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# Sea Ice Classification using RADARSAT-2 Dual Polarisation data

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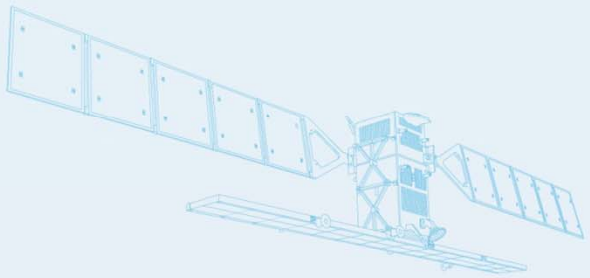
# Objectives

- To develop sea ice classification algorithms for SAR data for use in research and operational monitoring
- Investigate the capability of using dual-polarisation SAR data from ENVISAT, Radarsat-2 and Sentinel-1 for sea ice analysis
- To prepare for automated retrievals of sea ice parameters from present and future SAR satellites

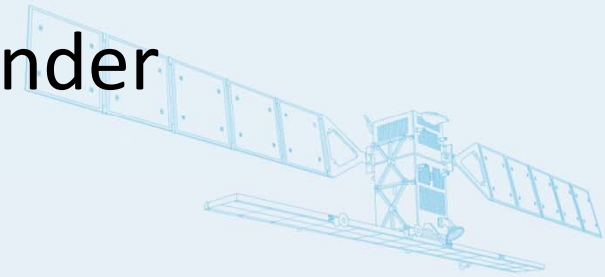
# Two phases

1. Develop and validate sea ice classification algorithms for analysis of large amounts of ENVISAT SAR HH-pol images
2. Extend and improve ice classification methods using dual-polarisation Radarsat-2 and Sentinel-1 data



# Classification of ENVISAT ASAR images

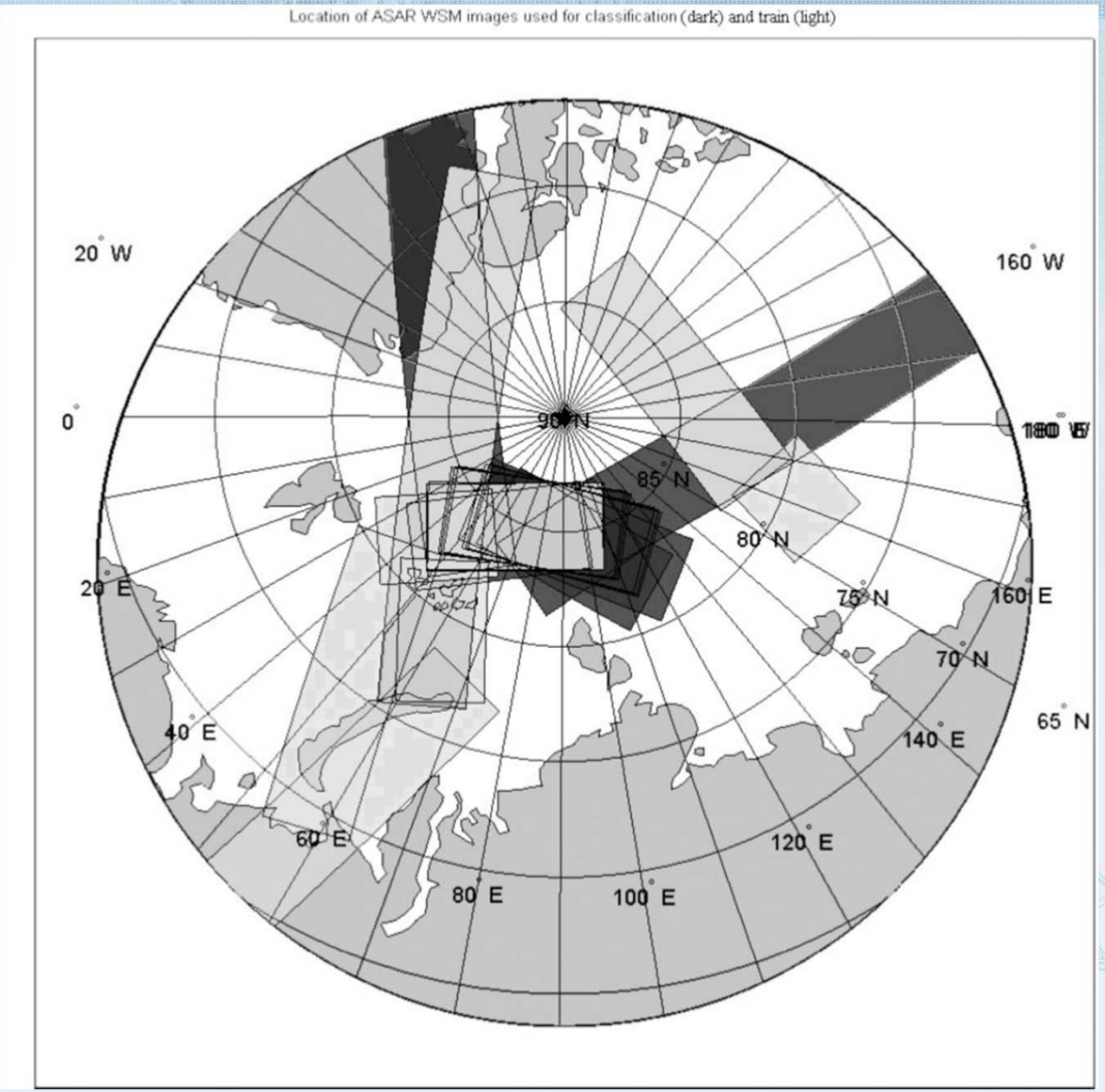
- Methods: a Neural Network –based algorithm and Bayesian algorithm
- Data sets: Wideswath data for winter conditions in high Arctic sea ice areas
- Validation data: independent analysis of images by ice experts
- Operational implementation under GMES/MyOcean



