Forest Ecology and Management 619 (2026) 124046

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Canopy gap age influences snow depth: Implications for gap-based silviculture on snowpack in the Sierra Nevada

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ARTICLE INFO

Dataset link: drivers, raw_data, snowdepth_TSA

Keywords:
Snowpack
Silviculture
Group selection
Canopy gap

ABSTRACT

Climate change is raising the elevation of rain-snow transition lines and accelerating spring snowmelt, posing increasing risks to California's regional ecosystems and water infrastructure. Research has shown that snow accumulation and retention are shaped by complex interactions with forest structure. Open-canopy gaps tend to preserve snowpack better than closed-canopy forests. However, it is unclear how long these advantages persist as forests regenerate. This study examines how canopy gap age, defined as years since group selection harvest, affects snow depth across twenty-eight canopy gaps in the north-central Sierra Nevada. Multiple Linear regression models indicated that each additional year of canopy gap age corresponded to a 4.8% decline in March snow depth and a 0.3-day acceleration in snow disappearance, though these coefficients should be interpreted as indicative of direction and relative magnitude rather than precise predictions. Greater snow depth and later snow disappearance dates were both associated with younger canopy gaps, with these benefits declining approximately linearly over 30–40 years as regenerating cohorts grew and canopy closure progressed. Multivariate Autoregressive State-Space models showed that gap age was not a strong predictor of day-to-day snow depth; the time series was dominated by ablation periods during which snow depth loss was broadly similar across age classes. Combined with visual inspection of the season's snow depth patterns, this suggests that gap age primarily influences end-of-season snow depth through differences established during accumulation events rather than during ablation periods. Gap age may serve as a practical proxy for structural forest characteristics that are difficult to measure yet critically influence end-of-season snow depth and presence, though replication is needed to assess the robustness and predictive utility of this relationship across multiple water years. From a forest management perspective, gap-based silviculture such as group selection harvesting is a promising starting point for maintaining greater snow depth as a co-benefit alongside other management objectives. Advancing this understanding will require multi-year observations, comprehensive snowpack measurements, and closer examination of how young regenerating vegetation influences snowpack.

1. Introduction

The Sierra Nevada snowpack is an essential source of water for California's diverse ecosystems and growing urban and rural populations. In an average year, the Sierra Nevada snowpack comprises 73% of the total regional runoff (Li et al., 2017). It delays the onset of the fire season by keeping surface fuels and soils moist further into the Mediterranean dry season (Bales et al., 2011; Holden et al., 2018). Delayed snowmelt is critical for maintaining freshwater flow and low stream temperatures, which support wildlife such as salmon and steelhead, among many other vulnerable species (Crozier et al., 2019). It also extends water supply to hydroelectric power infrastructure later into the summer when energy demand peaks (Kopytkovskiy et al., 2015). However, anthropogenically driven climate change is drastically altering the regional vegetation and hydrology of the Sierra Nevada. (Stewart et al., 2017; Schwartz et al., 2017; Westerling et al., 2006; Safford et al., 2012).

Based on business-as-usual climate projections, temperatures in the Sierra Nevada are expected to increase by 3.3–5℃ by the end of this century, leading to more rain-on-snow events and reduced snowpack

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https://doi.org/10.1016/j.foreco.2026.124046
Received 24 December 2025; Received in revised form 17 June 2026; Accepted 18 June 2026
Available online 25 June 2026
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(Dettinger et al., 2018; Knowles et al., 2006; Stewart et al., 2005). Though the total amount of precipitation may not change significantly (Dettinger et al., 2018), the earlier timing of snowmelt will likely threaten vulnerable species through habitat loss and elevated stream temperatures (Stewart et al., 2017; Leathers et al., 2025), increase both the frequency and severity of wildfires (Holden et al., 2018; Westerling et al., 2006), and threaten the supply of water to California's gray infrastructure that is essential for hydropower, irrigation, and human consumption (Lettenmaier and Lund, 2020). Finally, climate change is likely to lead to an upward movement of seasonal snowlines and increased rainfall (Roche et al., 2018). Although many of these changes are beyond regional land management control, researchers and managers continue to explore vegetation management alternatives that may mitigate anticipated snowpack changes.

Since the 1950s, researchers have demonstrated that forest cover has a strong effect on snowpack and snow disappearance dates (Lundquist et al., 2013; Varhola et al., 2010). Forests provide more shade compared to open areas, reducing solar radiation and daytime surface temperatures, which has a positive effect on snowpack (Varhola et al., 2010). Forests with low canopy density and high spatial heterogeneity also shelter snow from wind, which reduces redistribution of snow and delays snow ablation compared to exposed open areas (Pomeroy et al., 2002; Murray and Buttle, 2003). At the same time, dense canopies intercept more snow, which leads to less snow accumulation under trees (Moore and McCaughy, 1997). Trees also emit more longwave radiation compared to the atmosphere, increasing the rate of snow ablation under dense canopies compared to open areas (Essery et al., 2008; Lawler and Link, 2011). The primary driver of snow ablation is the energy balance of solar radiation, longwave radiation, sensible and latent heat fluxes (Boon, 2007). Heterogeneous forest cover thus creates complex, counteracting effects on snow cover as it increases longwave radiation but also decreases the total energy budget since it provides protection from solar radiation (Essery et al., 2008). Furthermore, forest cover reduces wind speed, which decreases the sensible and latent heat fluxes in the energy balance model (Mahat et al., 2013).

The counteracting effects of forest cover on snow are complex and difficult to model. However, a meta-analysis of snow-vegetation interactions revealed that regions with mean winter temperatures above −1℃, such as the Sierra Nevada, have later snow disappearance dates (SDD) in open areas (i.e., openings ranging from one-tree-height to clear cuts) compared to adjacent forested sites (Lundquist et al., 2013; Varhola et al., 2010). Beyond these meta-analyses, studies have found that many additional factors impact vegetation-snow interactions, including snowfall magnitude (Varhola et al., 2010), elevation (Tennant et al., 2017), slope and aspect (Tennant et al., 2017), wind speed (Woods et al., 2006), size of canopy gap (Golding and Swanson, 1978), and spatial distribution of trees (Veatch et al., 2009).

Given these findings, numerous studies have assessed whether strategically placed timber harvests, canopy gaps, and intensive thinning can increase snowpack in forest management contexts (Kittredge, 1953; Rothacher, 1965; Golding and Swanson, 1978; Krogh et al., 2020). Canopy gaps are discrete openings in the forest canopy, areas where mature trees have been removed or have died, that allow young vegetation to regenerate over time. Research comparing circular openings of various diameters found that canopy gaps with diameters of 2–3 tree heights optimized both snow accumulation and retention, demonstrating that small, distinct gaps outperform large openings such as clear cuts (Golding and Swanson, 1978). More recently, forest thinning designed to reduce wildfire risk in the Eastern Cascades of Washington State resulted in an increase in snow depth of between 16–30% depending on aspect, with the greatest gains in small to mid-sized gaps on north-facing slopes (Lumbrazo et al., 2026). Studies using fire as a disturbance have revealed similar scale-dependent patterns. Stevens (2017) found that while snowpack was greater under canopy openings at the individual tree scale, stand-level snowpack depth was greater in unburned forests with fine-scale heterogeneity compared to moderately burned forests. However, these studies primarily evaluate immediate or short-term effects of a recent clearing, leaving a critical gap in understanding how canopy openings perform as forests regenerate. The transition from an open canopy gap to a closed young forest is gradual and difficult to define by a single structural threshold like canopy cover. This transitional stage during the first 30–40 years of regeneration and its influence on snow depth is precisely what this study examines.

Managers must understand how these treatments perform over time to assess the long-term management outcomes of silvicultural systems intended for snowpack retention. The goal of creating gaps as part of a silvicultural system is to regenerate new cohorts of trees that recruit and re-form tall canopies, eventually undermining goals of snow retention unless canopy gaps or low tree density are maintained. However, research examining the temporal dynamics of snowpack retention in canopy gaps remains limited to a single study in Tenderfoot Creek Experimental Forest, Montana (Moore, 1997). It explored snow accumulation under eight successional stages of lodgepole pine after a fire, finding that snow water equivalent (SWE) decreases with stand age and that the addition of specific structural characteristics, such as species composition and canopy cover, led to better predictions for SWE (Moore, 1997).

