



The missing drifts: snow density heterogeneity from wind-packing exacerbates systematic underestimation of deep snow storage from the scale of nivation hollows to mountain ranges

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Abstract. Spatial estimates of snow water equivalent (SWE) often depend at least partially on extrapolation from sparse measurements, but wind drifts are frequently missing from the underlying observational datasets. Despite the increasing availability of airborne lidar surveys, which constrain snow depth variability in drifts, the contribution of wind-packing densification to SWE heterogeneity remains unknown. Here, we leverage extensive snow pit density profiles (78 total, including 14 at least 2 m deep) from the early ablation season across the Wind River Range (Wyoming, USA) to strategically constrain snow density in rarely sampled settings, including deep drifts, steep slopes, avalanche runouts, and high elevations. At the most extreme, complete vertical profiling of a 5.9 m drift in a nivation hollow reveals a bulk density of 585 kg m^{-3} , exceeding the predictions of global empirical models by 14 % to 35 %. In contrast, we contemporaneously observe bulk densities as low as 339 kg m^{-3} in adjacent forested areas. We scale up our snow density observations to full watersheds at the 3 m grid scale using a Bayesian statistical model weighted by a representativeness metric that is derived from airborne lidar snow depth data across multiple watersheds. The most representative density measurements are associated with alpine

snow drifts deeper than 2 m. Like most terrestrial monitoring networks, all 88 of the in-situ daily snow monitoring sites in Wyoming (SNOTEL) are located in relatively low-elevation forested areas, structurally excluding alpine wind drifts. Beyond this systematic underestimation of drift-related snow density, wind drifting also drives depth variations, compounding the underestimation of SWE heterogeneity in extrapolated datasets. Across three large-domain near-real-time gridded SWE datasets, the standard deviation of SWE across the mountain range is underestimated by 33 %–75 % relative to our lidar-based SWE map at the same 500 m grid-scale. These extrapolated datasets underestimate SWE by 65 %–73 % in a 1 km^2 glacial cirque basin despite only 2 %–17 % underestimation of the landscape mean. Despite the systematic underrepresentation of drifts in observational datasets, drifts are the most representative snowpack components in windy alpine mountains, so it is essential to account for drift impacts on both snow depth and density to capture the spatial distribution of SWE.

1 Introduction

Mountain snowpacks are a global water resource (Mankin et al., 2015), and quantifying seasonal snow water equivalent (SWE) is useful for predicting seasonal water supply availability (e.g., Pagano et al., 2004; Fleming et al., 2023), constraining the glaciological mass balance (e.g., Zemp et al., 2009; Dadić et al., 2010; Medley et al., 2013), and understanding mountain hydrology in general (e.g., Bales et al., 2006; Li et al., 2017). The spatial distribution of the snowpack provides a qualitatively different type of information beyond the basin-mean volume and is determined by physical processes interacting across a wide range of scales (Mott et al., 2010). Snowpack heterogeneity influences snowmelt runoff timing, peak flow magnitude, late-season runoff volumes, ecological processes, glacier dynamics, and more (Luce et al., 1998; Lundquist et al., 2005; Brauchli et al., 2017; Freudiger et al., 2017; Schneider et al., 2020; Marsh et al., 2024; Wigmore and Molotch, 2024; Boardman et al., 2025; Pfohl et al., 2026). Many methods have been proposed to quantify the spatial distribution of mountain snow water equivalent (SWE), broadly based on some combination of remote sensing, modeling, and extrapolation from terrestrial measurements (Dozier et al., 2016; Yang et al., 2023; Mortimer et al., 2024). Although many novel techniques have been proposed for spatial SWE estimation, most datasets that are widely available at landscape scales in near-real-time are based on combination of statistical extrapolation and data assimilation into physical models. Here, we test whether these widespread datasets and models capture the types of heterogeneity observed in field data from a heavily wind-affected alpine mountain region (Boardman et al., 2025). The contribution of snow density to overall snowpack heterogeneity remains particularly uncertain, since snow depth heterogeneity can be well-constrained through airborne lidar surveys (Painter et al., 2016), so we focus our investigation on the propagation of density heterogeneity into SWE.

Variability in snow depth and snow density both contribute to spatial heterogeneity in SWE. Field surveys and automatic monitoring stations can measure both of these properties, but measuring snow depth is comparatively easy, and density is expected to be less variable over space and time, so snow depth measurements have traditionally been much more abundant compared to density or SWE measurements (Elder et al., 1998; Erxleben et al., 2002; Sturm et al., 2010). In recent decades, the Airborne Snow Observatory (ASO) approach to lidar remote sensing (Painter et al., 2016) has further increased the discrepancy between abundant snow depth measurements and sparse density measurements (Raleigh and Small, 2017; Broxton et al., 2019b). Airborne lidar surveys can provide maps of snow depth across entire mountain ranges at resolutions of 1–3 m (Hopkinson et al., 2004; Deems et al., 2013; Painter et al., 2016). Converting these snow depth maps into SWE requires constraining

spatiotemporal variability in snow density across complex terrain, which is the largest source of uncertainty in lidar-based SWE surveys (Raleigh and Small, 2017). Snow density information is also useful for other remote sensing approaches to mapping SWE, including photogrammetry (e.g., Bühler et al., 2015; Nolan et al., 2015; Hu et al., 2023), some radar-based methods (e.g., Rutter et al., 2019; Tsang et al., 2022), and passive microwave methods (e.g., Venäläinen et al., 2021). Snow density may also be inverted from the combination of radar and lidar remote sensing in some conditions, i.e., in shallow dry snow (Meehan et al., 2024).

Several approaches have been developed to constrain snow density, including process-based modeling and data assimilation (e.g., Hedrick et al., 2018), empirical extrapolation from field measurements (e.g., Jonas et al., 2009), machine learning (e.g., Sun et al., 2024), or simple mean aggregation from automatic monitoring stations (e.g., Kirchner et al., 2014). However, these methods are limited by the sparsity of observational density data, especially in alpine locations (Molotch and Bales, 2006). Substantial uncertainties also arise in physical model-based approaches, as process-based snow models suffer from incomplete physics (Keenan et al., 2021) and uncertain forcing data (Raleigh et al., 2015). As a result, distributed model estimates of snow density are typically bias-corrected using the same sparse terrestrial measurements (e.g., snow pillows and field surveys). Hence, even model-based density fields are commonly influenced by extrapolation with respect to elevation-density trends, depth-density trends, and other density biases (Painter et al., 2016, and see also numerous ASO survey reports ca. 2020–2026). Wind-snow interactions are particularly important for capturing the distribution and density of alpine snow drifts, but wind fields are notoriously challenging to model in complex terrain (e.g., Raderschall et al., 2008; Mott and Lehning, 2010; Musselman et al., 2015). Data-driven empirical models of snow density are agnostic to uncertain process representations (Avanzi et al., 2015), but these correlations are often weak and inconsistent (López-Moreno et al., 2013; Wetlaufer et al., 2016). Moreover, in-situ and manual field measurements rarely constrain snow density in inaccessible locations such as high elevations, deep drifts, and steep slopes (Molotch and Bales, 2006; Wirz et al., 2011; Grünwald et al., 2013), limiting our ability to test, improve, and validate model assumptions about the dominant processes.

Spatial heterogeneity in snow density is the product of complex interactions between the atmosphere, the land surface, and the snowpack itself (Seligman, 1936; Mellor, 1964; Pomeroy et al., 1998). The evolution and spatial variability of snow density begins with the variable fresh snowfall density and unique depositional history of each location and year (Judson and Doesken, 2000; Roebber et al., 2003). As the snowpack evolves, a wide array of processes contribute to density variations, including the settling and compaction of snow grains, the percolation and refreezing of liquid water, and the metamorphosis or diagenesis of snow grains into dif-

ferent shapes (Anderson and Benson, 1963; Sommerfeld and LaChapelle, 1970; Colbeck, 1982; Brun, 1989; Marshall et al., 1999). In forested locations, tree canopies mediate snowpack dynamics by intercepting and releasing precipitation, decreasing solar radiation, increasing thermal radiation, and reducing wind speeds (Rutter et al., 2009; Varhola et al., 2010; Safa et al., 2021). The local microclimates created by forest canopies can further modulate snow density relative to open locations (Pomeroy et al., 1998; Bonner et al., 2022).

In addition to spatial (lateral) variability, snow density varies vertically as a consequence of depositional history, thermodynamic gradients, and mechanical stresses within the snowpack (Colbeck, 1991; Harper and Bradford, 2003; Hao et al., 2021). Strong snowpack temperature gradients (i.e., cold atmospheric conditions) can cause the development of low-density snow layers with large faceted crystals, particularly near the ground, which is known as “depth hoar” (Seligman, 1936; Akitaya, 1974; Sturm and Benson, 1997; Domine et al., 2018). Wind-blown snow is associated with the development of high-density surface layers (“wind slab”) due to the mechanical fracturing of snow grains during saltation (Comola et al., 2017) and possibly other processes involving humidity feedbacks, a phenomenon known as “wind-packing” (Mellor, 1964; Craven and Allison, 1998; Fierz et al., 2009; Sommer et al., 2017). Finally, deep snow evolves into firn and ultimately ice over multiple years through a combination of densification processes caused by overburden pressure and thermodynamic gradients, including grain rearrangement (compaction) and recrystallization (Anderson and Benson, 1963; Alley et al., 1982; Arnaud et al., 1998; Hörhold et al., 2011). Although the nuances of these processes have been considered in the observational literature for many decades, some physical densification processes are missing from the actual operational models used in near-real-time to estimate density fields in concert with airborne lidar snow depths. For example, the version of iSnobal used by Hedrick et al. (2018) to estimate SWE in combination with lidar data only considers temperature metamorphism, liquid water content, compaction from overburden pressure, and time since accumulation as a heuristic for unsimulated grain-scale processes. Thus, it is unknown to what degree the common practice of neglecting other controls on alpine snow density (wind-packing, avalanches, etc.) might impact near-real-time spatial SWE estimates that are used for water supply forecasting and other applications.

The density of deep alpine snow is especially poorly constrained despite considerable glaciological and hydrological importance. In-situ measurements of snow density, e.g., SNOw TELelemetry (SNOTEL) stations in the USA, are concentrated in forested regions within a relatively narrow elevation band, and these stations are not representative of the snowpack above treeline (Molotch and Bales, 2006). However, prior assessments of SNOTEL representativeness (Molotch and Bales, 2006) have not addressed snow density heterogeneity. Manual field surveys likewise tend to ne-

glect inaccessible and potentially dangerous alpine regions, so complete snow pit profiles from deep alpine wind drifts are rare in the literature. For example, one of the most comprehensive and well-funded snow surveys recently conducted in the western USA (Meehan et al., 2024) obtained 155 snow pit density profiles over many weeks, but their deepest snow pit was 1.43 m, considerably less than the threshold of 1.5 to 2 m SWE (3 to 4 m snow depth) that is important for glacier resilience and streamflow timing in alpine regions (Boardman et al., 2025). Thus, the density of deep alpine wind drifts remains largely unconstrained.

Deep wind-drifted snow and avalanche debris persists later into the summer compared to nearby shallower snow, so deep snow has outsized importance for mediating streamflow timing and sustaining perennial snow and ice below the regional equilibrium line altitude (Luce et al., 1998; Florentine et al., 2018; Mott et al., 2019; Boardman et al., 2025). Prior studies of deep snow density tend to focus on the evolution of glacial firn, where multiple years of snow compaction leads to higher densities farther below the surface. For example, firn measurements from an Alaskan glacier show spring snow densities below 400 kg m^{-3} near the surface and exceeding 600 kg m^{-3} at a depth of roughly 10 m (Stevens et al., 2024). Seasonal snow overlying glaciers (i.e., snow that accumulates and melts each year instead of assimilating into the glacier) can also reach densities in excess of 600 kg m^{-3} during the ablation season (Gugerli et al., 2019). Unlike glacial firn, which persists across multiple years by definition, kilometer-scale snow transport by wind and avalanches can yield seasonal accumulation of 4–6 m SWE (3–9 times local mean snowfall), even in locations that become snow-free every year (Boardman, 2025b). Over geological timescales, these deep snow drifts coevolve with the local topography in a process known as “nivation.” The resultant “nivation hollows” are shallow topographic depressions caused by a positive feedback cycle between snow persistence and accelerated weathering: a deepening hollow causes a larger (and more persistent) snow drift by locally reducing the wind speed, and the persistent snow drift provides an enhanced source of meltwater that drives rock dissolution and other erosive processes (e.g., Henderson, 1956; Thorn, 1976; Dohrenwend, 1984).

To our knowledge, complete vertical snow density profiles from deep ($\geq 4 \text{ m}$) seasonal alpine wind drifts are not reported in the literature. Due to the logistical difficulty of digging and sampling very deep snow pits in remote wilderness settings, vertical snow density profiles are typically only measured over the upper 1–2 m of the snowpack, even in areas where total snow depths may be much deeper (e.g., Schaerer, 1988; Kanamori et al., 2005; Libois et al., 2014). It is thus an open question whether these shallower snow pits are sufficient to constrain alpine snow density at watershed scales. Tabler (1980) reports snow densities from deep artificial wind drifts (downwind of snow fences) measured using a Federal sampler (SWE coring tube), which does not pro-

vide information on vertical density heterogeneity. Sturm et al. (2001) measured the density of wind slab strata in a deep Arctic drift, finding a much higher bulk density compared to nearby tundra snow (mean 398 vs. 300 kg m⁻³), but they did not report complete ground-to-surface density profiles.

In the present study, we investigate snow density heterogeneity across an alpine mountain range by measuring complete vertical snow pit profiles in varied settings including deep drifts to address our first research question:

(1) To what extent does wind-packing contribute to heterogeneity in mountain snow density compared to other drivers of variability such as elevation, slope, forest cover, and avalanche debris?

We compare our snow pit observations to prior empirical density models and regional SNOTEL data in the context of lidar-based SWE mapping to address our second research question:

(2) How well do existing datasets and regression models account for snow density heterogeneity in an alpine region, and which snow pit measurements are most representative of the complete watershed snowpack?

Finally, we compare our data with other approaches to near-real-time spatial SWE quantification to address our third research question:

(3) How well do large-domain gridded SWE datasets account for snowpack heterogeneity across mountain watersheds, and what is the relative importance of density versus depth heterogeneity at watershed scales?

2 Methods

The present study focuses on the results of snow surveys conducted in the Wind River Range (WRR), Wyoming, USA, from 25 May through 2 June 2025, though we also present additional snow pit profiles collected at roughly the same point in the season during 2023, 2024, and 2026. This time-frame corresponds to the early ablation season in the WRR, and while the ephemeral low-elevation snowpack had already melted completely, portions of the high-elevation snowpack were not yet isothermal (snow temperature < 0 °C). Prior snowpack modeling, streamflow analysis, and extensive field experience suggests that most snowmelt occurs beginning in late May through July in alpine regions of the WRR (Boardman et al., 2025; Boardman, 2025b).

We begin by describing our field measurement protocols and survey design, and we subsequently analyze controls on snow depth and density using geospatial data and wind modeling. We then test several widely cited statistical snow density models to test whether they capture our measured axes of heterogeneity, and we compare our estimated SWE map with other near-real-time gridded SWE datasets across three watersheds (Fig. S1 in the Supplement) to evaluate the propagation of density heterogeneity.

All statistical hypothesis tests presented throughout are conducted using the Welch two-sample two-sided *t*-test or the Pearson product-moment correlation test as implemented in the R statistical programming language.

2.1 Field Campaigns

Our field surveys are designed to sample hypothesized endmembers of variability that are missing from the regional in-situ network: deep vs. shallow snow, low vs. high elevations, forested vs. open areas, different slope aspects, and unique types of snow such as avalanche debris. This is similar to the approach of Broxton et al. (2019b), who also used snow pits to constrain anticipated endmembers of variability. Unlike many snow field surveys, we prioritize snow density instead of depth measurements since high resolution depth data are available from contemporaneous airborne lidar surveys. Additionally, we only collect snow pit measurements instead of using a SWE coring tube (i.e., Federal sampler) because deep, high-density snow with thick ice layers is not conducive to inserting or retrieving a SWE coring tube by hand (Federal Wilderness regulations prohibit power tools), and in shallower snow, the rocky alpine ground is not conducive to obtaining a dirt plug to confirm that the ground was reached. Moreover, snow pits are widely regarded as the standard validation measurement technique against which other measurements are compared (e.g., López-Moreno et al., 2020; Kaasik et al., 2023).

We conducted three fieldwork campaigns during the 2025 spring season. The first survey (24–26 May) involved six participants and yielded 13 snow pits, with a primary goal of digging and sampling one very large pit (5.9 m depth). We dedicated nearly a full day to digging this large pit and began measurements on the second day of the survey (25 May). The second survey (30 May–1 June) was conducted by a single individual and involved a traverse across the WRR to measure high-elevation snow on both sides of the mountain crest, yielding 18 snow pits. The third survey (1 June) involved two participants and yielded 5 snow pits. Combined, our three backcountry survey routes cover a distance of roughly 90 km with about 5400 m of vertical elevation gain. Although we could sample more snow pits within a smaller area, traversing these substantial distances ensures that our measurements span a wide variety of representative terrain across the crest of the WRR (Fig. 1). Additional surveys were also conducted in late May to early June of 2023, 2024, and 2026, including both repeated measurements from sites sampled in 2025 and additional sites approximately 50 km to the south on the Wind River Indian Reservation (North and South Fork Little Wind River). Eight profiles were collected in 2023 (snow depth range 0.6–5.8 m), another 20 profiles were collected in 2024 (snow depth range 0.25–3.2 m), and another 14 profiles were collected in 2026 (snow depth range 0.35–5.6 m). We focus on the 2025 surveys, because this was the most comprehensive year of measurements spanning different environ-

ments, providing a snapshot of spatial heterogeneity while controlling for confounding variability caused by interannual weather patterns.

