Advancing Snow Depth Monitoring with Machine Learning and L-band InSAR Data: A Case Study Using SnowEx 2017 Data

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Abstract

Current snow depth mapping from space faces challenges in spatial coverage, revisit frequency, and cost. Spaceborne Lidar, although precise, incurs high costs, and Airborne Snow Observatory (ASO) snow depth data are confined geographically to the western United States, thereby necessitating the exploration of alternative, cost-effective methodologies for snow depth estimation. The forthcoming NASA-ISRO Synthetic Aperture Radar (NISAR) mission, with its 12-day global revisit cycle, introduces a promising avenue for cost-effective, large-scale snow depth estimation using L-band Interferometric SAR (InSAR) capabilities. This study demonstrates InSAR's potential for snow depth estimation via machine learning. Using 3m resolution L-band InSAR products over Grand Mesa, Colorado, we compared the performance of XGBoost, ExtraTrees, and Neural Networks across open, forested, and mixed terrains using RMSE, MBE, and *R²* metrics. XGBoost emerged as the superior model, registering RMSE values of 9.37cm, 9.28cm, and 9.84cm for open, mixed, and forested regions, respectively. Validation against in-situ snow depth measurements returned ~16cm RMSE. Our findings indicate that L-band InSAR, with its ability to penetrate clouds and cover extensive areas, coupled with machine learning, holds promise for enhancing snow depth estimation. This approach, particularly with the NISAR mission, may enable high-resolution (~10 m) snow depth mapping over extensive areas, provided suitable training data are available, offering a cost-effective complement to existing snow monitoring practices.

Keywords: Snow Depth, InSAR, Machine Learning, NISAR, Remote Sensing

# Introduction

Accurately measuring snow depth is critical for applications in hydrologic science, water resource management, and climate modeling (1). Seasonal snowpack acts as a natural reservoir, storing winter precipitation and gradually releasing meltwater in spring and summer as the temperature rises (1). Tracking snow accumulation and melt dynamics is instrumental in recharging rivers, lakes, and aquifers, thereby sustaining ecosystems and human activities. For instance, in California, the Sierra Nevada seasonal snowpack contributes approximately 70% of additional water storage to supplement the existing artificial reservoir system (2–4). However, monitoring snow depth, especially on a large scale, is fraught with challenges. The diverse and rugged terrain of mountainous regions makes it particularly difficult (5).

Traditionally, snow depth monitoring has relied upon in-situ measurements and airborne observations (6–9). However, these methods are often limited by geographical reach, temporal frequency, and financial resources. In-situ measurements are known for their accuracy and reliability, as they are often conducted manually using instruments such as snow probes and rulers or through automated snow telemetry stations (SNOTEL) (10). However, access to mountainous regions can be difficult during winter when snow monitoring is essential. Additionally, the resources required for frequent and widespread in-situ measurements, including financial and human capital, can be prohibitively high (9). Moreover, in-situ measurements, by their very nature, are discrete point measurements and thus cannot capture the full spatial heterogeneity of snow depth across a landscape (11).

Spaceborne remote sensing technologies such as Light Detection and Ranging (Lidar) provide high-precision snow depth, but cost prohibits comprehensive monitoring (9). Airborne Lidar and structure-from-motion surveys deliver detailed snow depth maps but are geographically limited (12,13). Satellite passive microwave sensors estimate basin average snow water equivalent yet suffer from coarse resolution (~25 km) (14,15). Optical remote sensing is weather-dependent and unable to penetrate dense forest cover (16,17). Additionally, while initiatives like the Airborne Snow Observatory (ASO) are making strides towards the broader use of Lidar technology, snow depth data is primarily collected in the western United States, leaving a significant geographical gap in snow monitoring. Consequently, the development of new spaceborne capabilities to map snow depth is an active area of research.

Amid the limitations of traditional snow monitoring methods and the challenges of Lidar acquisition on a global scale, the pursuit of alternative remote sensing technologies is imperative. The forthcoming NASA-ISRO (NASA-Indian Space Research Organization) Synthetic Aperture Radar (NISAR) mission, scheduled for launch in January 2024, appears promising in this regard. NISAR, equipped with an L-band radar, is set to observe nearly all of Earth's terrestrial and ice surfaces at an approximate resolution of 10 meters, with a revisit frequency of twice every 12 days (18). Operating within the 1-2 GHz frequency range, the L-band, with wavelengths between 15 to 30 centimeters, is conducive to the penetration of cloud cover and several meters of snowpack, facilitating all-weather, day-night snow monitoring. Repeat pass interferometric SAR (InSAR) acquisitions have demonstrated potential for quantifying snow properties, given SAR’s all-weather imaging and vegetation penetration capabilities (19,20). A recent study by Hoppinen et al.(20) employing repeat pass InSAR for monitoring snow water equivalent (SWE) over Idaho found strong correlations between retrieved SWE changes from SAR images and both in situ and modeled results. Tarricone et al. (19) utilized repeat-pass L-band InSAR to effectively estimate snow accumulation and ablation in the Jemez Mountains, NM, showcasing the capability of L-band InSAR in tracking changes in SWE. Studies have also shown promise in retrieving snow depth information from InSAR coherence, phase, and incidence angle data (21,22). Li et al. (22) used repeat-pass InSAR measurements in estimating snow depth and SWE in the Northern Piedmont Region of the Tianshan Mountains and found the snow depth estimation to be consistent with field survey results. With the promising capabilities of InSAR, the NISAR mission may be able to provide high-resolution (~10 m) snow depth estimates over large areas if appropriate snow depth observations for training are available.

Our goal in this work is to use repeat-pass L-band InSAR products to estimate total snow depth using Machine Learning algorithms. While InSAR is inherently more related to changes in snow depth rather than total snow depth, snow accumulation patterns tend to exhibit consistency. As such, the total snow depth before melt starts displays similar patterns to snow depth changes. Snow distribution patterns have been shown to exhibit intra- and inter-seasonal consistency despite differences in weather patterns and seasonal snowfall amounts (23–26). While the actual snow depths may change, the locations of deeper and shallower snow areas generally tend to be consistent.

Since the 1990s, Machine Learning algorithms have gained prominence in environmental remote sensing (27–29) and, over time, have proliferated across various application areas such as snow depth retrieval (30,31), snow density (32,33), and snow water equivalent (SWE) (34,35) predictions. Hu et al. (36) conducted a study using machine learning algorithms to fuse gridded snow depth datasets with inputs including geolocation, topography, and in-situ observations. The Random Forest algorithm proved to be the most proficient of the three learning machines tested. Liang et al. (37) applied the Support Vector Machine (SVM) to estimate snow depth in northern Xinjiang using data from visible and infrared surface reflectance, brightness temperature, and auxiliary information. The SVM method outperformed the Che algorithm in China (38) and the Artificial Neural Networks (ANN) utilized in Finland (31).

