GeoSpatial Survey Operations Manual

ADF&G photo

by

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I. INTRODUCTION

In Alaska and northwestern Canada, periodic estimates of population size are needed to manage moose populations (Bergerud and Manuel 1969; Timmerman 1974; Dalton 1990). During the 1980s and 1990s most managers relied on the stratified random sampling design of Gasaway et al. (1986), which evolved from earlier protocols promoted by Siniff and Skoog (1964) and Evans et al. (1966). The Gasaway survey uses stratified random sampling to provide estimates of precision around both population and composition estimates. It includes a sightability correction factor with an estimate of precision, and is suitable for all types of terrain and vegetation found within the boreal forest zone (Gasaway and DuBois 1987). However, random sampling has limitations when applied to spatially distributed observations that are nonrandom (Ver Hoef 2002). Geospatial survey methods that address the limitations of random sampling emerged in the 1990s with the increasing availability of GPS technology, GIS computer capabilities, and spatial statistics (Cressie 1993; Ver Hoef 2002). Geospatial methods have several advantages over previous survey designs including 1) estimation of moose numbers in small areas that are nested within larger survey areas, 2) increased precision, and 3) greater flexibility in sample design.

Beginning in 1997, trends in Alaska's moose populations were increasingly monitored with Ver Hoef's (2001, 2007) Geospatial Population Estimator (GSPE) (termed finite population block kriging in Ver Hoef 2001). There has been no single source of documentation describing both the field application and analysis of the GSPE. This manual fills that gap. It provides generalized descriptions of the spatial theories behind GSPE. It describes how to select the survey area, how to conduct the survey, and how the survey data can be analyzed.

In addition to this operations manual, web-based software is available for GSPE analysis. The software, developed by Rob DeLong and Jay Ver Hoef of the Alaska Department of Fish and Game, provides utilities to simplify or automate the steps in planning and conducting GSPE surveys. The software package, GSPE Moose Surveys, is available on the Alaska Department of Fish and Game's intranet website, http://winfonet.alaska.gov (WinfoNet). Access to this website is controlled by username and password. Users who wish to access the software can request a user account through the authors. For detailed instructions in the use of the GSPE Moose Survey software, please refer to this manual's companion document, *GeoSpatial Population Estimator Software User's Guide* (DeLong 2006), also available on WinfoNet at http://winfonet.alaska.gov/index.cfm?fuseaction=sandimoosesurveys.documentation.

II. THE GEOSPATIAL POPULATION ESTIMATOR (GSPE)

An understanding of the GSPE method must begin with a description of spatial correlation. First, consider that individual moose are not randomly distributed across the landscape. Instead, where you find one it is likely others are nearby, but finding one moose tells you very little about moose density 50 km away. That relationship, where the probability of finding a moose in a particular spot is partly predicted by the distance to other moose, is called spatial correlation. Spatial correlation can take 2 forms. Spatial autocorrelation is the spatial correlation of a variable, like moose density, with itself. Spatial cross correlation is the spatial correlation of any variable with a different variable, such as a spatial correlation between the density of cow moose and the density of calf moose.

Spatial correlation in moose populations can be used to increase precision and flexibility in survey methods. Classical statistics assume that no spatial correlation exists among samples used to calculate the mean and variance. This is satisfied when samples are chosen using a random sampling design (this is called a design-based approach). It is often more profitable, however, to model the spatial autocorrelation among data (this is called a model-based approach; Cressie 1993; Ver Hoef 2002). Geospatial statistical techniques measure and model the spatial correlation among the samples and use that model to predict population density and variance without the requirement of random sampling.

The GSPE overcomes 3 basic limitations inherent to methods that use classical statistics. First, classical statistics are limited in their ability to provide estimates for small areas within the larger survey because it is impractical to obtain sufficient sample size in the smaller area by random sampling alone. In contrast, the GSPE allows estimates for any arbitrary subset of the survey area. Those sample subsets, called *analysis areas*, can be specified before or after the survey. When separate surveys are conducted under similar conditions and rules, they may also be combined to produce estimates for the combined area. This flexibility is possible because the GSPE predicts a density estimate and associated prediction error for every unsampled unit within the survey area.

Modeling spatial correlation within a survey area creates a second advantage for geostatistical analysis. In random designs, a constant variance is assumed among all sample units (i.e., Zar 1974). In the GSPE, the standard errors predicted for unsampled units are often smaller when the unsampled unit is close to a sampled unit. That reduces the overall variance around geospatial estimates compared to similar surveys that are analyzed with classical statistics. Consequently, for a given cost, the estimate from a GSPE survey will probably be more precise.

Finally, because the observed spatial correlation is modeled into the estimate, the GSPE is not dependent upon random sampling (Ver Hoef 2002). Therefore you can choose sampling designs that are more convenient, more powerful, and less expensive than those required by classical statistics. For example, to get a more precise estimate for a particular analysis area, you simply direct more sampling into the analysis area. Nonrandom sampling also makes the

GSPE less vulnerable to weather interruptions because all sample units completed at the time of a weather interruption are used to calculate a density estimate. In a random design, if a sample unit from the randomly ordered list of sample units remains unfinished because of a weather interruption, then strictly speaking all units that are lower in the sampling order should be dropped from the analysis even if they have been sampled. This is necessary to maintain a true random sample.

Although the statistics used in the GSPE and the Gasaway survey methods are different, the field methods are similar. If you are familiar with the Gasaway survey you will easily adapt to the GSPE. In both the GSPE and Gasaway survey, areas are divided into discrete sample units, sample units are classified into density *strata,* and a subset of sample units from each stratum is selected and sampled.

In the basic GSPE analysis, no corrections are made to account for moose that were missed by observers in the surveyed sample units. Therefore, the GSPE estimate is for 'observable' moose, which is always an underestimate of the actual number of moose in the survey area. GSPE estimates from successive years should reflect trends in population parameters if surveys are applied correctly. The primary purpose of this manual is to promote understanding and proper field application of the basic GSPE survey method. If you need an estimate of true population size, GSPE survey data can be coupled with a sightability correction factor (SCF) to account for the unobserved moose in sampled units (Gasaway et al. 1986; Timmerman and Buss 1998). We offer a method for adopting the Gasaway Survey SCF for population estimates to the GSPE technique in Appendix A.

A CALCULATING A GEOSPATIAL POPULATION ESTIMATE

Calculating a GSPE population or ratio estimate involves measuring the spatial correlation among samples, modeling that relationship as a function of distance, then using that model to predict moose densities in unsampled sample units. The GSPE models spatial autocorrelation when computing both population and composition ratio estimates. Spatial cross correlation between strata is not modeled because it does not improve population estimates (Ver Hoef 2001), but it is modeled between the numerator and denominator of composition ratios. Both spatial autocorrelation and spatial cross correlation are modeled using the same process.

To illustrate the ideas of a GSPE analysis, we consider an example using a moose survey from Central Alaska (Fig 1).

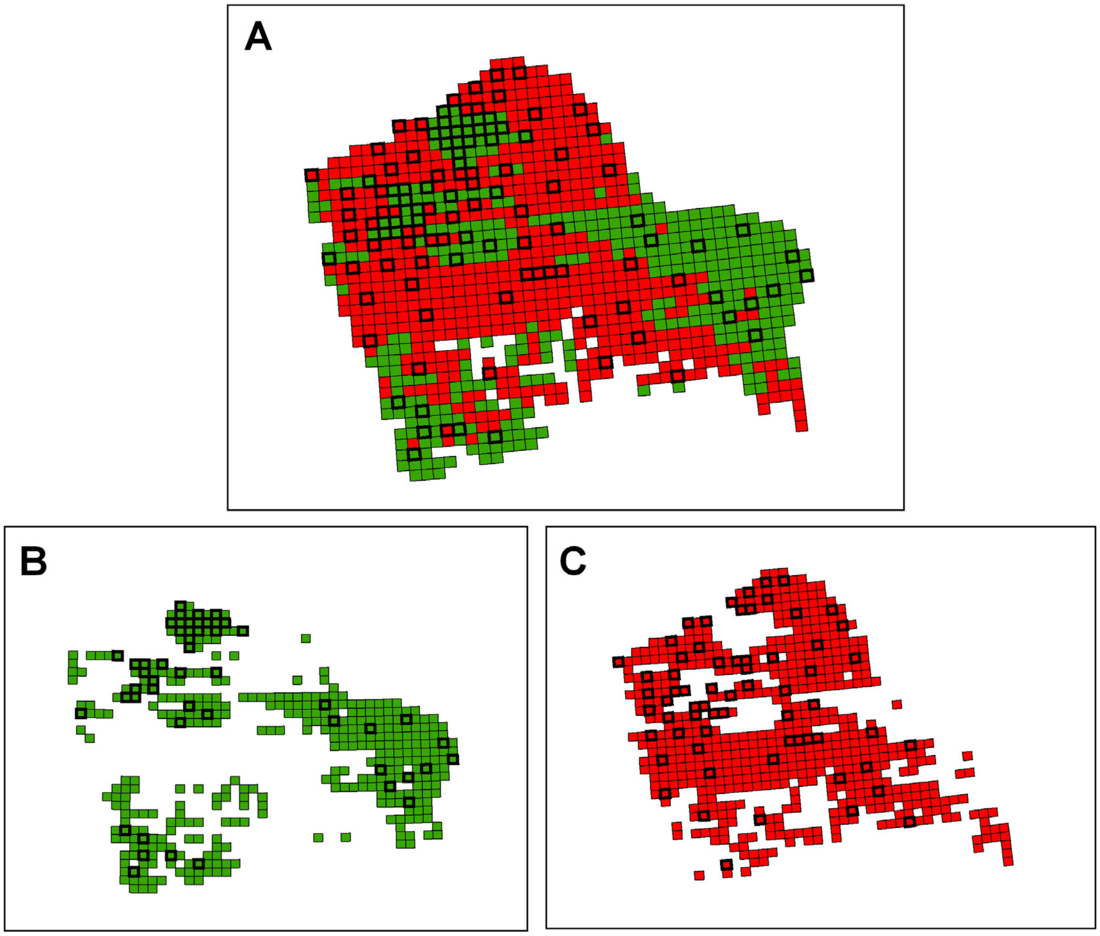

FIGURE 1 (A) Stratification and sampling for a moose survey in Central Alaska. The survey area is stratified into (B) low density and (C) high density. Sample units with a heavy border are those that were sampled.

GSPE calculations treat each stratum in a survey area independently. For this example, we will consider the high stratum from this survey (Fig 2).

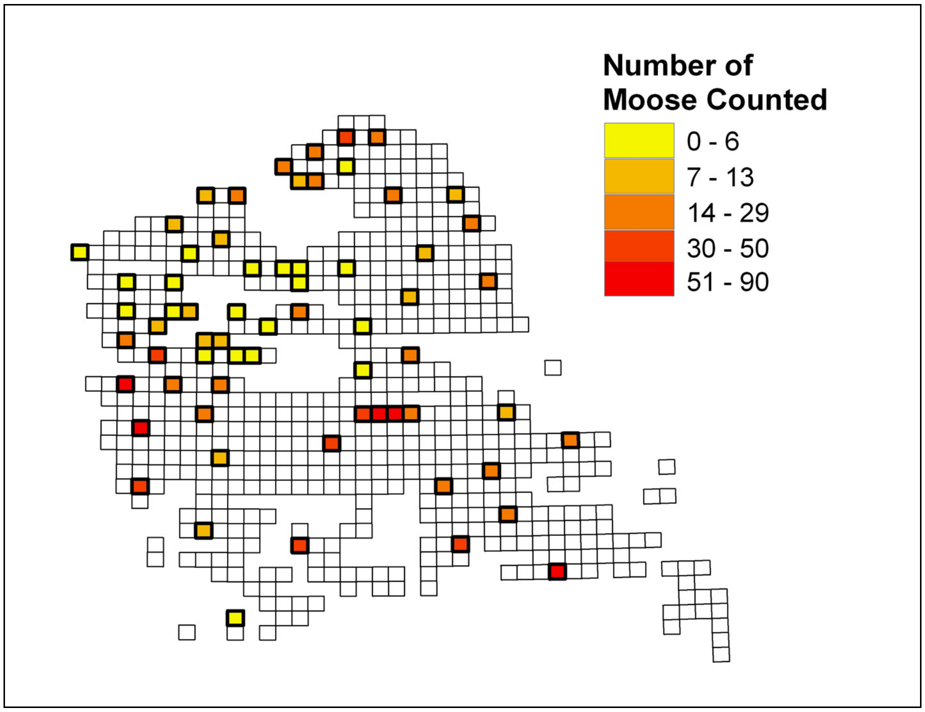

FIGURE 2 Sampling and survey results for the high stratum from the survey shown in Figure 1. Sampled units are shaded according to the number of moose observed during sampling. Red sample units had the highest number of observed moose and yellow sample units had the lowest.

First, the GSPE calculates the distance between every pair of sampled units, and the difference in observed moose densities between those pairs. Those density differences are expressed as *semivariances*,

$$\frac{(d_i - d_j)^2}{2} \tag{1}$$

where d_i is the density in i^{th} sample unit and d_j the density in the j^{th} sample unit. Plotting the semivariance as the response variable with distance as the independent variable, for distances up to 50 km, results in a *semivariogram cloud* (Fig 3).

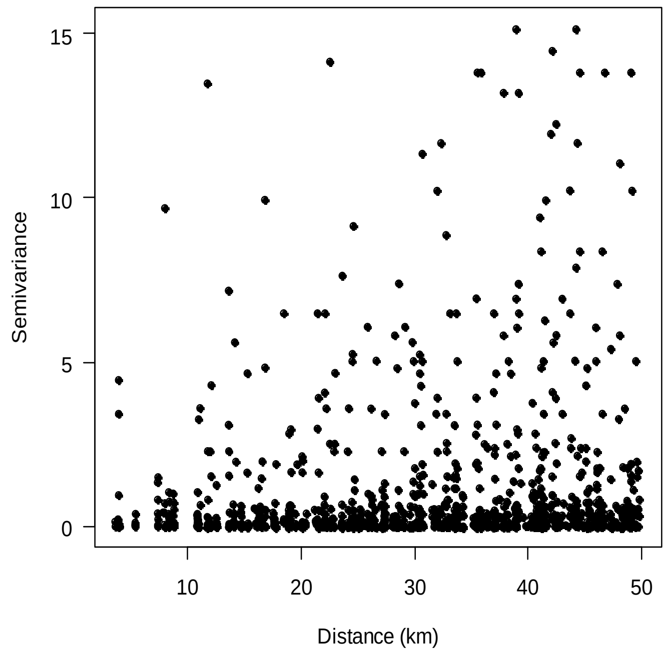

FIGURE 3 A semivariogram cloud depicting the distances between sampled units (x axis) and the semivariance measurements between those units (y axis) for the high stratum depicted in Figure 2

The semivariances from the semivariogram cloud are classified into 8 bins of equal distance intervals representing 8 rings of neighboring units lying at increasing distances from a sample unit. An *empirical semivariogram* is plotted using the mean semivariances within each bin as the response variables.

An empirical semivariogram cannot be used directly to predict moose density in unsampled units because it does not guarantee that we have a valid covariance matrix among samples (Cressie 1993). A model is fitted to the empirical semivariogram that does guarantee a valid covariance matrix (Fig 4). The GSPE uses an exponential variogram model, which has 3 fixed parameters: nugget, partial sill, and range, and is represented as

$$\hat{\gamma}(h) = \theta_{nugget} + \theta_{parsil}\left[1 - \exp\left(\frac{-\|h\|}{\theta_{range}}\right)\right] \qquad (2)$$

where $\hat{\gamma}(h)$ is the semivariance and h is the distance between 2 sample units. Several methods could be used to fit an exponential model to the empirical semivariogram. An obvious approach is to use a nonlinear least squares method, as would be used in regression. Another approach is restricted maximum likelihood, which is used in GSPE (Ver Hoef 2001).

The *fitted semivariogram* represents the spatial autocorrelation of moose density and is used to predict moose density in unsampled units (Ver Hoef 2001, 2002, 2007). When spatial autocorrelation of moose density is strong, the fitted semivariogram will be an upward sloping curve that extends out over longer distances. When spatial autocorrelation is weak, the fitted semivariogram will resemble a horizontal line. The stronger the autocorrelation of moose density is in a stratum, the greater the reduction in variance of the estimate that can be obtained using GSPE.

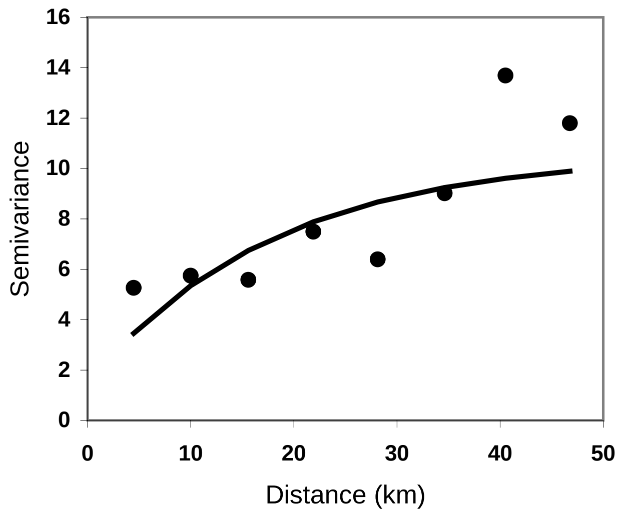

FIGURE 4 Empirical semivariogram overlaid with the fitted semivariogram function

Moose density is predicted for each stratum using a method called *finite population block kriging* (Ver Hoef 2001, Appendix B). Finite population block kriging can predict moose densities for single sample units, all sample units, or any collection of sample units within a survey area. The fitted semivariogram (Fig 4) forms the basis for prediction. To predict a single unsampled unit, individual samples are weighted according to how far the sampled units are from the unsampled unit. The weighted values are combined to predict a density for the unsampled unit. That process can be repeated for each unsampled unit in the survey area. A standard error associated with the individual predictions for unsampled units is also calculated.

Sampled units are assigned their known density. Figure 5 depicts prediction surfaces for moose density and standard error based on the observed moose counts in Figure 2 using a fitted model of spatial correlation (Fig 4). The standard error of sampled units is 0. The predicted standard error is smaller close to known densities and increases with distance from sampled units.

