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Forest structure has a strong relationship with abiotic components of the environment. For example, canopy morphology controls snow depth through interception and modifies incoming thermal radiation. In turn, snow water availability affects forest growth, carbon sequestration, and nutrient cycling. We investigated how structural diversity and topography affect snow depth patterns across scales. The study site, Grand Mesa, Colorado, is representative of many areas worldwide where declining snowpack and its consequences for forest ecosystems are increasingly an environmental concern. On the basis of a convolution neural network model (R^2 of 0.64; root mean squared error of 0.13 m), we found that forest structural and topographic metrics from airborne light detection and ranging (lidar) at fine scales significantly influence snow depth during the accumulation season. Moreover, complex vertically arranged foliage intercepts more snow and results in shallower snow depths below the canopy. Assessing forest structural controls on snow distribution and depth will aid efforts to improve understanding of the ecological and hydrological impacts of changing snow patterns.

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Both globally and in the western US, at least 40–50% of the freshwater budget originates from snow in mountainous areas (Viviroli *et al*. 2003). Predicting the timing and amount of stream flow requires information on snowpack properties (depth and distribution patterns) in hydrologic models. Variation in snow depth and extent is tied to accelerating climate change and subsequent snow decline (Mote *et al*. 2018), forest stress and mortality (Gleason *et al*. 2021), and potential loss of habitat (Thompson *et al*. 2021). Forest structure, such as the density and vertical and horizontal arrangement of the canopy, is an important control of snow depth and timing of snowmelt (Currier *et al*. 2022). In turn, ecosystem functions (such as mineral, nutrient, and water cycling) in high-altitude mountainous forests are dependent on snow depth and melt (Johnson *et al*. 2009). Ecosystem functions indirectly connect forest structural diversity and abiotic components of the environment. This is a mutual relationship, where canopy structural diversity influences snow depth and melt timing. Vegetation also modifies the impact of other controls (eg net radiation, topography, and wind) on snow. Recent estimates suggest that differences in vegetation may explain at least 50% of the variation in snow accumulation (Zheng *et al*. 2018), and that interception is a primary regulator of snow accumulation, with 60% of incoming precipitation intercepted by coniferous trees (Dickerson-Lange *et al*. 2017).

Scale-dependent relationships complicate explanations for how vegetation alters snow depth, as snow–vegetation interactions vary from individual tree to canopy levels (Webb *et al*. 2020; Hojatimalekshah *et al*. 2021). At the canopy level, snow under dispersed canopies receives higher shortwave radiation than snow under closed canopies, and dense canopies are dominated by longwave radiation. Ultimately, net radiation provides most of the energy for snowmelt in a region (Ellis *et al*. 2011; Roth and Nolin 2017). In addition to density, canopy height influences shading properties, with snow lingering longer in shaded areas (Pomeroy *et al*. 2009). Forests shelter snow from the wind, and during accumulation, canopy interception can be the predominant control on snow depth variation (Storck *et al*. 2002). During the ablation season, forests can control the energy balance under the canopy and delay or advance the melting process (Roth and Nolin 2017). A better understanding of the dynamics between vegetation structural diversity and snow will therefore improve forest and hydrologic management responses to climate change.

The mathematical concept of scale breaks – where transitions between scales occur – could help in identifying the appropriate horizontal and vertical scales for quantifying how vegetation structure controls snow distribution patterns and depth (White *et al*. 2008). When considering snow depth profiles (distance versus snow depth), scale breaks represent the separation between low and high frequency variations in snow depth and controlling factors. For instance, the snow surface is typically more homogeneous in treeless, open sites than in treed sites, indicating a low frequency control on snow depth. Conversely, high frequency variations in snow depth and corresponding controls (eg individual trees) may be relevant and thus mapped at smaller scales. Scale breaks separate the frequencies related to heterogeneity and homogeneity in snow depth patterns (Deems *et al*. 2006; Webb *et al*. 2020), and can

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be used to identify scales where statistical relationships between snow depth and biophysical processes are relatively constant (details in WebPanel 1).

