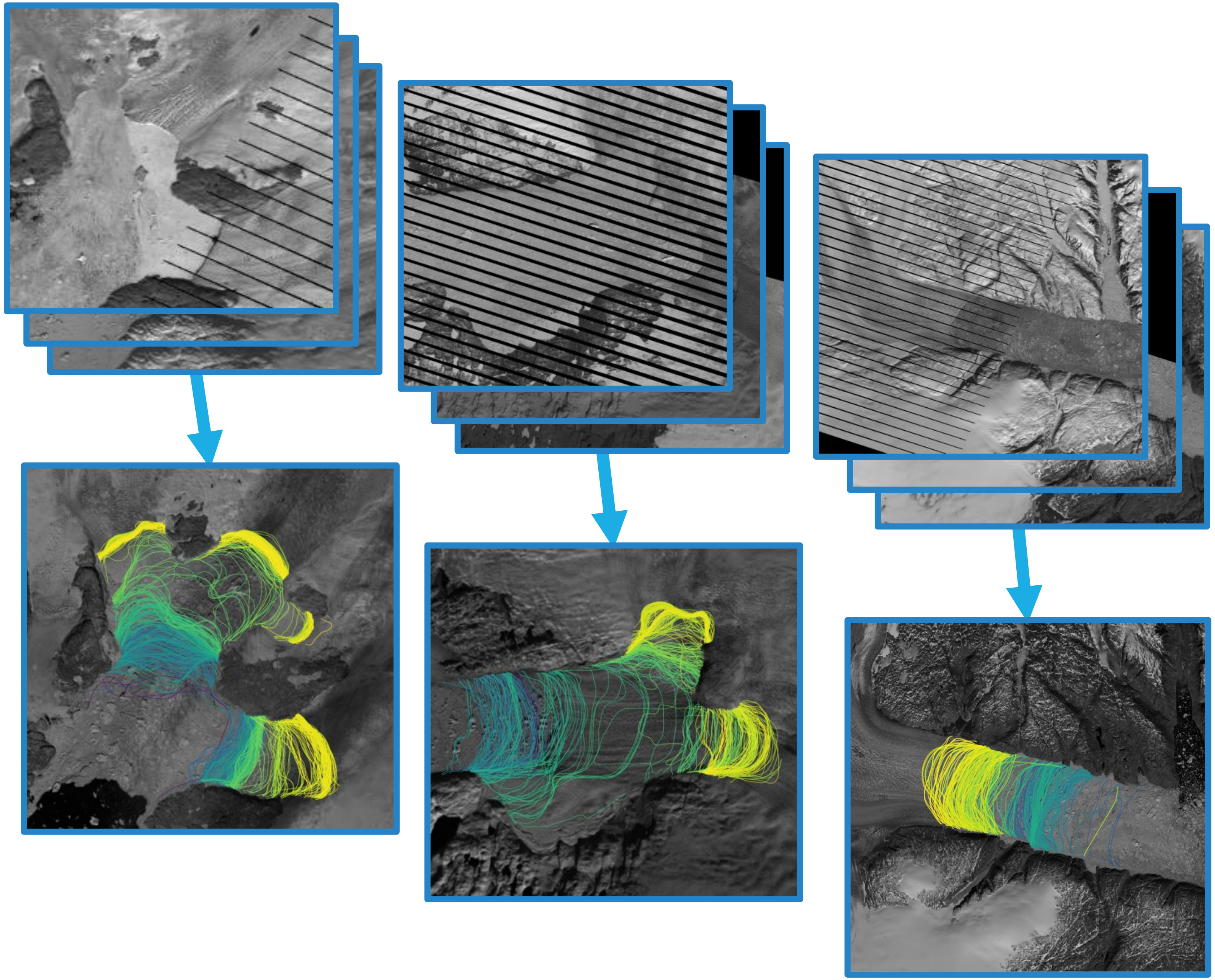

Automated Extraction of Glacial Features using Deep Learning

Daniel Cheng

Jet Propulsion Laboratory
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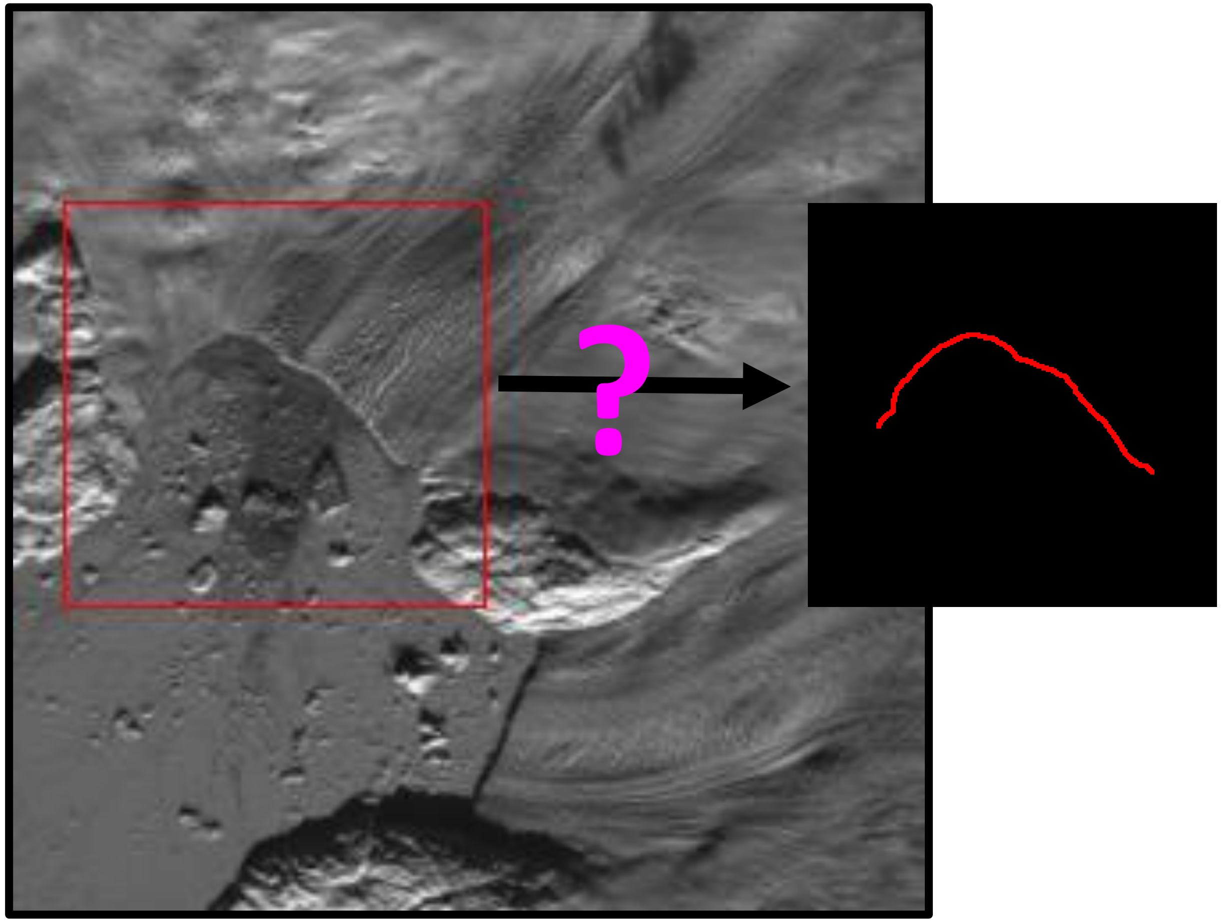
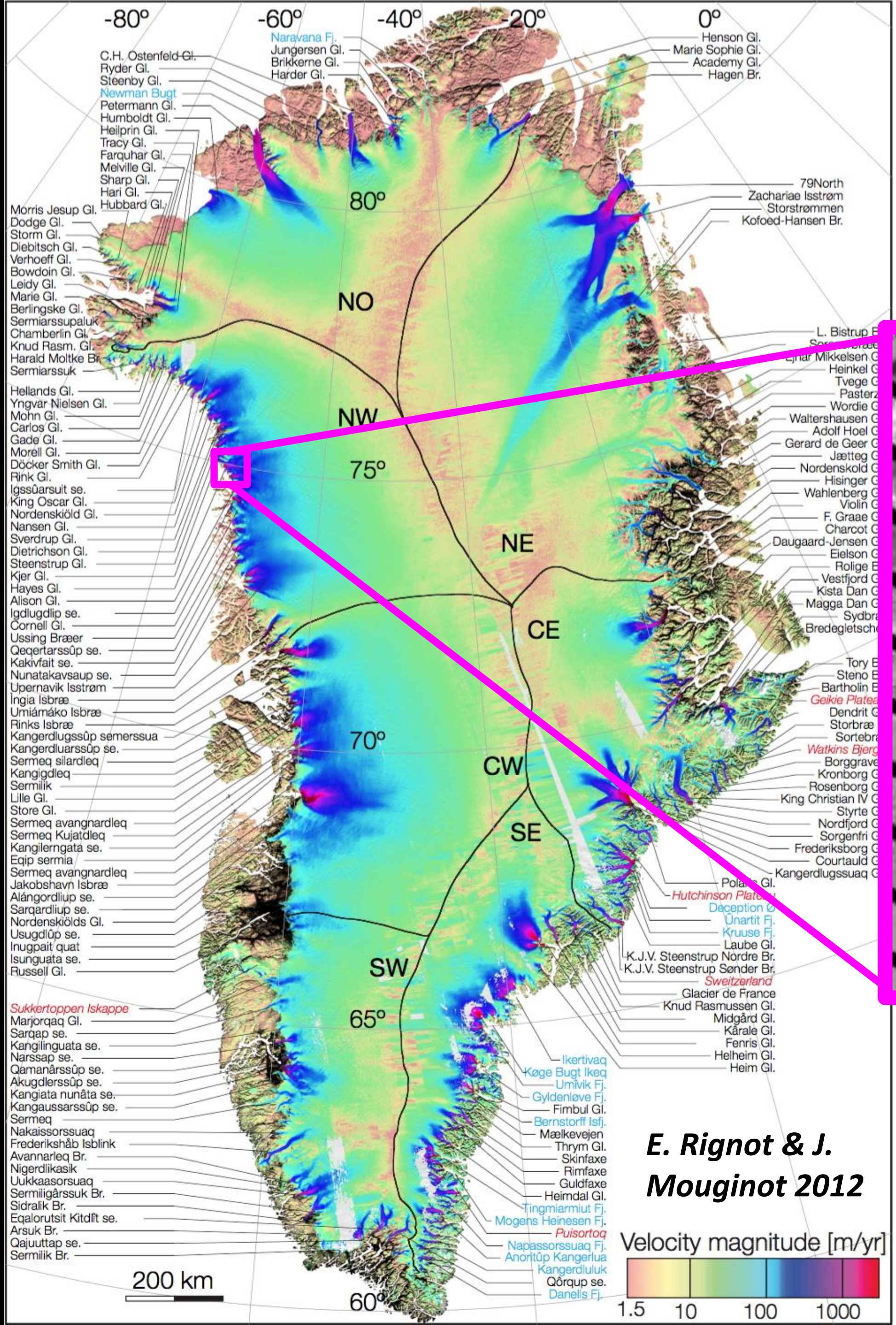
Outline

1. Motivation & Approach
2. Deep Learning & Methods
3. Results & Error Analysis
4. Existing & Future Work

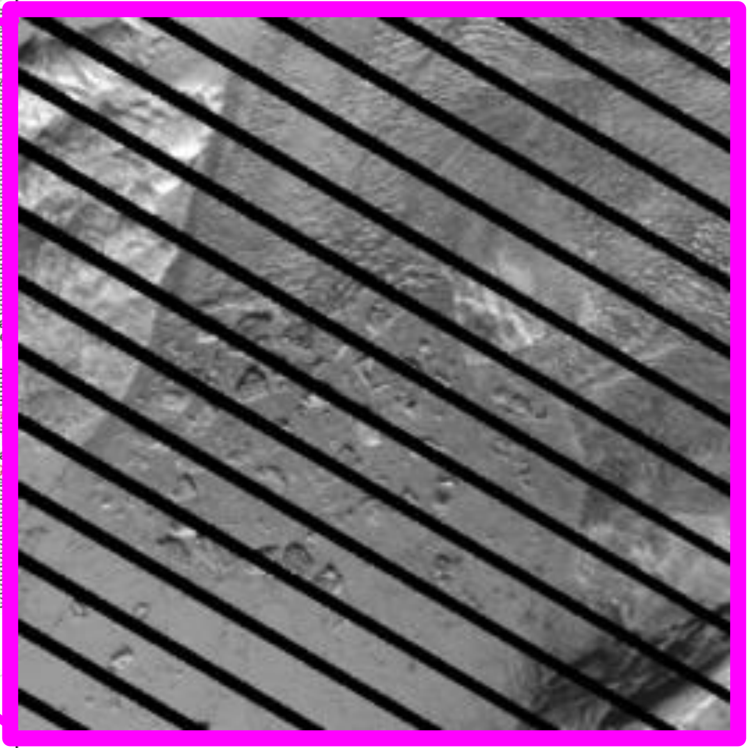


Motivation

- Determining where glaciers end is useful
- Manual labeling is time intensive, automatic labeling is non-trivial
- We use Deep Neural Networks (AI/Machine learning)
- Auto-label 20000+ subseasonal fronts over 66 basins



