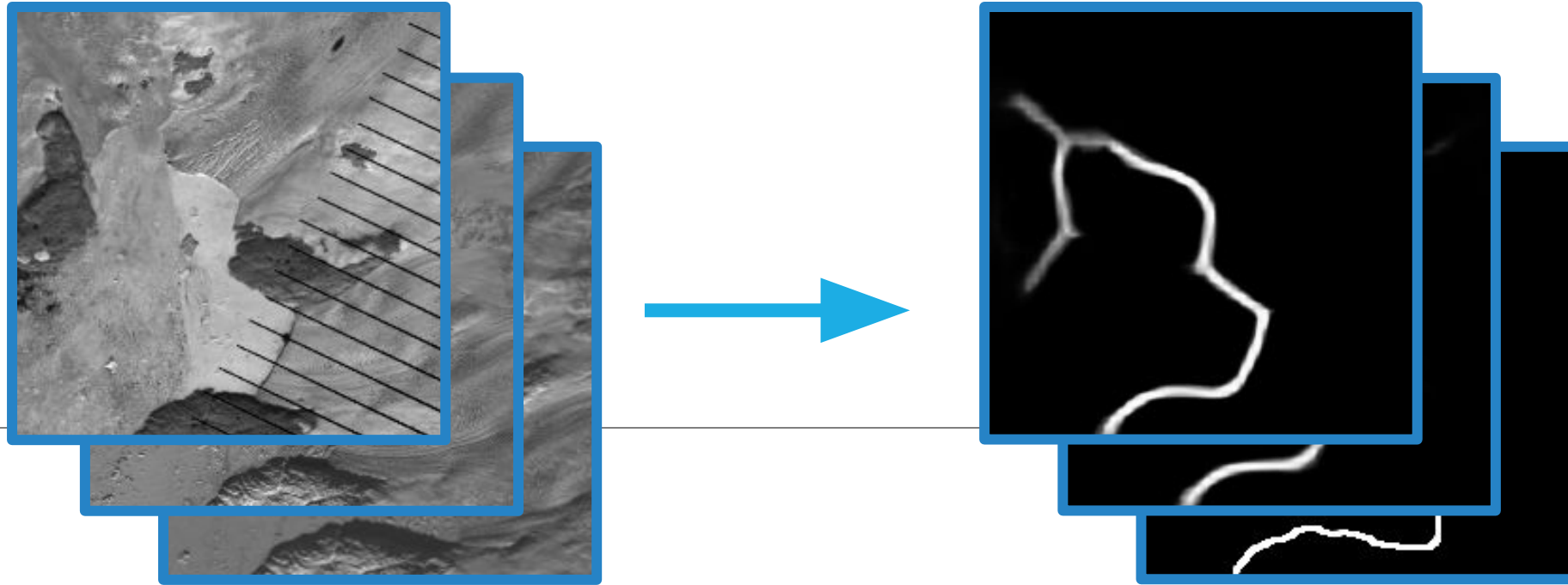


# CALFIN: A Calving Front Mask Dataset for West Greenland, 1972-2018



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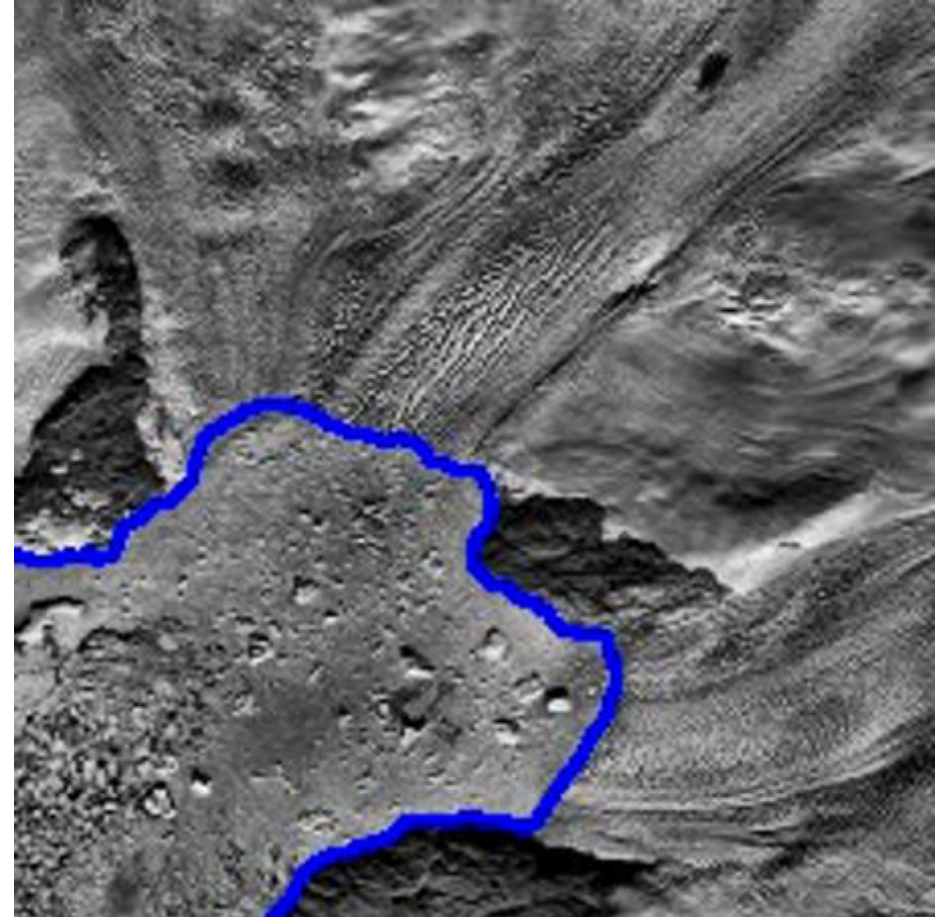
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# Motivation

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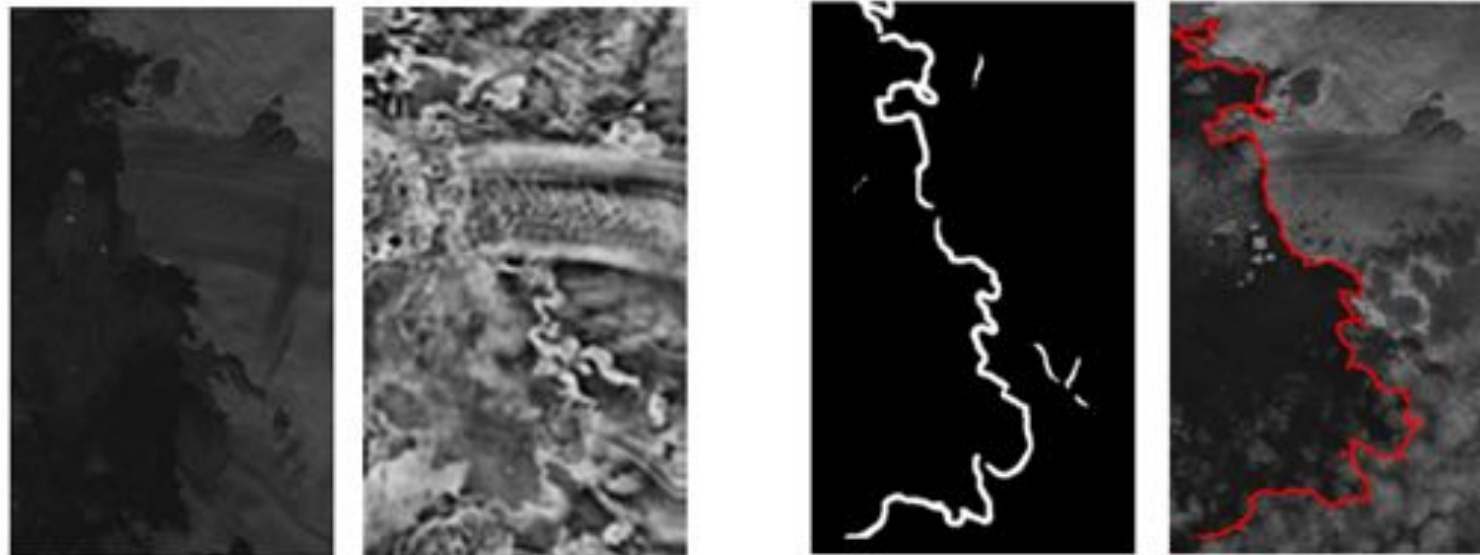
- ❖ Determining where glaciers end is useful data
- ❖ Manual labeling is time intensive
- ❖ Many glaciers not labeled, new data needs to be added



