Estimating Bedrock and Surface Boundaries with Confidence Intervals in Ice Sheet Radar Imagery Using MCMC

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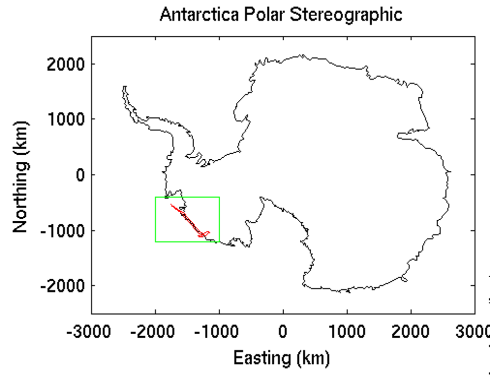
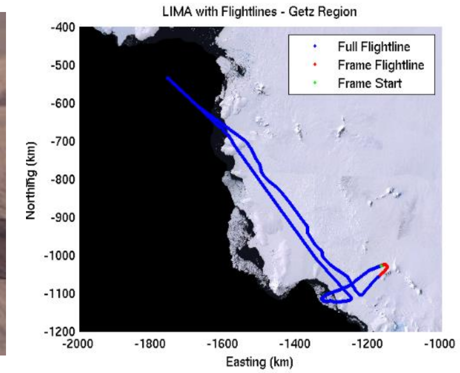
Climate Change and Implications

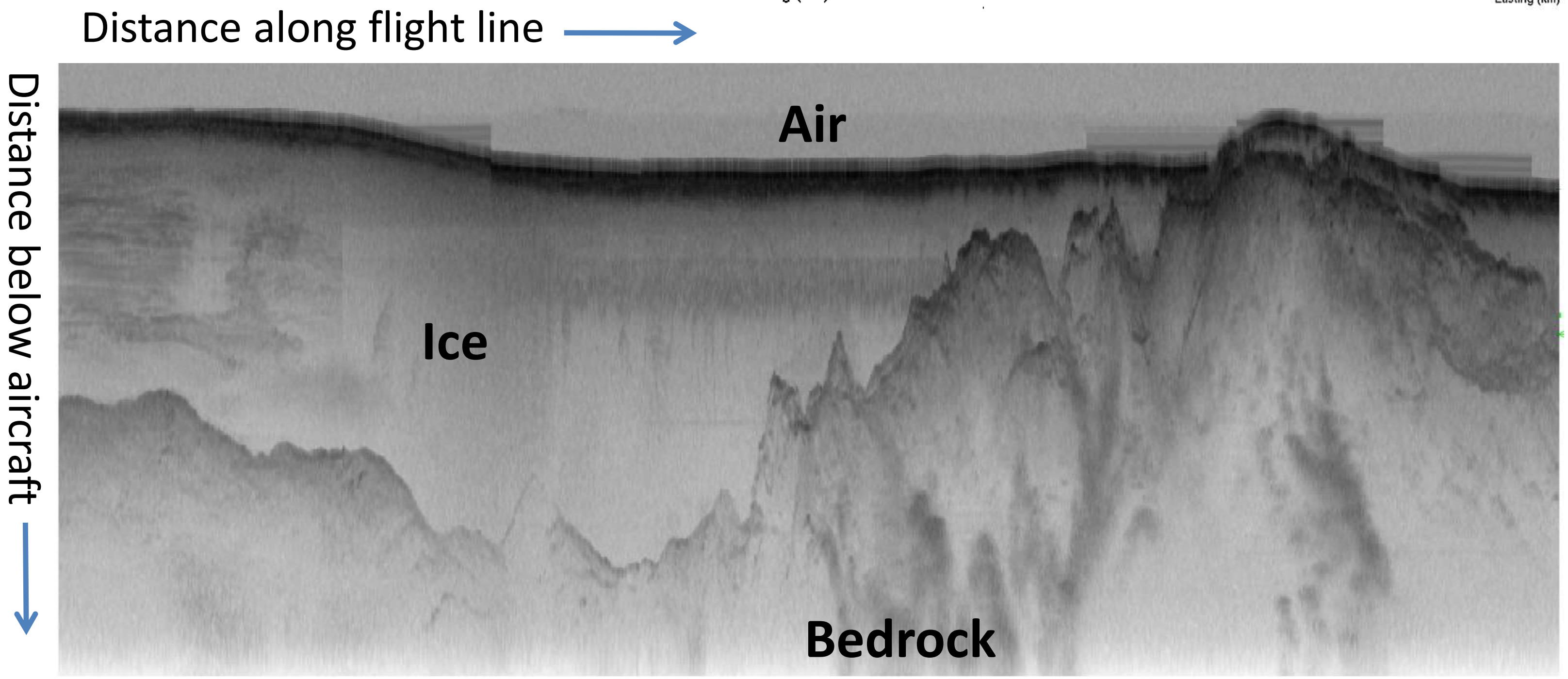
- Sea-level rise resulting from changing global climate is expected to directly impact millions of people living in low-lying coastal regions.
- Accelerated discharge from polar outlet glaciers is unpredictable and represents a significant threat
- Predictive models of ice sheet behavior would require knowledge of accumulation and bed conditions

