

Calving Front Machine (CALFIN)

Automated Calving Front Extraction & Deep Learning Methodology

for East/West Greenland, 1972-2019

Daniel Cheng¹, Yara Mohajerani¹, Michael Wood², Eric Larour², Wayne Hayes², Isabella Velicogna², and Eric Rignot^{1,2}

¹ University Of California at Irvine (UCI), Irvine, CA

² California Institute of Technology - Jet Propulsion Laboratory (JPL), Pasadena, CA

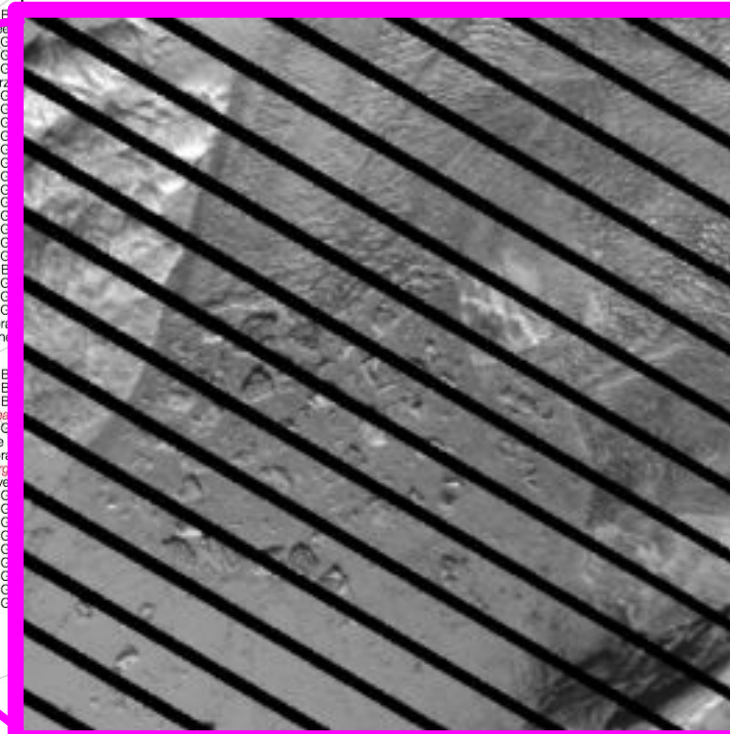
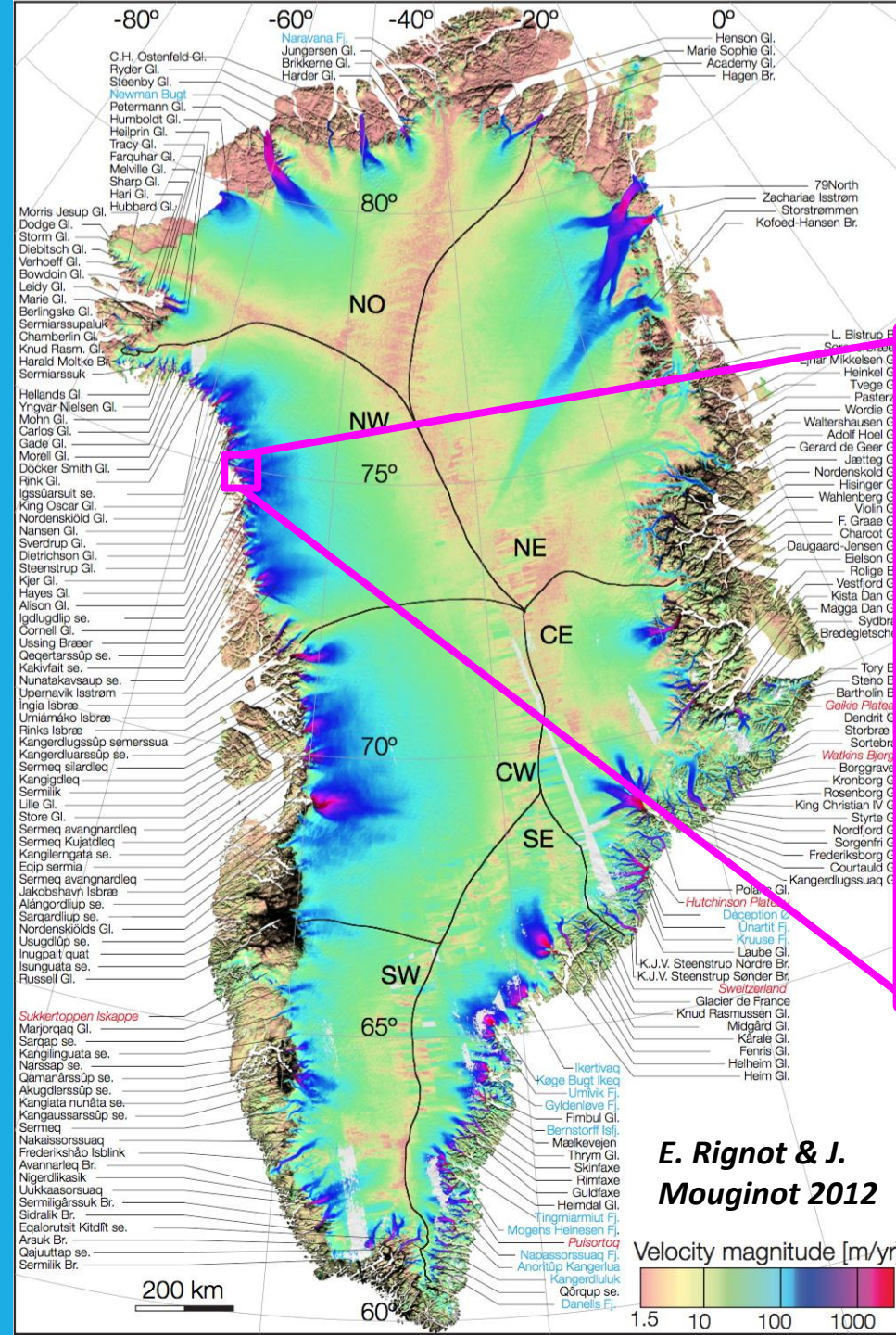


