Toward automated classification of brightness fronts in RADARSAT-2 images of the ocean surface.

SeaSAR 2012, 18 June 2012

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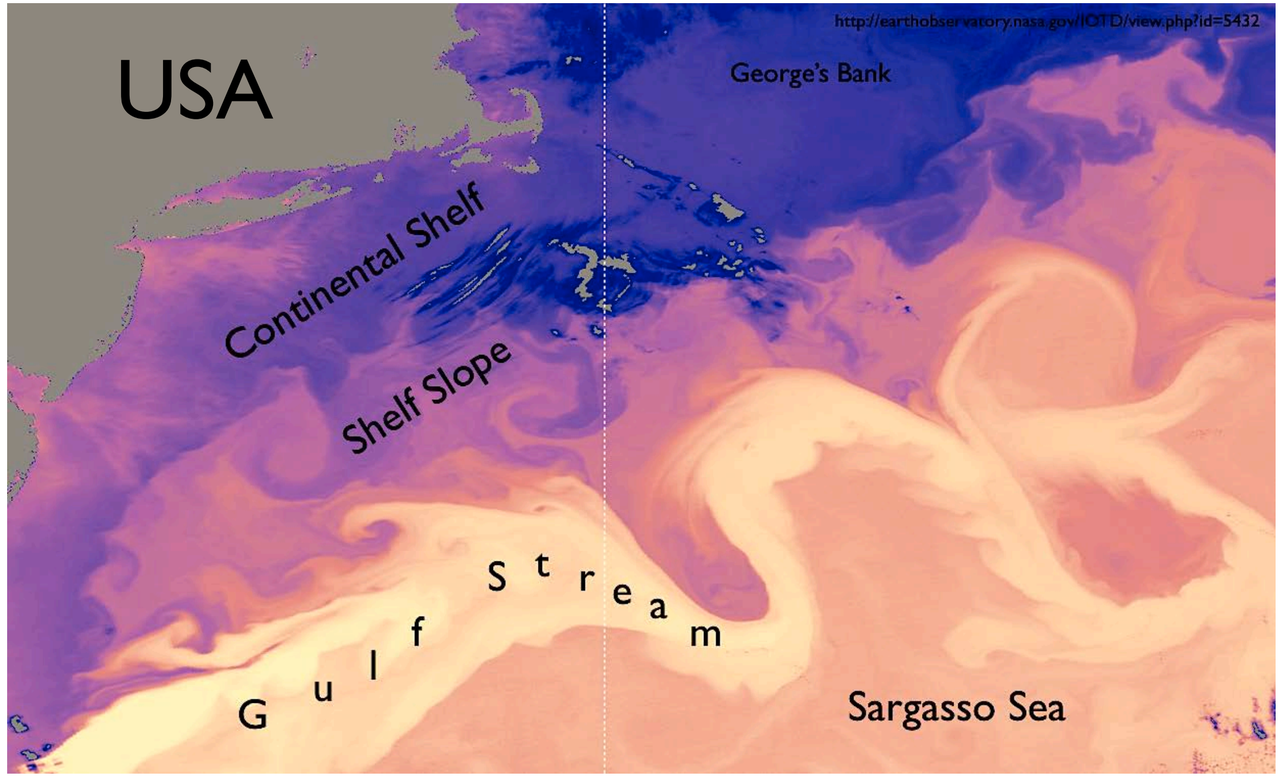
A big **thank you!** to the Canadian Space Agency's Government Related Initiatives Program, which funded our project.

GRIP supports and promotes the development and use of Earth observation technologies among Canadian industry, university researchers, and the Government of Canada.

Spaceborne Ocean Intelligence Network (SOIN)

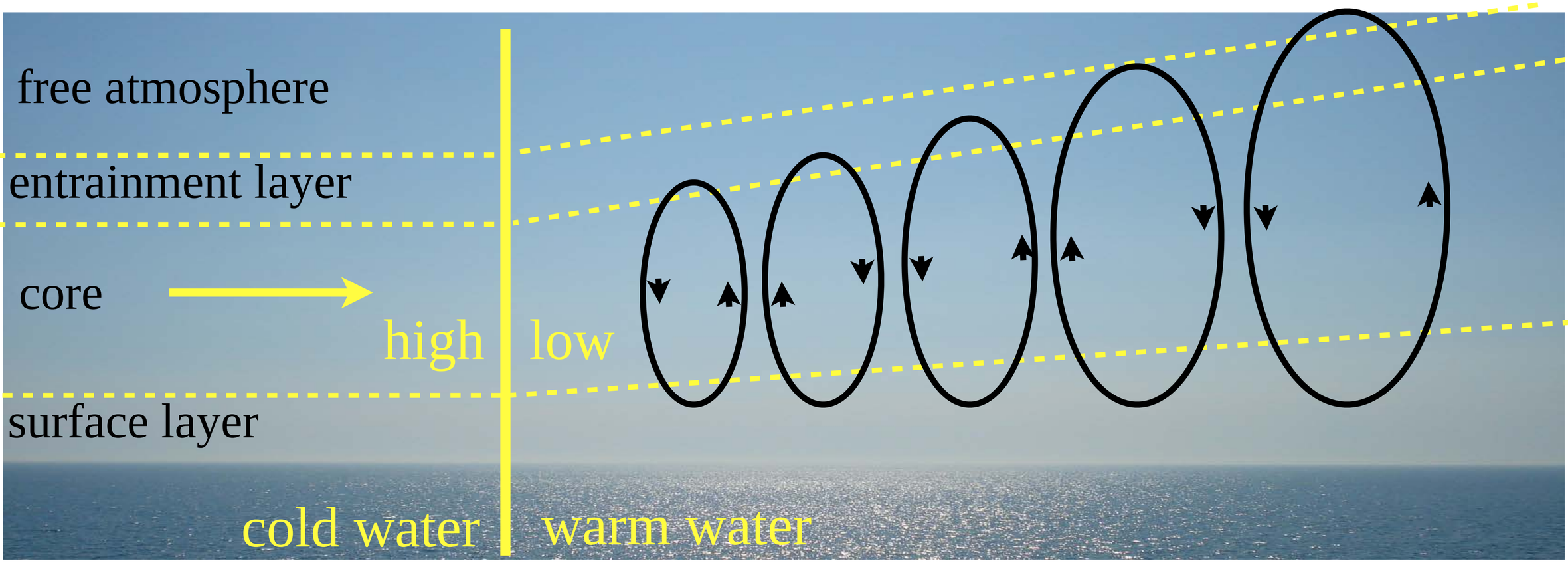
Meteorology and Oceanography Center (MetOc)

Canadian Space Agency + MacDonald Dettwiler and Associates Ltd.



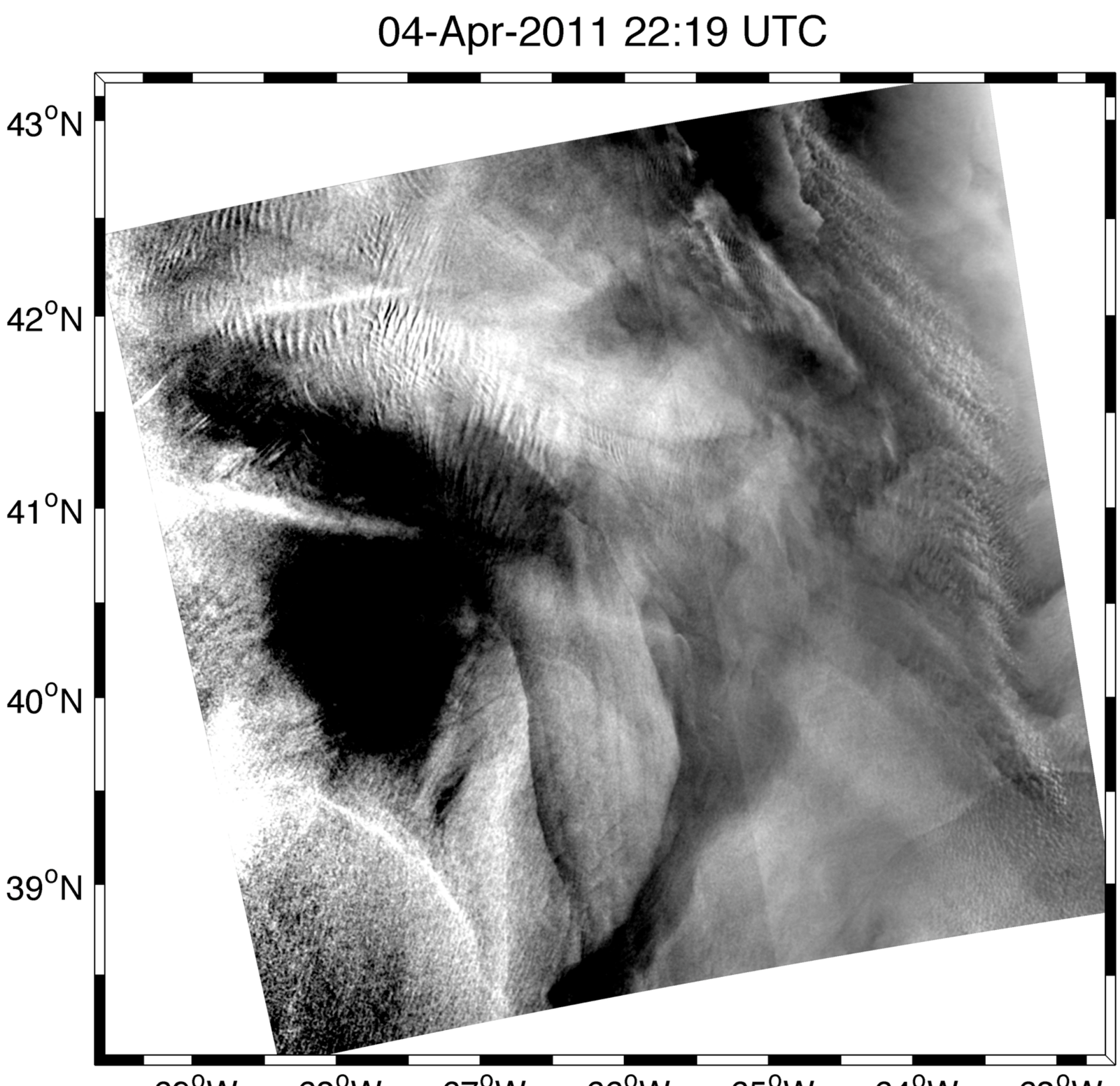
Use RADARSAT-2 images to help produce bi-weekly ocean feature analysis (OFA).

