Snow Depth Estimation from SAR Interferometry: addressing Radar Penetration and Calibration Challenges for Accurate Seasonal Monitoring

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Motivation & Challenges

Spatially comprehensive monitoring of seasonal snow depth (SD).

Limitations:

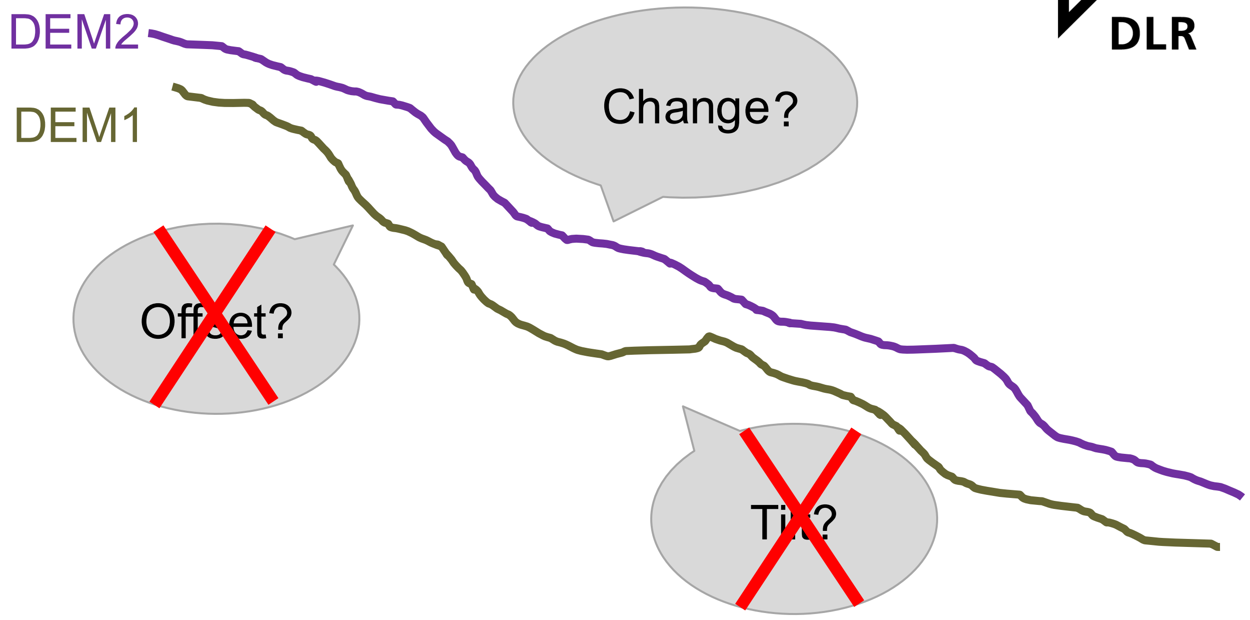
- In-situ: Precise but spatially limited.
- LiDAR: High accuracy, low temporal/spatial revisit.
- InSAR: Area-wide, weather-independent → But biased.

Critical Error Sources:

- Geometric: Residual offsets and tilts (due to baseline uncertainties).
- Physical: Radar wave penetration into the snowpack.

Raw DEMs → Mutual Calibration → DL Bias Penetration Compensation → SD Retrieval

Reference Free Mutual Calibration



Problem : Baseline uncertainties $(\Delta B_{\parallel}, \Delta B_{\perp})$

→ geometric tilts & offsets in DEMs.

Calibration using natural tie-points.

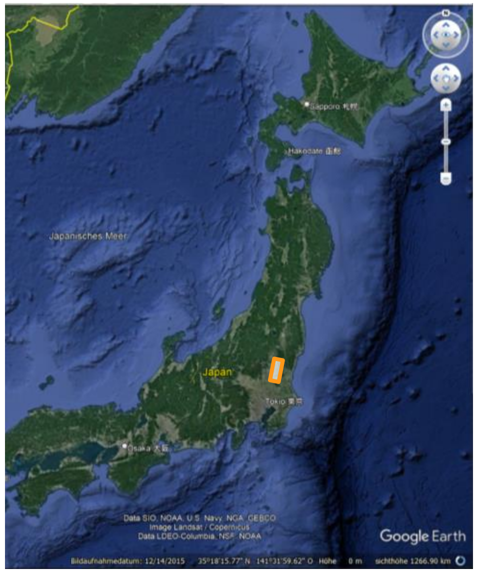
Methodology:

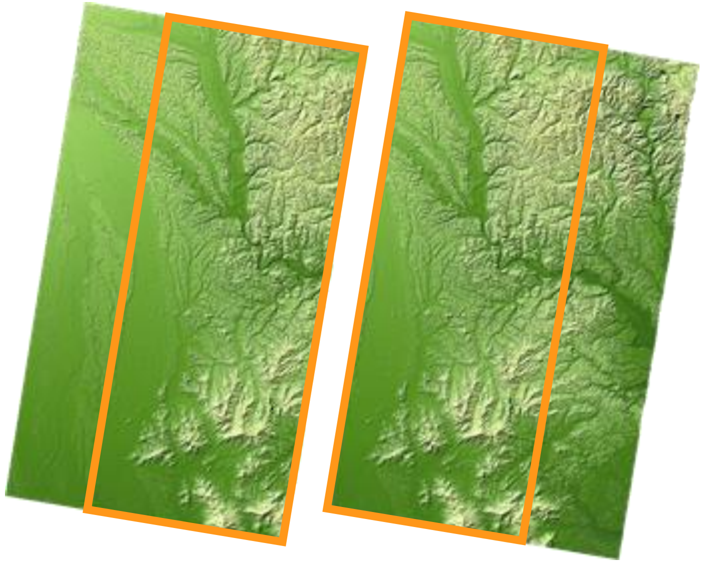
- Exploiting Sentinel-1 repeat-pass time series for selection of tie-points (TP), that are stable anchors derived from Persistent Scatterer Candidates (PSC).
- Estimation of a calibration surface (LS fitting) to remove offsets and tilts.