At each snow pit, we measure vertical density profiles following standard protocols (Kinar and Pomeroy, 2015). Most snow pits extend to the ground, identified by visual presence of rock/dirt. In 2025, two deep pits did not reach the ground due to time constraints, and we offset our height measurements for these pits using a combination of probe measurements and the 2025 lidar-based snow depths at the pit locations. Similarly, three of the deepest drifts measured in 2023 and 2026 (5.8, 5.6, and 4.0 m) were partially sampled to depths of 4.8, 2.6, and 2.0 m, respectively, and all other profiles were sampled to the ground.

We measure density using several 1000 cc triangular wedge cutters (Snowmetrics Inc.), with care to ensure that the cutter is fully filled but not over-pressed into the snow face. The cutter is used vertically, so that a representative section of the vertical layering structure is obtained. Snow density samples are measured using A&D HT-3000 and HT-5000 digital scales with 1 g precision. To maximize accuracy, we re-tare the density cutter at each snow pit location to account for varying amounts of residual liquid water adhering to the cutter. Additionally, we carefully wipe off excess snow and liquid water from the outside of the cutter after each measurement, and we wipe out any snow adhering to the inside corners of the cutter before each new measurement. Despite our attention to detail, the precision of our density measurements is affected by the challenges of sampling dense, icy snowy in remote alpine locations, in addition to the baseline uncertainty associated with all field density measurements (Proksch et al., 2016). In sections with density exceeding approximately 450 kg m^{-3} , we typically find it necessary to hammer in the density cutter. Brittle, icy snow can chip out of the cutter, and in some cases it is necessary to replace these chips manually to approximate a full cutter sample. This “messy” quality of the data is inherent to the challenge of sampling vertical density profiles in extreme conditions, i.e., thick ice layers and brittle sub-zero snow in remote wilderness settings. All cutters remain visually free of deformation during our measurements. As a precaution, since hammering the cutter into hard snow could potentially degrade its precise geometry, we use a separate dedicated cutter for softer snow measurements. Calibration by weighing the cutters when filled with liquid water indicates uncertainty of $< 1 \%$ in the nominal cutter volume.

We also record supplemental data for each snow pit and measure snow temperature profiles using an analog thermometer. Calibration of the thermometer in ice water shows a nominal 0°C . For each snow pit, we also take a variety of photos showing the regional setting and snow pit interior for archival reference and cross-checking with geospatial attributes such as forest cover. We record the location of each snow pit using a smartphone GPS, which has sufficient accuracy for our objective of estimating general geospatial at-

tributes such as elevation and slope. Anecdotally, residual excavations after re-filling our deepest snow pit remain clearly discernible in the airborne lidar data collected several days later, and our GPS point differs by less than 1 pixel (3 m).

2.2 Empirical Snow Density Models

To explore potential drivers of spatial variability in alpine snow density, we construct a statistical regression model fine-tuned to our snow pit datasets from each year, and we compare our results with several generalized empirical models from the literature to test whether these other models predict similar degrees of variability.

2.2.1 Bayesian Modeling from Snow Pit Data

Based on several previous years of regional snow measurements from the WRR, in Boardman et al. (2025) we posited an empirical density model with three variables: snow depth, elevation, and forest cover. The elevation and forest cover terms are nonlinear to represent a potential ripening elevation (where the density changes fastest) and the threshold-like effect of thin forest cover. Here, we extend this model to include linear relationships with the north slope and east slope variables introduced in Sect. 2.2.1. The updated version of the model (Eq. 1) has nine parameters ($\theta_1 - \theta_9$) and is sensitive to five variables (D = snow depth in m, E = elevation in km, C = fractional forest canopy cover, NS = north apparent slope in degrees, ES = east apparent slope in degrees).

$$\rho = \theta_1 + \theta_2 D + \frac{\theta_3}{1 + e^{-\theta_4(E - \theta_5)}} + \theta_6 \left(1 - \frac{\theta_7}{C + \theta_7} \right) + \theta_8 NS + \theta_9 ES \quad (1)$$

Elevation is extracted from the lidar DTM. To capture hillslope-scale slope/aspect relationships instead of spurious slopes (e.g., associated with individual talus blocks), we aggregate the DTM to 30 m resolution before calculating slope and aspect. Since aspect is discontinuous at $0-360^\circ$, we combine slope and aspect into the commonly used “north slope” and “east slope” metrics, sometimes referred to as “northness” and “eastness,” and defined as the apparent dip of the hillslope in the respective direction. Finally, we estimate forest canopy cover at each snow pit location. Our primary approach to forest cover is based on the RCMAP 30 m fractional tree cover dataset (Rigge et al., 2021), reprojected to 3 m using Lanczos spline interpolation. Like any gridded geospatial dataset, RCMAP exhibits erroneous values in some locations, so for some snow pits, we replace false zero values in RCMAP with estimates of canopy cover based on field observations and adjacent RCMAP pixels. Although the exact fractional forest cover value is uncertain for any single snow pit due to the nature of extracting point values from raster data, the categorization as “forested” or “open” is well-constrained by field observations.

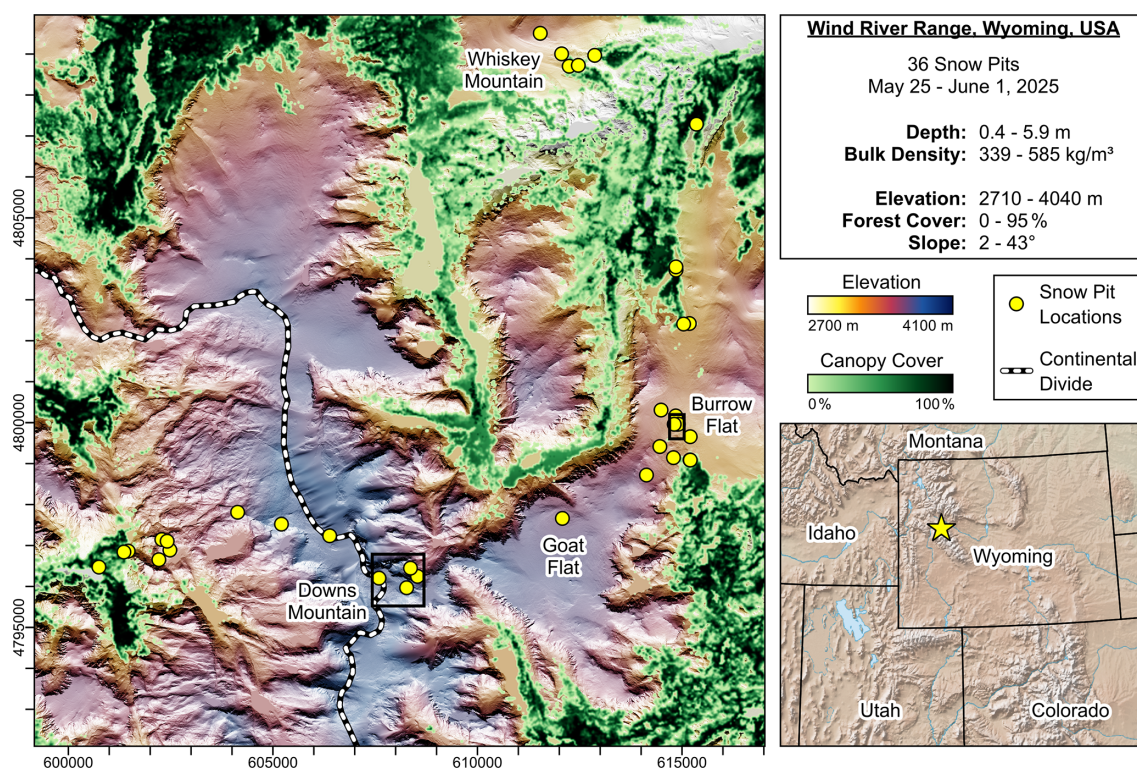


Figure 1. Overview map of snow pit locations and study site context within the Rocky Mountain region of the western United States. Tick marks show 1 km UTM intervals.

A Bayesian statistical framework provides estimates of the Eq. (1) parameters while simultaneously quantifying the uncertainty of the model. We sample Eq. (1) assuming a normal distribution of snow density errors with individual measurements weighted based on their “representativeness” compared to the entire lidar-surveyed snowpack, an approach first introduced by Boardman et al. (2025). Since this approach to weighted Bayesian model-fitting is key to the statistical robustness of our resulting gridded density field, we review the method in greater detail here. The representativeness score is intended to approximate the degree to which each snow pit is the best match for bulk SWE at the watershed scale, i.e., the most representative snow pits that those are similar to relatively large areas and/or relatively deep areas of the lidar-surveyed snowpack, since these large and/or deep areas store relatively more SWE (by definition).

Algorithm: Calculate Density Representativeness

1. Linearly re-scale predictor variables relative to valid range (0 to 6 m snow depth, 2500 to 4200 m elevation, 0 % to 100 % canopy cover, -90 to 90° north and east slope).
2. Randomly sample 10^6 pixels from the lidar snow depth map with sampling probability proportional to snow depth, since deeper areas hold more SWE per unit area and are thus proportionally more important to the landscape SWE. For example, a single 2 m pixel is twice as

likely to be sampled as a single 1 m pixel, but if there are twice as many 1 m pixels present on the landscape, both depth ranges would be sampled equally.

3. For each snow depth pixel sample:
 - a. Calculate the Euclidean distance between the re-scaled predictors at that pixel location and the re-scaled predictors for each snow pit.
 - b. Identify the snow pit that is closest (in predictor-space) to the pixel sample, and increment that snow pit’s “number of explained pixels” by one.
4. The representativeness of each snow pit is defined by its number of explained pixels divided by the 10^6 sample size, plus 1 % (so that each snow pit is guaranteed to be included in the model).

The above-defined snow pit representativeness score is used to implement a statistically rigorous weighted model-fitting procedure. Specifically, we perform weighted log-likelihood Bayesian sampling of the parameters in Eq. (1) using Hamiltonian Monte Carlo (HMC) implemented in Stan (Stan Development Team, 2023). The representativeness score is multiplied by the log likelihood of each snow pit observation, which pushes the model to more closely match snow pits that

are particularly representative (Eq. 2).

$$P(\theta | y, r) \propto P(\theta) \prod_{i=1}^N \mathcal{N}(y_i | \mu_i, \sigma)^{r_i} \quad (2)$$

In Eq. (2), the posterior parameter distribution (left side of equation) is proportional to the prior parameter distribution and the product of the normal probability density function raised to the power of the weights, with N datapoints, y indicating observations (snow pit densities), μ indicating the model mean, σ indicating model standard error, and r indicating the likelihood weights (representativeness score). Note that the weights are exponentiated in Eq. (2) because they are multiplicative with respect to the log-likelihood (the model optimization target). Prior parameter distributions (Fig. S2) are mildly informative to initialize the model into a physically plausible domain based on prior modeling in the WRR (Boardman et al., 2025), but the posterior distributions are substantially transformed, reflecting the impact of the data (Fig. S3).

The HMC Bayesian sampler receives 10 000 warmup iterations and generates 1000 final samples. Effective sample sizes and sample plots are consistent with convergence. We evaluate Eq. (1) using all 1000 parameter samples, thereby generating a Bayesian posterior distribution for snow density at each pixel, and we calculate the mean predicted density of each pixel to estimate SWE. We also evaluate the previous iteration of our snow density model (no NS or ES dependence) using the previously sampled 2024 parameter values (Boardman et al., 2025) to test whether snow density patterns repeat across years. We also re-fit the Eq. (1) model using the more limited 2026 dataset for further comparison and evaluation of interannual variability.

2.2.2 Comparison with Previous Literature Models

Next, we test several other empirical snow density models described in the literature, introduced here in chronological order (Table 1). Tabler (2003) models snow density based solely on a nonlinear function of snow depth, with parameter values based on measurements from artificial drifts created by snow fences in Wyoming. Jonas et al. (2009) similarly use monthly lookup tables to model density as a linear function of depth in the Swiss Alps. Since our measurements span the end of May and the first day of June, we average the Jonas et al. (2009) parameters from both months. Sturm et al. (2010) model density as a nonlinear function of depth and day of year, with parameter values based on snow climate class; Sturm et al. (1995) show that the WRR falls within the alpine climate class (Fig. 10 of that study). Bormann et al. (2013) model density using multiple linear regressions based on climatological metrics, with different combinations of variables selected for different regional classes. We evaluate two versions of the Bormann et al. (2013) model: one based on alpine sites from the USA, and one based on all

sites across Australia, the USA, and the former USSR. Hill et al. (2019) model density as an exponential function of depth, winter precipitation, the temperature difference between warmest and coldest months, and the day of water year.

The climatological models proposed by Bormann et al. (2013) require some adjustment for application to our field data, since these models were developed using continuous time series at long-term monitoring sites. We replace the maximum snow depth metric with the instantaneous snow depth at the time of our surveys. All climatological metrics are calculated from daily gridMET data (Abatzoglou, 2013) after interpolating the meteorological data from approximately 4 km resolution to 90 m resolution using Lanczos spline interpolation. As specified by Bormann et al. (2013), most climatological metrics are averaged across December–March of the accumulation season prior to our measurements, with the exception of the melt-refreeze metric, which is calculated for a site-specific snow cover season. Based on field observations, the snow cover season is assumed to be November–June for the WRR. The Bormann et al. (2013) models predict snow depth on 1 March, after which snow is assumed to densify at a constant rate. We apply the mean densification rate calculated by Bormann et al. (2013) for the USA alpine sites ($1.07 \text{ kg m}^{-3} \text{ d}^{-1}$) over the period from 1 March to the date of each snow pit measurement. Since the Hill et al. (2019) model is explicitly intended for use with multi-year climate normals from gridded data instead of weather data from a particular year, we evaluate this model directly using the 1991–2020 gridMET normals reprojected as above.

To test the sensitivity of landscape-scale snowpack quantification to density model assumptions, we also apply each of these density models to the entire northern WRR snowpack at the time of 1–2 June 2025, airborne lidar surveys. The climatological inputs are calculated at 30 m resolution for computation efficiency and resampled to the 3 m lidar snow depth resolution to estimate density. Congruent with our processing workflow for the dedicated WRR density model, all snow densities are clipped to a likely maximum range of $300\text{--}600 \text{ kg m}^{-3}$ based on our general understanding of prior literature and the range of observed variability. The 2024 and 2026 WRR density models are likewise applied to contemporaneous lidar depth maps from those years to produce annual SWE maps.

2.3 Lidar-Based Snow Depth and SWE Estimation

Repeat airborne lidar surveys provide high resolution topography and snow depth data that inform our analysis of alpine snow variability. The snow-free topography of the WRR is captured by lidar acquired on 18–19 August 2019, distributed as a digital terrain model (DTM) by the U.S. Geological Survey (USGS) as part of the 3DEP program. Since glaciers and perennial snow/ice features are rapidly melting in the WRR,

Table 1. Summary of empirical density models tested in this study. The snow density, ρ , is in units of kg m^{-3} . D = snow depth in m, E = elevation in km, C = fractional forest canopy cover, NS = north apparent slope in degrees, ES = east apparent slope in degrees, DOY = Julian day of year, DOWY = day of water year, $P1$ = December–March precipitation in cm d^{-1} , $P2$ = December–February precipitation in mm (1991–2020 climate normal), T_{avg} = December–March mean temperature in $^{\circ}\text{C}$, T_{diff} = mean temperature difference between warmest and coldest months in $^{\circ}\text{C}$ (1991–2020 climate normal), CDD = sum of daily mean temperatures below 0°C during December–March, Lat = latitude in degrees, MRF = fraction of days with maximum temperature $> 0^{\circ}\text{C}$ and minimum temperature $< 0^{\circ}\text{C}$ during local snow cover season. Note that the WRR 2024, 2025, and 2026 models are shown with median parameter values, but in practice, the density is predicted as an average across many Bayesian parameter samples. Equations are rearranged from their original form for readability and unit consistency.

Density Model	Equation
WRR 2024 Model (Boardman et al., 2025)	$\rho = 568 + 15D - \frac{222}{1 + e^{-6.3(E - 3.32)}} - 144\left(1 - \frac{0.06}{C + 0.06}\right)$
WRR 2025 Model (Eq. 1 of this study)	$\rho = 584 + 22D - \frac{307}{1 + e^{-1.5(E - 3.47)}} - 144\left(1 - \frac{0.26}{C + 0.26}\right) - 39\text{NS} - 36\text{ES}$
WRR 2026 Model (Eq. 1 of this study)	$\rho = 533 + 12D - \frac{188}{1 + e^{-3.9(E - 3.49)}} - 148\left(1 - \frac{0.30}{C + 0.30}\right) - 95\text{NS} - 50\text{ES}$
Tabler (2003)	$\rho = 522 - \frac{304}{1.485D}\left(1 - e^{-1.485D}\right)$
Jonas et al., 2009	$\rho = 14.5D + 415$
Sturm et al. (2010)	$\rho = 373.8\left(1 - e^{-0.12D - 0.0038\text{DOY}}\right) + 223.7$
Bormann et al. (2013) (Alpine Sites)	$\rho = (596 + 31.96 \ln P1 - 3.56 T_{\text{avg}} \ln D + 0.0392\text{CDD} - 3.94 \text{Lat} - 29.98 E) + 1.07(\text{DOY} - 60)$
Bormann et al. (2013) (Combined Sites)	$\rho = (566 + 47.95\text{MRF} + 32.67 \ln P1 + 22.44 \ln D - 3.82 \text{Lat} - 29.95 E) + 1.07(\text{DOY} - 60)$
Hill et al. (2019) (Ablation Season)	$\rho = \frac{1}{D \cdot 1000} 0.0481\left((D \cdot 1000)^{1.0395}\right)\left(P2^{0.1699}\right)\left(T_{\text{diff}}^{-0.0461}\right)\left(\text{DOWY}^{0.1804}\right)$

the snow-free DTM changes continually in many areas of the northern WRR. To account for annual ablation, we update the snow-free DTM using a dedicated glacier lidar survey conducted by Airborne Snow Observatories, Inc. (ASO) on 6 October 2024. Another lidar survey conducted by ASO on 1–2 June 2025, provides snow depth data at 3 m resolution across much of the WRR, including the full extent of our field surveys. Lidar surveys used for the 2024 and 2026 SWE maps were likewise conducted by ASO on 31 May 2024, and 28 May 2026, relative to end-of-ablation-season glacier lidar updates on 7 October 2023, and 26 September 2025, respectively. Processing procedures used to retrieve snow depth from the fusion of lidar and imaging spectrometer data are presented in Painter et al. (2016) and Boardman et al. (2025). In 2025, our final SWE map (using ASO lidar depths with densities estimated from Eq. 1) was delivered to water managers and stakeholders on 7 June, 5 d after the conclusion of the airborne surveys and 2 d after ASO’s delivery of the snow depth map. Similarly, the 2024 and 2026 SWE maps were delivered in near-real-time, making our study uniquely relevant for operational snowpack guidance and water supply

forecasting compared to retrospective analyses of snowpack patterns that are not available for management in real-time.