Machine learning and specifically deep learning algorithms, coupled with high-resolution remotely sensed data, provide information to map and model snow distribution in heterogeneous landscapes. Here, we designed a study based on varying vertical and horizontal resolutions of vegetation and topographic features to examine their effects on snow distribution patterns and depth in the accumulation season. We examined foliage height diversity (FHD) (a metric to quantify the vertical arrangement of foliage; Hojatimalekshah *et al.* 2021), canopy height, canopy percent cover, and topography as controls on snow. We also used light detection and ranging (lidar) data to analyze the data at fine scales, classifying controls of snow depth according to their scale of influence and linking the processes with the appropriate scale. We resampled to coarser horizontal scales using the scale breaks of the features, and then trained a deep learning model to explore the sensitivity of snow depth as an abiotic component of the environment as related to forest structural diversity. Our novel approach demonstrates the usefulness of scale breaks in disentangling complex drivers of snow depth variation in forest ecosystems, with the potential to inform forecasts of snow depth in an era of rapid climate change.

Methods

Our study area consisted of a 17-km × 3.5-km region on Grand Mesa, an extensive plateau environment in western Colorado, representing a data collection effort by the US National Aeronautics and Space Administration (NASA) SnowEx (https://snow.nasa.gov/campaigns/snowex) campaign in 2020 (Figure 1a). Although topography was considered in our analysis, the small range in elevation (2922–3336 m, increasing from west to east) of this region was ideal for investigating the role of vegetation structure on snow depth. Engelmann spruce (*Picea engelmannii*), the predominant tree species in the western part of the mesa, forms mixed assemblages with subalpine fir (*Abies lasiocarpa*) and aspen (*Populus tremuloides*) in the eastern section. Wind speeds generally decrease from west to east; a northeast wind is dominant in the west, whereas wind originates from the northwest in the center and eastern portions of Grand Mesa (Hojatimalekshah *et al.* 2021). Snowfall in the region from January to March 2020 was about 82 cm (www.worldweatheronline.com/grand-mesa-weather-averages/colorado/us.aspx). From late January to mid-February 2020, the mean, standard deviation, and range of snow depth was 95 cm, 17 cm, and 17–260 cm, respectively (Hiemstra *et al.* 2020).

Airborne lidar data were collected during two SnowEx campaigns in September 2016 (snow-off) and prior to melt (and during the accumulation season) in February 2020 (snow-on). We computed snow depth by applying the M3C2 method described in Hojatimalekshah *et al.* (2021), achieving a relative vertical accuracy of 7 cm based on the maximum standard deviation. Currier *et al.* (2019) found airborne-measured snow depths in Grand Mesa to be within 5 cm of terrestrial laser scanning data using the same 2016 (snow-off) and a similar snow-on (2017) dataset. Computations were made for the following topographic and vegetation metrics from the snow-off lidar data: bare earth elevation, slope, aspect, canopy height, canopy percent cover, and FHD. We calculated the FHD in three different voxel sizes (0.5 m, 1 m, and 2 m) to investigate the influence of different vertical scales on snow depth estimation. Wind was not considered because of the paucity of meteorological data (three stations across Grand Mesa) relative to the modeling requirements.

