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# Snow Accumulation Increases With Forest Structural Diversity in Low-Relief Catchments

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## ABSTRACT

In snow-dominated areas, runoff from winter precipitation can comprise up to 80% of the annual water budget. Warming winters are shifting snow precipitation to rain, shortening the snow accumulation and melt seasons, and increasing midwinter melt events and flooding during rain-on-snow events. At the same time, forests are changing in species composition and geographical extent, and forest-dominated catchments can mediate the effects of increased winter temperatures on snow dynamics. Here, we combine climatic data and high-resolution forest and snow observations to investigate the complex relationships between forest canopy structure and below-canopy snow depth in two low-relief Mississippi headwater catchments. To do so, we use a two-dimensional canopy cover metric (i.e., leaf area index) with forest canopy and understory surveys and catchment terrain (e.g., slope, aspect) to examine their joint influences on snow depth. Results show that (1) co-dominant tree density is a better predictor of peak snow depth over leaf area index, due to representation of both canopy overlap and interception and (2) canopy structural diversity increases peak snow depth. These results suggest that maintaining forest structural diversity not only contributes to forest health but also allows for a deeper snowpack, thereby increasing the potential for water storage in snow-dominated low-relief watersheds.

## 1 | Introduction

In many regions, snow is a crucial part of the annual water cycle. In a low-relief forested headwater catchments, snowmelt fills wetlands and surface water stores and can supply between 50% and 60% of critical groundwater recharge (Dripps and Bradbury 2010). Understanding the physical drivers of snow accumulation and melt in forested headwater catchments is complicated by the interaction between an increasingly erratic winter weather and changes in forest composition. While uncertainties remain over projections of future winter precipitation, steadily increasing winter temperatures will likely lead to shorter snow seasons, with more frequent mid-winter thaws and earlier spring melt (Barnett et al. 2005; Ford et al. 2020). These shifts in precipitation due to climate change—and their resulting impacts on snow dynamics—are further affected by changes in forest composition due to deforestation, fire, and disease, especially in regions on the boreal-temperate forest divide such as the upper Midwestern and Western United States (Angel et al. 2018). With approximately 17%–19% of the snow-covered area in the Northern Hemisphere overlapping with the extent of boreal forests, the effects of forest canopy on snow dynamics play an essential role in determining the snow contribution to the annual water balance. Changes in forest cover and composition will likely have a widespread impact on future water resource availability (Rutter et al. 2009; Musselman et al. 2021).

Canopy cover can both directly and indirectly influence winter and spring snow dynamics. Increased interception due to higher amount of canopy cover can directly reduce snow accumulation on the ground, while additional shading can directly reduce spring melt rates (Koivusalo and Kokkonen 2002; Gao et al. 2022). The changes in snow accumulation and depth can, in turn, indirectly shift the timing of spring melt as larger snowpacks tend to melt more slowly (Varhola et al. 2010; Molotch et al. 2009). Additionally, forest cover can influence snow dynamics indirectly through its impact on under canopy boundary layer conditions. For example, increased forest canopy reduces wind speed (Hedstrom and Pomeroy 1998) and increases interception, which in turn limits turbulent fluxes, evaporative losses (Link and Marks 1999), shortwave radiation (Ellis et al. 2011; Link and Marks 1999; Boon 2009), and blowing of snow (Dickerson-Lange et al. 2015), which then slows melt. On the other hand, increased losses to interception in combination with higher rates of midwinter melt due to higher latent and sensible heat under the canopy can lead to much earlier melt under dense forest cover (Cristea et al. 2014). An increase in longwave radiation in some dense conifer stands also results in earlier 'centre-of-mass' of the timing of the snowpack (by 12 days on average), generating higher amounts of peak snowmelt (Ellis et al. 2011; Cristea et al. 2014).

Still, these under canopy dynamics are further influenced by local climate and topography. In warm and wet regions as well as cold and dry regions, forests show higher sensitivity to changes in forest density than in cold and wet regions (Sun et al. 2022). Forest canopy effects on snowmelt can be influenced by physiographic features, with increased melting along north-facing slopes and decreased melting along south-facing slopes (Ellis et al. 2011; Murray and Buttle 2003). The effects of aspect and topography on snow distribution sometimes surpass the effects of forest canopy shading itself (Murray and Buttle 2003; Mazzotti et al. 2023). This sensitivity demonstrates that forest–snow interactions not only have counteracting mechanisms on a plot scale, but that these mechanisms are also mediated by the surrounding physical environment. It is therefore crucial to study forest canopy and snow interactions in a variety of seasonally snow-covered landscapes.

At the plot scale, forest cover is typically estimated using various metrics for canopy cover, such as leaf area index (LAI), plant area index, canopy closure, or sky view factor (Musselman et al. 2012). Leaf area index, the most common metric, can be calculated using hemispherical photographs of the forest canopy (Chen et al. 1991; Zhang et al. 2005; Teti 2003) or approximated from airborne laser scanning data (Varhola and Coops 2013). Leaf area index is useful in predicting physical (e.g., interception, wind protection) and thermodynamic (e.g., shading, longwave radiative transfer) effects on snow accumulation (Ellis et al. 2011; Hedstrom and Pomeroy 1998). Yet, LAI only provides a two-dimensional view of canopy density and does not account for the more complex forest structure dynamics that cause spatial variations in snow accumulation and melt. While LAI provides a good proxy for canopy density in many contexts, this oversimplification of forest structure may lead to discrepancies in snow accumulation models. One study found snow accumulation to be similar beneath canopies with up to a 13% difference in forest cover (Pomeroy et al. 2002), implying the existence of other secondary forest structures and meteorological controls on snow accumulation.

We examine several potential metrics of secondary forest structure such as canopy classification, tree size and structural diversity, and their influence on snow accumulation and melt at plots with contrasting levels of canopy closure. We use high-resolution vegetation and snow data with three-dimensional modelling techniques to examine the following questions: (1) Under what levels of canopy closure, by canopy type (deciduous, coniferous or mixed), does LAI accurately predict snow depth and (2) how can plot-specific vegetation data augment two-dimensional LAI predictions of snow depth? We hypothesize that plots with high canopy closure (i.e., coniferous dominated plots) will have higher correlations with LAI, whereas plots with less canopy closure will have weaker correlations and be more heavily influenced by secondary forest structure controls. We use these results to focus on one physical forest process, snow interception, and show how a three-dimensional view of canopy structure and canopy overlap can inform and improve LAI-based snow predictions under both cover types. Additionally, we present a new metric for representing canopy structural diversity and its implications for snow accumulation beneath forest canopies.

