Snow Depth from Satellite Laser Altimetry: Co-registration, Bias Correction, and Statistical Downscaling

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Introduction

How to get snow depth by satellite altimetry?

This study presents a workflow by employing careful data co-registration, benchmarking of DEM uncertainties using ICESat-2 surface elevations from snow-free conditions as a reference, and applying a machine learning-based bias correction to derive accurate snow depths. Consequencely, the snow depth maps are then generated using an XGBoost regressor by statistically downscaling ERA5 Land snow depth timeseries with the derived snow depth, incorporating terrain, vegetation, and wind parameters (Fig. 1).

In the study case of mainland Norway, we collected 3968 granules of ICESat-2 coverage from 2018 Oct 14 to 2022 Oct 12. After dropping NaN values, our measurements on land surface comprised 14,918,709 segments. Of these segments, 4,9590,085 were snow-free on land excluding moving terrain (i.e., permanent ice and inland water), while 9,2130 ,030 segments had snow cover. We used the national DEM products DTM1 and DTM10 to make elevation differences with ICESat-2 segments. To evaluate the potential applicability of our approach globally and assess the impact of vegetation on our results, we used Copernicus GLO30 and FABDEM (Forest And Buildings removed Copernicus DEM). Finally, we validated our snow depth products via airborne lidar snow surveys.