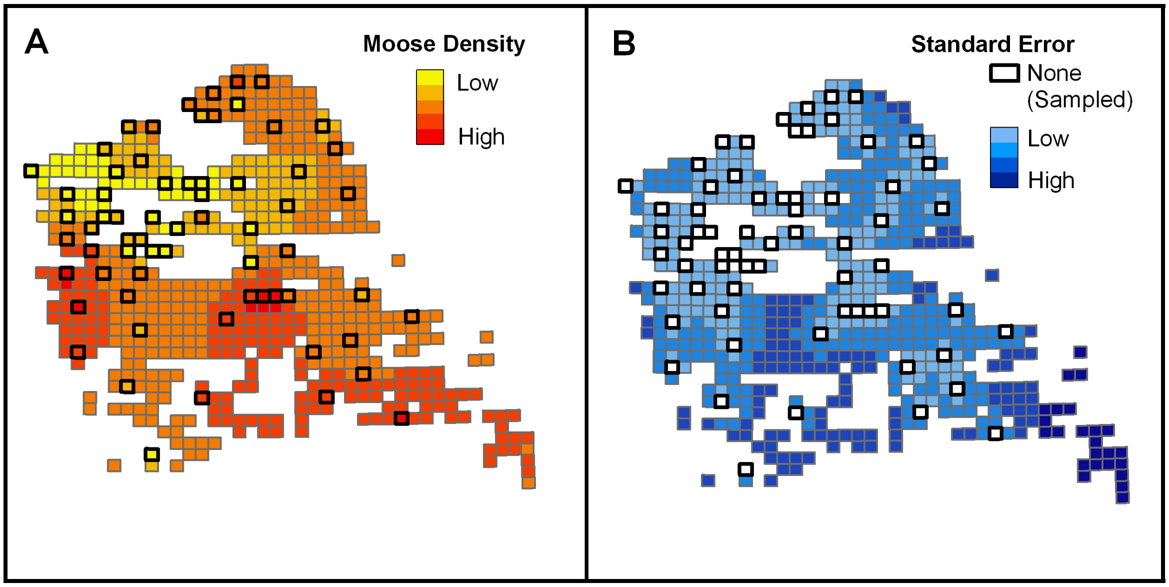

FIGURE 5 Surface of (A) predicted moose density and (B) standard error for each unsampled unit in the high stratum. In A, red units have the highest predicted densities and light yellow have the lowest predicted densities. In B, light blue units have the lowest and dark blue units have the highest standard error. Sample units with a heavy border are those that were sampled.

Predicted moose density is multiplied by unit area for each unsampled unit to convert to moose per unit. Conceptually, all of those predictions could be summed and added to counts from sampled units to calculate the population estimate for the stratum. That is the basic idea of the GSPE, although the mathematics are a little bit different. It would be difficult to combine all of the standard errors from unsampled units to calculate the variance of the total due to the correlations among the predictions. The GSPE develops the appropriate variance, calculates a population estimate and variance for each stratum, and then combines them to produce a population or ratio estimate for the entire analysis area (Fig 6).

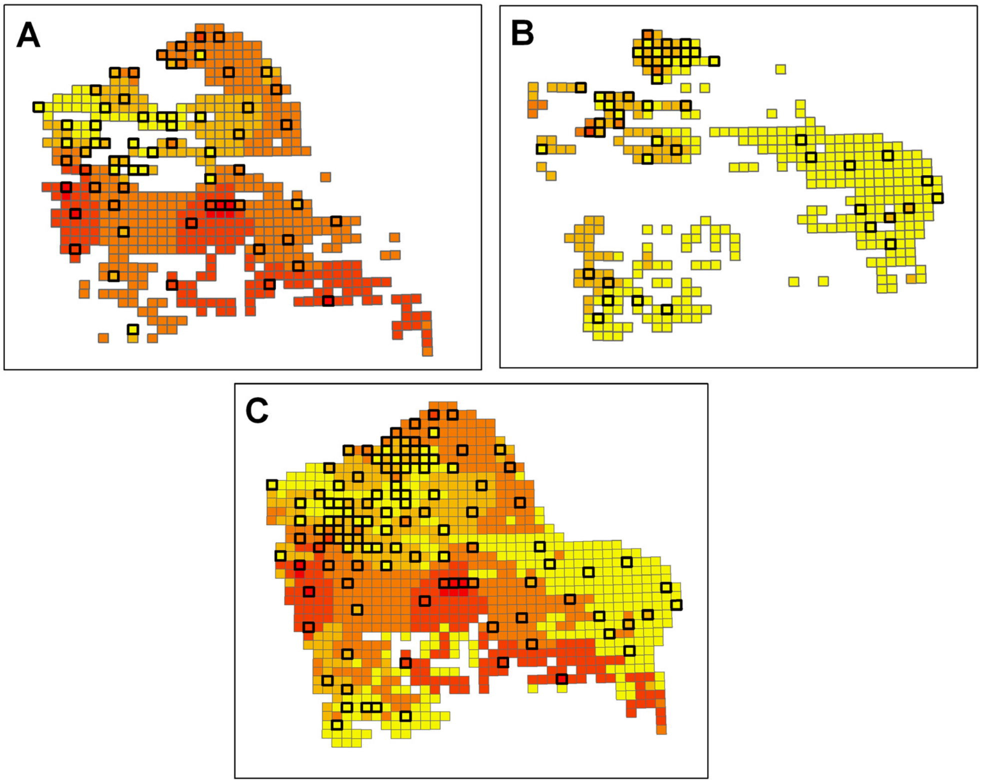

FIGURE 6 Separate estimates of total moose are calculated for (A) the high and (B) low stratum. These estimates are combined to produce a (C) population estimate. Highest estimated and observed moose numbers are in red, lowest are in yellow. Sample units with a heavy border are those that were sampled.

III. DEFINING THE SURVEY

The moose survey software on WinfoNet automates many of the tasks associated with defining a survey. For instructions on performing these tasks in WinfoNet, please refer to the *GSPE Software User's Guide*.

A DELINEATING A SURVEY AREA

GSPE survey areas should be at least 777 km^2 (300 mi^2). Smaller areas have insufficient numbers of sample units to generate GSPE estimates, so rather than sampling, a total count is more appropriate. Upper limits on the size of GSPE survey areas are dictated by logistics. The GSPE has been applied in survey areas as large as 28,490 km^2 (11,000 mi^2).

A practical way to delineate survey boundaries is to align them with previously established management boundaries. For example, wildlife management agencies are likely to use existing game management unit boundaries to facilitate application of population estimates to hunting regulations, and other wildlife management decisions. However, you must consider the following biological issues before arbitrarily aligning a survey area with a game management unit boundary.

Moose populations are often migratory, or have migratory subpopulations, so it is important to consider the variability in timing associated with your population's arrival and departure from wintering areas. Within wintering areas, changing snow depths can cause further shifts in moose distribution, especially along altitudinal gradients and among habitats (Ballard et al. 1991:26; Hundertmark 1998:330). Changes in population size over time can also cause shifts in moose distribution. For example, during a population increase, moose may begin to appear in marginal habitats that you previously considered unimportant. Your GSPE surveys will more accurately reflect long-term trends in moose abundance if you initially select survey boundaries that encompass the potential extent of the moose population's distribution under a variety of conditions.

B CREATING SAMPLE UNITS

A standard grid of sample units is provided in WinfoNet that meets the requirements of the GSPE method. You may use that standard grid or customize your own sample units to meet the following criteria. Sample units must have clearly defined boundaries and cannot overlap, but they do not need to be contiguous, nor is there a required shape. Sample units should be similar in size to maintain consistent sampling effort and to simplify survey protocols. Each unit must have a unique identifier (ID). For WinfoNet, that ID must be an integer, or a character string ≤10 characters with no spaces. If you combine multiple surveys, all sample units need to be uniquely identified.

Sample units should be 12 km^2 (4.5 mi^2) to 21 km^2 (8 mi^2). If units are smaller, GSPE predictions for unsampled units become unstable and increase the variance around population and ratio estimates. Units larger than 21 km^2 (8 mi^2) increase pilot and observer fatigue, are more often interrupted by weather, increase the cost per sample, and may not allow sufficient sample sizes to compute a GSPE. Larger sample units also tend to be more difficult to stratify because they potentially contain more diverse habitat. See Timmerman and Buss (1998) for a review of considerations when sizing sample units.

Standard Sample Unit Grid

The standardized grid of sample units that was developed for the GSPE technique currently covers most of Alaska and northern Canada (Fig 7). Portions of that grid can be extracted as separate survey areas. If you are planning a survey that lies outside of the existing grid, we recommend you contact the authors and request a grid extension. The extension will be added to the master grid in WinfoNet so you can use the web-based software to set up your survey.

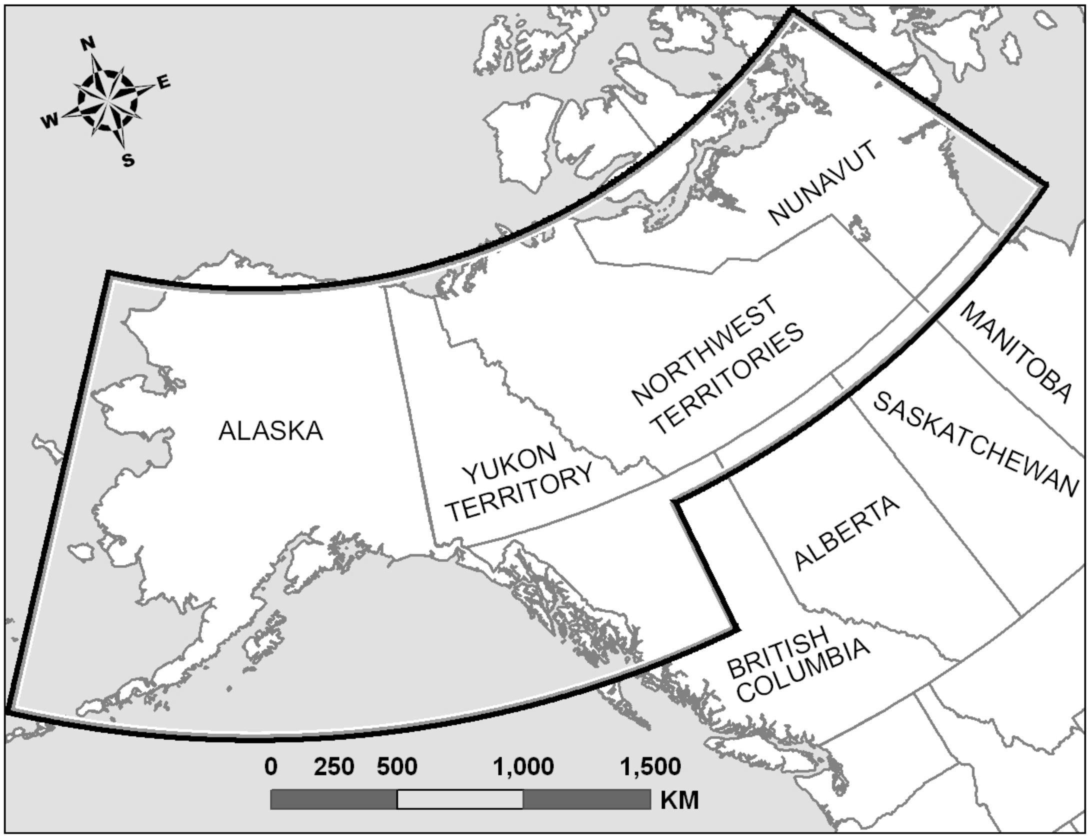

FIGURE 7 Extent of the standard sample unit grid for the GSPE method (in black)

We recommend using the standard grid because it is a simple, consistent method of dividing survey areas into sample units and provides a common framework among GSPE surveys. The grid was designed to:

- Provide a contiguous, non-overlapping surface of sample units over Alaska and northern Canada.
- Use a survey unit size that conforms to both minimum and maximum area requirements.
- Establish sample unit boundaries based on GPS technology rather than terrain features.
- Establish a system of globally unique sample unit identifiers that allows sample units from anywhere in the grid to be combined for analysis. Ideally these identifiers should convey the unit's location.

For example, because sample units were of uniform size and shape, Maier et al. (2005) were able to use these sample units from a wide range of survey areas for a landscape analysis of moose habitat.

The standard sample units designed for the GSPE are based on 2 minutes of latitude and 5 minutes of longitude (Fig 8). Those intervals produce sample units whose areas vary with latitude from approximately 13.5 km^2 (5.2 mi^2) in the north near Coldfoot, Alaska (67º15'36"N, 150º11'36"W) to around 20.1 km^2 (7.75 mi^2) in the south near Prince Rupert, British Columbia (54º25'36"N, 130º02'35"W).

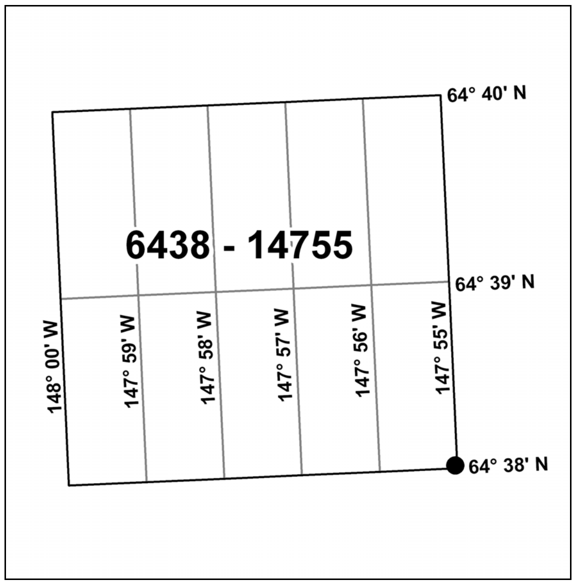

FIGURE 8 The recommended sample unit is 2 minutes latitude, 5 minutes longitude. The coordinates of the southeast corner of the sample unit (black dot) are the unit ID value.

The coordinates of the southeast corner of each sample unit are used as a unique identifier for each sample unit. For example, a sample unit occupying the area between 64º38'N, 147º55'W and 64º40'N, 148º00'W is given an ID of 6438-14755 (Fig 8). The projection of those coordinates is in North American Datum 1927 (NAD27), which corresponds with current USGS topographic maps. Because the coordinate identifier is lengthy, a second local identifier is often used for reference on data sheets and survey maps. The local identifier usually begins with 1 and is numbered systematically over the survey area (Fig 9).

The standard grid of sample units is described by a database in WinfoNet that contains the unique ID, area, and coordinates for the center (*centroid*) of each sample unit. Within Alaska, the game management unit is also described for each sample unit. The standard grid and database can be downloaded as an ESRI (Redlands, California, USA) polygon shapefile from WinfoNet.

Standard vs. Custom Sample Units

The standard grid of sample units offers several advantages over customized grids. The identifiers, centroids, boundary coordinates, and areas of all standardized sample units already exist in the WinfoNet database. To use a customized grid you will need to measure and enter those values. Field maps for any new survey within the standard grid are quickly plotted with GIS from the existing database, but maps of custom grids may have to be digitized or drawn manually. If you and others consistently use the standard grid you can combine multiple, independent surveys to produce a single population estimate, and you can improve estimates and sampling efficiency by "borrowing" sampled units from nearby survey areas.

Although there are compelling advantages to the standard master grid, you may need to customize your sample units to sample from an existing survey design created for other species or other techniques. If you do customize, the basic rules still apply. For WinfoNet, each sample unit needs a unique identifier ≤10 characters long, the coordinates for the sample unit centroid must be available in decimal degrees, and each sample unit's area must be measured and between 12 km^2 (4.5 mi^2) and 21 km^2 (8 mi^2). Sample units of arbitrary shape may be used, but you should avoid shapes where the centroid falls outside the sample unit boundary (e.g., crescent shapes).

Delineating Sample Units in the Survey Area

Desirable survey area boundaries often lie along rivers, ridge tops, or other well-defined curvilinear features, but sample unit boundaries in the standard grid are rectangular. Consequently peripheral sample units may not smoothly fit survey boundaries and you must decide which boundary sample units to exclude from the survey area. Predetermined, consistently applied criteria should guide your decisions. Commonly, units are excluded if less than 50% of the unit lies within the survey boundary, but you may choose to apply other rules depending on circumstances specific to your area. You may also wish to exclude units that contain no habitat which lie within the survey boundary. Again, establish predetermined decision criteria. For example, if moose are rarely found above a certain elevation, a reasonable rule might exclude a unit if more than 90% of the unit lies above that elevation. The final set of sample units in a survey area should only contain those sample units that have some chance of being sampled.

Analysis Areas

The GSPE will calculate population estimates for subsets of the survey area. Those *analysis areas* may consist of blocks of sample units, or they may contain scattered noncontiguous sample units if you are looking at population estimates based on such things as landownership or habitat types.

The precision of an estimate for an analysis area is unrelated to its size. High-precision estimates of population size are simultaneously possible in the large survey area and multiple analysis areas. You can define analysis areas during the initial survey setup, or they can be added or changed later. However, if analysis areas need more intensive sampling they must be identified before selecting the sampled units.

Survey Timing

We recommend you conduct moose surveys during the same 4- to 6-week season each year to provide the most consistent data for population trends. The most suitable season will depend upon your local conditions of snow cover, available light, typical weather patterns, antler casting, and moose migration. Depending on those variables you may choose an early winter (fall), midwinter (winter), or late winter (spring) survey season. Fall surveys are typically conducted after adequate snow has accumulated and before antler casting begins. At arctic/subarctic latitudes, daylight also becomes a limiting factor late in the fall season. Most fall surveys in Interior Alaska occur between 20 October and 5 December. Fall is generally the preferred season for moose surveys because sightability is greater (Gasaway et al. 1986:19) and sex:age ratios are most accurate.

Winter surveys are conducted after antler casting begins. In subarctic regions, surveys during this period are impractical because of low temperature and light conditions. In southern moose ranges, snow conditions are most reliable during winter, but antler casting confounds classification of bulls, so winter surveys only yield reliable estimates for combined adults and calves.