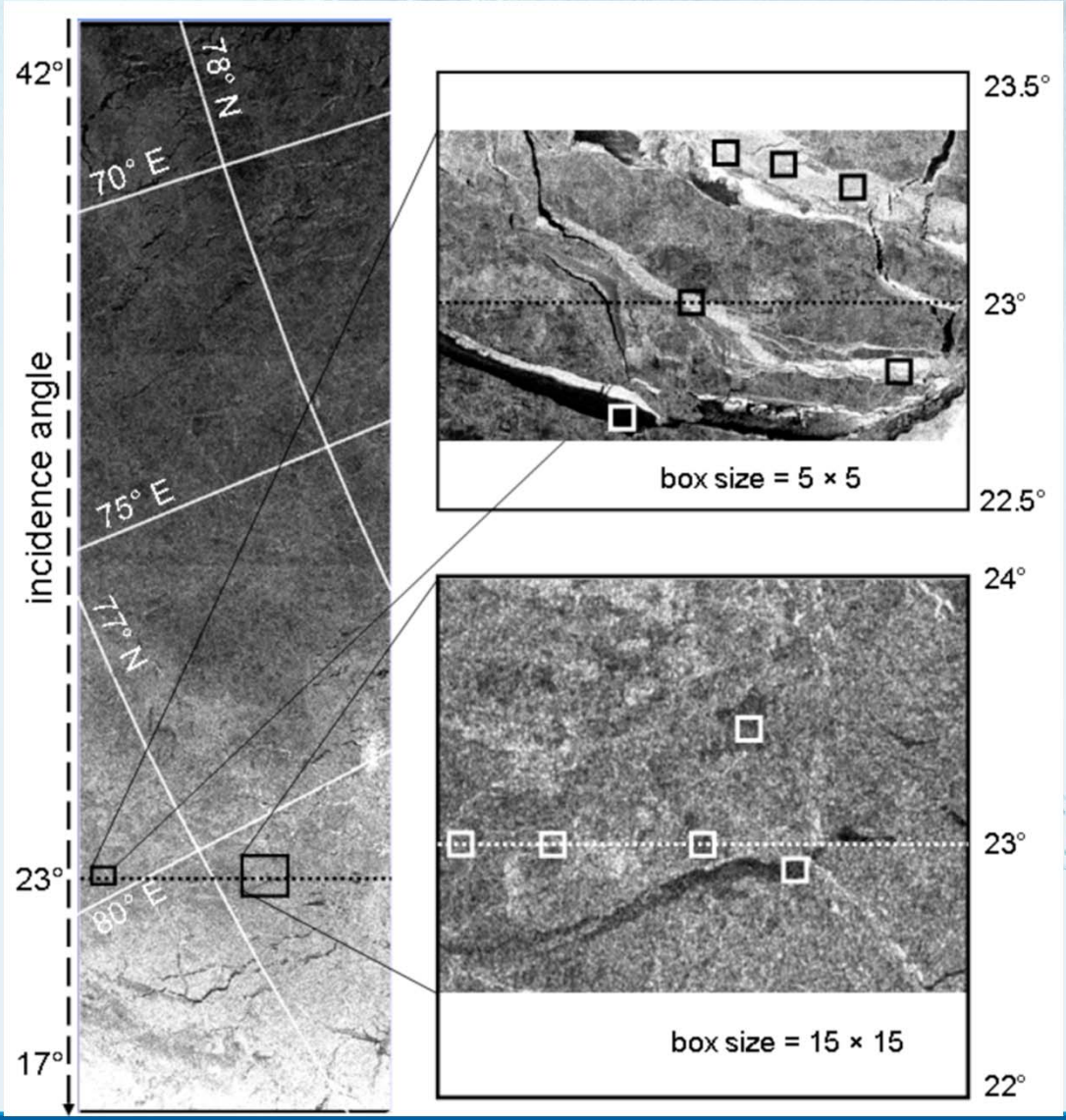
# Location of ASAR images

Grey stripes: 12 images used for training

Dark stripes: 20 images used for classification



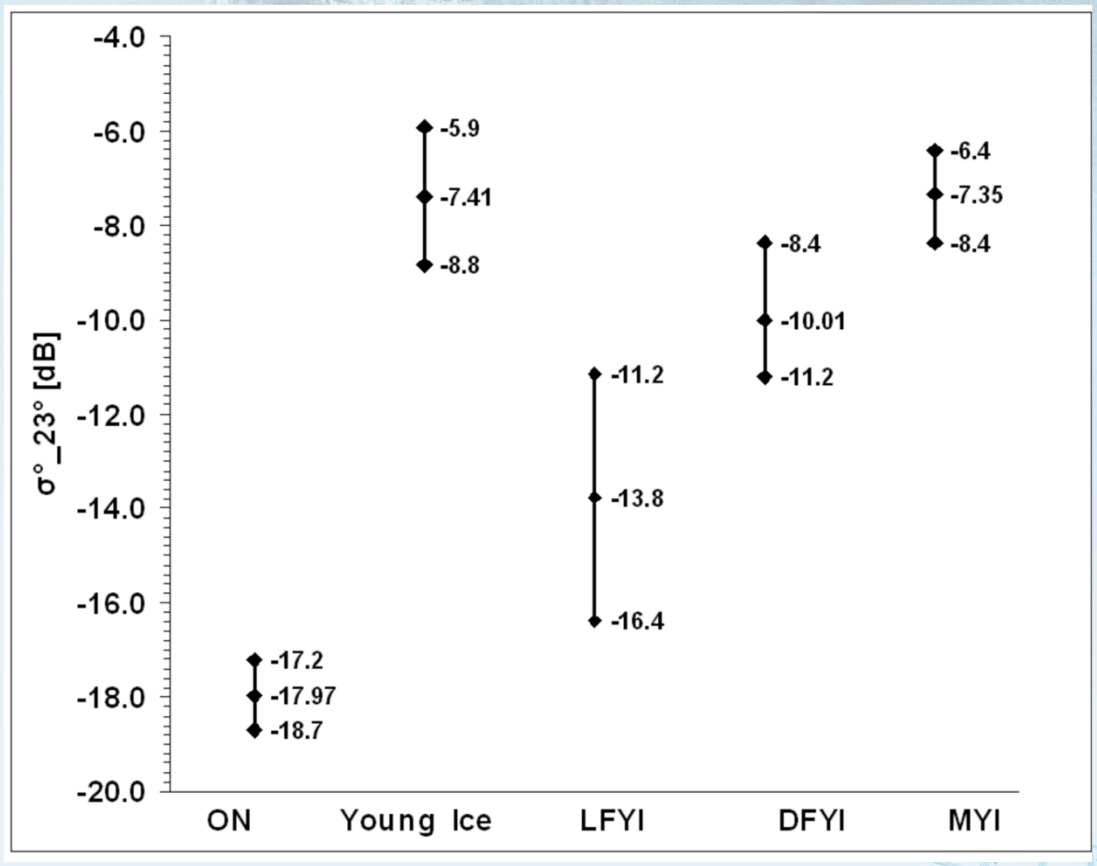
# Estimation of $\sigma^0$ for different ice types and incidence angle




Five ice types were analysed for sigma-0

- Young ice
- Open water /Nilas
- Level firstyear ice
- Deformed firstyear ice
- Multiyear ice

# Sigma-0 range for the five ice types



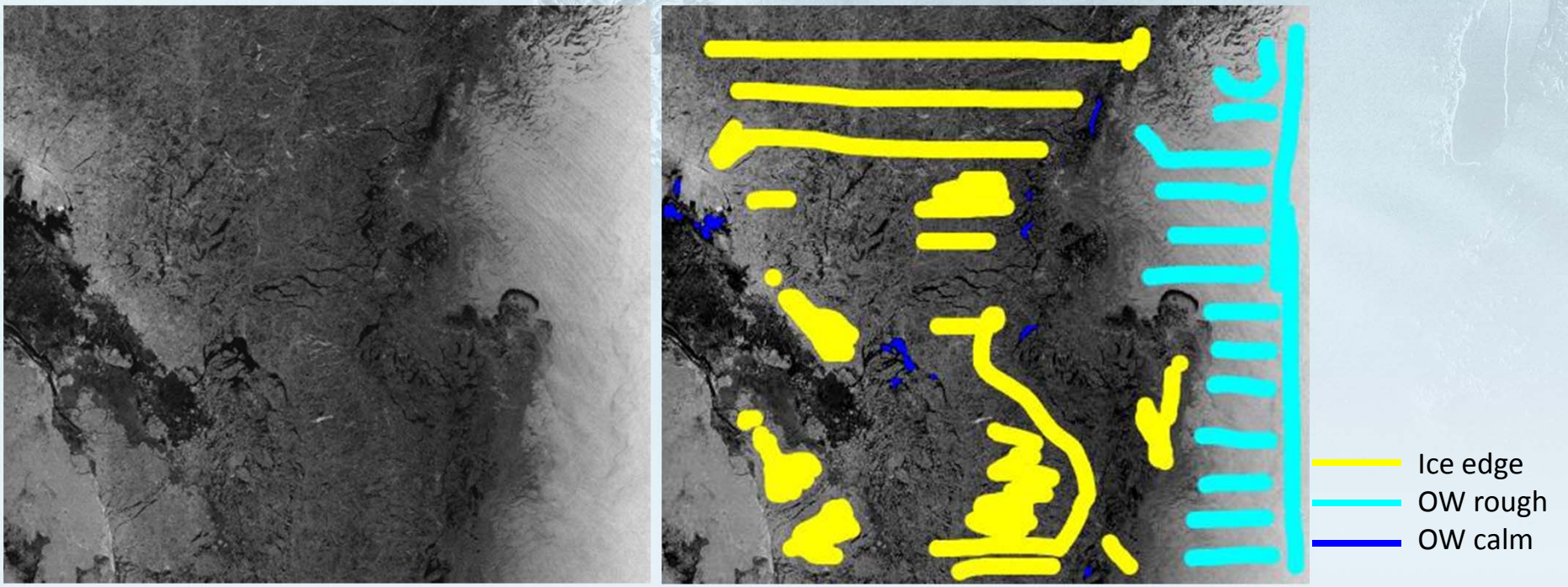

Estimated σ° values for various ice types derived from calibrated ENVISAT Wideswath SAR images, normalized to 23° incidence angle.