E. Rignot & J. Mouginot 2012



Hayes Glacier, 2006 April 06, Landsat 7 *(USGS).*

Adverse Conditions

Calving Front Performance

Match/Correct
ML Prediction
Ground Truth

a) Shadows

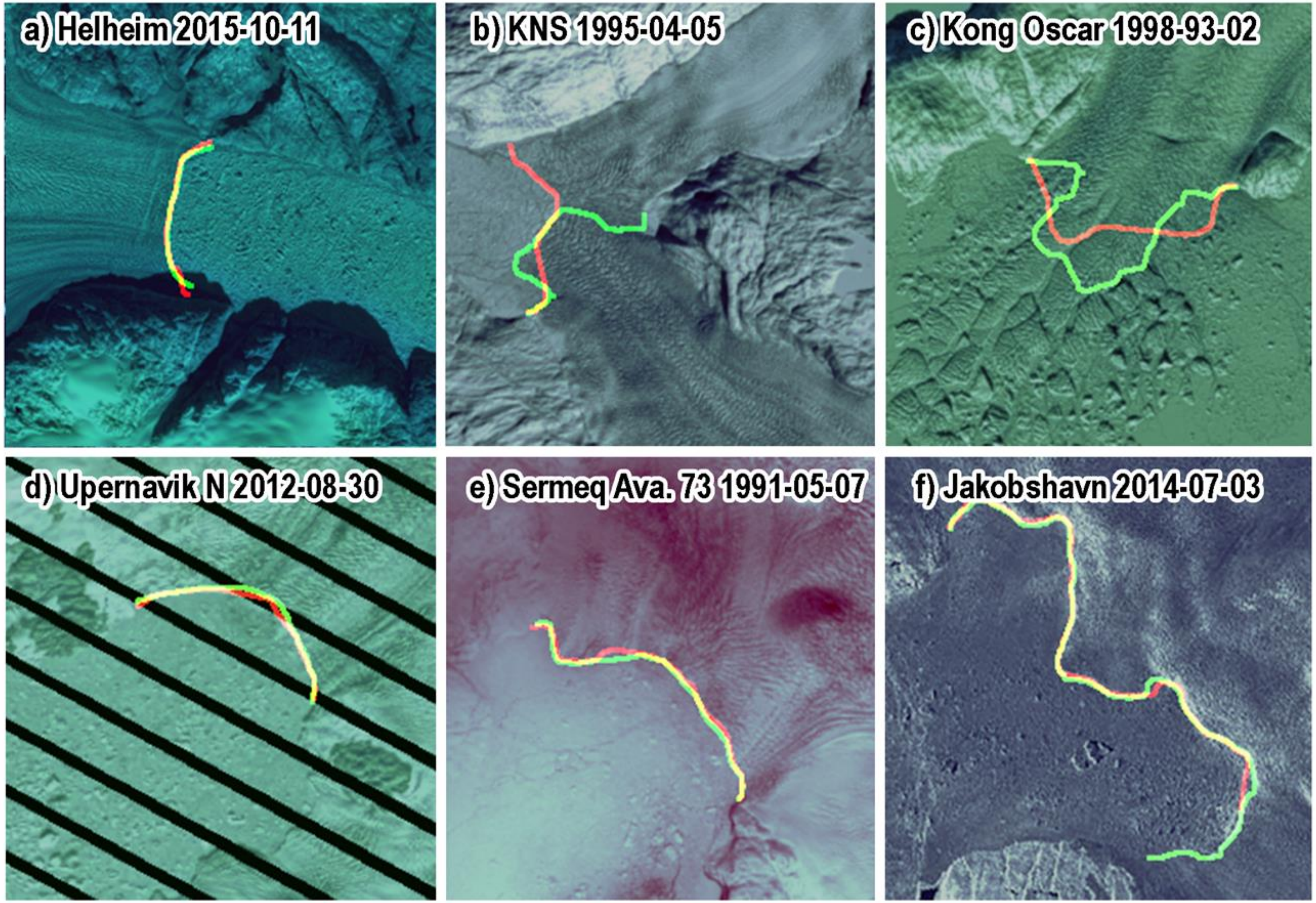
b) Unclear Termini

c) Ice Tongues

d) Landsat 7 SCE

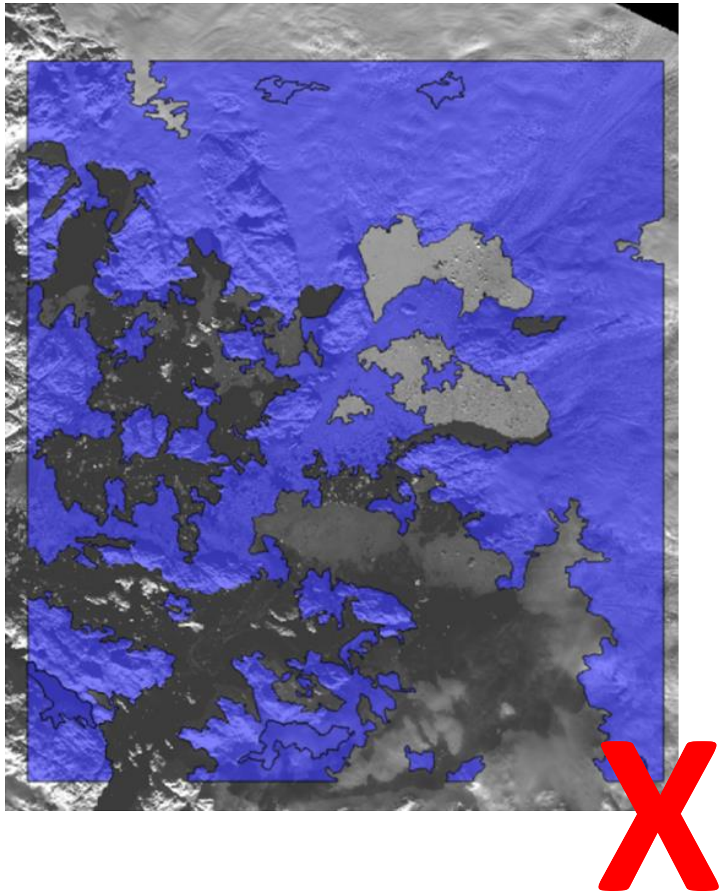
e) Clouds

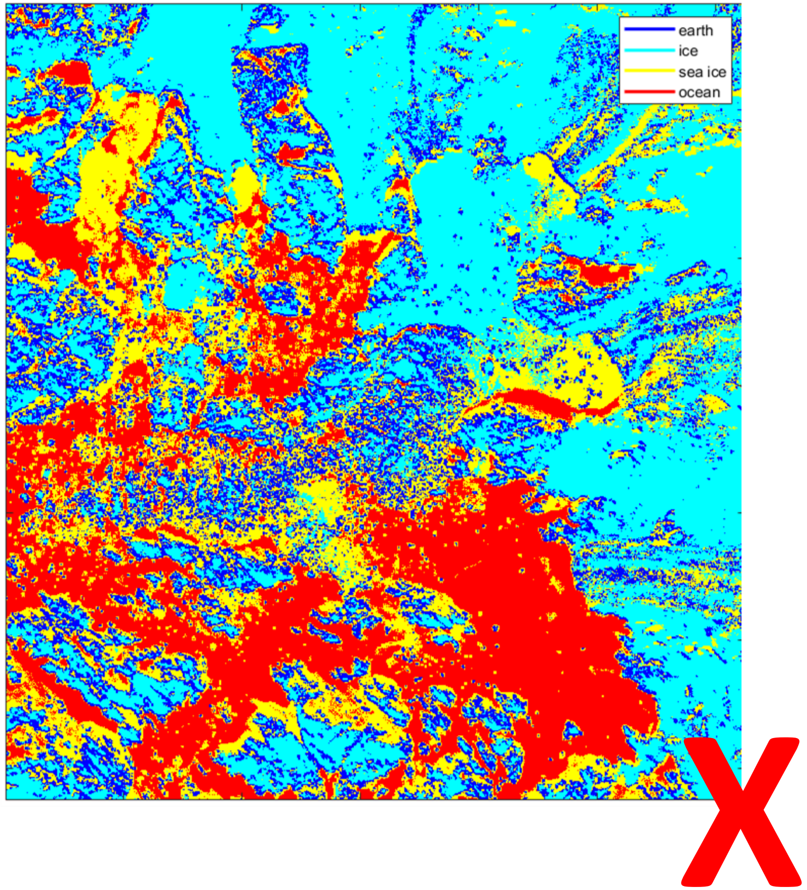
f) SAR/Multi Sensor Handling



Approach

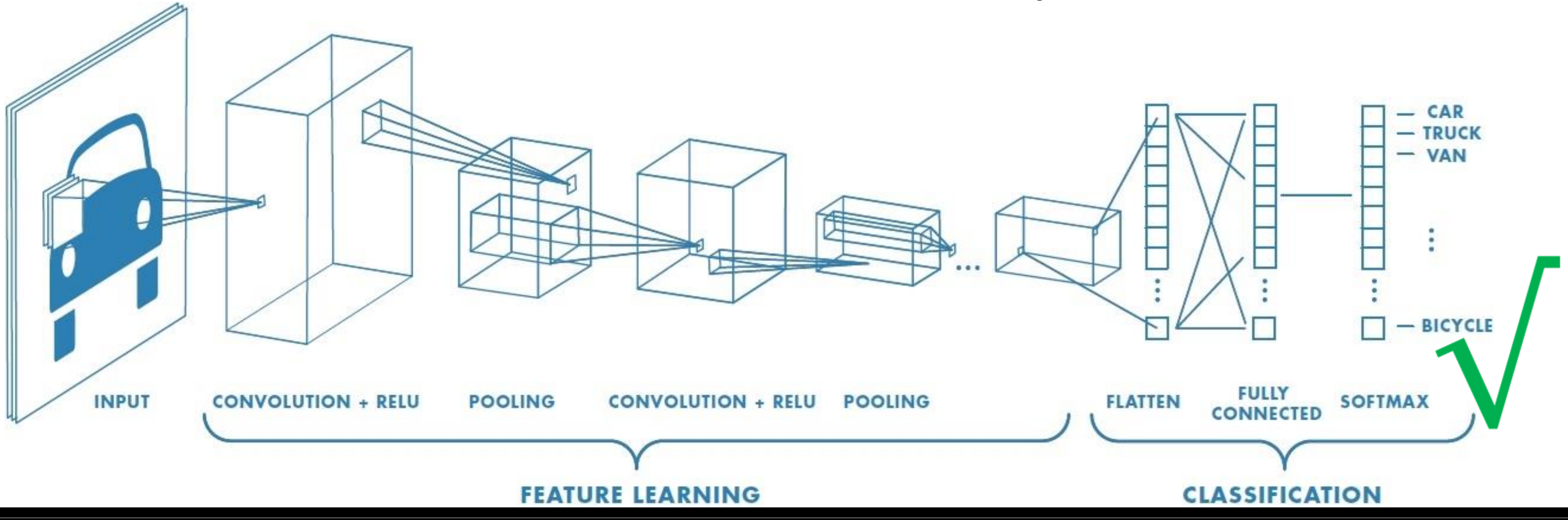
- Edge detection not enough
- Texture analysis not robust
- Neural networks provide solution





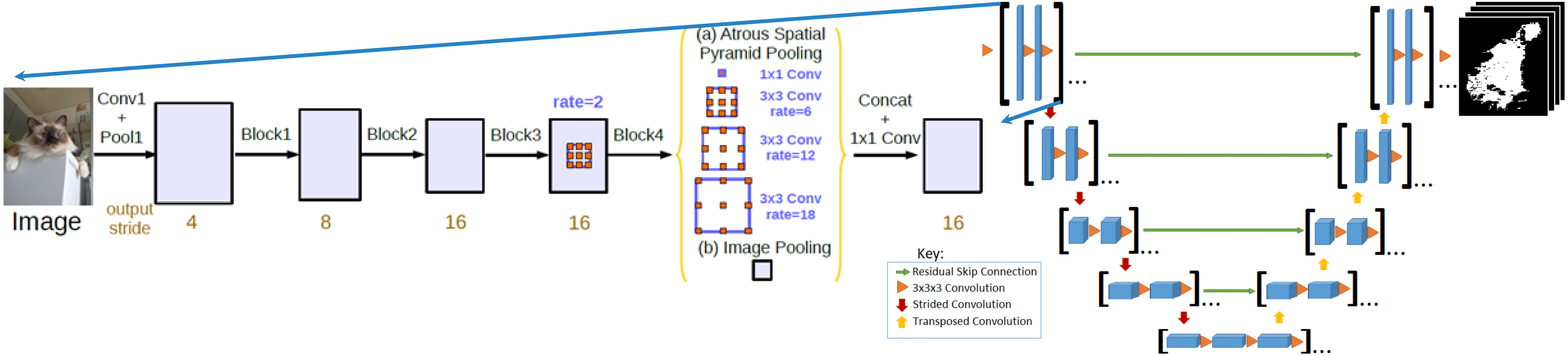
Approach – Neural Networks

- NNs automatically learn features and relations between features
- Convolutional NNs allow for shared filters, shared local context



Deep Learning- Neural Networks

- UNet CNNs allow for shared near-global context, pixel-level segmentation, and efficient computation (O Ronneberger, 2015)
- DeeplabV3+ with Xception backbone offers state of the art results (LC Chen, 2018)