Marine Atmospheric Boundary Layer

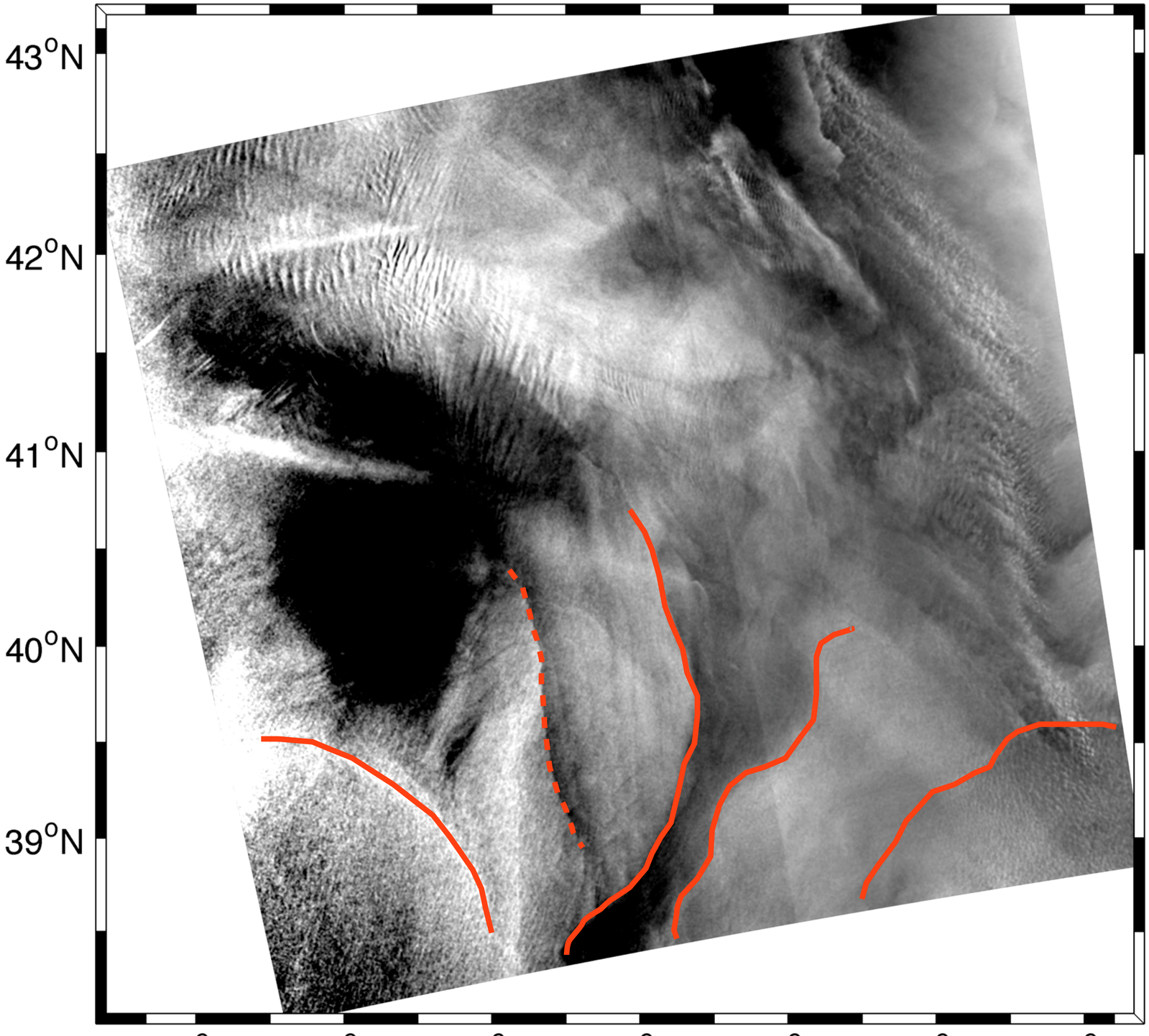


SST fronts are often visible in SAR images because the heat flux on the warm side of a front drives several atmospheric processes (convection as depicted above, the formation of cross-front pressure gradients, thermal wind effect) that result in stronger winds that roughen the ocean surface and enhance backscatter.

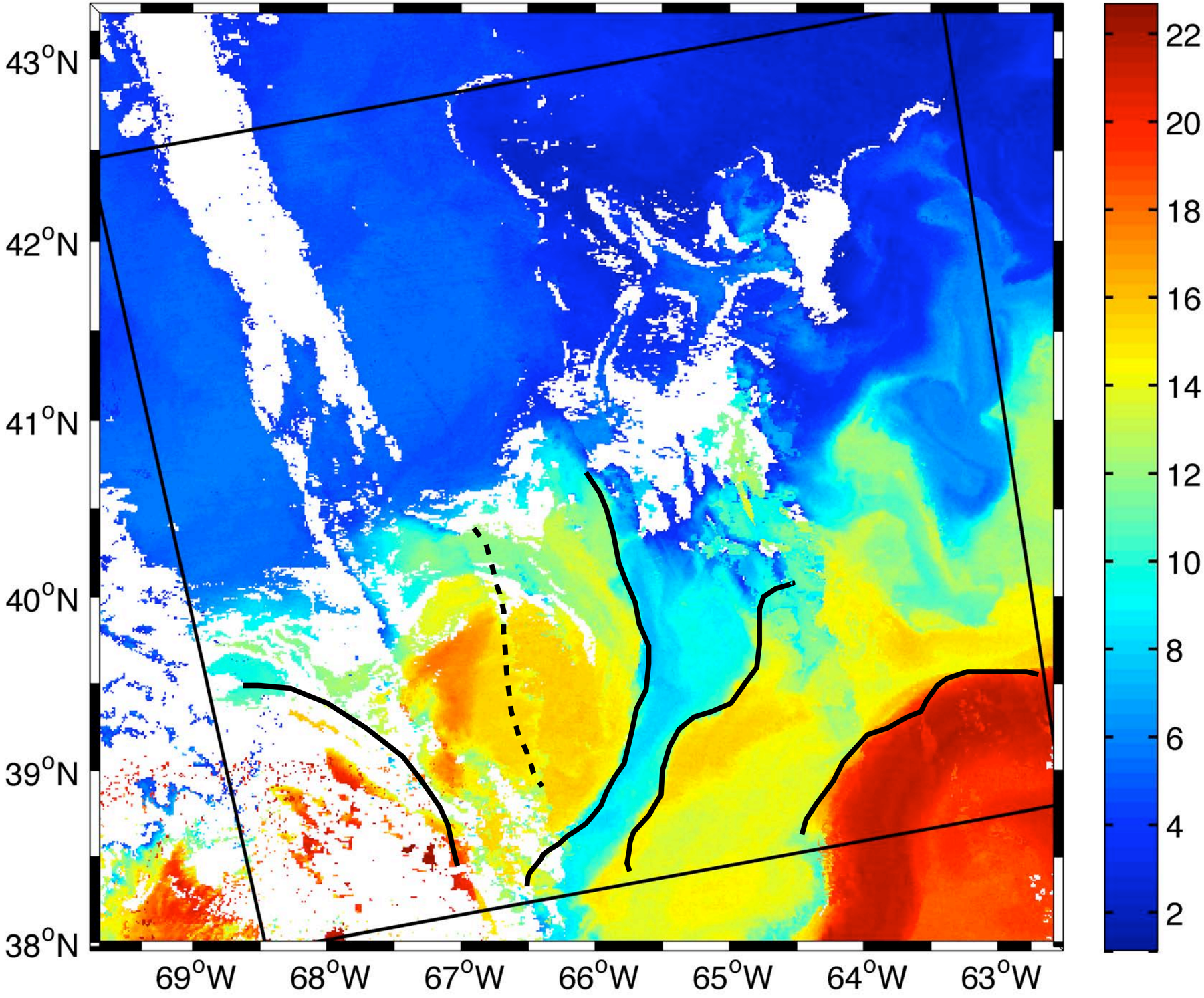
RADARSAT-2
C-band VV
ScanSAR Wide
500 km x 500 km