# Image texture parameters used as input layers to the Neural Network

1 – average sigma-0 for the given ice type,
2 – energy,
3 – correlation,
4 – inertia or contrast,
5 – cluster prominence,
6 – homogeneity,
7 – entropy,
8 – 3rd central statistical moment of brightness,
9 – 4th central statistical moment of brightness.

The Stuttgart Neural Network Simulator (SNNS) is used, where visual interpretation of a set of SAR images is done for training of the a neural network before classification can start. The textural features are calculated for the subsets of the training images

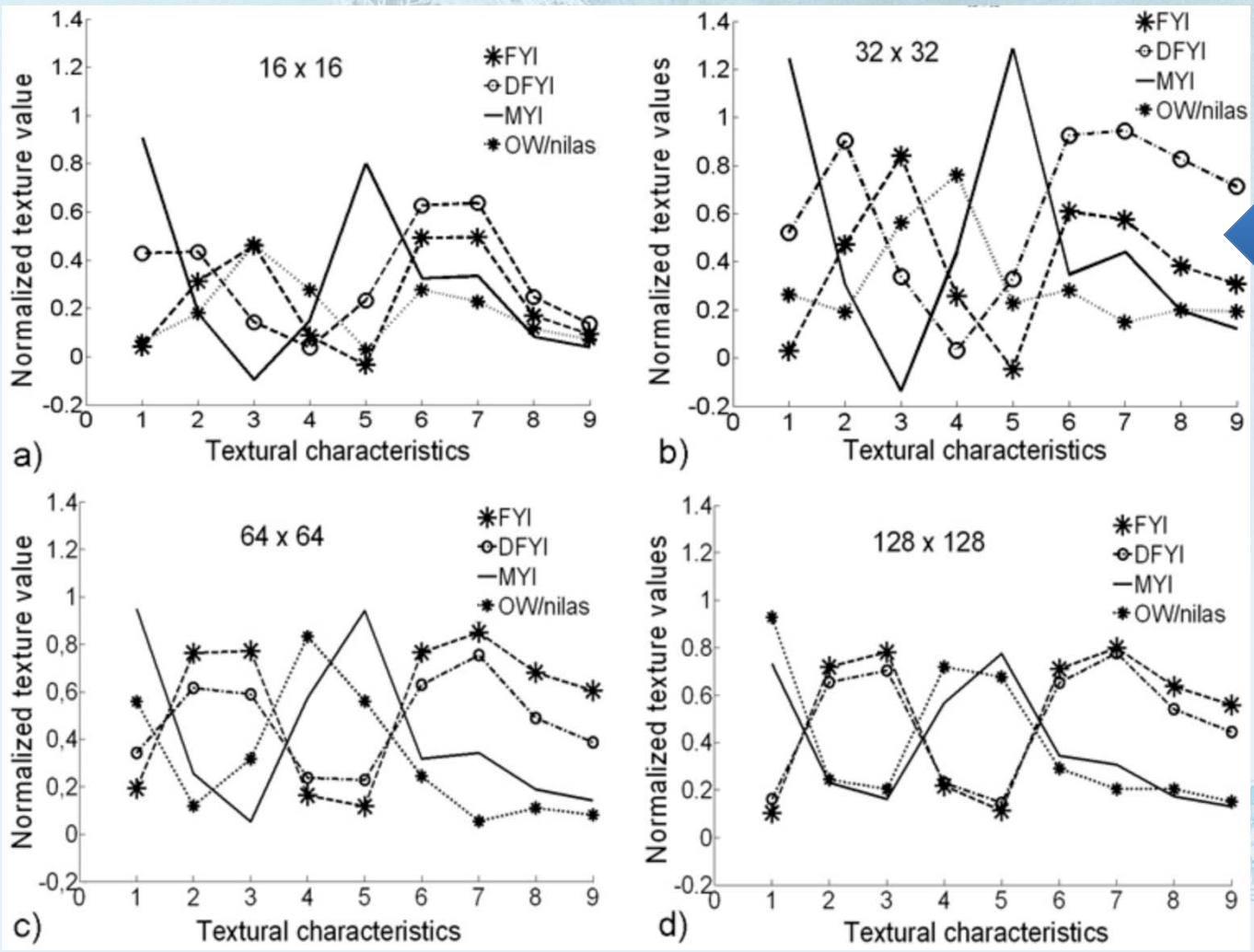
# Selection of training data in SAR images



