

DEEP LEARNING SEISMIC WAVEFORMS TO PREDICT SEA ICE PROPERTIES

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BACKGROUND

- **Accurate, continuous estimates** of sea-ice properties are critical for understanding a warming Arctic.
- **Current** inversion methods are **computationally expensive**, limiting real-time applications, see [1, 2].
- We propose replacing these techniques with convolutional **neural networks** (CNNs) to **capture the underlying relationships** from data.
- The CNNs are **trained on physically informed synthetic waveforms** to infer sea-ice thickness.

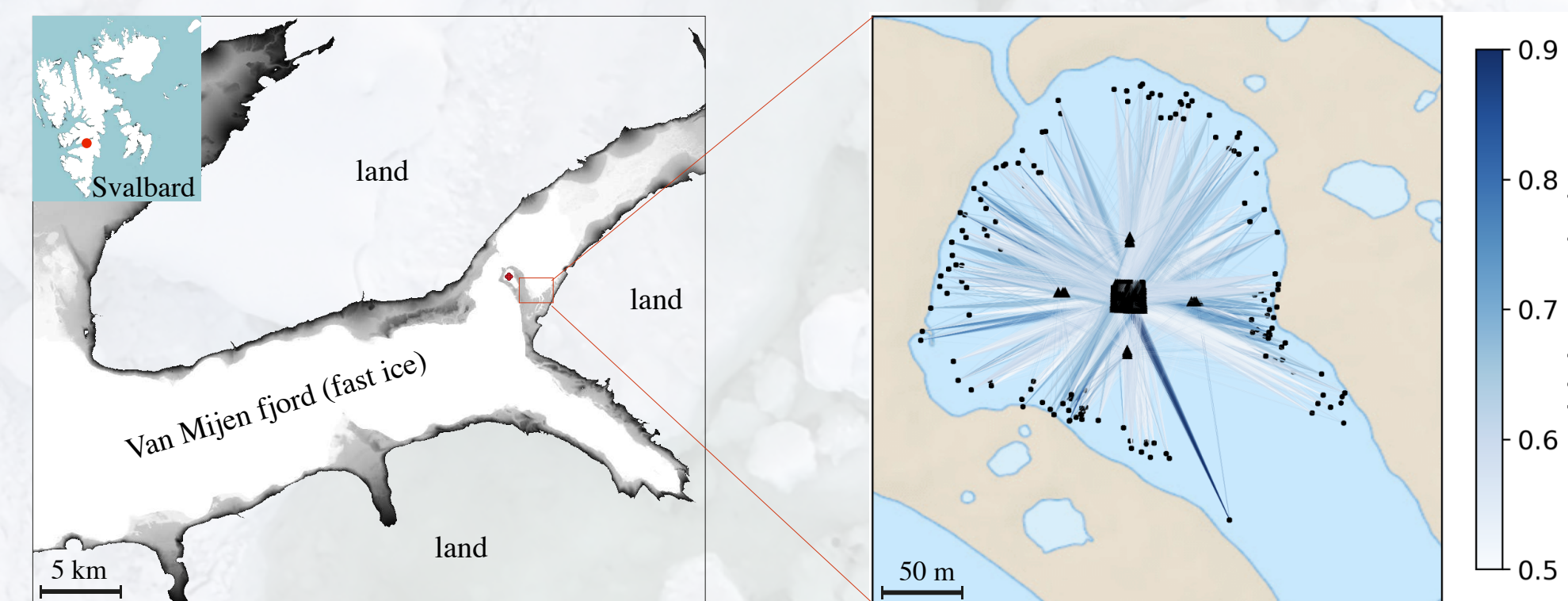


Fig. 1: Field site in Svalbard, Norway; inversion results shown on the right.

TRAINING DATA

- Currently, we **train on** physics-informed **synthetic data** from the forward model to **better control** inverse problem **complexity**.
- Our forward model is restricted to the **flexural wave**, which is **sensitive to ice thickness**.
- Training **inputs and targets are normalized** per sample to $[-1, 1]$ before model input.
- We focus on **lightweight architectures**, to ease later in-situ integration, see [3]. Transformer architectures are not considered due to high number of parameters.

