

## 2024 AERIAL MOOSE SURVEY

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### INTRODUCTION

Each year we conduct an aerial survey in northeastern Minnesota to estimate moose (*Alces alces*) abundance and monitor and assess changes in the overall status of the state's largest deer species. The primary objective of this survey is to estimate moose abundance, percent calves, and calf:cow and bull:cow ratios. These demographic data help us to: 1) determine and understand the population's long-term trend (decreasing, stable, or increasing), sex-age 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) contribute to sound management strategies.

### METHODS

The survey area is approximately 5,945 mi<sup>2</sup> (~3.8 million acres; Lenarz 1998, Giudice et al. 2012) and includes the Boundary Waters Canoe Area Wilderness (Figure 1). We estimate moose numbers and age and sex ratios by flying transects within a stratified sample of plots randomly drawn from a sampling frame that covers most of the moose range in northeastern Minnesota (Figure 1). We used historic observations of moose, habitat information, and the extensive field experience of moose managers and researchers to stratify the sampling frame into low-, medium-, and high-density plots based on whether 0-2, 3-7, or 8 or more moose, respectively, would be expected (on average) to be observed in a specific plot. To keep the stratification current, we periodically review the stratification scheme about every 5 years. We conducted the last stratification review in October 2018 and the next review will occur later this year. Stratification helps to improve precision of the estimates (i.e., compared to a simple random sample). In 2012, we modified the stratification scheme by adding a 4<sup>th</sup> stratum (referred to as "long-term habitat plots") to better understand moose use of disturbed areas and evaluate the effect of forest disturbance on moose density over time. Initially, we selected 9 plots that have undergone or will undergo significant disturbance by wildfire, prescribed burning, or timber harvest. We survey the same habitat plots each year in order to better document temporal trends. In 2022, we added a 10<sup>th</sup> habitat plot (plot 208; part of the 2021 Greenwood Lake wildfire). This year we surveyed 53 plots (43 randomly sampled and 10 habitat plots; see Figure 1).

The sampling frame (designed in 2005) contained 435 uniform rectangular plots (~5 mi x 2.7 mi; ~13.3 mi<sup>2</sup>) oriented east to west (Figure 1). Sample plots were surveyed using helicopters (OH-58A, MD500E, and Bell-206B3) flying 200-350 ft above-ground-level at 52-69 mph on east-west transects spaced ~0.3 mi apart, with search intensities that averaged 3.6 min/mi<sup>2</sup> (range: 1.9-5.6). Survey crews consisted of a MNDNR pilot and, 2 observers (one seated behind the pilot). 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 field personnel.

We accounted for visibility bias using a sightability model (Giudice et al. 2012). The model was developed during 2004-2007 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 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.

Since 2004, we have used the SightabilityModel package (Fieberg 2012) in the R programming language (R Core Team 2023) to compute annual population estimates for NE Minnesota. These estimates are adjusted for both sightability and sampling. We also annually compute composition ratios that include calf:cow, calf:total (proportion calves), and bull:cow ratios. We use these ratios as indices of annual productivity and breeding viability (given a polygamous mating system). For historic compatibility, we compute composition ratios using the combined ratio estimator (Cochran 1977:165), which accounts for the sampling design but not sightability.

Historic population estimates have moderate levels of sampling uncertainty, which makes it difficult to compare annual estimates with confidence, especially when differences are relatively small. The strength of the survey is describing trends in population estimates and composition ratios. For example, the significant population decline that occurred between 2009 and 2013 is readily evident in our time series, even with moderate levels of sampling uncertainty. In theory, we could reduce sampling uncertainty by increasing the number of plots surveyed, but we are already pushing the limits of what we can realistically accomplish given staff, equipment, and financial constraints. An alternative approach to improving precision is to consider moving from our current design-based estimator to a model-assisted estimator (e.g., state-space model; Auger-Methe 2021) or a fully model-based estimator (e.g., Fieberg et al. 2013, ArchMiller et al. 2018). The latter research used moose-survey data from NE Minnesota. 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. Similar to last year, we explored using alternative estimators to estimate moose abundance and temporal trends. However, to avoid confusion, the main report continues to focus on traditional estimators, and results from alternative estimators are limited to qualitative summaries in Addendum A.