These works and others found in the literature have highlighted the potential of machine learning in producing improved snow depth predictions. However, a common limitation across many of these studies is the constrained spatial coverage, which can be attributed to the scarcity of global snow depth data and the prohibitive costs associated with acquiring Lidar data globally. This study aims to develop a snow depth prediction system using L-band InSAR products and machine learning algorithms. Specifically, we will compare the performance of three machine learning algorithms: eXtreme Gradient Boosting (XGBoost) (39), Extremely Randomized Tress (ExtraTrees) (40), and Artificial Neural Networks (ANN) (41). We will also investigate the impact of land cover on snow depth prediction accuracy.

The objective of this work is divided into three broad aspects:

1. to test the effectiveness of L-band InSAR products in estimating total snow depth using Machine Learning algorithms,
2. to analyze the effect of land cover type on the performance of the Machine Learning models and
3. to understand the relative importance of each input feature in snow depth estimation.

The study area is stratified into open areas, forested areas, and a combination of both to evaluate the impact of land cover on model performance. Our research is motivated by the need for a global snow depth prediction system that is accurate, cost-effective, and scalable. L-band InSAR is a promising technology for snow depth prediction because it can penetrate through clouds and forest cover, and it can be deployed over large areas. Machine learning algorithms can be used to extract snow depth information from L-band InSAR data in a robust and efficient manner.

We believe that our research has the potential to complement existing snow monitoring practices by facilitating cost-effective, high-resolution, and extensive snow depth data acquisition. Our findings could lead to the development of a global snow depth prediction system that provides valuable information for water resource management, flood forecasting, and avalanche hazard assessment, provided that accurate and representative training data is available.

# Data and Methods

# In the previous section, we introduced the problem of snow depth estimation and discussed the advantages of using L-band InSAR data and machine learning for this task. In this section, we will describe the data and methods used in this study to train and evaluate machine learning models for snow depth estimation using L-band SAR data.

## Study Area

This study was conducted in Grand Mesa, a flat-topped mesa in western Colorado, USA (39.1°N, 107.9°W). Grand Mesa is the highest flat-topped mesa in the world (42), and it features diverse terrain with elevations from 2,600 to 3,700 m above sea level. Its vegetation ranges from open shrublands and grasslands to coniferous subalpine forests. Grand Mesa experiences a seasonal snowpack, typically peaking in April and melting through June.

## Data

## The data for our study was sourced from NASA's 2017 SnowEx campaign (43), a pioneering initiative aimed at better understanding how to measure the water contained in snow, especially in diverse and forested environments (43). The campaign represented a concerted effort to develop remote sensing tools and techniques for global Snow Water Equivalent mapping (43). This campaign was primarily conducted in two locations in Colorado, USA: Grand Mesa and Senator Beck Basin. Our focus in this work is on Grand Mesa (Figure 1). SnowEx datasets are publicly available on NSIDC, and their utility has been demonstrated across hackweeks (44) and publications.

The campaign spanned from September 2016 to July 2017, with the Intense Observation Period (IOP) taking place from February 6 to 25, 2017 (45). During this period, a multitude of measurements were collected, including data from cloud-absorption radar, ground-penetrating radar, synthetic aperture radar, Lidar, airborne video, base station and rover measurements, and snow pit measurements (43,45). In this study, we focus on the L-band InSAR products and high-resolution Airborne Lidar data collected during the campaign. Our study site within Grand Mesa spans approximately 70 square kilometers, and all data used in this study has a resolution of 3 meters. The details of each data type's collection and use are outlined in the following sections.

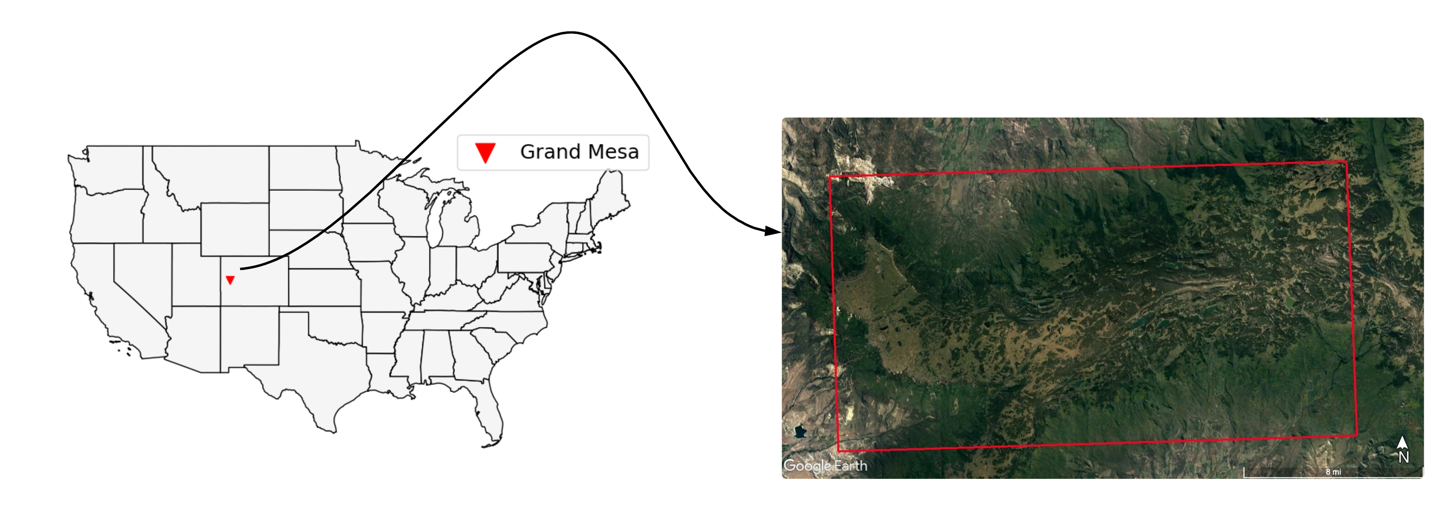


Figure 1. Study Site: Grans Mesa, Colorado. The large red rectangle outlines a 9.25 x 32 km target area that was imaged by all airborne sensors. The natural gradient of Snow Water Equivalent (SWE) increases from west to east, and the forest cover also naturally varies across the region (43).

### Lidar Snow Depth Measurements

Lidar, an acronym for Light Detection and Ranging (46,47), is a remote sensing method that uses light in the form of a pulsed laser to measure distances (48,49). The lidar snow depth data used in this study was collected by the NASA Airborne Snow Observatory (ASO) as part of the 2017 SnowEx campaign on two dates: September 20, 2016, and February 8, 2017. The September 20 flight was a "no-snow" flight, which means that the lidar data was collected before any snow had fallen on the ground. The February 8 flight was a "snow-on" flight, which means that the lidar data was collected after the snow had fallen on the ground. The ASO lidar has a spatial resolution of 3 meters and a vertical accuracy of 15 centimeters. The lidar data was processed to produce a digital elevation model (DEM) for each date. The snow depth was then calculated by differencing the two DEMs. In addition to snow depth, lidar provides elevation and vegetation height measurements (see Figure 2). This information can be used to improve the accuracy of snow depth estimates and can also serve as baseline predictors.