# What is CALFIN?

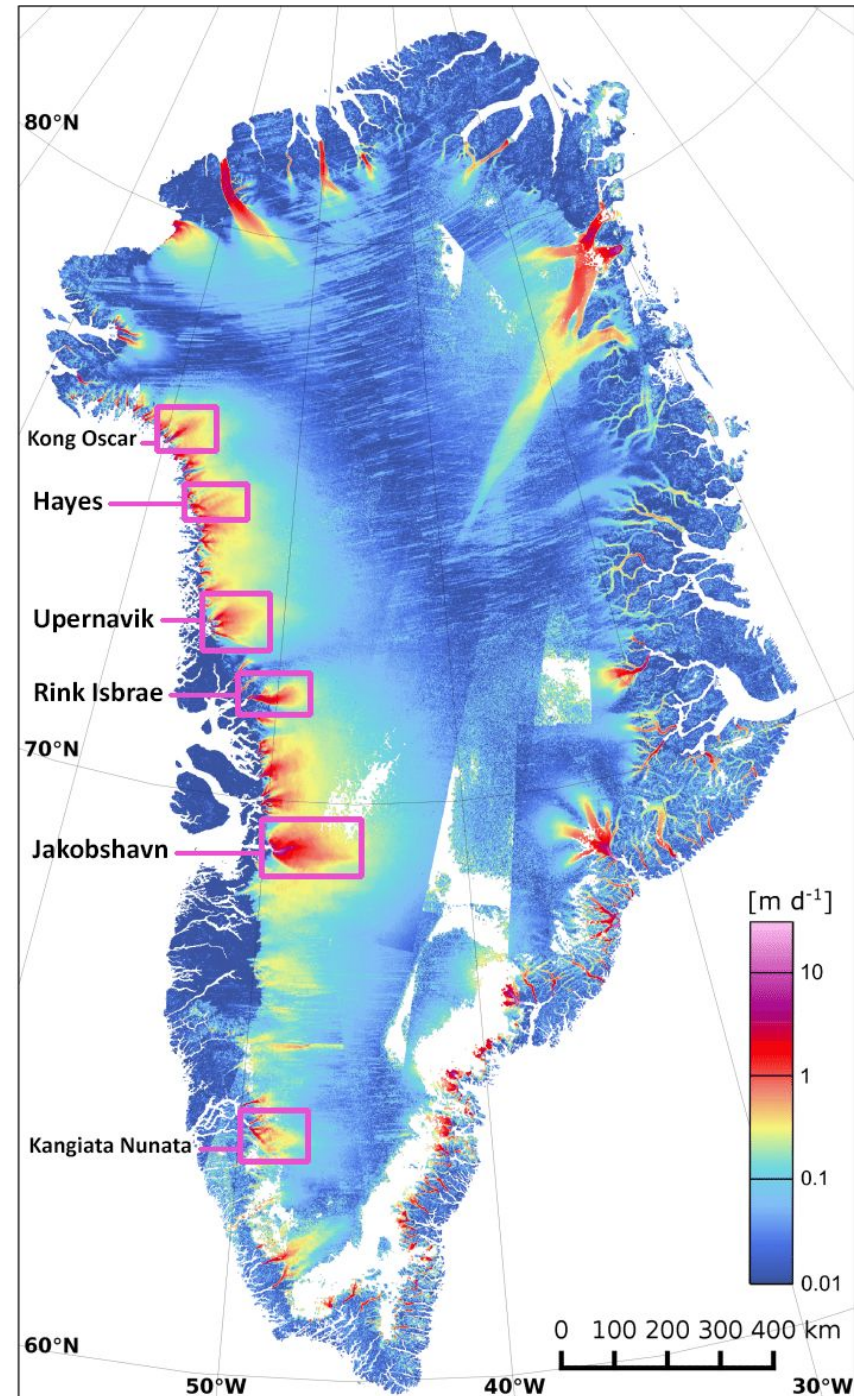
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- ◆ Dataset of calving front masks for West Greenland
- ◆ Data source: Landsat, 1972-2018.
- ◆ Automated with convolutional neural network tool, CALFIT



# Spatial Coverage

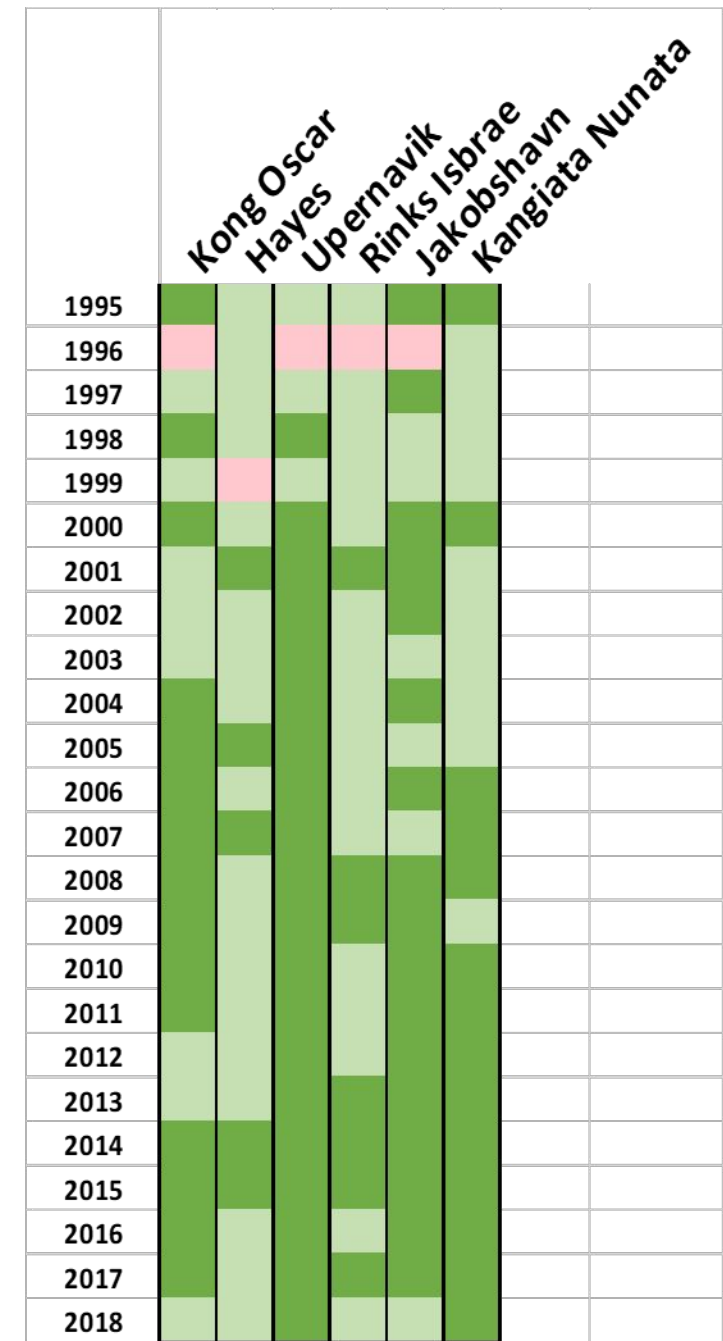
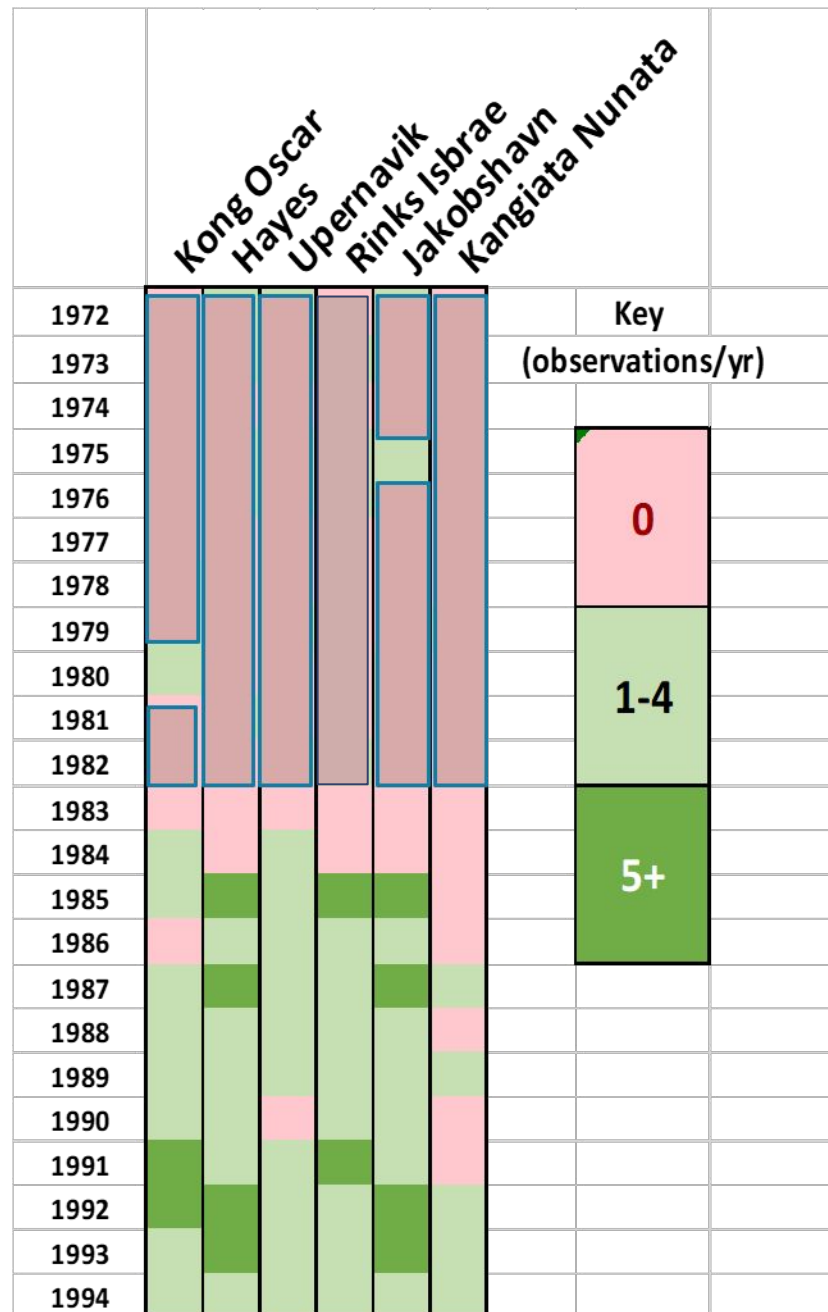
- ◆ Data availability along West Greenland, for the 6 highlighted basins
  - ◆ Plotted over velocity map (Naglar, 2015)
- ◆ Basins selected for equal sampling of coastline
- ◆ Basins selected for study potential/high velocities





