DEPARTMENT OF NATURAL RESOURCES

2022 Aerial Moose Survey

Glenn D. DelGiudice, Forest Wildlife Populations and Research Group
John H. Giudice, Biometrics Unit

Introduction

Each year we conduct an aerial survey in northeastern Minnesota to estimate the moose (*Alces alces*) population and to monitor and assess changes in the overall status of the state's largest deer species. Specifically, the primary objectives of this annual survey are to estimate moose abundance, percent calves, and calf:cow and bull:cow ratios. These demographic data help us to 1) best determine and understand the population's long-term trend (decreasing, stable, or increasing), composition, and spatial distribution; 2) set the harvest quota for the subsequent State hunting season (when applicable); 3) with research findings, improve our understanding of moose ecology; and 4) otherwise contribute to sound future management strategies. This annual survey was not flown in 2021 due to safety considerations associated with the Covid-19 pandemic.

Methods

The survey area is approximately 5,985 mi^2 (almost 4 million acres, Lenarz 1998, Giudice et al. 2012). We estimate moose numbers and age and sex ratios by flying transects within a stratified random sample of 436 total survey plots that cover the full extent of moose range in northeastern Minnesota (Figure 1). To keep the stratification current, all survey plots are reviewed and re-stratified as low, medium, or high moose density about every 5 years, based on past survey observations of moose, locations of recently harvested moose, and extensive field experience of moose managers and researchers. Low, medium, and high density classes are based on whether up to 2, 3–7, or 8 or more moose, respectively, would be expected to be observed in a specific plot. The most recent complete re-stratification review was conducted in October 2018. Additionally, individual plots may be re-stratified after each annual survey as warranted by aerial observations. Stratification is most important to optimizing precision of our survey estimates. In 2012, we added a 4th stratum to the survey approach, represented by a series of 9 plots (referred to as "habitat plots"), which have already undergone, or will undergo significant disturbance by wildfire, prescribed burning, or timber harvest. These same 9 plots are surveyed each year in an effort to better understand moose use of disturbed areas and evaluate the effect of forest disturbance on moose density over time. In total, this year we surveyed 53 (43 randomly sampled and 10 habitat plots) of the 436 plots; we included a 10th habitat plot (number 208) to facilitate monitoring moose response to the 2021 Greenwood Lake Fire.

All 436 survey plots in the grid (designed in 2005) are 13.9-mi^2 rectangles (5 x 2.77 mi), oriented east to west, with 8 flight-transects similarly oriented and evenly spaced 0.3 mi apart. A Minnesota Department of Natural Resources (MNDNR) Enforcement pilot and a Forestry pilot flew the 2 helicopters used to conduct the survey—1 Bell Jet Ranger (OH-58) and 1 MD500E. We determined the sex of moose using the presence of antlers or the presence of a vulva patch (Mitchell 1970), nose coloration, and bell size and shape. We identified calves by size and behavior. We used the program DNRSurvey on tablet-style computers (Toughbook®) to record survey data (Wright et al. 2015). DNRSurvey allowed us to display transect lines superimposed on aerial photography, topographical maps, or other optional backgrounds to observe each aircraft's flight path over the selected background in *real time*, and to efficiently record data using a tablet pen with a menu-driven data-entry form. Two primary strengths of this aerial moose survey are the consistency and standardization of the methods since 2005 and the long-term consistency of the survey team's personnel, survey biometrician, and geographic information system (GIS) specialists.

We accounted for visibility bias using a sightability model (Giudice et al. 2012). This model was developed between 2004 and 2007 using adult moose that were radiocollared as part of a study of survival and its impact on dynamics of the population (Lenarz et al. 2009, 2010). Logistic regression indicated that "visual obstruction" (VO) was the most important covariate in determining whether radiocollared moose were observed. We estimated VO within a 30-ft radius (roughly 4 moose lengths) of the observed moose. Estimated VO was the proportion of a circle where vegetation would prevent you from seeing a moose from an oblique angle when circling that spot in a helicopter. If we observed more than 1 moose (a group) at a location, VO was based on the first moose sighted. We used uncorrected estimates (no sightability correction) of bulls, cows, and calves, adjusted for sampling, to calculate the bull:cow and calf:cow ratios at the population level (i.e., using the combined ratio estimator; Cochran 1977:165).

Recently, Fieberg et al. (2013) and ArchMiller et al. (2018) developed alternative model-based abundance estimators that allow for time-series modeling (TSM) of multiyear survey counts and, potentially, modeling of animal populations over space and time. An important advantage of model-based estimators is that information can be shared across time or space to help increase the precision of annual population estimates and smooth estimated trends over time. This year, solely for the purpose of exploring a potentially improved method of estimating moose abundance, we applied the Bayesian TSM methods of ArchMiller et al. (2018) to our 2005-2022 moose-survey data (see Addendum A) and qualitatively compared the derived estimates to our conventional abundance and trend estimates. Similar applications and comparisons of estimating bull:cow and calf:cow ratios may be explored in the future.