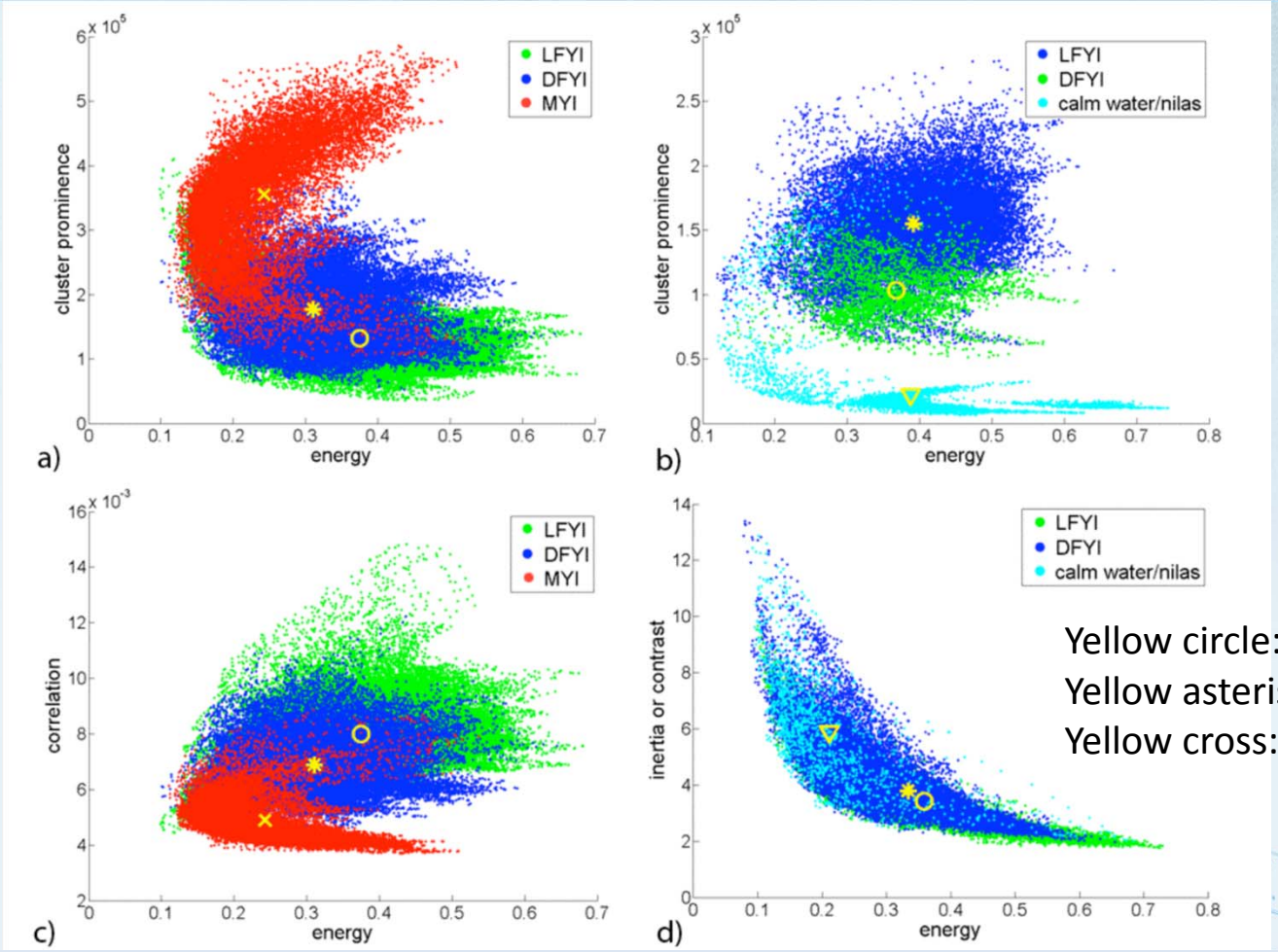

10 Dec 2007

Textural image parameters are computed based on Grey Level Co-occurrence Matrix (GLCM). GLCM describes the frequency of one gray tone (backscatter values) appearing in a specified spatial linear relationship with another gray tone, within the investigation area..

# Identify textural parameters that separate the ice types well



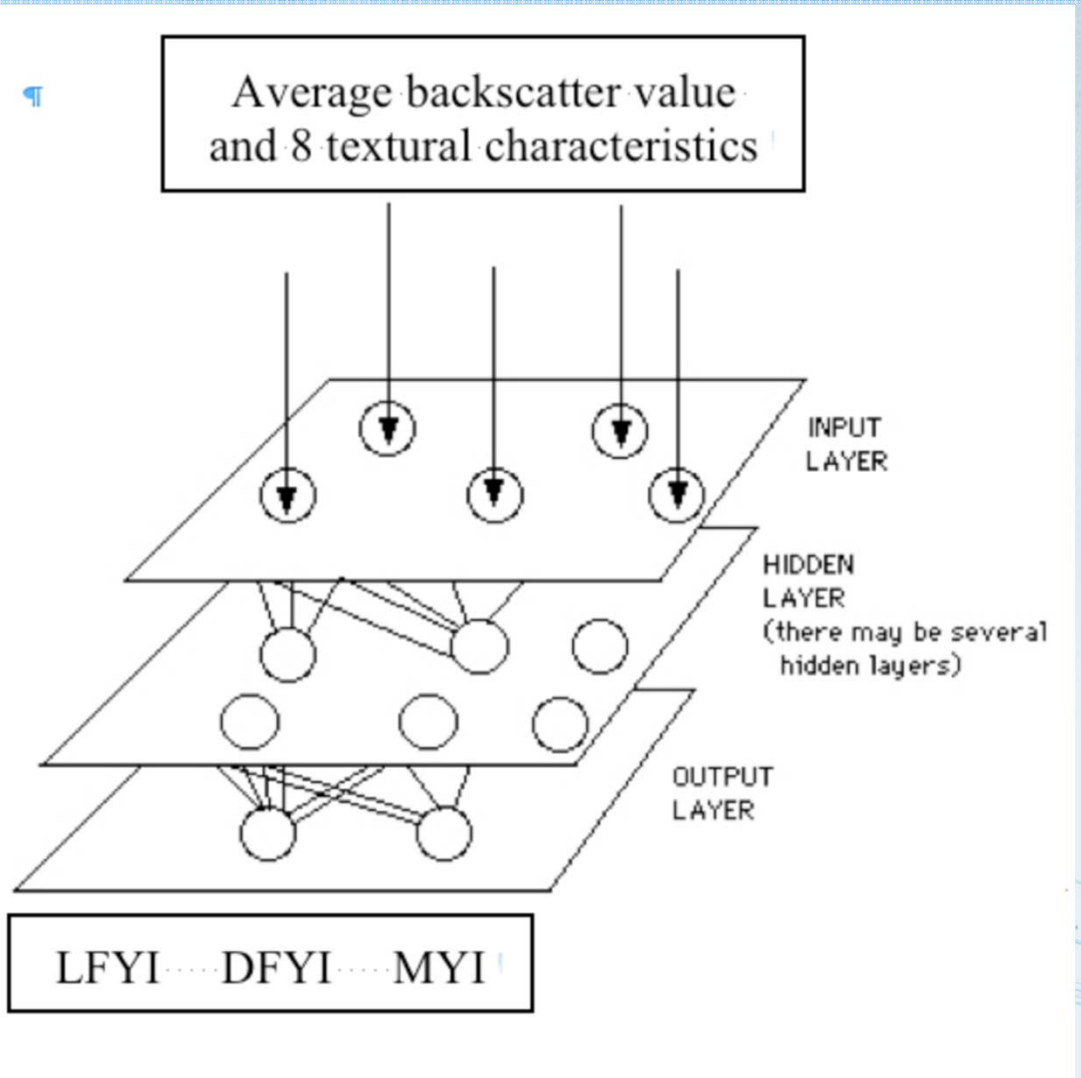
# Separation of ice classes by pairs of textural parameters