## **RESULTS AND DISCUSSION**

We surveyed 53 sample plots consisting of 15 low-, 18 medium-, and 10 high-density plots, and 10 habitat plots (Figure 1). The survey required 12 survey days between 17 Jan and 02 Feb to complete, which is slightly longer than usual (annual mean = 9 days; range: 8 to 10) because we were limited to 1 aircraft for much of the survey. We also started 10 days later than usual due to marginal snow conditions. Generally, 8” of snow cover is our minimum threshold depth for conducting the survey. Only 26% of survey plots in 2024 had snow depths  $\geq 8$ ”, but overall survey conditions were rated as fair-to-good for 100% of the plots. Furthermore, survey intensity, aircraft speed and height, etc. were very similar to values observed in previous surveys (see Giudice 2024).

Crews this year observed 323 moose (148 bulls, 120 cows, 43 calves, 12 unclassified adults) on 39 (74%) plots with an average of 8.3 moose per “occupied” plot. For comparison, apparent occupancy (ignoring detectability) in the previous 19 years ranged from 65-95% (mean = 81%),

and the mean moose count/occupied plot ranged from 6.4-18.5 (annual mean = 11.0). Crews observed an average of 3.8 moose groups per occupied plot (range: 1-10) in 2024 compared to an average of 5.5 groups/plot (annual range: 3.0-9.3) in the previous 19 years. The average group size in 2024 was 2.2 moose (range: 1-8) compared to a mean of 2.0 (range: 1.8-2.4) in the previous 19 years. Visual obstruction estimates in 2024 averaged 41% (range: 0 to 90) and the average estimated detection probability was 0.57 (range: 0.20 to 0.85). The latter is similar to mean values observed in previous years (range: 0.52 to 0.66; see Giudice 2024).

After adjusting for sampling and sightability, the estimated moose population in northeastern Minnesota was 3,470 moose (90% CI: 2,570–4,940) (Table 1, Figure 2). Bulls, cows, and calves accounted for about 48%, 35%, and 17% of the estimated population total, respectively. Estimated overall bull density was 0.28 bulls/mi<sup>2</sup> (90% CI: 0.19 to 0.43). However, it varied by stratum: 0.17 bulls/mi<sup>2</sup> (90% CI: 0.09 to 0.46) in the low stratum, 0.34 bulls/mi<sup>2</sup> (90% CI: 0.21 to 0.58) in the medium stratum, 0.61 bulls/mi<sup>2</sup> (90% CI: 0.41 to 1.04) in the high stratum, and 0.60 bulls/mi<sup>2</sup> (90% CI: 0.51 to 0.84) in the habitat-plot stratum. This year's estimated calf:cow ratio was 0.51 (90% CI: 0.39 to 0.62) and the bull:cow ratio was 1.33 (90% CI: 1.04 to 1.62). This year's calf:cow ratio is higher than last year's point estimate (0.38) and is the highest estimated ratio since 2005 (Figure 3). However, there is moderate-to-high levels of sampling uncertainty associated with our ratio estimates. Thus, it is difficult to separate true annual change from sampling variation when comparing ratio estimates among years (Figure 3). The calf:total ratio (proportion calves) closely mirrors the calf:cow ratio but with slightly less annual variability (Figure 3). The bull:cow ratio increased slightly compared to last year, but precision of the bull:cow ratio is relatively poor (Figure 4). Furthermore, there is a lot of sampling variation in the bull:cow time series that likely reflects annual variation in the classification process and, possibly, how bulls and cows are distributed in space. The calf:cow ratio is better in this regard.

Although we know from field studies that fertility (pregnancy rates) of the population's adult females has been robust (Lenarz et al. 2010; DelGiudice, unpublished data), overall, survey results suggest that calf survival remains relatively low. 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. However, 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).