## 2 | Methods

### 2.1 | Field Sites: Marcell Experimental Forest, Grand Rapids, MN

The forested catchments used in this study are located within the USDA Forest Service Marcell Experimental Forest (MEF, Lat. 47:31:52 N, Long. 93:28:07 W) near Grand Rapids, Minnesota, USA. The MEF has six peatland-dominated research catchments that have been instrumented and monitored since the 1960s. The north-central Minnesota climate is strongly continental with warm, humid summers and cold, dry winters with seasonally frozen ground. From 1961 to 2019, mean annual temperature at the MEF was 3.5°C (Sebestyen et al. 2021). Average annual air temperature has been increasing by 0.4°C per decade since 1961 with warming occurring across all seasons, especially the winter months (January–March, 0.7°C per decade, Sebestyen et al. 2011; Dymond et al. 2014). Annual precipitation averages 79 cm, with one-third of precipitation falling in the form of snow. Snow cover starts in late October and November and usually lasts until March or April of the following year. There has been no change over time in maximum snow water equivalent (SWE) under coniferous, deciduous, or open areas between 1961 and 2009 (Sebestyen et al. 2011).

We study the S2 and S6 reference catchments (Figure 1). Each catchment has a central raised-domed bog surrounded by an upland forest on mineral soils. The S2 research catchment is 97 000 $m^2$ (9.7 ha), including a 32 000 $m^2$ (3.2 ha) peatland. The uplands are dominated by deciduous aspen (*Populous tremuloides*, *Populous grandidentata*) and maple (*Acer rubrum*, *Acer saccharum*) trees in the overstory. The peatland is dominated by black spruce (*P. mariana*) and *Sphagnum* mosses. The S6 research catchment is 89 000 $m^2$ (8.9 ha) in size including a 20 000 $m^2$ (2.0 ha) peatland. The S6 uplands are conifer-dominated with

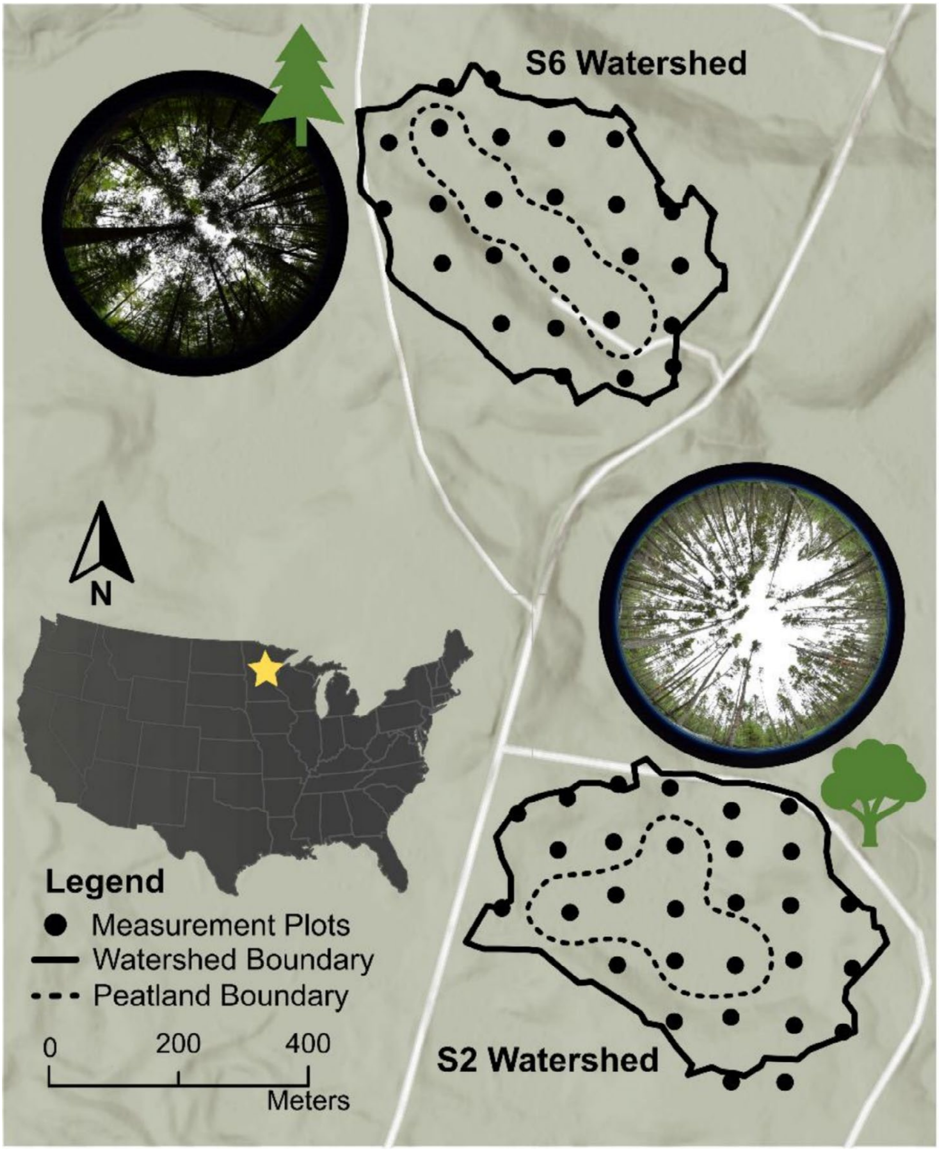


**FIGURE 1** | The 54 plots where snow depth and vegetation were sampled at the S2 and S6 Watersheds within the Marcell Experimental Forest (MEF), Grand Rapids, Minnesota, USA, superimposed over a digital elevation model of the site with their relative geographical locations. Solid lines depict the catchment boundaries and dashed lines show the approximate bog boundaries. Inset LAI photos show the typical upland cover for each catchment: Deciduous for S2 and coniferous for S6.

white spruce (*Picea glauca*), balsam fir (*Picea balsamea*), and red pine (*Pinus resinosa*). Like the S2 catchment, the S6 bog is dominated by black spruce (*P. mariana*), tamarack (*Larix laricina*) and *Sphagnum* mosses.

