DEPARTMENT OF NATURAL RESOURCES

2026 Aerial Moose Survey

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Introduction

Each year the Minnesota Department of Natural Resources, Fond du Lac Band of Lake Superior Chippewa and 1854 Treaty Authority conduct an aerial survey in northeastern Minnesota to estimate moose (*Alces alces*) abundance and monitor 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^2 (~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 review the stratification scheme about every 5 years. We conducted the last stratification review in October 2025 and plan to conduct the next review in 2030. 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 4th 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 to better document temporal trends in response to disturbance. In 2022, we added a 10th habitat plot (plot 208; part of the 2021 Greenwood Lake wildfire). Plots 403 and 117 were discontinued as habitat plots in 2025 and 2026, respectively, while plots 57 and 126 were added as habitat plots in 2026 for long-term timber management monitoring (plot 57) or wildfire monitoring (plot 126). 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^2) oriented east to west (Figure 1). Sample plots were surveyed using two helicopters (i.e., OH-58As during 2004–2008 and 2010–2016, an OH-58A and an Enstrom in 2009, an OH-58A and an MD500E during 2017–2023, and an MD500E and a Bell-206B3 since 2024) 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^2 (range: 1.9-5.6). Survey crews consisted of a 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 use a tablet-based data collection protocol that uses Quick Capture (flight paths), Field Maps (species observations), and Survey 123 (survey plots) software and data-entry interfaces developed by A. Bontrager and E. Bott, MNIT DNR, in 2025. The combination of software 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 radio-collared 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 radio-collared 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 one moose (i.e., 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 2026) 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 comparability, we compute composition ratios using the combined ratio estimator (Cochran 1977:165), which accounts for the sampling design but not sightability.

Results and Discussion

In 2026, 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 7 January and 29 January to complete, which was ~3 days longer than average (annual mean = 9.2 days; range = 8–12), mostly because of limited availability of the Bell aircraft. Generally, 8" of snow cover is our minimum threshold depth for conducting the survey. Almost all survey plots in 2026 had snow depths >8" (94.3%), and overall survey conditions were rated as good for 94.3% of the plots. Furthermore, survey intensity, aircraft speed and height, etc. were very similar to values observed in previous surveys (see Verheijen 2026).

Crews this year observed 385 moose (163 bulls, 143 cows, 63 calves, and 16 unclassified adults) on 45 (85%) plots, with an average of 8.6 moose per "occupied" plot. For comparison, apparent occupancy (ignoring detectability) in the previous 21 years ranged from 42% to 91% (mean = 70%), and the mean moose count in occupied plots ranged from 4.8 to 14.0 moose (mean = 7.9 moose). In 2026, survey plots contained a weighted average of 3.6 moose groups per occupied plot (range = 1–18 groups) compared to a weighted average of 4.0 groups/plot (annual range = 2.3–7.3 groups) in the previous 21 years. The weighted average group size in 2026 was 1.8 moose (range = 1–6 moose) compared to a weighted mean of 2.0 moose (range = 1.7–2.4 moose) in the previous 21 years. Visual obstruction estimates in 2026 averaged 42% (range = 0–90%), and the average estimated detection probability was 0.56 (range = 0.20–0.85). The latter is similar to mean values observed in previous years (range = 0.52–0.66; see Verheijen 2026).

After adjusting for sampling and sightability, the estimated moose population in northeastern Minnesota was 4,470 moose (95% CI = 3,354–6,173 moose; Table 1, Figure 2). Bulls, cows, and calves accounted for about 40.8%, 41.0%, and 18.2% of the estimated population total, respectively. Estimated overall bull density was 0.37 bulls/mi^2 (95% CI = 0.21–0.42), but varied by stratum: 0.12 bulls/mi^2 (95% CI = 0.07–0.27) in the low stratum, 0.42 bulls/mi^2 (95% CI = 0.27–0.70) in the medium stratum, 0.73 bulls/mi^2 (95% CI = 0.43 to 1.41) in the high stratum, and 0.63 bulls/mi^2 (95% CI = 0.49–0.98) in the habitat-plot stratum.