To ensure the accuracy of the snow depth data, all areas with snow depth greater than 2 meters were removed from the dataset. Additionally, the data was divided into three categories based on land cover type:

* Open areas: areas with no vegetation or vegetation heights lesser than 0.5 meters.
* Forested areas: areas with vegetation height greater than or equal to 0.5 meters
* A combination of both open and forested areas.

The resulting training dataset contains 3162483, 2154481, and 5316966 snow depth measurements for open areas, forested areas, and a combination of both, respectively. Table 1 shows the snow depth statistics for each land cover type in the training data. The mean snow depth is approximately 1.06 meters in open areas, which is slightly higher than that of the forested areas at 1.10 meters. The range of snow depth across all areas is from 0 meters, indicating no snow, to a maximum of 2 meters, demonstrating the variability in snow accumulation across different terrains.

A collage of different colored images

Description automatically generated

Figure 2. Lidar products from the study site. Top-left: Lidar-derived vegetation height with a color range from 0 to 20 meters, transitioning from darker hues (short) to yellow (taller vegetation). Top-right: ASO snow depth with a range from 0 to 2 meters, where greener areas indicate deeper snow and lighter patches represent minimal cover. Bottom-left: Lidar-derived elevation, spanning approximately 2950 to 3150 meters, with darker shades indicating lower terrains and yellow highlighting higher elevations. Bottom-right: L-Band InSAR Wrapped Phase with a color scale ranging from -π to +π, capturing ground displacements.

Table 1. Summary Statistics of L-band InSAR products and ASO-derived Snow Depth, Elevation, and Vegetation Height (all at 3m resolution) across various land cover types in the training set. The table provides the count, mean, standard deviation (Std), minimum (Min), 25th percentile (25%), median (50%), 75th percentile (75%), and maximum (Max) values for each product within open, forested, and the full dataset subsets.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Subset** | **Product** | **Count** | **Mean** | **Std** | **Min** | **25%** | **50%** | **75%** | **Max** |
| Open Areas | Amplitude | 3162483 | 0.12 | 0.07 | 0.02 | 0.09 | 0.11 | 0.13 | 3.55 |
| Unwrapped Phase | 3162483 | -7.92 | 0.81 | -15.22 | -8.44 | -8.01 | -7.33 | -0.06 |
| Coherence | 3162483 | 0.64 | 0.13 | 0 | 0.56 | 0.66 | 0.73 | 0.98 |
| Incidence Angle | 3162483 | 0.92 | 0.12 | 0.28 | 0.84 | 0.94 | 1 | 1.95 |
| Bare Earth DEM | 3162483 | 3044.3 | 57.66 | 2492.03 | 3019.76 | 3035.7 | 3076.63 | 3157.36 |
| Wrapped Phase | 3162483 | -1.39 | 0.95 | -3.14 | -2.06 | -1.55 | -0.88 | 3.14 |
| Elevation (m) | 3162483 | 3048.59 | 57.67 | 2501.13 | 3023.21 | 3039.76 | 3081.8 | 3168 |
| Snow Depth (m) | 3162483 | 1.06 | 0.29 | 0 | 0.87 | 1.07 | 1.26 | 2 |
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|  |  |  |  |  |  |  |  |  |  |
| Forested Areas | Amplitude | 2154481 | 0.39 | 0.18 | 0.01 | 0.28 | 0.35 | 0.46 | 6.11 |
| Unwrapped Phase | 2154481 | -8.73 | 0.81 | -15.26 | -9.18 | -8.67 | -8.23 | -0.47 |
| Coherence | 2154481 | 0.48 | 0.15 | 0.01 | 0.36 | 0.47 | 0.59 | 0.97 |
| Incidence Angle | 2154481 | 0.79 | 0.22 | 0.14 | 0.65 | 0.82 | 0.94 | 1.95 |
| Bare Earth DEM | 2154481 | 2957.34 | 154.86 | 2490.96 | 2868.17 | 3003.47 | 3076.56 | 3157.38 |
| Vegetation Height (m) | 2154481 | 8.46 | 5.25 | 0.5 | 4.15 | 8.16 | 12.08 | 34.62 |
| Wrapped Phase | 2154481 | -1.03 | 1.67 | -3.14 | -2.26 | -1.69 | -0.09 | 3.14 |
| Elevation (m) | 2154481 | 2969.23 | 153.87 | 2500.2 | 2881.58 | 3015.56 | 3087.97 | 3168 |
| Snow Depth (m) | 2154481 | 1.1 | 0.26 | 0 | 0.95 | 1.11 | 1.25 | 2 |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Full Dataset | Amplitude | 5316966 | 0.23 | 0.18 | 0.01 | 0.1 | 0.15 | 0.33 | 6.11 |
| Unwrapped Phase | 5316966 | -8.25 | 0.9 | -15.26 | -8.76 | -8.28 | -7.69 | -0.06 |
| Coherence | 5316966 | 0.57 | 0.16 | 0 | 0.46 | 0.59 | 0.7 | 0.98 |
| Incidence Angle | 5316966 | 0.87 | 0.18 | 0.14 | 0.77 | 0.9 | 0.99 | 1.95 |
| Bare Earth DEM | 5316966 | 3009.08 | 116.27 | 2490.91 | 3007.16 | 3031.87 | 3076.62 | 3157.36 |
| Vegetation Height (m) | 5316966 | 3.47 | 5.3 | 0 | 0 | 0.18 | 6.38 | 34.62 |
| Wrapped Phase | 5316966 | -1.24 | 1.3 | -3.14 | -2.14 | -1.6 | -0.76 | 3.14 |
| Elevation | 5316966 | 3016.44 | 114.41 | 2500.2 | 3012.44 | 3036.38 | 3084.2 | 3168 |
| Snow Depth (m) | 5316966 | 1.07 | 0.28 | 0 | 0.9 | 1.09 | 1.26 | 2 |

### L-band InSAR Products

Interferometric Synthetic Aperture Radar (InSAR) is a radar technique that calculates the distance between the radar antenna and the ground surface by comparing the phase difference of two or more radar images (50). InSAR uses two SAR images to generate an interferogram, which is a measure of the change in distance between the ground and the SAR sensor between the two image acquisitions. InSAR can be used to measure a variety of surface changes, including deformation, subsidence, and ice sheet movement.

The L-band SAR frequency range is 1 to 2 gigahertz (GHz), which corresponds to a wavelength range of 30 to 15 centimeters (cm). L-band SAR signals can penetrate several meters of snow (19) and a useful degree of vegetation, which allows the InSAR data to be used to measure snow depths, even in forested areas. L-band SAR signals are also less sensitive to atmospheric moisture than other SAR bands, which makes the InSAR data more reliable in all weather conditions. As part of the 2017 SnowEx, the NASA Jet Propulsion Laboratory (JPL) L-Band UAVSAR sensor was flown across Grand Mesa during February and March. This L-band data serves as the input features in our study.