## 2.2 | Vegetation and Snow Collection

Two types of data were collected for this project: snow data and canopy data, which were collected around 54 (25 in S6, 29 in S2) plot centres across the uplands and peatlands within each catchment. From 2022 to 2024 snow data were collected along a 50-m resolution grid in both S2 and S6 (Figure 1). Snow depth was collected using an avalanche probe at each plot centre, which was walked along a set transect line to ensure minimal disturbance to the snowpack. For the plot centre, peak snow depth was determined to be the maximum depth (cm) of the snowpack for each Water Year (WY; October 1–September 30, e.g., WY 2023; October 1, 2022–September 30, 2023).

Hemispherical photos were taken at each snow sampling location in August 2022 and December 2022 to quantify summer and winter LAI, respectively (Welles and Norman 1991; Welles and Cohen 1996). Photos were taken using a Nikon 3300 camera and fisheye lens 0.3 m from the plot centre in each of the cardinal directions; LAI was then calculated from the photos using GAP light analyzer software (Frazer et al. 1999). Leaf area index values are unitless and typically range from 0 (bare ground) to 4.5 (dense conifer forest) but values as high as 7 can be obtained (Norman and Campbell 1989). The four values were averaged for a LAI estimate at each survey plot. These photos also contained elements of tree trunks and branches which could qualify them as estimates of plant area index; however, the term LAI is used throughout this study for consistency with other snow–canopy interactions literature. Vegetation was surveyed in the summer of 2023 at each plot. Overstory was catalogued in an 8 m radius circle surrounding the plot centre. Tree species, diameter-at-breast height (DBH), canopy crown classification (suppressed, intermediate, co-dominant, and dominant trees), and distance from the plot centre were recorded for all trees over 9 cm DBH. Understory woody ($\geq$1.3 m height) and herbaceous species quantity were recorded in a 2 m by 2 m square around the plot centre. During data post-processing, individual trees were categorized as deciduous or coniferous based on the species, and a fractional proportion of co-dominant canopy (pCo) and coniferous canopy (pCon) at each plot was calculated. Additional catchment data such as slope and aspect at each snow sampling location was derived from a 2 m resolution digital elevation model (DEM).

## 2.3 | Data Analysis and Canopy Modelling

### 2.3.1 | Initial Statistical Analysis and Variable Importance

To determine the effectiveness of LAI in predicting peak snow depth across various plot compositions, initial linear regression models were run on three groupings of plots: coniferous (pCon $\geq$ 0.66), mixed (0.33 $\leq$ pCon $\leq$ 0.66), and deciduous (pCon $\leq$ 0.33). A mixed effects model was run on each subset of data using 'water year' as an indicator variable for high (2023 WY) and low (2024 WY) snow conditions. Relationships were considered significant at a $p$-value of 0.05 or smaller. The correlation coefficient, $R^2$, root mean squared error (RMSE), and $p$-values were each used to compare model effectiveness across the three cover types.

A random forest analysis was run on the combined vegetation and catchment data to determine the most influential catchment characteristics in determining peak snow depth. The random forest algorithm used a 80/20 train-test split and 100 decision trees of the full S2 and S6 snow data for both water years. Highly correlated ($R^2 \geq 0.5$) and partially redundant forest inventory variables (i.e., proportion of coniferous trees and proportion of deciduous trees) were removed from the analysis, and tuning was done to optimize random forest tree depth and testing data accuracy. Variable importance was pulled from the random forest algorithm using Shapely Additive Explanations (SHAP) values (Lundberg and Lee 2017) and separated using the 'water year' indicator variable for high and low snow depth in the two water years. A SHAP value corresponds to the impact that a given variable has on the model result (i.e., peak snow depth) with a higher absolute value denoting a higher impact on the model result. For a given model variable, such as co-dominant canopy, low values of that variable coincident with more positive SHAP values would indicate an inverse relationship between that variable and the model results.

### 2.3.2 | 3D Canopy Architecture Simulation

We developed a three-dimensional canopy architecture model to estimate the effect of canopy structure on peak snow depth. Simulations were done using Rhinoceros 3D with the Grasshopper plugin for algorithmic modelling (Robert McNeel and Associates 2023). The purpose of this three-dimensional model was to estimate the inherent physical property of canopy overlap, which is not readily measurable in situ in forests. For each plot, tree DBHs and distances from the plot centre were randomly generated for the number of trees measured at the plot from a normal distribution fitted to the mean and standard deviation of the field data. Tree azimuth, taken from the plot centre, was randomly sampled from a uniform distribution bounded at 0° and 365°. Over 100 simulations, this method of azimuth generation offered a distribution of potential tree layouts around the plot centre. To add the three-dimensional representation, coniferous trees were modelled as geometric cones with a tree height and crown width calculated using allometric equations for *P. mariana* (Bush et al. 2024). For deciduous species, crown shape was not considered due to the absence of foliage, and trees were represented as cylinders with a height calculated from allometric equations for *A. rubrum* (Bush et al. 2024). Repeating this process for each tree on a given plot gave a geometric estimation of the canopy shape which could be used to estimate overlap and canopy cover.

### 2.3.3 | Canopy Structure Metrics

For the three-dimensional simulated data, canopy structure was represented via two metrics: canopy overlap and canopy cover. Canopy overlap was calculated as the difference between the total canopy volume (i.e., the summation of the volumes of each tree) and the union of the tree volumes. The canopy overlap calculation allowed for multiple counting of canopy overlaps if more than two tree canopy shapes overlapped in the same location. Canopy cover was defined as the total canopy volume or the geometric union of all simulated trees. A conceptual diagram showing these metrics in two dimensions is shown in Figure 2. The three-dimensional canopy structure model was run for 100 iterations to determine the mean canopy overlap and cover estimates at each plot. Peak snow was not simulated in the three-dimensional model. Instead, the values of mean canopy overlap and cover were correlated with peak snow depth measured at the respective sites to develop a linear model for snow depth from canopy overlap and cover.

