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Statistical emulation of hyper-resolution mechanistic snow modeling assesses forest management and the importance of tree arrangement

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A R T I C L E I N F O

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A B S T R A C T

Forests are changing rapidly due to drought, disease, wildfire, and forest management, with unknown impacts on snowmelt resources. While hyper-resolution forest hydrology models capture the effects of canopy cover amount and arrangement on snowpack, they are too complex for landscape-scale assessments. Here, we evaluated two statistical approaches to emulate high-resolution (1 m) mechanistic model maps of snow variables for future application in forest management and drew inferences about topographic vs. forest canopy controls. We tested a simple landscape classification using one or more of topographic northness, canopy cover, and surrounding forest arrangement and machine learning (ML) models of varying complexity to emulate maps of peak SWE, liquid water input, and snow cover duration (SCD) from the 3-D forest hydrology model SnowPALM, which was previously trained using lidar and daily Snowtography. We evaluated three winters at three mid-scale study areas (∼50 ha) in the southwestern US spanning gradients of SCD and forest type. All approaches emulated areal mean values within <2 %. Landscape classification captured 50–80 % of spatial variability, while ML explained 88–98 %. Increasing ML complexity was needed to emulate snow maps having greater spatial variability, which tended to occur where SCD was greatest: at high/cold sites, in cold/wet winters, and in locations shaded by terrain or nearby trees. Warm/dry forests were adequately modeled using canopy cover. These results demonstrate a generalizable approach for future upscaling of forest snow measurements through sequential mechanistic and statistical modeling for hydrologically informed forest management.

1. Introduction

Snowpack is a globally vital water resource for mountain ecosystems, agriculture, and other societal needs, but long-term changes in winter weather and land cover are altering the land surface partitioning of snow between sublimation and melt as well as melt timing (Bales et al., 2006; Mote et al., 2018; Musselman et al., 2021; Qin et al., 2020; Viviroli et al., 2007). In western North America, recent decades have seen an acceleration in forest disturbances enhanced by reduced precipitation and rising temperatures including drought mortality, pathogens, and especially wildfire (Abatzoglou et al., 2021; Coop et al., 2020; Hicke et al., 2016; Steel et al., 2023; Venturas et al., 2021). After a century of management focus to suppress wildfires, there has been a proliferation of forest management efforts aimed at reducing forest densities and fuel loads to improve forest health and reduce risks of uncharacteristically severe fires through selective harvest, prescribed burning, and/or managed fire (McIntyre and Schultz, 2020; Moreau et al., 2022; Stephens et al., 2021). Decadal-scale forest restoration efforts to reduce fire risk over millions of hectares include the Collaborative Forest Landscape Restoration Program (CFLRP https://www.fs.usda.gov/restoration/CFLRP/) (Kooistra et al., 2022; U.S. Department of Agriculture, 2015), the Wildfire Crisis Strategy (US Forest Service, 2022), and several executive orders. These management efforts largely aim to return forests to their natural range of canopy cover and spatial arrangement and reduce the risk of forest disturbances such as severe wildfires and droughts. However, changes in the amount and spatial arrangement of

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forest canopy can also alter forest hydrology, especially in snowmelt-dominated watersheds (Biederman et al., 2015; 2014; Brown et al., 2005; Dwivedi et al., 2024a; Stednick, 1996). Present forest restoration programs therefore represent a unique, timely opportunity to better understand and potentially influence hydrologic outcomes for future forests and downstream water supplies.

Forest management influences both canopy cover amount and its spatial arrangement (Belmonte et al., 2021), both of which have substantial impacts on snowpacks in forested areas. While topography and winter weather are first-order controls on snow distribution and dynamics (Anderton et al., 2004; Gustafson et al., 2010; Trujillo et al., 2007; Winstral and Marks, 2002), the amount of forest cover can have large impacts on radiation balance, seasonal snow sublimation, and the amount and timing of snowmelt (Biederman et al., 2014; Lundquist et al., 2013; Molotch et al., 2009; Sankey et al., 2015; Svoma, 2017; Varhola et al., 2010; Veatch et al., 2009). Increasingly, the spatial arrangement of canopy (i.e. size and arrangement of canopy clusters and gaps) is recognized as an important regulator of snow energy and mass balance (Broxton et al., 2015; Currier and Lundquist, 2018; Dwivedi et al., 2024a; Lundquist et al., 2018; Mazzotti et al., 2020). Forest spatial arrangement often results in high spatial heterogeneity of peak snow water equivalent (SWE), liquid water input (LWI, the sum of snowmelt and winter rain), and snow covered duration (SCD) across forested landscapes (Dwivedi et al., 2024a). Our recent work across sites with varying SCD showed that snow variability was dominated by canopy cover effects on interception at warmer sites with shorter-duration ephemeral snowpack, whereas it was increasingly affected by topography and canopy spatial arrangement at wetter/colder sites and in wetter/colder years with longer-duration stable seasonal snowpack (Dwivedi et al., 2024a).

Highly resolved snow observations are needed to quantify how snowpack and its variability are affected by forest cover and arrangement under different topographic and climatic conditions (Mazzotti et al., 2021). Airborne lidar can provide high spatial resolution snapshots of snow depth, forest canopy and topography as well as snow water equivalent (SWE) when combined with maps of snow density (Broxton et al., 2019; Painter et al., 2016; Yang et al., 2023). Spatiotemporal snowpack observations, such as daily snow depth photographs collected by Snowtography (Broxton et al., 2019; Dickerson-Lange et al., 2015; Dwivedi et al., 2023a; Payton et al., 2021) track the temporal evolution of snow depth along transects that span gradients of forest-snow environments (e.g. under canopy, forest edge, open), where snow is differently influenced by interception and exposure to radiation and wind (Currier and Lundquist, 2018; Mazzotti et al., 2020). The spatiotemporal combination of highly-resolved snow lidar and the Snowtography time series provides a powerful dataset for model training and testing (Dwivedi et al., 2024a).

With high-precision measurement and modeling of forest management scenarios, it is now possible to understand management effects on the amount and timing of snowmelt. Mechanistic models play a key role in representing how forest management alters snow water resources. Representation of underlying processes tends to make mechanistic models more applicable for conditions of weather and management beyond the calibration range (Rakhmatulina et al., 2021). Furthermore, mechanistic models provide useful estimates of key variables that are difficult to measure directly, such as snowmelt fluxes distributed across mosaics of forest canopy and topography (Dwivedi et al., 2024a). However, there remains an important gap between the hyper-resolution modeling of forest-snow interactions at the scale of individual trees (~1 m) and the coarser scales used in most snow, hydrologic and land surface models and datasets (e.g. remote sensing pixel, hillslope, forest restoration cut unit) (Cederstrom et al., 2024; Livneh et al., 2015). Such coarse-scale models usually rely on leaf area index or canopy cover averaged over relatively large model pixels. Coarse-scale models may be improved for snow performance by attributing within-pixel fractions to forested and unforested cover types, which are then weighted to calculate coarse pixel mass and energy balance (Sun et al., 2022). This approach neglects to reproduce important snow processes regulated by the three-dimensional structure of forest in the neighborhood surrounding an element of snowpack (Mazzotti et al., 2021), which can be represented by hyper-resolution models such as SnowPALM (Broxton et al., 2015) and FSM2 (Mazzotti et al., 2020). Several studies have evaluated means to coarsen hyper-resolution modeling and datasets by various strategies and illustrated the importance of representing small-scale variability of forest-snow processes related to 3-D geometric structure (e.g. Broxton et al., 2015; Mazzotti et al., 2021; Mott et al., 2023).

Hydrologically-informed forest management requires the spatially explicit representation of fine-scale forest structure, yet hyper-resolution models are technically challenging and time-consuming, and their application for landscape-scale forest projects (thousands of ha) is computationally expensive. In this work, we explore several statistical approaches for bridging the gap between hyper-resolution mechanistic forest snow modeling over moderate spatial extents (~50 ha) and upscaling to landscape-scale forest projects (thousands of ha) in future work. We conduct all evaluations over three winters with a wide range of winter weather, so that the resulting trained models may be applied over years with different characteristics. In this paper we do not perform upscaling but instead explore the capability of statistical methods to emulate maps of snow hydrologic variables from the hyper-resolution SnowPALM model while retaining the 1 m resolution of the SnowPALM maps. Our goal is to provide practitioners with practical options to efficiently predict and assess the hydrologic impacts of forest management actions; the methods evaluated attempt to balance maximizing accuracy with minimizing the complexity of data inputs, user skill requirements, and computational time. Therefore, we use prior field measurements, empirical analyses, and mechanistic modeling to guide data input selection rather than including all data inputs that could feasibly be brought to bear for statistical prediction. In future work, we will use the approaches developed here to upscale SnowPALM maps of moderate extent to evaluate the impacts of landscape-scale forest restoration while retaining the 1 m resolution needed to represent fine scale forest-snow interactions. While hyper-resolution mechanistic modeling will generally require forest practitioners to rely on academic or agency partners to provide model output for modest spatial extents, the snow model emulation approaches illustrated herein improve the accessibility of hyper-resolution snow variable mapping to inform forest management at large scales.

In snow hydrology, statistical models have been used to emulate maps of snow depth and SWE (Bair et al., 2018; Broxton et al., 2019; Elder et al., 1998; Musselman et al., 2008; Veatch et al., 2009). Statistical models can be advantageous mainly due to lower user skill requirements and computational time as compared to mechanistic models. Despite the burgeoning use of machine learning (ML) in hydrology (Kratzert et al., 2019), there have been relatively few efforts to use ML to predict effects of forest management on snowpack, likely due to a lack of training and evaluation datasets at the fine scale of individual trees (~1 m) (however, see Krogh et al., 2020). Importantly, ML emulation of field measurements does not offer a practical way to quantify snowmelt. Therefore, we begin the present work with hyper-resolution (1 m) maps of snowpack and snowmelt from a mechanistic model and then evaluate statistical emulation methods including a “class means” approach, which takes mean values of target variables after classifying the landscape by 1–3 variables representing topography, forest cover, and forest structure, or by ML models with three different levels of complexity (input datasets, user skill requirements, and computational time).

