Received: 8 May 2024 | Revised: 7 August 2024 | Accepted: 19 August 2024

DOI: 10.1002/wsb.1555

WILDLIFE SOCIETY BULLETIN Open Access

RESEARCH ARTICLE

Changing snow conditions are challenging moose (*Alces alces*) surveys in Alaska

Todd J. Brinkman[1] | **Kalin A. Kellie**[1] | **Adele K. Reinking**[2] | **Glen E. Liston**[2] | **Natalie T. Boelman**[3]

[1]Institute of Arctic Biology, University of Alaska Fairbanks, 2140 Koyukuk Dr., Fairbanks, AK 99775, USA

[2]Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, CO 80523, USA

[3]Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY 10964, USA

Correspondence
Todd J. Brinkman, Institute of Arctic Biology, University of Alaska Fairbanks, 2140 Koyukuk Dr., Fairbanks, AK 99775, USA.
Email: tjbrinkman@alaska.edu

Funding information
NASA Arctic-Boreal Vulnerability Experiment, Grant/Award Number: 80NSSC19M0109

Abstract

Snow conditions are changing rapidly across our planet, which has important implications for wildlife managers. In Alaska, USA, the later arrival of snow is challenging wildlife managers' ability to conduct aerial fall (autumn) moose (*Alces alces*) surveys. Complete snow cover is required to reliably detect and count moose using visual observation from an aircraft. With inadequate snow to help generate high-quality moose survey data, it is difficult for managers to determine if they are effectively meeting population goals and optimizing hunting opportunities. We quantified past relationships and projected future trends between snow conditions and moose survey success across 7 different moose management areas in Alaska using 32 years (1987–2019) of moose survey data and modeled snow data. We found that modeled mean snow depth was 15 cm (SD = 11) when moose surveys were initiated, and snow depths were greater in years when surveys were completed compared to years when surveys were canceled. Further, we found that mean snow depth toward the beginning of the survey season (1 November) was the best predictor of whether a survey was completed in any given year. Based on modeled conditions, the trend in mean snow depth on 1 November declined from 1980 to 2020 in 5 out of 7 survey areas. These findings, coupled with future projections, indicated that by 2055, the delayed onset of adequate snow accumulation in the fall will prevent the completion of moose surveys over roughly 60% of Alaska's managed moose areas at this time of the year. Our findings can be used by wildlife managers to guide decisions related to the future reliability of aerial fall moose surveys and help to identify timelines for development of alternate measurement and monitoring methods.

KEYWORDS

Alces alces, climate change, future projections, management, moose, population surveys, snow

INTRODUCTION

As a result of climate change, snow conditions are changing rapidly throughout the Circumpolar North (Bokhorst et al. 2016). In general, the spatial extent, temporal duration, and thickness of snow have declined over the last 50 years (Bokhorst et al. 2016, Pulliainen et al. 2020, Mudryk et al. 2021). Snow conditions are likely to continue to decline over the next century based on climate projections (Intergovernmental Panel on Climate Change 2023). The effects of snow changes on wildlife and their habitat are poorly understood (Berteaux et al. 2016, Niittynen et al. 2018, Boelman et al. 2019, Reinking et al. 2022), and even less is known about the impacts of altered snow patterns on wildlife management programs. This is concerning because many wildlife research and monitoring techniques (e.g., snow-track surveys, E-DNA collection, animal capture by helicopter, density estimates) require certain snow conditions for successful implementation (Jacques et al. 2009, Squires et al. 2012, Franklin et al. 2019). As an example, management programs relying on visual detection using aerial wildlife surveys during winter may be particularly vulnerable to reduced snow because of the role snow cover plays in improving animal detection (Kellie et al. 2019, Delisle et al. 2023). An understanding of the relationships between snow and the success of research and monitoring techniques is therefore critical, because it may help wildlife managers prepare for and adapt monitoring programs in response to changing snow conditions.

In Alaska, changes in the onset and persistence of accumulated snow are already hindering well-established monitoring techniques for estimating moose (*Alces alces*) population density and demographics. This is particularly true of fall (autumn) aerial surveys that depend on snow to provide a white backdrop that improves visual detection of these dark-colored ungulates when viewed from above. Increasingly unpredictable snow conditions in the fall are challenging managers' ability to conduct surveys aimed at estimating population density and composition (i.e., age and sex). In a recent poll of Alaska moose managers, inadequate snow cover was identified as the primary reason that surveys were canceled (Kellie et al. 2019). Incomplete snow coverage (i.e., typically deep enough snow to cover the ground or vegetative surface) reduces the visual contrast between the ground and the moose, reducing an observer's ability to detect the animals, thereby inflating uncertainty in population-level estimates (Christ 2011, Kellie et al. 2019). Historically, moose surveys were initiated in mid-October of each year because adequate snow accumulation was uncommon before then (Olsson et al. 2003), and to avoid aircraft disturbance during both the regulated hunting season (typically in September; Alaska Department of Fish and Game 2023) and the peak of moose breeding season (late September–early October). Surveys end in mid-December because, in more northerly locations, the duration of daylight becomes too short (<5 hours; Kellie and DeLong 2006) to complete moose survey protocols, and moose begin shedding their antlers (~15 December), which prevents visual collection of critical data on sex and the age of male moose because antler width is used as an index of age (Young and Boertje 2018). In Alaska, distinguishing sex using secondary characteristics (e.g., body size and vulva patch) can be challenging because aerial surveys are conducted from fast-moving (129–145 kph), fixed-wing aircraft that are flying at altitudes ranging 90–215 m above the ground (Kellie and DeLong 2006). The vulva patch can be relatively small on some female moose, difficult to see when the moose is bedded, and obscured when snow accumulates on the fur (Oswald 1998). However, moose survey protocols outside of Alaska have reliably used the vulva patch on female moose to identify sex (Alberta Sustainable Resource Development Fish and Wildlife Division 2010).

Without adequate estimates of moose density and demography, it is difficult for managers to determine if they are effectively meeting population goals while also optimizing hunting opportunities. For example, high uncertainty in moose density estimates may force managers to err on the side of caution by restricting hunting opportunities to avoid the risk of overharvest (Boyce et al. 2012). Although moose managers in Alaska recognize that dynamics in snow conditions strongly influence their ability to conduct fall surveys (Kellie et al. 2019), the quantitative association between snow conditions and moose survey success has not been assessed. Such information can facilitate planning for future monitoring efforts, which is especially important in Alaska and northern Canada where temperatures are increasing 2–3 times faster than the global average, and the onset of winter conditions is increasingly delayed (Box et al. 2019).

The overarching goal of our study is to gain quantitative understanding of how past and future dynamics in fall snow conditions have and will influence(d) the feasibility of aerial moose population surveys in Alaska. To achieve this goal, we have 2 objectives: 1) estimate and describe past relationships between modeled snow conditions and successful completion of moose surveys in the fall; and 2) make spatially and temporally explicit projections of the future probability of successful aerial moose surveys as fall snow conditions continue to deteriorate. In addition to the direct implications of our study on moose population management, by having snow scientists and wildlife managers working closely together we demonstrate a novel collaborative approach that can be applied to other wildlife species and monitoring programs in ecosystems where snow plays an important role (Magoun et al. 2007, Pedersen et al. 2021, O'Donoghue et al. 2022, Reinking et al. 2022).

STUDY AREA

We assessed the relationships between modeled snow conditions and completion of fall aerial moose surveys in 7 survey areas across 6 Game Management Unit (GMU) subunits in Alaska, USA: 14A, 15A, 18, 20A, 20D South, and 25D East and 25D West (Figure 1). We selected survey areas based on the following criteria: 1) opportunity to capture spatial variation in fall snow conditions across moose survey areas; 2) availability of consistent and long-term moose survey data; and 3) interest in project participation from local area biologists. There are 9 major climate divisions within the moose range of Alaska (Bieniek et al. 2012) and our 7 survey areas capture 5 of those divisions. The 5 climate divisions captured encompass the vast majority (≈80–90%) of area where long-term data on moose aerial surveys exists. Our survey areas do not adequately represent the North Slope division (area north of Brooks Mountain Range), the coastal areas along the gulf of southern Alaska, and the Bristol Bay division (southwest Alaska including northern part of the Aleutian chain; see Bieniek et al. [2012] for specific locations). Therefore, our survey areas are representative of climatic regions in the core area of moose range where surveys are most common, but do not adequately represent areas where moose have expanded into in recent decades (Tape et al. 2016). However, snow onset and accumulation in moose habitat (elevations <750 m) in these underrepresented areas are similar to our study sites (Lader et al. 2020).