This year's estimated calf:cow ratio was 0.44 (95% CI = 0.29–0.59) and the bull:cow ratio was 1.09 (95% CI = 0.74–1.43). This year's calf:cow ratio is down from the high point estimate from 2024, but remains on the high end compared to the long-term average (Figure 3). However, there are 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 decreased by 30.8% 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.

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 (0.44−0.49) 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 11% from last year's point estimate (Table 1, Figure 2). However, sampling uncertainty is moderately high in this survey (see 95% CIs). It is therefore 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 3,700–3,800 moose (Figure 2). 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, 95% confidence intervals, calf:cow ratios, percent calves in the population, percent cows with twins, and bull:cow ratios from aerial surveys in northeastern Minnesota, 2005–2026. Note: the survey was not conducted in 2021 due to the Covid-19 pandemic.

Year	Population estimate	95% CI	Calf:Cow	% Calves	% Cows w/ twins	Bull:Cow
2005	8,160	5,738 – 12,131	0.52	19	9	1.05
2006	8,840	6,438 – 12,578	0.34	13	5	1.09
2007	6,860	5,057 – 9,643	0.29	13	3	0.89
2008	7,890	5,765 – 11,188	0.36	16	2	0.77
2009	7,840	6,001 – 10,508	0.32	14	2	0.94
2010	5,700	4,338 – 7,703	0.28	13	3	0.83
2011	4,900	3,695 – 6,699	0.24	13	1	0.65
2012	4,230	3,085 – 6,036	0.36	15	6	1.08
2013	2,760	2,055 – 3,841	0.33	12	3	1.23
2014	4,350	3,035 – 6,625	0.44	17	5	1.24
2015	3,450	2,475 – 5,065	0.29	13	2	0.99
2016	4,020	3,089 – 5,427	0.42	17	6	1.03
2017	3,710	2,886 – 4,922	0.36	15	5	0.91
2018	3,030	2,203 – 4,385	0.37	15	5	1.25
2019	4,180	3,095 – 5,887	0.32	13	2	1.24
2020	3,150	2,268 – 4,579	0.36	18	4	0.89
2021	-	-	-	-	-	-
2022	4,700	3,234 – 7,242	0.45	19	4	0.94
2023	3,290	2,345 – 4,845	0.38	16	7	1.26
2024	3,470	2,422 – 5,271	0.51	17	8	1.33
2025	4,040	2,978 – 5,687	0.41	12	7	1.57
2026	4,470	3,354 – 6,173	0.44	18	10	1.09