For the field data, canopy structural diversity was characterized by adapting a version of the Hill–Simpson Diversity Index (Simpson 1949) for vertical canopy structure. The Hill–Simpson Diversity Index ($S$, Equation (1)) is a measure of the variability within a plot and is less sensitive to outliers than the Shannon Diversity Index (Roswell et al. 2021).

$$S = \frac{1}{\sum_{i=1}^{CC} p_i^2} \tag{1}$$

where $S$ is calculated as a sum of the proportion ($p_i$) of trees in each canopy crown class by number of trees (CC: dominant, co-dominant, intermediate, and suppressed) at each plot to approximate a value for vertical structural diversity.

$$\Theta_d = \frac{S}{N} \tag{2}$$

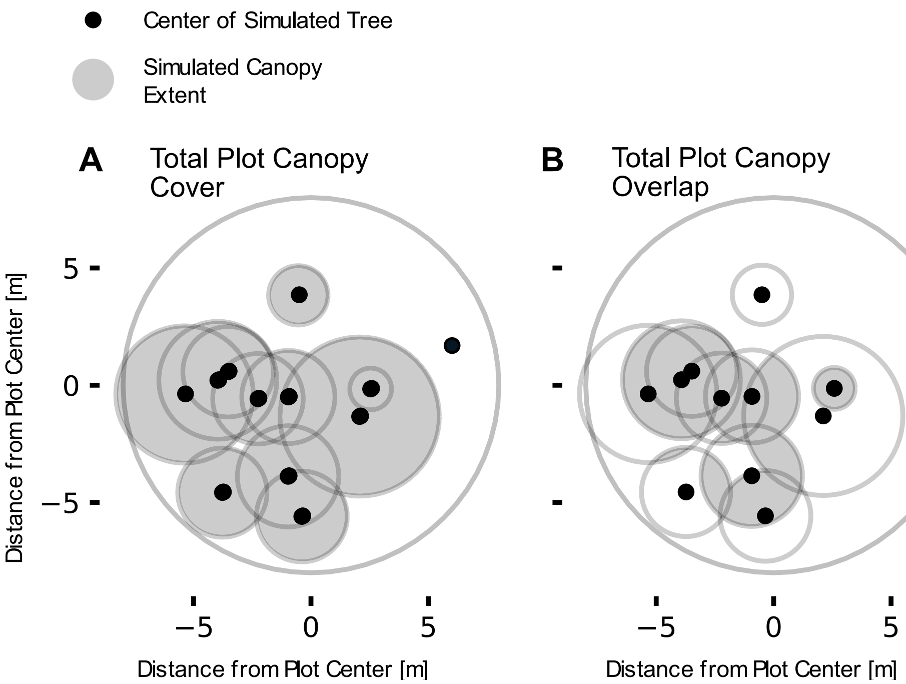


**FIGURE 2** | Conceptual diagram of two-dimensional canopy structure. Dark points show simulated tree location while grey outlines show canopy width. Additional shaded regions denote areas used to compute canopy cover (A) and canopy overlap (B).

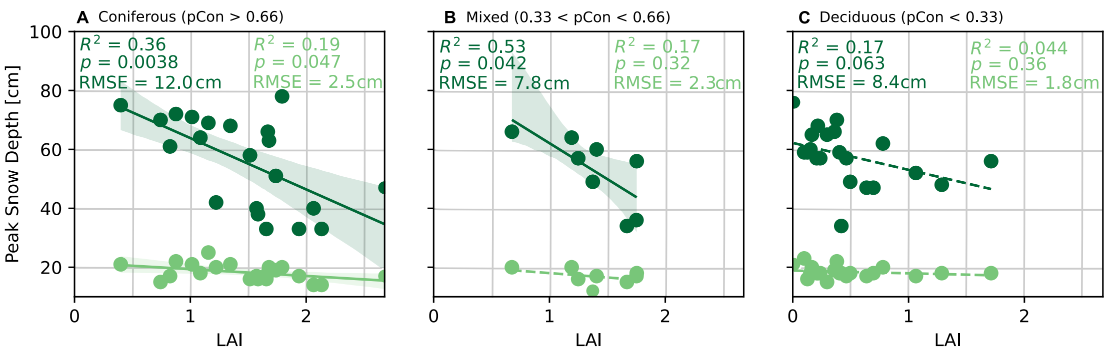


**FIGURE 3** | Peak snow depth predicted by LAI at all plots by dominant cover type: (A) coniferous dominated plots with more than 66% of trees being coniferous, (B) mixed plots with between 33% and 66% of trees being coniferous, and (C) deciduous dominated plots with less than 33% of trees being coniferous. Light green denotes the low snow year (2024 WY) while dark green denotes the high snow year (2023 WY). Shaded regions around significant regressions (solid lines) denote the 95% confidence interval.

The adapted Hill–Simpson Index was combined with the number of trees at the plot ($N$) to develop a new index for normalized canopy structural diversity at a plot ($\Theta_d$, Equation (2)). The index was then correlated with peak snow depth data at each plot for each water year to determine the relationship between normalized canopy structural diversity and snow accumulation.

## 3 | Results

### 3.1 | Effects of LAI Versus Co-Dominant Trees on Peak Snow Depth

Snow depth data showed high spatial and temporal variability among upland plots within each catchment. Peak snow depth during the 2023 WY, a high snow season, was between 33 and 78 cm beneath the canopy, while peak snow depth during the 2024 WY, a low snow season, was between 12 and 25 cm. The LAI across the 54 plots ranged from 0.01 (open) to 2.68 (closed) with a mean LAI of 1.04. Under dense coniferous forest cover (21 of 50 vegetation plots), LAI was a good prediction of peak snow depth during both water years—$R^2$ values ranged from 0.36 (high snow; $p = 0.0038$) to 0.19 (low snow; $p = 0.047$; Figure 3A). Under mixed canopy (eight vegetation plots) LAI was correlated with peak snow depth during the water year with higher snow only ($p = 0.042$; Figure 3B). Leaf area index was not correlated with peak snow depth for either water year ($p = 0.063$ and 0.36, respectively) under the dense deciduous canopy (21 vegetation plots, Figure 3C), nor for the mixed-canopy forests when overall snowfall was lower (2024 WY; $p = 0.32$; Figure 3B).