Convolutional neural networks (CNN), a machine learning approach, are increasingly being used in ecology for a range of applications relating to image classification and object detection (Brodrick *et al.* 2019). "Deep CNN" is a deep learning technique that searches for a shape through input image features and learns texture and content by extracting different arrangements of edges. Each edge is restored in a layer from general patterns to progressively more detailed ones. The algorithm learns the link between edges and combines those to construct the output pattern and the content. We trained a deep CNN (Figure 1b) to predict snow depth as a function of topography and canopy structural metrics (WebPanel 2), with the resulting prediction used as a tool to understand the control of vegetation and topography on snow depth. We tiled the data into 250-m × 250-m areas (n = 952 images), selecting 70% for training and 30% for testing. We reserved 20% of the training data for optimizing model parameters, and used the test data for the final model evaluation. To evaluate CNN's capacity for generalization, we relied on the test data, because doing so would illustrate a realistic perspective of the controls' effect on the spatial variation of snow depth (rather than a predictive capability for snow depths). We contrasted the fine-scale dataset (1-m images) with a coarse scale dataset by resampling the 1-m data based on the scale breaks of each feature.

Scale breaks

To investigate the influence of scale on snow depth prediction, we computed scale breaks for each image and individual feature (Figure 1c). For example, the median scale break for canopy height is about 10 m, indicating higher tree height variation when spaced less than 10-m apart and lower tree height variation above 10-m spacing (WebFigure 2). We selected the smaller scale break value for analysis between those calculated in north–south and east–west directions. Individual features were filtered with a median filter using window sizes equal to scale breaks. We used each feature's scale break to determine the coarse resolution analysis and applied the same deep learning network architecture (Figure 1b) for fine and coarse resolution data analyses (see WebPanel 2 for details about the network architecture).

Results

The minimum and maximum scale breaks were 3 m and 123 m, respectively (Figure 1c). The median scale break calculated for snow depth was greater than the breaks of all other features. Using the deep CNN network, the training, validation, and test R^2 for snow depths reached 0.65, 0.63, and 0.64 for fine resolution and 0.48, 0.48, and 0.44 for coarse resolution data analysis, respectively. Note that the fine resolution data analysis was at 1-m horizontal resolution, whereas the coarse resolution data analysis was dependent on the scale break for each feature (ranging from 3 to 123 m) for each of the 952 images. The mean squared error of the whole model reached 0.017 m^2 (root mean squared error of 0.13 m) and 0.019 m^2 (root mean squared error of 0.14 m) using fine and coarse resolution inputs, respectively. The R^2 values for the test and training datasets were close in value, indicating that the models did not overfit.

The predicted snow depth (median R^2 of 0.64; WebFigure 1) in the fine resolution analysis preserved the original snow depth pattern (Figure 2). The elevation (digital elevation model, DEM) and FHD using a 2-m voxel size were the most important features for the fine resolution dataset (Figure 3). When we replaced elevation and FHD (at 2-m voxel size) with noise, the R^2 dropped to <0.1 and < 0.4, respectively. Replacing other features with noise did not yield similar drops in R^2 values, further indicating the importance of elevation and FHD. In contrast, at coarser scales, canopy height became the most important feature (Figure 3) for predicting snow depth, followed by FHD at 2-m voxel size. The coefficient of variation indicated that topographic and vegetation metrics together predicted 40% and 64% of snow depth variation in coarse and fine resolution data, respectively.

