10.6.1 Background

Another kind of critical measurement error is when the measured detected area and the targeted region's area refer to two different measurements of area. More explicitly, when a density is given for a region, it is often given in terms of the two-dimensional area (base area) measured from a map and does not include the increased surface area caused by hills and valleys in the terrain. On the contrary, when an observer is out in the field, the detected distance is recorded as if a tape measure was laid on the ground. This measured distance is not equal to the distance between the two points if they were measured off a map (See Figure 10.3.1). As a result, the detected areas used to estimate density are for the surface area, not for the base area, but they are often viewed as the density for the base area. This discrepancy will result in biased estimates of population size if the density estimate for the surface area is multiplied by the base area.

If the slope of the terrain is known, theoretically, one can transform the detected surface area to the detected base area using the relationship $y'=y\cos\beta$. The objective of the study reported in this section was to demonstrate the bias in the density estimate when measures of detected area (surface area) do not correspond to the targeted area (base area) and demonstrate the need to transform the data.

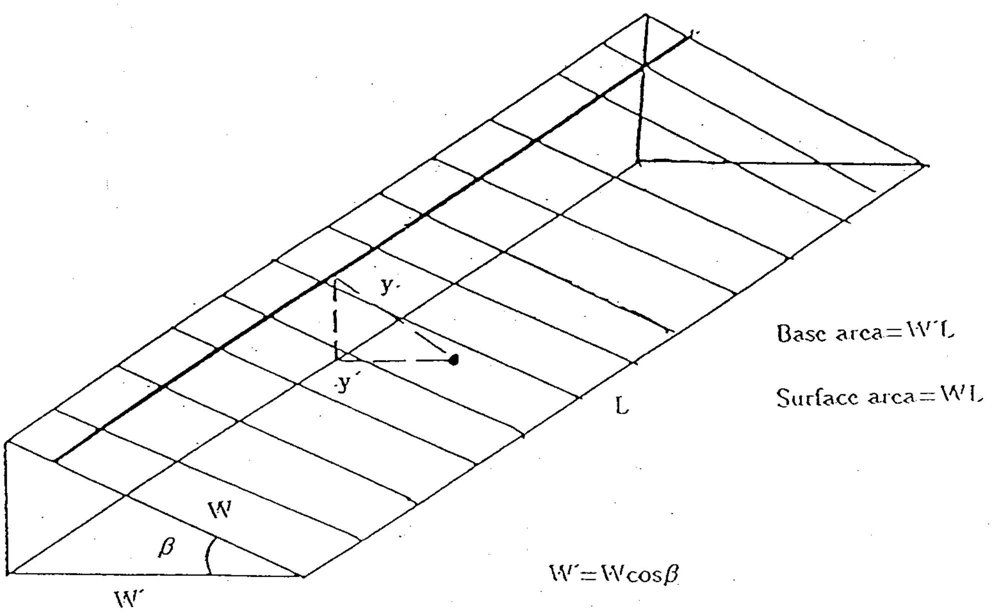


Figure 10.6.1 Comparison of the measured detected area when measured on the actual ground surface versus that measure off a map.

10.6.2 Simulation Study

To address these objectives, plots with a base area of 210 hectares were created with four different degrees of slope (variable SLOPE in VABS); $\pi/18$, $\pi/9$, $\pi/6$, and $\pi/3$. The detected area was measured in terms of the surface area then transformed to the detected base area. All three density estimates were calculated using the transformed and the untransformed data. The base density was fixed at 15 birds per hectare; corresponding surface densities are 14.8, 14.1, 13.0, and 7.5 birds per hectare, respectively (See Appendix E).

10.6.3 Results

From Table 10.6.1 and 10.6.2, it is clear that the density estimates derived from the detected area are in accordance with the density in terms of the surface area. Once the detected areas are transformed, the resulting density estimates have the desired coverage for the base area density.

Table 10.6.1 Coverage* of nominal CI for density of base area

		Cum-D		FS		EPS	
	SLOPE	y	$y\cos\beta$	y	$y\cos\beta$	y	$y\cos\beta$
95% CI							
	$\pi/18$	.980	.984	.946	.956	.916	.954
	$\pi/9$	.950	.986	.928	.958	.682	.938
	$\pi/6$	.842	.956	.816	.968	.292	.938
	$\pi/3$	.254	.870	.006	.966	.000	.952
99% CI							
	$\pi/18$	.990	.994	.992	.990	.976	.990
	$\pi/9$	.986	.996	.982	.996	.838	.978
	$\pi/6$	.992	.996	.934	.996	.504	.986
	$\pi/3$	.382	.924	.034	.998	.002	.980

*Critical values for α=.05 are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).

10.6.4 Conclusions

This study shows the importance of evaluating what is actually being measured. Note that this study only dealt with the measurement affecting the width of the area surveyed: the measurement of the length of the transect needs also to correspond to the dimension of the targeted area.

Table 10.6.2 Results for dimension of area: True density=15 birds/hectare

		Mean (se)					
		Cum-D		FS		EPS	
	SLOPE	y	ycosβ	y	ycosβ	d	ycosβ
$\hat{D}$	$\pi/18$	15.0	15.2	14.7	14.9	14.20	14.41
		(2.7)	(2.8)	(2.0)	(2.1)	(.75)	(.76)
	$\pi/9$	14.5	15.4	14.1	15.0	13.53	14.39
		(2.6)	(2.8)	(2.1)	(2.2)	(.77)	(.82)
	$\pi/6$	13.4	15.4	13.1	15.1	12.51	14.45
		(2.9)	(3.3)	(1.9)	(2.2)	(.77)	(.88)
	$\pi/3$	7.7	15.4	7.6	15.2	7.33	14.65
		(1.6)	(3.3)	(1.4)	(2.8)	(.67)	(1.35)
$\hat{SE}(\hat{D})$	$\pi/18$	4.2	4.2	2.19	2.23	1.10	1.11
		(3.3)	(3.3)	(.38)	(.38)	(.26)	(.27)
	$\pi/9$	4.1	4.1	2.12	2.25	1.05	1.12
		(2.8)	(2.8)	(.42)	(.45)	(.25)	(.82)
	$\pi/6$	3.9	3.9	2.03	2.35	1.01	1.16
		(2.8)	(2.8)	(.40)	(.47)	(.24)	(.28)
	$\pi/3$	3.0	3.0	1.49	2.98	0.81	1.63
		(2.7)	(2.7)	(.39)	(.78)	(.23)	(.47)

10.7 Overall Conclusions

The variable area survey should not be used to estimate density when:

(1) there is not 100% detectability on the transect and the probability of detection is not known for any other fixed distance,

(2) movement of birds or lack of visibility prevents the observer from detecting and negating multiple counts,

(3) bird abundance prevents the observer from being able to record all birds detected,

(4) observers are unable to measure distance within moderate random error.

Furthermore, there must be a correspondence between the measured detected area and the measured area of the region.

Evidence in this chapter suggest that the EPS is sensitive to violations of the standard assumptions that affect the tail area of the detectability curve and the FS and Cum-D are sensitive too those that affect the curve near the transect line.

11 DIFFERING DETECTION CURVES AND POOLING DATA

11.1 Motivation

The probability of detecting a bird at a given distance will vary as observational, biological, and environmental factors vary. Recognition of these factors has lead to skepticism regarding variable area surveys and their supporting statistical analysis (Dawson 1981, Verner 1985). Buckland (1980) stated that one can think of the total data set of detections as arising from pooled subsets of data that correspond to differing detection curves. Most factors will vary over space and time; for this reason, replicate transects are unlikely to have a constant detectability curve within and between themselves.

Some of the questions concerning differing detection curves are: (1) how robust is the variable area survey to differing detection curves? and (2) can data sets be pooled to increase sample size when detectability differed between sets. This chapter addresses these issues. The first and third sections examine the robustness of the variable area survey to differing detection curves. The second section discusses pooling data.

11.2 Variable Traversing Pace Within a Transect

11.2.1 Background

According to Reynolds et al. (1980), rates of travel along a transect vary with terrain, complexity of vegetation, and number of birds seen. As the traversing rate varies so does detectability (Section 6.5). Although much of this variability can be reduced by training observers, some variability is inclined to still exist. The objective of this section is to examine how the variable area survey performs when the traversing rate does vary, resulting in differing detectability curves within a transect.

11.2.2 Simulation Study

This study was similar to the one discussed in Section 6.5, but the average traversing rate was held constant between observers and the variance of the log-logistic variate was varied: at one extreme the transect was traversed at a nearly constant pace and on the other extreme the pace constantly fluctuated (Table 11.2.1).

Table 11.2.1 Parameter levels for log-logistic distribution for different traversing rates.

Observer	TT	SDTT	Mean time to traverse 1000 meters (minutes)	Standard deviation to traverse 1000 meters
1	-3.689	.0068	25	0.31
2	-3.690	.0276	25	1.25
3	-3.694	.0551	25	2.50
4	-3.700	.0827	25	3.75
5	-3.709	.1103	25	5.00
6	-3.720	.1378	25	6.25
7	-3.734	.1654	25	7.50

11.2.3 Results

There was no apparent difference between the density estimates (Figure 11.2.1) and the coverage of the 95% and 99% nominal confidence intervals for density (Table 11.2.2).

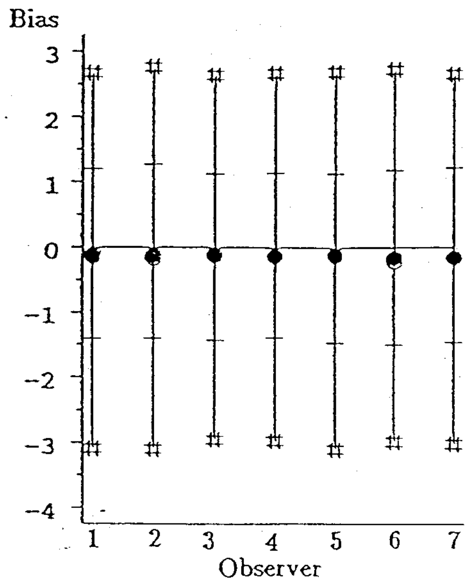


Figure 11.2.1 Bias of density estimates for constant average traversing rates between observers but with an increasingly uneven traversing pace within observers.

Table 11.2.2 Coverage* of nominal CI for different variabilities of traversing rates: FS estimator.

	Traversing Rate Variability						
Study II	.31	1.25	2.5	3.75	5	6.25	7.5
Nominal level 95%	.972	.956	.958	.954	.964	.970	.962
Nominal level 99%	.996	.996	.998	.998	.994	1.000	.996

*Critical values for $\alpha = .05$ are .934 (H_0:p $\geq$ .95) and .982 (H_0:p $\geq$ .99).
95% Cochran's Q statistic=9.48 (P=.14).
99% Cochran's Q statistic=6.67 (P=.35).

11.2.4 Conclusions

These results indicate that the variable area density estimate has the ability to pool data from continuously changing detectability curves in order to estimate a representative detectability curve for the whole transect and provide an adequate estimate of density. These results do not imply that observers can stop and watch birds for any length of time, but the variation in walking speed inherent of varying terrain is not a concern, unless extreme.

To test the tolerance of the variable area estimator for pooling detectability measures, a further study may divide the transects in sections where the mean traversing rats differs between sections.

11.3 Pooling Data

11.3.1 Background

To estimate density accurately and precisely via the variable area survey, 100 or more independent bird detections are necessary. It is difficult to acquire 100 detections under similar detectability conditions, especially for uncommon birds. To increase sample size, Ramsey et al. (1987) suggested that data gathered under different detectability curves can be pooled after the detected areas are adjusted for covariates that are known to influence detectability. This pooled data set can be used to examine detectability and then to derive adjusted density estimates for the different entities. Basically, Ramsey et al. (1987) treats effective area as a scale parameter for detection areas and uses the logarithm of effective area as a link to the covariates.

The questions concerning this approach are: (1) how robust are variable area survey density estimates to varying detection curves? and (2) when should adjusted data be pooled and effective area estimates be adjusted for covariates? This section deals with these questions.

11.3.2 Simulation Study

To examine the robustness of the variable area survey to different detectability curves, different transects were traversed with different detectabilities curves. Density was estimated using adjusted and unadjusted pooled data.

To adjust for the covariates, VABS employs Ramsey's et al. (1987) suggestion of using that least squares estimates for the coefficients in the regression equation,

$$\ln(Y_i)=\beta_0+\sum_{j=1}^{p}\beta_j X_j$$

where $X_1,\ldots X_p$ are linearly independent covariates. After the coefficients are estimated, each data point Y_i is adjusted using the equation

$$Y_i'=Y_i \exp(-\sum\hat{\beta}_j X_j).$$

Pooling the adjusted data, the cumulative density is estimated as $\sum\hat{D}_j$, where the D_j's are the individual transect's density estimates,

$$\hat{D}_j=\frac{n_j}{\hat{\alpha}\exp(\sum\hat{\beta}_j X_j)}.$$

When there were just two transects, the least squares equations for $\hat{\beta}_0$ and $\hat{\beta}_1$ were used, but for more than two transects, the Gauss elimination method was used to solve the set of linear equations. The Gauss elimination method was sufficient for this study, but problems with inverting the matrix occurred when there were extreme differences in detectability. A method that transforms a given matrix into a more desirable form and has been ranked high in numerical stability and efficiency, such as the orthogonal triangular algorithm suggested by Kennedy and Gentle (1980), would be more suitable.

The first two studies simulated the traversing of five transects. The bootstrap estimate of the standard error of $\hat{D}$ was calculated using two different bootstrap samples: (1) A bootstrap sample of the original data was drawn and all previously mentioned steps to adjust the data were taken to estimate density. (2) A bootstrap sample of the adjusted data was drawn from which estimates of area were calculated. The last four studies had an increasing difference in detectabilities between the two traversed transects. For the adjusted data, the bootstrap sample was drawn from the original data, but the numerator of the density estimate was calculated by three methods: (1) The n_i's were held fixed and summed. (2) A bootstrap sample of the n_i's from the different transects were summed. (3) To represent the number of detections in a common area, the n_i's where adjusted using the equation,

$$n_i' = \hat{D}_i \, e^{-\beta_i x_i},$$

before a bootstrap sample was drawn and then readjusted,

$$n_j'' = n_i' e^{\beta_j x_j},$$

for the j^{th} bootstrap sample. Table 11.3.1 list the values of the variables that were varied in VABS between transects. See Appendix K for programming details.

Table 11.3.1 Variable levels for studies on varying detectability curves.

Transect	DA	PERF	THETA	DA	Tree Density	Bird Density
Study I						
1	.05	85	.125	100	0	2
2	.06	80	.10	90	0	2
3	.07	75	.075	80	0	2
4	.08	70	.05	70	0	2
5	.09	60	.025	60	0	2
Study II						
1	.07	75	.125	100	10	2
2	.07	75	.10	90	100	2
3	.07	75	.075	80	200	2
4	.07	75	.05	70	250	2
5	.07	75	.025	60	300	2
Study III						
1	.07	75	.3	100	0	5
2	.10	70	.1	70	0	5
Study IV						
1	.07	75	.3	100	0	5
2	.15	65	.01	60	0	5
Study V						
1	.07	75	.3	100	0	5
2	.175	60	.007	50	0	5
Study VI						
1	.07	75	.3	100	0	5
2	.20	55	.003	40	0	5

11.3.3 Results

The average number of detections for each transect traversed and the average percent of these detections made by audio means is reported in Table 11.3.2. The density estimates in Study I and II, where detectability differed slightly, appear comparable except for a possible small difference in the variance (Table 11.3.3 and Figure 11.3.1). Coverage of the confidence intervals for density was sufficient when the bootstrap sample was drawn from the original data but noticeably low when drawn from the adjusted data. Hence, it appears necessary to account for the variation in the coefficient estimates if desired coverage is going to be achieved for the density estimates.

Table 11.3.2 Observer statistics.

Transect	Number Detect Mean	(se)	%Audio Mean	(se)
Study I				
1	36.9	(3.9)	39.8	(15.0)
2	29.0	(3.8)	35.2	(8.9)
3	23.3	(3.7)	27.2	(9.4)
4	19.1	(3.7)	18.5	(9.2)
5	15.0	(3.4)	8.7	(7.4)
Study II				
1	26.2	(3.7)	37.5	(9.4)
2	21.7	(3.9)	36.3	(10.7)
3	18.7	(3.5)	34.5	(11.2)
4	16.8	(3.5)	29.2	(11.2)
5	16.0	(3.4)	23.2	(9.8)
Study III				
1	80.8	(6.0)	81.1	(4.5)
2	42.3	(5.6)	38.8	(7.2)
Study VI				
1	80.8	(6.0)	81.0	(6.0)
2	20.9	(4.3)	6.5	(5.8)
Study V				
1	81.1	(6.1)	81.1	(4.7)
2	16.1	(3.8)	4.2	(5.1)
Study VI				
1	81.2	(6.2)	81.2	(4.5)
2	12.3	(3.5)	1.5	(3.6)

Studies III-VI demonstrated the increasing need to adjust the data as differences in detectabilities increase. As the difference in detectabilities increased, the estimates derived from the unadjusted data increasingly underestimated density, especially the EPS density estimates (Figure 11.3.2). Adjustment of the data improved the density estimates; however, the variance of the estimates increased as the differences in detectabilities increased. Not accounting for the variance in the numerator of the density estimate provided sufficient coverage for the FS and Cum-D estimates until the differences in detectability became extreme and the standard errors were underestimated. It is necessary to account for the variation in the n_i's when using the EPS. Table 11.3.3 and Figure 11.3.3 show that adjusting the n_i's for area before drawing a bootstrap sample was optimal, compared to using unadjusted n_i's in the bootstrap sample. Figure 11.3.3 through 11.3.5 show that this methodology resulted in some very wide intervals; however, this was likely the result of having only two transects to draw a bootstrap sample of n_i from. Future runs of VABS should increase the number of transects with different detectabilities to confirm these conjectures.

Table 11.3.3 Results of pooling data (Study I and Study II): True Density=2 birds/hectare.

Method	Est.	Coverage* 95%	99%	Mean (se) $\hat{D}$		$\hat{SE}(\hat{D})$	
Study I							
Unadjusted	Cum-D	.978	.990	1.99	(.42)	.79	(.64)
	FS	.982	.996	2.05	(.31)	.36	(.08)
	EPS	.716	.816	2.00	(.24)	.13	(.05)
Adjusted (original)	Cum-D	.982	.994	2.10	(.44)	.68	(.58)
	FS	.984	1.000	2.07	(.42)	.50	(.11)
	EPS	.968	.992	2.19	(.31)	.45	(.40)
(adjusted)	Cum-D	.954	.948			.57	(.51)
	FS	.864	.944			.34	(.07)
	EPS	.586	.754			.15	(.05)
Study II							
Unadjusted	Cum-D	.954	.972	2.00	(.53)	.90	(.76)
	FS	.962	.986	2.02	(.39)	.39	(.10)
	EPS	.912	.960	2.00	(.31)	.34	(.15)
Adjusted (original)	Cum-D	.966	.992	2.05	(.49)	.79	(.62)
	FS	.976	.994	2.11	(.44)	.49	(.11)
	EPS	.966	.992	2.19	(.36)	.56	(.77)
(adjusted)	Cum-D	.896	.988			.63	(.52)
	FS	.860	.948			.32	(.09)
	EPS	.770	.892			.22	(.10)

*Critical values for $\alpha = .05$ are .934 (H_0:$p \geq .95$) and .982 (H_0:$p \geq .99$).

11.3.4 Conclusions

In conclusion, detected areas and density estimates should be adjusted for covariates if differences in detectability are noticeable or if separate density estimates are needed. Extreme differences in detectability should be avoided since precision will be poor. For the EPS and when differences in detectabilities are extreme, accounting for the n_i's in the bootstrap estimate of standard error is necessary. When overdispersion or clustering of birds occurs, it is perceptible that accounting for the variance in the n_i's will be necessary to achieve the desired coverage for all estimates. The concern Verner (1985) and Dawson (1981) have about non-constant detectability appears unjustified, since the variable area survey methodology will provide accurate density estimates without adjustments when differences are moderate, and with covariate adjustment, accurate density estimates can be calculated when differences are noticeable.

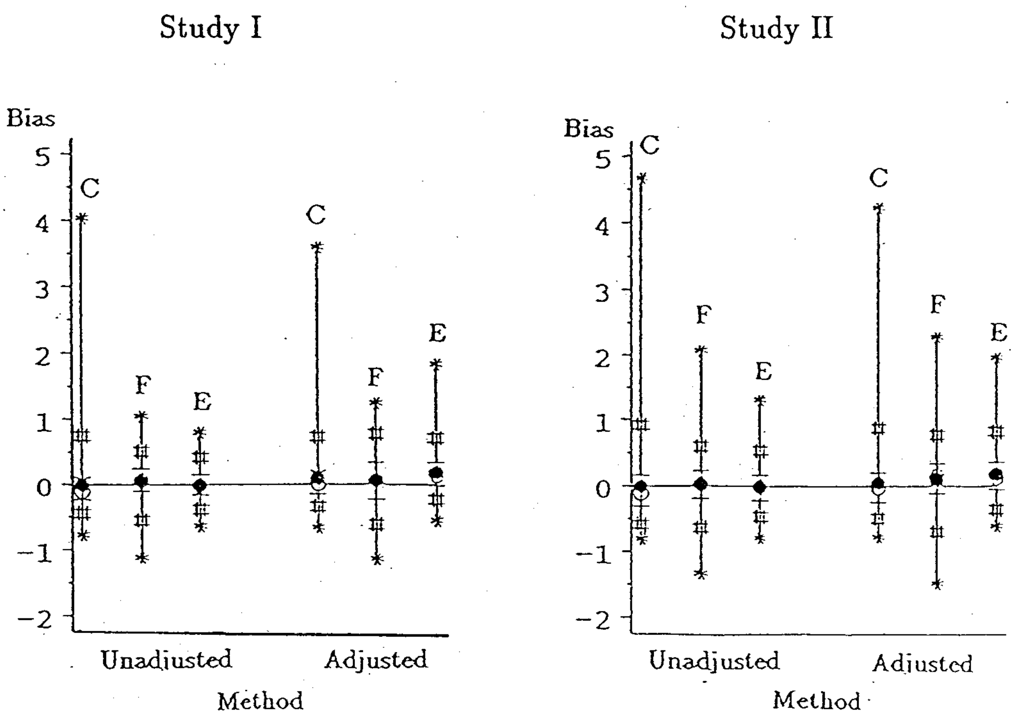


Figure 11.3.1 Bias of density estimates for Study I and II for unadjusted and adjusted data for all three estimators. Code: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (−) 1^{st} & 3^{rd} quartiles, (#) 5^{th} & 95^{th} percentiles.

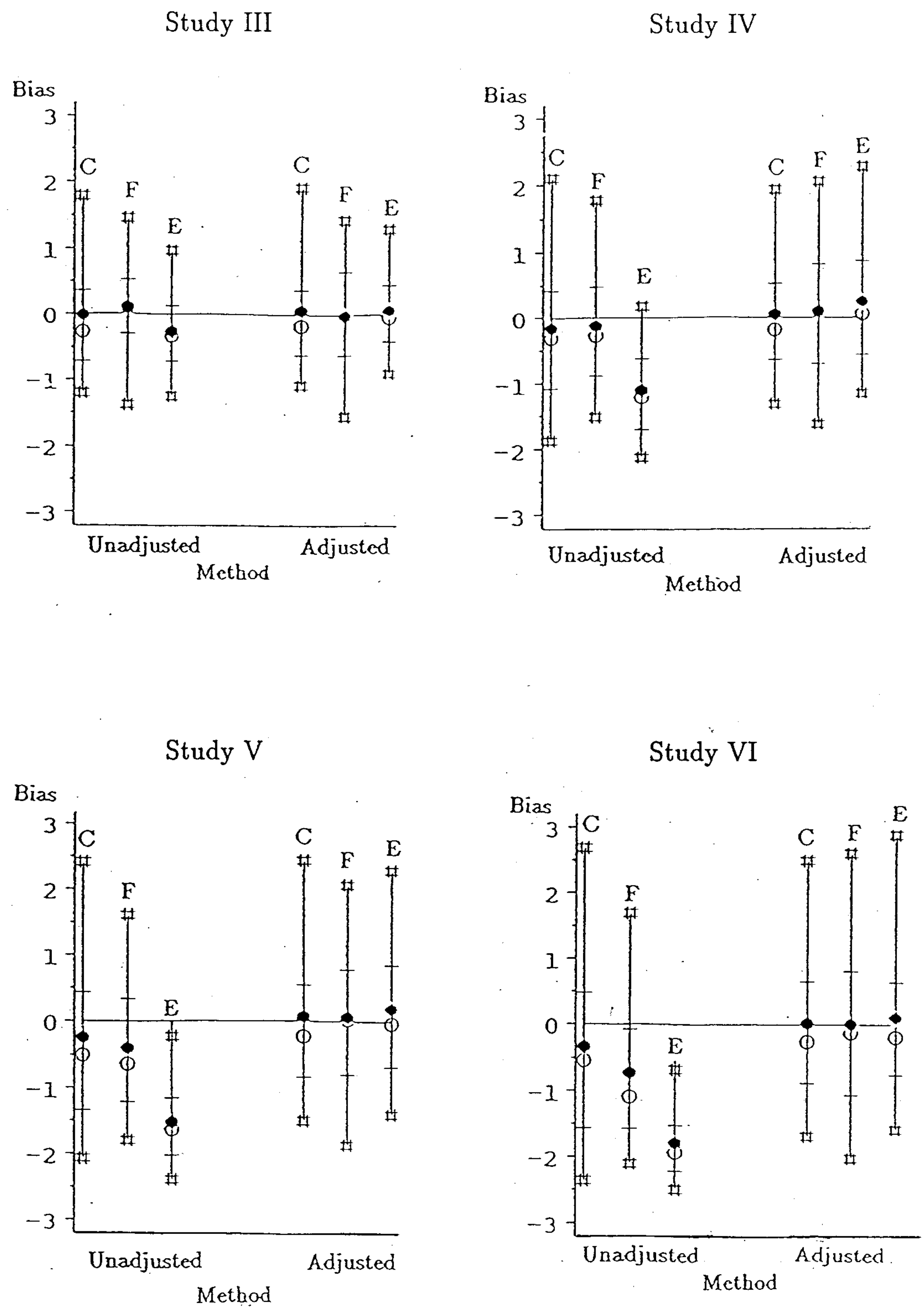


Figure 11.3.2 Bias of density estimates for Study III to VI for unadjusted and adjusted data for all three estimators. Code: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartiles, (#) 5^{th} & 95^{th} percentiles.

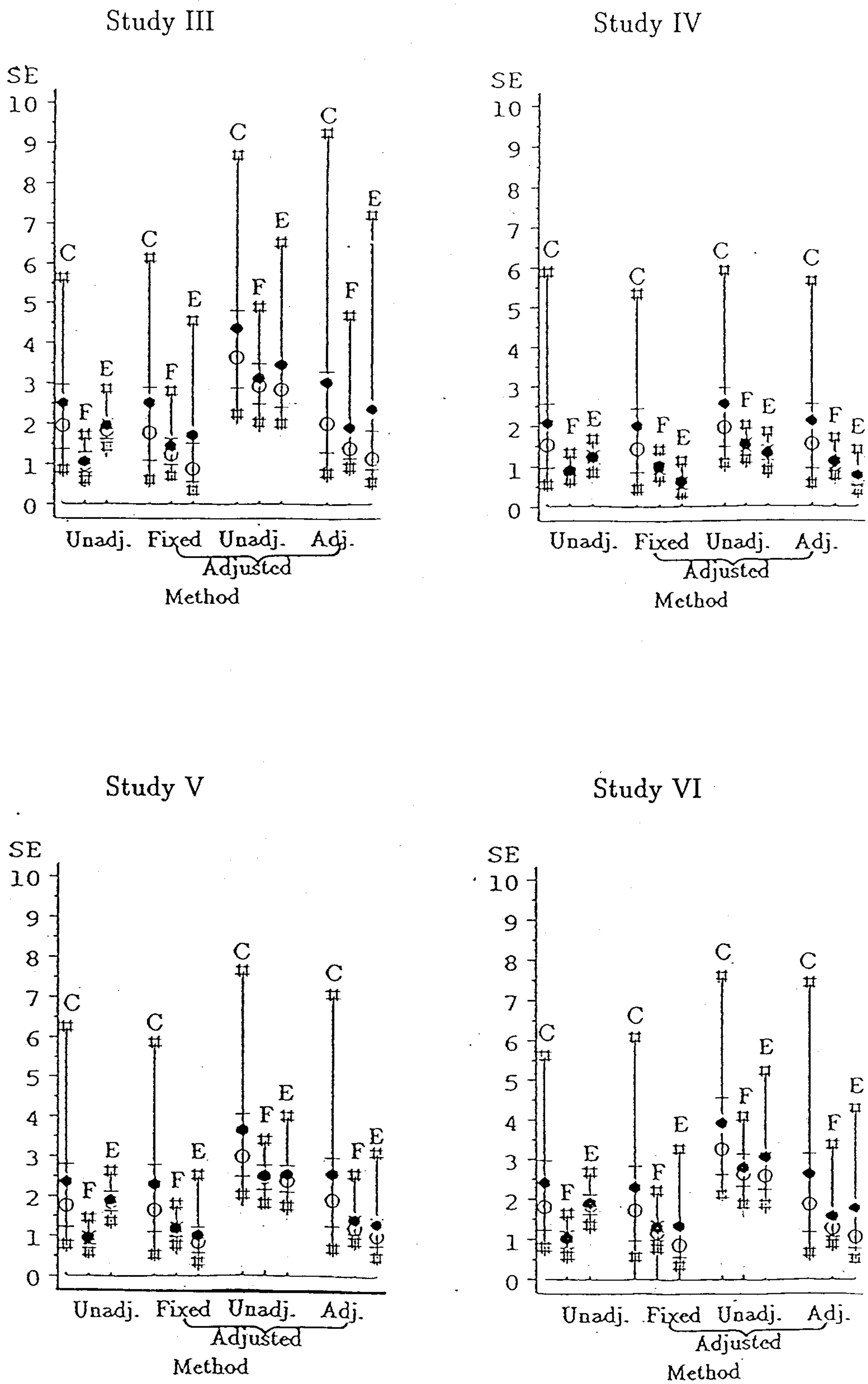
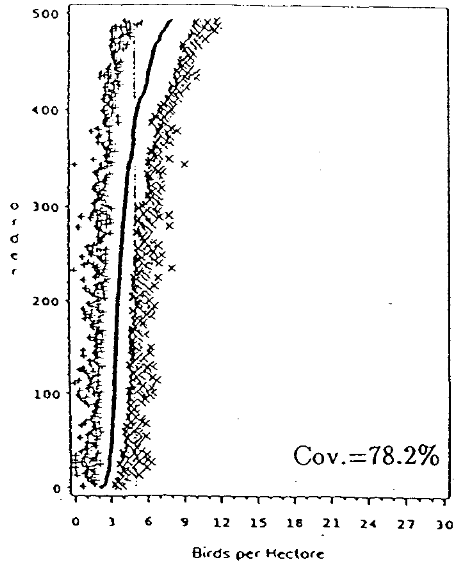
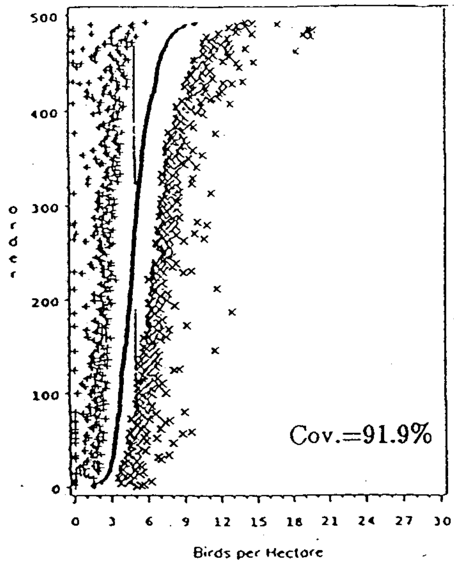


Figure 11.3.3 Estimated standard errors for the density estimates for Study III to VI for all methods and estimators (Cov.=coverage). Code: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (–) 1^{st} & 3^{rd} quartiles, (#) 5^{th} & 95^{th} percentiles.

Unadjusted Areas



Adjusted Areas
(n_i's are fixed)



Adjusted Areas
(n_i's adjusted)

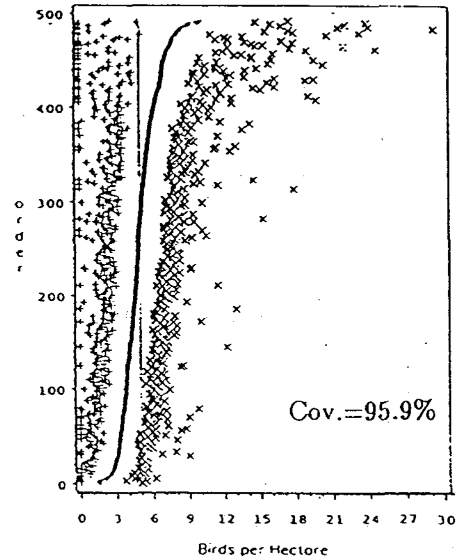


Figure 11.3.4 Ordered FS density estimates and corresponding 95% confidence limits for pooled data (Cov.=coverage). Above figures are from Study VI when data is (1) pooled without adjusting and when (2) data is adjusted, but the bootstrap estimate of standard error is calculated with (2a) n fixed n and (2b) n_i's are adjusted.