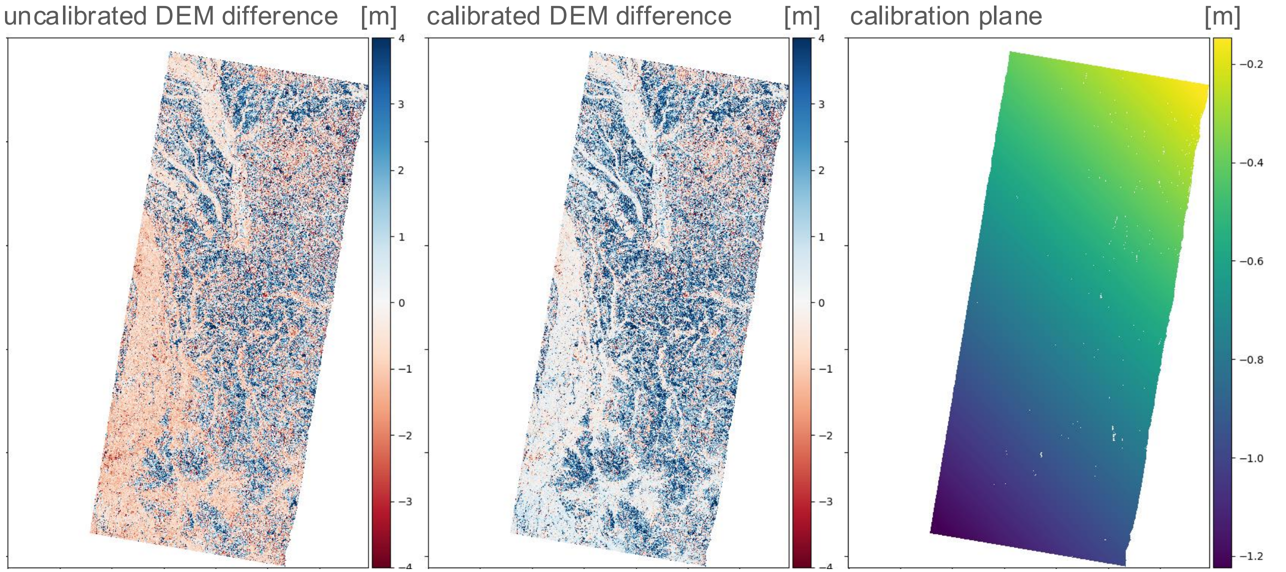
$$\Delta_{cal}(TP) = h_{TanDEM,ref}(TP) - h_{TanDEM,i}(TP) \quad \rightarrow \quad h_{TanDEM,cal,i} = h_{TanDEM,i} + \Delta_{cal}$$

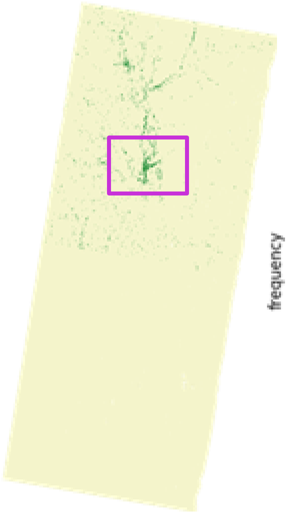
No dependency on external GPS or LiDAR ground truth; fully scalable.