This year's population estimate is up 5% from last year's point estimate (Table 1, Figure 2). However, sampling uncertainty is moderately high in this survey (see 90% CIs) and, thus, it is often difficult to make statistically confident statements about the magnitude of annual population changes unless those changes are relatively large. This level of uncertainty is common in wildlife surveys, 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., snow depth, ambient temperature) on their movements, and 5) interaction of these and other factors. Thus, the best use of survey results is for monitoring population trends over several years rather than focusing on the magnitude of differences in annual estimates, including composition ratios.

Based on aerial surveys and research results (e.g., Lenarz et al. 2009, 2010; Severud 2017; Carstensen et al. 2017; Severud et al. 2019, 2020, 2022), we can say with reasonable confidence the moose population in NE Minnesota declined steeply between 2009 and 2013 and has since more-or-less stabilized at around 3,700 moose (Figure 2; also see Addendum A). The term “stabilized” as used here does not mean the population is constant, but rather true annual changes appear to be reasonably small (on average) and random (some years are up, and some are down). Furthermore, we caution there might be a small underlying population trend (a true mean rate of change that is either positive or negative), but it would be difficult to detect over the short term given the limitations of our survey. Finally, we caution that current population trends do not predict future population trends because underlying demographic factors affecting population abundance can change over time.

## **ACKNOWLEDGMENTS**

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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, 2005–2024. Note: the survey was not conducted in 2021 due to the Covid-19 pandemic.

Year	Population estimate	90% CI	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
2023	3,290	2,480 – 4,560	0.38	16	6	1.26
2024	3,470	2,570 – 4,940	0.51	17	6	1.33

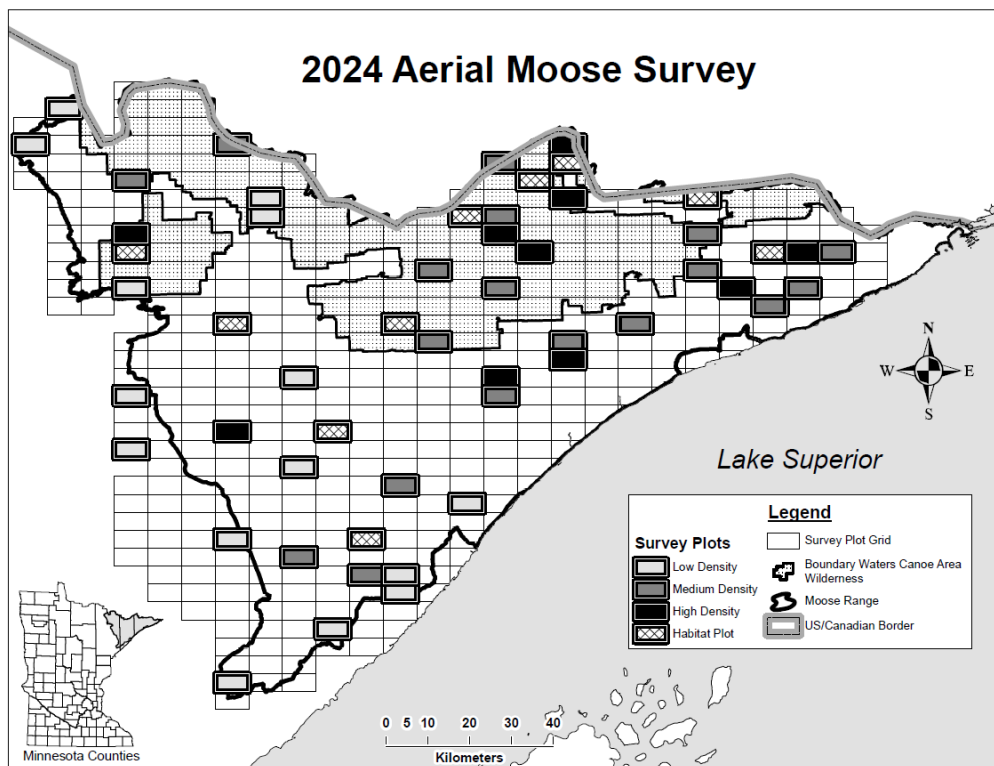


Figure 1. Moose survey area, sampling frame, and the 53 sample plots flown in the 2024 aerial moose survey.