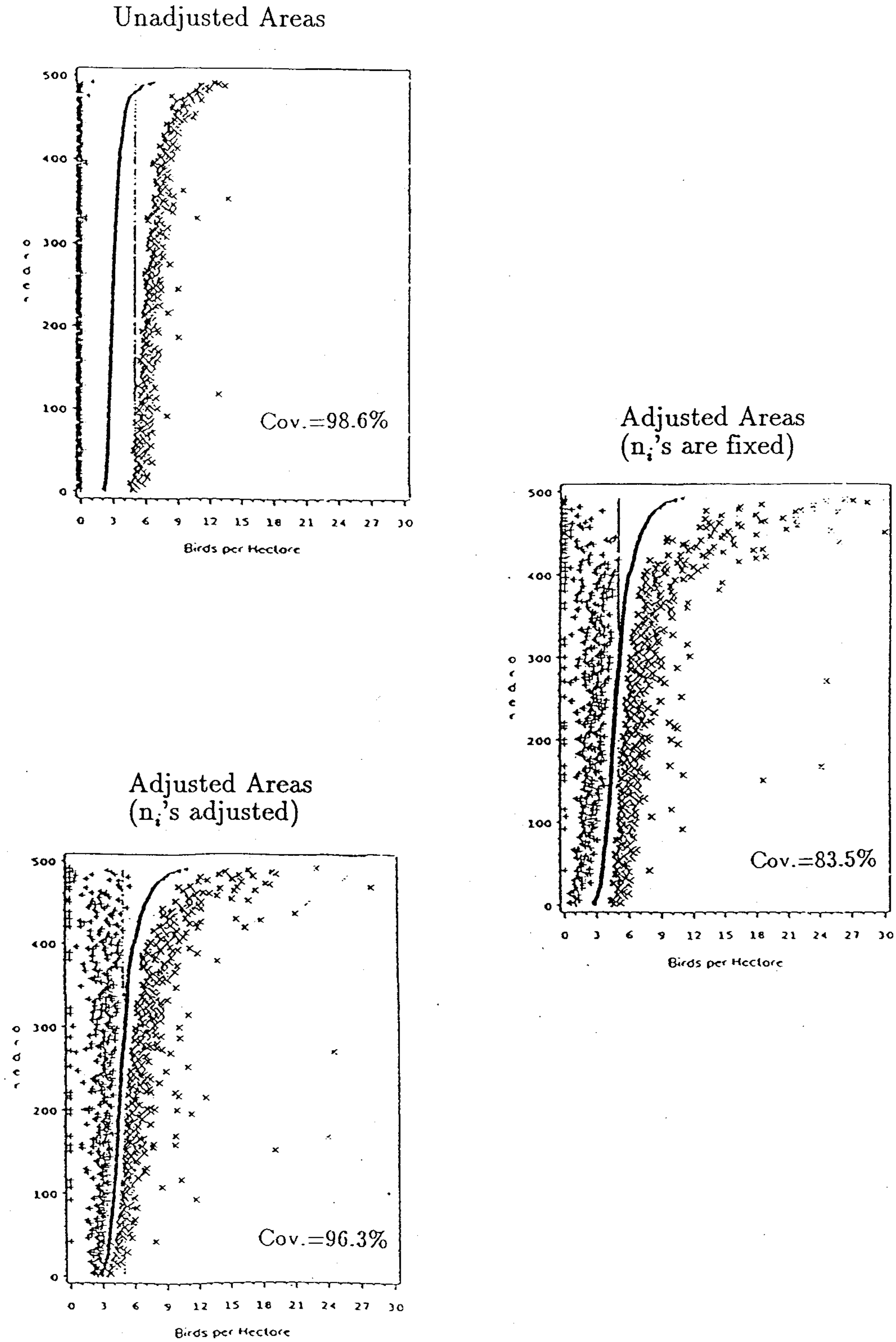


Figure 11.3.5 Ordered EPS density estimates and corresponding 95% confidence limits for pooled data (Cov.=coverage). Above figures are from Study VI when data is (1) pooled without adjusting and when (2) data is adjusted, but the bootstrap estimate of standard error is calculated with (2a) n fixed and (2b) n_i's are adjusted.

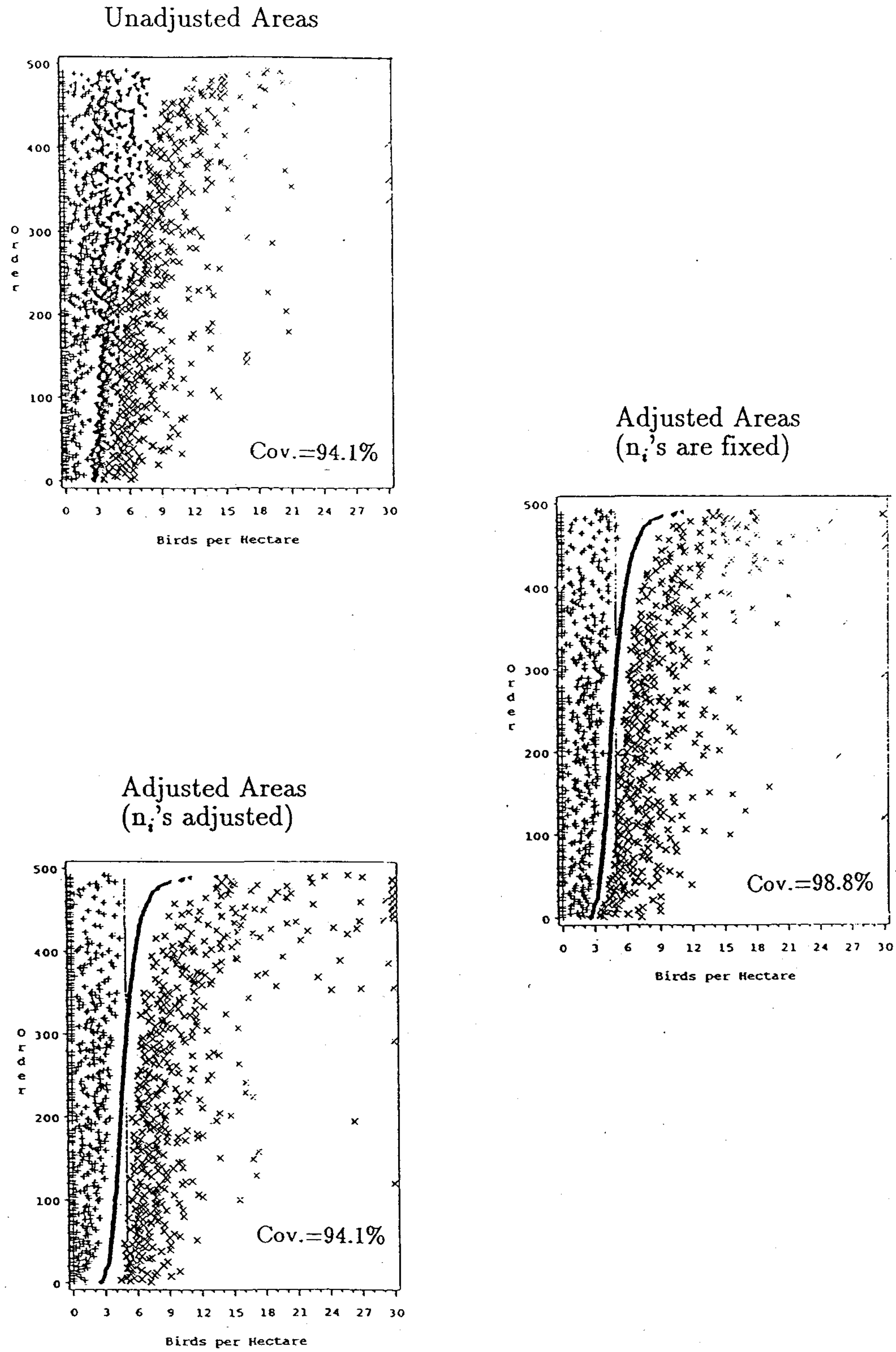


Figure 11.3.6 Ordered Cum-D density estimates and corresponding 95% confidence limits for pooled data (Cov.=coverage). Above figures are from Study VI when data is (1) pooled without adjusting and when (2) data is adjusted, but the bootstrap estimate of standard error is calculated with (2a) n fixed and (2b) n_i's are adjusted.

11.4. Birds Perch in Trees on a Hillside

11.4.1 Background

What happens to the variable area density estimate when the transect is placed along a forested hillside? Figure 11.4.1 demonstrates that two birds, one uphill and the other downhill of the observer, perched on a tree equal distance away from the observer and at the same height have equivalent recorded detected areas, yet their detection probabilities are different.

The objective of the studies reviewed in this section was to examine how robust the variable area density estimates are to differing detectability curves attributed to birds perched in trees on a hillside. The program DETECT was altered such that the distance between the bird and the observer was

$$\text{DIST}=\begin{cases} (y^2+x^2+h^2-2xh\cdot\cos(\frac{\pi}{2}+\beta_0))^{\frac{1}{2}} & (\text{obsx-b}_x)\leq 0 \\ (y^2+x^2+h^2-2xh\cdot\cos(\frac{\pi}{2}-\beta_0))^{\frac{1}{2}} & (\text{obsx-b}_x)>0 \end{cases}$$

where $x=|\text{obsx-b}_x|$, $y=|\text{obsy-b}_y|$, h=bht (height above ground level, and β_0=slope. See Appendix E.

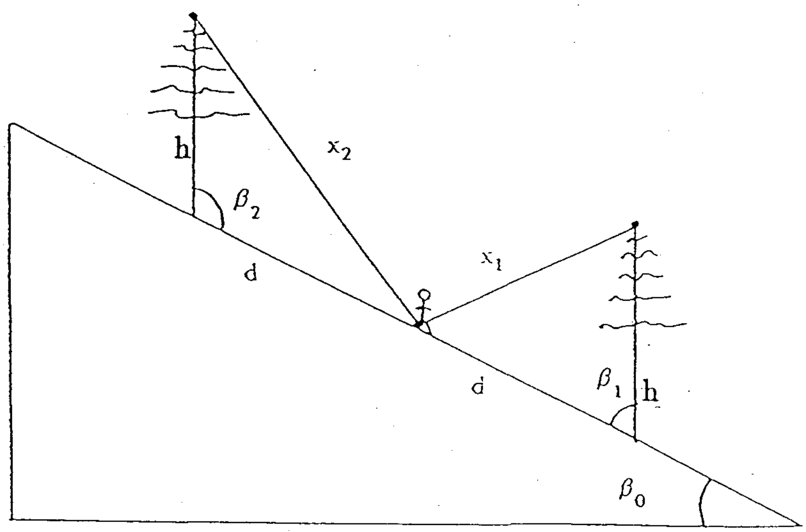


Figure 11.4.1 Equal detected distances for two birds that are an unequal distances from the observer when the birds are perched in trees on a hillside.

11.4.2 Birds at a Fixed Height

The first study did not include a slope or trees but just placed birds a fixed height, BHT, above ground level. Hence, the detectability curve did not vary within a fixed height, but as the fixed height became greater the detectability curve declined more rapidly. As HT increased, the density estimates for all models were low indicating that the effective area surveyed was being overestimated, especially for the EPS estimator (Table 11.4.1 and Figure 11.4.2). Beware, as the bird's height above ground level increases, the probability of detection for a bird above the transect line (y=0) decreases, explaining the increasing negative-biased density estimates.

Table 11.4.1 Results for birds at a fixed height.

	BHT	Cum-D	Mean FS	EPS
$\hat{D}$	10	10.2	9.9	10.0
	20	10.3	10.0	10.0
	30	10.2	9.9	9.9
	40	9.8	9.8	9.5
	50	9.1	9.3	8.9
$\hat{SE}(\hat{D})$				
	10	3.8	1.9	1.1
	20	3.8	1.9	1.2
	30	4.0	1.9	1.2
	40	4.2	1.9	1.3
	50	4.0	1.9	1.4

11.4.3 Birds at a Random Height

The second study was similar to the first study, but the height the bird was placed at was selected from a U(0,HT) distribution. This study differs from the previous because detectability curves now vary within the gathered data set. With this variation in height, the detectability curves were not as steep, and the tails were longer. For the higher heights, the density estimates appear to be less bias for birds at a random height than at a fixed height (Table 11.4.2, Slope=0). This result suggests that the variable area survey is robust to some variability in the detection curves, but all birds on the transect line must be detected.

The third study included a slope on the terrain as well as birds at a random height, increasing the variability in detection. The FS and Cum-D models had accurate density estimates; however, the EPS had a tendency to underestimate density (Table 11.4.2).

Table 11.4.2 Mean estimates of $\hat{D}$ and $\hat{SE}$ for birds located at a random height.

	HT	Slope	Means Cum-D	FS	EPS
$\hat{D}$					
	10	0	10.3	10.2	10.5
		$\pi/18$	10.2	10.1	9.6
		$\pi/9$	10.1	9.8	9.6
		$\pi/6$	10.3	10.0	9.7
	20	0	10.3	10.6	10.5
		$\pi/18$	10.2	9.8	9.7
		$\pi/9$	10.3	10.0	9.6
		$\pi/6$	10.2	10.0	9.6
	30	0	10.2	10.6	10.4
		$\pi/18$	10.1	10.1	9.6
		$\pi/9$	10.2	10.0	9.7
		$\pi/6$	10.1	9.9	9.6
	40	0	10.2	10.3	9.7
		$\pi/18$	10.0	10.0	9.5
		$\pi/9$	10.1	10.0	9.5
		$\pi/6$	10.2	10.1	9.6
	50	0	10.0	10.3	9.6
		$\pi/18$	10.1	10.0	9.5
		$\pi/9$	10.1	10.1	9.5
		$\pi/6$	9.9	9.9	9.5
$\hat{SE}(\hat{D})$					
	10	0	4.0	2.0	1.4
		$\pi/18$	3.4	1.8	.9
		$\pi/9$	3.4	1.8	1.0
		$\pi/6$	3.8	1.9	1.0
	20	0	4.6	1.9	1.8
		$\pi/18$	3.4	1.8	.9
		$\pi/9$	3.6	1.8	1.0
		$\pi/6$	3.9	1.9	1.1
	30	0	4.9	1.9	2.0
		$\pi/18$	3.5	1.8	1.0
		$\pi/9$	3.3	1.8	1.0
		$\pi/6$	3.6	1.9	1.1
	40	0	4.9	1.8	2.1
		$\pi/18$	3.4	1.8	1.0
		$\pi/9$	3.5	1.8	1.0
		$\pi/6$	3.8	1.9	1.1
	50	0	4.9	1.9	2.3
		$\pi/18$	3.6	1.8	1.1
		$\pi/9$	3.8	1.8	1.1
		$\pi/6$	3.9	1.9	1.2

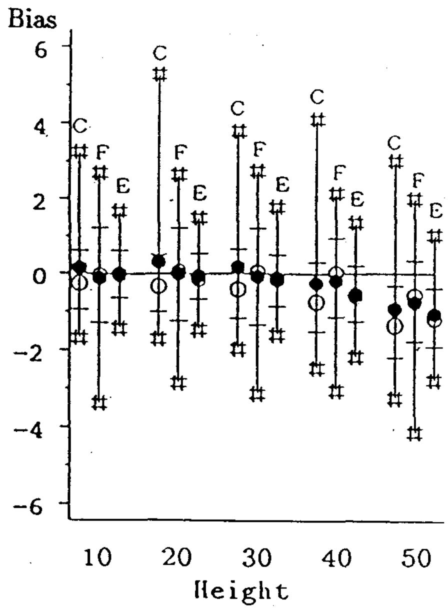


Figure 11.4.2 Bias of density estimates for birds at a fixed height (slope=0). Symbols: (C) Cum-D, (F) FS, (E) EPS, (•) mean, (∘) median, (−) 1^{st} & 3^{rd} quartile, (#) 5^{th} and 95^{th} percentile.

11.4.4 Robustness of Density Estimates to Birds Perched in Trees on a Hillside

The final study placed birds perched in trees on a hillside. This study differs from the others, because of the additional factors introduced by placing birds in trees. The bird's location on a tree was determined randomly. The height of a tree ranged from about 2.5 meters to 70 meters. Tree density was fixed at 100 trees per hectare and bird density was fixed at 20 birds per hectare.

All estimators tended to underestimate density (Figure 11.4.3 and 11.4.5); however, the slope appeared to have little influence. This final study involves multiple factors that could account for the underestimation of density. Previous simulations did not implicate vegetation or bird distribution as a cause for negative-biased bird density estimates when there were 100 trees per hectare. However, the previous two sections would suggest that either $g(0) \neq 1$ or differing detectability curves could be the cause of negative-biased density estimates.

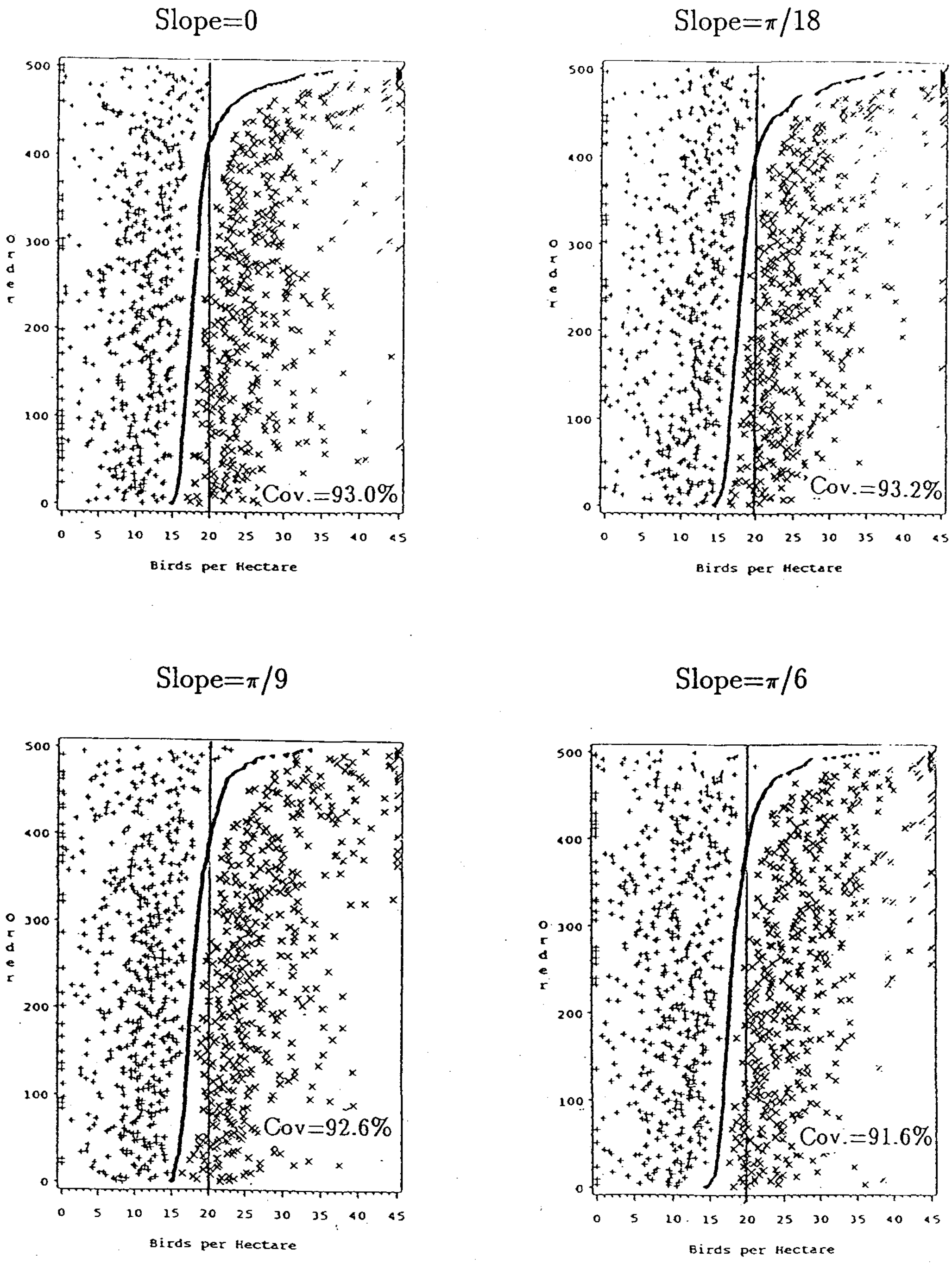


Figure 11.4.3 Ordered Cum-D density estimates and corresponding 95% confidence limits for birds perched in trees on a hillside (Cov.=coverage).

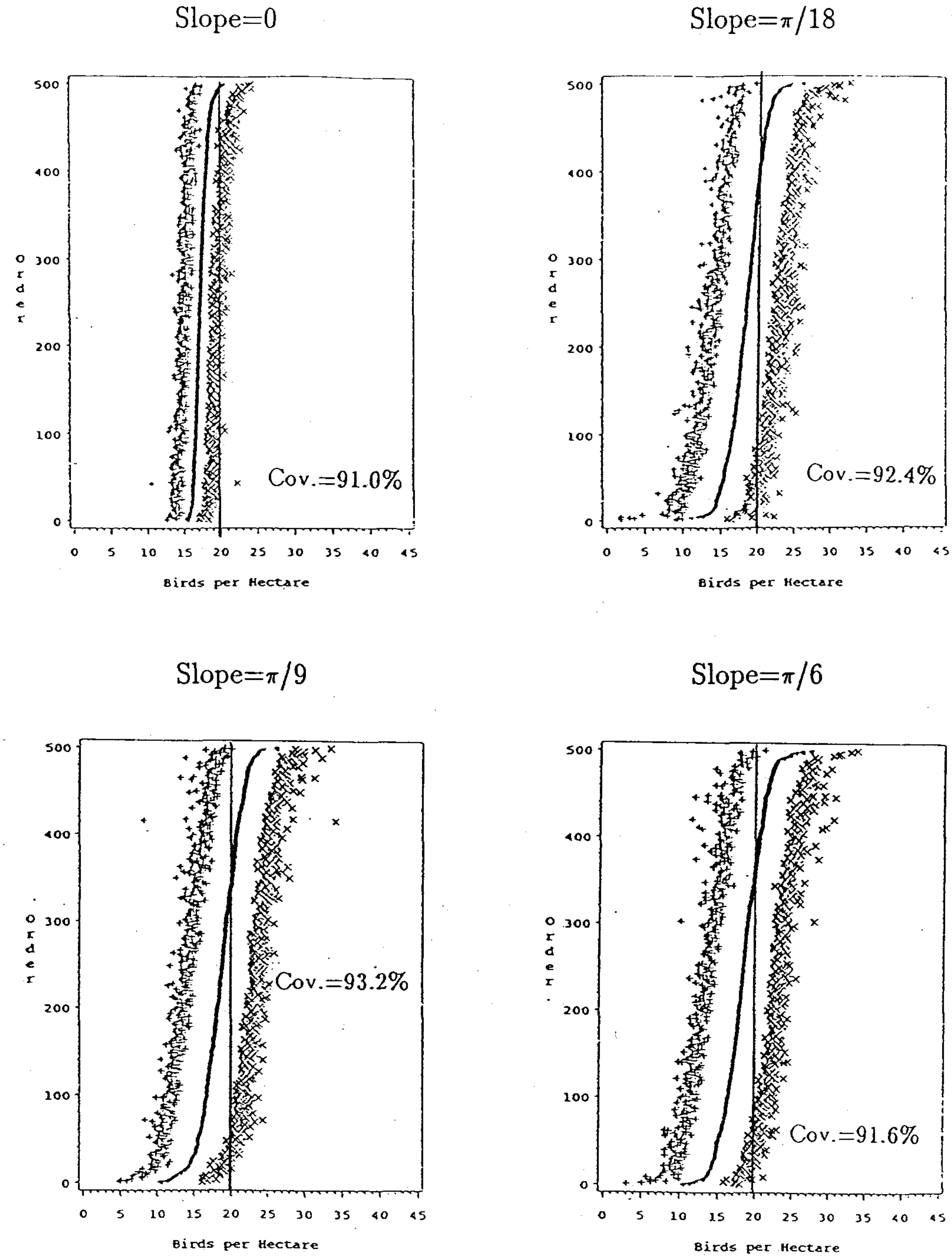


Figure 11.4.4 Ordered FS density estimates and corresponding 95% confidence limits for birds perched in trees on a hillside (Cov.=coverage).

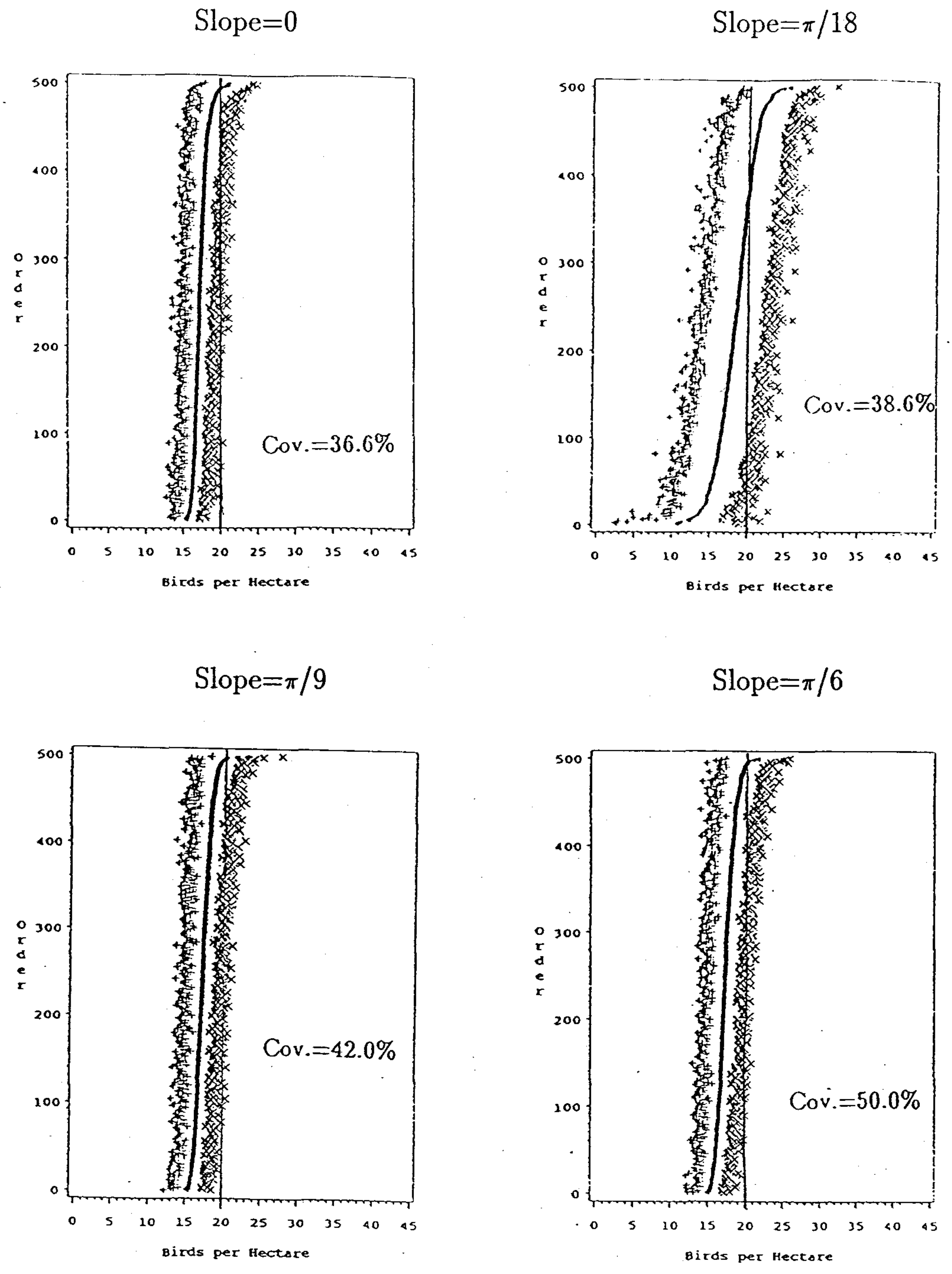


Figure 11.4.5 Ordered EPS density estimates and corresponding 95% confidence limits for birds perched in trees on a hillside (Cov.=coverage).

11.4.5 Conclusions

If differing detection curves are the cause of the negative-biased density estimates seen in the last study, then covariates accounting for the height of the bird's location is detected at and whether the bird is uphill or downhill from the observer should provide more accurate density estimates. If birds are perched high enough above the observer that the assumption g(0)=1 is invalid, then variable area surveys should not be used to estimate density.

In the previous studies, the height of the bird's location was limited by the variable HT or the heights of the generated trees. Evidence suggest that height will become more of a factor if birds are counted that are in flight above tree line. For this reason and the problems brought on by bird movement, birds detected in flight should not be counted unless the point from which flight originated can be determined and is within the region. Birds that take quick, short flights, such as swallows and flycatchers, to feed on insects may be an exception to this rule.

11.5 Overall Conclusions

The variable area survey is robust to moderate differing detection curves; however, areas should be adjusted for covariates known to influence detectability significantly. Any factor that is known to influence detectability should be controlled, and if significant differences in detectability are unavoidable, the factor should be treated as a covariate and detected areas appropriately adjusted.

Data sets can be pooled if they are adjusted for covariates. In this manner, detections of uncommon species can be pooled with detections of similar but more abundant species in order to derive adjusted density estimates of the uncommon species.

12 FURTHER WORK

The previous chapters have supported the use of the variable area survey to estimate density and monitor populations when critical assumptions are meet. However, there are still several questions that need to be answered such as: (1) How should confidence intervals for density be approximated? (2) What procedures should be used to select the estimator? (3) How do the interactions between the various factors influence bird counts? (4) What are the benefits of the variable circular plot? The next four sections describe how VABS can be used to address these questions.

12.1 Approximating Confidence Intervals for Density

Proper approximations of confidence intervals will achieve the nominal level of coverage. Lehmann (1986) stated that an 'ideal' confidence interval is one which is short when it covers the true parameter value but not necessarily otherwise. Throughout this study, approximate confidence intervals for density appeared to have coverage at least as large as nominal values when critical assumptions were not violated and factor levels were not extreme. At times, especially for the Cum-D estimator, coverage appeared to be higher than the nominal level. High coverage is an indication that the approximate confidence interval being calculated are not 'ideal', because confidence intervals are wider than necessary.

Previous studies have examined the coverage of confidence intervals, but the majority of these have focused on the FS estimator. Both Buckland (1982) and Quang (1990) found that coverage rates were generally smaller than their nominal values, especially for the analytic confidence interval (eq. 2.3.1). Buckland claimed that the analytic confidence interval yields, at best, 90% confidence for 95% nominal confidence intervals even for 'well-behaved' detection functions. Buckland observed in his study that the length of the confidence interval was very dependent on the number of terms incorporated in the FS; length increased simultaneously with m. Indicating that confidence intervals conditional on the FS stopping rule may be too narrow.

Both Quang and Buckland selected detected distances from distributions belonging to parametric families (half-normal, half-Cauchy, exponential, and modified beta families) when examining coverage. When coverage was low, the question of whether the method used to calculated the confidence interval was inappropriate, or the FS estimator was not robust to the shape of the detectability curve was not addressed. This is particularly noticeable in Quang's paper, where he stated that coverage was the poorest when the detection curve was peaked at 0. This is a case where the FS model has been found to provide a poor fit to the detection curve.

Quang (1990), Buckland (1988), and VABS used bootstrap methods to estimate variance and approximate confidence regions. Quang (1990) proposed using the confidence interval,

$$[\hat{D}-z\frac{\sqrt{n}\hat{s}_m}{2L},\hat{D}+z\frac{\sqrt{n}\hat{s}_m}{2L}],$$

where $z=z_{1-\alpha/2}$ is the appropriate percentile point of the standard normal distribution, and $\hat{s}_m$ is the common bootstrap estimate of the standard error of $\hat{f}(0)$. Quang found that observed coverage of the FS intervals fell short of the nominal value.

Buckland (1982) examined the analytic method, jackknife method, and two Monte Carlo methods for estimating confidence intervals. The first Monte Carlo method used the equation for the analytic method with the common bootstrap estimate of standard error for $\hat{f}(0)$. In the second method, the number of detections in the i^{th} bootstrap sample n_i, (i=1,(1),1000), were generated as a random Poisson variate with a mean of n. From the original sample $(y_1,\ldots,y_n)$, n_i random samples were selected from which $\hat{f}_i^*(0)$ and $\hat{D}_i^*=n_i\hat{f}_i^*(0)/2L$ were estimated and ordered. The percentile method (Efron and Tibshirani, 1986) was then used to estimate the confidence region.