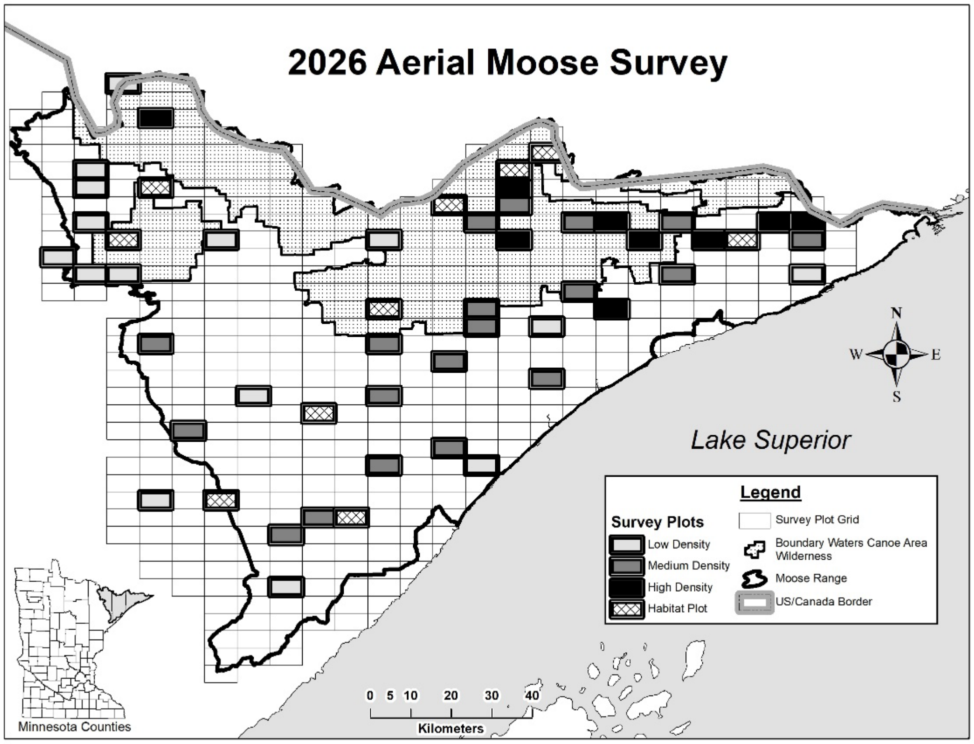

Figure 1: Moose survey area, sampling frame, and the 53 sample plots flown in the 2026 aerial moose survey.

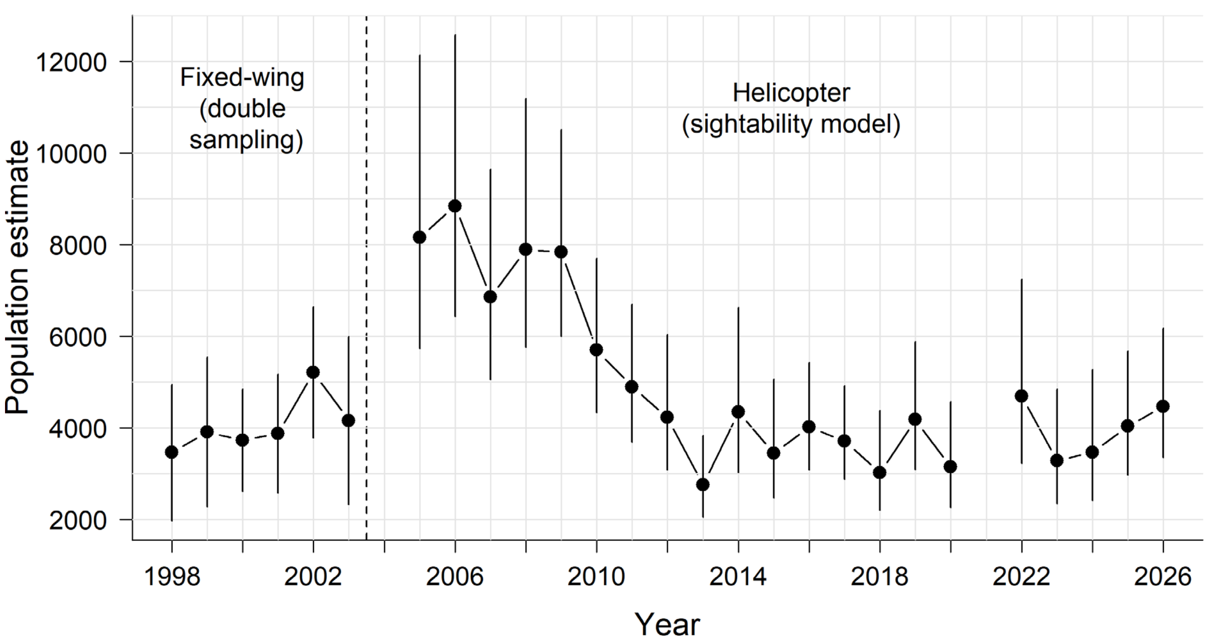

Figure 2: Aerial-survey estimates (with 95% CIs) of moose abundance in NE Minnesota, 1998–2026. Note: the 1998-2003 survey period is not directly comparable to 2005-2026 estimates. It is shown here for documentation only. Additionally, the survey was not conducted in 2021 due to the Covid-19 pandemic.