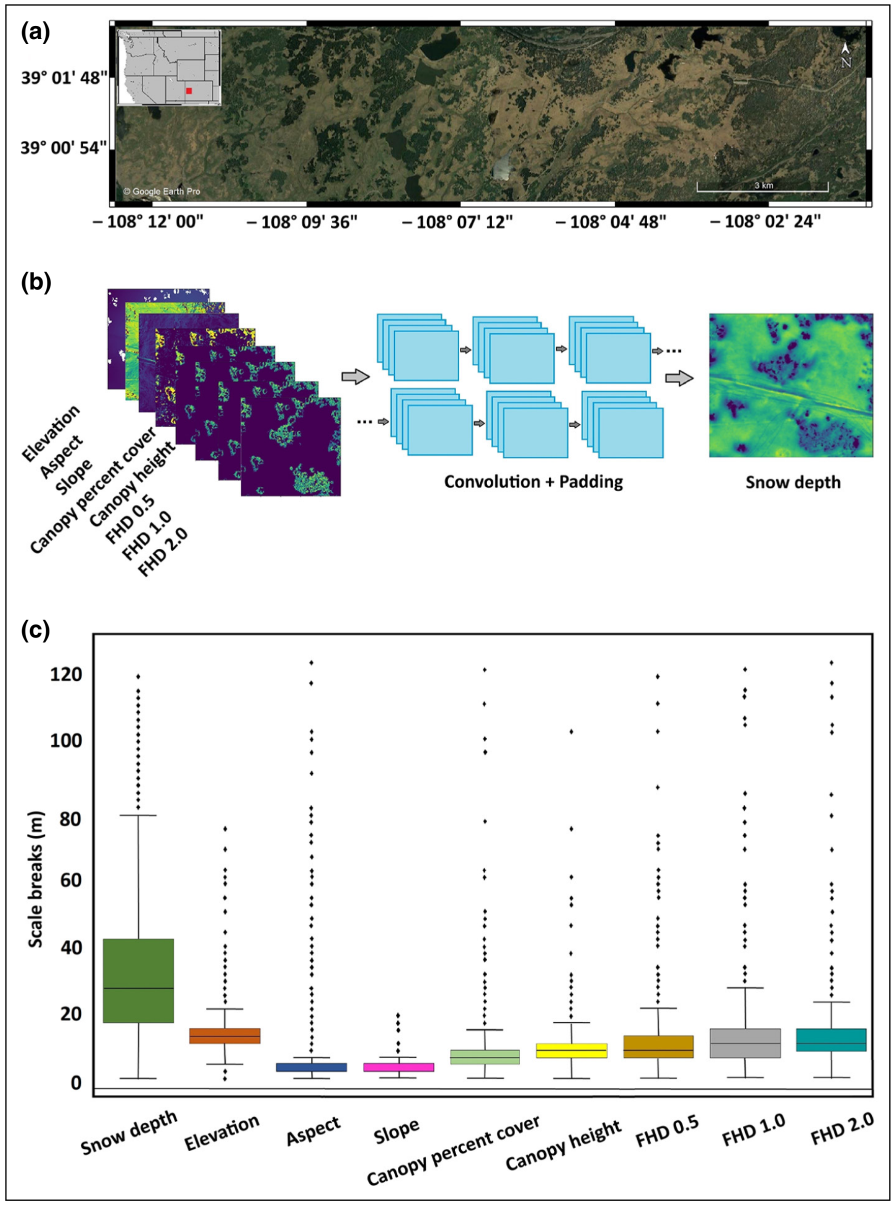

Figure 1. (a) Grand Mesa, Colorado, with inset of the western US. Image credit: © Google Earth Pro. (b) Deep learning network for estimating snow depths; passing the input image features through the network results in the predicted snow depth of the region. (c) Boxplot of scale breaks for snow depth, elevation, aspect, slope, canopy percent cover, canopy height, and foliar height diversity (FHD) with voxel sizes of 0.5 m, 1.0 m, and 2.0 m. Horizontal lines within boxes depict median values, boxes represent the interquartile range (25th–75th percentiles), whiskers (vertical lines) represent 1.5 × interquartile range, and solid diamonds depict outliers.

Discussion

The results of our analysis demonstrate the importance of accounting for complex scale-dependence of the predominant controls of snow depth. Snow depth variation at fine scales is driven by the interception of snow by individual trees and their vertical structure. At coarser resolutions and in the absence of elevation variation, canopy height strongly controls snow distribution, likely because canopy height affects snow sheltering and shading. While FHD influences snow depth at both fine and coarse spatial scales, elevation is an influential control at fine scales. However, coarsening the resolution reduced the importance of elevation relative to vegetation metrics. In this instance, the importance of canopy height increased but not enough to compensate for the reduced importance of elevation, diminishing the model's predictive capacity. The elevation gradient across Grand Mesa is minimal and the coarser dataset represents a smoother elevation gradient, which reduces its effect on snow depth