Buckland recommends Method 2 if the sample size is less than 50 and Method 1 for larger samples. Method 2 is more robust against skewness than both Method 1 and the analytic method. The jackknife method was found to be comparable with the Monte Carlo methods only when the number of replicate lines were large.

12.1.1 VABS versus Analytical Confidence Intervals

The objective of the next two simulation studies is to begin examining the question of approximating confidence intervals. The first simulation study compares the coverage of normal confidence intervals used in VABS (Section 4.11) with those estimated using the analytical equation.

Table 12.1.1 shows evidence that the analytical normal confidence intervals have insufficient coverage, whereas the VABS normal bootstrap confidence intervals have sufficient coverage. The analytical estimates have a noticeably high percentage of narrow intervals occurring when density is overestimated (Figure 12.1.1). This is likely attributed to a smaller number of coefficients in the FS, in this circumstance. The length of the confidence intervals are more consistent and appealing when the bootstrap estimate of standard error is used. Hence, the analytical confidence intervals length is dependent on the number of terms in the FS and coverage is generally smaller than nominal values, supporting Buckland and Quang's results. Evidence suggest that the estimate of the standard error of the density estimate in VABS is preferable to the analytical method commonly used for the FS model.

Table 12.1.1 Coverage* of 95% and 99% nominal normal confidence intervals from analytical and bootstrap techniques.

Standard error used	Nominal Level	
	95%	99%
Analytical	83.6%	90.4%
Bootstrap Estimate	96.0%	99.0%

*Critical regions for α=.05 are .934 (H_0:p $\geq$ .05) and .982 (H_0:p $\geq$ .01)

12.1.2 Normal versus Percentile Confidence Intervals

The second simulation study compares the bootstrap normal confidence intervals with that of the percentile confidence intervals. Only the results of the FS and EPS confidence intervals are reported, since it has already been recognized that the bootstrap technique is inadequate for the Cum-D under the current methodology of selecting k.

Both methods provide sufficient coverage (Table 12.1.2) with the mean length of the confidence intervals being very similar (Table 12.1.3). The ratio of tail lengths are close to one (Table 12.1.4), indicating a fairly symmetric distribution. Normal probability plots of the density estimates do not indicate a significant departure from normality, except possibly in the tails (Figure 12.1.2).

There is not sufficient evidence to indicate that normal confidence intervals are inferior or to justify the increase in the amount of computer time needed to calculate percentile confidence intervals.

Table 12.1.2 Coverage* of nominal normal bootstrap confidence intervals and percentile confidence intervals.

	FS		EPS	
	Normal	Percentile	Normal	Percentile
90% Nominal Level	91.6%	91.6%	97.4%	95.8%
95% Nominal Level	96.0%	96.2%	98.4%	98.4%
99% Nominal Level	98.6%	99.0%	99.8%	99.2%

Table 12.1.3 Confidence interval lengths.

	Means (se)			
	FS		EPS	
	Normal	Percentile	Normal	Percentile
90% Nominal Level	6.233	6.093	3.861	3.830
	(.043)	(.044)	(.035)	(.034)
95% Nominal Level	7.427	7.375	4.601	4.598
	(.054)	(.047)	(.044)	(.041)
99% Nominal Level	9.757	10.031	6.044	6.138
	(.068)	(.056)	(.054)	(.057)

Table 12.1.4 Ratio of confidence interval tails Ratio=(upper limit-est)/(est-lower limit).

	Mean (se)	
	FS	EPS
90% Nominal Level	1.142	1.206
	(.033)	(.008)
95% Nominal Level	1.128	1.258
	(.030)	(.008)
99% Nominal Level	1.143	1.374
	(.027)	(.011)

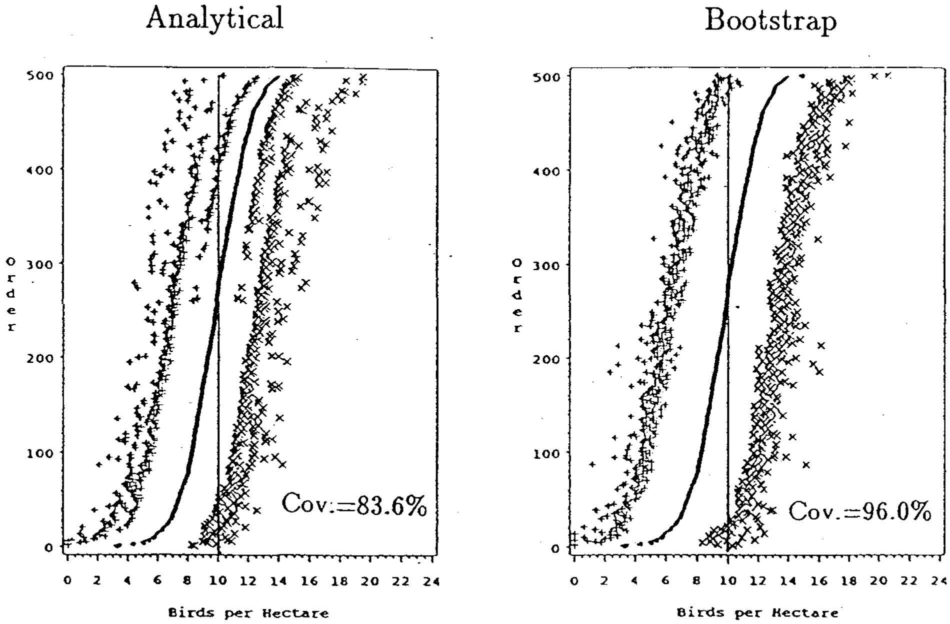


Figure 12.1.1 Ordered FS density estimates and corresponding 95% normal confidence limits with analytical and bootstrap estimates of standard error (Cov.=coverage).

The EPS confidence intervals are narrower and more conservative than the FS confidence intervals, providing more evidence that the EPS is a more precise estimate of density than the FS (Figure 12.1.3 and 12.1.4). As previously noted, the EPS confidence intervals appear to be wider when density is overestimated. An explanation of this could be that the EPS underestimates area surveyed and is more variable when a tail is present.

In conclusion, the estimated confidence regions that VABS calculates appear to have adequate coverage when assumptions are met; however, it is unknown at this time if they are 'ideal'. It is apparent that more work needs to be done on this topic before confidence in a particular method of estimating confidence intervals for density can be obtained. One on the biggest assets of VABS is that methods of approximating the confidence interval for density can be compared knowing the true value of density. The bootstrap methods proposed by Quang and Buckland should be compared to those which VABS uses. Furthermore, confidence intervals using Efron's accelerated bias-corrected percentile method (Efron 1987), Percentile-t (Hall 1988), and some of the two sample bootstrap techniques (Hall and Martin 1988), such as Beran's prepivoting (Beran 1987), should be investigated.

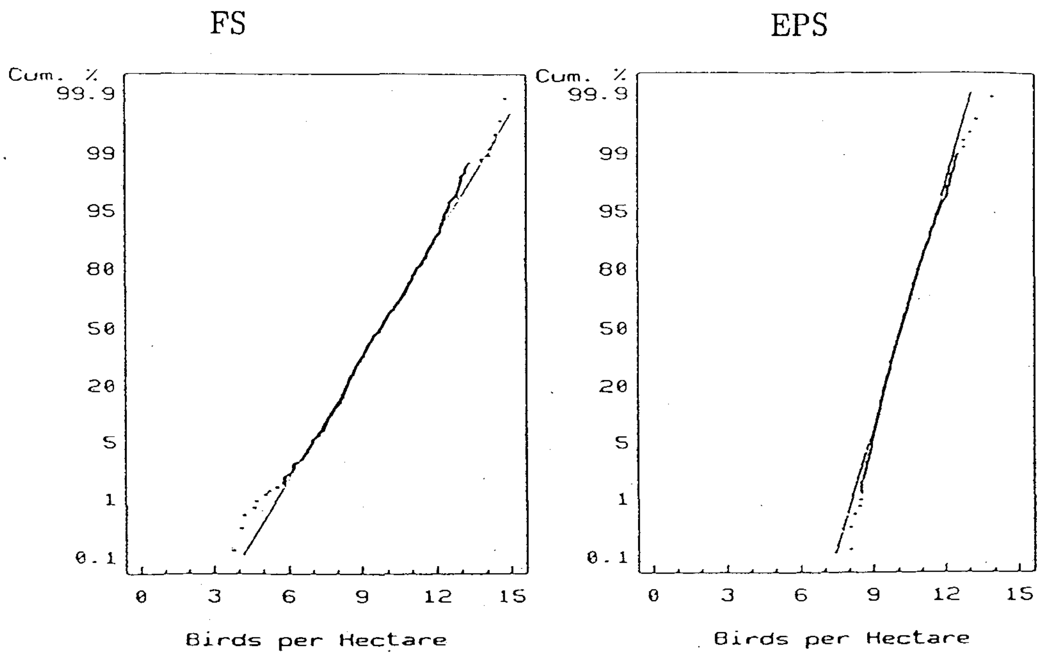


Figure 12.1.2 Normal probability plots for FS and EPS density estimates.

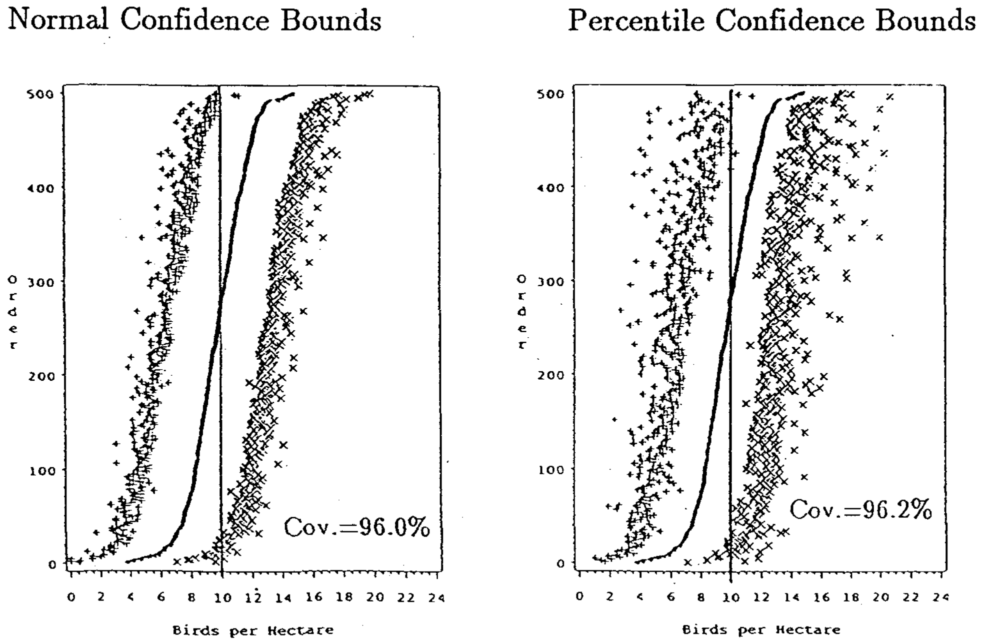


Figure 12.1.3 Ordered FS density estimates and corresponding approximate 95% confidence limits approximated using the bootstrap estimated standard error with normal confidence intervals and the percentile confidence limits (Cov.=coverage).

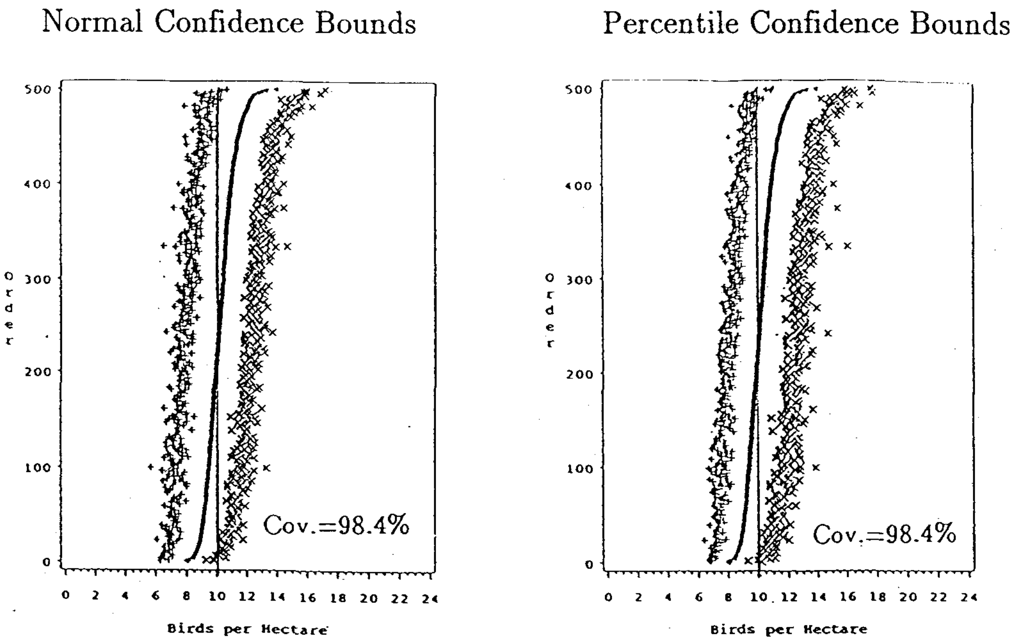


Figure 12.1.4 Ordered EPS density estimates and corresponding approximate 95% confidence levels approximated using the bootstrap estimated standard error with the normal confidence interval and the percentile confidence levels.

12.2 Choosing the Estimator

This study did not concern itself with the proper selection of an estimator; however, this is a critical step when analyzing variable area survey data. If using χ^2 goodness-of-fit tests or likelihood statistics, it is often possible to find several estimators that provide a good fit to the data set but that give rise to a wide range of density estimates. Furthermore, it is possible to have good fits to the observed detectability curves but have bias density estimates, particularly when there are counting errors. Buckland (1985) and others (Burnham et al. 1980) have often selected the estimator with the smallest standard error as the best estimator, but this density estimate could be bias, and corresponding approximate confidence intervals may have insufficient coverage. Poor coverage can be a result of the standard error being underestimated or the confidence region incorrectly approximated. Proper coverage should be a consideration when determining what estimator to use and the best estimate of standard error. Unfortunately, unless the true density is known one cannot assess if nominal coverage is being obtained. With VABS, the true density is known.

When deciding what estimators to use, it is important to examine the observed histogram. Several estimators have been proposed in the past, and most of these have particular shapes of the detectability curve that inhibits a proper fit. Buckland (1985) argues that data sets that exhibit a shoulder present few problems, but reliable estimation is not possible from line transect data unless a shoulder exist. VABS has shown that the EPS and the Cum-D can fit curves that do not exhibit a shoulder and still provide reliable density estimates. The FS is not robust to the lack of a shoulder. The EPS has a more flexible curve and frequently has better precision than the FS; however, it is more sensitive to values in the tail of the curve. If there is a steep decline in detectability, the Cum-D tends to overestimate density; however, the Cum-D appears to be robust to other shapes of the detectability curve.

If bird movement or some other factor is present that causes the observed detected area to be different from the true detected area, caution must be taken in selecting the estimators: it is essential that the estimated curve represent the true detectability curve.

Although the FS, EPS, and Cum-D were the only estimators used in VABS, this does not imply that they are the best estimators. Buckland (1985) evaluated several estimators and some of these estimators should be further analyzed before any judgments. Some of the estimators that may be worthwhile to examine are the hazard-rate (Hayes and Buckland, 1983), polynomial (Anderson and Posphala 1970; Gates and Smith 1980), and Hermite polynomials (Kendall and Stuart 1969) .

Buckland (1985) determined that Hermite polynomials are better suited to fitting a density function than simple polynomials, although they do fit poorly in tails of a distribution that is markedly skew. As with the FS, the Hermite estimated detection function is not constrained to be nonincreasing. Buckland (1985) concluded that a one-term Hermite polynomial seems to provide a more plausible shape for the detection function than the one-term FS, especially when the shoulder of the function is not wide or data coarsely grouped. Furthermore, additional terms alter the shape of the Hermite estimated function less dramatically than for the FS.

The hazard-rate (Hayes and Buckland 1983) has a shoulder, which is often very flat, for all plausible hazards. Distinctively from a proposed shape, the hazard-rate has a derived shape, although it arises from a restricted family of hazards. Buckland (1985) stated that he was unclear how realistic this family is and how closely the hazard-rate fits the true detection function when the hazard belongs to a different family of hazards.

In conclusion, a lot more work needs to be done concerning the selection of the proper estimator of area. The program VABS could be used to assess what estimators are appropriate under different circumstances. Furthermore, VABS could be used to test protocols of selecting the best estimator from a group of estimators that have been selected.

12.3 Interactions of Factors

It is unlikely that just one factor influencing bird counts will very during the survey. Instead, the observer must consider the multiple factors that are apt to vary during the survey and how they may interact. To examine these interactions, factorial designs with the variables incorporated into VABS can be used. For example, a factorial design could vary the rate of movement, bird's vocalization rate, and tree density to examine how these three factors interact to influence bird counts.

12.4 Variable Circular Plot

At this point, VABS has only been used to simulate the traversing of line transects. With a line transect survey, the observer is continuously moving along the transect and counting birds, whereas for the variable circular plot, bird counts are gathered only at stations for a fixed period of time. Because birds counts are gathered differently for the variable circular plot, the influence that some of the factors have on bird counts are different.

Remaining at a station for a fixed time period enables the observer to detect, with near certainty, all the birds close to the station. With this advantage, factors, such as dense vegetation and movement, that violate the critical assumption $g(0)=1$ when a line transect is used may not violate the assumption when a variable circular plot is used.

With the variable circular plot, counting periods at a station can be adjusted to reduce the effect of a factor on bird counts. The advantages of increasing the counting period are:

(1) Birds that are inconspicuous or vocalize infrequently have a higher chance of being detected.

(2) Birds that react to the presence of the observer by becoming silent and immobile may resume more normal behavior.

(3) In an area of high bird density, the observer has more time to make careful identifications and to record distances accurately.

The disadvantages are:

(1) Birds that are initially beyond the range of detection have a greater chance of moving close enough to be detected.

(2) The chance of recording a single bird more than once increases, because the bird may move or the observer may forget its location.

(3) The observer's ability to detect birds may decline because of boredom.

(4) The observer has greater freedom to allocate effort among species.

(5) There is more time for birds to be attracted by the observer's presence.

(Scott et al. 1981).

VABS could be used to simulate the variable circular plot survey and to determine if the variable circular plot is more robust to dense vegetation and bird movement. Also with bird movement, the counting period could be varied to find the optimal time period to reduce the effect of the factors that are influencing the bird counts.

13 CONCLUSIONS

13.1 When the Variable Area Survey can be used to Estimate Density.

Variable area density estimates are reliable when a sufficient number of birds are detected, critical assumptions are valid, and extreme conditions are absent. Furthermore, the variable area survey is robust to many of the factors that Verner (1985) and Dawson (1981) questioned. In essence, their skepticism about using variable area density estimates to monitor population trends is, for the most part, unwarranted.

Approximately 100 detections are necessary to select the proper estimator of detectability and derive precise density estimates. The number of detections can be increased by surveying a greater area or pooling data. If detections are gathered under different detectability curves, detected areas that are adjusted for covariates can be pooled to examine detectability. Once detectability is examined, separate adjusted density estimates can be derived for separate entities (bird species, habitats).

When critical assumptions are valid, the variable area survey is a practical method to estimate bird density. Critical assumptions of the variable area survey are:

(1) N varies stochastically about a mean DA.

(2) $\alpha = \int_0^\infty g(y)dy < \infty$.

(3) Measurements of detected area correspond to the targeted area: base area or surface area.

(4) g(0)=1 or the probability of detection is known for some other value of y.

(5) Detection distance are measure without systematic error or excessive random error.

(6) No bird is counted more than once at each station or on each transect.

(7) Each bird detected is recorded.

The first two assumptions define what is being estimated and are not expected to be invalid. The third assumption has often been overlooked, yet violation of this assumption will result in biased density estimates. However, this bias can easily be reedified by transforming, as prescribed in Section 10.6, the detected areas. The assumption $g(0)=1$ is a critical assumption that is susceptible to violation. There are situations, such as dense vegetation and bird movement, when the violation of this assumption can be avoided by using the variable circular plot, instead of the line transect. Validity of these assumptions can frequently be achieved with well designed surveys and properly trained observers.

Other commonly stated assumptions are not critical. With proper precautions and excluding extreme cases, the variable area survey is robust to invalidity of the assumptions:

(1) Birds occupy fixed locations during the survey period.
(2) Conditional on N, birds are distributed uniformly over the region R, independent of the density D.
(3) The locations of different birds are independent of each other.
(4) Detections of different birds are independent events.
(5) The detectability curve is constant

The assumption of immobility is frequently invalid for mobile birds. The variable area survey is robust to movement that does not prevent birds originally at $y=0$ from being detected or cause duplicate counts. (Random movement where an equivalent number of birds is detected at $y=0$ as originally were located at $y=0$ is acceptable.) It is imperative that the area surveyed be estimated with an estimator robust to movement (EPS); otherwise, the true detectability curve must be estimated, not the observed curve. The popular FS estimates the observed curve; therefore, it is not robust to movement.

Density can still be estimated accurately when birds not are uniformly distributed, locations of different birds are dependent of each other, and detections of different birds are dependent events. However, with any of these conditions, the variance of $\hat{D}$ can only be accurately estimated if the variation in $\hat{D}$ due to the variation in n is taken into account. To accurately estimate density, the transects need to be placed randomly in the targeted region and run the direction of the anticipated density gradient. Transect lines that follow railroad tracks, roads, ridge tops, fences, telephone lines, and stream bottoms can result in bias density estimates, because these objects are known to attract or repel some species of birds. When the detectability of a bird in a cluster is dependent on cluster size, the cluster should be treated as the primary object and cluster size as a covariate. If individual bird densities are being estimated, correct counts of cluster sizes are necessary.

Without covariate adjustments, the variable area survey is robust to moderate variability in detectability curves; however, some estimators are less robust to this variability, such as the EPS. Covariate adjustments substantially increase the robustness of the variable area survey to nonconstant detectability curves. If differing detectability curves are noticeable or suspected between different observers, habitats, weather conditions, cluster sizes, etc.; covariate adjustments are recommended, especially if using the EPS.

The variable area survey is robust to many of the factors that affect bird counts. In general, density estimates will be reliable until a factor or a combination of factors reach levels where a critical assumption is invalid or a noncritical assumption is no longer robust to the factor(s). Table 13.1 lists the several factors that were programed into VABS and classifies them into the following categories: (1) The variable area survey will provide reliable density estimates within reasonable levels of the factor (YES). (2) The variable area survey will provide reliable density estimates only to a moderate level of the factor (SOMETIMES). (3) The variable area survey does not provide reliable density estimates, and a solution to the problem does not look probable at this time (NO). (4) There still exist problems with the variable area density estimate, but a solution to the problem looks probable (MAYBE).

When determining why a factor causes unreliable density estimates, one must ask themselves: (1) Did the factor reduce the number of bird detections to a level where the proper estimator of detectability could not be determined or precise density estimates obtained? (2) A critical assumptions was invalid, such as $g(0)=1$? (3) Was the true detectability curve fitted properly? (4) Were the estimators of detectability robust to the true shape of the curve? (5) If detectability curves varied, was the data handled properly before pooling? (6) Were standard errors estimated properly? and (7) Were confidence regions approximated correctly?

Table 13.1 Ability of the variable area survey to cope with factors

Factor*	YES	SOMETIMES	NO	MAYBE
Visual Detectability	X (assumption g(0)=1 is important)			
Audio Detectability	X			
Frequency of Bird Calls	X			
Traversing Pace	X (if bird movement does not become a problem)			
Nonconstant Traversing Pace	X			
Different Detectabilities	X			
Bird Distribution	X ($\hat{se}(\hat{D})$ need to be determined)			
Bird Distribution Dependent on Vegetation	X ($\hat{se}(\hat{D})$ need to be determined)			
Clustered Population	X (if all birds in detected cluster counted)			
(otherwise)				X
Random Movement		X (level of robustness depends on the pattern of flight)		
Avoidance		X (FS not robust)		
Hide		X (FS not robust)		
Attraction		X (FS not robust)		
Counting Error			X (unless minimal)	
Saturation			X (unless minimal)	
Measurement error	X (if random)		X (systematic)	
Vegetation	X (dense vegetation threatens g(0)=1)			
Slope	X			
Trees on Hillside	X (a tall forest could spell trouble)			

*Specifics on 'safe bounds' are found in the sections concerning the factor.

13.2 Guidelines for Variable Area Surveys

When designing a variable area survey, decisions need to be made concerning the kind of survey to be conducted, the design of the survey, and the covariates to be recorded. Properly designed surveys can:

(1) Avoid or control detrimental factors.

(2) Prevent extreme differences in the detectability curve.

(3) Provide reliable adjusted density estimates for separate entities.

(4) Maximize the area surveyed, increasing precision.

(5) Provide a sufficient number of detections.

Although each survey will be unique, there are some general guidelines that should be followed when designing a variable area survey.

(1) Observers should be selected and trained in a manner that will maximize the area surveyed, i.e.
   (a) Observers should be tested for audio and visual acuity and if possible standardized by elimination and corrective devices (glasses, hearing aids).
   (b) Observers need to be trained to quickly and accurately identify a bird and estimate its detected distance.

(2) Observers must follow a protocol that reduces the variability in factors and minimizes the risk of detrimental factors, i.e.
   (a) The pace a transect is traversed at should be as constant as possible.
   (b) When bird movement is a factor, observers traversing a line transect must maintain a rapid pace and not stop or slow down to observe birds.
   (c) To minimize the risk of bird movement in response to the observer, proper conduct must be maintained by all observers.
   (d) Observers must be consistent in the birds they count. Recording unnecessary birds can distract the observer and bias the density estimate. For example, birds flying above the vegetation should not be counted.

(3) The detected distance used to estimate detected area must be defined carefully and clearly. Is density referring to the base area or the surface area?

(4) For factors influencing detectability, covariates representing the level of the factor should be recorded.

(5) Detrimental levels of factors, such as bad weather, should be avoided.

(6) The kind of survey chosen should take into account terrain and bird behavior. The variable circular plot may be more suitable in dense vegetation, whereas line transects may be more suitable when birds move in response to a stationary observer.

(7) Surveys should be conducted during the time of day and season when the bird under study is most conspicuous, both in terms of visual and audio detectability.

(8) The observer's traversing speed or time at a station needs to be fast (short) enough to prevent bird movement from becoming a detrimental factor but slow (long) enough to maximize detectability.

Even when critical assumptions are valid and detrimental levels of factors have not occurred, density estimates can be unreliable if data is incorrectly analyzed. Errors apt to bias density estimates are:

(1) Improper selection of the detectability curve estimator.

(2) Data is pooled without adjusting for factors significantly influencing detectability.

The selection of the proper estimator of the detectability curve is a topic in need of further research (see Section 12.2). The lessons regarding data analysis that have been learned in this study are:

(1) The estimated detectability curve needs to be representative of the true detectability curve (base on the location of the bird when the survey began) and not the observer detectability curve (based on the location where the observer detected and recorded the bird at). An estimated curve can fit the observed areas and be biased.

(2) Curves that are restricted to being monotonically decreasing (EPS, Cum-D) are more robust to the observed detected areas being unequal to the true detected areas than curves that are not restricted to this form (FS).

(3) Factors that influence detectability and vary moderately over the survey should be treated as covariates in the analysis.

(4) The estimator of the standard error of $\hat{D}$ needs to be selected based on the distribution of birds.

(5) Approximating confidence intervals using normal confidence regions may be incorrect (see Section 12.1).

(6) In regards to the Fourier series:

    (a) The FS is sensitive to detections close to the transect line.

    (b) The FS is not robust to movement.

    (c) The FS does not fit curves that do not have a distinct shoulder.

    (d) The analytical estimate of standard error (Burnham et al. 1980) tends to be negatively-biased.

(7) In regards to the exponential power series:

   (a) The EPS appears to be more precise than the FS and Cum-D, yet it appears to be susceptible to small biases.

   (b) The EPS is not robust to unadjusted differing detectability curves.

   (c) The EPS is sensitive to tail area values, generally overestimating area when no tail is present and underestimating area when a long tail is present.

   (d) The estimate of the variation of $\hat{D}$ needs to take into account the variation in n, regardless of how the birds are distributed.

(8) In regards to the cumulative distribution:

   (a) The protocol to select the ordered detected area used to estimate the slope of the cumulative distribution at zero needs to be revised.

   (b) The Cum-D is sensitive to detections close to the transect.

   (c) The common bootstrap estimate of standard error is inappropriate to estimate se($\hat{D}$).

13.3 Testing for Trends

The variable area survey has the ability to produce accurate density estimates for counts with different detectabilities. Hence, if detectabilities do vary between counts, the variable area density estimates are reliable enough to monitor populations. On the other hand, if detectability does vary between counts, unadjusted simple counts will give erroneous results when monitoring populations. Since it is unlikely that detectability is constant between counts, variable area density estimates – not simple counts – should be used to monitor populations.

13.4 Benefits of VABS

The program VABS has many features that can aid an investigator in designing a variable area survey. If birds of known characteristics are going to be counted, these characteristics can be programed into VABS. The influences these characteristics have on the shape of the detectability curve and what estimators are robust to these shapes can be studied. Variables under control of the observer can be varied to help determine optimal conduct on the transect. For example, if song birds are mobile, the average song frequency and average speed of movement can be programed, and then the traversing pace of the observer can be varied in order to determine the optimal average traversing pace. If the optimal line transect traversing pace and the optimal time spent at a variable circular plot station are determined, VABS can aid in the decision of what kind of variable area survey to use. Further benefits of VABS were mentioned in Chapter 12. In conclusion, VABS can be a valuable tool in the development of variable area surveys.

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APPENDICES

APPENDIX A

Formulation of the Blind Area Caused by a Tree

Using the formula for a circle, let

$$f(x)=\begin{cases} \sqrt{r^2-(x-h)^2}+k & y \geq k \\ -\sqrt{r^2-(x-h)^2}+k & y < k\,. \end{cases}$$

The slope of the tangent line to the circle is

$$f'(x)=\begin{cases} \dfrac{-(x-h)}{\sqrt{r^2-(x-h)^2}} & y \geq k \\ \dfrac{(x-h)}{\sqrt{r^2-(x-h)^2}} & y \geq k. \end{cases}$$

Using the previous two equations, the slope of the two tangent lines and the points of tangency can be found by solving simultaneously the equations:

$$(1)\ (y\text{-obsy})=\frac{-(x-h)}{\sqrt{r^2-(x-h)^2}}(x-\text{obsx}) \quad \text{and } y=\sqrt{r^2-(x-h)^2}+k \text{ for } y \geq k$$

$$(2)\ (y\text{-obsy})=\frac{(x-h)}{\sqrt{r^2-(x-h)^2}}(x-\text{obsx}) \quad \text{and } y=-\sqrt{r^2-(x-h)^2}+k \text{ for } y < k.$$

Both of these equations reduce to solving the equation,

$$(x-h)^2[(\text{obsx-h})^2+(\text{obsy}-k)^2]-2r^2(x-h)(\text{obsx}-h)+r^2(r^2-(\text{obsy-k})^2)=0.$$

Hence,

$$x=\begin{cases} \dfrac{-b \pm \sqrt{b^2-4ac}}{2a}+h & \text{obsy} \neq k \\ -\dfrac{b}{2r} & \text{obsy}=k, \end{cases}$$

for

$$a=(\text{obsx-h})^2+(\text{obsy-k})^2,$$
$$b=-2r^2(\text{obsx-h}),$$
$$c=r^2(r^2-(\text{obsy-k})^2).$$

Since $a > 0$, it follows that $x_L = \min(x_L, x_H)$ and $y_L = \min(y_L, y_H)$ for

$$x_L = \frac{-b - \sqrt{b^2 - 4ac}}{2a} + h$$

$$x_H = \frac{-b + \sqrt{b^2 - 4ac}}{2a} + h$$

$$y_L = -\sqrt{r^2 - (x-h)^2} + k$$

$$y_H = \sqrt{r^2 - (x-h)^2} + k.$$

If $T_1 = (t_{11}, t_{12})$ is the point of tangency that creates α_1 and $T_2 = (t_{21}, t_{22})$ is the point of tangency that creates α_2, the properties of geometry establish that

$$d[(t_{11}, t_{12});(obsx, obsy)] = d[(t_{21}, t_{22});(obsx, obsy)],$$

and thus

$$(t_{11} - obsx)^2 + (t_{12} - obsy)^2 = (t_{21} - obsx)^2 + (t_{22} - obsy)^2.$$

Hence, the points of tangency are such that

$$|t_{11} - obsx| \leq |t_{22} - obsx| \Leftrightarrow |t_{12} - obsy| \geq |t_{22} - obsy|,$$

and

$$|t_{11} - obsx| > |t_{22} - obsx| \Leftrightarrow |t_{12} - obsy| < |t_{22} - obsy|$$

from which it follows that

$$(t_{11} t_{12}) = \begin{cases} (x_L, y_H) & h \geq obsx; k \geq obsy \\ (x_H, y_H) & h \geq obsx; k < obsy \\ (x_L, y_L) & h < obsx; k \geq obsy \\ (x_H, y_L) & h < obsx; k < obsy \end{cases}$$

$$(t_{21} t_{22}) = \begin{cases} (x_H, y_L) & h \geq obsx; k \geq obsy \\ (x_L, y_L) & h \geq obsx; k < obsy \\ (x_H, y_H) & h < obsx; k \geq obsy \\ (x_L, y_H) & h < obsx; k < obsy. \end{cases}$$

APPENDIX B

Formulation of the Estimation of the Loggamma Function

Using Stirling's formula

$$\log(\Gamma(z))=(z-\frac{1}{2})\log(z)-z+\frac{1}{2}\log(2\pi)+\frac{1}{12z}-\frac{1}{360z^3}+\frac{1}{1260z^5}-\frac{1}{1680z^7}+\sum_{j=1}^{n}\frac{B_{2j}}{2j(2j-1)x^{2j-1}}+R_n(x),$$

where B_r is the r^{th} Bernoulli number, and the fact that $\Gamma(z+1)=z\Gamma(z)$. VABS approximates the loggamma function as

$$\log(\Gamma(x)) \doteq \log\left(\frac{\Gamma(x+k)}{x(x+1)(x+2)\ldots(x+k-1)}\right),$$

where k is large enough such that z=x+k can be estimated accurately by

$$\log(\Gamma(z)) \doteq (z-\frac{1}{2})\log(z)-z+z+\frac{1}{2}(2\pi)+\frac{1}{12z}-\frac{1}{360z^3}+\frac{1}{1260z^5}-\frac{1}{1680z^7}.$$

For this approximation $R_n(z) \leq |\frac{5}{5940z_9}|$. Since single precision is being used (precision is only to 6-9 digits) selecting k such that $x+k > 5$ and $x+k-1 < 5$ should suffice since $R_n(5) \leq 4.310\text{x}10^{-10}$.