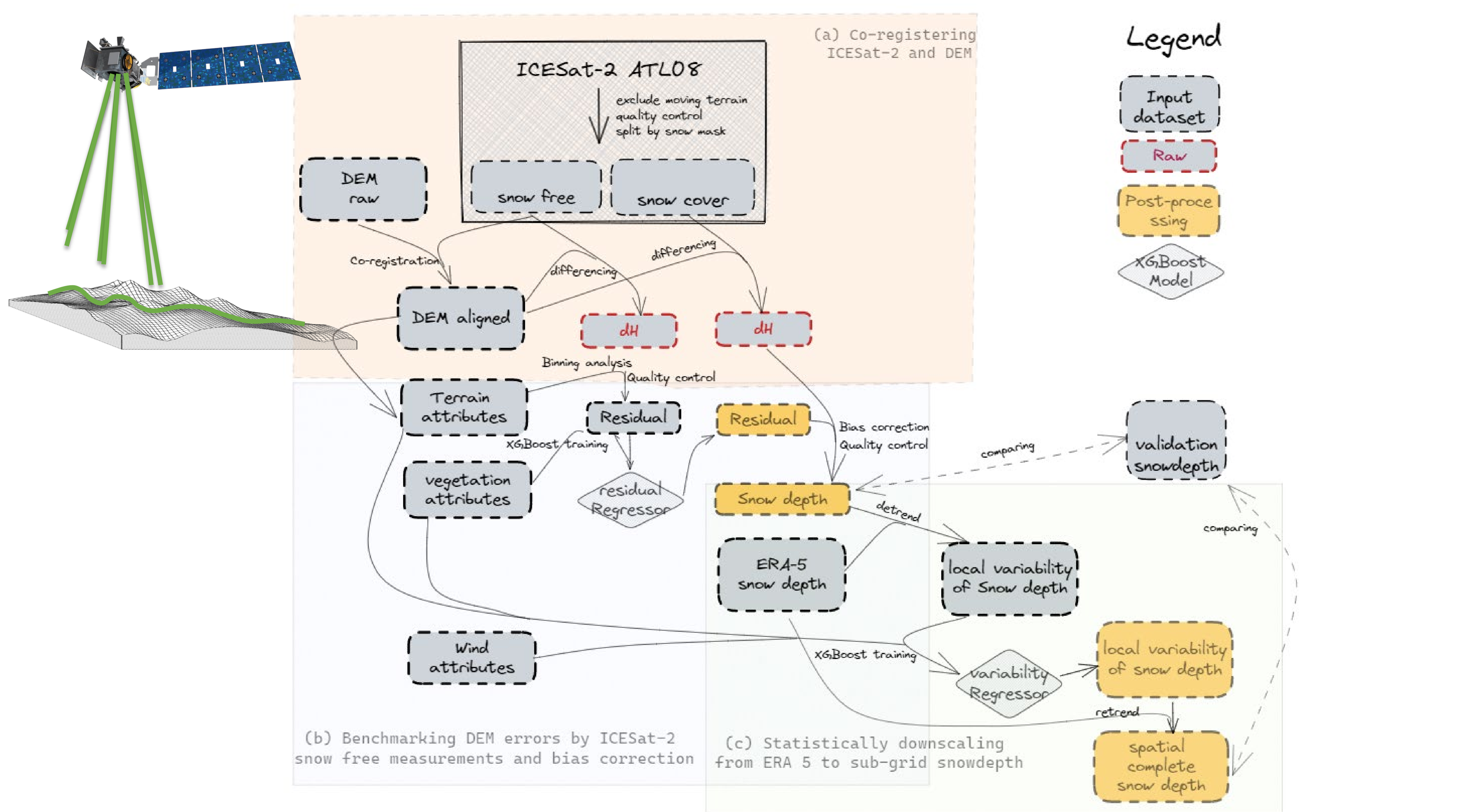


Fig 1. The proposed methodology. Firstly, DEMs are co-registered and aligned to generate raw elevation differences (a). The snow-off segments, terrain and vegetation features are utilized as training data for a regressor that can eliminate biases for snow-on segments (b). Subtracting the snow depth with ERA-5 snow depth ('detrend') enables us to depict local variability of snow depth. Finally, another regressor is trained and implemented to predict local variability of snow depth in any location and at any time (c).

Challenges & Objectives

There are several technical challenges that need to be addressed:

- The surface elevation change of seasonal snow is relatively insignificant compared to the scale of uncertainties in DEMs.
- While the commonly used NuthKaab co-registration (Nuth and Kaab, 2011) method efficiently handles geo-referencing errors on the pixel and sub-pixel levels, it is limited in handling the different resolutions and the computationally intensive tasks, which is particularly time-consuming for fine resolution datasets and global applications.
- Biases are widely present in DEMs due to variations in data sources or acquisition dates; these discrepancies create challenges in achieving spatial consistency within the models.
- Moreover, DEM are made of difference sources or difference acquisition data make it difficult. And this methodology requires snow-off DEM, thus such as high-resolution Arctic DEM is not applicable.
- Finally, the satellite's acquisition pattern is sparse both in time and space, resulting in a need for additional data to produce a spatially complete snow-depth map.

In response to the challenges, our objectives are:

- Co-register high-resolution DEM efficiently by a new algorithm, namely Gradient Descending Coregistration (GDC).
- Investigate the trade-off between the quality and availability of DEMs by benchmarking of DEM uncertainties using ICESat-2 snow-free measurements as a reference
- Remove biases in the DEM using machine learning methods trained on ICEsat-2 snow-free measurements.
- Derive snow depth from ICEsat-2 snow-on measurements and bias-free DEM. And generate a spatially complete snow depth map by downscaling ERA5 Land data, incorporating terrain, vegetation, and wind parameters.