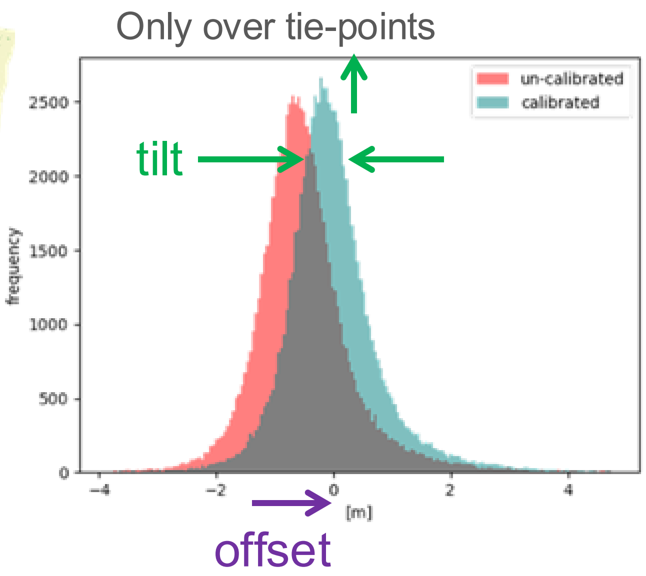
Example of Mutual Calibration

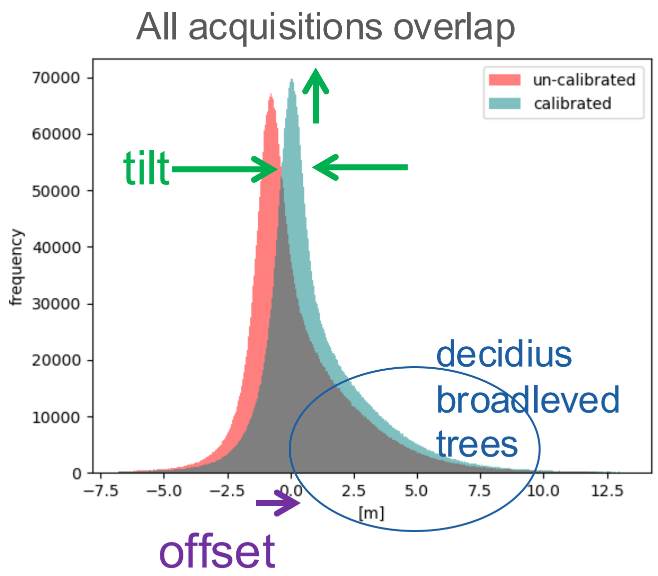












Radar Penetration

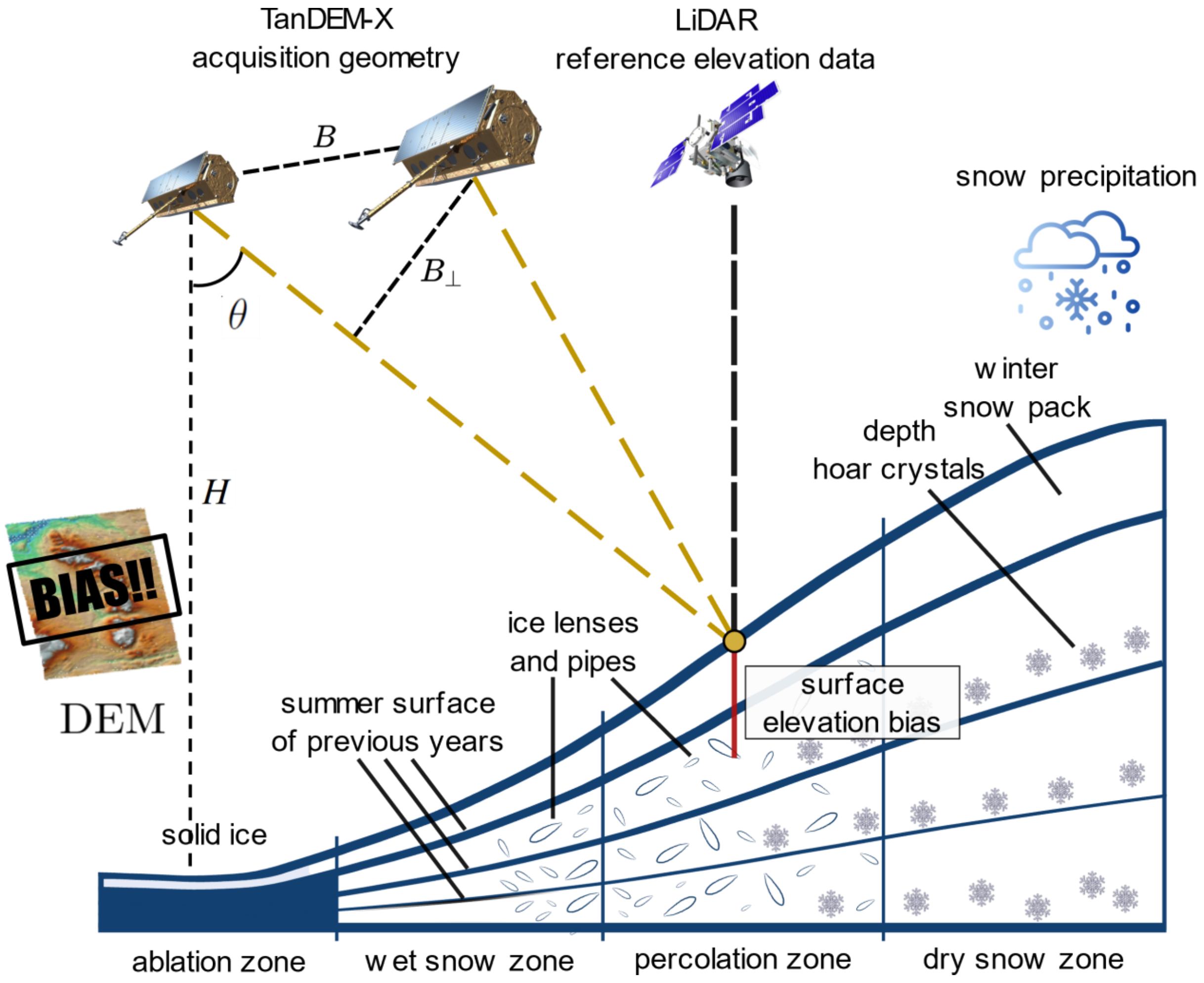
Mean Phase Center ≠ Topographic Surface.

Factors Influencing Penetration:

- Frequency
- Incidence angle
- Snow density
- Water content

Strategy:

DL for regressing Δh bias from SAR features.



Physical Modeling & Reference Generation

InSAR height to topographic surface accounting for refraction and dielectric properties

$$h_{surface} = h_{TanDEM} + \Delta h \cdot \frac{\sqrt{\varepsilon_r}\cos\theta}{\cos\theta_r}$$

Empirical reference generation ($\boldsymbol{\Delta} h$) non-coincident LiDAR and InSAR data, the penetration bias is extracted as:

$$\Delta h = (h_{TanDEM-X,\mathrm{cal}} - h_{\mathrm{Li}DAR}) \cdot \frac{\cos\theta_r}{\sqrt{\varepsilon_r}\cos\theta} + n$$

Noise Factor $\boldsymbol{n}$ represents residual errors from temporal displacement (snow drift, accumulation/melt) and topography.

Pretext and Downstream Regression Tasks

Challenge is sparsity of Δh for training

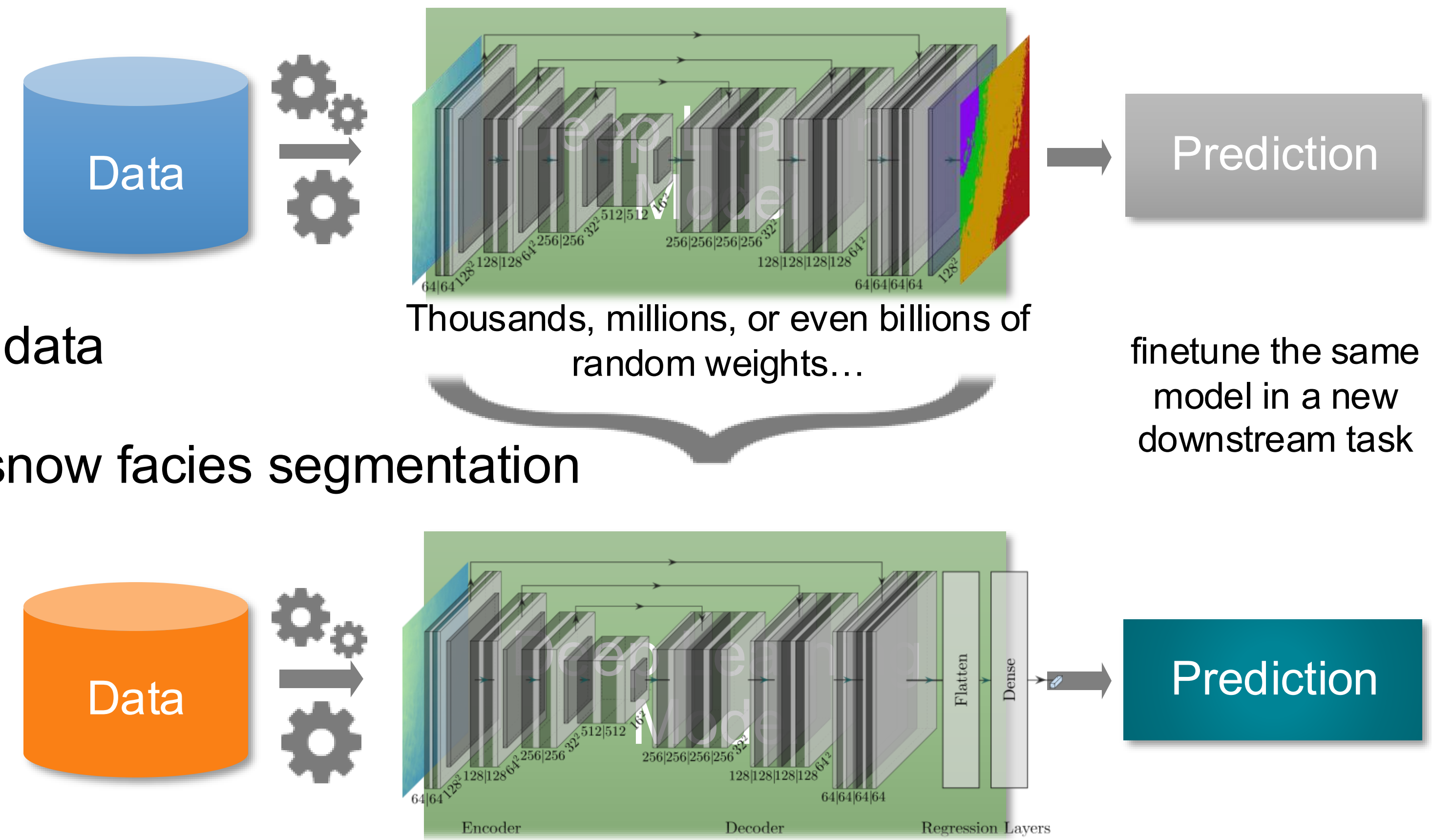
Strategy:

- Random init → overfitting on sparse data
- Pretrained backbone → leveraging snow facies segmentation
- Knowledge transfer

Benefit:

- Reduces training data requirements
- Improves convergence

Task A
Snow facies segmentation



Pretrained, relevant weights

Task B
Surface elevation bias regression

A. Becker Campos, A. Diez-Latteur, J-L. Bueso-Bello, M. Braun and P. Rizzoli, "A Snow Properties-Aware Deep Learning Framework for Penetration Bias Estimation of Tandem-X DEMs over Ice Sheets," Remote Sensing of Environment, 2026.

Deep Learning Approach

Comprehensive testing on Greenland

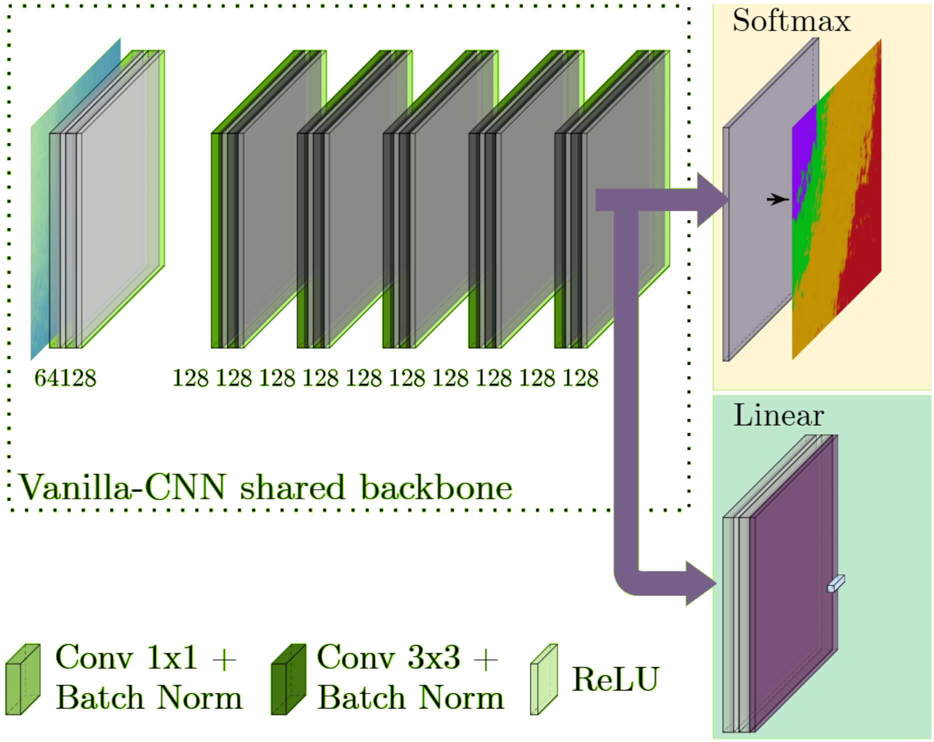
Models: U-Net & CNN-based architecture.

Input Feature Cube:

- Backscatter projections: β^0, γ^0.
- Coherence: $\gamma_{\mathrm{Tot}}, \gamma_{\mathrm{vol}}$.
- Geometry: $\theta_{\mathrm{inc}}, h_{\mathrm{amb}}$.