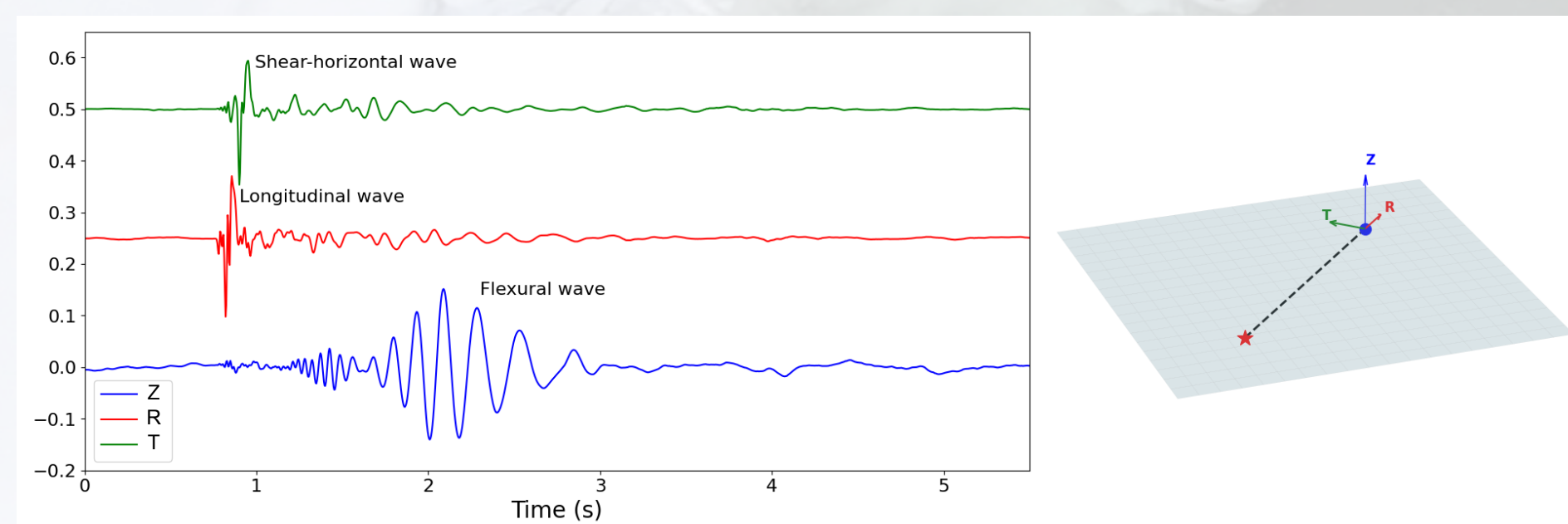


Fig. 2: Wavetypes for different axes in a thin ice sheet. Note that only the flexural wave exhibits dispersion. Shear and longitudinal waves are not suited for ice thickness estimation.