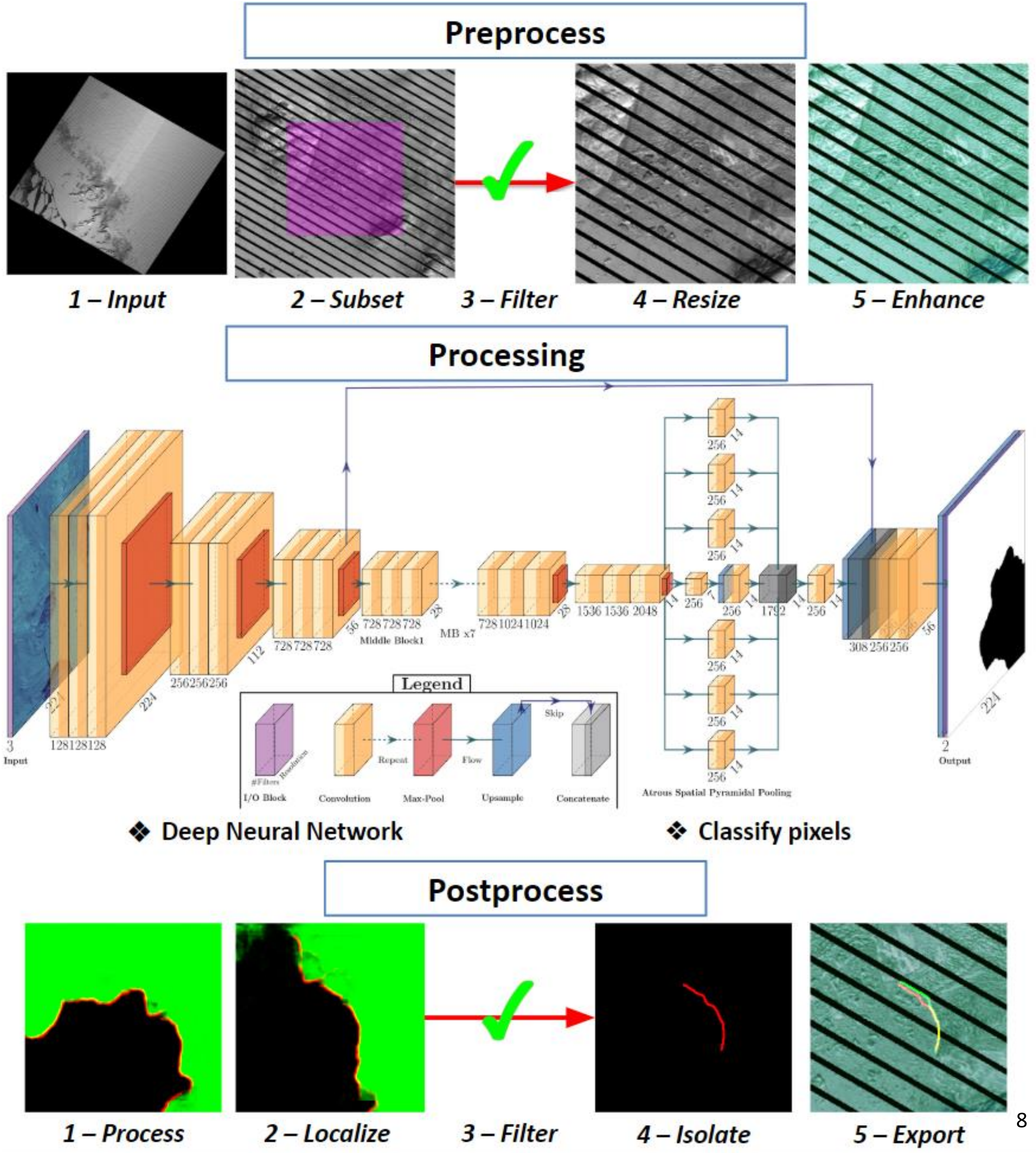
Method

Automated pipeline

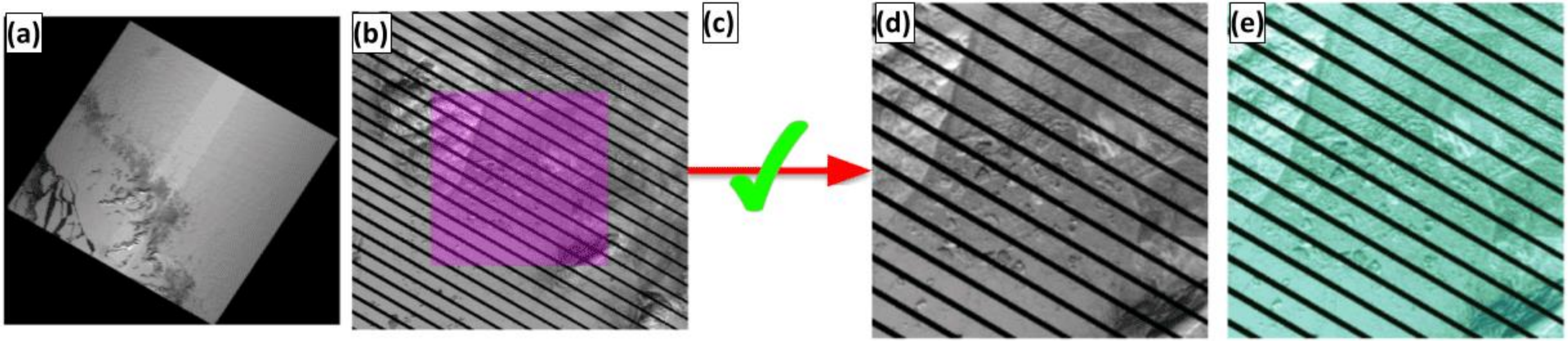
Pre-process Landsat satellite imagery

Process and classify pixels with Neural Network

Post-process to extract vectorized calving front



Method - Pre-processing



a) Get Raster Input

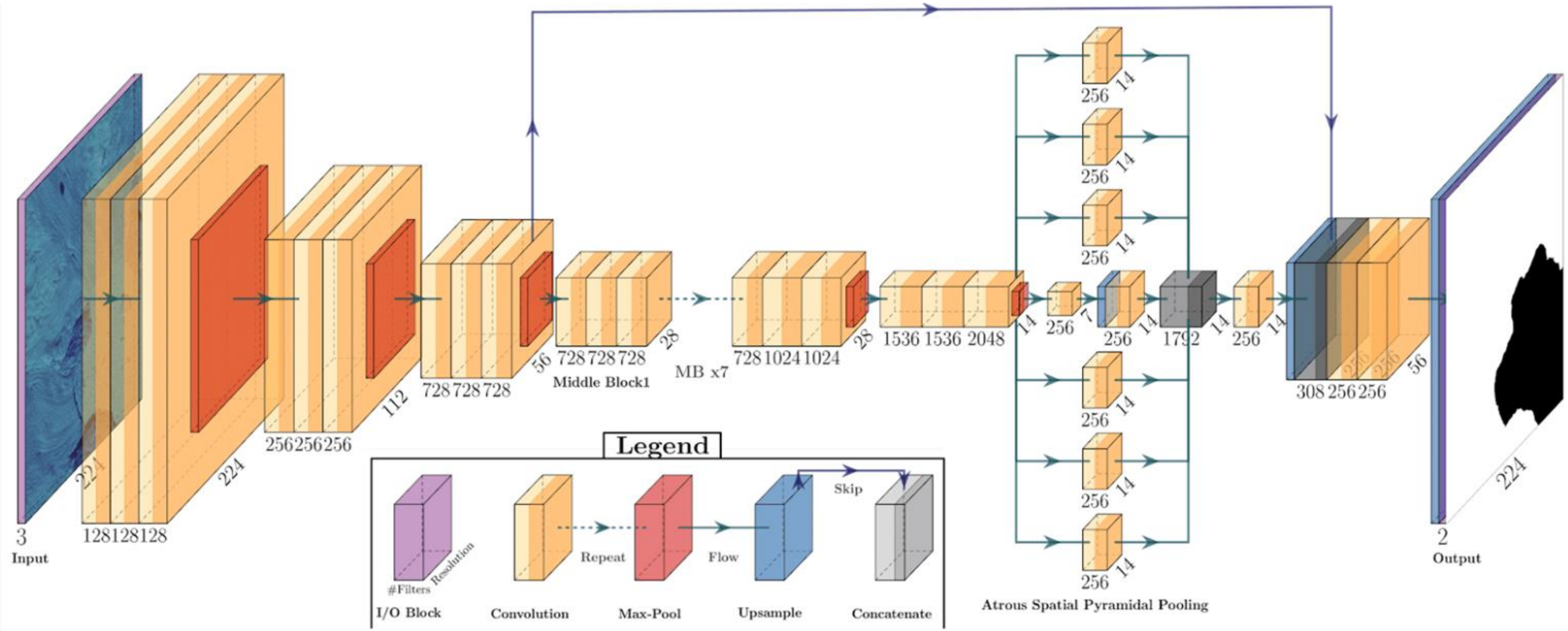
b) Subset the Input

c) Filter subsets

d) Resize subsets

e) Enhance details

Method – Processing



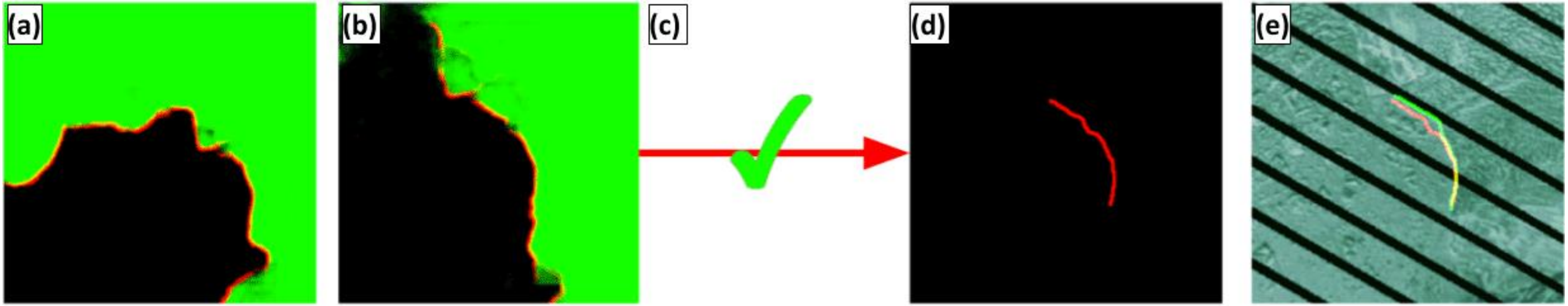
❖CALFIN Neural Network (CALFIN-NN)

❖Classifies pixels

Method - Processing Insights

- Network architecture was iterative
- More “information” = better accuracy/faster training
- Augment data, but be careful with non-affine transforms/distortions
- Don’t label edges directly - edge filter after augmentation
- Training data was made manually, and must be created consistently

Method - Post-processing



a) Isolate calving fronts

b) Reprocess isolated subsets

c) Filter subsets

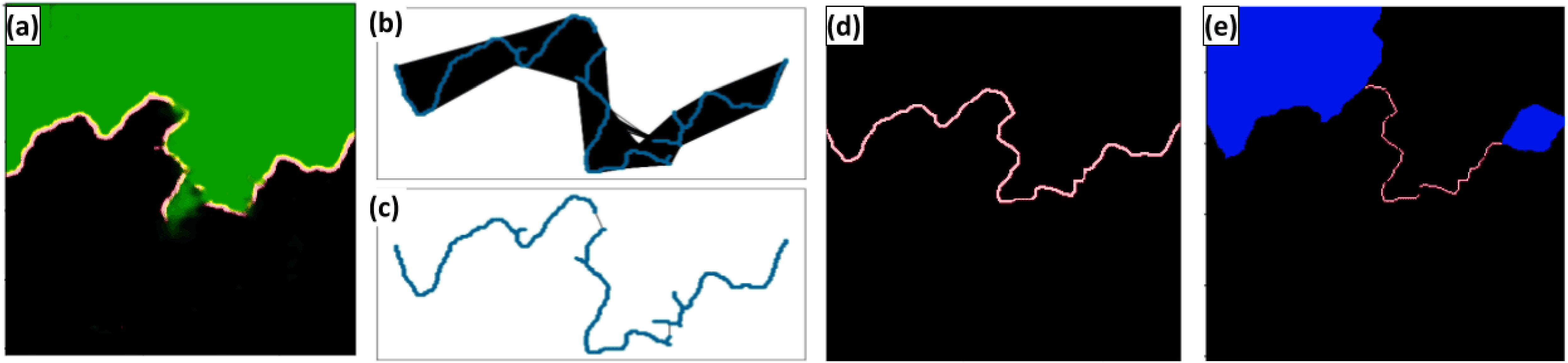
d) Reisolate calving fronts

d) Export and validate

Method - Post-processing Insights

- Pixel-level mask not as useful as poly-line, polygon
- Gaps in predicted output are processed during vectorization
- Treat as Tourist Trip Design Problem (longest path through min. spanning tree with optional/weighted nodes)
- Polygonization requires both calving front and ocean mask outputs