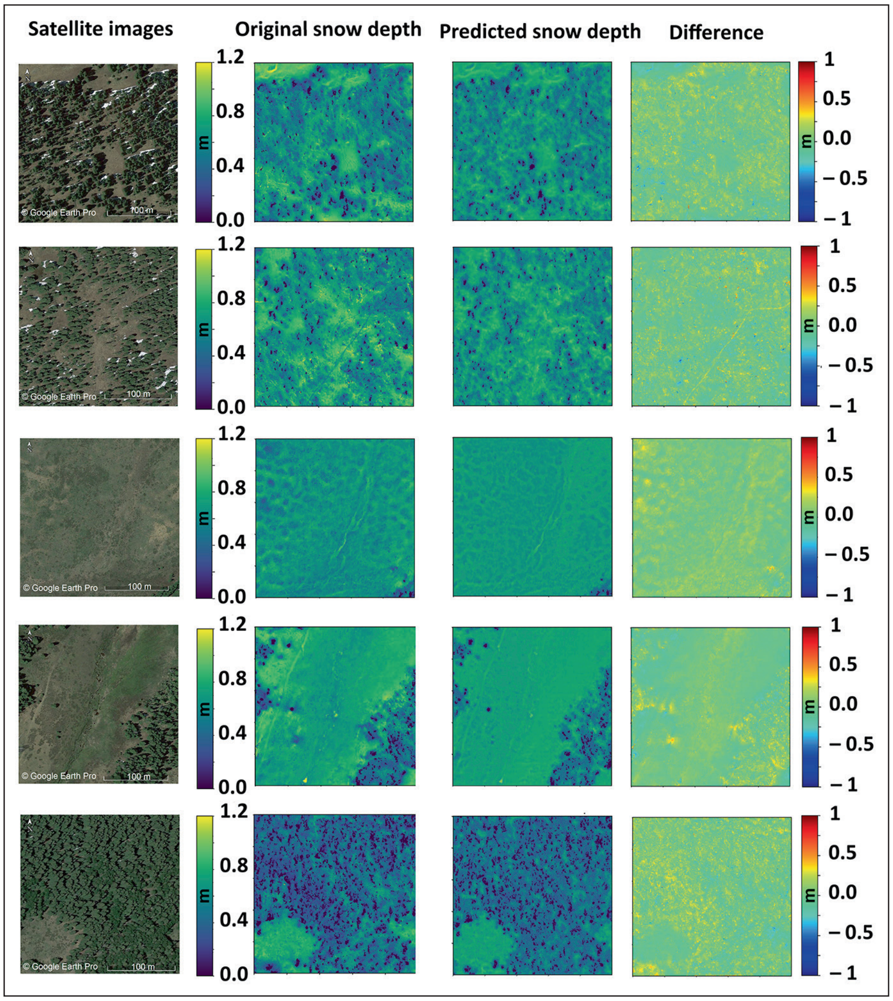

Figure 2. Satellite imagery (first column), original snow depth (second column), predicted snow depth (third column), and the difference between the original and predicted snow depths (fourth column) for five random images of the test data. Each image is 250 m × 250 m. Image credits: © Google Earth Pro.

(in contrast, the heterogeneous nature of the surface and its effect on snow distribution is apparent in the fine scale analysis).

Overall, the lower predictive ability of the coarser dataset is due to the median scale breaks for topography and vegetation, which are smaller than the snow depth scale breaks (Figure 1c). The spatial variation in snow depth is smoother than the variation in topography and vegetation structure at coarser scales, indicating that other controls with larger breaks (eg wind) are required for accurate snow depth estimates at coarser scales (Trujillo *et al.* 2009). This is likely the case for open, nonforested areas; whereas in forested regions, canopies (eg canopy height) control snow depth variation. Disparities between surface roughness lengths at the windward and leeward aspects of forest canopies, as well as variable fluid dynamics between the two sides, could cause different scale breaks and snow accumulation in clearings close to the forest boundary and within the forest (Webb *et al.* 2020). Although 1-m resolution wind vectors were unavailable for our study area, future research incorporating high-resolution wind direction and speed data as inputs in the CNN will help elucidate the relative controls of wind to vegetation features across scales.