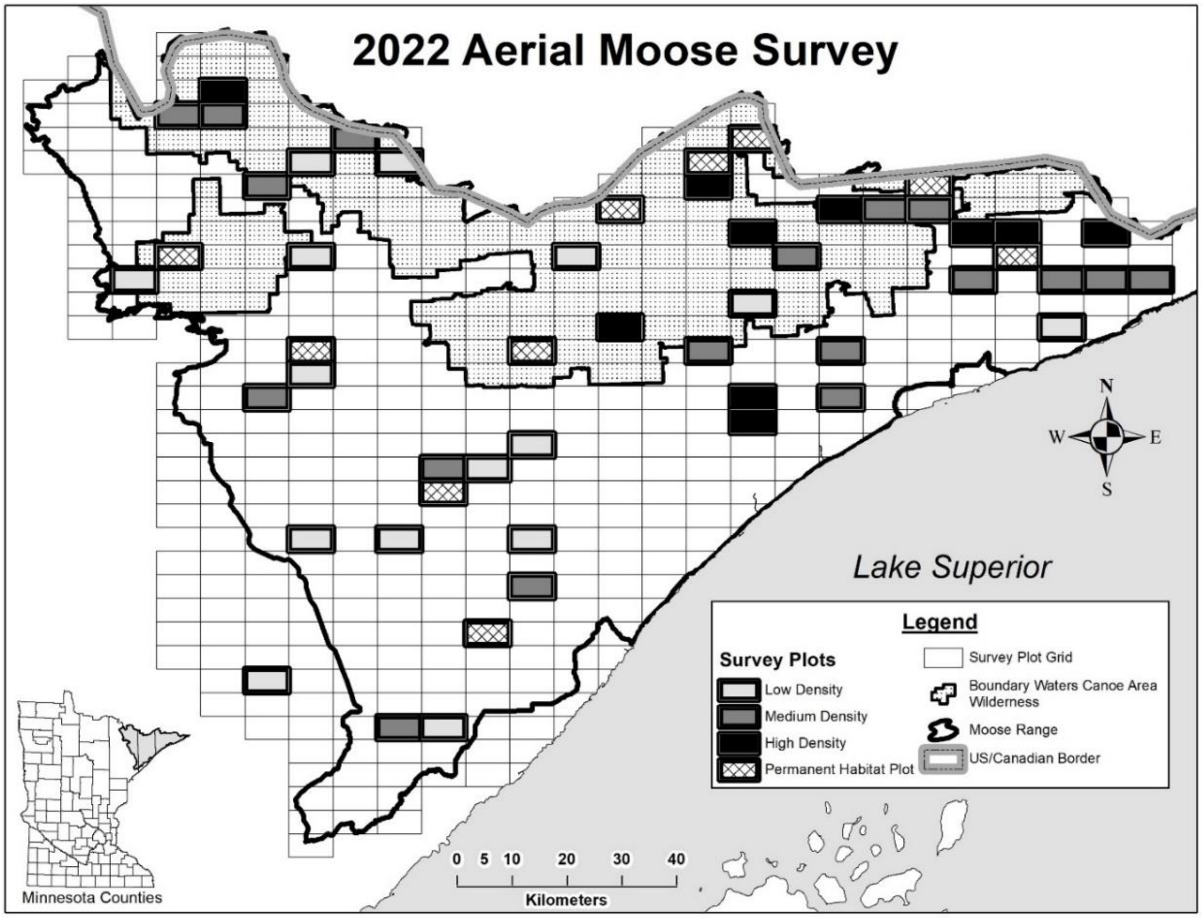
Results and Discussion

The survey was conducted from 6 to 14 January 2022. It consisted of 8 actual survey days to fly the 53 plots. This year, based on optimal allocation analyses, we surveyed 15 low-, 18 medium-, and 10 high-density plots, and the 10 habitat plots (Giudice 2022). Generally, 8" of snow cover is our minimum threshold depth for conducting the survey. Snow depths were 8"−16" and greater than 16" on 38% and 62% of the sample plots, respectively. Overall, survey conditions were rated as good for 94%, fair for 6%, and poor for 0% of the plots when surveyed. Average survey intensity was 45 minutes/plot (13.9 mi^2) and ranged from 35 to 55 minutes/plot (Giudice 2022).

This year 373 moose were observed on 40 (75%) of the 53 plots surveyed (a total 737 mi^2), which is more than the 308 moose observed on 39 of 52 plots during the 2020 survey. An average of 9.3 moose (range = 1–33) were observed per "occupied" plot. Plot occupancy during the past 16 years when the survey was flown averaged 81% (range = 65–95%) with a mean 11.4 moose observed per occupied plot. This year the average group size was 1.8 moose, similar to the previous 16 years (2 moose), and ranged from 1 to 6 moose per group. This year's 373 observed moose included 151 bulls, 154 cows, 62 calves, and 6 unclassified adults. Overall, estimated VO averaged 44% (range = 5−85%) and average estimated detection probability was 0.55 (range = 0.23−0.83). Both VO and detection probability have remained relatively constant since 2005.

After adjusting for sampling and sightability, we estimated the population in northeastern Minnesota at 4,700 (3,440–6,780, 90% confidence interval [CI]) moose (Table 1, Figure 2). As can be noted from the 90% confidence intervals associated with the population point estimates, statistical uncertainty inherent in aerial wildlife surveys can be quite large, even when surveying large, dark, relatively conspicuous animals such as moose, against a white background during winter. This is attributable to the varied (1) occurrence of dense vegetation, (2) habitat use by moose, (3) behavioral responses to aircraft, (4) effects of annual environmental conditions (e.g.,

Figure 1. Moose survey area and 53 sample plots flown in the 2022 aerial moose survey.



snow depth, ambient temperature) on their movements, and (5) interaction of these and other factors. Consequently, year-to-year statistical comparisons of population estimates are *not* supported by these surveys. These data are best suited to establishing long-term trends; even short-term trends must be viewed cautiously.