The Data

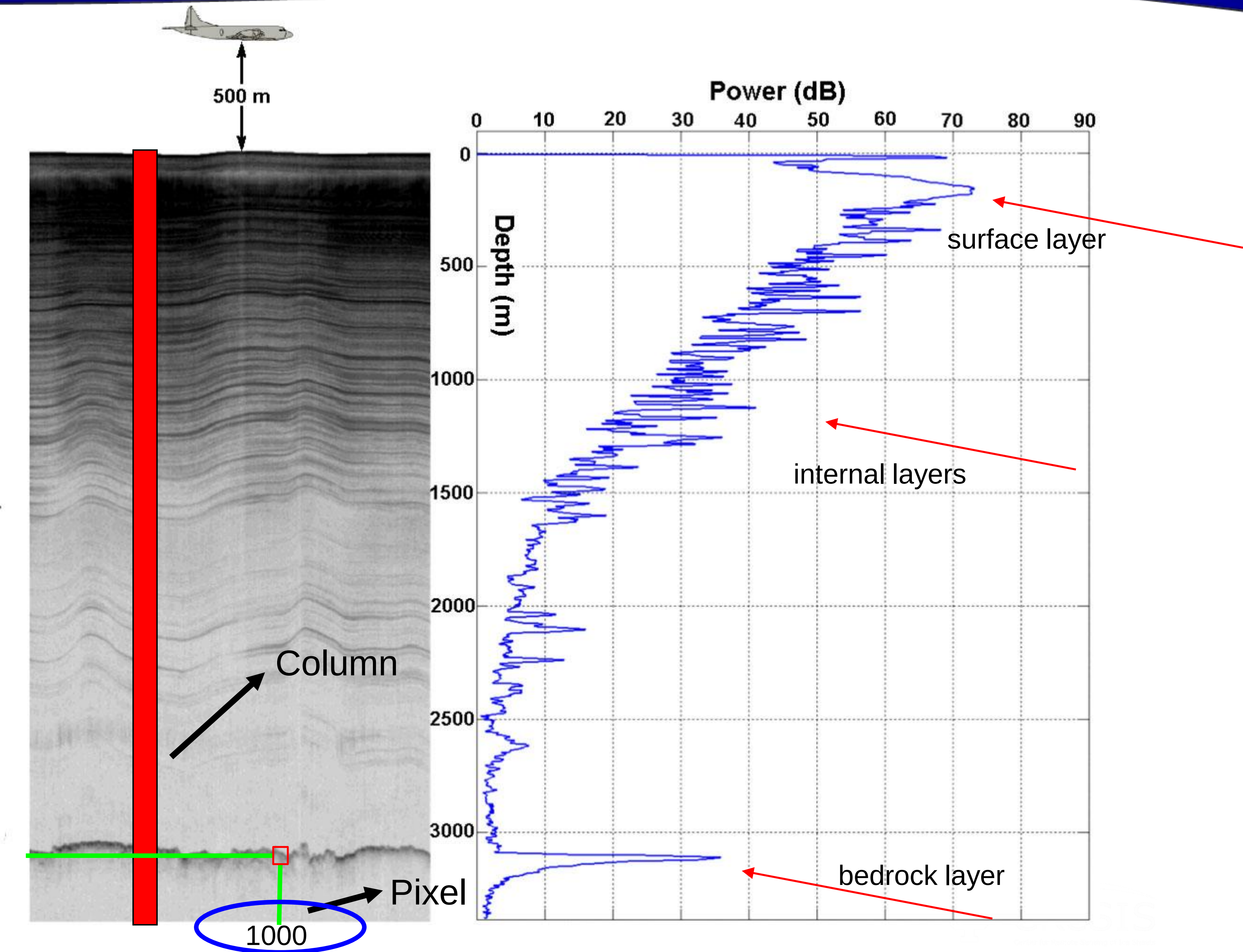
Collected with multichannel coherent depth radar sounder in Antarctica during the 2009 field campaign