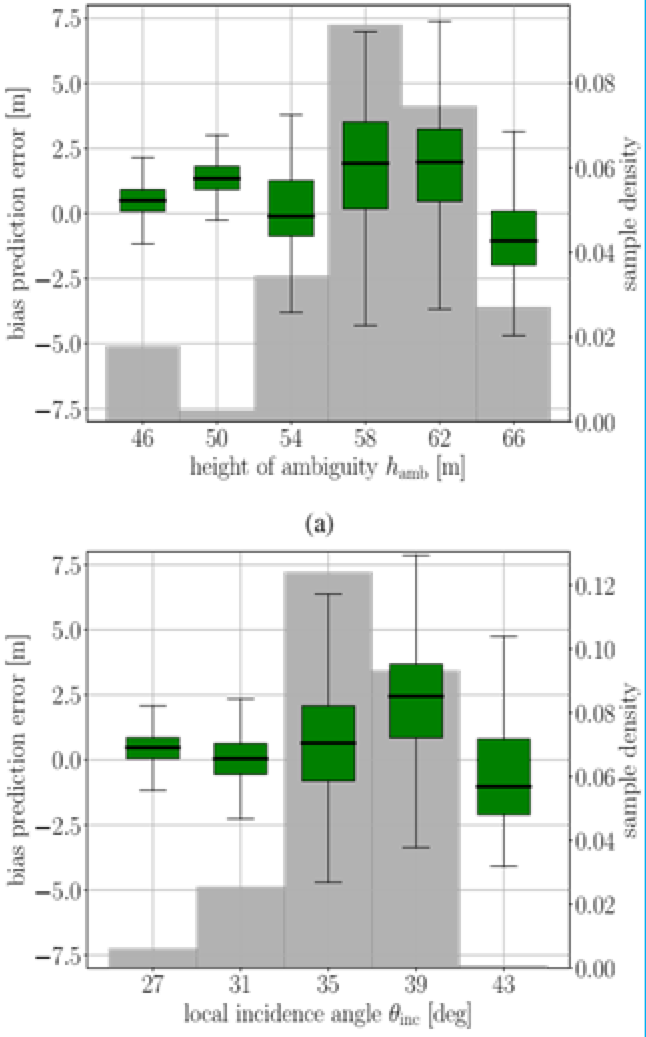
Target: Δh

→ Different combinations no substantial influence. **Pretext!**

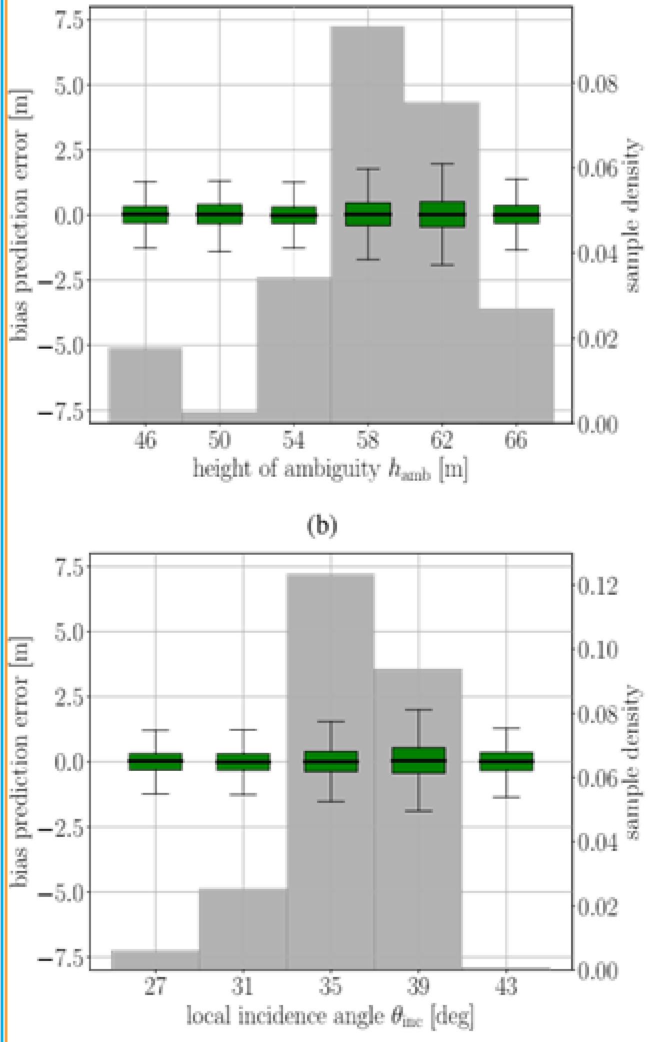


Multitask with pretext training for Greenland baseline model

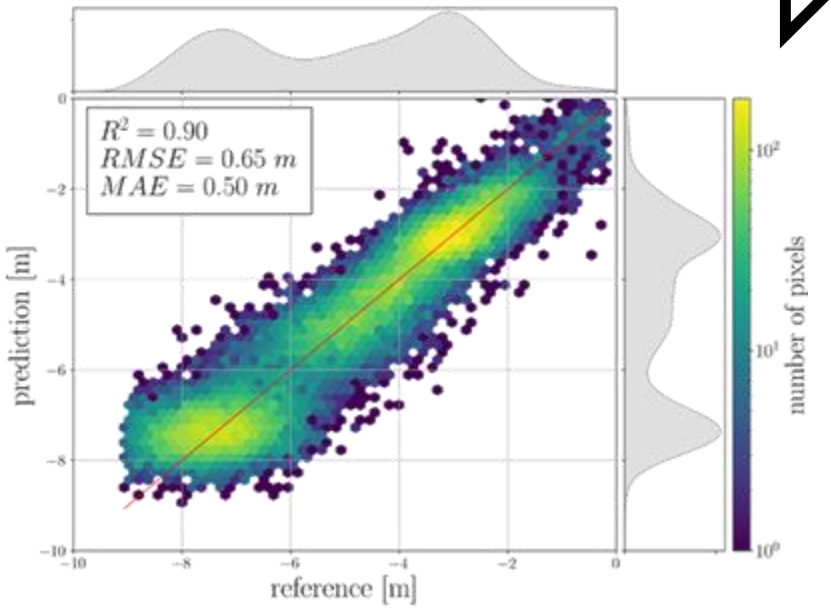
Deep Learning Approach

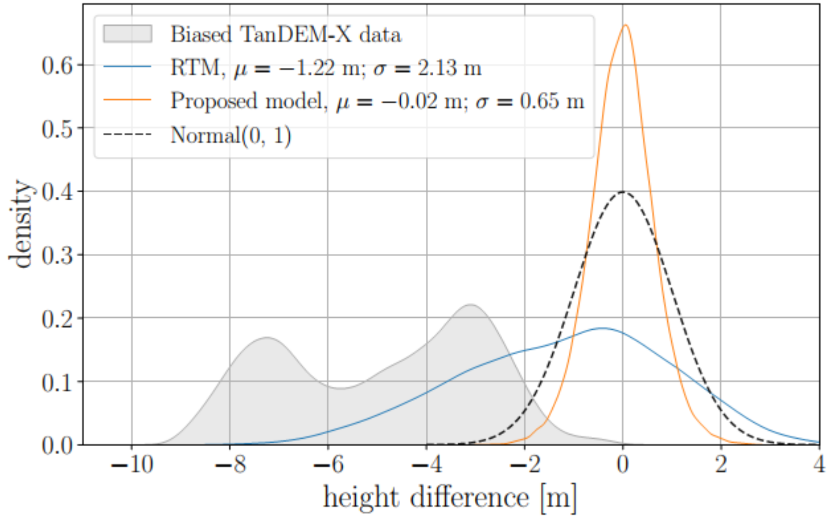


Physical Model (c)



DL Model (d)





Model Architecture & Transfer Learning

Addressing the Out-of-Distribution (OOD) problem caused by steep slopes and varying acquisition geometries, as well as scarcity of reference data in complex alpine terrain or other remote regions.

Pre-training → Fine-tuning

Pre-training (Greenland): Multitask learning (snow facies + bias regression) with pretext.

Regional Adaptation: Transferring weights to target regions.