1 Gradient Descending Co-registration

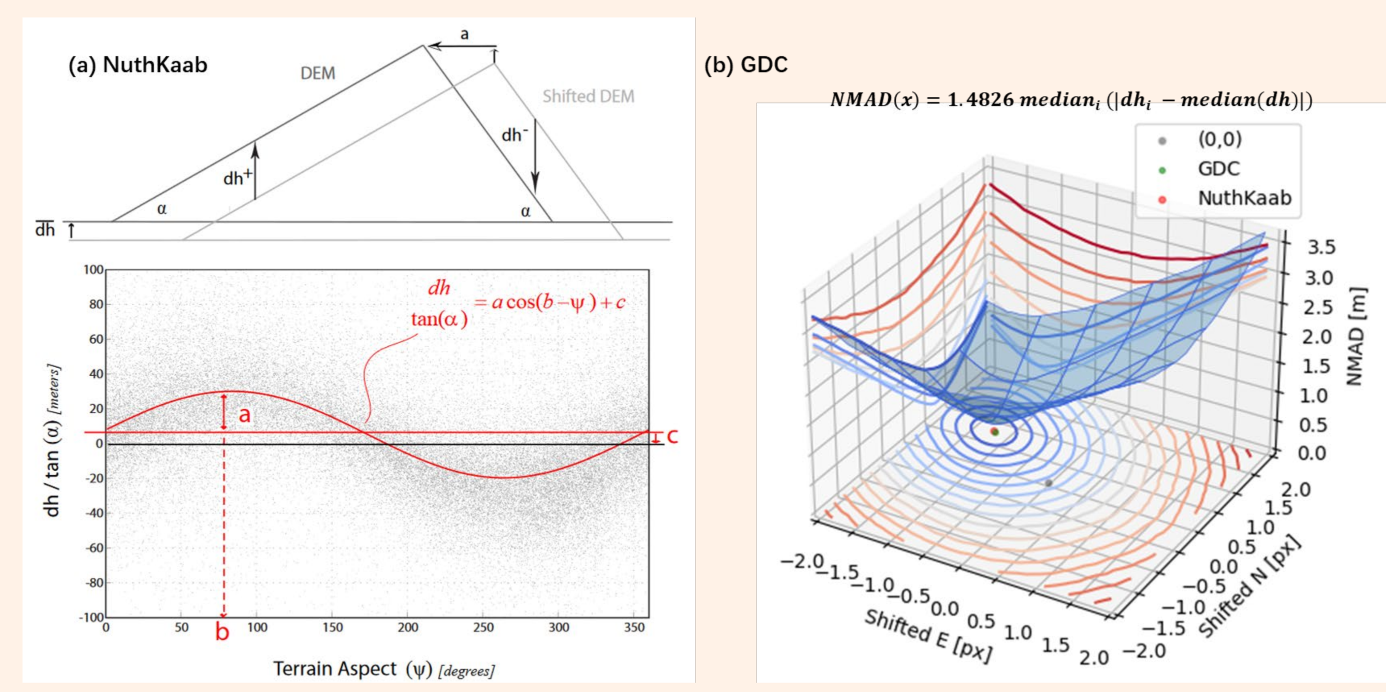


Fig 2. NuthKaab Co-registration and Gradient Descending Co-registration (GDC). A 2D scheme presents elevation difference (dh) induced by a DEM shift in a curve line (a). It suggests a statistical solution where the dispersion is related to aspect, slope, shifted direction and vertical bias. By solving the equation, it gives a vector to shift the DEM back (Nuth and Kaab, 2011). On the other hand, GDC present dh in a curved surface, it aims finding the shift matrix using gradient descending algorithm, resulted in the local minimal of NMAD (b).

2 Bias correction

The categories are used as a feature for regression tree training in the XGBoost model (Fig 3). Upon applying bias correction, we observed improvements on median biases and NMAD (Fig 5,6).