2.4 Comparison with Other Datasets

Finally, we compare several other near-real-time gridded SWE datasets with our lidar-based dataset. Snow datasets selected for this comparison must be available in near-real-time, i.e., with a latency of days, since water supply forecasting (and related management guidance) is one of the primary motivations for annual snow surveys in the western USA. Additionally, we disregard very coarse datasets (larger than roughly 1 km resolution) that are unlikely to capture the relevant sub-watershed scales in the WRR region. We identify three qualifying datasets for this comparison: the SNOW Data Assimilation System (SNODAS) daily SWE product distributed by the National Oceanic and Atmospheric Administration (Barrett, 2003), a regression-based SWE product (CU-SWE) distributed by the University of Colorado (Yang et al., 2022), and a neural network-based SWE product (SWANN) distributed by the University of Arizona (Broxton

et al., 2016, 2019b, 2024). For consistency and clarity, we refer to the two university experimental SWE products by their respective university names, i.e., U. Colorado SWE and U. Arizona SWE. The native resolutions of these products vary between 500 m for the U. Colorado dataset and $1/120^\circ$ (approximately 800–1000 m) for SNODAS and the U. Arizona dataset. For each of these products, in addition to the lidar-based SWE maps, we interpolate missing grid cell values using the average within a 3×3 kernel and reproject to a common 500 m resolution using the weighted average of overlapping cells. Using both the native resolution and the 500 m resolution, we calculate and compare cumulative distribution functions (CDF) for SWE within each of three watershed boundaries encompassing our field survey area.

2.5 Wind-Topography Modeling

We also use the ASO snow-on and snow-off lidar topography data to explore the relationship between spatial snow density heterogeneity and wind speed to test the hypothesis that wind-topography interactions can explain observed snowpack heterogeneity in our deepest sampled location. Slower wind speeds in sheltered locations can contribute to snow deposition and deep drift formation, which may also impact density due to wind-packing. We simulate wind speed for a 2.2 km^2 domain surrounding a major drift where our deepest snow pit is located. The WindNinja software (Wagenbrenner et al., 2019) leverages a computational fluid dynamics module based on a Reynolds-Average-Navier-Stokes (RANS) solver implemented in OpenFOAM (Weller et al., 1998). We use WindNinja to implement a RANS simulation of the wind field through a 3 m mesh restructured from the 1 m lidar DTM. We initialize WindNinja with a single 20 m s^{-1} west-to-east wind speed at a height of 10 m with a ground roughness length of 0.1 m (grass setting), and we sample the simulated wind field at 1 m height after 1000 RANS solver iterations. Since our goal is merely to obtain an indicative map of faster/slower wind speeds, the precise numeric values are less important than the spatial pattern. This combination of settings proves satisfactory for illustrating the general slowdown and speedup of wind in the simulation domain, though it is merely a snapshot of hypothetical conditions and does not account for variability and uncertainty in the actual wind speed and direction. Secondly, we repeat this simulation with an altered DTM representing the snow surface, calculated by adding the 2025 ASO lidar snow depth to the 2019 snow-off topography.

3 Results

Across the 4 years 2023–2026, we obtained 78 snow pit profiles, representing a cumulative snow depth of more than 98 m sampled at 10 cm resolution (984 density cutter measurements, not counting repeats). Our especially intensive

2025 field surveys yielded snow density data from 36 snow pits, 20 of which are at least 1 m deep and six of which are at least 2 m deep, with one 4 m pit and one 5.9 m pit. This volume of snow pit data is considerably larger than typically used for estimation of spatial density fields in lidar-based SWE mapping applications: for example, Kirchner et al. (2014) averaged snow density from 16 stations, Broxton et al. (2019b) measured 17 snow pits (plus additional transects using a SWE coring tube), and Trujillo et al. (2025) relied on a snow density model with validation metrics from 11 sites in disparate mountain ranges. Other snow lidar surveys in the Wind River Range have relied on modeled densities with as few as two in-situ measurements used for bias-correction and validation (see ASO Green River report for Upper Colorado River Commission survey on 30 May 2025). Some lidar-based snow surveys have used as many as 155 snow pits (Meehan et al., 2024), but in that study, none of the pits were deeper than 2 m and the resulting spatial SWE data were not available in near-real-time. Most prior snow surveys in the western USA rarely measure snow pits deeper than 2 m; for example, the deepest pit measured by Broxton et al. (2019b) is 1.18 m, and only two of their pits are deeper than 1 m. The unusually extensive dataset of 155 snow pits from Meehan et al. (2024) still only has a maximum measured depth of 1.43 m. Our study thus provides a unique opportunity to test the hypothesis that underrepresentation of deep snow density in prior surveys may lead to systematic biases when these data are extrapolated to windy alpine regions that are characteristic of the crucial mountain headwater regions in the U.S. Rocky Mountain region (Bales et al., 2006).

We first summarize the variability of measured snow density across the WRR (Fig. 1), focusing on the spatial heterogeneity between locations and the vertical profiles within individual snow pits from the 2025 field campaign. We then analyze two locations in greater detail: a remarkably dense drift occupying a nivation hollow, and a high-elevation region illustrating a variety of interacting controls on density. Finally, we evaluate how missing snow density heterogeneity propagates into watershed-scale SWE quantification through comparisons with prior regression models and extrapolated SWE datasets.

3.1 Snow Density Variability

Our measurements reveal systematic heterogeneity in ablation-season alpine snow density, both spatially and within individual pits (Fig. 2). Similar patterns of snow density heterogeneity are also apparent in the data from other years (Fig. 2), but we focus our analysis on the 36 density profiles from 2025 to control for confounding interannual variability in accumulation and densification processes (Fig. S4). The coefficient of variation (CV) among all 36 locations sampled in 2025 is 13 % relative to a mean of 450 kg m^{-3} . The mean vertically integrated density (entire snow pits) varies between 339 and 585 kg m^{-3} , and indi-

vidual density measurements (within pits) vary between 247 and 688 kg m⁻³. The snow in forested areas is significantly ($p < 0.001$) less dense compared to snow in open areas (mean 405 vs. 471 kg m⁻³). There is a significant correlation between snow depth and density ($r = 0.59$, $p < 0.001$), and snow at least 2 m deep is significantly ($p = 0.02$) more dense than snow that is less than 2 m deep (mean 497 vs. 438 kg m⁻³). Additionally, snow at higher elevations is generally less dense. Although there is no significant correlation directly between elevation and density due to confounding variability, snow above 3500 m is significantly less dense ($p < 0.01$) than snow below 3500 m considering only non-forested locations (437 vs. 490 kg m⁻³). However, we emphasize that these relationships are subject to multicollinearity, which prevents any straightforward interpretation. For example, there are significant correlations between elevation and forest cover ($r = -0.63$, $p < 0.001$) and between snow depth and forest cover ($r = -0.41$, $p = 0.01$) simply due to the existence of a treeline elevation and the lack of deep snow (> 2 m) in forested areas.

There is less vertical variability in snow density compared to the spatial variability between pits, but vertical variability is still substantial. Considering only the 2025 snow pits, the standard deviation across all 485 individual density measurements is 75 kg m⁻³, which reduces to 46 kg m⁻³ after subtracting the mean of each snow pit from the constituent intra-pit measurements. For comparison, the standard deviation of bulk density across all 36 pits is 57 kg m⁻³, which is 22 % more variable than the intra-pit vertical variability. Nevertheless, vertical trends in snow density can reveal salient information about physical processes operating in the snowpack that are missed by vertically integrated average measurements (such as those obtained from snow pillows or SWE coring tubes).

Isolating patterns of vertical density variability reveals several distinct categories of depth-density trends in the 2025 dataset (Fig. 3). Most of the snow pits in forested areas have significant ($p < 0.05$) trends toward lower density near the ground ($N = 8$, or 73 % of forested locations), and the other three have insignificant trends. Two of the three forested snow pits with insignificant depth-density trends nevertheless have lower-density snow near the ground, but the 10 cm vertical sampling resolution is too sparse for the trend to rise to statistical significance in shallow snow. Among the 25 snow pits in open areas (non-forested), 13 have significant trends toward lower density near the ground and 11 have no significant trend. Interestingly, the snow pits with significant trends toward lower density near the ground have widely varying snow depths, from 0.4 to 3.3 m. From field observations, we note that lower snow densities near the ground are commonly associated with depth hoar, i.e., faceted crystals caused by vapor gradients in shallow snow, though similar trends also emerge in deeper snow due to overlying avalanche debris and potentially other controls on densification.

Deep wind drifts exhibit different depth-density relationships compared to shallower snow. The deepest snow pit (5.9 m) has no significant trend with depth, a finding that we explore further in Sect. 3.2. The second-deepest (4.0 m) snow pit provides the sole example of a significant trend toward increasing density closer to the ground ($r = -0.53$, $p < 0.001$), a pattern that was also observed in a repeat measurement from another year ($r = -0.57$, $p < 0.001$). Notably, this deep pit location is at a relatively high elevation (3820 m) and had a mean temperature below freezing, which we explore further in Sect. 3.3. Thus, the lower density near the surface at this location could be associated with relatively fresh snow that has not undergone as much metamorphosis as the deeper, older snow.

3.2 Deep Drift Profile: Nivation Hollow

Measuring the density of a very deep snow drift was a key goal of our 2025 field surveys, since these deep drifts are salient features of the WRR landscape (Boardman et al., 2025; Boardman, 2025b). In this section, we focus our analysis on a wind drift occupying a nivation hollow at roughly 3280 m elevation near Burrow Flat in the Dinwoody Creek watershed (Figs. 1 and S5). Figure 4 provides an overview of our nivation hollow study site, including photographs of the drift surface and the interior of our deepest snow pit. A longitudinal profile across the nivation hollow shows how a nearly planar snow surface overlies a topographic concavity, which results in exceptionally deep snow near the middle of the drift (4–6 m).

A 5.9 m deep pit near the center of the nivation hollow reveals a remarkably high snow density, with a range of 515–688 kg m⁻³ and a mean of 585 kg m⁻³. There is no significant trend in density with depth for this deep pit ($r = 0.15$, $p = 0.24$). Nevertheless, the upper 2 m of the profile has a slightly higher density compared to the lowest 2 m of the profile (mean 595 vs. 582 kg m⁻³), though this difference is not statistically significant. The deep drift remains quite dense even near the surface: the top meter has a bulk density of 588 kg m⁻³, and the top 10 cm has a density of 597 kg m⁻³, both of which are higher than the pit average. These measurements support our qualitative observation that it is quite easy to walk on the surface of the nivation hollow drift without sinking in or “postholing,” in contrast to nearby shallower snow.

We note several substantial ice layers (1–3 cm thick) beginning at a height of 2.2 m above the ground in the Burrow Flat nivation hollow drift. No horizontal ice layers are apparent below this height. Ice layers are more frequent closer to the surface, which may contribute to the higher bulk density of the upper 2 m of the pit. Notwithstanding, we still observe exceptionally high densities in deeper layers with no visible ice (e.g., 605, 628, and 684 kg m⁻³ at 0.4–0.5, 1.3–1.4, and 1.4–1.5 m heights, respectively). A re-frozen preferential “flow finger” (Marsh and Woo, 1984) was encountered at

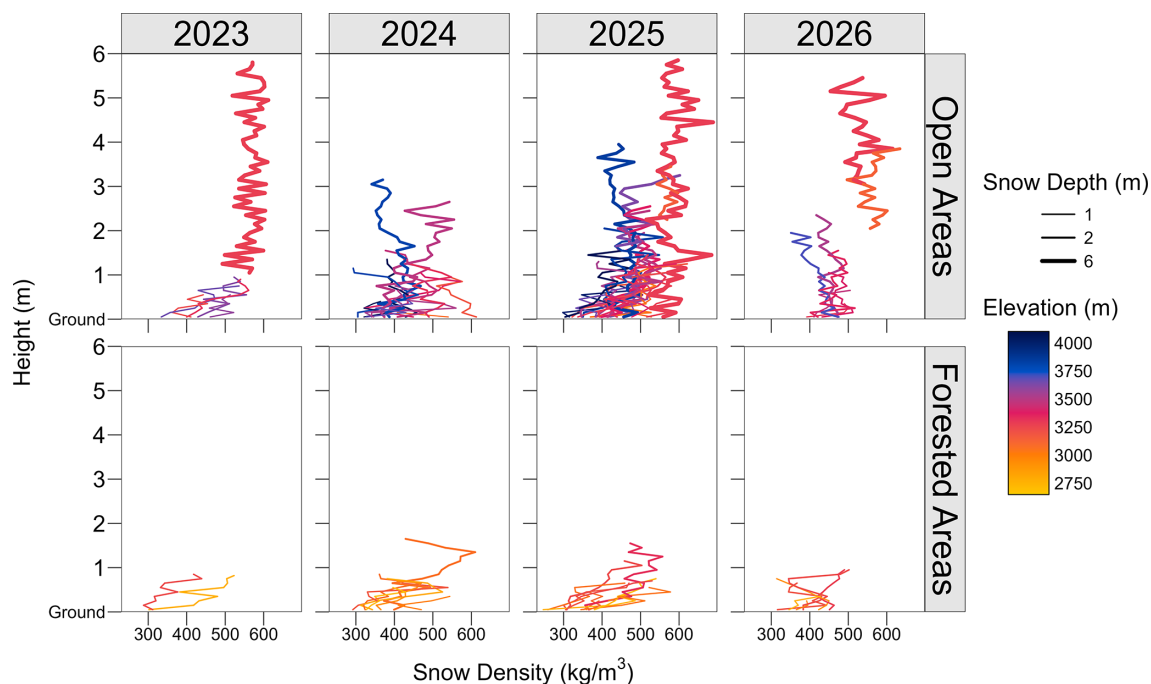


Figure 2. Vertical snow density profiles from 78 snow pits across 4 years. The sampling resolution is 10 cm vertically. Note the non-representativeness of forested areas with respect to both snow depth and density. Similar patterns of heterogeneity are apparent across years, and the scale of this variability depends on the unique history of accumulation and densification processes occurring each year.

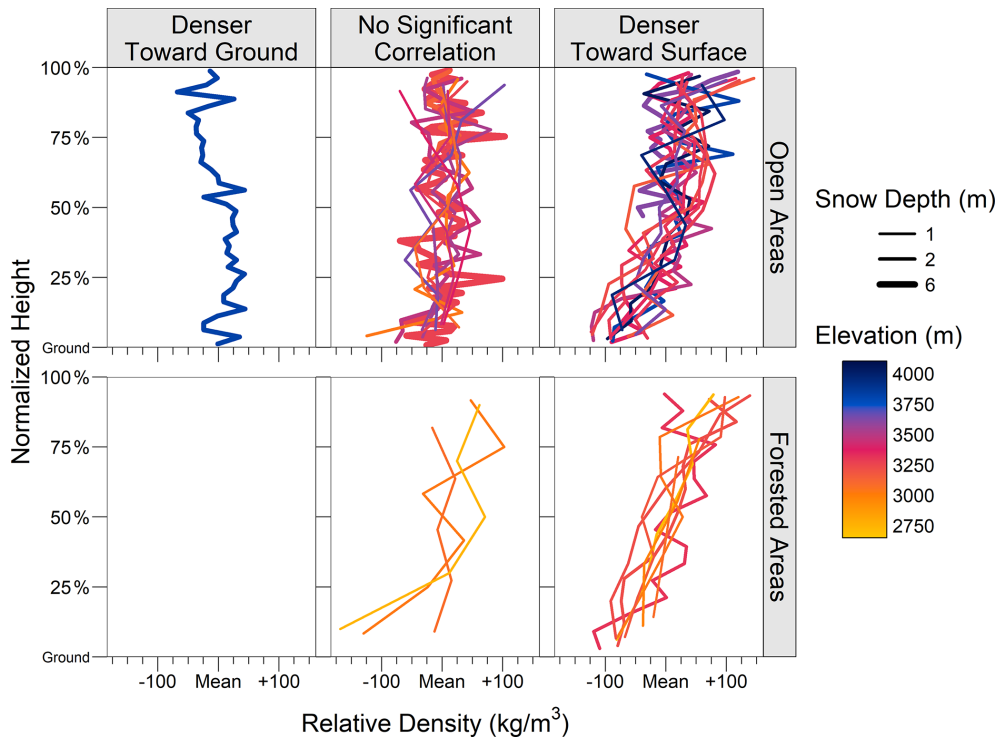


Figure 3. Vertical density trends relative to the bulk density of each snow pit (only considering the 36 snow pits from 2025). Most snow pits have trends toward denser snow near the surface or no trend, and only one location has a trend toward denser snow near the ground. The threshold for trend significance is $p < 0.05$ using Pearson's product-moment correlation test.