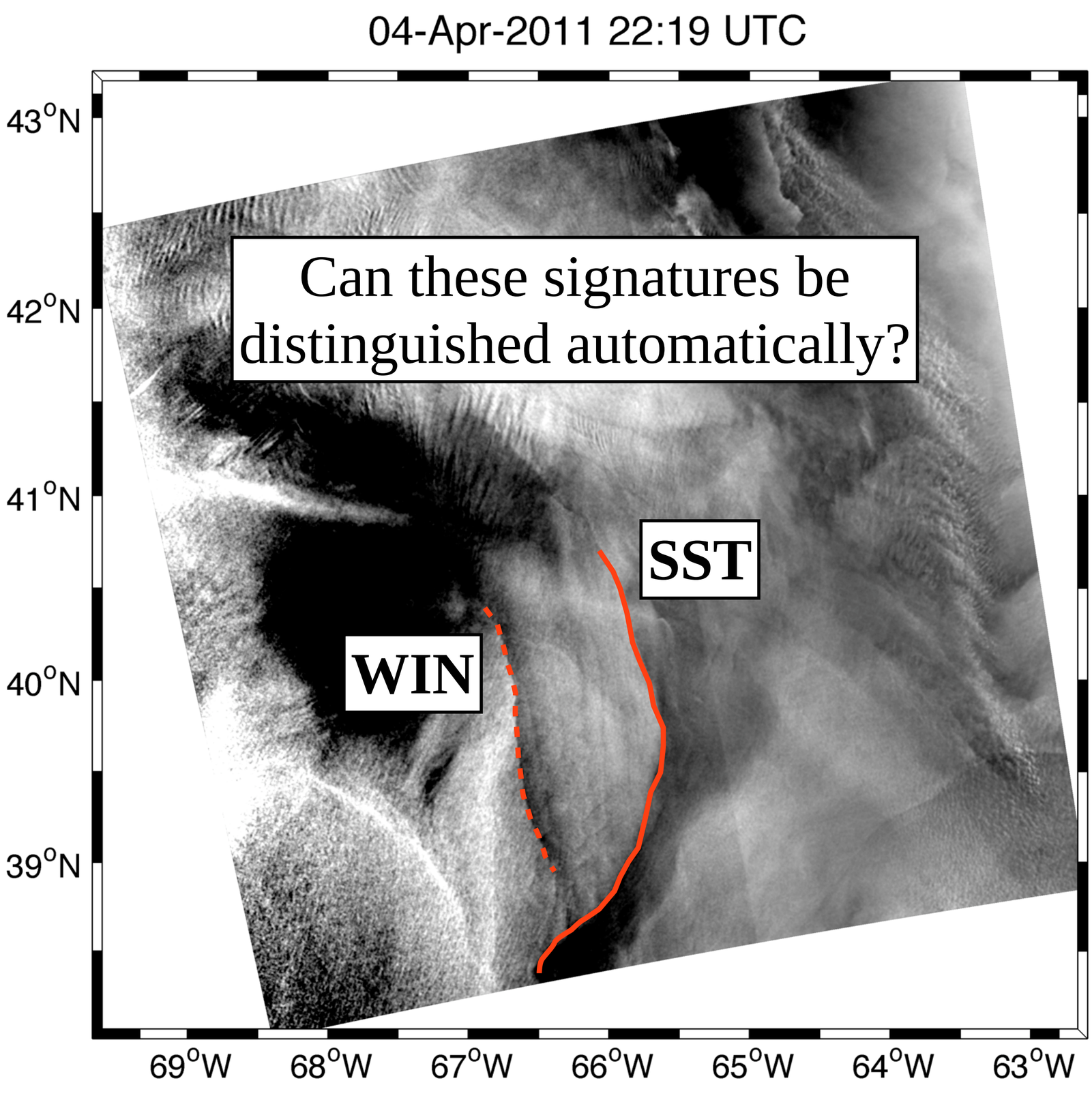


04-Apr-2011 22:19 UTC

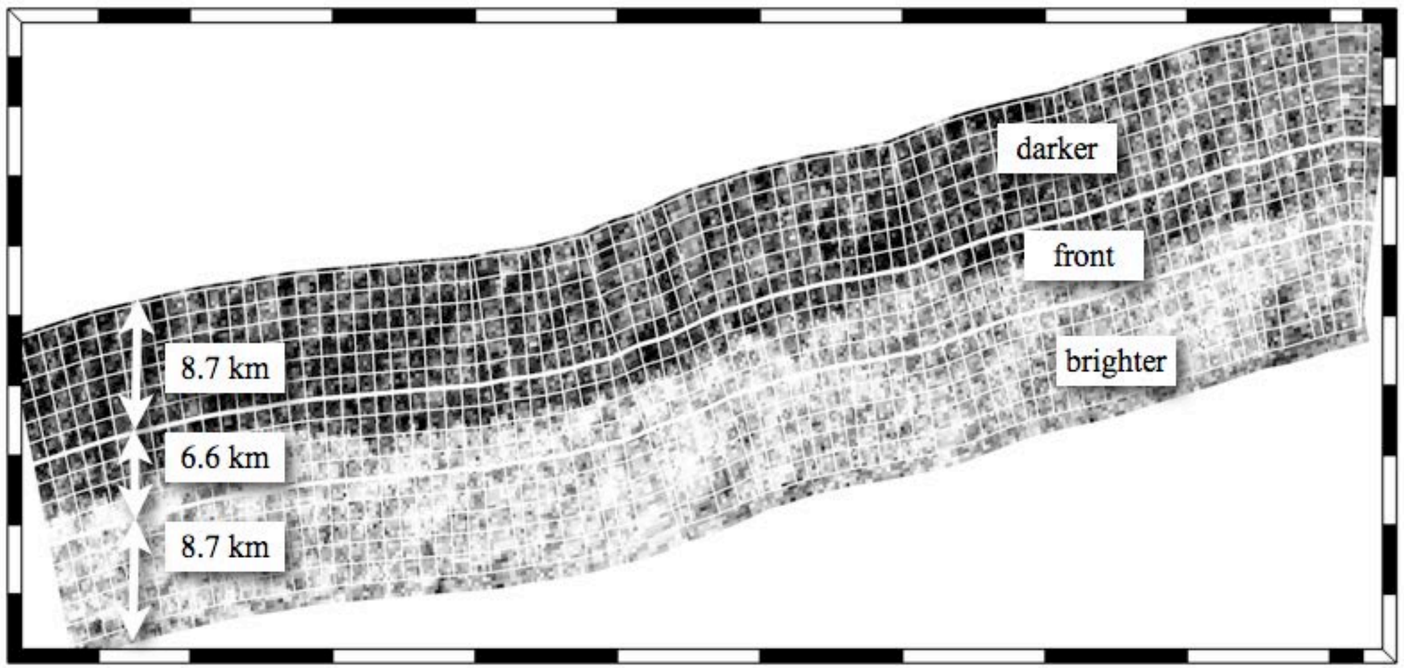


SST (degrees C) 04-Apr-2011




04-Apr-2011 22:19 UTC
43°N
42°N
41°N
40°N
39°N
69°W
68°W
67°W
66°W
65°W
64°W
63°W
Can these signatures be distinguished automatically?
SST
WIN

The current paradigm (e.g., vegetation & sea-ice classification) is to use local textural measures to inform a statistical classifier.



Capture fronts using a Canny edge detector.

Build a Local Curvilinear Coordinate System to extract textural and contextual information on both sides and astride the front.

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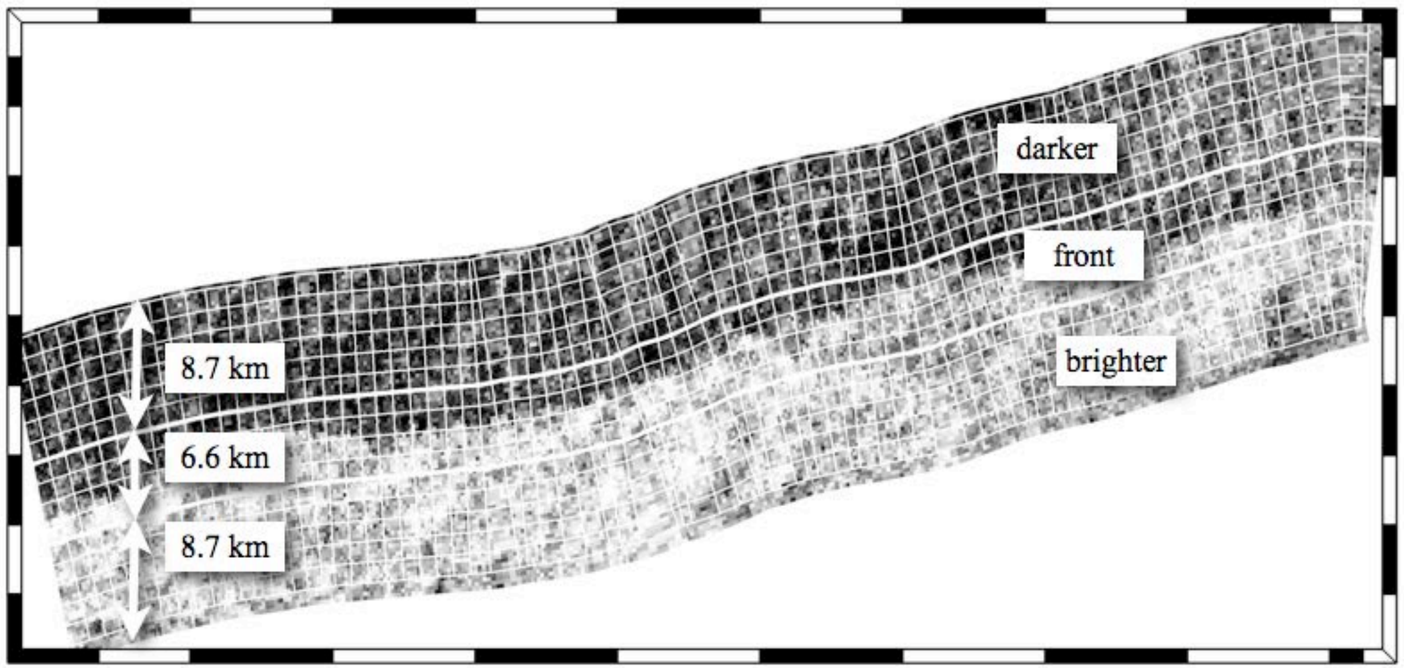


Image	Region	Measures
locSAR locSDW locAW locCW locDIV locCRL	brighter front darker	contrast correlation energy dissimilarity entropy homogeneity μ σ
locSDW	θ d_{cw}	μ σ