Here we evaluate these two statistical approaches for emulating high-resolution (1 m) SnowPALM maps of peak SWE, snow cover duration (SCD) and liquid water inputs from combined snowmelt and winter rain (LWI) across gradients of ephemeral to stable seasonal snowpack and of ponderosa to mixed conifer forest at mid-scale study areas (~50 ha) in the highlands of northern Arizona, US. Specifically, we address the following questions: 1) How well can the spatial variability of snowpack and snowmelt be emulated at the spatial resolution of individual trees (1 m) using statistical approaches? 2) How much does emulation accuracy improve with increasing complexity of input datasets, user skill requirements, and computational time? 3) What is the importance of 3-dimensional representation of topography and/or tree arrangement over sites and years with a gradient of snow-covered duration? 4) What level of model complexity is warranted across sites with different winter weather, topography, and forest structure? Collectively, answers to these questions can inform practical, efficient options for future upscaling of hyper-resolution mechanistic forest snow modeling to make hydrologic assessment of forest management projects. The overall workflow of field observations → mechanistic modeling → statistical emulation developed here and in Dwivedi et al. (2024a) provides a flexible template for future upscaling work to inform forest restoration projects or other large-scale disturbance assessments.

2. Study area description

Evaluation of statistical snow map emulation approaches was carried out at three forested, mid-scale study areas (~50 ha each) in the highlands of northern and eastern Arizona, U.S. (Fig. 1, Table 1). These study areas are in the headwaters of the Salt River, Verde River and Little Colorado River, which are of vital importance for millions of people in the Phoenix metropolitan area and across the Lower Colorado River Basin. These areas were selected to represent three dominant forest types (Fig. 1) of the 1 M ha of forested area within the Four Forests Restoration Initiative (4FRI). 4FRI is a landscape-scale effort by the US Forest Service and multiple partners to increase forest resilience across four national forests, mainly through mechanical thinning and prescribed burning to reduce tree density, alter spatial arrangement of remaining trees, and reduce fuels loads to natural ranges of variability (www.4fri.org; https://www.fs.usda.gov/4fri). Our study areas range in size between 51 and 66 ha and therefore contain 5.1–6.6 x 10^6 1 m model pixels each. Study areas comprise mostly level terrain (<5 % slope), but each area has small portions with slopes up to 30 %, making them representative of the mostly gentle terrain of existing and planned forest restoration treatments of 4FRI. Within 4FRI (Fig. 1), 82 % of the forested area is dominated by ponderosa pine (*Pinus ponderosa)*. We divided the ponderosa pine areas equally into dry and wet portions (hereafter P-dry and P-wet) using a threshold mean annual precipitation (MAP) of 564 mm, the spatial median value in 30-year PRISM data. Higher-elevation 4FRI treatments occur within a dry mixed conifer (M-con) forest dominated by pine and fir species. MAP in these M-con forests can vary between ~600 and 1000 mm, but a defining characteristic of M-con areas is that due to cold temperatures, the snowpack is usually stable, persisting from establishment at the winter's onset until a single melt period in spring. Taken together, the three study areas represent a gradient from ephemeral to stable seasonal snowpack (P-dry < P-wet < M-con) as reflected by the increases in snow cover duration across study areas in any given year (Table 1, see also Dwivedi et al., 2024).

The P-Dry study area is located at an elevation of 2240 m (Table 1) in the 4FRI Chimney Springs forest management project, which has been the subject of several hydrological and ecological studies (Belmonte et al., 2021, 2022; Dwivedi et al., 2024a; Sankey and Tatum, 2022). P-dry is climatologically driest of the three study areas, with long-term mean Nov-Apr precipitation and temperature of 241 mm and 3.0 °C, respectively (data since 2008 from Fort Valley SNOTEL station 1121, located 6 km to the northwest and at the same elevation). Snowpack is often ephemeral, with multiple midwinter melt events (Dwivedi et al., 2024, their Fig. 1) and lower snow cover duration than the other study areas (Table 1). After mechanical thinning occurring over ~90 % of the site in 2018–2019, forest overstory canopy cover averages 17 %, consisting mainly of ponderosa pine with small amounts of Gambel oak (*quercus gambeli)*, and Rocky Mountain juniper (*Juniperis scopulorum)*.

The P-Wet study area is co-located with the Baker Butte SNOTEL (station 308) at an elevation of 2220 m and has been included in several recent studies of how forests regulate snowpack and soil moisture (Broxton et al., 2019; 2020; Dwivedi et al., 2023a; b; 2024a). P-wet is warmer than P-dry but receives substantially greater snowfall, with long-term mean Nov-Apr precipitation and temperature of 389 mm and 6.2 °C, respectively. Snowpack is moderately stable (intermediate SCD, Table 1), with occasional midwinter melt events (Dwivedi et al., 2024a). There is no record of forest management at P-wet for at least the last 60 years, with overstory cover averaging 46 %, consisting mainly of ponderosa pine with small amounts of Douglas fir (*Pseudotsuga menziessi*) and Gambel oak.

The M−Con study area is co-located with the Maverick Fork SNOTEL (station 617) at an elevation of 2800 m and has been included in the same studies cited above for P-wet. While this area receives less average

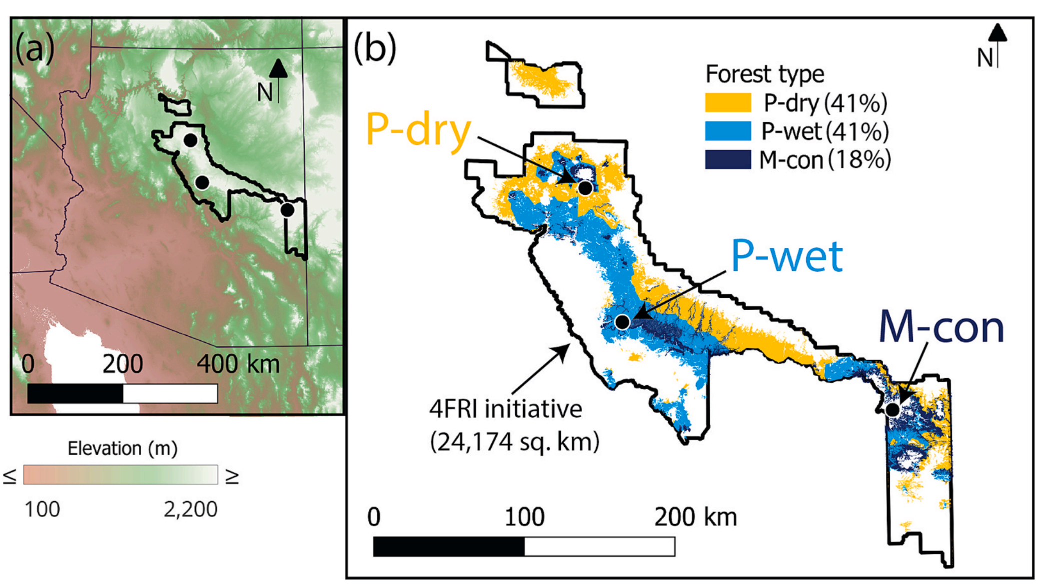

Fig. 1. (a) Location and elevation of the Four Forests Restoration Initiative (4FRI) in Arizona, US, (b) 4FRI area showing the three major forest types. In (b), percentages shown in the legend indicate the proportion of forested 4FRI area of each forest type: Dry Ponderosa (P-dry), Wet Ponderosa (P-wet) and Mixed Conifer (M-con). White areas in (b) are non-forest vegetation.

Table 1
Study area characteristics.

Site	Elev. (masl)	Area (m^2)	Canopy Cover (%)	[a]Winter P (mm) 2018 2019 2020	[a]Winter T (C) 2018 2019 2020	Peak SWE (mm) 2018 2019 2020	[b]SCD (days) 2018 2019 2020	Forest disturbance
Dry Ponderosa (P-dry)	2240	655,389	17	71 274 288	3.9 2.3 3.0	10 56 61	9 101 78	Mechanical thinning, 2018
Wet Ponderosa (P-wet)	2220	500,500	46	162 483 587	7.8 5.0 5.6	53 183 140	44 114 115	None recent
Mixed Conifer (M-con)	2800	508,515	15	107 483 373	3.5 0.9 1.8	53 323 254	54 138 143	Partially burned in Wallow Fire, 2011

[a] Mean winter temperature and open-area precipitation values for winter (November – April). [b]Snow cover days (SCD) is the sum of days with SWE > 2.5 mm at the SNOTEL station.

winter precipitation than P-wet (293 mm), the colder winter temperature (2.1 °C) results in a persistent seasonal snowpack and the greatest SCD in each study year (Table 1). The M-con area contains large montane meadows and mixed conifer tree species with 15 % overstory canopy cover, mostly ponderosa pine (*Pinus ponderosa*), Douglas-fir (*Pseudotsuga menziesii*), white fir (*Abies concolor*), southwestern white pine (*Pinus strobiformisand*), and aspen (*Populus tremuloides*) (Broxton et al., 2020). A portion of M-con was burned at medium to high severity during the Wallow Fire in 2011.

