TECHNISCHE UNIVERSITÄT DRESDEN DLR AWI AI-CORE esa

ESA Living Planet Symposium 2022

C1.07 ML4Earth: Machine Leaning for Earth

Mapping glacier calving fronts by deep leaning: assessing multi-spectral, textural and topographic input features

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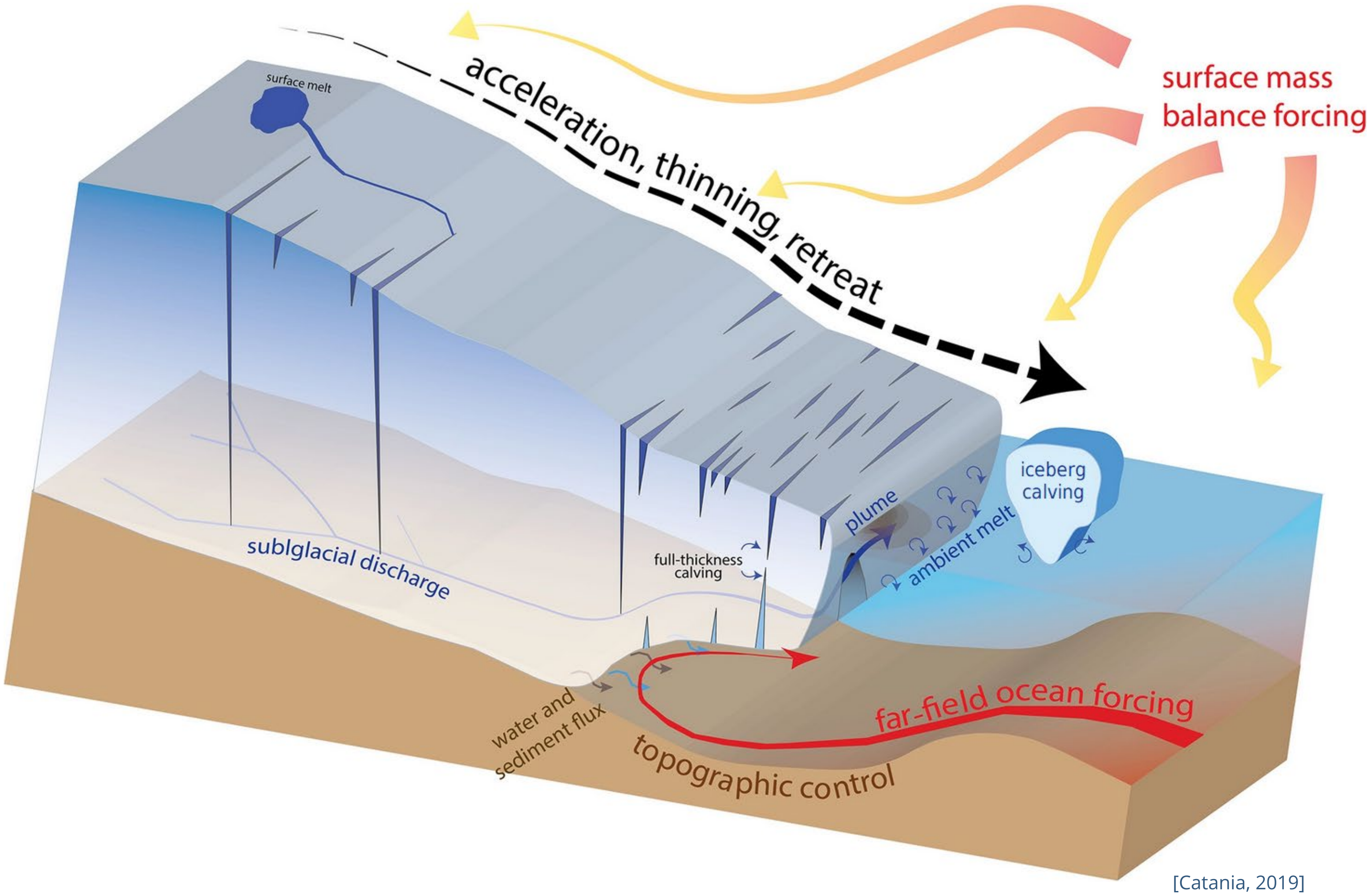
[6]Universität Bremen, Fachbereich Geowissenschaften, Bremen, Germany

[B. Ebermann, 2017]

Motivation



[Catania, 2019]

Motivation

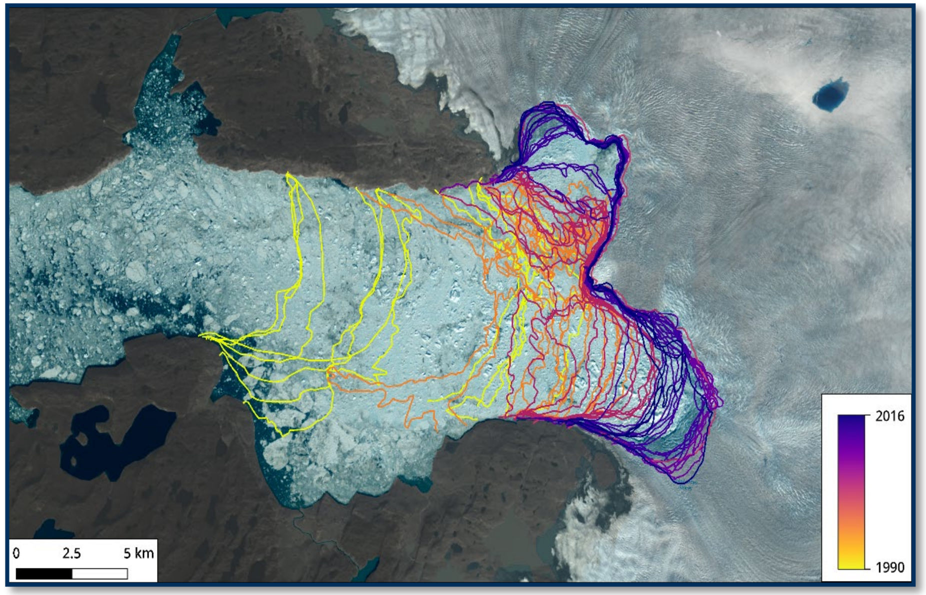

Landsat Program


EOS
TERRA
ASTER
CERES
MISR
MODIS
MOPITT
NASA-GSFC


opernicus
Europe's eyes on Earth

Motivation

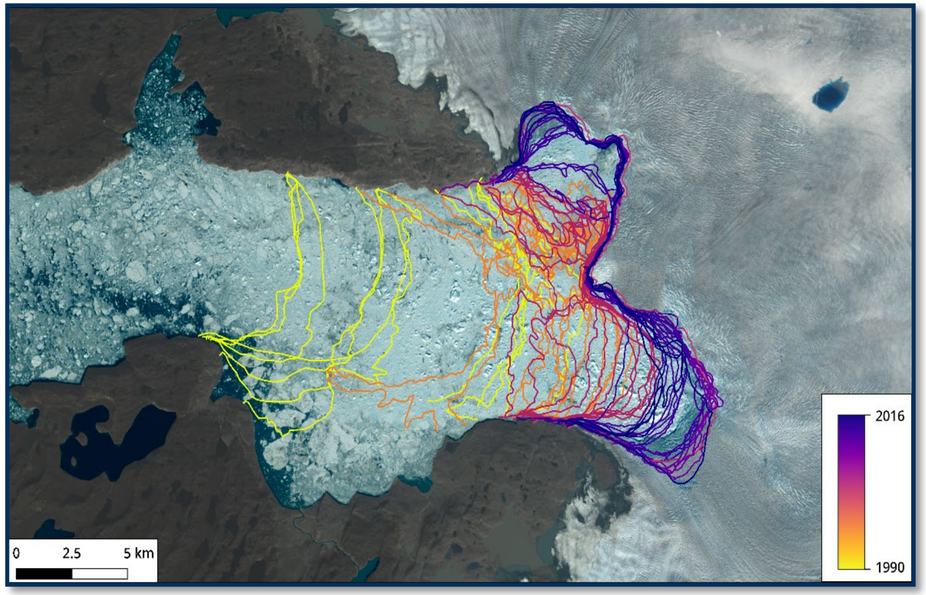
?