In subarctic areas, surveys are possible again in late winter or spring before snow melt. In Alaska, spring surveys are often conducted between mid-February and late March. However, sightability can be lower during spring because the high sun angle reflecting off the snow increases the contrast between shadowed and exposed areas. That reduces sightability of moose in forested areas and moose often use forested areas during spring to avoid deep snow and solar heat (Lynch 1975; Novak 1981). Carefully consider the potential effects of reduced sightability in your survey area before conducting spring surveys (Gasaway et al. 1986).

Survey Maps

Small maps (8.5" × 11", 8.5" × 14", or 11" × 17") in the stratification and survey aircraft facilitate navigation and depict the location of units assigned to other aircraft. Those maps can be generated in GIS by joining the survey database from WinfoNet with a shapefile from the standard grid. Survey areas are usually divided into a series of double-sided maps. The front side displays a 1:250,000 scale topographic map overlaid with sample units and labeled with primary or secondary IDs (Fig 9). The reverse side of the map (Fig 10) depicts the same sample units with no background and lists unit IDs (latitude and longitude of the southeast corner) along with the secondary IDs (if used). To make the maps legible, you will need to print at a scale of approximately 1:300,000. Laminate for long-term use if the survey boundary does not change. A poster-sized map depicting the entire survey area, selected sample units, major landmarks, fuel caches, and other information is useful at the base camp to keep track of daily progress.

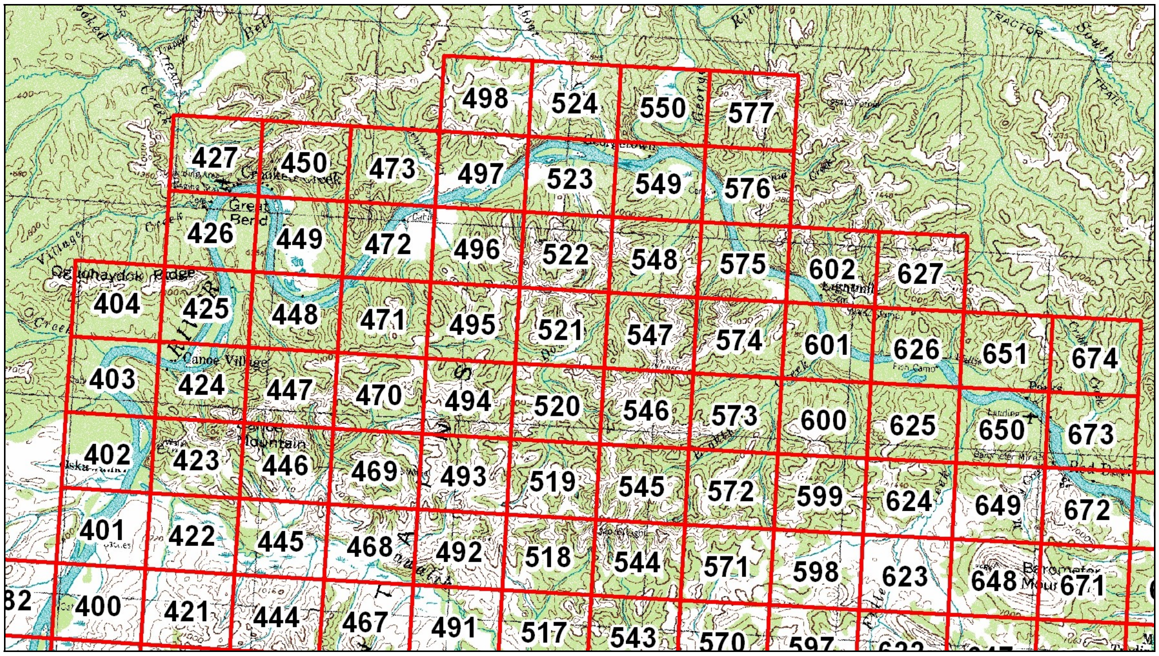

FIGURE 9 Sample of the front side of a survey map. A 1:250000 scale USGS map is displayed behind the sample units to aid navigation. Units are labeled with a local ID for easy reference.

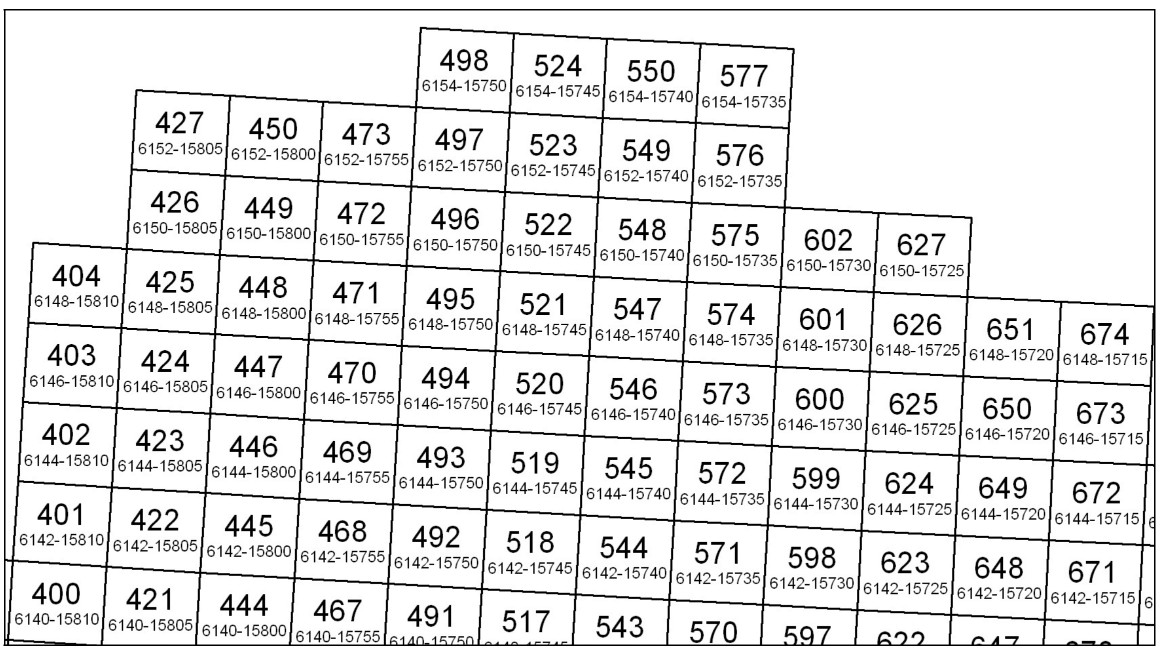

FIGURE 10 Sample of the reverse side of the survey map depicted in Figure 9. Units are labeled with a local ID for easy reference, and the globally unique ID, which references southeast corner of each unit in decimal minutes.

IV. STRATIFYING THE SURVEY AREA

Stratification is a classification of sample units based on expected moose density. Stratification increases the precision of the population estimate by minimizing differences among sample units within a stratum. Stratification is accomplished by direct observation on aerial surveys (field stratification), or by using previous knowledge to categorize units based on expected moose density (desktop stratification). Stratification should be determined prior to, and independent of, survey observations.

With the GSPE, stratification is limited to 2 strata: high moose density (high stratum) and low moose density (low stratum). Northern regions are typically characterized by large areas of relatively low moose density interspersed with small areas of higher moose density. To date, approximately 70% of stratified sample units (n = 34,300) have been classified as low stratum in Alaska. The preponderance of low stratum sample units, and the absence of moose in most of them, can reduce the variance for the overall population estimate if the low stratum is kept 'pure' and we attempt to confine most of the variation to the high stratum. The low stratum should be reserved for sample units having few or no moose, but the number of moose in a low stratum unit is related to moose density in the total survey area. In low-density populations, the low stratum units commonly have 0–3 moose. In higher density populations lows may have up to 5 moose.

GSPE sample units are relatively small and moose commonly move between them during the course of a survey. However, if moose move from one stratum to another, the benefits of stratification are lost. Stratification should be done in blocks of sample units. That 'broad brush' approach resists breakdown of the stratification because even if moose move between units, it is less likely they will move between strata. Also, avoid a checkered pattern of highs and lows, and avoid classifying units as lows immediately adjacent to highs if there is a good possibility moose will move into those low units during the survey. It is a good idea to map your preliminary stratification results to identify areas where the strata are checkered, or units are isolated.

A FIELD STRATIFICATION

We recommend direct aerial observation for initial stratification whenever possible. A partial stratification can be substituted if funding, staff availability, or weather precludes a full stratification survey. In a partial stratification only sample units of questionable density are stratified using direct aerial observation, and sample units that are almost certainly either high or low density are classified without examination. Desktop stratification of new survey areas should be avoided.

You should use 1 pilot and 3 observers for stratification (Gasaway et al. 1986), but 2-place aircraft can be used if conducting a partial stratification, or if 4-place aircraft are not available. Stratification is cost-effective at airspeeds of 120–160 mph (104–140 knots) (Gasaway et al. 1986), and transects should be flown at an altitude of 800–1500 ft above ground level so observers see most of each sample unit. Typically, the observer seated next to the pilot takes responsibility for assisting with navigation among the sample units, recording observations, and evaluating habitat. The most experienced observer in the stratification crew should be assigned these duties. The backseat observers search for moose and count moose tracks.

Observers should be instructed on the proper search distance from the aircraft prior to stratification flights. This will focus observer effort in the proper sample units and help reduce variation in search effort among observers. One possibility is to mark wing struts with tape to serve as a reference point for the outer limits of the search area during a transect.

Transects for stratification can be flown either along the boundary lines between units (Fig 11B) or across the centers of units (Fig 11A). In areas where moose density is consistently low, stratification is most efficient at a higher altitude flying along boundary-line transects. Fly the boundary between every other row of sample units. Observers on the right and left side of the aircraft must stratify separate units, evaluating habitat up to ~4 km from the aircraft. This allows 2 sample units to be stratified per 2 minutes of latitude or 5 minutes of longitude. Boundary line stratification requires less time than centerline stratification, but stratification error may increase because of lower search intensity per sample unit. Stratification using boundary line transects requires experienced observers in the rear seats who are capable of both evaluating habitat and judging stratum.

When a survey area contains a large number of units that each contain a few moose, centerline transects provide better resolution. For example, if a sample unit contains 5–8 moose, the low search intensity of boundary-line transect may miss critical moose sign, causing the unit to be misclassified into the low stratum. Centerline transects are flown along the center of each row or column of sample units, stratifying one unit every 2 minutes of latitude (north–south transects) or 5 minutes of longitude (east–west transects; Fig 11A). Observers must evaluate habitat out to the boundary of the unit (about 2.1 km), but all observers are simultaneously evaluating the same unit.

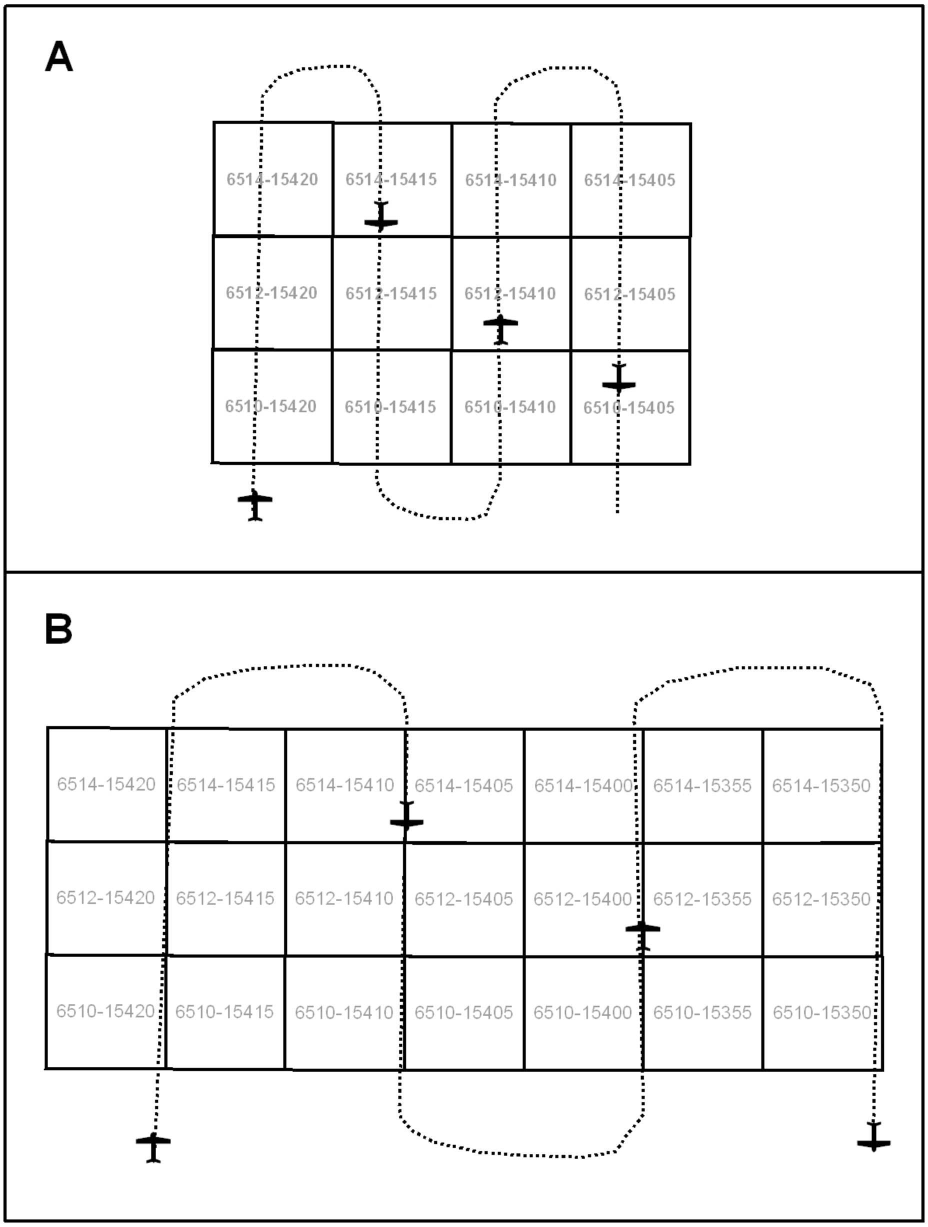

FIGURE 11 Illustration of transects used for stratification flights. Note that only one unit is stratified at a time using (A) centerline transects, with both right and left observers recording information about the same unit. Two sample units are stratified simultaneously, one on the left and one on the right side of the aircraft when flying (B) boundary line transects.

Observations of moose, moose tracks, and moose habitat from the stratification flight are used to classify sample units into high or low stratum. For each sample unit, record relative proportions of habitat types, numbers of moose, and moose tracks seen on the data form (Fig 12). Stratification criteria often vary between survey areas, but within a given survey area you should adhere to strict decision-making criteria so stratification remains consistent across units. Stratification decisions must not be affected by knowledge of actual samples taken during the survey.

You can assign sample units to a stratum during the stratification flight or during a review of the recorded observations after the flight. If stratification decisions are made during the flight, they should be made immediately as the aircraft exits each sample unit, the observers should individually render an opinion on the appropriate classification (high or low) and their consensus is recorded on the form.

Stratification Location:____________________________________ Date:_______________
Pilot:______________ Observer:___________________ Aircraft:_____________

Habitat Description: LS (low shrub); TS (tall shrub); MSD (mixed spruce/deciduous)
D (deciduous forest); S (spruce forest); Non (nonhabitat)

SU No.	Strat	Habitat Description	Moose Tracks	Moose Seen	Comments
1					
2					
3					
4					
5					

FIGURE 12 A portion of a stratification form that records habitat, moose tracks, and moose seen

B DESKTOP STRATIFICATION

When there is not enough funding to stratify even a portion of the survey area, stratification can be done in the office using existing knowledge of moose distribution and density. Although such a “desktop” stratification significantly reduces the overall cost of a GSPE survey, expect the precision of the population estimate to also decline. Desktop stratification relies on indirect measures to predict moose density, increasing the probability of stratification error.

If circumstances require a desktop stratification, use habitat, elevation, and historic density to predict moose distribution. Satellite imagery may be available for your survey area, but image interpretation may require consultation with a GIS technician. Vegetation maps can be particularly useful where moose are concentrated along riparian corridors, but use caution interpreting winter moose distribution from habitats used by moose during summer (Schwartz and Renecker 1998:438).

Some moose populations concentrate in high-elevation shrub zones in early winter, often in the foothills of major mountain ranges (Gasaway et al. 1986). Elevation data may be useful if you can identify elevations associated with the shrub transition zone. Aspect and percent slope have also been used to describe areas of increased moose density, and plotting favorable slopes and aspects may improve desktop stratification.

In some survey areas there may be historical data on moose distribution gathered during previous studies. However, historical data may no longer be accurate because of plant succession and disturbance. Generally, moose distribution data that is >10 years old should be verified visually or compared with a recent satellite image.

C STRATIFICATION DEGRADATION

Moose distribution and density can change by season, by year and over several years, degrading stratification accuracy. Applying stratification from one season to a survey flown in another season could reduce survey precision because population movements commonly occur between seasons. Similarly, stratifications from previous years will likely degrade with time as a result of environmental changes. If there is a large difference in snow depth between the stratification year and the survey year, verify the stratification in a few units before beginning your survey. If moose distribution has substantially changed, a more extensive restratification will be necessary. If wildland fire occurs in a survey area you can partially restratify by mapping the fire boundary and restratifying the affected units. Surrounding units may also need restratification if moose have moved out of the fire zone.

Gradual changes such as changes in moose population and plant succession also degrade stratification over time. You can use the actual moose counts from surveyed units to update your stratification for future surveys. Updating stratification in this manner is less expensive than regular stratification flights. However, updates are only made to the stratification when an error is found after sampling and no stratification information is obtained from unsampled units. Expect more stratification errors in surveys with stratifications updated in this manner than you would expect in surveys with fresh, presurvey stratifications.

If you do not survey an area for several years, you will likely have to conduct at least a partial stratification before a new survey. Successional habitat that has not changed suddenly (e.g., by fire) will need to be restratified every 5 to 7 years. If the moose population is rapidly increasing or declining, stratification should be more frequent (3–5 years) because the distribution of moose may change with population size.