The following L-band InSAR products, all of which are at 3-meter resolution, were used in this work:

* **Coherence (CO):** Coherence is a measure of the similarity between two SAR images. Areas with high coherence have similar phases and amplitude in both images, indicating little change in the landscape between the two radar acquisitions. Low coherence values indicate that the landscape has changed significantly or that there is noise in the data.
* **Incidence Angle (IA):** The incidence angle is the angle between the SAR beam and the ground surface. The incidence angle affects the backscatter signal from the ground, and it must be considered when interpreting InSAR data.
* **Bare Earth DEM (BDEM):** A bare earth digital elevation model (DEM) is a digital representation of the ground surface without vegetation or other features. Bare earth DEMs are used to remove the effects of topography from InSAR data.
* **Wrapped Phase (WP):** The wrapped phase is the phase difference between the two SAR images. In SAR and interferometry, phase is crucial. Each pixel in a SAR image has a phase value that corresponds to the distance between the satellite sensor and the ground target, modulated by the wavelength of the radar signal. The phase of a radar wave at any given point is influenced by the travel distance of the radar signal to that point and back. When two SAR images are acquired from slightly different positions in repeat-pass interferometry, the phase difference between corresponding pixels in the two images can be calculated. This phase difference, referred to as the interferometric phase or wrapped phase, contains valuable information about the ground surface, such as elevation or displacement. The term "wrapped" refers to the fact that the phase values are cyclic, i.e., a phase value of 2π is equivalent to a phase value of 0. Thus, the phase values "wrap" around at intervals of 2π.
* **Amplitude (AM):** The amplitude is the magnitude of the backscatter signal from the ground. For example, surfaces that are rough at the scale of the radar wavelength or have a higher dielectric constant (such as wet surfaces) will generally backscatter more of the radar signal and thus have a higher amplitude. Conversely, smoother surfaces or those with a lower dielectric constant will backscatter less of the signal, resulting in a lower amplitude.
* **Unwrapped Phase (UW):** The unwrapped phase is the phase difference between the two SAR images after it has been processed to remove the cycle “wrapping”. It provides a continuous measure of the distance between the radar antenna and the ground surface, which is crucial for generating accurate topographic maps and measuring changes in the Earth's surface.

It is important to note that InSAR measures changes in surface distance or surface deformation. Therefore, to use InSAR for estimating total snow depth, we must assume that the snow patterns are consistent. In other words, we must assume that the total snow depth before melt starts displays similar patterns to snow depth changes. This assumption is generally valid, but it is important to be aware of it. L-band InSAR data will be available from the NISAR mission at a 12-day temporal resolution, which has the potential to complement existing snow depth measurement practices. The InSAR products are displayed in Figure 3, and their summary statistics are displayed in Table 1.

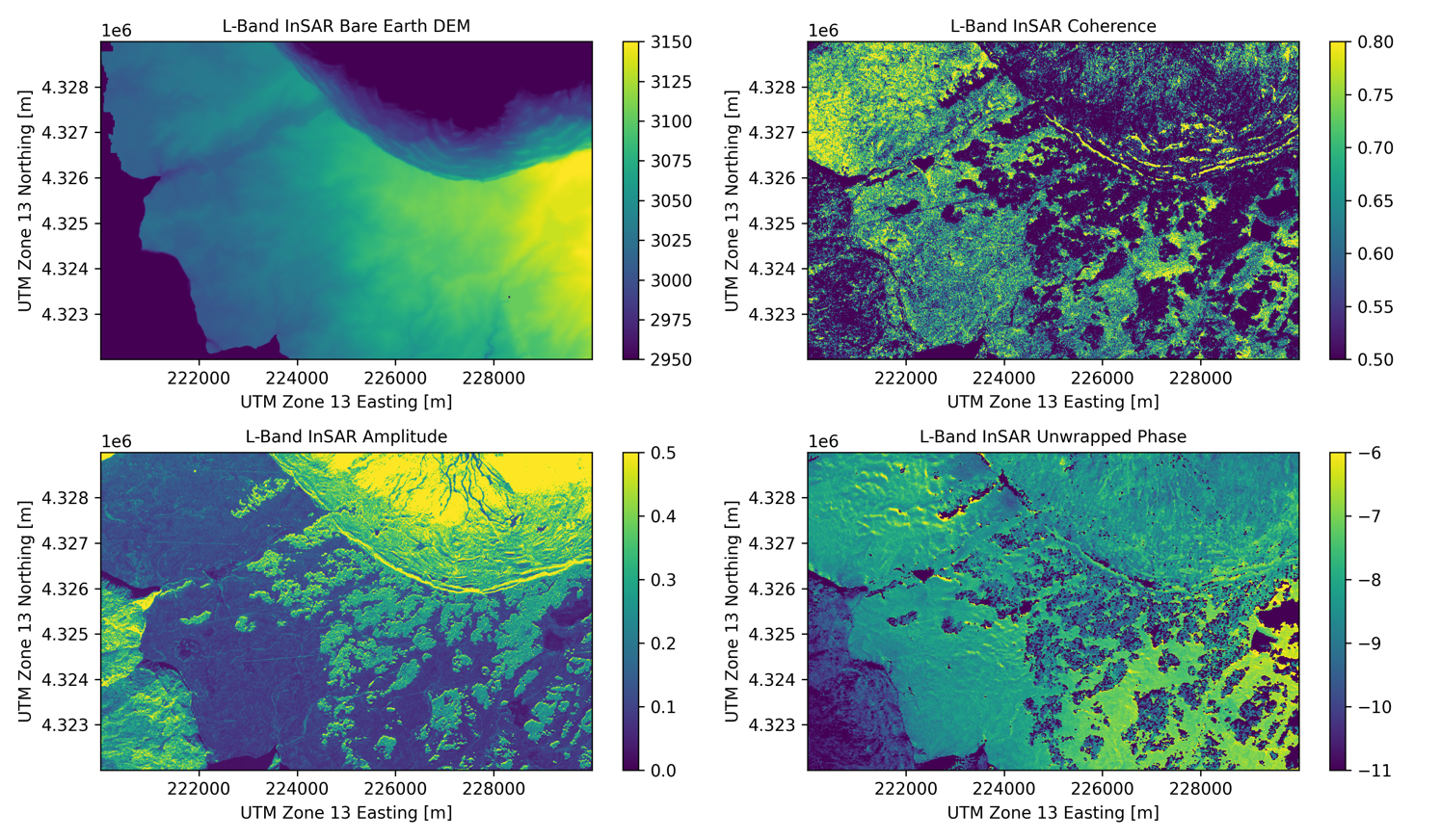


Figure 3. L-band InSAR products: Displaying (top-left) the Bare Earth DEM illustrating elevation variances between 2950 and 3150 meters, (top-right) Coherence metrics highlighting values from 0.50 to 0.80, (bottom-left) Amplitude values capturing signal intensities between 0.0 and 0.5, and (bottom-right) the Unwrapped Phase revealing phase shift values from roughly -11 to -6.