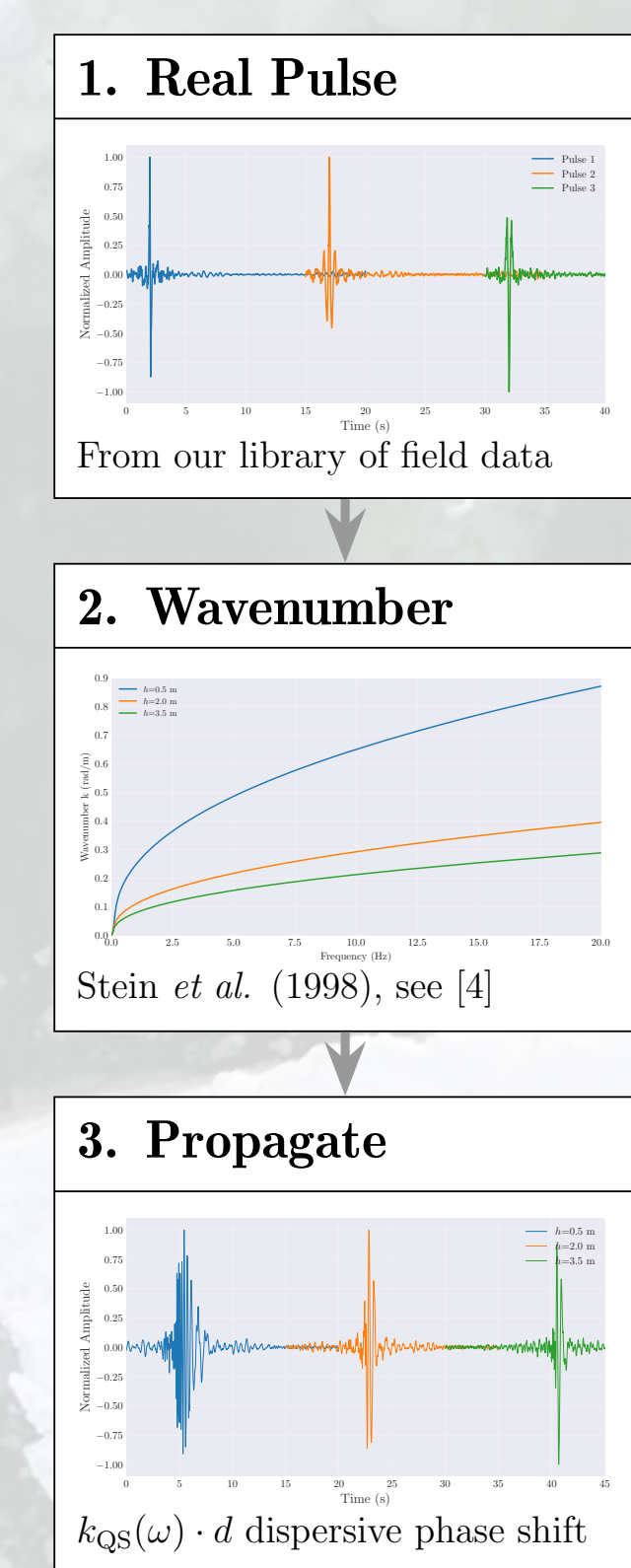


Fig. 3: Our forward model.

Pulses are derived from Svalbard field data.