Our survey areas covered 64,432 km^2 and were located primarily in boreal forest. This ecotype is a mix of coniferous (white spruce [*Picea glauca*] and black spruce [*P. mariana*]) and deciduous (birch [*Betula papyrifera*], aspen [*Populus* spp.], and willow [*Salix* spp.]) forest with low-lying lakes, wetlands, scrub bogs, and herbaceous meadows (Chapin et al. 2006). Other dominant large mammals within survey areas include grizzly bears (*Ursus arctos*), black bears (*U. americanus*), and wolves (*Canis lupus*), with some overlap with caribou (*Rangifer tarandus*) populations. Mean daily high temperatures (1981–2010) at the beginning (mid-October) and end (mid-December) of moose surveys were 5.8°C and −3.5°C, respectively, in our most southern area (15 A), and −3.4°C and −17.8°C,

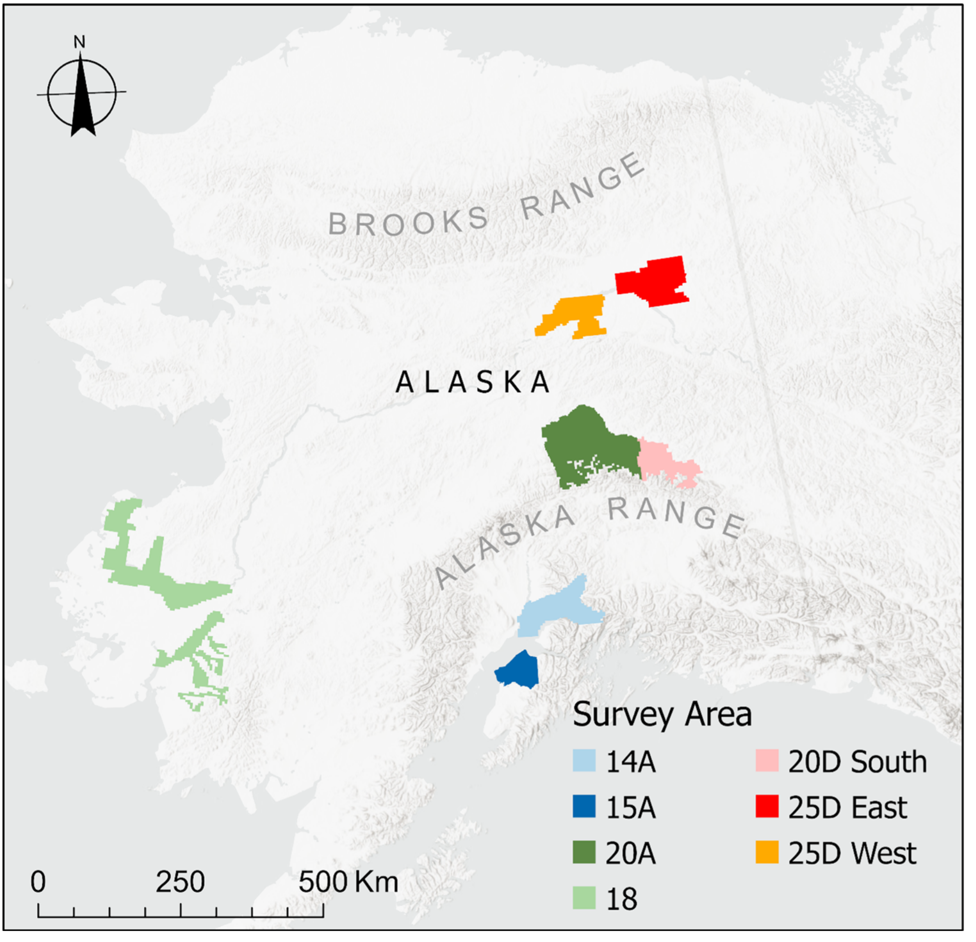

FIGURE 1 Seven moose management areas in Alaska, USA, where we assessed the associations between snow conditions and completion of fall moose surveys, from 1987 to 2019.

respectively in our most northern areas (25D East and West; Western Regional Climate Center 2023). Duration of daylight at the end of the moose survey season (15 December) was 5 hrs 45 min at our most southern area (15A) and 2 hrs 21 min at our most northern areas (25D East and West).

METHODS

Moose surveys

Moose surveys were conducted from an aerial platform, such as a fixed-wing Piper Super Cub or Bellanca Scout, and survey protocols were implemented after complete snow cover. Survey techniques changed throughout our study period as computers and navigation systems became more sophisticated. Until the late 1980s, biologists conducted complete census of large units (i.e., trend count areas) using topographic maps for navigation. Later, in the early 1990s, surveys encompassed trend count areas by larger survey areas, divided the entire area into similarly-sized units, and adopted a stratified random sampling design (Gasaway et al. 1986). Finally, in the early 2000s, when global positioning system (GPS) units became common in small aircraft, a survey technique was adopted that allowed navigation of randomly-sampled, rectangular units along lines of latitude and longitude (Kellie and DeLong 2006). Survey units excluded areas that are not commonly used by moose (e.g., elevations >750 m). Usually, the goal of a moose survey was to estimate moose density and composition (i.e., age, sex). However, biologists sometimes only attempted to collect composition data for a variety of reasons, including short weather windows, pilot availability, marginal snow conditions, or budgetary constraints. When these conditions could not be surmounted, biologists sometimes canceled surveys altogether. Agency reports usually provided a qualitative assessment of survey conditions and an explanation of the reasoning for incomplete or canceled surveys.

Most moose surveys require 5–10 flying days per survey area and time varies with weather conditions, length of daylight, and distance of area from takeoff location (Kellie and DeLong 2006). Each aircraft carries a single pilot-observer pair and the number of aircraft (1–5) depends on survey area size. Aircraft fly at an altitude of 90–215 m and maintain an average airspeed of approximately 129–154 kph to efficiently cover survey units. Survey areas contain multiple units and each pilot-observer team can survey 5–6 units per day at the recommended search intensity of 3–4 min/km^2. The pilot-observer team documented moose detections on a standardized moose census form (Kellie and DeLong 2006) that distinguishes moose sex, age, and if cows are accompanied by calves. The form also requires the pilot-observer team to record who the observers were (accounts for observer experience), rate the quality of the survey (excellent, good, fair, poor), and characterize search conditions (e.g., snow conditions, light intensity, habitat type). Direct observations of moose are recorded and density estimates include a sightability correction factor established by Gasaway et al. (1986).

Moose survey areas

We referenced agency reports and worked with biologists in 7 different moose survey areas throughout Alaska (Figure 1) to compile annual information detailing if and when fall moose surveys were conducted between 1987 and 2019. If aerial surveys were scheduled but canceled, we used agency reports to determine if the cancellation was explicitly tied to poor snow conditions. Only snow-specific cancellations explicitly mentioned in reports were included as canceled samples in our dataset. We censored area-years where surveys were not conducted and the reason unspecified, or where reasons were unrelated to snow conditions, such as cancellations because of limited pilot availability or budget constraints. In our dataset, we recorded the following information: year, whether a moose survey was completed or canceled in the fall, start and end date of completed survey, survey type (e.g., population estimate, trend count, composition), comments on snow conditions in report, and citation of where data were found. After we compiled publicly available information, we shared the dataset with the biologists currently managing each survey area. Area biologists provided a careful review of summarized data and cancellation/survey information for recent surveys not yet available in reports. We considered the dataset finalized after receiving confirmation of accuracy of moose survey years and approval from biologists within each survey area.

Modeling snow conditions

We used SnowModel (Liston and Elder 2006) to generate daily snow information for the survey season (15 October–15 December) for each year (1987–2019) that moose surveys were planned in each survey area. SnowModel consists of a suite of modeling tools that can be used to produce fit-for-purpose environmental and snow-related datasets at user-defined spatial and temporal scales (Liston et al. 2020). SnowModel applications have used spatial resolutions ranging from 1 m × 1 m to 25 km × 25 km, over spatial domains ranging from single points to continental, and over temporal periods ranging from hours to decades. The SnowModel system combines meteorological (i.e., weather) data with topographic and land cover inputs to simulate, in realistic and physics-based ways, snow distribution and evolution processes, such as surface energy exchanges and snowmelt, or snow redistribution by wind (Liston et al. 2007). SnowModel inputs included the following: 1) meteorological information via National Aeronautics and Space Administration (NASA) Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2; Gelaro et al. 2017), which included air temperature, precipitation, relative humidity, wind speed, and wind direction forcing data; 2) topographic information from United States Geological Survey (USGS) 3D Elevation program (3DEP; Stoker and Miller 2022) digital elevation model products; and 3) land cover data from the North American Land Change Monitoring System (NALCMS; Commission for Environmental Cooperation 2010) land cover classification data. To ensure that SnowModel outputs were representative of observed snow conditions, we assimilated (i.e., synthesized using SnowAssim sub-model; Liston and Hiemstra 2008) Natural Resources Conservation Service (NRCS) Snow Telemetry (SNOTEL) snow water equivalent (SWE) and temperature observations (Serreze et al. 1999). These data allowed us to more accurately quantify the precipitation inputs contributing to simulated snowfall and more closely match the spatial distribution of observed snow onset dates in resulting model outputs. A thorough discussion of the 174 equations meant to numerically represent real-world processes controlling snow property distributions and evolutions, as well as a detailed review of SnowModel limitations and uncertainties, are provided by Liston et al. (2020).