D STRATIFICATION ENTRY

Enter your stratification data into WinfoNet to prepare for sampling. You can enter additional stratification classes (e.g., medium density) or other data such as moose or track counts if you want to archive that information for future reference in the WinfoNet database, but those additional data will not be used in the population analysis. Consult the “Editing the Survey Definition” section in the *GSPE Software User's Guide* for detailed instructions on how to define the strata in your survey. The “Stratification” section in the *GSPE Software User's Guide* contains instructions on entering the stratum assignments for individual sample units.

V. SELECTING SAMPLE UNITS TO SURVEY

After stratification, a subset of the sample units in the survey area must be selected for sampling. Your sample must be large enough to produce an acceptable precision for the population estimate, it must be partitioned by stratum, and it must be distributed spatially over the survey area. You can concentrate additional sampling effort in areas of particular management concern to improve the precision of results in those areas. The "Sample Selection" section in the *GSPE Software User's Guide* contains instructions on randomizing the sample units in the survey, performing an initial selection, and identifying subjectively placed samples.

A SAMPLING DENSITY

Sampling density affects the precision of the population estimate. The GSPE program requires at least 20 samples to generate an estimate for each stratum, but a minimum of 30 samples per stratum is desirable to get a good semivariogram fit to the spatial correlation. We recommend sampling at least 50 units in the high stratum, because observations are more variable in the highs. After you have selected your units for sampling, examine each stratum to ensure all unsampled units are within 50 km (~8 units) of sampled units. Select additional units for sampling to eliminate these "holes."

If you cannot afford to sample 80 units, we recommend that you reduce the number of low stratum units sampled before reducing the number of units from the high stratum that are sampled. If you can afford to sample more than 80 total units, select additional units from the high stratum. If the stratification was done correctly, additional sampling from the lows is unlikely to substantially improve variance. At typical sampling densities for the low stratum, the particular sampling density used has little relationship to the variance obtained for that stratum (Fig 13A). Usually there are fewer high stratum units than low stratum units, so it is possible to sample a large proportion of the highs to reduce variance (Fig 13B). Lower variance results from closer proximity of unsampled units to sampled units so placing additional samples in obvious gaps in the sampling pattern will improve variance. Ultimately, at a sampling density of 100% (total census), the variance for the estimate is 0 (Fig 13B).

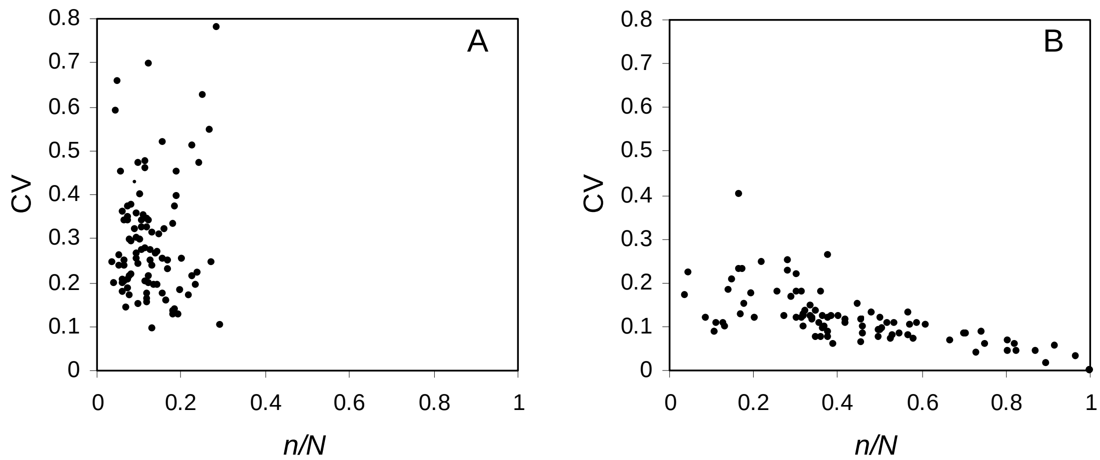

FIGURE 13 The relationship between coefficient of variance (se/estimate) and sampling density (*n*/*N*) for (A) low and (B) high strata for 94 GSPE surveys conducted in Alaska, the Yukon Territory, and the Northwest Territories between 1997 and 2005

The relationship between the number of sample units sampled and the size of the survey area is not as important for the reduction of variance as is the spatial distribution of samples. The relationship between the precision of survey estimates and the proportion of the total survey area sampled shows a great deal of variability (Fig 14). Within a typical range of sampling densities you can improve the variance of estimates more effectively by optimizing the spatial distribution of your sample than by simply increasing the sample size.

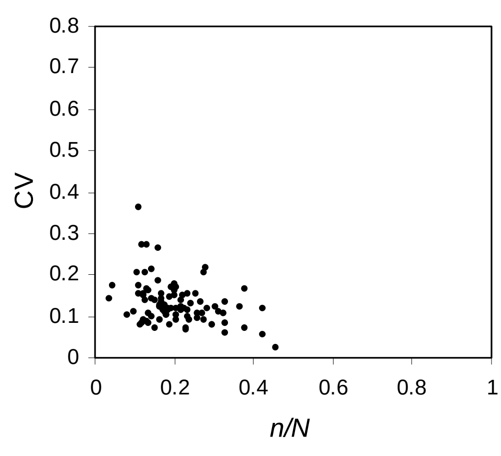

FIGURE 14 The relationship between coefficient of variance (se/estimate) and sampling density (*n*/*N*) in the total survey area for 94 GSPE surveys conducted in Alaska, the Yukon Territory, and the Northwest Territories between 1997 and 2005

There is a cost tradeoff between increasing sampling density and surveying more frequently. Frequent surveys can improve detection of population trends, but only if estimate precision is high enough to detect those trends. Smoothing techniques are available that use the correlation among estimates to reduce the variance of each estimate after 5 or more surveys have been conducted. We discuss one smoothing technique that has been applied to GSPE estimates from Interior Alaska later in this manual (Section VII. C Smoothing Estimates).

B SAMPLING APPROACHES

Systematic sampling, random sampling, paired sampling, and other objective sampling designs are compatible with the GSPE survey method. The primary restriction on sampling is to avoid selection or exclusion of sample units for subjective reasons (e.g., biologist preference or logistical difficulty). Predictions for unsampled units are calculated by either interpolation or extrapolation in the kriging process. Unsampled units that lie between sampled units are predicted through interpolation; those that lie beyond all sampled units are predicted through extrapolation (Fig 15). Prediction variance is higher for extrapolated than for interpolated units. Therefore, systematically choosing some units on the periphery of each stratum will reduce the number of extrapolated units and the total variance (Fig 15). You must evaluate the sample placement for each stratum separately because estimates are calculated independently for each stratum.

When calculating population estimates for analysis areas within a larger survey area, consider increasing sampling effort in those areas. Only unsampled units contribute to variance, so increased sampling will reduce the variance in the analysis area. If every unit in the analysis area is sampled, the variance is reduced to zero.

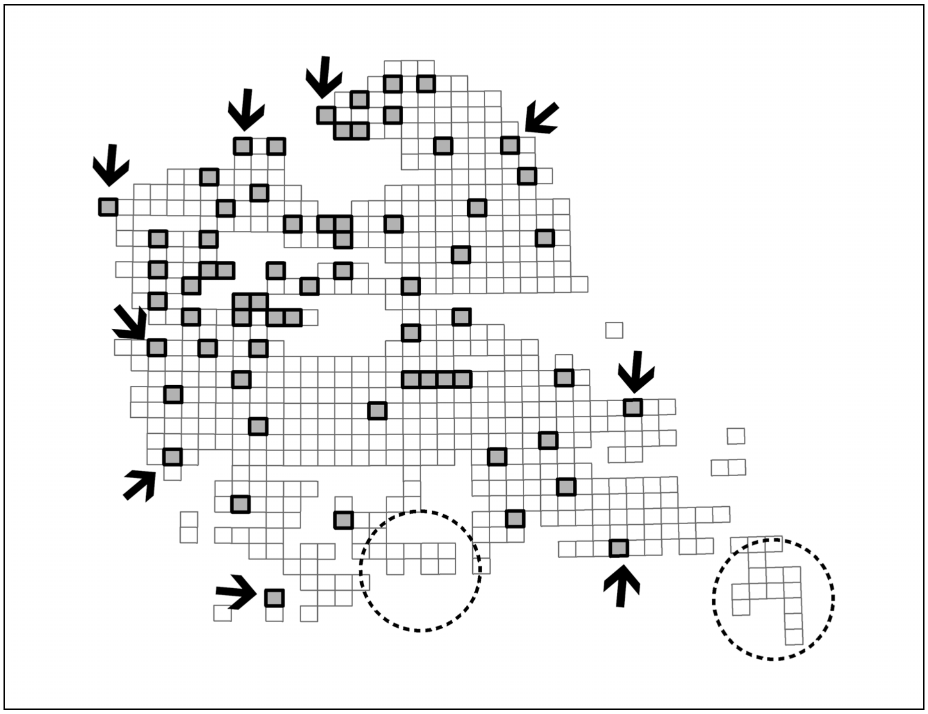

FIGURE 15 Depiction of a survey area with arrows pointing to peripheral samples. The circled areas are under sampled and estimates in those areas will be extrapolated.

A common sampling approach is to randomly select most of the sample units by stratum. The remaining sample units are selected nonrandomly to fill "holes," increase sampling in special areas, and to sample the survey area periphery. The most efficient way to determine placement of the nonrandomly selected samples is to plot the random sample on a map or grid, and visually inspect for deficiencies in the sample distribution. A typical allocation would be to select 80–90% of the sample units randomly and the remaining 10–20% nonrandomly.

Spatial sampling and ferry times can be improved if adjacent pairs of sample units are chosen across the survey area (DuBois 2004). One method to set up a paired sample is to first determine the number of sample units you wish to fly within a stratum (n_i). Divide this number by 2 to obtain the number of sample pairs for that stratum (n_{ip}). Now divide the total number of sample units within the stratum (N_i) by the number of sample pairs, n_{ip}, for that stratum. This number (N_{ig}) represents the approximate size of each group of sample units from which a sample pair will be chosen. Assign the sample units in the stratum into n_{ip} groups, each containing approximately N_{ig} sample units. You can assign sample units to these groups based on similarities in habitat or expected densities, but you should try to ensure that the sample units in each group are adjacent or close to each other.

From each of the n_{ip} groups, randomly select a single sample unit for sampling. Then randomly select an additional sample unit from the group that is adjacent to the first. These adjacent pairs of sample units will be the sample taken from that stratum (Fig 16). One reason that the second sample unit is placed adjacent to the first is that it allows better estimation of the variogram at short distances, which allows better predictions and variance estimates.

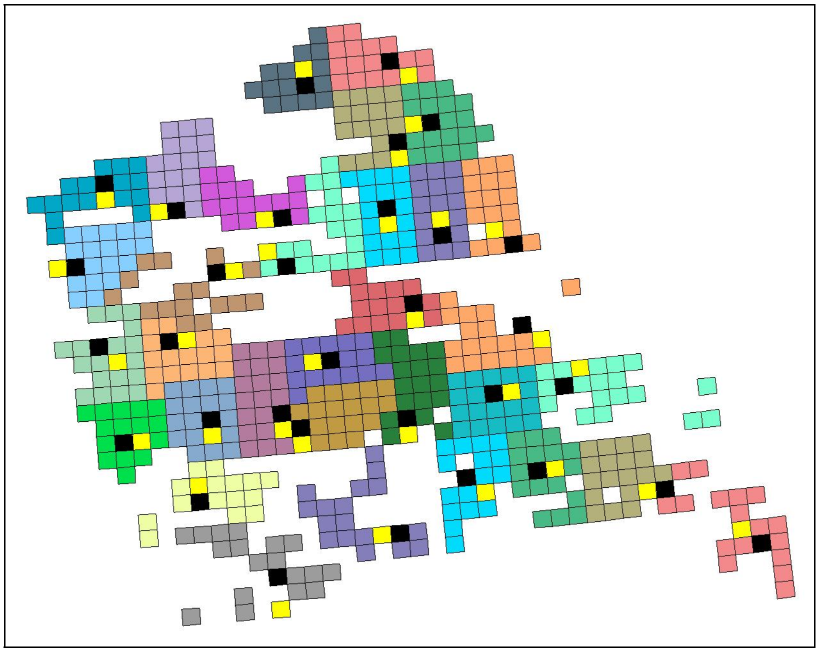

FIGURE 16 Example of a paired sampling strategy applied to a stratum. Thirty-two sample pairs were chosen from groups containing from 17 to 21 sample units. Sample unit colors represent the group assignments for sampling. Black squares represent randomly selected sample units. Yellow squares represent adjacent units also selected for sampling.

VI. CONDUCTING THE SURVEY

A D ATA COLLECTION

Data for each sample unit are recorded on individual data forms (Fig 17). Forms may be downloaded from WinfoNet as Microsoft Word® (Microsoft Corporation, Redmond, Washington, USA) documents. Those forms can be modified to accommodate unique circumstances, but all data forms should include descriptive information such as date, observer–pilot names, general location, survey name, unit name/number, aircraft type, a brief written description of the survey area, survey start, and survey stop times for the sample unit. Start–stop time information is useful in evaluating search effort to ensure enough time is spent in each unit to maintain consistent sightability.

In the example forms (Figs 17–19), checkboxes are provided so observers can evaluate 4 factors that affect survey quality: snow cover, light level, weather, and observer errors. Less than optimal conditions may ultimately affect the population estimate. For example, if the last half of the survey was conducted during high winds, that may help explain a lower-than-expected estimate.

Bull moose are commonly classified by antler size in fall surveys (Figs 17 and 18). For detailed descriptions of bull classifications, see Timmerman and Buss (1998:577). Cows are generally classified according to the number of accompanying calves. In winter and spring surveys, antler casting prevents reliable distinction between bulls and cows, and typically those surveys categorize moose into adults and calves (Fig 19). On all 3 example data forms (Figs 17–19), each group of moose is entered on one line. For example, a group of 2 cow–calf pairs and 1 lone cow would be entered as a "2" in the "Cow w/1" field and a "1" in the "Cow w/0" field. Total moose are summed by line and by column, with a grand total count in the lower right corner. When summing total moose for the unit, remember to break down groups into individual moose (i.e., 1 cow w/2 = 3 moose).

Time spent recording data during the survey detracts from time spent searching for moose. Therefore you should construct data forms to minimize the required recording time. Recording peripheral data such as latitude–longitude of groups, habitat type, or sighting of other species also detracts from search intensity. If you want to collect location data, you can use a GPS waypoint to reference that data in your notes and then retrieve the actual coordinates at the end of the survey.

Page ___ of ___ Form MC2 2/24/98

SEARCH IDENTIFICATION

Date: ________ SU #: __________
GMU: ________
Location: ____________________
Observer: ____________________
Pilot: ____________________
Aircraft Type: ________ Temp (F) __________

SEARCH TYPE
(check one or both)
☐ Standard
~ 6.5- 8 min/mi^2
☐ Intensive
~ 10- 12 min/mi^2
Strata: ________
Area (mi^2): ________

SEARCH TIME
(in minutes)
Stop@ ______________
Start@ ______________
Elapsed ______________

OVERALL SURVEY RATING: ☐ Excellent ☐ Good ☐ Fair ☐ Poor

SEARCH CONDITIONS

SNOW AGE
☐ 1. Fresh
☐ 2. < 1 week
☐ 3. >1 week

LIGHT TYPE
☐ 1. Bright
☐ 2. Flat

SNOW COVER
☐ 1. Complete
☐ 2. Some Low veg Showing
☐ 3. Bare Ground Showing

LIGHT INTENSITY
☐ 1. High
☐ 2. Medium
☐ 3. Low

% PREDOMINANT HABITAT TYPE IN SU
___ 1. Open lower elevation, predom shrub, riparian, or wetland
___ 2. Mixed Open Forest with some shrub understory
___ 3. Dense Spruce Forest
___ 4. Dense Deciduous Forest Birch, Aspen, etc. Few Shrubs
___ 5. Subalpine Shrub
___ 6. Burn
___ 7. Other (describe):

CHECK ADDITIONAL CONDITIONS THAT MAY HAVE AFFECTED THE QUALITY OF THE SEARCH

☐ Classification Errors
☐ Uncooperative Pilot
☐ Inadequate Search Effort
☐ Short on Fuel
☐ Windy/Turbulent
☐ Other (Explain):
☐ Inadequate Snow Cover
☐ Inexperienced Pilot
☐ Movement In/Out Of Intensive
☐ Movement In/Out of SU
☐ Improper Aircraft
☐ Poor Light
☐ Inexperienced Observer
☐ Too Many Moose in Intensive (>15)
☐ Observer Airsick
☐ Low Clouds or Fog
☐ Poor Visibility/Snow on Trees
☐ Problems finding SU Boundaries
☐ Observer Sleeping

		Bulls			Cows				MISC			
In SCF Plot?	Group No.	Yrlg	Med	Lrg	Cow w/0	Cow w/1	Cow w/2	Cow w/3	Lone Calf	Unk	Total Moose	Remarks/Waypoint/Lat-Lon
☐	1.	1			1	1					4	
☐	2.		1	2							3	
☐	3.											
☐	4.											
☐	5.											
☐	6.											
☐	7.											
☐	8.											
☐	9.											
☐	10.											
☐	11.											
☐	12.											
☐	13.											
☐	14.											
☐	15.											
Additional Lines on Back of Sheet if Needed												
Survey Summary (Do not add calves to cows in column totals)												
	1-15	1	1	2	1	1					7	
	16-49											
	Total	1	1	2	1	1					7	

FIGURE 17 Front side of a fall survey data form with 3 bull classifications.