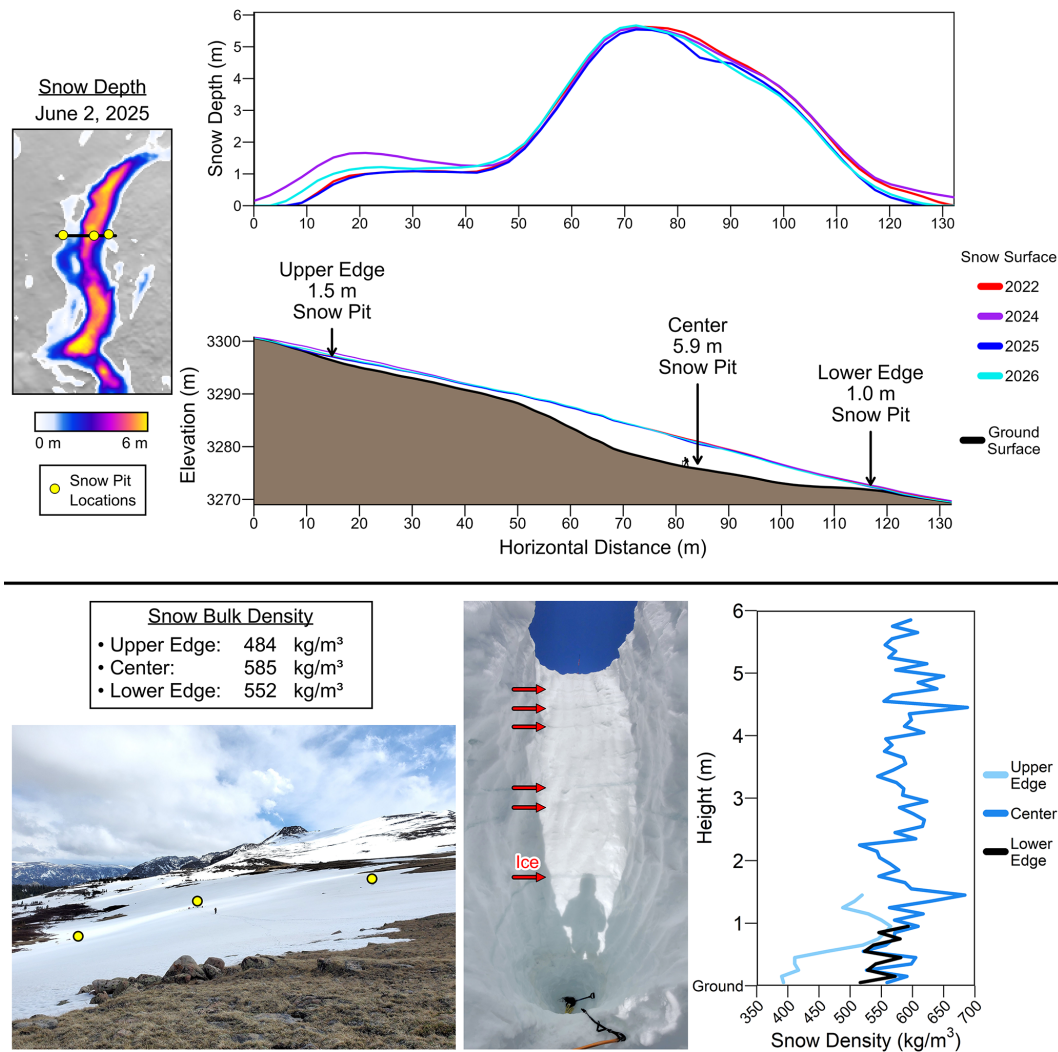


Figure 4. Snow depth profiles (longitudinal) and snow density profiles (vertical) from the Burrow Flat nivation hollow. Note that the longitudinal surface profile has the same horizontal and vertical scales. The human figure near the center snow pit arrow (in the longitudinal profile) has an approximate height of 1.8 m (6 ft), and human figures are also visible in the overview photograph near the center snow pit. The deviation in the 2025 snow depth profile is the result of our partially refilled center snow pit excavation. Major ice layers are indicated in the closeup photograph with red arrows, but there are also many thin ice layers near the surface that are not indicated.

approximately 1.0–1.4 m height, but we chose to avoid sampling this anomalous feature and instead sampled adjacent snow without visible ice. Surprisingly, our lowest-density measurement (515 kg m^{-3} at 2.2–2.3 m height) is associated with the deepest and thickest ice layer (approximately 3 cm thick). Our highest-density measurement (688 kg m^{-3} at 4.4–4.5 m height) is also associated with several thinner ice layers. One explanation for this discrepancy could be different amounts of liquid water pooling/refreezing above and below the different ice layers, especially if the ice layers create preferential lateral flow pathways. However, these ice-layer measurements are also relatively uncertain due to the inherent challenge of sampling brittle ice with a metal density cutter,

and the anomalous weights could be the result of measurement error.

Additional snow pit measurements reveal that density remains unexpectedly high near the lower edge of the nivation hollow, but snow at the upper edge is more comparable to the density of nearby locations. Based on prior fieldwork, we anticipated that shallower snow ($< 2 \text{ m}$) would have a lower density more in line with the $350\text{--}450 \text{ kg m}^{-3}$ range of typical ablation-season alpine snow. While this is largely true at the landscape scale (Fig. 2), a 1.0 m snow pit near the lower edge of the nivation hollow has a bulk density of 552 kg m^{-3} , only 6 % lower density than the deep pit near the middle of the drift. Interestingly, the 10 samples from this shallower snow pit have a high correlation with the lowest 10 samples

from the deep pit ($r = 0.76$, $p = 0.01$), indicating that both locations have similar density stratigraphy near the ground. This increases our confidence that vertical density variations are physically meaningful (not just the result of random sampling error), and seemingly implies that the processes controlling densification are independent of snow depth within parts of the nivation hollow drift. In contrast, a 1.5 m snow pit near the upper edge of the nivation hollow shows a different signature: its bulk density of 484 kg m^{-3} is 17 % lower than the center of the drift, and there is no significant correlation between the vertical density variation of the 1.5 m pit and the bottom 1.5 m of the deep pit ($r = 0.23$, $p = 0.41$). The upper edge of the nivation hollow drift fits within the density range of surrounding snow (bulk density range $444\text{--}488 \text{ kg m}^{-3}$ across five other pits in non-forested locations). Due to the large amount of work required to sample a single $\sim 6 \text{ m}$ snow pit profile (approximately nine person-days, or 1.5 d with six people), it was infeasible to sample additional lateral variability within the deepest part of the drift. However, future studies may consider measuring multiple profiles within a single snow pit to reduce potential measurement errors.

Wind simulations and repeat lidar observations indicate that the nivation hollow reduces wind speed until it fills with snow, resulting in an apparent self-limiting drift behavior (Fig. 5). The mid-July imagery in Fig. 5A shows how the deep drift persists through much of the summer after most other snow has melted, though field observations indicate that it melts out completely by September, at least in most years. Simulating the wind speed 1 m above the underlying ground surface results in a wind speed pattern that closely mirrors the snow depth pattern (Fig. 5B, D–G). Wind speeds are greatly reduced where the concave nivation hollow creates a sheltered zone, similar to the functioning of artificial snow fences. Snow transport is reduced in areas with lower wind speeds, which reduces the suspension and saltation fluxes, causing drift formation. Consequentially, there is a strong negative correlation between ground wind speed and snow depth ($r = -0.71$, $p < 0.001$). However, as the nivation hollow begins to fill with drifted snow, the topographic concavity has less effect on the wind speed. The wind speed 1 m above the 2025 snow surface is much faster than the wind speed 1 m above the ground surface (Fig. 5C). In areas with $> 4 \text{ m}$ snow depth, the mean wind speed is 143 % faster above the snow surface compared to the ground surface.

The nivation hollow wind drift stores nearly the same amount of snow each spring (Figs. 4–5) despite widely varying seasonal snowfall. For example, based on spatially complete lidar depth data with densities constrained by our fieldwork, we estimate that the surrounding Dinwoody Creek watershed has a mean snowpack storage of 0.21 m SWE on 2 June 2025, compared to 0.34 m on 31 May 2024, which is 37 % less in 2025 at nearly the same point in the season. However, areas of the nivation hollow with $> 4 \text{ m}$ snow depth in 2025 (0.015 km^2 area) had a mean snow depth decrease of

0.36 m relative to 2024, representing an estimated SWE volume storage difference of only 7 % in those locations. Similarly, in 2026, the watershed-mean SWE was 20 % lower than 2025, but the nivation hollow held almost exactly the same amount of SWE (0.5 % less). As illustrated in the Fig. 4 profile and Fig. 5 D–G, nearly identical snow surface elevations are observed by four different airborne lidar surveys: 11 June 2022; 31 May 2024; 1–2 June 2025, and 28 May 2026. The snow depth correlations between all six pairs of lidar surveys (2022–2026) range between $r = 0.984$ and $r = 0.996$ ($p < 0.001$) in the drift vicinity at the 3 m grid scale (Fig. 5D–F). Hence, the nivation hollow drift is largely insensitive to interannual variability.

Another nivation hollow at a similar elevation of 3140 m on nearby Whiskey Mountain (Fig. 1) exhibits a similarly high bulk snow density. A partial snow pit in this nivation hollow drift (top 1.3 m sampled of 3.5 m total depth) has a bulk density of 567 kg m^{-3} , again with no significant depth-density trend ($r = -0.02$). This represents the second-highest mean snow density recorded during our 2025 field surveys, and all three snow pits with mean densities above 500 kg m^{-3} are associated with wind drifts in nivation hollows (Burrow Flat drift center, Whiskey Mountain drift, Burrow Flat drift lower edge).

Similar patterns repeat in the nivation hollows across years (Fig. 2). Partial snow pit profiles from deep nivation hollow drifts collected in 2023 and 2026 show similarly high bulk densities: means of 568 , 526 , and 564 kg m^{-3} for drifts with depths of 5.8 , 5.6 , and 4.0 m depth, respectively. Although these profiles only extend through the upper 2.0 to 4.9 m of the drifts, we similarly observe that there is no statistically significant trend of density with respect to depth within these additional three deep nivation hollow drifts.

3.3 Deep Drift Profile: High Elevation

We now analyze snow density at a second deep drift location, this time at a higher elevation with a different topographic setting, and we compare our observations to surrounding snow pits that illustrate a variety of interacting controls on density (Fig. 6). Downs Mountain (4071 m elevation) is the northernmost 4000 m peak on the Rocky Mountain Continental Divide, providing a unique combination of extreme alpine conditions. A 1.6 m snow pit in a drift near the summit (4040 m) has a much lower density of 401 kg m^{-3} compared to lower-elevation snow of a similar depth, e.g., 471 kg m^{-3} in a 1.1 m snow pit at 3630 m elevation on the nearby Goat Flat plateau (Fig. 1). A 0.8 m snow pit on a steep (43°) north-facing slope also has a relatively low density of 393 kg m^{-3} despite being at a similarly low elevation as the relatively dense Goat Flat snow pit (471 kg m^{-3}). Compared to the nearby summit and north-facing snow pits, 4.0 m deep snow pit in an extensive drifted snowfield at 3820 m elevation has a substantially higher density of 457 kg m^{-3} , though this is still much less dense than the nivation hollow drifts. Part of this

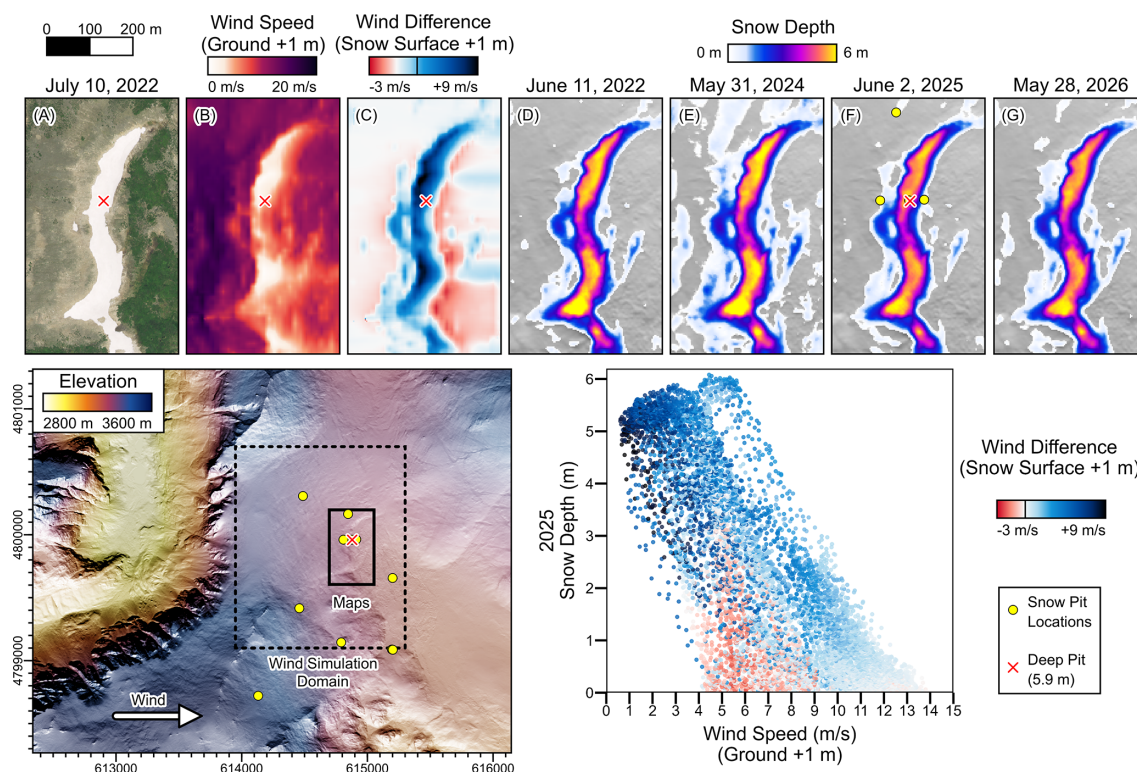


Figure 5. Wind speed simulations and annual snow depth maps associated with the Burrow Flat nivation hollow.

difference in snow density between the deep nivation hollow drift and the deep Downs Mountain snowfield is associated with the latter's 540 m higher elevation, as we show in Sect. 3.4. Finally, a partial snow pit in an avalanche runout zone has the highest bulk density observed in the Downs Mountain vicinity (483 kg m^{-3}), and individual blocks of recent wet slide debris have even higher densities in the range of $558\text{--}638 \text{ kg m}^{-3}$.

The deeply drifted snowfield on the downwind (east) side of Downs Mountain has a substantially higher density than shallower snow at comparable elevations. The three other snow pits above 3800 m have a bulk density of 409 compared to 457 kg m^{-3} in the 4.0 m pit, a difference of about 12 %. Considering that one of these three other high-elevation pits is also fairly deep (2.1 m/ 438 kg m^{-3} , near Hunters Hump in the Green River watershed), the drift density is even more pronounced when comparing it only to relatively shallow high-elevation snow (e.g., 387 kg m^{-3} for a 0.8 m pit near the upper edge of the Continental Glacier). Conversely, snow density increases rapidly at lower elevations, and even shallow snow is denser than the deep snowfield at altitudes only 200–250 m lower (e.g., 1.1 m/ 471 kg m^{-3} at 3630 m elevation and 0.8 m/ 490 kg m^{-3} at 3580 m elevation). Thus, deep wind drifts exhibit consistently higher densities compared to nearby shallower snow, but the absolute magnitude of drift density also depends on elevation and slope/aspect, and hence the snow metamorphosis legacy of the local microcli-

mate. Similar patterns of high-elevation snow density heterogeneity are observed in other years (Fig. 2). However, the absolute magnitude of bulk density depends on the specific year, and high elevation (3800 m) drifts as deep as 3.2 m can have bulk densities as low as 398 kg m^{-3} , or 59 kg m^{-3} lower than observed in 2025, at roughly the same time of year due to interannual variability in the processes that control densification (such as the onset of freeze-thaw cycles).

Despite the onset of ablation at most places in the WRR by the time of our 2025 surveys in late May and early June, some high-elevation snow remained colder than the freezing point, potentially contributing to density variability. Only two of our 36 snow pits show temperatures more than one degree below zero, which is the precision of our analog thermometer. These two cold locations are the Downs Mountain summit drift (mean -2.4°C , range -0.5 to -5.0°C) and the Downs Mountain deep drifted snowfield (mean -2.0°C , range -0.5 to -4.0°C). Interestingly, the second-highest snow pit (3980 m elevation) shows nearly isothermal temperatures (all temperatures between -1.0 and -0.5°C), demonstrating that elevation (and air temperature, by proxy) is not the only control on snowpack temperature. Notably, this high-elevation snow pit is half as deep as the Downs Mountain summit drift (0.8 vs. 1.6 m). The coldest temperatures in the Downs Mountain summit drift are near the ground surface, and the snowpack warms to zero near the surface, which suggests that this difference in temperature may be the result

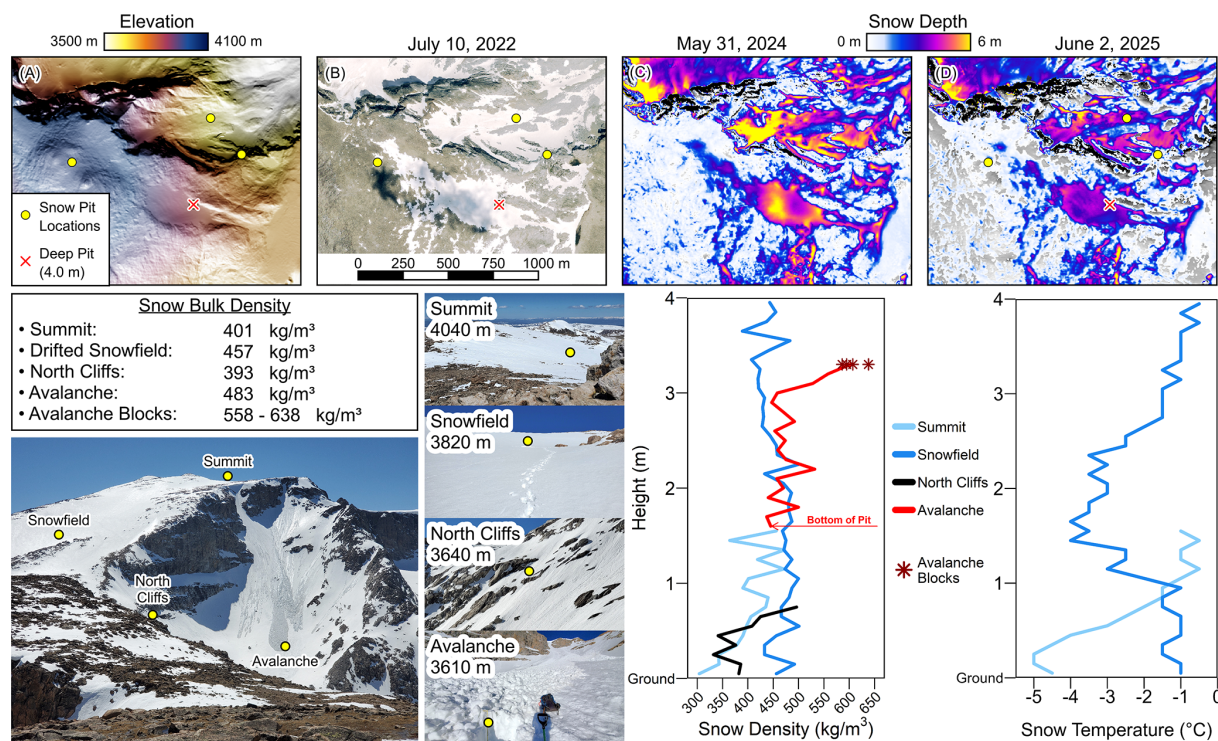


Figure 6. Snow depth maps, density/temperature profiles, and photos of four snow pits in the Downs Mountain environs.

of seasonal and/or diurnal insulation effects from the deeper snowpack. Likewise, the deep snowfield reaches a temperature of zero near the surface, though it also warms to zero near the ground, with the coldest snow at a height of 1.4–2.4 m (near the middle of the profile).