APPENDIX C

Base Program of VABS

This appendix contains the basic program of VABS from which alterations and additions were made in order to simulate the factors that were studied. For this study, the simulations were run on either a SUN 3/60, SPARCstation 2, or SPARCstation IPX computer.

```
      PROGRAM VABS
C     THIS VERSION OF VABS IS THE BASE PROGRAM USED TO GENERATE
C     A PLOT CONSISTING OF TREES AND BIRDS AND THEN SIMULATE AN
C     OBSERVER WALKING THE TRANSECT AND DETECTING BIRDS.
      DOUBLE PRECISION ISEED
      INTEGER NREP(10)
      REAL PERP(300),BIRD(300,5),L,W,TREE(10000,3)
      PARAMETER(PI=3.141593)
      COMMON ISEED,L,W
      COMMON /BTREE/TREE,NT,RMAX /BBIRD/BIRD,NBIRD
      COMMON /AREA/PERP,NREP,NDECT
      OPEN (6,FILE='output.out',STATUS='NEW')
C     SPECIFY ISEED, WHERE ISEED IS THE SEED TO GENERATE RANDOM
C     NUMBERS.  NUMBER NEEDS TO BE LESS THAN 2,147,483,647.
      ISEED=93847611.D0
C     SPECIFY LENTH (DIRECTION WALKING TRANSECT) AND WIDTH OF
C     PLOT THAT WANT TO CREATE.  UNITS ARE IN METERS.
C     L IS THE LENGTH OF THE PLOT AND TRANSECT
C     W IS THE WIDTH OF THE PLOT (W NEEDS TO BE LONGER THAN
C     2*(MAXIMUM DETECTION DISTANCE).
      L=1000
      W=210
C     DVA IS THE VISUAL ANGLE THRESSHOLD IN DEGREES.  REASONABLE
C     VALUES RANGE FROM .067 TO .117 DEGREES ALTHOUGH  IT CAN BE
C     AS LOW AS .05 AND AS HEIGH AS .33.
      DVA=.067
      DVA=(PI*DVA)/180.0
C     TT IS THE MEAN TIME SPENT AT EACH GRID POINT, I.E. WALKING
C     PACE PER METERS, UNITS FOR TIME SHOULD BE IN METERS.   THE
C     WALKING PACE FOR EACH GRID POINT WILL BE SELECTED FROM
C     THE LOGISTIC DISTRIBUTION.
      TT=-3.690
C     SDTT IS BETA FOR LOGISTIC DEVIATE
      SDTT=.0276
C     THETA IS THE FREQUENCY OF VOCALIZATIONS (BIRD CALLS PER
C     MINUTES).
      THETA=.3
      THETA=1.0/THETA
C     PERF IS THE MAX ANGLE OF OBSERVERS PERIPHERAL VISION IN
C     DEGREES.  RECOMMEND USING BETWEEN 60 AND 90 DEGREES.
C     PROGRAM NEEDS TO BE CHANGED IF PERF GT 90 DEGREES.
      PERF=75.0
```

```
      PERF=(PI*PERF)/180.0
C     BETA0 AND BETA1 CORRESPOND TO
C     LN(DIST)=BETA0+BETA1*(ANGLE SIGHT).
C     BETA0 IS CALCULATED USING DVA.
      BETA1=.038
C     DA IS THE OBSERVER'S AUDIO DETECTION THRESHOLD IN
C     DECIMETERS.  VALUES HAVE RANGED AS HIGH AS 400 METERS.
      DA=100.0
C     RBIRD IS THE DENSITY OF BIRDS DESIRED PER HECTARE.
      NBIRD=10
      NBIRD=NINT((L*W)*FLOAT(NBIRD)*.0001)
C     CHOOSE IF WANT AN UNEVEN AGE FOREST (EVEN=0) OR AN EVEN
C     AGED FOREST (EVEN=1).  FOR UNEVEN ROUTINE NEED TO SPECIFY
C     IN THE TREE SUBROUTINE THE PARAMETERS FOR THE EXPONENTIAL
C     DISTRIBUTION USED TO GENERATE THE DBH'S FOR THE TREES.
C     FOR THE EVEN ROUTINE NEED TO SPECIFY THE MAXIMUM FOR THE
C     MEAN DBH OF THE CLUSTERS.  ALSO, NEED TO ASSIGN MEAN
C     CLUSTER SIZES AND SE FOR DBH GROUPS.
      EVEN=0
C     CHOOSE NUMBER OF TREES PER METERS SQUARE: RECOMMEND  BE
C     LESS THAN OR EQUAL TO .03 (300 TREES PER HECTOR): DEN.
C     NT IS NUMBER OF TREES WANT IN PLOT.
      DEN=.03
      NT=NINT(L*W*DEN*.0001)
C     SPECIFIY THE NUMBER OF SECTIONS CUT TRANSECT IN, TO OBTAIN
C     A BOOTSTRAP SAMPLE THAT ACCOUNTS FOR THE VARIATION IN N.
      NI=10
      DO 10 I=1,5
        WRITE(6,*) 'REP  ',I,' SEED ',ISEED
        NDECT=0
        DO 42 II=1,NI
 42       NREP(II)=0
        CALL TREES(EVEN)
        CALL BIRDS(THETA)
        CALL DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,NI)
        DENB=FLOAT(NBIRD)*10000/(L*W)
        WRITE(6,*) 'DENSITY PER HECTARE ',DENB,' NDECT ',NDECT
        CALL ORDIT(NDECT,PERP)
        CALL CUMD(NDECT,PERP,EFAR)
        CALL FOSER(NDECT,PERP,LCUT,AREA)
        CALL EPMLE(NDECT,PERP,EST,G)
        DCUMD=FLOAT(NDECT)/EFAR
        DFS=FLOAT(NDECT)/AREA
        DEPS=FLOAT(NDECT)/EST
        WRITE(6,*) 'BIRD CUMD ',DCUMD,' FS ',DFS,' EP ',DEPS
C       SAMPLE SIZE TO DRAW FOR BOOTSTRAP SAMPLE.
        N2=NDECT
C       NUMBER OF BOOTSTRAP REPS.
        M=100
        CALL BSTRAP(NDECT,N2,M,ACD,SCD,DCD,UCD,AFS,SFS,DFS,
     *   UFS,AWB,SWB,DWB,UWB,ME,CUMDD,FOSERD,EPMLED,NI)
        WRITE(6,*)'CD AVE ',ACD,' SD ',SCD,' MIN ',DCD,
     *    ' MAX ',UCD
```

```
      WRITE(6,*) 'FS AVE ',AFS,' SD ',SFS,' MIN ',DFS,
    *   ' MAX ',UFS
      WRITE(6,*) 'EP AVE ',AWB,' SD ',SWB,' MIN ',DWB,
    *   ' MAX ',UWB
 10   CONTINUE
      END

      SUBROUTINE BIRDS(THETA)
C     THIS PROGRAM DISTRIBUTES BIRDS ONTO THE PLOT CREATED IN VABS
C     BIRD(I,1)-LOCATION ON X-AXIS, BIRD(I,2)-LOCATION ON Y-AXIS
C     BIRD(I,3)-CODE FOR DETECTECTION, BIRD(I,4)-TIME BETWEEN
C     CALLS, BIRD(I,5)-PROBABILITY OF DETECTION.
      DOUBLE PRECISION DRAND,ISEED
      REAL BIRD(300,5),L,W,IX,IY
      COMMON ISEED,L,W
      COMMON /BBIRD/BIRD,NBIRD
      DATA IYREG,JYREG/1,0/
      NB=NBIRD
      DO 40 J=1,NBIRD
        N=0
 200    N=N+1
        IF (N.GT.100) THEN
        WRITE(6,*) 'PLACING BIRDS BOMBED '
        STOP
        ENDIF
        IX=W*SNGL(DRAND(ISEED))
        IY=L*SNGL(DRAND(ISEED))
        DO 50 II=1,NB-1
 50     IF (((BIRD(II,1).GE.IX-.1).AND.(BIRD(II,1).LE.IX+.1))
    *    .AND.*((BIRD(II,2).GE.IY-.1).AND.(BIRD(II,2).LE.IY+.1)))
    *    GO TO 200
        BIRD(J,1)=IX
        BIRD(J,2)=IY
        BIRD(J,3)=1.0
        BIRD(J,4)=REXP(THETA,ISEED)
        BIRD(J,5)=1.0
 40   CONTINUE
      NN=NBIRD-1
      DO 510 J=1,NN
        L=J
        JJ=J+1
        DO 620 I=JJ,NBIRD
          IF (BIRD(L,2).LT.BIRD(I,2)) GO TO 620
          L=I
 620    CONTINUE
        DO 530 II=1,5
          T=BIRD(L,II)
          BIRD(L,II)=BIRD(J,II)
 530      BIRD(J,II)=T
 510  CONTINUE
 105  LL=0
      DO 540 J=1,NN
        IF (BIRD(J,2).EQ.BIRD(J+1,2)) THEN
```

```
          IF (BIRD(J,1).GT.BIRD(J+1,1)) THEN
            DO 550 II=1,5
              T=BIRD(J,II)
              BIRD(J,II)=BIRD(J+1,II)
              BIRD(J+1,II)=T
              LL=1
 550        CONTINUE
          ENDIF
        ENDIF
 540  CONTINUE
      IF (LL.GT.0) GO TO 105
      RETURN
      END

      SUBROUTINE TREES(EVEN)
C     THIS PROGRAM HAS AN OPTION FOR EVEN AGED FOREST (EVEN=1) OR
C     AN UNEVEN AGED FOREST (EVEN=0).
C     EVEN=1 DISTRIBUTES TREES OF AN EVEN AGED FOREST IN AGE
C     CLUSTERS AND PLACES AGE CLUSTERS RANDOMLY IN THE PLOT.
C     WITHIN AN AGE CLUSTER THE DBH IS NORMALLY DISTRIBUTED
C     EVEN=0 CREATES AN UNEVEN AGED FOREST THAT IS UNIFORMLY
C     DISTRIBUTED ON THE SPECIFIED PLOT.  THE DIAMETERS ARE
C     GENERATED FROM THE EXPONENTIAL DISTRIBUTION. REPLACE ARRAYS
C     WITH APPROPRIATE VALUES.
C     TREE(I,1)-LOCATION ON X-AXIS, TREE(I,2)-LOCATION ON Y-AXIS
C     TREE(I,3)-RADIUS OF TREE (MULTIPLY BY 3 IF HAVE FOLIAGE).
      DOUBLE PRECISION DRAND,ISEED
      INTEGER EVEN
      REAL LAMDA,TREE(10000,3),L,W,ICX,ICY,MDBH
      COMMON ISEED,L,W
      COMMON /BTREE/TREE,NT,RMAX
      RMAX=0
      L=1
C     REPLACE XM WITH DESIRED PARAMETER TO GENERATE DBH EXP. DIST.
C     UNITS SHOULD BE IN CENTIMETERS AND REPRESENT MEAN DBH VALUES
C     XM SHOULD BE ON THE LOW SIDE, I.E. BETWEEN 10 AND 20.
      XM=10.0
C     IF TREES IN CLUSTER NORMALY DISTRIBUTED SPECIFY STANDARD
C     DEV. OF COHORT IN METERS: VALUES BETWEEN 12 AND 18.
      STD=7
      DO 10 I=1,NT
        IF (EVEN.EQ.0) THEN
          NUM=1
        ELSE
C       SELECTING MEAN TREE DIAMETER.
 102      MDBH=NINT(REXP(XM/100,ISEED))
          IF (MDBH.LE..05) GO TO 102
C         ASSIGN MEAN CLUSTER SIZE AND SE FOR DBH GROUPS.
          SDK=.1*MDBH
          IF (MDBH.LT.1) THEN
             LAMDA=-10*MDBH+11
          ELSE
             LAMDA=1.0
```

```
          ENDIF
C         GENERATING TREES IN CLUSTER USING POISSON DIST.
          NUM=IPOIS(LAMDA,ISEED)+1
C         SELECTING WHERE CENTER OF CLUSTER LOCATED.
          CX=W*SNGL(DRAND(ISEED))
          CY=L*SNGL(DRAND(ISEED))
C         SELECTING DBH OF TREE FROM NORMAL DIST.
        ENDIF
        DO 20 J=1,NUM
          IF (EVEN.EQ.0) THEN
 202        DBH=(REXP(XM/100.0,ISEED))
            IF (DBH .LE. .05) GO TO 202
          ELSE
            NJ=0
 300        NJ=NJ+1
            IF (NJ.GT.100) THEN
              WRITE(6,*) 'ERROR IN DBH EQ 0'
              STOP
            ENDIF
            DBH=MDBH+RND(ISEED)*SDK
            IF (DBH .LE. .05) GO TO 300
          ENDIF
          TREE(L,3)=DBH*5.0
          IF (TREE(L,3).GT.RMAX) RMAX=TREE(L,3)
C         LOCATING TREES IN THE PLOT.
          ICOUNT=0
 600      ICOUNT=ICOUNT+1
          IF (ICOUNT.GT.100) THEN
            WRITE(6,*) 'GENERATING TREES BOMBED AT 1'
            STOP
          ENDIF
          IF (EVEN.EQ.1) THEN
            N=0
 400        N=N+1
            IF (N.GT.100) THEN
              WRITE(6,*) 'GENERATING TREES HAS BOMBED AT 3'
              STOP
            ENDIF
            ICX=CX+RND(ISEED)*STD
            IF ((ICX.LE.0).OR.(ICX.GT.W)) GO TO 400
            ICY=CY+RND(ISEED)*STD
            IF ((ICY.LE.0).OR.(ICY.GT.L)) GO TO 400
          ELSE
            ICX=W*SNGL(DRAND(ISEED))
            ICY=L*SNGL(DRAND(ISEED))
          ENDIF
          IF (L.EQ.1) GO TO 100
          DO 30 II=1,L-1
            DX=ABS(ICX-TREE(II,1))
            DY=ABS(ICY-TREE(II,2))
            BET=TREE(L,3)+TREE(II,3)
            IF (DX.GT.BET) GO TO 30
            IF (DY.GT.BET) GO TO 30
```

```
          DIST=SQRT(DX*DX+DY*DY)
          IF (DIST.LE.BET) GO TO 600
30      CONTINUE
100     TREE(L,1)=ICX
        TREE(L,2)=ICY
        L=L+1
        IF (L.GT.NT) GO TO 200
20    CONTINUE
10  CONTINUE
200 NN=NT-1
    DO 610 J=1,NN
      L=J
      JJ=J+1
      DO 620 I=JJ,NT
        IF (TREE(L,2).LT.TREE(I,2)) GO TO 620
        L=I
620   CONTINUE
      DO 630 II=1,3
        T=TREE(L,II)
        TREE(L,II)=TREE(J,II)
630     TREE(J,II)=T
610 CONTINUE
605 LL=0
    DO 640 J=1,NN
      IF (TREE(J,2).EQ.TREE(J+1,2)) THEN
        IF (TREE(J,1).GT.TREE(J+1,1)) THEN
          DO 650 II=1,3
            T=TREE(J,II)
            TREE(J,II)=TREE(J+1,II)
            TREE(J+1,II)=T
            LL=1
650       CONTINUE
        ENDIF
      ENDIF
640 CONTINUE
    RETURN
    END

    SUBROUTINE DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,NI)
C   THE SUBROUTINE SIMULATES THE TRAVERSING OF A TRANSECT
C   LINE.  AUDIO DETECTION AS WELL AS VISUAL DETECTION IS
C   SIMULATED AT EACH METER.
    DOUBLE PRECISION DRAND,ISEED
    INTEGER OBSX,OBSY,OBSXX,OBSYY,NREP(10),DIRECT
    REAL MAXDIST,DIST,TIME(1000),PERP(300),BLIND(10000,5),
   * LAMDA,GV,BIRD(300,5),DVA,TT,SDTT,PERF,BETA1,DT,
   * TREE(10000,3),L,W
    PARAMETER(PI=3.141593,PI2=1.570796,PI4=.785398)
    COMMON ISEED,L,W
    COMMON/BTREE/TREE,NT,RMAX /BBIRD/BIRD,NBIRD
    COMMON /AREA/PERP,NREP
    NDECT=0
    K3=0
```

```
      K2=0
      K=0
      DO 42 I=1,NI
 42     NREP(I)=0
      DV=.05/TAN(DVA*0.5)
      BETA0=LOG(DV*.021715)
C     CHOOSING THE PLACEMENT OF THE TRANSECT LINE ACCORDING TO THE
C     UNIFORM DISTRIBUTION.
C     CALCULATING THE MAXIMUM DISTANCE A BIRD CAN BE AND STILL BE
C     DETECTED.
      MAXDIST=MAX(DA,DV)
      IF (MAXDIST.GE.W/2.) THEN
        WRITE(6,*) 'MAXDIST IS GREATER THAN W/2'
        STOP
      ENDIF
C     SELECTING LOCATION OF TRANSECT.
      OBSXX=W/2
      OBSYY=1
C     SELECTING TIME SPENT WALKING BETWEEN POINTS (1 METER).
      NTIMES=L
      DO 31 I=1,NTIMES
 31     TIME(I)=RLOG(TT,SDTT,ISEED)
      DO 32 I=1,NBIRD
        AAA=ABS(OBSXX-BIRD(I,1))
        IF (AAA.GT.DA) GO TO 32
        A=DA**2-(OBSXX-BIRD(I,1))**2
        IF (A.LT.0.0) GO TO 32
        IF (A.EQ.0) THEN
          AA=0
        ELSE
          AA=SQRT(A)
        ENDIF
        YMIN=BIRD(I,2)-AA
        YMAX=BIRD(I,2)+AA
        IMIN=NINT(YMIN)
        IF (IMIN.LE.0) IMIN=1.0
        IMAX=NINT(YMAX)
        IF (IMAX.GE.NTIMES) IMAX=NTIMES
        TOTAL=0
        DO 33 J=IMIN,IMAX
 33       TOTAL=TOTAL+TIME(J)
        IF (TOTAL.LT.BIRD(I,4)) GO TO 32
        NDECT=NDECT+1
        BIRD(I,3)=2.0
        JREP=(BIRD(I,2)*NI)/L+1
        NREP(JREP)=NREP(JREP)+1
        PERP(NDECT)=AAA*.0002*L
 32   CONTINUE
      NAUDIO=NDECT
      WRITE(6,*) 'THE NUMBER DETECTED BY AUDIO ',NAUDIO
C     STARTING TO WALK TRANSECT.
      DO 11 OBSY=OBSYY,IFIX(L)
        NBLIND=0
```

```
C       AT THIS POINT HAVE LOCATION OF OBSERVER (OBSX,OBSY) AND
C       FOCUS ANGLE SO BEGIN THE DETECTION PROCESS. SEARCHING THE
C       SEMI-CIRCLE WITH CENTER(OBSX,OBSY) AND RADUIS MAXDIST FOR
C       POSSIBLE BIRD DETECTIONS.
        OBSX=OBSXX
C       CHECKING IF TREES ARE ON THE TRANSECT.
        II=K
 101    II=II+1
        IF (II.GT.NT) GO TO 102
        IF (TREE(II,2)+RMAX.LT.OBSY) THEN
          K=II
          GO TO 101
        ELSEIF ((TREE(II,2)-RMAX).GT.OBSY) THEN
          GO TO 102
        ELSEIF ((TREE(II,2)-TREE(II,3)).GT.OBSY) THEN
          GO TO 101
        ELSEIF ((TREE(II,2)+TREE(II,3)).LT.OBSY) THEN
          GO TO 101
        ELSE
 103      IF (TREE(II,1)+TREE(II,3).LT.OBSX) THEN
            IF (II.EQ.NT) GO TO 102
            IF (TREE(II+1,2).EQ.TREE(II,2)) THEN
              II=II+1
              GO TO 103
            ELSE
              GO TO 101
            ENDIF
          ELSEIF ((TREE(II,1)-RMAX).GT.OBSX) THEN
 105        IF (II.EQ.NT) GO TO 102
            IF (TREE(II+1,2).EQ.TREE(II,2)) THEN
              II=II+1
              GO TO 105
            ELSE
              GO TO 101
            ENDIF
          ELSEIF ((TREE(II,1)-TREE(II,3)).GT.OBSX) THEN
            IF (II.EQ.NT) GO TO 102
            IF (TREE(II,2).EQ.TREE(II+1,2)) THEN
              II=II+1
              GO TO 103
            ELSE
              GO TO 101
            ENDIF
          ELSE
            DX=TREE(II,1)-OBSX
            DY=TREE(II,2)-OBSY
            R2=TREE(II,3)**2
            DIST=SQRT(DX*DX+DY*DY)
            IF (DIST.GT.TREE(II,3)) THEN
              GO TO 101
            ELSE
              IF (DX.EQ.0) THEN
                IF ((OBSY.LT.10).OR.(DX*DX+(OBSY-10-TREE(II,2))**2
```

```
     *          .GT.R2)) THEN
                  DIRECT=1
                  IF (DRAND(ISEED).LT.0.5) DIRECT=-1
                ENDIF
              ELSEIF (DX.GT.0) THEN
                DIRECT=1
              ELSE
                DIRECT=-1
              ENDIF
              IF (DIRECT.EQ.1) THEN
                OBSX=IFIX(TREE(II,1)+SQRT(R2-DY*DY)+1)
              ELSE
                OBSX=IFIX(TREE(II,1)-SQRT(R2-DY*DY))
              ENDIF
            ENDIF
          ENDIF
        ENDIF
C        STARTING OF PROCESS OF CREATING BLIND SPOTS AND LOOKING FOR
C       BIRDS.
 102    II=K2
        YMIN=OBSY-DV
        IF (YMIN.LT.0) YMIN=0
        YMAX=OBSY+DV
        IF (YMAX.GT.L) YMAX=L
        XMIN=OBSX-DV
        XMAX=OBSX+DV
        Y2MIN=YMIN-RMAX
        IF (Y2MIN.LT.0) Y2MIN=0
        Y2MAX=YMAX+RMAX
        IF (Y2MAX.GT.L) Y2MAX=L
        X2MIN=XMIN-RMAX
        X2MAX=XMAX+RMAX
 111    II=II+1
        IF (II.GT.NT) GO TO 112
        IF (TREE(II,2)+RMAX.LT.OBSY) THEN
          K2=II
          GO TO 111
        ELSEIF ((TREE(II,2)+TREE(II,3)).LT.OBSY) THEN
          GO TO 111
        ELSEIF (TREE(II,2).GT.Y2MAX) THEN
          GO TO 112
        ELSEIF (TREE(II,2)-TREE(II,3).GT.YMAX) THEN
          GO TO 111
        ELSE
 113      IF ((TREE(II,1)+TREE(II,3)).LT.XMIN) THEN
            IF (II.EQ.NT) GO TO 112
            IF (TREE(II+1,2).EQ.TREE(II,2)) THEN
              II=II+1
              GO TO 113
            ELSE
              GO TO 111
            ENDIF
          ELSEIF (TREE(II,1).GT.X2MAX) THEN
```

```
  GO TO 111
ELSEIF ((TREE(II,1)-TREE(II,3)).GT.XMAX) THEN
  IF (II.EQ.NT) GO TO 112
  IF (TREE(II,2).EQ.TREE(II+1,2)) THEN
    II=II+1
    GO TO 113
  ELSE
    GO TO 111
  ENDIF
ELSE
  DX=ABS(TREE(II,1)-OBSX)
  DY=ABS(TREE(II,2)-OBSY)
  R2=TREE(II,3)**2
  DIST=SQRT(DX*DX+DY*DY)
  IF (DIST-TREE(II,3).GT.DV) THEN
    GO TO 111
  ELSE
    NBLIND=NBLIND+1
    BLIND(NBLIND,1)=II
    A=(OBSX-TREE(II,1))**2+(OBSY-TREE(II,2))**2
    B=-2*R2*(OBSX-TREE(II,1))
    C=R2*(R2-(OBSY-TREE(II,2))**2)
    DD=B**2-4*A*C
    IF (OBSY.EQ.TREE(II,2)) THEN
      D=0
    ELSE
      D=SQRT(B**2-4*A*C)
    ENDIF
    XL=-1*(B+D)/(2*A)+TREE(II,1)
    XL2=(XL-TREE(II,1))**2
    XH=(-B+D)/(2*A)+TREE(II,1)
    XH2=(XH-TREE(II,1))**2
    IF (TREE(II,1).GE.OBSX) THEN
      IF (TREE(II,2).GT.OBSY) THEN
        T11=XL
        T12=SQRT(R2-XL2)+TREE(II,2)
        T21=XH
        T22=-SQRT(R2-XH2)+TREE(II,2)
      ELSE
        T11=XH
        T12=SQRT(R2-XH2)+TREE(II,2)
        T21=XL
        T22=-SQRT(R2-XL2)+TREE(II,2)
      ENDIF
    ELSE
      IF (TREE(II,2).GE.OBSY) THEN
        T11=XL
        T12=-SQRT(R2-XL2)+TREE(II,2)
        T21=XH
        T22=SQRT(R2-XH2)+TREE(II,2)
      ELSE
        T11=XH
        T12=-SQRT(R2-XH2)+TREE(II,2)
```

```
                T21=XL
                T22=SQRT(R2-XL2)+TREE(II,2)
              ENDIF
            ENDIF
            IF (T12.NE.OBSY) THEN
              BLIND(NBLIND,2)=ATAN(ABS((T11-OBSX)/(T12-OBSY)))
              IF (T11.LT.OBSX) BLIND(NBLIND,2)=-BLIND(NBLIND,2)
            ELSE
              BLIND(NBLIND,2)=-1*PI/2
            ENDIF
            IF (T22.NE.OBSY) THEN
              BLIND(NBLIND,3)=ATAN(ABS((T21-OBSX)/(T22-OBSY)))
              IF (T21.LT.OBSX) BLIND(NBLIND,3)=-BLIND(NBLIND,3)
            ELSE
              BLIND(NBLIND,3)=PI/2
            ENDIF
            IF (T11.NE.T21) THEN
              BLIND(NBLIND,4)=(T22-T12)/(T21-T11)
              BLIND(NBLIND,5)=T22-T21*BLIND(NBLIND,4)
            ELSE
              BLIND(NBLIND,4)=-999
              BLIND(NBLIND,5)=-B/(2*A)
            ENDIF
            DO 555 JJ=1,NBLIND-1
              IF ((BLIND(NBLIND,2).GE.BLIND(JJ,2)).AND.
     *         (BLIND(NBLIND,3).LE.BLIND(JJ,3))) THEN
                KK=IFIX(BLIND(JJ,1))
                IF (DIST.GT.SQRT((OBSY-TREE(KK,1))**2+
     *           (OBSX-TREE(KK,2))**2)) THEN
                  NBLIND=NBLIND-1
                  GO TO 111
                ENDIF
              ENDIF
 555        CONTINUE
          ENDIF
        ENDIF
      ENDIF
      GO TO 111
C     CHECKING VISUAL FIELD FOR BIRDS DETECTION.
 112  NN=NBLIND-1
      DO 510 J=1,NN
        L=J
        JJ=J+1
        DO 620 I=JJ,NBLIND
          IF (BLIND(L,2).LT.BLIND(I,2)) GO TO 620
          L=I
 620    CONTINUE
        DO 530 II=1,5
          T=BLIND(L,II)
          BLIND(L,II)=BLIND(J,II)
 530      BLIND(J,II)=T
 510  CONTINUE
        II=K3
```

```
121     II=II+1
        IF (II.GT.NBIRD) GO TO 11
        IF (BIRD(II,3).EQ.2) GO TO 121
        IF (BIRD(II,2).LT.OBSY) THEN
          K3=II
          GO TO 121
        ENDIF
        YY=BIRD(II,2)-FLOAT(OBSY)
        IF (YY.GT.DV) GO TO 11
122     XX=BIRD(II,1)-FLOAT(OBSX)
        IF (XX.LT.-DV) THEN
          IF (II+1.GT.NBIRD) GO TO 11
          IF (BIRD(II,2).NE.BIRD(II+1,2)) THEN
            GO TO 121
          ELSE
            II=II+1
            GO TO 122
          ENDIF
        ENDIF
        IF (XX.GT.DV) THEN
603       IF (II+1.GT.NBIRD) GO TO 11
          IF (BIRD(II,2).EQ.BIRD(II+1,2)) THEN
            II=II+1
            GO TO 603
          ELSE
            GO TO 121
          ENDIF
        ENDIF
        DIST=SQRT(XX**2+YY**2)
        IF (DIST.GT.DV) THEN
          IF (XX.LT.OBSX) THEN
            IF (II+1.GT.NBIRD) GO TO 11
            IF (BIRD(II,2).EQ.BIRD(II+1,2)) THEN
              II=II+1
              GO TO 122
            ELSE
              GO TO 121
            ENDIF
          ELSE
123         IF (II+1.GT.NBIRD) GO TO 11
            IF (BIRD(II,2).EQ.BIRD(II+1,2)) THEN
              II=II+1
              GO TO 123
            ENDIF
            GO TO 121
          ENDIF
        ENDIF
        IF (BIRD(II,1).EQ.OBSX) THEN
          W=0
        ELSEIF (BIRD(II,1).LT.OBSX) THEN
          IF (BIRD(II,2).EQ.OBSY) THEN
            W=-1*PI2
          ELSE
```

```
          W=-1*ATAN(ABS(XX/YY))
        ENDIF
      ELSE
        IF (BIRD(II,2).EQ.OBSY) THEN
          W=PI2
        ELSE
          W=ATAN(ABS(XX/YY))
        ENDIF
      ENDIF
      IF (ABS(W).GT.PERF) GO TO 121
      DO 24 JJ=1,NBLIND
        IF (BLIND(JJ,2).GT.W) GO TO 124
        IF ((BLIND(JJ,2).LE.W).AND.(BLIND(JJ,3).GT.W)) THEN
          IF (BLIND(JJ,4).EQ.-999) THEN
            IF (ABS(BIRD(ii,1)).GT.ABS(BLIND(JJ,5))) then
              GO TO 121
            ENDIF
          ELSE
            BMAX=BLIND(JJ,4)*BIRD(II,1)+BLIND(JJ,5)
            IF (BIRD(II,2).GT.BMAX) THEN
              GO TO 121
            ENDIF
          ENDIF
        ENDIF
 24   CONTINUE
 124  IF (XX.EQ.0) THEN
        BIRD(II,5)=0
        GO TO 121
      ENDIF
      LAMDA=EXP(BETA0-BETA1*ABS(W))
      IF (DIST.GT.EXP(LOG(DV)-BETA1*ABS(W))) THEN
        GV=0.0
      ELSE
        GV=EXP(-DIST/(LAMDA*10))
      ENDIF
      BIRD(II,5)=BIRD(II,5)*(1-GV)
      GO TO 121
C     AT THIS TIME MOVE TO NEXT METER.
 11   CONTINUE
C     HAVE ENDED SEARCHING PLOT FOR BIRDS.  TEST EACH BIRD FOR
C     VISUAL DETECTION.
     DO 30 II=1,NBIRD
      IF (BIRD(II,3).EQ.2) GO TO 30
      IF (BIRD(II,5).EQ.1.0) GO TO 30
      BIRD(II,5)=1-BIRD(II,5)
      IF (BIRD(II,5).GT.1.0) THEN
        WRITE(6,*) 'ERROR IN PROB. '
        STOP
      ENDIF
      RANDOM=DRAND(ISEED)
      IF (RANDOM.LE.BIRD(II,5)) THEN
C     BIRD IS DETECTED.
        NDECT=NDECT+1
```

```
      BIRD(II,3)=2
      JREP=(BIRD(II,2)*NI)/L+1
      NREP(JREP)=NREP(JREP)+1
      PERP(NDECT)=ABS(BIRD(II,1)-OBSX)*.0002*L
    ENDIF
 30   CONTINUE
      WRITE(6,*) 'AUDIO ',NAUDIO,' VISUAL ',NDECT-NAUDIO
      RETURN
      END

      SUBROUTINE ORDIT(N,X)
C     THIS TAKES AN ARRAY 'X' OF LENGTH OF 'N' AND RETURNS THE
C     ARRAY ORDERED IN INCREASING ORDER OF MAGNITUDE
C     BASED ON PROGRAM BY RAMSEY
      DIMENSION X(N)
    5 L=0
      DO 10 I=1,N-1
      IF(X(I).GT.X(I+1)) THEN
        T=X(I+1)
        X(I+1)=X(I)
        X(I)=T
        L=1
      END IF
   10 CONTINUE
      IF(L.GT.0) GO TO 5
      RETURN
      END

      SUBROUTINE CUMD(N,X,EFAR)
C     THIS RETURNS THE 'EFAR' = EFFECTIVE AREA FROM THE CUMULATIVE
C     DISTRIBUTION ESTIMATOR OF WILDMAN&RAMSEY (1985) BASED ON 'N'
C     DETECTION AREAS (ORDERED), 'X'.  PROGRAM PROVIDED BY RAMSEY.
      DIMENSION X(N)
      DIMENSION XV(2000),YV(2000),DE(2000)
      YV(1)=0.
      XV(1)=0.
      DE(1)=999999999.
      K=1
      J=SQRT(1.*N)-1
    5 IF(J.GE.N) GO TO 20
      K=K+1
      J=J+1
      YV(K)=FLOAT(J)*1.
      XV(K)=X(J)
   10 L=K-1
      DR=XV(K)-XV(L)
      IF(DR.LE.0.) GO TO 15
      DE(K)=(YV(K)-YV(L))/DR
      IF(DE(K).LT.DE(L)) GO TO 5
   15 XV(L)=XV(K)
      YV(L)=YV(K)
      K=L
      GO TO 10
```

```
20 L=K-1
   IF(XV(1).NE.XV(k)) GO TO 25
   K=1
25 LM=K
   K=2
   L=3
30 IF(L.GT.LM) GO TO 35
   YM=YV(L)-YV(L-1)
   T=YV(2)*LOG(DE(2))+YM*LOG(DE(1))
  *  -(YM+YV(2))*LOG((YM+YV(2))/(XV(L)+XV(2)-XV(L-1)))
   IF(T.GE.2.) GO TO 35
   L=L+1
   GO TO 30
35 EFAR=XV(L-1)*N/YV(L-1)
   RETURN
   END

      SUBROUTINE FOSER(N,X,LCUT,AREA)
C     THIS CALCULATES THE FOURIER SERIES ESTIMATOR OF EFFECTIVE
C     'AREA' SURVEYED.  THE INPUT DATA AREA 'N'=THE NUMBER OF
C     OF DETECTIONS AND 'X' = THE ORDERED ARRAY OF DETECTION
C     AREAS.  THE OUTPUTS ARE THE EFFECTIVE 'AREA' AND
C     'LCUT' = THE NUMBER OF TERMS IN THE FOURIER
C      SERIES EXPANSION.  NOTE:  THIS ROUTINE DOES NOT TRUNCATE  2%
C     OF THE DATA. ONLY 5 TERMS ARE ALLOWED IN THE FOURIER SERIES.
C     PROGRAM PROVIDED BY RAMSEY
      DIMENSION X(N)
      W=X(N)
      A=1./W
      K=1
      C=A*SQRT(2./(N+1.))
      PI=355./113.
    5 B=0.
      DO 10 J=1,N
   10 B=B+COS(K*PI*X(J)/W)
      B=2.*B/N/W
      T=ABS(B)
      IF(T.LE.C) GO TO 20
      A=A+B
      IF(K.EQ.5) GO TO 25
      K=K+1
      GO TO 5
   20 K=K-1
   25 LCUT=K
      AREA=1./A
      RETURN
      END
```

```
      SUBROUTINE EPMLE(N,X,EST,G)
C     THIS PROGRAM CALCULATES THE ESTIMATED AREA USING THE
C     EXPONENTIAL POWER SERIES WITH UNKNOWN SHAPE.
C     PROGRAM BASED ON ONE PROVIDED BY RAMSEY.
      DIMENSION X(N)
      G=.25
      CALL LOGLIK(N,X,G,XLL)
   15 GG=G
      XLB=XLL
   20 G=G+.25
      IF(G.GT.10.) GO TO 30
      CALL LOGLIK(N,X,G,XLL)
      IF(XLL.GT.XLB) GO TO 15
      GO TO 20
   30 G=GG
      T=0.
      DO 40 I=1,N
      IF(X(I).LE.0.) GO TO 40
      ZP=(X(I)/X(N))**G
      T=T+ZP
   40 CONTINUE
      Z=1.+1./G
      CALL LOGGAM(Z,GO)
      EST=(EXP(GO))*X(N)*(G*T/N)**(1/G)
      RETURN
      END

      SUBROUTINE LOGLIK(N,X,G,XLL)
C     THIS SUBROUTINE CALCULATES THE VALUE OF THE LOG-LIKELIHOOD
C     FUNCTION FOR THE EPMLE, WITH NO COVARIATES.
C     INPUTS ARE: N=NUMBER OF DATA POINTS,
C                 X=ARRAY OF ORDERED DETECTION AREAS,
C                 G=CURRENT VALUE OF THE GAMMA PARAMETER.
C     OUTPUT IS XLL = LOG LIKELIHOOD.
C     NOTE:  THIS USES THE MAXIMAL INVARIANT STATISTIC.
      DIMENSION X(N)
      Z=N/G
      CALL LOGGAM(Z,GO)
      XLL=GO-LOG(G)
      Z=1.+1./G
      CALL LOGGAM(Z,GO)
      XLL=XLL-N*GO
      SC=1
      DO 10 J=1,N-1
   10 SC=SC+(X(J)/X(N))**G
      XLL=XLL-N*(LOG(SC))/G
      RETURN
      END
```

```
      SUBROUTINE LOGGAM(Z,G0)
C     THIS SUBROUTINE RETURNS AS G0 THE LOGARITHM OF THE GAMMA
C     FUNCTION OF THE ARGUEMENT Z.
      G0=-LOG(Z)
    5 Z=Z+1.
      G0=G0-LOG(Z)
      IF(Z.LT.200.) GO TO 5
      Z=Z+1.
      G0=G0+(LOG(710./113.))/2.-Z+(Z-.5)*LOG(Z)+1./(12.*Z)
      G0=G0-1./(360.*(Z**3))+1./(1260.*(Z**5))-1./(1680.*(Z**7))
      RETURN
      END

      SUBROUTINE BSTRAP(N1,N2,M,ACD,SCD,DCD,UCD,AFS,SFS,DFS,UFS
     *   ,AWB,SWB,DWB,UWB,ME,CUMDD,FOSERD,EPMLED,NI)
C     THIS ROUTINE GIVES BOOTSTRAP ESTIMATES OF EFFECTIVE AREA
C     SURVEYED, USING THE CUMD AND THE FOURIER SERIES ESTIMATORS.
C       INPUTS: X  = DATA VECTOR (LENGTH N1) OF AREAS
C       OUTPUTS:
C           A__ = AVERATE OF __ ESTIMATES
C           S__ = STANDARD DEVIATION OF __ ESTIMATES
C           D__ = SMALLEST __ ESTIMATE
C           U__ = GREATEST __ ESTIMATE
C     PROGRAM BASED ON ONE PROVIDED BY RAMSEY
      DOUBLE PRECISION DRAND,ISEED,K
      DIMENSION PERP(300),Y(300),NREP(10)
      COMMON ISEED,L,W
      COMMON /AREA/PERP,NREP
      ACD=0.
      SCD=0.
      DCD=9999999.
      DFS=DCD
      UCD=-DCD
      UFS=UCD
      AFS=0.
      SFS=0.
      AWB=0.
      SWB=0.
      DWB=DCD
      UWB=UCD
      ME=M
      DO 50 I=1,M
      DO 30 J=1,N2
      Z=SNGL(DRAND(ISEED))
      K=(ISEED/(2147463647/N1))+1
      Y(J)=PERP(K)
   30 CONTINUE
      SUM=0.
      DO 31 J=1,NI
        Z=SNGL(DRAND(ISEED))
        K=(ISEED/(2147463647/NI))+1
        SUM=SUM+FLOAT(NREP(K))
   31 CONTINUE
```

```
      CALL ORDIT(N2,Y)
      CALL CUMD(N2,Y,EFAR)
      CALL FOSER(N2,Y,LCUT,AREA)
      CALL EPMLE(N2,Y,EST,G)
      FOR=FLOAT(N2)/AREA
      CUM=FLOAT(N2)/EFAR
      EP=SUM/EST
      ACD=ACD+CUM
      SCD=SCD+CUM**2
      AFS=AFS+FOR
      SFS=SFS+FOR**2
      AWB=AWB+EP
      SWB=SWB+EP**2
      IF (DWB.GT.EP) DWB=EP
      IF (UWB.LT.EP) UWB=EP
      IF(DCD.GT.CUM) DCD=CUM
      IF(UCD.LT.CUM) UCD=CUM
      IF(DFS.GT.FOR) DFS=FOR
      IF(UFS.LT.FOR) UFS=FOR
 50   CONTINUE
      SCD=SCD-ACD*ACD/FLOAT(M)
      SFS=SFS-AFS*AFS/FLOAT(M)
      SWB=SWB-AWB*AWB/FLOAT(M)
      SCD=SQRT(SCD/FLOAT(M-1))
      SFS=SQRT(SFS/FLOAT(M-1))
      SWB=SQRT(SWB/FLOAT(M-1))
      ACD=ACD/FLOAT(M)
      AFS=AFS/FLOAT(M)
      AWB=AWB/FLOAT(M)
      RETURN
      END

      FUNCTION RLOG(ALPHA,BETA,ISEED)
C     GENERATES LOG-LOGISTIC DEVIATES
C     RANDOM DEVIATES GENERATED USING INVERSE METHOD
C     INPUT
C         ALPHA=MEAN OF LOGISTIC DISTRIBUTION
C         BETA=STANDARD DEVEIATION=(BETA*PI)/SQRT(3)
C         ISEED=SEED NUMBER FOR GENERATE UNIFORM VARIATE
      DOUBLE PRECISION DRAND,ISEED
      R=DRAND(ISEED)
      RLOG=ALPHA+BETA*LOG(R/(1.0-R))
      RLOG=EXP(RLOG)
      RETURN
      END

      FUNCTION REXP(XM,ISEED)
C     INPUT
C       XM=MEAN OF EXPONENTIAL DISTRIBUTION
C       ISEED=SEED NUMBER FOR GENERATE UNIFORM VARIATE
C     OUTPUT
C     EXPON(XM,ISEED)=RANDOM VARIATE IN [0,INF) FROM AN EXP DIST.
      DOUBLE PRECISION DRAND,ISEED
```

```
      ICOUNT=0
 100  R=DRAND(ISEED)
      ICOUNT=ICOUNT+1
      IF (ICOUNT.GT.100) THEN
        WRITE(6,*) 'EXP GENERATOR FAILED '
        STOP
      ENDIF
      IF (R.LE.0.0) GO TO 100
      REXP=-XM*ALOG(R)
      RETURN
      END
```