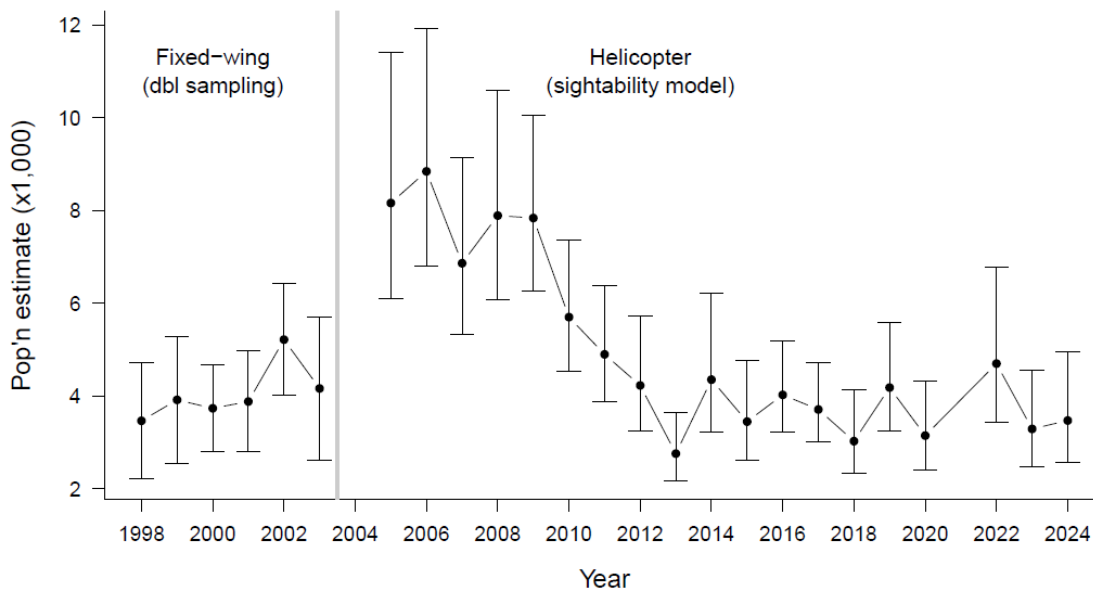


Figure 2. Aerial-survey estimates (with 90% CIs) of moose abundance in NE Minnesota, 1998–2024. Note: the 1998–2003 survey period is not directly comparable to 2005–2024 estimates. It is shown here for documentation only.