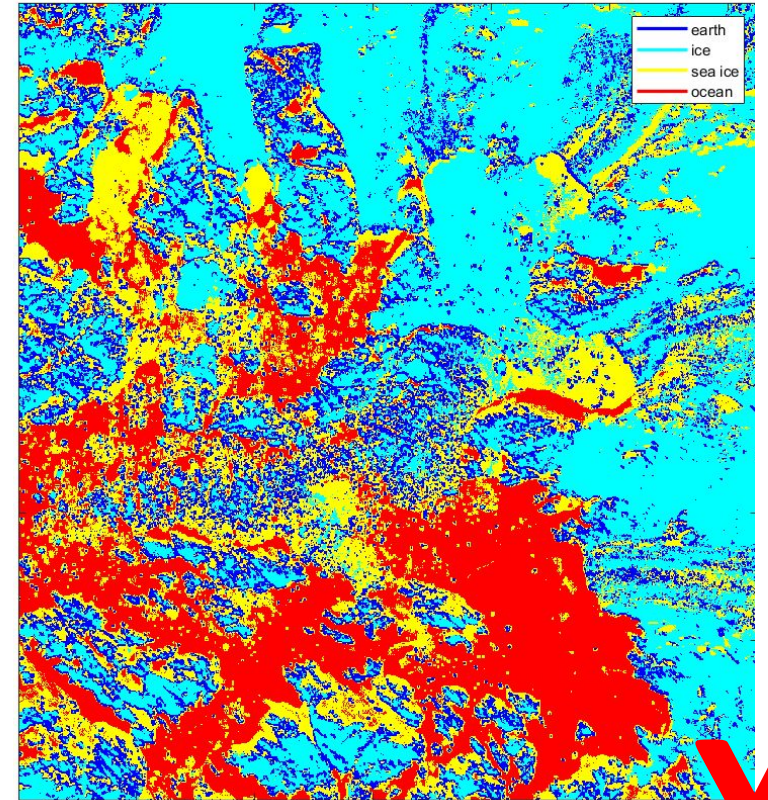
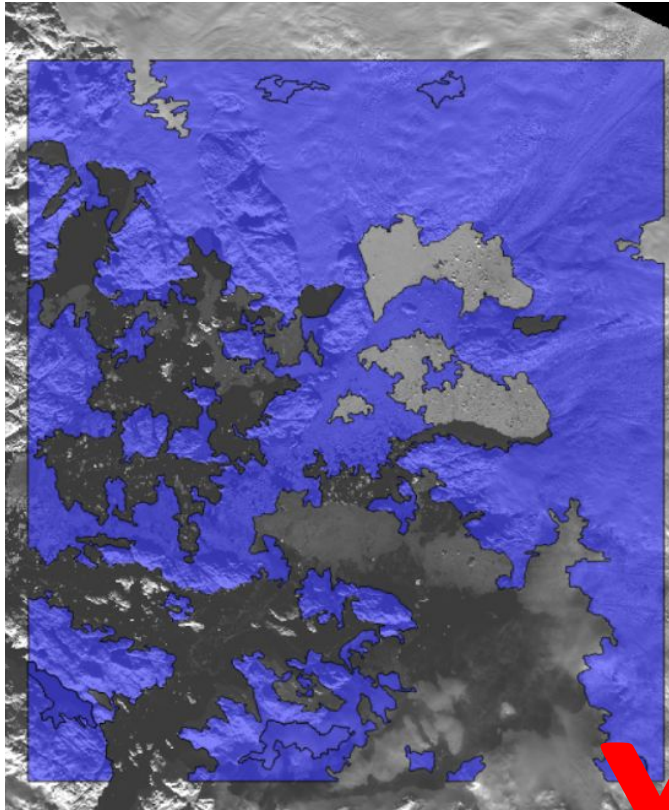
# Temporal Coverage

- ❖ Landsat availability per year, for all 6 basins.
- ❖ Gaps due to clouds or lack of classifier confidence
- ❖ Color key shows rough number of observations per year.