Snow temperature had an inconclusive relationship with density at the time of our 2025 surveys. There is a weak negative correlation between density and temperature in the deep snowfield ($r = -0.37$, $p = 0.02$), unlike the shallower summit drift, which has a strong positive density-temperature correlation ($r = 0.73$, $p = 0.001$). In the case of the shallower non-isothermal pit, we observe depth hoar (loose facets) near the ground, but the temperature profile is reversed compared to what we would expect for depth hoar formation, which is typically associated with colder surface temperatures and warmer snow near the ground. This temperature reversal could be indicative of the transition between the accumulation and ablation season, as the snowpack ripens and warms from the top down. In contrast, the deep snowfield does not exhibit depth hoar and shows a significant trend toward increased density with depth, which is rare in the WRR at the time of our spring snow surveys (Fig. 3). It is possible that the colder temperatures near the ground (Fig. 6) could be related to permafrost, which can be associated with patterns of snowpack redistribution in alpine environments (Luetschg et al., 2004; Kenner et al., 2017). All of the snow pits in the Downs Mountain vicinity have at least some ice layers, so melt-freeze processes and liquid water percolation probably

also contribute to density variations, even though parts of the vertical profile remain below freezing. In 2024, the snowpack ripening elevation (above which temperatures fall below 0 °C) closely matched the fastest rate of change implied by the elevation-dependent term of the snow density regression (Boardman et al., 2025), and at the time of our 2026 surveys, the snowpack was mostly 0 °C at all elevations. The variable seasonal progression of elevation-dependent ripening is reflected in changes to the elevation-dependent terms of the density models (Table 1).

3.4 Empirical Snow Density Models

We now shift to analyzing statistical models of snow density heterogeneity, which are used to assess systematic variability and propagate point measurements to the watershed scale. We do not attempt to benchmark the “best” empirical models from the prior literature, and there are too many models for an exhaustive comparison in this study. Instead, we focus on a few widely used models with a range of complexity and predictor variables to conduct a broad sensitivity analysis.

A nonlinear regression model (Eq. 1) can satisfactorily explain density differences between most snow pits in our 2025 dataset. We exclude the two pits from the edges of the nivation hollow since they are not representative of most areas of the snowpack with similar depth. Across the other 34 snow pits, the fitted model has a root-mean-square-error (RMSE) of 26 kg m⁻³, which is 6 % error relative to the mean

of 447 kg m^{-3} . The coefficient of determination for density variability is $R^2 = 0.76$ across all 34 of these pits, which increases to $R^2 = 0.94$ considering only the densities of the eight pits $> 2 \text{ m}$ deep.

All of the fitted model parameters in Eq. (1) describe relationships that match physical expectations (Fig. 7). The model indicates higher densities at lower elevations, in deeper snow, and in open areas (conversely, density is lower in forested areas). Elevation is a proxy for air temperature, and lower elevations are associated with more melt-freeze cycles and an earlier start to snowpack metamorphosis, leading to higher densities. Snow depth is a proxy for wind drifting and avalanching, which can increase density by fracturing and sintering grains. We expect that forest canopy cover may be associated with lower density snow due to a combination of factors including wind shelter, shade, and nighttime longwave radiation, which could reduce the number of melt-freeze cycles. The model also identifies slightly lower densities on north-facing and east-facing slopes, consistent with fewer melt-freeze cycles caused by overall shading and reduced late-afternoon sun exposure when temperatures are warmest. Since Bayesian sampling (Sect. 2.2.1) inherently quantifies and propagates parameter uncertainty, we can robustly estimate confidence intervals for these effect sizes. The fitted model is represented by a multivariate posterior distribution (Fig. S3), and the spread of this distribution rigorously quantifies the uncertainty of the model with respect to the interaction of all five variables (Eq. 1). The linear depth-density relationship has an uncertainty of 9 % (CV of posterior parameter distribution for θ_2 in Eq. (1), with a 95 % confidence interval of 18 to 26 kg m^{-3} increase in density per meter increase in depth (bulk density variability between locations, not vertical density trends). The parameter distributions for elevation and canopy cover are less straightforward due to nonlinearity, but 100 % of the parameter samples are negative for θ_3 and θ_6 , indicating very high confidence that forests and high elevations produce lower densities. The linear relationships with north and east slope are more weakly constrained due to the limited slope of our observations (max 43°), but the posterior parameter distribution still provides 96 % confidence that north-facing slopes have lower densities and 90 % confidence that east-facing slopes have lower densities. Similar snow density relationships are detected by the 2024 and 2026 regression models (Table 1). Although the directionality of each effect is consistent across years, in some years snow density is more or less sensitive to different predictors, presumably reflecting interannual variability in the specific processes driving densification (e.g., warmer years may be less sensitive to elevation if the whole snowpack has ripened by the late-May timeframe).

No single variable dominates the prediction of snow density (Fig. 7). Instead, observed snow densities are the result of interactions between multiple factors, e.g., high-elevation deep snow may have the same density as low-elevation shallow snow. This finding is strikingly apparent in Fig. 7: al-

though the directionality and magnitude of the response to each individual predictor is well constrained by the ensemble of Bayesian parameter samples, the observed snow densities vary widely across any single predictor. Together, however, the seven-variable model explains most of the observed spatial variability ($r = 0.86$), as shown by the scatterplot of modeled and measured snow density in the WRR 2025 panel of Fig. 8. The simpler model from 2024 (no slope/aspect dependence), which was fitted to data from 2023–2024 and published prior to the collection of the 2025 data (Boardman et al., 2025), also achieves a reasonably strong correlation ($r = 0.76$) with the 2025 data. Similarly, the 2026 WRR model (Table 1) correlates with the 2025 data ($r = 0.82$), but the 2026 model was supplemented with 11 high-elevation snow pits from 2023–2025 (due to weather constraints during the 2026 surveys), so the 2025–2026 comparison is not strictly independent. Nevertheless, the similarity of 2025–2026 models, and especially the completely independent 2024–2025 models, bolsters our finding that patterns of density heterogeneity repeat across years.

All five of the tested previous empirical snow density models systematically underestimate the heterogeneity of the WRR snowpack. Each of the panels of Fig. 8 illustrates a different approach to empirical density modeling reported in the literature (Table 1) and evaluated at our snow pit locations. All of these models include at a minimum a regression on snow depth, which itself has a reasonably strong correlation with density across our snow pits ($r = 0.59$, $p < 0.001$), though this relationship is scattered (cf. depth-sensitivity panel of Fig. 7). Since the models proposed by Tabler (2003), Jonas et al. (2009), and Sturm et al. (2010) exclusively use snow depth to infer spatial variability in snow density using various linear and non-linear equations, these models offer little to no additional predictive skill relative to the raw depth-density correlation. By accounting for additional meteorological effects, we would expect the Bormann et al. (2013) multiple linear regression models to account for additional variability. However, since site-specific meteorological data are not available (unlike at the stations where the models were developed), the interpolated gridded meteorological data offer minimal additional predictive skill for snow density. Thus, the Bormann et al. (2013) models, as adapted for this study, produce similar correlations as the other models ($r = 0.57$ for the alpine model and $r = 0.59$ for the combined global site model). The Bormann et al. (2013) global (all-site combo) model has lower bias than the alpine model in the WRR, so we use the global model to evaluate watershed metrics discussed subsequently. The Hill et al. (2019) model also uses gridded climate data (Table 1), but the regression is insufficiently sensitive to snow depth in the WRR, yielding the lowest correlation across all of the tested models ($r = 0.31$) and largest bias (-20%). The underestimation of density by the Hill et al. (2019) model may partly result from the relatively low December–February estimated precipitation (mean 0.182 m across snow pit locations) compared to

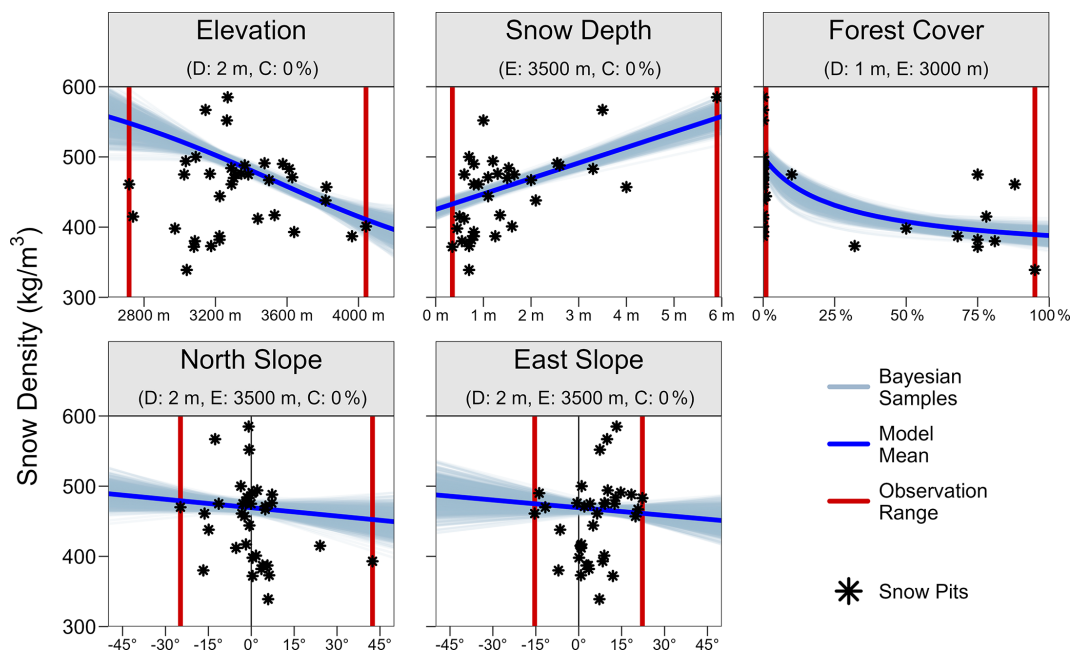


Figure 7. Evaluation of the 2026 WRR statistical snow density model with respect to individual variables (Eq. 1, Table 1). In each panel, all other variables are held constant, and the snow density response is predicted with respect to a single variable (e.g., for elevation, the snow depth is held constant at 2 m with 0 % forest cover). D = snow depth, C = forest cover, E = elevation. All topographic slopes are flat except as specified. Snow pit measurements are shown to illustrate the range of variability, but since each snow pit corresponds to a unique combination of all five predictors, the snow pit points are not expected to fit the univariate sensitivity tests shown here.

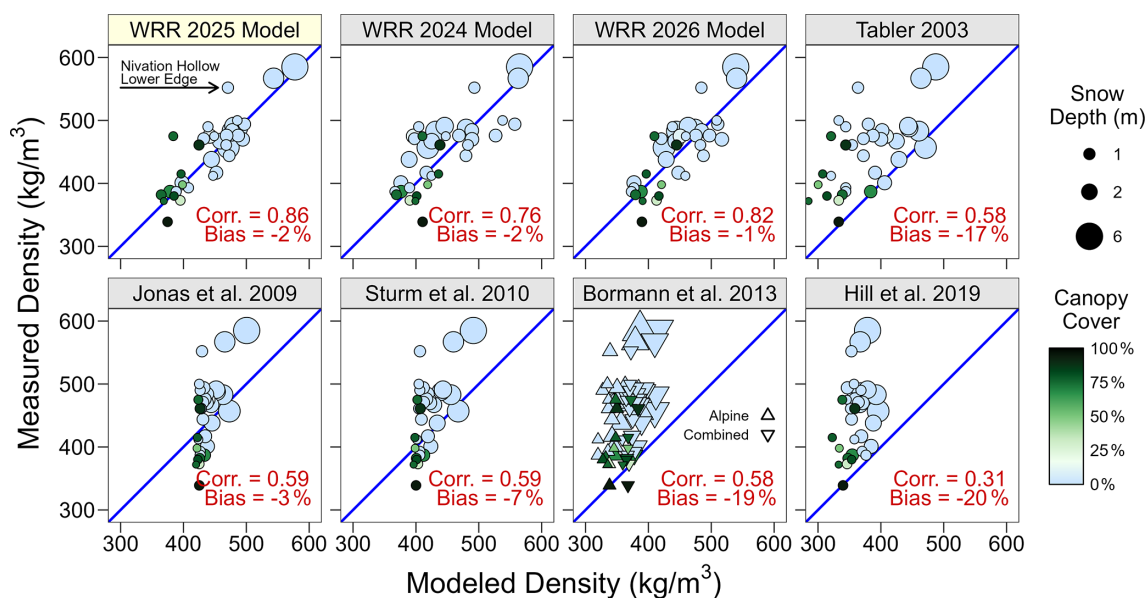


Figure 8. Comparison of measured snow densities with predicted density from various empirical models (Table 1). The WRR 2025 model is directly fit solely to this dataset, the WRR 2024 model is fit to WRR observations from 2023–2024, and the WRR 2026 model is fit to observations from 2023–2026. The other models are based on an array of global observations presented in the literature, and are not necessarily intended for general extrapolation. Correlation and bias for the Bormann et al. (2013) models are reported as averages between the alpine model and the model based on all combined global sites. Note that all of the prior literature models substantially underestimate the highest densities, and most models neglect the density contrast between snow in forested and open areas.

the relatively deep measured snow (mean 1.46 m across snow pit locations), since much of the Rocky Mountain snowpack accumulates in spring storms occurring after the December–February “winter precipitation” period (Serreze et al., 2001; Trujillo and Molotch, 2014). This low winter precipitation estimate (from gridMET) is roughly congruent with the map presented by Hill et al. (2019) in their Fig. 5B, and the resulting large density bias highlights the risk of relying on gridded climate data aggregated over an arbitrary time period (defined by specific “winter” months) as opposed to the more direct depth-density approach taken by most other models, which can implicitly account for the full accumulation season.

Surprisingly, none of the prior literature density models considered here quantitatively parameterize the effect of forest cover, though forest cover is sometimes considered qualitatively (Sturm et al., 1995) when choosing the appropriate climate class for the Sturm et al. (2010) model. Except for the Tabler (2003) model, which has similar bias between forested and open locations, the other models all have significantly more negative biases (greater underestimation of snow density) in non-forested locations, with a statistically significant difference in the bias at the $p < 0.01$ level for all other prior models except Hill et al. (2019), which has a significant bias difference at $p < 0.02$. The explicit consideration of forest cover in Eq. (1) of this study removes this systematic bias, i.e., the difference in forested and non-forested bias for our WRR 2025 and WRR 2024 models is not statistically significant ($p = 0.44$ and 0.45 respectively). The observed density contrast between low-density forest snow and high-density snow in open drifted areas is especially apparent in the Fig. 9 maps. Although the Tabler (2003) indirectly captures this effect because of the confounding effect of snow depth (i.e., forest snow is generally shallower), this model predicts the same low density for shallow snow everywhere, whereas our measurements indicate a systematically higher density in non-forested areas (Figs. 2 and 7).

3.5 Impact of Snow Density Heterogeneity at the Watershed Scale

Neglecting the high density of alpine wind drifts can lead to substantial underestimation of the total SWE volume in mountain watersheds. Noting again that most of the prior literature snow density models (Fig. 8) are not specifically calibrated to the WRR, applying these models to the 2025 lidar snow depth map can nevertheless inform expectations for the potential sensitivity of SWE to different assumptions about density variability. Indeed, some of these models (e.g., Hill et al., 2019) are explicitly intended to convert depth to SWE at large scales in support of water resource projects. In the three watersheds where our snow pits are located (Torrey Creek, Dinwoody Creek, and upper Green River watersheds; Fig. S1), the watershed-average snowpack storage on 1–2 June 2025, is 0.18, 0.21, and 0.26 m SWE, respectively, estimated

using the lidar depth and the 2025 WRR Bayesian regression model (Eq. 1). Relative to this baseline, the Tabler (2003) model predicts 9 %–13 % less total SWE in these three watersheds, the Jonas et al. (2009) model predicts 3 %–5 % less SWE, the Sturm et al. (2010) model predicts 5 %–8 % less SWE, the Bormann et al. (2013) models predict 16 %–18 % less SWE (all-site model) or 22 %–24 % less SWE (alpine model), and the Hill et al. (2019) model predicts 18 %–20 % less watershed-total SWE.