Past aerial survey and research results have indicated that the long-term trend of the population in northeastern Minnesota has been declining since 2006 (Lenarz et al. 2010, DelGiudice 2020). However, recent data suggest the population has at least stabilized and may even be increasing slightly, corroborated by a piecewise polynomial curve (Figure 3). This year's population estimate is only 47% less than the peak estimate in 2006 (early in the trend), compared to being 64% less in 2020, when the survey was last conducted. Although the long-term declining linear trend (2005−2022) remains statistically significant (r^2 = 0.593, P< 0.001, Figure 2), the overall strength of the decline has been weakened by recent population estimates. These conclusions are further supported by our Bayesian time-series model (Addendum A). As predicted, the TSM approach reduced uncertainty associated with annual population estimates and smoothed the changes between consecutive years and over the long-term (2005−2022) (Addendum A). But regardless of the method, we caution that current population trends do not necessarily predict future population trends, because underlying demographic factors affecting population abundance can change over time.

Table 1. Estimated moose abundance, 90% confidence intervals, calf:cow ratios, percent calves in the population, percent cows with twins, and bull:cow ratios from aerial surveys in northeastern Minnesota, 2005–2022. *The survey was not conducted in 2021 due to the Covid-19 pandemic.

Survey	Estimate	90% Confidence Interval	Calf: Cow	% Calves	% Cows w/ twins	Bull: Cow
2005	8,160	6,090 – 11,410	0.52	19	9	1.04
2006	8,840	6,790 – 11,910	0.34	13	5	1.09
2007	6,860	5,320 – 9,150	0.29	13	3	0.89
2008	7,890	6,080 – 10,600	0.36	16	2	0.77
2009	7,840	6,270 – 10,040	0.32	14	2	0.94
2010	5,700	4,540 – 7,350	0.28	13	3	0.83
2011	4,900	3,870 – 6,380	0.24	13	1	0.64
2012	4,230	3,250 – 5,710	0.36	15	6	1.08
2013	2,760	2,160 – 3,650	0.33	12	3	1.23
2014	4,350	3,220 – 6,210	0.44	17	3	1.24
2015	3,450	2,610 – 4,770	0.29	13	3	0.99
2016	4,020	3,230 – 5,180	0.42	17	5	1.03
2017	3,710	3,010 − 4,710	0.36	15	4	0.91
2018	3,030	2,320 – 4,140	0.37	15	4	1.25
2019	4,180	3,250 – 5,580	0.32	13	3	1.24
2020	3,150	2,400 – 4,320	0.36	18	2	0.90
2022	4,700	3,440 – 6,780	0.45	19	3	0.94

Figure 2. Point estimates, 90% confidence intervals, and a linear trend line of moose abundance in northeastern Minnesota, 2005–2022 ($y = -301x + 610455$, $r^2 = 0.593$, $P < 0.001$). Note: The 2005 survey was the first to be flown with helicopters, and to include a sightability model and a uniform grid of east-west oriented, rectangular 13.9-mi^2 plots. *The survey was not conducted in 2021 due to the Covid-19 pandemic.