RADARSAT-2 SCNA (C-band, VV) with QuikSCAT Winds

302 SST + 193 WIN = 495 Labeled Edges

Gulf Stream North Wall Search Region

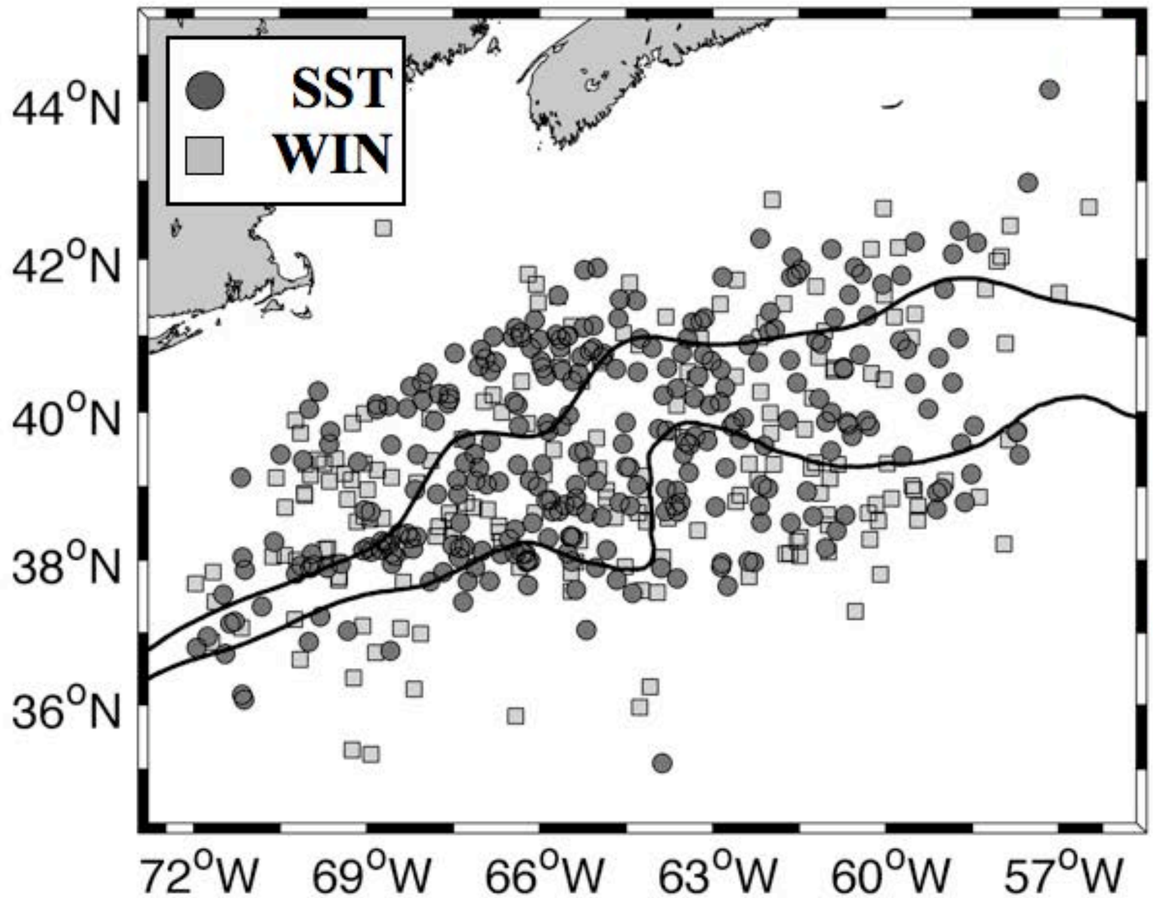
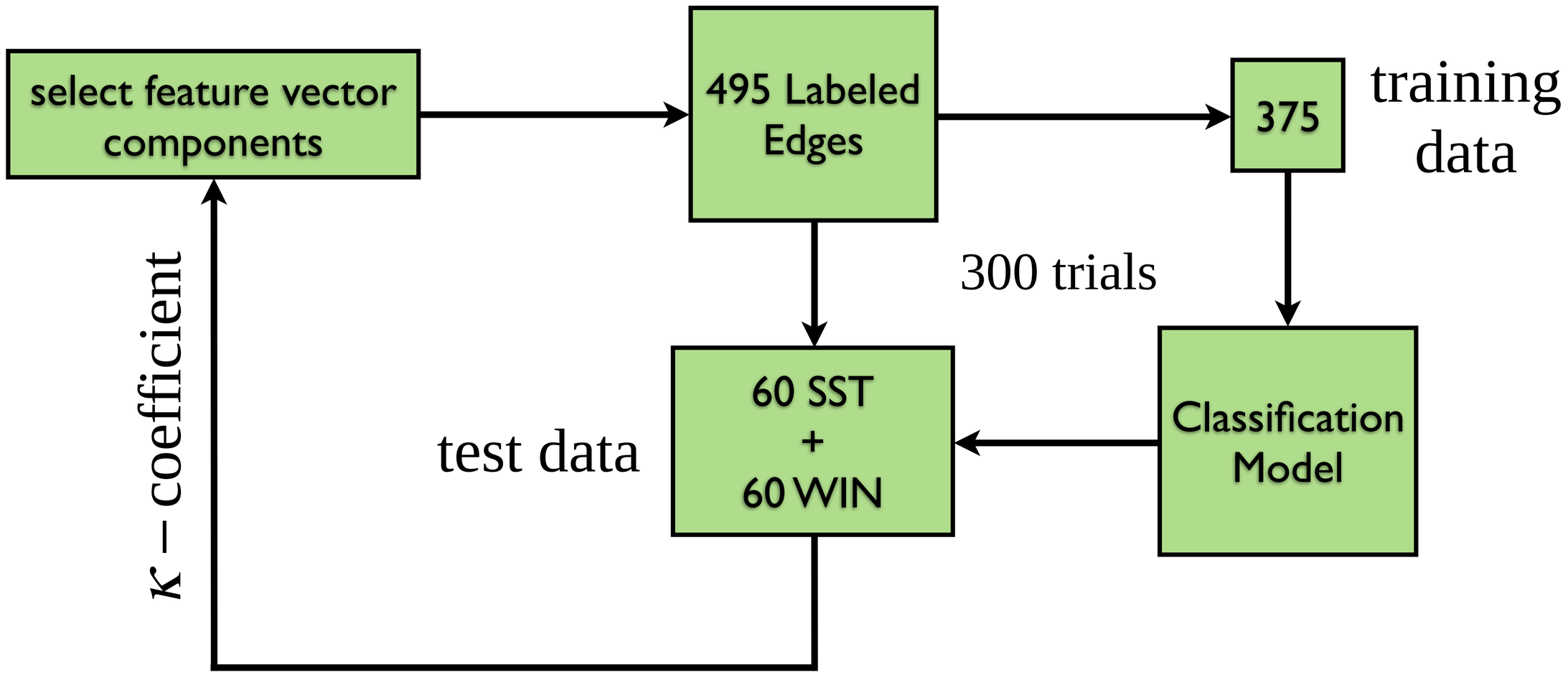


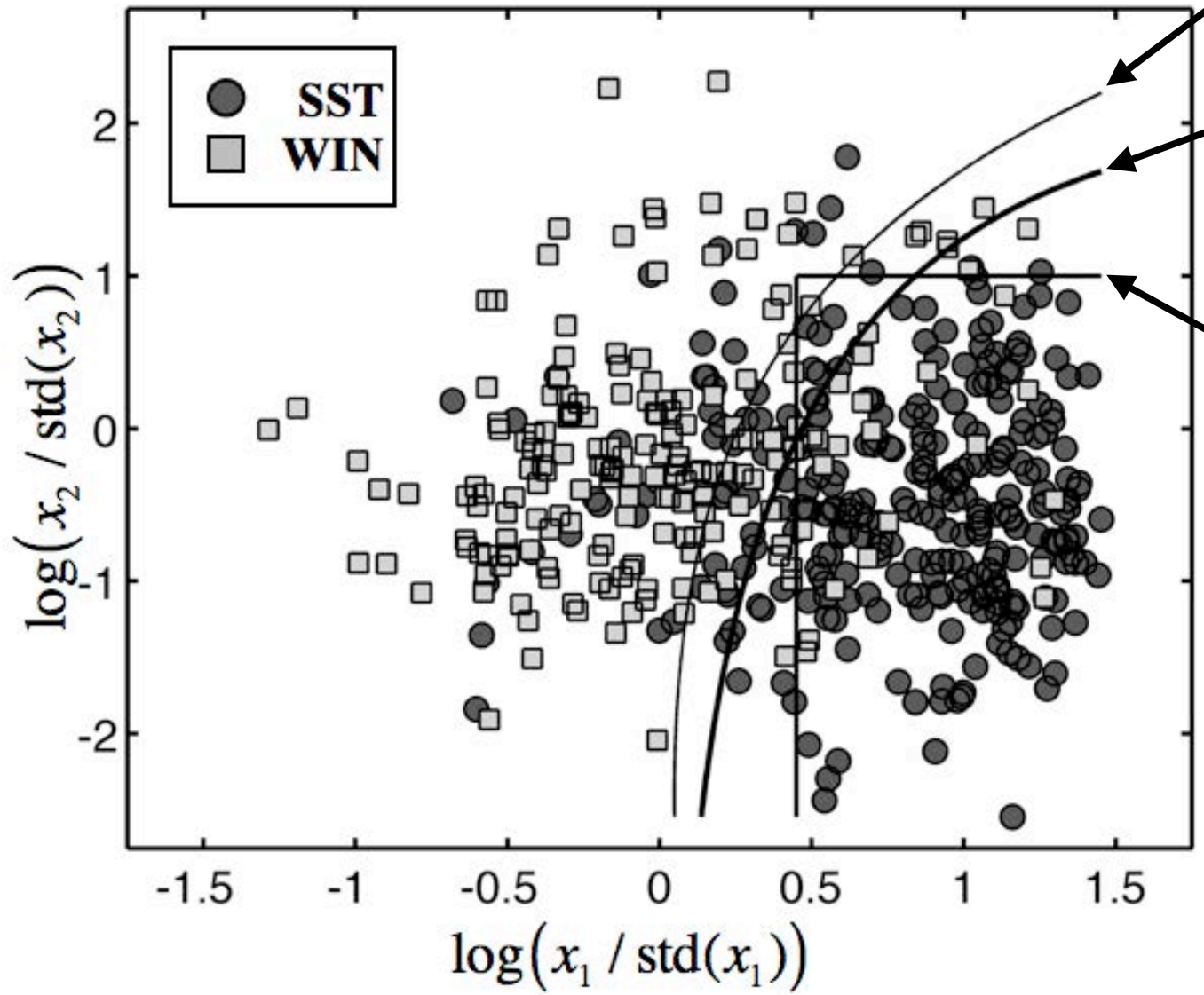
Image	Region	Measures
locSAR locSDW locAW locCW locDIV locCRL	brighter front darker	contrast correlation energy dissimilarity entropy homogeneity μ σ
locSDW	θ d_{cw}	μ σ

feature vector = 148 measures associated with each labeled edge

Only candidate SST front signatures.

