AI4IS

AI predictions of icebergs in Antarctica

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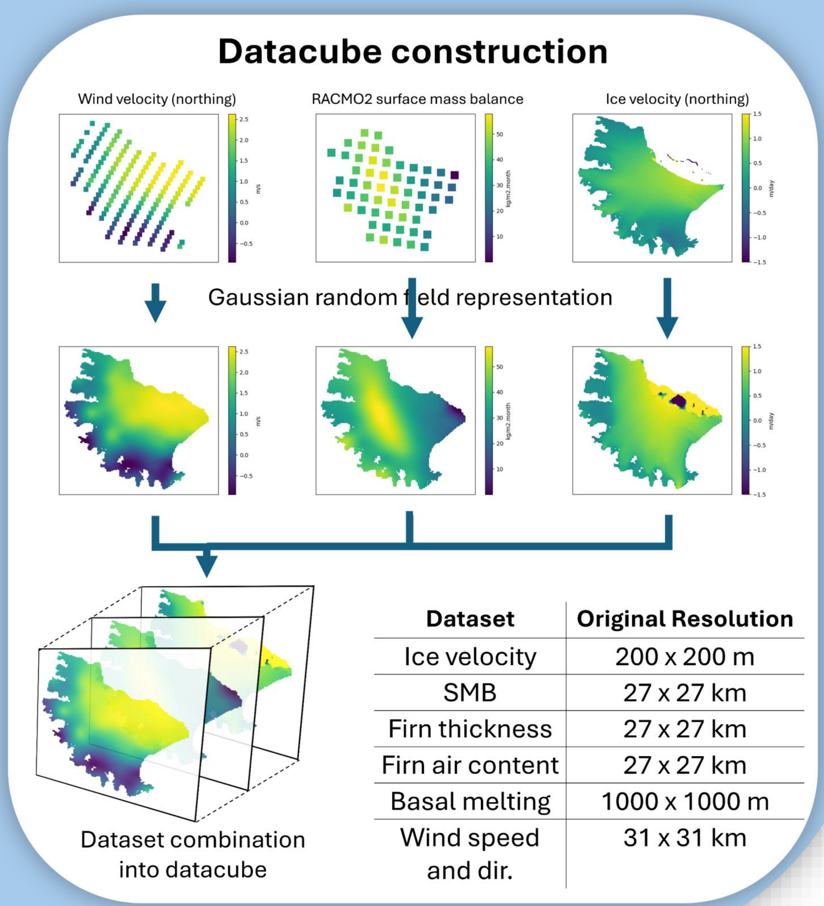
1. We use Gaussian Random Field representation to generate a homogenised datacube from heterogeneous data.

Ice shelf calving is natural process, controlled by internal ice properties, glaciological stresses and external ocean-atmosphere forcing. Observations and **datasets characterising these controls exist in a variety of heterogeneous formats,** including vectors, shapefiles, and gridded products. We use Gaussian Random Field (GRF) representation in the **R-INLA** package to bring these data onto a shared grid - the datacube [1].

This produces a multi-dimensional, pixel-based representation that facilitates the application of scene-classification AI techniques, & a wider range of analyses that benefit from **homogeneous, co-registered data,** such as statistical modelling and data integration workflows, while enabling **uncertainties to be consistently quantified and propagated** through subsequent analyses.



Dataset	Original Resolution
Ice velocity	200 x 200 m
SMB	27 x 27 km
Firn thickness	27 x 27 km
Firn air content	27 x 27 km
Basal melting	1000 x 1000 m
Wind speed and dir.	31 x 31 km

2. The datacube is ingested by an AI model, trained on the A68 calving event from the Larsen C ice shelf.

We investigated the predictability of the 2017 A68 calving event - an iceberg more than four times the size of Rome - using an Attention U-Net architecture **trained on 15 years of labelled calving data,** including 2017 [2]. The model performs spatially explicit, pixel-wise learning of calving-relevant features. Training employed the AdamW optimiser with Focal Loss, with the gamma parameter tuned to improve performance on rare and edge-case events. Random data augmentations were applied to enhance generalisation and transferability. To assess the contribution of individual layers, we conducted ablation experiments - **an explainable AI (XAI) analysis.**

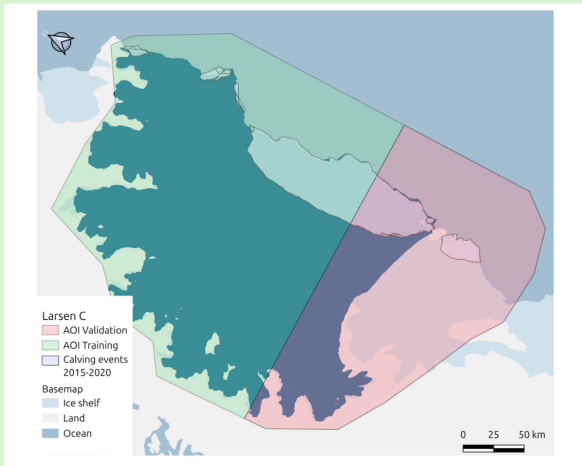


Figure 2: Data split, showing data coverage (dark blue). Calving events between 2015-2020 in light blue, with the major event of A-68 being the largest.