Method - Post-processing



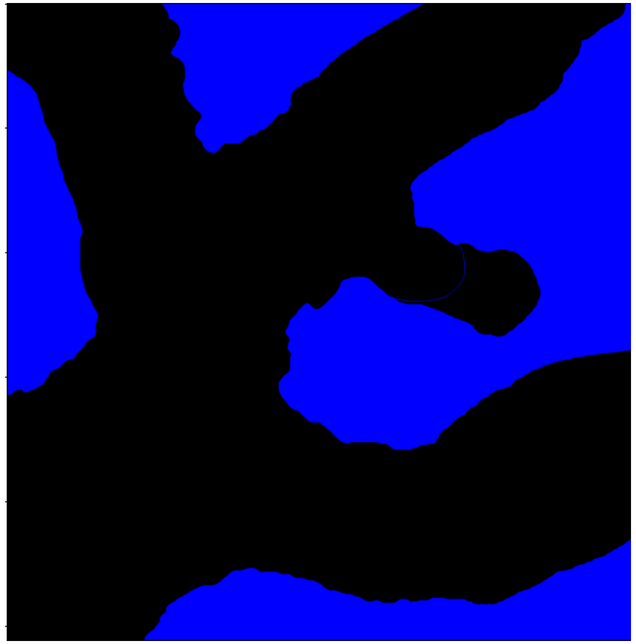
a) Extract coastline mask

b/c) Find longest path in min. spanning tree

d) Rasterize coastline

e) Isolate calving front

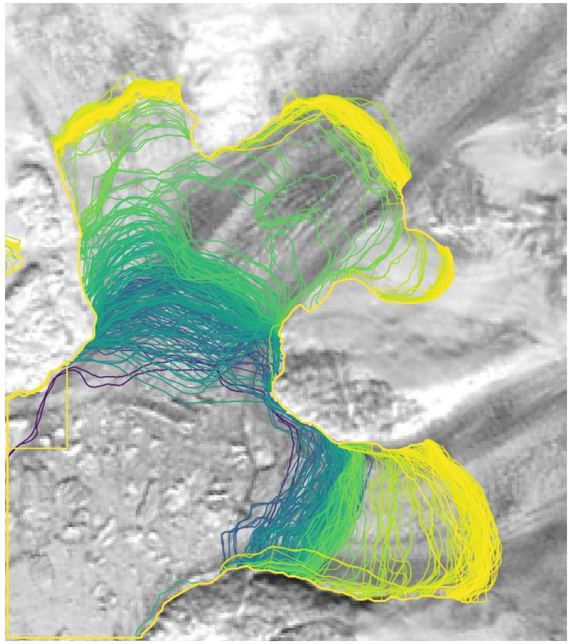
Method - Polygonization



a) Create fjord boundary mask

b) Rasterize fronts

c) Classify each section



d) Vectorize

Error Analysis

Measuring Error

Mean/Median Distance

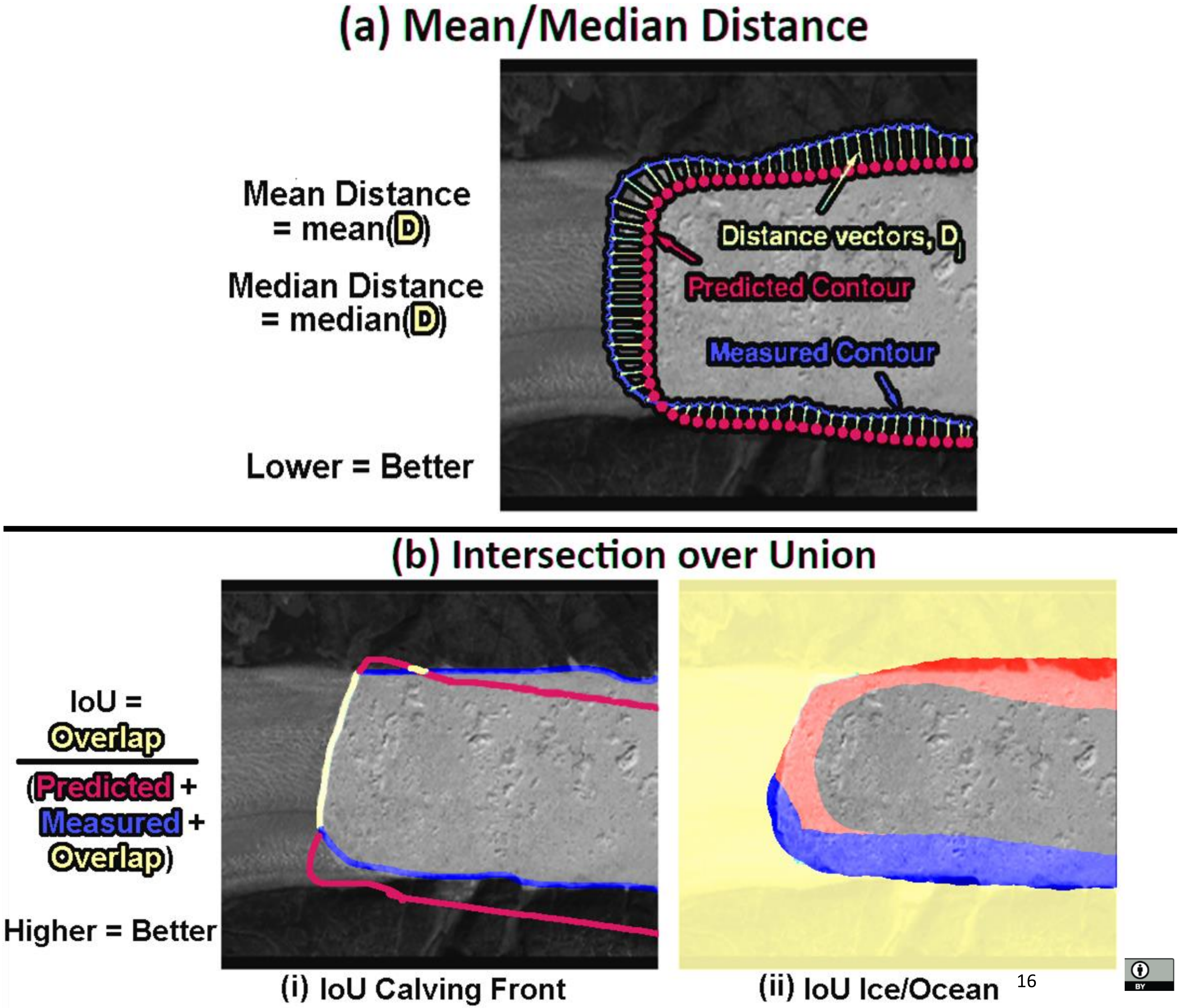
- IoU Coastline = edge overlap
- IoU Ice/Ocean = mask overlap

Intersection over Union

- IoU Coastline = edge overlap
- IoU Ice/Ocean = mask overlap

Evaluate validation sets

- CALFIN (CALFIN-VS)
- Zhang et al. 2019 (Z-VS)
- Mohajerani et al. 2019 (M-VS)
- Baumhoer et al. 2019 (B-VS)



Error Analysis

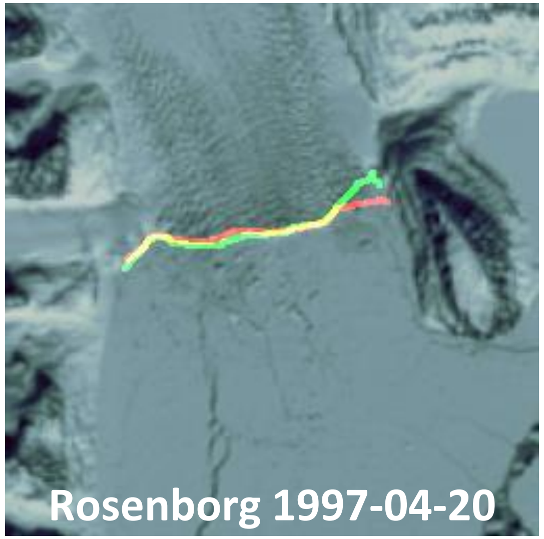
CALFIN Validation set

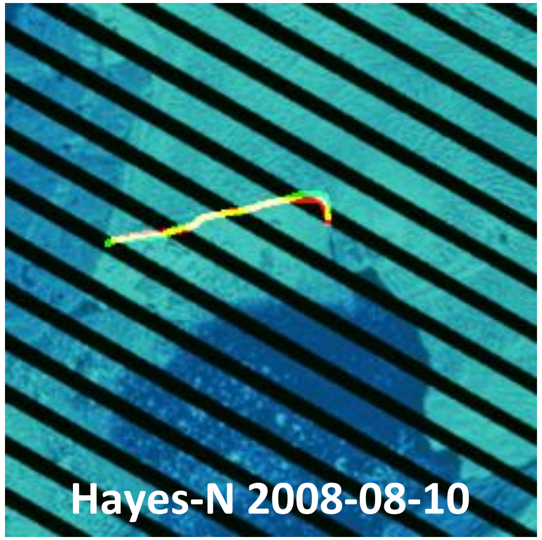
162 unseen images

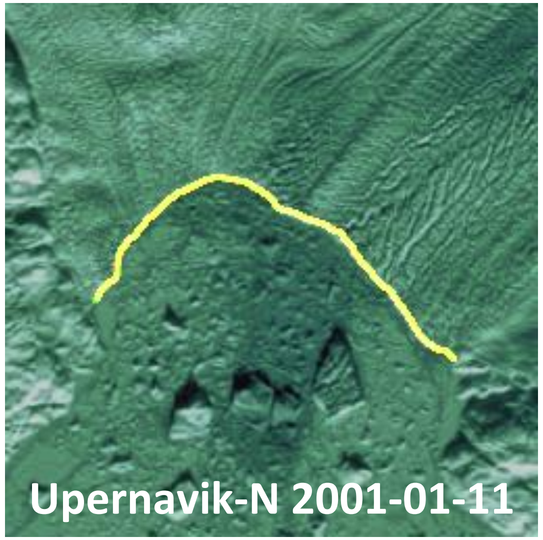
Most adverse conditions handled well

Ice tongues need work

Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
CALFIN-VS	CALFIN-NN	2.25px, 86.76m	1.21px, 44.59m	0.4884	0.9793







Error Analysis

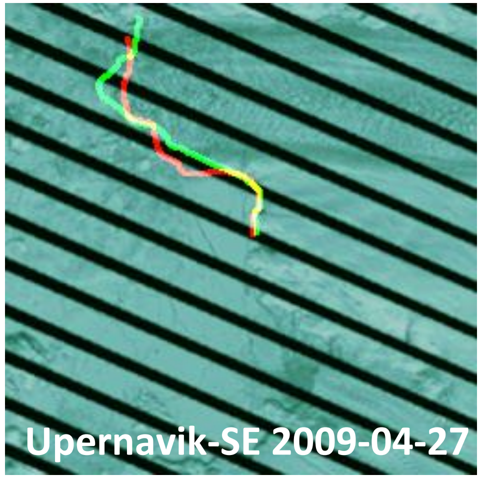
CALFIN-VS L7SCE only

- Only images that have Landsat 7 Scanline Corrector Errors
- Higher error, as expected

CALFIN-VS L7SCE none

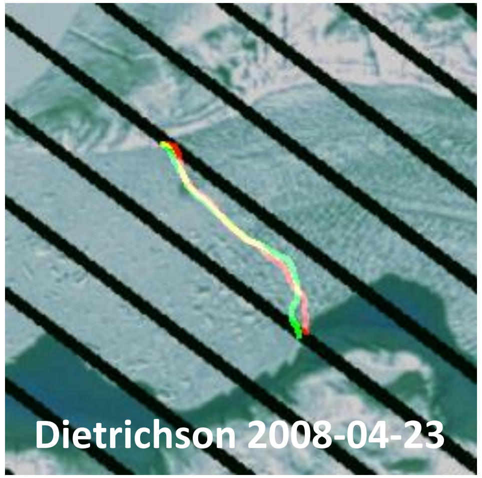
- Lower error, as exp

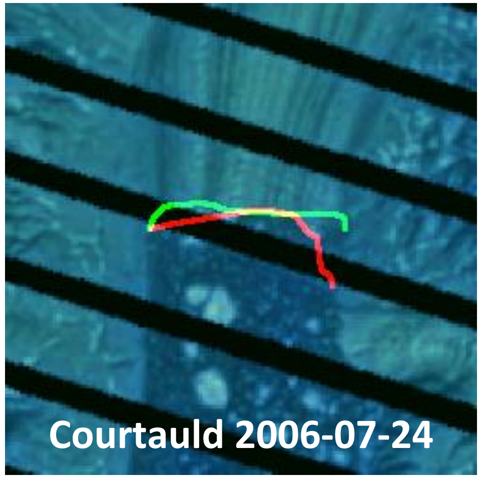
Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
CALFIN-VS L7SCE only	CALFIN-NN	2.22 px, 91.93 m	1.33 px, 49.24 m	0.4888	0.9766
CALFIN-VS L7SCE none	CALFIN-NN	2.27 px, 81.65 m	1.16 px, 44.01 m	0.4880	0.9819


