CORRECTION OF THE PENETRATION BIAS FOR INSAR DEM VIA SYNERGETIC AI-PHYSICAL MODELING: A GREENLAND CASE STUDY

Islam Mansour[1,2], Georg Fischer[1], Ronny Hänsch[1], Irena Hajnsek[1,2] and Konstantinos Papathanassiou[1]

[1] Microwaves and Radar Institute, German Aerospace Center (DLR), Weßling, Germany
[2] Institute of Environmental Engineering, ETH Zürich, Zürich, Switzerland

ABSTRACT

Rapid changes in the Greenland Ice Sheet require precise elevation monitoring to understand ice dynamics and predict sea level rise. X-band Interferometric Synthetic Aperture Radar (InSAR) has the potential for this purpose but is limited by microwave signal penetration biases, which can be a few meters. We present a novel hybrid modeling approach that integrates machine learning (ML) with physical models to enhance the estimation of the elevation bias in InSAR data at X-band. Our method addresses the limitations of traditional physical modeling techniques by parameterizing the vertical structure function using a ML model. This approach combines machine learning as input for the physical model. The results demonstrate the improvements in correcting elevation biases, thus increasing the accuracy of X-band InSAR DEMs over Greenland. This advancement has the potential for more precise elevation estimation and ice-sheet monitoring.

Index Terms— X-band InSAR, TanDEM-X DEM, Elevation Monitoring, Hybrid Modeling, Machine Learning

1. INTRODUCTION

Recent advances in Synthetic Aperture Radar (SAR) remote sensing have significantly improved our ability to monitor glaciers and ice sheets, offering systematic and frequent observations of polar regions. The capability of SAR to penetrate dry snow and ice provides valuable subsurface geophysical information, but it complicates the retrieval of consistent Digital Elevation Models (DEMs) due to penetration biases. Previous studies utilizing TanDEM-X DEM in Greenland have revealed a penetration bias of the order of a few meters comparing the InSAR DEM to altimeter and stereophotogrammetric measurements [1], [2]. This study introduces a novel hybrid modeling approach that integrates machine learning and physical models to estimate and correct penetration biases in X-band InSAR data from Greenland. Our approach aims to enhance the accuracy of elevation measurements, which is crucial to understanding ice dynamics and projecting sea level rise. The penetration bias depends on factors such as acquisition geometry (baseline configuration and incidence angle), snow and ice properties (e.g. melting, presence of fresh snow, grain size, refrozen melt features in the firn, and seasonal variation). Various approaches have been developed that rely on modeling and machine learning to compensate for this penetration bias, including empirically derived or model-based estimates [1], [3]. We introduce a novel approach that leverages the synergies between machine learning and a model-based framework to address this penetration bias. We demonstrate this with TanDEM-X data acquired over the Greenland ice sheet in 2017. This InSAR DEM dataset is corrected using a hybrid-based modeling technique, and the results are benchmarked against a DEM derived from IceBridge ATM LiDAR.

2. STUDY AREA

For the investigation and assessment, we use a test site that covers a large transition across glacier zones starting from the summit towards the east coast of Greenland during 2017, providing a large elevation diversity. Greenland, with its vast ice sheets, is a critical area for investigating the impacts of climate change on glacial dynamics and associated processes. The study area extends over varying altitudes, ranging from coastal regions to elevations of 3500 m. This altitudinal diversity allows us to capture a wide spectrum of glacier zones at different elevation, which is crucial for training a robust generalizable hybrid model.

3. DATASET

We use single-baseline SAR imagery acquired from TanDEM-X in 2017 to derive the InSAR DEM products of our study area. As reference data for training and validation, we use NASA IceBridge ATM LiDAR-derived elevations and aim to use the CryoSAT-2 radar altimeter for verification of the model [4], [5].

3.1. TanDEM-X InSAR DEM

We opt for 14 TanDEM-X CoSSC acquisitions available over Greenland, spanning from the summit to the East Coast. Our selection criteria ensure temporal and spatial alignment with the 2017 IceBridge data, as shown in Figure 1.