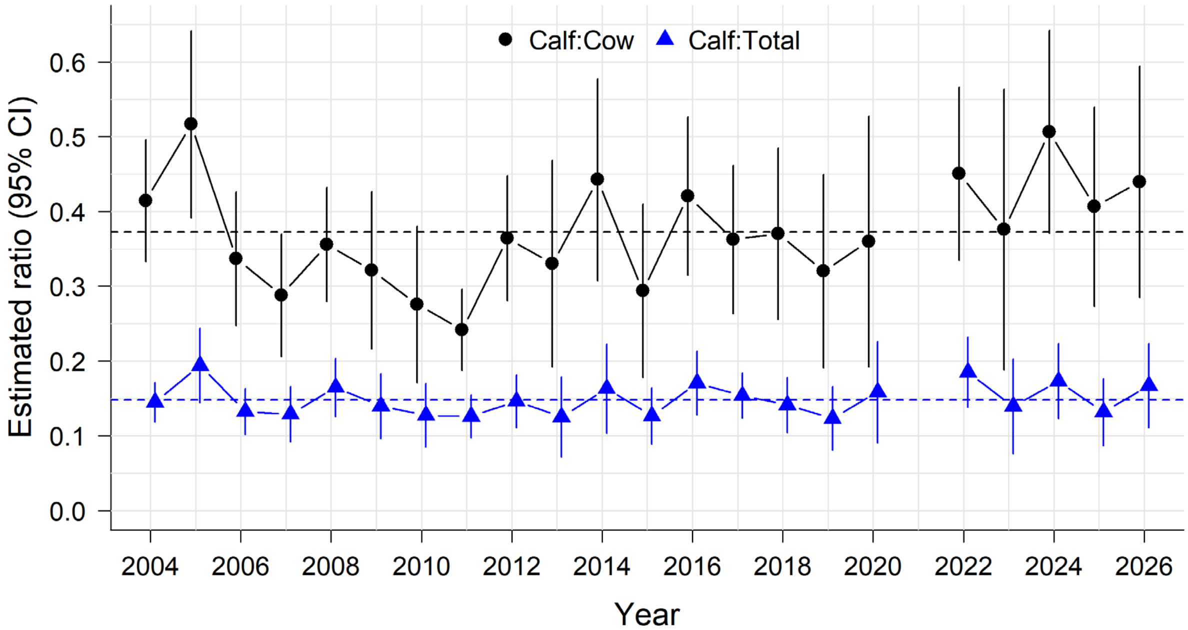

Figure 3: Estimated calf:cow ratios (black circles, with 95% CI) and proportion calves (blue triangles, with 95% CI) from aerial moose surveys in northeastern Minnesota, 2004–2026. Note: the survey was not conducted in 2021 due to the Covid-19 pandemic.