How these dynamics translate to Sierra Nevada mixed-conifer forests remains unknown. Group selection harvesting is a type of uneven-aged silviculture practiced primarily for timber production, regeneration, and canopy heterogeneity. In California, group selection harvests are commonly used to create canopy gaps that mimic smaller natural disturbances. These gaps are legally limited to 0.1–1 ha in size, with gaps in this study ranging from 0.1 to 0.7 ha. With the exception of Moore (1997), studies examining how managed canopy gaps perform over time are scarce, especially for the Sierra Nevada. Snow depth represents one of several ecosystem co-benefits of gap-based silviculture that remains poorly quantified, particularly as forests regenerate following harvest. Since gap-based silviculture can be designed to sustain young canopy gaps indefinitely, it is critical to understand the age at which canopy gaps lose their effectiveness at retaining snow. This study characterizes how snow depth and snow presence change as canopy gaps age following group selection harvest, providing a foundation for evaluating snow depth as one consideration within multi-objective forest management. Using group selection units harvested between 1976 and 2018 as proxies for time since canopy gap formation, we measured daily snow depth over the 2020–2021 winter season. We tested the following hypotheses:

H1. : Including canopy gap age as a predictor leads to significant improvement in the prediction of end-of-season snow depth and snow disappearance date (SDD), beyond forest structure and site characteristics alone.

H2. : Canopy gap age influences how weather drivers such as temperature, precipitation, wind, and solar radiation affect daily snow depth over time. Constraining covariate (driver) effects by gap age classes leads to a statistically more meaningful Multi-variate Autoregressive State-space (MARSS) model.

H3. : Canopy-gap age serves as a stronger predictor of snow depth change during accumulation and ablation periods than individual vegetation metrics (e.g., shrub cover, basal area, tree density).

2. Methods

2.1. Site description

The study units were located at Blodgett Forest Research Station (BFRS), a University of California research forest. BFRS is in the Sierra Nevada mixed-conifer belt in El Dorado County, CA, USA (38° 54' 45" N, 120° 39' 27" W). The dominant tree species include ponderosa pine (*Pinus ponderosa*), sugar pine (*Pinus lambertiana*), Douglas-fir

(*Pseudotsuga menziesii*), white fir (*Abies concolor*), incense-cedar (*Calocedrus decurrens*), California black oak (*Quercus kelloggii*), tanoak (*Notholithocarpus densiflorus*) and Pacific dogwood (*Cornus nuttallii*). Though giant sequoia (*Sequoiadendron giganteum*) is not native to the immediate area, BFRS is situated between native groves and has planted giant sequoia since 1974. Understory vegetation within the study units consists primarily of deerbrush (*Ceanothus integerrimus*) and the shrub form of tanoak (*Notholithocarpus densiflorus*). Elevations range from 1200 m to 1500 m, with an annual mean cumulative snowfall depth of 254 cm. BFRS was chosen due to its extensive archive of inventory data, and because it is representative of the central Sierra Nevada's mixed-conifer belt. Located within the elevation zone (<1830 m) where snowpack is projected to decline by 60% due to climate change (Dettinger et al., 2018), BFRS provides an ideal setting to study snow-vegetation interactions in forests vulnerable to warming temperatures. Most importantly, BFRS also contains a well-developed chronosequence of gap ages that is not available anywhere else in the western US.

2.2. Site selection

Ecological silviculture that builds resilience by creating canopy heterogeneity can be accomplished with gap-based silviculture, especially through group selection harvesting (York, 2024). We selected twenty-eight canopy gaps harvested between 1976 and 2018 with canopy gaps ranging from 0.1 to 0.7 hectares—a size range shown to effectively support regeneration of all species in mixed-conifer forests (York et al., 2025). Standard reforestation practices were used following gap harvests, including herbicide to control shrub cover 2–4 years after planting and pre-commercial thinning 12–16 years after planting. In addition, we included two control sites outside group-selection areas to represent vegetation structure extremes: one mature stand with no harvesting in the past century to represent the high canopy density resulting from fire suppression and passive management and one frequently burned stand that has experienced three prescribed fires over the past two decades, resulting in moderate canopy closure and an open understory. This frequently-burned stand has not been harvested.

Two control sites representing mature forests without recent gap-based silviculture were included to provide a meaningful comparison beyond the oldest harvested gap (44 years) and to capture the full range of forest structural conditions expected across the successional trajectory. These stands were last harvested approximately a century ago. To integrate them into the multiple linear regression analysis, we assigned both control sites a canopy-gap age of 60 years, which falls within the typical rotation age range of 50–80 years, for Sierra Nevada mixed-conifer forests (O'Hara, 2004). This age represents a theoretical point in stand development where natural succession or management history could yield conditions similar to those observed in the control stands. The two control sites differ in management histories, and assigning both the same age does not fully capture their structural differences. To assess the sensitivity of our results to the control sites' assigned age, we repeated all analyses with control site ages set to 50, 60, 70, and 80 years, and with control sites excluded entirely. In all cases, age remained a statistically significant predictor that outcompeted other structural variables with consistent directional results; only the magnitude of the age coefficient varied (see Supplementary Material, Tables S1-S10). Results should therefore be interpreted in terms of the direction and pattern of age effects rather than precise coefficient values.

2.3. Data collection

2.3.1. Independent variables

We collected vegetation and topographic characteristics for each site, along with canopy gap age. The canopy gap age, vegetation, and topographic variables were used as predictors for the March snow depth, snow disappearance date, and snow accumulation/ablation multiple linear regression analyses. Although they represented considerable effort, ground-based measurements were chosen over remote sensing approaches because the structural complexity of young regenerating stands requires fine-scale vegetation characterization that exceeds the spatial resolution of accessible remote sensing products.

Plot centers for vegetation measurements were defined using north-south and east-west centerlines in ArcGIS Pro (Esri Inc, 2021), based on GPS-delineated unit boundaries. These coordinates were exported to global positioning devices to guide field placement. Vegetation measurements were taken in a 0.04-hectare circular plot around the gap center (Fig. 1). While efforts were made to place the plot center precisely at the GIS-derived coordinates, adjustments (≤5 m) were sometimes necessary to ensure a clear line of sight between the height pole placed at the plot center and the time-lapse camera. These poles served as both plot center markers and snow depth measurement sticks for the time-lapse photos.

Vegetation and site data were collected in October 2021 within each 0.04-ha plot. Measured attributes included: aspect (degrees), slope (percent), basal area per hectare (m^2 ha^{-1}), trees per hectare (stems ha^{-1}), shrub cover (to the nearest 5%), average shrub height (m), and average neighboring canopy height (m). Given how young the regeneration in many of the gaps were, all stems reaching breast height (1.68 m) were counted as "trees". To capture the dense clusters of small-diameter stems that may intercept snow differently than larger trees, we separately quantified trees per hectare for stems between 0.1 and 7.6 cm at diameter at breast height (DBH). This threshold was selected based on field observations showing that stems below this size generally represented a distinct younger, structural cohort characterized by high stem density and flexible branches that might influence snow interception differently. Canopy cover was not included as a predictor because standard measurement tools such as the moosehorn densitometer were insufficient for distinguishing regenerating understory vegetation from emerging canopy in these young stands. Canopy gap age and gap size were obtained from BFRS harvest data. Elevation was not included as a predictor due to low variation within BFRS (1330 ± 70 m).

The daily weather data used in the time-series analysis was collected from the Remote Automatic Weather Station (RAWS) located on BFRS. We collected daily average temperatures, average wind speeds, solar radiation, and precipitation data between December 1, 2020, and April 30, 2021. To create a continuous variable of precipitation that captured both the type and intensity of precipitation events for time-series modeling, we used an interaction variable, precipitation multiplied by average temperature (P × T).

The P × T interaction variable functions as follows: when precipitation occurs above 0°C, P × T yields positive values indicating rain events; when precipitation occurs below 0°C, P × T yields negative values indicating snow events; and when no precipitation occurs, P × T equals zero regardless of temperature. The magnitude of P × T reflects

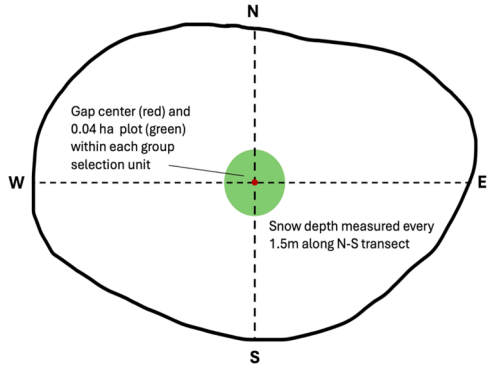


Fig. 1. Conceptual illustration of the plot center of an irregular-shaped group selection stand. Vegetation characteristics were measured within the 0.04-ha plot (green), while snow depth was measured along the N-S transect.

precipitation intensity, allowing the model to account for both light and heavy precipitation events while distinguishing their phase. This single continuous variable captures the relationship between temperature, precipitation amount, and precipitation type that drives snowpack accumulation and ablation processes.