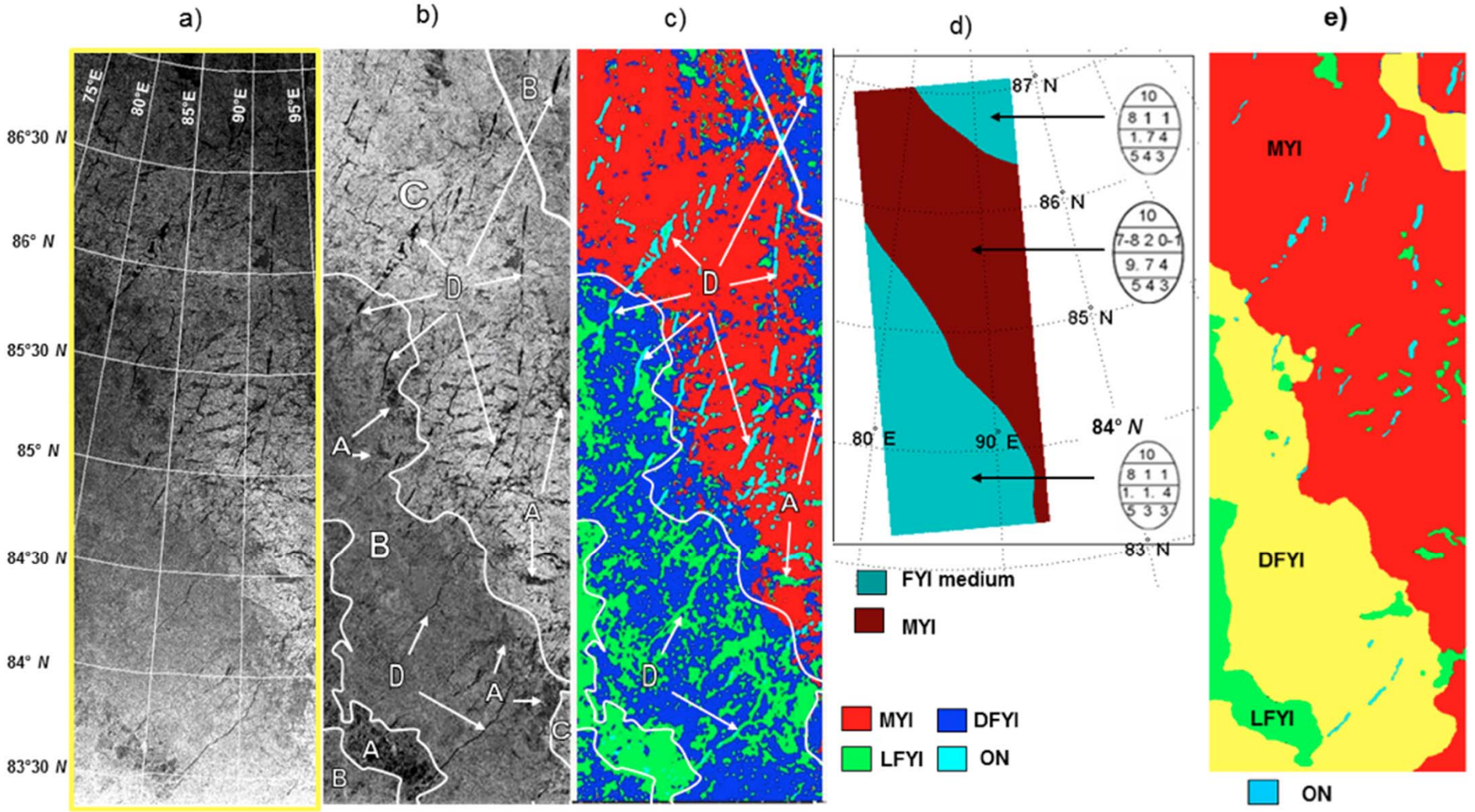

Yellow circle: center of LFYI
Yellow asterisk: center of DFYI
Yellow cross: center of MYI

Four examples of scatter plots showing how two textural features calculated from subimages in ENVISAT Wideswath data can be used to classify ice types (LFYI, ON, DFYI and MYI).

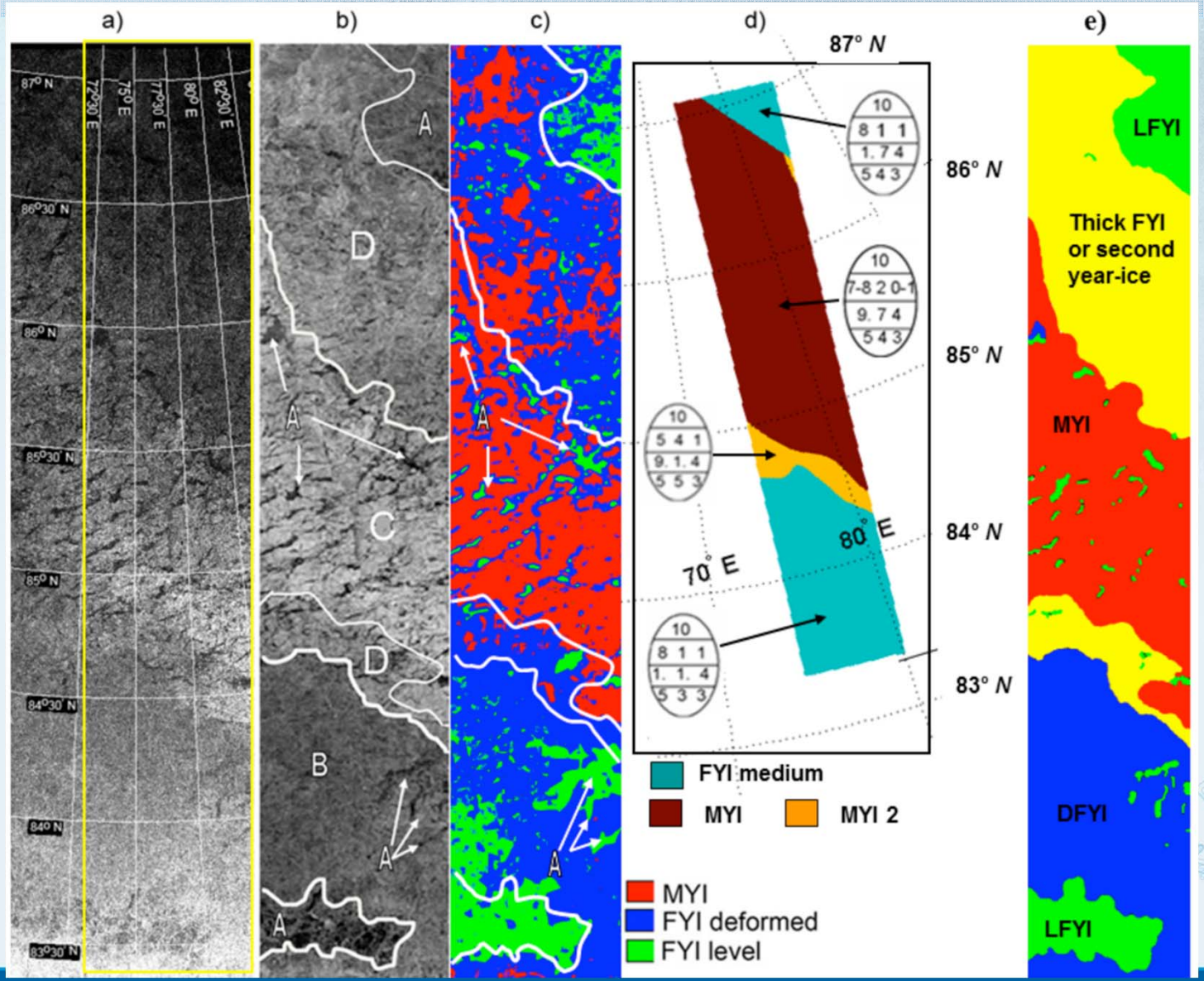
# Neural Network Topology



# Classification result: 18 January 2008



# Classification results: 04 February 2008



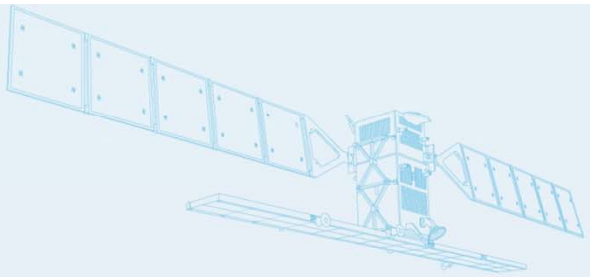
# Comparison of classification with expert analysis