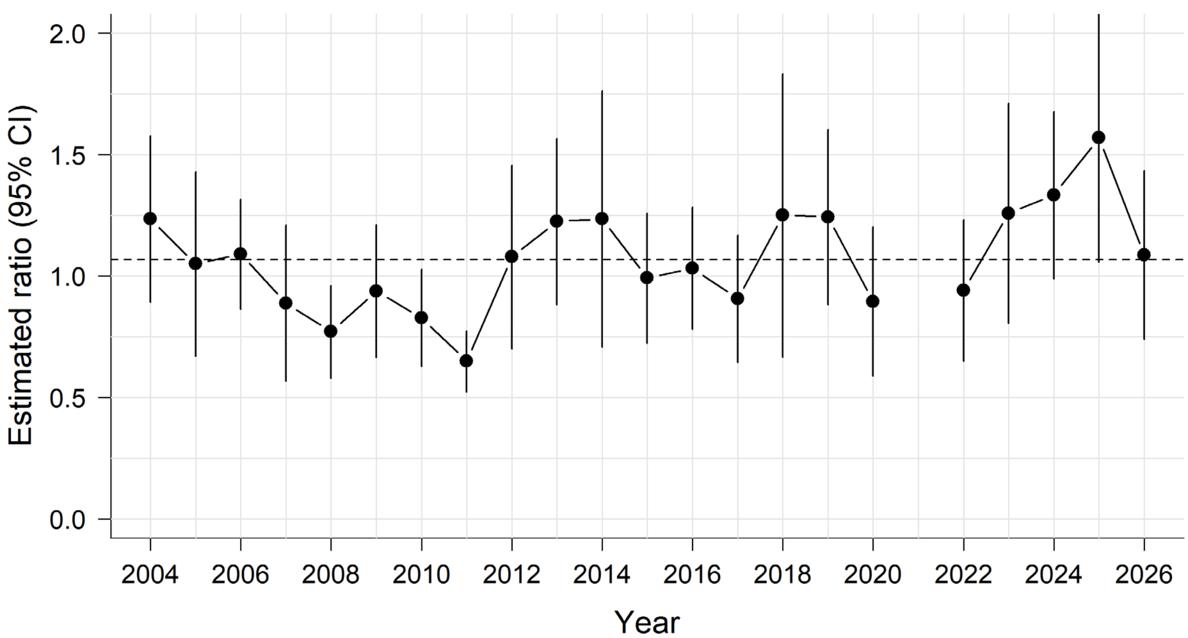

Figure 4: Estimated bull:cow ratios (with 95% CI) from aerial moose surveys in northeastern Minnesota, 2004–2026. Note: the survey was not conducted in 2021 due to the Covid-19 pandemic

Addendum A: Bayesian State-Space Model

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Introduction

When it comes to analyzing moose observation data as collected by the aerial survey, there are three clear analytical approaches. The first approach, and currently used, is a design-based estimator (referred to as a modified Horvitz-Thompson estimator; HT) which uses 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 (because of moderate-to-high sampling variation), large inter-annual variation (because it treats 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 improve these issues is not a viable alternative in this case.

Two alternative analytical approaches that could provide potential solutions to the problems described above include model-assisted estimators (approach 2) and fully model-based estimators (approach 3; *sensu* Gregoire 1998, Chambers and Clark 2012). An example of the model-assisted approach would be to use our design-based estimates (including sampling uncertainty) as input in a Bayesian state-space model (*sensu* Auger-Methe 2021). State-space 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 finite rate of change (lambda), and some annual variation in the true growth rate). Bayesian state-space 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 third approach, a fully model-based Bayesian estimator, switches the focus 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 (HT) that we currently use—which is important for validating 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 above). Similarly to a model-assisted estimator (approach 2, state-space model), a fully model-based Bayesian estimator would be able to provide population numbers of individual population segments (bulls, cows, calves, unclassified adults) and use these estimates to calculate composition ratios. However, there are several additional benefits of a fully model-based estimator compared to design-based (approach 1) or model-assisted estimators (approach 2). First, because the number of moose groups, group sizes, and group composition are modeled directly, it would be possible to estimate the effects of covariates (e.g., weather, habitat conditions) on each of those three parameters. Second, implementing potential breakpoints in the population trajectory into the analysis would be straightforward. Third, a fully model-based Bayesian approach could account for spatial covariates (e.g., habitat data) and potentially generate spatially explicit population estimates.

In this addendum, we show the benefits of the model-assisted estimator (approach 2, Bayesian state-space model) over the current design-based estimator (approach 1, HT). Specifically, using moose survey data from 2004–2026, we estimated overall moose abundance, finite rate of change (lambda) in population numbers, and cow-calf ratios for each year, and compared estimates of all three metrics between the two analytical approaches. The development of a fully model-based estimator (approach 3) might be a target for future research and no results from such an estimator are shown here (see Conclusions).

Results and Discussion

As expected, population estimates from the Bayesian state-space model (i.e., approach 2, model-assisted estimator) are more precise than HT estimates (i.e., approach 1, currently used design-based estimator) by reducing annual sampling uncertainty and shrinking extreme estimates back toward the mean. The result is a smoother, more realistic population trajectory (Figure 5). A good example is the population estimate for 2004, which we traditionally do not report because it was unrealistically high (first year of the sightabilty-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; Figure 5).

The model assisted state-space model suggests the population has more-or-less stabilized since 2013 and continues to bounce along at around 3,600 animals. This year’s point estimate is up slightly (2.6%) from the 2025 estimate, which was up 4.5% from the 2024 estimate, potentially suggesting an upward trend in population numbers during the last couple years (Figure 5). However, small fluctuations in population numbers over time in response to the larger fluctuations in HT-based estimates are to be expected. Furthermore, the 95% credible intervals of estimates from 2013-2026 overlap, which makes it difficult to separate sampling noise from small but true annual differences.