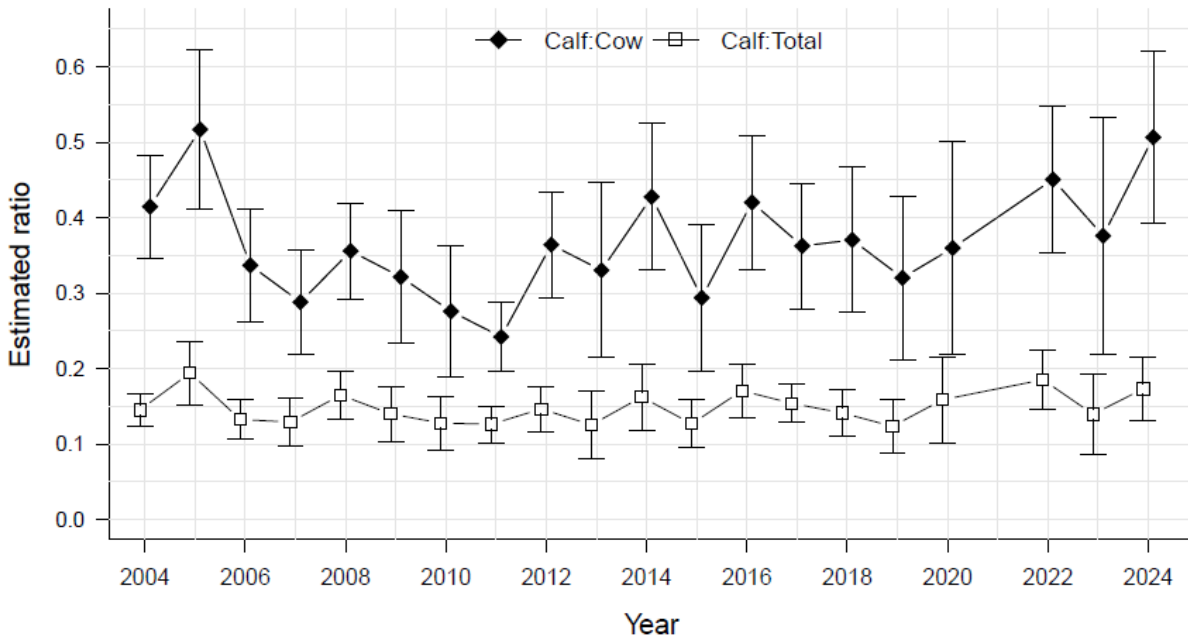


Figure 3. Estimated calf:cow ratios (solid diamonds, with 90% CI) and proportion calves (open squares, with 90% CI) from aerial moose surveys in northeastern Minnesota, 2004–2024. Note: the survey was not conducted in 2021 due to the Covid-19 pandemic.

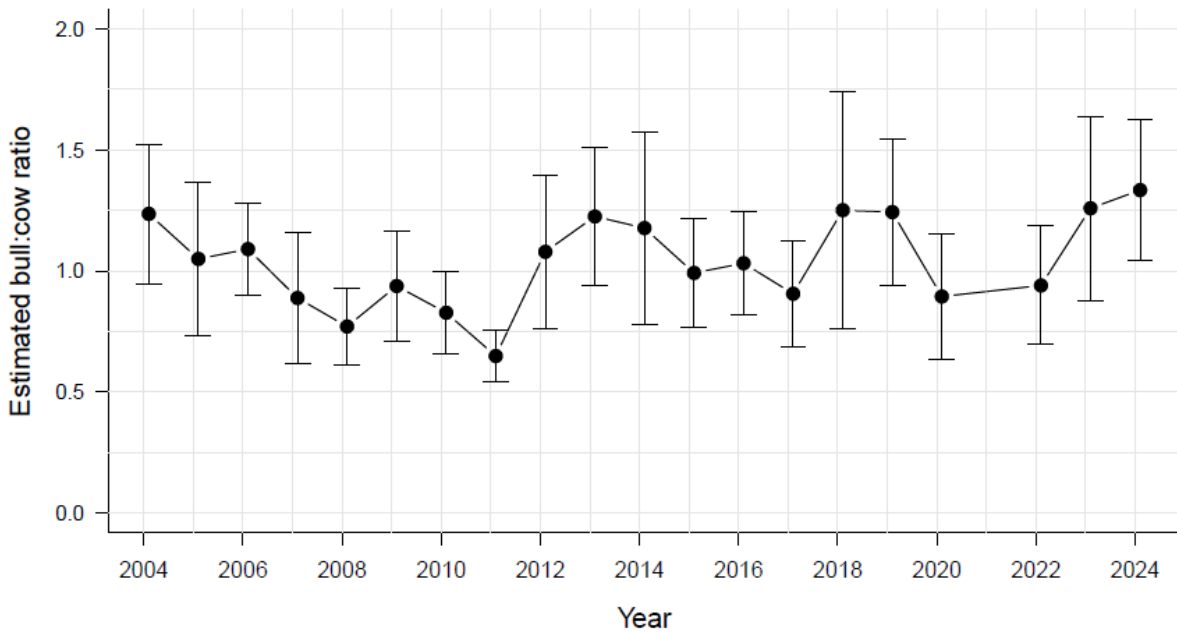


Figure 4. Estimated bull:cow ratios (with 90% CI) from aerial moose surveys in northeastern Minnesota, 2004–2024. Note: the survey was not conducted in 2021 due to the Covid-19 pandemic.