Field-observed patterns of snow density heterogeneity repeat across years, although the sensitivity to different predictors (elevation, depth, etc.) varies year-to-year (Fig. 10) according to the WRR 2024–2026 regression models (Table 1). Considering all 3 m grid cells with snow depth > 0.2 m, the median density varies from 425–448 kg m⁻³ across 3 years (during the same late-May to early-June timeframe), which is a fractional variation of 5 %. The highest-density 99th percentile similarly varies by 6 % (521–553 kg m⁻³), but the lowest-density 1st percentile only varies by 3 % (355–364 kg m⁻³). In addition to changes in the snow density relationships across the terrain, these interannual variations are responsive to differences in the spatial extent of drifts and low-elevation forested snow each year. In light of the tremendous natural variability of mountain snowpacks and the wide range of measured densities, it is noteworthy that such similar patterns are observed year to year. Compared to the large range of discrepancies from the prior literature models (Figs. 8–9), a single year of targeted local field surveys can thus have a substantial impact on reducing lidar-based SWE quantification uncertainty. Nevertheless, snow density still exhibits notable spatial patterns of change between years at the watershed scale (Fig. 10). Compared to 2025, bulk snow density was 32 % and 45 % less sensitive to depth in 2024 and 2026, respectively (θ_2 in Table 1). However, snow density was about 75 % and 28 % more sensitive to elevation in 2024 and 2026, respectively (comparing the predicted effect of elevation at 4000 vs. 3000 m elevation using median parameter values from Table 1). Interestingly, the impact of forest cover on snow density is the most consistent across years, with 19 % greater sensitivity in 2024 and < 1 % lower sensitivity in 2026 (comparing the predicted effect of 100 % forest cover, Table 1). Despite these differing sensitivities between years, the overall landscape-scale pattern of snow density remains more consistent due to the relative rarity of the most extreme environments. In other words, most of the landscape has similar snow density across years, while the deepest drifts and highest elevations are more sensitive to interannual variability.

Metrics related to deep snow storage are particularly sensitive to bulk density assumptions in the absence of local field data. Previous analysis of the WRR snowpack suggests that the amount of snow deeper than some minimum threshold, e.g., SWE > 2 m, is related to inter-watershed differences in late-summer streamflow and glacier mass loss (Boardman et al., 2025). Our 2025 SWE map based on ASO

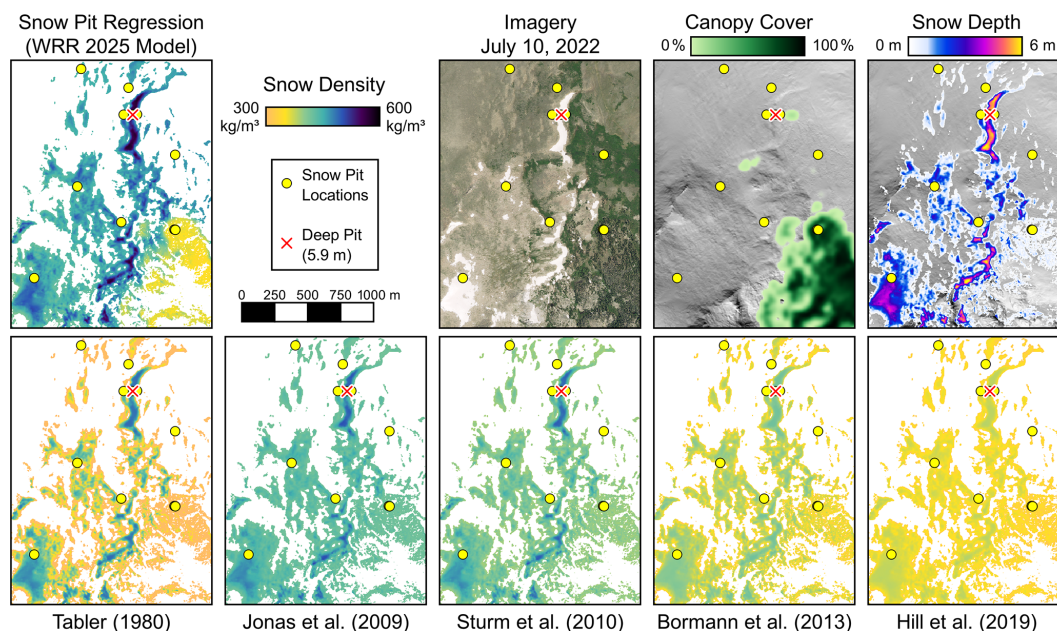


Figure 9. Snow density maps in the region surrounding the Burrow Flat nivation hollow study site (location also shown in Figs. 1, 4, and 5). All of the maps are based on empirical relationships with the lidar-derived snow depth at 3 m resolution in addition to other variables for some models (Table 1); the global combo model is used for Bormann et al. (2013) since it outperformed the alpine model. Note the strong contrast between low-density snow in the forested area and high-density snow in the deep nivation hollow drift identified by the snow pit regression. Additional snow pits in nearby forest areas (outside map extent) further support this contrast.

lidar and the WRR-specific density model (Eq. 1) indicates that 34 %, 26 %, and 10 % of the total snowpack is stored in areas with $\text{SWE} > 2$ m in the Torrey, Dinwoody, and Green River watersheds, respectively. Relative to this baseline, all of the tested prior literature density models underestimate the watershed-total amount of snow storage in places with > 2 m SWE by 14 %–57 % in Torrey Creek, 14 %–67 % in Dinwoody Creek, and 27 %–78 % in the upper Green River. Even deeper snow ($\text{SWE} > 4$ m) is relevant for constraining certain snow science topics such as snow transport (Boardman, 2025b). At the time of our surveys, we estimate that areas with $\text{SWE} > 4$ m account for about 6 %, 2 %, and 0.5 % of the total snowpack in the Torrey, Dinwoody, and Green River watersheds, respectively. Analogously, the prior literature snow density models underestimate the amount of snowpack storage in areas with $\text{SWE} > 4$ m by 41 %–90 % in Torrey Creek, 42 %–88 % in Dinwoody Creek, and 34 %–81 % in the upper Green River. However, it is important to note that these percentages are calculated only considering the grid cells with SWE exceeding a discrete threshold in each respective map, so this underestimation is compounded by the shrinking number of grid cells that qualify for inclusion with $\text{SWE} > 2$ m or $\text{SWE} > 4$ m when deep snow density is underestimated (i.e., the SWE is not underestimated by 90 % in any single grid cell, but the total volume in areas with SWE strictly exceeding 4 m is underestimated by up to 90 %).

Despite the underestimation of deep snow storage by the prior literature density models, all of the lidar-based SWE

maps still exhibit much higher spatial heterogeneity compared to the other near-real-time gridded SWE datasets (Fig. 11, Table 2). It is no surprise that the lidar-based SWE maps capture more heterogeneity at the native 3 m resolution, since the other gridded datasets are two orders of magnitude coarser (500+ m) and thus incapable of capturing heterogeneity associated with nivation hollows, cornices, and similar fine-scale snowpack features. However, even after averaging all maps to the same 500 m resolution, the lidar-based SWE map exhibits considerable spatial heterogeneity that is not represented in the SNODAS, U. of Colorado, or U. of Arizona datasets, probably because mountain-scale snow-atmosphere coupling processes (Mott et al., 2018) are missing from the underlying gridded climate datasets and poorly represented by the small range of variability in the SNOTEL network. Within the combined three-watershed area, the lidar-based SWE map shows an area of 16.8 km² with > 1 m of average SWE at 500 m resolution, while the U. of Colorado dataset only shows an analogous area of 0.8 km² and the other two datasets have zero area with > 1 m SWE. The standard deviation of 500 m average SWE is 56 % higher, 75 % higher, and 33 % higher in the lidar-based map compared to the SNODAS, U. of Colorado, and U. of Arizona SWE maps, respectively. Remarkably, the SNODAS mean SWE is only 2 % lower than the lidar-based mean SWE, but the single deepest grid cell (500 m average) in SNODAS is 61 % lower, and SNODAS has 36 % more snow-free area, indicating a severe underestimation of spatial heterogeneity

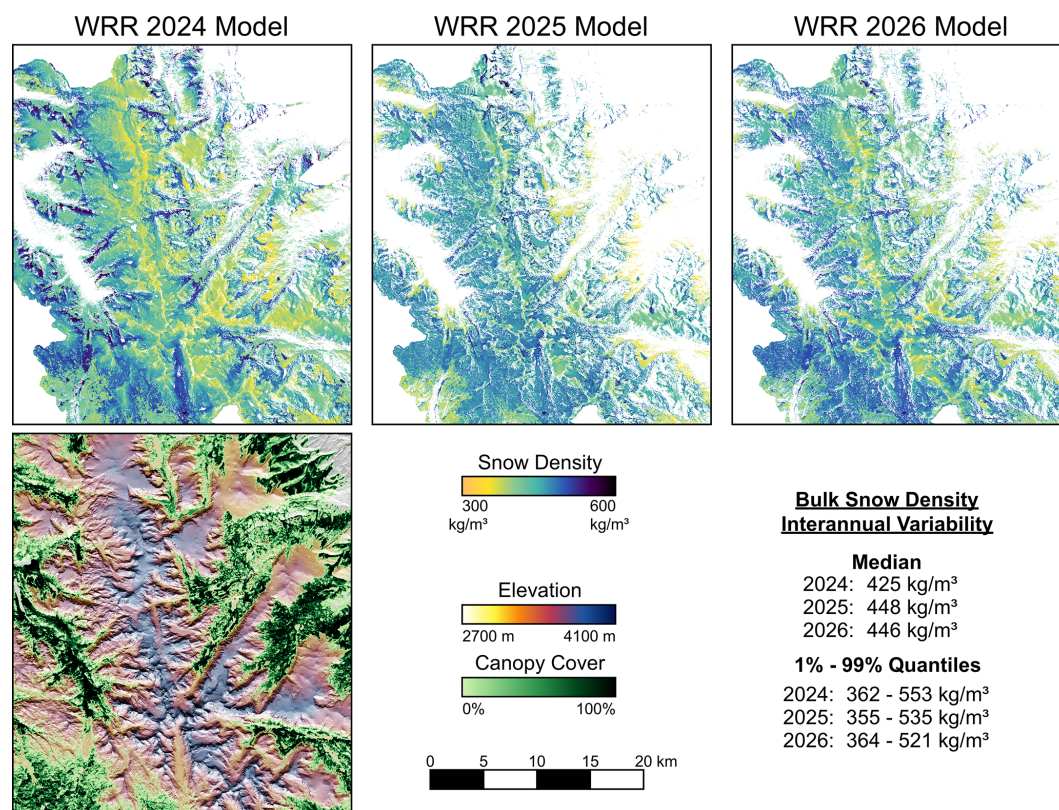


Figure 10. Comparison of snow density maps in the northern WRR estimated using airborne lidar depth maps and annual Bayesian regression models (Table 1). Snow density maps and statistics are masked to only include areas with lidar-based snow depth > 0.2 m. Although the broad patterns of density heterogeneity are consistent, snowpack settings such as high elevations, deep drifts, and forested areas exhibit differing levels of sensitivity each year.

within the snow-covered area. Even when further averaging the maps to 1000 m resolution (Fig. S6), the lidar-based SWE map has 52 % higher standard deviation compared to SNODAS. Aggregated to the same 1000 m resolution, the lidar-based map shows an area of 8 km² with > 1 m SWE compared to zero area with > 1 m SWE in SNODAS despite the near-identical mean SWE in both datasets.

Snow density is an important control on watershed-scale SWE heterogeneity, but all of the lidar-based datasets exhibit more spatial heterogeneity (regardless of which density model is used) in comparison to any of the non-lidar gridded SWE datasets (Table 2). The non-lidar SWE datasets underestimate the watershed-average mean SWE by 2 % to 17 % compared to an underestimation of 12 % on average across all five prior literature density models. At 500 m resolution, the non-lidar gridded SWE datasets underestimate the deepest 90th, 99th, and 99.9th SWE percentiles by a mean of 25 %, 48 %, and 52 %, respectively, while the prior literature density models underestimate the same percentiles by a mean of 11 %, 12 %, and 17 % at 3 m resolution. When considered as a percentage uncertainty, deep snow metrics are relatively more sensitive to snow depth (lidar vs. non-lidar) than snow density (snow pits vs. literature models), and the depth

becomes relatively more important compared to density at more extreme SWE percentiles. However, when considering the absolute sensitivity of the SWE distribution, there is a mean difference of 0.09 m SWE between the snow pit and literature-based density assumptions for the 90th SWE percentile compared to a 0.26 or 0.65 m difference at the 99th and 99.9th percentiles, respectively. Thus, the density constraint has the largest absolute impact on estimated SWE in the deepest parts of the snowpack, as density errors scale multiplicatively with depth.

4 Synthesis and Discussion

Although the underestimation of snowpack heterogeneity is a widely recognized challenge, few if any studies have previously quantified the impact of representative snow density data at the watershed scale. Most directly, Raleigh and Small (2017) tested the impact of density heterogeneity for lidar-based SWE maps, but the role of wind-packing on drift density remains unconstrained both by the models and the flat meadow snow courses used for that study. The most direct prior study of SNOTEL representativeness by Molotch and Bales (2006) focused on snow cover persistence and did

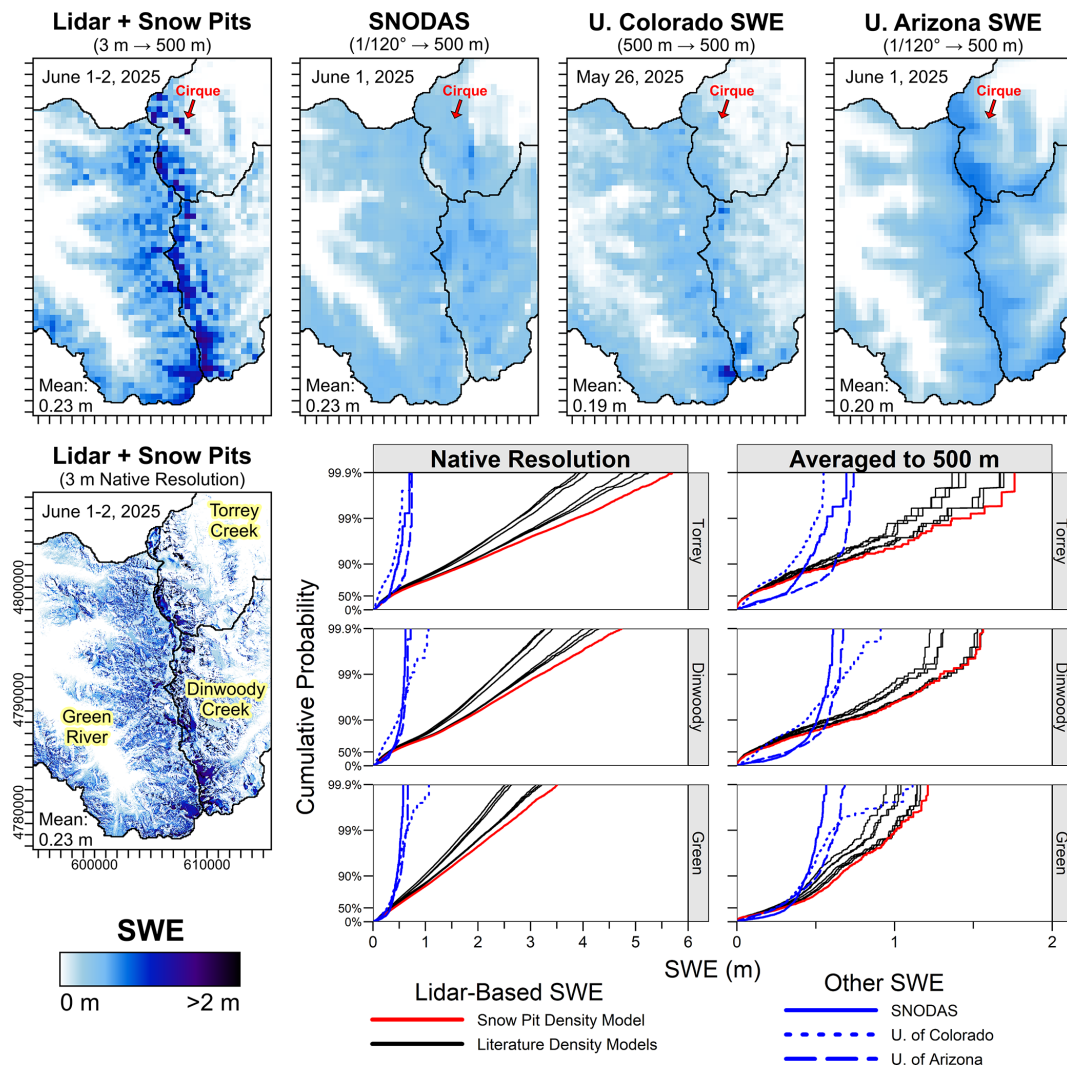


Figure 11. Comparison of gridded SWE datasets in the northern WRR study area. Inset plots show the cumulative distribution function of spatial SWE variability within each map (note logarithmically transformed scale on vertical axis). All datasets are averaged to the same 500 m resolution for consistency (upper panels), though the lidar-based dataset is also shown at the native 3 m resolution for comparison. Regardless of the density model assumptions, the lidar-based SWE map exhibits more spatial heterogeneity than the other datasets, which drastically underestimate the magnitude and spatial extent of deep snow zones. Nevertheless, density model assumptions can also substantially alter the cumulative SWE distribution.

not consider snow density; moreover, that study examined a montane watershed with only 11 % of its area above timberline, compared to 76 % of the area in our study. Recent model development studies aimed at reproducing snowpack heterogeneity from a process-based perspective rarely examine (or even mention) snow density, preferring instead to work exclusively with snow depth (e.g., Reynolds et al., 2024), and the usage of constant density fields is acknowledged as a potential contributing factor to model errors (Helbig et al., 2024). Modeling studies that consider wind interactions with snow density (e.g., to determine erodibility for transport) still tend to use highly simplified assumptions, such as a uniform 300 kg m^{-3} for re-deposited snow (Quéno et al., 2024). Be-

yond the role of wind-packing in drifts, the impact of forests on the vertical profile of snow density is considered “an unexplored research topic” (Mazzotti et al., 2023). Clearly, knowledge of snow density lags knowledge of snowpack heterogeneity more broadly. Assumptions about snow density are especially rarely tested in alpine environments, because density data from deep wind drifts, avalanche zones, steep slopes, and high elevations are sparse. To address this gap, our study leverages an unprecedented variety of direct observations from a windy alpine environment to test prevailing assumptions and evaluate the impact of snow density heterogeneity on watershed-scale SWE mapping.