We produced daily snow variables during 1980–2020 at a 180 m × 180 m spatial resolution within moose survey GMUs. This spatial scale was selected to balance the goal of an accurate representation of snow conditions with the spatial scale at which these snow processes are likely to be relevant for moose (Reinking et al. 2022). The snow variables produced included snow depth and snow-covered fraction; these were selected because of their likely role in contributing to the effective whiteness of the landscape. To calculate the snow-covered fraction, we determined the proportion of each 30 m × 30 m sub-grid cell within each 180 m × 180 m simulation cell (i.e., $n = 36$) for which snow depth was greater than the height of vegetation. The canopy heights assigned to each NALCMS land cover class (used in SnowModel to represent snow-holding depths) were used as the vegetation height values; these assigned canopy heights are based on typical heights for each land cover classification (Liston and Elder 2006).

For our analysis, we averaged daily snow variables within the moose survey boundary. Because these boundaries changed over time, we clipped SnowModel raster layers to a year-specific mask defined by the boundary of surveyed areas for whole-area surveys (e.g., trend counts and composition surveys) or a dissolved outer boundary of all units if a random sampling design was used. To mask SnowModel raster layers during years where surveys were canceled, we used the intended survey boundary, which was derived from a combination of report descriptions and prior and subsequent surveys.

Similar to our moose survey dataset, initial SnowModel outputs were shared with participating biologists in each survey area. Consultation with these biologists helped us qualitatively assess the accuracy and utility of the model outputs, and to improve SnowModel products in iterative, subsequent simulations. For example, discussions with local biologists about initial SnowModel outputs revealed that because the time period of interest was the early snow accumulation season, it was crucial to ensure correct modeling of early season snow evolution. This focus on earlier snow accumulation periods guided the assimilation methods used to integrate observational data with the model. To accurately simulate snow onset date and ensure that precipitation was beginning to fall as snow instead of rain at the correct time of year, we adjusted air temperature inputs based on SNOTEL station observations. The result was improved correlation with both ground station data and the biologists' documented experiences.

Statistical analysis

All statistical analyses were performed in the computer program R (R Core Team 2023). For the years that moose surveys were completed, we used a one-way ANOVA to determine whether survey initiation date differed among survey areas (Chambers et al. 1992). We then used a mixed linear regression model with survey area as a random effect to understand whether there was a trend in the start date of moose surveys over time (lmer function of lme4 package, v. 4.3.1; Bates et al. 2015). We used effect sizes (eta-squared [η^2]; Cohen 1988) from a Mann-Whitney U Test to estimate whether snow variables differed between canceled and completed survey years on 2-week intervals (e.g., 15 Oct, 1 Nov, 15 Nov) throughout the survey season. We assumed negligible, small, moderate, and large effect sizes (eta-squared [n^2]) to be <0.01, >0.01–<0.06, >0.06–<0.14, and >0.14, respectively (Cohen 1988).

We examined whether SnowModel variables could explain the probability of completing or canceling a survey by formulating logistic regression models for mixed effects fit by maximum likelihood using the Laplace approximation (glmer function of lme4 package; Agresti 2013). The canceled/completed survey outcome was the 0/1 binary response, and the snow variable on the analysis date was the fixed effect. Survey initiation dates were absent for canceled surveys, so we analyzed dates every 2 weeks throughout the survey season (15 October–15 December). Survey type was excluded from models because this variable was absent for canceled surveys. We determined whether survey area should be included as a random effect in the model using a Kruskal-Wallis approach (Kruskal and Wallis 1952) to test for differences in snow variables among survey areas. We used Pearson's method to assess correlation between snow variables and among analysis dates to determine which variables could be combined in models. We selected the model that best described the data using the Akaike's Information Criterion corrected for small sample size (AIC_c; Burnham and Anderson 2002). We used the Conditional R^2 to describe the proportion of variance explained by both the fixed and random effects (Johnson 2014). We predicted separate survey probability curves for each random effect group, and the average change in probability across all groups relative to the snow variable, using a multilevel bootstrapping approach and 1,000 samples with replacement for each group level (Agresti 2013). Our data were too sparse to split into training and testing data, so we assessed the accuracy of our top model using a bootstrapping approach with k-fold cross-validation with 5 folds and 1,000 bootstrap samples ($k = 5$ folds, $n = 1{,}000$ bootstrap samples; performance package; Lüdecke et al. 2021).

Past and future trends of fall survey conditions

We examined past trends in snow variables from 1980 to 2020 using the survey season date from the model that best explained survey outcome. We clipped snow raster layers in each area to the most recent survey boundary for each year from 1980 to 2020 and calculated the mean pixel value. For each study area, we examined trends in snow over time using a Mann-Kendall test ($\alpha = 0.05$), modified by Hamed and Rao (1998) to correct for serial correlation (modifiedmk package) and calculated the magnitude of trend using a Thiel-Sen estimate of slope (Sen 1968; zyp package). The Mann-Kendall trend test (Mann 1945, Kendall 1975) is a nonparametric, rank-based approach widely used to test for significant trends in meteorological data such as precipitation (Kliengchuay et al. 2024) and snow depth (Sadeqi et al. 2024).

We forecasted the near-future (30-year; 2025–2055) trends in completing a moose survey across the entire state of Alaska at a 4-km × 4-km spatial resolution. We assumed that the recent (past 15-year; 2005–2020) trajectory in the trend in modeled mean snow depth on the initiation date of completed surveys would continue into the future at a consistent slope. We used our modeled trends to produce future projections, rather than running predictive SnowModel simulations driven with global climate model data, run under different greenhouse gas scenarios (though see Greaves et al. 2023 for an example of using SnowModel with climate projections for an Alaska application). This method was selected because of its grounding in local, recent observation history. Moreover, using observed trends over our time frame avoided many of the issues inherent in projected climate data, including coarse spatial or temporal resolution (e.g., 20 km x 20 km grid cells or monthly wind speeds) or uncertainty values that are larger than the projected changes (Walsh et al. 2018). For a survey to be completed in the future, we assumed 2 survey conditions needed to be met each year by the end (15 December) of the fall survey season. First, the forecasted snow depth needed to reach the overall mean modeled snow depth estimated across our 7 study sites at the initiation date of past completed surveys. Second, there needed to be enough (i.e.,

≥5) daylight hours in the specific area (pixel location) to ensure adequate light to complete a survey. In addition, we imposed the requirement that the grid cell had an elevation ≤750 m (therefore considered possible moose habitat under current conditions). We assumed that if the required snow depth and daylight conditions were not met by 15 December in a grid cell during a future year, then fall surveys would no longer be feasible in that location. If these conditions were met in a grid cell by 15 December for every future year, we assumed that fall moose surveys would be a viable option in that location, at least through 2055. Within each raster cell, we estimated the number of years until fall moose surveys will no longer be feasible (i.e., year when required conditions are no longer met).

RESULTS

SnowModel data

To evaluate SnowModel output uncertainty relative to observational snow data, we compared SnowModel-produced snow onset dates and daily snow depths (cm) to observed values in the 6 study areas containing a SNOTEL station (all areas excluding GMU 18). For all years and those 6 study areas, the average observed snow onset date was 17 October ($\bar{x}$ day of year = 291.7; SE ± 1.19), and the average modeled snow onset date was 18 October ($\bar{x}$ day of year = 292.7; SE ± 1.23). The correlation (r) between observed and modeled snow onset date was 0.99, with an R^2 value of 0.97. Similar performance was observed in our assessment of daily snow depths. Across years and study areas, the average SNOTEL-measured daily snow depth was 11.44 cm (SE ± 0.07) and the average SnowModel-produced daily snow depth was 11.32 cm (SE ± 0.06). The correlation (r) between observed and modeled snow depths was 0.88, with an R^2 value of 0.78 (Figure 2).

Moose surveys

We assessed 170 moose survey years (129 completed, 41 canceled) across 7 survey areas between 1987 and 2019 (Table 1). The mean start date for all completed surveys was 12 November (SD = 12) and differed by 20 days among survey areas from 1 November (SD = 8) in GMU 25D East to 20 November in GMU 18 (SD = 12; Table 1). Mean start date was significantly different among survey areas (one-way ANOVA, $F_{6,122} = 6.961$, $P < 0.001$), but there was no significant trend in the survey start date over the study period (slope = 0.2, Marginal R^2/Conditional R^2 = 0.021/0.268, $P = 0.064$). Across all survey areas, mean modeled snow depth was 15 cm (SD = 11) and snow-covered fraction was 33% (SD = 19%) on survey start date (Table 1).