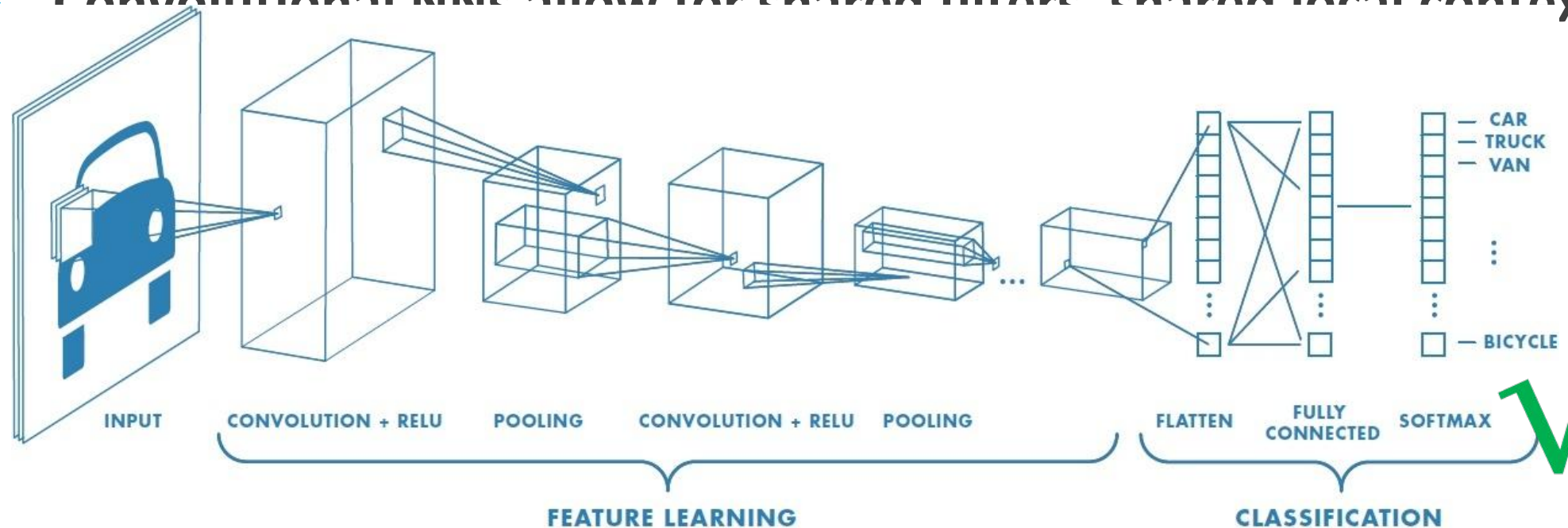
# Approach

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



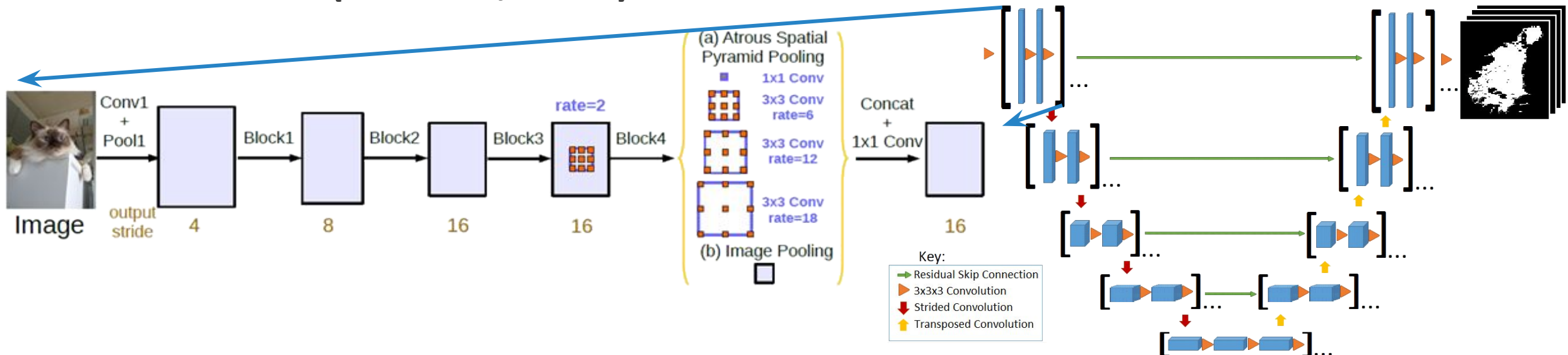
# Approach – Neural Networks

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



# CALFIT - Architecture

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





# CALFIT Insights

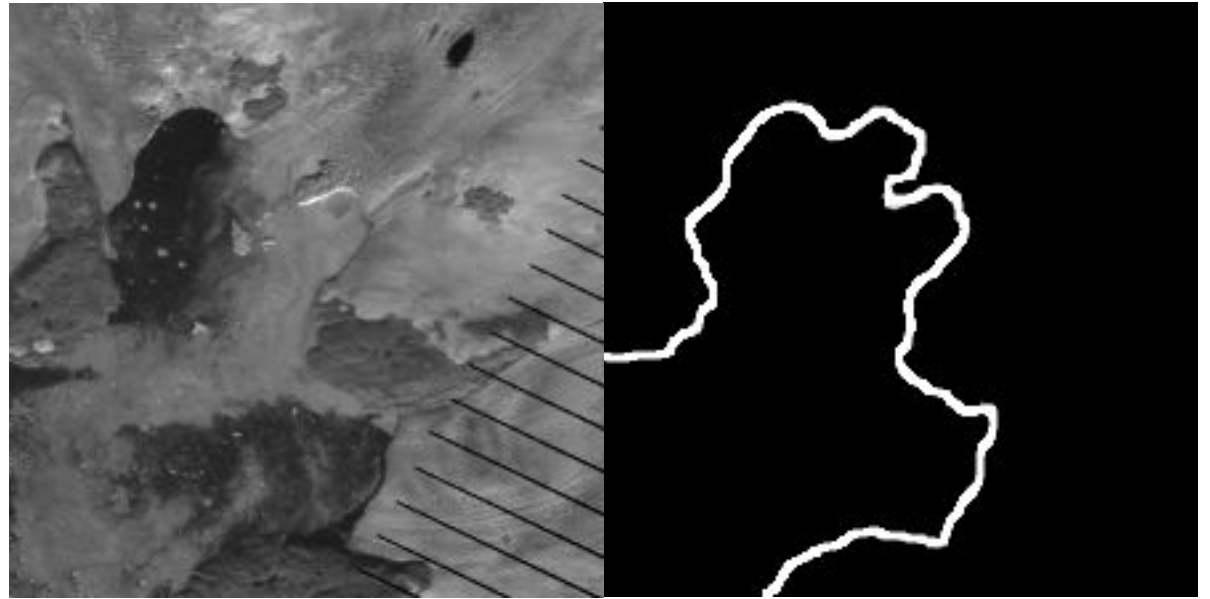
- ◆ Global context is needed
- ◆ Local context not as important
- ◆ Strong dependence on having full front + glacial ice
- ◆ Train on problematic images
- ◆ Augment data, but be careful with scale/distort

Architecture	Best IoU
UNet 256 32-4-2	0.3802
Deeplabv3+ MobileNetV2 224	0.6956
Deeplabv3+ MobileNetV2 256	0.6026
<b>Deeplabv3+ Xception 224</b>	<b>0.8794</b>
Deeplabv3+ Xception 256	0.8986
Deeplabv3+ Xception 384	0.8257
Deeplabv3+ Xception 512	0.6956