Table 2. Comparison of SWE metrics within the combined Torrey Creek, Dinwoody Creek, and upper Green River watersheds. All five non-WRR literature models from Fig. 9 are averaged for the “Lidar + Avg. of Literature Models” entry. Except for the comparison between the snow pit density model and the literature density models at the native 3 m resolution, all gridded datasets are averaged to 500 m resolution for consistency.

Dataset	Mean SWE (m)	90th, 99th, 99.9th Percentile SWE (m)	Std. Dev. SWE (m)	Area With SWE > 1 m (km ²)
Lidar + Snow Pits (3 m)	0.229	0.79, 2.25, 3.82	0.49	55.8
Lidar + Avg. of Five Literature Models (3 m)	0.202	0.70, 1.99, 3.17	0.43	46.8
Lidar + Snow Pits (500 m)	0.230	0.63, 1.17, 1.56	0.28	16.8
SNODAS (at 500 m)	0.226	0.45, 0.56, 0.61	0.18	0
U. Colorado SWE (at 500 m)	0.190	0.43, 0.61, 0.91	0.16	0.8
U. Arizona SWE (at 500 m)	0.201	0.53, 0.66, 0.71	0.21	0

4.1 Understanding the Remarkably High Density of Deep Alpine Wind Drifts

In our WRR dataset, the highest bulk snow densities are associated with deep wind drifts at relatively low elevations. Although avalanche debris is the densest snow within the high-elevation Downs Mountain vicinity, even avalanche debris is less dense than the lower-elevation nivation hollow drift, both when considering the bulk density of each snow pit (483 vs. 585 kg m⁻³) or the highest density of any individual measurement (638 vs. 688 kg m⁻³). Unlike glacial firn, which densifies at greater depths (e.g., Stevens et al., 2024), the 5.9 m snow drift density profile exhibits no significant depth-density trend. Since snow near the surface of the drift exceeds the vertically integrated bulk density, it seems that overburden pressure is a negligible driver of densification in the nivation hollow drift. This is in contrast to common process-based models used with lidar data, such as iSno²bal, wherein overburden pressure is stated as the assumed driver of densification with depth (Hedrick et al., 2018). Thus, snow lidar surveys relying on modeled density fields may mischaracterize the relationship between depth and density in heavily wind-affected regions such as the WRR. Our finding of constant high density with depth is congruent with expectations for dense packing of snow grains in wind drifts (e.g., Jellinek, 1959; Anderson and Benson, 1963), though ours appears to be the first literature account of a vertical density profile (at 10 cm resolution) from a 5–6 m drift in an alpine mountain environment. Thus, we are uniquely positioned to test hypotheses about drift density in a mountain environment that is important for western water resources (Bales et al., 2006; Li et al., 2017), as opposed to the Arctic tundra and ice sheet contexts of many older snow drift studies (e.g., Anderson and Benson, 1963; Benson and Sturm, 1993; Craven and Allison, 1998; Sturm et al., 2001; Libois et al., 2014; Parr et al., 2020).

Since our deepest drift profile is very dense even in sections without visible ice layers, and since adjacent snow with a similar microclimate is much less dense, we infer that melt-freeze processes are also unlikely to be the dominant driver

of the density contrast between deep and shallow snow. Instead, wind-packing is the obvious explanation for the uniformly high bulk density, which is supported by the distinctive drift morphology (Fig. 4) and wind-topography interactions (Fig. 5). Kotlyakov (1966) found that freshly deposited Antarctic snow can exceed a density of 400 kg m⁻³ when deposited during winds of roughly 15–30 m s⁻¹ (visualized in Fig. III-4 of Mellor, 1964), far exceeding the typical density of new snow (Tabler, 2003). Consequentially, the correlation between snow depth and density (deeper drifts are generally denser) is not necessarily a causal relationship in windy locations, i.e., depth is not the cause of density variability. Rather, snow depth may function as a proxy for the intensity of wind-driven accumulation processes such as fragmentation during saltation (Comola et al., 2017), which causes wind-packing snow densification (Sommer et al., 2017). In other words, the process of drifting increases both the depth and density of certain snowpack locations. Although this finding might be a trivial consequence of spherical geometry from the perspective of grain-scale snow science (Jellinek, 1959; Anderson and Benson, 1963), Tabler (2003) emphasizes “the pressure of overlying snow” when introducing the relationship between drift depth and density, which would logically lead to greater densities at deeper depths (since there is no overlying snow at the surface), in contrast to our observations. This discrepancy in the prior snow drift literature indicates that our first-in-class complete density profiles from deep alpine drifts contribute additional evidence in support of wind-packing as the dominant driver of the depth-density correlation in drifted locations. Moreover, grain-scale wind-packing effects on snow density are rarely considered in operational near-real-time SWE quantification (i.e., not considered in the iSno²bal density model used by Hedrick et al., 2018). In another example, a recent intermediate-complexity layer-wise snow density model (H2SWE) also does not consider wind-packing, instead parameterizing exclusively the effects of metamorphism and deformation (Winkler et al., 2021), and this class of model is predominantly applied in wind-sheltered areas (Magnusson et al., 2025). Obviously,

the effect of wind-packing on snow density not captured by in-situ stations (i.e., SNOTEL) that are located predominantly in sheltered forest locations (Molotch and Bales, 2006).

Despite the strong depth-density relationship identified in our study, deep snow can be much less dense in wind-sheltered environments. Complete vertical density profiling of a snow pit at the Central Sierra Snow Laboratory (CSSL, California, USA) by the authors on 16 March 2023, yielded a bulk density of 377 kg m^{-3} despite a snow depth of 4.6 m (Fig. S7). This CSSL snow pit was located in a forest clearing below timberline, and the deep snow was the result of high precipitation in water year 2023, not the result of drifting. Compared to our deep snow drift profiles from the WRR (526, 568, and 585 kg m^{-3} bulk densities for drifts > 5 m deep), the CSSL profile provides further support for the importance of wind-packing, since deep snow in a wind-sheltered region exhibits a similarly low density to the shallow forest snow observed in our study. The depth-density relationship in our study is a consequence of the fact that snow transport (wind drifting and avalanches) drives depth variability in alpine regions.

Wind-packing densification also provides evidence for salient topographic controls on spatial snowpack patterns and the potential repetition of these patterns across years (Pflug and Lundquist, 2020). Our computational fluid dynamics modeling of nivation hollow wind speeds in Fig. 5 demonstrates how concave terrain features could plausibly create self-limiting snow drifts, potentially explaining the spatial density variations observed in these locations. The difference in wind speed between the ground and snow surface (Fig. 5C) indicates that as the drift grows, the nivation hollow becomes less effective at reducing near-surface wind speeds, limiting further growth of the drift and producing the nearly identical snow surface profile observed in different years (Fig. 4). This self-limiting behavior could explain why the lower edge of the drift matches the density stratification near the ground in the deep pit: early wind-packed snow covers both areas similarly, but the middle of the nivation hollow continues accumulating snow after the lower edge reaches its equilibrium profile. This behavior could also explain the lower density at the upper edge of the drift, since the top of the drift would only fill with snow after the rest of the drift volume has already accumulated, leaving less time for metamorphosis and densification at the upper edge. Similar drift-trapping behavior in topographic concavities is observed in other alpine environments (e.g., Niwot Ridge; Berg, 1986), but our study provides a unique opportunity to visualize this behavior with multiple years of lidar data and computationally verify the underlying wind behavior (Fig. 5). A self-limiting drift-trapping process could also explain why perennial ice patches in similar nivation hollows exhibit very thin annual accumulation layers (Meulendyk et al., 2012; Chellman et al., 2021; Alt et al., 2024). Regardless of the total annual snowfall, a wind-limited equilibrium drift profile could

limit net accumulation to match the slow rate of annual compaction, producing the observed thin ice patch accumulation layers. In contrast to the self-limiting nivation hollow location, which exhibits near-identical snow accumulation each year (Fig. 5D–F), the higher elevation drifts in the Downs Mountain vicinity vary widely between years (Fig. 6C–D). The repeat application of lidar surveys across years can thus be used to distinguish filling and non-filling drift zones (Benson and Sturm, 1993; Parr et al., 2020).

The processes controlling snow drift density are relevant for SWE quantification even at watershed scales. Nivation hollows with drifts as large as the one in Figs. 4–5 are infrequent across the WRR, but snow drifts in general are common in alpine regions. Looking beyond watershed-scale SWE quantification, the nivation hollow drift is also interesting from the perspective of periglacial geomorphology and alpine ecology (Thorn, 1976; Wigmore and Molotch, 2024), since meltwater from this drift (which persists throughout most of the summer) contributes to accelerated weathering and sustains a downslope wetland (Fig. S5). In addition to our exceptionally deep drift profiles (Fig. S7), our numerous other complete snow pits from the WRR alpine environment constrain drift density across gradients of depth and topography. Neglecting the higher density of deep drifts can lead to systematic underestimation of watershed-scale snowpack storage by as much as 24 % (Sect. 3.5). This bias is exacerbated when considering metrics of snowpack heterogeneity, as watershed-total deep snow storage metrics are underestimated by 14 %–78 % (SWE > 2 m) and 34 %–90 % (SWE > 4 m) since the area meeting a respective threshold also decreases when SWE is underestimated in any particular grid cell (e.g., a grid cell underestimated at 3.9 m SWE no longer counts for the SWE > 4 m metric). Although these precise depth thresholds are merely illustrative, deep snowpack metrics in general are important for accurate understanding of snow accumulation processes (Boardman, 2025b) and snowmelt processes shaping glacier resilience and streamflow seasonality (Boardman et al., 2025), so underestimating the SWE heterogeneity in a watershed could severely hinder these derivative analyses. The lack of any snow pits deeper than 2 m in many prior lidar-based SWE mapping studies (e.g., Broxton et al., 2019b; Meehan et al., 2024) limits the utility of these prior datasets for snowpack quantification in alpine mountain regions, where drifts frequently exceed several meters in depth (Fig. 11).

4.2 Underestimation of Snow Density Heterogeneity by Empirical Models

Existing empirical snow density models systematically underestimate the spatial heterogeneity of snow density in the WRR, affecting snowpack analyses at scales ranging from individual snow pits to kilometer-scale watershed metrics (Figs. 8–10). We identify three primary sources of missing heterogeneity: (1) underestimation of snow density in drifted

areas affected by wind-packing, (2) failure to quantify systematic differences in snow density between forested and open alpine areas, and (3) missing topographic and micro-climatic controls on snow density.

Although each of the prior literature density models (Table 1) considers snow depth as a predictor variable for density, the models tend to underestimate the magnitude of this relationship in the WRR (Fig. 8). Across all 36 snow pits, the literature models have mean biases between -3% and -23% , which is a reasonable level of skill given that these models are based on mean annual densification rates measured in various locations globally, and the literature models are not necessarily intended for precise snow density prediction at a particular location in a particular year. Nevertheless, it is noteworthy that all five of the literature models systematically underestimate the density of the deep nivation hollow drift (Fig. 4) by -14% to -35% , even the models with minimal bias across all snow pits (Fig. 8). The underlying measurements upon which these models are based do not capture the full range of natural snowpack variability. For example, despite the vast amount of data (11 147 depth-density pairs) used by Jonas et al. (2009), there are no pairs with snow depth > 3.5 m (Fig. 3 of that study). Moreover, deep snow measurements are relatively infrequent in these large model-fitting datasets, leading to models that do not fully capture this heterogeneity (even within the maximum measured range) due to regression dilution and mean centralization. Despite the much smaller size of our dataset (36 snow pits), we structured our survey design to strategically include extreme endmembers, including two complete pits in high- and low-elevation deep drifts of 4–6 m (Figs. 4 and 6). Across the three-watershed region considered here (Fig. 11), 21 % of all non-zero lidar snow depth measurements have depth > 2 m, constituting an estimated 56 % of the total SWE volume, while 22 % of our snow pits are at least 2 m deep, suggesting that deep snow density may still remain under-represented. Prior studies have sometimes only achieved weak or inconclusive empirical models of snow density (e.g., $R^2 = 0.29$ to 0.39 for modeled vs. measured density, Broxton et al., 2019b), which could be partially attributable to sampling a small range of snowpack variability (e.g., snow pit depth range of 0.15 to 1.18 m in that study). Our wide range of sampled snow densities and depths (Fig. 2) manifests in an empirical model describing snow density variations across a relatively large range ($R^2 = 0.76$ for 34 snow pits or 0.94 for the eight pits > 2 m, Figs. 7–8).

Snow is systematically denser in open areas compared to forested areas (Figs. 2 and 7). This fact, which is trivial to anyone who spends much time walking in the mountains, is nevertheless rarely tested statistically. The forest-open density contrast has been recognized by other studies (Bonner et al., 2022; Meehan et al., 2024), but this distinction remains unaccounted in most large-domain empirical density models (Table 1). Surprisingly, it appears that gridded canopy cover datasets (e.g., RCMAP used here) have not been previously

considered as a predictor for empirical snow density models despite the widespread availability of gridded vegetation datasets. Meehan et al. (2024) did consider gridded vegetation metrics derived from lidar (height and distance to vegetation) in their small-domain density extrapolation, but our use of a continental-scale forest cover dataset is more germane to water supply studies across large river basins. For example, gridded canopy cover would naturally fit into the Hill et al. (2019) modeling framework, but it was not considered in their initial list of potential variables (Eq. 6 of that study) despite the consideration of other gridded terrain datasets (e.g., elevation). Perhaps one reason for the historic oversight of gridded vegetation data in prior snow density regressions could be attributed to the overrepresentation of in-situ stations in forested regions, obscuring the forested-open density contrast in the convenience-sampling datasets upon which prior empirical models are often based (e.g., Bormann et al., 2013; Hill et al., 2019). Additionally, SNOTEL-type monitoring stations are typically located within forest gaps, blurring the distinction between “open” and “forested.”

An important caveat on our inter-model comparisons is that many of the tested models are being pushed beyond their intended scope. For example, we evaluate the Sturm et al. (2010) model using the regression for the alpine climate class based on the map from Sturm et al. (1995), but Sturm et al. (1995) note that mountain snowpacks are a special case that may not fit into any single other climate class because of the high degree of spatial heterogeneity. This caveat from Sturm et al. (1995) seems to present a roadblock to SWE estimation across large mountain domains, since the meteorological data required to choose the appropriate climate classes are not available at high resolutions over entire mountain ranges. However, our nonlinear regression with only five independent variables (Eq. 1) can explain most of the observed variability (Fig. 8), suggesting that the problem of mountain snow heterogeneity is far from unsolvable. Since these snow pit locations are strategically situated to capture likely endmembers of variability, and since similar patterns repeat across our WRR survey datasets from different years (Fig. 8), it appears that our regression approach can successfully explain the majority of density heterogeneity across a mountain region using a parsimonious and physically interpretable set of five variables that are available in any lidar-surveyed region (depth, elevation, forest cover, and north/east slope). Further evaluation of our regression model structure in other mountain ranges with different climates and vegetation could inform to what degree these relationships are generalizable beyond the WRR.

4.3 Missing Snow Density Heterogeneity in the SNOTEL Network

Much of the missing heterogeneity in prior snow density models (Sect. 4.2) appears to stem from the non-representativeness of in-situ monitoring sites where snow

density data are routinely collected, since several of the empirical models are fitted to similar in-situ datasets. In the WRR specifically, all 13 of the currently active (and one other inactive) SNOTEL stations are located below treeline, with a maximum elevation of 3070 m, which is lower than 97 % of the SWE volume at the time of our 2025 surveys (Fig. 12). As a result, all but three of the WRR stations were snow-free at the time of our 2025 field surveys. These three stations show inconsistent day-to-day variability indicative of snow bridging and other quality control issues (Goodison et al., 1981), which is exacerbated by the shallow low-elevation snowpack at this time in the season (depth range 0.05–0.51 m). Further, colocation issues between the snow pillow (which measures SWE) and the snow depth sensor (which measures snow depth) could contribute to inconsistent density calculations, especially when the low-elevation snowpack is shallow and patchy (Goodison et al., 1981). More broadly, all of the 88 active SNOTEL stations in the State of Wyoming are located in forested settings, with adjacent trees visible in each of the station photos. Figure S3 to Boardman et al. (2025) further illustrates how SNOTEL stations do not capture the range of density variability observed in the WRR. Empirical density models based on SNOTEL thus lack the data necessary to constrain snow density variations above treeline in the WRR (Fig. 9). This missing heterogeneity highlights the statistical problem with the convenience sampling used by Bormann et al. (2013), Hill et al. (2019), and others, whereby the automatically collected and easily accessible SNOTEL dataset is used for regression modeling without consideration of whether the constituent stations actually constrain the relevant axes of variability (e.g., forested vs. open, high vs. low elevation, deep vs. shallow snow).

Our representativeness score introduced in Sect. 2.2.1 provides robust statistical evidence that our snow pits in deep alpine drifts are more representative of the watershed snowpack compared to the SNOTEL locations (Fig. 13). The two most-representative snow pits have snow depths around 2.6 m with densities around 490 kg m^{-3} , more than twice as deep as the deepest ablation-season snow depth (after peak SWE) recorded at any SNOTEL in Wyoming in 2025 (1.16 m). As discussed previous (Sect. 4.1), the absolute deepest drifts are relatively rare across the landscape, but nevertheless the two deepest snow pits (4.0 and 5.9 m) have the third- and fourth-highest representativeness scores. From Fig. 13, it is obvious why extrapolating from the SNOTEL depth-density relationship (or bias-correcting physical models based on SNOTEL data) could lead to unreliable results in the WRR, because the SNOTEL data overlap the least-representative snow pit locations, with anomalously shallow depths and widely scattered densities. Databases built from manual field measurements also reflect the common practice of ignoring heterogeneity caused by snow drifts. For example, Hill et al. (2019) suggest that participants in the Community Snow Observations program should “avoid measure-

ments in areas of significant wind scour or deposition” in order to “ensure their recorded depth measurements are as representative as possible,” but wind drifts can actually be the most representative types of snow in mountain environments (Fig. 13). Similar representativeness problems occur widely when comparing small-scale measurements (i.e., in-situ or lidar-derived) to kilometer-scale grids (Meromy et al., 2013). Although the low elevation bias of stations in the SNOTEL network (strictly below treeline) generally causes an underestimation of the snowpack in alpine terrain (Molotch and Bales, 2006), sampling exclusively flat locations can also lead to snowpack overestimation in some cases due to under-sampling of wind-scoured areas (Grünwald and Lehning, 2015).