Snow-covered fractions were similar (n^2 effect size = <0.01 to 0.02) between completed and canceled surveys during 2-week interval dates from the beginning (15 October) to end (15 December) of the season (Figure 3). Therefore, snow-covered fractions were not included in further analysis. Snow depths were greater on each 2-week interval date (n^2 effect size = 0.05 to 0.08) during completed surveys as compared to canceled (Figure 3). Snow depths were highly correlated across 2-week interval dates (r = 0.41 to 0.98), so univariate logistic models were performed for each interval date. We found differences among survey areas for snow depth ($\chi^{26} = 71$ $P < 0.001$), so we included survey area as a random effect in all models. Our top 3 models included snow depth during the earliest analysis dates (Table 2). Our model including snow depth on 1 November best explained survey outcome, with the odds of completing a survey increasing by a factor of 1.21 (CI = 1.08–1.37) for every 1-cm increase in snow depth on that date. Although the initial probability of conducting a moose survey varied among survey areas from 28% to 62%, all models displayed a probability of >90% when modeled snow depth on 1 November is >20 cm (Figure 4A). When the probability of surveying is averaged over all survey areas, the lower confidence interval of survey probability ($\alpha = 0.05$) crosses the 90% threshold when snow depth is >15 cm on 1 November (Figure 4B). This model had a 68.7% estimated accuracy ($\alpha = 0.05$, CI = 61.5%–80.2%).

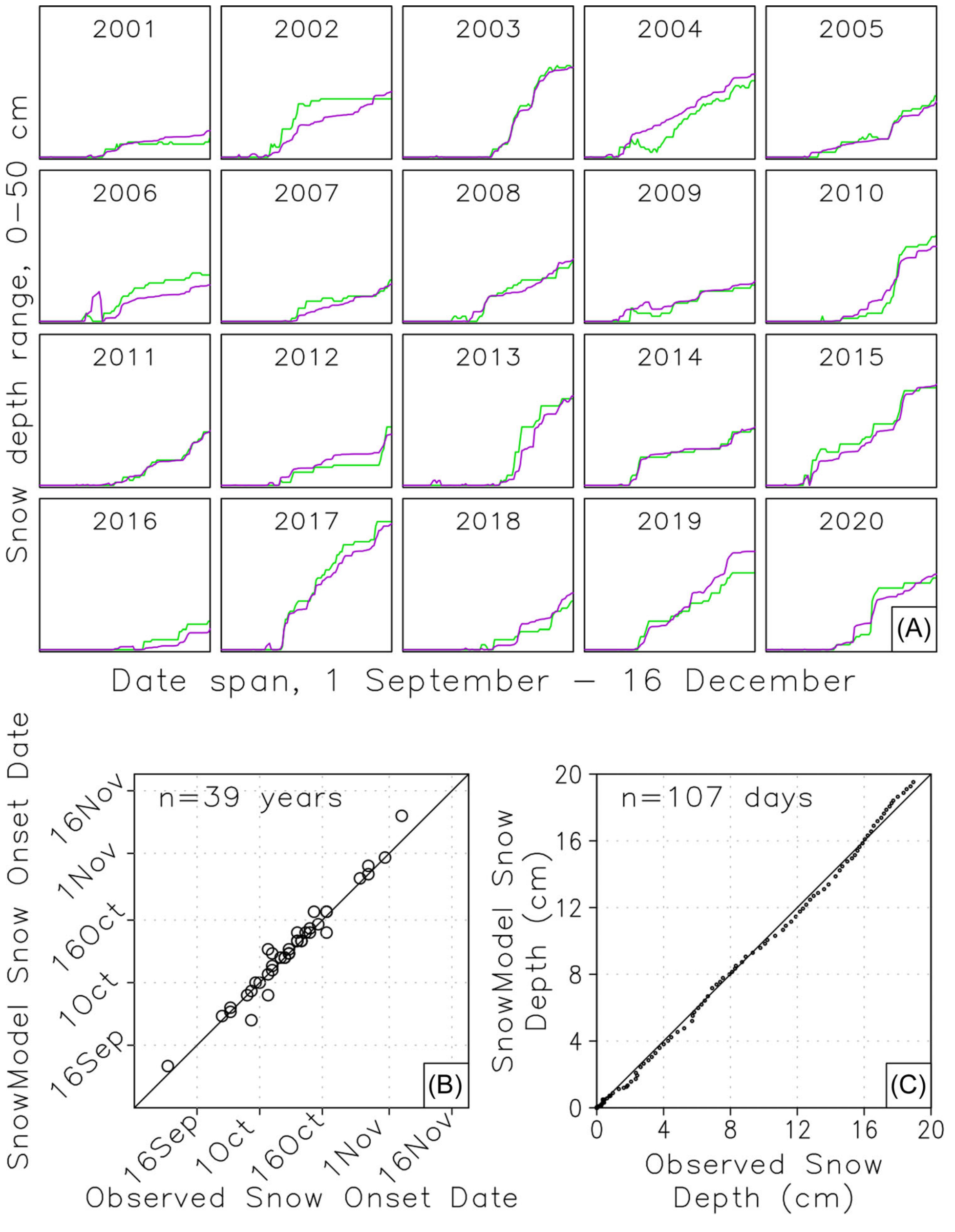

FIGURE 2 The relationships between observed snow depths and estimated snow depth using SnowModel for one moose management area in Interior Alaska. (A) The upper 20 small panels display the daily snow onset and snow depth progression (green = observations, purple = SnowModel) for the entirety of Game Management Unit 25D (this includes 2 of our 7 study areas: 25D East and 25D West), for the 20 most recent simulation years (2001–2020). The x-axis (date) in each panel spans from 1 September through 16 December, and the y-axis (snow depth) in each panel spans from 0 cm to 50 cm. (B) Observed and simulated snow onset date (2 of the 41 simulation years did not have snow-onset observations, thus $n = 39$ years). (C) Observed and simulated snow depth (cm), averaged over all years and all observations for each day from 1 September through 16 December (107 days each year).

TABLE 1 Sample sizes of completed and canceled fall moose surveys and mean survey start date (SD in days), mean modeled snow-covered fraction percent, and mean modeled snow depths in cm in 7 survey areas across Alaska, USA, 1987–2019.

Survey area	Canceled (*n*)	Completed (*n*)	Total (*n*)	Survey start date (SD)	Snow-covered fraction (SD)	Snow depth (SD)
14A	6	19	25	17 Nov (13)	62.0 (20.5)	31 (15)
15A	6	24	30	18 Nov (11)	15.5 (4.2)	7 (3)
18	4	10	14	20 Nov (12)	43.0 (26.9)	20 (11)
20A	6	22	28	11 Nov (11)	23.9 (14.0)	15 (5)
20D South	3	24	27	07 Nov (8)	41.2 (4.4)	17 (8)
25D East	6	16	22	01 Nov (8)	28.1 (8.8)	7 (4)
25D West	10	14	24	10 Nov (10)	26.1 (6.6)	10 (3)
All	41	129	170	12 Nov (12)	33.4 (19.7)	15 (11)

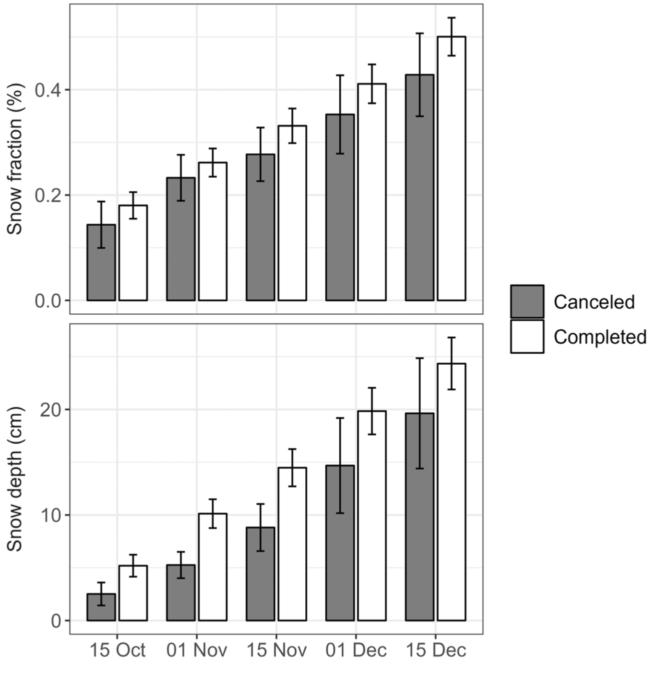

FIGURE 3 Mean modeled (A) snow-covered fraction (%) and (B) snow depth (cm) during 2-week interval dates from beginning (15 October) to end (15 December) of fall moose surveys in Alaska, USA. Figure data include all survey areas ($n = 7$) and years (1987–2019) where survey outcomes (completed $n = 129$, or canceled $n = 41$) were recorded.