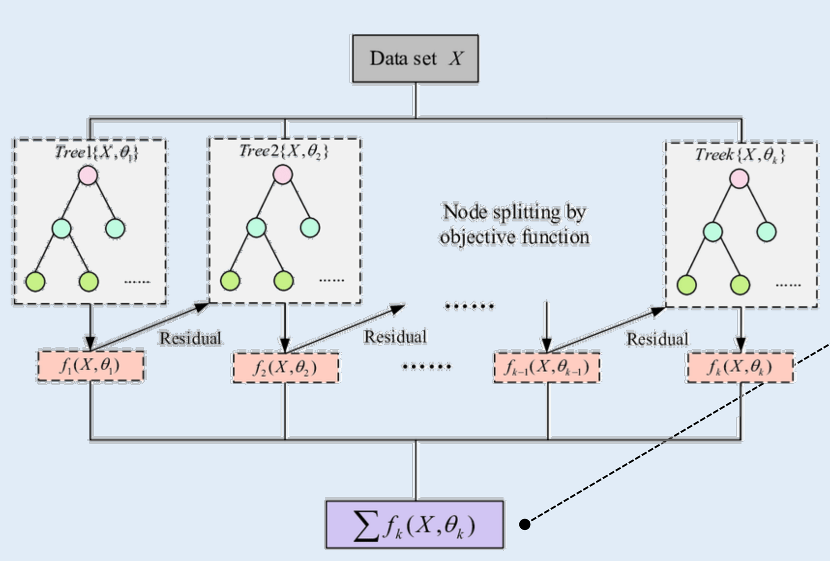


Fig 3. XGBoost builds an ensemble of decision trees. Each tree consists of nodes that represent decision rules. It split the data into smaller subsets based on the input features. The objective function measures the difference between the predicted values and the actual values, and is optimized through gradient boosting. The final prediction is the sum of predictions from all the individual trees in the model.

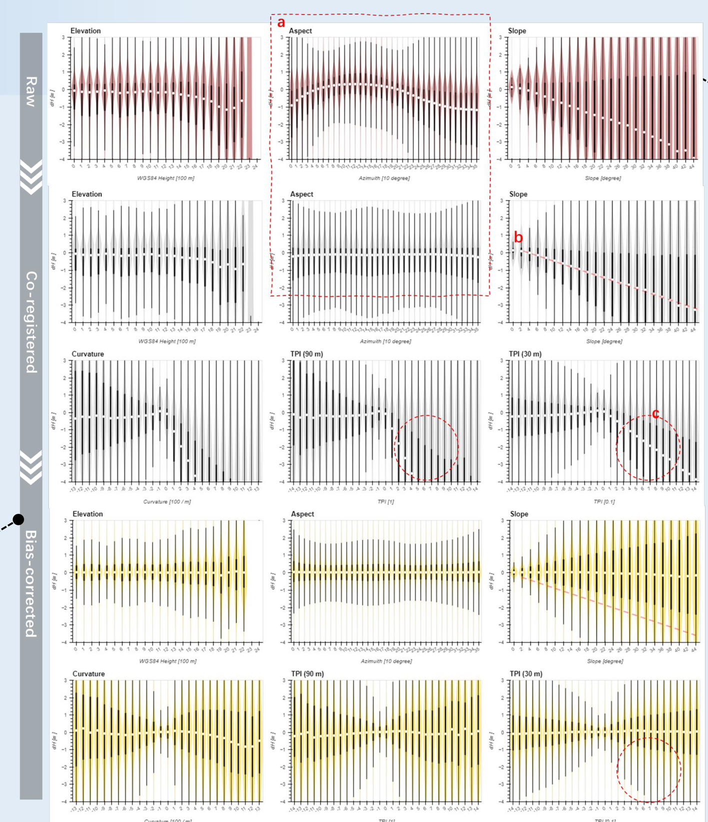


Fig 4. Data binning of residuals between DTM1 and ICESat-2 snow-off segments. The thick black bar represent the -25% to 75% quantiles, and the white dot (median) does not locate at the middle, indicating the widespread negative biases before biases correction. Assect results show that there is 'no' shift-induced error after GDC (a).