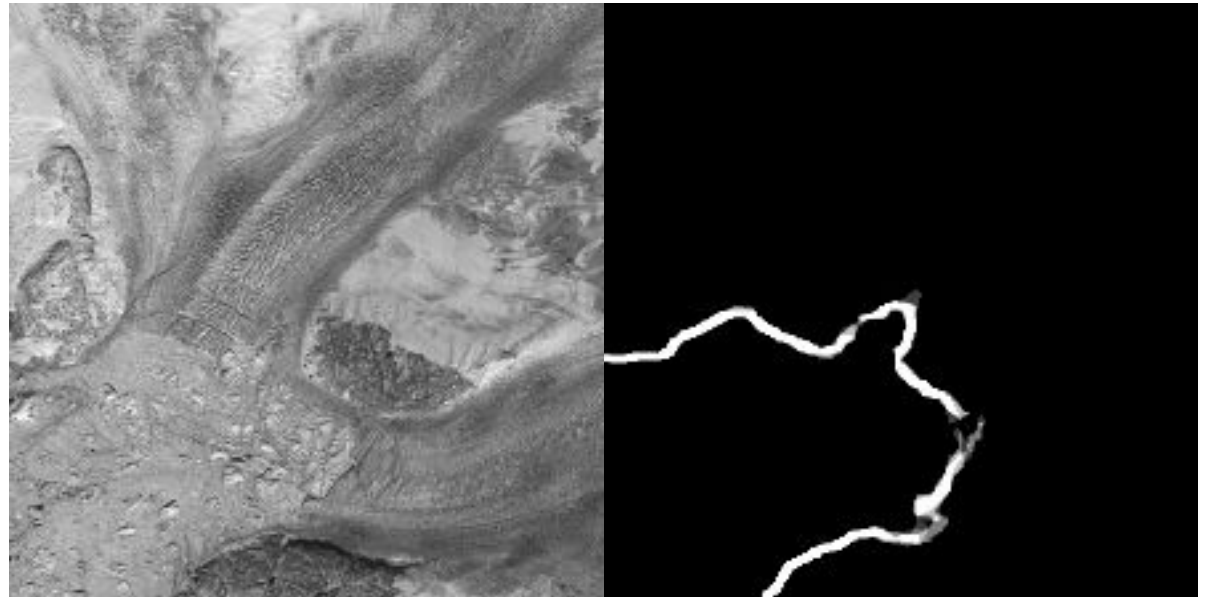
# Results & Error Analysis

## ◆ Upernavik

- ◆ Able to capture glacial tongues
- ◆ Uses texture gradient to detect ice mélange boundary



Upernavik-NE 2007-08-10

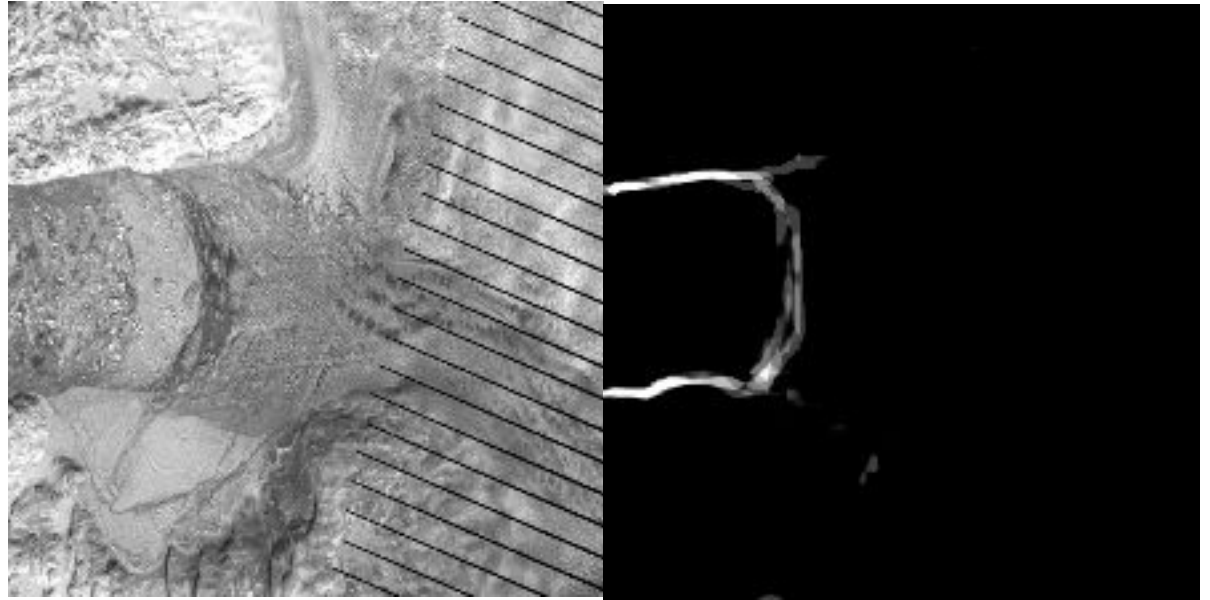


Upernavik-NE 1988-05-16

# Results & Error Analysis

## ◆ Jakobshavn

- ◆ Ice mélange causes uncertainty
- ◆ Manageable with postprocessing
- ◆ Compression/scaling may decrease accuracy



Jakobshavn 2004-04-10

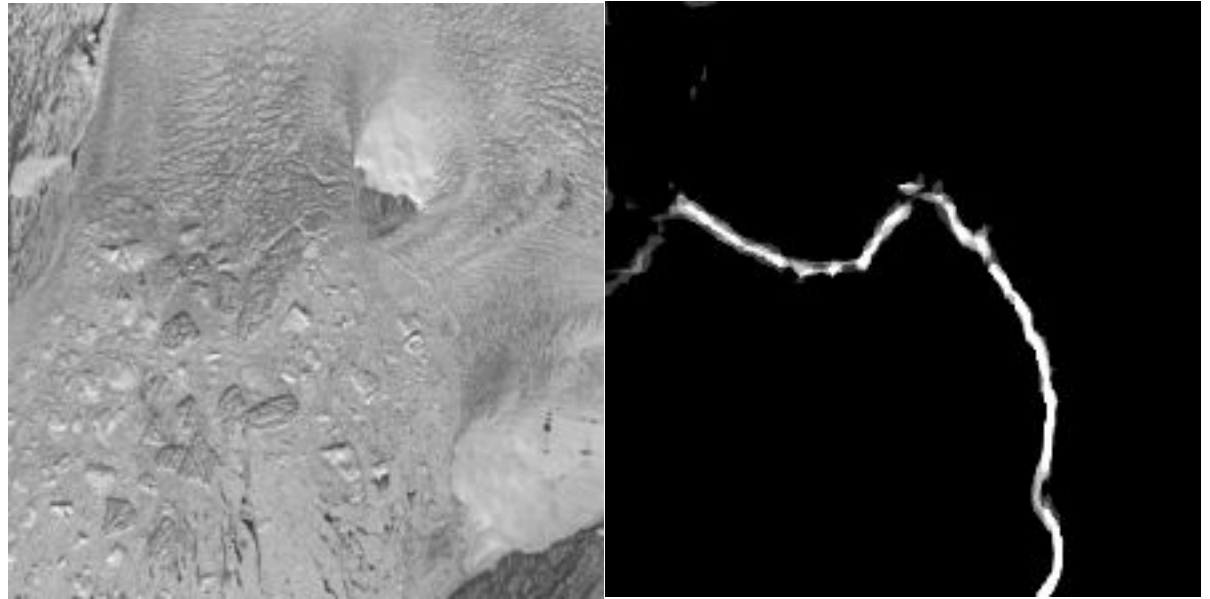


Jakobshavn 2011-04-21

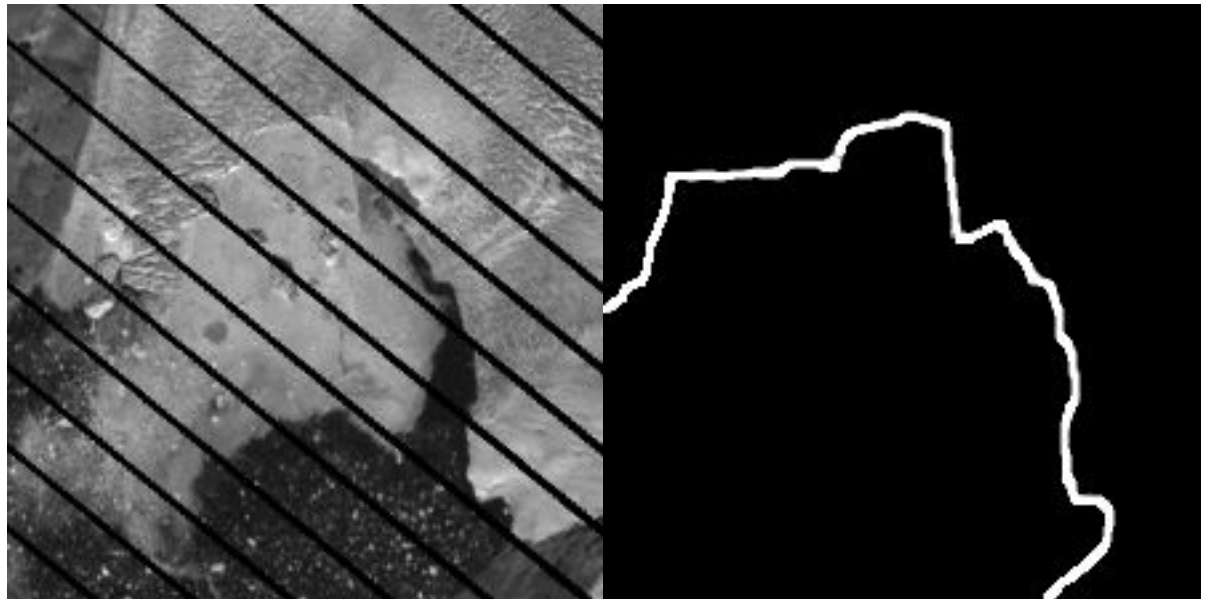
# Results & Error Analysis

## ◆ Hayes

- ◆ Extra training allows ice mélange to be more clearly separated
- ◆ Not as consistent due to complexity of fronts