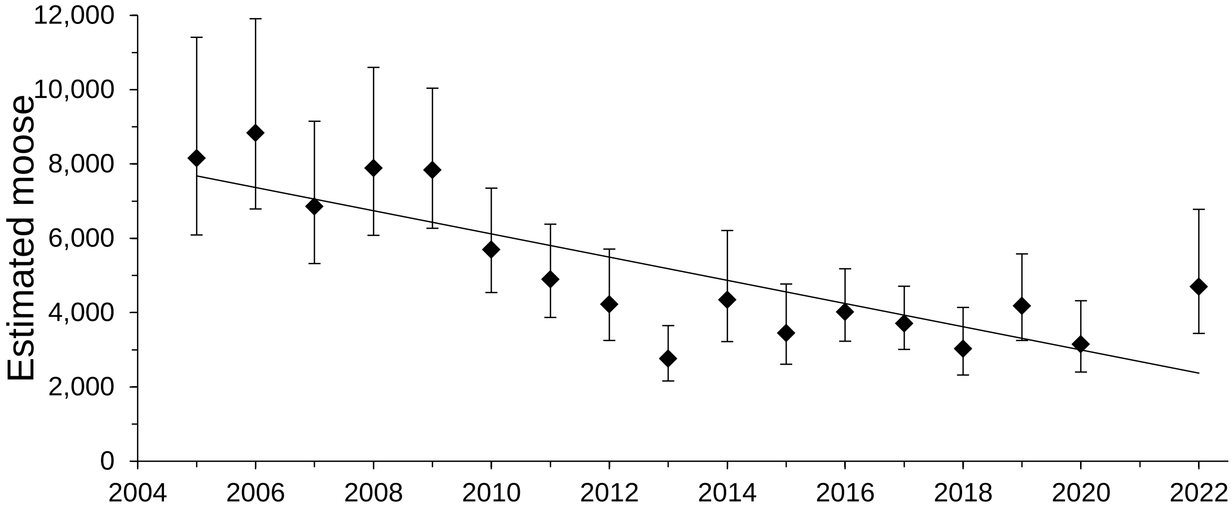
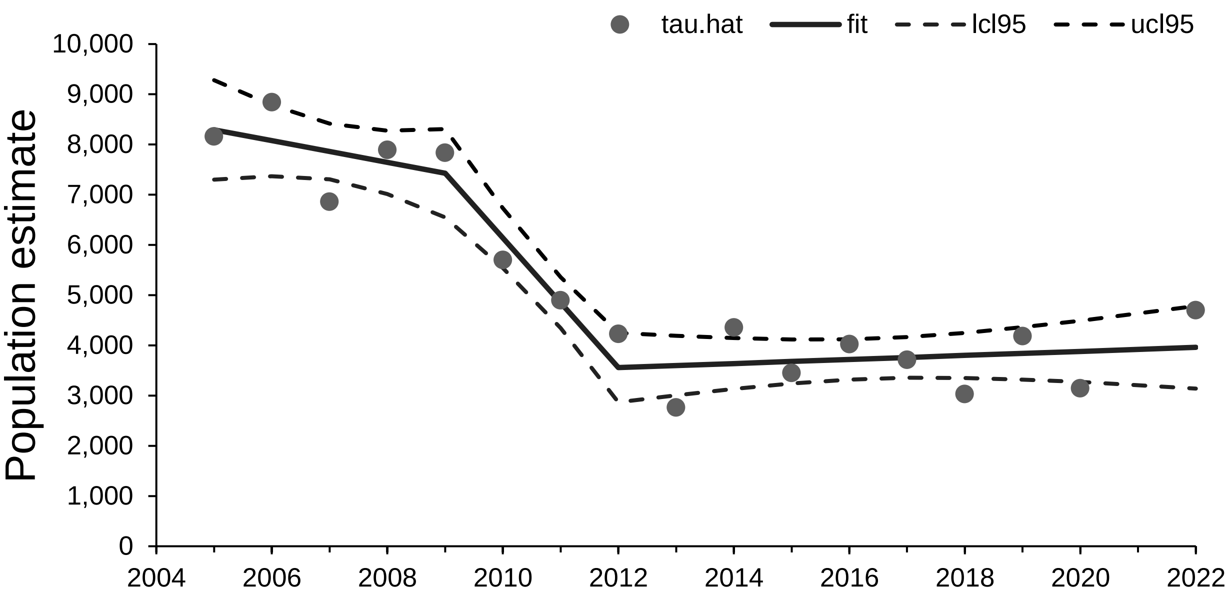


Figure 3. Point estimates, 95% confidence intervals (dashed lines), and a piecewise polynomial curve of moose abundance in northeastern Minnesota, 2005−2022 (Giudice 2022). This curve shows a change in the short-term slope of the trend from 2012 to 2022 compared to 2009 to 2012.



The January 2022 calf:cow ratio of 0.45 is notably greater than the 16-year average since 2005 (0.35, Table 1, Figure 4). Calves were 17% of the total 373 moose actually observed and represented 19% of the estimated population (Table 1, Figure 4). Twin calves were observed with 5 of the 154 (3%) cow moose (Table 1). Although we know from recent field studies that fertility (pregnancy rates) of the population's adult females has been robust, overall, survey results indicate calf survival to January 2022 remains relatively low, albeit somewhat improved compared to most years since the population decline began following the 2006 survey (Table 1). Calf survival during the January−April interval can decline markedly (Schrage et al., unpublished data), and annual spring recruitment of calves (survival to 1 year old) can have a significant influence on the population's performance and dynamics. Findings of a recent field study documented similar low calf survival (0.442−0.485) to early winter in 2015−16 and 2016−17 (Obermoller 2017, Severud 2017, Severud et al. 2019). Calf survival by spring 2017 (recruitment) had declined to just 0.33. But it is also important to note that adult moose survival has the greatest long-term impact on annual changes in the moose population (Lenarz et al. 2010). Consistent with the recent relative stability of the population trend, the annual survival rate of adult GPS-collared moose changed little (85–88%) during 2014−2017 (Carstensen et al. 2017), but was slightly higher than the previous long-term (2002−2008) average of 81% (Lenarz et al. 2009).

The January 2022 estimated bull:cow ratio (0.94, Table 1; Figure 5) is similar to the long-term average of 1.00 during 2005–2020, but greater than the mean ratio of 0.87 observed during 2009−2012, when the population decline was steepest. However this ratio has been as low as 0.64 (2011) during the steep decline. During the recent 11-year (2012−2022) trend of stability, the average bull:cow ratio has been 1.10. However, due to the notable annual variability associated with the bull:cow ratios, the apparent upward trend line is not statistically meaningful (Figure 5).

Figure 4. Estimated calf:cow ratios (solid diamonds, dashed trend line) and percent calves (open squares, solid trend line) of the population from aerial moose surveys in northeastern Minnesota, 2005–2022. *The survey was not conducted in 2021 due to the Covid-19 pandemic.