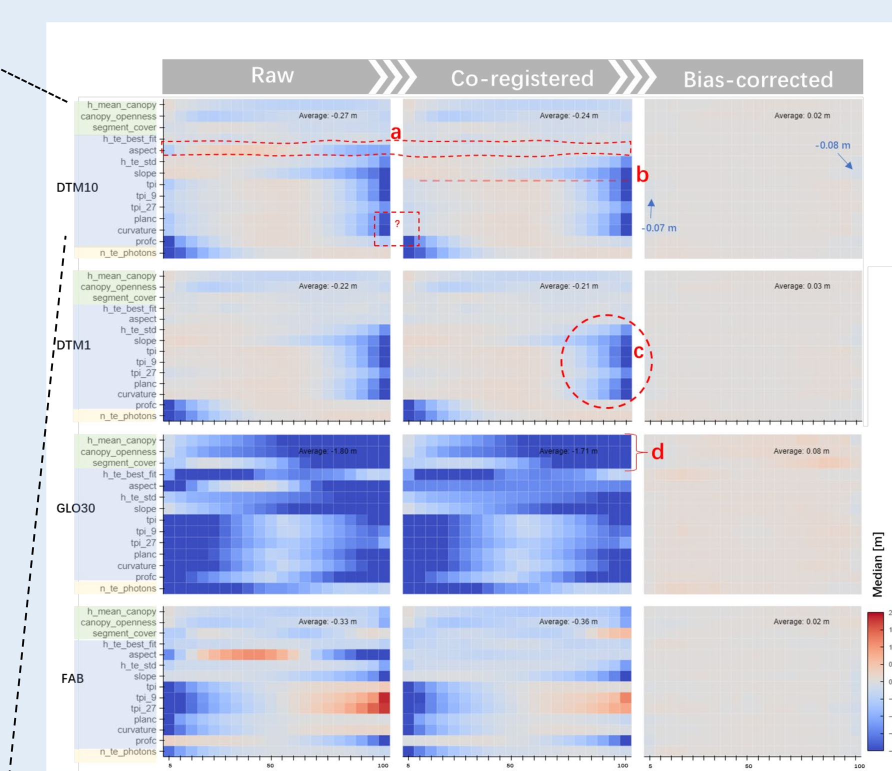


Fig 5. The median of residuals in DTM1, DTM10 Copernicus GLO30, and FABDEM. Each cell represents 5% quantiles of dataset. The significant negative bias has been identified