2.3.2. Dependent variables

Between March 20–22, 2021, near the typical peak snowpack period for this elevation, we measured snow depth in situ along a north–south transect running the full length of each of the 28 group selection units. For the two control sites lacking visible boundaries, we used a 20 m N–S transect that intersected the plot center. Snow depth was recorded every 1.5 m using an avalanche probe, and the average depth across the transect was calculated and recorded as March snow depth.

Time-lapse cameras mounted near each plot center captured four images per day of a height pole, providing a continuous visual record of snow depth across different lighting and weather conditions (Fig. 2). We installed a 2-m height pole at the center of each 0.04-ha plot within each group selection unit, following methods similar to Hedrick and Marshall (2014). The poles were marked every 2 cm to allow visual estimation of snow depth to the nearest centimeter. Snow presence was recorded if there was any snow visible in the image, regardless of whether it was located at the base of the height pole. We recorded the snow disappearance date (SDD), defined as the first day of complete snow absence in the entire image for the season, expressed as the nth day of 2021 for the multiple linear regression analysis.

Since some poles settled slightly into the forest floor (1–3 cm) upon installation, all snow depth measurements were recorded relative to the top of the litter layer to maintain consistency. We manually reviewed the photos to determine daily maximum snow depth from December 1, 2020, to April 30, 2021. Of the original thirty time-lapse installations, twenty-five produced time series data, after excluding sites affected by treefalls, equipment failure, and SD card malfunctions. Snow was minimal in early winter, with December snowstorms depositing very little snow that melted rapidly. Model fitting was optimized by focusing on the period with sustained snow presence; we restricted the time series analysis to January 21, 2021, through April 3, 2021, resulting in twenty-five time series with 73 time-steps each. Within this period, six discrete accumulation events and four ablation events were identified. Accumulation events were defined as periods of sustained snow depth increase corresponding to discrete storm events and ablation events as periods of continuous snow depth decrease between storm cycles or until snow depth reached zero at the end of the season. Event boundaries were determined manually by examining the time-series snow depth data along with the time-lapse photos as a visual reference. Accumulation events were bounded by the day before storm onset and the last day of sustained depth increase. Ablation events were bounded by the first day following storm cessation and the last day of continuous depth decrease.

Due to intermittent hardware failures and occasional obstruction of camera lenses by snow during storms, the number of observations varied among events. Most hardware issues occurred after mid-winter site visits conducted to replace SD cards and verify data collection, suggesting independence from storm events. However, in a few cases, direct snow accumulation on lenses or snow-laden branches obstructed the cameras, potentially introducing minor bias into accumulation rate estimates during those specific events.

2.4. Statistical analysis

2.4.1. Data processing and data transformation

Prior to analysis, several vegetation and site variables required processing to ensure suitability for statistical modeling. Aspect, originally measured in degrees (0–360°), was converted into two continuous topographic variables, northness and eastness, by using trigonometric functions combined with slope, following Tennant et al. (2017): Northness $= \cos(\text{aspect} \times \pi/180) \times \text{slope}$; Eastness $= \sin(\text{aspect} \times \pi/180) \times \text{slope}$. This transformation addresses the circular nature of aspect data by creating linear variables that capture slope orientation while incorporating the influence of terrain steepness. In this framework, a northness of $+1$ indicates a perfectly north-facing steep slope, while -1 indicates a perfectly south-facing steep slope. Similarly, an eastness of $+1$ indicates a perfect east-facing steep slope, and -1 indicates a perfectly west-facing steep slope. Values near zero indicate either a gentle slope or a direction perpendicular to that axis (i.e. a west-facing slope would have a northness close to zero).

Due to the high correlation between small-diameter trees per hectare (0.1–7.6 cm at DBH) and total trees per hectare, we derived a new predictor variable, which we called small-tree ratio. This variable was calculated as the proportion of trees less than 7.6 cm DBH relative to total trees per hectare, which captures the relative contribution of small-diameter stems to stand structure without the collinearity introduced by retaining both variables.

This processing yielded eleven independent variables for use in all subsequent regression analyses: canopy gap age, gap size, slope, northness, eastness, basal area per hectare, total trees per hectare, small-tree ratio, average shrub height, percent shrub cover, and average neighboring canopy height. Variance inflation factor (VIF), which measures how much the behavior of an independent variable is influenced by its correlation with other independent variables, was calculated for all predictors to assess multicollinearity. Most variables exhibited VIF values below 3, with two predictors (basal area and shrub cover) approaching but not exceeding 5, indicating acceptable levels of multicollinearity (Marcoulides and Raykov, 2019) that would not substantially compromise model interpretation.

Preliminary exploratory analysis through visual plotting revealed that March snow depth exhibited non-normal distribution characteristics. Log-transformation of March snow depth improved normality and better satisfied the assumptions of multiple linear regression.

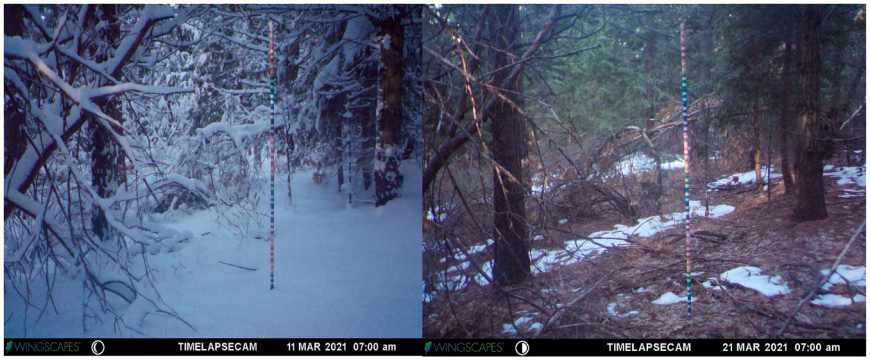


Fig. 2. The time-lapse camera view was centered on the height pole, which allowed daily snow depth measurements. Snow presence was recorded if there was snow in the image, regardless of whether it was located at the base of the height pole. These images are from a 31-year-old group selection stand, taken 10 days apart.

2.4.2. Effect of canopy gap age on end-of-season snow metrics (H1)

We tested our first hypothesis using Analysis of Variance (ANOVA) tests to compare nested models predicting March snow depth and snow disappearance date (SDD) with and without age as a predictor. To identify the most parsimonious subset of explanatory variables (excluding age) for predicting log-transformed March snow depth, we employed best subset regression using the ols_step_best_subset function from the olsrr R package (Hebbali, 2020). This function systematically evaluates all possible combinations of predictors and identifies the best model for each number of parameters based on Akaike Information Criterion (AIC) scores, along with corresponding Predicted R-squared and Adjusted R-squared values.

After identifying the model with the lowest (best) AIC score for log-transformed March snow depth, we created a corresponding subset model that included all the same predictors plus age. We then conducted an ANOVA test comparing these nested models to determine whether adding age significantly improved model performance. This process was repeated for the snow disappearance date analysis.

Following the ANOVA tests, we sought to identify the most parsimonious models for both March snow depth and SDD. To accomplish this, we reran the ols_step_best_subset function with age included as a candidate predictor from the outset, allowing the algorithm to evaluate all possible combinations of variables including age. Given the sample size of 30 ($n = 30$ for March snow depth, $n = 26$ for SDD), we used corrected Akaike Information Criterion (AICc) for model selection, which penalizes model complexity more heavily and is recommended for small samples (Burnham and Anderson, 2002). Among models within $\Delta AICc < 4$ of the top-ranked model, we selected the most parsimonious model (i.e., fewest predictors) to avoid overfitting. The model selection process was identical for both response variables.