RADAR Imagery

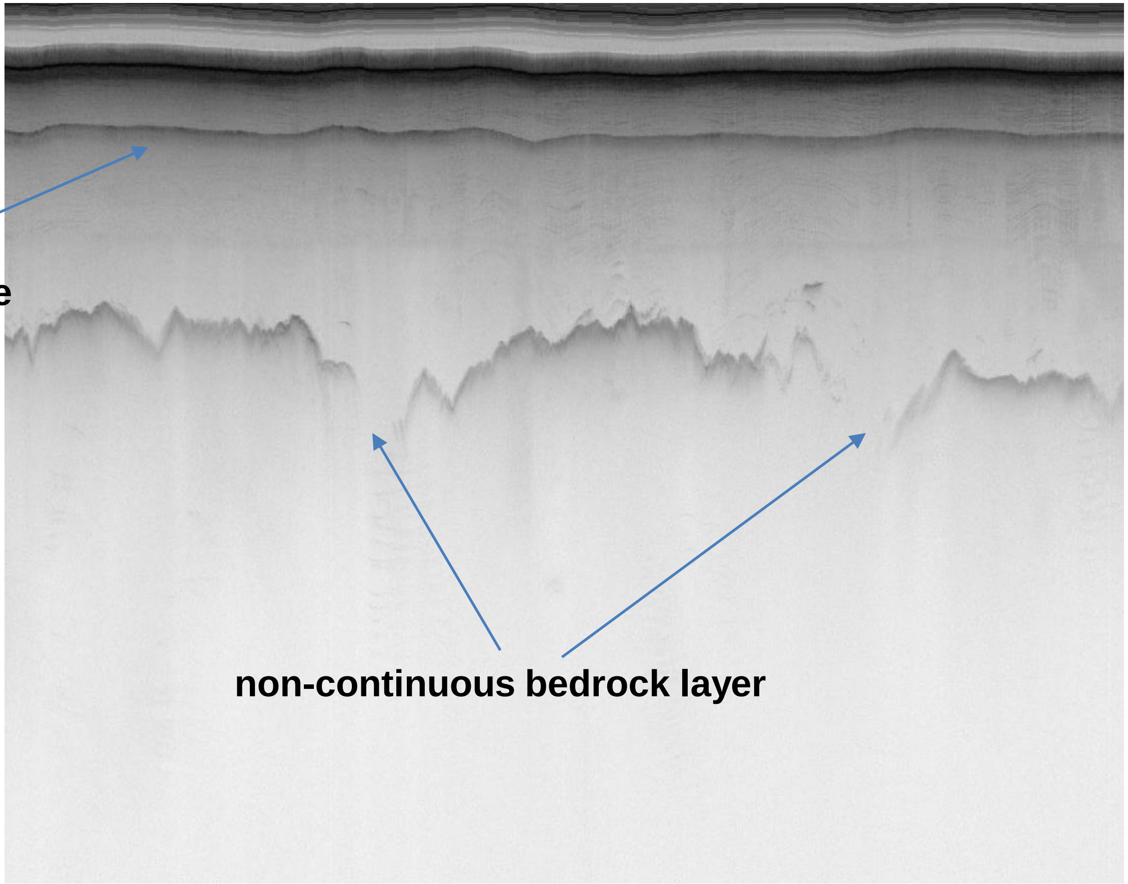


The Layers

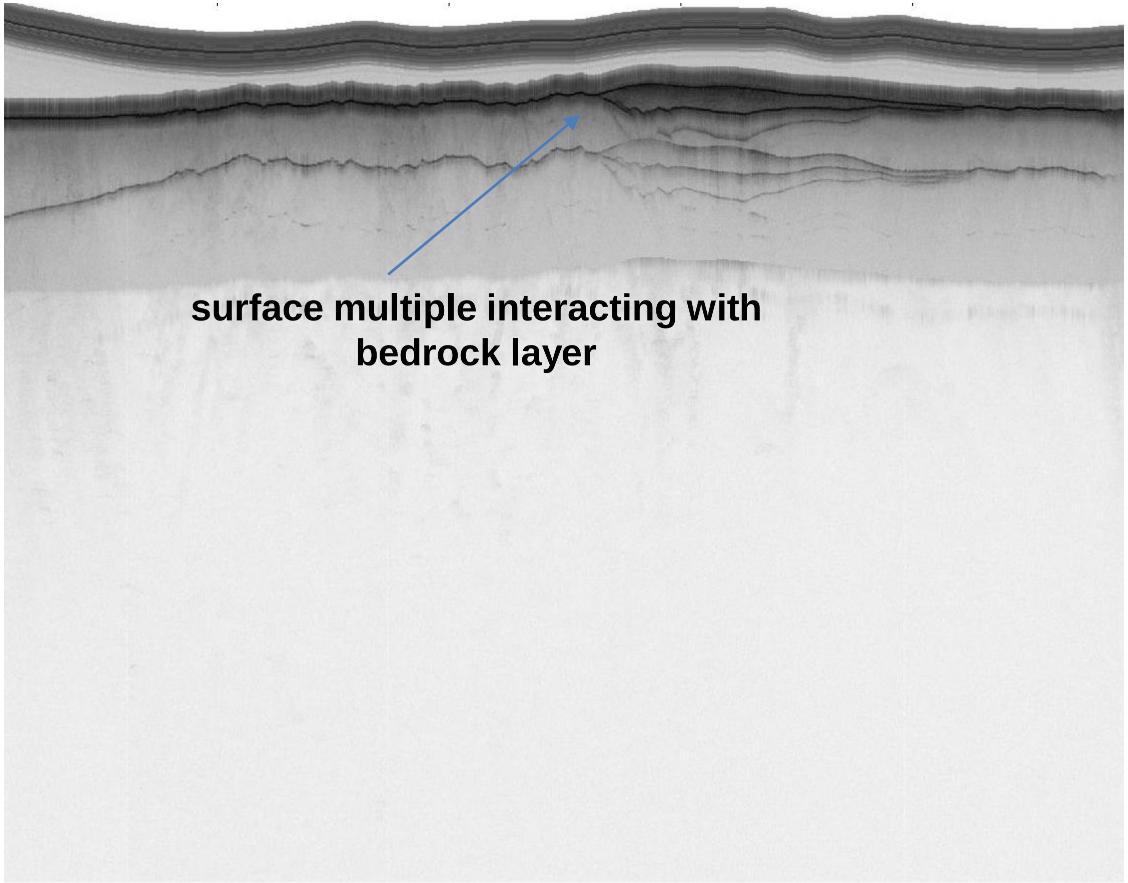
- Information from Layers are incorporated into climate models for determining ice thickness and accumulation rates

- Layer:
  - continuity across an ice sheet links cores and time scales, shows correlations
  - discontinuity suggest problems (crevasses, etc)
  - diving into bed show basal melting
  - shape contributes to climate record