In prior work at these study areas (Broxton et al., 2019; 2020; Dwivedi et al., 2023a; 2024a), it was determined that variability in Peak SWE, SCD, and LWI was strongly predicted by terrain northness, NN = sin(slope) × cos(aspect), canopy cover (CC = vertical projection), and snow environment (SE), which classifies the position of a model pixel

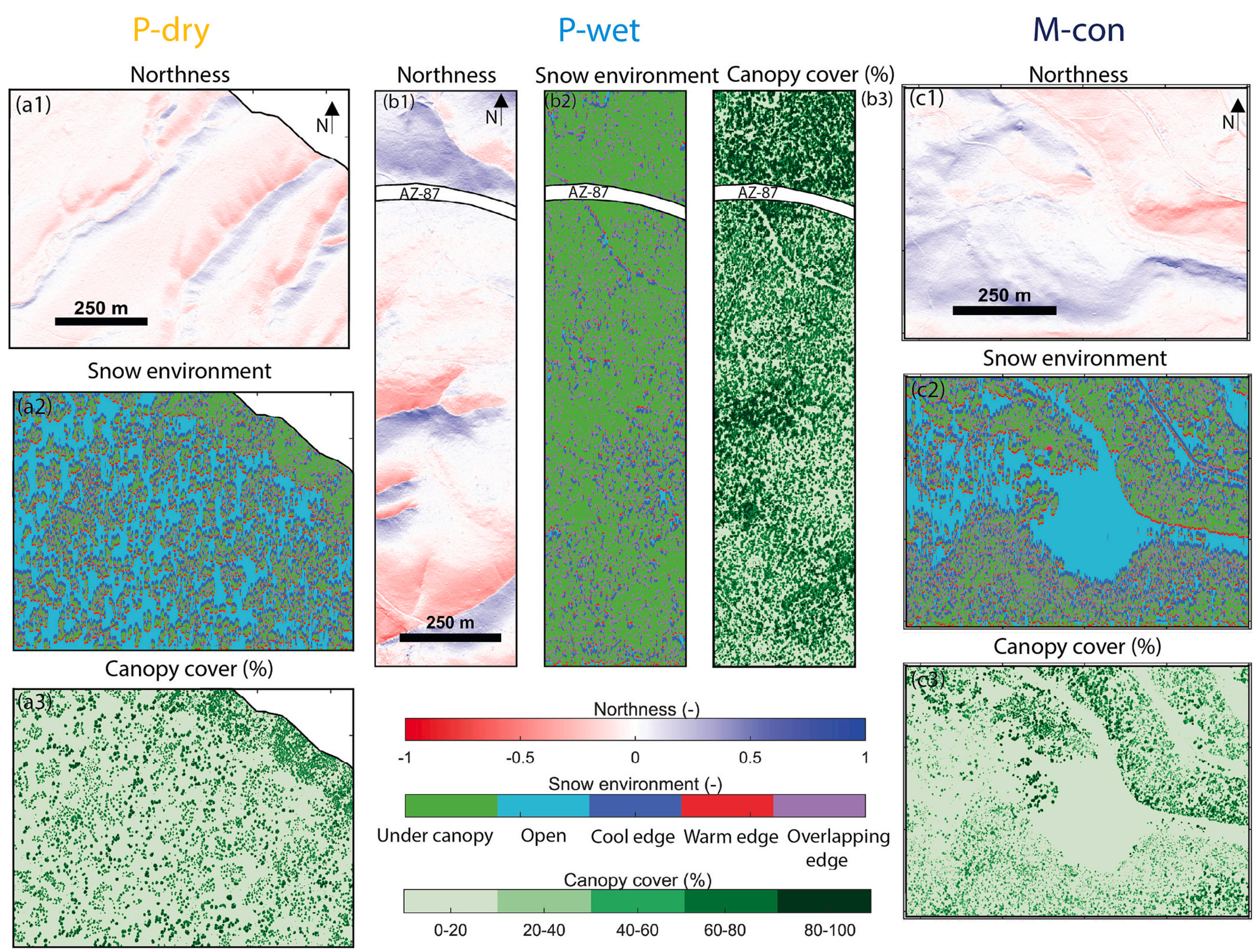

Fig. 2. Maps of physiographic variables used to predict variability in snow hydrology target variables including northness, snow environment, and canopy cover for each study area. For snow environment, OE = Overlapping Edge (i.e. small canopy opening), WE = warm edge, CE = cool edge, O = open (far from canopy), UC = under canopy. The white arc in maps of the P-wet study area is Arizona Highway 87, which has been masked from the analysis.

with respect to the surrounding forest canopy (under canopy (UC), open areas far from canopy (O), sunny, warm edges (WE), shaded cool edges (CE), and overlapping edges (OE), which are small gaps near canopy to both north and south (Currier and Lundquist, 2018; Mazzotti et al., 2020)) (Fig. 2). Local Snowtography data were used to define cool edges as extending 10 m north from the canopy edge, while warm edges extend 5 m south from the canopy edge (for details see Dwivedi et al., 2024). East and west facing edges can sometimes be important for snow dynamics due to wind effects at stand edges (Webb et al., 2020) but our prior work at these and similar sites showed east and west edges to be relatively unimportant as compared with north and south (Broxton et al., 2015; 2020).

3. Methods

3.1. Methods overview

This paper evaluates two statistical emulation approaches (Fig. 3, Table S1), each with progressive levels of complexity (input datasets, operator skill, and computation time), for reproducing high-resolution (1 m) maps of three hydrologic target variables: peak snow water equivalent (peak SWE), liquid water input (LWI), and snow cover duration (SCD) (Fig. 4). LWI is the sum of snowmelt and winter rainfall and is sometimes referred to as terrestrial water input or net water input. Peak SWE has often been used as a proxy for LWI, assuming peak SWE translates into snowmelt. This assumption is reasonable only for stable seasonal snowpacks with a single melt and not for ephemeral snowpacks with multiple winter melt pulses and/or significant winter rain. SCD is important because 1) the longer the snowpack lasts, the more it is susceptible to be sublimated as a function of weather, terrain, and nearby forest canopy and 2) long-lasting snowpack means that LWI occurs later, shortening the period of summer soil moisture drought and associated fire risk. The class means approach (Fig. 3a) classified each study area pixel (1 m) using between one and three topographic and/or forest canopy predictor variables, then assigned to each pixel the mean value of the target variable (peak SWE, SCD, LWI) for all pixels in each unique grouping of classes. An example unique grouping is: Under Canopy environment, Northness between 0.8 and 1.0, and Canopy Cover between 20 % and 40 % (further details given in Section 3.3). The second approach was to generate a prediction of the target variable for each pixel with random forest machine learning (ML) models using three groups of predictor variables with increasing complexity (Fig. 3b). These two approaches were evaluated across each study area over three years with widely differing winter weather (Table 1). 2018 was climatologically very warm and dry with respect to SNOTEL records (Dwivedi et al., 2024a), while 2019 was cool and wet, and 2020 had intermediate winter weather in terms of precipitation, temperature, and SCD. Although 2019 and 2020 had similar winter precipitation amounts, the cooler temperatures of 2019 resulted in a greater fraction of winter precipitation falling as snow (Dwivedi et al., 2023a) and larger peak SWE (Table 1).

3.2. SnowPALM: snow physics and lidar mapping model

Maps of hydrologic target variables (Fig. 4) were developed for each study area using SnowPALM, a mechanistic forest hydrology model representing snowpack mass and energy balance daily at 1 m spatial resolution (Broxton et al., 2015; Dwivedi et al., 2024a; Krogh et al., 2020). Fig. 4 presents normalized values to maximize visualization of spatial variability within each site for sites that have widely differing mean values (Table 1). For purposes of this study, SnowPALM maps constitute the "truth", and we evaluate the skill of statistical approaches to reproduce these maps. SnowPALM represents 3-D spatially explicit interactions of precipitation, radiation and wind with topography, forest height, and canopy cover to represent solar radiation partitioning (i.e. shadowing), canopy temperature and thermal radiation balance. A key feature of SnowPALM is representing forest hydrologic processes through parameterization of individual trees using information from one or more collections of airborne lidar data (terrain, canopy height, canopy cover, snow depth) in combination with any available snow time series data. Importantly, SnowPALM estimates daily fluxes of water lost to the atmosphere including snow sublimation from canopy and snowpack. Spatial variability in snow sublimation is among the most

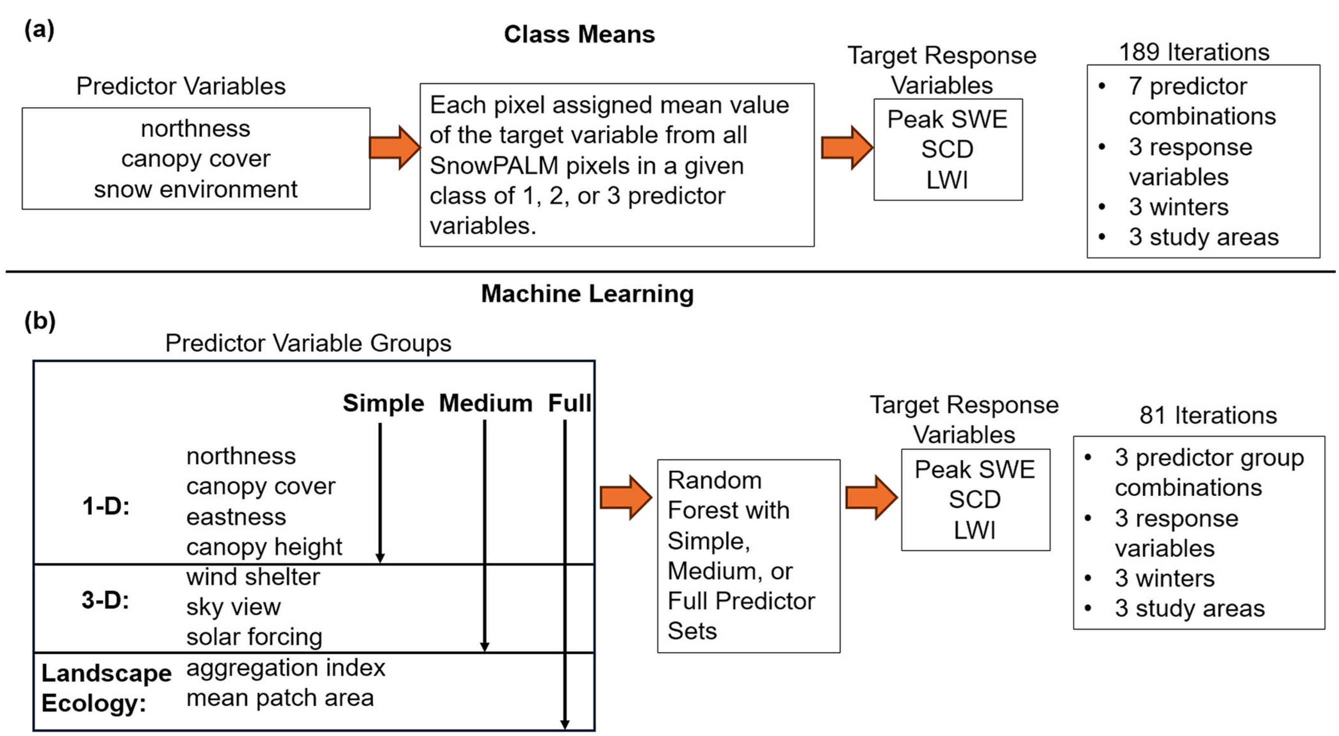

Fig. 3. Schematic of statistical emulation methods evaluated for reproducing maps of hydrologic target response variables from the mechanistic SnowPALM model including (a) class means and (b) machine learning. Details of each approach and of predictor variables are given in Sections 3.2 and 3.3.