2.4.3. Age-dependent weather effects on daily snow depth: MARSS analysis (H2)

We tested whether canopy gap age influences weather-driven snow depth change using Multivariate Auto-Regressive State-Space (MARSS) models (Holmes et al., 2012). We hypothesized that models grouping sites by age would outperform both an ungrouped control model and models grouped by static characteristics, since age proxies directional changes in vegetation structure (e.g. taller, denser canopies over time) associated microclimate conditions. The MARSS framework fits multivariate time-series models using constrained parameter estimation. Model performance was evaluated using AICc scores. Each MARSS model can be written as:

$$x_t = Bx_{t-1} + u + Cc_{t-1} + w_t \quad , \quad w_t \sim MVN(0, Q) \tag{1}$$

$$y_t = Zx_t + v_t \quad , \quad v_t \sim MVN(0, R) \tag{2}$$

Eq. (1) describes the state process of latent snow depth dynamics, where x_t is the vector of unobserved snow depth across sites at time t. The matrix B is an identity matrix, assuming that snow depth in one gap does not influence snow depth in other gaps. The vector u represents drift. The matrix C contains coefficients linking covariates (temperature, P × T, wind, and solar radiation) to snow depth dynamics, while c_{t-1} represents the covariate data (lagged by one day). Covariates were z-score normalized to allow comparison of coefficient magnitudes across variables with different absolute scales. These covariate effect groupings were then manipulated to test whether canopy gap age or other site characteristics modified weather effects. The term w_t is the process error with a mean of 0 and process error variance Q. Eq. (2) describes the observation process, where y_t is the observed snow depth at each site. The matrix Z maps latent states to observed measurements and is an identity matrix across all models, assuming uniform observation processes. The term v_t captures observation error, with a mean 0 and variance R.

The fundamental distinction between control and grouped models was the structure of matrix C. The control model allowed each site unique covariate coefficients (100 total: 4 drivers × 25 sites), permitting independent weather responses. Conversely, grouped models constrained sites within categories to share coefficients, thereby reducing estimated parameters. For parsimony and statistical power, grouped models were limited to two categories.

All eleven site characteristics were categorized into two bins using k-means clustering. Each predictor was fitted as a separate MARSS model with the modified C matrices constraining the 25 sites into "low" and "high" categories (e.g., age-low vs. age-high). This ensured that model comparisons reflected the ecological relevance of variable groupings rather than differences in the number of parameters, though the control model inherently had more parameters.

After model fitting and AICc-based selection, we validated the best-performing model through bootstrap resampling with 1000 replicates. This procedure yielded empirical distributions for parameter estimates, from which we calculated standard errors and confidence intervals for the weather driver effects.

To assess whether the binary groupings obscured finer-scale variations in snow depth dynamics, we conducted supplementary visualization analyses. We plotted the time-series data with sites grouped into four age categories (0–11, 12–24, 25–45, and 46 + years) using k-means breaks. This approach allowed visual assessment of snow depth dynamics across age gradients beyond the binary statistical classifications. Similar visualizations were created for top-performing predictors from both MARSS (basal area) and multiple linear regression (TPH and percent shrub cover) analyses for comparison.

2.4.4. The effect of canopy gap age on snow depth change during accumulation and ablation periods (H3)

To test whether canopy gap age outperforms individual vegetation metrics in predicting snow depth change, we separated the January-to-April time series into accumulation and ablation periods, identifying six accumulation events and four ablation periods. The number of accumulation and ablation events differ because some storms paused and resumed snowfall across consecutive days. One accumulation event was excluded because heavy snowfall obscured more than half of the cameras. The remaining accumulation events had sample sizes of 20, 16, 23, 23, and 21, while the four ablation periods had sample sizes of 19, 23, 22, and 19.

Accumulation and ablation rates were calculated for each event. Accumulation rate for this study was defined as the rate of change in snow depth during a storm period:

$$\frac{\text{snow depth on last day of storm} - \text{snow depth day before storm onset}}{\text{duration of storm (days)}} \tag{3}$$

Ablation rate was defined as the rate of change in snow depth during a melt period:

$$\frac{\text{snow depth on first day of ablation} - \text{snow depth on last day of ablation (or day snow depth reached 0)}}{\text{duration of ablation period (days)}} \tag{4}$$

These calculations provided measures of snow depth change during each event. We then used the ols_step_best_subset function from the olsrr R package to identify predictor subsets for each event, with canopy gap age included in the subsetting process. The "best" models were selected based on AICc score to account for small sample sizes and to reduce the risk of overfitting.

3. Results

3.1. Effect of canopy gap age on end-of-season snow metrics (H1)

Canopy gap age emerged as a significant predictor of both March snow depth and snow disappearance date, with younger gaps consistently associated with deeper snow later into the season. To contextualize these findings, Tables 1 and 2 summarizes the eleven predictors and two response variables used in the multiple linear regression (MLR) and analysis of variance (ANOVA) tests for Hypothesis 1.

3.1.1. March snow depth analysis

The initial base model (excluding canopy gap age) identified slope, TPH, and neighboring canopy height as the optimal predictors of March snow depth (log-transformed). Adding canopy gap age to this model significantly improved model fit ($F(1, 24) = 9.01$, $p = 0.006$; Supplementary Material, Table S11). When canopy gap age was included in the model selection process, the optimal model contained age, TPH, and percent shrub cover, which were all statistically significant (Table 3). This three-predictor model substantially outperformed the base + age model. Model coefficients indicated that a one-year increase in age corresponded to a 4.8% decrease in March snow depth, while an increase of 100 TPH led to a 1.9% increase in snow depth. Additionally, a 10% increase in shrub cover resulted in a 17.2% reduction in March snow depth. In other words, young gaps with higher tree density and limited shrub cover had the deepest snow in March.

3.1.2. Snow disappearance date analysis

Snow disappearance date (SDD) exhibited similar patterns to log-transformed March snow depth. The initial base model selection (without age) identified gap size and small-tree ratio as the strongest predictors. Including canopy gap age to the base model significantly improved model performance ($F(1, 20) = 8.05$, $p = 0.010$; Table S11). When age was incorporated into the model selection, the three-predictor model's AICc score was only 0.15 points lower than the two-predictor model. We selected the more parsimonious two-predictor model (age and TPH), which demonstrated significantly higher adjusted R^2 than the base model. Both predictors significantly affected snow disappearance timing. Each additional year of canopy gap age accelerated snow disappearance by 0.3 days, while an increase of 100 trees per hectare delayed snow disappearance by 0.2 days. Snow persisted longer in younger gaps with higher tree densities.

3.2. Age-dependent weather effects on daily snow depth: MARSS analysis (H2)

3.2.1. MARSS model selection and performance

Twelve MARSS models were fitted to test different grouping approaches for constraining weather responses. The control model, which allowed for independent weather responses across all sites, exhibited a substantially higher AICc score (1101.7) than all grouped models (Table S12). This was expected given that the grouped models inherently require fewer parameters.

Contrary to expectations, the basal area-constrained model achieved the lowest AICc score (951.0), outperforming the age-constrained model (956.0). The TPH-constrained model (952.8) and shrub cover-constrained model (954.9) also performed competitively. The age-constrained model's modest performance (8th out of 12 models) indicates that while age may influence cumulative snow depth in March, it is less important for daily snow depth dynamics than hypothesized.

3.2.2. Weather driver effects for the best MARSS model

Bootstrap analysis of the basal area model revealed that wind and temperature were the dominant weather drivers affecting daily snow depth, while solar radiation effects were minimal (Table S13, Figure S14). High-basal-area sites ($\geq$26 m^2/ha) showed greater sensitivity to both wind (−0.163 vs −0.100) and temperature (−0.0251 vs −0.0194) than low-basal-area sites. The 95% confidence intervals overlapped for all weather variables, indicating no statistically significant differences between groups though a weak trend may exist.

3.2.3. Temporal patterns across site groupings

To address the limitations of the binary MARSS groupings, we visualized the snow depth time series using four categories per predictor to examine finer-scale patterns. Canopy gap age showed the clearest visual differentiation in snow depth patterns (Fig. 3a). Younger sites (0–11 years) maintained consistently higher snow depths throughout the season, retaining 15–20 cm into late March, while the oldest sites (46 + years) had consistently lower snow depths and approached zero by early March. The contrast between age's weak MARSS performance and its clear visual patterns motivated the event-based analysis in Hypothesis 3 to better isolate snow depth change during accumulation and ablation periods.

Basal area groupings showed consistent patterns overall, with the 10–27 m^2 ha^{-1} group maintaining the highest snow depths across the season (Fig. 3b). The highest basal area group (55 + m^2 ha^{-1}) behaved inconsistently, at times showing the lowest snow depths of all groups and at other times ranking the second highest. Trees per hectare was difficult to interpret due to camera malfunctions in the highest density sites during early season. However, the highest two TPH categories—representing young, crowded stands prior to pre-

Table 1
Summary Statistics for the 28 group selection sites and the 2 control sites.