Challenges Processing RADAR Imagery

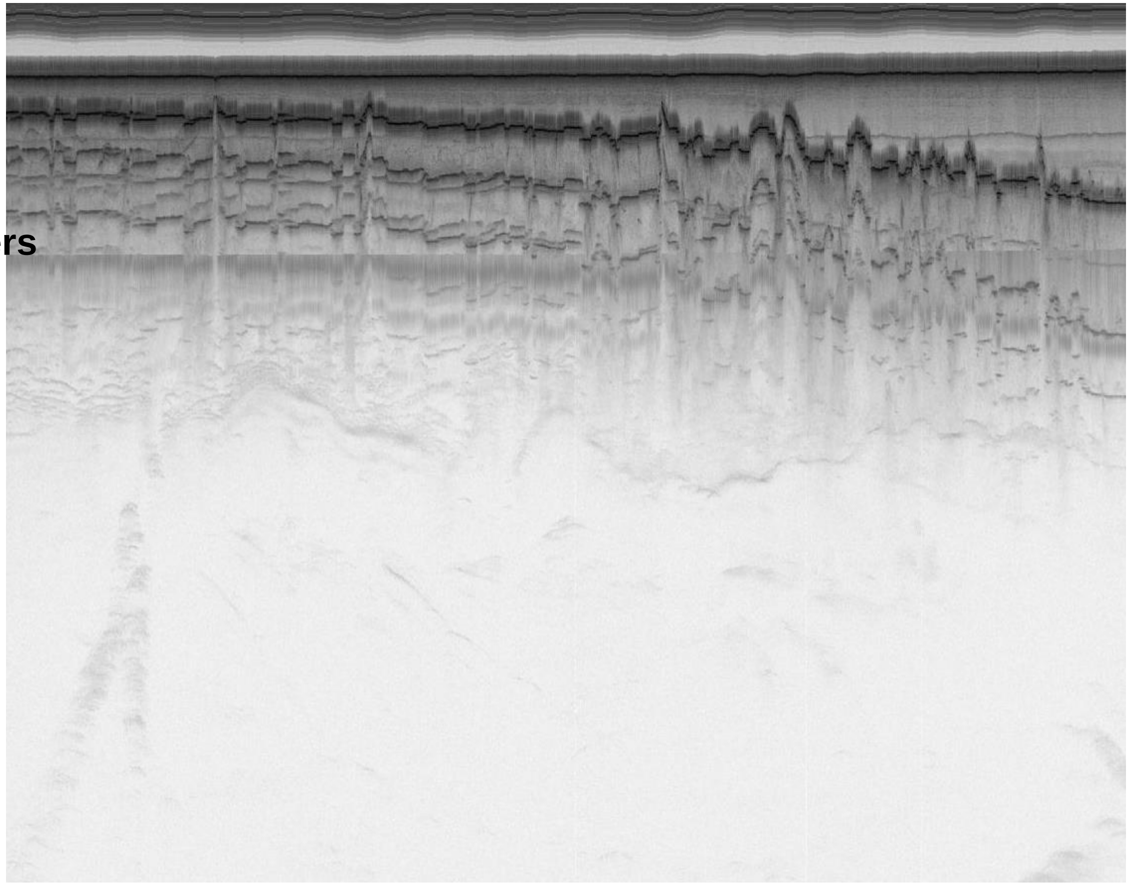


Challenges Processing RADAR Imagery



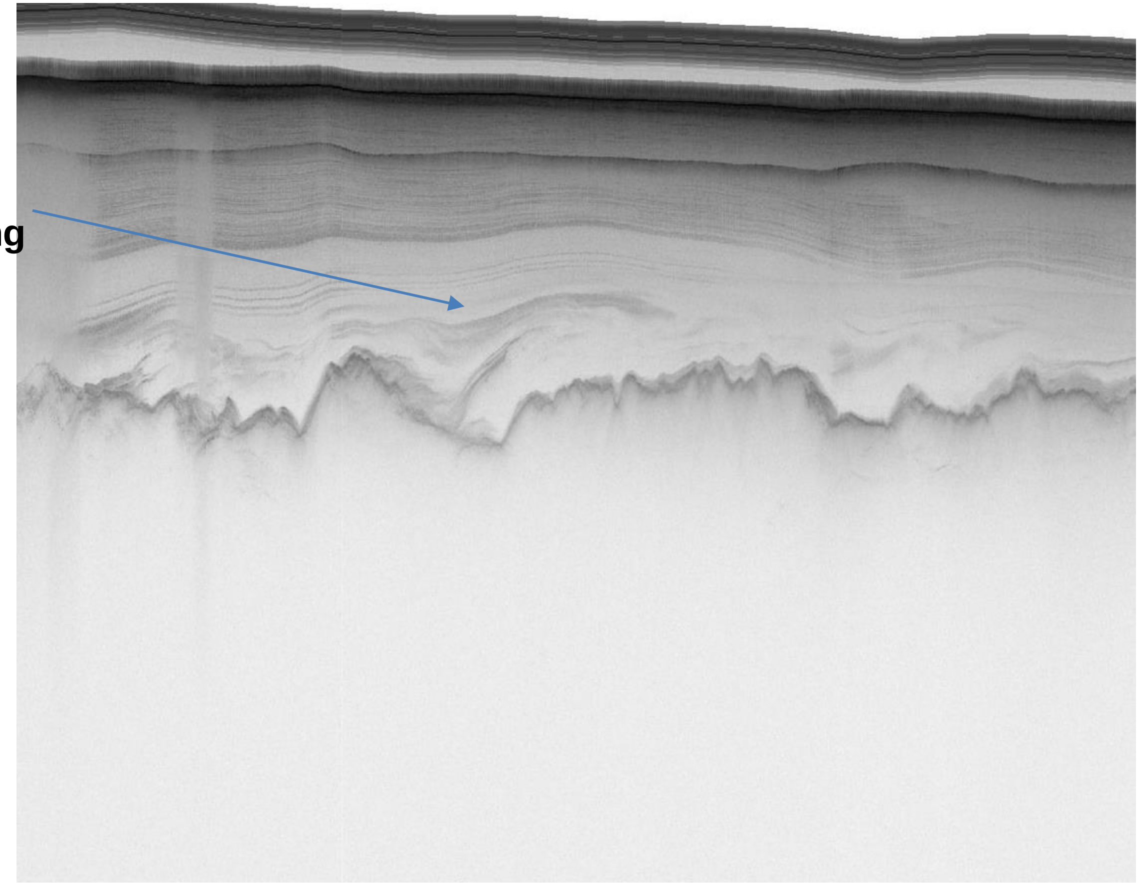
Challenges Processing RADAR Imagery

multiple bedrock layers



Challenges Processing RADAR Imagery

scattering



Bedrock and Surface Approaches…

- Active Contours ("Snakes"), Edge Detector

Automated Polar Ice Thickness Estimation From Polar Radar Imagery
International Geoscience and Remote Sensing Symposium (IGARSS) 2010
Christopher Gifford, Gladys Finyom, Michael Jefferson, MyAsia Reid, Eric Akers, and Arvin Agah

- Statistical Map Generation and Segmentation

A Technique for the Automatic Estimation of Ice Sheet Thickness and Bedrock Properties from Radar Sounder Data Acquired at Antarctica
International Geoscience and Remote Sensing Symposium (IGARSS) 2012
Ana-Maria Illisei, Adamo Ferro, and Lorenzo Bruzzone

- Active Contours ("Level Sets")

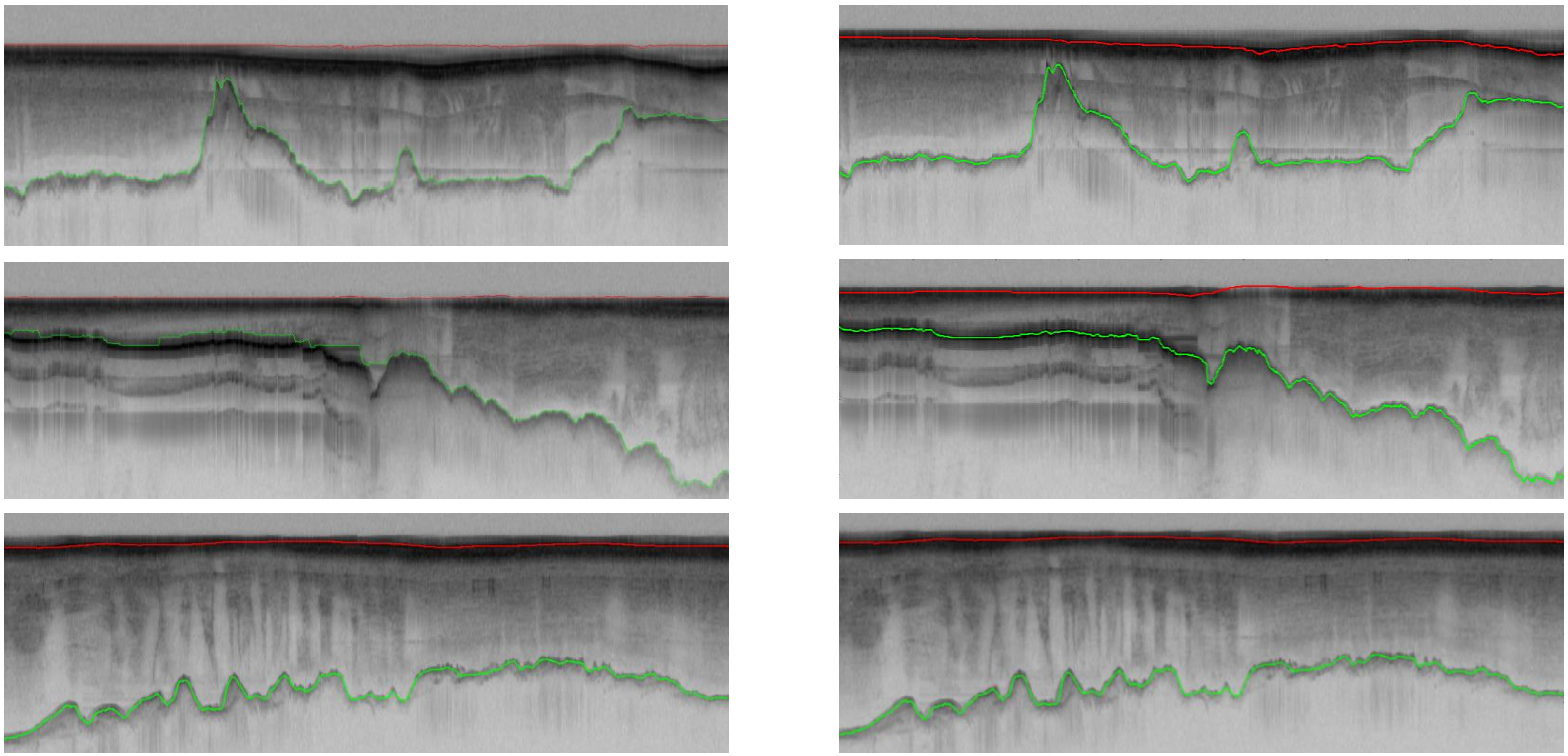
A Semi-Automated Approach for Estimating Bedrock and Surface Layers from Multichannel Coherent Radar Depth Sounder Imagery Radar Imagery
SPIE Remote Sensing 2013
Jerome E. Mitchell, David J. Crandall, Geoffrey C. Fox, Maryam Rahnemoonfar, and John D. Paden