For each land cover type, we fitted three models:

* Model 1: The first model uses only elevation as input, and this model serves as the baseline model in this work. Mathematically, we write:

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* Model 2: This model uses only InSAR products as input features. The model is represented mathematically as follows:

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* Model 3: This model combines the InSAR products and the Lidar vegetation height. This is used to evaluate the effect of vegetation height on the model performance.

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| --- | --- | --- |
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Where is the various learning machines fitted, is the vegetation height, and is the snow depth. It is important to note that the open areas only have models 1 and 2 because, in the open areas, vegetation height is assumed to be 0.

## Methods

Our methodology for estimating snow depth from InSAR products using machine learning models comprised several key steps, which are outlined below.

### Data Preprocessing

Data preprocessing was the foundational step in our methodology, preparing the dataset for compatibility with our Machine Learning algorithms. The raw remote sensing data spanned numerous rater layers at a native 3m resolution. Each rater layer represents approximately 7km x 10km area on the ground, with each pixel representing an averaged value over a 3m x 3m area. We first restructured the raster into pixel-wise tabular data frames to enable vector-based preprocessing. After concatenating all variables, we inspected for noise, missing observations, and outliers that could potentially affect the models' learning. All missing values, snow depths greater than 2 meters, and all pixel values coded as -9999 were dropped from the analysis. This is because erroneous pixels were coded as -9999 from the data source, and snow depths exceeding 2 meters were deemed less likely based on expert consultation and probe measurements conducted at the study site. No missing value imputation was done as we have an abundance of data points (> 7 million dense pixel observations). This maintained dataset integrity without needing imputation techniques that can propagate uncertainties. These data cleaning steps resulted in usable data of 6646208 observations.

After data cleaning, we split our data into three disjoint subsets:

* Training Set: 80% of the data was used for training the models.
* Tuning Set: 10% of the data was used for hyperparameter tuning and to prevent overfitting during model training. Note that using a tuning set for hyperparameter optimization is an alternative to cross-validation for large datasets.
* Testing Set: The remaining 10% of the data was used to test the models' performance.

Following the partitioning, all input features were converted into a common scale with a mean of zero and a standard deviation of one using the z-score standardization approach. This will prevent potential domineering effects from variables with larger raw value ranges during model training. We have chosen the z-score standardization approach because it ensures outliers are handled more properly (51). The normalized version of every observation in feature is obtained by:

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Where is the standardized value, and are the mean and standard deviation of variable from the training set.

### Model Selection and Training

Once the data were appropriately prepared, we proceeded to the next phase: model selection and training. We evaluated and compared three machine learning algorithms: Extremely Randomized Trees (Extra Trees), eXtreme Gradient Boosting (XGBoost), and artificial neural networks (ANN). These models were chosen because they have been shown to perform well on a variety of remote sensing data (52,53). For hyperparameter tuning, we used the Optuna framework (54). Optuna is an open-source hyperparameter optimization framework in Python that is designed to optimize the hyperparameters for machine learning models. Unlike traditional grid search, Optuna utilizes a Tree-structured Parzen Estimator (TPE) algorithm (55), a Bayesian optimization algorithm, which tends to find optimal hyperparameters faster and with fewer function evaluations compared to grid search. This efficient search approach proved to be especially advantageous given the large dataset involved in our study. The details of the hyperparameters tuned for each model can be found in Table A1 in the appendix.

#### Extremely Randomized Trees

Extra Trees is an ensemble algorithm that averages predictions across a pre-defined number of randomized decision trees to improve accuracy and control overfitting. The "extra" in Extra Trees stands for extremely randomized, indicating that at each split in the learning process, the features and cut points are chosen in a random manner, hence reducing the variance of the model. Due to this extreme randomization, Extra Trees are faster than Random Forest and hence suitable for large datasets. Mathematically, the prediction from an extra tree regressor can be expressed as:

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Where is the total number of trees in the ensemble and is the prediction of the *t*-th tree for the input vector .

In our analysis, the optimal hyperparameters for the Extra Trees model were identified using Optuna. The optimal number of trees in the forest was found to be 100. The maximum depth of the trees was set to None, indicating that the nodes are expanded until they contain fewer than the minimum samples required to split, allowing the trees to grow to their full depth. Finally, the mean squared error was used as the measure of split quality at each node. These hyperparameter settings were found to provide the best performance on the tuning set. The details of these hyperparameters can be found in Table A1 in the appendix.

#### eXtreme Gradient Boosting

XGBoost is another ensemble learning algorithm, but unlike Extra Trees, it builds a sequence of decision trees instead of a forest of decision trees. XGBoost operates by sequentially constructing weak learners (decision trees), with each tree aiming to correct the errors made by the previous one. This process of sequential error correction is known as *Boosting*. At each iteration, a weak learner is trained to approximate the gradient of the loss function (the residual errors). Boosting is then achieved by iteratively updating the residual errors when a new learner is added to the ensemble. This methodology of leveraging the gradient of the loss function to guide the boosting process is known as *Gradient Boosting*. XGBoost uses a variant of the Gradient Boosting algorithm called *Newton boosting*, which attaches weights to the residuals through the Hessian (second-order derivative of the loss function). With this, observations with larger errors have more weight. XGBoost takes Newton boosting to the extreme by regularizing the loss functions and introducing efficient tree learning with parallelizable implementation. This “extreme” attribute of XGBoost makes it suitable for large datasets.

In our analysis, the optimal hyperparameters for the XGBoost model were identified using Optuna, as detailed in Table A1 in the appendix. The objective was set to minimize the squared error between the predicted and actual values. We used a learning rate of 0.05 to control the step size at each iteration while moving toward a minimum of the loss function. The depth of the trees was set to grow unrestricted to allow the model to learn complex relationships in the data. A total of 1000 trees were grown using a histogram-based training method to accelerate the training process.

#### Artificial Neural Network

Artificial Neural Network (ANN) is an ensemble of linked artificial neurons organized into input, hidden, and output layers. Each neuron receives inputs, performs mathematical operations on these inputs, and passes the output to the next layer. Every connection between nodes has an associated weight; the optimal weights are learned during training. The input layer holds the features, with one node per input feature, and the output layer holds the network’s prediction. The number of neurons in the hidden layers is determined through model tuning. In this study, we employed a Feed-forward Neural Network (FNN), a type of ANN where connections between nodes do not form a cycle, making it suited for learning non-linear and complex relationships in data.