The model-assisted state-space model also does a good job of permitting the mean finite rate of change to vary over time. For example, the mean rate of change during 2004–2009 was 0.935 (95% CI = 0.859–1.020) compared to the steep decline during 2010–2013 (mean = 0.857, 95% CI = 0.783–0.934) and the more recent (2014–2026) period of stability (1.014, 95% CI = 0.973–1.054; Figure 6). This is accomplished by modeling the finite rate of change as a random variable from a normal distribution with an estimated mean of 0.968 and a relatively large estimated standard deviation of 0.144.

Conclusions

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

2. The model-assisted estimator (approach 2, state-space model) allows the sharing of information among years which 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 design-based method (approach 1, HT) because of high sampling uncertainty (e.g., the sample data may not be representative in some years). Thus, regardless of whether we use the design-based or model-assisted 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 (design-based versus model-assisted), the big-picture conclusions are consistent for the 2005-2026 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 3,600–3,800 moose). However, these trends are easier to visualize using the model-assisted state-space model. This is further demonstrated by estimates of calf-cow ratios (Figure 7), where large annual variation in design-based estimates (HT) makes it hard to detect underlying trends. Do note that state-space models currently do not seem to improve the precision of compositional ratios, because abundance estimates for specific population segments (bulls, cows, calves) used in the calculation of composition ratios come with a certain degree of uncertainty themselves.

4. Compared to the design-based estimator (approach 1, HT), the model-assisted state-space model (approach 2) 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, and spatially explicit population estimates.

5. The state-space model (approach 2) is simple to fit and easy to explain. Nevertheless, historic population estimates can change (albeit trivially in most cases) with the addition of new data (years) or if model and/or distributional assumptions are modified in the future. However, values derived using the design-based estimator (approach 1) are estimates too; the only reason they do not change is that we treat each year as independent in the design-based approach (i.e., the estimates ignore potentially useful information from surveys in adjacent years).

6. The fully model-based Bayesian model (approach 3) is currently in development but could provide important benefits in the long term. It would provide an intuitive way of modeling smoothed population trajectories of individual population segments (bulls, cows, calves) by directly modeling the number of moose groups, group size, and group composition, and would allow the estimation of covariate effects (e.g., weather, habitat conditions) on each of those three parameters. Furthermore, implementing potential breakpoints in the

population trajectory into the analysis would be straightforward. Finally, a fully model-based Bayesian approach could account for spatial covariates (e.g., habitat data) and generate spatially explicit population estimates. Whether this is feasible and what levels of uncertainty we can expect when generating sub-regional population estimates is another area of potential research and advancement.

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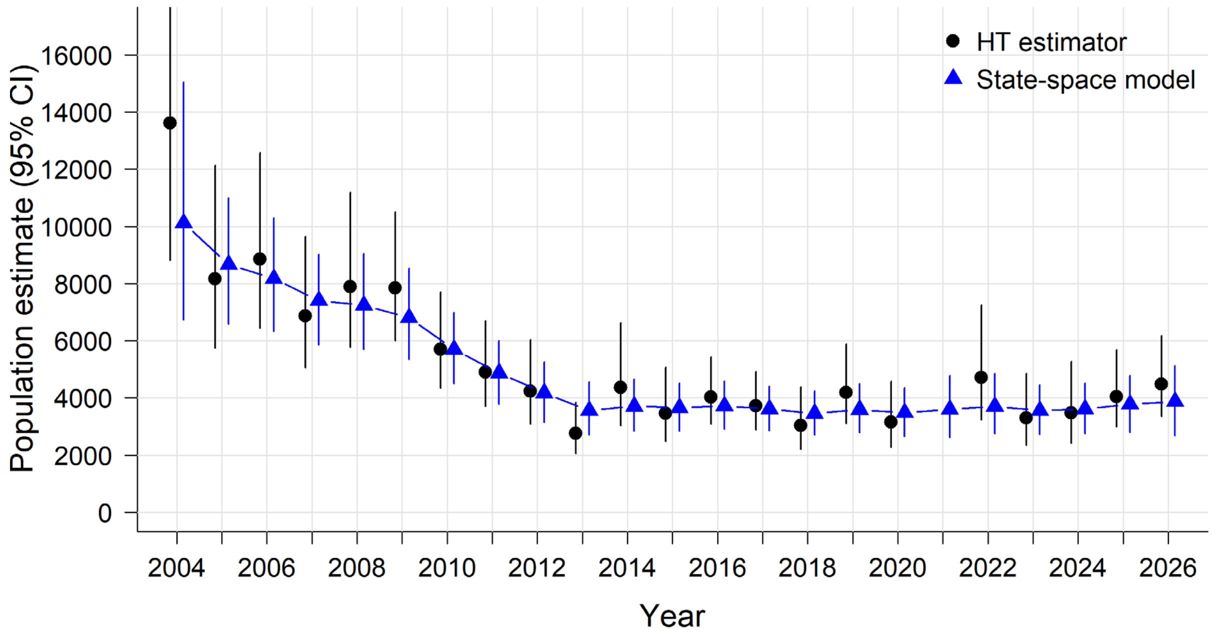