Crandall et al, “**Layer-finding in Radar Echograms using Probabilistic Graphical Models**”, International Conference on Pattern Recognition (ICPR), 2012.

- Developed an automated layer detection method, which used an statistical graphical model for integrating local and global features.
  - Technique developed from simplistic model and solved for layer boundaries incrementally, producing a single answer

Approach

Ground-Truth



David J. Crandall, Geoffrey C. Fox, and John D. Paden, "**Layer-finding in Radar Echograms using Probabilistic Graphical Models**", International Conference on Pattern Recognition (ICPR), 2012.

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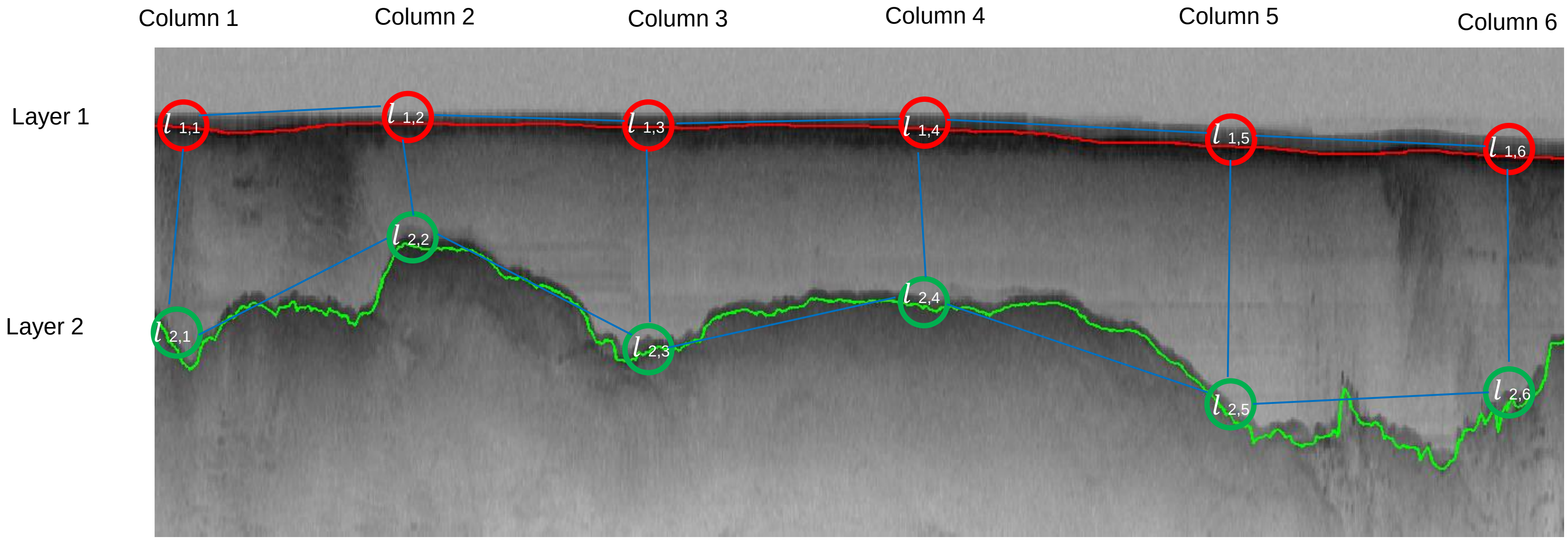
  - Technique developed from simplistic model and solved for layer boundaries incrementally, producing a single answer

We have improved the model by solving for layer boundaries simultaneously and providing confidence intervals, which can aid in glaciologists in determining correct layer boundaries

The Model

- Identify K=2 layer boundaries (surface and bedrock) boundaries in each column of a m x n radar image
  - Let $L_i = (l_{i,j}, \ldots, l_{i,j})$ depict the row coordinate of layer boundary i in column j



Goal: Find a labeling for entire image, $L = (L_1, \ldots, L_k)$

Probabilistic Formulation

- The problem of layer detection is posed as a probabilistic graphical model based on the following assumptions:

1. Image characteristics determined by local layer boundaries
2. Variables in L exhibit a Markov property with respect to their local neighbors

Probabilistic Formulation

- The problem of layer detection is posed as a probabilistic graphical model based on the following assumptions:

$$P(L|I) \propto P(I|L)P(L)$$

Likelihood term models how well labeling agrees with image

Prior term models how well labeling agrees with typical ice layer properties

Probabilistic Formulation

- The problem of layer detection is posed as a probabilistic graphical model based on the following assumptions:

1. Image characteristics determined by local layer boundaries

$$P(I|L) = \prod_{i=1}^{k} \prod_{j=1}^{n} P(I|l_{i,j})$$

2. Variables in L exhibit a Markov property with respect to their local neighbors

Probabilistic Formulation

- The problem of layer detection is posed as a probabilistic graphical model based on the following assumptions:

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2. Variables in L exhibit a Markov property with respect to their local neighbors

$$P(L) \propto \prod_{i=1}^{k} \prod_{j=1}^{n} P\left(l_{i,j} \middle| l_{i,j-1}\right) P\left(l_{i,j} \middle| l_{i-1,j}\right)$$