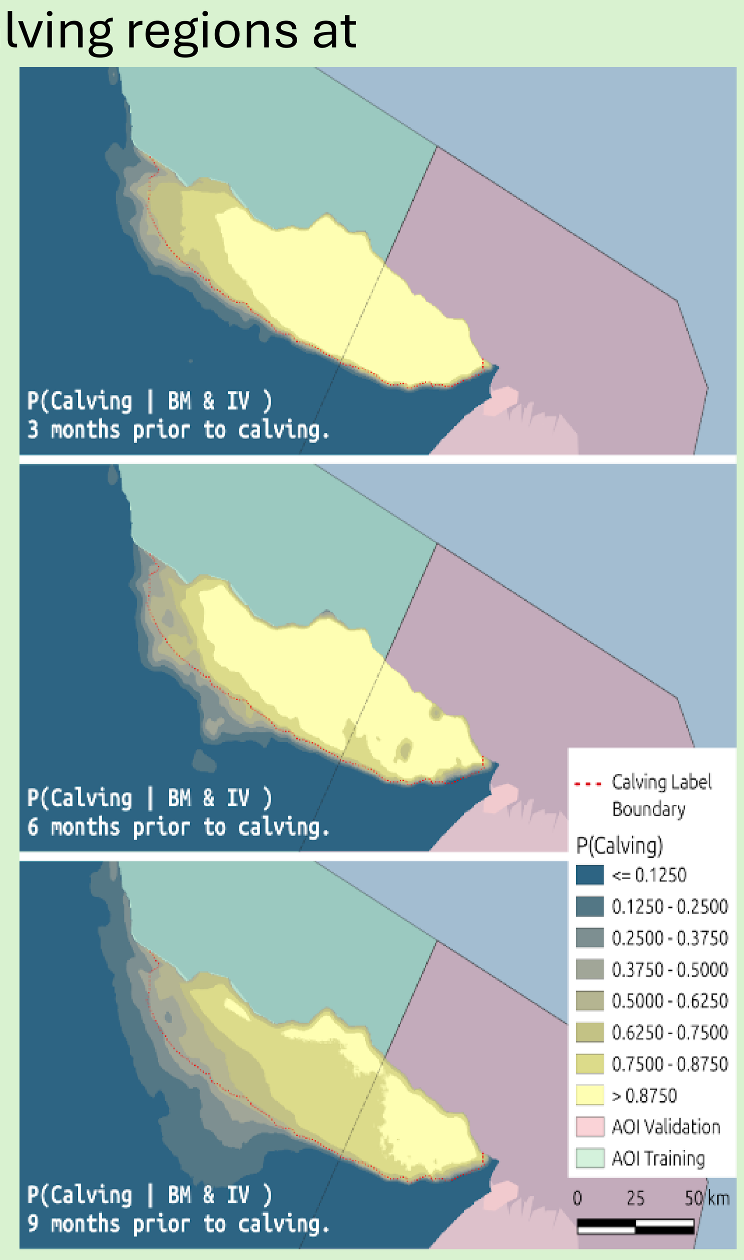
Model Summary

Model	
Model	Attention U-Net [6]
Activation	ReLU
Encoder Blocks	5
Base channels	16
Output channels	2
Optimizer	
Algorithm	AdamW [5]
Learning Rate	0.001
β_1	0.9
β_2	0.9
Weight Decay	0.1
Loss	
Loss Function	Focal Loss [4]
γ	3
classes	(no-calving, calving)
class weights	[1, 2]
reduction	mean
Data Augmentation	
Input-shape	364×364
Rotation	$\theta \in [0, \pm 45°)$
P(Horiz.flip)	0.5
P(Vert.flip)	0.5
Center Clip	256×256

See also: Hay et al., 2025, 'Predicting calving events in Antarctica using Machine Learning'

3. The trained model is then used successfully to predict the A68 event, with a range of lead times.

The U-Net models achieved **F1 scores ≥ 0.9** when predicting calving areas. Semantic segmentation outputs provide probabilistic maps of calving likelihood based on data from *N* months prior to the event. Visual inspection demonstrates accurate delineation of observed calving regions at probabilities > 0.5 up to nine months in advance (right). Prediction confidence increases as lead time decreases: the predicted calving area becomes more tightly constrained, and **by *N* = 3 months, probabilities exceed 0.75 across most observed calving regions.** XAI results indicate that ice velocity and basal melt provide the strongest predictive signals, consistent with fracture mechanics theory. Ice velocity emerges as the dominant predictor, reflecting strain-rate gradients that control crevasse initiation and fracture propagation near ice fronts [3,4].



4. We repeated this for a different ice shelf, and early results are promising. Next step – Digital Twin?

To assess workflow transferability, we repeated the analysis for **Pine Island Glacier (PIG),** which calves more frequently than Larsen C. The model was trained on three PIG calving events using ice velocity and strain-rate fields, identified as key predictors at Larsen C. Performance was evaluated using spatially independent train-test splits, yielding **F1 scores of ~0.8 across all lead times** (below); evaluation on a temporally independent, leave-one-year-out event is ongoing. Despite differences in forcing sensitivity - Larsen C being more influenced by atmospheric forcing - the comparable skill suggests **transferable calving-relevant dynamics.** We aim to extend this framework to the remainder of the Antarctic Ice Sheet (e.g. via DTC-IS) and to other regions, such as Svalbard (through Svalbard DT).

Lead time	3-month	6-month	9-month	12-month
F1 score	0.8367 ± 0.0016	0.7874 ± 0.068	0.8161 ± 0.05	0.8276 ± 0.0067

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References:
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[2] M. Qi et al. "A 15-Year Circum-Antarctic Iceberg Calving Dataset Derived from Continuous Satellite Observations". In: Earth System Science Data 13.9 (2021), pp. 4583–4601. DOI: 10.5194/essd-13-4583-2021.
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