Optimal Model by Forward Selection with Validation





Logistic Regression

Maximum Likelihood

Binary Tree Regression

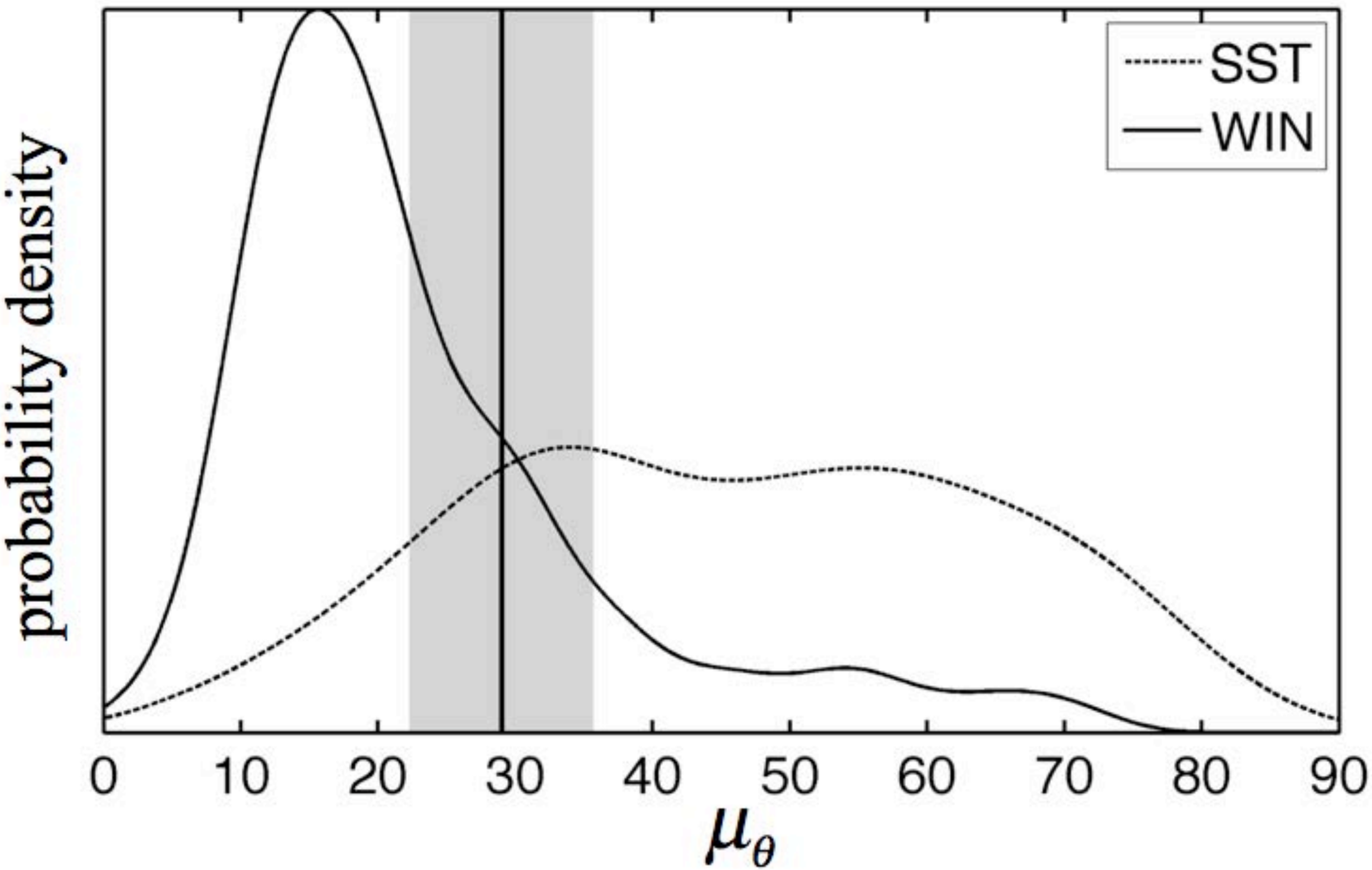
0.70

Model	$\bar{\kappa}$	99% range for κ
Logistic Regression	0.60 ± 0.01	(0.43, 0.78)
Maximum Likelihood	0.63 ± 0.01	(0.43, 0.80)
Binary Tree	0.63 ± 0.01	(0.45, 0.77)

Accuracy ~ 80%

x_1 = mean wind direction with respect to the front (a.k.a. μ_θ)

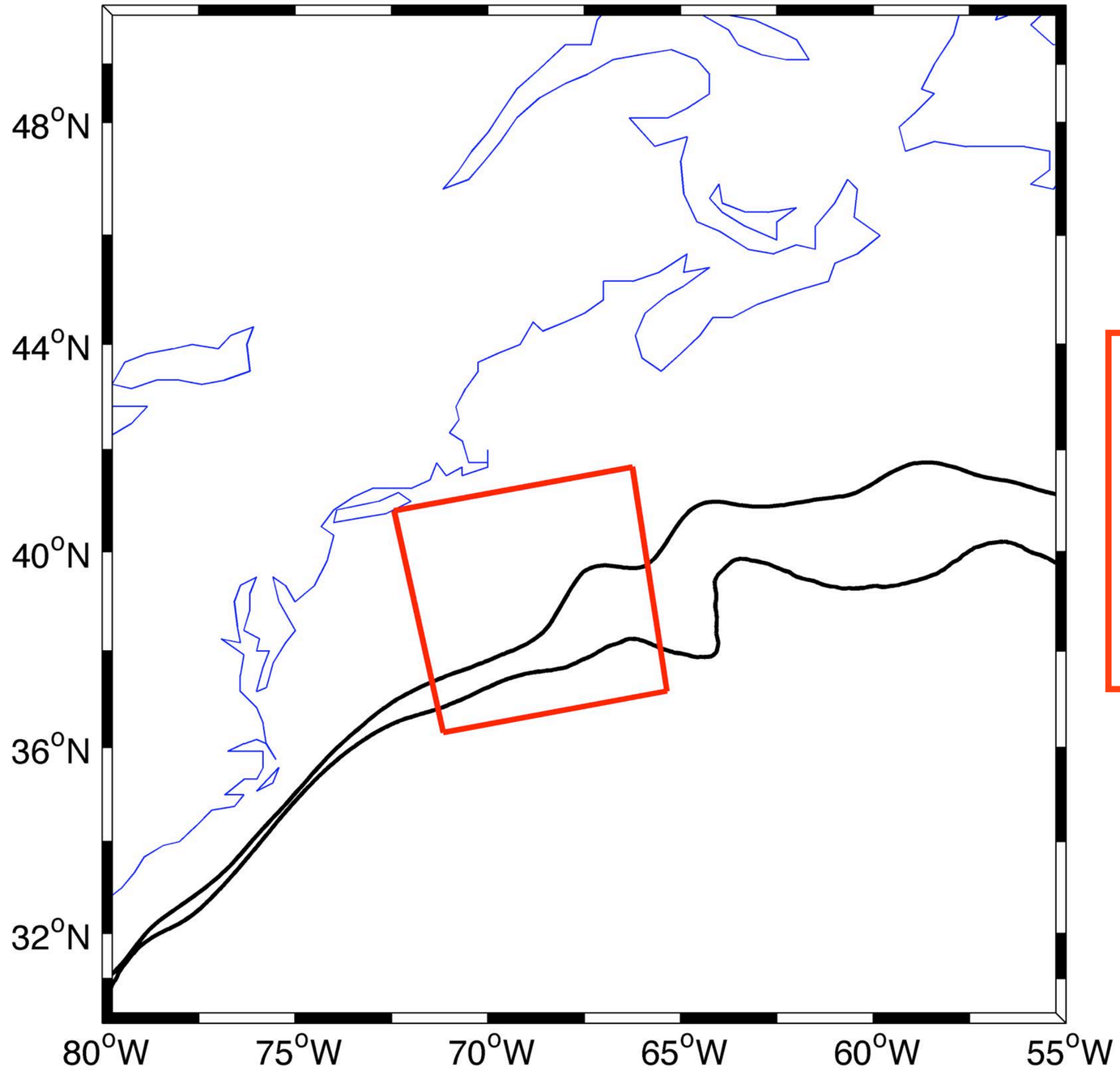
x_2 = standard deviation of SAR in the front region



Reference: Jones, C. T., T. D. Sikora, P. W. Vachon, J. Wolfe, and B. DeTracey, 2012: Toward automated classification of brightness fronts in RADARSAT-2 images of the ocean surface. Under review by the Journal of Atmospheric and Oceanic Technology.