The number of co-dominant trees had the highest impact on peak snow depth in the SHAP analysis, surpassing that of LAI. After eliminating highly correlated and redundant variables

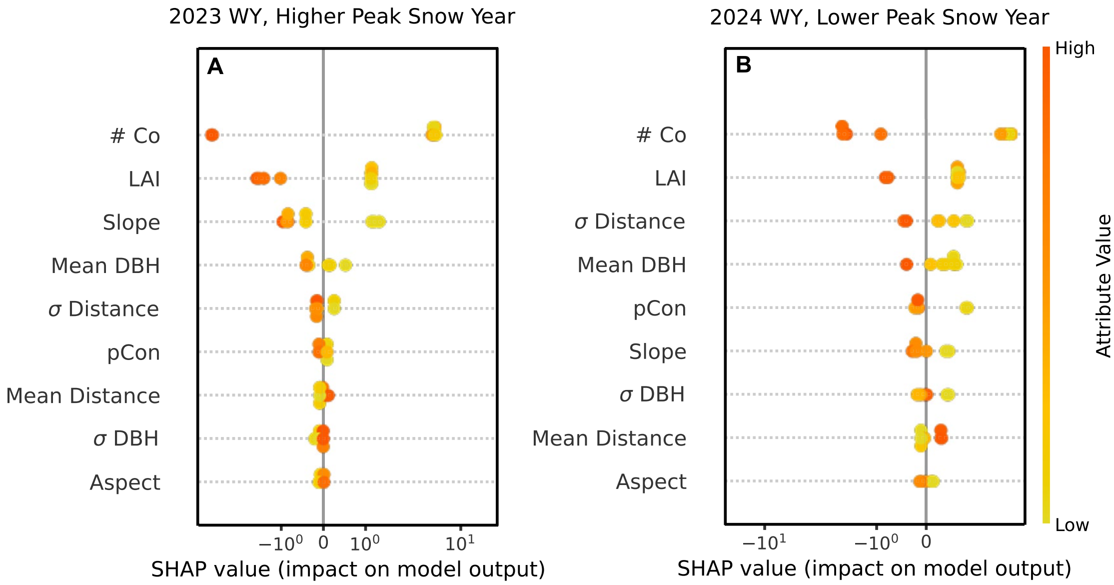


**FIGURE 4** | Results of a SHAP test for variable importance using 100 decision trees on peak snow depth data. From top to bottom variables are shown in order of calculated importance. Points are shaded according to attribute value (red: high predictor value; orange: low predictor value). Results on the left (A) are from 2023, the higher snowfall water year, and results on the right (B) are from 2024, the lower snowfall water year.

(see Figure S1), tree location (mean distance, standard deviation of distance), tree size (mean DBH, $\sigma$DBH), plot characteristics (aspect, slope), LAI, proportion of coniferous trees, and number of trees in the co-dominant canopy were selected for the random forest analysis. The random forest model had an RMSE of 6.91 cm, a training accuracy of 0.91, and a testing accuracy of 0.90. The SHAP analysis ranks predictor variables of peak snow depth from the highest to lowest absolute SHAP value (Figure 4). Points in Figure 4 are shaded by the value of the predictor variables, or attributes; for example, Figure 4A shows that high values of co-dominance (in red) had a negative impact (indicated by the negative SHAP values) on the model output (i.e., lower peak snow depth) and lower values of co-dominance (in orange) had a positive impact (i.e., higher peak snow depth). For both study years, the number of trees in the co-dominant canopy was the highest-ranked predictor of peak snow depth, surpassing the impacts of LAI on peak snow depth. However, during the year with higher overall snowfall (2023 WY) LAI and slope had higher impacts on peak snow depth while LAI and variability in spacing (i.e., standard deviation of distance from plot centre) were more important in the water year with lower snowfall (2024 WY). In both years, increases in the number of trees in the co-dominant canopy led to lower peak snow depth beneath the canopy.

### 3.2 | 3D Canopy Model and the Effect of Canopy Overlap

The three-dimensional canopy model highlights the difference between LAI and co-dominant canopy in predicting peak snow depth by focusing on the magnitude of canopy overlap (Figure 5). Increasing canopy overlap was strongly correlated with decreases in peak snow depth. Canopy cover computed from the three-dimensional canopy structure model was inversely correlated with peak snow depth in the 2023 WY (higher snowfall; $p = 0.001$) and not significantly correlated in the 2024 WY (lower snow; $p = 0.011$; Figure 5, top). On the other hand, canopy overlap was inversely correlated with peak snow depth in both years ($p = 4.6\mathrm{e}{-5}$ and 0.021, respectively; Figure 5C,D).

Canopy overlap and LAI were similar predictors of peak snow depth. Residuals from the two linear regression models are shown in Figure 6A,B where points above the line in (B) are plots where the overlap model had a lower residual and points below the line had higher residuals. Neither model had demonstrably lower residuals than the other with one model performing better at certain sampling plots than the other model. Typically, peak snow depth for coniferous upland plots were modelled better by LAI than for sparse trees in bogs, which were modelled better by the canopy overlap model. Plots with higher coniferous cover had larger variations in residuals between the two models.

Vertical normalized canopy structural diversity correlated with peak snow depths across all cover types. The canopy diversity index $\Theta_d$ had a positive correlation with peak snow depth in water years with both high and low snow in dense deciduous, coniferous, and mixed cover types (Figure 7). Independently, the number of trees was inversely correlated with peak snow depth in both years ($p = 8.2\mathrm{e}{-5}$ and $p = 0.03$, respectively) and the Hill–Simpson Index was only directly proportional to peak snow depth in the water year with high snow ($p = 0.031$). A linear model fit using LAI shows comparable $R^2$ and RMSE values for coniferous and mixed cover types and higher values for deciduous cover types ($R^2 = 0.42$ and 0.05 compared to $R^2 = 0.17$ and 0.04 for high and low snow water years using LAI, respectively). Fitting the diversity index data using a piecewise function yielded higher values of $R^2$ than the linear regression, which, due to the increased parameterization, was less directly comparable to the LAI model. However, combined, the piecewise canopy structure index had higher or equal $R^2$ and lower or equal RMSE than