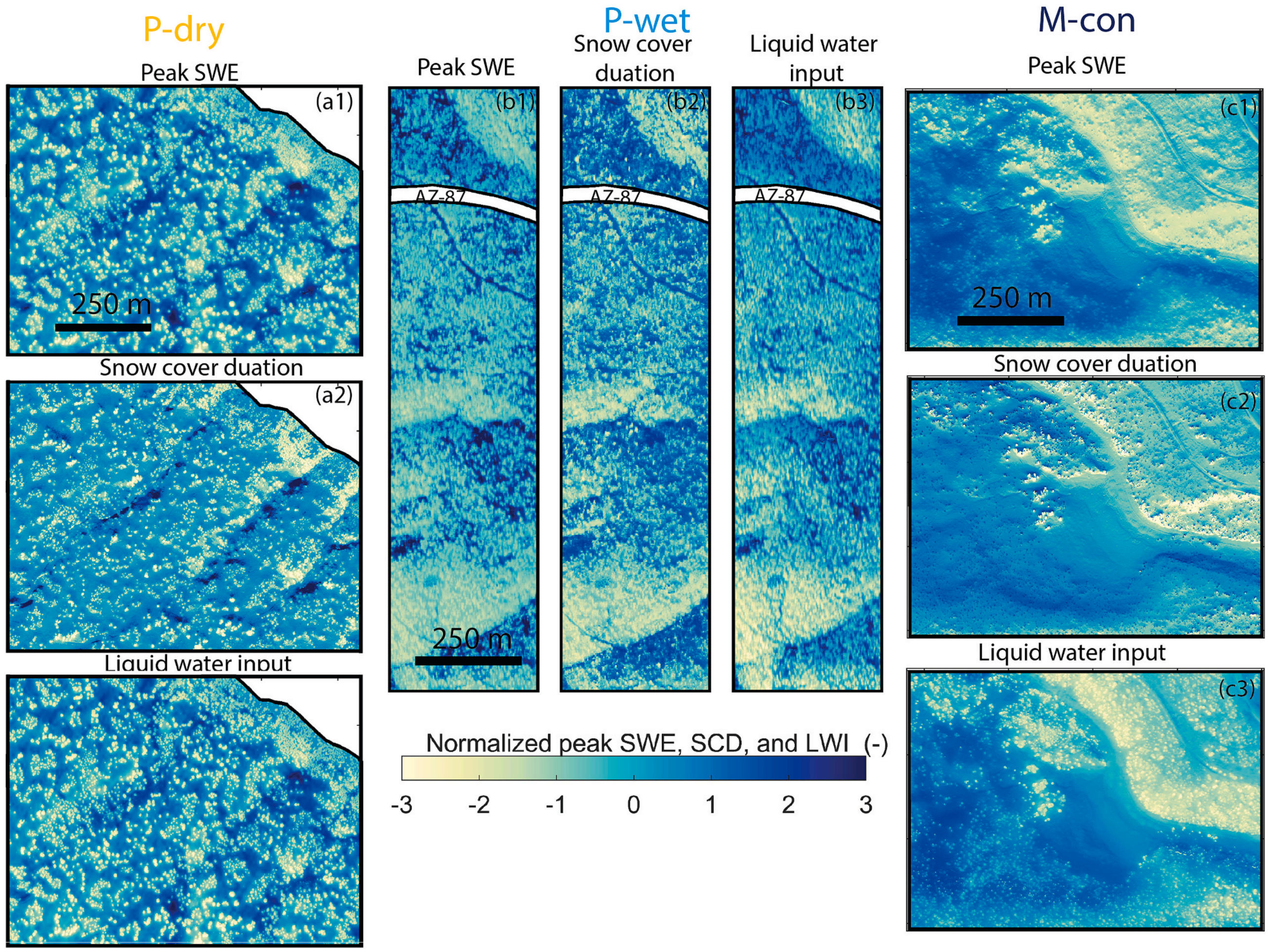

Fig. 4. Maps of target hydrologic response variables for the intermediate weather year 2020 including annual peak snow water equivalent (SWE), snow cover duration (SCD), and liquid water input (LWI) from the sum of snowmelt and winter rain. Maps are from the mechanistic SnowPALM model calibrated for each study area with 1 or 2 lidar snow depth maps and 3–6 years of daily snow depths at 20–35 locations per area from Snowtography. For other years, see Figs. S1 and S2. To allow consistent visualization, each map is presented as a normalized z-score. For mean and standard deviation of each map, see Table 2, SnowPALM row. Scale bars are 250 m in all panels. Colormap by Zhaoxu Liu https://www.mathworks.com/matlabcentral/fileexchange/120088-200-colormap accessed 30 June 2025.

important consequences of 3-D forest structure (Broxton et al., 2015; Sexstone et al., 2018).

We previously calibrated SnowPALM for the three dominant forest types in the 4FRI initiative region by jointly targeting snow depth maps from study area-wide airborne lidar snapshots and daily snow depth time series over 3–6 years at between 20 and 35 locations across small-scale study sites (~1 ha) within each of the present mid-scale (~50 ha) study areas (Dwivedi et al., 2024a). Snow depths were measured by Snowtography (remote automated snow depth photographs of graduated snow stakes) (Dwivedi et al., 2023a; Payton et al., 2021). Model-data optimization of daily snow depth time series divided all Snowtography stakes among one of the five snow environment classes created by the position of trees in proximity to each snow stake. Because the prior calibrations in Dwivedi et al., (2024) were conducted for ~1 ha intensive study sites in mostly-level portions of each study area, some small adjustments in model parameters were made to best match lidar depth maps over the mid-scale study areas used here (~50 ha, Fig. 2). It is important to acknowledge that SnowPALM calibration requires substantial skill and resources, and that most of that work was done prior to this paper (Dwivedi et al., 2024a).

3.3. Class-means approach to predicting snow hydrology target variables

The simplest approach for statistical emulation of hydrologic target variables was to first classify each pixel of a study area based upon topographic and/or forest canopy variables (Fig. 2) and then use the mean value of the target hydrologic variable (Fig. 4) for each unique grouping of classes as the prediction for all pixels in that group (Fig. 3a). Many prior studies have shown that spatial variability of snow across forested sites is controlled by topography and vegetation (Anderton et al., 2004; Bewley et al., 2010; Broxton et al., 2020; Jost et al., 2007; Sexstone et al., 2018; Varhola et al., 2010). For each 1-m pixel, the canopy cover ranged from 0-100 % and was divided into five classes using equal intervals. Northness was classified into six bins as follows: [−0.3 to −0.1, −0.1 to 0, 0 to 0.1, and 0.1 to 0.3]. An important distinction is that the snow environment classification considered any pixel with CC > 10 % to be under canopy (UC), and all pixels with CC < 10 % were assigned to one of the other four snow environments. Therefore, a map of canopy cover contains information about varying levels of canopy cover (%) that is not contained in a snow environment map (Fig. 2). Together, these three predictor variables were expected to explain significant amounts of spatial variability in peak SWE, SCD, and LWI, and they can be produced with straightforward raster calculations in any geographic information system (Table S1). The class means emulation approach has a presumed high degree of availability to a project scientist making hydrologic predictions in a forest management or disturbance assessment. The only inputs required are a digital elevation model (DEM) and canopy cover model (CCM), which are widely available from airborne lidar coverage (US Geological Survey, 2024).

At each of the three study areas, the class-means approach was used as follows to generate a prediction map of each target hydrologic variable using each of the 7 possible combinations of the 3 predictor variables taken 1, 2, or 3 at a time (Fig. 3a). First, a SnowPALM map of a target hydrologic variable (e.g. peak SWE, Fig. 4(a1)) was divided spatially into quarters, with 75 % of the pixels (~375,000) used for model training and 25 % (~125,000) reserved for model prediction. This division of training and validation pixels was conceptually simple and maintained adequate distance between a majority of the training and prediction pixels during each iteration, reducing possible spatial autocorrelation between training and prediction areas. Second, the study area was classified according to the given predictor variable set. Third, the mean value of peak SWE was calculated for each unique group. Fourth, these class-mean values were taken as the prediction of peak SWE across the remaining 25 % of the pixels reserved for prediction. These steps were repeated four times, reserving a different 25 % of the site for prediction each iteration, until a complete prediction map of the study area was achieved. This process was repeated for each target hydrologic variable over three winters with varying weather.

Each class-means prediction map was compared with the corresponding SnowPALM map using coefficient of determination (R^2) and the spatial efficiency metric (SPAEF), which accounts for the correlation, variability, and bias between maps (Koch et al., 2018). A variable importance assessment was made as follows: 1) Calculate R^2 between the class-means prediction map and the SnowPALM map for the full model with all three predictor variables [northness × canopy cover × snow environment] for a given hydrologic variable and year; 2) Remove one predictor variable and note the decline in R^2, representing the importance of the removed variable; 3) Normalize the declines in R^2 by the sum of these declines for all three variables.