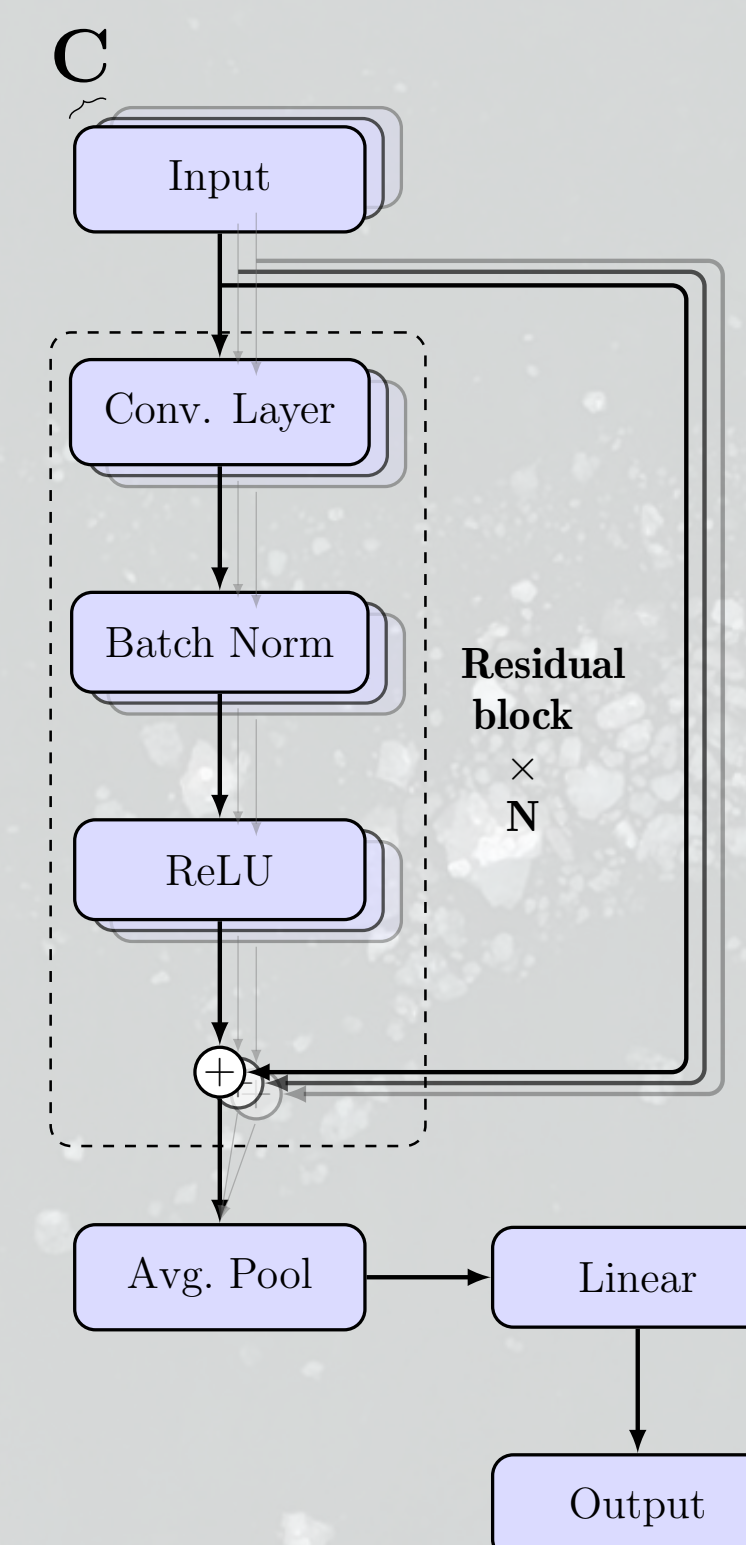


Fig. 4: A simplified version of our CNN architecture, see [5].

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TRAINING EXPERIMENTS

Black: values fixed in dataset (not learned)
Red: values varying across samples

Less than 5% mean absolute percentage error

Exp. No.	Task	Waveforms	Targets	Complexity	Performance
1	1D Ice Thickness Estimation	1	1 Ice Thickness	Low	✓
2	1D Source Distance Estimation	1	1 Source Distance	Low	✓
3	1D Ice Thickness & Source Distance Estimation	1	1 Source Distance, 1 Ice Thickness	Medium	✗
4	1D Ice Thickness & Source Distance Estimation with multiple sensors	3	1 Source Distance, 1 Ice Thickness	Medium	✓
5	2D Source Location Estimation	3	Source Location	High	✓
6	2D Ice Thickness Estimation with given Source Location	3	3 Ice Thicknesses	High	~
7	2D Ice Thickness & Source Location Estimation	3	3 Ice Thicknesses, Source Location	Very High	✗