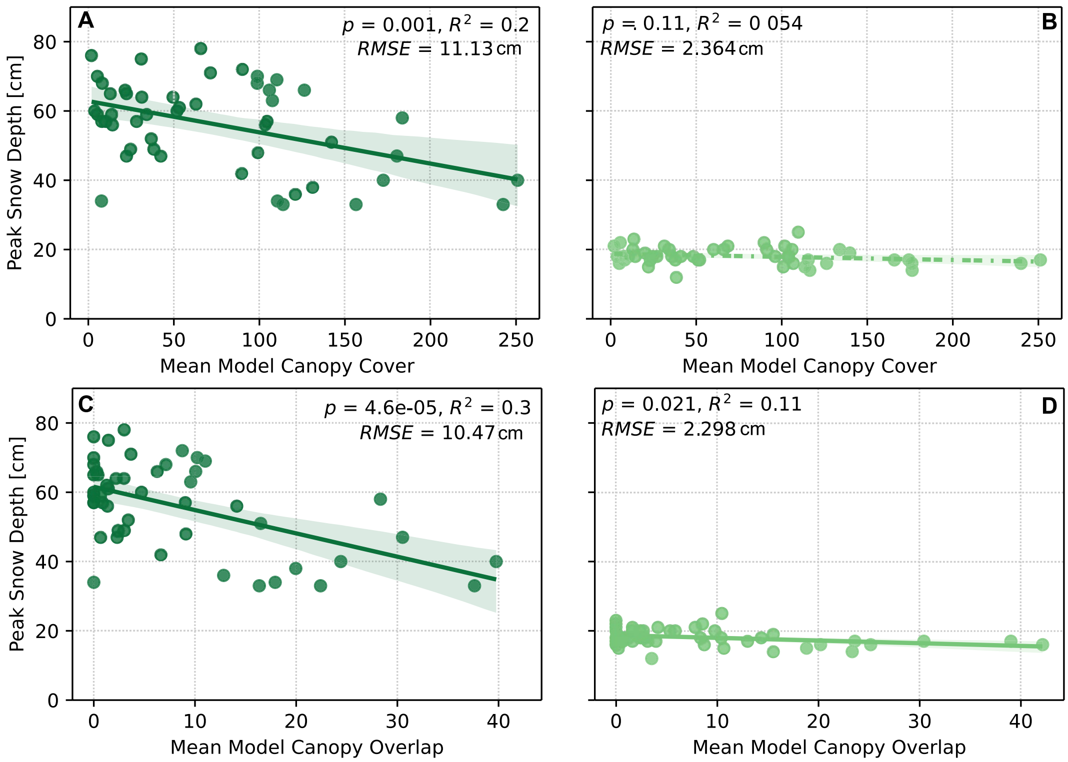


**FIGURE 5** | Results from the 3D canopy architecture simulation showing the correlation between (A, B) canopy cover, (C, D) canopy overlap and peak snow depths across all plots. Plots A and C show results in the 2023 WY (high snow) and plots B and D show results in the 2024 WY (low snow). Lines show the estimated least squares regression line while shading represents a 90% confidence interval around the mean.

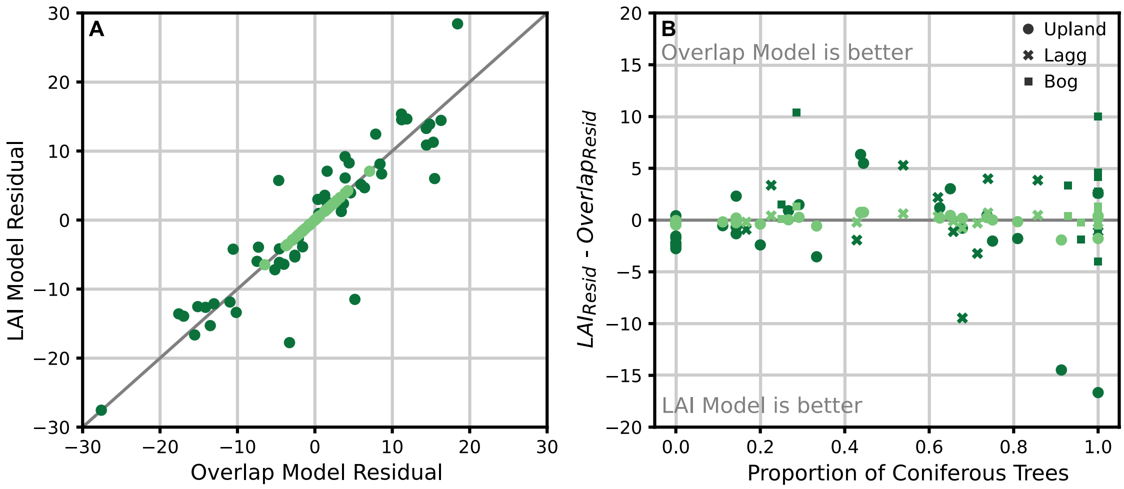


**FIGURE 6** | Comparison of model results between the regression model for LAI and the regression model for canopy overlap. (A) Residuals from each model. (B) The difference in residuals between each model by canopy co-dominance. Points above the line are plots where the canopy overlap model had lower residuals and points below the line show plots where the LAI model had lower residuals. Light green denotes the water year with lower snow (2024 WY) while dark green denotes the year with higher snow (2023 WY).

LAI in all years under all canopy types (Figure 7). The full model across all cover types can be found in Figure S2.

## 4 | Discussion

We explored the utility of three-dimensional vs. two-dimensional metrics to assess how forest structure controls snow accumulation below forest canopies. Many current forest canopy metrics used in snow hydrology studies, such as DBH or LAI, are two-dimensional approximations of canopy structure (Musselman et al. 2012; Varhola et al. 2010; Sun et al. 2022; Gelfan et al. 2004; Hedstrom and Pomeroy 1998; Broxton et al. 2015). Here, we demonstrated that co-dominant tree density can enhance predictions of peak snow depth. We found that LAI is effective in predicting snow depths at plots with high proportions of coniferous trees and in years with higher snowfall inputs. However, snow depths in years with lower input of snow and plots with