Jet Propulsion Laboratory
California Institute of Technology



Motivation

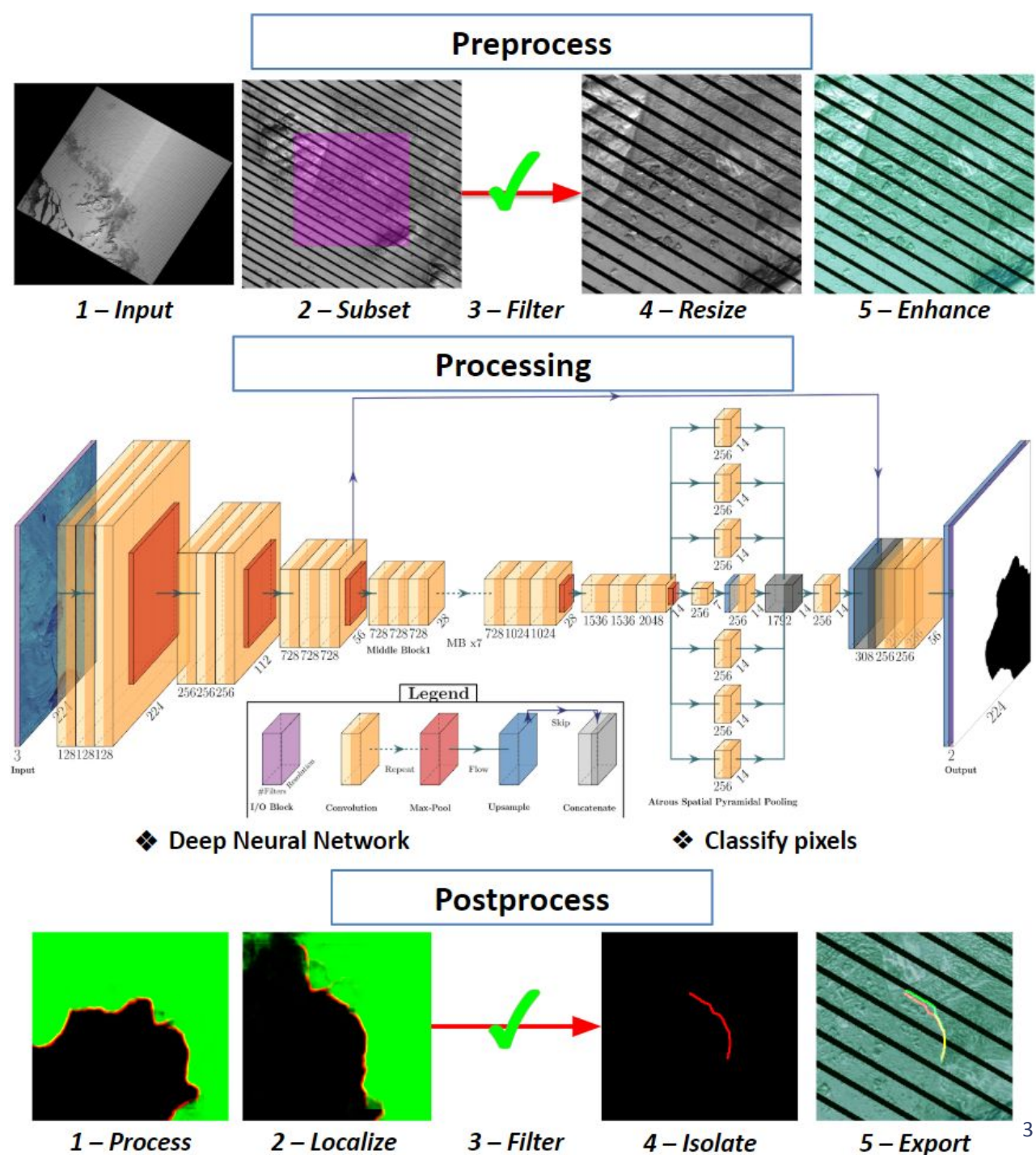
- ❖ Determining where glaciers end is useful
- ❖ Manual labeling is time intensive, automatic labeling is non-trivial
- ❖ We use Deep Neural Networks (AI/Machine learning)
- ❖ Auto-label 17000+ subseasonal fronts over 66 basins



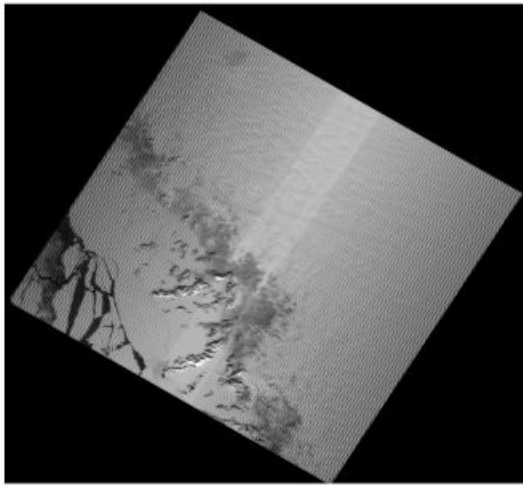
Hayes Glacier, 2006 April 06,
Landsat 7.

Method

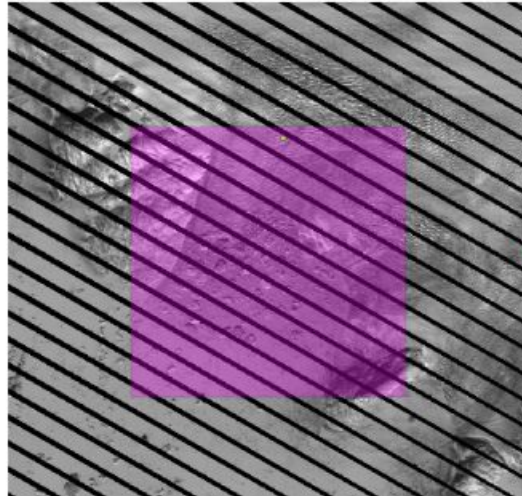
- ❖ Automated pipeline
- ❖ Pre-process Landsat satellite imagery
- ❖ Process and classify pixels with Neural Network
- ❖ Post-process to extract vectorized calving front



Method - Pre-processing



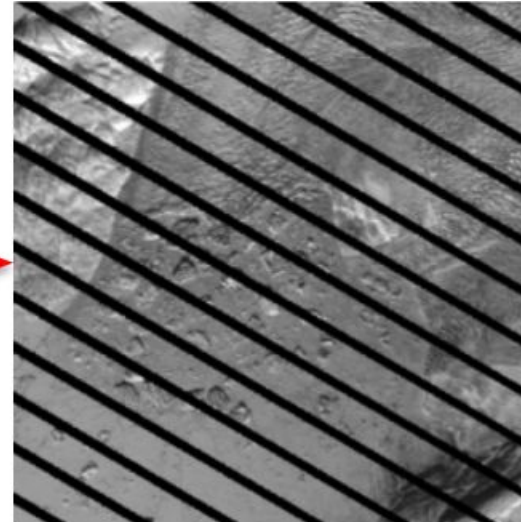
1 – Input
*raw Landsat
GeoTIFF image
with <20% clouds*



