Correction of TanDEM-X InSAR DEM Penetration Bias Using Physics-Informed Neural Networks: A Case Study of the Greenland Ice Sheet

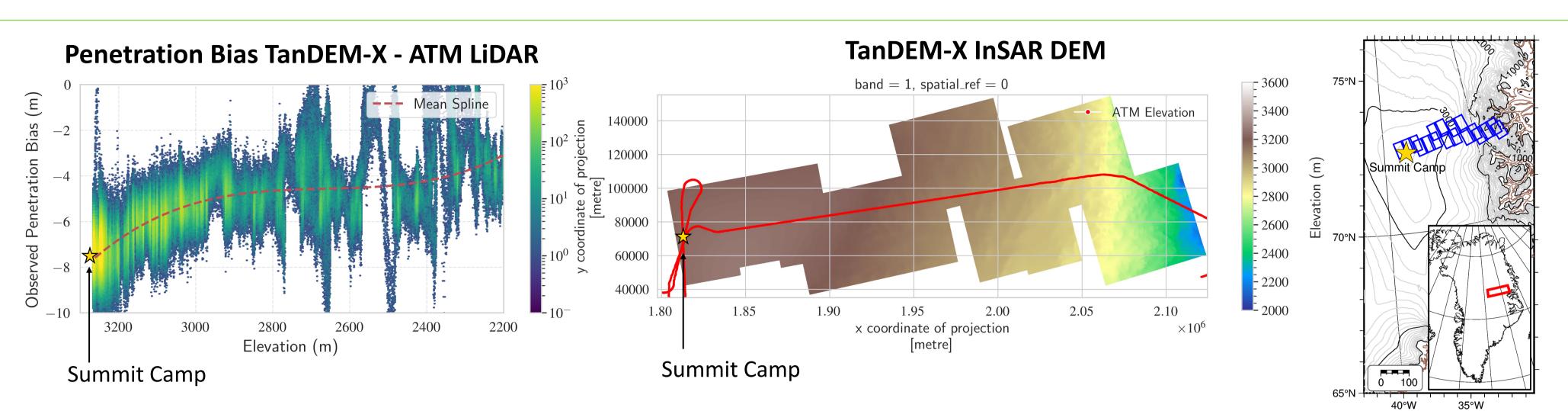
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Study Area and Dataset

Motivation: Compensating for InSAR elevation biases caused by penetration over ice sheets.

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

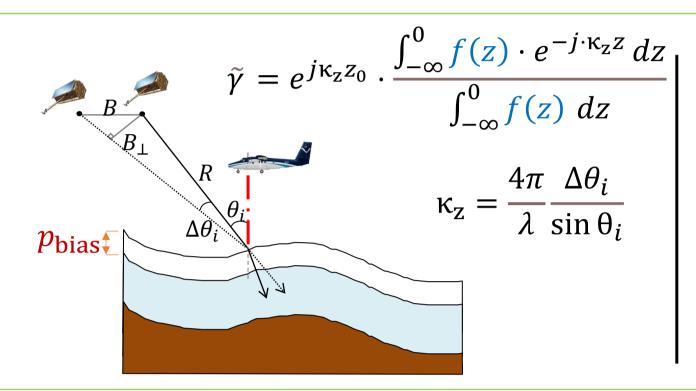
- Location: Greenland, from summit to east cost.
- Dataset: TanDEM-X SAR scenes (Jan-Mar 2017) and NASA IceBridge ATM LiDAR (Mar 2017).



Estimation of Penetration Bias

Physical Modeling¹:

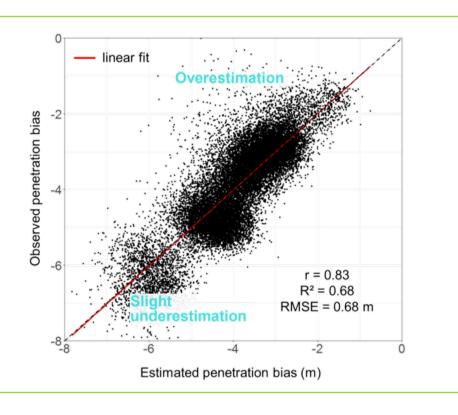
- scattering distribution vertical f(z) (e.g., Exponential, Weibull) to model InSAR volume decorrelation and coherence.
- Invert the InSAR Phase Center Depth $\angle \gamma$ to estimate penetration depth.



Linear Regression/ML²:

- Applies statistical linear regression models to adjust measured values and minimize bias.
- Implements correction functions across all scenes to correct elevation estimates.