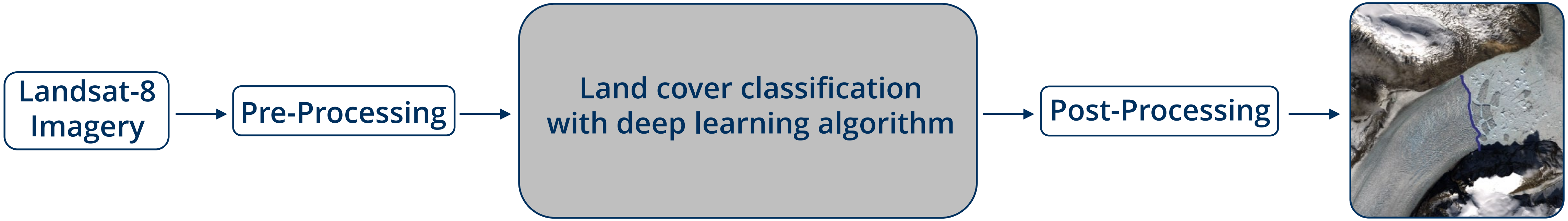


Motivation

?

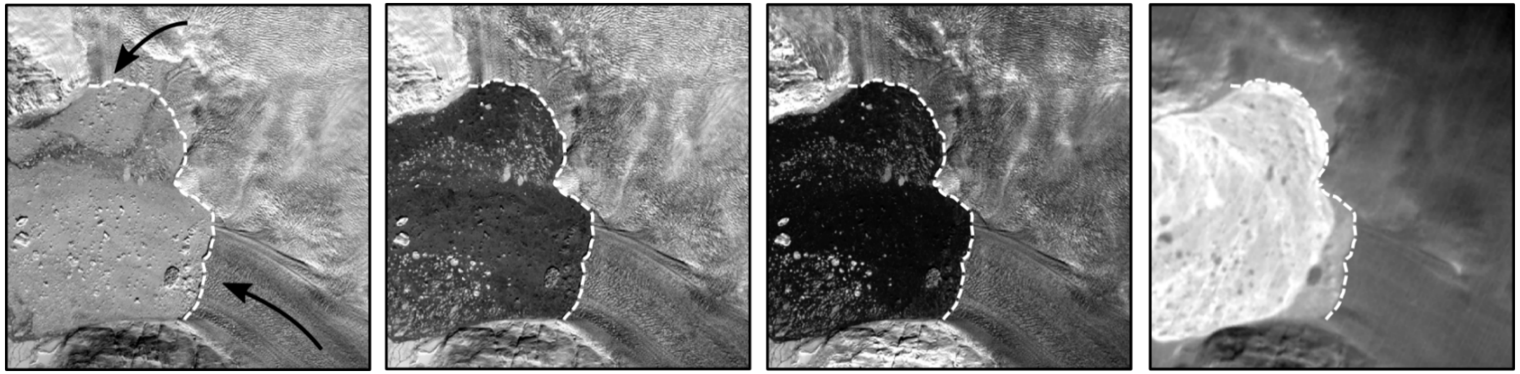
- Scalable
- Robust
- Accurate




Landsat-8
Imagery
Pre-Processing
Land cover classification
with deep learning algorithm
Post-Processing

Input data:

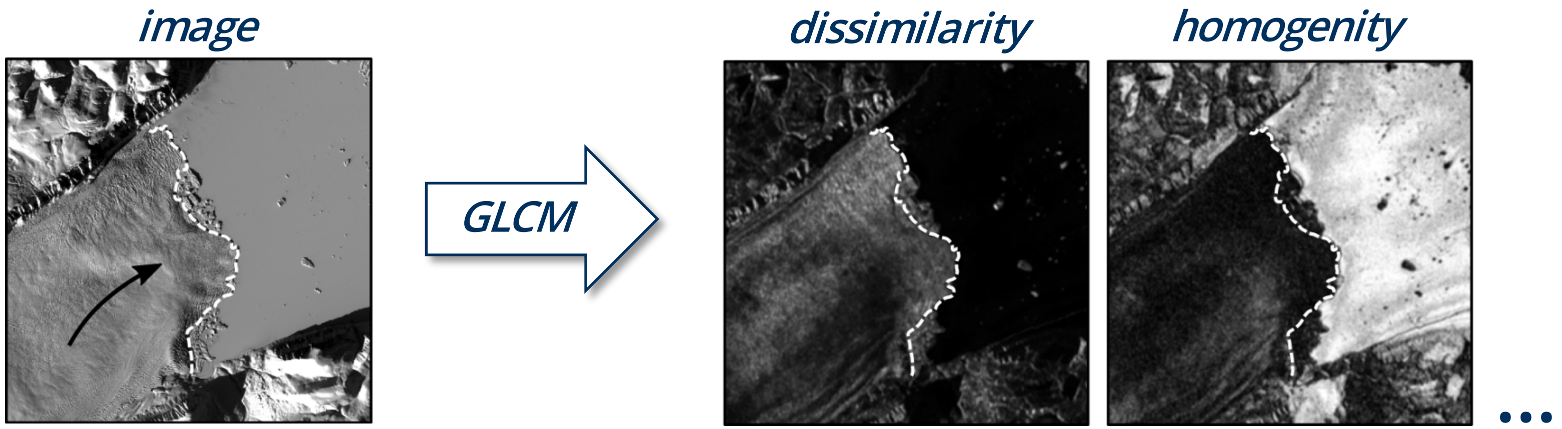
- Multi-spectral bands



Landsat-8 Imagery → Pre-Processing → Land cover classification with deep learning algorithm → Post-Processing →

Input data:

- Multi-spectral bands
- Textural features

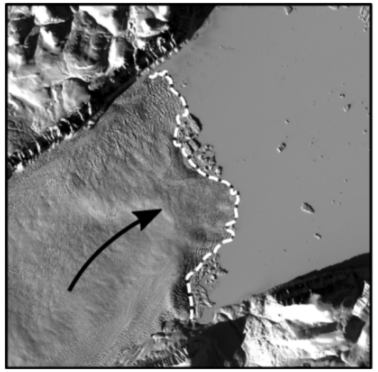


Landsat-8 Imagery → Pre-Processing → Land cover classification with deep learning algorithm → Post-Processing →

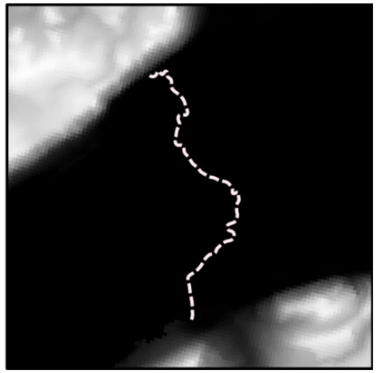
Input data:

- Multi-spectral bands
- Textural features
- Topography data

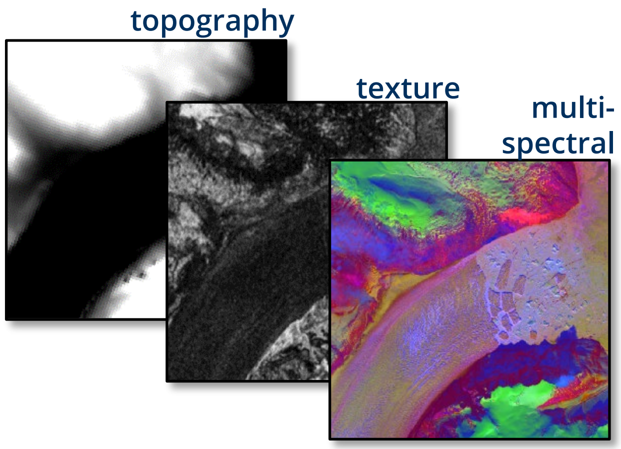
image



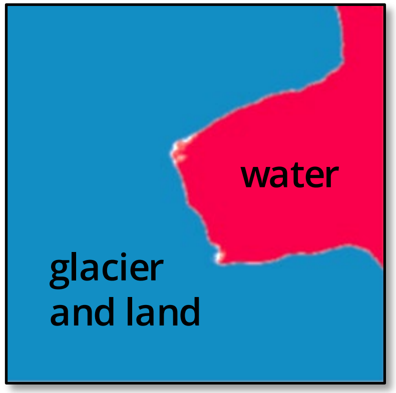
bedrock topography



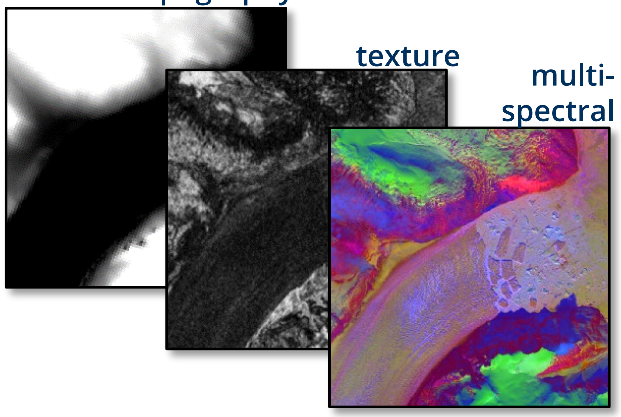
Landsat-8 Imagery → Pre-Processing → Land cover classification with deep learning algorithm → Post-Processing →



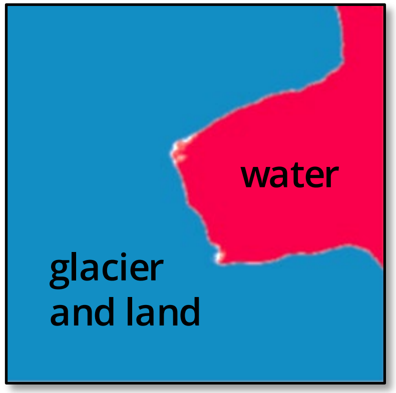
Land cover classification



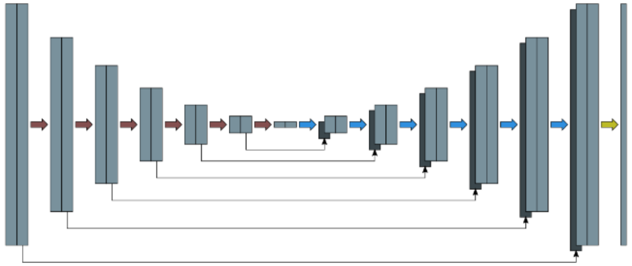
Landsat-8 Imagery → Pre-Processing → Land cover classification with deep learning algorithm → Post-Processing →



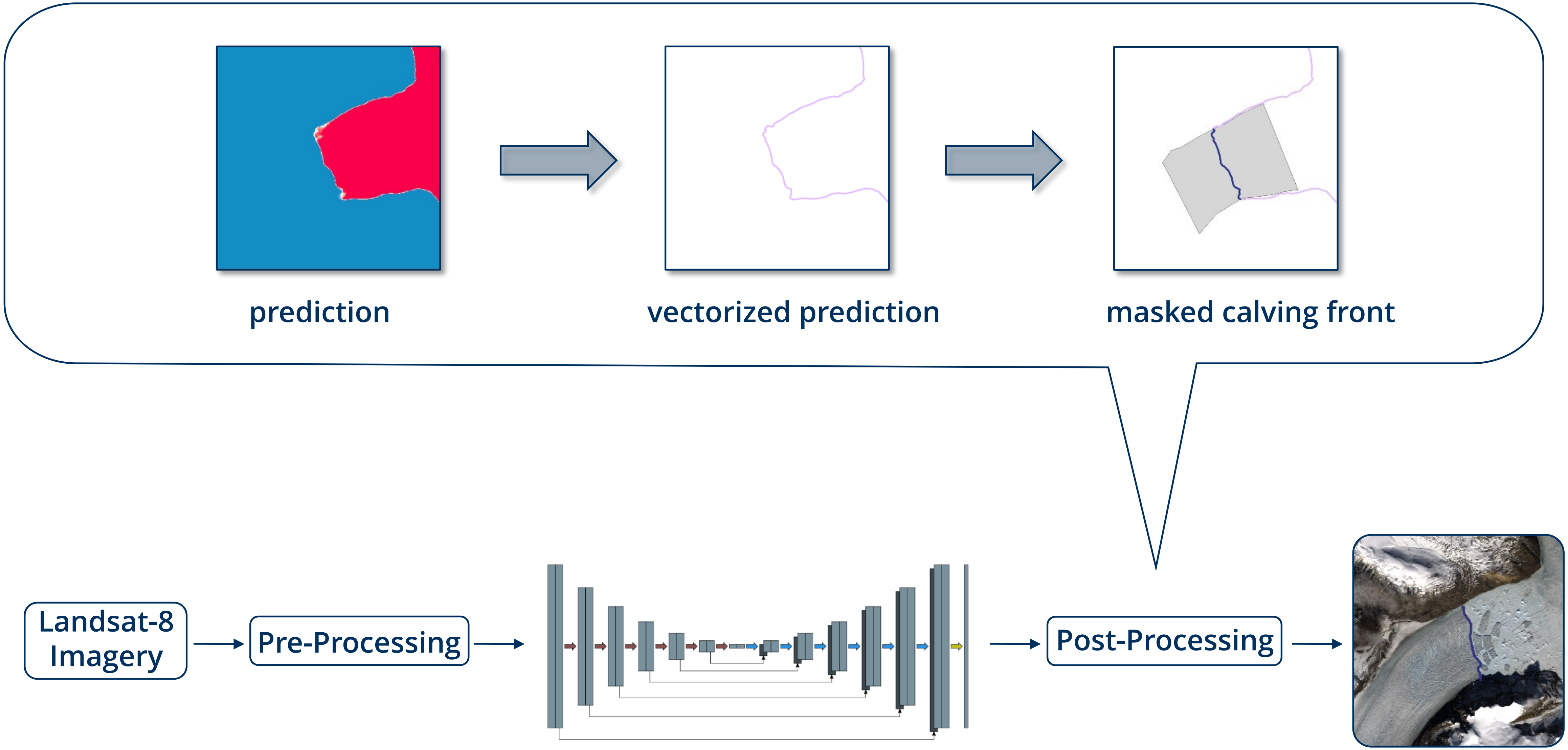
Land cover classification



Landsat-8 Imagery → Pre-Processing →



→ Post-Processing →


prediction
vectorized prediction
masked calving front
Landsat-8 Imagery
Pre-Processing
Post-Processing