Figure 5: Aerial-survey estimates (with 95% CIs) of moose abundance in NE Minnesota, 2004–2026, estimated using a Horvitz-Thompson (HT) estimator (design-based, approach 1, black circles) or a Bayesian state-space model (model-assisted estimator, approach 2, blue triangles). A HT-estimator-based population estimate is missing for 2021, because the survey was not conducted in 2021 due to the Covid-19 pandemic.

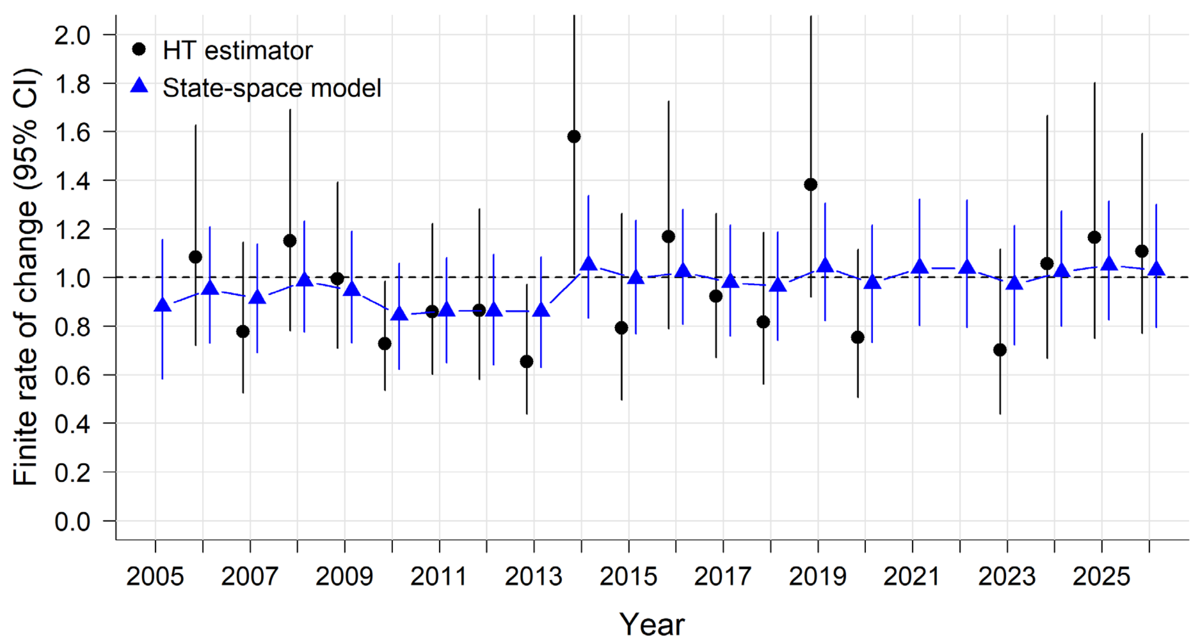

Figure 6: Finite rates of change (lambda; with 95% CIs) of moose abundance in NE Minnesota, 2004–2026, estimated using a Horvitz-Thompson (HT) estimator (design-based, approach 1, black circles) or a Bayesian state-space model (model-assisted estimator, approach 2, blue triangles). HT-estimator-based estimates of lambda are missing for 2021 and 2022, because the survey was not conducted in 2021 due to the Covid-19 pandemic.