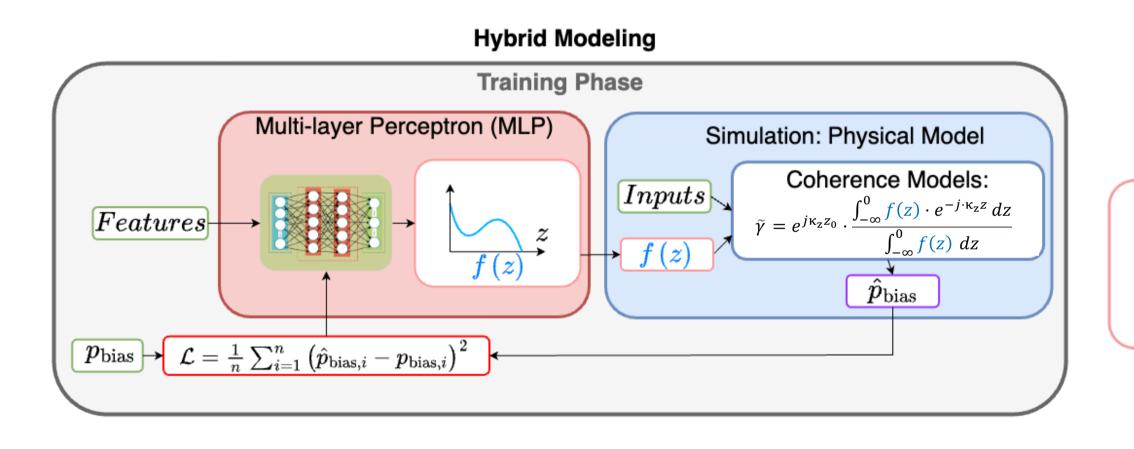
Input Features



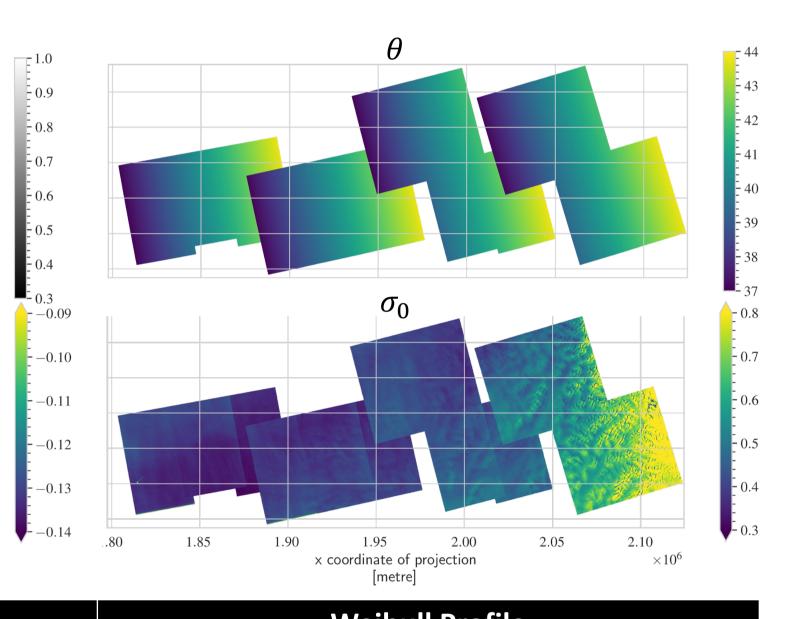
Methodology: Hybrid Method (Physics-informed Neural Networks)

Hybrid Method (Physics-informed Neural Networks):

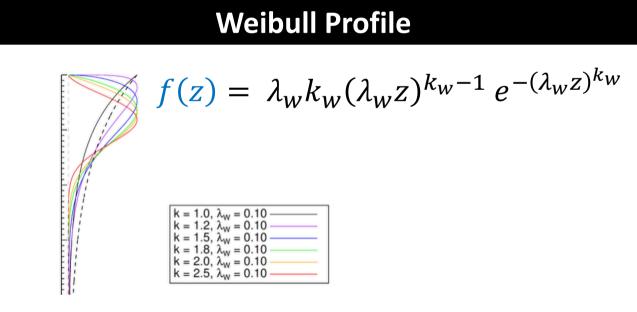
- Combines ML with physical modeling for enhanced bias correction.
- Input features include interferometric coherence and other SAR-derived metrics.
- Learn a scattering distribution (e.g., Exponential, Weibull) to compensate for the underlying assumptions of the physical model.