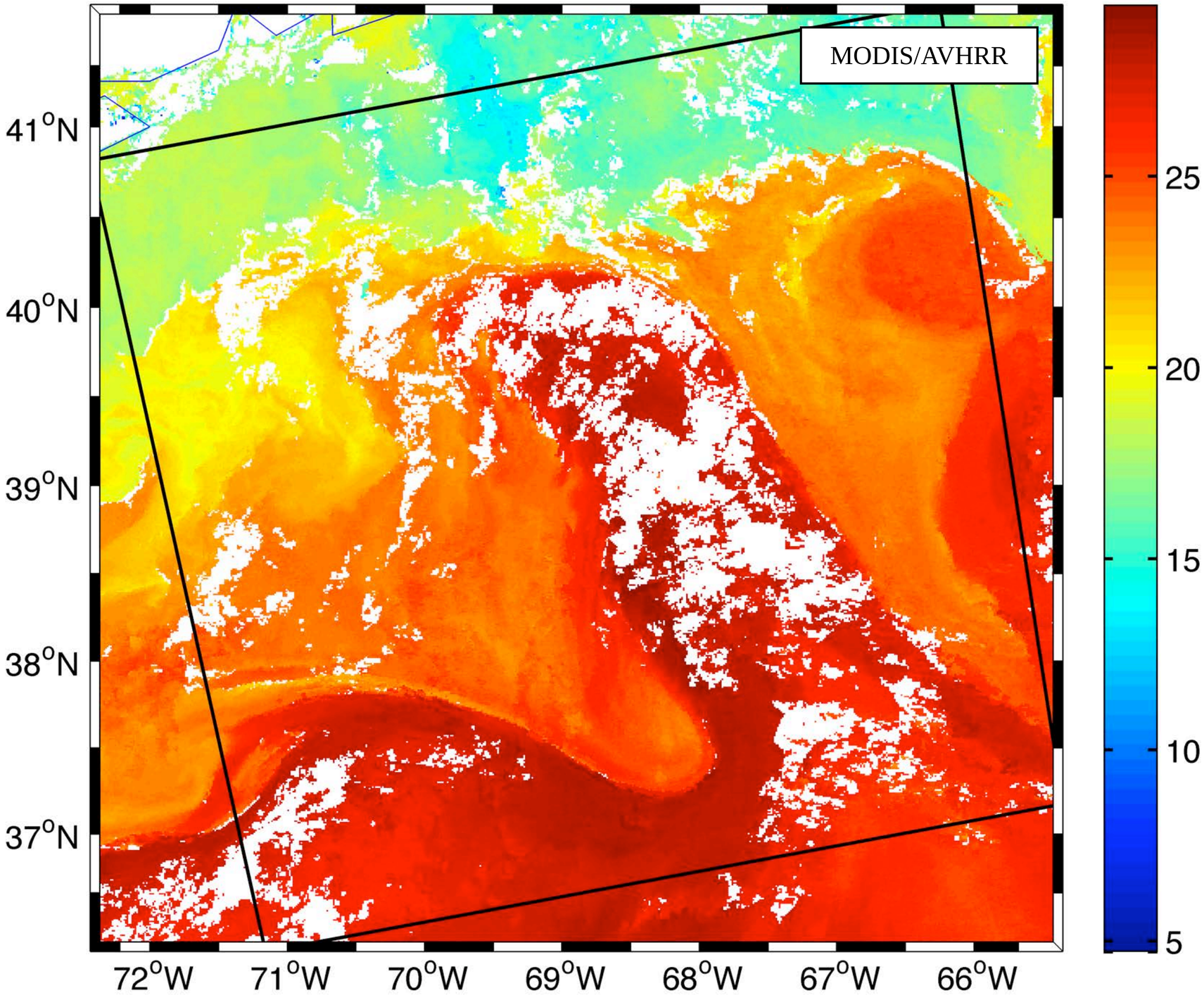
Water-mass boundary detection,

22-Sep-2011 22:32 UTC

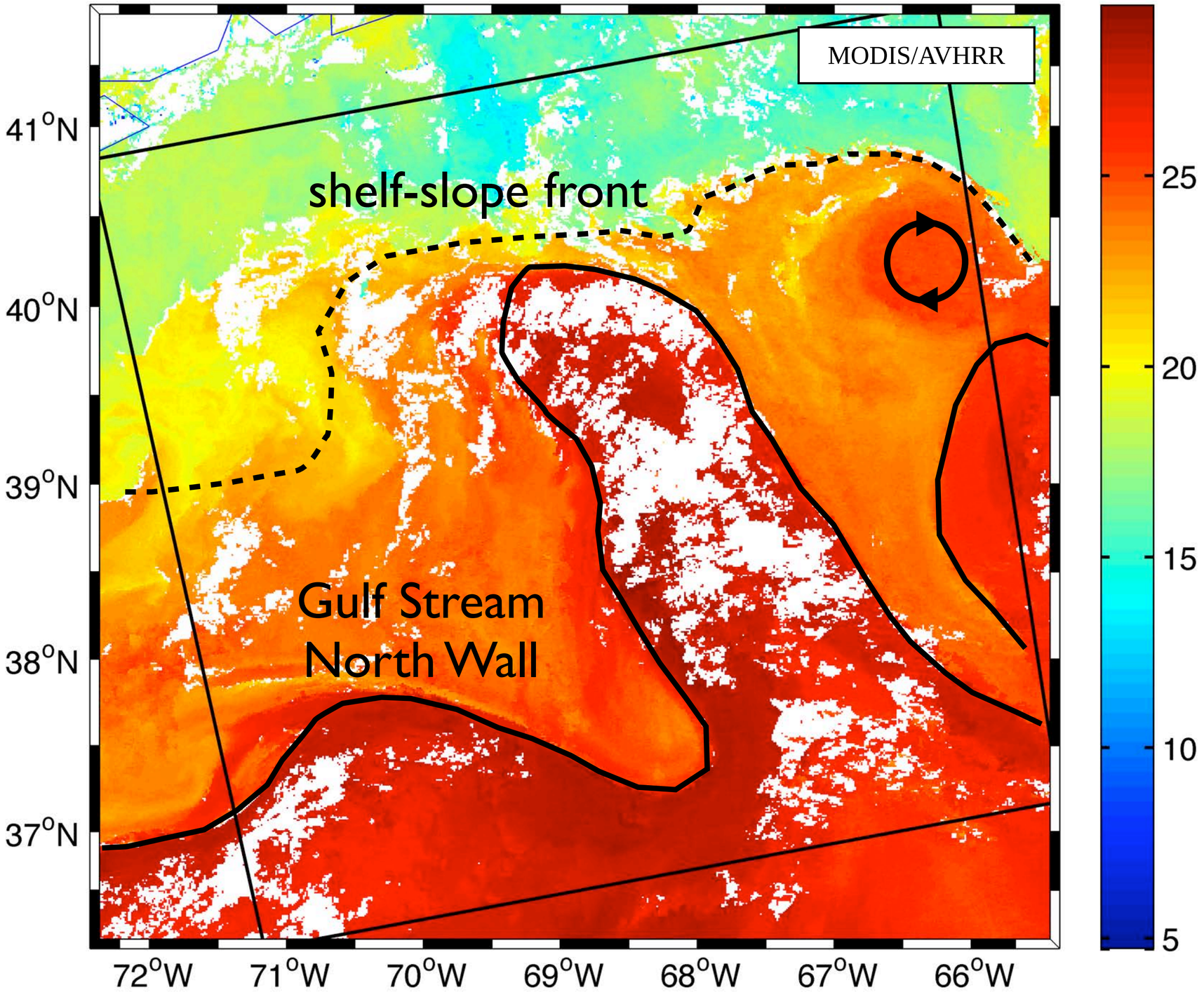


geographic extent of RADARSAT-2 SCWA image, 500 km on each side

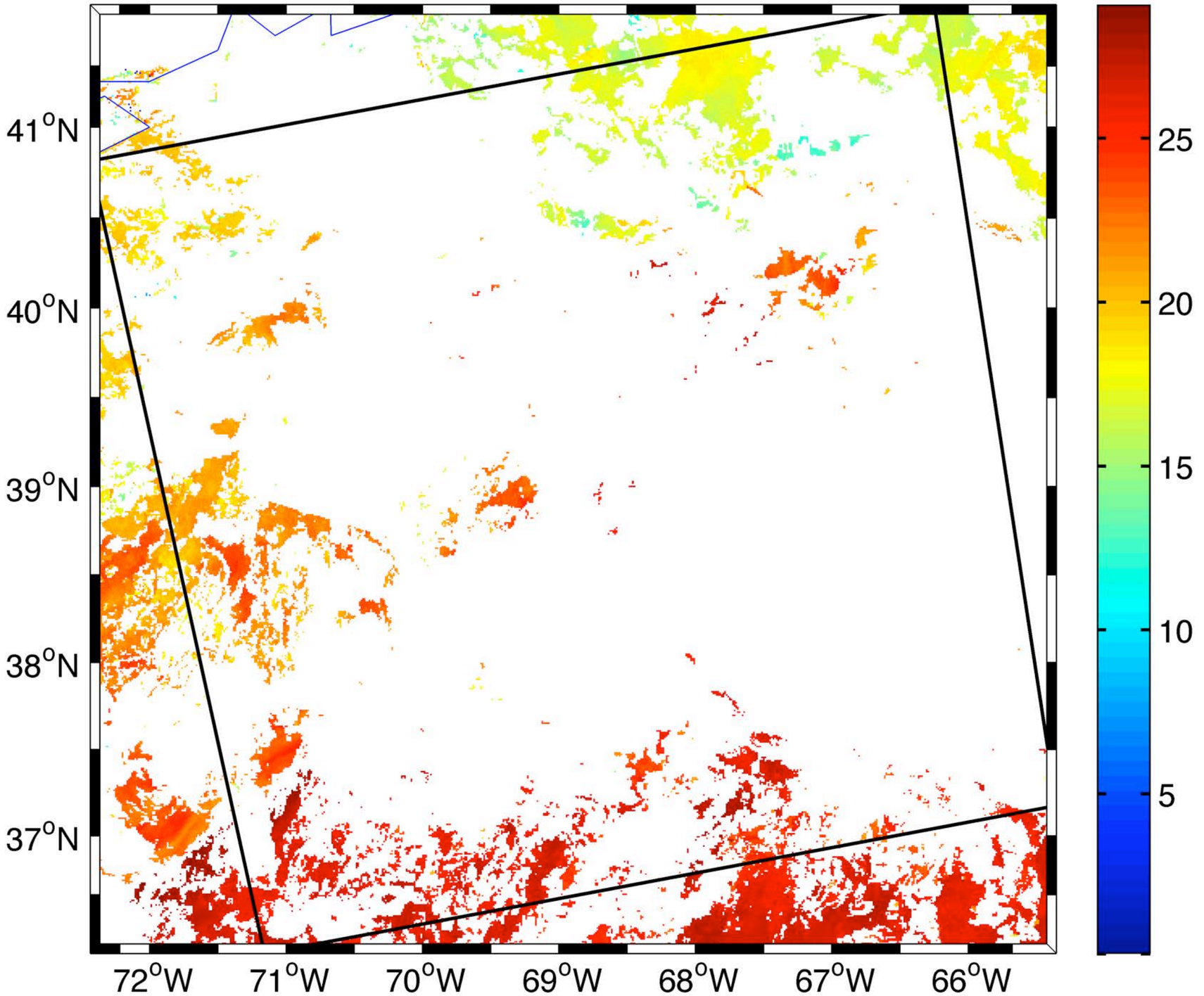