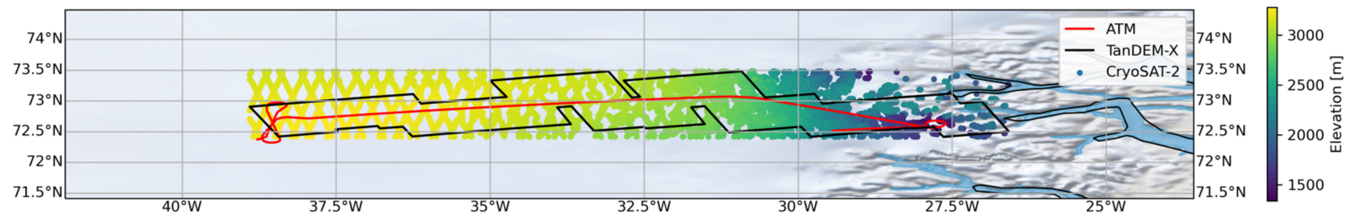

Figure 1: Map of TanDEM-X, NASA IceBridge ATM and CryoSAT-2 data.

Post-processing was conducted to derive the following products: InSAR elevation, coherence γ, backscatter σ_0, angle of incidence θ, vertical wavenumber κ_z, and reference elevation to the same map projection. However, achieving vertical calibration for the generated InSAR elevation proved to be a challenge. Calibration involved using the official TanDEM-X global DEM as a reference DEM in the InSAR processing [6]. Additional calibration steps accounted for the surface elevation change between the TanDEM-X global DEM and our 2017 data using surface elevation change data from ESA Greenland CCI [7]. Further, a constant offset between TanDEM-X and ATM at rock surfaces on the coast was removed. Figure 2 shows the penetration bias observed in the TanDEM-X calibrated DEM compared to the training reference DEM from ATM LiDAR. As expected, the penetration bias increases with elevation [1], [2].

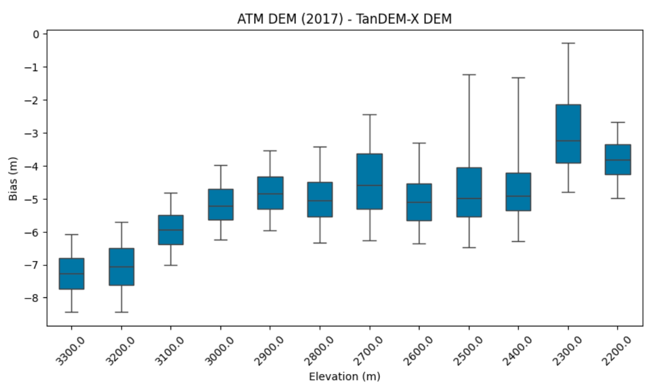

Figure 2: Penetration Bias in the TanDEM-X DEM when compared to ATM DEM.

3.2. IceBridge and CryoSat-2 Data

To train the hybrid model and evaluate the performance of the hybrid DEM penetration bias estimation, we use surface elevation data from the Airborne Topographic Mapper (ATM), obtained during the IceBridge survey. Its positional accuracy over the flat ice sheet is maintained within a margin of less than 1 m. For our assessment of DEMs, we rely on the IceBridge ATM DMS L3 Ames Stereo Pipeline Photogrammetric DEM dataset [4]. The original resolution of the IceBridge dataset is resampled to 25 m for our analysis, with an estimated error of approximately 0.12 m.

4. METHODOLOGY

4.1. Penetration Bias Estimation with Physical Model

The physical model to estimate penetration depth is based on a correlation between the InSAR observation space and the vertical scattering distribution in the snow, firn and ice, which depends on geophysical parameters (e.g. density, structure and grain size).

The main observable of interferometric SAR, the interferometric complex coherence, denoted as $\tilde{\gamma}$, serves as a representation of the cross-correlation between two interferometric acquisitions $s_1(\vec{w})$ and $s_2(\vec{w})$. This coherence metric is scaled between zero and one and is acquired at a specified polarization indicated by the unit vector $\vec{w}$ and defined as:

$$\tilde{\gamma}(\vec{w}) = \frac{\langle s_1(\vec{w}) s_2^*(\vec{w}) \rangle}{\sqrt{\langle s_1(\vec{w}) s_1^*(\vec{w}) \rangle \langle s_2(\vec{w}) s_2^*(\vec{w}) \rangle}} \tag{1}$$