Upernavik-SE 2009-04-27


Rink-Isbrae 2005-08-08


Kangerlussuaq 2012-04-19


Dietrichson 2008-04-23


Courtauld 2006-07-24

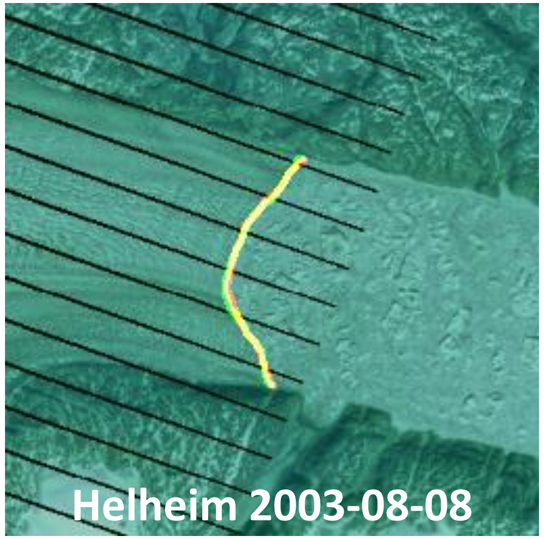
Error Analysis

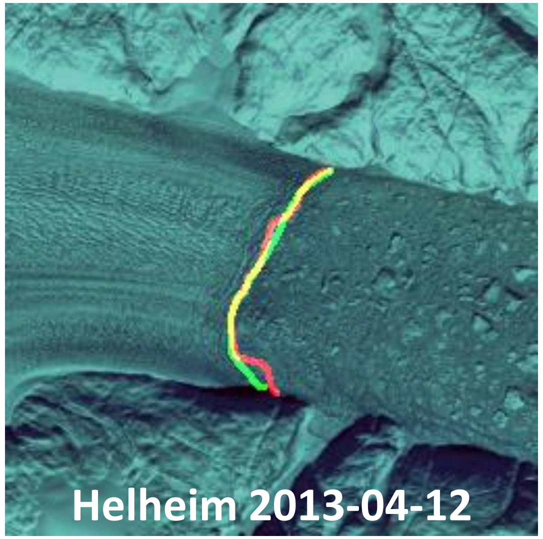
CALFIN-VS Helheim

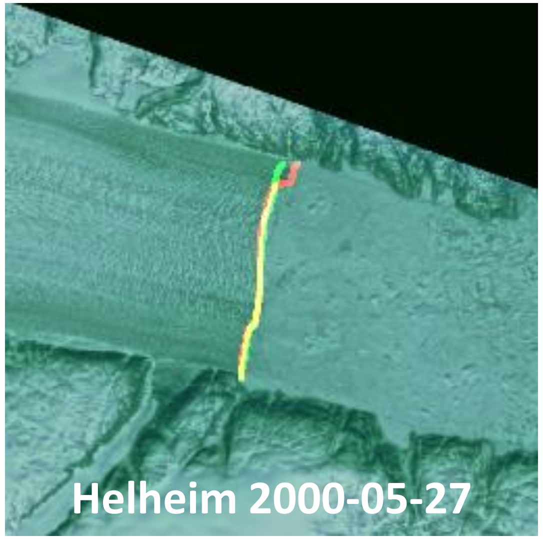
- Handles Multiscale/L7 SCE
- Error near fjord walls
- Provides strong evidence of generalization

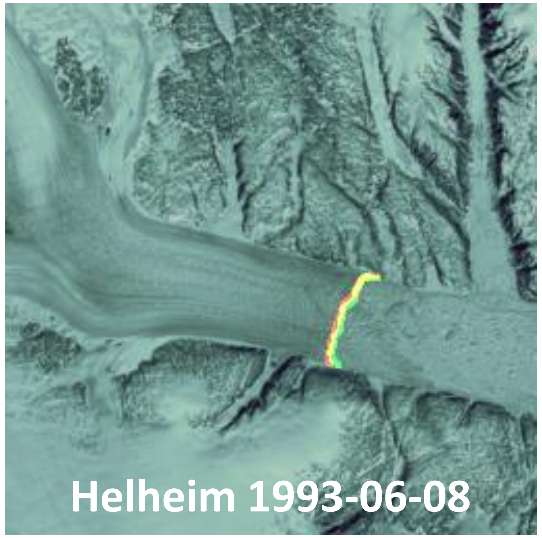
Match/Correct
ML Prediction
Ground Truth

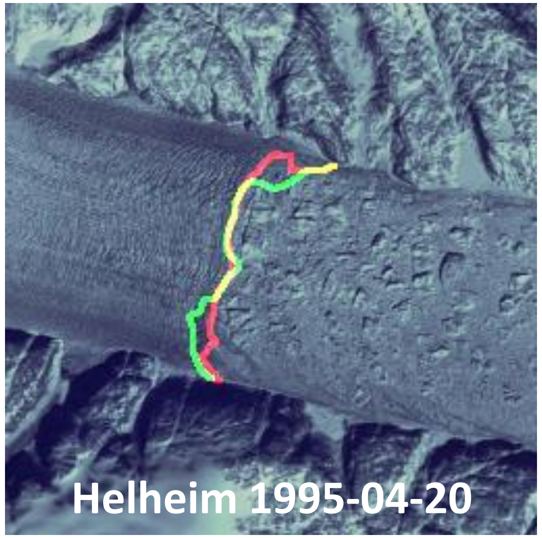
Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
CALFIN-VS Helheim	CALFIN-NN	2.24px, 121.47m	1.71px, 86.60m	0.5039	0.9623











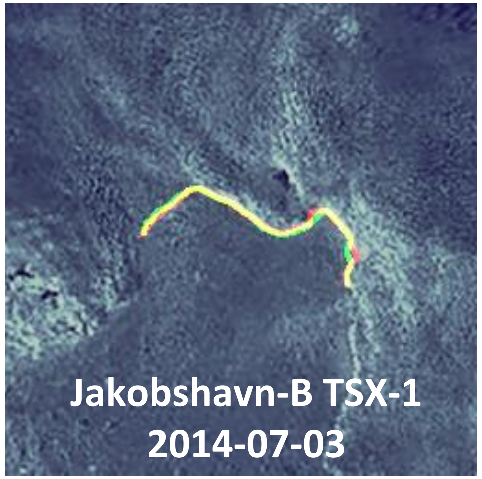
Error Analysis

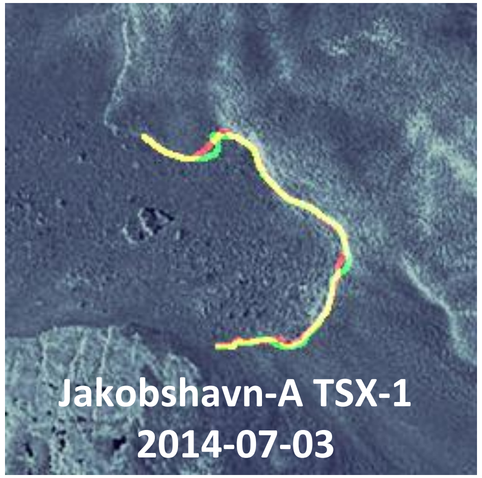
Zhang et al. 2019

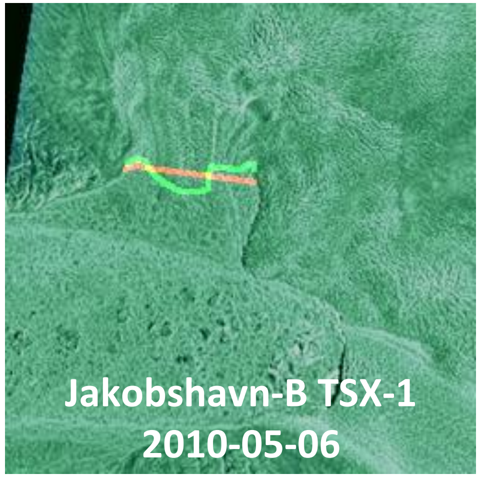
6 TerraSAR-X Jakobshavn images

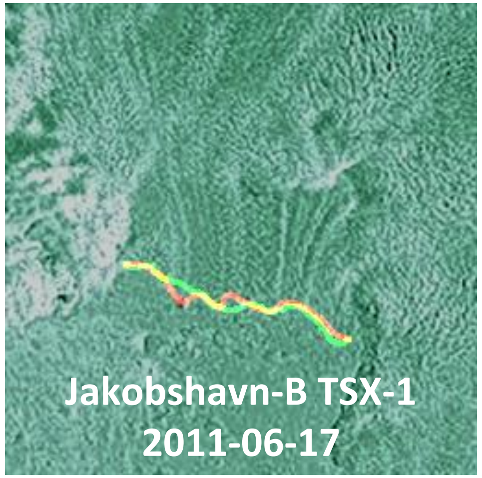
On par with original study

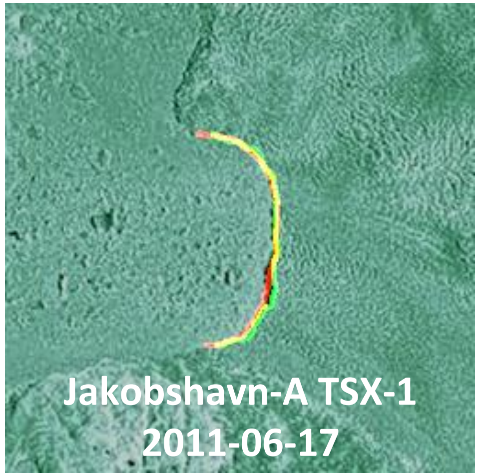
Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
Z-VS	CALFIN-NN	2.11 px, 115.24 m	1.65 px, 77.29 m	0.3832	0.9761
Z-VS	Z-NN	17.3 px, 104 m	N/A	N/A	N/A











Match/Correct
ML Prediction
Ground Truth

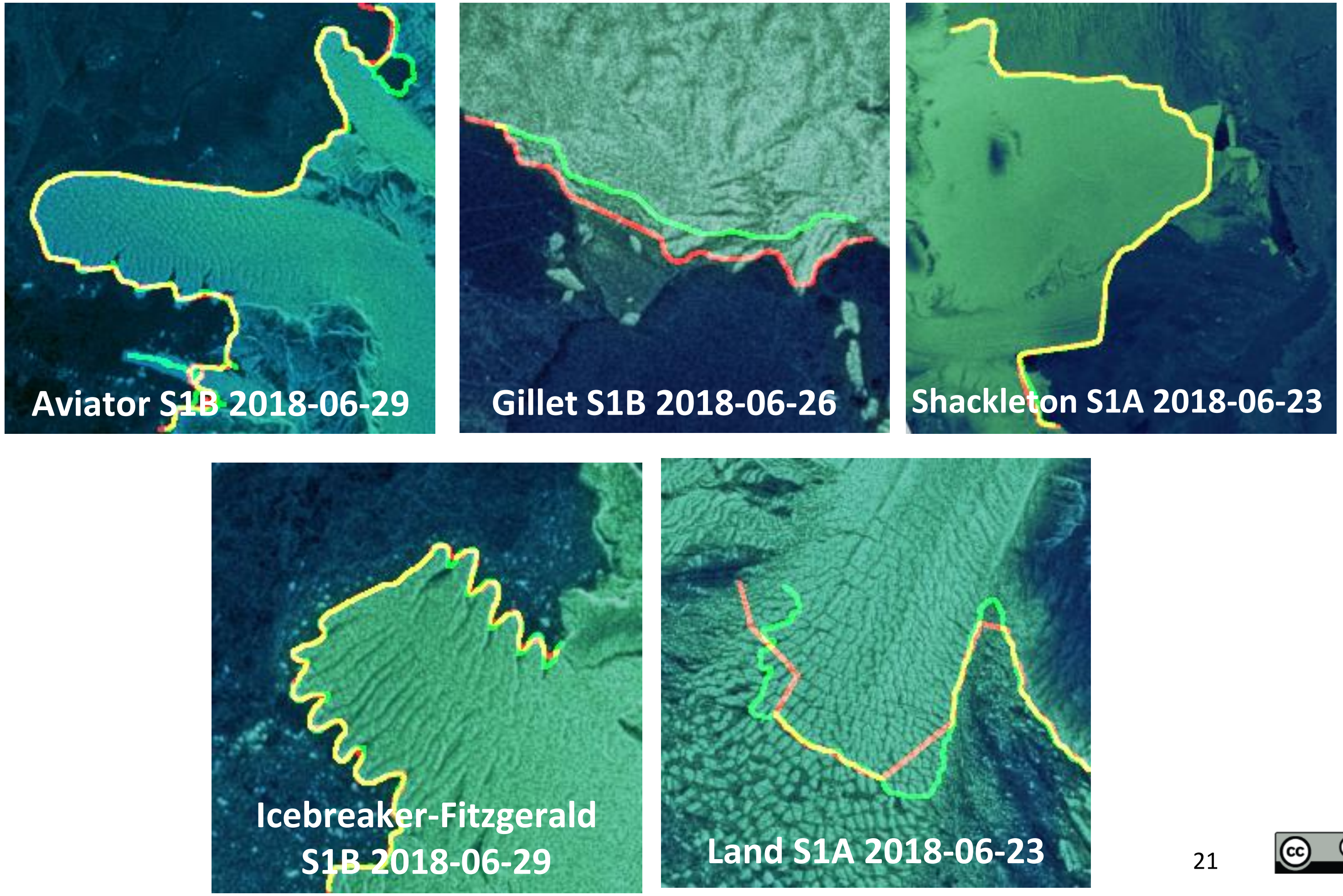
Error Analysis

Baumhoer et al. 2019

62 Sentinel-1 SAR Antarctica images

Subpar but reasonable performance w.r.t. original study

Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
B-VS	CALFIN-NN	2.35 px, 330.63 m	0.74 px, 112.75 m	0.6451	0.9879
B-VS	B-NN	2.69 px, 108 m	N/A	N/A	0.905