Zero-mean Gaussian penalizes discontinuities in layer boundaries across columns

Repulsive term prevents boundary crossing

Statistical Inference

- Finding L, which maximizes $\mathrm{P}(L \mid I)$ involves inference on a Markov Random Field
  - estimate full joint distribution using Gibbs sampling

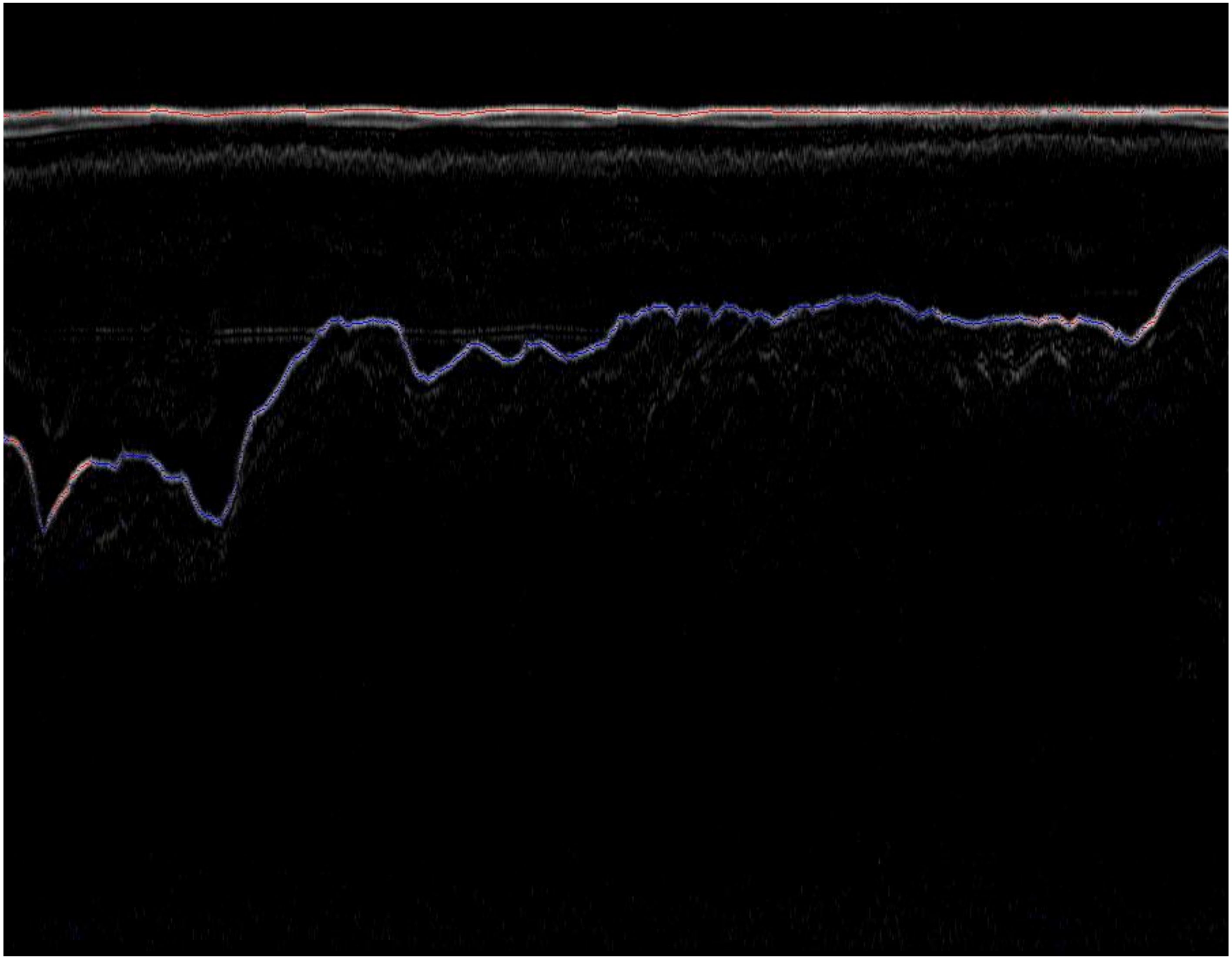
- Gibbs Sampling (MCMC)
  - approximates the joint distribution by iteratively sampling from the conditional distribution

- Layer location determined by the mean of posterior samples, which approximates the expectation of the joint distribution

Confidence Intervals

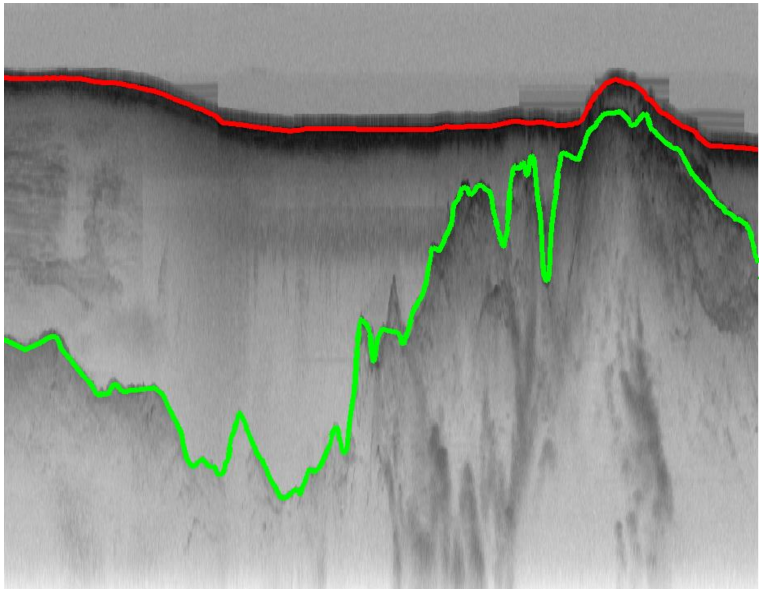
- Confidence intervals provide quality control for label accuracy in distinguishing between bedrock and surface boundaries
- 2.5% and 97.5% of the posterior sample determine a 95% interval
  - 94.7% of surface boundaries and 78.1% of bedrock boundaries are within confidence intervals.