Devon Ice Cap

Aletsch

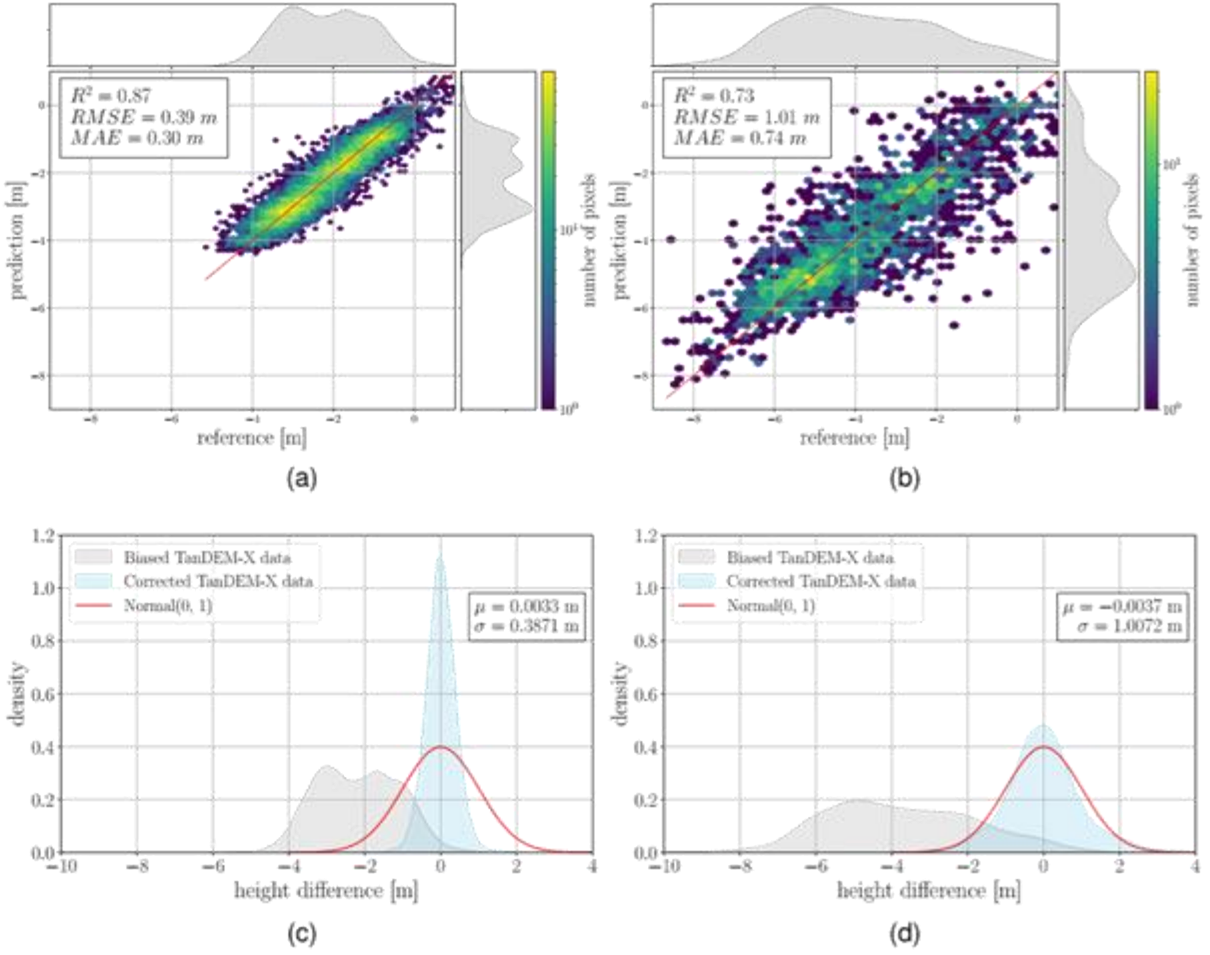
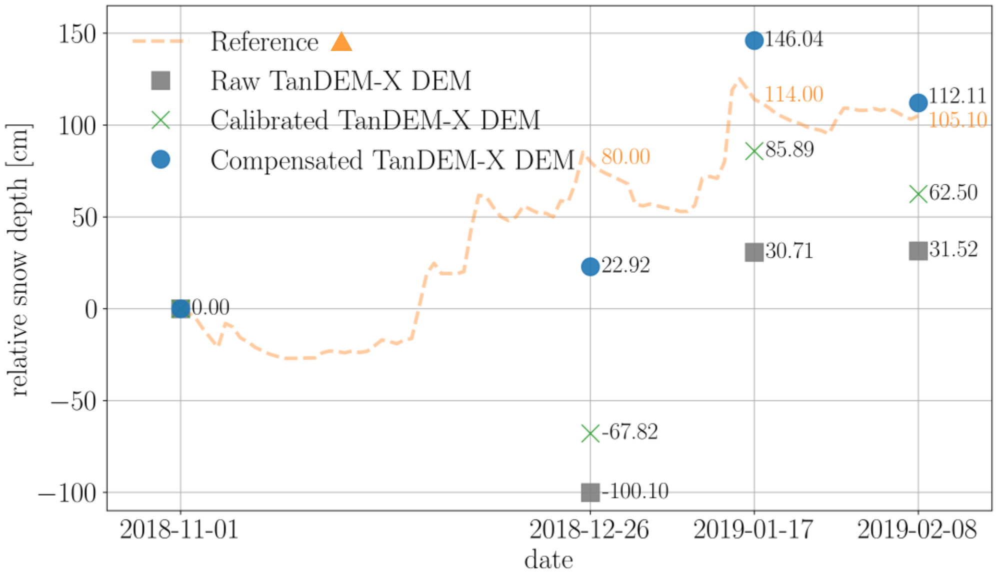
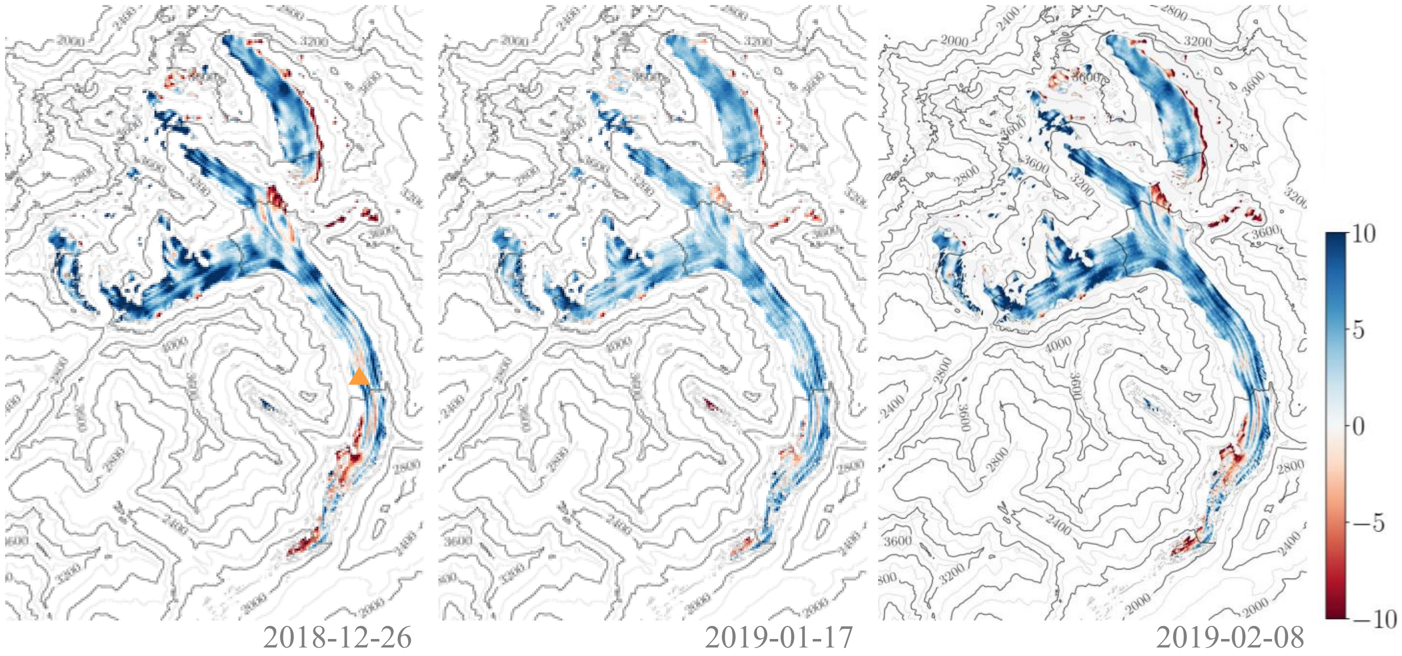