The listed function subprograms can be found in the following references:

1. DOUBLE PRECISION FUNCTION DRAND(ISEED)
   RANDOM NUMBER GENERATOR FOR UNIFORM DIST. REF. SCHRAGE 'A MORE PORTABLE FORTRAN RANDOM NUMBER GENERATOR' ACM TRANS ON MATH. SOFT. VOL. 5, NO 2, JUNE 1979,132-138.

2. FUNCTION RND(ISEED)
   FUNCTION GENERATES A STANDARD RANDOM NORMAL DEVIATE, USING THE POLAR BOX MULLER METHOD. PROGRAM CODE FROM DAGPUNAR, JOHN 'PRINCIPLES OF RANDOM VARIATE GENERATION' (1988).

3. FUNCTION IPOIS(E,ISEED)
   FUNCTION GENERATES A RANDOM POISSON VARIATE CALLING EITHER POIS1(E) (E<EC) OR IPOIS2(E) (E>=EC).
   PROGRAM CODE FROM DAGPUNAR, JOHN: 'PRINCIPLES OF RANDOM VARIATE GENERATION' (1988).

4. FUNCTION GAMMA(S,ISEED)
   FUNCTION GENERATES A RANDOM VARIATE IN [0,INFINITY) FROM A GAMMA DISTRIBUTION WITH DENSITY PROPORTIONAL TO GAMMA**(S-1)*EXP(-GAMMA),
   USING BEST'S T DISTRIBUTION METHOD.
   USE ONLY FOR SHAPE PARAMETER GREATER THAN 1.
   PROGRAM CODE FROM DAGPUNAR (1988).

APPENDIX D

Subroutines for Different Bird Distributions

The following subroutines were added or replaced in VABS in order to create different types of bird dispersion:

```
      SUBROUTINE BIRDS(THETA)
C     THIS PROGRAM DISTRIBUTES BIRDS ONTO SUB-HECTARE PLOTS|
C     DIMENSIONS OF THE PLOT SHOULD BE SUCH THAT IT DIVIDES EVENLY
C     INTO SQUARE HECTARE PLOTS.
      DOUBLE PRECISION DRAND,ISEED
      REAL BIRD(600,5),L,W,IX,IY,LY,LX
      COMMON ISEED,L,W
      COMMON /BBIRD/BIRD,NBIRD
      K=0
      IBIRD=0
      XR=W*.01
      YR=L*.01
      LY=0
      R=XR*YR
      RN=NBIRD/R
C     WRITE(6,*) 'NUMBER OF REGIONS ',R,' MEAN NUMBER BIRDS ',RN
      DO 10 I=1,IFIX(YR)
        LX=0
        UY=LY+100
        DO 20 JJ=1,IFIX(XR)
          UX=LX+100
C         FOR AN OVER-DISPERSED MODEL USE THE FOLLOWING ALGORITHM
C          SWITCHING S AND RN TO MEET REQUIREMENTS
          S=2.5
          RN=GAMMA(S,ISEED)
          RN=RN*4
          NR=IPOIS(RN,ISEED)
C         IF CREATING UNDER-DISPERSION SET NR=10, GENERATES 10
C         BIRDS IN EACH SUBPLOT
C         NR=10
C         IF CREATING POISSON SCATTERING OF BIRDS SELECT NR SUCH
C         THAT IT IS A POISSON DEVIATE WITH A MEAN OF 10
C         RN=10
C         NR=IPOIS(RN,ISEED)
C         WRITE(6,*) 'NUMBER BIRDS IN REGION ',NR
          IBIRD=IBIRD+NR
          DO 40 J=1,NR
            K=K+1
            N=0
 200        N=N+1
            IF (N.GT.100) THEN
              WRITE(6,*) 'PLACING BIRDS BOMBED '
              STOP
            ENDIF
            IX=100.*SNGL(DRAND(ISEED))+LX
```

```
            IY=100.*SNGL(DRAND(ISEED))+LY
            DO 50 II=1,NB-1
50        IF (((BIRD(II,1).GE.IX-.1).AND.(BIRD(II,1).LE.IX+.1))
     *       .AND.((BIRD(II,2).GE.IY-.1).AND.(BIRD(II,2).LE.IY+.1)))
            GO TO 200
            BIRD(K,1)=IX
            BIRD(K,2)=IY
            BIRD(K,3)=1.0
            BIRD(K,4)=REXP(THETA,ISEED)
            BIRD(K,5)=1.0
40        CONTINUE
          LX=UX
20      CONTINUE
        LY=UY
10    CONTINUE
      NBIRD=IBIRD
      NN=NBIRD-1
      DO 510 J=1,NN
        L=J
        JJ=J+1
        DO 620 I=JJ,NBIRD
          IF (BIRD(L,2).LT.BIRD(I,2)) GO TO 620
          L=I
620     CONTINUE
        DO 530 II=1,5
          T=BIRD(L,II)
          BIRD(L,II)=BIRD(J,II)
530       BIRD(J,II)=T
510   CONTINUE
105   LL=0
      DO 540 J=1,NN
        IF (BIRD(J,2).EQ.BIRD(J+1,2)) THEN
          IF (BIRD(J,1).GT.BIRD(J+1,1)) THEN
            DO 550 II=1,5
              T=BIRD(J,II)
              BIRD(J,II)=BIRD(J+1,II)
              BIRD(J+1,II)=T
              LL=1
550         CONTINUE
          ENDIF
        ENDIF
540   CONTINUE
      IF (LL.GT.0) GO TO 105
      END
```

APPENDIX E

Subroutines to Create Slopes and Distribute Birds in Trees

(Used in Section 8.3, 10.6, and 11.4)

To place birds perched in trees, the dimensions for the vectors BIRD and TREE need to be increased to BIRD(500,6) and TREE(7000,4). Furthermore, the following subroutine must be substituted in for the subroutine BIRDS in the base program of VABS. If the height above the ground that the bird is located at is not taken into accounted, bird(j,6) needs to be set to zero.

To place birds in trees, the trees are considered to be cone shaped and the birds are placed randomly on the surface of this cone.

```
      SUBROUTINE BIRDS(THETA)
C     THIS PROGRAM DISTRIBUTES BIRDS ONLY IN TREES.
      DOUBLE PRECISION DRAND,ISEED
      REAL BIRD(500,6),L,W,IX,IY,TREE(7000,4)
      COMMON ISEED,L,W
      COMMON /BTREE/TREE,NT,RMAX /BBIRD/BIRD,NBIRD
      PARAMETER(PI=3.141592654,BASE=0.017453736)
      DATA IYREG,JYREG/1,0/
      NB=NBIRD
      DO 40 J=1,NBIRD
        N=0
 200    N=N+1
        IF (N.GT.100) THEN
          WRITE(6,*) 'PLACING BIRDS BOMBED '
          STOP
        ENDIF
        ID=IFIX(NT*SNGL(DRAND(ISEED)+1)
        BHT=0
        BRAD=(TREE(ID,4)-BHT)*BASE
        ALPHA=2*PI*SNGL(DRAND(ISEED))
        IX=TREE(ID,1)+BRAD*COS(ALPHA)
        IY=TREE(ID,2)+BRAD*SIN(ALPHA)
c      WRITE(6,*) 'ID ',ID,' IX ',IX,' IY ',IY,' BHT ',BHT
        DO 50 II=1,j-1
 50       IF (((BIRD(II,1).GE.IX-.1).AND.(BIRD(II,1).LE.IX+.1))
     *      .AND.((BIRD(II,2).GE.IY-.1).AND.(BIRD(II,2).LE.IY+.1)))
     *      GO TO 200
        BIRD(J,1)=IX
        BIRD(J,2)=IY
        BIRD(J,3)=1.0
        BIRD(J,4)=REXP(THETA,ISEED)
        BIRD(J,5)=1.0
C       Height bird is above ground
        BIRD(J,6)=BHT
 40   CONTINUE
      NN=NBIRD-1
      DO 510 J=1,NN
        L=J
```

```
      JJ=J+1
      DO 620 I=JJ,NBIRD
        IF (BIRD(L,2).LT.BIRD(I,2)) GO TO 620
        L=I
620   CONTINUE
      DO 530 II=1,6
        T=BIRD(L,II)
        BIRD(L,II)=BIRD(J,II)
530     BIRD(J,II)=T
510 CONTINUE
C   HAVE JUST FINISHED SORTING BY THE Y COORDINATE NOW FOR X|
105 LL=0
    DO 540 J=1,NN
      IF (BIRD(J,2).EQ.BIRD(J+1,2)) THEN
        IF (BIRD(J,1).GT.BIRD(J+1,1)) THEN
          DO 550 II=1,6
            T=BIRD(J,II)
            BIRD(J,II)=BIRD(J+1,II)
            BIRD(J+1,II)=T
            LL=1
550       CONTINUE
        ENDIF
      ENDIF
540 CONTINUE
    IF (LL.GT.0) GO TO 105
    RETURN
    END
```

The following lines must be replaced or inserted into the main program of VABS in order to create a plot representing the surface area instead of the base area (W and L are set to correspond to the base area in the main program of VABS). Also, the vector PPERP(300) must be declared when necessary.

```
      NBIRD=NINT((L*W)*RBIRD*.0001)
      DENSITY=NBIRD*10000/(L*W)
      SLOPE=PI/3
      ADJ=COS(SLOPE)
      W=W/ADJ
      SDEN=NBIRD*1000/(L*W)
      WRITE(6,*) 'TARGET DENSITY ',DENSITY ,' SURFACE ',SDEN
      DO 10 I=1,250
        WRITE(6,*) 'REP  ',I,' seed ',ISEED
        DO 20 J=1,NBIRD
20        IF (BIRD(J,3).EQ.2) BIRD(J,3)=1
        CALL BIRDS(THETA)
        CALL DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,NREP,
     *  NI,PPERP,ADJ)
        CALL ORDIT(NDECT,PERP)
        CALL ORDIT(NDECT,PPERP)
        CALL CUMD(NDECT,PERP,EFAR)
        CALL CUMD(NDECT,PPERP,PEFAR)
        CALL FOSER(NDECT,PERP,LCUT,AREA)
```

```
      CALL FOSER(NDECT,PPERP,LLCUT,PAREA)
      CALL EPMLE(NDECT,PERP,EST,G)
      CALL EPMLE(NDECT,PPERP,PEST,PG)
      CUMDD=FLOAT(NDECT)/EFAR
      PCUMDD=FLOAT(NDECT)/pEFAR
      WRITE(6,*) 'Z ',CUMDD,' PZ ',pCUMDD
      FOSERD=FLOAT(NDECT)/AREA
      PFOSERD=FLOAT(NDECT)/pAREA
      WRITE(6,*) 'Z ',FOSERD,' PZ ',PFOSERD
      EPMLED=FLOAT(NDECT)/EST
      PEPMLED=FLOAT(NDECT)/PEST
      WRITE(6,*) 'Z ',EPMLED,' PS ',PEPMLED
      N2=NDECT
      M=100
      CALL BSTRAP(NDECT,N2,M,PERP,PERP,ISEED,CUMDD,PC,CUMDD,FSD,
     *  PFSD,EPD,PEPD,NREP,NI)
```

To calculate the detected area in terms of the base area and surface area, the line

PPERP(NDECT)=PERP(NDECT)*ADJ

must be added whenever the detected areas are being calculated in the subroutine DETECT. The vector PERP stores the detected areas in terms of the surface area, and the vector PPERP stores the detected area in terms of the base area. In the bootstrap routines, all commands for PERP are repeated for the vector PPERP.

To create a plot where birds are in trees located on a slope, the same instructions given when birds are located in trees and when there exist a slope need to be carried out. Whenever calculating the detection distance in the subroutine DETECT, the following lines must be substituted in. Note that the variable SLOPE must be stated in the CALL and SUBROUTINE statement.

```
      RP=ABS(OBSXX-BIRD(I,1))
      If (BIRD(I,1).EQ.OBSXX) THEN
        AAA=BIRD(I,6)
      ELSEIF (BIRD(I,1).LT.OBSXX) THEN
        AAA=SQRT(RP**2+BIRD(I,6)**2-2*RP*BIRD(I,6)*COS(PI2
     *    -SLOPE))
      ELSE
        AAA=SQRT(RP**2+BIRD(I,6)**2
     *      -2*RP*BIRD(I,6)*COS(PI2+SLOPE))
      ENDIF
```

APPENDIX F

Subroutines for Clustered Populations

The following version of the main program needs to replace the main program in VABS. This version of VABS generates clusters of birds and then calculates the density of individual birds as decribed in Section 8.4.

```
      PROGRAM VABS
C     THIS PROGRAM IS THE BASE PROGRAM TO GENERATE A PLOT WITH
C     CLUSTERED BIRD POPULATIONS AND THEN SIMULATES TRAVERSING A
C     TRANSECT DETECTING THE BIRDS BY VISUAL OR AUDIO DETECTION.
      DOUBLE PRECISION ISEED
C     THE DIMENSIONS FOR POINT ARE LENGTH BY WIDTH IN DECIMETERS
      REAL PERP(15000,4),BIRD(15000,7),NREP(10),L,W,MC,
     * CPERP(300),CL(300,4),NREPC(10),RCL(300,4),RCPERP(300)
     * BPERP(15000)
      PARAMETER(PI=3.141593)
      COMMON ISEED,L,W
      COMMON /BBIRD/BIRD,NBIRD,NCBIRD
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      COMMON /ACTUAL/RCL,RCPERP
      OPEN (6,FILE='fam2.out',STATUS='NEW')
C     SPECIFY ISEED, NUMBER NEEDS TO BE LESS THAN  2,147,483,647
      ISEED=1342765011.D0
C     SPECIFY LENTH (DIRECTION WALKING TRANSECT) AND WIDTH OF
C     PLOT THAT WANT TO CREATE.  UNITS ARE IN METERS
C     FOR L=W=100 HAVE A HECTOR
C     L IS THE LENGTH OF PLOT
C     W IS THE WIDTH OF THE PLOT ***NEEDS TO BE LONGER THAN
C       2*(MAXIMUM DISTANCE DETECTION CAN BE MADE)
      L=10000
      W=300
C     DVA IS THE VISUAL ANGLE THRESHOLD IN DEGREES
C     SEEMS REASONABLE TO USE AROUND .067 TO .117 DEGREES
C     ALTHOUGH COULD GO AS LOW AS .05 AND AS HIGHT AS .33
      DVA=.067
      DVA=(PI*DVA)/180.0
C     TT IS THE MEAN TIME SPENT AT EACH GRID POINT, I.E. WALKING
C     PACE PER METERS, UNITS FOR TIME SHOULD BE IN METERS.
C     THE WALKING PACE FOR EACH GRID POINT WILL BE SELECTED FOR
C     THE LOGISTIC DISTRIBUTION.
      TT=-3.6901
C     SDTT IS BETA FOR LOGISTIC DEVIATE
      SDTT=.0276
C     THETA IS THE FREQUENCY OF VOCALIZATION(BIRD CALLS PER
C      MINUTES)
      THETA=.1
      THETA=1.0/THETA
C     PERF IS THE MAX ANGLE OBSERVERS PERIPHERAL VISION IN
C       DEGREES RECOMMEND USING BETWEEN 60 AND 90 DEGREES
C     PROGRAM NEEDS TO BE CHANGED IF PERF GT 90 DEGREESS
```

```
      PERF=75.0
      PERF=(PI*PERF)/180.0
C     BETAO AND BETA1 CORRESPOND TO LN(DIST)=BETAO+BETA1*(ANGLE )
C     SIGHT) BETAO IS CALCULATED USING DVA
      BETA1=.038
C     DA IS THE OBSERVER'S AUDIO DETECTION THRESHOLD IN METERS
      DA=100.0
C     RBIRD IS THE DENSITY OF BIRDS clusters DESIRED PER HECTARE
      RBIRD=1.0
      NCBIRD=NINT((L*W)*RBIRD*.0001)
      NBIRD=0
C     MEAN NUMBER OF BIRDS IN A CLUSTER
      MC=2
C     SPECIFIY THE NUMBER OF SECTIONS CUT TRANSECT IN TO ACCOUNT
C     FOR VARIATION IN N
      NI=10
C     SET THE UPPER LIMIT OF DO LOOP TO NUMBER OF REPS WANT
C     DELETING COMMENT QUE FOR SUBROUTINES DESIRED.
C     THE GRID SUBROUTINE AND DETECT SUBROUTINE ARE NECESSARY
C     WRITE(6,*) 'KEY TO METHODS ESTIMATION FOR BOOTSTRAP.
C     WRITE(6,*) '1 BOOT ON TRUE MEAN CLUSTER '
C     WRITE(6,*) '2 BOOT ON WT. TRUE MEAN CLUSTER '
C     WRITE(6,*) '3 BOOT ON COV. ADJ. TRUE MEAN CLUSTER '
C     WRITE(6,*) '4 BOOT ON ADJ. AREA, TRUE SIZE'
C     WRITE(6,*) '5-1 DRUMMER METHOD USING MLE, TRUE SIZE'
C     WRITE(6,*) '5-2 RAMSEY ADDITIVE MODEL EPS, TRUE SIZE'
C     WRITE(6,*) '5-3 QUANG METHOD USING LS, TRUE SIZE'
C     WRITE(6,*) '6 DRUMMER-RAMSEY LS, CUMD, TRUE'
      DO 10 I=1,250
        WRITE(6,*) 'REP  ',I,' SEED ',ISEED
        CALL BIRDS(THETA,MC)
      DENB=FLOAT(NBIRD)*10000/(L*W)
      WRITE(6,*) 'KNOWN DENSITY PER HECTARE ',DENB
        CALL DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,
     *    NREP,NI,NREPC)
        DO 21 IJ=1,NDECT
 21       BPERP(IJ)=PERP(IJ,1)
        CALL ORDIT(NDECT,BPERP)
        CALL CUMD(NDECT,BPERP,EFAR)
        CALL FOSER(NDECT,BPERP,LCUT,AREA)
        CALL EPMLE(NDECT,BPERP,EST,G)
        DCUMD=FLOAT(NDECT)/EFAR
        DFS=FLOAT(NDECT)/AREA
        DEPS=FLOAT(NDECT)/EST
        WRITE(6,*) 'BIRD CUMD ',DCUMD,' FS ',DFS,' EP ',DEPS
C     SAMPLE SIZE TO DRAW FOR BOOTSTRAP REP
        N2=NDECT
C     NUMBER OF BOOTSTRAP REPS
        M=10
        CALL BSTRAP(NDECT,N2,M,BPERP,ISEED,nREP,NI)
        NCDECT=0
        DO 22 IJ=1,NDECT
          IF (PERP(IJ,3).EQ.1) THEN
```

```
          NCDECT=NCDECT+1
          CPERP(NCDECT)=PERP(IJ,1)
          CL(NCDECT,1)=PERP(IJ,2)
          CL(NCDECT,2)=1
          CL(NCDECT,3)=CPERP(NCDECT)
          CL(NCDECT,4)=PERP(IJ,4)
          RCPERP(NCDECT)=PERP(IJ,1)
          RCL(NCDECT,1)=PERP(IJ,2)
          RCL(NCDECT,2)=1
          RCL(NCDECT,3)=CPERP(NCDECT)
          RCL(NCDECT,4)=PERP(IJ,4)
        ELSE
          DO 23 IIJ=1,NCDECT
            IF (PERP(IJ,2).EQ.CL(IIJ,1)) THEN
              CL(IIJ,2)=CL(IIJ,2)+1
              RCL(IIJ,2)=RCL(IIJ,2)+1
              GO TO 22
            ENDIF
23        CONTINUE
        ENDIF
22    CONTINUE
      WRITE(6,*) 'NUMBER CLUSTERS DETECTED ',NCDECT
      CALL CLORDIT
      CALL ORDIT(NCDECT,CPERP)
      CALL SIZE(EMEAN,TMEAN,ESMAX,TSMAX)
      MM=2
      CALL QUINN(EMEAN,DEACD,DEAFS,DEAEP,
     *  DEWCD,DEWFS,DEWEP,NCDECT,QEMEAN,MM)
      CALL MADD(EDADD,MM)
      CALL COVAR(DECUM,DEFS,DEEPS,EB,EBV,EDEFAR,EDAREA,EDEST,MM)
      CALL GDRUM(EDRUM,MM)
      CALL LSDRUM(CEDRUM,FEDRUM,EEDRUM,MM)
      CALL QUANG(EQDEN,MM)
      MM=4
      CALL QUINN(TMEAN,DTACD,DTAFS,DTAEP,
     *  DTWCD,DTWFS,DTWEP,NCDECT,QTMEAN,MM)
      CALL MADD(TDADD,MM)
      CALL COVAR(DTCUM,DTFS,DTEPS,TB,TBV,TDEFAR,TDAREA,TDEST,MM)
      CALL GDRUM(TDRUM,MM)
      CALL LSDRUM(CTDRUM,FTDRUM,ETDRUM,MM)
      CALL QUANG(TQDEN,MM)
      WRITE(6,*) 'EST. MEAN CLUSTER SIZE ',EMEAN
      WRITE(6,*) 'CUMD ',DEACD,' FS ',DEAFS,' EP ',DEAEP
      WRITE(6,*) 'TRUE MEAN CLUSTER SIZE ',TMEAN
      WRITE(6,*) 'CUMD ',DTACD,' FS ',DTAFS,' EP ',DTAEP
      WRITE(6,*) 'WT. CLUSTER ESTIMATED MEAN',QEMEAN
      WRITE(6,*) 'CUMD ',DEWCD,' FS ',DEWFS,' EP ',DEWEP
      WRITE(6,*) 'TRUE MEAN WT CLUSTER SIZE ',QTMEAN
      WRITE(6,*) 'CUMD ',DTWCD,' FS ',DTWFS,' EP ',DTWEP
      WRITE(6,*) 'DENISTY ESTIMATES FOR ADJ.EST, EST CLUSTER'
      WRITE(6,*) 'FIX GAMMA EST. ',EDADD,' TRUE ',TDADD
      WRITE(6,*) ' CUM ',DECUM,' EFS ',DEFS,' EPS ',DEEPS
      WRITE(6,*) 'TRUE CLUSTER SIZE'
```

```
      WRITE(6,*) ' CUM ',DTCUM,' EFS ',DTFS,' EPS ',DTEPS
      WRITE(6,*) 'FIX GAMMA EDRUM',EDRUM,' TDRUM ',TDRUM
      WRITE(6,*) 'DRUM LS CD',CEDRUM,' FS ',FEDRUM,' EPS
     *     ',EEDRUM
      WRITE(6,*) 'DRUM LS CD',CTDRUM,' FS ',FTDRUM,' EPS
     * ',ETDRUM
      WRITE(6,*) 'QUANG EST. SIZE ',EQDEN,' TRUE ',TQDEN
      N2=NCDECT
      CALL CBSTRP(NCDECT,N2,M,ISEED,NREPC,NI,eb,ebv,tb,tbv,
     *   EDEFAR,EDAREA,EDEST,TDEFAR,TDAREA,TDEST)
 10   CONTINUE
      END
```