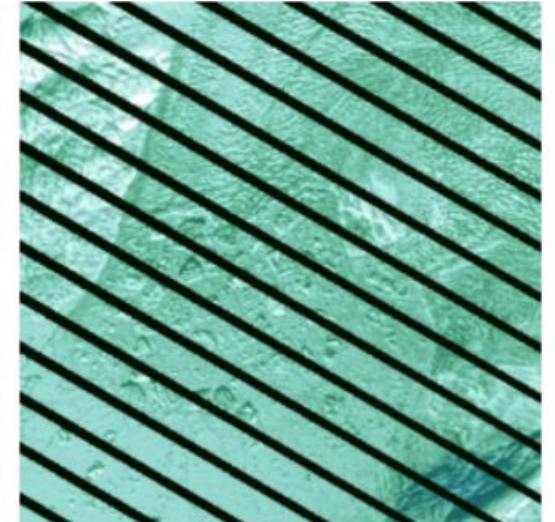
2 – Subset
*using QGIS, GDAL
domain Shapefile
to subset PNG*



3 – Filter
*clouded/
NODATA
images*

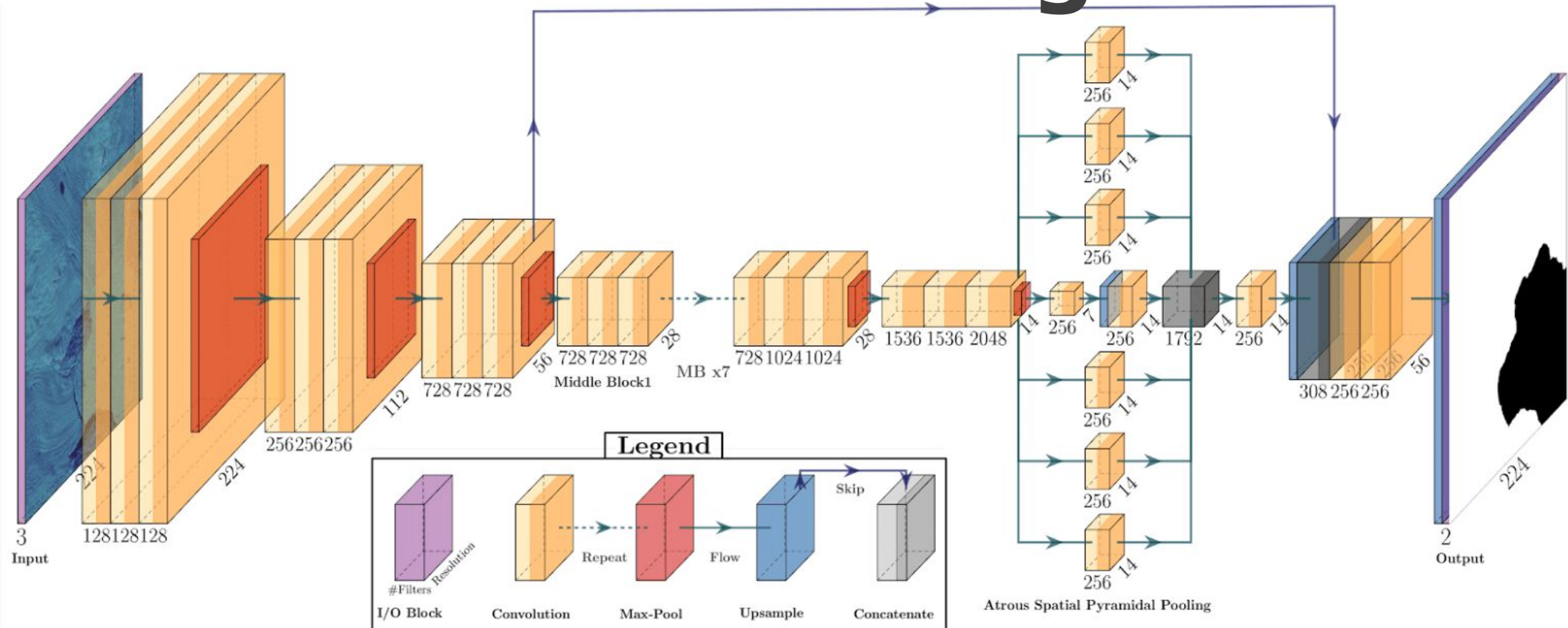


4 – Resize
*subset to
256x256*



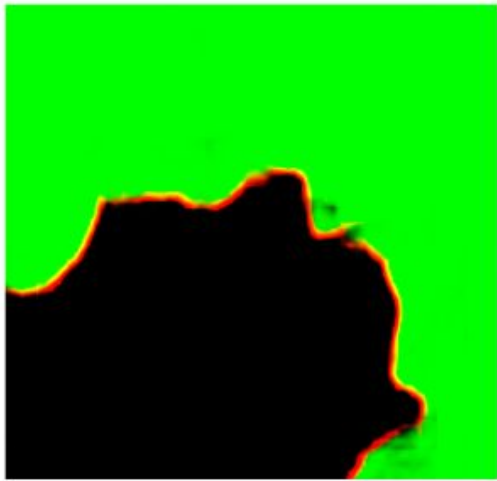
5 – Enhance
*by giving raw, HDR,
and auto-contrast
images to next step*

Method - Processing

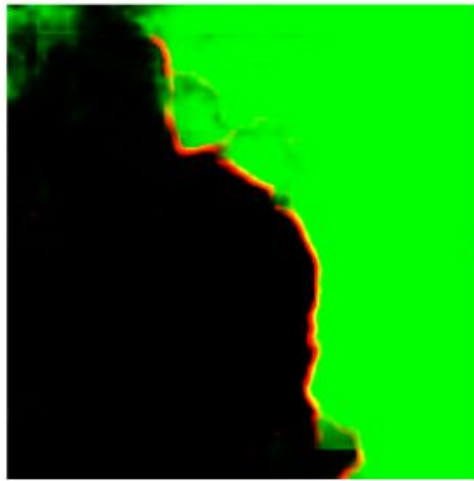


- ❖ CALFIN-NN = convolutional neural network, UNet-type, DeepLabV3+ Xception derivation
- ❖ 3 channel RGB input, 2-channel coastline/land-ice mask. ~29m parameters.
- ❖ Use 1500 manually delineated fronts for training. 65 epochs, 1wk train, 16ms inference

Method - Post-processing



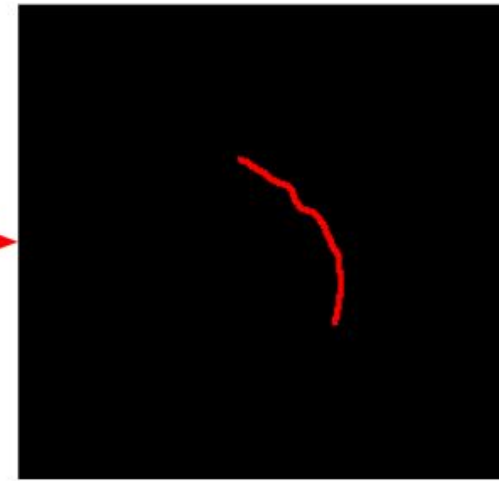
***1 – Get
processed
image***



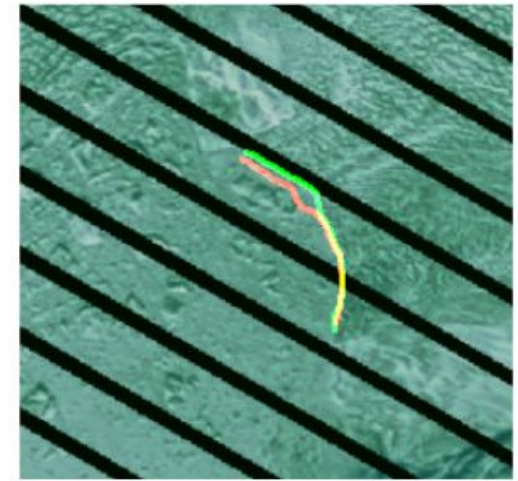
***2 – Isolate
and re-process
each front***