Reference dataset

Algorithm is **trained** and **validated** using **manual delineation**

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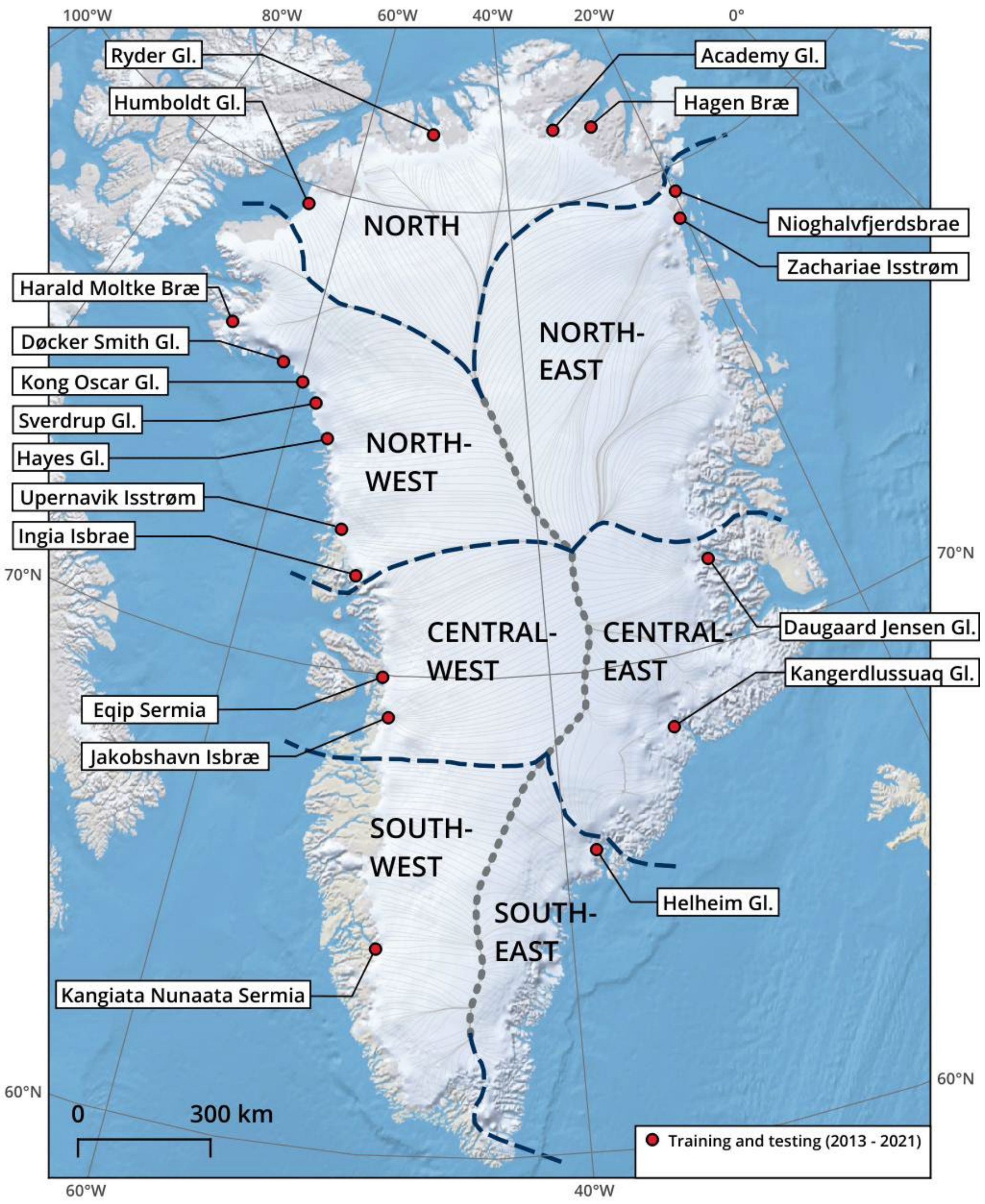
Training

- **698 images** over 18 glaciers from 2013 to 2019



Reference dataset

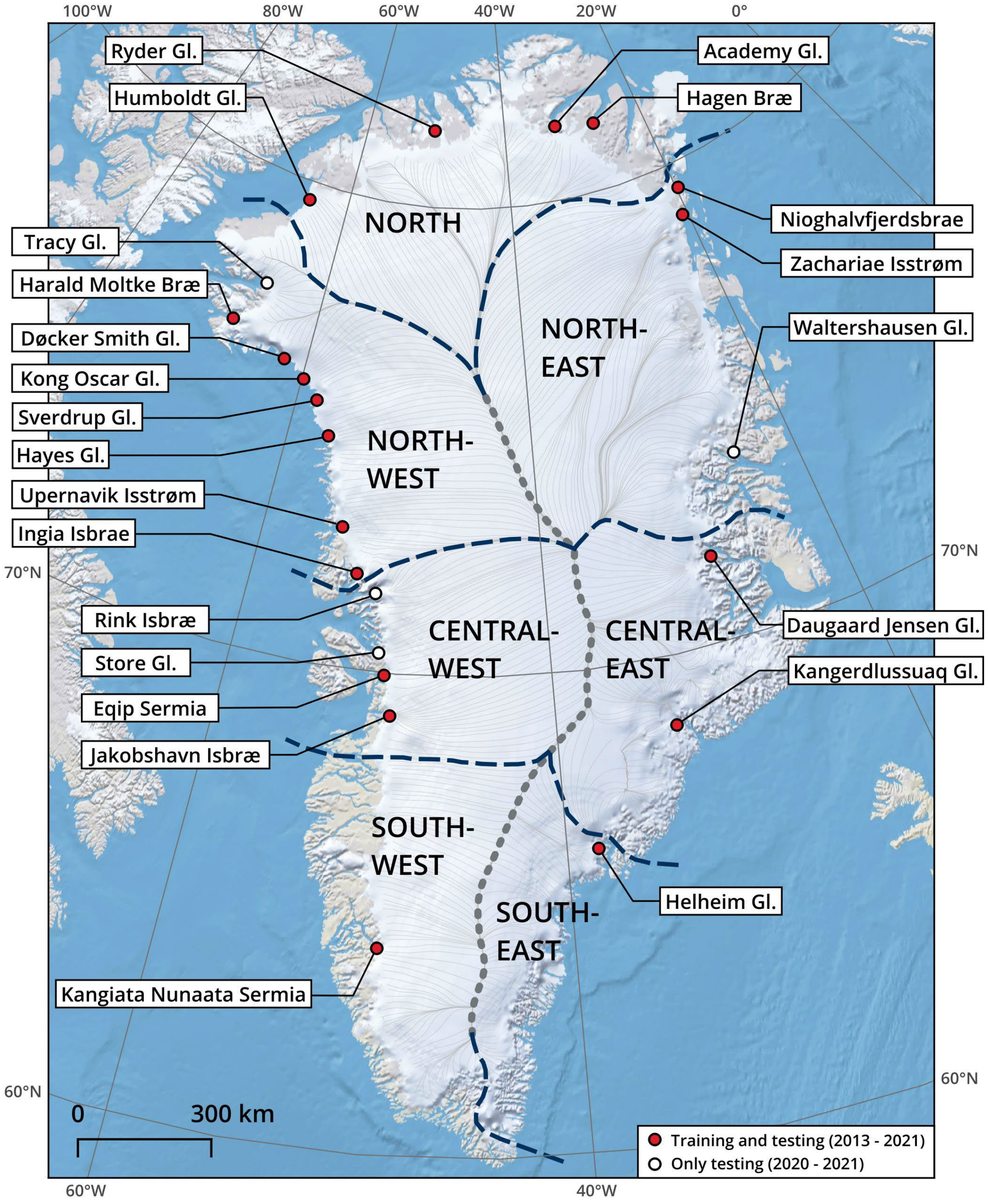
Algorithm is **trained** and **validated** using **manual delineation**