		Gap Sites (n = 28)			Control Sites	
Variable	**Unit**	**Min**	**Mean**	**Max**	**Unmanaged**	**Frequently Burned**
Canopy gap age	years	2	19	44	60	60
Slope	percent	0	17	41	12	18
Total trees per hectare	stems ha^{-1}	0	1513	6326	1384	272
Average shrub height	meters	0.0	1.0	2.7	0.0	0.0
Shrub cover	percent	0	12	60	0	0
Basal area per hectare	m^2 ha^{-1}	0	22	66	76	57
Average neighboring canopy height	meters	0	27	55	0	0
Size of canopy gap	hectares	0.1	0.3	0.7	0.3	0.3
Proportion of small trees	unitless	0.2	0.6	1.0	0.3	0.0
Northness	unitless	−1.0	−0.1	1.0	0.3	0.8
Eastness	unitless	−0.8	0	0.9	0.4	0.0

Table 2
Summary Statistics for Hypothesis 1. Gap units and control units are combined under the independent variables.

Variable	Unit	Shorthand	Min	Mean	Max	n
Independent Variables						
Canopy gap age	years	age	2	21	60	30
Slope	percent	slope	0	17	41	30
Total trees per hectare	stems ha^{-1}	TPH	0	1467	6326	30
Average shrub height	meters	avg shrub ht	0.0	0.9	2.7	30
Shrub cover	percent	per shrub cover	0	11	60	30
Basal area per hectare	m^2 ha^{-1}	BA	0.0	25.3	76.2	30
Average neighboring canopy height	meters	neighbor ht	0.0	25.1	55.5	30
Size of canopy gap	hectares	size	0.1	0.3	0.7	30
Proportion of small trees	unitless	small-tree ratio	0.0	0.6	1.0	28
Northness	unitless	northness	−1.0	0.0	1.0	30
Eastness	unitless	eastness	−0.8	0.0	0.9	30
Dependent Variables (H1)						
March snow depth (log-transformed)	unitless	ln(March sd)	0.00	1.89	3.28	30
Snow disappearance date	nth day of 2021	SDD	80.0	87.73	99.0	26

Table 3
Regression results for best subset models predicting ln(March snow depth) and snow disappearance date.

Dependent variables:	ln(March snow depth)	Snow Disappearance Date
Intercept	2.8590***	90.1318***
	(0.2788)	(1.5489)
Age	−0.0494***	−0.2591***
	(0.0083)	(0.0622)
TPH	0.0002*	0.0019*
	(0.0001)	(0.0007)
Shrub cover	−0.0173*	-
	(0.0075)	
Adjusted R^2	0.5707	0.4231
P-value	< 0.001***	< 0.001***
Observations	30	26

Standard Error (SE) in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

commercial thinning—showed greater snow depths late in the season (Fig. 3c). Shrub cover trends were largely inconsistent across most classes, though the 19–35% shrub cover class maintained the highest snow depths where data were available (Fig. 3d).

3.3. The effect of canopy gap age on snow depth change during accumulation and ablation periods (H3)

3.3.1. Snow accumulation events

Canopy gap age emerged as a statistically significant predictor in four of five accumulation events, consistently showing a negative relationship with snow depth increase during accumulation events (Table 4). In other words, older gaps saw a smaller increase in snow depth during storm events, with age coefficients ranging from −0.097 cm/day (Accum4, $p = 0.011$) to −0.410 cm/day (Accum2, $p = 0.002$).

Other variables exhibited less consistent patterns. Slope and small-tree ratio were significant for Accum4, basal area for Accum1, and eastness for Accum5. However, no predictor besides canopy gap age showed significance across multiple events, suggesting that storm-specific characteristics (e.g. wind speed and direction) influence which topographic and vegetation factors become important during individual accumulation events.

3.3.2. Snow ablation periods

Canopy gap age was a significant predictor of snow depth change for three of four ablation periods, but its directional effects were inconsistent (Table 5). Age demonstrated negative effects, meaning slower snow depth loss snowmelt in older gaps during Ablat1 ($\beta = -0.039$ cm/day $p = 0.006$) and Ablat3 ($\beta = -0.088$ cm/day, $p = 0.002$), suggesting. However, age showed a positive effect, meaning faster snow depth loss, during Ablat2 ($\beta = 0.033$ cm/day/year, $p < 0.001$). The final ablation period (Ablat4) yielded no significant predictors, possibly because some sites started with substantially higher snow depths, introducing variability that obscured any meaningful relationships. Small-tree ratio was consistently negative and statistically significant in the first three ablation periods. Slope and northness were significant only in Ablat1.

Model performance for the first three ablation periods (adjusted $R^2 = 0.58–0.71$) were better than for accumulation events (adjusted $R^2 = 0.39–0.63$). However, canopy gap age consistently predicted snow depth change during accumulation events (always a negative impact), while its effects on snow depth change during ablation periods varied in direction across the season.

4. Discussion

The presence of canopy gaps and their age proved to be fundamental factors of snow depth change. Younger gaps experienced greater snow accumulation, greater late-season snow depths, and later snow disappearance dates. Gap age's influence on snow depth change during ablation periods was less consistent, with both positive and negative effects observed. In the 2-bin MARSS models, the age-constrained model did not outperform other predictor-constrained models and generally exhibited weak performance across the 11 predictors, suggesting that canopy gap age has limited influence on day-to-day snow depth. Nonetheless, canopy gaps as a whole maintained higher snow depth compared to dense forested stands, and their efficacy at retaining snow appeared to decline as young cohorts established and matured within the gaps. These findings suggest that retaining the benefits associated with large snow depth likely requires a silvicultural system that plans for continuous creation of gaps. Gap-based silviculture that creates distinct canopy gaps is known to enhance several co-benefits, including the regeneration and growth of desired species, reduced wildfire risk, and biodiversity (York et al. 2025). Increased snow depth from this silvicultural practice is an additional co-benefit that warrants more studying to understand the broader snowpack dynamics and hydrological impacts.

4.1. The effect of canopy gap age on end-of-season snow metrics

Canopy gap age emerged as the dominant predictor of both log-transformed March snow depth and snow disappearance date, consistently outperforming vegetation structure and topography variables in model selection. TPH and percent shrub cover also contributed significantly to the final models, although they had less leverage than age. These findings suggest that maintaining young canopy gaps is the primary way in which snow depth and snow persistence can be increased and that within-gap vegetation management can also be important,