Statistical Inference

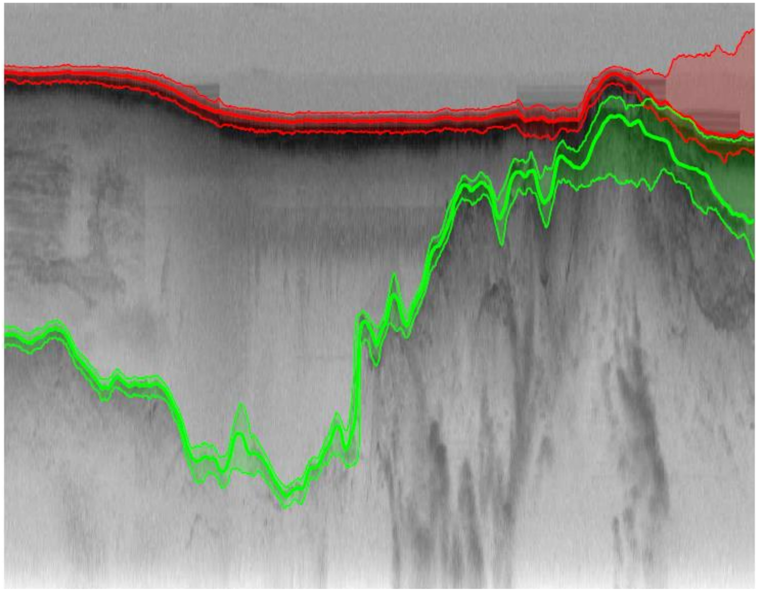


Experimental Results

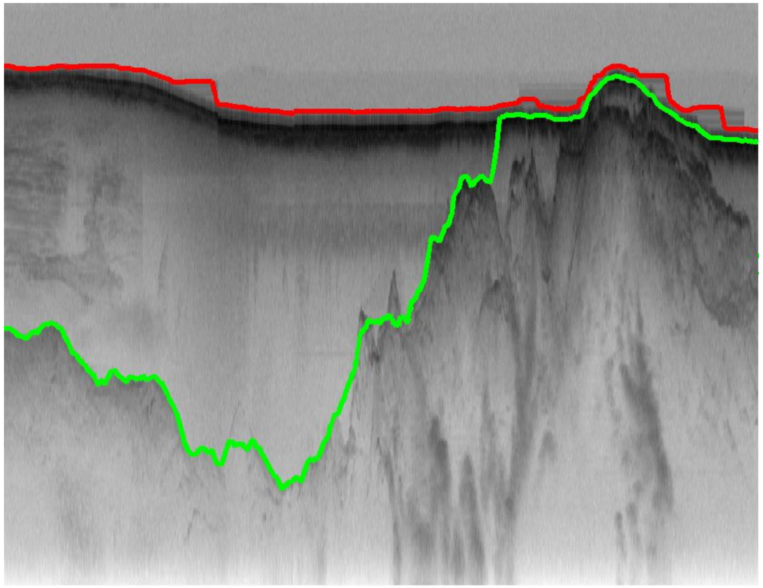
- Dataset contained 826 images acquired from an airborne multichannel coherent radar depth sounder for the NASA Operation Ice Bridge (OIB) program
  - same dataset and source code used in Crandall et. al
- Labeled images (ground-truth) are often noisy
  - automatically removed images with either incomplete or partially defined layers, leaving 560 images
- For each image, 10,000 samples were collected after a burn-in period of 20,000 iterations



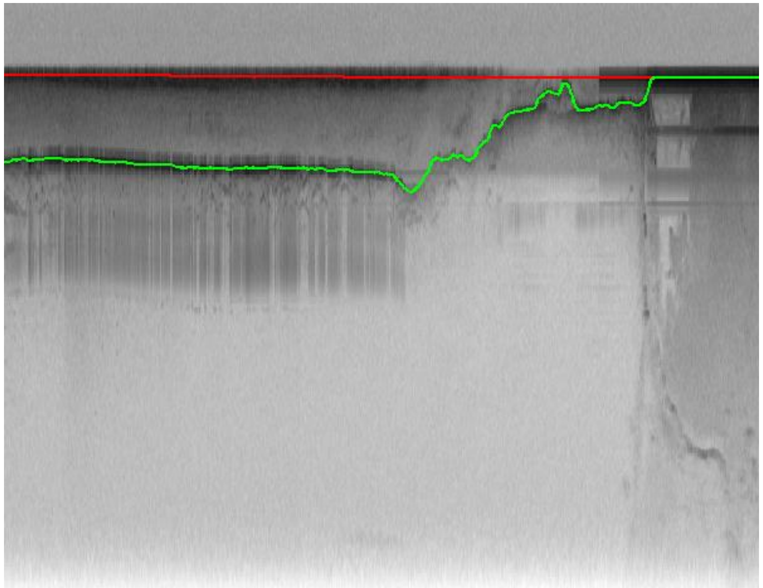
Ground-Truth



Our Approach



Crandall et al



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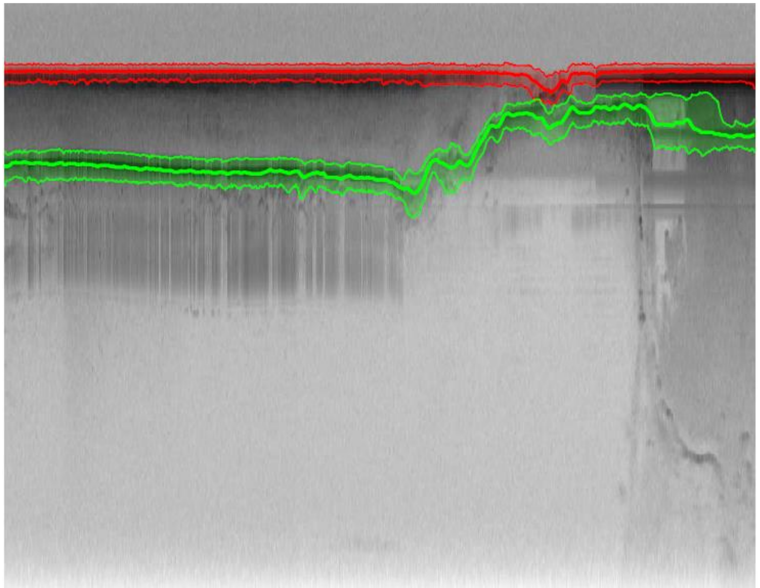