MOOSE CENSUS FORM

Page ___ of ___ Form MC1 2/24/98

SEARCH IDENTIFICATION

Date: ________ SU #: ________
GMU: ________
Location: ________
Observer: ________
Pilot: ________
Aircraft Type: ________ Temp (F) ________

SEARCH TYPE
(check one or both)

☐ Standard
~ 6.5- 8 min/mi^2
☐ Intensive
~ 10- 12 min/mi^2
Strata: ________
Area (mi^2): ________

SEARCH TIME
(in minutes)

Stop@ ________
Start@ ________
Elapsed ________

OVERALL SURVEY RATING: ☐ Excellent ☐ Good ☐ Fair ☐ Poor

SEARCH CONDITIONS

SNOW AGE
☐ 1. Fresh
☐ 2. < 1 week
☐ 3. >1 week

LIGHT TYPE
☐ 1. Bright
☐ 2. Flat

SNOW COVER
☐ 1. Complete
☐ 2. Some Low veg Showing
☐ 3. Bare Ground Showing

LIGHT INTENSITY
☐ 1. High
☐ 2. Medium
☐ 3. Low

% PREDOMINANT HABITAT TYPE IN SU
___ 1. Open lower elevation, predom shrub, riparian, or wetland
___ 2. Mixed Open Forest with some shrub understory
___ 3. Dense Spruce Forest
___ 4. Dense Deciduous Forest Birch, Aspen, etc. Few Shrubs
___ 5. Subalpine Shrub
___ 6. Burn
___ 7. Other (describe):

CHECK ADDITIONAL CONDITIONS THAT MAY HAVE AFFECTED THE QUALITY OF THE SEARCH

☐ Classification Errors
☐ Uncooperative Pilot
☐ Inadequate Search Effort
☐ Short on Fuel
☐ Windy/Turbulent
☐ Other (Explain):
☐ Inadequate Snow Cover
☐ Inexperienced Pilot
☐ Movement In/Out Of Intensive
☐ Movement In/Out of SU
☐ Improper Aircraft
☐ Poor Light
☐ Inexperienced Observer
☐ Too Many Moose in Intensive (>15)
☐ Observer Airsick
☐ Low Clouds or Fog
☐ Poor Visibility/Snow on Trees
☐ Problems finding SU Boundaries
☐ Observer Sleeping

In SCF Plot?	Group No.	Bulls					Cows				MISC		Total Moose	Remarks/Waypoint/Lat-Lon
		Yearling		Medium		Lrg	Cow w/0	Cow w/1	Cow w/2	Cow w/3	Lone Calf	Unk		
		=SF	>SF	31-40	41-5(	>50								
☐	1.	1					1	1	1				7	
☐	2.		1	2	1	1							5	
☐	3.													
☐	4.													
☐	5.													
☐	6.													
☐	7.													
☐	8.													
☐	9.													
☐	10.													
☐	11.													
☐	12.													
Additional Lines on Back of Sheet if Needed														
Survey Summary (Do not add calves to cows in column totals)														
1-12		1	1	2	1	1	1	1	1				12	
13-48														
Total		1	1	2	1	1	1	1	1				12	

FIGURE 18 Front side of a fall survey data form with 5 bull classifications

Page ___ of ___ Form MC3 2/24/98

SEARCH IDENTIFICATION		SEARCH TYPE (check one or both)	SEARCH TIMES (in minutes)
Date: ______	SU #: ______	☐ Standard ~ 6.5- 8 min/mi^2	Stop@ ______
GMU: ______		☐ Intensive ~ 10- 12 min/mi^2	Start@ ______
Location: ______			
Observer: ______			
Pilot: ______		Strata: ______	
Aircraft Type: ______	Temp (F) ______	Area (mi^2): ______	Elapsed ______

OVERALL SURVEY RATING: ☐ Excellent ☐ Good ☐ Fair ☐ Poor

SEARCH CONDITIONS

SNOW AGE	SNOW COVER	% PREDOMINANT HABITAT TYPE IN SU
☐ 1. Fresh	☐ 1. Complete	___ 1. Open lower elevation, predom shrub, riparian, or wetland
☐ 2. < 1 week	☐ 2. Some Low veg Showing	___ 2. Mixed Open Forest with some shrub understory
☐ 3. >1 week	☐ 3. Bare Ground Showing	___ 3. Dense Spruce Forest
LIGHT TYPE	LIGHT INTENSITY	___ 4. Dense Deciduous Forest Birch, Aspen, etc. Few Shrubs
☐ 1. Bright	☐ 1. High	___ 5. Subalpine Shrub
☐ 2. Flat	☐ 2. Medium	___ 6. Burn
	☐ 3. Low	___ 7. Other (describe):

CHECK ADDITIONAL CONDITIONS THAT MAY HAVE AFFECTED THE QUALITY OF THE SEARCH

☐ Classification Errors	☐ Inadequate Snow Cover	☐ Poor Light	☐ Low Clouds or Fog
☐ Uncooperative Pilot	☐ Inexperienced Pilot	☐ Inexperienced Observer	☐ Poor Visibility/Snow on Trees
☐ Inadequate Search Effort	☐ Movement In/Out Of Intensive	☐ Too Many Moose in Intensive (>15)	☐ Problems finding SU Boundaries
☐ Short on Fuel	☐ Movement In/Out of SU		
☐ Windy/Turbulent	☐ Improper Aircraft	☐ Observer Airsick	☐ Observer Sleeping
☐ Other (Explain):			

In SCF Plot?	Group No.	Adults	Calves	Unk.	Total Moose	Remarks
☐	1.	3	1		4	
☐	2.	5			5	
☐	3.	1	1		2	
☐	4.	1	1		2	
☐	5.					
☐	6.					
☐	7.					
☐	8.					
☐	9.					
☐	10.					
☐	11.					
☐	12.					
☐	13.					
☐	14.					
Additional Lines on Back of Sheet if Needed						
Survey Summary						
	1-14	10	3		12	
	14-49					
	Total	10	3		12	

FIGURE 19 Front side of a spring survey data form with adult and calf classifications

It is important to review data forms shortly after each flight to ensure the data has been recorded legibly, and to identify and correct errors. If you wait until the end of the survey, the proper corrections for illegible entries will probably be forgotten. The *GSPE Software User's Guide* contains instructions on how to define data classes for the survey in WinfoNet.

B F LYING THE SAMPLE UNITS

Survey Logistics

Most GSPE surveys, regardless of survey area size, require 5–10 flying days, depending on personnel, weather, daylight, and ferry distance. The number of units/aircraft/day varies with survey conditions, latitude, and time of year. During an autumn survey in northern regions, a pilot–observer team can survey 5–6 units per day at the recommended search intensity (3.1–3.9 min/km^2, 8–10 min/mi^2). When daylight increases in the spring, the same team might survey 8 units per day.

Each aircraft carries a single pilot–observer pair. Unless the survey area is very large, we recommend using between 3 and 5 aircraft for a survey. Less than 3 aircraft increases the duration of the survey and the chance of a weather interruption. More than 5 aircraft makes it difficult to maintain aircraft separation. Aircraft should be assigned to different parts of the survey area and pilots in adjacent areas need to maintain radio contact for collision avoidance. Survey aircraft should have tandem seating, the ability for slow flight in winter conditions, long-range fuel capacity, adequate visibility for back-seat passengers (i.e., windows should extend aft of the peripheral vision of the observer), a GPS unit, and a VHF radio. Small helicopters may also be used effectively as survey platforms. GPS units in the aircraft should be set to use the North American 1927 (NAD27) datum when displaying coordinates unless you have converted survey unit grid coordinates to some other datum.

Time spent flying to units (i.e., ferry time) can be significant, and should be considered when selecting a base for survey operations. If it is necessary to base out of a remote location, adequate lodging, meals, fuel, parking, and engine preheat accommodations can present significant challenges and greatly increase survey costs. To conduct a remote survey planning should begin well in advance of the survey season.

Survey Quality

Snow cover, wind, daylight, precipitation, terrain, habitat, and observer and pilot experience affect survey quality. Maintaining a high, consistent search intensity controls and compensates for environmental conditions while careful selection and training of pilots and observers minimizes human error. Each day, biologists and pilots should determine if environmental factors will provide suitable survey quality. If surveys are conducted under poor or marginal conditions they may not produce results comparable to previous or subsequent surveys in the same area.

Gasaway et al. (1986:19) provided a rating system to judge when snow conditions were adequate for surveying (Table 1). They recommended moderate to good snow conditions before starting a survey, and suggested observers routinely evaluate and record snow conditions within sampled units.

TABLE 1 Classification of snow conditions for sightability during aerial surveys. Reprinted from Gasaway et al. (1986:Table 4).

Age of snow classification	Snow coverage	Snow ranking
Fresh	Complete	Good
	Some low vegetation showing	Moderate
	Bare ground or herbaceous vegetation showing	Poor
Moderate	Complete	Good
	Some low vegetation showing	Moderate
	Bare ground or herbaceous vegetation showing	Poor
Old	Complete	Moderate
	Some low vegetation showing	Poor
	Bare ground or herbaceous vegetation showing	Poor

Survey quality declines when surveys are flown during poor weather conditions. When winds exceed 20 knots confine surveys to flat terrain, and avoid rough terrain where turbulence reduces survey quality and safety. In high winds it is difficult to circle moose and to maintain a constant search intensity if there is a strong downwind–upwind component to transects.

When surveys are conducted in winter, daylight is limited. On clear days, surveys can begin about sunrise and continue until sunset, but overcast skies reduce available daylight. Although twilight conditions are inadequate for surveying, aircraft can ferry to and from the survey area in twilight conditions to maximize available daylight for surveys.

Survey conditions may be acceptable when a light snow is falling. However, precipitation that creates difficult or dangerous flying conditions also lowers sightability of moose. The Federal Aviation Administration's visual flight rule minimums of 3 miles visibility and 1000 ft ceiling are usually adequate minimums for survey conditions in lowland sample units. Better conditions are required in hilly or mountainous terrain. If more than 1–2" of snow have fallen in the past 5–6 hours, moose may have snow on their backs, making them less visible during surveys. Some biologists delay the survey from a few hours up to a day after a heavy snow to increase the likelihood that moose have moved from their beds and shed the snow.

Habitat type affects sightability of moose during aerial surveys (Gasaway et al. 1986; Peterson and Page 1993), so observers must be cognizant of changes in habitat type and may need to make adjustments in survey patterns to accommodate reduced sightability. When surveying over tall forest, a higher altitude and decreased distance between transects provides overlap between transects and a more vertical view between the trees, thereby increasing sightability (Gasaway et al. 1986).

Search Intensity

Variable conditions of snow, light, and wind have an increasingly strong effect on sightability of moose as search intensity declines. Recognizing that, Ver Hoef recommended a search rate of 3.1–3.9 min/km^2 (8–10 min/mi^2) for GSPE surveys. Most conscientious pilot–observer teams searched at least 2.5–2.7 min/km^2 (6.5–7 min/mi^2) during surveys conducted in Alaska in recent years. There are currently no data that measure the effects of survey conditions on sightability of moose at that intensity. If search intensity is inadequate after completing a sample unit, particularly in the low stratum, additional passes can be flown through the best habitats (e.g., along a riparian drainage). The pilot should circle every moose or group of moose so the observer can count and classify individuals. Circling often reveals additional moose that were hidden from view on the first pass (Gasaway et al. 1986). Moose directly underneath the aircraft may also be missed, so flight patterns should be arranged to give observers a look at that terrain in subsequent passes.

In flat terrain, survey aircraft can fly along east–west or north–south transects. Transects are usually flown at 70–80 mph (61–70 knots). A transect usually takes about 3 minutes to complete. Spacing east–west transects 0.15 to 0.10 minutes of latitude apart will yield a search pattern of 15 to 21 transects. Spacing east–west transects 0.35 to 0.25 minutes of longitude apart will yield a search pattern of 16 to 21 transects (Fig 20). This will result in approximately 45–65 minutes of flight time in the sample unit if 0 to 5 moose are observed and circled (Fig 21). It will take additional time per unit if more than 5 moose are observed. Survey altitude should be approximately 300–800 ft above ground level depending on vegetation type.

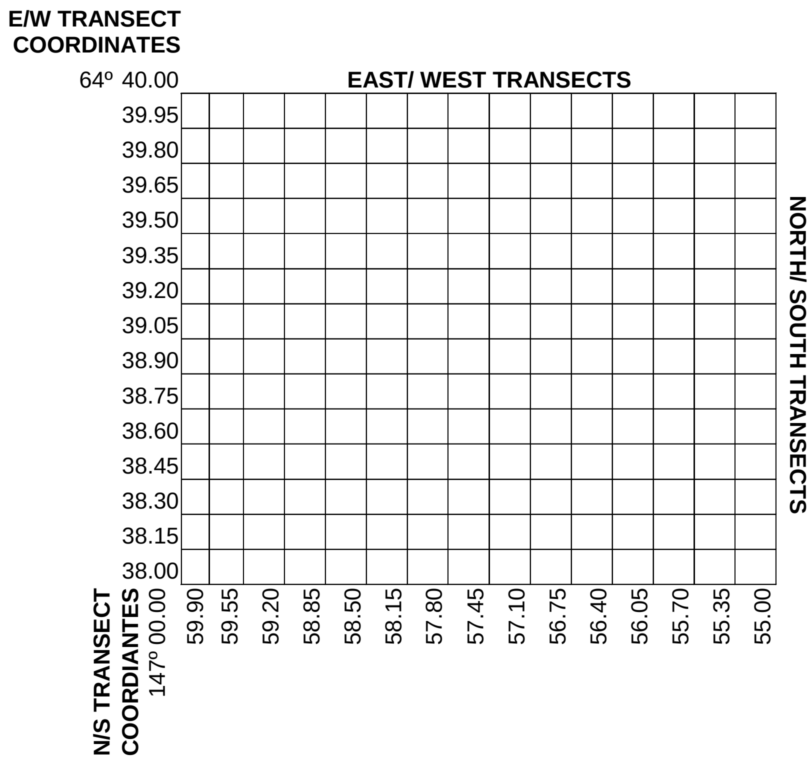

FIGURE 20 Fifteen transects flown east–west or 16 transects flown north–south across a sample unit yield a standard time of 40–55 minutes per unit and a search intensity of (2.5–2.7 min/km^2 (6.5–7 min/mi^2)

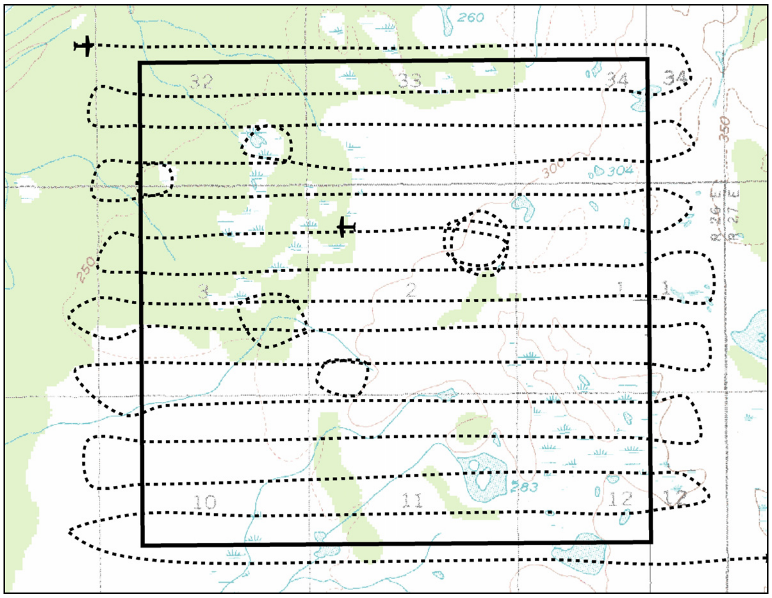

FIGURE 21 Depiction of line transects flown east–west over a survey unit in flat terrain. Note that 15 transects were made and some moose were circled.

Flying transects perpendicular to steep drainages results in rapidly changing aircraft altitudes above ground level, and lowers sightability where height above the terrain exceeds 1000 ft. Therefore, straight line transects in mountainous terrain are impractical. Instead, fly contour survey patterns parallel to the drainages to improve sightability (Gasaway et al. 1986; Fig 22). Fly the perimeter of the sample unit first to determine the extent of the unit and the optimum pattern for contour transects. A GPS unit with the track line feature can be used to ensure that contour transects completely cover the sample unit.

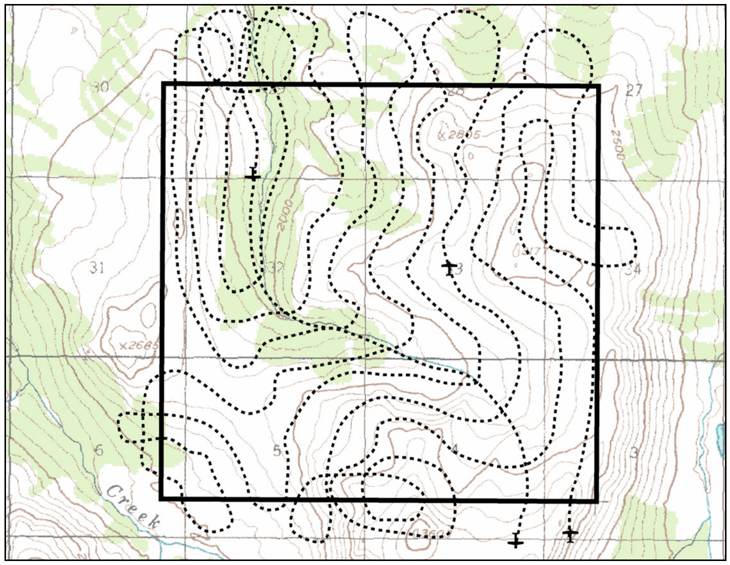

FIGURE 22 Depiction of contour transects flown in mountainous terrain. Note that no moose were circled and one additional pass was made up the bottom of the drainage.

Spiral transects (Gasaway et al. 1986) can also be used. They increase sightability of moose in forested habitats (Fig 23), but can be more dangerous at low airspeeds and are more difficult to fly correctly. They also add to pilot–observer fatigue. Spiral transects may be flown over portions of a sample unit with dense but good habitat to increase sightability in these areas while other transect types are used in portions of the sample unit where habitat is not as dense.