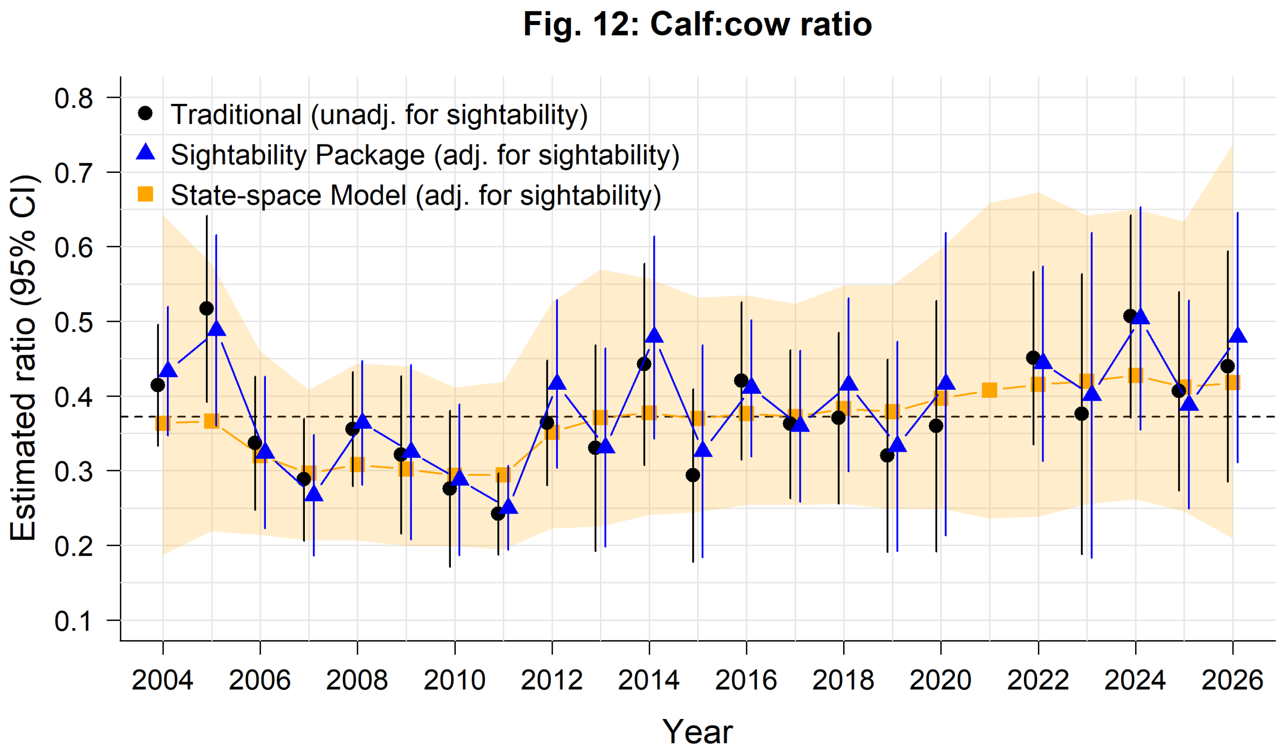

Figure 7: Aerial-survey estimates (with 95% CIs) of cow-calf ratios in NE Minnesota, 2004–2026, estimated using traditional methods that do not account for sightability (black circles), a Horvitz-Thompson estimator using the sightability package (design-based estimator, approach 1, blue triangles), or a Bayesian state-space model (model-assisted estimator, approach 2, orange squares). The dashed black line represents the long-term (2004–2026) average of the traditional cow-calf ratio estimates. Traditional and HT-estimator-based ratios are missing for 2021, because the survey was not conducted in 2021 due to the Covid-19 pandemic.