Past and future trends in fall survey conditions

The snow depth on 1 November decreased significantly (i.e., $P < 0.05$, $\alpha = 0.05$) from 1980 to 2020 in 5 of 7 study areas, and the magnitude of change differed greatly among these 5 areas (Figure 5). The largest decrease (slope = −0.75) was in GMU 14A, where modeled snow depth on 1 November decreased ~30 cm over the 41-year

TABLE 2 A comparison of performance among univariate logistic regression models explaining survey outcome (canceled versus completed) using snow depth (SD) on 2-week interval dates throughout the fall moose survey season (15 October–15 December) in Alaska, USA, 1987–2019. Survey data were collected in 7 different survey areas and survey area was included in all models as a random effect. We used the Conditional R^2 estimates, Akaike Information Criterion corrected for small sample size (AIC_c), change in AIC_c, model weight (w_i), and variable effects (odds ratio) to compare model fit.

Model variable	R^2	AIC_c	ΔAIC_c	w_i	Odds ratio	SE	P
SD (1 Nov)	0.423	173.8	0	0.943	1.21	0.07	0.001
SD (15 Nov)	0.285	179.6	5.8	0.051	1.11	0.04	0.004
SD (15 Oct)	0.146	184.7	10.9	0.004	1.14	0.06	0.013
SD (1 Dec)	0.092	188.3	14.5	<0.001	1.04	0.02	0.04
SD (15 Dec)	0.051	190.4	16.6	<0.001	1.03	0.02	0.086

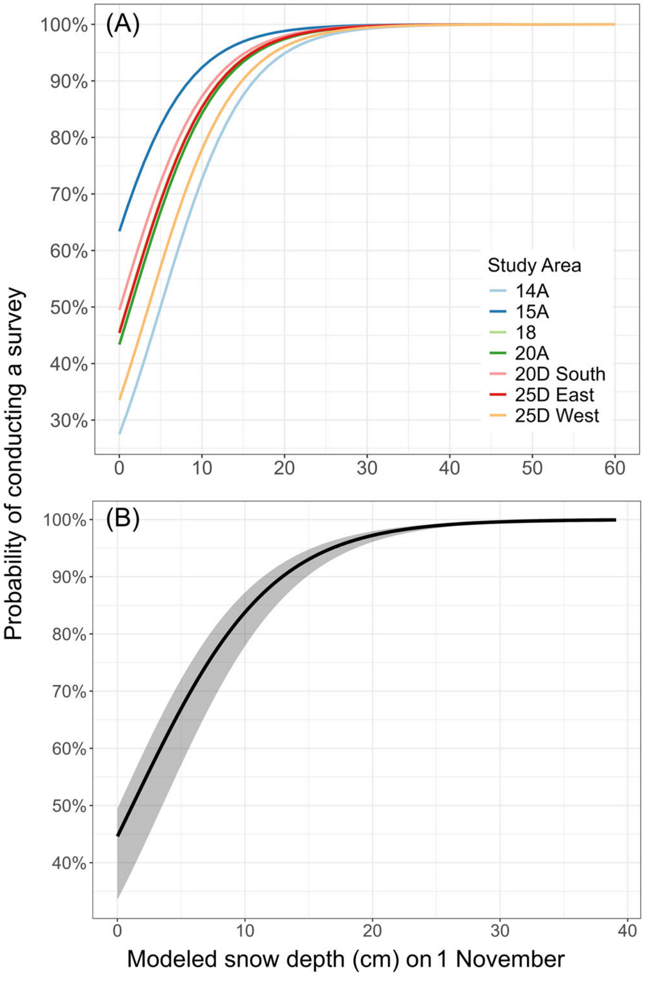

FIGURE 4 Predicted probability of completing a fall moose survey in Alaska, USA, at different modeled snow depths on 15 November, displayed as (A) differences in survey probability among moose survey areas (i.e., random effect groups), and (B) the average change in survey probability across all survey areas, with 25% and 75% quantiles depicted in gray.

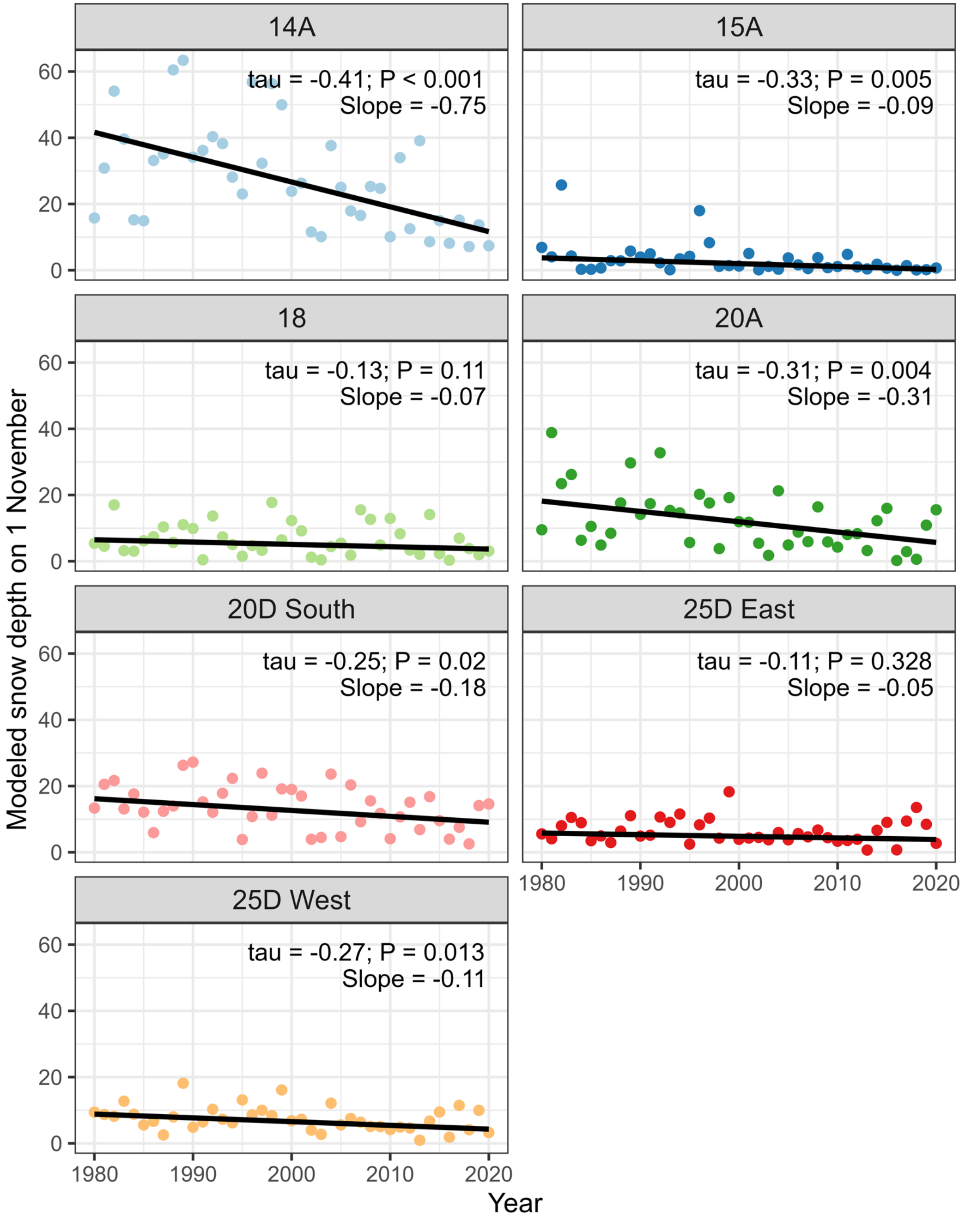

FIGURE 5 Trends in modeled mean snow depth on 1 Nov during 1980–2020 for 7 moose survey areas across Alaska, USA. Raw mean snow depths are plotted as points and overlayed with Sen's Slope lines to illustrate the magnitude of change. Data were analyzed using modified Mann-Kendall tests.

period (Figure 5). In contrast, 15A experienced a relatively small decrease in snow depth (slope = −0.09; Figure 5) during the same period.