**January 18, 2008**

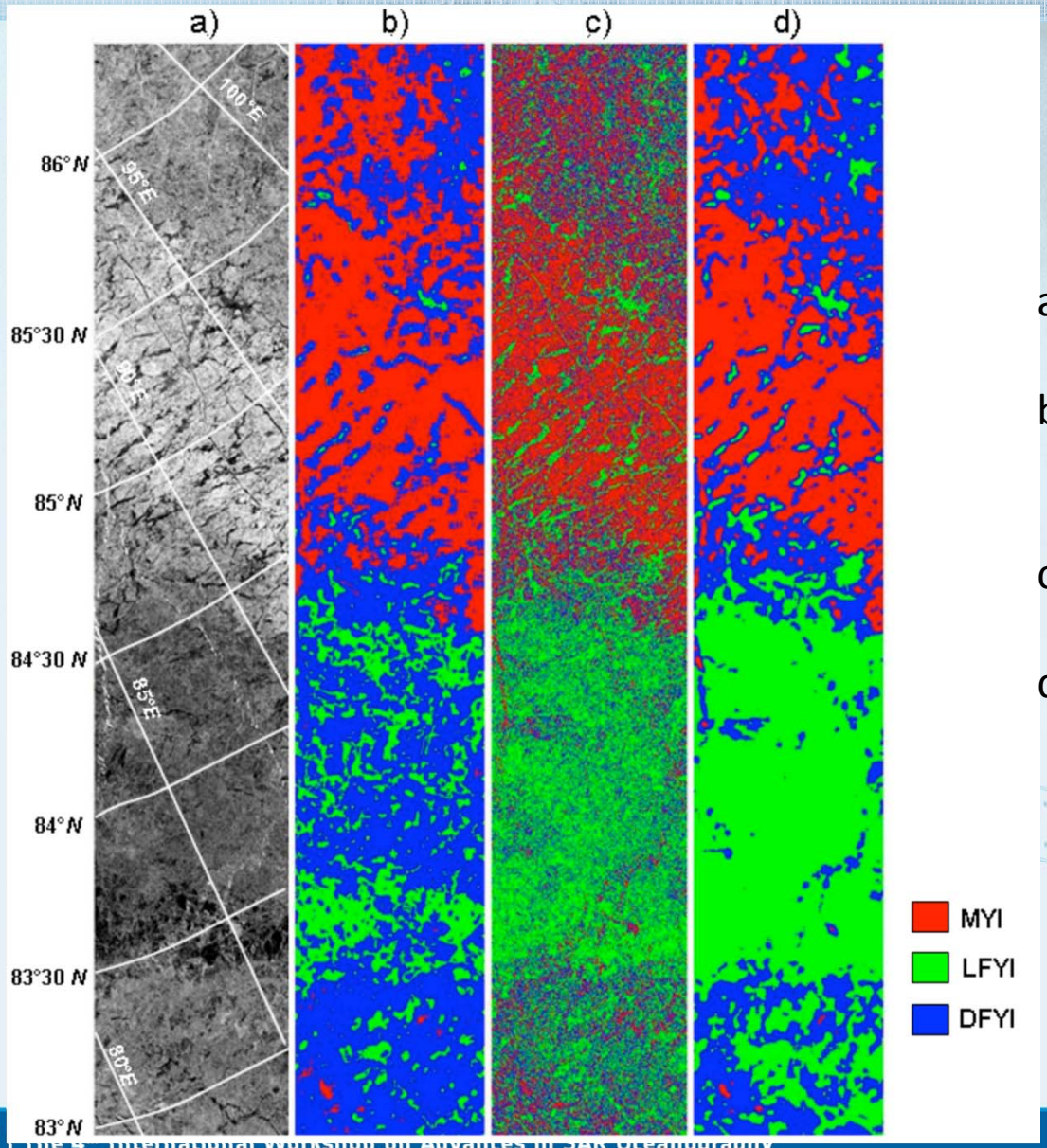
| *NN class. result* | *Vsual expert analisys zone * :* C | A | B | D |
|---|---|---|---|---|
| MYI | 64.76 | 6.49 | 25.37 | 3.39 |
| LFYI | 0.87 | 86.18 | 10.95 | 1.99 |
| DFYI | 1.26 | 23.58 | 73.49 | 1.67 |
| ON | 12.98 | 34.77 | 14.06 | 38.19 |

**February 04, 2008**

| *NN class. result* | *Vsual expert analisys zone * :* C | A | B+D |
|---|---|---|---|
| MYI | 72.15 | 2.46 | 25.35 |
| LFYI | 0.71 | 62.08 | 37.19 |
| DFYI | 15.61 | 11.06 | 73.29 |



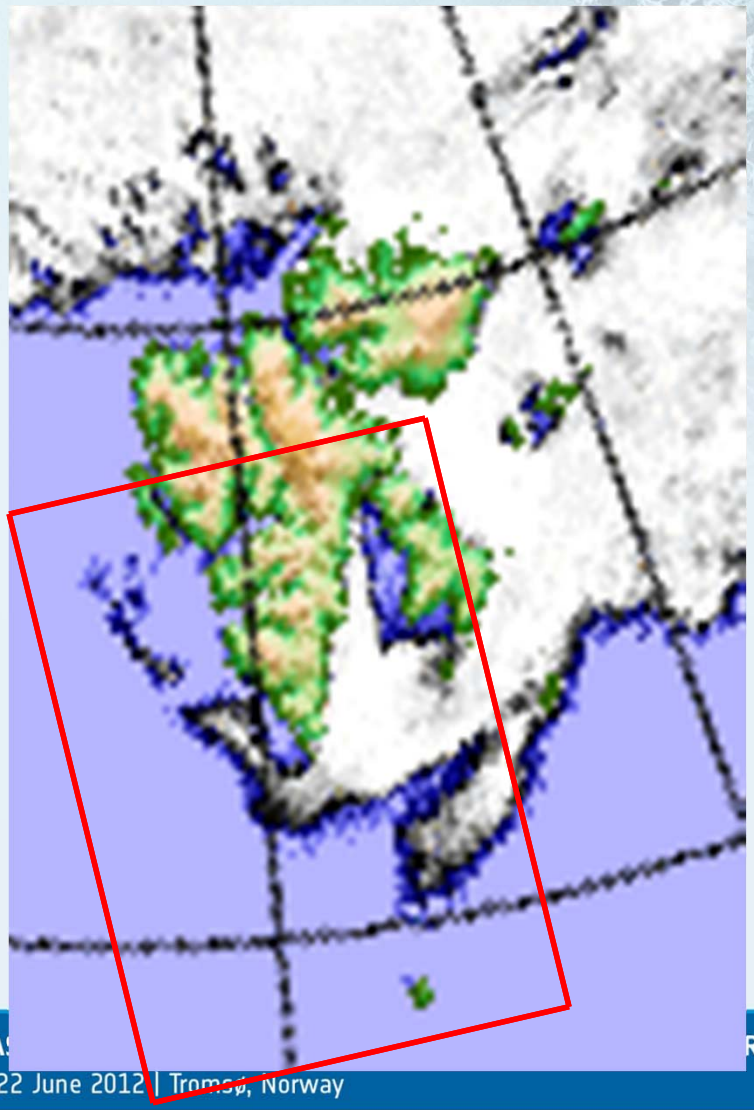
# Comparison of NN and Bayesian classification