The following subroutines needed to be substituted in for the previously given subroutines with the same name:

```
      SUBROUTINE BIRDS(THETA,MC)
C     THIS PROGRAM DISTRIBUTES BIRDS ONTO THE PLOT.  THIS
C     SPECIFIC VERSION ALLOWS FOR CLUSTERS TO BE DETECTED.
C     CLUSTER SIZE IS DETERMINED AS IN SECTION 8.2, ALL
C     FOUR DISTRIBUTIONS CAN BE OBTAINED IN THIS SUBROUTINE
C     BY PLACING 'C' APPROPRIATELY AND SPECIFING CORRECT
C     VALUE OF MC IN THE MAIN PROGRAM.
      DOUBLE PRECISION DRAND,ISEED
      INTEGER NC(300)
      REAL BIRD(15000,7),L,W,IX,IY,IXC(300),IYC(300),MC
      COMMON ISEED,L,W
      COMMON /BBIRD/BIRD,NBIRD,NCBIRD
      DATA IYREG,JYREG/1,0/
      NB=0
      DO 40 J=1,NCBIRD
        NC(J)=0
C100    NC(J)=IPOIS(MC,ISEED)
C100    NC(J)=(MC*SNGL(DRAND(ISEED)))+10
C       IF (NC(J).EQ.0) GO TO 100
 100    IIF=IPOIS(MC,ISEED)
        IF (IIF.EQ.0) GO TO 100
        DO 44 IJ=1,IIF
          X=DRAND(ISEED)
          IF (X.GE.0.AND.X.LT..1) FI=1
          IF (X.GT..1.AND.X.LT..5) FI=2
          IF (X.GT..5.AND.X.LT..65) FI=3
          IF (X.GT..65.AND.X.LT..8) FI=4
          IF (X.GT..8.AND.X.LT..95) FI=5
          IF (X.GT..95.AND.X.LE.1) FI=6
 44     NC(J)=NCc(J)+FI
        MIXC=0
 200    MIXC=MIXC+1
        IF (MIXC.GT.100) THEN
          WRITE(6,*) 'ERROR PLACING CLUSTERS'
          WRITE(6,*) 'MIX CLUSTERS ',J
          STOP
        ENDIF
```

```
      IXC(J)=W*SNGL(DRAND(ISEED))
      IYC(J)=L*SNGL(DRAND(ISEED))
      DO 50 II=1,J-1
50      IF (((IXC(II).GE.IXC(J)-10).AND.(IXC(II).LE.IXC(J)+10))
     *    .AND.((IYC(II).GE.IYC(J)-10).AND.
     *    (IYC(II).LE.IYC(J)+10))) GO TO 200
      DO 60 II=1,NC(J)
      MIX=0
201   MIX=MIX+1
      IF (MIX.GT.100) THEN
        WRITE(6,*) 'ERROR PLACING BIRDS'
        STOP
      ENDIF
        IX=IXC(J)+RND(ISEED)*2
        IY=IYC(J)+RND(ISEED)*2
        DO 70 IJ=1,NB-1
70         IF (((BIRD(IJ,1).GE.IX-.1).AND.(BIRD(IJ,1).LE.IX+.1))
     *       .AND.((BIRD(IJ,2).GE.IY-.1).AND.
     *      (BIRD(IJ,2).LE.IY+.1)))    GO TO 201
        IF ((IX.LT.0).OR.(IX.GT.W).OR.(IY.LT.0).OR.(IY.GT.L))
     *    THEN
           IF (II.EQ.1) GO TO 201
           GO TO 60
        ENDIF
        NB=NB+1
        BIRD(NB,1)=IX
        BIRD(NB,2)=IY
        BIRD(NB,3)=1.0
        BIRD(NB,4)=REXP(THETA,ISEED)
        BIRD(NB,5)=J
        BIRD(NB,6)=NC(J)
        BIRD(NB,7)=1
60    CONTINUE
40    CONTINUE
      NBIRD=NB
      WRITE(6,*) 'NUMBER OF CLUSTERS ',NCBIRD ,' NUMBER BIRDS
     *  ',NBIRD
      RETURN
      END

      SUBROUTINE DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,
     *  NREP,NI,NREPC)
C     THIS VERSION OF DETECTION IF FOR CLUSTERED POPULATIONS
C     WHEN DETECTION OF BIRDS IN THE SAME CLUSTER ARE DEPENDENT
      DOUBLE PRECISION DRAND,ISEED
      INTEGER OBSX,OBSY,NREP(NI),NREPC(NI)
      REAL DIST,TIME(10000),PERP(15000,4),L,W,LOGDV,
     *   LAMDA,GV,BIRD(15000,7),DVA,TT,SDTT,PERF,BETA1,DT,PR(300,4)
      LOGICAL KEYX,KEYY
      PARAMETER(PI=3.141593,PI2=1.570796,PI4=.785398)
      COMMON ISEED,L,W
      COMMON/BBIRD/BIRD,NBIRD,NCBIRD
      CLUSTER=0
```

```
      TTOTAL=0
      NDECT=0
      NAUDIO=0
      NVISUAL=0
      FA=0
      DO 42 I=1,NI
        NREPC(I)=0
42      NREP(I)=0
      DV=.05/TAN(DVA*0.5)
      LOGDV=LOG(DV)
      BETA0=LOG(DV*.021715)
      OBSX=W/2
      DO 31 I=1,IFIX(L)
31      TIME(I)=RLOG(TT,SDTT,ISEED)
       DO 11 OBSY=1,IFIX(L)
        IF (OBSY.GT.1) THEN
          DO 512 II=1,NBIRD
512         IF (BIRD(II,3).EQ.3) BIRD(II,3)=1
          DO 511 II=1,N
            ID=IFIX(PR(II,2))
            IF (BIRD(ID,3).EQ.2) GO TO 511
            BIRD(ID,7)=BIRD(ID,7)*(1-PR(II,4))
511       CONTINUE
        ENDIF
        HREP=0
321     IIB=0
        HREP=HREP+1
        FAUDIO=0
        DO 121 II=1,NBIRD
          IF (BIRD(II,3).EQ.2) GO TO 121
          YY=BIRD(II,2)-FLOAT(OBSY)
          IF (YY.GT.DA) GO TO 121
          XX=BIRD(II,1)-FLOAT(OBSX)
          IF (XX.GT.DA) GO TO 121
          DIST=SQRT(XX**2+YY**2)
          IF (DIST.GT.DA) GO TO 121
          BIRD(II,4)=BIRD(II,4)-TIME(OBSY)
          IF (BIRD(II,4).GT.0) THEN
            GO TO 121
          ELSE
            IF (BIRD(II,4).LT.FAUDIO) THEN
              FAUDIO=BIRD(II,4)
              IIB=II
              GO TO 121
            ENDIF
          ENDIF
121     CONTINUE
        IF (IIB.EQ.0) THEN
          IF(HREP.EQ.1) THEN
            GO TO 122
          ELSE
            GO TO 11
          ENDIF
```

```
      ELSE
        NDECT=NDECT+1
        NAUDIO=NAUDIO+1
        BIRD(IIB,3)=2
        CLUSTER=BIAD(IIB,5)
        IF (BIRD(IIB,2).EQ.OBSY) THEN
          FA=PI2
          IF (BIRD(IIB,2).LT.OBSX) FA=-FA
        ELSE
          FA=ATAN((BIRD(IIB,1)-FLOAT(OBSX))
     *       /(BIRD(IIB,2)-FLOAT(OBSY)))
        ENDIF
        IF (((BIRD(IIB,1)-FLOAT(OBSX)).GE.0).AND.
     *      ((BIRD(IIB,2)-FLOAT(OBSY)).LT.0)) FA=PI-FA
        IF (((BIRD(IIB,1)-FLOAT(OBSX)).LT.0).AND.
     *      ((BIRD(IIB,2)-FLOAT(OBSY)).LT.0)) FA=FA-PI
        JREP=(BIRD(IIB,2)*NI)/L+1
        NREP(JREP)=NREP(JREP)+1
        PERP(NDECT,1)=ABS(BIRD(IIB,1)-OBSX)*.0002*L
        PERP(NDECT,2)=BIRD(IIB,5)
        PERP(NDECT,3)=1
        PERP(NDECT,4)=BIRD(IIB,6)
        DO 56 IJ=1,NDECT-1
56        IF (PERP(IJ,2).EQ.PERP(NDECT,2)) PERP(NDECT,3)=0
        IF (PERP(NDECT,3).EQ.1) NREPC(JREP)=NREPC(JREP)+1
      ENDIF
122   N=0
      DO 123 II=1,NBIRD
        IF (BIRD(II,3).EQ.2) GO TO 123
        YY=ABS(BIRD(II,2)-FLOAT(OBSY))
        IF (YY.GT.DV) GO TO 123
        XX=ABS(BIRD(II,1)-FLOAT(OBSX))
        IF (XX.GT.DV) GO TO 123
        DIST=SQRT(XX**2+YY**2)
        IF (DIST.GT.Dv) GO TO 123
        IF (XX.EQ.0) THEN
          NDECT=NDECT+1
          CLUSTER=BIRD(ii,5)
          BIRD(II,3)=2
          FA=0
          JREP=(BIRD(II,2)*NI)/L+1
          NREP(JREP)=NREP(JREP)+1
          PERP(NDECT,1)=ABS(BIRD(II,1)-float(OBSX))*.0002*L
          PERP(NDECT,2)=BIRD(II,5)
          PERP(NDECT,3)=1
          PERP(NDECT,4)=BIRD(II,6)
          DO 57 IJ=1,NDECT-1
57          IF (PERP(IJ,2).EQ.PERP(NDECT,2)) PERP(NDECT,3)=0
          IF (PERP(NDECT,3).EQ.1) NREPC(JREP)=NREPC(JREP)+1
          GO TO 123
        ENDIF
        KEYX=.TRUE.
        IF (BIRD(II,1).LT.OBSX) KEYX=.FALSE.
```

```
KEYY=.TRUE.
IF (BIRD(II,2).LT.OBSY) KEYY=.FALSE.
IF (KEYX) THEN
  IF (KEYY) THEN
    IF (BIRD(II,2).EQ.OBSY) THEN
      ALPHA2=PI2
    ELSE
      ALPHA2=ATAN(XX/YY)
    ENDIF
    W=ABS(FA-ALPHA2)
    IF (W.GT.PI) W=2*PI-W
    IF (W.GT.PERF) THEN
      GV=0.0
    ELSE
      LAMDA=EXP(BETA0-BETA1*W)
      IF (DIST.GT.EXP(LOGDV-BETA1*W)) THEN
        GV=0.0
      ELSE
        IF (BIRD(II,5).NE.CLUSTER) THEN
          GV=EXP(-DIST/(LAMDA*10))
        ELSE
          GV=EXP(-DIST/(LAMDA*100))
        ENDIF
      ENDIF
    ENDIF
  ELSE
    IF (BIRD(II,2).EQ.OBSY) THEN
      ALPHA2=PI2
    ELSE
      ALPHA2=PI-ATAN(XX/YY)
    ENDIF
    W=ABS(FA-ALPHA2)
    IF (W.GT.PI) W=2*PI-W
    IF (W.GT.PERF) THEN
      GV=0.0
    ELSE
      LAMDA=EXP(BETA0-BETA1*W)
      IF (DIST.GT.EXP(LOGDV-BETA1*W)) THEN
      ELSE
        IF (BIRD(II,5).NE.CLUSTER) THEN
          GV=EXP(-DIST/(LAMDA*10))
        ELSE
          GV=EXP(-DIST/(LAMDA*100))
        ENDIF
      ENDIF
    ENDIF
  ENDIF
ELSE
  IF (KEYY) THEN
    IF (BIRD(II,2).EQ.OBSY) THEN
        ALPHA2=-PI2
    ELSE
      ALPHA2=ATAN(-XX/YY)
```

```
    ENDIF
    W=ABS(FA-ALPHA2)
    IF (W.GT.PI) W=2*PI-W
    IF (W.GT.PERF) THEN
      GV=0.0
    ELSE
      LAMDA=EXP(BETA0-BETA1*W)
      IF (DIST.GT.EXP(LOGDV-BETA1*W)) THEN
        GV=0.0
      ELSE
        IF (BIRD(II,5).NE.CLUSTER) THEN
          GV=EXP(-DIST/(LAMDA*10))
        ELSE
          GV=EXP(-DIST/(LAMDA*100))
        ENDIF
      ENDIF
    ENDIF
  ELSE
    IF (BIRD(II,2).EQ.OBSY) THEN
      ALPHA2=-PI2
    ELSE
      ALPHA2=ATAN(XX/YY)-PI
    ENDIF
    W=ABS(FA-ALPHA2)
    IF (W.GT.PI) W=2*PI-W
    IF (W.GT.PERF) THEN
      GV=0.0
    ELSE
      LAMDA=EXP(BETA0-BETA1*W)
      IF (DIST.GT.EXP(LOGDV-BETA1*W)) THEN
        GV=0.0
      ELSE
        IF (BIRD(II,5).NE.CLUSTER) THEN
          GV=EXP(-DIST/(LAMDA*10))
        ELSE
          GV=EXP(-DIST/(LAMDA*100))
        ENDIF
      ENDIF
    ENDIF
  ENDIF
ENDIF
IF (GV.GT.0) THEN
  N=N+1
  IF (BIRD(II,5).ne.CLUSTER) THEN
    PR(N,1)=GV*BIRD(II,7)
    PR(N,4)=GV
  ELSE
    PR(N,1)=GV
    PR(N,4)=GV
  ENDIF
  PR(N,2)=II
  PR(N,3)=BIRD(II,5)
ENDIF
```

```
123     CONTINUE
       NN=N-1
       IF (N.EQ.0) THEN
         GO TO 11
       ELSE
28      L=0
        DO 29 Ij=1,N-1
          IF (PR(IJ,1).LT.PR(IJ+1,1)) THEN
           DO 15 JJ=1,4
             T=PR(IJ+1,JJ)
             PR(IJ+1,JJ)=PR(IJ,JJ)
15           PR(IJ,JJ)=T
           L=1
         ENDIF
29     CONTINUE
       IF (L.GT.0) GO TO 28
       BMISS=1
       DO 30 II=1,N
         ID=IFIX(PR(II,2))
         IF ((BIRD(ID,3).EQ.3).AND.(BIRD(ID,5).NE.CLUSTER))
     *     GO TO 30
         IF (DRAND(ISEED).LE.PR(II,1)) THEN
           NDECT=NDECT+1
           NVISUAL=NVISUAL+1
           CLUSTER=BIRD(ID,5)
           BIRD(ID,3)=2
           IF (BIRD(ID,2).EQ.OBSY) THEN
             FA=PI2
             IF (BIRD(ID,2).LT.OBSX) FA=-FA
           ELSE
             FA=ATAN((BIRD(ID,1)-FLOAT(OBSX))/(BIRD(ID,2)-
     *         FLOAT(OBSY)))
           ENDIF
           IF (((BIRD(ID,1)-FLOAT(OBSX)).GE.0).AND.
     *       ((BIRD(ID,2)-FLOAT(OBSY)).LT.0)) FA=PI-FA
           IF (((BIRD(ID,1)-FLOAT(OBSX)).LT.0).AND.
     *       ((BIRD(ID,2)-FLOAT(OBSY)).LT.0)) FA=FA-PI
           JREP=(BIRD(II,2)*NI)/L+1
           NREP(JREP)=NREP(JREP)+1
           PERP(NDECT,1)=ABS(BIRD(ID,1)-OBSX)*.0002*L
           PERP(NDECT,2)=BIRD(ID,5)
           PERP(NDECT,3)=1
           PERP(NDECT,4)=BIRD(ID,6)
           DO 58 IJ=1,NDECT-1
58           IF (PERP(IJ,2).EQ.PERP(NDECT,2)) PERP(NDECT,3)=0
           IF (PERP(NDECT,3).EQ.1) NREPC(JREP)=NREPC(JREP)+1
           GO TO 122
         ELSE
          BIRD(ID,3)=3
         ENDIF
30      CONTINUE
       ENDIF
       GO TO 321
```

```
 11   CONTINUE
      WRITE(6,*) ' AUDIO  ',NAUDIO,' VISUAL ',Ndect-nAUDIO
      RETURN
      END

      SUBROUTINE BSTRAP(N1,N2,M,X,IX,NREP,NI)
C     THIS SUBROUTINE SELECTS A BOOTSTRAP SAMPLE OF INDIVIDUAL
C     DISTANCES AND THEN CALCULATES DENSITY WITH METHODS IGNORING
C     THE DEPENDENCE IN SIGHTINGS OF ANIMALS IN SAME CLUSTER
      DOUBLE PRECISION DRAND,IX,K
      DIMENSION X(N1),Y(15000),NREP(NI),A(3),S(3),D(3),U(3),AR(3)
      DO 10 I=1,3
        A(I)=0
        S(I)=0
        D(I)=9999999
 10     U(I)=-D(I)
      ME=M
      DO 50 I=1,M
      DO 30 J=1,N2
      Z=SNGL(DRAND(IX))
      K=N1*Z+1
      Y(J)=X(K)
 30   CONTINUE
      SUM=0.
      DO 31 J=1,NI
        Z=SNGL(DRAND(IX))
        K=(IX/(2147463647/NI))+1
        SUM=SUM+FLOAT(NREP(K))
 31   CONTINUE
      CALL ORDIT(N2,Y)
      CALL CUMD(N2,Y,EFAR)
      CALL FOSER(N2,Y,1CUT,AREA)
      CALL EPMLE(N2,Y,EST,G)
      AR(1)=FLOAT(N2)/EFAR
      AR(2)=FLOAT(N2)/AREA
      AR(3)=SUM/EST
      DO 20 II=1,3
        A(II)=A(II)+AR(II)
        S(II)=S(II)+AR(II)*AR(II)
        If (D(II).GT.AR(II)) D(II)=AR(II)
 20     If (U(II).LT.AR(II)) U(II)=AR(II)
 50   CONTINUE
      DO 40 II=1,3
        S(II)=S(II)-(A(II)*A(II))/FLOAT(M)
        S(II)=SQRT(S(II)/FLOAT(M-1))
 40     A(II)=A(II)/FLOAT(M)
      WRITE(6,*) 'BOOTSTRAP FOR NON-POOLED ESTIMATE'
      WRITE(6,200) A(1),S(1),D(1),U(1)
      WRITE(6,200) A(2),S(2),D(2),U(2)
      WRITE(6,200) A(3),S(3),D(3),U(3)
200   FORMAT(4(1X,f11.6))
      RETURN
      END
```