Recent trends (2005–2020) indicated that the date at which snow depths reach 15 cm is arriving up to 14 days later (nearly one day later each year) in some of our study sites (Figure 6). We used the overall mean modeled snow depth

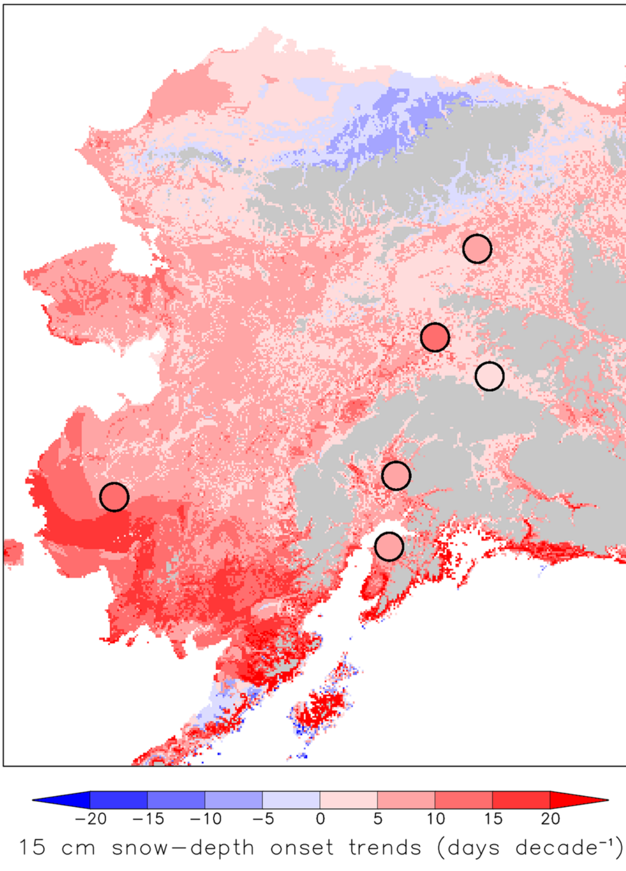

FIGURE 6 Trends (converted to days per decade) in onset date of 15-cm snow depth (redder color shades represent delayed snow onset, bluer color shades represent earlier snow onset) over 15 years (2005–2020) obtained by modeling snow conditions in moose range across Alaska, USA. Positive numbers indicate a delayed onset. The colored circles surrounded by black rings are the corresponding trends calculated from Natural Resource Conservation Service Snow Telemetry (SNOTEL) observations. The gray areas are elevations >750 m that are assumed to be habitat unused by moose.

(15 cm) on the first day of completed moose surveys as our estimate of the snow depth needed to initiate fall moose surveys in the future (Table 1). Across the study area, 15 cm of snow depth was reached an average of 13 days (SD = 7 days) after the initial snow onset date. We predicted that snow depths of 15 cm by December 15 will become increasingly less likely over the next four decades (Figure 7). Snow depths across western and southcentral Alaska may be insufficient for initiating population estimate surveys in the next 10–20 years (Figure 7). Over the next 30 years, our simulations suggested that the delayed onset of adequate snow accumulation in the fall will prevent completion of fall moose surveys during this time of the year for over 62% of Alaska's managed moose management areas (a reduction of surveyable area from 953,000 km^2 to 361,000 km^2), with surveys becoming infeasible over 74% of moose management areas within the next 40 years (Figure 7).

DISCUSSION

Adequate accumulation of snow is a requirement and good predictor of fall moose survey completion in Alaska. We found that in a given year, whether or not modeled snow depths have reached 15 cm by 1 November was a strong determinant of survey completion. In boreal ecosystems, snow depths of 15 cm cover most understory and ground

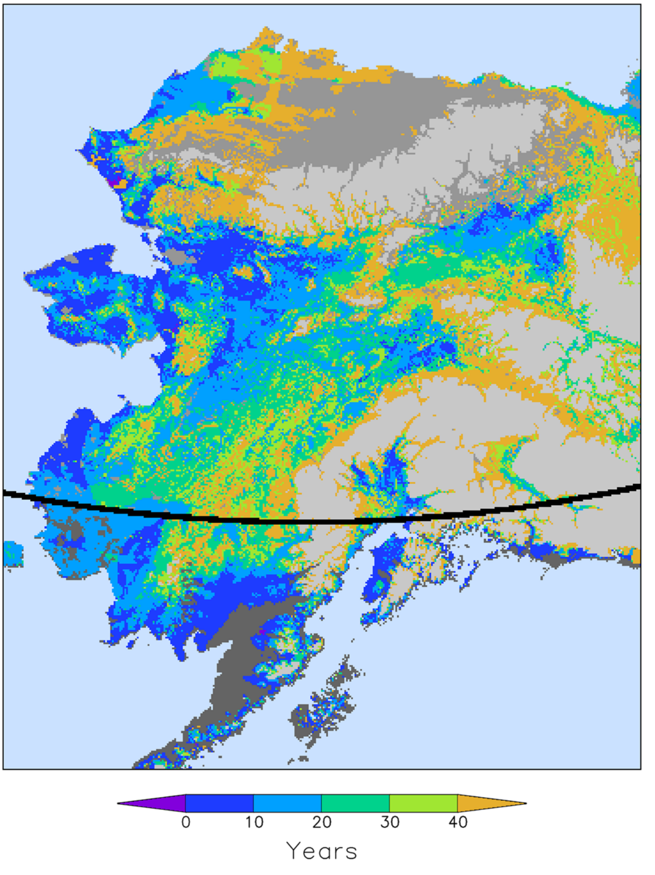

FIGURE 7 Projection of when fall aerial moose survey techniques will likely no longer be possible (years from present) in Alaska, based on the need for a 15-cm snow depth before December 15. Color shades above the black line (61.3° N latitude) are the number of years until the 15-cm snow depth onset date will overlap with insufficient daylight (<5 hours), and color shades below the 61.3° latitude line are the number of years until the 15-cm snow depth threshold will likely not be met before the 15 December fall survey deadline. Blank (gray) areas represent one of 3 situations: (1) south of the 61.3° N latitude line, where some areas never reach 15-cm snow depth by 15 December (dark grey); (2) north of the 61.3° N latitude line, where the 15-cm snow depth onset date at some locations is becoming earlier in the year (medium gray); or (3) the location has an elevation >750 m, which is assumed to be habitat unused by moose (light gray).

vegetation (Thompson et al. 2004). This creates a white background that assists surveyors with effective moose detection. Although mean grass and sedge heights can reach 44 cm in Interior Alaska (Thompson et al. 2004), these nonwoody understory plants easily succumb to the weight of snow accumulation, thereby getting buried well before snow depths reach plant height (White et al. 2010).

Snow depths during the first half of the season were the best predictors of survey completion. We speculate that early-season snow depths were stronger predictors of survey outcome because biologists begin assessing snow conditions early in the season and usually survey as soon as snow conditions allow adequate sightability of moose. Also, early season snow depths are highly correlated with mid- and late-season depths, giving biologist some insight into survey completion probability as the season progresses. Additionally, by mid-season, some survey pilots may have committed to other survey areas with adequate snow accumulation, limiting availability of aircraft to conduct surveys: another major limitation to survey completion (Kellie et al. 2019).

Declining trends across 41 years (1980–2020) of modeled snow depths illustrated how changing snow conditions are becoming increasingly challenging for fall moose surveys, especially in southern and western Alaska, where the onset of winter occurs later in the year. Although snow depth on 1 November decreased for most survey areas, the initiation date of completed surveys did not become later. Stability in survey initiation over our documented study period (1987–2019), despite later arrival of adequate snow conditions, was likely because of improved weather forecasts, modern navigation equipment in aircraft, and more flexible sampling designs. During recent decades, these advances have allowed biologists to initiate surveys more quickly after, or in synchrony with, the arrival adequate snow conditions. These nuances introduced bias into our estimates of change in survey initiation, based on empirical survey start dates. Eventually, advances in equipment and modifications in sampling design are unlikely to sustain fall surveys as a reliable technique for monitoring moose and informing moose management decisions.

Our spatial approach to the examination of snow conditions for surveying during 1980–2020 allowed us to examine the relative impact of changing snow conditions on a monitoring technique used across a vast and varied landscape. Variation in snow depth and the magnitude of decline provided an illustration of differing impacts to moose survey programs across Alaska. Quantification of these regional differences provides context for discussion of priorities at state and regional management levels and may help to justify differences in priority when discussing the relative urgency of implementing alternatives to fall moose surveys (e.g., Kellie et al. 2019).

Our model projections indicated that future snow conditions may not support fall moose surveys; 3 to 4 decades from now, snow conditions in the majority of Alaska's moose habitat may be insufficient to successfully conduct fall moose surveys for estimation of population density and demography. We found that if later snow onset date trends do indeed continue, moose surveys in many locations of central and northern (>61.3°N) Alaska may be hindered because the modeled 15-cm snow depth threshold required to conduct surveys is unlikely to be achieved by the date on which aerial surveys are limited by either the number of daylight hours or male moose having dropped their antlers.