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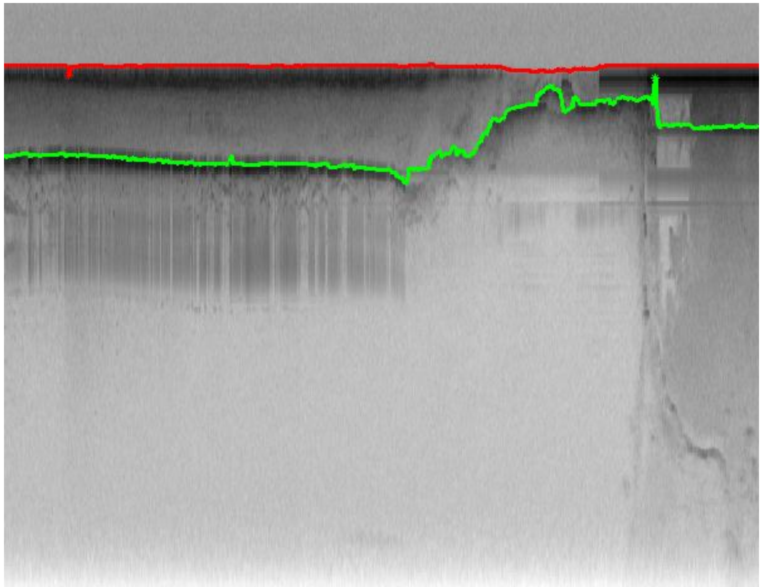

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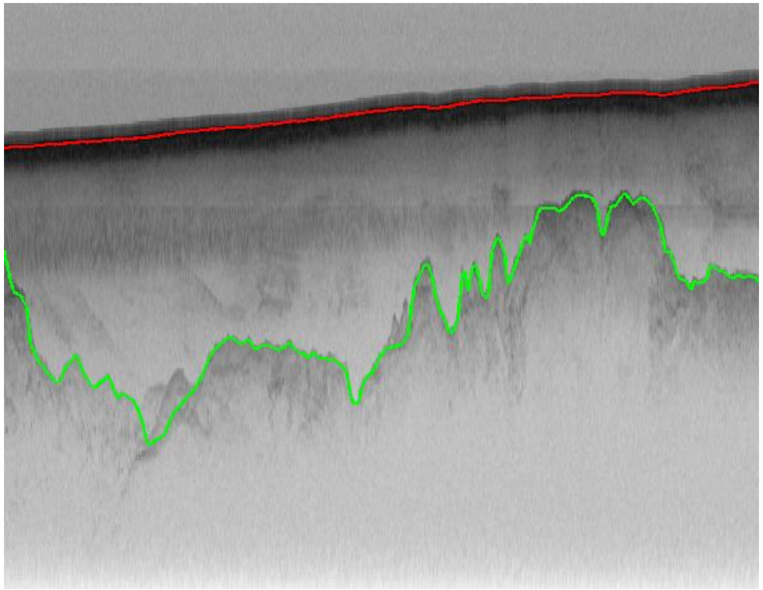

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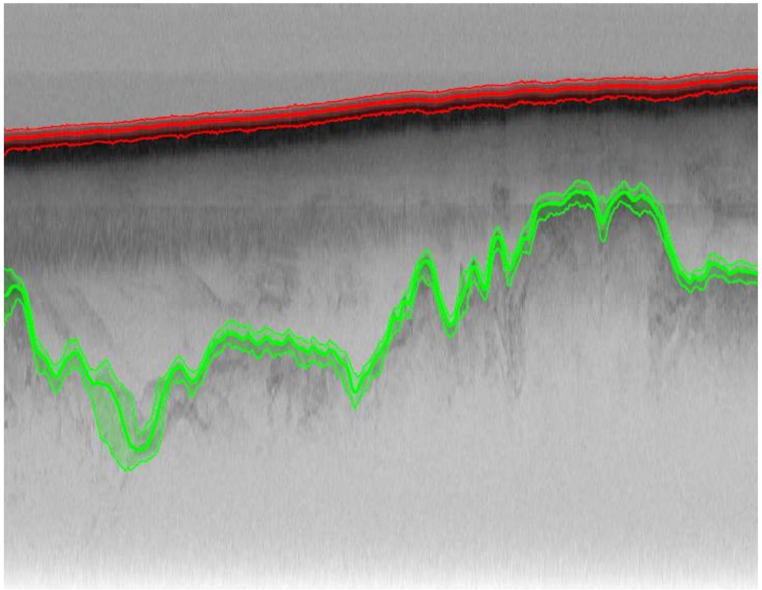

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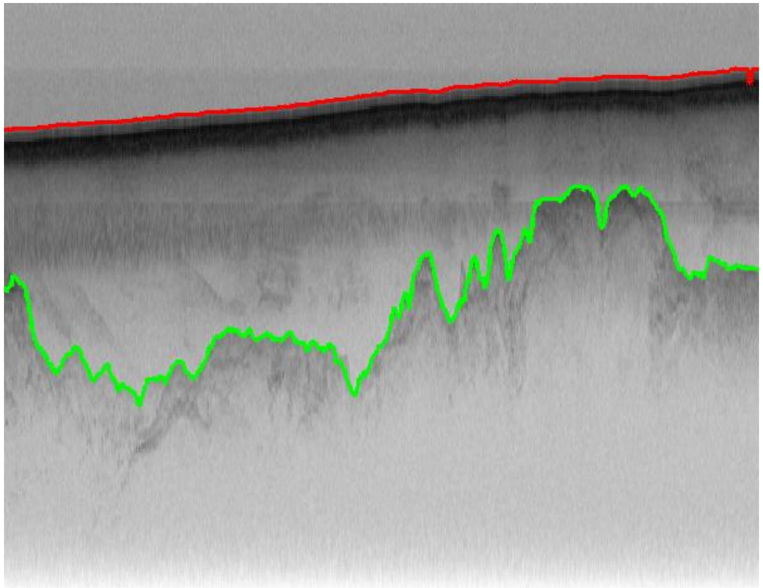

Crandall et al

Quantitative Results

Approach	Mean Error		Median Mean Error	
	Surface	Bedrock	Surface	Bedrock
Crandall et. al	22.3	43.1	10.6	14.4
Our	9.3	37.4	5.9	9.1

Error measured in terms of absolute column-wise difference compared to ground-truth, summarized with average mean deviation and median mean deviation across echograms, in pixels.

Conclusions

- Improved automatic approach to layer boundary identification, specifically bedrock and surface layers
  - Used MCMC to sample from the joint distribution over all possible layers
  - reduced labeling error by 50% with respect to Crandall et. al for bedrock and surface layers
- Estimated confidence intervals, which could improve climate models based upon a belief of the correct layer boundary
  - 94.7% of surface boundaries and 78.1% of bedrock boundaries are within confidence intervals.

Future Work and Acknowledgments

- Identify near surface internal layers (multiple layers)
  - more advanced sampling techniques
- Better metrics for label quality

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QUESTIONS