3.4. *Machine learning models for predicting snow hydrology target variables*

Random-forest ML models, while expected to reproduce snow maps with higher accuracy than the class-means approach, represent a greater level of complexity to develop (Fig. 3, Table S1). Here, ML modeling was conducted using the Ranger package (version 0.16.0) (Wright and Ziegler, 2017) in the R coding environment (version 4.3.3) (R Core Team, 2021). Nine ML candidate predictor variables were computed from lidar-based digital elevation, canopy cover, and canopy height models. The nine predictors were then grouped into three sets as follows: The simplest predictor set (hereafter, "1-D predictors") comprises basic variables known to regulate snowpack, sublimation and snowmelt and that are likely to be available to a practitioner working with maps of terrain and forest structure including northness, canopy height, and canopy cover (Fig. 2). The next level of complexity was a set of 3-D predictors involving consideration of the surrounding terrain and forest structure including wind shelter index, which assesses wind effects of surrounding terrain and vegetation on each snowpack pixel, sky view factor, which is the fraction of sky visible from a snowpack pixel, and solar forcing index, which is the ratio of winter-integrated incoming solar radiation on a given snowpack pixel as compared to that of an unvegetated horizontal plane. 3-D predictors were calculated using the System for Automated Geoscientific Analyses (SAGA) software (version 7.8.2; https://www.saga-gis.org). The SI section S1 lists the SAGA commands used. The final predictor set, "landscape ecological predictors" included the mean patch area (the average size of continuously connected patches of adjacent trees, m^2) and aggregation index (the degree of aggregation vs. dispersion of canopy patches, 0–100 %). These metrics describing the spatial arrangement of trees and open areas within forests were calculated with the R Package *Landscapemetrics* (Hesselbarth et al., 2019). Several other landscape ecological predictors describing forest patch size and distribution were evaluated but not selected due to high correlation with mean patch area and/or aggregation index. Snow environment was not used in ML models because it contains similar information to other variables already included and forces discretization where continuous information is available for modeling and prediction (e.g. solar forcing index).

For each study area, target variable, and year, ML models were constructed with three levels of predictor complexity (Fig. 3, Table S1). The simplest models (ML-simple) used only the 1-D predictors, while ML-medium added 3-D predictors and ML-full added the landscape ecology metrics and therefore used all 9 possible predictors. To ensure fair comparison, ML modeling approaches used a similar workflow for model training, prediction, and assessment of variable importance as described above for the class-means approach.

4. Results

4.1. *Class-means approach to emulating hyper-resolution snow maps*

Spatial variability in snow variables was highly related to northness, canopy cover, and snow environment with respect to the structure of surrounding forest. At P-wet for example, the SnowPALM map liquid water input (LWI) increased with northness (Fig. 5, compare rows) and decreased with canopy cover (Fig. 5, compare lines within right column panels). Open areas tended towards greater LWI than under-canopy areas, with forest edges having intermediate amounts of LWI. Both snow environment and canopy cover had greater effects on LWI with increasing northness, as indicated by the greater dispersion of the pdf plots in the middle and lower rows of Fig. 5.

The class-means approach reproduced up to 58–81 % of the spatial variability (R^2) for annual peak SWE, 46–81 % for snow cover duration, and 45–74 % for liquid water input when using all three predictors (Fig. 6, see SE × CC × NN). This approach was equally successful in climatologically wet, dry, and intermediate winters at M-con and P-wet ($\Delta R^2 < 5$ % among years), but larger interannual differences in model performance among years were noted for P-dry ($\Delta R^2 = 15$–20 %).

Across the study area gradient of SCD (Table 1), there were changes in the importance of class-means predictors (Fig. 6 compare rows, also Fig. S5), moderate differences among winters at a given study area (Fig. 6 compare lines within a panel, also Fig. S5), and relatively small differences in predictor importance across target variables (Fig. 5 compare columns). Across the study area gradient of increasing SCD (P-dry < P-wet < M-con, Table 1), canopy information (canopy cover and snow environment) was more important at lower SCD, while topographic information (northness) was more important at higher SCD (Fig. 6, Fig. S5). Similarly, among the variable-weather years at both P-dry and P-wet, the importance of canopy information (CC, SE) relative to topographic information (NN), was enhanced in the warm/dry year and reduced in the cool/wet year. In other words, topographic information was of greater importance for longer duration snowpacks, whether across the study area gradient of snow cover duration or in colder/wetter winters at a given study area (Fig. 5, Table 1). When snow cover duration was low, canopy information was more important.

4.2. *ML approach to emulating hyper-resolution snow maps*

Random-forest ML models with nine predictor variables describing topography and vegetation (ML-full) predicted 88–98 % of the spatial variability (R^2) in peak SWE, snow cover duration, and LWI over all sites and years (Fig. 7). There was little difference in model performance (R^2) over the three years with widely differing weather (Fig. 7) except at P-dry, where target variable magnitudes were very low in the warm/dry year (Table 1). ML models using only northness as a predictor captured increasing amounts of spatial variability in target variables across the site climatic gradient of SCD, with 26–43 % at P-dry, 35–52 % at P-wet, and 60–80 % at M-con, again suggesting that topography is a more important predictor at higher/cooler sites with greater SCD (Table 1). Meanwhile, the importance of canopy cover alone decreased with increasing site SCD (SI Fig. S6, S7, S8).

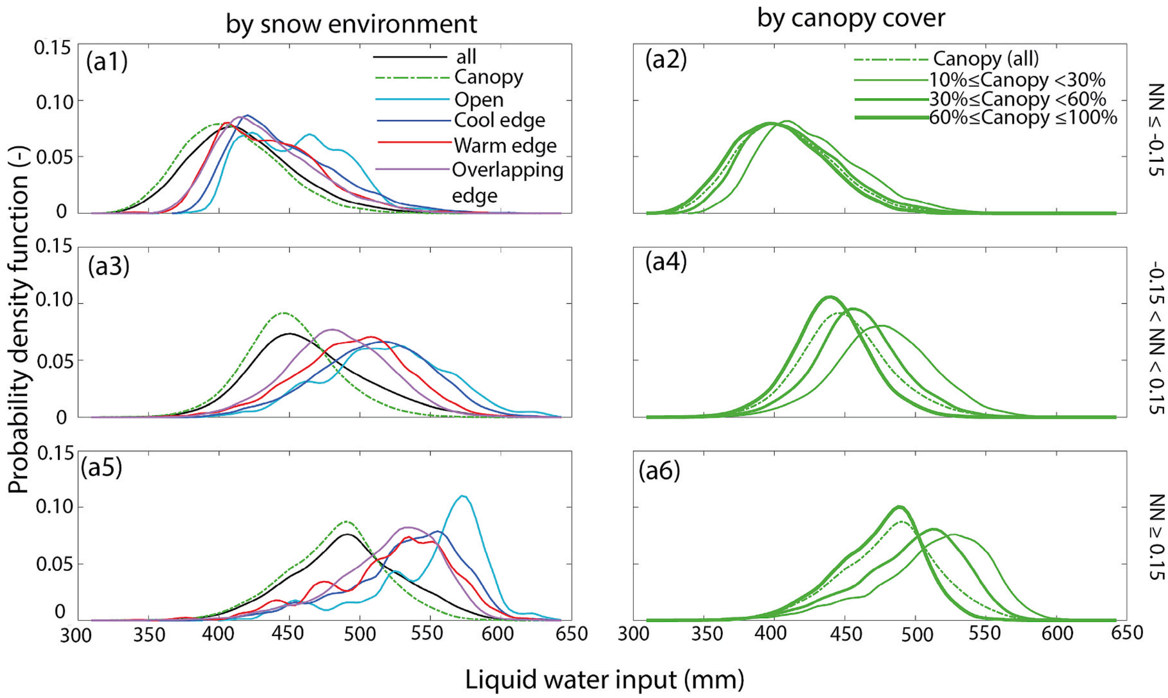

Fig. 5. Normalized probability density functions (pdf) of liquid water input for the wet ponderosa (P-wet) study area during the average weather winter of 2020 (the map shown in Fig. 3 (b3)) based on the SnowPALM map. Rows classify the study area by northness (NN). The left column shows LWI for all points in the given northness class as well as for each snow environment. The right column shows LWI for all under-canopy points in the given northness class and by classes of canopy cover. For the two other study areas, see Figs. S3 and S4. Note that for easier visualization, canopy cover (right column) is displayed in three bins instead of the five equal intervals used for the class means approach.

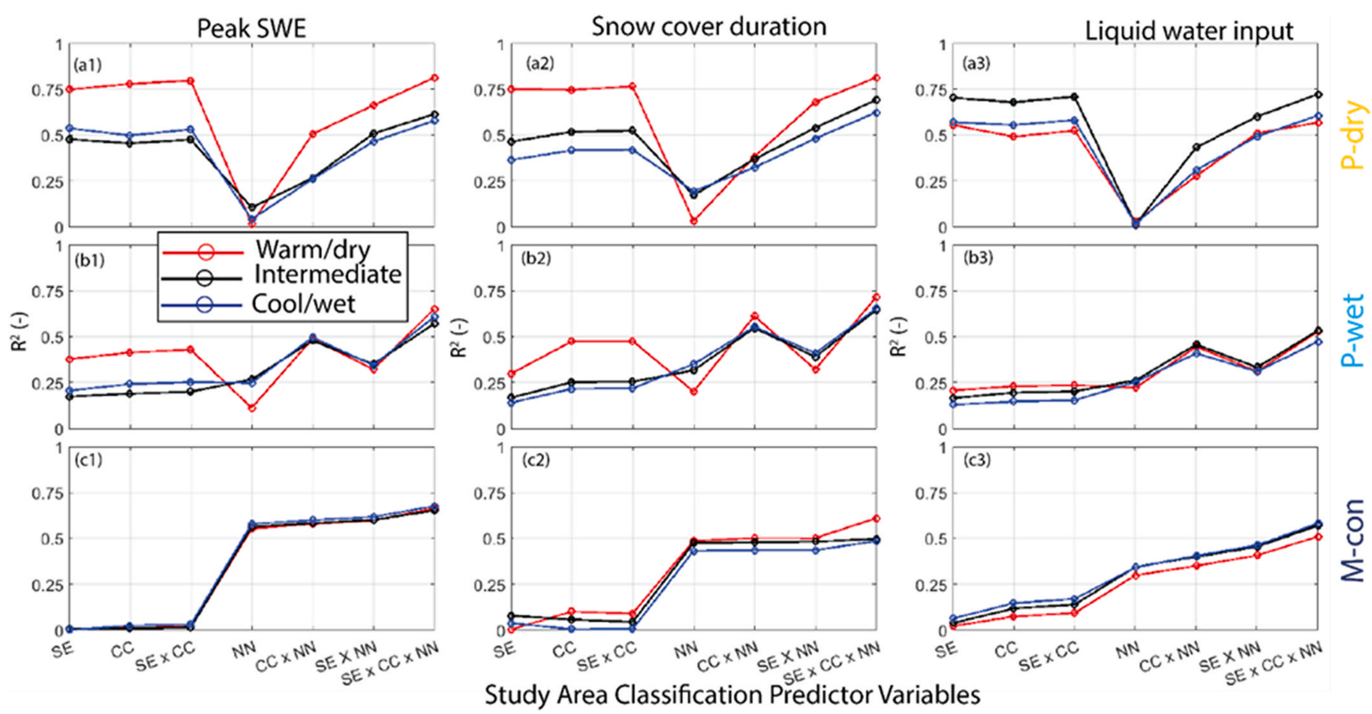

Fig. 6. Coefficient of determination between SnowPALM maps of target variables and predictions based on the class means approach. The order of predictor variable combinations (horizontal axis) was arbitrarily assigned using the R^2 rank-order of liquid water input for M-con (lower right panel). SE = snow environment, CC = canopy cover, and NN = northness. Each row is for one area, while each column indicates one hydrologic target variable. SWE = snow water equivalent. Line colors indicate results for winters with varying climate. Predictor importance is shown in Fig. S5.