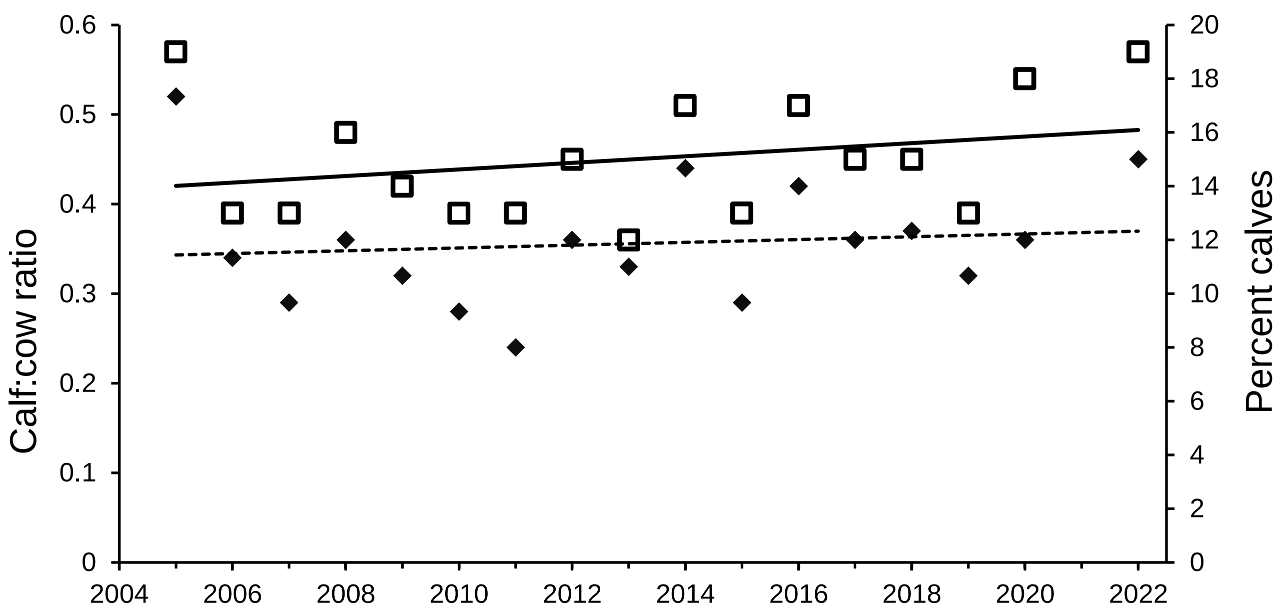
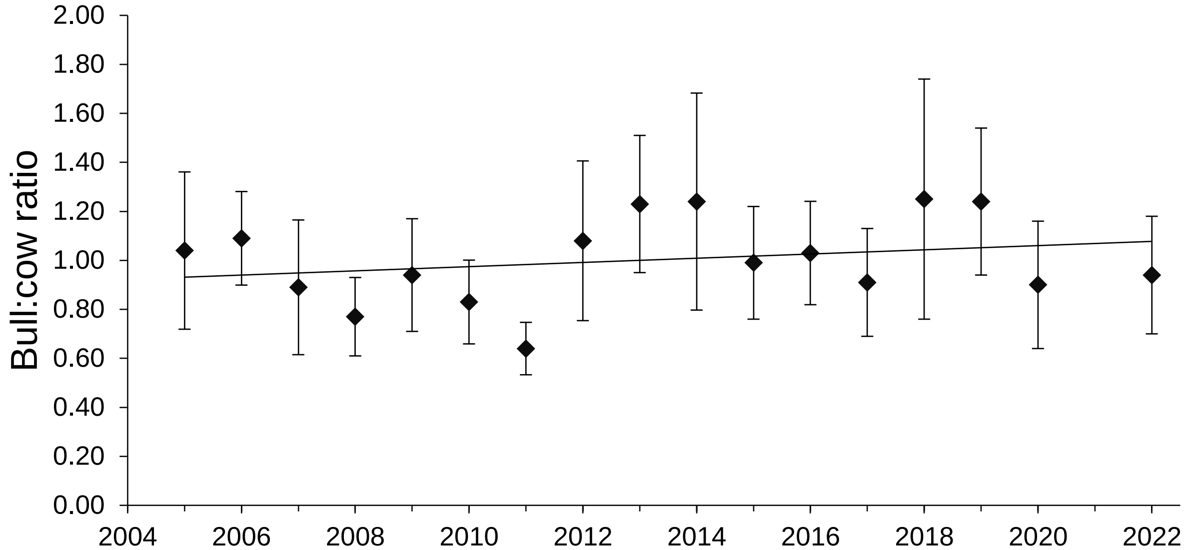


Figure 5. Estimated bull:cow ratios, 90% confidence intervals, and trend line from aerial moose surveys in northeastern Minnesota, 2005–2022. *The survey was not conducted in 2021 due to the Covid-19 pandemic.



Acknowledgments

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Addendum A: Exploring an Alternative Mode of Inference

John H. Giudice, Wildlife Biometrics Unit
Glenn D. DelGiudice, Forest Wildlife Populations and Research Group

Introduction

We currently use a design-based estimator (referred to as a modified Horvitz-Thompson estimator; mHT) with data from aerial surveys and a sightability model to compute estimates of moose abundance in northeastern Minnesota (see DelGiudice and Giudice 2022). Design-based estimators are analytical formulas derived from the principles of survey sampling (Cochran 1977, Thompson 2002). Design-based estimators are generally robust and have proven to be a useful and popular approach in wildlife population estimation. However, in the case of the moose survey, there are some important limitations, including imprecise annual estimates (due to high sampling uncertainty), large inter-annual variation (due to treating survey years as independent), and in some cases, estimates of population change that are biologically suspect. Furthermore, sampling issues in the low-density stratum and the inability to make inferences to sub-regions of the NE moose range (the Small Area Estimation conundrum) are problematic. Significantly increasing the sampling effort to ameliorate these issues is not a viable alternative in this case.