120000 80000 60000 120000



Exp. Profile $f(z) = \sigma_v^0 e^{\frac{2z}{d_{\rm pen}}}$ d_{pen} = 10 m d_{pen} = 20 m d_{pen} = 30 m d_{pen} = 40 m d_{pen} = 50 m



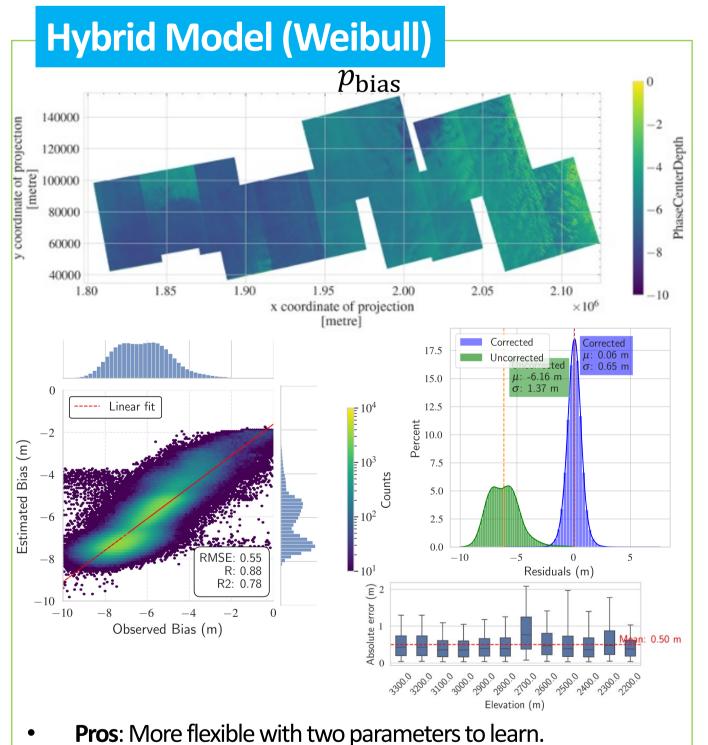
PM Model (Exp.) $p_{ m bias}$ x coordinate of projection - Linear fit Pros: Easy to understand and provides consistent results across different InSAR geometries.

Cons: Uses only the direct relationship between InSAR coherence y and penetration bias, based on simplified

Hybrid Model (Exp.) $p_{ m bias}$ x coordinate of projection Linear fit Observed Bias (m)

Pros: Combines strengths from PM and ML approaches for robustness/accuracy with limited labeled data.

Cons: Complex to develop and implement.



Cons: Requires additional work to tune it.

Benefit of Terrabyte

- **High-Performance Computing for PhD Research:**
- It allows running multiple simulations for the hybrid modeling approach in parallel with changing optimization parameters. This significantly reduces computational time:
 - From one week using local institute infrastructure. To only a few hours on Terrabyte's HPC capabilities.
- **GPU Usage for Hybrid Modeling Development:**
- It accelerates the training process for a hybrid modeling approach by:
 - Leveraging GPU power for faster neural network computation.
 - Effectively handling large datasets, reducing bottlenecks during training.
 - To only a few hours on Terrabyte's HPC capabilities.
- Impact on PhD Workflow:
- Enables quicker experimentation—an essential component for promptly achieving research milestones.

Conclusion

assumptions of f(z).

Results

- **Enhanced DEM Accuracy:**
- Corrected DEMs exhibit higher precision and reliability.
- **Penetration Bias Reduction:**
 - Achieved MAE of approximately 0.5 meters across different elevation ranges.
- **Effectiveness of Physics-Informed ML:**
- Successfully corrects biases even with an unbalanced training dataset.
- Delivers superior overall performance with limited training data.

[1] S. Abdullahi, B. Wessel, M. Huber, A. Wendleder, A. Roth, and C. Kuenzer, "Estimating Penetration-Related X-Band InSAR Elevation Bias: A Study over the Greenland Ice Sheet," Remote Sensing, vol. 11, no. 24, Art. no. 24, Jan. 2019, doi: 10.3390/rs11242903. [2] G. Fischer, K. P. Papathanassiou, and I. Hajnsek, "Modeling and compensation of the penetration bias in InSAR DEMs of ice sheets at different frequencies new," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 2698–2707, 2020, doi: 10.1109/JSTARS.2020.2992530.