Variable importance showed the greatest interannual differences at P-dry (Fig. S6), very little at M-con (Fig. S8), and an intermediate amount at P-wet (Fig. S7). At P-dry, canopy cover and canopy height were most important for prediction of peak SWE and SCD during the warm dry year, but in other years northness, sky view, and solar forcing had importance similar to the 1-D canopy predictors. For LWI at P-dry,

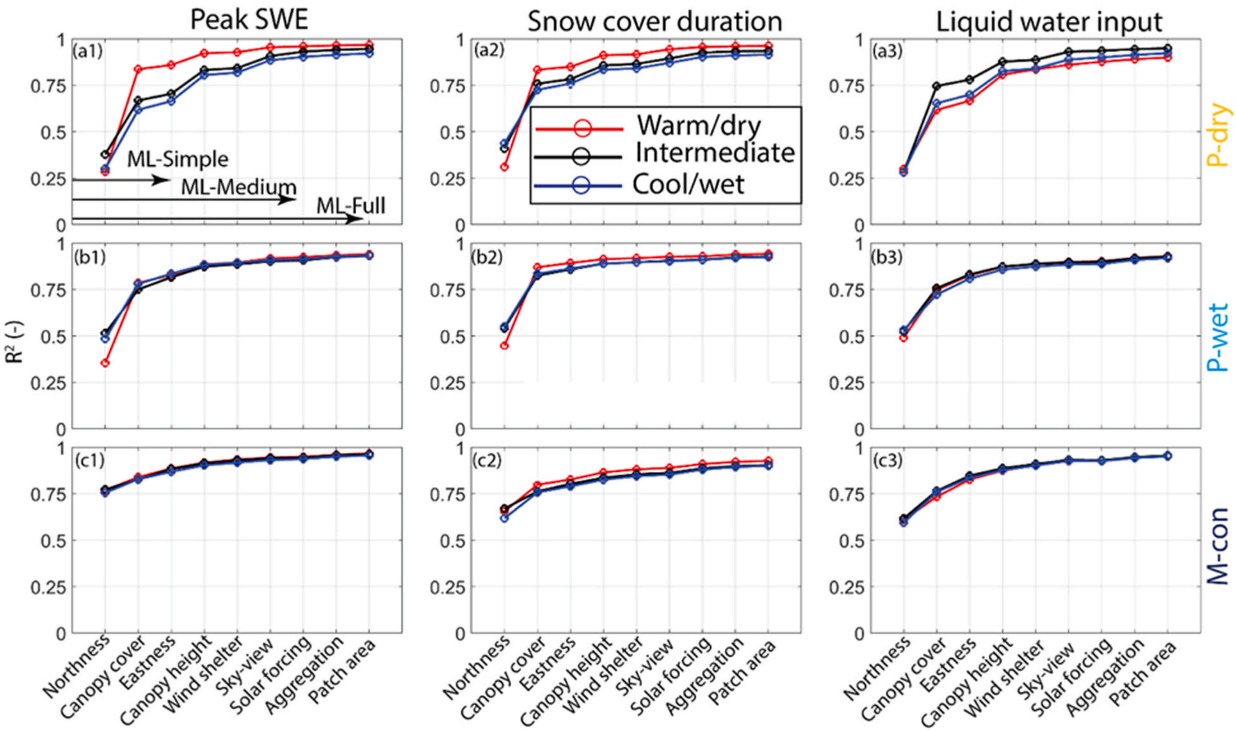

Fig. 7. Coefficient of determination between target variable predictions based on random forest ML models, sequentially adding each predictor indicated on the horizontal axis, and target maps produced by the mechanistic model SnowPALM. Each row is for one site, while each column indicates a hydrologic outcome variable. SWE = snow water equivalent. Line colors indicate a warm/dry winter, an intermediate winter, and a cool/wet winter. The three levels of ML complexity are marked only on the upper-left panel but apply to all sites and variables (see Fig. 3b).

however, canopy cover and canopy height were the most important predictors in all years. At P-wet, northness and canopy cover were always the most important predictors, with northness decreasing and canopy cover increasing in importance in the warm dry year (Fig. S7). At M-con (Fig. S8) in all years, northness was the most important predictor for peak SWE and SCD, while northness and canopy cover tended to co-dominate for LWI.

To inform model selection for practical applications, we assessed the importance of each of the three groups of predictor variables: 1-D, 3-D, and landscape metrics (Fig. 8). At all study areas and years, the 1-D

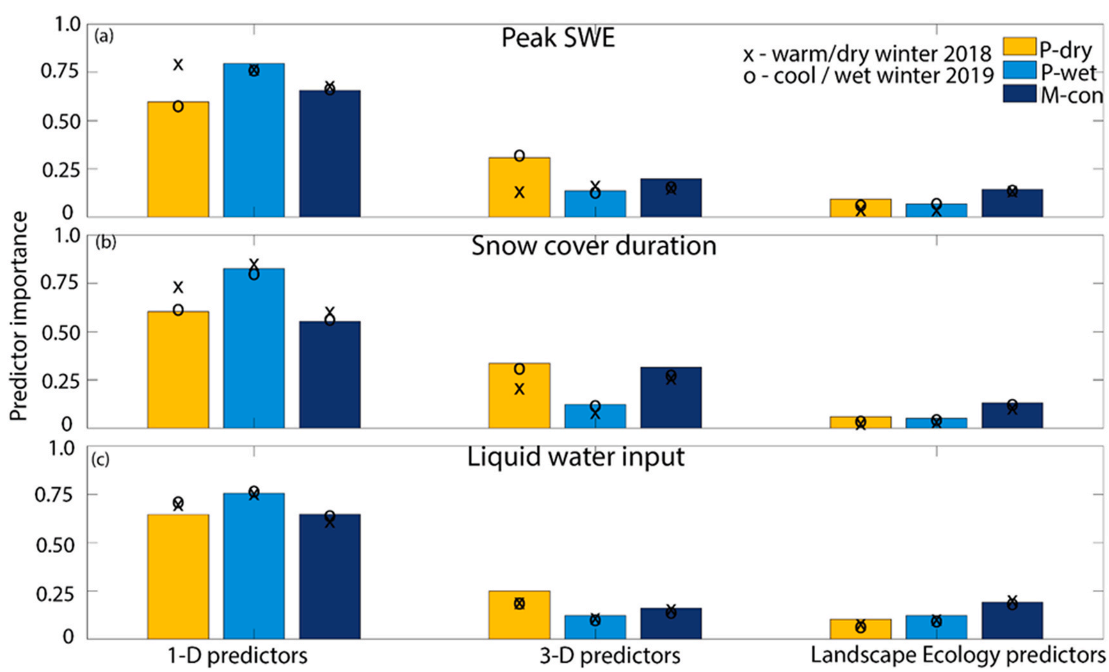

Fig. 8. Predictor importance of three groupings of machine learning predictor variables of increasing complexity, for Peak SWE (a), Snow cover duration (b) and Liquid water input (c). Predictor group importance was determined by permuting that entire group from the ML-full model, one at a time. For a given model (bars of the same color in any panel), the group predictor importance sums to 1. Bars indicate the average weather winter 2020. "x" indicates the warm/dry winter 2018, and "o" indicates the cool/wet winter 2019.

predictor group was attributed most of the importance (58–80 %), consistent with individual predictor importance results showing that northness was dominant in cool/wet conditions, while canopy cover became more important in warm/dry conditions with more ephemeral snowpack (Figs. 6, 7, Figs. S6, S7, S8). The 3-D variable group assessing the wind and radiation effects of the surrounding topography and forest geometry accounted for 15–32 % of predictor group importance for any of the target variables, with larger values at P-dry and M-con than at P-wet. The landscape ecology predictor group assessing the arrangement of trees in patches and gaps accounted for 5–20 % of group importance, with the largest values for LWI at the M-con site. At a given study area, predictor importances were similar across all years except at P-dry, where 1-D predictors were even more important in the warm/dry year, and 3-D predictors were increasingly important during the cool/wet year.

4.3. Residuals of statistical emulation approaches vs. mechanistic model maps

All four emulation methods accurately reproduced the mean values of each target hydrologic variable across each study area (Table 2), with differences <2 %. The main improvement seen with increasing model complexity (class means < ML-simple < ML-medium < ML-full) was improved representation of spatial variability (Table 2, spatial standard deviation approaching the SnowPALM value). This was also observed with monotonically increasing spatial correlation quantified by the spatial efficiency metric SPAEF (Fig. 9 for LWI. For Peak SWE and SCD, see SI Figs. S9 and S10).

To better inform model selection decisions for future practical applications, we evaluated the average LWI residuals of each emulation model across the study areas, representing a gradient of average SCD, across bins of northness, and among the snow environments created by the arrangement of nearby canopy for the average weather year 2020 (Fig. 10). LWI residuals were generally smallest at P-dry and largest at M-con, where increasing model complexity contributed larger improvements in LWI accuracy. At all sites, LWI residuals were generally small (less than ~10 mm magnitude) in the under-canopy environment. Model accuracy for forest edges was improved the most by increasing model complexity at study areas with longer-duration snowpack and for pixels with more southerly exposure (i.e. moving towards the upper right panels of Fig. 10). For open areas, model accuracy benefited the most from increasing complexity at study areas with longer-duration snowpack but for pixels with more northerly exposure (moving toward lower right panels of Fig. 10).