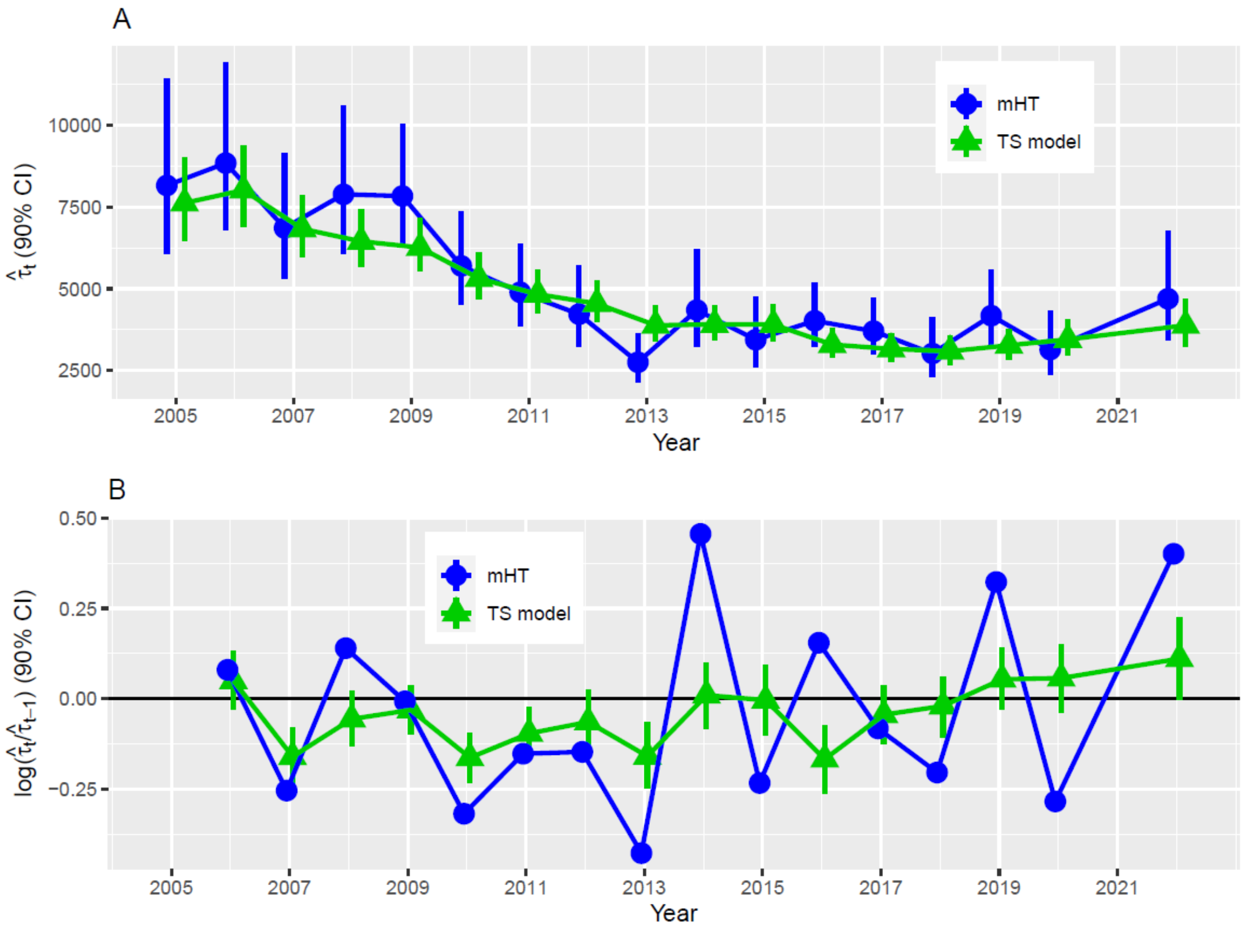
One potential solution is to explore an alternative model-based mode of inference (*sensu* Gregoire 1998, Chambers and Clark 2012). Under this paradigm, the focus switches from expanding the sample using analytical formulas and survey weights (design-based inference) to prediction/imputation (for unsampled plots) given the sample data, survey design, and distributional assumptions about how plot counts (moose groups) and group sizes are distributed over space (e.g., survey strata) and time (e.g., survey years). In 2011, Dr. John Fieberg of the MNDNR Wildlife Biometrics Unit (now a faculty member at the University of Minnesota) began research on a model-based estimator for the MN moose survey. He eventually published a peer-reviewed paper (Fieberg et al. 2013) that described a Bayesian model-based estimator that closely mimicked the design-based estimator (mHT) that we currently use. This is important, because it validates model and distributional assumptions that are integral to model-based estimators. The authors also noted the power and flexibility of their model-based approach for addressing complicated sampling issues (e.g., see the previous paragraph). ArchMiller et al. (2018) expanded on this research by developing a temporally smoothed Bayesian time-series model (TSM) estimator that allowed information on stratum-specific plot counts to be shared among survey years, which resulted in more precise population estimates and greatly reduced inter-annual variability. The TSM approach also has the potential to generate spatially explicit population estimates, which is a continuing area of research by Dr. Althea ArchMiller and Dr. John Fieberg.