Error Analysis

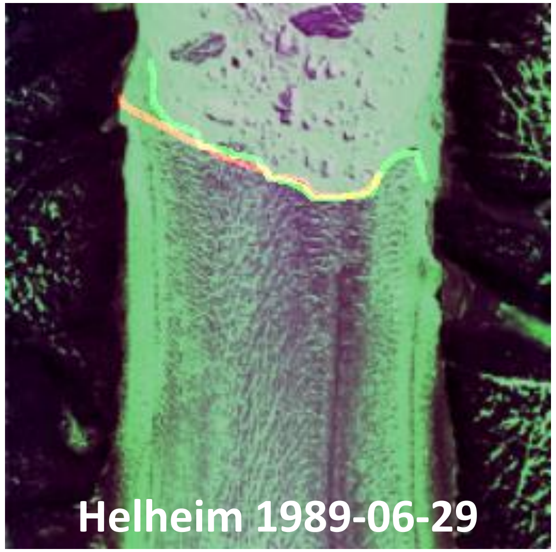
Mohajerani et al. 2019

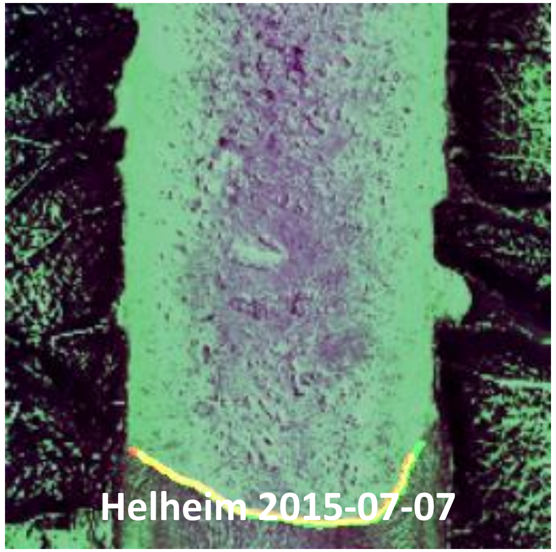
- 10 Landsat Helheim images
- On par with original study

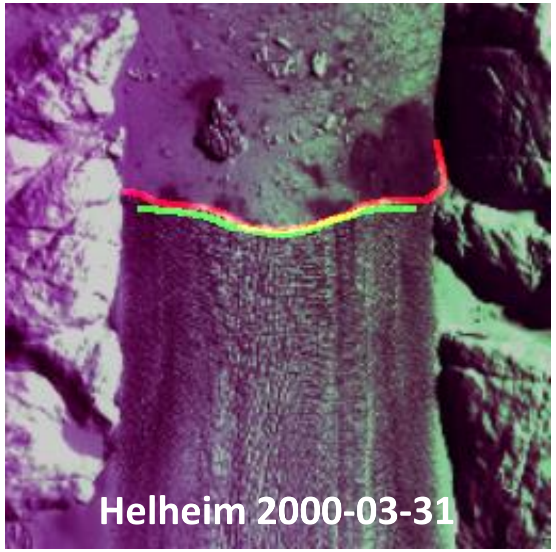
Model Intercomparison

- Retrain M-NN, isolate only model
- We outperform M-NN

Validation Set	Training Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
M-VS	CALFIN-TS	CALFIN-NN	2.56 px, 97.72 m	2.55 px, 97.44 m	0.3332	N/A
M-VS	M-TS	M-NN	1.97 px, 96.31 m	N/A	N/A	N/A
CALFIN-VS L7SCE none	CALFIN-TS	CALFIN-NN	2.27 px, 81.65 m	1.16 px, 44.01 m	0.4880	0.9819
CALFIN-VS L7SCE none	CALFIN-TS	M-NN	4.45 px, 201.35 m	1.25 px, 50.52 m	0.4935	0.9699





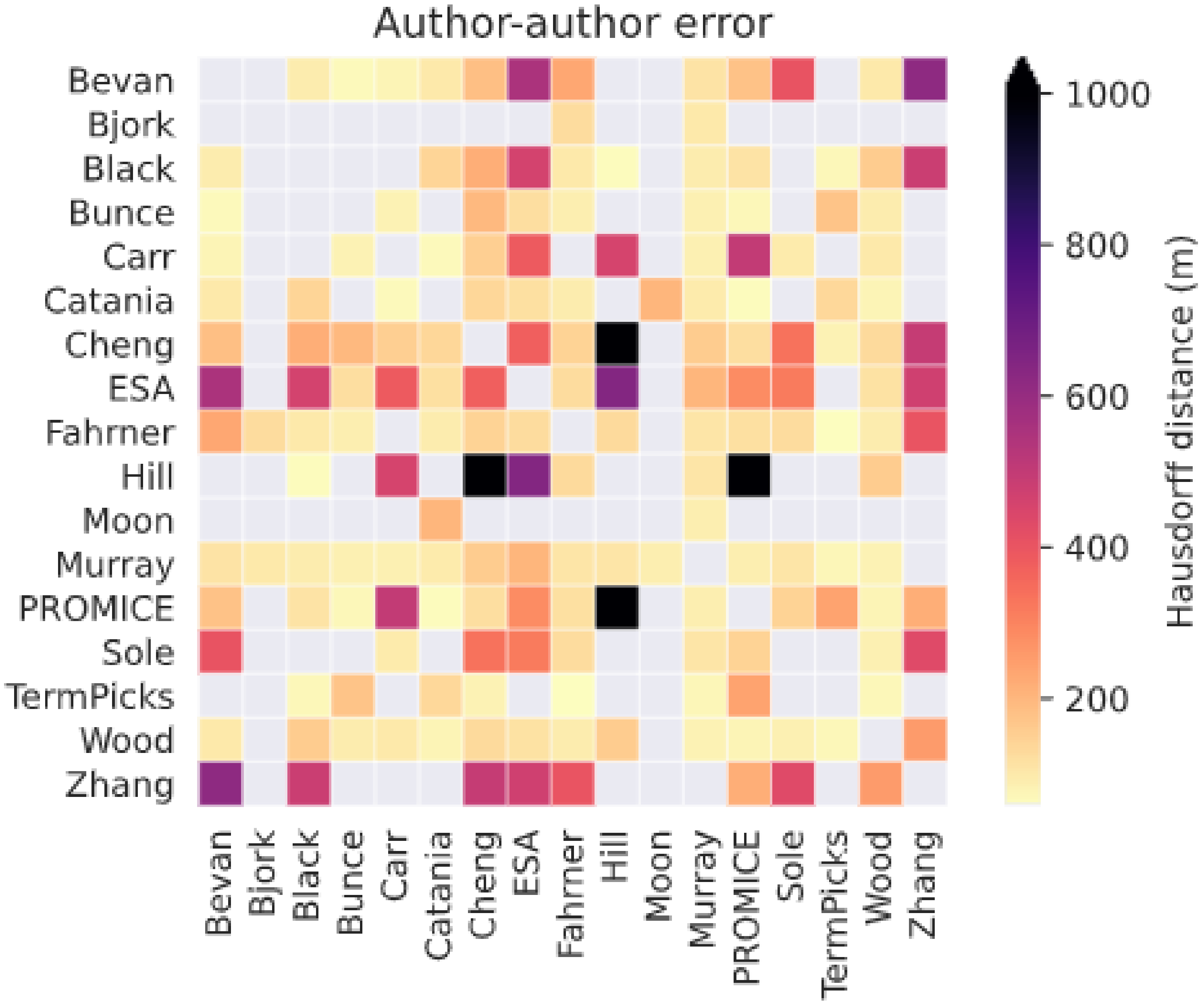


Error Analysis

TermPicks

Comparison

- Compare manual and automated methods
- Cheng (CALFIN) on par with most others (107m)
- Discrepancy with Hill explained by focus on North Greenlandic glaciers (Kong-Oscar)