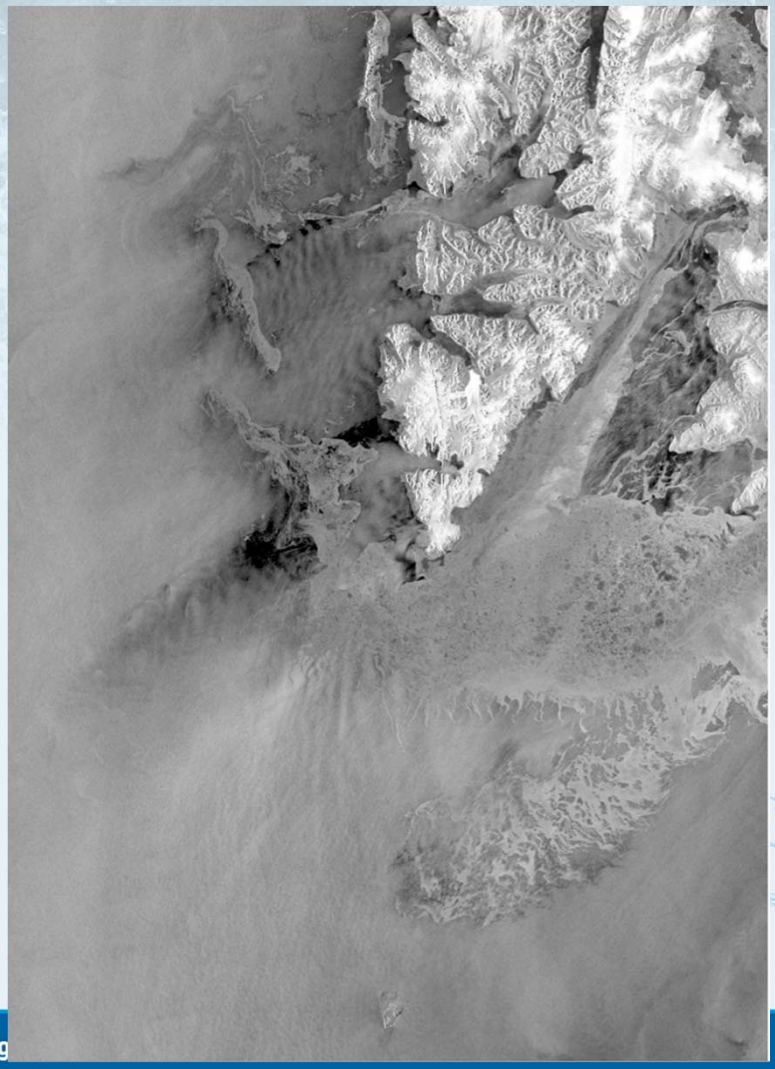

a) Subset of SAR image from 14 January 2008;
b) result of NN classification for 3 sea ice types;
c) Bayesian approach classified image;
d) Bayesian approach classified image by averaging 32×32 cells