The spatially- and temporally-explicit modeling tool (SnowModel) that we applied to quantify snow conditions can help state and federal wildlife agencies to proactively adapt to rapidly changing northern environments. In this application, SnowModel provided novel and useful snow information that was tightly correlated with past real-world management decisions and can be used to guide future decisions across Alaska. Our spatially comprehensive snow data can be used to estimate the feasibility of monitoring moose in a new management area, including setting an expectation of survey frequency, which is an important component of modeling population trends and providing timely harvest recommendations. In addition, snow data can provide wildlife managers with insights that can be used to directly evaluate the suitability of specific locations for surveying, identify survey timelines, and even consider alternative survey approaches. For example, we found that snow depths when surveys were initiated differed across survey areas. Moose managers can use area-specific snow depths to inform when snow conditions are adequate to conduct surveys in their area. Different snow-depth needs may shorten or extend survey timelines in certain areas, as compared to our projections. Moose researchers working at lower latitudes of North America already apply alternative methods. For example, researchers at lower latitudes have shown that aircrafts equipped with Forward Looking Infrared (FLIR) technology can be an effective tool for detecting moose in heavily-forested landscapes (McMahon et al. 2021). Managers also may consider conducting population surveys in the spring (i.e., February or March) when snow conditions and daylight are more likely to be sufficient. However, with male moose not having antlers at this time, other methods (e.g., cameras, DNA, hunter observations, identification of vulva patch; Oswald 1998, Boyce and Corrigan 2017, Furnas et al. 2018, Moll et al. 2022) would be required to estimate age and sex composition, because this information is critical to the management of moose hunting. Managers need to be aware that bias can be introduced from merging moose population composition data with population estimates collected at different times (Paragi et al. 2017).

The comprehensive snow map produced by this study could also be used to inform stratification of surveys. For example, in low-snow years managers may want to have a different stratification than in high-snow years where moose are more concentrated. This may help managers anticipate how many units they will need to survey to achieve desirable statistical variance (i.e., more units needed for low-density, dispersed distributions than in highly stratified distributions). Our map shows variation in timing of 15 cm of snow accumulation within individual survey areas, suggesting that managers could use snow depth information to prioritize surveying units where snow depth is adequate and postpone low-snow areas until after additional snow fall. This would require near-real-time snow modeling, which would benefit from installation of more meteorological and snow-measurement field stations in remote areas (Boelman et al. 2019).

MANAGEMENT IMPLICATIONS

Quantifying the current and future relationships between the successful implementation of moose surveys and modeled snow conditions may help managers adapt to an increasingly dynamic environment with increasingly delayed snow onset. Detailed information on spatial and temporal snow variability may provide moose managers with the information needed to directly evaluate local monitoring options and timelines, understand regional differences, and to proactively prepare and plan for a different climatic future. Assuming predicted snow trends continue, using fall aerial surveys that rely on visual observation to estimate moose density will no longer be feasible across roughly 60% of moose management areas in Alaska within 3 to 4 decades.

ACKNOWLEDGMENTS

Funding was provided by NASA Arctic-Boreal Vulnerability Experiment (ABoVE). We thank the Alaska Department of Fish Game, United States Fish and Wildlife Service and their staff including M. Bertram, J. Herreman, T. Hollis, K. Krenz, B. Lake, K. Oster, B. Schmidt, and T. Peltier for helping with review of moose survey data and providing comments on earlier drafts.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS STATEMENT

NA.

DATA AVAILABILITY STATEMENT

All data and code are available upon request.

ORCID

Todd J. Brinkman http://orcid.org/0000-0001-5375-4840

REFERENCES

Alaska Department of Fish and Game. 2023. Alaska Hunting Regulations. Alaska Department of Fish and Game, Juneau, Alaska, USA. https://www.adfg.alaska.gov/index.cfm?adfg=wildliferegulations.hunting. Accessed 8 Oct 2023.

Alberta Sustainable Resource Development Fish and Wildlife Division. 2010. Aerial ungulate survey protocol manual. Alberta Government, Alberta, Canada. https://open.alberta.ca/publications/aerial-ungulate-survey-protocol-manual. Accessed 6 Aug 2024.

Agresti, A. 2013. Categorical Data Analysis. Third Edition. John Wiley & Sons, Hoboken, New Jersey, USA.

Bates, D., M. Mächler, B. Bolker, and S. Walker. 2015. Fitting linear mixed-effects models using lme4. Journal of Statistical Software 67:1–48.

Berteaux, D., G. Gauthier, F. Domine, R. A. Ims, S. F. Lamoureux, E. Lévesque, and N. Yoccoz. 2016. Effects of changing permafrost and snow conditions on tundra wildlife: critical places and times. Arctic Science 3:65–90.

Bieniek, P. A., U. S. Bhatt, R. L. Thoman, H. Angeloff, J. Partain, J. Papineau, F. Fritsch, E., Holloway, J. E. Walsh, C. Daly, et al. 2012. Climate divisions for Alaska based on objective methods. Journal of Applied Meteorology and Climatology 51:1276–1289.

Boelman, N. T., G. E. Liston, E. Gurarie, A. J. Meddens, P. J. Mahoney, P. B. Kirchner, G. Bohrer, T. J. Brinkman, C. L. Cosgrove, J. U. Eitel, et al. 2019. Integrating snow science and wildlife ecology in Arctic-boreal North America. Environmental Research Letters 14:010401.

Bokhorst, S., S. H. Pedersen, L. Brucker, O. Anisimov, J. W. Bjerke, R. D. Brown, D. Ehrich, R. L. Essery, A. Heilig, S. Ingvander, et al. 2016. Changing Arctic snow cover: a review of recent developments and assessment of future needs for observations, modelling, and impacts. Ambio 45:516–537.

Box, J. E., W. T. Colgan, T. R. Christensen, N. M. Schmidt, M. Lund, F. J. W. Parmentier, R. Brown, U. S. Bhatt, E. S. Euskirchen, V. E. Romanovsky, et al. 2019. Key indicators of Arctic climate change: 1971–2017. Environmental Research Letters 14:045010.

Boyce, M. S., P. W. Baxter, and H. P. Possingham. 2012. Managing moose harvests by the seat of your pants. Theoretical Population Biology 82:340–347.

Boyce, M. S., and R. Corrigan. 2017. Moose survey app for population monitoring. Wildlife Society Bulletin 41:125–128.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer, New York, New York, USA.

Chambers, J. M., A. Freeny, and R. M. Heiberger. 1992. Chapter 5. Analysis of variance; Designed experiments. Statistical Models *in* S. J. M. Chambers and T. J. Hastie, editors. Champan and Hall/CRC, Boca Raton, Florida, USA.

Chapin, F. S., M. W. Oswood, K. Van Cleve, L. A. Viereck, and D. L. Verbyla, editors. 2006. Alaska's changing boreal forest. Oxford University Press, New York, New York, USA.

Christ, A. M. 2011. Sightability correction for moose population surveys. Alaska Department of Fish and Game. Final Wildlife Research Report. ADF&G/DWC/WRR-F-2011-1. Juneau, Alaska, USA.

Cohen, J. 1988. Statistical Power Analysis for the Behavioral Sciences. 2nd edition. Lawrence Erlbaum Associates, New York, New York, USA.

Commission for Environmental Cooperation. 2010. North American Environmental Atlas: Mapping North America's Shared Environment. http://www.cec.org/publications/mapping-our-shared-environment/. Accessed 15 Jan 2024.

Delisle, Z. J., P. G. McGovern, B. G. Dillman, and R. K. Swihart. 2023. Imperfect detection and wildlife density estimation using aerial surveys with infrared and visible sensors. Remote Sensing in Ecology and Conservation 9:222–234.

Franklin, T. W., K. S. McKelvey, J. D. Golding, D. H. Mason, J. C. Dysthe, K. L. Pilgrim, J. R. Squires, K. B. Aubry, R. A. Long, S. A. Greaves, et al. 2019. Using environmental DNA methods to improve winter surveys for rare carnivores: DNA from snow and improved noninvasive techniques. Biological Conservation 229:50–58.

Furnas, B. J., R. H. Landers, S. Hill, S. S. Itoga, and B. N. Sacks. 2018. Integrated modeling to estimate population size and composition of mule deer. The Journal of Wildlife Management 82:1429–1441.

Gasaway, W. C., S. D. DuBois, D. J. Reed, and S. J. Harbo. 1986. Estimating moose population parameters from aerial surveys. Biological Papers of the University of Alaska 22:1–108.

Gelaro, R., W. McCarty, M. J. Suárez, R. Todling, A. Molod, L. Takacs, C. A. Randles, A. Darmenov, M. G. Bosilovich, R. Reichle, et al. 2017. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). Journal of Climate 30(14):5419–5454.

Greaves, H. E., N. T. Boelman, T. J. Brinkman, G. E. Liston, L. R. Prugh, and A. K. Reinking. 2023. Simulating future climate change impacts on snow- and ice-related driving hazards in Arctic-boreal regions. Environmental Research Letters 18:025006.

Hamed, K. H., and A. R. Rao. 1998. A modified Mann-Kendall trend test for autocorrelated data. Journal of Hydrology 204: 182–196.

Intergovernmental Panel on Climate Change. 2023. Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Core Writing Team, H. Lee and J. Romero [eds.]). IPCC, Geneva, Switzerland.

Jacques, C. N., J. A. Jenks, C. S. Deperno, J. D. Sievers, T. W. Grovenburg, T. J. Brinkman, C. Swanson, and B. A. Stillings. 2009. Evaluating ungulate mortality associated with helicopter net-gun captures in the Northern Great Plains. The Journal of Wildlife Management 73: 1282–1291.