***3 – Filter
unconfident
predictions***



***4 – Fit
line and mask
static coastline***



***5 – Export
and validate
Shapefile***

Results

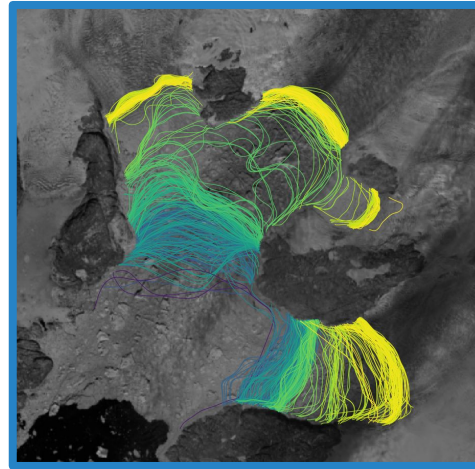
◆ Data Release

◆ Shapefile Polylines

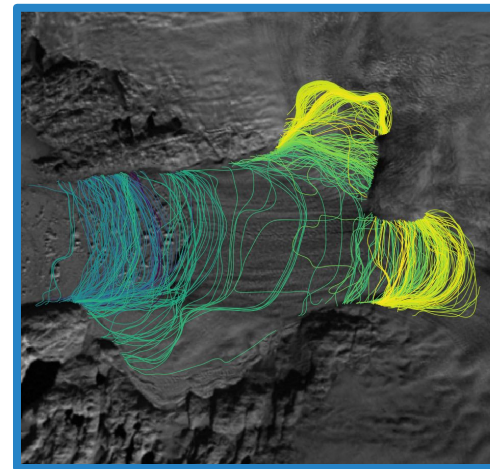
- 19909 total fronts,
- 17912 auto-picked
- 1997 manual

◆ Includes Training data, GeoTIFF subsets, Neural Network weights

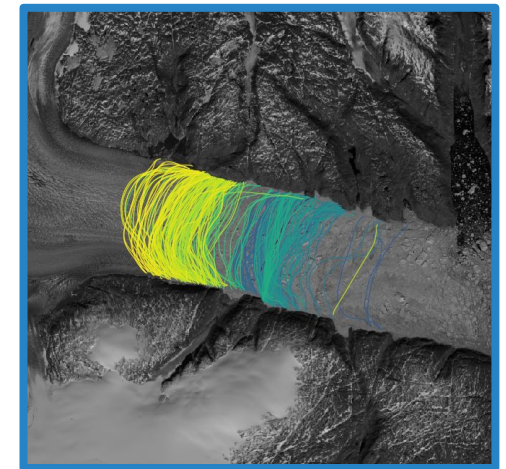
◆ Release on DataDryad & NSIDC pending approval



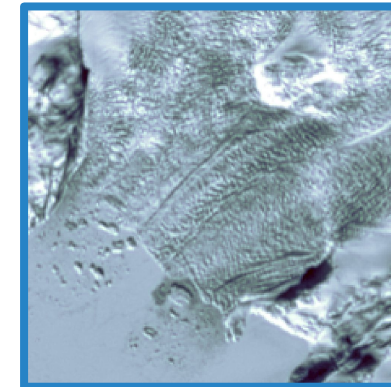
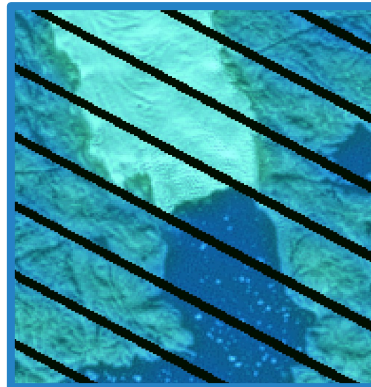
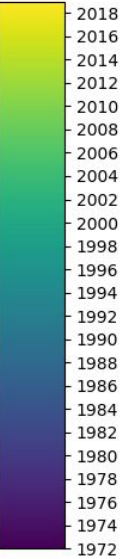
Upernavik



Jakobshavn



Helheim



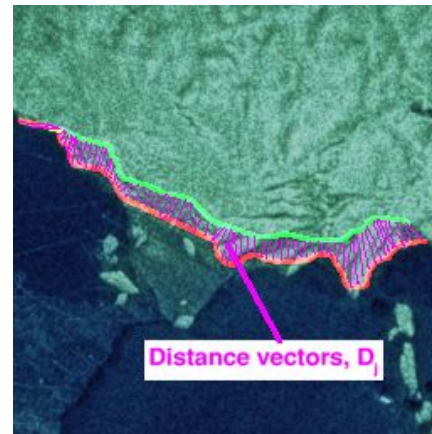
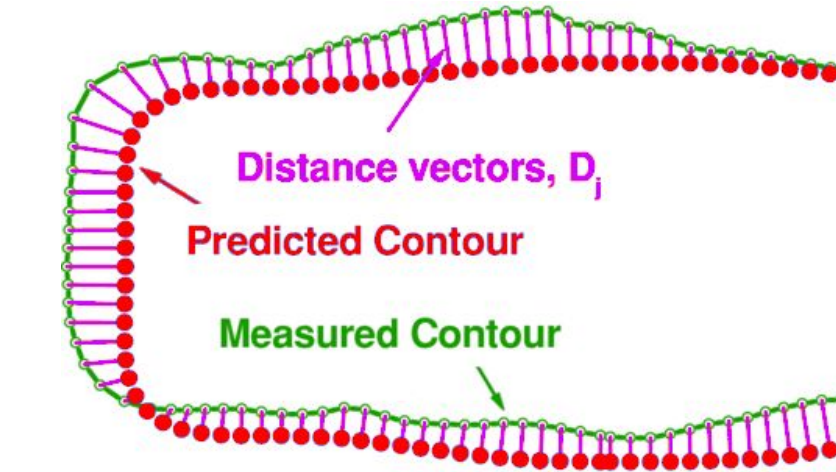
Training & validation data for 66 basins, plus 51 Antarctic basins from Zhang, Mohajerani, and Baumhoer

Results

Measuring Error

- Mean/Median Distance between predicted and true front
 - Calculated per pixel
 - Similar to method of transects (Baumhoer)
- Intersection over Union
 - Measures overlap between ground truth and prediction
 - IoU Coastline = edge overlap
 - IoU Ice/Ocean = mask overlap

Mean/Median Distance



Mean Distance = $\text{mean}(D)$

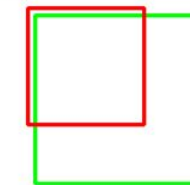
Median Distance = $\text{median}(D)$

Lower = Good

Intersection over Union

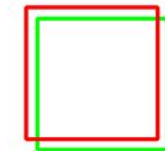
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

IoU: 0.4034



Poor

IoU: 0.7330



Good

IoU: 0.9264



Excellent

Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
CALFIN	<u>CALFIN</u>	2.25px, 86.76m	1.21px, 44.59m	0.4884	0.9793

Results

❖ Inter-model Comparison

❖ Retrain/test UNet model by

Mohajerani et al.