in slope and TPI (topography position index) categories (b & c). The GLO30 has severe negative biases on vegetation as a DSM.

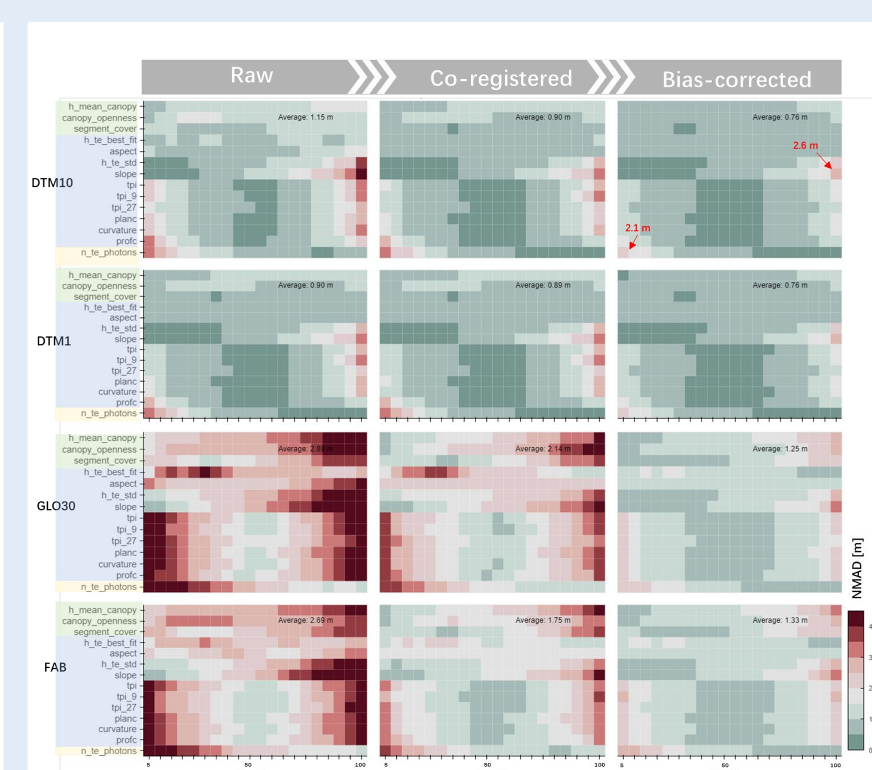
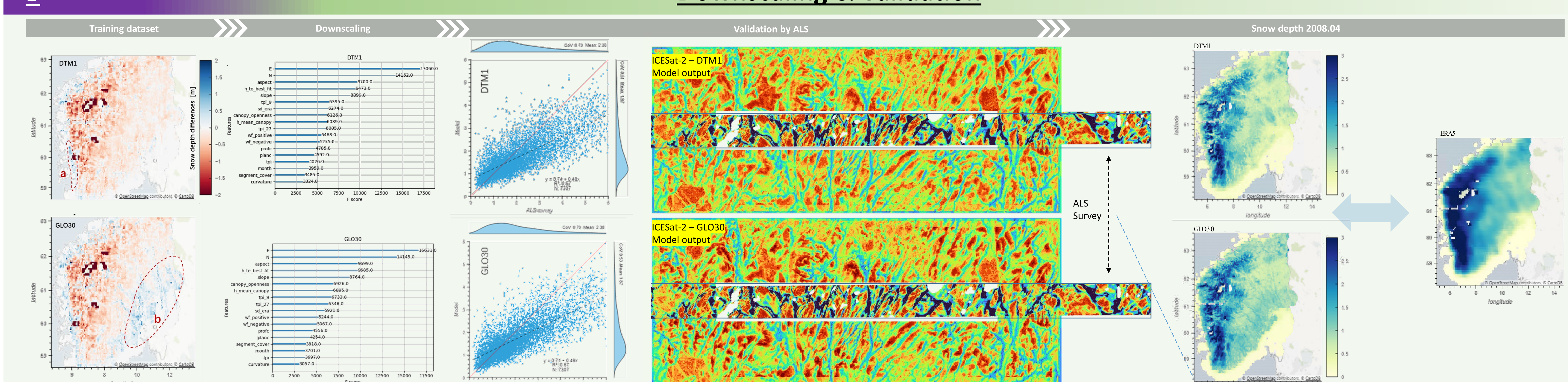