Johnson, P. C. 2014. Extension of Nakagawa & Schielzeth's R2GLMM to random slopes models. Methods in Ecology and Evolution 5:944–946.

Kellie, K. A., K. E. Colson, and J. H. Reynolds. 2019. Challenges to monitoring moose in Alaska. Alaska Department of Fish and Game, Wildlife Management Report ADF&G/DWC/WMR-2019-1, Juneau, Alaska, USA.

Kellie, K. A., and R. A. DeLong. 2006. Geospatial survey operations manual. Alaska Department of Fish and Game. Fairbanks, Alaska, USA.

Kendall, M. G. 1975. Rank correlation methods. Charles Griffin, London, UK.

Kliengchuay, W., R. Mingkhwan, N. Kiangkoo, S Suwanmanee, N. Sahanavin, J. Kongpran, H. Wai Aung, and K. Tantrakarnapa. 2024. Analyzing temperature, humidity, and precipitation trends in six regions of Thailand using innovative trend analysis. Scientific Reports 14:7800.

Kruskal, W. H., and W. A. Wallis. 1952. Use of ranks in one-criterion variance analysis. Journal of the American Statistical Association 47:583–621.

Lader, R., J. E. Walsh, U. S. Bhatt, and P. A. Bieniek. 2020. Anticipated changes to the snow season in Alaska: elevation dependency, timing and extremes. International Journal of Climatology 40:69–187.

Liston, G. E., and K. Elder. 2006. A distributed snow-evolution modeling system (SnowModel). Journal of Hydrometeorology 7:1259–1276.

Liston, G. E., R. B. Haehnel, M. Sturm, C. A. Hiemstra, S. Berezovskaya, and R. D. Tabler. 2007. Simulating complex snow distributions in windy environments using SnowTran-3D. Journal of Glaciology 53:241–256.

Liston, G. E., and C. A. Hiemstra. 2008. A simple data assimilation system for complex snow distributions (SnowAssim). Journal of Hydrometeorology 9:989–1004.

Liston, G. E., P. Itkin, J. Stroeve, M. Tschudi, J. S. Stewart, S. H. Pedersen, A. Reinking, and K. Elder. 2020. A Lagrangian snow-evolution system for sea-ice applications (SnowModel-LG): Part I—Model description. Journal of Geophysical Research: Oceans 125(10):e2019JC015913.

Lüdecke, D., M. S. Ben-Shachar, I. Patil, P. Waggoner, and D. Makowski. 2021. performance: an R package for assessment, comparison and testing of statistical models. Journal of Open Source Software 6:3139

Magoun, A. J., J. C. Ray, D. S. Johnson, P. Valkenburg, F. N. Dawson, and J. Bowman. 2007. Modeling wolverine occurrence using aerial surveys of tracks in snow. The Journal of Wildlife Management 71:2221–2229.

Mann, H. B. 1945. Nonparametric tests against trend. Econometrica: Journal of the Econometric Society 13:245–259.

McMahon, M. C., M. A. Ditmer, E. J. Isaac, S. A. Moore, and J. D. Forester. 2021. Evaluating unmanned aerial systems for the detection and monitoring of moose in northeastern Minnesota. Wildlife Society Bulletin 45:312–324.

Moll, R. J., M. K. Poisson, D. R. Heit, H. Jones, P. J. Pekins, and L. Kantar. 2022. A review of methods to estimate and monitor moose density and abundance. Alces: A Journal Devoted to the Biology and Management of Moose 58: 31–49.

Mudryk, L. R., A. E. Chereque, C. Derksen, K. Luojus, and B. Decharme. 2021. Terrestrial Snow Cover. NOAA Arctic Report Card 2021. https://doi.org/10.25923/16xy-9h55. Accessed 15 Jan 2024.

Niittynen, P., R. K. Heikkinen, and M. Luoto. 2018. Snow cover is a neglected driver of Arctic biodiversity loss. Nature Climate Change 8:997–1001.

O'Donoghue, M., B. G. Slough, K. Poole, S. Boutin, E. J. Hofer, G. Mowat, D. Murray, and C. J. Krebs. 2022. Snow track counts for density estimation of mammalian predators in the boreal forest. Wildlife Research 50:425–434. https://doi.org/10.1071/WR21159

Olsson, P. Q., M. Sturm, C. H. Racine, V. Romanovsky, and G. E. Liston. 2003. Five stages of the Alaskan arctic cold season with ecosystem implications. Arctic, Antarctic, and Alpine Research 35:74–81.

Oswald, K. 1998. Moose aerial observation manual. Ontario Ministry of Natural Resources, Northeast Science & Technology. City, Canada.

Paragi, T. F., K. A. Kellie, J. M. Peirce, and M. J. Warren. 2017. Movements and sightability of moose in Game Management Unit 21E. Alaska Department of Fish and Game, Final Wildlife Research Report ADF&G/DWC/WRR-2017-2. Juneau, USA.

Pedersen, S. H., T. W. Bentzen, A. K. Reinking, G. E. Liston, K. Elder, E. A. Lenart, A. K. Prichard, and J. M. Welker. 2021. Quantifying effects of snow depth on caribou winter range selection and movement in Arctic Alaska. Movement Ecology 9:48.

Pulliainen, J., K. Luojus, C. Derksen, L. Mudryk, J. Lemmetyinen, M. Salminen, J. Ikonen, M. Takala, J. Cohen, T. Smolander, et al. 2020. Patterns and trends of Northern Hemisphere snow mass from 1980 to 2018. Nature 581(7808):294–298.

R Core Team. 2023. R: a language and environment for statistical computing. Version 4.3.2. R Foundation for Statistical Computing, Vienna, Austria.

Reinking, A. K., S. H. Pedersen, K. Elder, N. T. Boelman, T. W. Glass, B. A. Oates, S. Bergen, S. Roberts, L. R. Prugh, T. J. Brinkman, et al. 2022. Collaborative wildlife–snow science: integrating wildlife and snow expertise to improve research and management. Ecosphere 13(6):e4094.

Sadeqi, A., M. Irannezhad, S. Bahmani, K. A. Jelodarlu, S. A. Varandili, and Q. B. Pham. 2024. Long-term variability and trends in snow depth and cover days throughout Iranian mountain ranges. Water Resources Research 60:e2023WR035411.

Sen, P. K. 1968. Estimates of the regression coefficient based on Kendall's Tau. Journal of the American Statistical Association 63:1379–1389.

Serreze, M. C., M. P. Clark, R. L. Armstrong, D. A. McGinnis, and R. S. Pulwarty. 1999. Characteristics of the western United States snowpack from snowpack telemetry (SNOTEL) data. Water Resources Research 35:2145–2160.

Squires, J. R., L. E. Olson, D. L. Turner, N. J. DeCesare, and J. A. Kolbe. 2012. Estimating detection probability for Canada lynx *Lynx canadensis* using snow-track surveys in the northern Rocky Mountains, Montana, USA. Wildlife Biology 18: 215–224.

Stoker, J., and B. Miller. 2022. The accuracy and consistency of 3D Elevation Program data: a systematic analysis. Remote Sensing 14:940.

Tape, K. D., D. D. Gustine, R. W. Ruess, L. G. Adams, and J. A. Clark. 2016. Range expansion of moose in Arctic Alaska linked to warming and increased shrub habitat. PLoS ONE 11(7):e0160049.

Thompson, C., J. Beringer, F. S. Chapin III, and A. D. McGuire. 2004. Structural complexity and land-surface energy exchange along a gradient from arctic tundra to boreal forest. Journal of Vegetation Science 15:397–406.

Walsh, J. E., U. S. Bhatt, J. S. Littell, M. Leonawicz, M. Lindgren, T. A. Kurkowski, P. A. Bieniek, R. Thoman, S. Gray, and T. S. Rupp. 2018. Downscaling of climate model output for Alaskan stakeholders. Environmental Modelling & Software 110:38–51.

White, K. S., G. W. Pendleton, and E. Hood. 2010. Effects of snow on Sitka black-tailed deer browse availability and nutritional carrying capacity in southeastern Alaska. The Journal of Wildlife Management 73:481–487.

Western Regional Climate Center. 2023. Climatological Data Summaries: Alaska. https://wrcc.dri.edu/summary/Climsmak.html. Accessed 7 Nov 2023.

Young Jr., D. D., and R. D. Boertje. 2018. Age-related antler characteristics in an intensively managed and nutritionally stressed moose population. Alces: A Journal Devoted to the Biology and Management of Moose 54:37–44.

Associate Editor: Mark Smith.

How to cite this article: Brinkman, T. J., K. A. Kellie, A. K. Reinking, G. E. Liston, and N. T. Boelman. 2024. Changing snow conditions are challenging moose (*Alces alces*) surveys in Alaska. Wildlife Society Bulletin 48:e1555. https://doi.org/10.1002/wsb.1555