The primary limitations of the TSM approach are that it is computationally expensive (e.g., it takes 4 days to run on a high-end computer) and it currently only generates estimates of the total population (vs. age/sex and stratum-specific population estimates). We resolved the first issue by purchasing a high-end desktop computer that is dedicated to biometrics simulation work. The second issue will be part of future work on the TSM estimator; in the interim, we can apply composition ratios (generated using conventional estimators) to the TSM population estimate to derive estimates of bulls, cows, and calves. Thus, as part of our continued effort to improve inferences from the moose survey, we fit the TSM estimator to moose survey data from 2005-2022 and compared it to conventional estimates derived using the design-based mHT approach. In this addendum, we describe the results of this exploratory analysis and discuss the potential benefits and challenges of using the TSM approach going forward.

Results and Discussion

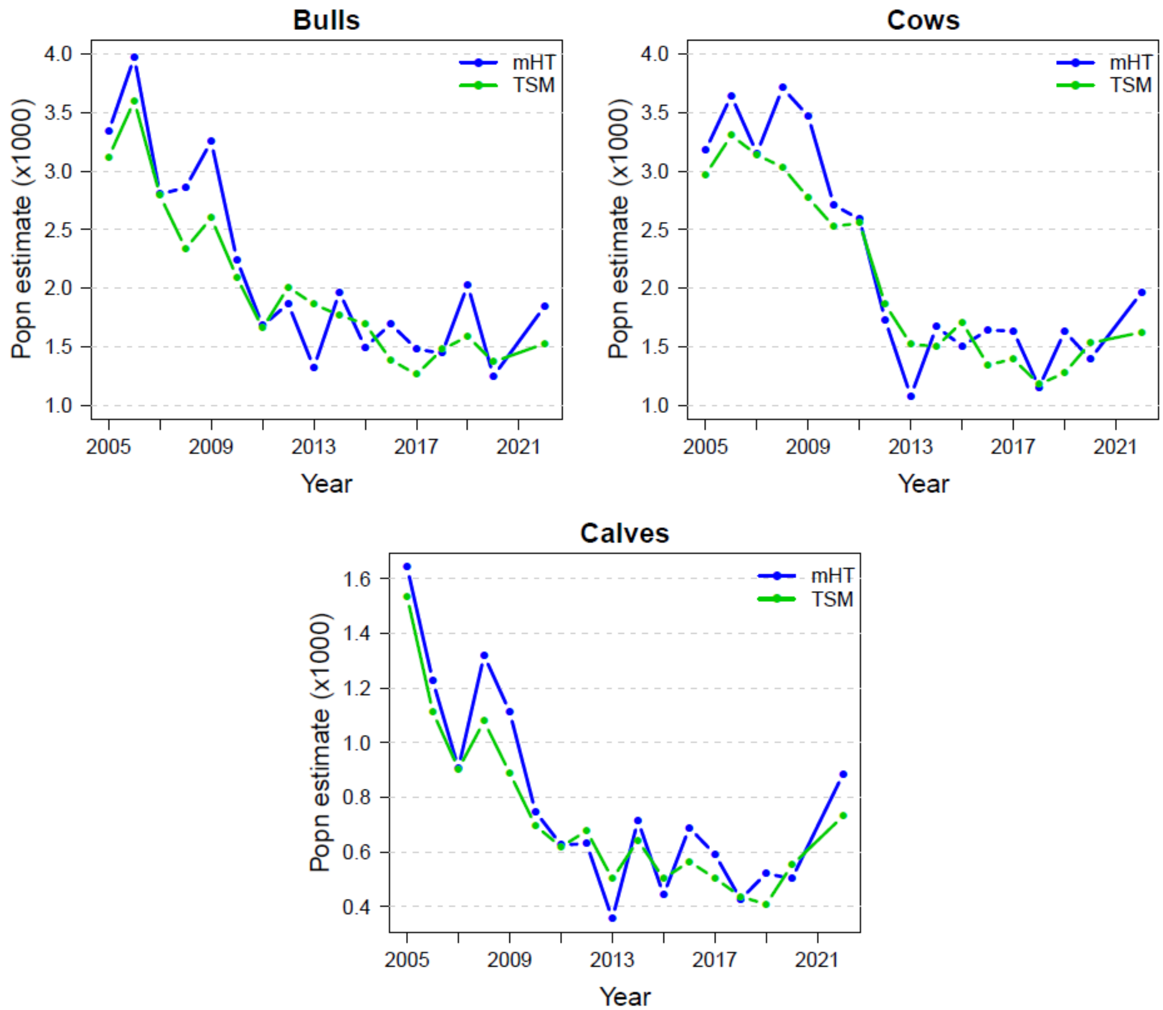
Similar to the findings of ArchMiller et al. (2018), the TSM estimator generated more precise population estimates than the mHT estimator (Figure 1A) and it greatly reduced inter-annual variability in both estimates of abundance and log rates of population change (Figure 1A,B). The estimated log rates of change from the TSM approach are also more biologically plausible, especially for a species with relatively low reproductive potential (e.g., see years 2013-2015 and 2019-2022 in Figure 1B). Likewise, it is easier to visualize estimated population trend(s)

Figure 1. **A**) Moose population estimates (with 90% confidence intervals) from the TSM estimator (green) compared to the conventional mHT estimator (blue). **B**) Estimated log rates of population change (0 = no change, + = increase, – = decrease) using the TSM estimator (green) compared to the conventional mHT estimator (blue).