No significant predictive performance

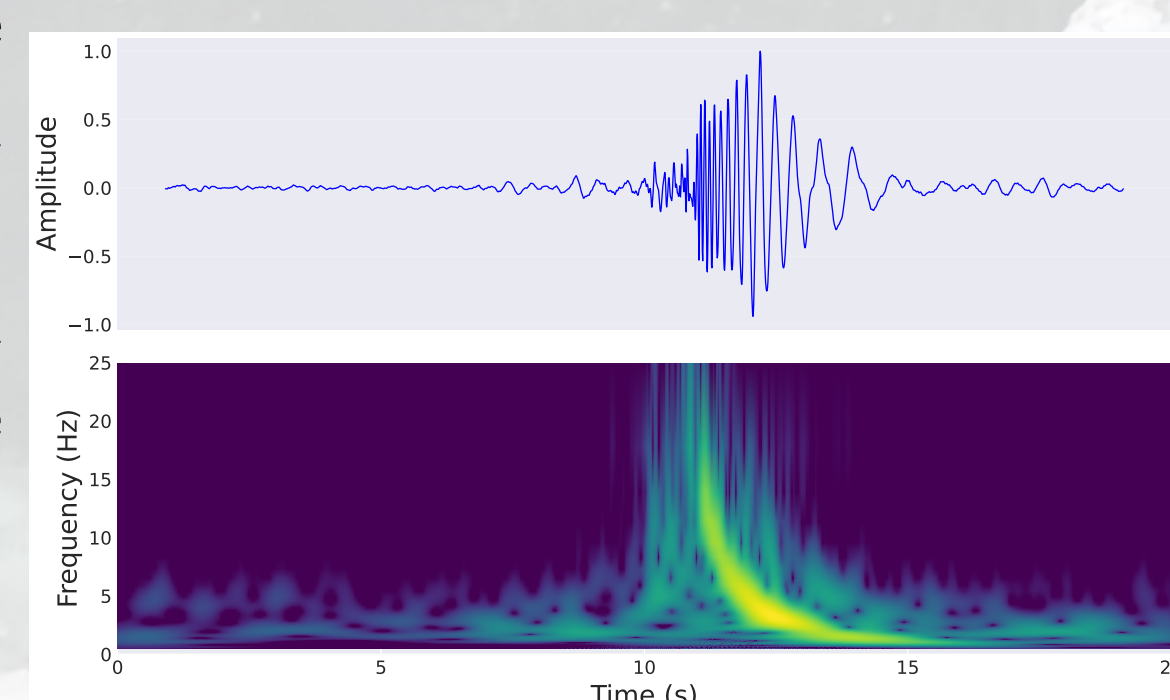
OUTLOOK

- We will explore **integrating physical equations** into the loss function (physics-informed neural networks, PiNNs).
- Non-dispersive **longitudinal and shear waves** will be used to better constrain source location estimation.
- Once realistic experiments (e.g., Exps. 6–7) show promise, we will **train on field data** to evaluate generalization.