Hayes 1992-07-03



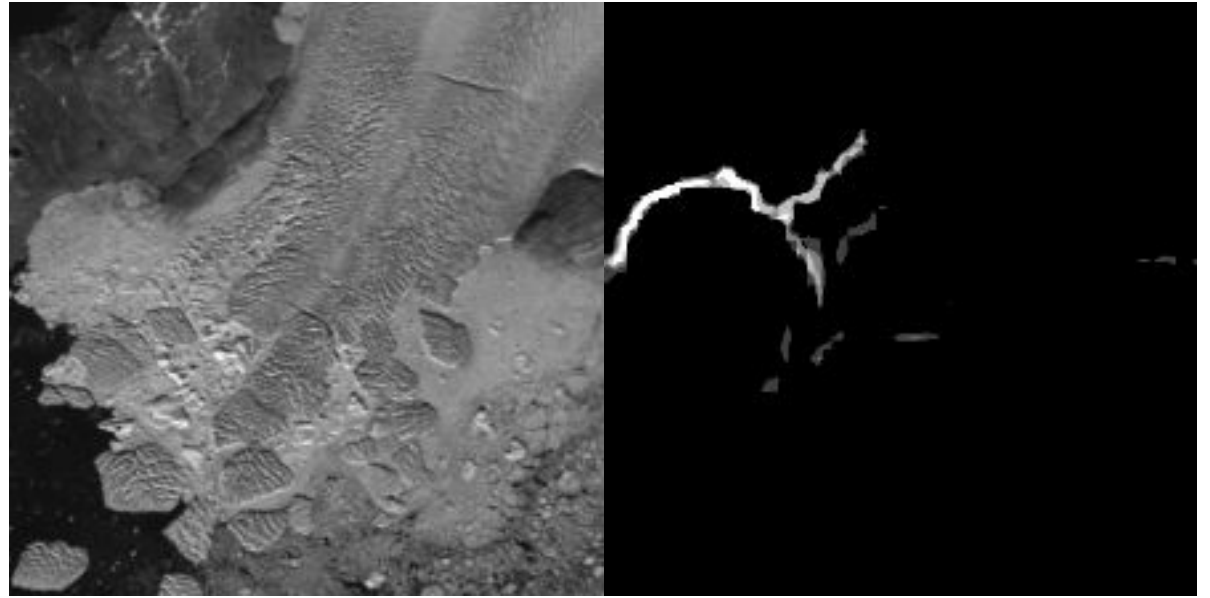
Hayes 2008-07-30



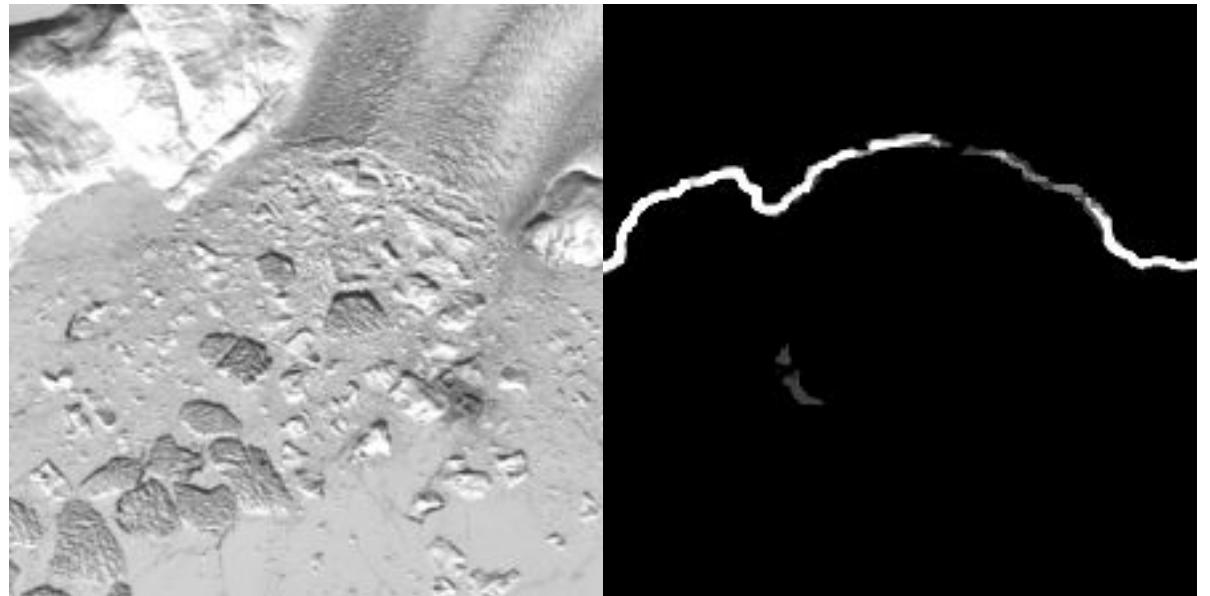
# Results & Error Analysis

## ◆ Kong-Oscar

- ◆ Worst accuracy all around
- ◆ Requires additional training



Kong-Oscar 2000-08-07

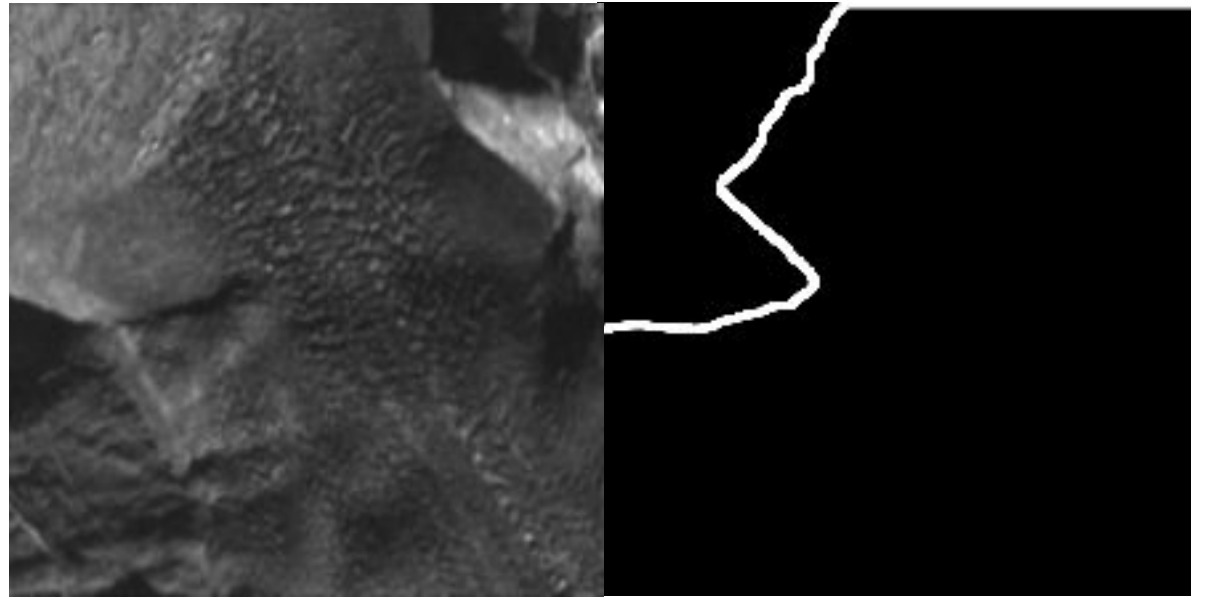


Kong-Oscar 2003-05-03

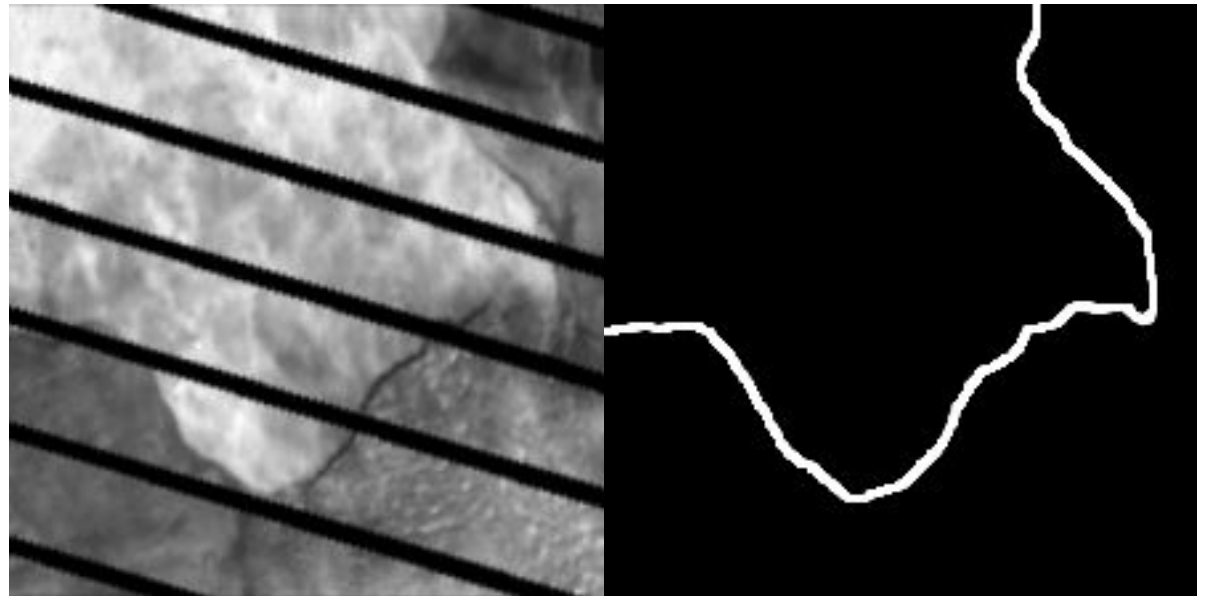
# Results & Error Analysis

## ◆ Kangiata-Nunata

- ◆ Handles light cloud cover/Landsat 7 scanline errors
- ◆ Shows signs of overfitting/memory effects