with the TSM approach compared to the mHT approach where it can be difficult to separate true population changes from sampling noise, especially when comparing annual estimates (Figure 1A). Nevertheless, the big-picture conclusion from both methods is the same: the population declined significantly from a high of about 8,000 animals in 2005-2006 to a low of about 3,000 animals, and it has only recently (the last 4-5 years) exhibited signs of slow but positive population growth. It is just easier to visualize with the TSM approach. However, we caution that survey estimates (from either method) should not be the only metric used to inform management decisions. The greatest utility comes from combining survey estimates with ancillary information from the aerial survey (e.g., proportion of moose with hair loss), directed field studies (e.g., annual estimates of survival and fecundity, moose health research, snow-urine analysis, habitat research), and professional on-the-ground expertise.

Figure 2. Population estimates for bulls, cows and calves based on the TSM estimator (green) compared to the conventional mHT estimator (blue). Note: these are approximations based on applying conventionally derived composition ratios (bull:cow and calf:cow) to mHT and TSM population estimates.



Composition-specific population estimates exhibit slightly less inter-annual variation when derived using TSM population estimates, whereas overall trends are similar for both approaches. Nevertheless, annual variation in subpopulation estimates is high for both approaches and probably reflects sampling uncertainty more than process variation (i.e., true annual variation in composition rates). The ultimate issue with subpopulation estimates is large sampling uncertainty associated with conventionally derived composition-ratio estimates, especially calf:cow and bull:cow ratios (see DelGiudice and Giudice 2022). Resolving this issue is more complicated than the challenge of estimating overall abundance. Thus, we urge caution when making inferences about composition-specific population estimates, regardless of whether they are based on mHT or TSM population estimates.

Conclusions

1. If we treat years as independent, then the model-based approach mimics our conventional design-based estimator. The code looks different, but the assumptions and estimates are fundamentally the same.
2. Treating years as independent is fine, but sometimes it can lead to estimated population changes that are not biologically reasonable (especially for a species with low reproductive potential). In addition, the precision of annual estimates is relatively poor.

3. Allowing the sharing of information among years (TSM) helps smooth out annual fluctuations and reduces uncertainty in annual population estimates. However, we acknowledge that smoothed estimates (TSM method) could occasionally mask a true large population change (e.g., high winter mortality due to an epizootic event), at least until additional years of data are available for the time series. Nevertheless, one could make similar incorrect conclusions under the mHT method because of high sampling uncertainty (e.g., the sample data may not be representative in some years). Thus, regardless of whether we use the mHT or TSM method, it is important to consider ancillary information from surveys (e.g., proportion of moose with hair loss), directed field studies (e.g., annual estimates of survival and pregnancy rates), and professional on-the-ground expertise when making management decisions.

4. Regardless of the approach (mHT vs. TSM), the implications are consistent: there was a significant population decline from a high of about 8,000 moose to a low of about 3,000 moose, but the population appears to have at least stabilized and there is some evidence of slow, positive growth the last 4-5 years. The trend is just easier to visualize with the TSM approach.

5. Compared to the mHT approach, the Bayesian TSM approach offers more flexibility to deal with sampling and estimation issues, including missing data, sampling and estimation issues in the low-density strata, non-linear trends, spatially explicit population estimates, etc.

6. The TSM approach has many potential benefits, but we acknowledge there are some limitations too. It is computationally expensive (computer time) and requires a high-level of technical expertise to modify and run the analysis each year. The TSM estimator is complicated and thus challenging to explain to a lay audience (the black-box conundrum). Historic population estimates can change (albeit trivially in most cases) with the addition of new data (years), with each model run (due to the simulation-component of the Bayesian TSM), or if model and/or distributional assumptions are modified in the future.

7. We could theoretically estimate composition ratios via the TSM approach too, but it would take a lot of coding work and some new assumptions. We currently use the Combined Ratio Estimator (Cochran 1977:165) to compute composition ratios, which means they do not depend on sightability or the mHT estimator. Furthermore, ratio statistics are not population totals and do not need to be expanded for sampling; thus, if the sample is representative, then the estimated ratios should be too. Unfortunately, the precision of our ratio estimates is relatively poor and inter-annual variability is high, which limits the utility of our composition ratios as monitoring metrics (especially cow:calf and bull:calf ratios). Nevertheless, for simplicity and consistency, we could continue to use our conventional estimator to compute composition ratios and simply apply those ratios to the TSM estimate to derive subpopulation estimates, although we would still recommend caution when making management decisions based on subpopulation estimates.

Next Steps

1. At least for the next few years, we will continue to use our conventional mHT-derived population estimates to make management and harvest decisions. Even if or when we switch to the TSM approach for inference, we will likely continue to compute mHT-derived population estimates because it is an efficient method and would provide a check on model-based estimates. The challenge will be how to present the two estimates in way that will not cause confusion with our constituents.

2. We will continue to conduct research on the TSM estimator, including some additional investigative work on the temporal smoother (e.g., number and location of nodes) and the potential for deriving smoothed estimates of composition ratios and subpopulation components (cows, bulls, calves).

3. Dr. Althea ArcMiller and Dr. John Fieberg are working on a Bayesian TSM approach that could account for spatial covariates and potentially generate spatially explicit population estimates.

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