5. Discussion

This study evaluated two statistical emulation approaches for their skill in reproducing highly resolved maps of snowpack and snowmelt from a hyper-resolution forest snow model (Fig. 3, Table S1). These approaches represent a range of practical applications for future landscape-scale assessment of management or disturbance. The importance of topography, canopy cover, and canopy geometric arrangement (Fig. 2) for predicting snowpack and snowmelt variables (Fig. 4) was quantified over three winters with varying weather (Table 1).

All models tested reproduced highly accurate estimates of the mean of seasonal peak SWE, snow cover duration and liquid water inputs across ~50-ha study areas, but more complex models improved (increased) the representation of spatial variability at 1 m resolution within study areas (Table 2, Fig. 9). Simple landscape classification by topography, vegetation cover, and snow environment with respect to the arrangement of nearby canopy predicted between 42 and 80 % of spatial variability in target variables (Fig. 6, Fig. 9). Random forest machine learning predicted between 88 and 98 % of the variability when provided a ML-full model of nine predictor variables (Fig. 7, Fig. 9). Results from all approaches support the idea that topographic variables (e.g. northness) are important snow hydrology predictors when and where snow cover duration is greater (Fig. 8, Fig. S5). This increasing importance of topography to predict target variables was seen across study areas with different climates and among years when snow cover duration varied with weather (Figs. S5–S8). Simple 1-dimensional canopy cover became an important predictor when and where snow was ephemeral, supporting the idea that canopy interception dominates snow variability when SCD is low (Dwivedi et al., 2024a). Accordingly, simple upscaling models appear adequate for the P-dry study area, where SCD is generally lowest, while greater model complexity substantially improves accuracy at the P-wet and M-con study areas where SCD is greater (Fig. 10).

The results of this work provide several themes to guide accurate future upscaling of snowpack and snowmelt variables. First, the simple class-means approach provides sufficient accuracy in several situations. If an assessment is needed for a heavily forested area (i.e. mostly the under-canopy snow environment), the class-means approach is sufficient (Fig. 10, green lines). Additionally, the class-means approach works well across relatively warm/dry areas, where snow is ephemeral, and spatial variability in snow hydrology is largely explained by canopy cover and/or snow environment (Fig. 6, Fig. S5, Fig. 10). This is likely because when snow ablates rapidly, there is minimal time for forest canopy effects on energy balance to alter snow partitioning or melt timing; interception dominates snow variability and can be predicted by canopy cover. Since all four upscaling models evaluated here provided highly accurate reproduction of spatial means in seasonal peak SWE,

Table 2
Model estimates of hydrologic target variables by study area for the average weather winter 2020[a]

	Peak SWE (mm)			SCD (days)			LWI (mm)		
	P-dry	P-wet	M-con	P-dry	P-wet	M-con	P-dry	P-wet	M-con
SnowPALM	50.7 (6.8)	109.9 (42.2)	207.9 (78.0)	52 (8)	94 (24)	136 (17)	230.8 (21.7)	459.7 (46.9)	297.8 (57.2)
Class Means	51.5 (5.6)	110.5 (33.8)	209.8 (63.5)	52 (7)	94 (19)	137 (12)	232.7 (18.3)	460.3 (33.6)	300.7 (44.3)
ML-simple	50.4 (5.7)	110.2 (37.9)	205.6 (71.4)	51 (7)	94 (22)	136 (14)	230.1 (18.2)	459.7 (40.9)	294.2 (51.1)
ML-medium	50.5 (6.1)	110.1 (38.1)	205.2 (73.3)	51 (7)	94 (22)	136 (15)	230.3 (19.3)	459.8 (41.1)	295.3 (52.7)
ML-full	50.6 (6.3)	110.1 (38.7)	206.0 (74.1)	52 (7)	94 (22)	136 (15)	230.6 (19.9)	459.8 (42.2)	296.0 (54.0)

[a] Shown are mean (standard deviation) of hydrologic target variables Peak SWE, LWI, and SCD for each of three study areas as produced by the SnowPALM mechanistic model and four statistical emulation approaches. SWE = peak snow water equivalent, LWI = liquid water input from snowmelt plus winter rain, SCD = snow cover duration.

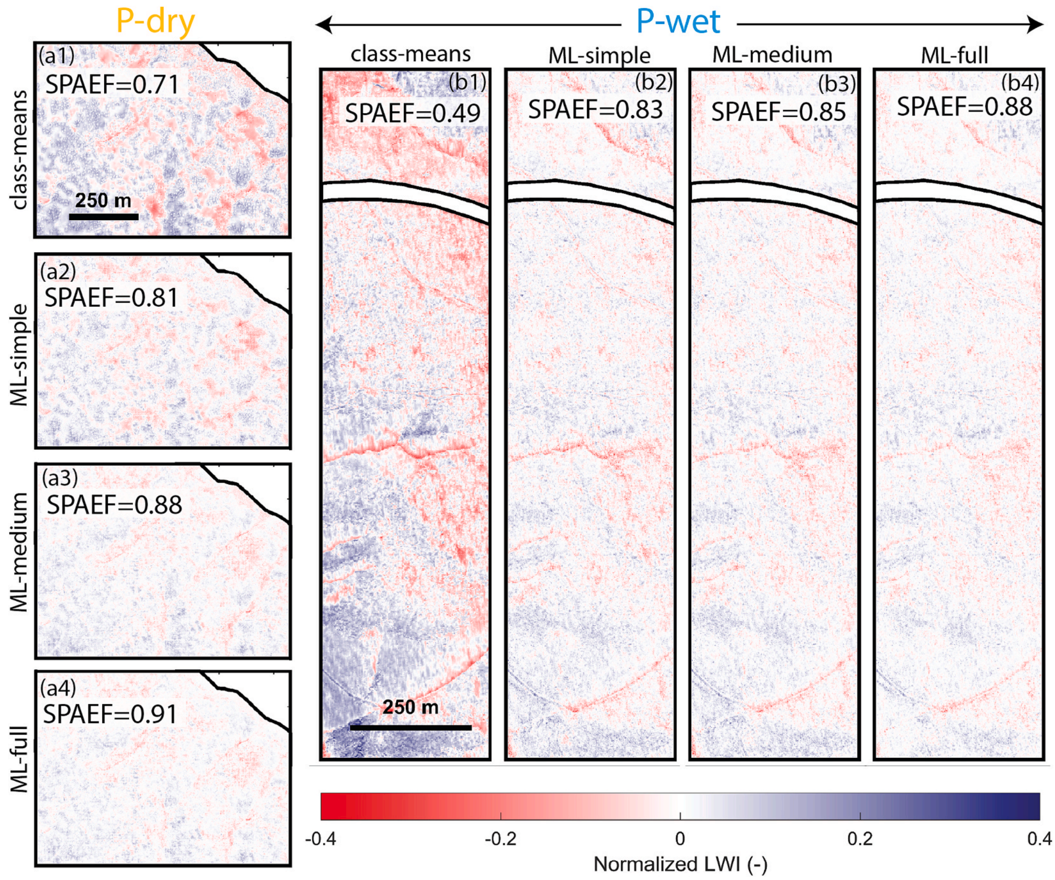

Fig. 9. Liquid water input (LWI) residuals between the mechanistic SnowPALM model and each statistical emulation approach (Class-means full model, ML-simple, ML-medium, ML-full). To facilitate display of variables with different ranges across sites, residuals are normalized using the mean value of the SnowPALM model LWI (Table 2). Shown is the intermediate weather year 2020. For peak SWE and SCD, see Figs. S9 and S10. SPAEF is the Spatial Efficiency Metric (see Section 3.3).

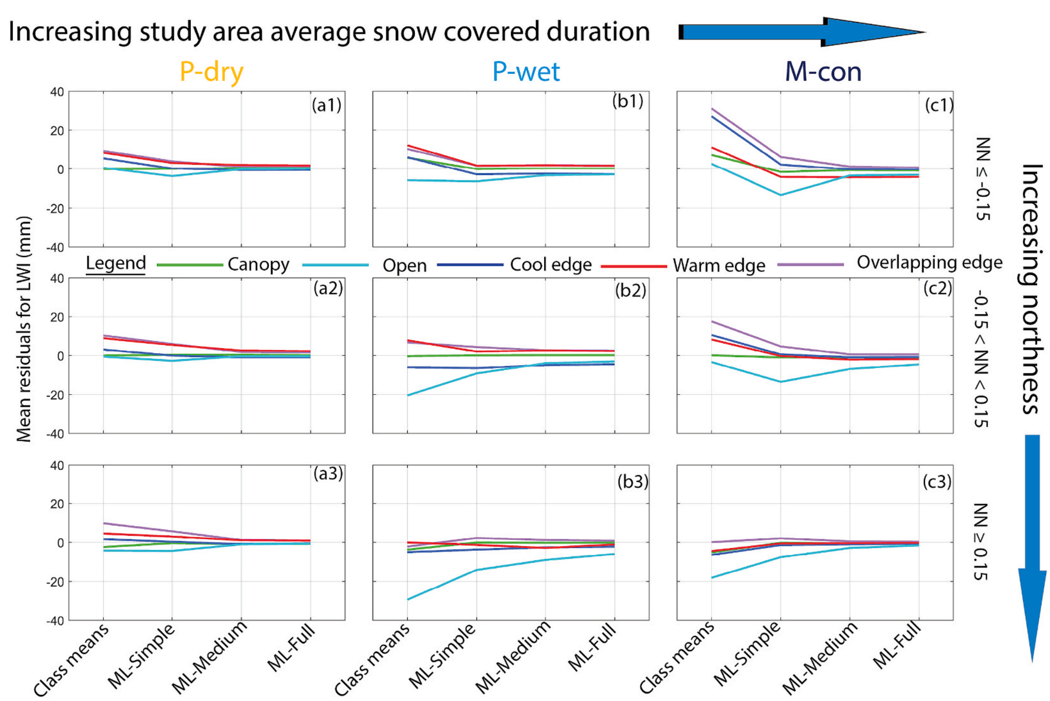

Fig. 10. Liquid water input (LWI) residuals by snow environment for the four emulation models of increasing complexity. Columns indicate study areas arranged by increasing average snow cover duration (Table 1). Rows indicate model pixels at each study area binned by northness. Line styles indicate snow environments (Fig. 4). For peak SWE and SCD, see Figs. S14 and S15.