The following subroutines need to be added to VABS:

```
      SUBROUTINE SIZE(EMEAN,TMEAN,ESMAX,TSMAX)
C     THIS PROGRAM CALCULATES BASIC STATISTICS ON THE ERROR OF
C      CLUSTER SIZE
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      EMIN=999
      EMAX=0
      SUME=0
      SUME2=0
      TCMEAN=0
      DO 10 IJ=1,NCDECT
        TCMEAN=TCMEAN+CL(IJ,4)
        ERROR=CL(IJ,4)-CL(IJ,2)
        IF (ERROR.LT.EMIN) EMIN=ERROR
        IF (ERROR.GT.EMAX) EMAX=ERROR
        SUME=SUME+ERROR
 10     SUME2=SUME2+ERROR*ERROR
      EMEAN=FLOAT(NDECT)/FLOAT(NCDECT)
      TMEAN=TCMEAN/FLOAT(NCDECT)
      WRITE(6,*) 'EST. MEAN SIZE ',EMEAN,' TRUE MEAN SIZE ',TMEAN
      EEMEAN=SUME/FLOAT(NCDECT)
      RSUM=SUME2-FLOAT(NCDECT)*EEMEAN*EEMEAN
      ESD=SQRT(RSUM/FLOAT(NCDECT))
      WRITE(6,*) 'MEAN SIZE ERROR ',EEMEAN,' SD ',ESD,' MIN
     *  ',EMIN, ' MAX ',EMAX
      RETURN
      END

      SUBROUTINE MADD(DDAD,M)
C     THIS SUBROUTINE CALCULATES THE MSE ESTIMATES FOR ALPHA AND
C     BETA FOR G=.25,(.25),10 AND SELECTS THE SET OF PARAMETERS
C     THAT PROVIDES THE LARGEST VALUE OF THE LOG-LIKELIHOOD
C     FOR RAMSEY'S LINK FUNCTION
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      EG=0.25
      EB=.0
      Z=1.+1./EG
      CALL LOGGAM(Z,G0)
      TT=0
      DO 35 I=1,NCDECT
        IF (CL(I,3).LE.0) GO TO 35
        ZP=(CL(I,3)/CL(NCDECT,3))**EG
        TT=TT+ZP
 35   CONTINUE
      EA=(EXP(G0))*CL(NCDECT,3)*(EG*tT/NCDECT)**(1/EG)
      CALL ALOGLIK(EG,EB,EA,EXLL,M)
 15   EBB=EB
      EGG=EG
      EAA=EA
      EXLB=EXLL
```

```
 40   EG=EG+.25
      IF (EG.GT.10) GO TO 50
      CALL ALOGLIK(EG,EB,EA,EXLL,M)
      IF (EXLL.GT.EXLB) GO TO 15
      GO TO 40
 50   EB=EBB
      EG=EGG
      EA=EAA
      DDAD=0
      DO 60 IJ=1,NCDECT
        ZZ=CL(IJ,M)/(CL(IJ,M)**EB)
 60     DDAD=DDAD+(ZZ/EA)
      RETURN
      END

      SUBROUTINE ALOGLIK(G,SB,SA,XLL,M)
C     THIS SUBROUTINE FINDS THE MLE OF ALPHA AND LAMBDA
C     GIVE AN VALUE FOR GAMMA, COMPLEMENTS THE SUBROUTINE MADD.
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      L=0
      Z=1.+1./G
      CALL LOGGAM(Z,B1)
      B1=(EXP(B1))**G
      SUM2=0
      DO 20 I=1,NCDECT
 20     SUM2=SUM2+(CL(I,M)-1)
 5    L=L+1
      IF (L.GT.100) THEN
        WRITE(6,*) 'DRUM DID NOT CONVERGE IN 100 REPS'
        GO TO 15
      ENDIF
      SUM1=0
      SUM3=0
      SUM32=0
      DO 10 I=1,NCDECT
        A1=CL(I,M)-1
        A2=(CL(I,3)/(EXP(SB*A1)))**G
        A12=A1*A2
        A112=(A1**2)*A2
        SUM1=SUM1+A2
        SUM3=SUM3+A12
        SUM32=SUM32+A112
 10   CONTINUE
      XLL=-((NCDECT*LOG(SA))+(SB*SUM2)+((B1/(SA**G))*SUM1))
      XLA=(G*B1*(1/SA**(G+1))*SUM1)-(NCDECT/SA)
      XLB=(G*(B1/(SA**G))*SUM3)-SUM2
      AA=(NCDECT/(SA**2.))-(G*(G+1.)*B1*(1/SA**(G+2.))*SUM1)
      BB=-1*(G**2)*B1*(1/SA**(G+1.))*SUM3
      DD=-1*(G**2)*(B1/(SA**G))*SUM32
      DEN=1/(AA*DD-(BB**2.))
      ADDA=DEN*(DD*XLA-BB*XLB)
      ADDL=DEN*(AA*XLB-BB*XLA)
```

```
      IF (L.EQ.1) THEN
        SA=SA-ADDA
        IF (SA.LE.0) SA=SA+ADDA
        XLL2=XLL
        S2A=SA
        ADD2A=ADDA
        S2B=SB
        SB=S2B-ADDL
        ADD2L=ADDL
        GO TO 5
      ELSEIF (ABS(XLL-XLL2).LT. .0001) THEN
        GO TO 15
      ELSEIF (XLL.LT.XLL2) THEN
        ADDA=ADD2A/2
        SA=S2A-ADDA
        IF (SA.LE.0) SA=S2A
        ADD2A=ADDA
        ADDL=ADD2L/2
        SB=S2B-ADDL
        ADD2L=ADDL
        GO TO 5
      ELSE
        SA=SA-ADDA
        IF (SA.LE.0) SA=S2A
        S2A=SA
        XLL2=XLL
        ADD2A=ADDA
        S2B=SB
        SB=S2B-ADDL
        ADD2L=ADDL
        GO TO 5
      ENDIF
 15   CONTINUE
      RETURN
      END

      SUBROUTINE CLORDIT
C     THIS PROGRAM SORTS THE MATRIX ROWS BY AREA.
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
 5    L=0
      DO 10 I=1,NCDECT-1
        IF (CL(I,3).GT.CL(I+1,3)) THEN
          DO 20 J=1,4
            T=CL(I+1,J)
            CL(I+1,J)=CL(I,J)
 20         CL(I,J)=t
          L=1
        ENDIF
 10   CONTINUE
      IF (L.GT.0) GO TO 5
      RETURN
      END
```

```
      SUBROUTINE QUANG(QDEN,M)
C     THIS SUBROUTINE CALCULATES DENSITY USING THE METHODOLOGY
C     PROPOSED BY QUANG
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      W=CL(NCDECT,3)
      PI=355./113.
      R=0
 15   R=R+1
      IF (R.EQ.5) GO TO 25
      TRI=0
      TRI2=0
      DO 30 I=1,NCDECT
        B=CL(I,M)*COS(PI*R*CL1(I,3)/X)
        TRI=B+TRI
        TRI2=B*B+TRI2
 30   CONTINUE
      RIGHT=((NCDECT**2)-NCDECT+1)*((TRI/NCDECT)**2)
      IF (TRI2.LT.RIGHT) GO TO 15
 25   R=R-1
      MESS1=0
      MESS2=0
      DO 40 I=1,NCDECT
        DO 50 J=1,IFIX(R)
 50       MESS2=COS(PI*j*CL(I,3)/W)+MESS2
 40     MESS1=MESS1+CL(I,M)*(1+2*MESS2)
      QDEN=MESS1/W
      RETURN
      END

      SUBROUTINE GDRUM(DRUM,M)
C     THIS SUBROUTINE CALCULATES THE MSE ESTIMATES FOR ALPHA AND
C     LAMBDA FOR G=.25,(.25),10 AND SELECTS THE SET OF PARAMETERS
C     THE PROVIDES THE LARGEST VALUE OF THE LOG-LIKELIHOOD
C     FOR DRUMMER AND MCCDONALD LINK FUNCTION
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      EG=0.25
      ES=.0
      Z=1.+1./EG
      CALL LOGGAM(Z,G0)
      TT=0
      DO 35 I=1,NCDECT
        IF (CL(I,3).LE.0) GO TO 35
        ZP=(CL(I,3)/CL(NCDECT,3))**EG
        TT=TT+ZP
 35   CONTINUE
      EA=(EXP(G0))*CL(NCDECT,3)*(EG*tT/NCDECT)**(1/EG)
      CALL GLOGLIK(EG,ES,EA,EXLL,M)
 15   ESS=ES
      EGG=EG
      EAA=EA
      EXLB=EXLL
```

```
 40     EG=EG+.25
        IF (EG.GT.10) GO TO 50
        CALL GLOGLIK(EG,ES,EA,EXLL,M)
        IF (EXLL.GT.EXLB) GO TO 15
        GO TO 40
 50     ES=ESS
        EG=EGG
        EA=EAA
        EY=0
        DO 80 I=1,NCDECT
          EYP=CL(I,M)**(1-ES)
 80       EY=EY+EYP
        DRUM=EY/EA
        RETURN
        END

        SUBROUTINE GLOGLIK(G,SL,SA,XLL,M)
C       THIS SUBROUTINE FINDS THE MLE OF ALPHA AND LAMBDA GIVEN A
C       VALUE FOR GAMMA, ATTACH WITH THE SUBROUTINE GDRUM
        REAL CL(300,4),CPERP(300)
        COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
        L=0
        Z=1.+1./G
        CALL LOGGAM(Z,B1)
        B1=EXP(B1)
 5      L=L+1
        IF (L.GT.100) THEN
          WRITE(6,*) 'DRUM DID NOT CONVERGE IN 100 REPS'
          GO TO 15
        ENDIF
        SUM1=0
        SUM2=0
        SUM3=0
        SUM32=0
        DO 10 I=1,NCDECT
          A1=LOG(CL(I,M))
          A12=A1**2
          SUM2=SUM2+A1
          A2=(CL(I,3)/(CL(I,M)**SL))**G
          SUM1=SUM1+A2
          SUM3=SUM3+A1*A2
          SUM32=SUM32+A12*A2
 10     CONTINUE
        XLL=-(NCDECT*LOG(SA)+(((B1/SA)**G)*SUM1)+SL*SUM2)
        XLA=(g*(B1**G)*(1/SA**(G+1))*SUM1)-(NCDECT/SA)
        XLLAM=(G*((B1/SA)**G)*SUM3)-SUM2
        AA=(NCDECT/(SA**2.))-(G*(G+1.)*(B1**G)*(1/SA**(G+2.))*SUM1)
        BB=-1*(G**2)*(B1**G)*(1/SA**(G+1.))*SUM3
        DD=-1*(G**2)*((B1/SA)**G)*SUM32
        DEN=1/(AA*DD-(BB**2.))
        ADDA=DEN*(DD*XLA-BB*XLLAM)
        ADDL=DEN*(AA*XLLAM-BB*XLA)
        IF (L.EQ.1) THEN
```

```
          SA=SA-ADDA
          IF (SA.LE.0) SA=SA+ADDA
          XLL2=XLL
          S2A=SA
          ADD2A=ADDA
          S2L=SL
          SL=S2L-ADDL
          ADD2L=ADDL
          GO TO 5
        ELSEIF (ABS(XLL-XLL2).LT. .0001) THEN
          GO TO 15
        ELSEIF (XLL.LT.XLL2) THEN
          ADDA=ADD2A/2
          SA=S2A-ADDA
          IF (SA.LE.0) SA=S2A
          ADD2A=ADDA
          ADDL=ADD2L/2
          SL=S2L-ADDL
          ADD2L=ADDL
          GO TO 5
        ELSE
          SA=SA-ADDA
          IF (SA.LE.0) SA=S2A
          S2A=SA
          XLL2=XLL
          ADD2A=ADDA
          S2L=SL
          SL=S2L-ADDL
          ADD2L=ADDL
          GO TO 5
        ENDIF
 15     CONTINUE
        RETURN
        END

        SUBROUTINE LSDRUM(CDRUM,FDRUM,EDRUM,M)
C       THIS PROGRAM FINDS THE LEAST SQUARES ESTIMATE FOR THE
C       EQUATION LN(X)=B0+B1*LN(CLUSTER SIZE) AND THEN ADJUST THE
C       DATA AND POOLS THE DATA IN ORDER TO ESTIMATE ALPHA AND LAMDA
C       ESTIMATES THE DENSITY ACCORDING TO DRUMMER AND McDONALD
        REAL CL(300,4),CPERP(300),X(300,2),YLN(300),BHAT(2),
      *  DPERP(300)
        COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
        DO 74 II=1,NCDECT
          X(II,1)=1
C       USE CL(II,2) IF EST. SIZE AND CL(II,4) IF TRUE SIZE
          X(II,2)=ALOG(CL(II,M))
          IF (CL(II,3).NE.0) THEN
            YLN(II)=ALOG(CL(II,3))
          ELSE
            YLN(II)=ALOG(.0001)
          ENDIF
 74     CONTINUE
```

```
      SUMX=0
      SUMY=0
      DO 211 II=1,NCDECT
        SUMX=X(II,2)+SUMX
 211    SUMY=YLN(II)+SUMY
      MEANX=SUMX/FLOAT(NCDECT)
      MEANY=SUMY/FLOAT(NCDECT)
      SXX=0
      SYY=0
      SXY=0
      DO 212 II=1,NCDECT
        SXX=SXX+(X(II,2)-MEANX)**2
        SYY=SYY+(YLN(II)-MEANY)**2
 212    SXY=SXY+((X(II,2)-MEANX)*(YLN(II)-MEANY))
      BHAT(2)=SXY/SXX
      BHAT(1)=MEANY-(BHAT(2)*MEANX)
      DO 30 II=1,NCDECT
 30     DPERP(II)=CL(II,3)/(CL(II,M)**BHAT(2))
      CALL ORDIT(NCDECT,DPERP)
      CALL CUMD(NCDECT,DPERP,AFAR)
      CALL FOSER(NCDECT,DPERP,LCUT,AREA)
      CALL EPMLE(NCDECT,DPERP,EST,G)
      CDRUM=0
      FDRUM=0
      EDRUM=0
      DO 50 IJ=1,NCDECT
        ZZ=CL(IJ,M)/(CL(IJ,M)**BHAT(2))
        CDRUM=CDRUM+(ZZ/AFAR)
        FDRUM=FDRUM+(ZZ/AREA)
 50     EDRUM=EDRUM+(ZZ/EST)
      RETURN
      END

      SUBROUTINE QUINN(CMEAN,QCUMD,QFOSER,QEPMLE,
     *  WCUMD,WFOSER,WEPMLE,NEPM,QMEAN,M)
C     THIS PROGRAM CALCUTATES THE DENISTY USING ESTIMATES
C     SUGGESTED BY QUINN
C     BOTH THE MEAN AND LOG WEIGHTED MEAN ARE USED
      REAL CL(300,4),CPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      ENUM=0
      EDEN=0
      DO 10 IJ=1,NCDECT
        IF (CL(IJ,M).EQ.1) THEN
          ENUM=CL(IJ,M)/LOG(CL(IJ,M)+.0001)+ENUM
          EDEN=1/LOG(CL(IJ,M)+.0001)+EDEN
        ELSE
          ENUM=CL(IJ,M)/LOG(CL(IJ,M))+ENUM
          EDEN=1/LOG(CL(IJ,M))+EDEN
        ENDIF
 10   CONTINUE
      CALL CUMD(NCDECT,CPERP,EFAR)
      CALL FOSER(NCDECT,CPERP,LCUT,AREA)
```

```
      CALL EPMLE(NCDECT,CPERP,EST,G)
      CCUMD=FLOAT(NCDECT)/EFAR
      CFOSER=FLOAT(NCDECT)/AREA
      CEPMLE=FLOAT(NEPM)/EST
      QCUMD=CMEAN*CCUMD
      QFOSER=CMEAN*CFOSER
      QEPMLE=CMEAN*CEPMLE
      QMEAN=ENUM/EDEN
      WCUMD=QMEAN*CCUMD
      WFOSER=QMEAN*CFOSER
      WEPMLE=QMEAN*CEPMLE
      RETURN
      END

      SUBROUTINE COVAR(AECUM,AEFS,AEEPS,EBHAT,EBVAR,
     *  AEEFAR,AEAREA,AEEST,M)
C     THIS PROGRAM USES LEAST SQUARES TO FIT LNX=B0+B1*(CLUSTER
C     SIZE) AND THEN ADJUST THE DATA AND FITS THE ADJUSTED
C     DATA BY THE CUMD, F.S., AND EPS METHODS
      REAL CL(300,4),CPERP(300),X(300,2),YLN(300),BHAT(2),
     *  ADPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      COMMON /ADJUST/ADPERP
      DO 74 II=1,NCDECT
        X(II,1)=1
C     USE CL(II,2) IF EST. SIZE AND CL(II,4) IF TRUE SIZE
        X(II,2)=CL(II,M)-1
        IF (CL(II,3).NE.0) THEN
          YLN(II)=ALOG(CL(II,3))
        ELSE
          YLN(II)=ALOG(.0001)
        ENDIF
 74   CONTINUE
      SUMX=0
      SUMY=0
      DO 211 II=1,NCDECT
        SUMX=X(II,2)+SUMX
 211    SUMY=YLN(II)+SUMY
      MEANX=SUMX/FLOAT(NCDECT)
      MEANY=SUMY/FLOAT(NCDECT)
      SXX=0
      SYY=0
      SXY=0
      DO 212 II=1,NCDECT
        SXX=SXX+(X(II,2)-MEANX)**2
        SYY=SYY+(YLN(ii)-MEANY)**2
 212    SXY=SXY+((X(II,2)-MEANX)*(YLN(II)-MEANY))
      BHAT(2)=SXY/SXX
      BHAT(1)=MEANY-(BHAT(2)*MEANX)
      DO 30 II=1,NCDECT
 30     ADPERP(II)=CL(II,3)*EXP(-(CL(II,M)-1)*BHAT(2))
      CALL ORDIT(NCDECT,ADPERP)
      CALL CUMD(NCDECT,ADPERP,AEEFAR)
```

```
      CALL FOSER(NCDECT,ADPERP,LCUT,AEAREA)
      CALL EPMLE(NCDECT,ADPERP,AEEST,G)
      AECUM=0
      AEFS=0
      AEEPS=0
      DO 42 IJ=1,NCDECT
        ZZ=CL(IJ,M)/(EXP(BHAT(2)*(CL(IJ,M)-1)))
        AECUM=AECUM+(ZZ/AEEFAR)
        AEFS=AEFS+(ZZ/AEAREA)
 42     AEEPS=AEEPS+(ZZ/AEEST)
      RETURN
      END

      SUBROUTINE CBSTRP(N1,N2,M,IX,NREPC,NI,EB,EBV,TB,tBV,
     *     EDEFAR,EDAREA,EDEST,TDEFAR,TDAREA,TDEST)
C     THIS SUBROUNTINE SELECTS A BOOTSTRAP SAMPLE OF CLUSTERS AND
C     THEN CALCULATES BOOTSTRAP ESTIMATES AS LISTED IN SECTION 8.2
      DOUBLE PRECISION DRAND,IX,K
      INTEGER NREPC(NI)
      REAL CL(300,4),CPERP(300),RCL(300,4),RCPERP(300),
     *  EAPERP(300),TAPERP(300),ACD(6,3),SCD(6,3),DCD(6,3),
     *  UCD(6,3),D(6,3),DACD(2,3),DSCD(2,3),DDCD(2,3),DUCD(2,3),
     *  AREA(2,3),ADPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      COMMON /ACTUAL/RCL,RCPERP
      COMMON /ADJUST/ADPERP
      DO 10 I=1,6
        DO 10 J=1,3
          ACD(I,J)=0
          SCD(I,J)=0
          DCD(I,J)=9999999
 10       UCD(I,J)=-DCD(I,J)
      DO 15 I=1,2
        DO 15 J=1,3
          DACD(I,J)=0
          DSCD(I,J)=0
          DDCD(I,J)=9999999
 15       DUCD(I,J)=-DDCD(I,J)
      ME=M
      DO 50 I=1,M
      CSUM=0
      TSUM=0
      DO 30 J=1,N2
        Z=SNGL(DRAND(IX))
        K=(IX/(2147463647/N1))+1
        CPERP(J)=RCL(K,3)
        CL(J,1)=RCL(K,1)
        CL(J,2)=RCL(K,2)
        CL(J,3)=RCL(K,3)
        CL(J,4)=RCL(K,4)
        EAPERP(J)=RCL(K,3)*EXP(-(RCL(K,2)-1)*EBHAT)
        TAPERP(J)=RCL(K,3)*EXP(-(RCL(K,4)-1)*TBHAT)
        CSUM=RCL(K,2)+CSUM
```

```
      TSUM=RCL(K,4)+TSUM
30   CONTINUE
     SUM=0.
     DO 31 J=1,NI
       Z=SNGL(DRAND(IX))
       K=(IX/(2147463647/NI))+1
       SUM=SUM+FLOAT(NREPC(K))
31   CONTINUE
       NSUM=INT(SUM)
       BEM=CSUM/FLOAT(N2)
       BTM=TSUM/FLOAT(N2)
       CALL CLORDIT
       CALL ORDIT(NCDECT,CPERP)
       MM=4
       CALL QUINN(BTM,D(1,1),D(1,2),
    *    D(1,3),D(2,1),D(2,2),D(2,3),NSUM,QTMEAN,MM)
       CALL MADD(D(5,2),MM)
       CALL COVAR(D(3,1),D(3,2),D(3,3),
    *   TBHAT,TBVAR,ATEFAR,ATAREA,ATEST,MM)
       CALL SIMPLE(TB,D(4,1),D(4,2),D(4,3),
    *   AREA(1,1),AREA(1,2),AREA(1,3),TAPERP,MM)
       CALL GDRUM(D(5,1),MM)
       CALL LSDRUM(D(6,1),D(6,2),D(6,3),MM)
       CALL QUANG(D(5,3),MM)
       DO 60 II=1,6
         DO 60 JJ=1,3
           ACD(II,JJ)=ACD(II,JJ)+D(II,JJ)
           SCD(II,JJ)=SCD(II,JJ)+D(II,JJ)**2
           IF (DCD(II,JJ).GT.D(II,JJ)) DCD(II,JJ)=D(II,JJ)
60         IF (UCD(II,JJ).lt.D(II,JJ)) UCD(II,JJ)=D(II,JJ)
       DO 65 II=1,1
         DO 65 JJ=1,3
           DACD(II,JJ)=DACD(II,JJ)+AREA(II,JJ)
           DSCD(II,JJ)=DSCD(II,JJ)+AREA(II,JJ)**2
           If (DDCD(II,JJ).GT.AREA(II,JJ))
    *        DDCD(II,JJ)=AREA(II,JJ)
65         If (DUCD(II,JJ).lt.AREA(II,JJ))
    *        DUCD(II,JJ)=AREA(II,JJ)
50   CONTINUE
     DO 70 II=1,6
       DO 70 JJ=1,3
         SCD(II,JJ)=SCD(II,JJ)-((ACD(II,JJ)*ACD(II,JJ))/FLOAT(M))
         SCD(II,JJ)=SQRT(SCD(II,JJ)/FLOAT(M-1))
70       ACD(II,JJ)=ACD(II,JJ)/FLOAT(M)
     DO 75 II=1,2
       DO 75 JJ=1,3
         DSCD(II,JJ)=DSCD(II,JJ)
    *      -((DACD(II,JJ)*DACD(II,JJ))/FLOAT(M))
         DSCD(II,JJ)=SQRT(DSCD(II,JJ)/FLOAT(M-1))
75       DACD(II,JJ)=DACD(II,JJ)/FLOAT(M)
     DO 80 II=1,6
         WRITE(6,*) 'ESTIMATOR ',II
         WRITE(6,200) ACD(II,1),SCD(II,1),DCD(II,1),UCD(II,1)
```

```
        WRITE(6,200) ACD(II,2),SCD(II,2),DCD(II,2),UCD(II,2)
 80     WRITE(6,200) ACD(II,3),SCD(II,3),DCD(II,3),UCD(II,3)
      MM=4
      CALL DELTA(DSCD,TB,TDEFAR,TDAREA,TDEST,MM)
 200  FORMAT(4(1X,f11.6))
      RETURN
      END

      SUBROUTINE DELTA(DSCD,EB,EDEFAR,EDAREA,EDEST,M)
C     THIS PROGRAM USES THE DELTA APPROXIMATION TO ESTIMATE THE
C     SE OF THE DENSITY ESTIMATE BY THE COVARIATE METHODOLOGY
C     THIS PROGRAM NEEDS TO BE RUN WITH CBSTRP SUBROUTINE
      REAL DSCD(2,3),CL(300,4),RCL(300,4),CPERP(300),RCPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      COMMON /ACTUAL/RCL,RCPERP
      ESUM1=0
      ESUM2=0
      DO 10 J=1,NCDECT
        EAB=EXP(EB*(RCL(J,M)-1))
        ESUM1=(RCL(J,M)/EAB)+ESUM1
 10     ESUM2=((RCL(J,M)*(RCL(J,M)-1))/EAB)+ESUM2
        DELCD=SQRT((((ESUM1**2)*SQRT(DSCD(1,1)))/(EDEFAR**4))
     *    +(((ESUM2**2)*EVB)/(EDEFAR**2)))
        DELFS=SQRT((((ESUM1**2)*SQRT(DSCD(1,2)))/(EDAREA**4))
     *    +(((ESUM2**2)*EVB)/(EDAREA**2)))
        DELEP=SQRT((((ESUM1**2)*SQRT(DSCD(1,3)))/(EDEST**4))
     *    +(((ESUM2**2)*EVB)/(EDEST**2)))
        WRITE(6,*) 'EST. SIZE CD ',DELCD,' FS ',DELFS,' EP ',DELEP
        RETURN
        END

      SUBROUTINE SIMPLE(EB,ESCD,ESFS,ESEP,EEFAR,EAREA,EEST,APERP,M)
C     THIS SUBROUTINE RUN WITH THE SUBROUTINE CBSTRP USES THE
C     BHAT ESTIMATES CALCULATED IN THE ORIGINAL DENSITY AND
C     CALCULATES THE BOOTSTRAP DENSITY ESTIMATES BY USING THE
C     ADJUSTED BOOTSTRAP AREA'S WITH THE ORGINAL BHAT ESTIMATES.
      REAL ADPERP(300),CL(300,4),RCL(300,4),CPERP(300),RCPERP(300)
      COMMON /CLUSTER/CL,CPERP,NCDECT,NDECT
      COMMON /ACTUAL/RCL,RCPERP
      COMMON /ADJUST/ADPERP
      CALL ORDIT(NCDECT,ADPERP)
      CALL CUMD(NCDECT,ADPERP,EEFAR)
      CALL FOSER(NCDECT,ADPERP,LCUT,EAREA)
      CALL EPMLE(NCDECT,ADPERP,EEST,G)
      ESCD=0
      ESFS=0
      ESEP=0
      DO 10 IJ=1,NCDECT
        ESCD=ESCD+CL(IJ,M)/(EEFAR*EXP(EB*(CL(IJ,M)-1)))
        ESFS=ESFS+CL(IJ,M)/(EAREA*EXP(EB*(CL(IJ,M)-1)))
 10     ESEP=ESEP+CL(IJ,M)/(EEST*EXP(EB*(CL(IJ,M)-1)))
      RETURN
      END
```

APPENDIX G

Subroutines for Bird Movement

The following subroutines and lines were altered or added to VABS in order to simulate movement. First, the dimensions of the vector BIRDS needs to be expanded to BIRD(800,9), and the variables determining the speed of the bird movement RALPHA and RBETA need to be added to the main program and passed on to the subroutine DETECT. To call the subroutine DETECT from the main program, the following command should be given

```
    CALL DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,
   *  NREP,NI,RALPHA,RBETA,THETA)
```

Substitute the following commands in the subroutine BIRDS. Columns 8 and 9 of the vector BIRD stores the detection distance between the bird and the observer and the corresponding probability of detection. If the bird and observer came closer than this distance, a random number is selected. If the random number is less than the probability of detection, then this detection distance is considered to be the distance where the bird is detected visually.

```
      BIRD(J,1)=IX
      BIRD(J,2)=IY
      BIRD(J,3)=1.0
      BIRD(J,4)=REXP(THETA,ISEED)
      BIRD(J,5)=1.0
      BIRD(J,6)=0.
      BIRD(J,7)=0.
      BIRD(j,8)=999.
      BIRD(j,9)=999.
```

The subroutine DETECT is altered so that birds are moving while the observer is traversing the transect. The following version of DETECT is for random movement.

```
      SUBROUTINE DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,
     *  NREP,NI,RALPHA,RBETA,THETA)
      DOUBLE PRECISION DRAND,ISEED
      INTEGER OBSX,OBSY,NREP(NI)
      REAL MAXDIST,DIST,TIME(1000),PERP(600),L,W,
     *   LAMDA,GV,BIRD(800,9),DVA,TT,SDTT,PERF,BETA1,DT
      PARAMETER(PI=3.141593,PI2=1.570796,PI4=.785398)
      COMMON ISEED,L,W
      COMMON/BBIRD/BIRD,NBIRD
      NDECT=0
      K3=0
      DO 42 I=1,NI
 42     NREP(I)=0
      DV=.05/TAN(DVA*0.5)
      BETA0=LOG(DV*.021715)
      MAXDIST=MAX(DA,DV)
```

```
      IF (MAXDIST.GE.W/2.) THEN
        WRITE(6,*) 'MAXDIST IS GREATER THAN W/2'
        STOP
      ENDIF
      OBSX=W/2
      DO 31 I=1,IFIX(L)
31      TIME(I)=RLOG(TT,SDTT,ISEED)
      DO 11 OBSY=1,IFIX(L)
        DO 121 II=1,NBIRD
          IF (BIRD(II,3).EQ.2) GO TO 121
          RMOVE=RLOG(RALPHA,RBETA,ISEED)*TIME(OBSY)*40
          AMOVE=DRAND(ISEED)*PI*2
          XMOVE=RMOVE*COS(AMOVE)
          YMOVE=RMOVE*SIN(AMOVE)
          BIRD(II,1)=BIRD(II,1)+XMOVE
          IF ((BIRD(II,1).LE.0).OR.(BIRD(II,1).GT.W)) GO TO 121
          BIRD(II,2)=BIRD(II,2)+YMOVE
          IF ((BIRD(II,2).LE.0).OR.(BIRD(II,2).GT.L)) GO TO 121
          YY=BIRD(II,2)-FLOAT(OBSY)
          IF (YY.GT.MAXDIST) GO TO 121
          XX=BIRD(II,1)-FLOAT(OBSX)
          IF (XX.GT.MAXDIST) GO TO 121
          DIST=SQRT(XX**2+YY**2)
          IF (DIST.GT.MAXDIST) GO TO 121
          IF (DIST.GT.DA) THEN
            IF (BIRD(II,7).EQ.1) THEN
              BIRD(II,6)=0.
              BIRD(II,7)=0.
              BIRD(II,4)=REXP(THETA,ISEED)
            ENDIF
          ELSE
            BIRD(II,7)=1.
            BIRD(II,6)=BIRD(II,6)+TIME(OBSY)
            IF (BIRD(II,6).GT.BIRD(II,4)) THEN
              NDECT=NDECT+1
              BIRD(II,3)=2.0
              JREP=(BIRD(II,2)*NI)/L+1
              NREP(JREP)=NREP(JREP)+1
              PERP(NDECT)=ABS(BIRD(II,1)-OBSX)*.0002*L
              GO TO 121
            ENDIF
          ENDIF
          IF (DIST.GT.DV) GO TO 121
          IF (BIRD(II,8).GT.DIST) THEN
             IF (BIRD(II,9).EQ.999) THEN
               BIRD(II,8)=DIST
               BIRD(II,9)=XX
             ELSE
               RANDOM=DRAND(ISEED)
               IF (RANDOM.LE.BIRD(II,5)) THEN
                 BIRD(II,8)=DIST
                 BIRD(II,9)=XX
               ENDIF
```

```
            ENDIF
          ENDIF
          IF (BIRD(II,1).EQ.OBSX) THEN
            W=0
          ELSEIF (BIRD(II,1).LT.OBSX) THEN
            IF (BIRD(II,2).EQ.OBSY) THEN
              W=-1*pi2
            ELSE
              W=-1*ATAN(ABS(XX/YY))
            ENDIF
          ELSE
            IF (BIRD(II,2).EQ.OBSY) THEN
              W=PI2
            ELSE
              W=ATAN(ABS(XX/YY))
            ENDIF
          ENDIF
          IF (ABS(W).GT.PERF) GO TO 121
          IF (XX.EQ.0) THEN
            BIRD(II,5)=0
            GO TO 121
          ENDIF
          LAMDA=EXP(BETA0+BETA1*ABS(W))
          IF (DIST.GT.EXP(LOG(DV)-BETA1*ABS(W))) THEN
            GV=0.0
          ELSE
            GV=EXP(-DIST/(LAMDA*10))
          ENDIF
          BIRD(II,5)=BIRD(II,5)*(1-GV)
121     CONTINUE
11     CONTINUE
      NAUDIO=NDECT
      DO 30 II=1,NBIRD
        IF (BIRD(II,3).EQ.2) GO TO 30
        IF (BIRD(II,5).EQ.1.0) GO TO 30
        BIRD(II,5)=1-BIRD(II,5)
        IF (BIRD(II,5).GT.1.0) THEN
          WRITE(6,*) 'ERROR IN PROB. '
          STOP
        ENDIF
        RANDOM=DRAND(ISEED)
        IF (RANDOM.LE.BIRD(II,5)) THEN
          NDECT=NDECT+1
          BIRD(II,3)=2
          JREP=(BIRD(II,2)*NI)/L+1
          NREP(JREP)=NREP(JREP)+1
          PERP(NDECT)=ABS(BIRD(II,9))*.0002*L
        ENDIF
30    CONTINUE
      WRITE(6,*) ' AUDIO  ',NAUDIO,' VISUAL ',NDECT-nAUDIO
      RETURN
      END
```

To simulate other types of movement, the variable MOVE was added to the main program and passed on to the subroutine DETECT, The following lines were deleted from the previous program:

```
RMOVE=RLOG(RALPHA,RBETA,ISEED)*TIME(OBSY)*40
AMOVE=DRAND(ISEED)*PI*2
XMOVE=RMOVE*COS(AMOVE)
YMOVE=RMOVE*SIN(AMOVE)
BIRD(II,1)=BIRD(II,1)+XMOVE
IF ((BIRD(II,1).LE.0).OR.(BIRD(II,1).GT.W)) GO TO 121
BIRD(II,2)=BIRD(II,2)+YMOVE
IF ((BIRD(II,2).LE.0).OR.(BIRD(II,2).GT.L)) GO TO 121
```

and the following lines added after

IF (DIST.GT.MAXDIST) GO TO 121

and before

IF (DIST.GT.DA) THEN.

(1) For avoidance:

```
      IF ((DIST.LT.MOVE).AND.(BIRD(II,3).NE.3)) THEN
        IF ((BIRD(II,3).EQ.4).OR.(DRAND(ISEED).LT.0.40)) THEN
          BIRD(II,3)=4
          RMOVE=RLOG(RALPHA,RBETA,ISEED)
          AMOVE=DRAND(ISEED)*PI-PI2
          XMOVE=RMOVE*COS(AMOVE)
          YMOVE=RMOVE*SIN(AMOVE)
          IF (BIRD(II,1).LT.OBSX) THEN
            BIRD(II,1)=BIRD(II,1)-XMOVE
          ELSEIF (BIRD(II,1).GT.OBSX) THEN
            BIRD(II,1)=BIRD(II,1)+XMOVE
          ELSE
            DIRECT=DRAND(ISEED)
            IF (DIRECT.LT..5) THEN
              BIRD(II,1)=BIRD(II,1)-XMOVE
            ELSE
              BIRD(II,1)=BIRD(II,1)+XMOVE
            ENDIF
          ENDIF
          BIRD(II,2)=BIRD(II,2)+YMOVE
          IF ((BIRD(II,1).LT.0).OR.(BIRD(II,1).GT.W).OR.
     *      (BIRD(II,2).LT.0).OR.(BIRD(II,2).GT.L)) THEN
            GO TO 121
          ENDIF
          YY=BIRD(II,2)-FLOAT(OBSY)
          XX=BIRD(II,1)-FLOAT(OBSX)
          DIST=SQRT(XX**2+YY**2)
          IF (DIST.GT.DV) GO TO 121
        ELSE
          BIRD(II,3)=3
        ENDIF

      ENDIF
```

(2) For hiding:

```
      IF (DIST.LT.MOVE) THEN
        BIRD(II,3)=2
        GO TO 121
      ENDIF
```

(3) For attraction when birds move if within MOVE meters from the observer.

```
      DIST=SQRT(XX**2+YY**2)
      ICHECK=0
C     USE .LT. IF MOVES WHEN WITHIN MOVE METERS AND .GT.
C     OTHERWISE
      IF (DIST.LT.MOVE) THEN
 558    ICHECK=ICHECK+1
        IF (ICHECK.GT.100) THEN
          WRITE(6,*) 'ATTRACTING FAILED'
          STOP
        ENDIF
        IF (DIST.LT.5) THEN
          TALPHA=LOG(DIST*.4398)
          RMOVE=RLOG(TALPHA,RBETA,ISEED)
        ELSE
          RMOVE=RLOG(RALPHA,RBETA,ISEED)
        ENDIF
        AMOVE=DRAND(ISEED)*PI-PI2
        XMOVE=RMOVE*COS(AMOVE)
        YMOVE=RMOVE*SIN(AMOVE)
        IF (BIRD(II,1).LT.OBSX) THEN
          BIRD1=BIRD(II,1)+XMOVE
        ELSEIF (BIRD(II,1).GT.OBSX) THEN
          BIRD1=BIRD(II,1)-XMOVE
        ELSE
          DIRECT=DRAND(ISEED)
          IF (DIRECT.LT..5) THEN
            BIRD1=BIRD(II,1)+XMOVE
          ELSE
            BIRD1=BIRD(II,1)-XMOVE
          ENDIF
        ENDIF
        BIRD2=BIRD(II,2)+YMOVE
        DIST2=SQRT((BIRD1-FLOAT(OBSX))**2+(BIRD2
     *      -FLOAT(OBSY))**2)
        IF (DIST2.GT.DIST) THEN
          GO TO 558
        ELSE
          DIST=DIST2
          XX=BIRD1-FLOAT(OBSX)
          YY=BIRD2-FLOAT(OBSY)
          BIRD(II,1)=BIRD1
          BIRD(II,2)=BIRD2
        ENDIF
        IF ((BIRD(II,1).LT.0).OR.(BIRD(II,1).GT.W).OR.
     *    (BIRD(II,2).LT.0).OR.(BIRD(II,2).GT.L)) THEN
```

```
        BIRD(II,3)=3
        GO TO 121
      ENDIF
    ENDIF
```

(4) For attraction when birds moved closer if over MOVE meters from the observer and avoided the observer if within MOVE/2 meters of the observer:

```
          IF ((DIST.LT.100).AND.(DIST.GT.MOVE)) THEN
 558        ICHECK=ICHECK+1
            IF (ICHECK.GT.100) THEN
              WRITE(6,*) 'ATTRACTING FAILED'
              STOP
            ENDIF
            RMOVE=RLOG(RALPHA,RBETA,ISEED)
            AMOVE=DRAND(ISEED)*PI-PI2
 559        XMOVE=RMOVE*COS(AMOVE)
            YMOVE=RMOVE*SIN(AMOVE)
            IF (BIRD(II,1).LT.OBSX) THEN
              BIRD1=BIRD(II,1)+XMOVE
            ELSEIF (BIRD(II,1).GT.OBSX) THEN
              BIRD1=BIRD(II,1)-XMOVE
            ELSE
              DIRECT=DRAND(ISEED)
              IF (DIRECT.LT..5) THEN
                BIRD1=BIRD(II,1)+XMOVE
              ELSE
                BIRD1=BIRD(II,1)-XMOVE
              ENDIF
            ENDIF
            BIRD2=BIRD(II,2)+YMOVE
            DIST2=SQRT((BIRD1-FLOAT(OBSX))**2+(BIRD2
     *        -FLOAT(OBSY))**2)
            IF (DIST2.GT.DIST) THEN
              GO TO 558
            ELSE IF (DIST2.LT.(MOVE/2)) THEN
              RMOVE=.5*RMOVE
              GO TO 559
            ELSE
              DIST=DIST2
              XX=BIRD1-FLOAT(OBSX)
              YY=BIRD2-FLOAT(OBSY)
              BIRD(II,1)=BIRD1
              BIRD(II,2)=BIRD2
            ENDIF
            IF ((BIRD(II,1).LT.0).OR.(BIRD(II,1).GT.W).OR.
     *        (BIRD(II,2).LT.0).OR.(BIRD(II,2).GT.L)) THEN
              BIRD(II,3)=3
              GO TO 121
            ENDIF
          ENDIF
          IF (DIST.LT.MOVE/2) THEN
            RMOVE=RLOG(RALPHA,RBETA,ISEED)
```

```
      AMOVE=DRAND(ISEED)*PI-PI2
      XMOVE=RMOVE*COS(AMOVE)
      YMOVE=RMOVE*SIN(AMOVE)
      IF (BIRD(II,1).LT.OBSX) THEN
        BIRD(II,1)=BIRD(II,1)-XMOVE
      ELSEIF (BIRD(II,1).GT.OBSX) THEN
        BIRD(II,1)=BIRD(II,1)+XMOVE
      ELSE
        DIRECT=DRAND(ISEED)
        IF (DIRECT.LT..5) THEN
          BIRD(II,1)=BIRD(II,1)-XMOVE
        ELSE
          BIRD(II,1)=BIRD(II,1)+XMOVE
        ENDIF
      ENDIF
      BIRD(II,2)=BIRD(II,2)+YMOVE
      IF ((BIRD(II,1).LT.0).OR.(BIRD(II,1).GT.W).OR.
*       (BIRD(II,2).LT.0).OR.(BIRD(II,2).GT.L)) THEN
        GO TO 121
      ENDIF
      YY=BIRD(II,2)-FLOAT(OBSY)
      XX=BIRD(II,1)-FLOAT(OBSX)
      DIST=SQRT(XX**2+YY**2)
    ENDIF
```

APPENDIX H

Subroutines for Counting Error

To simulate birds being counted twice, a new variable LOSE is introduced. If the bird moved more than LOSE meters, the observer has the possibility of counting it again. A bird can also be counted more than once, if it is in the detection range of the observer and then moves out. To keep track of a bird's behavior the matrix BIRD is expanded.