Fig. 4: Logarithmic-scale scatterplots of predicted and reference penetration bias for (a) Devon Ice Cap and (b) Aletsch Glacier; (c) and (d): corresponding residuals of biased (gray) and corrected TanDEM-X DEM data (blue) for each area.

Relative Snow Depth (ΔSD) over Aletsch Glacier





- Raw DEM: Fails to capture accumulation; shows non-physical surface drop.
- Calibrated DEM: Removes offsets but still underestimates seasonal gain.
- Compensated DEM: Correctly tracks the seasonal signal → 71% improvement.

Accuracy: MAE = 32 cm (Centimeter-scale precision).

Geodetic Mass Balance Estimation

Case Study: Sverdrup Glacier Basin (Devon Ice Cap)

Total volume change

$$\Delta V = r \sum \Delta h_{TanDEM-X}$$

Mass change assuming mean density

$$B_{geo} = \Delta V \cdot \rho, \quad \rho = 850 \pm 60\ kg\, m-3$$

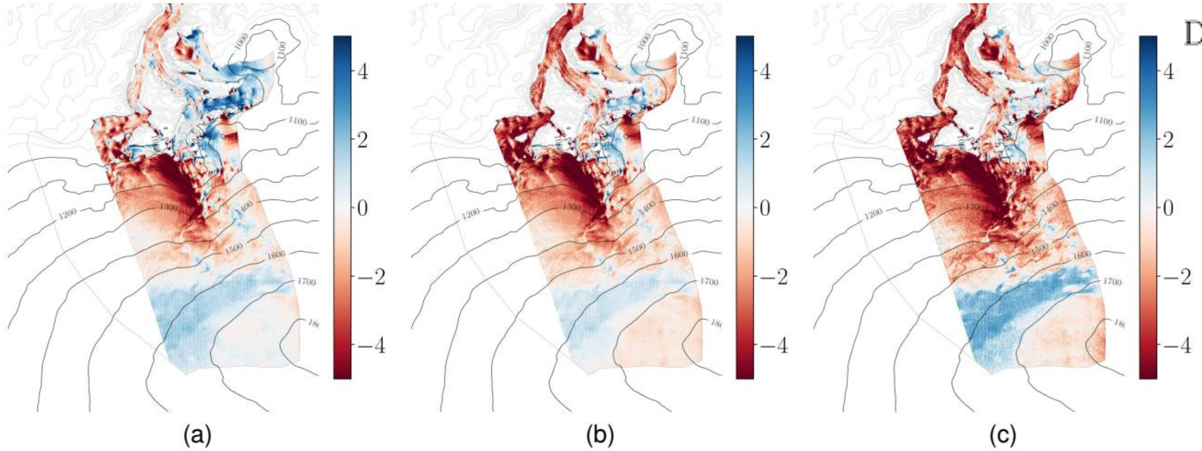
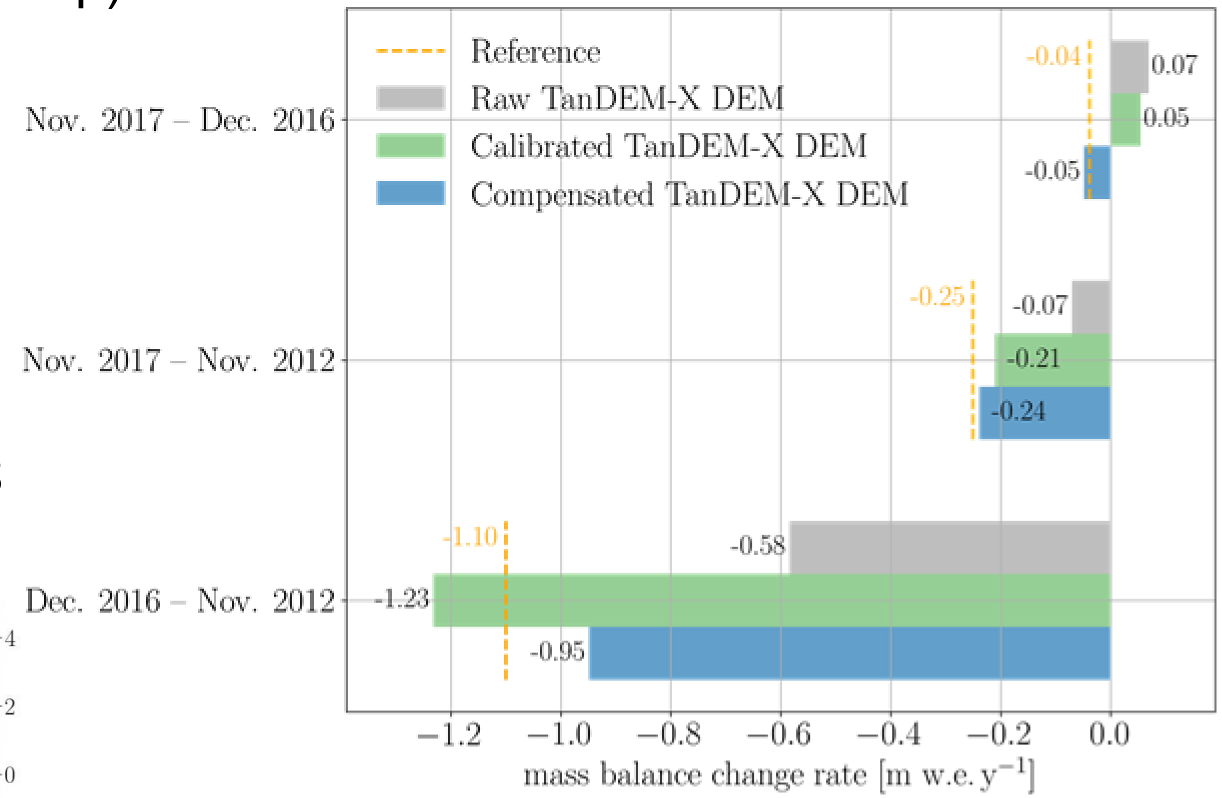