The location of the interferometric phase center, which is used to derive the InSAR DEM, is determined by $\frac{\angle\tilde{\gamma}}{\kappa_z}$. The penetration bias ($p_{\text{bias}}$) is then the difference between the phase center DEM_{InSAR}, located in the subsurface, and actual surface DEM_{Ref}, which is defined as:

$$p_{\text{bias}} = DEM_{InSAR} - DEM_{Ref} \tag{2}$$

The interferometric phase to height sensitivity is described by the vertical wavenumber κ_z,defined as follows:

$$\kappa_z = \frac{4\pi}{\lambda} \frac{\Delta\theta_i}{\sin\theta_i} \tag{3}$$

Here, λ represents the wavelength in free space, θ_i, is the incidence angle, and $\Delta\theta_i$ is the difference in θ_i introduced by the spatial baseline between acquisitions, as illustrated in Figure 3.

To estimate the penetration bias, which depends on the vertical scattering profile within a glacier volume for a single-baseline scenario, we initiate the process with the equation representing the complex coherence in a semi-infinite volume (following the correction of range spectral decorrelation) [8], [9]:

$$\tilde{\gamma} = e^{j\kappa_z z_0} \cdot \frac{\int_{-\infty}^{0} f(z) \cdot e^{-j \cdot \kappa_z z}\, dz}{\int_{-\infty}^{0} f(z)\, dz} \tag{4}$$

where the vertical coordinate z_0 is situated at the surface, and $f(z)$ is the unknown vertical structure function within the firn, illustrating the changes in the radar cross-section with depth [8]. Then the $f(z)$ can be substituted with any given profile, in the case of our experiment, we substitute with a backscattering profile for a uniform volume (UV), which is defined as [10], [11]:

$$f(z) = \sigma_v^0 e^{\frac{2z}{d_{\text{pen}}}} \tag{5}$$

where σ_v^0 is the nominal backscatter power per unit volume and d_{pen} is the one-way penetration depth. The vertical structure function f(z) in the subsurface of an ice sheet requires to consider the permittivity of the medium and its effects on refraction and propagation. For this, formulations using the vertical wavenumber in the volume $\kappa_{z_{\text{Vol}}}$ are found in literature. However, because the TanDEM-X DEMs were processed under the assumption of free-space propagation, also the penetration bias correction must be calculated with free-space permittivity and thus the free-space vertical wavenumber is κ_z applied.

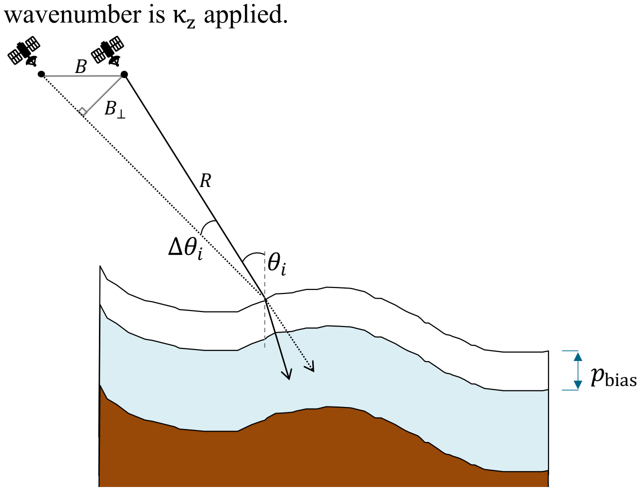

Figure 3: Interferometric geometry with penetration in the snow, firn and ice. *B* is the horizontal baseline, $B_\perp$ is the perpendicular baseline, *R* is the slant range distance, θ_i is the radar look angle, and $\Delta\theta_i$ is the change in radar look angle caused by the baseline.