The following lines need to be replaced or added to the main program of VABS:

(1) REAL PERP(2000),BIRD(800,10),NREP(10),L,W,lose

(2) Set the pace of bird movement by fixing the parameters of the log-logistic distribution.
RALPHA=-.1283
RBETA=.2757

(3) LOSE16.67
(4) CALL DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP, NREP,NI,RALPHA,RBETA,THETA,LOSE)

In the subroutine BIRDS used in random movement substitute in

```
      BIRD(J,1)=IX
      BIRD(J,2)=IY
C     BIRD(J,3) REPRESENT IF BIRD CAN BE DETECTED
      BIRD(J,3)=1.0
C     BIRD(J,4) REPRESENTS TIME BETWEEN CALL
      BIRD(J,4)=REXP(THETA,ISEED)
C     BIRD(J,5) IS THE PROBABILITY BIRD HAS NOT BEEN DETECTED
C     SINCE LAST CRITICAL MOVEMENT
      BIRD(J,5)=1.0
C     IS THE TIME OBSERVER IN RANGE OF HEARING BIRD CALL
      BIRD(J,6)=0.
C     CODE IF BIRD IN RANGE OF DETECTION (=1) OR NOT (=0)
      BIRD(J,7)=0.
      BIRD(J,8)=999
      BIRD(J,9)=999
C     STORES INFORMATION ABOUT LAST DETECTION MADE
      BIRD(J,10)=0.
      BIRD(J,11)=0.
      BIRD(J,12)=0.
 40   CONTINUE
      RETURN
      END
```

In the subroutine DETECT used for random movement use

```
      SUBROUTINE DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,
     *  NREP,NI,RALPHA,RBET,THETA,LOSE)
```

then substitute in after

```
          BIRD(II,1)=BIRD(II,1)+XMOVE
          BIRD(II,2)=BIRD(II,2)+YMOVE
```

the following lines:

```
          IF (BIRD(II,3).EQ.2) THEN
            DMOVE=SQRT((BIRD(II,1)-BIRD(II,9))**2+
     *        (BIRD(II,2)-BIRD(II,10))**2)
            IF(DMOVE.GT.LOSE) BIRD(II,3)=1.0
          ENDIF
```

Continue with

```
          IF ((BIRD(II,1).LE.0).OR.(BIRD(II,1).GT.W)) GO TO 121
```

Substitute in the following lines between

```
          IF (DIST.GT.MAXDIST) THEN
```

and

```
          IF (DIST.GT.DV) GO TO 121;
```

```
          IF (DIST.GT.MAXDIST) THEN
            IF (BIRD(II,7).EQ.0) THEN
              GO TO 121
            ELSE
              IF (BIRD(II,3).eq.1) THEN
                IF (BIRD(II,5).EQ.1.0) GO TO 131
                BIRD(II,5)=1-BIRD(II,5)
                IF (BIRD(II,5).GT.1.0) THEN
                  WRITE(6,*) 'ERROR IN PROB. '
                  STOP
                ENDIF
                RANDOM=DRAND(ISEED)
                IF (RANDOM.LE.BIRD(II,5)) THEN
                  NDECT=NDECT+1
                  BIRD(II,10)=BIRD(II,10)+1
                  BIRD(II,11)=BIRD(II,1)
                  BIRD(II,12)=BIRD(II,2)
                  JREP=(BIRD(II,2)*NI)/L+1
                  NREP(JREP)=NREP(JREP)+1
                  PERP(NDECT)=ABS(BIRD(II,1)-OBSX)*.0002*L
                ENDIF
              ENDIF
 131          BIRD(II,3)=1
              BIRD(II,5)=1
              BIRD(II,6)=0
              BIRD(II,4)=REXP(THETA,ISEED)
              BIRD(II,7)=0
            ENDIF
          ELSE
            BIRD(II,7)=1
```

```
          IF (BIRD(II,3).EQ.2) GO TO 121
          BIRD(II,6)=BIRD(II,6)+TIME(OBSY)
          IF (BIRD(II,6).GT.BIRD(II,4)) THEN
            NDECT=NDECT+1
            BIRD(II,10)=BIRD(II,10)+1
            BIRD(II,11)=BIRD(II,1)
            BIRD(II,12)=BIRD(II,2)
            BIRD(II,6)=BIRD(II,6)-BIRD(II,4)
            BIRD(II,4)=REXP(THETA,ISEED)
            NAUDIO=NAUDIO+1
            BIRD(II,3)=2.0
            JREP=(BIRD(II,2)*NI)/L+1
            NREP(JREP)=NREP(JREP)+1
            PERP(NDECT)=ABS(BIRD(II,1)-OBSX)*.0002*L
            GO TO 121
          ENDIF
          IF (BIRD(II,3).NE.2) THEN
            IF (DIST.GT.DV) GO TO 121
```

From DO 30 on down substitute in

```
      DO 30 II=1,NBIRD
      IF (BIRD(II,3).EQ.2) GO TO 30
      IF (BIRD(II,5).EQ.1.0) GO TO 30
      BIRD(II,5)=1-BIRD(II,5)
      IF (BIRD(II,5).GT.1.0) THEN
        WRITE(6,*) 'ERROR IN PROB. '
        STOP
      ENDIF
      RANDOM=DRAND(ISEED)
      IF (RANDOM.LE.BIRD(II,5)) THEN
        NDECT=NDECT+1
        BIRD(II,8)=BIRD(II,8)+1
        BIRD(II,9)=BIRD(II,1)
        BIRD(II,10)=BIRD(II,2)
        BIRD(II,3)=2
        JREP=(BIRD(II,2)*NI)/L+1
        NREP(JREP)=NREP(JREP)+1
        PERP(NDECT)=ABS(BIRD(II,1)-OBSX)*.0002*L
      ENDIF
 30 CONTINUE
    TWICE=0
    DO 335 II=1,NBIRD
    IF (BIRD(II,8).GT.1) THEN
        TWICE=TWICE+1
      ENDIF
 335 CONTINUE
    WRITE(6,*) ' AUDIO  ',NAUDIO,' VISUAL ',NDECT-NAUDIO
    WRITE(6,*) 'NUMBER BIRDS COUNTED AT LEAST TWICE ',TWICE
    RETURN
    END
```

APPENDIX I

Subroutines for Saturation

To simulate saturation a variable SAT is introduced. If more then SAT birds are counted in a specified interval (100 meters), then some of the birds go unaccounted for. To implement the algorithm, the vector BIRD needs to be expanded to 7 rows.

The following lines need to be replaced or added to VABS main program.

```
(1)    REAL PERP(500),BIRD(2000,7),NREP(10),L,W
(2)    SAT=3.0
       CALL DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,
         NREP,NI,SAT)
```

The following lines need to be added to BIRDS:

```
(1)          REAL BIRD(2000,7),L,W,IX,IY
(2) C    COLUMN 6 IS INTERVAL BIRD IS LOCATED IN AND 7 STORES LOCATION
    C      WHERE BIRD HAD GREATES PROBABILITY OF DETECTION.
         BIRD(J,6)=0
         BIRD(J,7)=0
```

The following subroutines need to be substituted in for the prevously given subroutines in VABS:

```
      SUBROUTINE DETECT(DVA,DA,TT,SDTT,PERF,BETA1,DT,NDECT,PERP,,
     *  NREP,NI,SAT)
C     THIS VERSION OF THE PROGRAM IS TO BE USED WHEN TESTING
C     THE EFFECT OF SATURATION.
      DOUBLE PRECISION DRAND,ISEED
      INTEGER OBSX,OBSY,OBSXX,NREP(NI),INTERVAL(300),COUNT
      REAL MAXDIST,DIST,TIME(1000),PERP(500),L,W,TPERP(2000,3),
     *   LAMDA,GV,BIRD(2000,7),DVA,TT,SDTT,PERF,BETA1,DT
      PARAMETER(PI=3.141593,PI2=1.570796,PI4=.785398)
      COMMON ISEED,L,W
      COMMON /BBIRD/BIRD,NBIRD
      NDECT=0
      COUNT=0
      K3=0
      INT=IFIX(L/10)
      DO 42 I=1,NI
 42     NREP(I)=0
      DO 43 I=1,INT
 43     INTERVAL(I)=0
      DV=.05/TAN(DVA*0.5)
      BETA0=LOG(DV*.021715)
      MAXDIST=MAX(DA,DV)
      IF (MAXDIST.GE.W/2.) THEN
        WRITE(6,*) 'MAXDIST IS GREATER THAN W/2'
        STOP
      ENDIF
```

```
      OBSXX=W/2
      NTIMES=L
      DO 31 I=1,NTIMES
31      TIME(I)=RLOG(TT,SDTT,ISEED)
      DO 32 I=1,NBIRD
        AAA=ABS(OBSXX-BIRD(I,1))
        IF (AAA.GT.DA) GO TO 32
        A=DA**2-(OBSXX-BIRD(I,1))**2
        IF (A.LT.0.0) GO TO 32
        IF (A.EQ.0) THEN
          AA=0
        ELSE
          AA=SQRT(A)
        ENDIF
        YMIN=BIRD(I,2)-AA
        YMAX=BIRD(I,2)+AA
        IMIN=NINT(YMIN)
        IF (IMIN.LE.0) IMIN=1.0
        IMAX=NINT(YMAX)
        IF (IMAX.GE.NTIMES) IMAX=NTIMES
        TOTAL=0
        DO 33 J=IMIN,IMAX
          TOTAL=TOTAL+TIME(J)
          IF (TOTAL.GE.BIRD(I,4)) THEN
            NDECT=NDECT+1
            BIRD(I,3)=2.0
            JREP=(BIRD(I,2)*NI)/L+1
            NREP(JREP)=NREP(JREP)+1
            TPERP(NDECT,1)=AAA*.0002*L
            TPERP(NDECT,2)=(FLOAT(J)/10.)+1.
            TPERP(NDECT,3)=1.0
            IBIRD=IFIX(TPERP(NDECT,2))
            INTERVAL(IBIRD)=INTERVAL(IBIRD)+1
            GO TO 32
          ENDIF
33      CONTINUE
32    CONTINUE
      NAUDIO=NDECT
      DO 11 OBSY=1,IFIX(L)
        OBSX=OBSXX
        II=K3
121     II=II+1
        IF (II.GT.NBIRD) GO TO 11
        IF (BIRD(II,3).EQ.2) GO TO 121
        IF (BIRD(II,2).LT.OBSY) THEN
          K3=II
          GO TO 121
        ENDIF
        YY=BIRD(II,2)-FLOAT(OBSY)
        IF (YY.GT.DV) GO TO 11
122     XX=BIRD(II,1)-FLOAT(OBSX)
        IF (XX.LT.-DV) THEN
          IF (II+1.GT.NBIRD) GO TO 11
```

```
          IF (BIRD(II,2).NE.BIRD(II+1,2)) THEN
            GO TO 121
          ELSE
            II=II+1
            GO TO 122
          ENDIF
        ENDIF
        IF (XX.GT.DV) THEN
603       IF (II+1.GT.NBIRD) GO TO 11
          IF (BIRD(II,2).EQ.BIRD(II+1,2)) THEN
            II=II+1
            GO TO 603
          ELSE
            GO TO 121
          ENDIF
        ENDIF
        DIST=SQRT(XX**2+YY**2)
        IF (DIST.GT.DV) THEN
          IF (XX.LT.OBSX) THEN
            IF (II+1.GT.NBIRD) GO TO 11
            IF (BIRD(II,2).EQ.BIRD(II+1,2)) THEN
              II=II+1
              GO TO 122
            ELSE
              GO TO 121
            ENDIF
          ELSE
123         IF (II+1.GT.NBIRD) GO TO 11
            IF (BIRD(II,2).EQ.BIRD(II+1,2)) THEN
              II=II+1
              GO TO 123
            ENDIF
            GO TO 121
          ENDIF
        ENDIF
        IF (BIRD(II,1).EQ.OBSX) THEN
          W=0
        ELSEIF (BIRD(II,1).LT.OBSX) THEN
          IF (BIRD(II,2).EQ.OBSY) THEN
            W=-1*PI2
          ELSE
            W=-1*ATAN(ABS(XX/YY))
          ENDIF
        ELSE
          IF (BIRD(II,2).EQ.OBSY) THEN
            W=PI2
          ELSE
            W=ATAN(ABS(XX/YY))
          ENDIF
        ENDIF
        IF (ABS(W).GT.PERF) GO TO 121
124     IF (XX.EQ.0) THEN
          BIRD(II,5)=0
```

```
          BIRD(II,7)=1
          BIRD(II,6)=FLOAT(OBSY/10)+1
          GO TO 121
        ENDIF
        LAMDA=EXP(BETA0-BETA1*ABS(W))
        IF (DIST.GT.EXP(LOG(DV)+BETA1*ABS(W))) THEN
          GV=0.0
        ELSE
          GV=EXP(-DIST/(LAMDA*10))
          IF (GV.GT.BIRD(II,7)) THEN
            BIRD(II,7)=GV
            BIRD(II,6)=(FLOAT(OBSY)/10)+1
          ENDIF
        ENDIF
        BIRD(II,5)=BIRD(II,5)*(1-GV)
        GO TO 121
11     CONTINUE
      DO 30 II=1,NBIRD
        IF (BIRD(II,3).EQ.2) GO TO 30
        IF (BIRD(II,5).EQ.1.0) GO TO 30
        BIRD(II,5)=1-BIRD(II,5)
        IF (BIRD(II,5).GT.1.0) THEN
          WRITE(6,*) 'ERROR IN PROB. '
          STOP
        ENDIF
        RANDOM=DRAND(ISEED)
        IF (RANDOM.LE.BIRD(II,5)) THEN
          NDECT=NDECT+1
          BIRD(II,3)=2
          JREP=(BIRD(II,2)*NI)/L+1
          NREP(JREP)=NREP(JREP)+1
          TPERP(NDECT,1)=ABS(BIRD(II,1)-OBSX)*.0002*L
          TPERP(NDECT,2)=BIRD(II,6)
          TPERP(NDECT,3)=BIRD(II,7)
          IBIRD=IFIX(TPERP(NDECT,2))
          INTERVAL(IBIRD)=INTERVAL(IBIRD)+1
        ENDIF
30    CONTINUE
      WRITE(6,*) ' AUDIO',NAUDIO,'  VISUAL ',NDECT-NAUDIO
      NN=NDECT-1
      DO 510 J=1,NN
        L=J
        JJ=J+1
        DO 620 I=JJ,NDECT
          IF (TPERP(L,2).LT.TPERP(I,2)) GO TO 620
          L=I
620     CONTINUE
        DO 530 II=1,3
          T=TPERP(L,II)
          TPERP(L,II)=TPERP(J,II)
530       TPERP(J,II)=T
510   CONTINUE
      JMAX=0
```

```
      DO 767 I=1,INT
        IF (INTERVAL(I).EQ.0) GO TO 767
        PRDECT=SAT/FLOAT(INTERVAL(I))
        JMIN=JMAX+1
        JMAX=JMAX+INTERVAL(I)
        DO 769 J=JMIN,JMAX
          IF (DRAND(ISEED).LT.(PRDECT*TPERP(J,3))) THEN
            COUNT=COUNT+1
            PERP(COUNT)=TPERP(J,1)
          ENDIF
769     CONTINUE
767   CONTINUE
      NDECT=COUNT
      WRITE(6,*) 'FINAL NUMBER DETECTED ',NDECT
      DO 770 J=1,NDECT
770     WRITE(6,*) PERP(J)
      RETURN
      END
```

APPENDIX J

Subroutines for Measurement Error

To create measurement error, a new array TPERP is introduced. This array contains the incorrect detection areas. The following lines need to be added to VABS in the main program:

(1) REAL PERP(300),BIRD(300,5),NREP(10),TREE(1,3),L,W,TPERP(300)

(2) For proportional error repeat the following lines for each level of measurement error:

```
      C=20
      DO 30 K=1,NDECT
30      TPERP(K)=PERP(K)-(PERP(K)/C)
```

For random error use the RLOG function for logistic deviates and the RRLOG for log-logistic variates.

```
      SQ3=SQRT(3.)
      DEN=50*PI
      DO 30 k=1,NDECT
        ALPHA=PERP(K)
        BETA=PERP(k)*SQ3/DEN
        TPERP(K)=RLOG(ALPHA,BETA,ISEED)
30      IF (TPERP(K).LE.0) TPERP(K)=0
```

(3)
```
CALL FOSER (NDECT,TPERP,LCUT,AREA)
FOSERD=FLOAT(NDECT)/AREA
CALL CALL BSTRAP(NDECT,N2,M,TPERP,ISEED,AFS,SFS,ME,
  FOSERD,NREP,NI)
WRITE(6,*) ' EST ',FOSERD,' FS AVE ',AfS,' SD ',SFS
```

The following subroutines need to be added or replaced in VABS:

```
      FUNCTION RLLOG(ALPHA,BETA,ISEED)
C     GENERATES LOG-LOGISTIC DEVIATES USING THE INVERSE METHOD
C     INPUT: ALPHA=MEAN OF LOGISTIC DISTRIBUTION
C            BETA=STANDARD DEVEIATION=(BETA*PI)/SQRT(3)
      DOUBLE PRECISION DRAND,ISEED
      R=DRAND(ISEED)
      RLLOG=ALPHA+BETA*LOG(R/(1.0-R))
      RLLOG=EXP(RLLOG)
      RETURN
      END

      FUNCTION RLOG(ALPHA,BETA,ISEED)
C     GENERATES LOG-LOGISTIC DEVIATES USING INVERSE METHOD
C     INPUT  ALPHA=MEAN OF LOGISTIC DISTRIBUTION
C            BETA=STANDARD DEVEIATION=(BETA*PI)/SQRT(3)
      DOUBLE PRECISION DRAND,ISEED
```

```
R=DRAND(ISEED)
RLOG=ALPHA+BETA*LOG(R/(1.0-R))
RETURN
END
```

APPENDIX K

Subroutines for Covariate Adjustments

To include various levels of detectability, the variables determining detectability are considered vectors with NOBS rows (NOBS represents the number of unique transect traversed). The values for each cell of these vectors has to be assigned in the main program of VABS. The variable PERP becomes a matrix whose first column contains the observed detected area, while the other rows contain information on the covariates. The matrix TP is added so that adjustments to the observed detected area can be carried out while still preserving the original matrix PERP from which bootstrap samples can be drawn.

Instead of splitting the line up into NI subsections to draw a bootstrap sample of the n_i's, the bootstrap sample is drawn from the number of detections for each NOBS level of detectability. To carry out this algorithm, the following lines need to be replaced or added to the main program of VABS:

```
(1) REAL PERP(300,2),BIRD(300,5),L,W,TREE(100,3),X(300),
   *  TP(300,2),DVA(5),PERF(5),THETA(5),DA(5),TT(5),SDTT(5),EB(5)

(2) COMMON /POINTS/NDECT,TP,X

(3)     DO 20 J=1,NOBS
          CALL DETECT(DVA(J),DA(J),TT(J),SDTT(J),PERF(J),BETA1,DT,
       *    NI,NOBS)
    20 CONTINUE

(4)     DO 43 II=1,NDECT
                TP(II,1)=PERP(II,1)
                TP(II,2)=PERP(II,2)
    43          X(II)=PERP(II,1)

(5) CALL COVAR(DECUM,DEFS,DEEPS,EB,NOBSs,BNREP)

(6) CALL BSTRP(NDECT,N2,M,ISEED,NOBS,EB,EDEFAR,EDAREA,EDEST,BNREP)
```

The following subroutines need to be replaced in VABS:

```
      SUBROUTINE BSTRP(N1,N2,M,IX,NOBS,TB,TDEFAR,TDAREA,
     * TDEST,BNREP)
C     THIS SUBROUTINE SELECTS A BOOTSTRAP SAMPLE OF INDIVIDUAL
C     DISTANCES AND THEN CALCULATES DENSITY.
      DOUBLE PRECISION DRAND,IX
      INTEGER NREP(5),BNREP(5),TBNREP(5)
      REAL PERP(300,2),A(4,3),S(4,3),D(4,3),U(4,3),AR(4,3),
     *   TAPERP(300),TP(300,2),X(300),TB(5),TBHAT(5)
      COMMON /AREA/PERP,NREP
      COMMON /ADJUST/ADPERP
      COMMON /POINTS/NDECT,TP,X
      DO 10 I=1,3
        DO 11 J=1,3
```

```
          A(I,J)=0
          S(I,J)=0
          D(I,J)=9999999
11        U(I,J)=-D(I,J)
10      CONTINUE
        ME=M
        DO 50 I=1,M
          DO 30 J=1,N2
            Z=SNGL(DRAND(IX))
            K=(IX/(2147463647/N1))+1
            X(J)=PERP(K,1)
            TP(J,1)=PERP(K,1)
            TP(J,2)=PERP(K,2)
            IF (PERP(K,2).EQ.1) THEN
              CORRECT=0
            ELSE
              CORRECT=TB(IFIX(PERP(K,2)))
          ENDIF
30          TAPERP(J)=PERP(K,1)*EXP(-CORRECT)
        SUM1=0.
        SUM2=0.
        DO 31 J=1,NOBS
          Z=SNGL(DRAND(IX))
          K=(IX/(2147463647/NOBS))+1
          SUM1=SUM1+FLOAT(NREP(K))
          IF (J.NE.1) THEN
            SUM=SUM+FLOAT(BNREP(K)*EXP(TB(J)))
          ELSE
            SUM=SUM+FLOAT(BNREP(K))
          ENDIF
31      CONTINUE
        SUM2=FLOAT(NINT(SUM2))
        CALL ORDIT
        CALL CUMD(EFAR)
        CALL FOSER(LCUT,AREA)
        CALL EPMLE(EST,G)
        AR(1,1)=FLOAT(N2)/EFAR
        AR(1,2)=FLOAT(N2)/AREA
        AR(1,3)=SUM/EST
        CALL COVAR(AR(2,1),AR(2,2),AR(2,3),TBHAT,NOBS,TBNREP)
        CORRECT=SUM1/FLOAT(N2)
        AR(3,1)=AR(2,1)*CORRECT
        AR(3,2)=AR(2,2)*CORRECT
        AR(3,3)=AR(2,3)*CORRECT
        CORRECT=SUM2/FLOAT(N2)
        AR(4,1)=AR(2,1)*CORRECT
        AR(4,2)=AR(2,2)*CORRECT
        AR(4,3)=AR(2,3)*CORRECT
          DO 60 II=1,4
            DO 60 JJ=1,3
              A(II,JJ)=A(II,JJ)+AR(II,JJ)
              S(II,JJ)=S(II,JJ)+AR(II,JJ)**2
              IF (D(II,JJ).GT.AR(II,JJ)) D(II,JJ)=AR(II,JJ)
```

```
60          IF (U(II,JJ).LT.AR(II,JJ)) U(II,JJ)=AR(II,JJ)
50    CONTINUE
      DO 70 II=1,4
        DO 70 JJ=1,3
          S(II,JJ)=S(II,JJ)-((A(II,JJ)*A(II,JJ))/FLOAT(M))
          S(II,JJ)=SQRT(S(II,JJ)/FLOAT(M-1))
70        A(II,JJ)=A(II,JJ)/FLOAT(M)
C     DO 80 II=1,4
          WRITE(6,*) 'ESTIMATOR ',II
          WRITE(6,200) A(II,1),S(II,1),D(II,1),U(II,1)
          WRITE(6,200) A(II,2),S(II,2),D(II,2),U(II,2)
80        WRITE(6,200) A(II,3),S(II,3),D(II,3),U(II,3)
200   FORMAT (4(5X,F11.6))
      RETURN
      END
```

The following subroutines need to be added to VABS in order to carry out the covariate adjustments:

```
      SUBROUTINE COVAR(AECUM,AEFS,AEEPS,BHAT,NOBS,TBNREP)
C     THIS PROGRAM USES LEAST SQUARES TO FIT LN(Y)=BX
C     AND THEN ADJUST THE DATA AND FITS THE ADJUSTED DATA BY
C     THE CUMD, F.S., AND EPS METHODS
      INTEGER P,NREP(5),TBNREP(5)
      REAL YLN(300),BHAT(5),XTX(5,5),X(300),TP(300,2),XX(300,5)
     *  ,AB(5,10),XTY(5),XTXINV(5,5),XBHAT(300),PERP(300,2)
      COMMON /AREA/PERP,NREP
      COMMON /POINTS/NCDECT,TP,X
      P=NOBS
      DO 74 II=1,NDECT
        XX(II,1)=1
        DO 10 J=2,NOBS
          IF (J.EQ.TP(II,2)) THEN
            XX(II,J)=1
          ELSE
            XX(II,J)=0
          ENDIF
10      CONTINUE
        IF (TP(II,1).NE.0) THEN
          YLN(II)=ALOG(TP(II,1))
        ELSE
          YLN(II)=ALOG(.0001)
        ENDIF
74    CONTINUE
      DO 33 II=1,P
        DO 33 J=1,P
          XTX(II,J)=0
          DO 33 K=1,NDECT
            XTX(II,J)=XTX(II,J)+XX(K,II)*XX(K,J)
33    CONTINUE
      N2=2*P
      DO 99 II=1,P
        DO 99 J=1,P
```

```
 99       AB(II,J)=XTX(II,J)
      DO 200 II=1,P
        DO 200 J=P+1,N2
 200      AB(II,J)=0.
      DO 300 II=1,P
 300    AB(II,P+II)=1.
      N2=2*P
      NDIM=P
      CALL ELIM(AB,P,N2,NDIM)
C     THIS SUBROUTINE COMES FROM: GERALD, CURTIS F. 'APPLIED
C     NUMERICAL ANALYSIS' 2ND EDITION, ADDISON-WESLEY PUBL.
C     MASSACHUSETTS, 1980 THIS SUBROUTINE SOLVES A SET OF
C     LINEAR EQUATIONS.
      DO 400 II=1,P
        DO 400 J=1,P
 400        XTXINV(II,J)=AB(II,J+P)
C     CALCULATING THE MATRIX X'Y
      DO 34 II=1,P
        XTY(II)=0
        DO 34 K=1,NDECT
 34       XTY(II)=XTY(II)+XX(k,II)*YLN(K)
C     CALCULATING Y'Y
      YTY=0
      DO 35 K=1,NDECT
 35    YTY=YTY+YLN(K)**2
C     CALCULATING ESTIMATES OF THE PARAMETERS
      DO 36 II=1,P
        BHAT(II)=0
        DO 36 K=1,P
 36       BHAT(II)=BHAT(II)+XTXINV(II,K)*XTY(K)
      EBHAT=BHAT(P)
C     CALCULATING SIGMA**2
      SIGMA=0
      DO 237 II=1,NDECT
        XBHAT(II)=0
        DO 226 K=1,P
 226      XBHAT(II)=XBHAT(II)+Xx(II,K)*BHAT(K)
 237     SIGMA=(YLN(II)-XBHAT(II))**2+SIGMA
      DO 238 II=1,P
        DO 238 J=1,P
          VARBHAT=(SIGMA/(float(nDECT)-2))*XTXINV(II,J)
 238    CONTINUE
      DO 30 II=1,NDECT
        IF (TP(II,2).EQ.1) THEN
          CORRECT=0
        ELSE
          CORRECT=BHAT(IFIX(TP(II,2)))
        ENDIF
 30     X(II)=TP(II,1)*EXP(-CORRECT)
      CALL ORDIT
      CALL CUMD(AEEFAR)
      CALL FOSER(LCUT,AEAREA)
      CALL EPMLE(AEEST,G)
```

```
      AECUM=0
      AEFS=0
      AEEPS=0
      DO 42 IJ=1,NOBS
        IF (IJ.NE.1) THEN
          ZZ=FLOAT(NREP(IJ))/(EXP(BHAT(IJ)))
          TBNREP(IJ)=NINT(ZZ)
        ELSE
          ZZ=FLOAT(NREP(IJ))
          TBNREP(IJ)=NINT(ZZ)
        ENDIF
      AECUM=AECUM+(ZZ/AEEFAR)
      AEFS=AEFS+(ZZ/AEAREA)
      AEEPS=AEEPS+(ZZ/AEEST)
42    CONTINUE
      RETURN
      END
```

APPENDIX L

Subroutines for Analytical and Bootstrap Confidence Intervals

To calculate the analytical estimate of standard error for the FS, the following lines need to be replaced and added to the main program of VABS:

```
      CALL ORDIT(NDECT,PERP)
      CALL FOSER(NDECT,PERP,LCUT,AREA,CA)
      FOSERD=FLOAT(NDECT)/AREA
      L=LCUT+1
      VARFO=0
      DO 30 K=2,l
        DO 40 J=2,l
          IF (J.EQ.K) THEN
            IF (2*J.GT.l) THEN
              COV=(2*(CA(1)**2)-(CA(J)**2))/(NDECT-1)
            ELSE
              COV=((CA(2*J)+2*CA(1))*CA(1)-(CA(J)**2))/(NDECT-1)
            ENDIF
          ELSE
            IF ((K+J).GT.l) THEN
              COV=((CA(ABS(K-J))*CA(1))-CA(K)*CA(J))/(NDECT-1)
            ELSE
         COV=((((CA(K+J)+CA(ABS(K-J)))*CA(1))-
     *           -CA(K)*CA(J))/(NDECT-1)
            ENDIF
        ENDIF
        VARFO=VARFO+COV
40      CONTINUE
30    CONTINUE
      FO=1/AREA
      VARD=(FOSERD**2)*((1/NDECT)+(VARFO/(FO**2)))
      SED=SQRT(VARD)
      WRITE(6,*) ' FS ',FOSERD,' SE ',SED
```

To calculate the approximate percentile confidence bounds as well as the normal confidence bounds, the following subroutines need to be substituted or added to VABS:

```
      SUBROUTINE BSTRAP(N1,N2,M,X,IX,DCUM,DFOR,DEP,NREP,NI,M2)
      DOUBLE PRECISION IX,DRAND,K
      REAL X(N1),Y(300),FOR(1000),CUM(1000),EP(1000)
      INTEGER NREP(ni),BNREP(10)
      RM=FLOAT(M)
      ACD=0.
      SCD=0.
      AFS=0.
      SFS=0.
      AEPS=0.
      SEPS=0.
      DO 50 I=1,M
```

```
      DO 30 J=1,N2
        ZZ=DRAND(IX)
        K=(IX/(2147463647/N1))+1
        Y(J)=X(K)
30    CONTINUE
      SUM=0.
      DO 31 J=1,NI
        ZT=DRAND(IX)
        K=(IX/(2147463647/NI))+1
        BNREP(J)=NREP(K)
        SUM=SUM+FLOAT(NREP(K))
31    CONTINUE
      CAll ORDIT(N2,Y)
      CAll CUMD(N2,Y,EFAR)
      CAll FOSER(N2,Y,LCUT,AReA)
      CALL EPMLE(N2,Y,EST,G)
      CUM(I)=FLOAT(N2)/EFAR
      FOR(I)=FLOAT(N2)/AREA
      EP(I)=SUM/EST
      SCUM=CUM(I)
      SFOR=FOR(I)
      SEP=EP(I)
      ACD=ACD+CUM(I)
      SCD=SCD+(CUM(I))**2
      AFS=AFS+FOR(I)
      SFS=SFS+(FOR(I))**2
      AEPS=AEPS+EP(I)
      SEPS=SEPS+(EP(I))**2
50  CONTINUE
    SCD=SCD-ACD*ACD/FLOAT(M)
    SFS=SFS-AFS*AFS/FLOAT(M)
    SEPS=SEPS-AEPS*AEPS/FLOAT(M)
    SCD=SQRT(SCD/FLOAT(M-1))
    SFS=SQRT(SFS/FLOAT(M-1))
    SEPS=SQRT(SEPS/FLOAT(M-1))
    ACD=ACD/FLOAT(M)
    AFS=AFS/FLOAT(M)
    AEPS=AEPS/FLOAT(M)
    WRITE(6,*) 'CUMD AVE ',ACD,' SD ',SCD
    WRITE(6,*) 'FS   AVE ',AFS,' SD ',SFS
    WRITE(6,*) 'EP   AVE ',AEPS,' SD ',SEPS
    CALL ORDIT(M,CUM)
    CALL ORDIT(M,FOR)
    CALL ORDIT(M,EP)
    UH=.995
    UL=.005
    M1U=IFIX(M*UH+.000001)
    M1L=IFIX(M*UL+.000001)
    M2U=M1U+1
    M2L=M1L+1
    D1U=FLOAT(M)*UH-FLOAT(M1U)
    D1L=FLOAT(M)*UL-FLOAT(M1l)
    CALL PERCENT(M,M1U,M1L,M2U,M2L,D1U,D1L,CUM,FOR,EP,UH,UL,
```

```
     * CCIU,CCL,FCIU,FCIL,ECIU,ECI1)
      UH=.975
      UL=.025
      M1U=IFIX(RM*UH+.000001)
      M1L=IFIX(RM*UL+.000001)
      M2U=M1U+1
      M2L=M1L+1
      D1U=FLOAT(M)*UH-FLOAT(M1U)
      D1L=FLOAT(M)*U1-FLOAT(M11)
      CALL PERCENT(M,M1U,M1L,M2U,M2L,D1U,D1L,CUM,FOR,EP,UH,UL,
     * CCIU,CCIL,FCIU,FCIL,ECIU,ECI1)
      UH=.950
      UL=.050
      M1U=IFIX(RM*UH+.000001)
      M1L=IFIX(RM*UL+.000001)
      M2U=M1U+1
      M2L=M1L+1
      D1U=FLOAT(M)*UH-FLOAT(M1U)
      D1L=FLOAT(M)*U1-FLOAT(M11)
      CALL PERCENT(M,M1U,M1L,M2U,M2L,D1U,D1L,CUM,FOR,EP,UH,UL,
     * CCIU,CCIL,FCIU,FCIL,ECIU,ECI1)
      RETURN
      END

      SUBROUTINE PERCENT(M,M1U,M1L,M2U,M2L,D1U,D1L,CUM,FOR,EP,
     * UH,UL,CCIU,CCIL,FCIU,FCIL,ECIU,ECI1)
C     THIS PROGRAM CALCULATES THE PERCENTILE CONFIDENCE LIMITS
C     INPUT:  M=NUMBER OF BOOTSTRAP REPS
C     M1U,...,D1L=ARE VALUES NEEDED TO GET CRITICAL VALUES
C     CUM,FOR,EP=VECTORS OF BOOTSRAP ESTIMATES OF DENSITY
C             UH=UPPER LEVEL PERCENTAGE POINT
C             UL=LOWER LEVEL PERCENTAGE POINT
C     OUTPUT: CCIU,CCIL=UPPER AND LOWER CRITICAL VALUES FOR CUMD
C             FCIU,FCIL=UPPER AND LOWER CRITICAL VALUES FOR F.S.
C              ECIU,ECIL=UPPER AND LOWER CRITICAL VALUES FOR E.P.S
      REAL FOR(M),CUM(M),EP(M)
      CCIU=CUM(M1U)+D1U*(CUM(M2U)-CUM(M1U))
      CCIL=CUM(M1L)+D1L*(CUM(M2L)-CUM(M1L))
      CCIU=CCIU+.5*(CUM(M2U)-CCIU)
      CCIL=CCI1+.5*(CUM(M2L)-CCI1)
      FCIU=FOR(M1U)+D1U*(FOR(M2U)-FOR(M1U))
      FCIL=FOR(M1L)+D1L*(FOR(M2L)-FOR(M1L))
      FCIU=FCIU+.5*(FOR(M2U)-FCIU)
      FCIL=FCI1+.5*(FOR(M2L)-FCI1)
      ECIU=EP(M1U)+D1U*(EP(M2U)-EP(M1U))
      ECIL=EP(M1L)+D1L*(EP(M2L)-EP(M1L))
      ECIU=ECIU+.5*(EP(M2U)-ECIU)
      ECIL=ECI1+.5*(EP(M2L)-ECI1)
      WRITE(6,*) ' PERC U1 ',UL,' CVL ',CCIL,' CVU ',CCIU
      WRITE(6,*) ' FS U1 ',UL,' CVL ',FCIL,' CVU ',FCIU
      WRITE(6,*) ' EP UL ',UL,' CVL ',ECIL,' CVU ',ECIU
      RETURN
      END
```