# Addendum A: Exploring Alternative Modes of Inference

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## 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. 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 moderate-to-high sampling variation), 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 alternative modes of inference, including model-assisted and model-based modes of inference (*sensu* Gregoire 1998, Chambers and Clark 2012). An example of the first would be to use our design-based estimates (including estimates of sampling uncertainty) in a Bayesian state-space model (*sensu* Auger-Methe 2021). These models can take many forms, but they have two basic components. The first component is an observation process that links observed counts (or, in our case, population estimates) to true abundance, which is the unknown parameter we want to estimate. This is usually accomplished by treating the observed counts as a random variable whose distribution is drawn from the true population but with sampling or observation error. The second component is a state process that describes the true state or population process (e.g., where true abundance in year  $t$  is a function of abundance in year  $t-1$ , a mean intrinsic rate of change, and some annual variation in the true growth rate). These models are relatively simple to fit and offer the benefit of improving the precision of annual estimates and reducing inter-annual variation by shrinking estimates toward the mean, especially when estimates have high levels of sampling uncertainty.

A model-based approach can also take many forms. In this application, 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) 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.

The primary limitations of the TSM approach are that it is computationally expensive (e.g., it takes 3 days to run on a high-end computer) and it currently only generates estimates of total population size (vs. age/sex and stratum-specific population estimates). The latter is also true for the state-space model. 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 and the state-space model. As part of our continued effort to improve inferences from the moose survey, we fit the TSM estimator to moose survey data from 2005-2024 and compared it to estimates derived using the design-based mHT approach and the state-space model. In this addendum, we describe the results of this alternative analysis and discuss the potential benefits and challenges of using either the state-space model or TSM approach going forward.

## **RESULTS AND DISCUSSION**

### **State-Space Model**

As expected, population estimates from the state-space model are more precise (i.e., the method reduces annual sampling uncertainty) and extreme estimates are shrunk back toward the mean, which results in a smoother, more realistic population trajectory (Figure A1, below). A good example of this is the population estimate for 2004, which we traditionally do not report because it was unrealistically high (re: first year of sightability-model approach) and precision was extremely poor. The state-space model shrunk this estimate back to a more reasonable number and greatly increased precision (relative to the original estimate). Another benefit is that we can generate population estimates for non-survey years such as 2021 (pandemic year; see Figure A1). The simple state-space model suggests the population has more-or-less stabilized since 2013 and continues to bounce along at around 3,700 animals. This year's point estimate is down slightly (3%) from the 2023 estimate, which was down 8% from the 2022 estimate (Figure A1); thus, suggesting a possible 2-year decrease. However, we have seen this before (e.g., 2016 to 2018). Furthermore, the CIs of estimates from 2013-2024 overlap, which makes it difficult to separate sampling noise from small but true annual differences. This model also does a good job of permitting the mean intrinsic rate of change to vary over time. For example, the mean intrinsic rate of change during 2004-2009 was  $-0.086$  compared to the steep decline during 2010-2013 (mean =  $-0.163$ ) and the more recent (2014-2024) period of relative stability ( $-0.007$ ). This is accomplished by modeling the intrinsic rate of change as a random variable from a normal distribution with a mean of  $-0.06$  and a relatively large SD ( $\sim 0.15$ ). This is a simplified approach compared to the TSM estimator, which uses a basis spline and change points to smooth the population trajectory. However, the state-space model approach appears to work reasonably well with the moose-survey dataset.

### **TSM Estimator**

Similar to the findings of ArchMiller et al. (2018), the TSM approach generated more precise population estimates than the mHT estimator (Figure A1), and it greatly reduced inter-annual variability in both estimates of abundance (Figure A1) and log rates of population change (Figure A2). 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 2019-2023 in Figure A2). Likewise, it is easier to visualize estimated population trends 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 A1). However, one caveat is that smoothed trends from the TSM estimator can be sensitive to the number and location nodes (change points) used in the basis spline. Based on the mHT time series and research findings, we would intuitively establish change points around 2009 and 2013 because that is where population trends appeared to

have changed. Conversely, in its current form the spline smoother in the TSM estimator selects nodes based on the 0.33 and 0.66 quantiles of the time series, which this year resulted in nodes at about 2011.3 and 2017.5 (Figure A1). The latter may partly explain why the TSM estimator indicated a slight population increase in 2023 and 2024, whereas the state-space estimator indicated small decreases (Figure A1). Regardless, the CIs overlap in both cases, which means the small annual differences in point estimates could partly reflect sampling noise.