4.2. Hybrid-Based Model

To accurately model and predict coherence and penetration bias, we define a loss function with the objective to minimize the discrepancies between the estimated and observed values of the coherence and penetration bias. Let $\hat{\gamma}$ represent the estimated coherence and $\hat{p}_{\text{bias}}$ the estimated penetration bias. The loss function $\mathcal{L}$ is formulated as the sum of the squared differences for coherence and penetration bias:

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} \left[\left(\hat{\tilde{\gamma}}_i - \tilde{\gamma}_i\right)^2 + \left(\hat{p}_{\text{bias},i} - p_{\text{bias},i}\right)^2 \right] \tag{6}$$

The implementation of the hybrid model involves the following steps:

1. **Input Features**: $\kappa_{z_{\text{Vol}}}$, θ_r, and $\tilde{\gamma}$.
2. **Neural Network Output**: Estimated d_{pen}
3. **Calculation of $f(z)$**: based on Equation 5
4. **Estimation of $\hat{\tilde{\gamma}}$ and $\hat{p}_{\text{bias}}$**: based on Equation 2 and Equation 4

The model is subject to the constraint that the estimated d_{pen} should be within the range of 0 to -50 meters. Figure 4 illustrates the training phase architecture, while Figure 5 shows the inference phase for estimating penetration bias. Such an architecture allows the incorporation of any generic function, $f(z)$, during the modeling process and to use more sophisticated parameterization of $f(z)$.

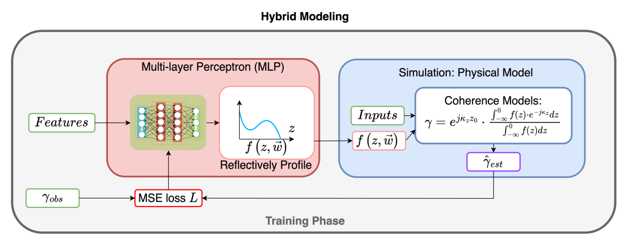

Figure 4: Schematic representation of the hybrid-based model (training phase).

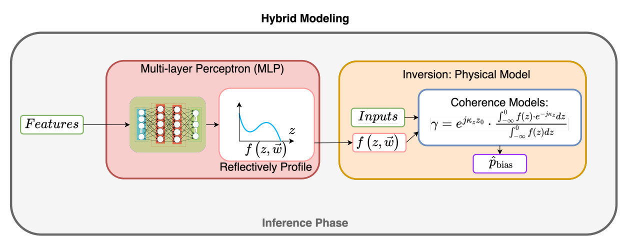

Figure 5: Schematic representation of the hybrid-based model (inference phase).

5. RESULTS

Using our hybrid-based model, we benchmark the performance of the corrected TanDEM-X DEM against the ATM DEM from 2017. The evaluation is conducted across a range of elevation intervals to assess the model's accuracy and reliability. Figure 6 presents a mosaic of the estimated penetration bias $\hat{p}_{\text{bias}}$ using the hybrid-based method for multiple TanDEM-X scenes. The results show the influence of different baseline configurations and incidence angles, manifesting as variations in penetration bias. The mosaic illustrates a general trend of deeper penetration at higher elevations (with the Greenland summit inside the scene on the very left), decreasing towards the coast (on the right), consistent with the observed bias shown in Figure 2.

The corrected TanDEM-X DEM demonstrates consistent accuracy across various elevation ranges. Figure 7 shows the

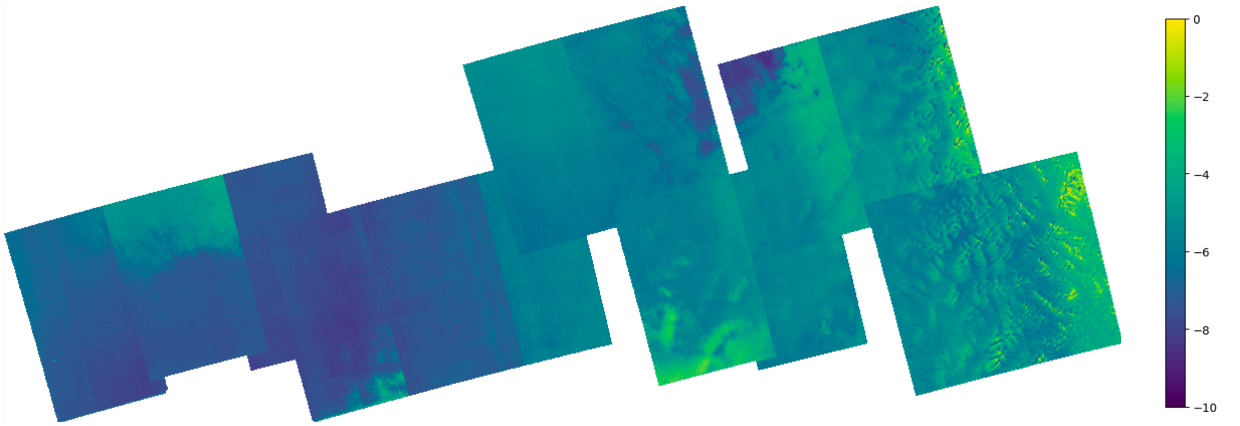

Figure 6: Mosaic of estimated $\hat{p}_{\text{bias}}$ using the hybrid-based method for multiple TanDEM-X acquisition with different incidence angles and baseline.