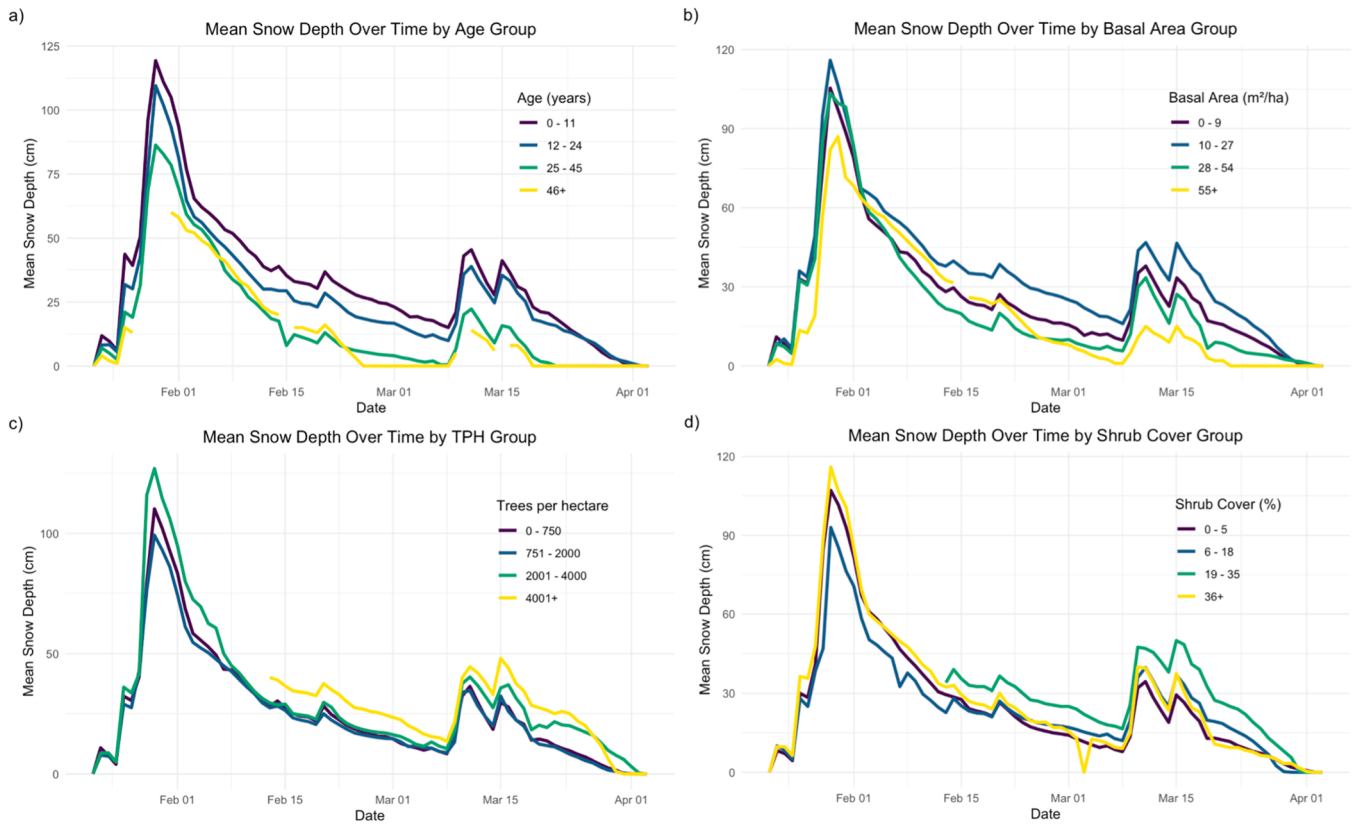


Fig. 3. Mean snow depth trajectories grouped by site characteristics: (a) canopy gap age, (b) basal area per hectare, (c) trees per hectare, and (d) percent shrub cover. Data gaps reflect periodic camera malfunctions during the study period.

Table 4
Regression results for best subset models predicting snow depth change for the five storm events.

Dependent variables:	**Accum1 (1/21/21–1/22/21)**	**Accum2 (1/24/21–1/25/21)**	**Accum4 (2/19/21–2/20/21)**	**Accum5 (3/8/21–3/15/21)**	**Accum6 (3/14/21–3/15/21)**
Intercept	13.6288**	34.4537***	6.0930**	11.0874***	9.5706*
	(3.6688)	(2.7244)	(1.6258)	(0.4302)	(3.4314)
Age	-	−0.4096**	−0.0973*	−0.0998***	−0.3196**
		(0.1085)	(0.0339)	(0.0188)	(0.0920)
Slope	0.1174	-	0.2012**	-	-
	(0.1157)		(0.0524)		
Northness	2.5382	-	-	0.9040	-
	(2.0547)			(0.4982)	
Shrub cover	−0.1025	-	-	-	−0.0884
	(0.0661)				(0.0808)
Basal area	−0.1487*	-	-	-	-
	(0.0500)				
Neighbor ht	−0.0722	-	-	-	-
	(0.0680)				
Small-tree ratio	-	-	−3.9352*	-	-
			(1.8372)		
Eastness	-	-	-	−1.5348*	-
				(0.5810)	
Size	-	-	-	-	17.6947
					(10.5800)
TPH	-	-	-	-	0.0009
					(0.0005)
Average shrub ht	-	-	-	-	1.6800
					(1.0569)
Adjusted R^2	0.2651	0.4689	0.4848	0.6328	0.3877
P-value	0.093	0.002**	0.002**	< 0.001***	0.026*
Observations	20	16	21	23	21

Standard Error (SE) in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5
Regression results for best subset models predicting the rate of snow depth change for the four ablation periods.

Dependent Variables:	Ablat1 (1/31/21–2/19/21)	Ablat2 (2/20/21–3/8/21)	Ablat3 (3/11/21–3/14/21)	Ablat4 (3/16/21–4/3/21)
Intercept	3.3388** (0.7589)	1.4325*** (0.3269)	10.2675*** (1.0442)	3.6543*** (0.5165)
Age	−0.0394** (0.0115)	0.0325*** (0.0070)	−0.0883** (0.0239)	-
Small-tree ratio	−1.8720* (0.6663)	−1.3551** (0.3988)	−6.5309*** (1.2883)	-
Slope	0.0705** (0.0202)	0.0221 (0.0108)	-	-
Size	3.5523 (1.6279)	-	-	-
Northness	−0.7730* (0.3255)	-	-	-
Eastness	0.66707 (0.3183)	-	-	-
Avg shrub height	-	-	-	0.3516 (0.3655)
Shrub cover	-	-	-	0.0217 (0.0210)
Neighbor canopy height	-	-	-	−0.0272 (0.0183)
Adjusted R^2	0.6691	0.7066	0.5797	0.06929
P-value	0.0034**	< 0.001***	0.0002**	0.2688
Observations	19	22	23	19

Standard error (SE) in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

albeit not as important as having forests that are heterogeneous in their canopy distribution.

Age consistently outperformed direct structural measurements such as basal area and tree density in predicting March snow depth and snow disappearance date, a pattern that requires mechanistic explanation. Most forest snow hydrology studies examine established stands with clearly defined canopy structure, with canopy cover as the main vegetation influence on snow processes (Essery et al., 2008; Lundquist et al., 2013; Varhola et al., 2010). However, our study focused on young stands regenerating within group selection harvests, presenting a different analytical challenge. At early successional stages, distinctions between overstory and understory blur, making traditional canopy cover metrics difficult to define and less meaningful. Rather than attempting to define the point at which a harvested gap becomes a "closed" stand, this study focuses on characterizing how snow depth changes continuously through the regenerating stage. For these developing stands in the 0–40-year age range, the temporal dimension of stand development may capture vegetation influences more effectively than structural measurements.

As expected, age demonstrated correlation with basal area ($r = 0.73$). Yet age consistently outcompeted basal area in model selection, suggesting that time since gap creation encapsulates developmental trajectories that static structural metrics cannot fully represent. As canopy gaps regenerate, they undergo complex successional changes. Early-stage gaps are typically shrub-dominated, but shrub cover declines as canopy closure reduces light availability. Tree density initially increases during the first 10–15 years, then decreases due to competitive self-thinning and management interventions such as pre-commercial thinning. Concurrently, basal area accumulates and vertical stratification develops, fundamentally altering vegetation-snow interactions. While these dynamics are somewhat predictable in large, even-aged stands (i.e. clearcuts), strong edge influences make them more complex in canopy gaps (York et al. 2025). Interactions between vegetation structure and snowpack are already complex, involving tradeoffs between interception, wind protection, shading, and radiative exchanges (Lundquist et al., 2013; Varhola et al., 2010). In mature forests where canopy cover, LAI, and basal area are high, greater interception and longwave radiation dominate these interactions, particularly in regions experiencing warmer winters, such as our study sites (Lundquist et al., 2013; Varhola et al., 2010).

The positive relationship between TPH and both March snow depth and snow disappearance date initially appears to contradict conventional forest snow hydrology literature, where greater forest density typically reduces snow accumulation (Lundquist et al., 2013; Varhola et al., 2010). However, this apparent contradiction reflects differences between our regenerating stands and the mature forests examined in most studies. Existing studies demonstrating negative relationships between forest density and snowpack typically use canopy cover, leaf area index (LAI), or basal area as density metrics (Gleason et al., 2021; Krogh et al., 2020; Varhola et al., 2010). These measures differ fundamentally from our TPH metric because they capture the characteristics of mature canopy structure.

In this study, all stems reaching breast height (1.68 m) were classified as trees to capture their potential influences on shading and interception within regenerating canopy gaps. This definition encompasses young regeneration and saplings, a size class that differs substantially from the mature forest stands examined in most studies. On average, trees less than 7.6 cm in diameter comprised 56% of total TPH but accounted for 20% of total basal area, indicating that high-TPH stands in our study were dominated by numerous small-diameter stems rather than large mature trees. These small-diameter trees have much less leaf area relative to their stem counts, and the positive association between TPH and snow depth suggests they did not reduce snow depth to the degree that mature canopy structure does in established forests.

Conversely, the negative relationship between shrub cover and March snow depth aligns with established understanding. Previous studies demonstrate that shrub protrusion results in lower albedo and increased longwave emission from shrub stems that accelerate snowmelt (Marsh et al., 2010; Pomeroy et al., 2006; Wilcox et al., 2019). Additionally, shrubs contribute to snow interception, though the relative importance of these mechanisms in our study system remains unclear.

The contrasting effects of trees (positive) and shrubs (negative) on March snow depth suggest that vertical structure and vegetation type may be as important as overall vegetation density in determining snow depth within young canopy gaps. While the shrub cover coefficient appears larger than the TPH coefficient, these variables have different units (percent versus count), precluding direct magnitude comparisons. Our findings show that high-density small-diameter trees, along with shrub cover, influence snow depth. However, their interception capacity, shading effects and other influences on the energy balance cannot be understood from snow depth measurements alone. Future research should consider small-diameter trees and shrub effects while incorporating more meaningful measurements of snowpack dynamics, such as snow density.