## 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. 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, precision of annual estimates is relatively poor.
2. Allowing the sharing of information among years (TSM or state-space model) helps smooth out annual fluctuations and reduces uncertainty in annual population estimates. However, we acknowledge that smoothed estimates 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, TSM, or state-space approach, it is important to consider ancillary information from surveys, directed field studies (e.g., estimates of survival and pregnancy rates), and professional on-the-ground expertise when making management decisions.
3. Regardless of the estimation approach (mHT, TSM, state-space model), the big-picture conclusions are consistent for the 2005-2024 survey period: there was a significant population decline from about 8,000-9,000 in 2005-2006 to a low of about 3,000-4,000 moose in 2013, but the population appears to have more-or-less stabilized since then (with annual estimates fluctuating around 3,400-4,000 moose). The trends are just easier to visualize with the TSM and state-space model approaches.
4. Compared to the mHT approach, the TSM and state-space approaches offer 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.
5. The TSM approach has many potential benefits, but we acknowledge there are some limitations too. It is computationally expensive (computer time), requires a high level of technical expertise to modify and run the analysis each year, and can be challenging to explain to a lay audience (the black-box conundrum). Conversely, the state-space model is simple to fit and much easier to explain. Nevertheless, in both cases, historic population estimates can change (albeit trivially in most cases) with the addition of new data (years), with each model run (for the simulation-based TSM approach), or if model and/or distributional assumptions are modified in the future. However, values derived with the mHT approach are estimates too; the only reason they do not change is that we treat each year as independent in the mHT approach.
6. We could theoretically estimate composition ratios via the TSM or state-space approach, 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. Sightability does not appear to have a large effect on estimated composition ratios. Nevertheless, we probably should

consider computing sightability-adjusted composition ratios to ensure subpopulation estimates (cows, bulls, calves) from the sightability model are consistent with reported composition ratios. Regardless, the precision of our ratio estimates is relatively poor and inter-annual variability is high, which limits the utility of our composition ratios as annual monitoring metrics (especially bull:cow ratios). Thus, our estimates of composition ratios would also benefit from using the TSM or state-space model approach.

## **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 switched 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 and state-space estimators, including some additional work on the TSM temporal smoother (e.g., using a random-walk approach). The latter is important because the nodes in the current smoother change location with the addition of new data, which might not be ideal given that there are some obvious change points in our time series (e.g., around 2009 and 2013). We also plan to do more research on the potential for deriving smoothed estimates of composition ratios and subpopulation components (cows, bulls, calves).
3. In theory, the Bayesian TSM approach could account for spatial covariates (e.g., habitat data) and generate spatially explicit population estimates. This is another area of potential research and advancement.

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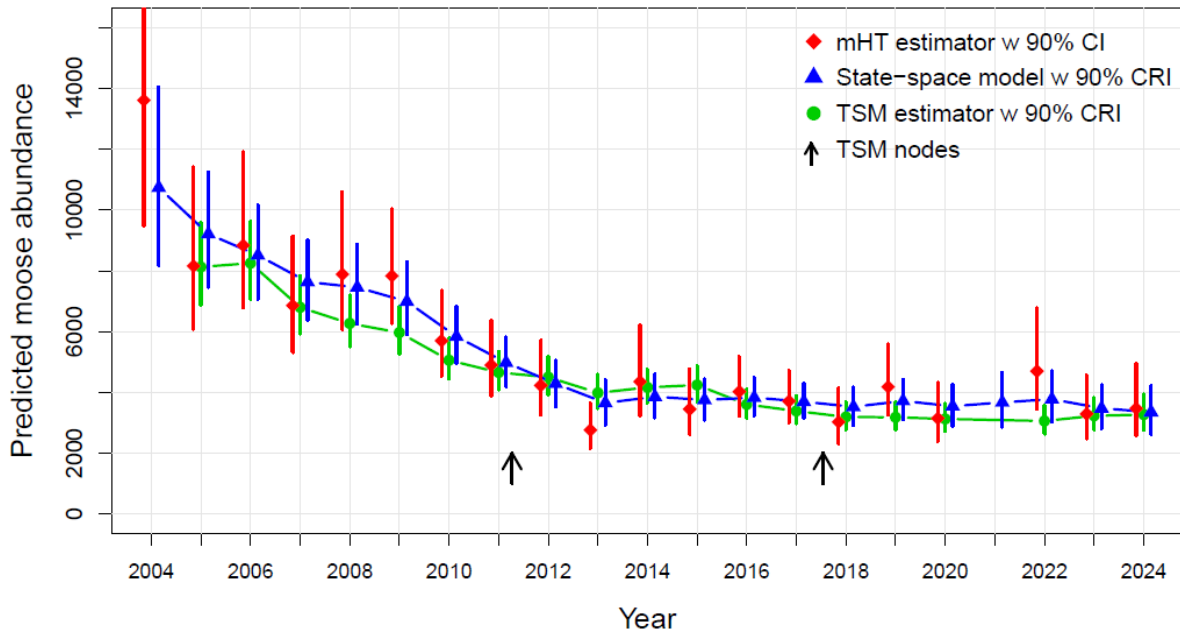