Energy fluxes also affect snow depth distribution within the canopies at different scales (for example, longwave radiation observed at smaller scales, and shortwave radiation as well as shading effects at larger scales) (Pomeroy *et al.* 2009). Although our method of computing scales for individual features of influence helps ascertain the maximum variations in snow depth, the results show that coarsened data captures lower snow depth variation in such ecosystems, which could ultimately lead to lower snow water equivalent (SWE) and therefore underestimation in stream flow and river basin modeling.

Snow depth variation under the canopy differs between the accumulation and ablation seasons (Roth and Nolin 2017). Tree structure affects snow depth through interception during the accumulation season and by sheltering/shading during the ablation season. Because our input data were from the accumulation season, we describe the role of the forest structure in the context of the interception process. We expect the same structural effects on snow depth throughout the accumulation season, across the range of forest composition in our study area. The use of multiple images in training the model simulates different vegetation covers and their effect on snow depth patterns. For example, we used 952 images representing a range in spruce, fir, and aspen vegetation structure. In this regard, our model may be applied to environments with similar vegetation structure and in areas with minimal elevation ranges. However, further tuning is required to account for different seasons (eg ablation), landscapes with different vegetation structure (eg deciduous and burned or other disturbance), and elevation ranges.

Our results imply that to predict snow depth under trees, we do not necessarily need to describe structural diversity using voxel sizes finer than 2 m. Quantifying structural complexity within the trees at scales below 2-m voxels does not have a major effect on predictions of snow–vegetation interactions. Based on this information, hydrologic models may improve snow depth and SWE estimates by adding a less complex vertical distribution of trees. For example, in the Distributed Hydrology–Soil–Vegetation Model (DHSVM) (Sun *et al.* 2022), it may be possible to replace generalized leaf area index values with 2-m voxel size FHD to provide more detailed energy balance information, where lidar is available. Moreover, a 2-m voxel size is larger than the uncertainty in the vertical resolution of spaceborne laser altimeters such as NASA's ICESat-2 and GEDI, which may be used for examining snow–vegetation relationships over greater areal extents. Although our results indicate that, at fine scales, FHD provides a superior model of snow depth, the relationship remained significant at coarser scales and may remain so for studies using such spaceborne platforms.

In a warming climate, spatial predictions of snow depth have management relevance for identifying areas where changing snow depth may severely impact ecosystems, hydrology, and microclimates. Our methods can be extended to coarser resolution satellite images that cover larger ecosystems (eg entire biomes) and improve our understanding of direct and indirect mediators between forest and different environmental components (eg biodiversity, functional richness, soil water availability, carbon fluxes). Our study shows upscaling forest structural information (canopy height and FHD) preserves the important diversity information that influences snow depth, and ultimately benefits our understanding of ecosystem functioning.

Using the approach demonstrated here, CNN may also be used in SWE calculations (the multiplication of snow density by depth). Typically, SWE maps use a constant snow density in their models. Ideally, to improve SWE modeling estimates, the use of a CNN should consider climate-related features specific to the study area. For example, dry and cold regions experience higher SWE peaks under sparse canopies (Sun *et al.* 2022). Because CNN is a supervised model, information about the relationship between snow density and vegetation will be helpful. Deep learning algorithms can represent snow density variations from the surface to the bottom of the snowpack as multilayer (bands) inputs, ultimately modeling multilayer density maps. In addition, different structures of tree species explain up to 75% of peak SWE changes (Faria *et al.* 2000). The FHD used in our model represents vertical canopy complexity and quantifies the interception effect regardless of species. Therefore, incorporating FHD in snow depth and density estimates may also enhance future CNN models of SWE.