SCD, and LWI (Table 2), if only the mean value is needed, it is recommended to use the low-complexity class-means approach informed by classes of northness, canopy cover, and snow environment (Fig. 2, Fig. 6). Second, ML models of increasing complexity can improve accuracy of spatial variability across the mosaic of environments created by topography, canopy cover, and canopy geometry (Fig. 7, Table 2, Fig. 9). Fine-scale spatial heterogeneity in snowpack and snowmelt amount and timing can be important for questions of melt partitioning between streamflow and forest evapotranspiration (Barnhart et al., 2020; Gordon et al., 2022; Musselman et al., 2017), characteristics of snow and soil moisture refugia (Strickfaden et al., 2023), albedo and energy balance (Boon, 2009), and fuels moisture and fire danger (Holden and Jolly, 2011). Third, selection of an appropriately complex model depends upon the climatological snow cover duration and northness of the location and upon the anticipated change in the frequency of various snow environments and canopy cover densities (Fig. 5). Increasing model complexity is more likely to improve accuracy at colder/wetter locations with greater snow cover duration (Fig. 10). At cold/wet locations such as M-con, increased model complexity is more likely to improve accuracy of open areas that also have high northness and to improve accuracy for forest edge environments in areas that are level or have northness <0. For example, consider an assessment of annual LWI consequences of an anticipated high severity fire that transforms a high-cover, mixed conifer forest into mostly open area on a south-facing aspect (Fig. 10-c1). Here, the class means approach is likely sufficient, because residuals for under canopy and open areas are both small. Alternatively, consider in the same forest a mechanical thinning into small forest clumps and gaps that leaves many warm, cool and overlapping edges. Here, the ML-medium model is recommended, because residuals decrease substantially for forest edge environments with increasing model complexity up until ML-medium.

This work suggests several important steps for managers concerned with the hydrologic impacts of forest management or forest disturbances. First, it is essential to map the terrain and forest canopy height and cover in the watersheds under consideration, ideally with airborne lidar maps, and to establish routine measurements of snowpack (e.g. with Snowtography, snow surveys by manual or airborne means, and/or point measurement stations such as SNOTEL) at small-scale study sites which are representative of the forest management domain (Dwivedi et al., 2023a). These site-scale data can be used to locally train a high-resolution mechanistic model (e.g. SnowPALM, FSM2, etc.) (Dwivedi et al., 2024a; Krogh et al., 2020; Mazzotti et al., 2020). Developing a locally trained mechanistic model requires specialized expertise that forest managers may need to seek through partnerships with academic or agency scientists. With maps of terrain, forests and mechanistic snow model output, managers will then be prepared to apply outcomes from this paper to make large-scale hydrologic assessments.

In addition to the direct importance of SCD for topics such as streamflow generation and wildfire risk (Musselman et al., 2017; Westerling et al., 2006), multiple lines of evidence suggest that SCD is a key variable mediating the value of increasing model complexity and informing the selection of predictor variables, consistent with prior work at these sites (Dwivedi et al., 2024a). This is probably because longer lasting snowpacks are subject to greater time of exposure to the integrated effects of weather, topography, and canopy, increasing the spatial variability of snow sublimation and melt. Northness and canopy arrangement were increasingly important with increasing SCD, while canopy cover was increasingly important with decreasing SCD, and this pattern held across study areas with different climatological SCD (Table 1) and across years of different weather (Fig. 6, Fig. 7, Figs. S5–S8). Interannual variability in predictor variable importance was especially notable at P-dry, where in ML models (Fig. S6) as winter weather goes from warm/dry to cool/wet, the importance of northness, sky view factor and SFI increases, while the importance of canopy cover and canopy height decreases for most variables. SCD seems to be an important variable across sites, among years, and even within sites by classes of northness, especially the P-dry site (note greater differences among pdf plots in middle and lower rows of Fig. 5), presumably due to greater SCD (Figs. 4-b1) in areas of greater northness (Figs. 2-b3). SCD is therefore a critical consideration when establishing snow measurements to inform future management. Site-level SCD may be assessed from existing records including NRCS SNOTEL or gridded datasets such as UA-SWE (Broxton et al., 2016). Furthermore, its variation across the mosaic of topography, forest cover, and snow environments may be readily assessed with low-cost Snowtography measurements or high-resolution remote sensing.

The future upscaling of hyper-resolution SnowPALM maps with statistical approaches can have broad application. SnowPALM model calibration should be performed over at least 3 years of data, preferably with significant interannual variability in winter weather. Calibration here was performed over an extent of ~50 ha, but we found parameters changed very little from prior values for three co-located 1-ha study sites in previous work (Dwivedi et al., 2024a). The statistical approaches were calculated separately for each of three years (cool/wet, average, and warm/dry), and it is recommended that forest management application consider an appropriate year or ensemble of years, which may vary depending upon management goals (e.g. spring percolation, summer soil moisture, summer low flows, etc.). The spatial extent of upscaling application could be quite large so long as lidar maps of terrain and canopy are available and the models are applied to areas with reasonably similar terrain, climate, and forest type. For example, the ML models developed here (Dwivedi et al., 2025) for dry ponderosa, wet ponderosa and mixed conifer collectively represent the predominant forest types being mechanically thinned in the 1 M ha 4FRI project and will be used to assess the impacts of 4FRI on snow hydrology in forthcoming work.

Beyond this region, the overall workflow presented here can be followed to develop landscape-scale hydrologic assessments in other regions. The workflow begins with ground measurements of snowpack, topography, forest cover and 3-D forest geometry. In our prior work, we gathered daily snow depths from Snowtography and airborne lidar over multiple years (Dwivedi et al., 2023a), but other data sources could be used. Next, we trained a mechanistic forest hydrology snow model (Dwivedi et al., 2024a). We used SnowPALM, but the workflow is not specific to one model, and other hyper-resolution models could be employed, such as FSM2 (Mazzotti et al., 2020). While a direct ML upscaling could be used to estimate any snow variables that have been directly measured such as peak SWE, SCD, or snow density (Broxton et al., 2019), here we rely on the mechanistic model in part because it estimates melt and therefore produces maps of LWI. The workflow presented here could be adapted to upscale other hydrologic variables of interest including daily time series of LWI (which could serve as precipitation inputs to a distributed catchment streamflow model) or soil moisture, which might be expected to vary across microclimates with some of the same predictor variables as used here for snowpack and snowmelt.

Since 2021, this author group and collaborators have established 18 new Snowtography sites in Arizona, Colorado, and Wyoming in an effort to evaluate much broader gradients of climate, forest type, and management regimes. When modeling such widely ranging environments, consideration should be given to the possibility that different variables will rise to greater importance (e.g. wind shelter index could be more important in more windy environments), including variables not considered here. There is also a need to expand measurements to new sites within the same forest-climate classes presented here, specifically to sites with a diversity of canopy cover and arrangement. This will address a limitation of the present work, which is that it involves post-hoc analyses of forest management rather than a designed experiment; differences in the importance of variables at the three selected study areas are likely influenced both by the changes in the prevailing mechanisms (i.e. across gradients of snow cover duration) and the differences in forest management. For example, P-dry has recent mechanical thinning, lower canopy cover, and different fractions of resulting snow environments than P-wet (Table 1, Fig. 2). Additionally, while the sites selected here have mostly level terrain (which is representative of much of the 4FRI project), measurement and modeling of steeper terrain could improve prediction of future management on steeper slopes, or of wildfire or pathogen impacts, especially in higher/colder/wetter areas with persistent snowpack.

6. Conclusions

This paper presents a key step in a generalizable workflow that leverages direct measurements of topography, forest canopy and snowpack to enable hydrologic assessment of large-scale forest management and disturbance and quantifies the shifting importance of topography, canopy cover, and 3D tree arrangement in controlling snowpack and snowmelt. Prior work established collection and processing of direct measurements and training of a mechanistic forest hydrology model. The main contributions of this paper are 1) illustrating efficient means by which a mechanistic model, trained with observations at a small site, can be emulated, thereby enabling future large scale hydrologic assessment, and 2) how the models trained in this process can be queried to illustrate the importance of topographic and forest controls for a given location and weather conditions. This workflow was illustrated using three hydrologic target variables of broad interest: peak SWE, SCD, and LWI, but it could be readily modified to other target variables including snow depth, soil moisture, or fuels moisture. The next step in this work will be the application of the emulation models developed here to assess the hydrologic impacts of landscape-scale forest restoration projects. Ultimately, this work can provide means to evaluate multiple scenarios of forest restoration that conserve snow water resources for forests and downstream water supply, in concert with wildfire risk reduction.

Author Contributions

JB, PB, and MR conceived the study. RD and PB conducted the snow modeling. RD and MR produced the figures. TW produced the landscape ecology metrics. JL, TW and BS contributed expertise on forest management and water resources management. All authors contributed to analysis and interpretation of data. JB wrote the initial manuscript draft. All authors contributed critical revision and intellectual content to the final submitted manuscript.

CRediT authorship contribution statement

Joel A. Biederman: Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ravindra Dwivedi:** Writing – review & editing, Visualization, Methodology, Formal analysis. **Patrick D. Broxton:** Writing – review & editing, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Travis Woolley:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Jackson M. Leonard:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Bohumil M. Svoma:** Writing – review & editing, Resources, Investigation, Conceptualization. **Marcos D. Robles:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2025.133886.

Data availability

The SnowPALM model outputs used in this work for all three field sites are available from (Dwivedi et al., 2024b). The input and target raster datasets, R codes, and trained random forest models for Peak SWE, SCD, and LWI for winters 2018, 2019, and 2020 for P-dry, P-wet, and M-con sites can be accessed from (Dwivedi et al., 2025).

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