Results

Data Release

Shapefile Polylines

- 22678 total fronts,
  - 20681 auto-picked
  - 1997 manual

Shapefile Polygons

- 22678 total fronts

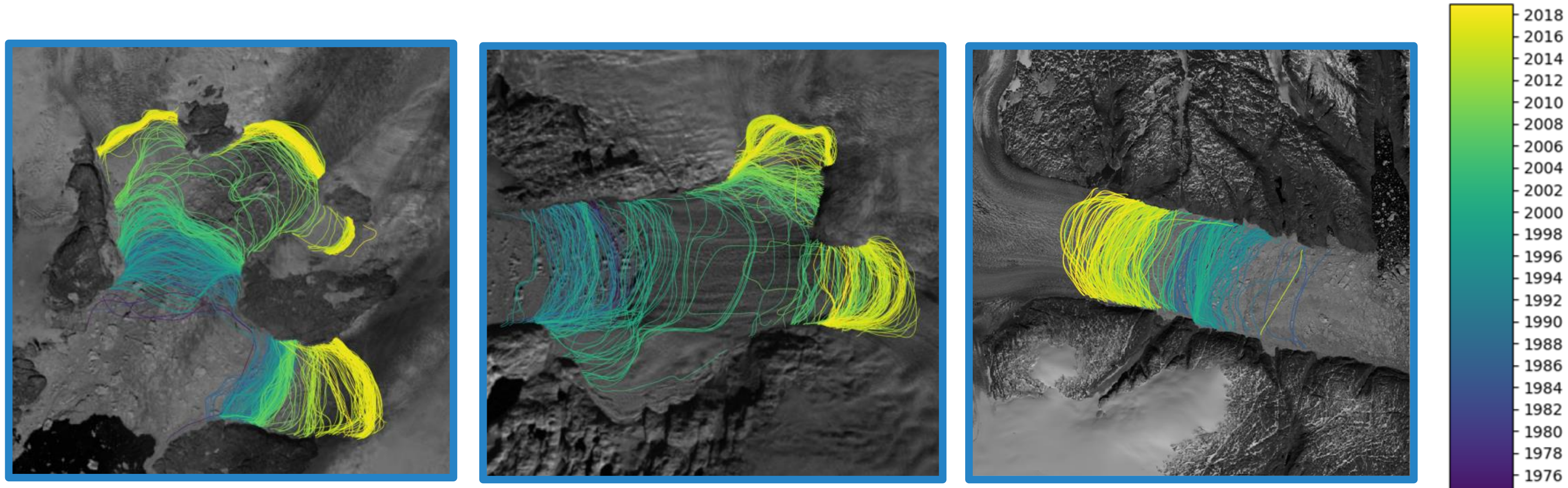
Includes Training data,

Neural Network weights

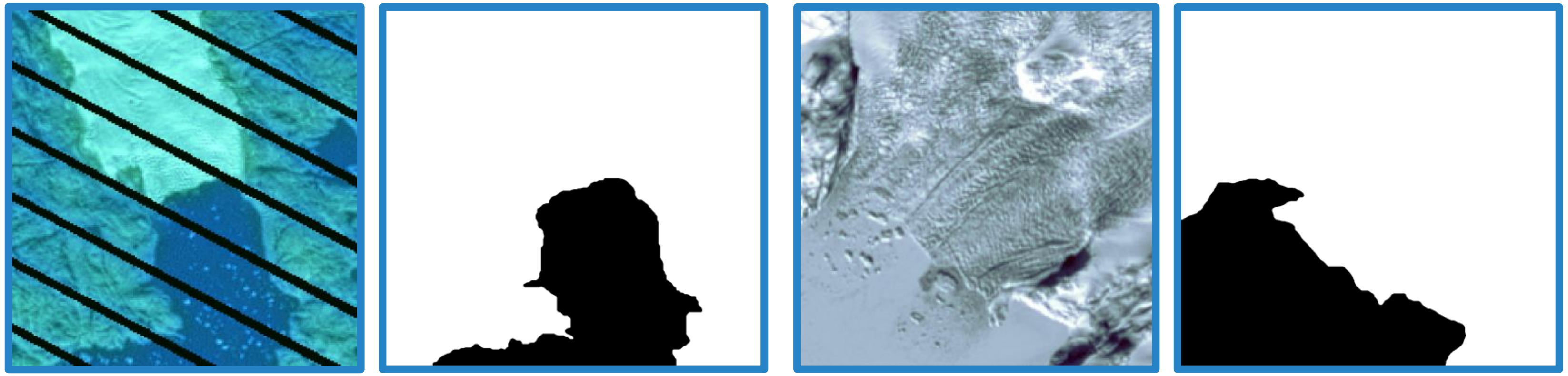
Released on National

Snow and Ice Data

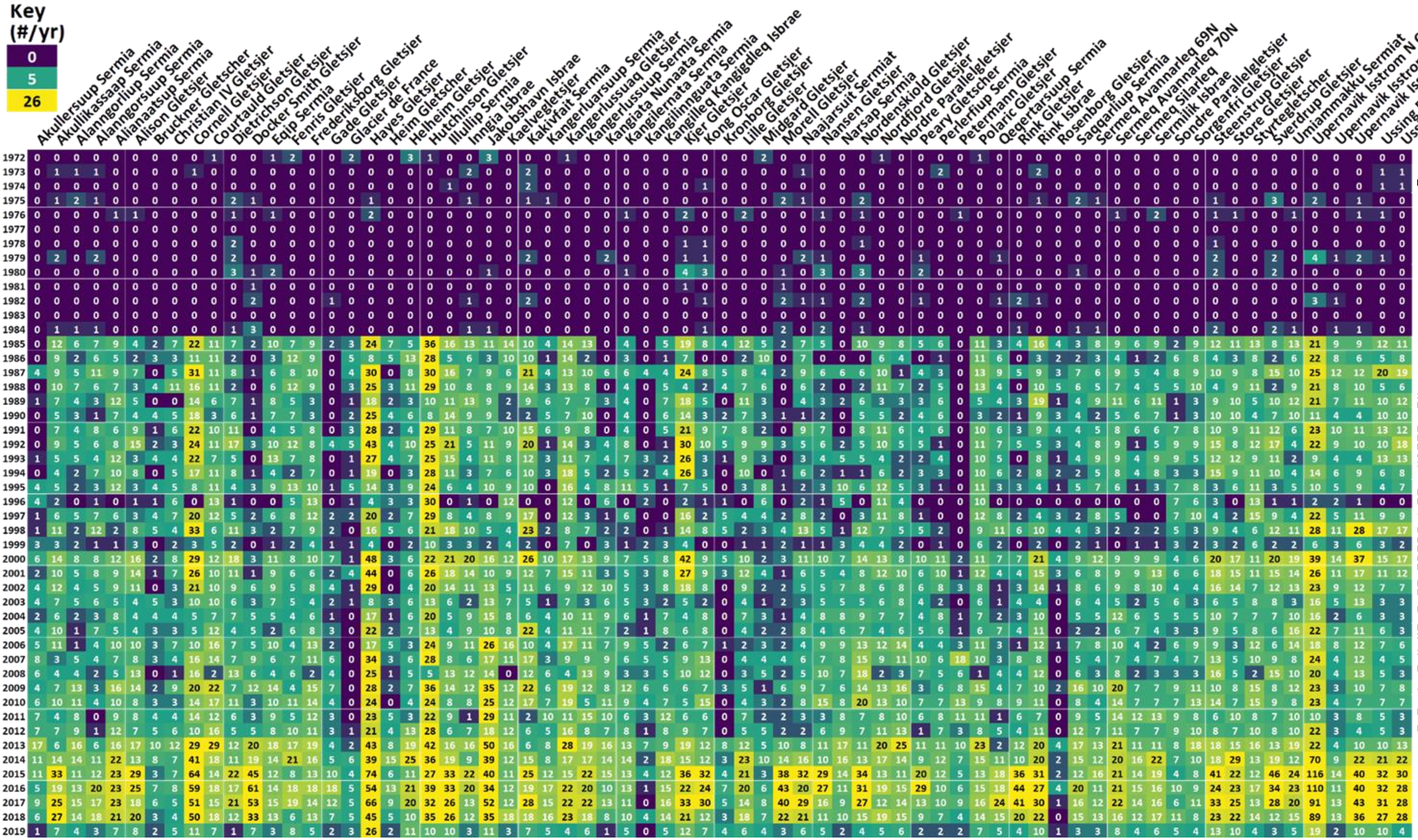
Center

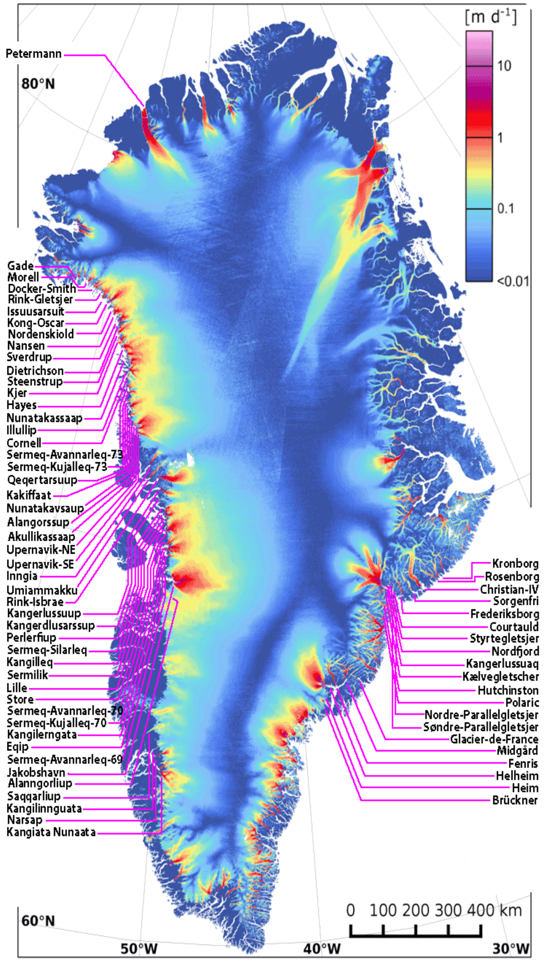


Upernavik　Jakobshavn　Helheim



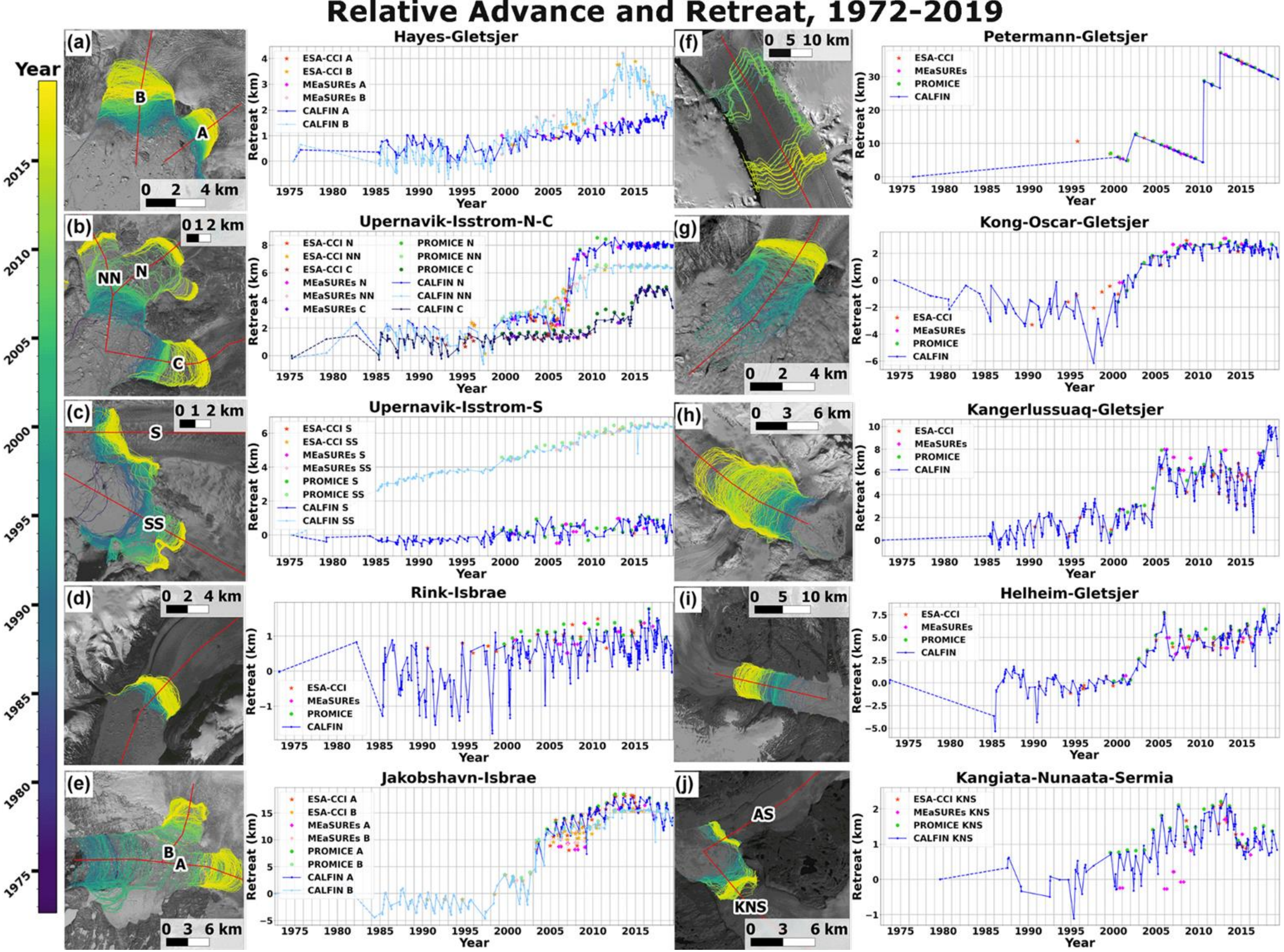
Training & validation data for 66 basins, plus 51 Antarctic basins from Zhang, Mohajerani, and Baumhoer