Training

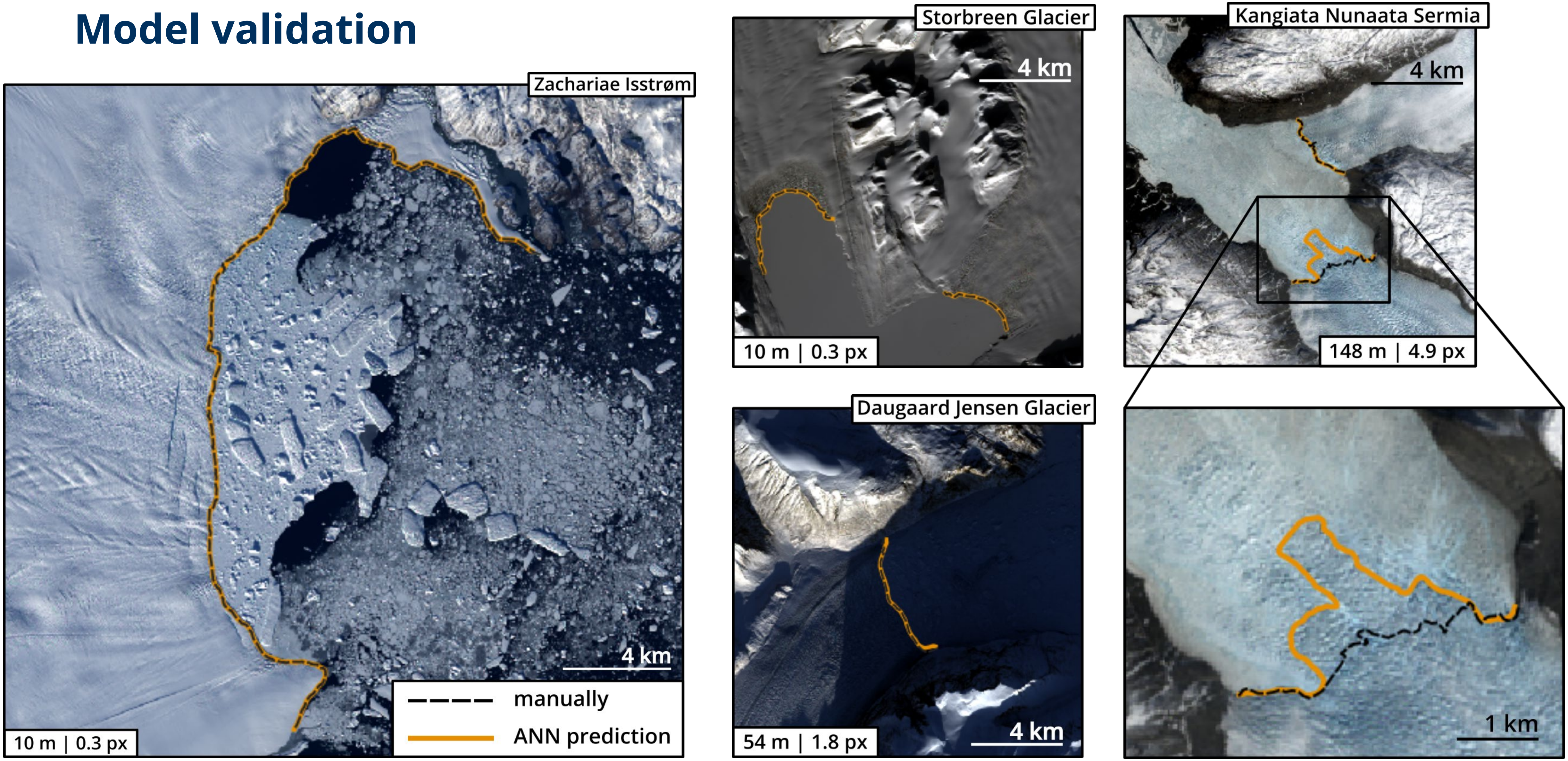
- **698 images** over 18 glaciers from 2013 to 2019

Testing

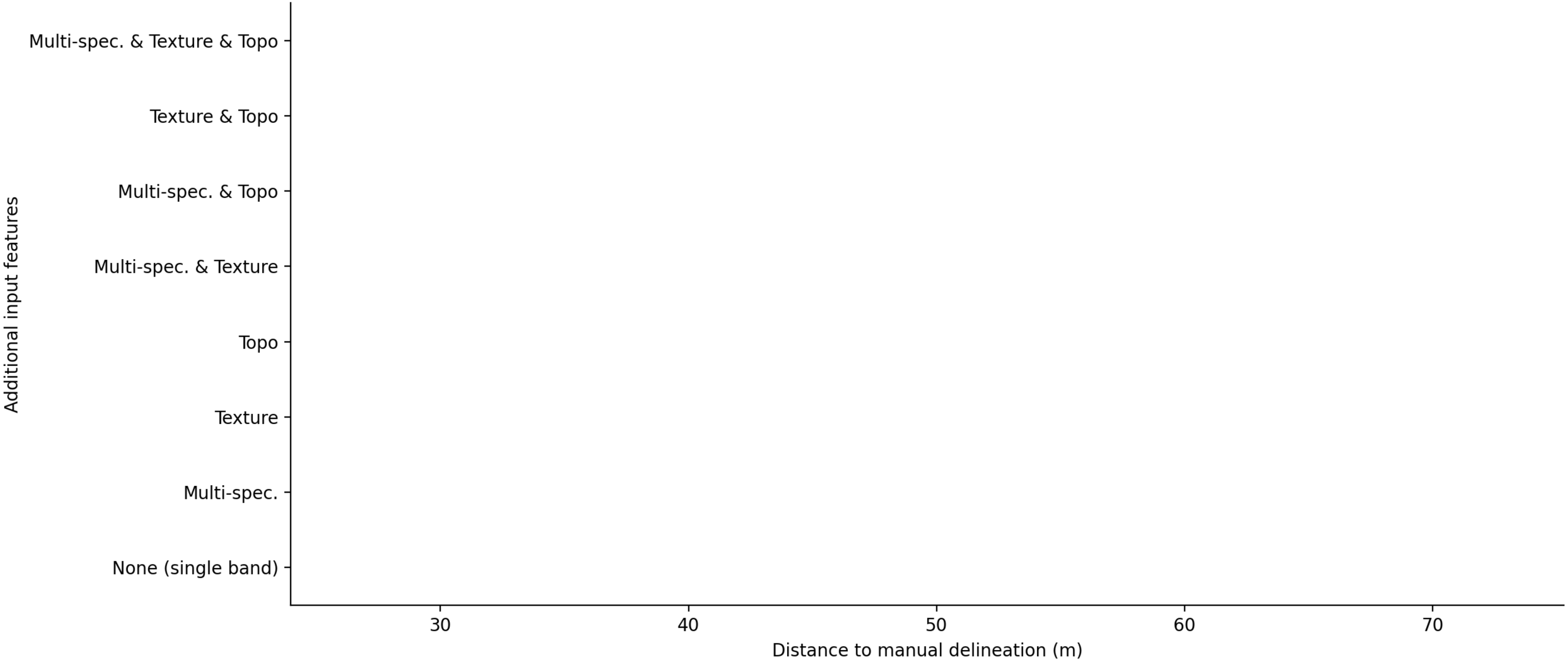
- **200 images** over 25 glaciers from 2020 and 2021