CURIOSITIES

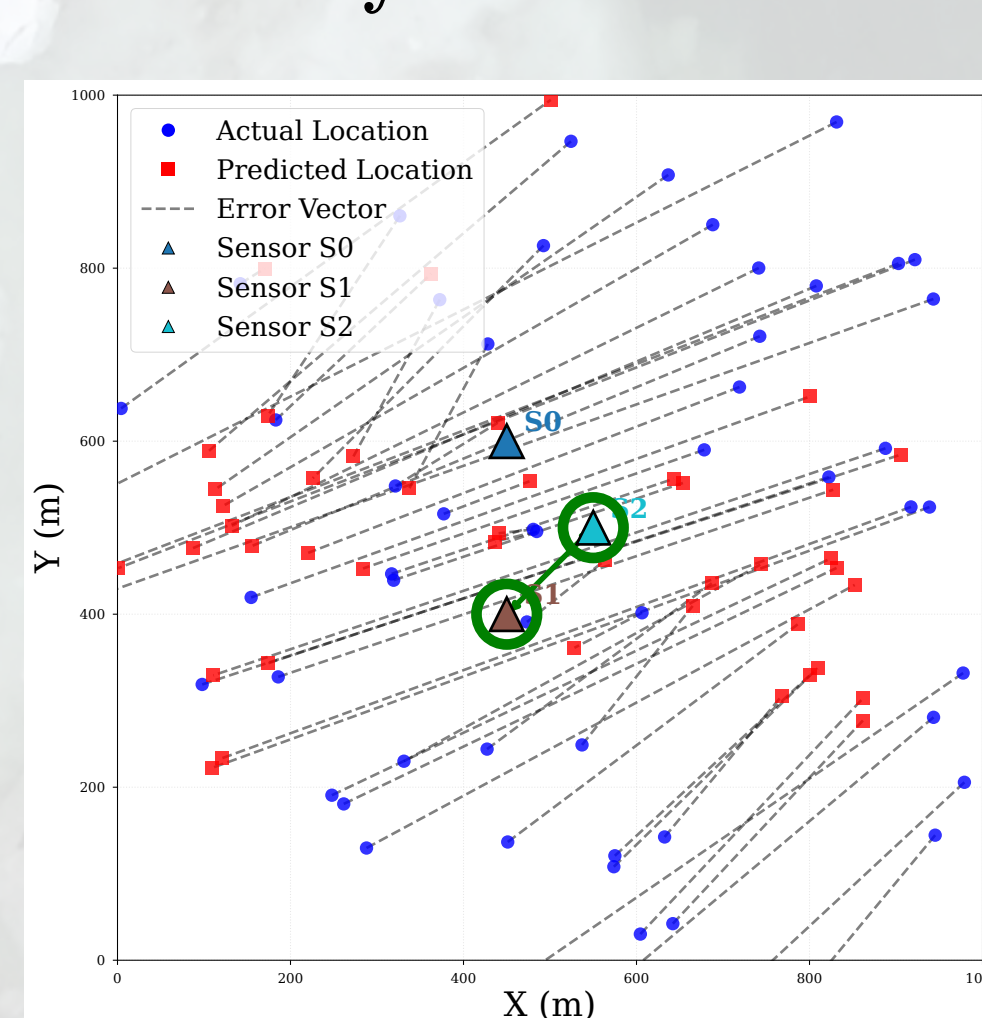
Input Waveforms vs. Spectrograms

The use of **spectrograms** reduces **RMSE** by up to 50% compared to **waveform** inputs. This stems from the **clearer** representation of **dispersion in spectrograms**, albeit with increased **model size** and **input data dimensionality**.



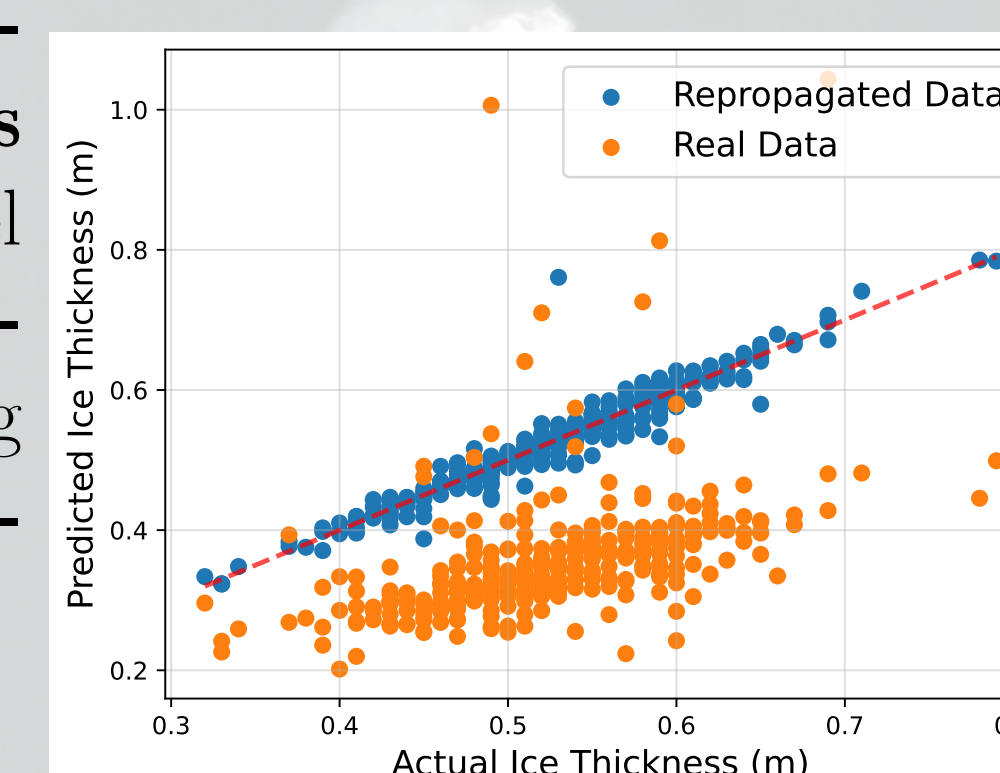
Implicit Learning of Sensor Geometry

During inference, **sensors 1 and 2** were permuted to **assess the spatial awareness** of the model. The resulting **symmetric shift in predictions** indicates that the model has **implicitly encoded** sensor positions.



Generalization to Field Data

When evaluated on real-world data, the model exhibits a **systematic underestimation**. However, **repropagating the real waveforms** through the forward model **restores accurate predictions**, highlighting **dependence on the training data distribution**.



REFERENCES

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- [3] Romain Bailly et al. "Multimodal Contrastive Learning on Time Series: Application to Various Scenario for Seismic Monitoring on Mars". In: *86th EAGE Annual Conference & Exhibition*. Vol. 2025. 1. European Association of Geoscientists & Engineers. 2025, pp. 1–5.
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