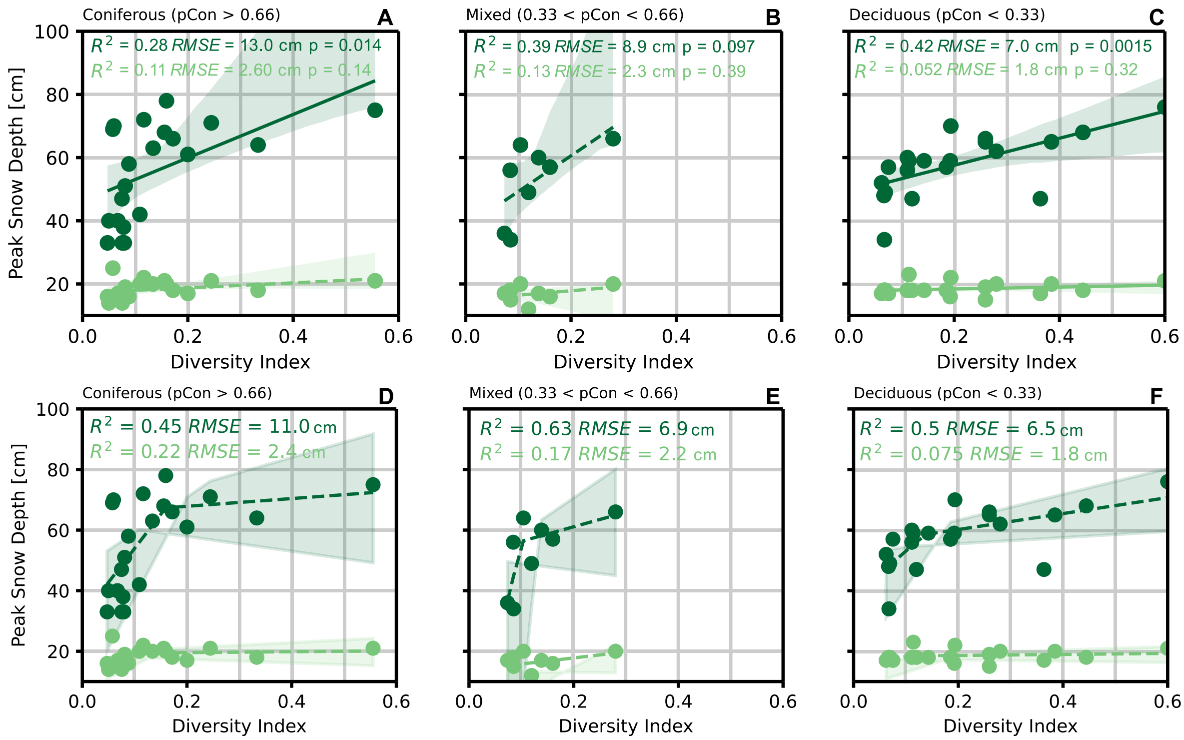


**FIGURE 7** | Peak snow depth predicted by the normalized structural diversity index, $\Theta_d$, at all plots by dominant cover type: (left) coniferous dominated plots with more than 66% of trees being coniferous, (centre) mixed plots with between 33% and 66% of trees being coniferous, and (right) deciduous dominated plots with less than 33% of trees being coniferous. The top row shows data fitted with a linear regression (same as that applied to the LAI data), and the bottom row shows the same points with piecewise regression fits. Light green denotes the water year with low snow (2024 WY) while dark green denotes the water year with high snow (2023 WY).

high proportions of deciduous trees are less well represented by LAI.

### 4.1 | Co-Dominance and the Importance of Canopy Overlap

Leaf area index has been traditionally used to infer the influence of multiple forest processes on snow accumulation—including physical snow interception, wind reduction, sheltering from blowing snow, canopy shading, and longwave radiation from trees (Lundquist et al. 2013; Ellis et al. 2011; Broxton et al. 2015; Musselman et al. 2012). However, we have shown that for forests in low-topographic relief catchments in the upper Midwestern USA, LAI does not fully capture three-dimensional information that can potentially mediate these forest processes. For instance, we found LAI to be an effective predictor of peak snow depth at plots with high proportions of coniferous trees (LAI between 0.40 and 2.68, Figure 3A) and decreased in importance with increasing deciduousness until LAI no longer significantly predicts peak snow depth at plots with low proportions of coniferous trees (LAI between 0.01 and 1.71, Figure 3C). This result is consistent with our hypothesis that LAI is a good predictor of peak snow depth at coniferous-dominated plots where the maximum LAI is highest (high canopy closure). However, its efficacy is highly dependent on canopy type.

Results from the random forest model and subsequent SHAP analysis showed that, consistent with our hypothesis, co-dominance in the canopy, used as a measure of canopy structure, was more effective than LAI in snow depth prediction in years with both high and low peak snow depth (Figure 4). This effect may be due to more overlapping among co-dominant tree types within a canopy, and LAI, which is derived from a single-point perspective photo and represents a measure of canopy closure, has limited ability to account for such vertical structure. By better representing the effects of canopy overlap, co-dominance was also better able to represent the effects of snow interception and sublimation, two physical forest processes associated with canopy overlap. Using a simple three-dimensional model to simulate forest structure at each of the plots, we showed that canopy overlap is effective for predicting peak snow depth in both high and low snow years (Figure 5, $p = 4.6\text{e}{-05}$ and 0.021, respectively). Furthermore, this is an inverse relationship, showing that increasing canopy overlap (i.e., increasing co-dominance) can drive decreases in peak snow depth (Figure 5).

However, the success of the canopy overlap model over LAI as a predictor of snow accumulation varied based on forest type. Taken as a whole, neither LAI nor the canopy overlap model showed superiority in model residuals (Figure 6). Although, the overlap model performed better than the LAI model in the bog, which is dominated by a sparser coniferous canopy with little canopy overlap, whereas the LAI model performed better in the upland plots, which have high proportions of dense coniferous trees. These contrasting performances may be attributed to the importance of interception in these different settings. For example, canopy coverage in the uplands is already dense—increases in overlap do not necessarily lead to increased interception and lower snow depths. In contrast, the canopy is sparser in the bog, and even small increments in canopy overlap lead to larger reductions in accumulated snow. Another non-physical reason for the discrepancy may be due to the simplified allometric equations used in this model. In this model, coniferous trees were represented using allometric equations for *P. mariana*, the dominant bog species, while deciduous tree species were all approximated using allometric equations for *A. rubrum*. Increasing the model complexity to include species-specific allometric equations for each simulated tree species in the three-dimensional forest structure would likely reduce this additional variation in the canopy overlap model.

### 4.2 | Snow Depth Increases With Structural Diversity

The newly developed normalized structural diversity metric, $\Theta_d$, based on the Hill–Simpson diversity metric, improved the representation of three-dimensional forest structure over LAI. It increases with structural diversity, *S*, and more so for plots with sparser canopy cover, *N*. Increases in normalized structural diversity represented by $\Theta_d$ correlated with increasing peak snow depths across all cover types (Figure 7). In each case, there was a large increase in peak snow depth at plots with low structural diversity followed by a slowed increase around a $\Theta_d$ threshold value of 0.1–0.2. It was for this reason that the additional piecewise model was fit to the diversity index data. While the linear model is a more accurate comparison (due to the number of parameters) to the initial LAI and snow depth plots in Figure 3, the piecewise function is useful for detecting threshold behaviour and a slowed response to increased structural diversity. When managing for snow retention, uneven-aged forest management strategies that promote structural diversity, such as single-tree selection or thinning approaches, could result in increased snow depths.