We designed a five-layer FNN using the PyTorch framework for our analysis. The architecture comprises one input layer, three densely connected hidden layers with 2048, 1500, and 1000 nodes, respectively, and one output layer. Rectified Linear Unit (ReLU) activation functions were used in the hidden layers to introduce non-linearity, while a linear activation function was employed in the output layer for snow depth estimation. The model was trained using the Adam (56) optimization algorithm with a learning rate of 0.0001 to minimize the Mean Squared Error Loss (MSELoss) between the predicted and actual snow depths. The training was conducted over 15 epochs with a batch size of 128. The hyperparameters for the FNN model were optimized using Optuna, with the details of the tuned hyperparameters presented in Table A1 in the appendix.

A diagram of a model

Description automatically generated

Figure 4. A flowchart illustrating the step-by-step methodology of our model training.

# Results

## Snow Depth Estimation

Table 2. Comparative Performance of FNN, Extra Trees, and XGBoost across Different Land Cover Types and Model Configurations. Values in Bold Fonts are the Best for each Metric.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model Name** | **Land Cover** | **Model Number** | **RMSE** | **MBE** | **R2** |
| FNN | Full Dataset | Model 1 | 0.2496 | 0.0115 | 0.218 |
| Model 2 | 0.165 | 0.0097 | 0.658 |
| Model 3 | 0.1554 | -0.009 | 0.6966 |
|  |  |  |  |  |
| Forested Areas | Model 1 | 0.2279 | 0.0059 | 0.2503 |
| Model 2 | 0.1688 | 0.0035 | 0.5888 |
| Model 3 | 0.1515 | -0.001 | 0.6686 |
|  |  |  |  |  |
| Open Areas | Model 1 | 0.2392 | 0.0024 | 0.3369 |
| Model 2 | 0.1596 | 0.0097 | 0.7047 |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
| Extra Trees | Full Dataset | Model 1 | 0.2363 | 0.0003 | 0.2989 |
| Model 2 | 0.1013 | 0.0003 | 0.8712 |
| Model 3 | 0.0991 | 0.0003 | 0.8767 |
|  |  |  |  |  |
| Forested Areas | Model 1 | 0.2065 | 0.0003 | 0.3844 |
| Model 2 | 0.1039 | **0.000041** | 0.8441 |
| Model 3 | 0.1049 | -0.0005 | 0.8413 |
|  |  |  |  |  |
| Open Areas | Model 1 | 0.2261 | 0.0012 | 0.4073 |
| Model 2 | 0.0998 | 0.0002 | 0.8845 |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
| XGBoost | Full Dataset | Model 1 | 0.2485 | 0.0003 | 0.2246 |
| Model 2 | 0.0974 | 0.0004 | 0.881 |
| Model 3 | **0.0928** | 0.0002 | 0.8919 |
|  |  |  |  |  |
| Forested Areas | Model 1 | 0.2275 | -0.0002 | 0.2531 |
| Model 2 | 0.1023 | 0.0002 | 0.8489 |
| Model 3 | 0.0984 | -0.0004 | 0.8601 |
|  |  |  |  |  |
| Open Areas | Model 1 | 0.2381 | 0.0009 | 0.3428 |
| Model 2 | 0.0937 | 0.0001 | **0.8982** |

We developed and evaluated FNN, Extra Trees, and XGBoost for estimating snow depth using repeat-pass InSAR data. Models were assessed on open terrain, forested regions, and a combined dataset with both land cover types. Key accuracy metrics included root mean square error (RMSE), mean bias error (MBE), and coefficient of determination (R2), as summarized in Table 2 and displayed in Figure 5. All results reported are based on the held-out testing set.

|  |
| --- |
| (a) |
| (b) |
| (c)    Figure 5. Comparative Performance Metrics of Snow Depth Estimation Models. Panel (a) displays the RMSE across all models, illustrating the accuracy of snow depth predictions. Panel (b) presents the *R2* values, reflecting the proportion of variance in the ASO snow depth that is predictable from the input features. Panel (c) shows the Mean Bias Error (MBE), indicating the average bias in the estimations compared to ASO measurements. |

Three iterative versions were implemented for each model. Model 1 used only elevation data, and it serves as the baseline model. Model 2 incorporated InSAR layers, including amplitude, coherence, and phase. Model 3 added vegetation height from lidar. By comparing model performance for Model 1 vs 2 vs 3, we evaluated the incremental value of the remote sensing predictors for improving snow depth estimation beyond using topography alone.

Our model comparison revealed distinct performance variations across different land cover types and model configurations. The baseline model provided a foundational understanding but demonstrated limited predictive power with *R2* values ranging from 0.218 to 0.4073 across the full dataset, forested and open areas.

Incorporating InSAR-derived attributes (Model 2) significantly increased the precision of snow depth estimates. This model configuration increased the *R2* values significantly, with the highest jump observed in open areas (*R2* = 0.8982). This improvement underscores the potential of InSAR data in capturing key variables influencing snow depth. The performance in forested areas also improved, reflected by an *R2* of 0.8489, which indicates that InSAR parameters contribute valuable information even in vegetated landscapes. Across the entire study area, the model attained an *R2* of 0.881, which is also a substantial increase from the baseline performance.

The addition of vegetation height to InSAR parameters in Model 3 further enhanced our predictions across all terrains. Adding vegetation height provided further gains, especially in forested areas where signal attenuation is higher. *R2* ranges from 0.6686 to 0.8601 for forested areas and 0.6966 to 0.8919 for the full dataset. While these findings are encouraging, they also highlight the need for further research to understand the multifaceted nature of snow depth variability.

XGBoost consistently outperformed other models across most configurations and land covers. Particularly, when applied to the full dataset, XGBoost’s Model 3 achieved the lowest RMSE (9.28 cm) and the second highest *R2* (0.8919), suggesting a superior ability to capture the variance in snow depth across varied terrains. For this work, XGBoost with Model 3 configurations on the full dataset will be considered the best model. Moving forward, results will be based on Model 3.

A diagram of a graph

Description automatically generated with medium confidence

Figure 6. XGBoost Residual Analysis. Left: A hexbin density plot comparing ASO-measured snow depths with predictions from the XGBoost model. Right: A histogram showing the frequency distribution of the residuals (ASO - XGBoost predicted snow depth)

In Figure 6, the hexbin density plot on the left illustrates the correlation between the estimated and observed snow depths, with the color intensity indicating the frequency of data points within each hexagonal bin. The diagonal concentration suggests a strong positive relationship, indicating the model's effectiveness in capturing the general trend of snow depth variability. The histogram on the right panel provides insights into the distribution of residuals, which are the differences between the ASO measurements and the XGBoost predictions. The narrow, almost symmetrical spread around zero implies that the model's predictions are predominantly accurate with minimal bias, although a slight skew towards negative values indicates a tendency for underestimation in certain instances.

A green and blue color

Description automatically generated with medium confidence

Figure 7. The left panel illustrates ASO sow depth with overlaid in-situ measurements (red circles), providing a reference for validation. The center panel displays the snow depth as predicted by the XGBoost model, showcasing the model's spatial estimation capabilities. The right panel quantifies the prediction error, highlighting areas of discrepancy and offering insights into model performance across the landscape.