4.4 Sources of Missing Heterogeneity in Extrapolated SWE Datasets

Boardman (2025) previously argued that kilometer-scale snow transport and redistribution is an underappreciated driver of mountain snowpack patterning in areas with alpine plateaus, and our analysis here indicates that common spatial snowpack datasets are indeed missing a considerable degree of kilometer-scale heterogeneity in the WRR (Fig. 11). This missing heterogeneity is ultimately explained, at least in part, by extrapolation from non-representative SNOTEL measurements. All three widely available near-real-time gridded SWE datasets analyzed here (SNODAS, U. Colorado SWE, U. Arizona SWE) are based at least in part on the SNOTEL stations discussed previously (Figs. 11–12). The SNODAS product uses a physically based snow model that is “nudged” to better match SNOTEL data, satellite-derived snow-covered area, and potentially other observations when available, though the precise methodology for data selection and assimilation in a particular region or year remains opaque and subject to agency personnel decisions (Barrett, 2003). The U. Colorado SWE product (sometimes called SWE-fusion) uses generalized linear regressions to extrapolate spatial SWE from SNOTEL data using physiographic variables, historical SWE patterns (where available), and satellite-derived snow-covered area (Schneider and Molotch, 2016; Yang et al., 2022). The U. Arizona SWE product (sometimes called SWANN) uses artificial neural networks to extrapolate spatial SWE from SNOTEL data and other in-situ data using gridded climatology and physiographic variables (Broxton et al., 2016, 2019a, 2024). All of these snowpack datasets are available in near-real-time (i.e., within a few days of the nominal date) and are widely used in research across the western USA related to water supply forecasting and other watershed-scale snowpack analyses. Also of note, each of these SWE products is dependent (at least in part) on the SNOTEL network, which is not representative of alpine mountains (Figs. 12–13).

Despite the limitations of gridded SWE datasets extrapolated from sparse measurements, these products are com-

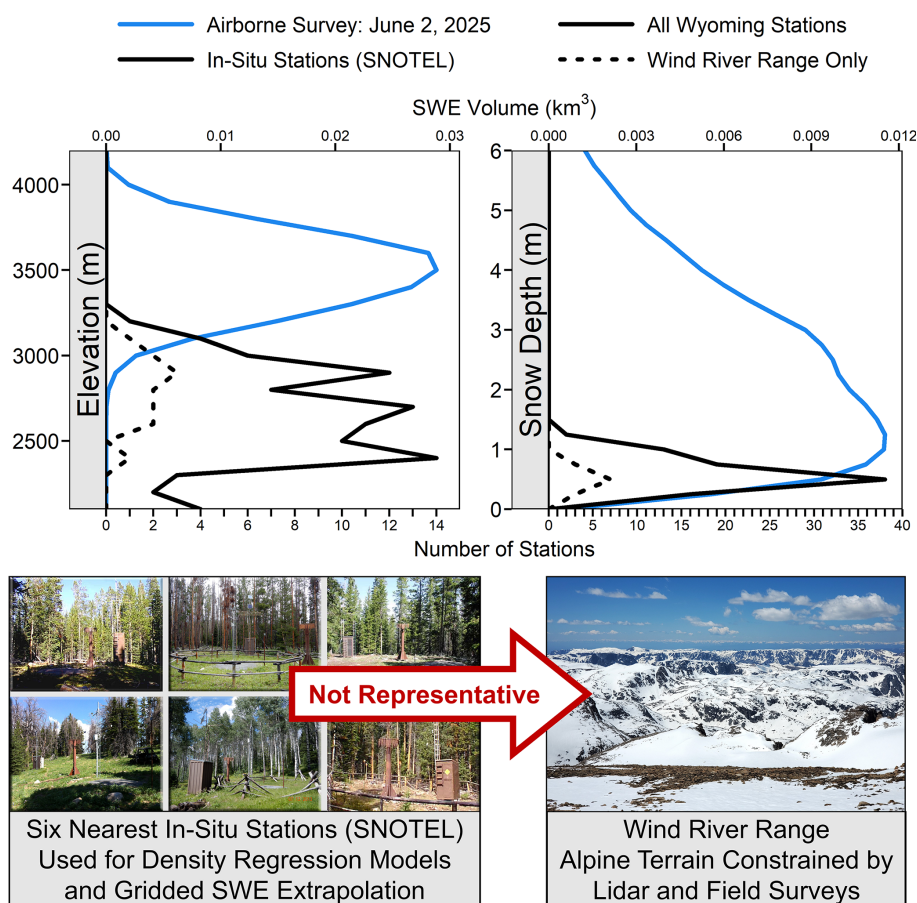


Figure 12. Comparisons of elevation and snow depth distribution of the northern WRR snowpack at the time of our 2 June 2025, airborne lidar survey. Note the dual axes on the plots: the top axis shows the volume of SWE (from lidar and snow pit density regression), and the bottom axis shows the number of SNOTEL stations within respective elevation or snow depth bands. The reported SNOTEL snow depth is the maximum depth observed at each site in water year 2025 (most SNOTEL sites were snow-free at the time of our lidar survey). The SNOTEL photos are USA Natural Resource Conservation Service (NRCS) stock photos (Public Domain). The alpine photo (by the authors) is from 31 May 2025 (nearly contemporaneous with the lidar survey), looking west into the Green River headwaters from Downs Mountain (Fig. 1).

monly used to represent heterogeneity without testing their representativeness. For example, Raleigh et al. (2025) used SNODAS and U. Arizona SWE as supplemental datasets to explicitly investigate spatial SWE heterogeneity across watersheds, but in wind-drifted alpine environments, these datasets completely fail to capture the observed patterns at 500 m scale, rendering it futile to search for “hot spots” within datasets that are neither spatially accurate nor statistically representative (Fig. 11). Other studies have likewise used, or perhaps misused, these extrapolated gridded datasets to represent grid-scale spatial heterogeneity across watersheds: SNODAS was used to optimize monitoring station locations (Keum et al., 2018), SNODAS was used for calibration of spatially distributed models (Tiwarei et al., 2024), and U. Arizona SWE was used to investigate spatial interactions between the snowpack and forest fires (Abolafia-Rosenzweig et al., 2022). It is unsurprising, yet critically important, that

snow drifts and other deep accumulation zones are entirely missing from large-domain gridded datasets, because extrapolation from non-representative station data logically leads to a dramatic underestimation of spatial heterogeneity at watershed scales (Figs. 11–13 and Table 2). Researchers considering SNODAS, U. Colorado SWE, or U. Arizona SWE as interchangeable proxies for “spatial SWE datasets” need to understand that these datasets are extrapolated from sparse measurements, which are not necessarily representative of the mountain regions where most snow is stored (Figs. 12–13). Thus, these extrapolated spatial datasets may be useful for estimating a lumped regional snowpack index, but they are unsuitable for studies addressing heterogeneity in the WRR (and likely also in similar alpine regions across the western USA). Our study also underscores the importance of independent validation data for testing common snow data products, which can otherwise become effectively unfalsifi-

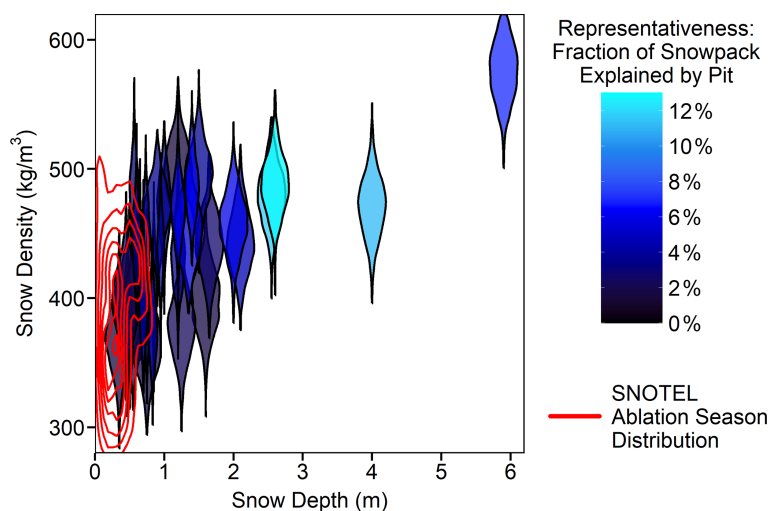


Figure 13. Representativeness of snow pit locations compared to the distribution of SNOTEL data from Wyoming during the 2025 ablation season (beginning from peak SWE at each of 88 SNOTEL locations). Each of the blue violin distributions represents the uncertainty of the Bayesian regression model with respect to a particular snow pit. Lighter blue colors indicate that a particular snow pit is more representative of the WRR lidar-surveyed snowpack as defined in Sect. 2.2.1. The red lines indicate contours of the probability density function (PDF) for the distribution of daily SNOTEL observations of snow depth and density ($N = 3676$). Note that the SNOTEL observations are exclusively clustered in the least-representative region (shallow snow depth), whereas the most-representative snow pits are between 2 and 4 m deep.

able due to assimilation of all available data (Hedrick et al., 2015). We do not intend to diminish the potential value of extrapolated SWE datasets as a first-order estimate of the lumped watershed-scale snowpack storage, but using these datasets for spatially explicit applications is misguided in alpine environments that lack representative in-situ data, like the WRR (Table 2).

Gridded SWE products that do not explicitly consider snow transport processes are unlikely to capture the spatial variability of SWE in windy landscapes (Lv et al., 2019), which poses a challenge for water resource assessments in the mountainous western USA (Li et al., 2017). For example, the red arrows in Fig. 11 indicate a particularly notable glacial cirque (43.370° , -109.671°) that collects snow from a roughly 3 km^2 upwind contributing “snowshed” (Boardman, 2025b). At 500 m resolution, this cirque location is represented by four grid cells with mean SWE of 1.1 to 1.7 m based on our 2025 lidar and snow pit density model. Within the same four 500 m grid cells, the non-lidar gridded datasets show mean SWE of 0.34–0.39 m (SNODAS), 0.25–0.46 m (U. Colorado), and 0.37–0.53 m (U. Arizona). Note that the U. Colorado dataset masks glacier locations, so those values are interpolated from neighboring cells (raw gridded SWE products are shown in Fig. S6). Comparing the total volume in these four grid cells, the non-lidar SWE datasets underestimate the deep snow storage in this cirque basin by about 65–73 % despite much closer agreement with the mean SWE across the whole landscape (e.g., as low as 2 % difference for SNODAS, Table 2). Analogously, the five literature density models (Table 1) underestimate the snow storage in the same four grid cells by 9 %–27 %. Accurate measurement of

snow depth (from lidar) greatly reduces the uncertainty of deep snow quantification regardless of the density assumption (Fig. 11), but underestimating the density of deep drifts and avalanche debris (Figs. 4 and 6) still causes a substantial underestimation of heterogeneity when applying the prior literature snow density models. Thus, accurate spatial SWE quantification requires accounting for both the extreme depth and extreme density of snow in cirque basins, nivation hollows, and other enhanced accumulation zones affected by both wind transport and avalanches (Fig. 6). Ultimately, these deep drift zones and glacial cirques create strong controls on hydrograph shape and upland water supply during the growing season (Boardman et al., 2025), so the enhanced heterogeneity of windy alpine landscapes cannot be ignored in sub-seasonal snow water supply forecasting and other water resource applications that are sensitive to runoff timing or peak flows (Pfohl et al., 2026).

4.5 Transferability

In a scientific era emphasizing “big data” and remote sensing (e.g., Dozier, 2011), tedious manual field measurements remain essential. Deep drifts, avalanche runout zones, and steep slopes are globally underrepresented in snow monitoring networks (e.g., Bormann et al., 2013) for obvious practical reasons. Unfortunately, these extreme alpine settings are also typically difficult and/or dangerous to sample manually. To obtain the data in Fig. 6, the lead author assumed personal responsibility (outside the scope of any institutional affiliation) for entering extreme terrain using technical mountaineering gear. These actions were taken after informed ac-

ceptance of the associated risks by an individual with extensive personal mountaineering experience in the study region, and obtaining similar measurements could be considered reckless in other circumstances. Moreover, the large amount of manual labor required to sample a very deep drift (Fig. 4) is also prohibitively time-consuming in most circumstances (back-of-the-envelope calculations show that we moved on the order of 10 000 kg of snow just to sample the single deepest 5.9 m snow pit). Our approach also necessitates coordinating the timing of fieldwork with flight planning logistics, which can be challenging in mountain environments with variable weather and multi-day backcountry approach hikes. Thus, comprehensive field surveys of alpine snow density may not always be practical for real-time water supply forecasting applications.

However, even sparse opportunistic measurements from extreme alpine environments can help constrain patterns of snow density that repeat across years (Figs. 8 and 10). These heterogeneous snow density zones are missing from the in-situ station network (Figs. 12–13) and can advance our understanding of the physical processes underlying variations in snowpack stratigraphy and densification (Figs. 3 and 5). A direct application of our regression model (Eq. 1 and Table 1) to other regions is unlikely to yield the correct mean density due to site-to-site and year-to-year variability, but we anticipate that our model might be useful to indicate the potential degree of spatial heterogeneity in other alpine regions associated with deep drifts and forest versus open areas. We suggest that a closer collaboration between snow scientists and the technical mountaineering community would be useful to further constrain snow heterogeneity in rarely sampled extreme alpine settings globally, but we emphasize that such measurements must be conducted responsibly, perhaps through partnership with professional mountain guides or similar services.

5 Conclusions

Although the challenge of capturing snowpack heterogeneity is widely recognized, the impacts of bulk density on spatial SWE are relatively unexplored due to a lack of representative data. In this study, we perform the first quantitative statistical tests of spatial SWE sensitivity to wind-packing drift effects (Sect. 3.5), develop new bulk density regression relationships with forest cover, elevation, and other variables (Sect. 3.4), and evaluate a new representativeness metric to explore why in-situ datasets (and SWE regressions based on in-situ measurements) fail to capture alpine snow drifts (Sect. 4.3). Our results show that drift-related snow density variations provide a salient control on watershed SWE distributions despite the first-order importance of drift-related snow depth variations (Fig. 11). Since in-situ monitoring sites (SNOTEL) are exclusively in forested areas, extrapolation from these in-situ

measurements systematically fails to capture the spatial distribution of the WRR snowpack (Figs. 11–12).

Accurate snow depth quantification, e.g., through airborne lidar, provides the key to first-order patterns of SWE heterogeneity, which is drastically underestimated by other near-real-time gridded SWE datasets (Fig. 11). However, the availability and quality of alpine snow density information continues to lag the expansion of lidar-based snow depth surveys. In this case, the 2025 ASO WRR lidar survey provided 3×10^7 non-zero snow depth measurements over the three watersheds considered here, 76 % of which are in non-forested areas, but there are only 13 automatic stations providing daily snow density measurements in the WRR, all of which are below treeline with non-representative (shallow) snow depths (Figs. 12–13). More than half of the total surveyed SWE volume is stored in areas with snow depth > 2 m, which is deeper than measured by any in-situ station (Fig. 12). Hence, manual measurements from deep drifts provide the most representative density measurements in alpine landscapes like the WRR mountains (Fig. 13).

Various physically based and empirical models have been proposed to infer snow density across mountain landscapes, but bias-correcting and validating these models requires representative field data spanning a wide range of environments. The measurements reported here constrain snow density in several rarely sampled settings (e.g., high elevations, avalanche debris, steep slopes, and deep drifts) that can be used to refine empirical parameterizations (e.g., the addition of gridded canopy cover as a regression variable), motivate the incorporation of missing processes into physically based models (e.g., the widely neglected effect of wind-packing), and inform future field survey plans to efficiently constrain heterogeneity based on repeating patterns (Fig. 10). Spatially explicit SWE estimates must account for the high bulk density and extraordinary depth of alpine wind drifts, which are structurally excluded from most ground-based surveys and in-situ monitoring networks. The missing wind-packing heterogeneity diagnosed here extends from the scale of individual nivation hollow drifts (Figs. 4–5) to kilometer-scale grid cells and watershed-scale snowpack statistics (Figs. 10–11 and Table 2). Synthesizing lidar depth surveys with strategic field density measurements can enhance near-real-time spatial SWE quantification, which benefits spatially resolved approaches to water supply forecasting, hydrological and glaciological studies, and other mountain snowpack assessments.

Code and data availability. The data from this study, as well as computer code for data processing and figures, are archived at <https://doi.org/10.5281/zenodo.17114675> (Boardman, 2025a). Lidar data products acquired commercially by Airborne Snow Observatories, Inc. are not included in this archive due to contractual restrictions but are publicly available at <https://ava.airbornesnowobservatories.com/> (last access: 28 August 2026).

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Author contributions. All authors contributed to data collection during the field surveys and reviewed the manuscript. ENB was the principal investigator for this project, designed the study, and wrote the first draft. AGF contributed to the methodology, validation, and writing. KLB, JAW, JWB, and AAH contributed to visualization and writing (revision). AAH additionally contributed to conceptualization and supervision.

Competing interests. The authors have the following competing interests: Author ENB is the owner of Mountain Hydrology LLC, which contracted for data acquisition and partially funded ENB. Author JWB has financial interests in Airborne Snow Observatories, Inc., which acquired the lidar data used here. Authors CAJ, SDS, JAW, and AAH received funding through a Mountain Hydrology LLC subaward to the University of Nevada, Reno.

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