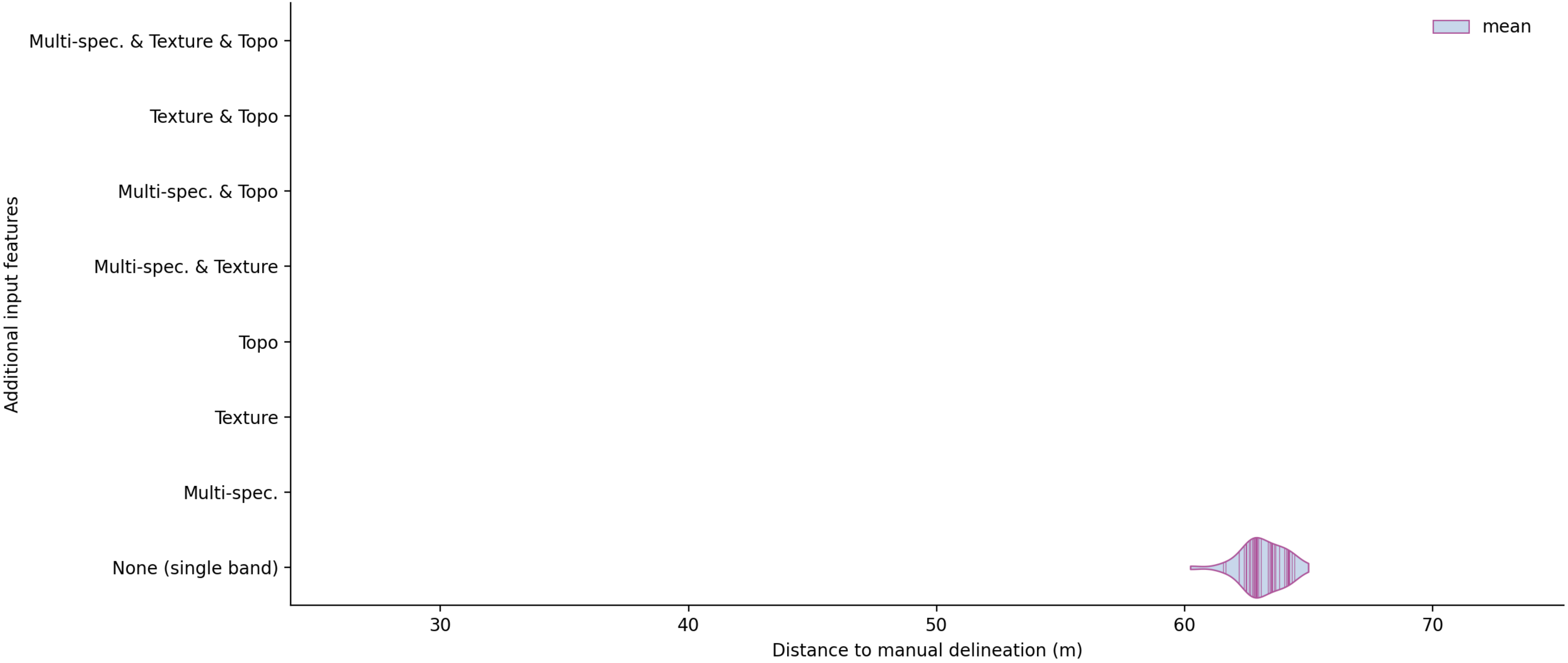
Model validation



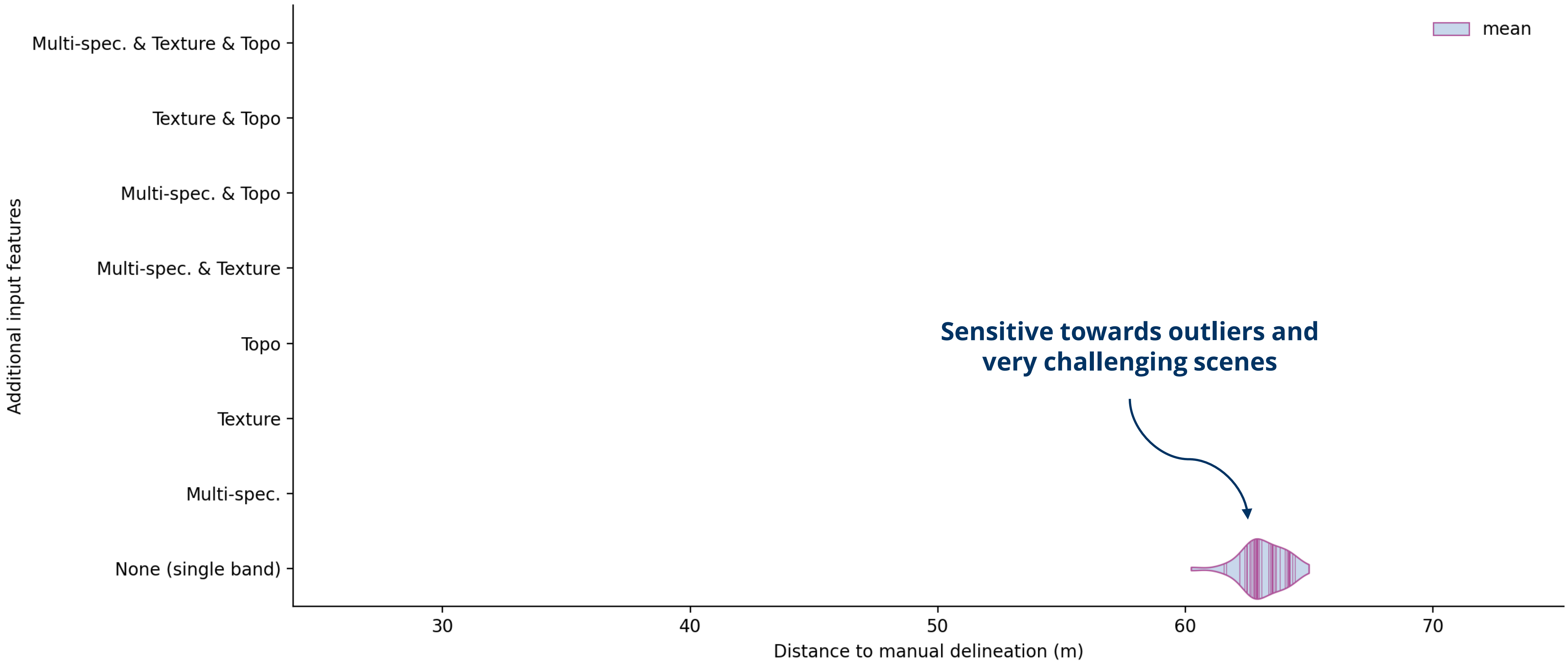
Feature importance



Feature importance

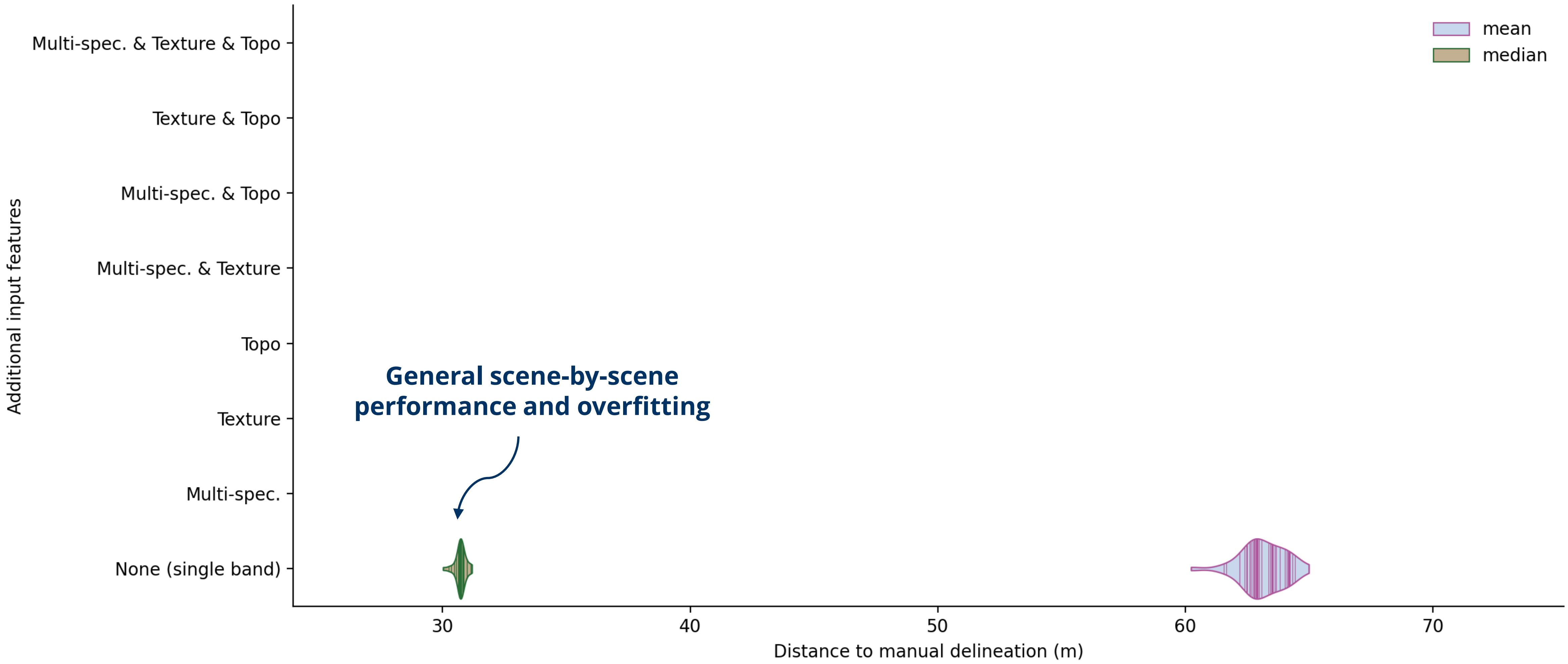


Feature importance

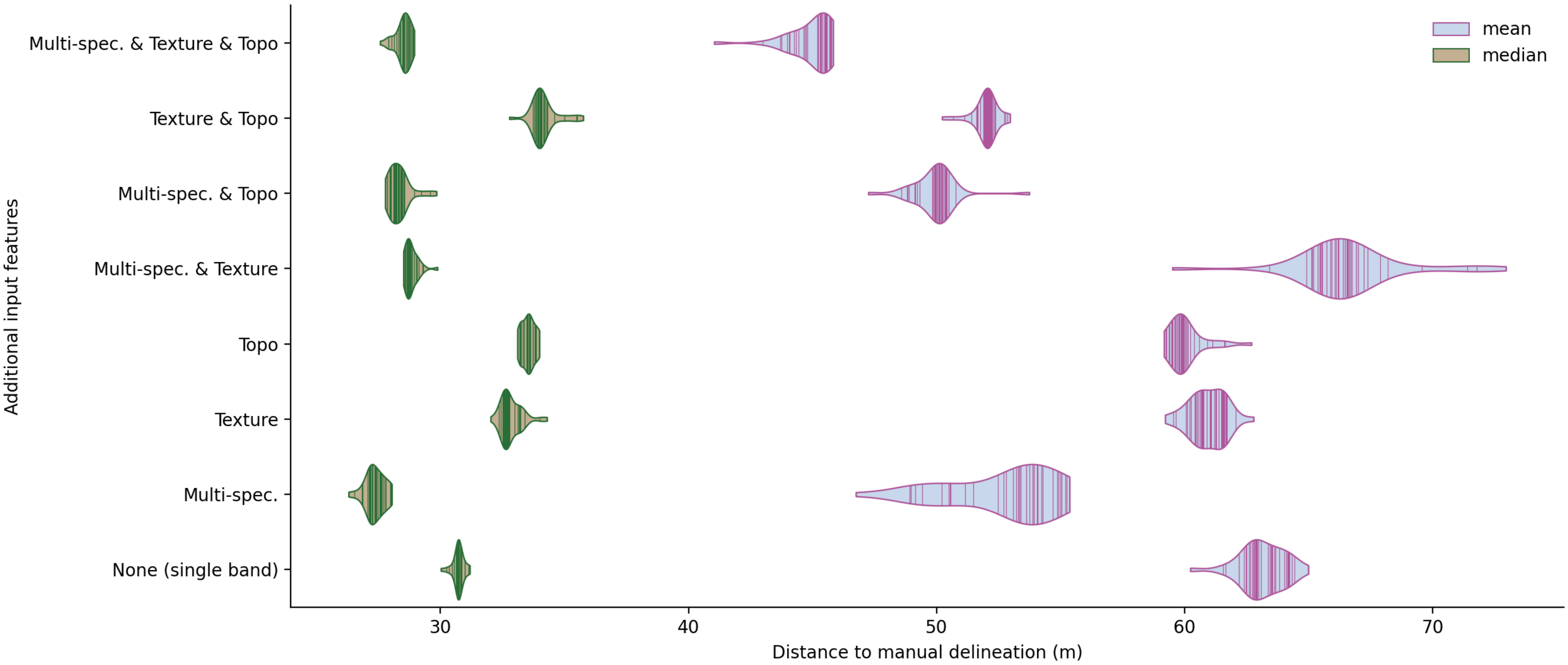


Sensitive towards outliers and very challenging scenes

Feature importance



Feature importance



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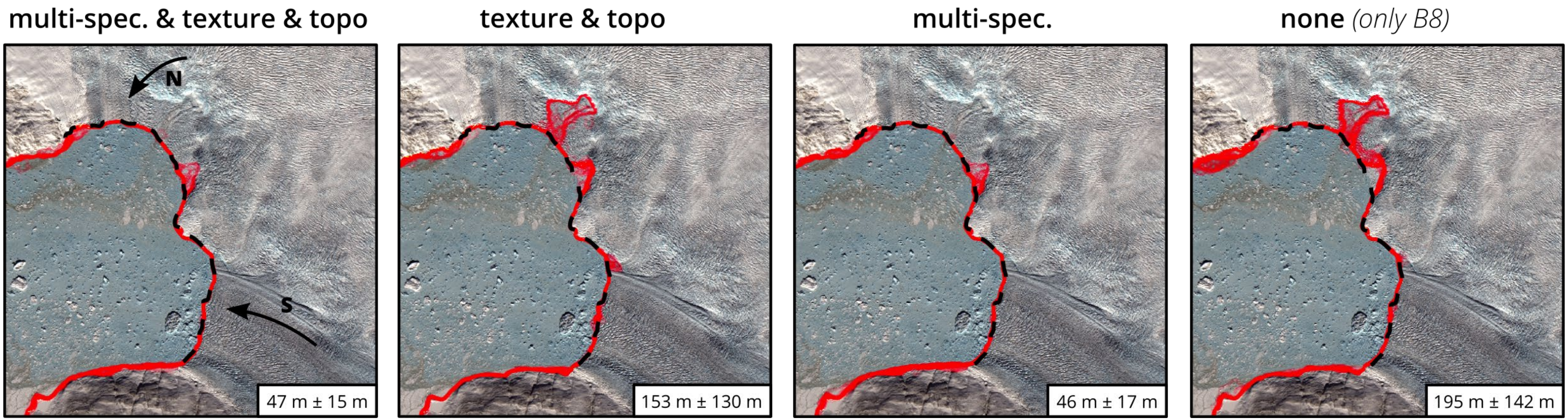
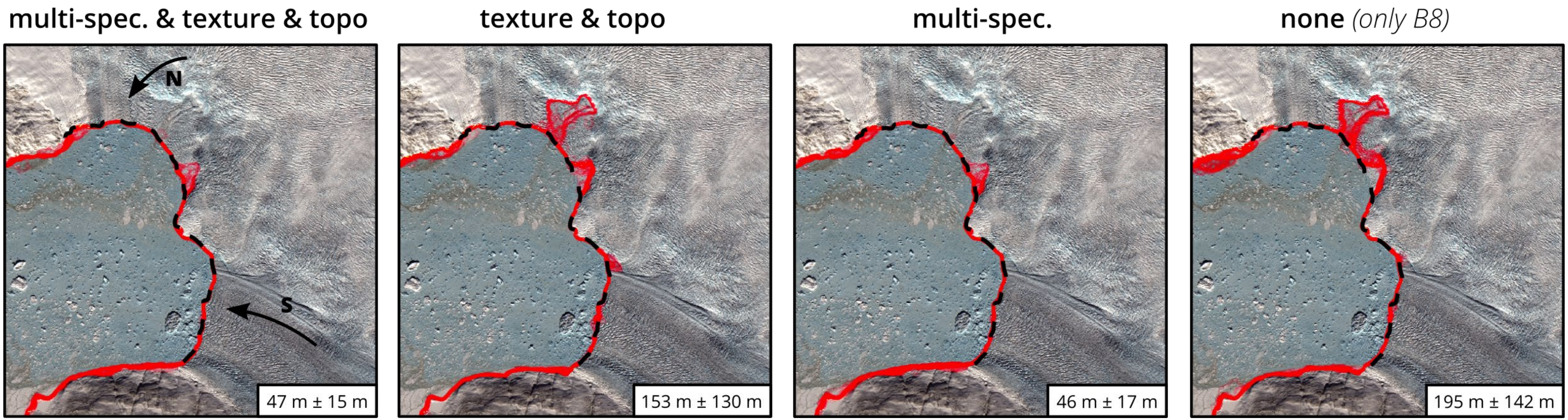
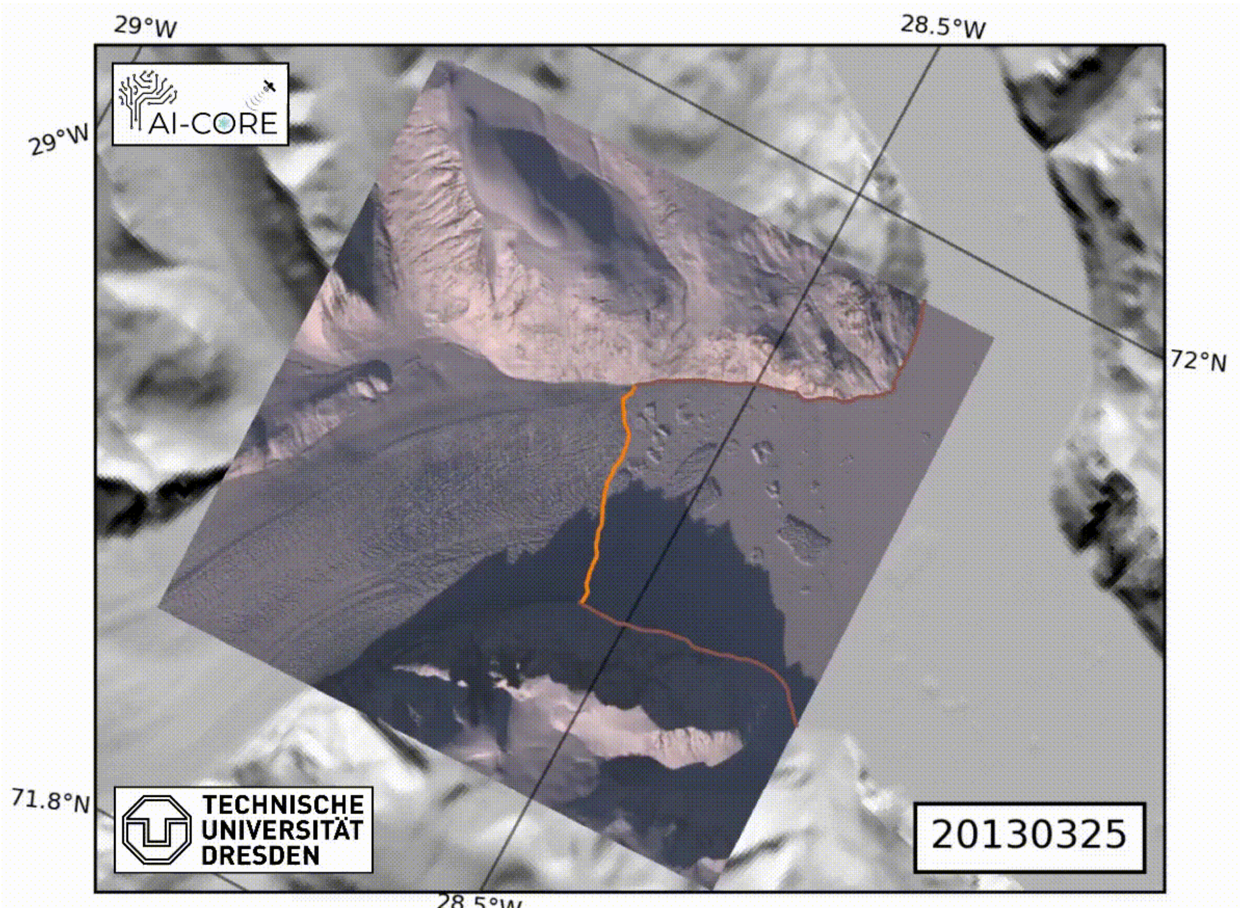


Feature importance



Loebel, E., Scheinert, M., Horwath, M., Heidler, K., Christmann, J., Phan, L., Humbert, A., Zhu, X. (2022): **Extracting glacier calving fronts by deep learning: the benefit of multi-spectral, topographic and textural input features**, *IEEE Transactions on Geoscience and Remote Sensing*, (under review).