Our data suggest a roughly linear decline in snow depth as canopy gaps age from initial harvest through approximately 30–40 years of regeneration, at which point end-of-season snow metrics approach those of mature stands. The two oldest control sites—representing fire-suppressed mature forest and a frequently burned mature open stand—exhibited minimal March snow depth (0 and 0.6 cm, respectively), while young gaps retained up to 25 cm. Given the uncertainty in control site age assignment described in the methods, these results should be interpreted in terms of the direction and general pattern of gap age-related snow depth decline rather than as precise quantitative predictions.

These findings have important implications for understanding how forest management practices influence snow depth. First, they suggest that gap-based silviculture is likely better at improving desired snow patterns compared to even-aged silviculture or low-intensity fuel treatments that do not alter canopy heterogeneity. The 40-year window during which harvested gaps retain more snow than mature forests

suggests that age-class distributions resulting from management activities could significantly affect snow depth patterns. A gap-based silvicultural system would sustain these snow benefits by creating canopy gaps periodically and indefinitely. For example, a forest that had 10% of its area converted to canopy gaps every 10 years would eventually maintain 30–40% of its area within "sweet-spots" of snow retention. This is not a management prescription the authors are recommending, as the optimal rotation age would also need to account for other silvicultural objectives, site conditions, and ecological constraints beyond the scope of this study. Rather, it illustrates how managers can estimate the proportion of forest area likely to have greater snow depth. Further snow enhancement could come from management of tree density and shrub cover with prescribed fire or other treatments within young gaps. These gap creation and vegetation treatments are aligned with broader goals of reducing fire severity in Sierra Nevada forests.

4.2. Age-dependent weather effects on daily snow depth

The MARSS time-series analysis revealed that grouping sites by shared characteristics substantially improved model performance compared to treating sites independently, confirming that between-site similarities in weather-snow relationships can be leveraged for more parsimonious modeling. However, the relative performance of canopy gap age diverged notably from patterns observed in the end-of-season MLR analysis. While canopy gap age dominated the prediction of March snow depth and snow disappearance date, the age-constrained MARSS model ranked only 8th among the eleven predictor-constrained models. Instead, the basal area-constrained model achieved the lowest AICc score, followed closely by TPH and shrub cover, suggesting that these structural variables are better at capturing snow depth variation from daily weather changes.

This disconnect reflects different temporal scales: the MLR analysis examined end-of-season outcomes from an entire winter's accumulation and ablation processes, while the MARSS models assessed daily weather responses. Age performed well as a predictor of end-of-season snow depth but does not strongly differentiate day-to-day snow depth response to weather variables.

The bootstrap analysis for the BA-constrained model revealed that wind and temperature were the dominant weather drivers, with high-basal-area sites demonstrating greater sensitivity to both. The enhanced temperature sensitivity in high-basal-area sites aligns with established understanding: greater vegetative mass emits more longwave radiation, accelerating melt during warm periods (Lundquist et al., 2013; Roth and Nolin, 2017). The stronger wind effect in high-basal-area sites may relate to reduced shrub cover (due to canopy closure), though the mechanisms of wind redistribution, sublimation, or other processes cannot be determined by snow depth measurements alone. Similarly, the weaker association between solar radiation and snow depth at high- basal-area sites is consistent with greater canopy shading at denser stands, though the underlying energy balance processes cannot be directly assessed from snow depth measurements. The low-basal-area sites were more sensitive to the precipitation $\times$ temperature interaction variable, showing greater changes in daily snow depth.

Despite basal area's superior performance in the MARSS analysis, visual examination of age, TPH, shrub cover, and basal area trends across four class groupings revealed that age produces the clearest differentiation in snow depth throughout the season (Fig. 3a). This discrepancy highlights an important distinction: basal area may better predict how sites respond differently to daily weather inputs, while age more powerfully explains why some sites consistently maintain greater snow depth regardless of daily fluctuations. The parallel pattern of snow depth decrease during ablation periods suggests relatively similar rates of loss across age classes. These trends combined with the regression results for the March snow depth suggest that age-related differences in snow depth are established during accumulation events rather than ablation periods. During brief but critical accumulation periods, younger gaps consistently developed greater snow depths than older gaps, though whether this reflects reduced canopy interception, enhanced wind deposition, or other mechanisms cannot be distinguished by snow depth measurements alone. These differences in snow depth persisted at relatively similar rates of loss across age classes through the ablation periods.

In contrast, the visual trends for basal area and shrub cover show notably less consistent patterns (Figs. 3b and 3d). The highest basal area group ($\geq$55 m^2/ha) does not maintain a consistent rank throughout the season, at times showing the lowest snow depth and at other times the second highest snow depth. Shrub cover trends are similarly difficult to interpret, with no group consistently maintaining higher or lower snow depth relative to the others across the full season apart from the 19–35% shrub cover class (which has partial missing data). These crossing trajectories suggest that the influence of basal area and shrub cover on snow depth may shift during the season, potentially reflecting changes in the relative importance of competing processes such as interception, shading, and longwave radiation emission under different weather conditions. However, the mechanisms driving these patterns cannot be determined from snow depth measurements alone, and the inconsistency of these trends across the season warrants further investigation with more comprehensive measurements of the sub-canopy energy balance.

Data limitations may further explain the discrepancy between the multiple linear regression and time-series model outcomes. The two-bin approach for the MARSS modeling, while necessary given our sample size of twenty-five time-series, likely obscures more nuanced patterns in weather sensitivity across the full variation of vegetation structure or canopy gap age. Three- or four-bin groupings would likely be better at capturing relationships between predictors and weather responses if a larger sample were available. However, these constraints primarily affect the precision of our daily weather sensitivity estimates rather than the broader end-of-season snow patterns we observed.

4.3. The effect of canopy gap age on snow depth change during accumulation and ablation periods

The event-based analysis provides key insight into how canopy gap age influences snow depth at discrete temporal scales, revealing that age exerts its strongest influence during accumulation events while its effects during ablation periods are inconsistent.

Canopy gap age emerged as a statistically significant predictor in four of five analyzed storm events, consistently demonstrating a negative relationship with accumulation rate; older gaps experienced less snow depth increase during storms. The exception was the first major storm of the season (Accum1), where basal area was the sole significant predictor, possibly reflecting different early-season conditions before a base snowpack was established. The coefficient magnitudes for age varied substantially across storms (-0.097 to -0.410 cm/day), suggesting that storm-specific meteorological conditions modulate the strength of age effects. This reduced accumulation in older gaps is aligned with the expected increase in canopy interception as tree crowns expand, though this mechanism cannot be confirmed by snow depth measurements alone.

Age effects on ablation rates were less consistent. Age was significant in three of four ablation periods but varied in direction: negative during Ablat1 and Ablat3 (slower snow depth loss in older gaps) and positive during Ablat2 (faster snow depth loss in older gaps). The mid-season Ablat2 period, during which older gaps experienced faster snow depth loss, coincided with notably warmer temperatures (0.8–2.6°C higher than during Ablat1 and Ablat3). During cooler ablation periods (Ablat1 and Ablat3), older gaps experienced slower snow depth loss. These bidirectional age effects over the season may have contributed to the relatively similar rates of snow depth loss, preserving the snow depth differences established during accumulation events.

The final ablation period (Ablat4) showed no significant predictors, likely due to high late-season heterogeneity as some sites had melted out while others retained deep snow. This heterogeneity meant that "ablation rate" was calculated over vastly different temporal windows for different sites, obscuring relationships between site characteristics and melt rates.

These results imply that forest structure influences snow depth primarily through accumulation events, not ablation periods. Age-related vegetation development was consistently associated with lower snow depth accumulation, while snow depth loss during ablation periods was relatively similar across sites and appeared more strongly influenced by weather conditions.

4.4. Management implications and further research directions

Current models characterizing snow-canopy interactions require detailed forest structure data and advanced instrumentation such as LiDAR that remain inaccessible to most forest managers (Krogh et al., 2020; Roth and Nolin, 2019; Strasser et al., 2011). These models must resolve complex and often counteracting physical processes including interception, wind protection, shading, and longwave radiation emission (Varhola et al., 2010). For similar forest ecosystem types experiencing comparable successional trajectories, canopy gap age—or equivalently, years since last harvest—may provide a practical and effective proxy for predicting snow depth change during accumulation events and end-of-season snow metrics like March snow depth and snow disappearance date. This finding substantially reduces the operational complexity of predicting snow depth to a single, readily available variable. While age does not capture all physical complexities or site-specific nuances, its consistent performance suggests that managers could potentially use harvest records to identify which group selection stands are likely to have greater snow depth and later snow presence.