Figure A1. Comparison of moose population estimates (with 90% CIs) from the design-based Horvitz-Thompson estimator (mHT, red diamonds), state-space model (blue triangles), and the TSM estimator (green dots). The location of TSM nodes are denoted with arrows.

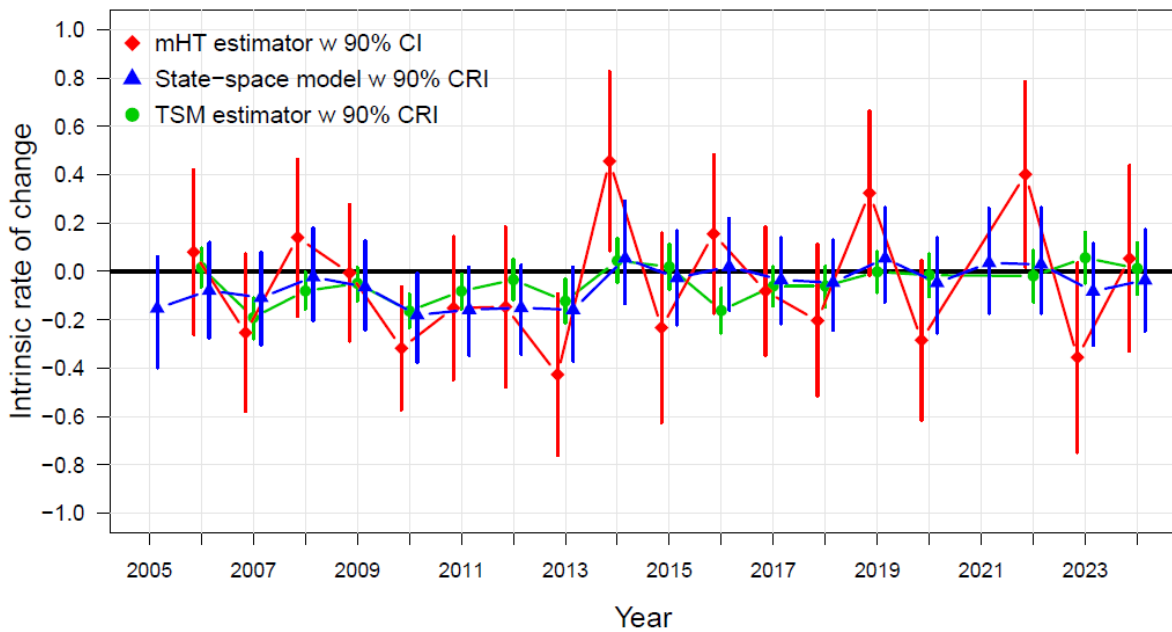


Figure A2. Estimated intrinsic rates of annual population change (0 = no change, + = increase, - = decrease) based on the conventional mHT estimator (red diamonds), state-space model (blue triangles), and TSM estimator (green dots).