Product for Greenland 2013 – 2021



Landsat-8 imagery courtesy of the U. S. Geological Survey

	2013	2014	2015	2016	2017	2018	2019	2020	2021
Kangiata Nunaata Sermia	5	23	19	17	13	17	15	13	23
Helheim Glacier	13	33	24	29	27	17	35	29	31
Kangerdlussuaq Glacier	19	42	29	38	39	40	47	40	43
Jakobshavn Isbræ	15	29	29	26	25	25	34	25	30
Eqip Sermia	13	33	32	29	32	35	37	31	29
Store Glacier	18	40	39	38	36	40	43	35	33
Rink Isbrae	20	43	45	44	40	37	46	37	52
Daugaard Jensen Glacier	13	30	26	38	30	29	43	28	56
Ingia Isbræ	18	30	33	44	41	38	49	47	44
Upernavik Isstrøm	6	19	40	33	36	35	46	43	37
Waltershausen Glacier	13	20	27	28	29	39	46	34	41
Hayes Glacier	13	33	42	46	40	46	64	40	46
Sverdrup Glacier	14	38	53	48	46	45	60	56	59
Kong Oscar Glacier	9	26	44	38	44	34	48	44	48
Døcker Smith Glacier	4	25	42	42	38	37	57	53	45
Harald Molke Brae	16	41	51	51	50	53	54	55	52
Tracy Glacier	19	46	58	54	47	54	51	58	49
Humboldt Glacier	7	34	39	45	39	40	50	48	33
Zachariae Isstrøm	15	46	42	60	68	60	73	52	42
Nioghalvfjerdsbræ	20	38	41	64	65	51	63	48	66
Hagen Brae	51	66	119	127	126	135	104	97	116
Academy Glacier	55	60	128	127	113	119	108	97	111
Ryder Glacier	43	53	100	105	88	114	98	107	96

> 9000 calving front positions with sub-weekly sampling outside polar night

Key takeaways

- Parameterizing calving is essential for understanding glacier dynamics and for constraining our model projections

- Deep learning provides effective tools for automated mapping of calving front locations
  - → robust: mean distance error < 60 m
  - → accurate: median distance error < 30 m
  - → scalable: delineation in under 1 second

- Inputs matter! Multi-spectral information lead to more accurate predictions compared to single bands inputs

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