These findings should be interpreted within the temporal and spatial scope of this study. Data were collected over a single winter season (2020–2021), which had well-below average precipitation, with Central Sierra Nevada snowpack reaching only 63% of normal SWE on April 1, 2021 (Castellano et al., 2021). The strength and direction of the gap age and snow depth relationship may vary across years with different precipitation totals, storm timing, or temperature patterns, and the coefficients reported here should not be applied prescriptively. Multi-year replication would be needed to assess the robustness of these relationships across wet and dry winters.

In addition, data were collected within a single elevation band (1200−1500 m) and with modest sample size, which limits generalizability across broader elevational gradients, forest types, and climatic conditions. Comparative studies examining group selection versus alternative silvicultural approaches that also increase canopy heterogeneity would provide more insight on landscape-scale strategies for enhancing snow depth. Furthermore, this study only measured snow depth and snow presence, whereas more comprehensive assessments of forest-snow interactions have incorporated snow water equivalent, snow density, canopy interception, sublimation, and sub-canopy energy balance components including shortwave and longwave radiation fluxes (Lundquist et al., 2013; Roth and Nolin, 2017; Varhola et al., 2010), leaving the processes underlying the observed snow depth patterns uncharacterized here.

The association between high-density small-diameter trees and deeper late-season snow depth observed here differs from patterns reported in mature forest stands, suggesting that understory vegetation warrants closer examination. A greater small-tree ratio corresponded with less snow depth change during both accumulation events and ablation periods. Qualitative observations further suggest that gaps with some shrub presence and many small trees were associated with greater snow depth, indicating that some vegetative cover may be preferable to bare ground — a relationship with potential implications for pre-commercial thinning decisions. Future studies should consider high-resolution structural characterization of small-diameter trees and shrubs through tools such as LiDAR alongside direct measurements of energy balance variables to better understand the mechanisms driving snowpack patterns in young regenerating gaps.

A number of research gaps remain from this study: At what diameter size or density do trees' shading benefits balance longwave radiation losses? Is there an optimal level of shrub cover for snow retention? How do these relationships vary across broader elevational gradients and forest types? How does group selection compare quantitatively to alternative silvicultural approaches that also increase canopy heterogeneity? Do significant changes in snow depth and snow disappearance date meaningfully impact water resources? Answering these questions will require comparative studies in different geographies with expanded sampling designs and high-resolution vegetation and snowpack measurements.

For managers aiming to increase snow depth on their forested lands, group selection harvesting may be a promising management strategy, particularly when compared to passive management that allows development of dense, closed-canopy conditions. An uneven-aged forest managed through group selection, featuring gaps of varying ages distributed across the landscape, would maintain a greater proportion of forest in age classes associated with greater snow depth while simultaneously enhancing other attributes that contribute to overall forest resilience. The snow depths associated with young canopy gaps in this study are consistent with recent experimental evidence from the Eastern Cascades, where small to mid-sized canopy gaps between 4 and 16 m in diameter showed the greatest snow depth gains following forest thinning treatments (Lumbrazo et al., 2026). This spatial and temporal heterogeneity represents a key advantage of the group selection approach over even-aged stand treatments. However, managers whose primary objective is to influence water supply timing or water yield should interpret these findings cautiously. Greater snow depth and later snow disappearance dates provide only a partial picture of the processes that affect hydrological outcomes. To make meaningful inferences about downstream water availability, future studies in similar forest types would need to incorporate more comprehensive snowpack and water balance measurements including snow water equivalent, snow density, sublimation, canopy interception, and evapotranspiration in addition to the metrics measured in this study.

The present study examined forests in the rain-snow transitional elevation zone, which represents a critical management area. These forests are more operationally accessible than high-elevation sites due to lower elevations, yet they are also most vulnerable to climate-driven snowpack losses. As warming temperatures continue shifting the rain-snow transition upward in elevation, snowpack as a co-benefit becomes increasingly important for safeguarding water resources while supporting overall forest health and resilience. The relationship between canopy gap age and snow depth and snow disappearance date documented here provides a useful starting point for incorporating snow depth considerations into forest management decisions, while acknowledging that more comprehensive measurements are needed to draw broader hydrological conclusions.

5. Conclusion

This study demonstrates that canopy gap age serves as an accessible and powerful predictor of snow depth and snow disappearance date in Sierra Nevada mixed-conifer forests managed through group-selection harvesting. Three key findings emerge from our integrated analysis of end-of-season metrics, daily time series, and discrete accumulation and ablation events.

First, snow depth declines approximately linearly over 30–40 years as canopy gaps regenerate, eventually approaching snow depths similar to mature, closed-canopy stands. Young gaps (0–11 years) with high-density small-diameter trees were consistently associated with greater snow depth and later snow disappearance dates, while older gaps

(30–40 + years) showed progressively shallower snow depths approaching those of mature closed-canopy forest. The mechanisms underlying this pattern cannot be determined from snow depth measurements alone, but canopy gap age provides a practical predictor of snow depth outcomes across different age classes.

Second, our event-based analysis suggests that age-related differences in snow depth were established primarily through accumulation events rather than ablation periods. Older gaps consistently showed lower snow depth increases during storms, and these differences persisted through the remainder of the season. This pattern is consistent with the strong performance of age in predicting end-of-season outcomes such as March snow depth and snow disappearance date while showing weaker performance in daily time-series models. Whether the lower accumulation in older gaps reflects greater canopy interception, reduced wind deposition, or other processes cannot be determined from snow depth measurements alone, but the pattern suggests that accumulation events may be a more important source of age-related variation in snow depth than ablation periods.

Third, from an operational standpoint, canopy gap age is readily available from harvest records and was a consistent predictor of snow depth and snow disappearance date in this study. However, additional data across broader spatial and temporal scales are needed before it can be reliably used as a practical proxy for identifying stands likely to retain greater snow depth. Its accessibility makes it feasible to incorporate snow depth considerations into forest planning for resource-limited management agencies. However, because snow depth declines as gaps regenerate toward closed-canopy conditions, sustained benefits require continuous gap creation through ongoing group selection harvesting. A forest managed with gaps of varying age classes distributed across the landscape can maintain a greater proportion of its area in age classes associated with greater snow depth while simultaneously achieving multiple objectives, including wildlife habitat diversity, fuel heterogeneity, and forest resilience. Expanding this work across broader spatial and temporal scales will be essential for translating these findings into reliable management guidance.

While strategic silvicultural interventions cannot offset large-scale climatic shifts, maintaining young canopy gaps through group selection harvesting could be one practical tool for increasing snow depth in mid-elevation Sierra Nevada forests. The relationships in this study offer forest managers a starting point for incorporating snowpack benefits into silvicultural planning in these climatically vulnerable transitional zones.

CRediT authorship contribution statement

Sabrina Chui: Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Gregory Verutes:** Writing – review & editing. **Tessa Maurer:** Writing – review & editing. **Robert York:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Matthew D. Potts:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During manuscript preparation, the authors used Claude (Anthropic) to assist with statistical analysis code, data visualization, and language refinement to improve clarity, conciseness, and flow. This manuscript would be about 3000 words longer without the use of AI. All AI-generated content was reviewed, edited, and verified by the authors, who take full responsibility for the published work.

Funding

This work was supported by the University of California, Berkeley and Blue Forest.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

I thank the UC Berkeley programs and fellowships that provided financial support for this research. I also thank Blue Forest for supporting manuscript preparation.

Field assistance was essential to this project's success. Annapurna Holtzapple and Kestrel Grevatt assisted with rebar cutting, snow depth stake construction, and field installation. Carina Bilodeau and Saumitra Kelkar helped take vegetation measurements in the most challenging field sites. Kestrel Grevatt and Nic Dutch assisted with in-situ snow depth measurements.

I am grateful to my undergraduate research assistants—Lianne Wong, Case Arends, Daniela Paredes Robles, and Valerie Hammer—for processing over 18,000 trail camera images and for teaching me valuable lessons about mentorship.

Dr. Rob York and Dr. Matthew Potts provided invaluable guidance throughout my master's research and continued support afterwards. Dr. Tessa Maurer and Dr. Gregg Verutes offered helpful insights and manuscript edits. Finally, I thank Matthew Francis for his unwavering support and encouragement.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2026.124046.

Data availability

https://github.com/sabrina-chui/Canopy-gap-age-snowpack-study-2025

drivers, raw_data, snowdepth_TSA (Github)

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