Kangiata-Nunata 2000-02-22

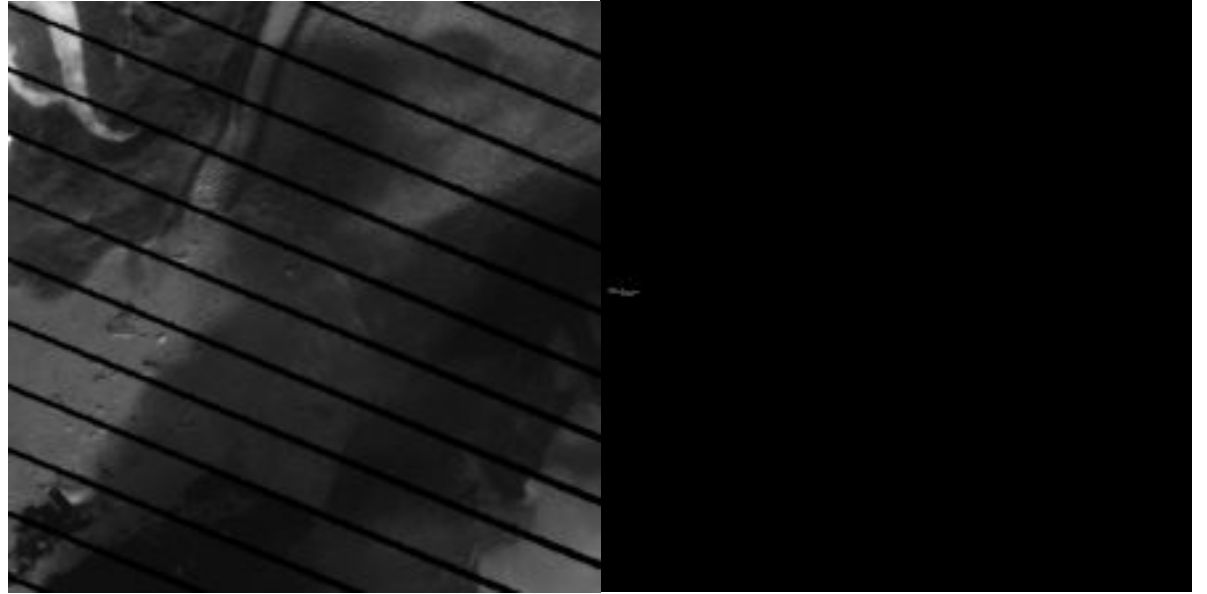


Kangiata-Nunata 2009-08-09

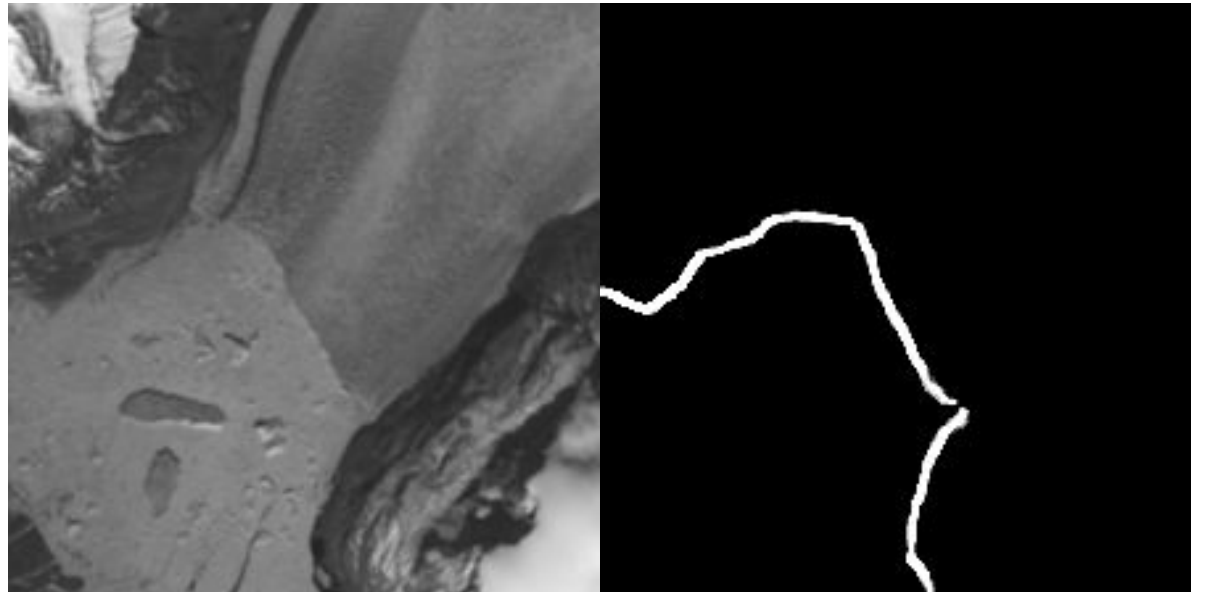
# Results & Error Analysis

## ◆ Rink Isbrae

- ◆ Some images need to be manually labeled and retrained on



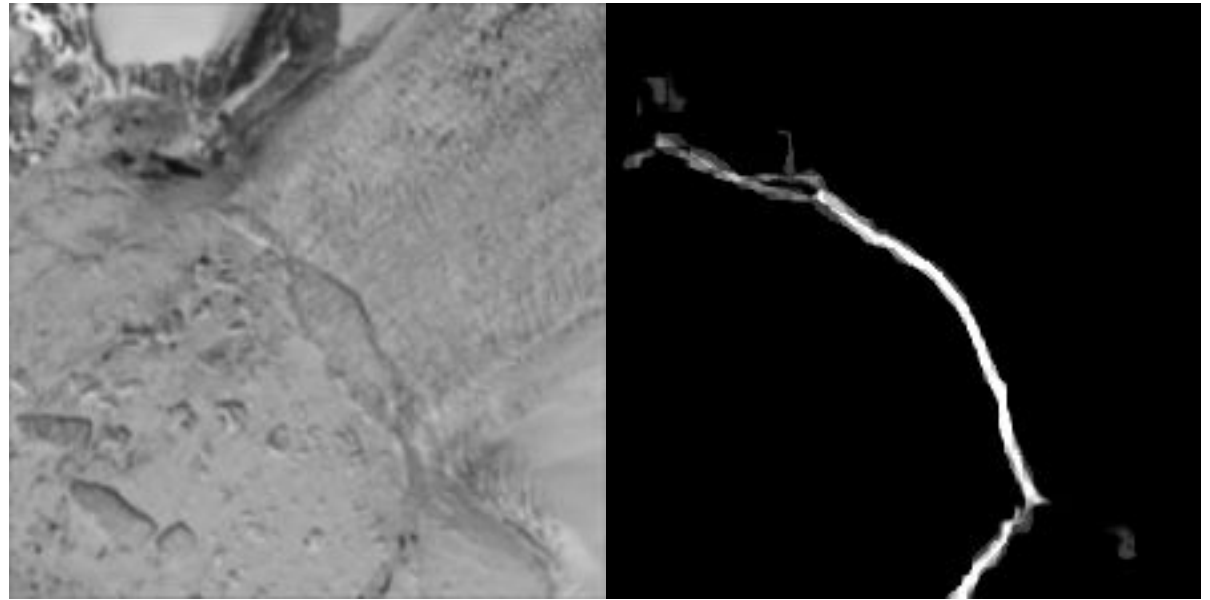
Rink-Isbrae 2004-09-13



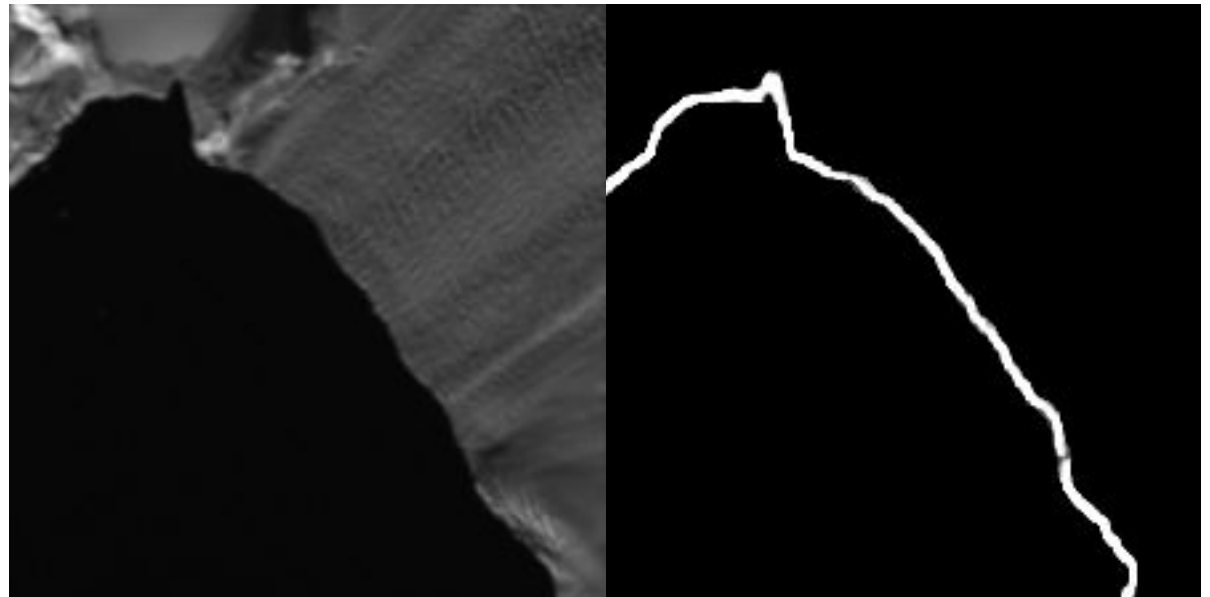
Rink-Isbrae 2018-05-23

# Results & Error Analysis

- ◆ Docker-Smith North
  - ◆ Sparsely trained
  - ◆ Calving events handled well
  - ◆ Higher texture contrast, higher confidence
- ◆ **Key goal:** generalization



Docker-Smith-N 1997-06-18

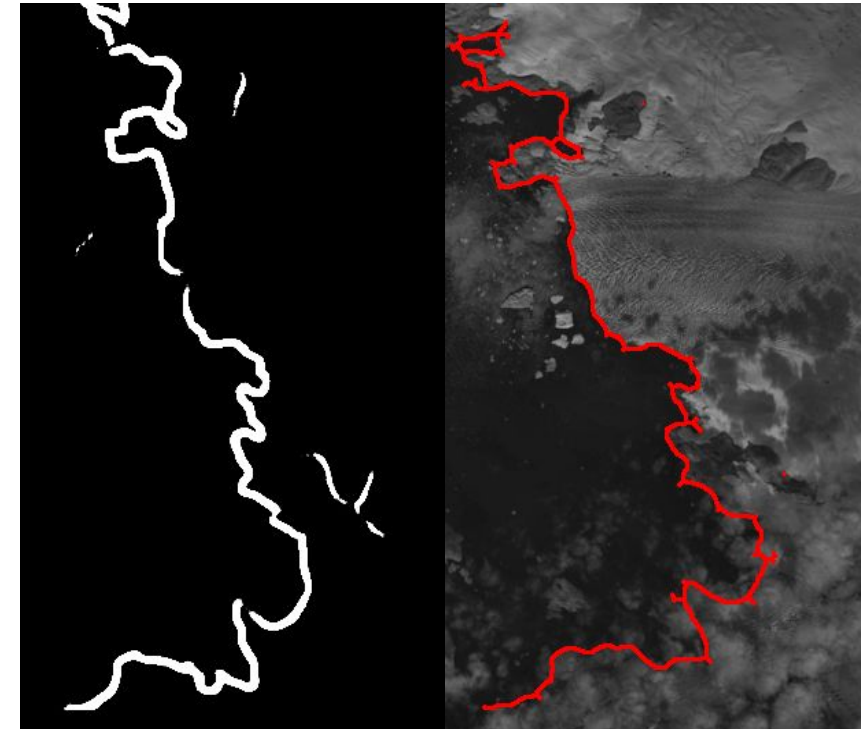


Docker-Smith-N 1997-09-22



# Future Work - Postprocessing

- ◆ Issues:
  - ◆ Pixel level mask not as useful as poly-line
  - ◆ Temporal information is not propagated
- ◆ Solution:
  - ◆ Use OpenCV to manually get 1<sup>st</sup> contour
  - ◆ Initialize line and evolve it over time
  - ◆ Use NN output to inform evolution



# Future Work

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- ❖ Spatial resolution – accuracy tradeoff
  - ❖ Larger input size offers theoretical improvements, practical drawbacks
- ❖ Additional data incorporation/evaluation
  - ❖ SAR
  - ❖ Non-marine terminating glaciers
  - ❖ Existing SHP extraction/comparison
- ❖ Preliminary results: <https://www.ics.uci.edu/~dlcheng/>
  - ❖ Level 0 Product – unprocessed masks
  - ❖ Level 1 Product – postprocessed Shapefiles

# Acknowledgements

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- ◆ CALFIN exists alongside/builds on existing work
- ◆ Similar 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

# Thank you!

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