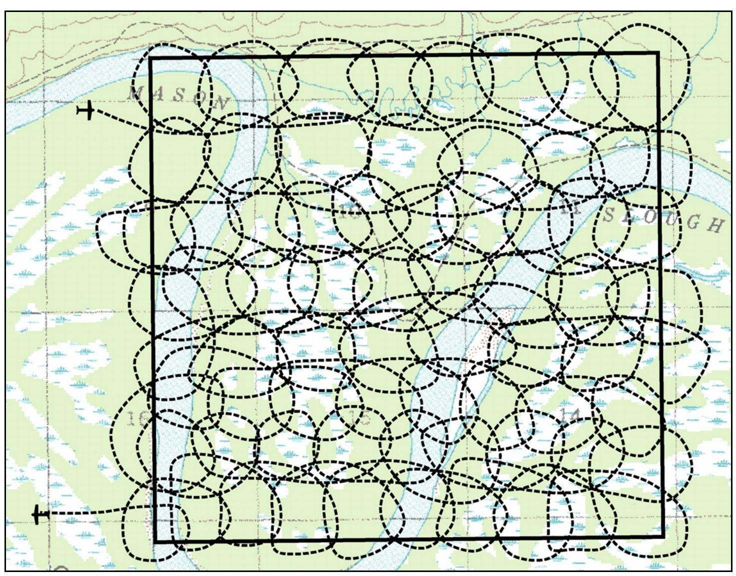

FIGURE 23 Depiction of spiral transects over flat terrain. This type of transect may be useful in areas of high moose concentration if a GPS unit is used to ensure total coverage of the unit and assign waypoints to groups of moose.

Crew Performance

Pilots and observers need to spend most of their search time looking for moose out of opposite sides of the aircraft so that the entire ground path is under constant observation. There is little time for organizational tasks once the survey flight begins. Before each flight pilots and observers should become familiar with the data forms and survey protocols (e.g., search intensity, sex and age classifications, and transect navigation). Both crew members should also know the flight sequence for their assigned sample units, the appropriate communication frequencies, and the location of nearby sample units that are to be flown by other aircraft.

Inexperienced observers fail to see up to 50% of the moose seen by experienced observers (LeResche and Rausch 1974), and inexperienced observers or pilots may have difficulty classifying moose by sex and age. To minimize the effects of inexperience, place experienced pilots with inexperienced observers and experienced observers with new pilots. Assign inexperienced crews to low-density sample units for the first few days.

The pilot is responsible for flying the unit safely and systematically. The pilot must judge whether survey conditions are safe, airspeed and altitudes are suitable for survey conditions, and determine the best direction to fly transects (east–west versus north–south versus terrain contours). In addition, the pilot should remain in radio contact with other survey pilots to monitor their position, report approaching weather, and to assist in relaying communications until all aircraft are safely on the ground.

The observer is responsible for data quality. That includes legible and thorough completion of data forms, adhering to survey protocols, recording start and stop times, and providing the pilot with coordinates as they navigate to new units. Observers are responsible for maintaining survey methodology while in the air and suggesting corrections when necessary. Both crewmembers must ensure that sample units are flown systematically within all portions of the sample unit and moose are not counted twice.

Data Entry

Survey data can be entered each night, if Internet access is available, or in one session at the end of the survey. If Internet access is not available, data may be entered into an Microsoft Excel spreadsheet and uploaded to WinfoNet at a later time. The section “Editing Observation Data” in the *GSPE Software User's Guide* contains detailed instructions on entering the survey data. After data entry is completed, or during break points in the entry, data can be downloaded from WinfoNet and archived. Data entry should be checked against original data before running any analyses.

VII. RUNNING YOUR ANALYSIS

A THE INPUT

You can calculate population and ratio estimates once survey observations are entered into WinfoNet. In the WinfoNet software, inputs are provided to specify the analysis area for the estimate. In addition, you can specify the fields used for strata, sampled units, and sample unit areas. If sample units from the standard grid were used in the survey, you can accept the default values for these inputs.

The *analysis column* is the column that contains the number of observed moose to be used in the calculations. This column can be one of the sex or age classes collected during the survey or some function of those classes. An analysis column calculator is provided to specify the sex–age class or function to be used in the analysis column. The calculator lists the survey data classes (i.e., sex and age categories) collected in your survey. The classes you specified during survey setup appear in all uppercase letters (e.g., cow with one calf = “COW_W_1”), while calculated fields derived from these classes appear in mixed-case letters (e.g., “TotalMoose”). You can specify one of the survey data classes collected in your survey, one of the precalculated fields supplied, or you can manipulate those columns with the analysis calculator to estimate particular age and sex segments of the population. For example, if we assume that the sex ratio of the calves surveyed was 50F:50M, you can obtain an estimate of the number of male calves in the population using the equation “0.5*[TotalCalves].” For ratio estimates, the calculator may be used for both the numerator and the denominator of the ratio. For example, to calculate calves per 100 cows, you specify the numerator as “[TotalCalves]” and the denominator as “[TotalCows]/100” (TABLE 2).

TABLE 2 Common biological parameters used in moose management and their associated equations in the analysis calculator of the WinfoNet software application for the GSPE. Note that some of the biological parameters assume a 50:50 ratio of females to males within calf or yearling cohorts.

Biological parameter	Analysis calculator for population estimates	
Total Bull Calves	[TotalCalves]/2	
Yearling Bulls	[YBULL_GTSF] + [YBULL_SF]	
Total Yearlings	2*([YBULL_GTSF] + [YBULL_SF])	
Biological Parameter	Analysis Calculator for Ratio Estimates	
	Numerator	Denominator
Calves:100 Cows	[TotalCalves]	[TotalCows]/100
Bulls:100 Cows	[TotalBulls]	[TotalCows]/100
Yearling Bulls:100 Cows	[YBULL_GTSF] + [YBULL_SF]	[TotalCows]/100
Calves:100 Adults	[TotalCalves]	[TotalAdults]/100

B THE OUTPUT

The request parameters section of the output summarizes data that were used to calculate the estimate (Fig 24). If a ratio estimate was calculated, both the numerator and denominator input are listed. In addition, the request parameters section provides the column used for stratification, moose count and unit area. A hyperlink is provided in this section that allows you to inspect the input file used to create the population estimate. This link points to a comma-delimited text file of the data entered into the analysis.

Request Parameters	
Numerator Column:	[TotalCalves]
Denominator Column:	[TotalCows]/100
Analysis Area:	InTotSurvey
Strata Column:	StratName
Counted Column:	Counted
Unit Area Column:	AreaMi
Right click to download data used to calculate estimate.	

FIGURE 24 Request parameters resulting from a GSPE ratio estimate calculating calves:100 cows.

The results section (Fig 25) provides GSPE estimates and associated confidence intervals. For ratio estimates, the ratio, numerator and denominator estimates are all provided along with standard errors and confidence intervals for 80%, 90%, and 95% levels of confidence. The confidence intervals are listed as both numbers of moose and as proportions of the mean.

Results

Ratio Estimate		Confidence Intervals		
		Confidence	Interval (moose)	Interval (proportion of the mean)
Ratio Estimate:	26.96011	80%	23.64632 30.27390	0.1229144
Standard Error:	2.585761	90%	22.70691 31.21331	0.1577590
		95%	21.89211 32.02811	0.1879814

Numerator Estimate		Confidence Intervals		
		Confidence	Interval (moose)	Interval (proportion of the mean)
Numerator Estimate:	2513.89	80%	2221.463 2806.317	0.1163247
Standard Error:	228.1823	90%	2138.563 2889.216	0.1493011
		95%	2066.661 2961.119	0.1779032

Denominator Estimate		Confidence Intervals		
		Confidence	Interval (moose)	Interval (proportion of the mean)
Denominator Estimate:	93.2448	80%	83.56075 102.92884	0.1038562
Standard Error:	7.556501	90%	80.81546 105.67413	0.1332979
		95%	78.43433 108.05527	0.1588343

FIGURE 25 Results from a GSPE ratio estimate calculating calves:100 cows

The sample details section summarizes sampling by total sample units, total survey area, selected sample units, surveyed area, and the total number of moose counted (Fig 26). Those summaries are given for each stratum and also totaled. You can use this section to cross-reference raw data such as the number of units that were sampled and the number of units in the survey area.

Sample Details

Total Samples

	stratum	sample.sizes
1	HIGH	599
2	LOW	388
11	TOTAL	987

Total Area

	stratum	total.area
1	HIGH	3482.610
2	LOW	2264.248
11	TOTAL	5746.858

Numerator Counted

	stratum	counted
1	HIGH	208
2	LOW	63

Sample Sizes

	stratum	sample.sizes
1	HIGH	65
2	LOW	47
11	TOTAL	112

Area Sampled

	stratum	sampled.area
1	HIGH	376.232
2	LOW	272.500
11	TOTAL	648.732

Denominator Counted

	stratum	counted
1	HIGH	7.64
2	LOW	1.75

FIGURE 26 Sample details from a GSPE ratio estimate calculating calves:100 cows

The estimate details section gives the details of the empirical and fitted semivariograms used to model spatial correlation among samples (Fig 27). Those are given separately for each stratum, and separately for numerator and denominator if a ratio estimate was calculated. The binned semivariances from the empirical semivariograms (gamma) are provided together with the parameter estimates (nugget, partial sill, and range) for the fitted semivariograms.

Estimate Details

Numerator

Stratum	Name 1 HIGH	Name 1 LOW
Empirical Semi-Variogram	distance gamma np 1 4.469132 0.1729636 30 2 10.009041 0.1900190 162 3 15.593389 0.1770950 204 4 21.896862 0.2659466 268 5 28.134587 0.2640888 340 6 34.632469 0.3282920 336 7 40.536241 0.4196883 338 8 46.758980 0.3681787 362	distance gamma np 1 4.976427 0.15094144 48 2 9.493729 0.06310339 122 3 15.004118 0.11469710 134 4 21.668711 0.08628614 144 5 28.228776 0.07939032 162 6 34.615885 0.11289564 136 7 40.336385 0.09096107 106 8 46.814212 0.11934534 94
Parameter Estimates	0.05513802 0.38177023 24.80024374	7.402181e-02 2.578617e+04 1.350415e+08

Denominator

Stratum	Name 1 HIGH	Name 1 LOW
Empirical Semi-Variogram	distance gamma np 1 4.469132 0.0001922381 30 2 10.009041 0.0002649742 162 3 15.593389 0.0002660095 204 4 21.896862 0.0003375809 268 5 28.134587 0.0002883721 340 6 34.632469 0.0004144506 336 7 40.536241 0.0006083559 338 8 46.758980 0.0005231114 362	distance gamma np 1 4.976427 3.721686e-05 48 2 9.493729 2.634745e-05 122 3 15.004118 4.338734e-05 134 4 21.668711 3.926338e-05 144 5 28.228776 3.268000e-05 162 6 34.615885 3.703781e-05 136 7 40.336385 4.342601e-05 106 8 46.814212 5.334875e-05 94
Parameter Estimates	8.401166e-05 3.391678e-04 1.686056e+01	1.472859e-05 5.650889e-05 2.628348e+01

FIGURE 27 Estimate details resulting from a GSPE ratio estimate calculating calves:100 cows. The parameter estimates for the exponential fitted semivariogram are, in order from left-to-right, the nugget, the partial sill, and the range.

You can use these values to plot the empirical and fitted semivariograms for your survey if you want to examine the spatial correlation measured in your survey data. In Figure 28 we plot the gamma values against the binned distances for our example to form the empirical semivariogram for each stratum provided in the numerator output of Figure 27. Using Equation 2 for the exponential semivariogram:

$$\hat{\gamma}(h) = \theta_{nugget} + \theta_{parsil}\left[1 - \exp\left(\frac{-\|h\|}{\theta_{range}}\right)\right] \tag{2}$$

and the parameter estimates, the fitted semivariograms for high and low strata were added to Figure 28 to compare the spatial correlation of moose density measured in each stratum. Typically, there is less spatial correlation in the low stratum.

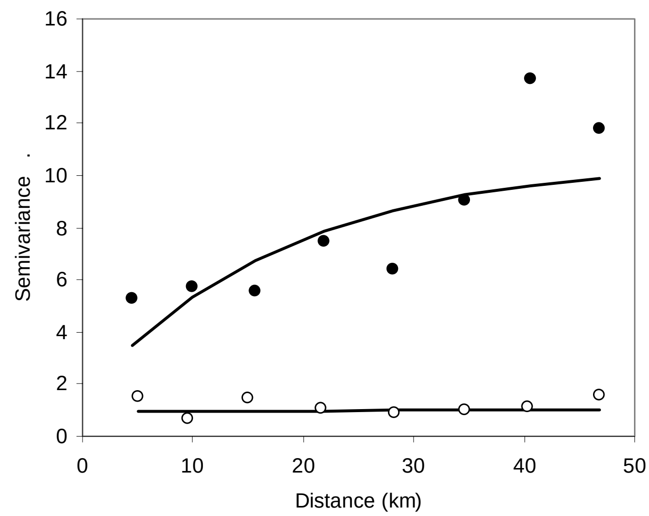

FIGURE 28 Empirical and fitted semivariograms for the high and low stratum from the estimate details in Figure 27. Black circles are the binned semivariance values for the high stratum, and white circles are the binned semivariance values for the low stratum.

Maps

A map of the survey area is provided (Fig 29) that displays the stratification and the surveyed sample units. Review the map to make sure stratification and sampling data were entered correctly. The map should be archived as a summary record of the sample design and can be copied and inserted into management and research reports.

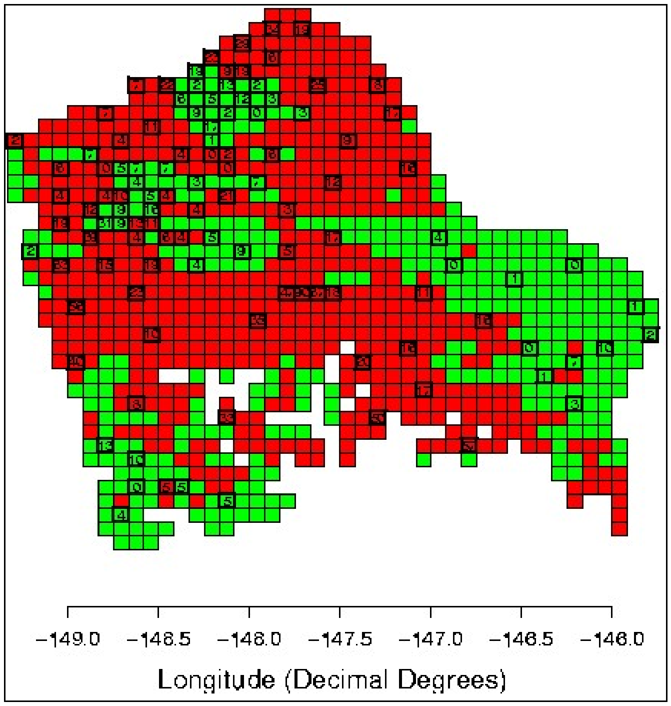

FIGURE 29 Output map. High stratum is depicted in red, low stratum is depicted in green. Surveyed sample units are outlined in bold black.

C SMOOTHING ESTIMATES

After 5 estimates have been obtained for a survey area, the estimates can be used in a random effects regression to detect population trend and “smooth” over the variation of individual estimates. The basic idea is that yearly estimates can be improved by borrowing information from other years, whereas the GSPE uses only a single year of data. This smoothing reduces the variance of individual estimates, giving them tighter confidence intervals. Consider the advantages of estimate smoothing if you are trying to decide whether to conduct intensive surveys every 3–4 years or less intensive surveys every year. The smoothing technique greatly increases the appeal of obtaining lower-sample estimates on a more regular basis because confidence intervals can later be tightened after the first 5 estimates have been calculated. That also makes trend detection easier because estimates are obtained on a regular basis. These ideas were introduced by Morris (1983) and ecological examples were given by Ver Hoef (1996). This smoothing regression is applied using a Bayesian program written for WinBUGS. The code for the smoothing technique is available upon request.

VIII. ACKNOWLEDGMENTS

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X. APPENDIX A: INTENSIVE SCF METHOD FOR GSPE ESTIMATES

This appendix describes how to apply the SCF technique used in Gasaway et al. (1986) to a GSPE survey. The SCF technique will require additional time and cost. It will also limit the sampling flexibility of the GSPE method. One of the main drawbacks to retrofitting the Gasaway SCF method to the GSPE technique is the intermixing of classical and geostatistics. The sampling flexibility provided by the assumptions of the GSPE (see Section V.B) must be forfeited to combine the estimate with the SCF because the calculations for the SCF require a random sampling design. Random sampling protocol should be followed, however, we believe it is reasonable to use the 90% random, 10% subjective rule to select sample units for a GSPE with SCF. The paired sampling method can also still be used for sampling, but only one unit from each pair can be chosen for intensive SCF.

Gasaway et al. (1986) recommends intensively sampling a portion of 50–100% of the sampled units in a survey. This typically results in ~ 15–30 *intensive samples* for a Gasaway survey. The GSPE uses smaller sample units than the Gasaway technique, and more sample units are sampled (i.e., n = 30 for a Gasaway versus n = 100 for a GSPE). A similar level of intensive sampling would result in ~ 50–100 intensive samples with the GSPE. Intensive samples should be flown in both strata.

We recommend collecting a minimum of 15 intensive samples per stratum. Beyond that minimum, you may want to include additional intensive samples to tighten variance around the SCF estimate. Intensively sampled sample units should be selected at random from the pool of sample units selected for sampling. The intensive sample should be flown immediately after completing the standard survey of the unit. Pilot–observer teams should not know if a given sample unit has been chosen for intensive sampling until after the unit is sampled at the standard rate. The observer should have a list of assigned sample units that have been chosen for intensive sampling, but should not consult that list until standard sampling is complete. That prevents the pilot from altering the standard survey to "improve" performance on the intensive sample. Observers must assign each observed moose or group of moose to a quadrant during all standard searches in all sample units. In those sample units not selected for an intensive search, those data are not used. Whether it will be needed remains unknown until after the standard search is completed. To choose a portion of a sample unit for intensive sampling, divide the sample unit into 4 quadrants (i.e., NE, SE, NW, SW). Randomly choose a quadrant for intensive sampling.