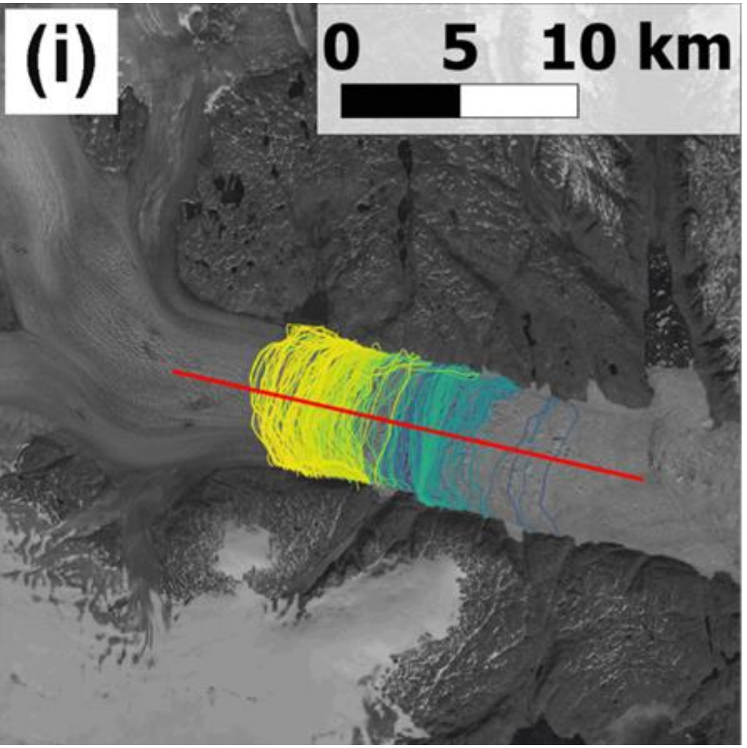


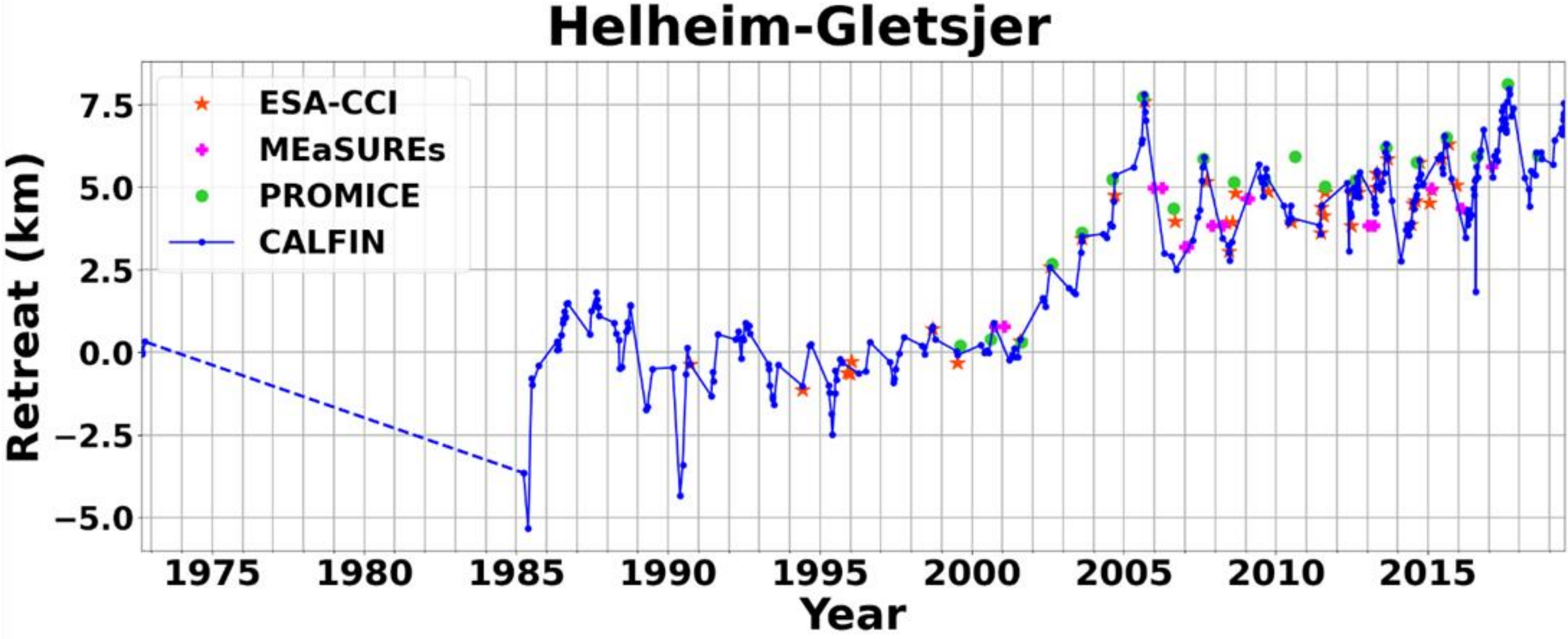
Nagler,

Results - Spatial/Temporal Coverage

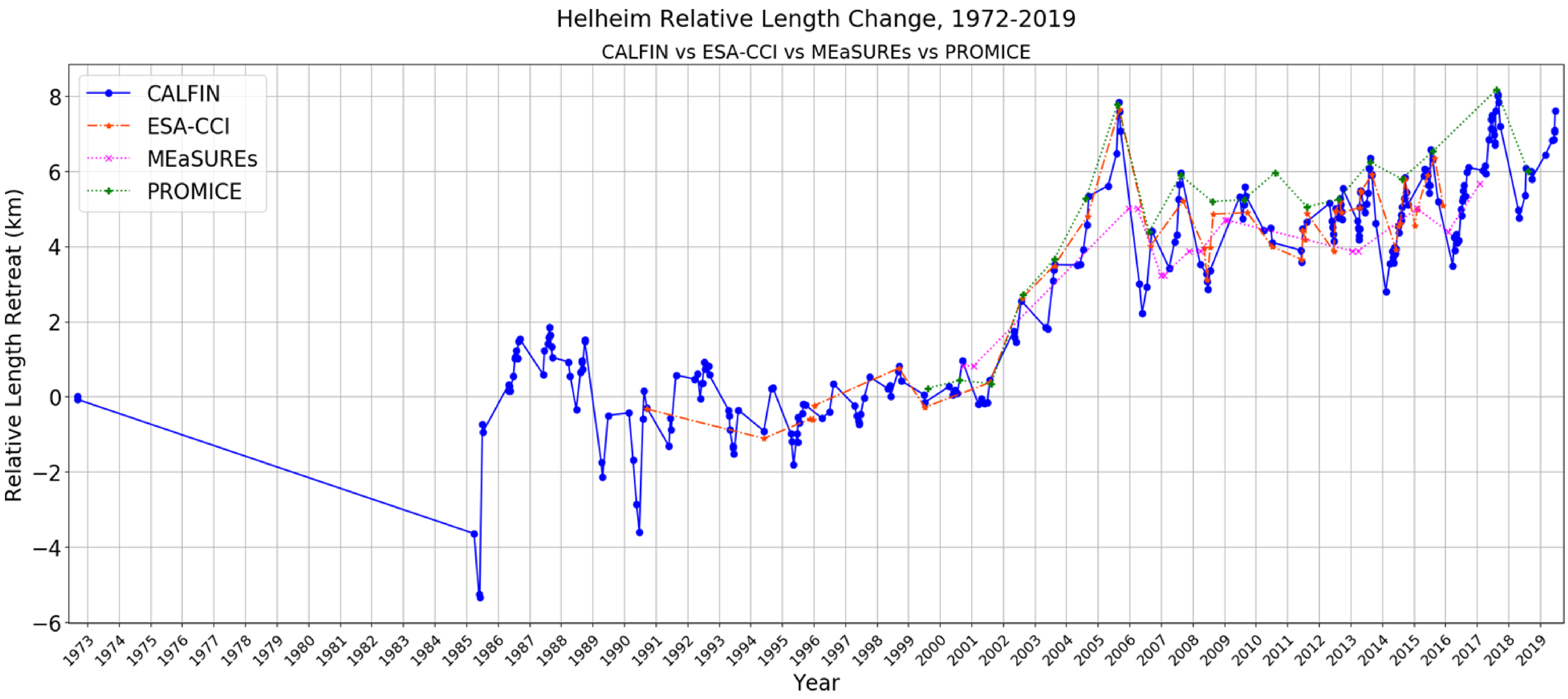


Results - Comparison With Existing Work

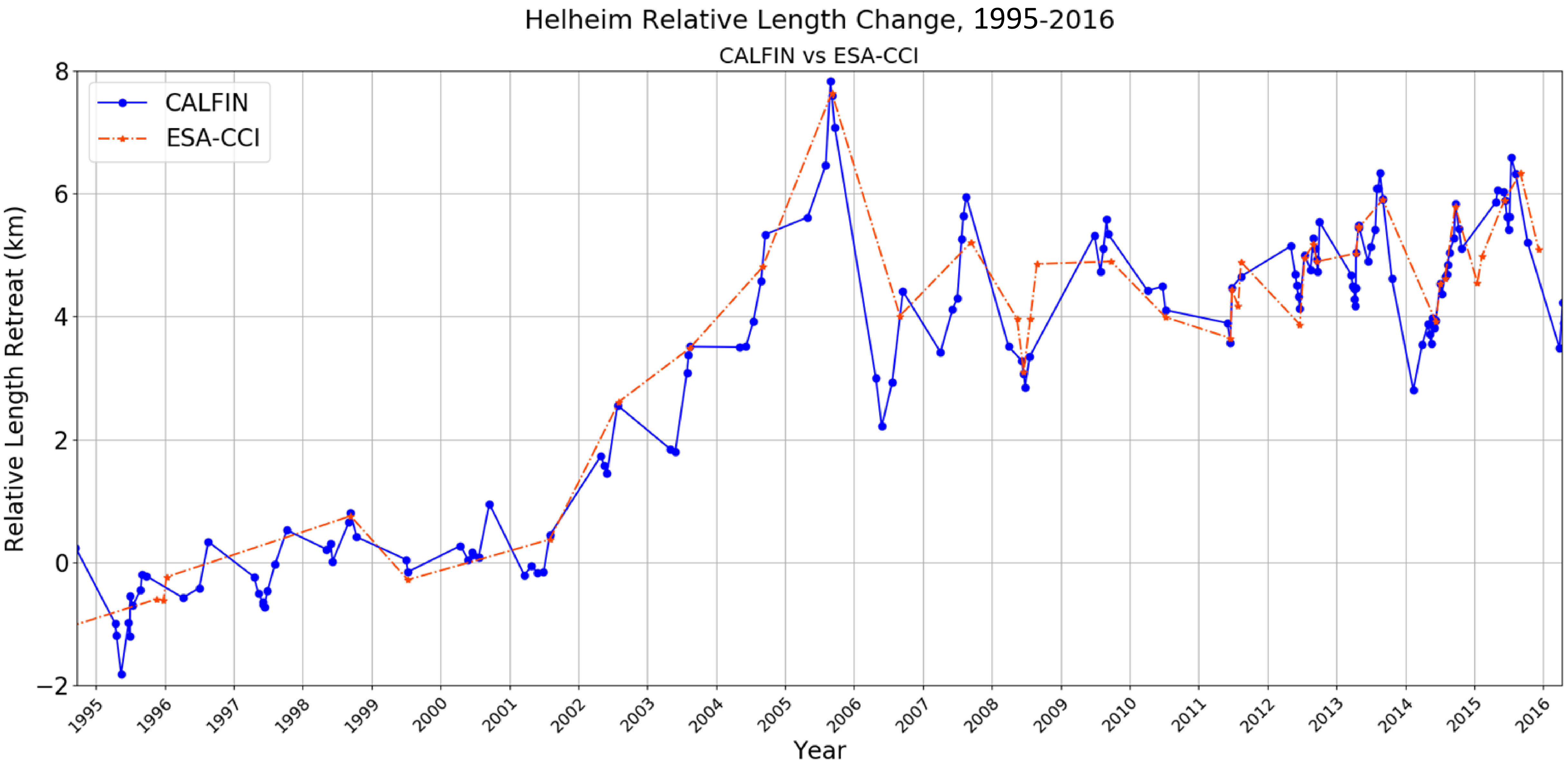




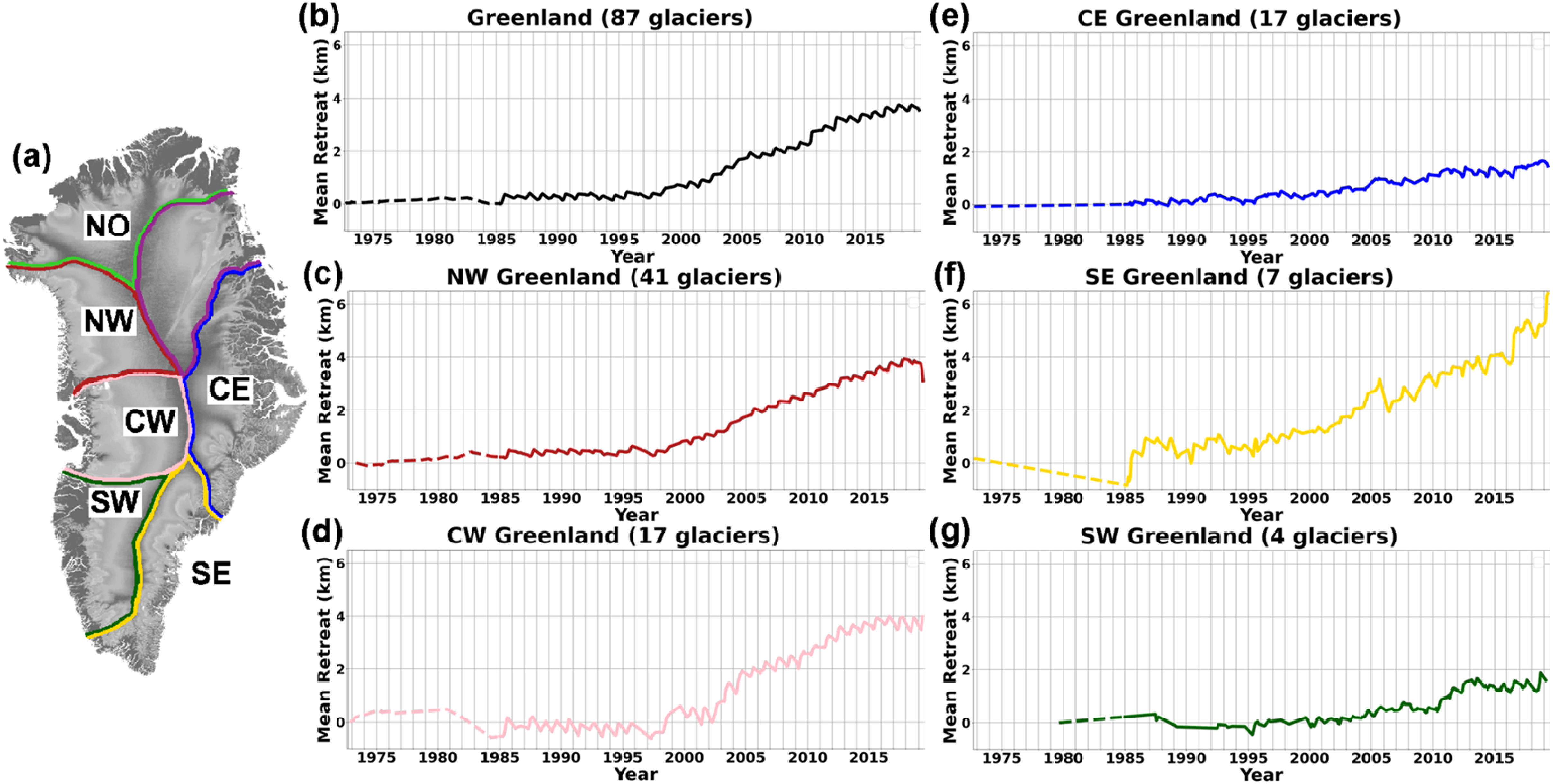
Results - Comparison With Existing Work



Results – Comparison With Existing Work



Results – Comparison With Existing Work



Results - Regional Trends

Conclusion & Future Work

- ❖ Conclusion
  - ❖Human level accuracy of ~100m for all Greenland is possible & achieved
  - ❖Multi-sensor handling (Sentinel/SAR) is possible & is achieved
  - ❖Neural Networks viable for glacial feature extraction
- ❖ Future work
  - ❖Modeling with Ice-sheet and Sea-level System Model (ISSM)
  - ❖Extended Feature Detection (iceberg, sediment plume, etc.)
  - ❖Increased spatio-temporal coverage (using Sentinel, Antarctica, etc.)

Thanks!

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References & Related Work

- **Daniel Cheng, Wayne Hayes, Eric Larour, Yara Mohajerani, Michael Wood, Isabella Velicogna, and Eric Rignot.** Calving Front Machine (CALFIN): Glacial termini dataset and automated deep learning extraction method for Greenland, 1972–2019. The Cryosphere, 15(3), 1663–1675.
- **Yara Mohajerani, Michael Wood, Isabella Velicogna, and Eric Rignot.** Detection of glacier calving margins with convolutional neural networks: A case study. Remote Sensing, 11(1), 2019
- **Enze Zhang, et al.** Automatically delineating the calving front of Jakobshavn Isbrae from multi-temporal TerraSAR-X images: a deep learning approach. The Cryosphere Discussions, 2019:1–20, 2019.
- **Celia A. Baumhoer, Andreas J. Dietz, and Claudia Kuenzer.** Automated Extraction of Antarctic Glacier and Ice Shelf Fronts from Sentinel-51 Imagery Using Deep Learning, Remote Sensing, 11, 2529.
- **Sophie Goliber, et al,** TermPicks: A century of Greenland glacier terminus data for use in machine learning applications, The Cryosphere Discuss., in review, 2021.