SST (degrees C) 20-Sep-2011



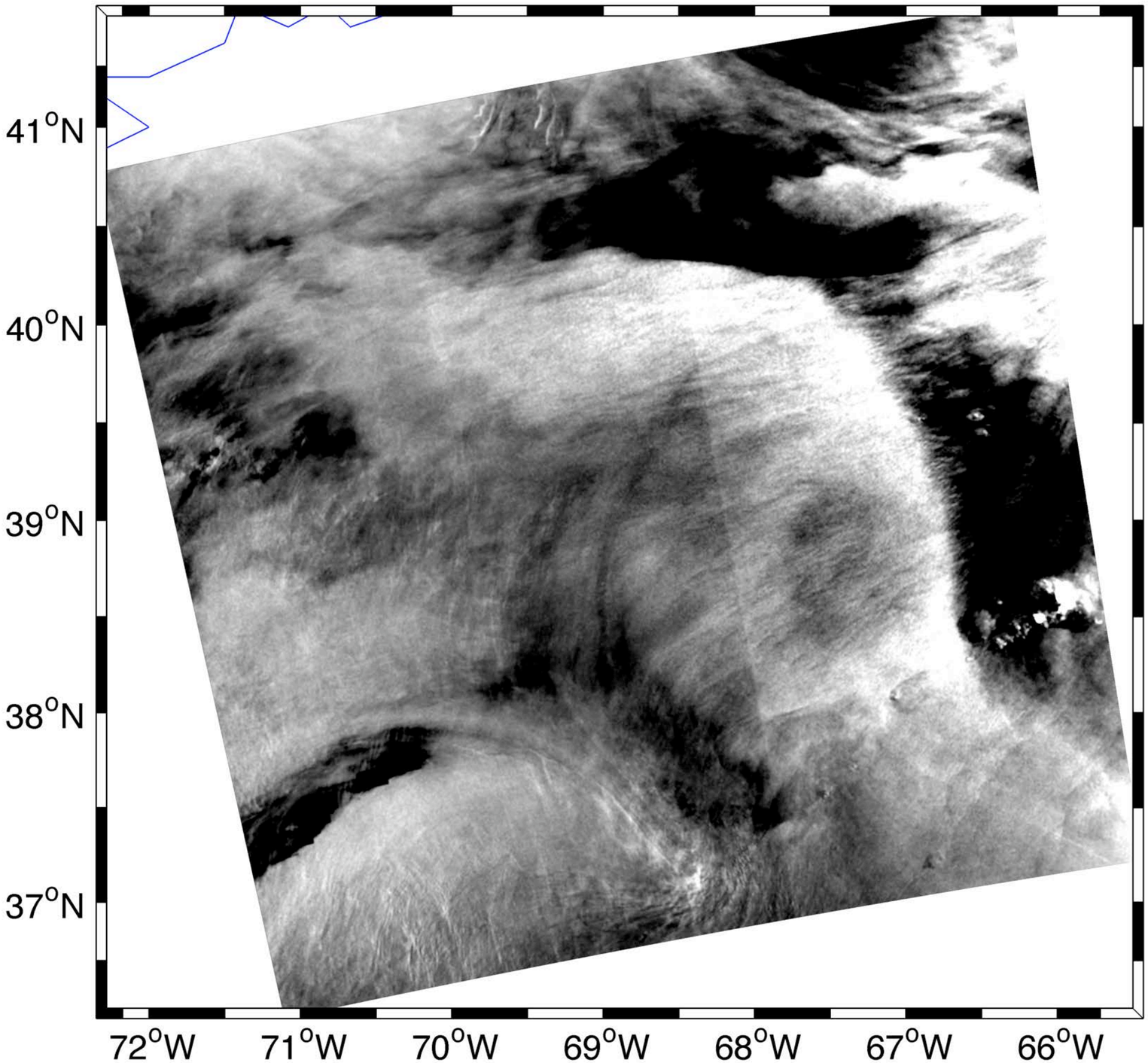
SST (degrees C) 20-Sep-2011



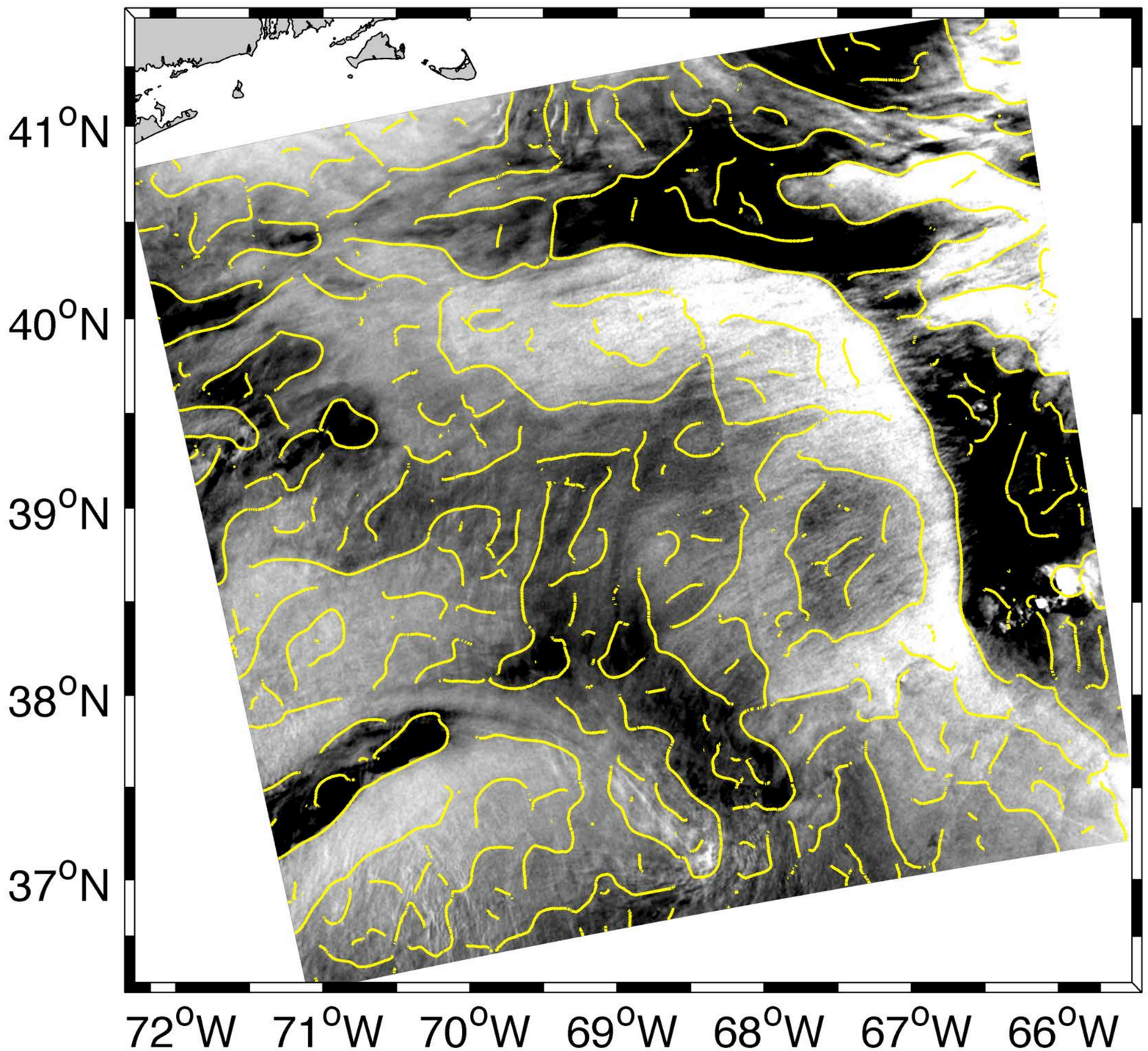
SST (degrees C) 22-Sep-2011



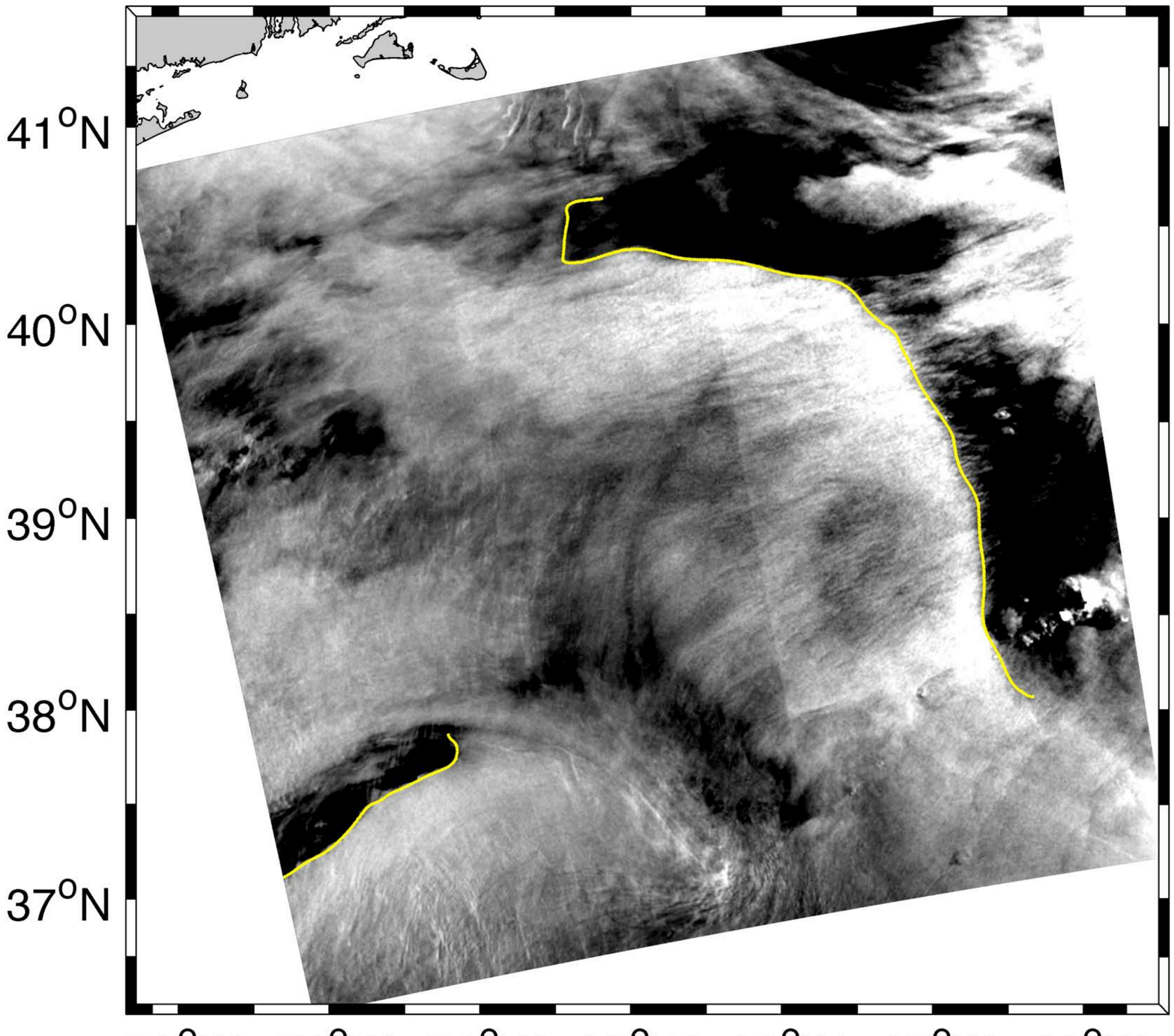
RADARSAT-2 SCWA C-band VV Image
22-Sep-2011 22:32 UTC