In Figure 7, the left panel depicts ASO snow depths, with in-situ depth measurements marked by red circles, serving as ground truth for validation purposes. The center panel represents the XGBoost model’s predictions, which visually appear to capture the spatial variability observed in the Lidar data, suggesting good model performance. The right panel quantifies the prediction error, visually encoded to emphasize areas of underestimation or overestimation by the model. The right panel indicates no specific patterns of underestimation versus overestimation.

## Feature Importance

To quantify the contribution of individual features to snow depth prediction, we employed two complementary methods: the gain metric from the XGBoost model and SHapley Additive exPlanations (SHAP) (57). The *gain*, derived from the XGBoost framework, measures the average contribution of each feature to reducing the mean squared error loss across all trees within the model. This method offers an initial insight into the relative importance of features based on their utility in constructing the predictive model. However, gain-based importance can be misleading for high cardinality (many unique values) features and may not fully capture the nuanced interactions between features. To address this, we also utilized SHAP values, which provide a more comprehensive and stable measure of feature importance by considering the contribution of each feature to every possible combination of features in the dataset (58). SHAP originates from concepts in cooperative game theory, and it computes the importance of a feature by distributing the predictive contribution among features in a model, akin to dividing payoffs among collaborating players. Although SHAP analysis is computationally expensive, particularly for large datasets, its ability to offer clear and consistent interpretations of the features' impact on the model's output makes it a valuable tool for in-depth feature importance analysis.

The feature importance displayed in Figure 8 is based on XGBoost’s Model 3 for the full dataset since this configuration yielded the best RMSE. Using SHAP values, the most influential variables were unwrapped phase, bare earth DEM, and amplitude. Gain-based importance also showed unwrapped phase, DEM, and amplitude as the top 3 predictors, aligning with SHAP. This indicates their high sensitivity for estimating snow depth from InSAR.

A close-up of a graph

Description automatically generated

Figure 8. Comparative Analysis of Feature Importance: SHAP vs. XGBoost Gain for Model 3 (Full Dataset).

Unwrapped phase and bare earth DEM were consistently the top two predictors, highlighting the importance of topography and absolute phase values sensitive to path length. Amplitude backscatter ranked 3rd, providing information on surface roughness and structure. When stratified by land cover, unwrapped phase and DEM remained among the top features in open areas, while Incidence Angle rose in significance, followed by Amplitude. For forested areas, Bare Earth DEM was the leading feature, highlighting the complex relationship between the topography and snow accumulation beneath the canopy. Vegetation height also became more important in forests, ranking 3rd compared to 5th overall. This confirms vegetation's role in attenuating radar signals in dense cover. Feature importance plots for forested and open areas can be found in Figure A3 in the appendix.

## In-Situ Validation

To provide an independent assessment of model accuracy, predicted snow depths were validated against in-situ observations collected as part of the 2017 NASA SnowEx campaign (59). Manual measurements were taken using either a standard, handheld 3-meter-long probe or a shorter GPS-equipped 1.2-meter MagnaProbe. The GPS technology in the MagnaProbe provides a position accurate to ±2.5 m (60). During the intense observation period (February 6th to 25th), a total of 27,081 snow depth measurements were taken at intervals of approximately 3 meters.

Validation was done using a 3-meter buffer approach, where the average snow depth within a 3-meter radius of each in-situ observation was calculated. The ASO snow depth used for developing our models was from February 8. Hence, the data used for validation were measurements taken on February 8 alone. A total of 1777 depth measurements were taken on February 8.

The buffer analysis yielded 234 observations for comparison against the ASO dataset and the complete model prediction (training and testing prediction). This analysis resulted in 69 observations when the buffer analysis was applied only to the testing set. The validation details are displayed in Table 3.

The lidar snow depth achieved an RMSE of 15.85 cm and *R2* of 0.332 versus in-situ measurements, which aligns with the ~15 cm accuracy of airborne lidar snow depths. Snow depths predicted by XGBoost across the entire study area achieved a similar RMSE of 16.02 cm and *R2* of 0.318 compared to the in-situ observations. This confirms effective generalization without substantial overfitting. When considering the testing set alone, the model exhibited an RMSE of 19.705 cm and an *R2* of 0.095, indicating decreased predictive accuracy.

Table 3. Validation of Lidar and XGBoost snow depth predictions against in-situ observation

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **RMSE (cm)** | **R2** | **Sample Size** |
| ASO Lidar | 15.853 | 0.332 | 234 |
| XGBoost (whole) | 16.020 | 0.318 | 234 |
| XGBoost (test) | 19.705 | 0.095 | 69 |

Overall, the in-situ validation provides confidence in the modeling framework, with XGBoost predictions showing accuracy approaching the lidar training data. The low *R2* obtained from validation using only the testing might be due to small sample size. It is plausible that a larger set of in-situ observations could enhance the model's validation, potentially leading to improvements in its generalizability.

A graph of a graph showing a line and a red line

Description automatically generated with medium confidence

Figure 9. Snow depth validation using in-situ measurements: The closer the data aligns with the diagonal line, the more accurate the snow depth estimates are in comparison to in-situ measurements. Left: XGBoost (over the entire dataset) versus in-situ measurements. Center: ASO depths versus in-situ depths. Right: XGBoost (testing set) versus in-situ measurements.

## Discussion

### Model Performance

This study explored the potential of machine learning for snow depth prediction using data from NASA JPL's UAVSAR sensor, which employs L-band radar for InSAR measurements. We developed and compared three machine learning algorithms – Extra Trees, XGBoost, and Feed-Forward Neural Networks, each selected for their robustness in handling complex datasets. To accommodate the heterogeneity of the landscape, we partitioned the study area into forested and open regions, as well as a combined dataset. Within each land cover category, we developed three distinct models: a baseline model using only elevation data, a second model incorporating InSAR parameters, and a third model combining InSAR parameters with vegetation height to capture the complex dynamics in snow deposition. Notably, the addition of vegetation height improved model performance across all area partitions, a finding that aligns with the importance of vegetation structure in influencing snow accumulation and melt patterns. Vegetation height directly influences snow distribution patterns, with taller vegetation potentially intercepting snowfall and affecting the underlying snowpack, this finding aligns with the works of (61,62). XGBoost consistently outperformed other algorithms, achieving (RMSE = 9.28 cm, *R2* = 0.89) for the combined dataset, (RMSE = 9.84 cm, *R2* = 0.86) in forested areas, and (RMSE = 9.37 cm, *R2* = 0.90) for open areas. The model performed better in open areas than in forested areas. This is likely because forests have a more complex structure than open areas, which can scatter and attenuate the InSAR signal. Additionally, trees can intercept snowfall, making it more difficult to measure snow depth beneath the canopy accurately. The improved performance of the model in open areas is also good news, as open areas are often more important for water resources than forested areas. For example, snowmelt in open areas contributes directly to streamflow, while snowmelt in forested areas is often delayed due to the buffering effect of the trees. Although our models performed better in open areas, the difference in accuracies is insignificant. This can be attributed to the fact that L-band data is less sensitive to the forest structure. This finding is consistent with the work of Hosseini (63), where he found the L-band to be less sensitive to the forest structure than P-band data. The best RMSE was found on the combined dataset, suggesting that the vegetation height added useful information that helped the model learn across diverse terrain. This enhanced performance implies the potential of a single and robust model to reliably estimate snow depth in varied terrains, which can enhance the efficiency of large-scale snow monitoring efforts.