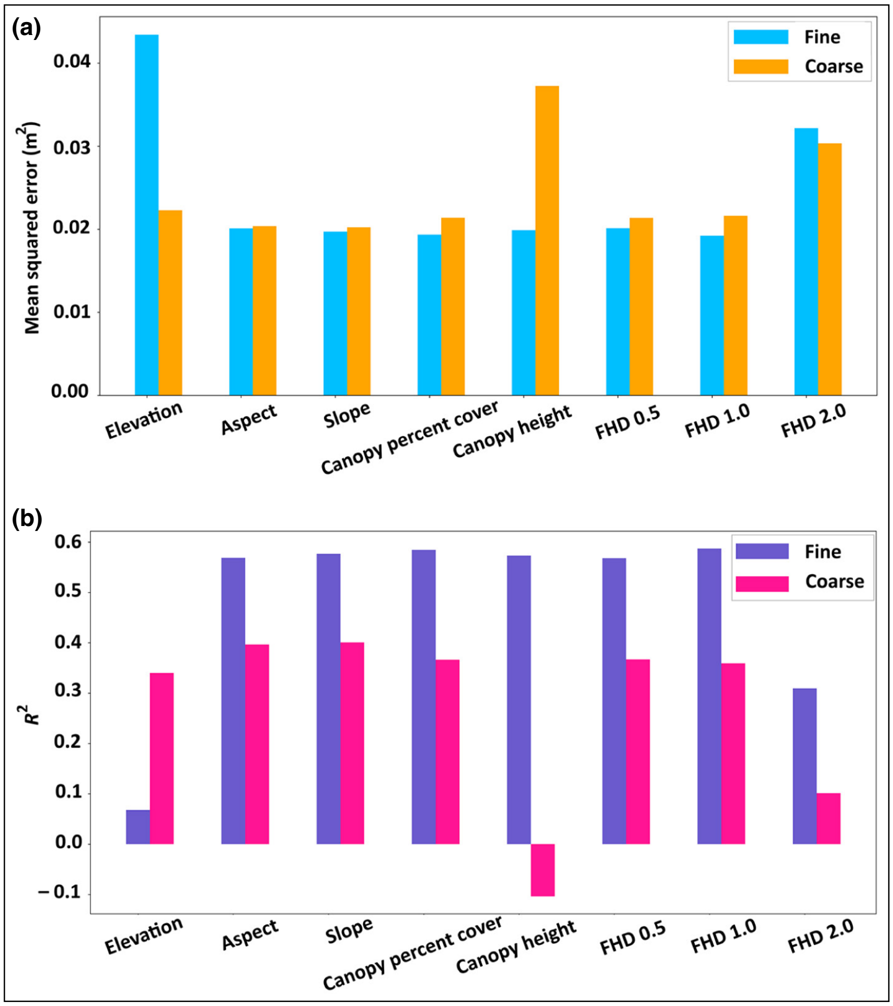

Figure 3. (a) Mean squared error (MSE) and (b) R^2 after replacing the corresponding features with noise for fine and coarse resolution datasets. Foliar height diversity (FHD) with voxel sizes of 0.5 m, 1.0 m, and 2.0 m. Lower R^2 and higher MSE values represent high importance of the feature (eg digital elevation model and FHD for the fine scale, FHD for the coarse scale).

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Data Availability Statement

Data are permanently archived with Boise State University's ScholarWorks (Hojatimalekshah *et al.* 2022). Novel code is provided as private-for-peer review via https://github.com/ahmadhojati/FEE-special-issue.

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Supporting Information

Additional, web-only material may be found in the online version of this article at http://onlinelibrary.wiley.com/doi/10.1002/fee.2584/suppinfo