Fig 6. The NMAD of residuals in DTM1, DTM10 Copernicus GLO30, and FABDEM. After correction, DTM1 and DTM10 measurements had less than 1 m and 0.5 m NMAD on median and low slopes category in 65% and 35% of cases after correction, respectively. Furthermore, the bias correction significantly improved GLO30 results, with 40% of measurements being less than 1 m NMAD on the low slopes category .

3 Downscaling & Validation



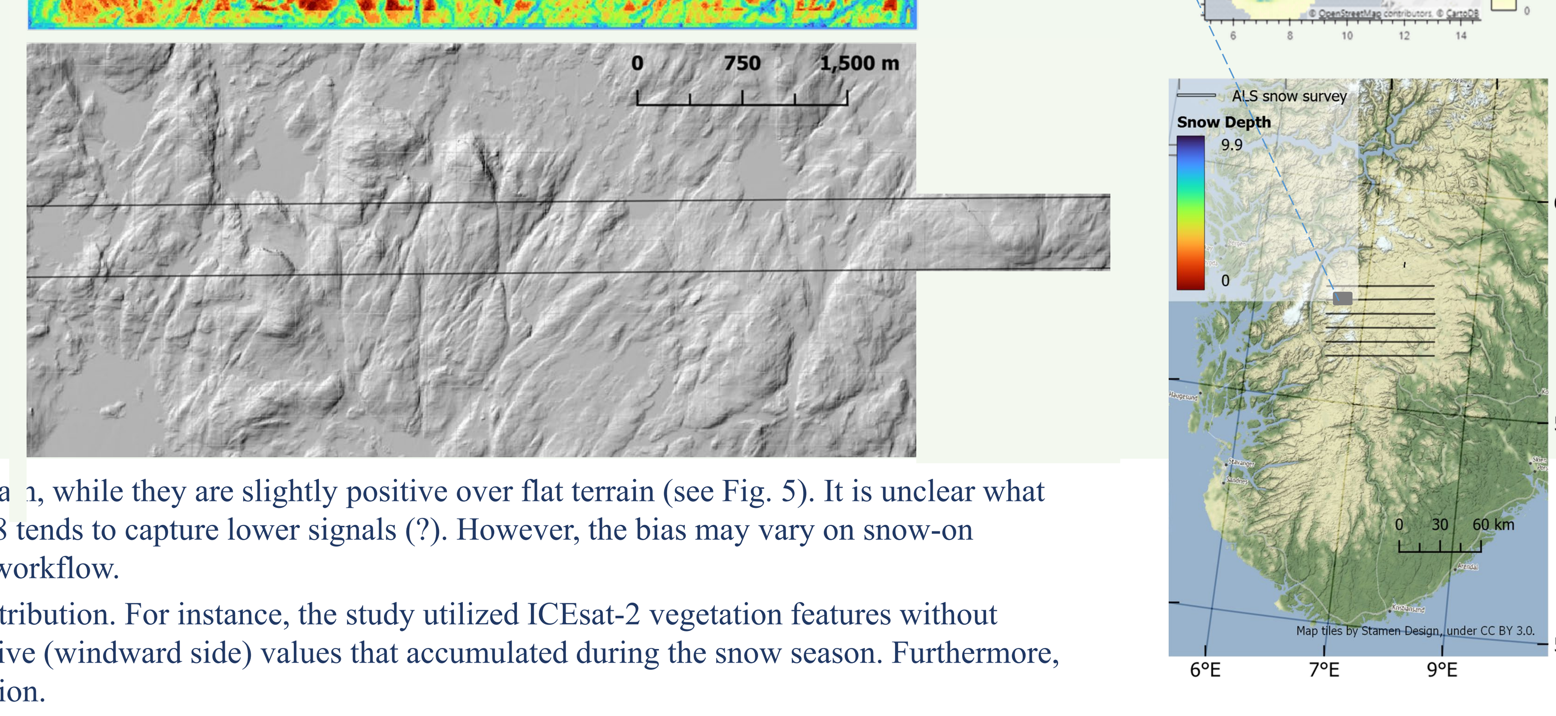


Fig 7. Snow Depth Downscaling and Validation by Laser scanning. The snow depth training dataset utilized in this step was derived from ICESat-2 snow-on segments, spanning from 2018 to 2022. The monthly average of snow depth from ERA5 Land in April 2008 was down-scaled and compared with the ATL survey conducted by NVE for validation purposes. In terms of differences of ERA5 Land snow depth and ICESat-2 derived snow depth, the main control factors in regression is eastness and northness, then aspect, elevation, slope, TPI and others. The results obtained for all six passes exhibited an R-squared value of 0.67, indicating a median degree of correlation. In the west segment of Pass 2, a map was created to visualize the comparison of down-scaled snow depth with that obtained via the ATL survey. Further, the national scale map are presented.

Acknowledgement

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Limitation and Discussion

(1) The snow-off measurements obtained by ICESat-2 exhibit a significant negative bias over convex terrain, while they are slightly positive over flat terrain (see Fig. 5). It is unclear what mechanism underlies this observation, but it could suggest that the ground finding algorithm of ATL08 tends to capture lower signals (?). However, the bias may vary on snow-on surfaces due to reduced surface roughness and higher reflectivity, which is a key uncertainties of this workflow.
(2) The features employed for downscaling snow depth cannot fully account for all variations in snow distribution. For instance, the study utilized ICEsat-2 vegetation features without considering seasonal differences. The wind-aspect factor was divided into positive (leeside) and negative (windward side) values that accumulated during the snow season. Furthermore, it is multiplied by monthly wind speed in the power of 3 to serve as a proxy for snow-wind redistribution.
(3) Consequencly, the primary concern raised by validation is that there exists a negative tail for thick snow depths (Fig. 7).
(4) Does ERA5 Land overestimate the snow depth?
(5) It is possible to use Copernicus GLO30 after correction in global snow depth retrieval.