### Feature Importance

We conducted feature importance using SHAP and gain metrics from XGBoost. This is because the SHAP feature importance provides more reliable and stable ranking, and the gain metrics can be misleading for features with high cardinality. Figure 8 shows an agreement between the importance of the feature from both SHAP's and XGBoost’s gain. Unwrapped phase, bare earth DEM, and amplitude are the top three influential features. Unwrapped phase emerged as the most influential predictor, as it is a direct indicator of topographic and snow cover changes, hence its strong influence on the model’s predictive power. The bare earth DEM's importance is similarly intuitive; it represents the underlying topography, which is fundamental in understanding snow accumulation patterns. Topography relates to snow depth through factors like elevation, slope, and aspect (64). Higher elevations experience more snowfall, north-facing slopes retain snowpack longer in the northern hemisphere, and leeward areas develop drifts. The bare earth DEM provides the terrain context to model these topological influences on snow accumulation. Amplitude, ranking third in importance, suggests that the backscatter intensity, which is affected by surface characteristics, including roughness and snow density, is also a significant predictor. This aligns with findings in literature where backscatter properties have been directly correlated with snow depth. Kings et al. (65) found a strong correlation between Ku-band backscatter and snow depth in the tundra. The remaining features, like incidence angle and coherence, showed lower importance. One potential reason is decorrelation over the interferometric interval on the dynamic snow surface. Further analysis is warranted to fully explain the relative feature contributions.

When the data was stratified by open vs forested land cover, some notable differences emerged in the feature importance (Figure S3). In open areas, unwrapped phase and bare earth DEM remained the top two predictors, followed by incidence angle and then amplitude. This aligns with the overall importance rankings and reinforces the primacy of topography and phase for snow depth estimation in open terrain. However, in forested regions, bare earth DEM took the top spot, followed by incidence angle and vegetation height. Unwrapped phase dropped to fourth. The decreased ranking of the unwrapped phase in forests is likely because dense vegetation attenuates and scatters the radar signal, reducing the phase’s sensitivity to snow depth variations below the canopy. Meanwhile, vegetation height became the third most important variable, confirming its role in correcting for signal attenuation effects in forested areas. These land cover-specific feature importance findings provide useful insights. The unwrapped phase appears most valuable in open areas where radar penetration is uncompromised, while bare earth DEM and vegetation structure take precedence in forests. This points to potential pathways for improving InSAR snow depth retrieval through optimal parameterization tailored to different land cover regimes.

### In-situ Validation

Validation against in-situ snow depth measurements provides an independent assessment of model accuracy. The lidar training data achieved 15.85 cm RMSE versus in-situ points, aligned with its expected accuracy. For the optimized XGBoost model, predictions across the entire study area achieved 16.02 cm RMSE compared to in-situ data, indicating minimal overfitting during training. The model effectively learned real relationships between InSAR signals and physical snow depth. When evaluating only the reserved 10% testing subset, XGBoost RMSE increased slightly to 19.71 cm. This highlights some generalization errors, likely because the testing data within the 3m buffer of in-situ depths did not fully represent the diversity of land cover and terrain conditions across the study area. However, further investigation is warranted to ascertain this claim. In conclusion, the close performance of the XGBoost model to the ASO data in terms of RMSE is encouraging, particularly considering the complexities associated with modeling snow depth. Future work could explore the integration of additional features, model refinement, and an expanded in-situ measurement dataset to further enhance model accuracy and reliability.

## Answers to Objectives

### Objective 1: Effectiveness of L-band InSAR Products for Snow Depth Prediction

Our study successfully demonstrated the potential of L-band InSAR products for snow depth estimation using machine learning algorithms. The XGBoost model achieved promising performance, with an RMSE of 9.37 cm and an *R²* of 0.90 on the test dataset when only InSAR products were used as predictors, indicating the effectiveness of L-band InSAR data in capturing the information necessary for accurate snow depth estimation. The comprehensive result can be found in Table 2. These findings lay a foundation for the utilization of data from the upcoming NISAR mission, which will provide global L-band InSAR coverage.

### Impact of Land Cover on Model Performance

The performance of the models varied across land cover categories, with slightly better results in open areas compared to forested areas. This difference is likely attributable to the complex structure of forests, which can scatter and attenuate the InSAR signal, making it more challenging to accurately measure snow depth beneath the canopy. However, the integration of vegetation height data improved model accuracy across all land cover types, indicating that accounting for vegetation structure is critical in snow depth modeling using InSAR data.

### Objective 3: Understanding the Relative Importance of Input Features

Through the application of SHAP and gain metrics, we identified the key factors influencing snow depth estimation. Unwrapped phase, bare earth DEM, and amplitude were identified as the most influential features, consistent with previous studies using InSAR data for snow depth estimation. These features capture the essential physical parameters governing snow accumulation and melt patterns. See Figure 8 for feature importance.

# Conclusion and Future Work

This study serves as a proof of concept for the potential of machine learning to estimate snow depth using L-band InSAR data. The XGBoost model demonstrated promising performance, and the feature importance analysis provided valuable insights into the relationships between input features and the target variable. The upcoming NISAR mission, with its global L-band InSAR coverage, presents a unique opportunity to further advance this approach. With the availability of NISAR data, we can expand the validation dataset, incorporate additional data sources, and explore alternative machine learning approaches, potentially leading to even more accurate snow depth estimation. The success of this approach hinges on the availability of representative training data. With sufficient and diverse training data, machine learning models can effectively capture the complex relationships between snow depth and its influencing factors, enabling accurate snow depth prediction. With the advent of NISAR and continued research efforts, we can harness the power of machine learning to potentially improve water resource management.

However, further investigation is needed to fully realize the potential of this approach. Specifically, future work will focus on the following:

* Exploring model transferability: Can we develop models that perform well on new datasets without the need for retraining?
* Analyzing model performance at 10-50 meter resolution: Can we achieve similar performance using lower-resolution data, which is more widely available?
* Incorporating advanced computer vision approaches: Can we improve performance using 2D estimation methods such as Convolutional Neural Networks (66) and Vision Transformers (67) instead of pixel-wise approaches?

By addressing these questions, we can further advance the field of machine learning-based snow depth prediction and contribute to more accurate and reliable snow monitoring and forecasting systems.

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