We recommend conducting the high intensity searches at 3.9–4.6 min/km^2 (10–12 min/mi^2) using spiral transects (see Section VI.B) to maximize sightability (Gasaway et al. 1986). The number of moose seen during the regular search of that quadrant and the number of moose seen during the intensive search of that quadrant should be recorded. Start and stop times for the intensive search should also be recorded to verify the search intensity used. These data can be used in the calculations provided below to compute an SCF for each stratum of your survey and combined with population estimates computed using the GSPE software to obtain a bounded population estimate corrected for sightability.

Notation here is consistent with Gasaway et al. (1986) and Becker and Reed (1990).

1) When setting up your survey, define all the sample units in each stratum as separate analysis areas.

2) Calculate the SCF estimate for each stratum (Cochran 1977; Becker and Reed 1990) as:

$$S\hat{C}F_{io} = (\sum_k u_{ik} / \sum_k v_{ik}) + [n_{io} s_{iuv}^2 / (\sum_k v_{ik})^2] - [n_{io} s_{iv}^2 \sum_k u_{ik} / (\sum_k v_{ik})^3] \qquad (1)$$

where

n_{io} =The number of plots surveyed with an intensive search in the ith stratum.

u_{ik} =The number of moose seen during the intensive search in the kth sightability plot of the ith stratum, $k=1,2,\ldots,\ n_{io}$

v_{ik} =The number of moose seen during the standard search in the kth sightability plot of the ith stratum, $k=1,2,\ldots,\ n_{io}$

$$s_{iuv}^2 = [\sum_k u_{ik} v_{ik} / (n_{io} - 1)] - \{(\sum_k u_{ik} \sum_k v_{ik}) / [n_{io}(n_{io} - 1)]\}$$

and $s_{iv}^2 = [\sum_k v_{ik}^2 / (n_{io} - 1)] - \{(\sum_k v_{ik})^2 / [n_{io}(n_{io} - 1)]\}$

3) Calculate the variance of the SCF for each stratum (Cochran 1977; Becker and Reed 1990) as:

$$V(S\hat{C}F_{io}) = (n_{io} s_{qs}^2) / [(\sum_k v_{ik})^2] \qquad (2)$$

where

$$s_{qs}^2 = (\sum_k u_{ik}^2 - 2S\hat{C}F_{io} \sum_k u_{ik} v_{ik} + S\hat{C}F_{io}^2 \sum_k v_{ik}^2) / (n_{io} - 1)$$

4) Calculate GSPE estimates separately for your high and your low stratum using the analysis areas set up in step 1) and the WinfoNet software.

5) Calculate the expanded population estimate, corrected for sightability as:

$$\hat{T}_e = \sum_i \hat{T}_i S\hat{C}F_{io} \qquad (3)$$

where

$\hat{T}_i =$ The estimate of observable moose in the i[th] stratum from the GSPE software

6) Calculate the variance for the expanded population estimate as (Goodman 1960)

$$V(\hat{T}_e) = \sum_i \{S\hat{C}F_{io}^2[V(\hat{T}_i)] + \hat{T}_i^2[V(S\hat{C}F_{io})] - [V(S\hat{C}F_{io})][V(\hat{T}_i)]\} \quad (4)$$

where

$V(\hat{T}_i) =$ The square of the standard error of the estimate of observable moose in the i[th] stratum from the GSPE software

7) Calculate the degrees of freedom of the expanded population (Satterthwaite 1946) estimate as:

$$v(\hat{T}_e) = \left(\frac{V(\hat{T}_e)^2}{\sum_i \left(\frac{V(\hat{T}_{ie})^2}{v(\hat{T}_{ie})} \right)} \right) \quad (5)$$

where

$\hat{T}_{ie} = \hat{T}_i S\hat{C}F_{io}$

$V(\hat{T}_{ie}) = S\hat{C}F_{io}^2[V(\hat{T}_i)] + \hat{T}_i^2[V(S\hat{C}F_{io})] - [V(S\hat{C}F_{io})][V(\hat{T}_i)]$

$v(\hat{T}_{ie}) = n_{io} - 1$

8) If you have determined a sightability correction factor to account for the number of moose missed in intensive searches (Gasaway et al. 1986), it can be applied to the expanded population estimate to obtain a total population estimate

$$\hat{T} = \hat{T}_e SCF_c \quad (6)$$

where

$SCF_c =$ a site specific sightability correction factor accounting for the number of moose missed in intensive searches

The variance of the total population estimate is

$$V(\hat{T}) = V(\hat{T}_e)SCF_c^2 \tag{7}$$

XI. APPENDIX B: FINITE POPULATION BLOCK KRIGING

Predicting Finite Populations from Spatially Correlated Data

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KEY WORDS spatial statistics, geostatistics, block kriging, covariance, small area estimation, stratified random sampling, variogram

Abstract

Classical sampling methods can be used to estimate the mean of a finite or infinite population. Block kriging also estimates the mean, but of an infinite population in a continuous spatial domain. In this paper, I consider a finite population version of block kriging. The data are assumed to come from a spatial stochastic process. Minimizing mean-squared-prediction errors yields best linear unbiased predictions that are a finite population version of block kriging. Block kriging of finite populations has versions comparable tosimple random sampling and stratified sampling, and includes the general linear model. This method has been tested for several years for moose surveys in Alaska, and an example is given where results are compared to stratified random sampling.

1. INTRODUCTION

Monitoring ecological populations is an important goal for both academic research and management of natural resources. Successful management of moose populations in Alaska depends on obtaining estimates of moose abundance at regular intervals throughout the state. The Alaska Department of Fish and Game developed aerial survey methods to estimate and monitor moose populations (Gasaway et al. 1986). The methods of Gasaway et al. (1986) use stratified random sampling and are based on classical sampling principles that rely on design-based inference, which are very robust. Very few assumptions are required because the distribution for inference comes from the sample design, which is known and under our control. In this paper we will be interested in estimating (predicting) the mean or total number of moose from a fixed geographic area. For design-based methods, sample plots are chosen at random, moose are counted in these plots, and inference is derived from the inclusion probability for sample units (i.e., Horwitz-Thompson estimation). For moose surveys there are a finite number of sample units and so finite population methods are used.

There are some problems with design-based methods. Because few assumptions are required, they may lack power in cases where further assumptions are justified. This appears to be especially true in the case of "small area" estimation, which refers to making an estimate on a smaller geographic area within the overall study area. There may be few or no samples within that small area, so that design-based estimation may not be possible or variances become exceedingly large. An alternative is to assume that the data were generated by a stochastic process and use model-based approaches (see, e.g., Fay and Harriot 1979, Ghosh and Meeden 1986, and Prasad and Rao 1990).

The basic problem considered in this paper is the estimation of some function of the sample units, call it $\tau(\mathbf{z})$, where $\mathbf{z}$ is a vector of the realized values of a spatial stochastic process for all the sample units of a finite population. The function $\tau(\mathbf{z})$ could be the population mean, population total, or the mean or total of a subset of sample units that have few or no observed samples. The goal is to use a predictor based on the set of observed samples $\hat{\tau}(\mathbf{z}_s)$, where $\mathbf{z}_s$ is a vector of observed values for sampled units (see e.g., Bolfarine and Zacks 1992, pg. 6). Geostatistical models and methods are used (for a review, see Cressie, 1993). Geostatistics has been developed for point samples. Because points are infinitesimally small, an infinite population is assumed. The average value over some area can be predicted using methods such as block kriging, which uses aggregation. Thus it appears that this is closely related to small area estimation, but where samples come from point locations rather than a finite set of sample units. In this paper, I consider the case where we have a finite collection of plots and we assume that the data were produced by a spatial stochastic process. It appears this has not been considered in detail. I develop a finite population version of block kriging (FPBK) which has been successfully used for estimating and monitoring moose abundance in Alaska and the Yukon.

1.1 Quick Review of Universal Block Kriging

Kriging is a spatial prediction method that is formulated by minimizing the mean-squared-prediction errors (MSPE), also known as the prediction variance. This treatment follows Cressie (1993, pg. 151). Kriging can be formulated by using variograms or covariance. Here, we show the covariance results. Suppose the data follow some linear model,

$$\mathbf{z} = \boldsymbol{\mu} + \boldsymbol{\delta}, \tag{1}$$

where $\boldsymbol{\mu} = \mathbf{X}\boldsymbol{\beta}$ and $\mathbf{X}$ has dimensions $n \times p$. Assume that the spatial random variable $Z(\mathbf{s})$ is defined at each location $\mathbf{s}$ in some region $\mathcal{D} \subset \mathcal{R}^d$. Define second-order stationarity for the random errors $\boldsymbol{\delta}$ as follows: $E[\delta(\mathbf{s})] = \mathbf{0}$ so that $E[Z(\mathbf{s})] = \mu(\mathbf{s}) = \mathbf{x}'(\mathbf{s})\boldsymbol{\beta}$ for all $\mathbf{s} \in \mathcal{D}$, and that the covariance,

$$C(\mathbf{h}) \equiv cov[\delta(\mathbf{s}), \delta(\mathbf{s}+\mathbf{h})], \tag{2}$$

exists and depends only on $\mathbf{h}$. For universal block kriging, define

$$Z(B) \equiv \int_B Z(\mathbf{s})d\mathbf{s}/|B|, \tag{3}$$

and

$$\mu(B) \equiv \int_B \mu(\mathbf{s})d\mathbf{s}/|B|,$$

for some area $B \subset \mathcal{D}$ where $|\mathbf{B}|$ is the area (volume) of B, assuming that the integrals exist for the process $\{Z(\mathbf{s})\}$ (see Cressie, 1993, pg. 106). $Z(B)$ is a random variable for the average value within the block B, and $\mu(B)$ is the expected value within the block. Data are collected at n locations, and assume the data are a realization of the random vector $\mathbf{z} \equiv [Z(\mathbf{s}_1), Z(\mathbf{s}_2), ..., Z(\mathbf{s}_n)]$. Let $\mathbf{a}'\mathbf{z}$ be a linear predictor for the random variable $Z(B)$, subject to the unbiasedness constraint $E(\mathbf{a}'\mathbf{z}) = E[Z(B)]$. Then universal block kriging uses (2) to minimize the MSPE; that is, find a $\boldsymbol{\lambda}$ such that

$$E[\mathbf{a}'\mathbf{z} - Z(B)]^2 - E[\boldsymbol{\lambda}'\mathbf{z} - Z(B)]^2 \geq 0 \tag{4}$$

for all $\mathbf{a}$ such that $\mathbf{a}'\mathbf{z}_k$ is unbiased. Minimizing $E[\boldsymbol{\lambda}'\mathbf{z} - Z(B)]^2$ in (4) in terms of covariances yields the set of equations,

$$\begin{pmatrix} \boldsymbol{\Sigma} & \mathbf{X} \\ \mathbf{X}' & \mathbf{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{\lambda} \\ \mathbf{m} \end{pmatrix} = \begin{pmatrix} \mathbf{c}_B \\ \mathbf{x}_B \end{pmatrix}, \tag{5}$$

where $\mathbf{c}_B = [c_1(B), c_2(B), ..., c_n(B)]'$ with $c_i(B) \equiv \int_B C(\mathbf{s} - \mathbf{s}_i)d\mathbf{s}/|B|$ for $i = 1, 2, ..., n$, and $\mathbf{x}_B = [x_1(B), x_2(B), ..., x_p(B)]'$ with $x_j(B) \equiv \int_B x_j(\mathbf{s})d\mathbf{s}/|B|$ for $j = 1, 2, ..., p$. The solution of (5) for $\boldsymbol{\lambda}$ and $\mathbf{m}$ yields the block BLUP $\widehat{Z}(B) = \boldsymbol{\lambda}'\mathbf{z}$, which can be written as

$$\widehat{Z}(B) = \mathbf{c}_B'\boldsymbol{\Sigma}^{-1}(\mathbf{z} - \widehat{\boldsymbol{\mu}}) + \widehat{\mu}_B, \tag{6}$$

where $\widehat{\boldsymbol{\mu}} \equiv \mathbf{X}\widehat{\boldsymbol{\beta}}_{GLS}$ and $\widehat{\mu}_B \equiv \mathbf{x}_B'\widehat{\boldsymbol{\beta}}_{GLS}$ with $\widehat{\boldsymbol{\beta}}_{GLS} = (\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{z}$. The block kriging variance is given by

$$\begin{aligned} E[\boldsymbol{\lambda}'\mathbf{z} - Z(B)]^2 &= \sigma^2_{B,B} - \mathbf{c}_B'\boldsymbol{\Sigma}^{-1}\mathbf{c}_B \\ &+ \mathbf{d}_B'(\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1}\mathbf{d}_B, \end{aligned} \tag{7}$$

where $\sigma^2_{B,B}$ is $\int_B\int_B C(\mathbf{s} - \mathbf{u})d\mathbf{s}d\mathbf{u}/|B|^2$ and $\mathbf{d}_B = (\mathbf{x}_B - \mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{c}_B)$.

2. BLOCK PREDICTION FOR FINITE POPULATIONS

One objective of finite population sampling is to estimate the average or total of the values that are actually realized, rather than the mean of some superpopulation from with the data were drawn. The equivalent objective is prediction, not estimation, for spatial processes in model-based approaches. That is, the goal is to *predict* a function of the actual values that occurred, not *estimate* unobservable parameters of a model (see Cressie, 1993, pgs. 13-16 for more details). To formulate this more clearly, suppose that $\mathbf{z}$ is a vector of random variables on a finite spatial lattice. The spatial lattice D is a set that can be indexed, each location denoted by i, $i = 1, 2, ..., N$. The random variable Z_i is located at the ith site in the lattice. Let $\tau(\mathbf{z}) = \mathbf{B}'\mathbf{z}$ be a vector of random variables to be predicted, where $\mathbf{B}$ is the $N \times k$ matrix $[\mathbf{b}_1 | \mathbf{b}_2 | \ ... \ | \mathbf{b}_k]$. For example, $\mathbf{b}_j = (1/N)(1, 1, ..., 1)'$ would be the average of the realized values of $\mathbf{z}$ in D. Notice that here $\mathbf{b}'\mathbf{z}$ acts as the finite version of $Z(B)$ in (3). Other possibilities are $\mathbf{b}_j = (1, 1, ..., 1)'$, which is the total of the realized values of $\mathbf{z}$ in D, and $\mathbf{b}_j = (0, 0, ...0, 1, 1, ..., 1, 0, ..., 0, 0)'$ which is the total of the realized values of $\mathbf{z}$ for some subregion (small area) in D. Data are collected from a subset of D, call it the $n \times 1$ vector $\mathbf{z}_s$, and let the unsampled locations be denoted by the $(N - n) \times 1$ vector $\mathbf{z}_u$, and write $\mathbf{z} = (\mathbf{z}_s', \mathbf{z}_u')$. We want some linear combination of the data, call it $\widehat{\tau}(\mathbf{z}_s) = \mathbf{A}'\mathbf{z}_s$, in order to predict $\mathbf{B}'\mathbf{z}$.

Definition 1 *Mean-Squared Prediction Error (MSPE) Matrix*

Let the MSPE matrix for any particular $\mathbf{A}$ be,

$$\mathbf{M}_A = E(\mathbf{A}'\mathbf{z}_s - \mathbf{B}'\mathbf{z})(\mathbf{A}'\mathbf{z}_s - \mathbf{B}'\mathbf{z})'. \quad (8)$$

Definition 2 *Best Linear Unbiased Predictor (BLUP)*

The matrix $\mathbf{\Lambda}$ is BLUP if,

1) $E(\mathbf{\Lambda}'\mathbf{z}_s) = E(\mathbf{B}'\mathbf{z})$, and

2) $\mathbf{M}_A - \mathbf{M}_\Lambda$ is non-negative definite for every $\mathbf{A} \neq \mathbf{\Lambda}$.

For the rest of this paper, assume that $\mathbf{z}$ follows the linear model, $\mathbf{z} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\delta}$, or

$$\begin{pmatrix} \mathbf{z}_s \\ \mathbf{z}_u \end{pmatrix} = \begin{pmatrix} \mathbf{X}_s \\ \mathbf{X}_u \end{pmatrix} \boldsymbol{\beta} + \begin{pmatrix} \boldsymbol{\delta}_s \\ \boldsymbol{\delta}_u \end{pmatrix}, \quad (9)$$

where $\mathbf{X}$ is a matrix of fixed effects, $\boldsymbol{\beta}$ is a parameter vector, $E(\boldsymbol{\delta}) = \mathbf{0}$, and

$$var(\boldsymbol{\delta}) = \begin{pmatrix} \mathbf{\Sigma}_{ss} & \mathbf{\Sigma}_{su} \\ \mathbf{\Sigma}_{us} & \mathbf{\Sigma}_{uu} \end{pmatrix}.$$

To find the BLUP, we need to establish the uniform unbiased conditions for the predictor and then find the $\mathbf{\Lambda}$ that "minimizes" the MSPE matrix.

2.1 Uniform Unbiasedness Conditions

We need to consider all $\mathbf{A}$ such that $E(\mathbf{A}'\mathbf{z}) = E(\mathbf{B}'\mathbf{z})$ for all $\boldsymbol{\beta}$ in the linear model (9). Taking expectations, we see that $\mathbf{A}'\mathbf{X}_s\boldsymbol{\beta} = \mathbf{B}'\mathbf{X}\boldsymbol{\beta}$ for every $\boldsymbol{\beta}$, so that implies $\mathbf{A}'\mathbf{X}_s = \mathbf{B}'\mathbf{X}$, or

$$\mathbf{A}'\mathbf{X}_s = \mathbf{B}_s'\mathbf{X}_s + \mathbf{B}_u'\mathbf{X}_u, \quad (10)$$

where $\mathbf{B}' = [\mathbf{B}_s' | \mathbf{B}_u']$.