- Similar median metrics
- Outliers/L7 SCE cause issues

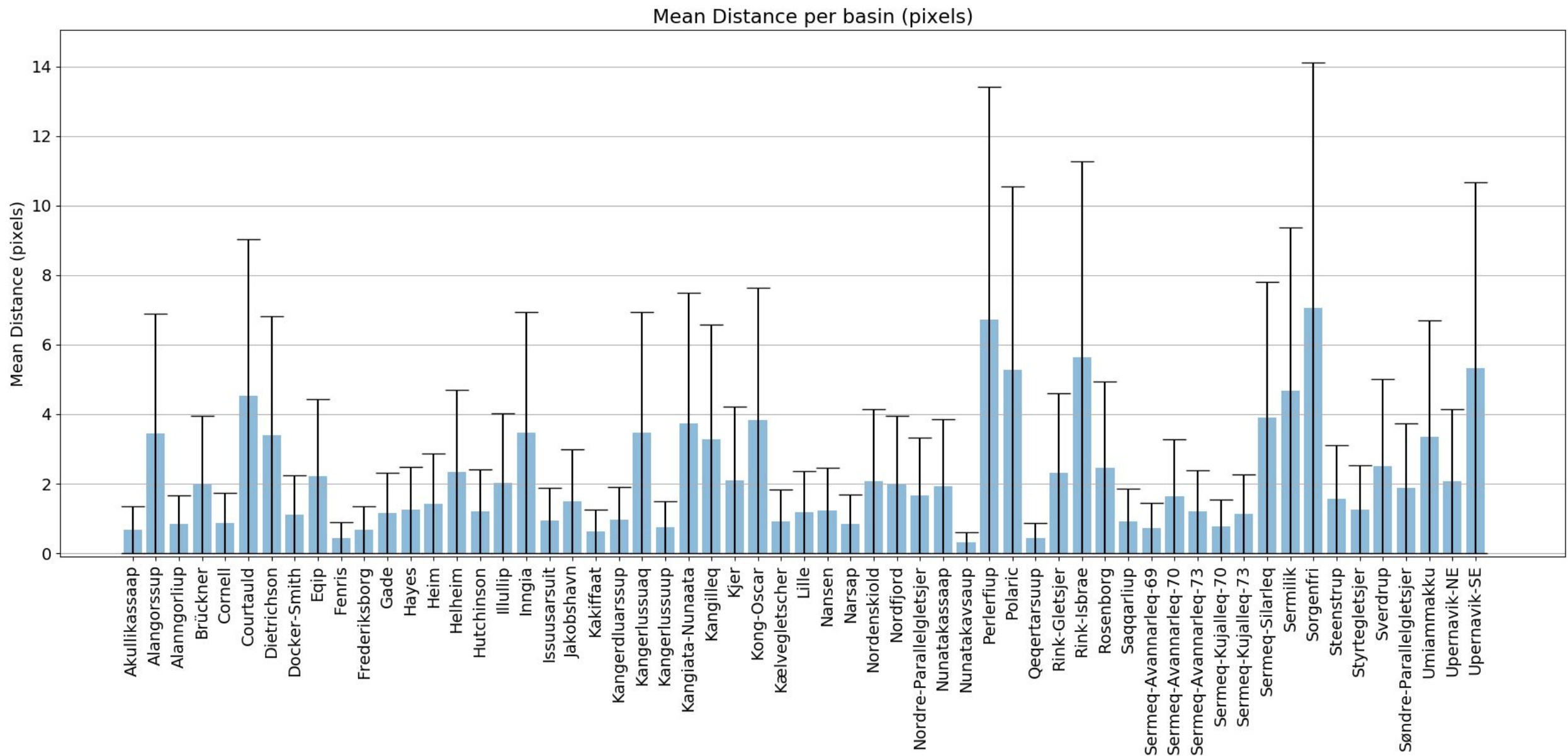
❖ Run CALFIN on validation

data from Mohajerani,

Zhang, & Baumhoer

- CALFIN is competitive and generalizes well
- See EGU2020-4486 for Celia Baumhoer's work

Validation Set	Model	Mean Distance	Median Distance	IoU Coastline	IoU Ice/Ocean
CALFIN	<u>CALFIN</u>	2.25px, 86.76m	1.21px, 44.59m	0.4884	0.9793
CALFIN	Mohajerani	4.45px, 201.35m	1.25px, 50.52m	0.4935	0.9699
Mohajerani	<u>CALFIN</u>	2.56px, 97.72m	2.55px, 97.44m	0.3332	N/A
Mohajerani	Mohajerani	1.97px, 96.31m	N/A	N/A	N/A
Zhang	<u>CALFIN</u>	3.56px, 284.22m	1.69px, 114.50m	0.3739	0.9778
Zhang	Zhang	17.3px, 104m	N/A	N/A	N/A
Baumhoer	<u>CALFIN</u>	3.36px, 543.47m	0.95px, 127.87m	0.5959	0.9873
Baumhoer	Baumhoer	2.69px, 108m	N/A	N/A	0.905

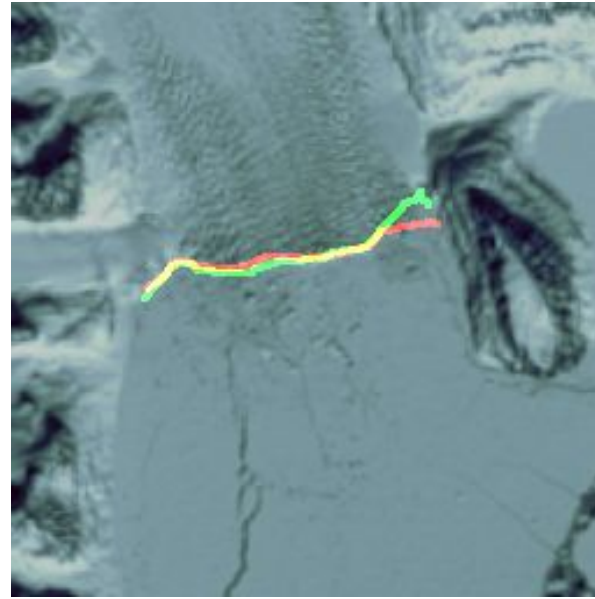
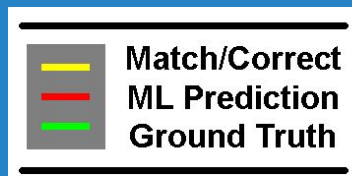