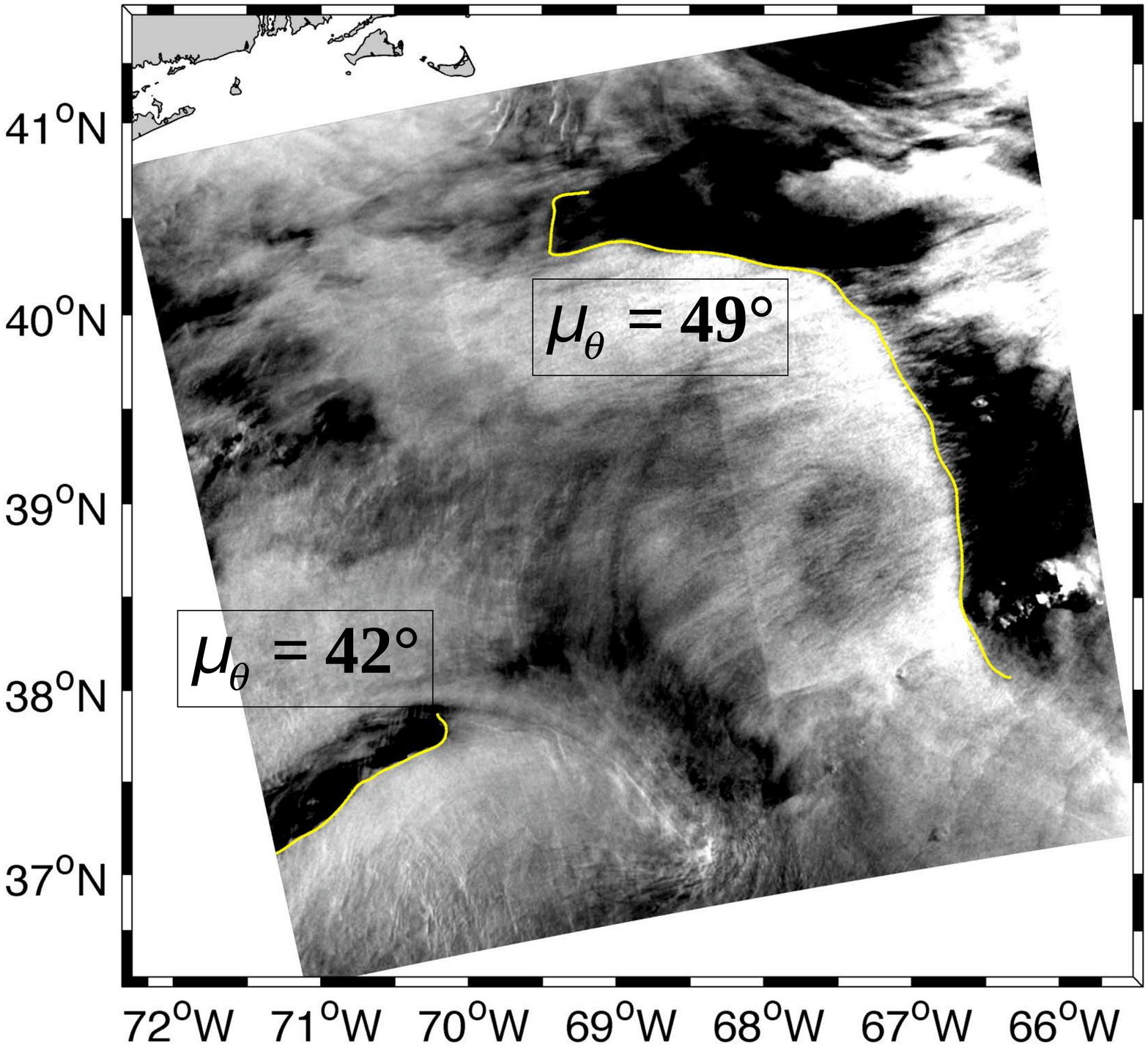
Canny Edges

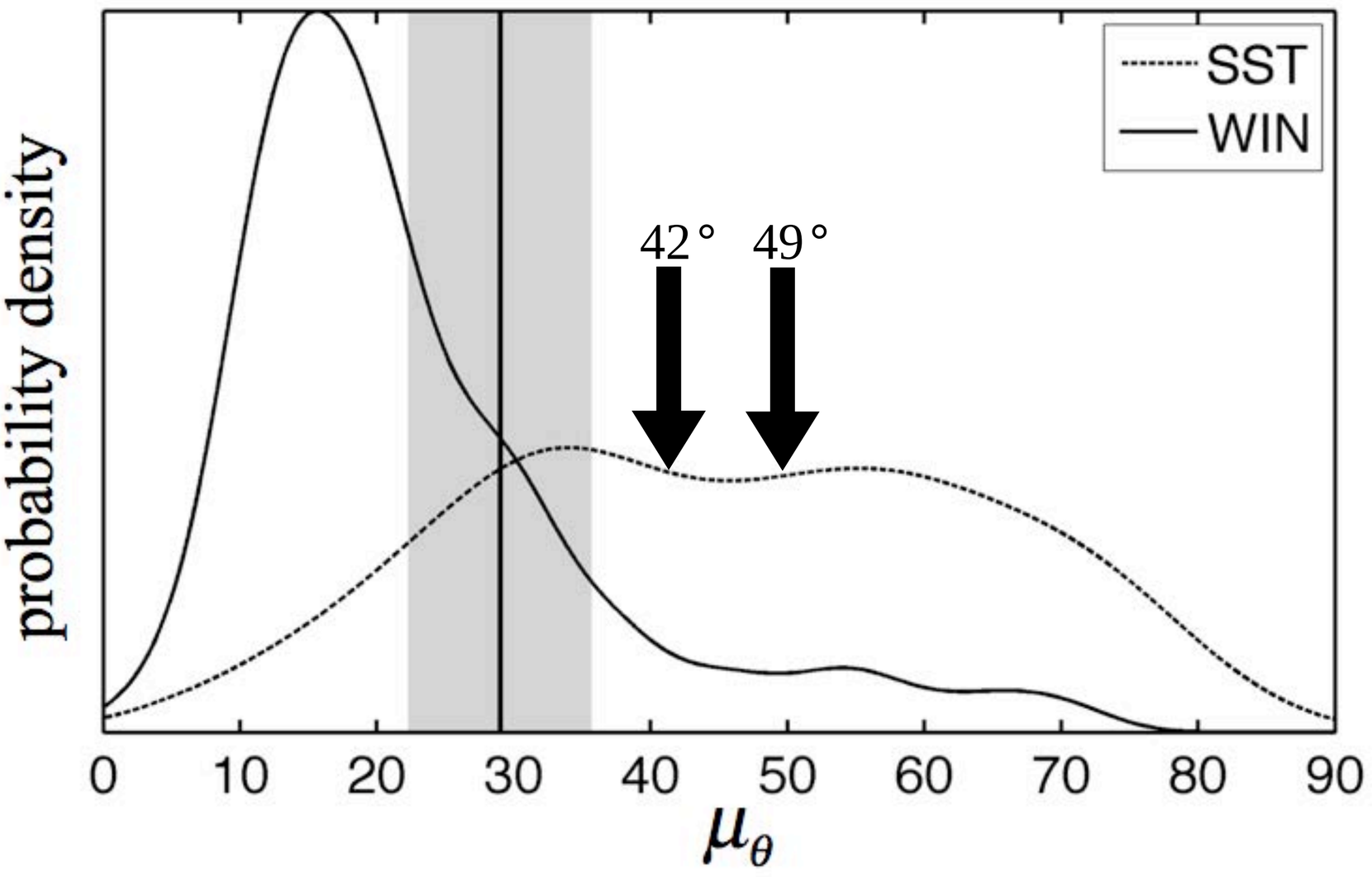


Filtered Edges

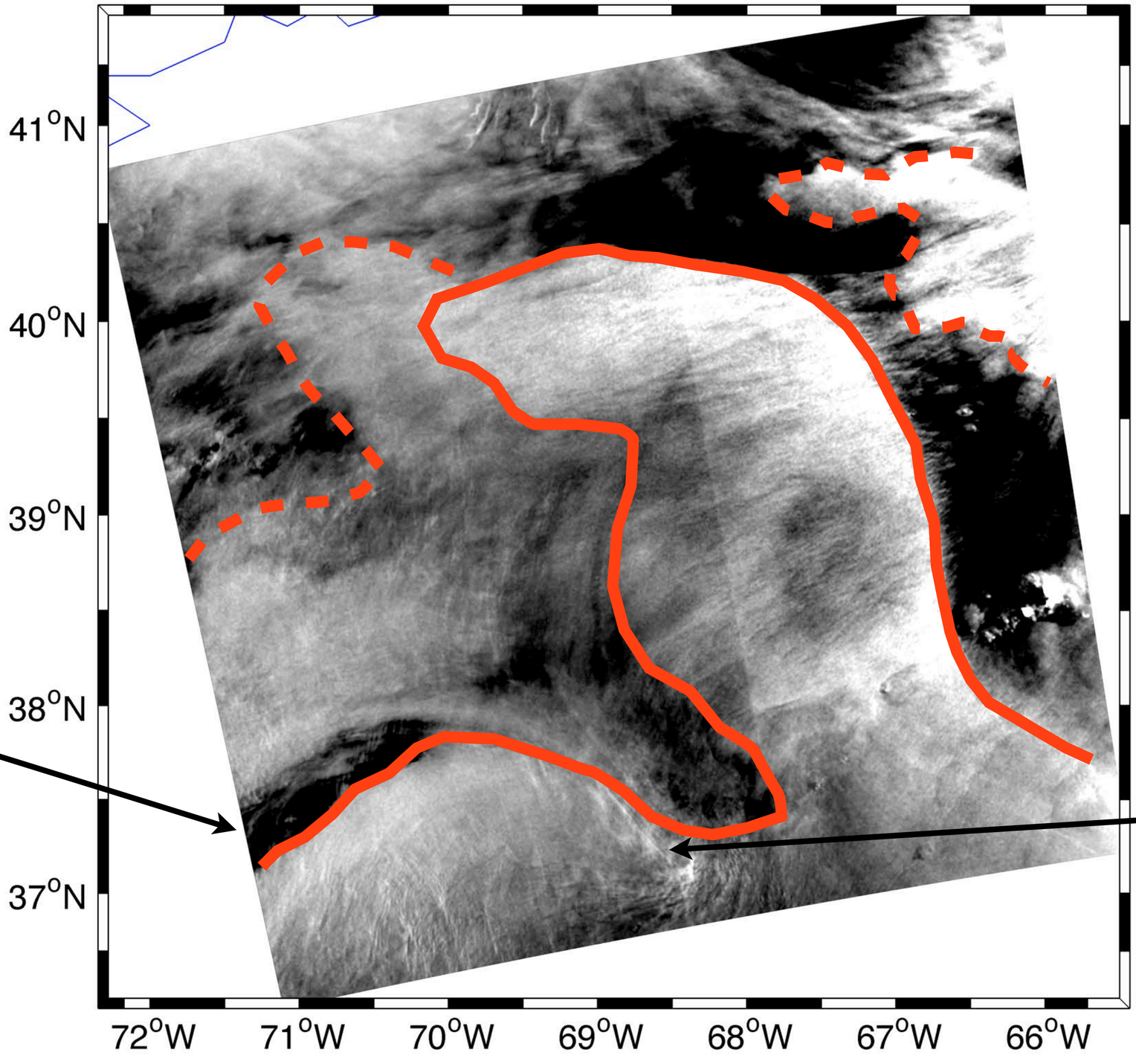


Classified as SST Front Signatures




probability density
SST
WIN
42°
49°
0
10
20
30
40
50
60
70
80
90
μ_θ

22-Sep-2011 22:32 UTC



Project Closing March 2013:

- Our GRIP-funded project will complete its six-year lifetime at the end of March 2013.
- The methods will be fully implemented at MetOc Halifax during the next six months. This will include sessions to train personnel how to recognize signatures of atmospheric and oceanic processes in RADARSAT-2 images.
- In the developmental study, SST fronts were identified with an accuracy of about 80%. We expect we can raise this to nearly 100% using a combination of automated and manual input.
- We are working with MetOc Esquimalt on the Canadian west coast to implement similar methodology.
- **An excellent follow-on study, if funded, would be to evaluate the operational performance of the methodology (e.g., How informative R2 above AVHRR?)!**

New Directions

Our results indicate that it may not be possible to accurately classify ocean SAR features using local measures (wind direction excepted).

Features can be discriminated using image-wide contextual cues, and also using cues from SAR data across time (e.g., *a priori* location of SST fronts), and from other data sources (sea-surface temperature, sea-surface height anomaly, model-assimilated data, etc.).

The question is: How can we make use of contextual information in a purely automated system?

A possible answer: Auto-associative Artificial Neural Network

POINT: categorical contextual information can be utilized survey-fashion to mimic the thought processes of the analyst.

- **The objective** : is to formalize the thought process of an experienced analysts by using a standardized set of questions to assist the novice analyst.
- **Classification** : can be based on the resulting categorical feature vectors that quantify contextual cues across space/ time/data sources.
- **Auto-associations** : consisting of sets of cues that tend to occur together and implicate specific phenomena can be determined by training the auto-associative neural network.

Unlike the local texture approach, the auto-associative neural network is ideal for the development of a *general ocean feature classification algorithm*.

This approach is worth exploring in a future study!

A big **thank you!** to the Canadian Space Agency's Government Related Initiatives Program.

And thank you for your attention.