2.2 Prediction for Finite Populations

Similar to equations (4), the BLUP is found by finding $\mathbf{\Lambda}$ such that

$$\begin{aligned} E(\mathbf{A}'\mathbf{z}_s - \mathbf{B}'\mathbf{z})(\mathbf{A}'\mathbf{z}_s - \mathbf{B}'\mathbf{z}) - \\ (\mathbf{\Lambda}'\mathbf{z}_s - \mathbf{B}'\mathbf{z})(\mathbf{\Lambda}'\mathbf{z}_s - \mathbf{B}'\mathbf{z}) \end{aligned} \quad (11)$$

is non-negative definite for all $\mathbf{A}$ such that $\mathbf{A}'\mathbf{z}_s$ is unbiased. By minimizing the MSPE matrix, we obtain the prediction equations,

$$\begin{pmatrix} \mathbf{\Sigma}_{ss} & \mathbf{X}_s \\ \mathbf{X}_s' & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{\Lambda} \\ \mathbf{M} \end{pmatrix} = \begin{pmatrix} \mathbf{\Sigma}_{ss} & \mathbf{\Sigma}_{su} \\ \mathbf{X}_s' & \mathbf{X}_u' \end{pmatrix} \begin{pmatrix} \mathbf{B}_s \\ \mathbf{B}_u \end{pmatrix}, \quad (12)$$

which can be compared to equations (5). When (12) are solved for $\mathbf{\Lambda}$, the FPBK predictor is,

$$\widehat{\tau}(\mathbf{B}'\mathbf{z}) = \mathbf{\Lambda}'\mathbf{z}_s = \mathbf{B}_s'\mathbf{z}_s + \mathbf{B}_u'\widehat{\mathbf{z}}_u, \quad (13)$$

where,

$$\widehat{\mathbf{z}}_u = \mathbf{\Sigma}_{us}\mathbf{\Sigma}_{ss}^{-1}(\mathbf{z}_s - \widehat{\boldsymbol{\mu}}_s) + \widehat{\boldsymbol{\mu}}_u, \quad (14)$$

$\widehat{\boldsymbol{\mu}}_u = \mathbf{X_u}\widehat{\boldsymbol{\beta}}_{GLS}$ and $\widehat{\boldsymbol{\mu}}_s = \mathbf{X_s}\widehat{\boldsymbol{\beta}}_{GLS}$ with $\widehat{\boldsymbol{\beta}}_{GLS} = (\mathbf{X}_s'\mathbf{\Sigma}_{ss}^{-1}\mathbf{X_s})^{-1}\mathbf{X_s}'\mathbf{\Sigma}_{ss}^{-1}\mathbf{z}_s$. The predictor (14) can be compared to (6). The FPBK predictor (13) is now seen as multiplying the observed sample values times their corresponding coefficients from $\mathbf{B}_s$, and then using universal block kriging to predict all other unsampled units, and these predictions are multiplied by their corresponding coefficients in $\mathbf{B}_u$.

2.3 Prediction Variance (MSPE)

Substituting the solution for $\mathbf{\Lambda}$ for $\mathbf{A}$ in (8), we obtain the MSPE (also called prediction variance) of FPBK,

$$\mathbf{M}_{\mathbf{\Lambda}} = \mathbf{B}'\mathbf{\Sigma}\mathbf{B} - \mathbf{C}'\mathbf{\Sigma}_{ss}^{-1}\mathbf{C} + \mathbf{D}'\mathbf{V}\mathbf{D}, \quad (15)$$

where

$\mathbf{C} = \mathbf{\Sigma}_{ss}\mathbf{B}_s + \mathbf{\Sigma}_{su}\mathbf{B}_u$,
$\mathbf{D} = \mathbf{X}'\mathbf{B} - \mathbf{X_s}'\mathbf{\Sigma}_{ss}^{-1}\mathbf{C}$, and
$\mathbf{V} = var(\widehat{\boldsymbol{\beta}}_{GLS}) = (\mathbf{X}_s'\mathbf{\Sigma}_{ss}^{-1}\mathbf{X}_s)^{-1}$.

Equation (15) can be compared to (7). In (15), the quantity $\mathbf{B}'\mathbf{\Sigma}\mathbf{B}$ is the variance of $\mathbf{B}'\mathbf{z}$, and assuming $\boldsymbol{\beta}$ is known, the prediction variance of $\mathbf{B}'\mathbf{z}$ is $\mathbf{B}'\mathbf{\Sigma}\mathbf{B} - \mathbf{C}'\mathbf{\Sigma}_{ss}^{-1}\mathbf{C}$. The additional term $\mathbf{D}'\mathbf{V}\mathbf{D}$ arises because we are estimating $\boldsymbol{\beta}$, where $\mathbf{D}$ is, in some sense, the distance between predicted points in the design matrix $\mathbf{B}'\mathbf{X}$ and that of the observed design matrix $\mathbf{C}'\mathbf{\Sigma}_{ss}^{-1}\mathbf{X}_s$. Equation (15) can be simplified for computing purposes,

$$\mathbf{M}_{\mathbf{\Lambda}} = \mathbf{B}_u'(\mathbf{\Sigma}_{uu} - \mathbf{\Sigma}_{us}\mathbf{\Sigma}_{ss}^{-1}\mathbf{\Sigma}_{su} + \mathbf{W}'\mathbf{V}\mathbf{W})\mathbf{B_u},$$

where $\mathbf{W} = \mathbf{X}_u' - \mathbf{X_s}'\mathbf{\Sigma}_{ss}^{-1}\mathbf{\Sigma}_{su}$. If $\mathbf{B}$ has more than one column, the prediction variances of each $\mathbf{b}_j$ are contained as diagonal elements of $\mathbf{M}_{\mathbf{\Lambda}}$ and prediction covariances between $\mathbf{b}_j$ and $\mathbf{b}_{j'}$ are contained as the off-diagonal elements of $\mathbf{M}_{\mathbf{\Lambda}}$.

2.4 Connections to Sampling Theory

Suppose we are interested in predicting the mean over a lattice of N sites. Then $\mathbf{B} = \mathbf{b} = (1/N)(1, 1, ..., 1)'$. Let $\mathbf{\Sigma}_{ss} = \sigma^2\mathbf{I}_n$ where $\mathbf{I}_n$ is the $n \times n$ identity matrix, $\mathbf{\Sigma}_{uu} = \sigma^2\mathbf{I}_{N-n}$ where

$\mathbf{I}_{N-n}$ is the $(N-n)\times(N-n)$ identity matrix, $\boldsymbol{\Sigma}_{su}=\boldsymbol{\Sigma}'_{us}=\mathbf{0}$, and $\mathbf{X}=\mathbf{1}_N$, where $\mathbf{1}_N$ is a vector of N ones. Then from (13) $\boldsymbol{\Lambda}=\boldsymbol{\lambda}=(1/n)\mathbf{1}_n$ and the predictor is the sample mean

$$\boldsymbol{\lambda}'\mathbf{z}_s=\bar{z}. \tag{16}$$

Likewise, from (15) the

$$\text{MSPE}=(\sigma^2/n)(1-f), \tag{17}$$

where $f=(n/N)$ is the sampling fraction and $1-f$ is the finite population correction factor. Of course, equation (16) is the same estimator of the mean that is used in simple random sampling (e.g., Thompson, 1992, pg. 13) and equation (17) is the variance of the mean estimator used in simple random sampling (e.g., Thompson, pg. 15).

Next, consider stratified sampling. Allow each stratum to be a separate random process, independent from each other, each with its own mean and variance. These are model-based assumptions that are equivalent to stratified random sampling (SRS),

$$\mathbf{X}=\begin{pmatrix}\mathbf{1}_{n_1} & \mathbf{0}\\ \mathbf{0} & \mathbf{1}_{n_2}\\ \mathbf{1}_{N_1-n_1} & \mathbf{0}\\ \mathbf{0} & \mathbf{1}_{N_2-n_2}\end{pmatrix}, \tag{18}$$

and

$$\begin{aligned}\boldsymbol{\Sigma}_{ss} &= \begin{pmatrix}\sigma_1^2\mathbf{I}_{n_1} & \mathbf{0}\\ \mathbf{0} & \sigma_2^2\mathbf{I}_{n2}\end{pmatrix},\\ \boldsymbol{\Sigma}_{uu} &= \begin{pmatrix}\sigma_1^2\mathbf{I}_{N_1-n_1} & \mathbf{0}\\ \mathbf{0} & \sigma_2^2\mathbf{I}_{N_2-n2}\end{pmatrix},\end{aligned}$$

where $\mathbf{z}=(\mathbf{z}_{s,1},\mathbf{z}_{s,2},\mathbf{z}_{u,1},\mathbf{z}_{u,2})'$. Suppose that now we want to predict the total, $\mathbf{B}=\mathbf{b}=\mathbf{1}_n$. Then, from (13) we obtain the predictor,

$$\boldsymbol{\lambda}'\mathbf{z}_s=N_1\bar{z}_{s,1}+N_2\bar{z}_{s,2}. \tag{19}$$

From (15),

$$\begin{aligned}\text{MSPE}=&(N_1^2\sigma_1^2/n_1)(1-f_1)\\ &+(N_2^2\sigma_2^2/n_2)(1-f_2),\end{aligned} \tag{20}$$

where $f_1=(n_1/N_1)$ and $f_2=(n_2/N_2)$. Of course, equation (19) is the same estimator of the mean that is used in SRS (e.g., Thompson, 1992, pg. 103) and equation (20) is the variance of the mean estimator used in SRS (e.g., Thompson, pg. 103).

Equations (17) and (20) demonstrate that equation (15) is a version of block kriging that provides a reduction in variance when sampling finite populations.

2.5 Modeling Autocorrelation

To make full use of model-based assumptions, we will need to estimate $\boldsymbol{\Sigma}$ by modeling the spatial autocorrelation in the data. We need to estimate each of the (i,j) entries in $\boldsymbol{\Sigma}$. One such model for spatial covariance (2) is the exponential model,

$$C(\mathbf{h}|\boldsymbol{\theta})=\begin{cases}\theta_1+\theta_2 & \mathbf{h}=0,\\ \theta_2\exp(-||\mathbf{h}||/\theta_3) & \mathbf{h}\neq 0,\end{cases} \tag{21}$$

where $\mathbf{h}=\mathbf{s}_j-\mathbf{s}_i$. There are many others (see Cressie, 1993, pg. 61). It is possible to estimate the parameters of $C(\mathbf{h}|\boldsymbol{\theta})$ using method moments for variograms or covariances (see Cressie, 1993, pg. 69) and then weighted least squares (see Cressie, 1993, pg. 99), or by using restricted maximum likelihood (REML, Patterson and Thompson, 1971, 1974); see Cressie (1993, pg. 92) for spatial REML. In the example below, I will use REML. As a visual diagnostic, I compute the empirical semivariogram,

$$\hat{\gamma}(\mathbf{h})=\frac{1}{2|N(\mathbf{h})|}\sum_{N(\mathbf{h})}[z(\mathbf{s}_i)-z(\mathbf{s}_j)]^2, \tag{22}$$

where $\mathbf{h}=\mathbf{s}_j-\mathbf{s}_i$, $N(\mathbf{h})=\{(\mathbf{s}_i,\mathbf{s}_j):\mathbf{s}_j-\mathbf{s}_i=\mathbf{h}\}$ and $|N(\mathbf{h})|$ is the number of distinct elements in $N(\mathbf{h})$. The fitted model covariance (21) is readily converted to a semivariogram using the relationship, $\gamma(\mathbf{h}|\boldsymbol{\theta})=C(\mathbf{0}|\boldsymbol{\theta})-C(\mathbf{h}|\boldsymbol{\theta})$.

3. EXAMPLES USING MOOSE SURVEY DATA

I give an example from a moose survey conducted in Alaska in the fall of 1999. The survey area was game management unit (GMU) 20A, shown as the darkened area within the state of Alaska in Figure 1.

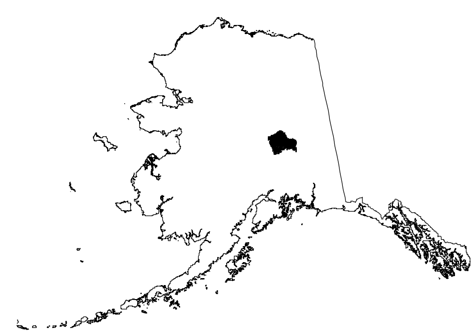

Fig. 1. Map of Alaska, GMU 20A

The survey was flown in November after there was sufficient snow cover to allow moose to be readily observed. Moose surveys involve five basic elements that include, 1) defining the survey area, 2) stratifying the area, 3) selecting a sample, 4) surveying the sample of units within the area, and 5) analyzing the data. Within a survey area, sample units are laid out in a grid. The north-south boundaries are based on even increments of latitude (2 minutes, starting at 0) and the east-west boundaries are based on increments of longitude (5 minutes, starting at 0). At around 64 degrees latitude, sample unit size is approximately 15 square kilometers. The total area of the survey was 14878 square kilometers. Figure 2 shows an enlarged view of the 20A survey area.

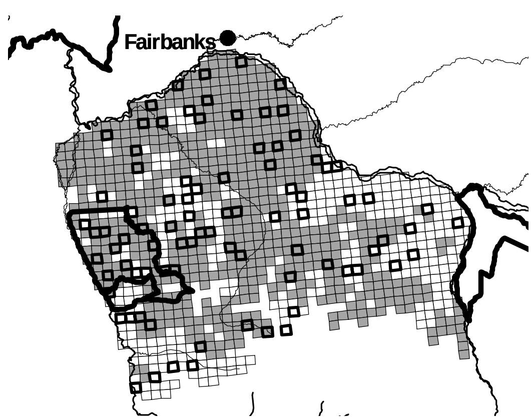

Fig. 2. GMU 20A stratification and samples

The area was stratified into two strata: relatively low moose density (shown as white in Fig. 2) and relatively high moose density (shown by grey in Fig 2), based on the biologist's knowledge of habitats, moose, and their distribution in previous years. The low stratum consisted of 338 sample units and the high stratum consisted of 649 sample units. After the area was stratified, a random sample of 86 samples was drawn with 52 from the high stratum and 34 from the low stratum. The sample units were flown and all moose were counted from the air within each sample. The sampled units are shown with a heavy border in Figure 2. All counts were first changed to density by dividing the counts by the area of each sample, which varied slightly due to the narrowing of longitude as one moves north. An average of 0.973 moose per square kilometer was counted in the high stratum, and an average of 0.398 moose per square kilometer was counted in the low stratum. The covariance between sample units was estimated using an exponential model (21) and REML (see Cressie, pg. 92). The distance between sample units was computed in kilometers from the center of one sample unit to the center of another. For the high stratum, the estimated parameters in (21) were $\theta_1 = 2.614$, $\theta_2 = 0.670$, and $\theta_3 = 23.26$. The empirical semivariogram (22) and the fitted model (21) for the high stratum are given in Fig. 3.

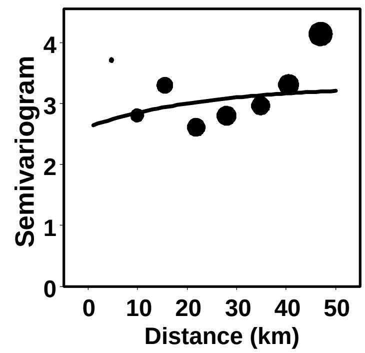

Fig. 3. Semivariograms for high stratum.

In Fig. 3, the size of the circle indicates the number of pairs of locations used for each distance class in the empirical semivariogram, and the line is the fitted model. For the low stratum, the estimated parameters in (21) were $\theta_1 = 0.000$, $\theta_2 = 2.102$, and $\theta_3 = 15.99$. The empirical semivariogram (22) and the fitted model (21) for the low stratum are given in Fig. 4.

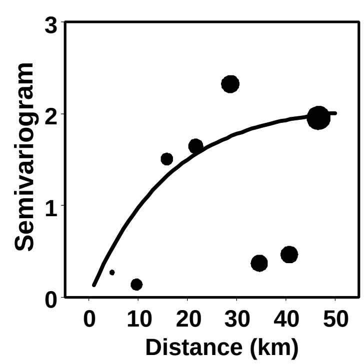

Fig. 4. Semivariograms for low stratum.

All covariances between the two strata are assumed to be 0. The fitted models, given above, are used to fill in the (i, j) entries in $\mathbf{\Sigma}$. Using the estimated $\mathbf{\Sigma}$ and $\mathbf{B} = \mathbf{b} = (1/N)(1, 1, ..., 1)'$ and $\mathbf{X}$ as in (18), the predictor FPBK (13) of the average moose density per sample was estimated to be 0.7613 moose per square kilometer, or a total of 11327 moose in the whole study area. The estimated standard error of the average moose denisty using (15) was 0.0043, yielding an estimated standard error of 978 for the total number of moose. For comparision, using SRS (e.g., Thompson, 1992, pg. 103), the estimate of total moose abundance was 11535 with an estimated standard error of 985. It is generally true that if there is autocorrelation in the data, prediction will be more precise when it uses information about the autocorrelation; thus FPBK has slightly smaller variance than SRS. Using the same fitted variogram model, it is possible to make a prediction for any subset of samples; i.e., small area estimation. Fig. 2 also shows the Ferry Trail Managment Area (FTMA) outlined in bold on the left. FPBK yielded an estimate of 1437 moose in the FTMA with a standard error of 153. The SRS estimate using only the samples within the FTMA subset (13 highs and 4 lows) yielded an estimated 1535 moose with an estimated standard error of 227. For small area estimation, the estimated standard error of FPBK was significantly smaller than that of SRS.

4. DISCUSSION AND CONCLUSIONS

Based on twenty different moose surveys over 3 years, the application of geostatistical ideas to finite population sampling gives three main advantages over classical sampling: 1) FPBK is usually more precise than SRS, 2) FPBK allows small area estimation, and 3) FPBK allows nonrandom sampling designs, giving biologists greater flexibility. FPBK also has an advantage over block kriging because FPBK incorporates a finite population correction factor that reduces the prediction variance. In the example above, approximately 9% of the population was sampled, and it often gets as high as 30% for moose surveys in Alaska.

SRS allows a separate variance for each stratum. The analogy for a model-based approach is to have a separate spatial process for each stratum. Geostatistical methods assume a constant variance for a spatial process, and stratification helps meet that assumption. When considering multiple spatial processes induced by stratification, it is possible (even desirable) to model cross-correlation between strata processes. I have investigated this for moose surveys in Alaska and found little or no cross-correlation so that it did not affect the predictions or standard errors. An alternative to stratification is transforming the data to stabilize variance. This is useful when continuous covariates (e.g., elevation) are used in the design matrix of the linear model. These methods require an unbiased backtransformation (similar to transgaussian kriging, Cressie, 1993, pg. 137), and results will be presented later.

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