estimated $\hat{p}_{\text{bias}}$ for all acquisitions, indicating a trend of deeper penetration at higher elevations and decreasing towards the coast. This pattern aligns with the observed bias trend in Figure 2.

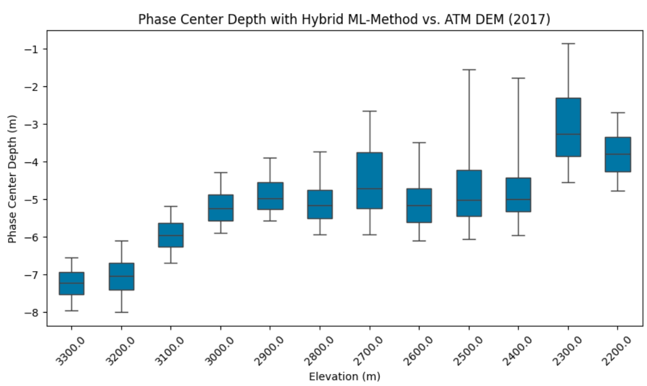

Figure 7: Shows the prediction of the penetration bias for the TanDEM-X DEM using the hybrid-based method for different elevation ranges.

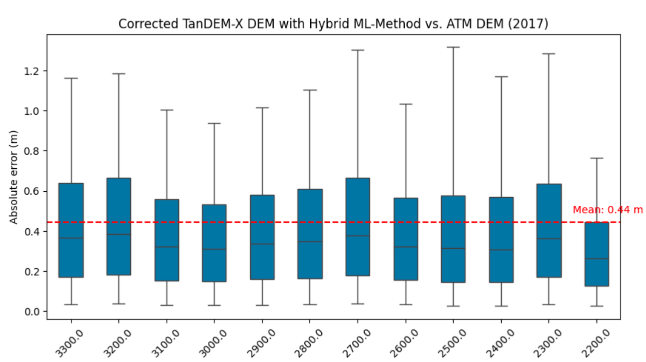

Figure 8: Presents the absolute error distribution of the corrected TanDEM-X DEM using the hybrid-based method compared to the ATM DEM for different elevation ranges.

Figure 8 illustrates the absolute error distribution of the corrected TanDEM-X DEM using the hybrid-based method compared to the ATM DEM for different elevation ranges. The corrected DEM's accuracy remains consistent across elevation ranges, with MAE values reflecting a substantial improvement over the original penetration bias values in Figure 2. The hybrid-based model significantly improved the accuracy of the TanDEM-X DEM. The overall mean absolute error (MAE) across all elevation intervals was approximately 0.44 meters. This reduction in error demonstrates the model's ability to effectively correct for penetration bias, leading to more precise elevation measurements.

The hybrid-based model effectively combines the strengths of traditional model-based methods and empirical approaches to correct penetration bias. Initial results indicate that this method can enhance the accuracy and reliability of corrected DEMs over the Greenland ice sheet. The hybrid-based method offers a robust and adaptable solution, capable of managing variability in baseline configurations with a limited training dataset. Additionally, this approach demonstrates flexibility in incorporating multi-modal data as input features that can be utilized for the physical model.

6. SUMMARY

This study introduces a novel methodology to compensate for penetration bias in InSAR-derived DEMs caused by the microwave signal's propagation into ice. By integrating physical modeling with machine learning techniques, we significantly enhanced the accuracy of TanDEM-X DEMs compared to ATM DEMs, achieving a mean absolute error of approximately 0.44 meters across different elevation ranges. The hybrid model's success highlights the potential of combining machine learning with physical models to correct elevation biases in X-band InSAR data, leading to more precise elevation estimates. Future work will involve comparing the corrected TanDEM-X DEM with CryoSat-2 DEM for further validation.

6. REFERENCES

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