Fig. 7: Elevation changes of TanDEM-X DEMs over the Devon Ice Cap for the 2012 – 2017 period for all considered cases: (a) raw, (b) calibrated, and (c) compensated DEMs.

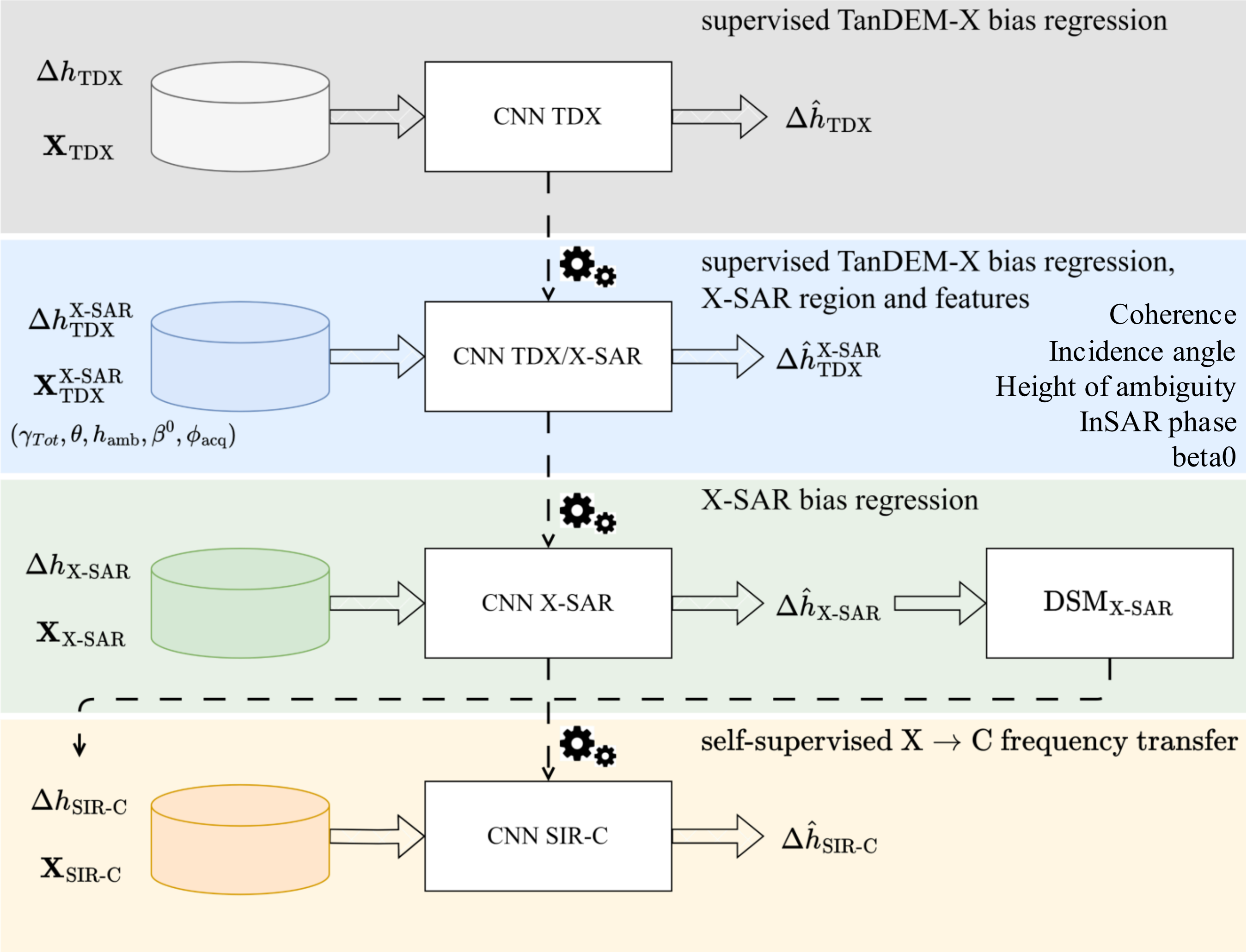


Work in progress: Multi-Frequency Bias Regression

Frequency Transition Logic

Hypothesis: Overlapping data with similar HoA and incidences angles share similar bias characteristics.

1. Supervised regression TanDEM-X → X-SAR
2. Refinement of X-SAR model to map true surface
3. Self-supervised Transfer (X → C)



Airborne L-Band F-SAR data

Conclusions

- Combining S-1 Mutual Calibration and DL Penetration Correction removes biases allowing to quantify SD.
- Centimeter precision for relative SD estimation with InSAR is achievable.
- Transfer learning allows deploying models in data-poor regions using data-rich "anchor" domains (e.g., Greenland). → Scalability
- Framework is adaptable for upcoming X, C, and L-band missions to provide reliable cryosphere monitoring.