Results - Mean Distance Intervals by Basin

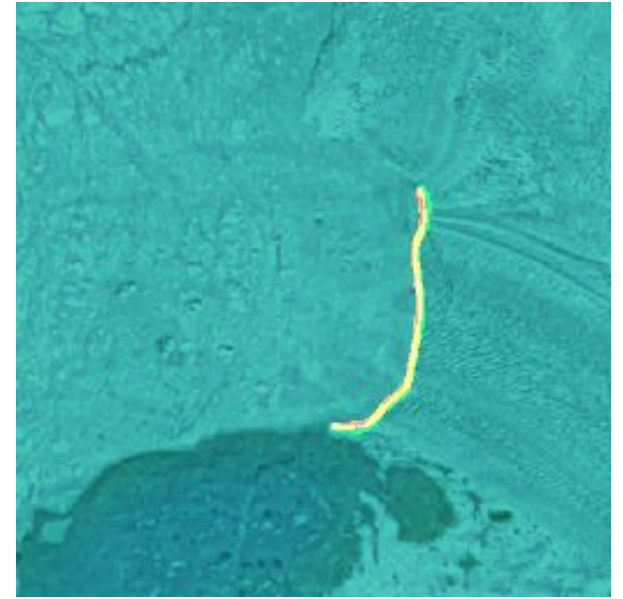
Error Analysis

Validation set

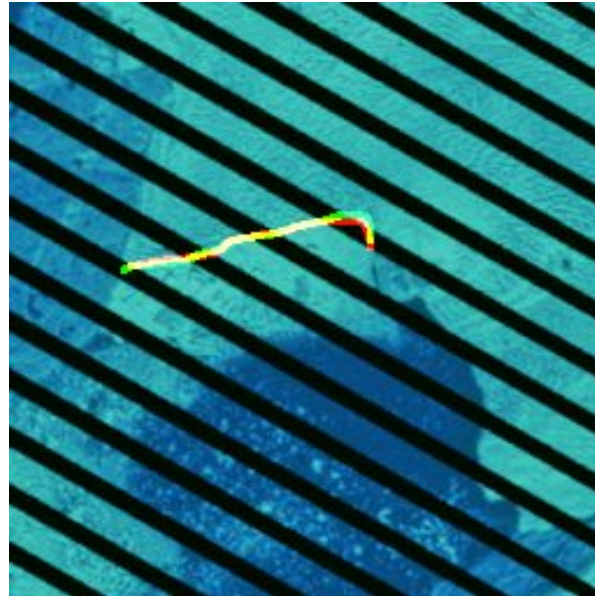
- 162 unseen images
- Most adverse conditions handled well
- Ice tongues need work
- Mean Error:
 - 2.25 ± 0.02 pixels
 - 86.76 ± 0.73 meters



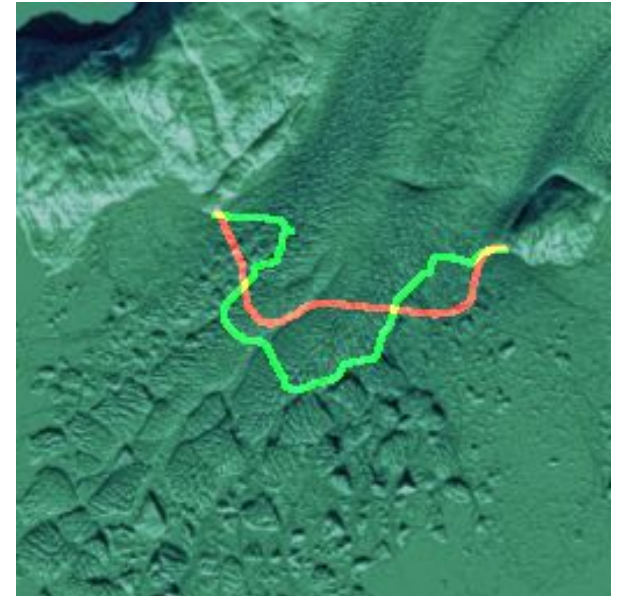
Rosenborg 1997-04-20



Jakobshavn-E 2017-06-02



Hayes-N 2008-08-10

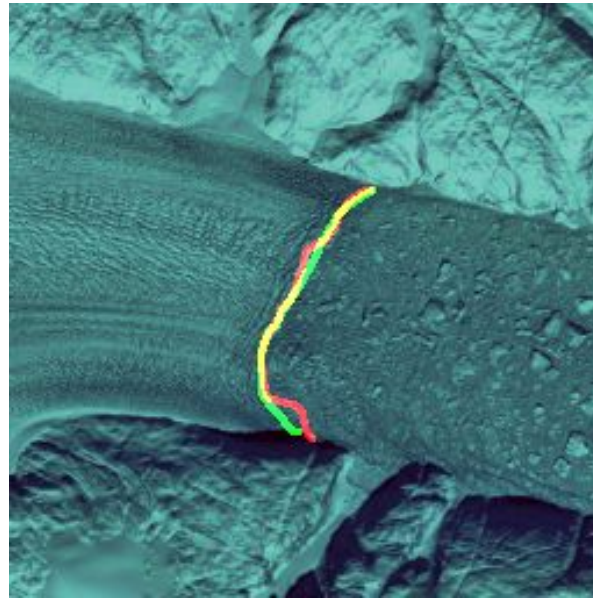


Kong-Oscar 1998-03-26 ¹²

Error Analysis

❖ Helheim

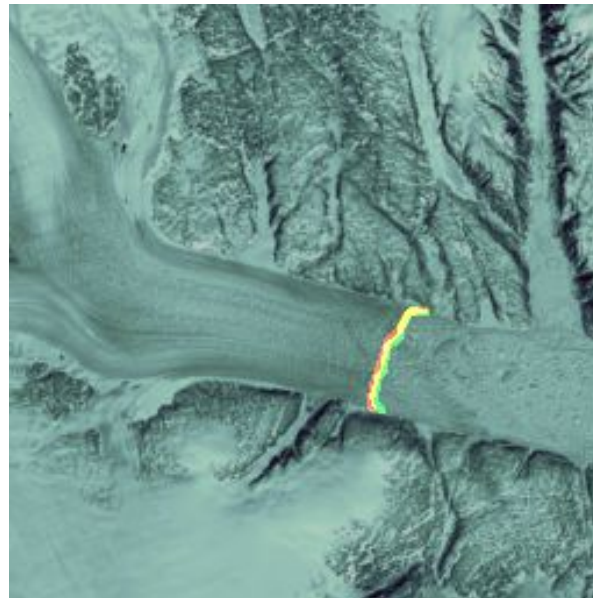
- ❖ Handles Multiscale/L7 SCE
- ❖ Error near fjord walls
- ❖ Provides strong proof of generalization
- ❖ Mean Error:
 - 2.34 ± 0.12 pixels
 - 124.05 ± 6.40 meters