### 4.3 | Interpreting the Role of Structural Diversity

While structural diversity as defined in this paper has not been explicitly studied, the effects of forest cover on snow have been widely examined across the Western United States. A recent comprehensive study focusing on forest–snow interactions across the Western U.S. under different climates found that forest canopy density in dry and cold climates (such as those in northern Minnesota) and wet and warm climates had greater effects on peak SWE and snow accumulation than dry and warm and wet and cold climates (Sun et al. 2022). Part of this disparity is due to the negligible amount of incoming solar radiation during the winter in dry and cold climates, which limits the amount of early-season melt across any canopy type. Therefore, in dry and cold, increases in snowpack accumulation should be predominantly driven by decreases in canopy density. At the MEF, our results are consistent with the framework presented by Sun et al. (2022), as we see clear forest controls on snow accumulation. Sun et al. (2022) also hypothesized that low-density canopy will have a more variable effect on snow accumulation than high-density canopy, which are also corroborated by our findings (Figure 7). Any differences in the magnitude of snow interception processes, especially in low-density stands, could be because our bog plots are dominated by black spruce (*P. mariana*) which has a different canopy shape and height than that simulated by Sun et al. (2022).

Similar analyses across western U.S. forests suggest that forest edge effects exert strong controls on snow accumulation and ablation (Currier and Lundquist 2018; Dickerson-Lange et al. 2021; Essery and Pomeroy 2004; Hiemstra et al. 2002, 2006; Geddes et al. 2005). In one analysis, differences in temperature, wind protection, solar radiation, and forest architecture between two edges of the same forest led up to a 38% difference in snow accumulation (Currier and Lundquist 2018). In some cases, the difference in accumulated snow between edges was greater than the difference between open and closed canopy (Currier and Lundquist 2018); in others, the wind-blowing effect was so great that snowpack beneath the forest and along the forest edge was significantly greater than in open areas (Geddes et al. 2005). The effects of forest edges can also be extrapolated to forest gaps where it has been shown that in gaps at least half as large as the surrounding tree height snowpack is significantly higher along the north-facing edges (Biederman et al. 2014). This relationship and the fact that south-facing aspects result in earlier melt-out than Dwivedi et al. (2024) indicate the importance of shading as a control in forest edges and gaps. At the MEF, the 'edges' exist along the circumference of the bog, where there is a shift in the basal area and composition of the forest. There may be unrecognized or unquantified edge effects that are absent from our normalized structural diversity index. This source of variability could also be why we see higher RMSE in the coniferous-dominated bog plots (Figure 7) and why there is no clear difference between the LAI model and the overlap-based model at most lagg (forest edge) and bog (forest gap) plots (Figure 6B). Expanding the forest structure index presented in this paper to include forest edge may be able to capture some of these disparities potentially caused by forest edge interactions. In the meantime, the benefits of the index in predicting snow accumulation under diverse canopy coverage should always be considered in conjunction with forest edge dynamics.

## 5 | Conclusion

We evaluated the utility of a three-dimensional canopy structure model to improve the estimation of snow accumulation in an upland–peatland forest complex. Here, plot-specific vegetation data were used to show that co-dominant canopy, and the canopy overlap it represents, is an important indicator in predicting peak annual snow depths, more so than LAI.

Managing the upland forest to increase structural diversity has already been shown to yield other forest ecosystem benefits in addition to snow accumulation such as regeneration, species composition, and fire susceptibility (Pimont et al. 2011; Ziegler et al. 2017; Pelz et al. 2015). Currently, many Western USA forest management practices are oriented towards maintaining forest health, fire suppression, or promoting snow retention. However, going forward, it is essential to consider these processes mutually. Forest management for snow retention typically includes thinning for open gaps and reducing forest density to increase the snow retention in open areas (Dickerson-Lange et al. 2021). As climate change progresses and winter precipitation shifts from snow to rain (Berghuijs et al. 2014), snowpack dynamics in boreal forests are being altered, complicating resource management decisions (Dickerson-Lange et al. 2021). Lower snowpack size and earlier snowmelt can lead to summer soil drought and increased fire risk (Jain et al. 2024). On the ecosystem level, snow has been shown in Northeastern USA watersheds to act as an insulator for the soil and smaller snowpacks can expose roots to damaging frosts (Tierney et al. 2001; Cleavitt et al. 2008) risking increases in tree mortality, and consequently, fire fuel. Developing management strategies that target increasing forest structural diversity in the Midwest will not only decrease fire risk, reduce plant mortality, and increase species diversity, but also—as this study shows—lead to higher snow accumulation and snow water retention.

Recent advances in aerial, satellite, and ground-based remote sensing technologies for determining tree and stand height (Magnussen and Boudewyn 1998; Li et al. 2012; Morsdorf et al. 2004) and other forest canopy measurements (Varhola and Coops 2013; Varhola et al. 2014; Maas et al. 2008) allow the estimation of the diversity index for large catchments beyond the limitations of plot-level vegetation surveys. Using tree height variation within a stand as a measure of vertical structural diversity, these remote sensing techniques could further improve estimation of snow accumulation patterns across larger catchments.

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#### Conflicts of Interest

The authors declare no conflicts of interest.

#### Data Availability Statement

The data and codes that support the findings of this study are openly available at https://github.com/mwdjones/canopycontrols-2025.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section. **FIGURE S1:** Correlation heatmap showing all variables collected from the vegetation surveys and calculated from local DEMs. Darker greens show more positively correlated variables and light yellows show more negatively correlated variables. Only significant correlations ($p \leq 0.05$) are shown. Variables of tree location (mean distance, standard deviation of distance), tree size (mean DBH, standard deviation of DBH), plot characteristics (aspect, slope), LAI, proportion of coniferous trees, and number of trees in the co-dominant canopy were kept for the random forest analysis. **FIGURE S2:** Full results for the diversity regression analysis showing (left) the dependence of snow depth on both the Hill-Simpson Diversity Index and the number of trees on the plot. Shading is based on the percentage of the maximum annual snow depth for each year. Symbols represent the 2023 high snow year in circles and the 2024 low snow year in xs. (right) shows the full piecewise regression for all plots under all covertypes. Light green denotes the low snow 2024 year while dark green denotes the high snow 2023 year.