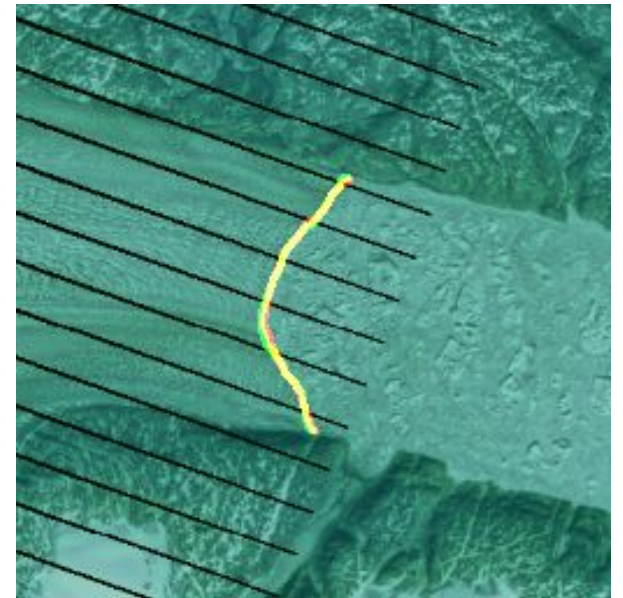
Helheim 2013-04-12



Helheim 2000-05-27



Helheim 1993-06-08



Helheim 2003-08-08

Error Analysis

❖ L7 Scanline Errors

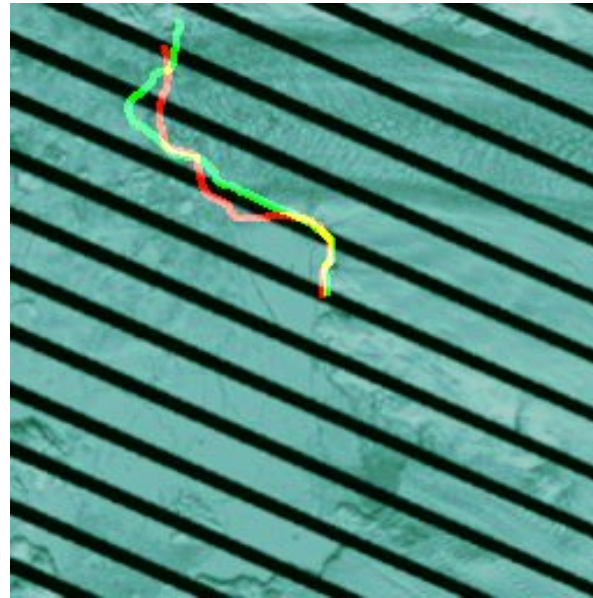
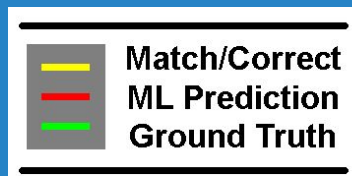
❖ Higher than average error as expected, but still good

❖ No L7 SCE Mean Error:

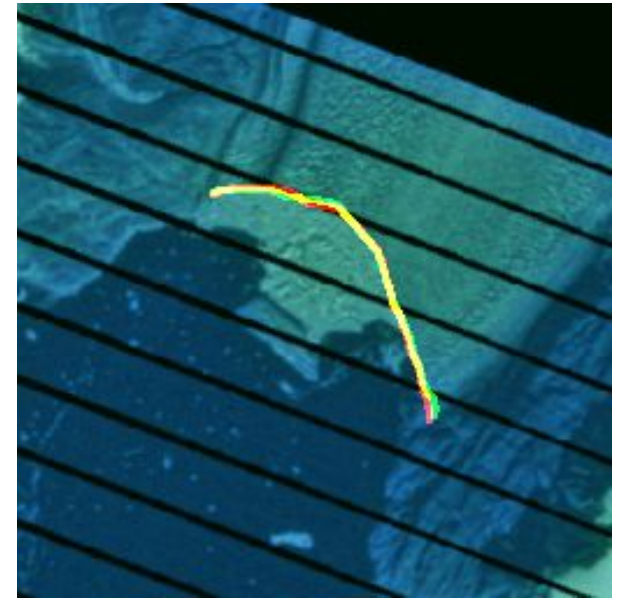
◦ 2.27 ± 0.07 px, 81.65 ± 2.65 m

❖ Only L7 SCE Mean Error:

◦ 2.22 ± 0.07 px, 91.93 ± 3.04 m



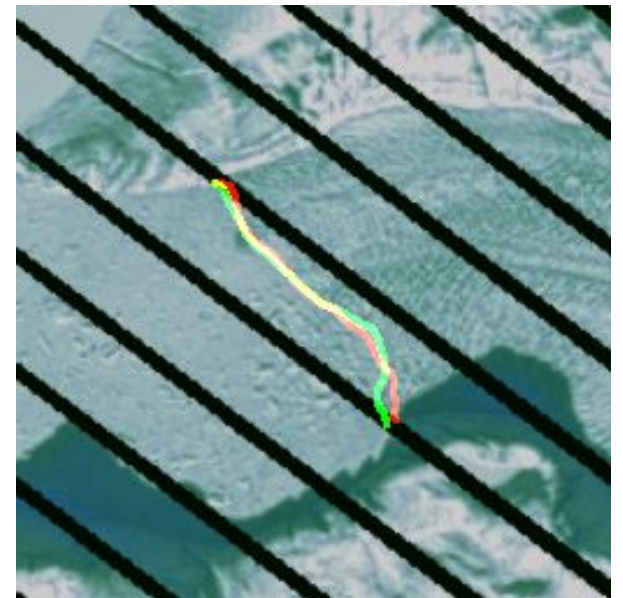
Upernavik-SE_2009-04-27



Rink-Isbrae 2005-08-08



Kangerlussuaq 2012-04-19



Dietrichson 2008-04-23

Error Analysis

❖ Non-Landsat data

❖ More training needed

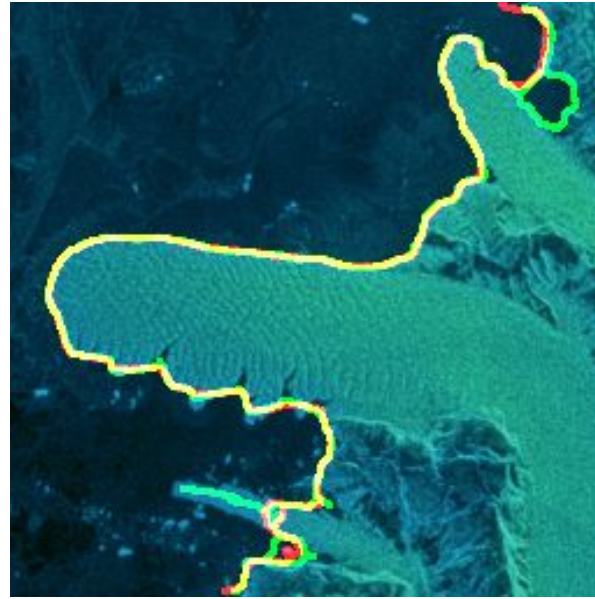
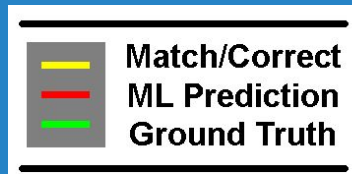
❖ Zhang TerraSAR-X Error:

- 3.56px, 284.22m

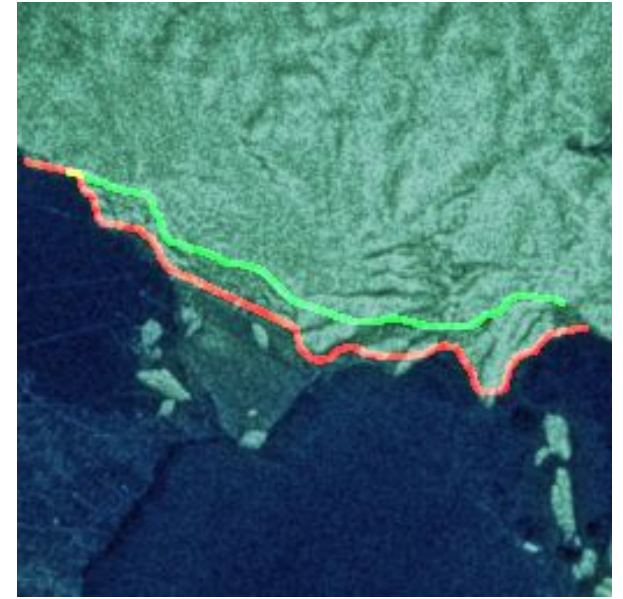
❖ Baumhoer Sentinel-1 Error:

- 3.36px, 543.47m

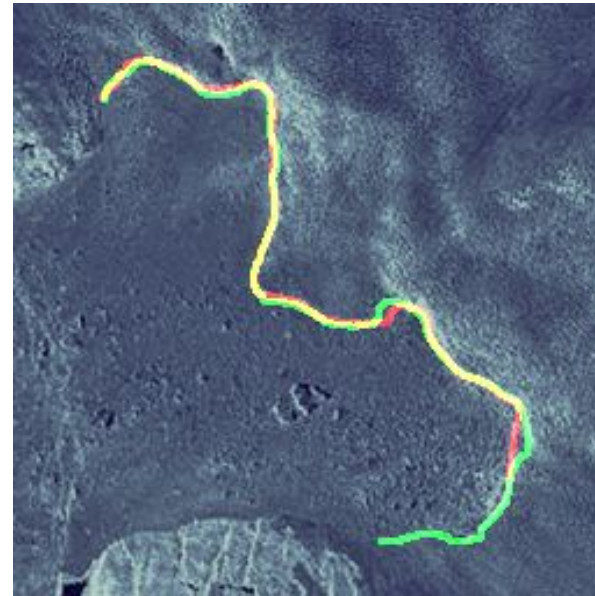
❖ MODIS too low res (250m)



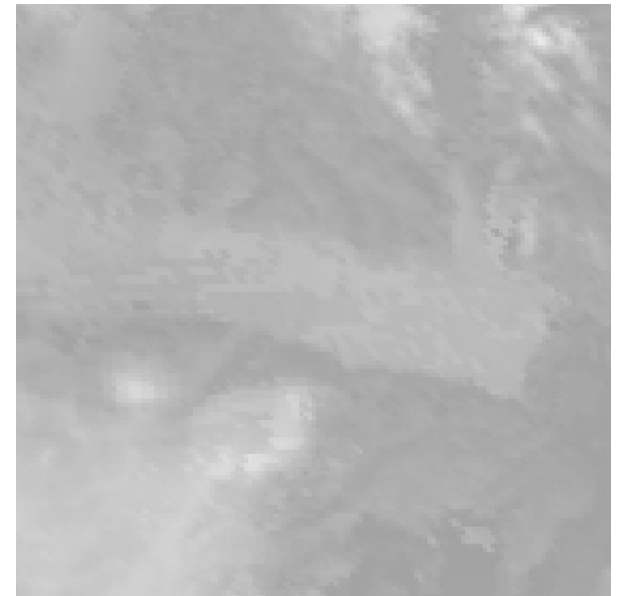
Aviator TSX 2018-06-29



Gillet S1B 2018-06-26



Jakobshavn TSX 2014-07-03

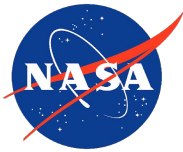


Helheim MODIS 2015-09-27

Conclusion & Future Work

- ❖ Publication & Data Release still in progress!
- ❖ Accuracy target for release: <100m for all domains achieved
 - ❖ Increased Accuracy, Spatial Resolution, Spatial Coverage
 - ❖ Multi-sensor handling (Sentinel/SAR)
- ❖ Collaboration with IcePicks
 - ❖ See Sophie Goliber in this session at EGU2020-11237
 - ❖ Other Feature Detection (iceberg, grounding line, sediment plume, etc.)
 - ❖ Unified Calving Front/Feature Database

Thank you!



Jet Propulsion Laboratory
California Institute of Technology



jpl.nasa.gov - uci.edu

Daniel Cheng - dlcheng@uci.edu

Wayne Hayes - whayes@uci.edu

Eric Larour - Eric.Larour@jpl.nasa.gov

Yara Mohajerani - ymohajer@uci.edu

Michael Wood - mhwood@uci.edu

Isabella Velicogna - isabella@uci.edu

Eric Rignot - erignot@uci.edu

Thanks @ ISSM Team, Friends, and Family

References & Related Work



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, Taryn Black, and Ginny Catania. “IcePicks: a Collaborative Database of Greenland Outlet Glacier Termini” EGU, EGU2020, 6 May 2020



Jukes Liu, Ellyn Enderlin, Andre Khalil. “Greenland Marine Glacier Terminus Mapping in Satellite Imagery Using the Automated 2D Wavelet Transform Modulus Maxima (WTMM) Segmentation Method.” AGU, AGU, 11 Dec. 2019



Soroush Rezvanbehbahani, Leigh Stearns, Ramtin Keramati, Siddharth Shankar. Automating Iceberg Detection in Greenland Using Deep Learning on High to Moderate-Resolution Optical Imagery. AGU, AGU, 11 Dec. 2019