# Test of ice-water discrimination in the MIZ

AMSRE-ice concentration 28 April 2010

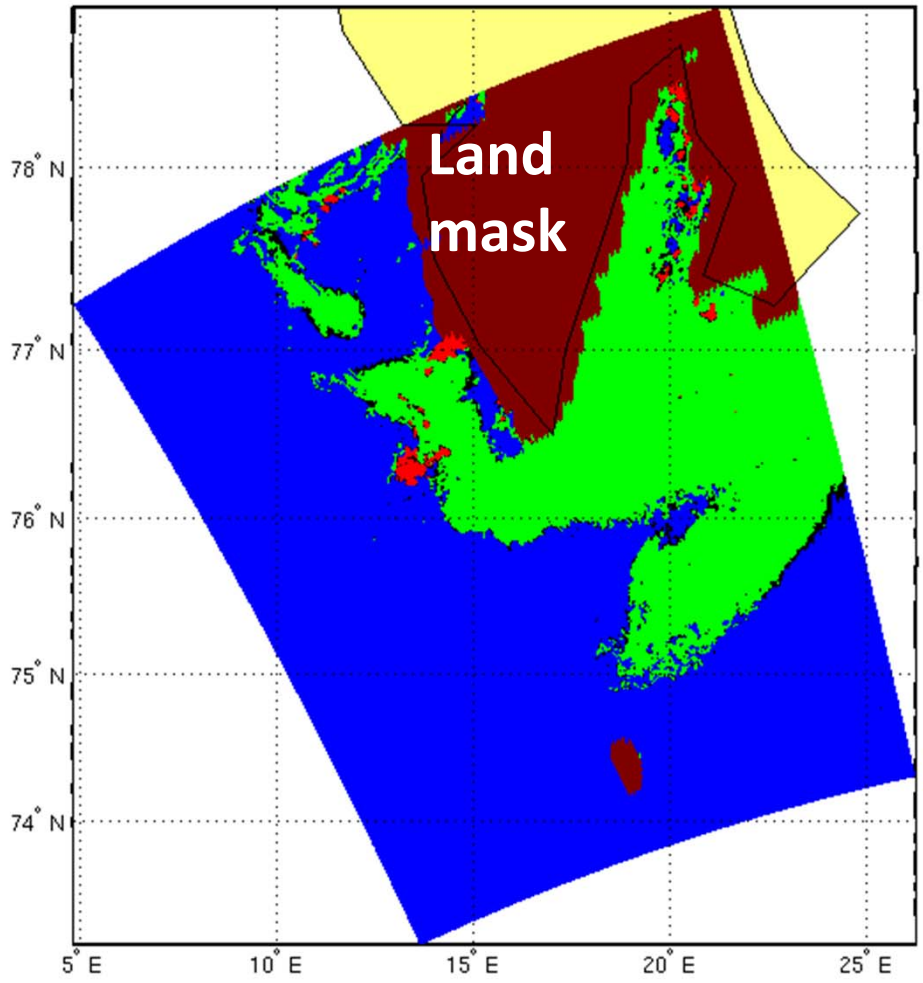


ENVISAT ASAR subimage

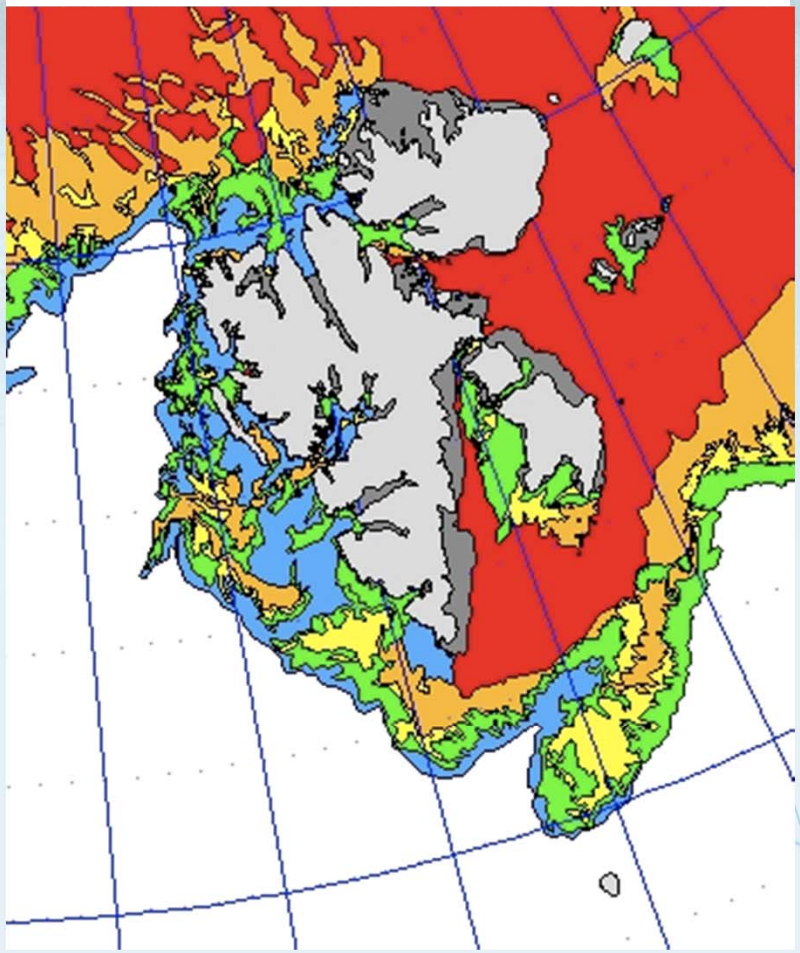


# NN-classification of ice-water using AMSR-E open ocean mask

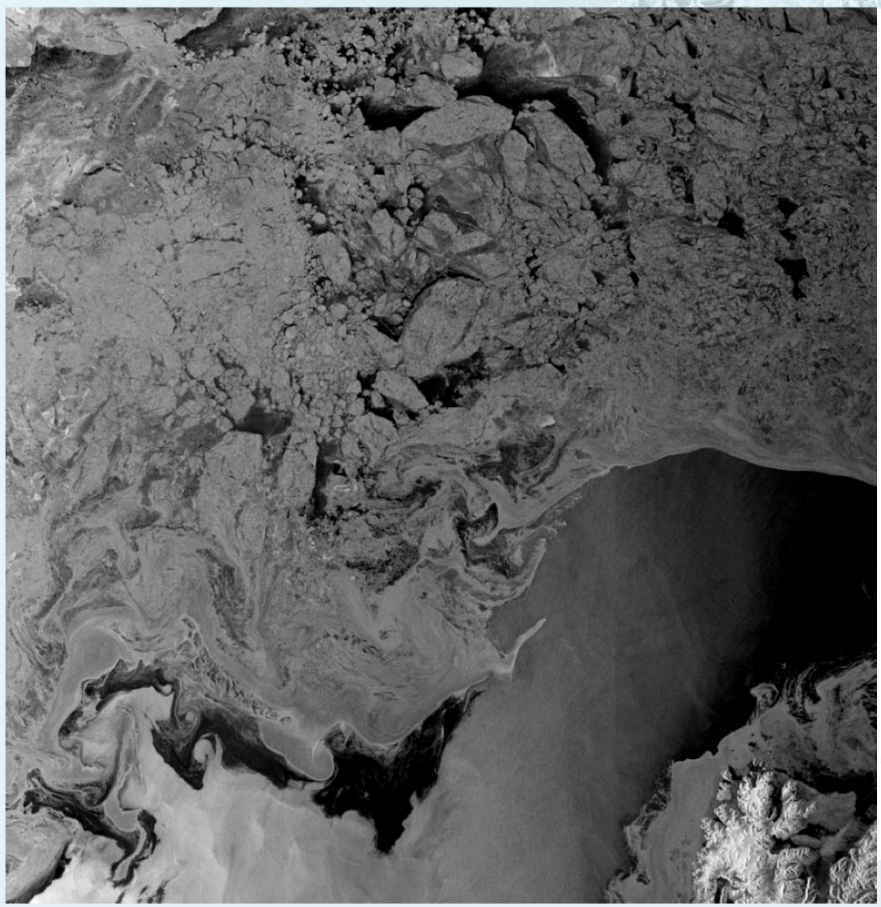
Classification result (red: unclassified)

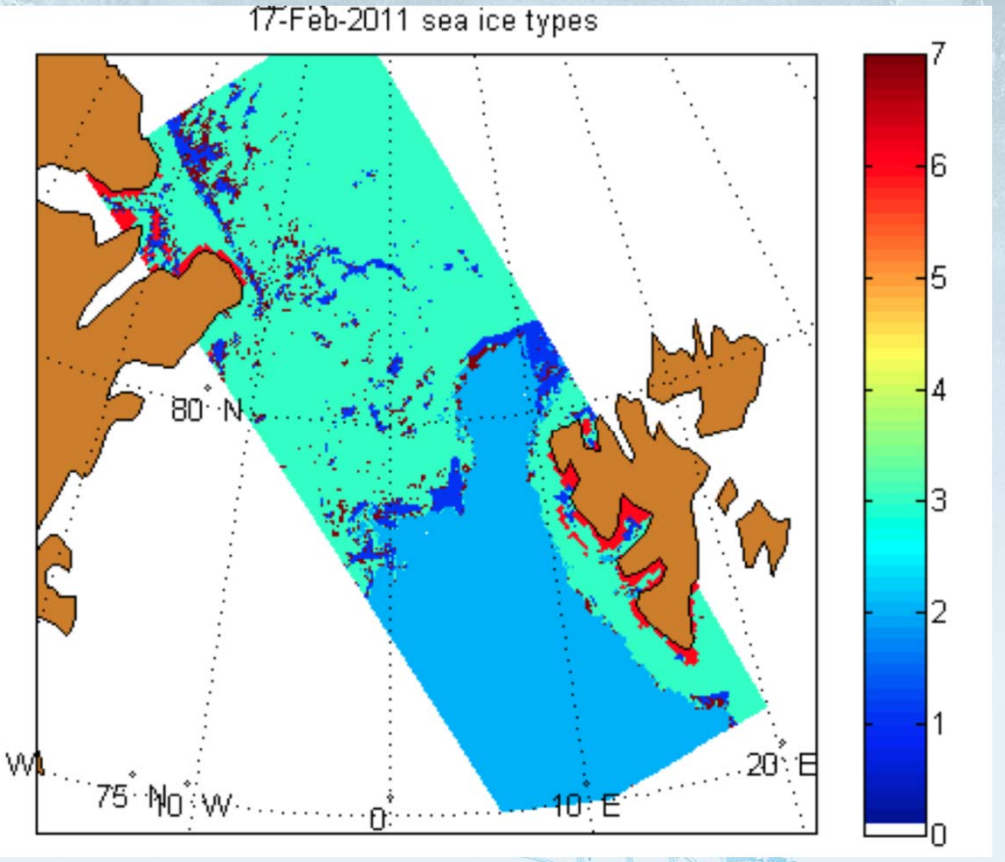



Comparison with regional ice chart



# Validation of ice – ocean discrimination in the MIZ



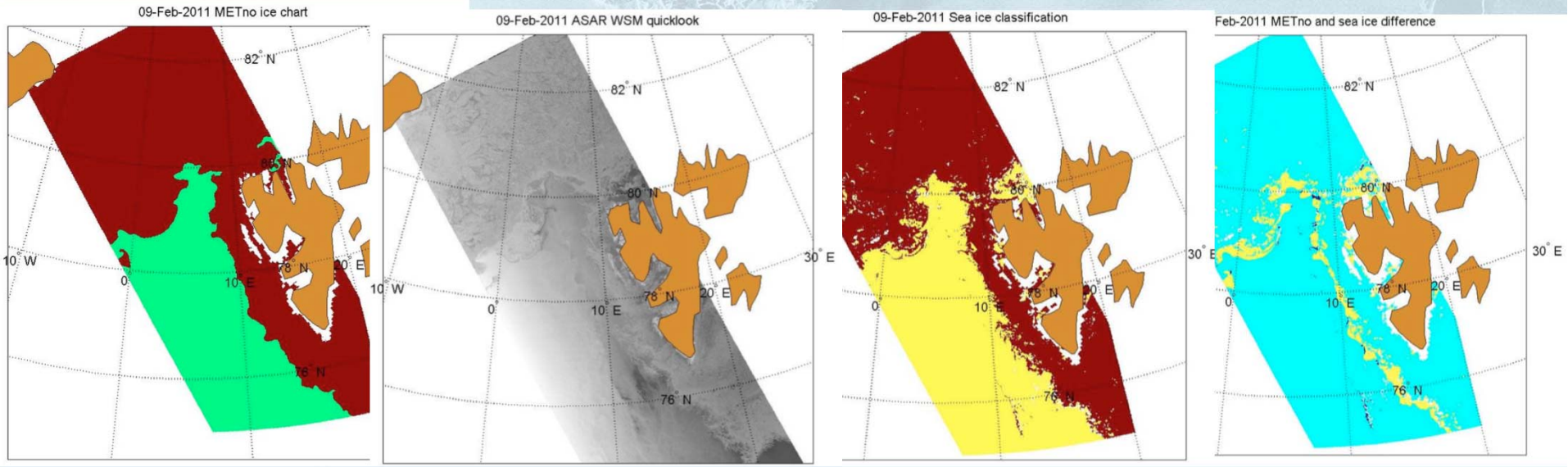



Dark blue: open water, grease ice, nilas
Light blue: open water
Light green: sea ice
Red: unclassified

# Validation of ice-water discrimination against ice charts

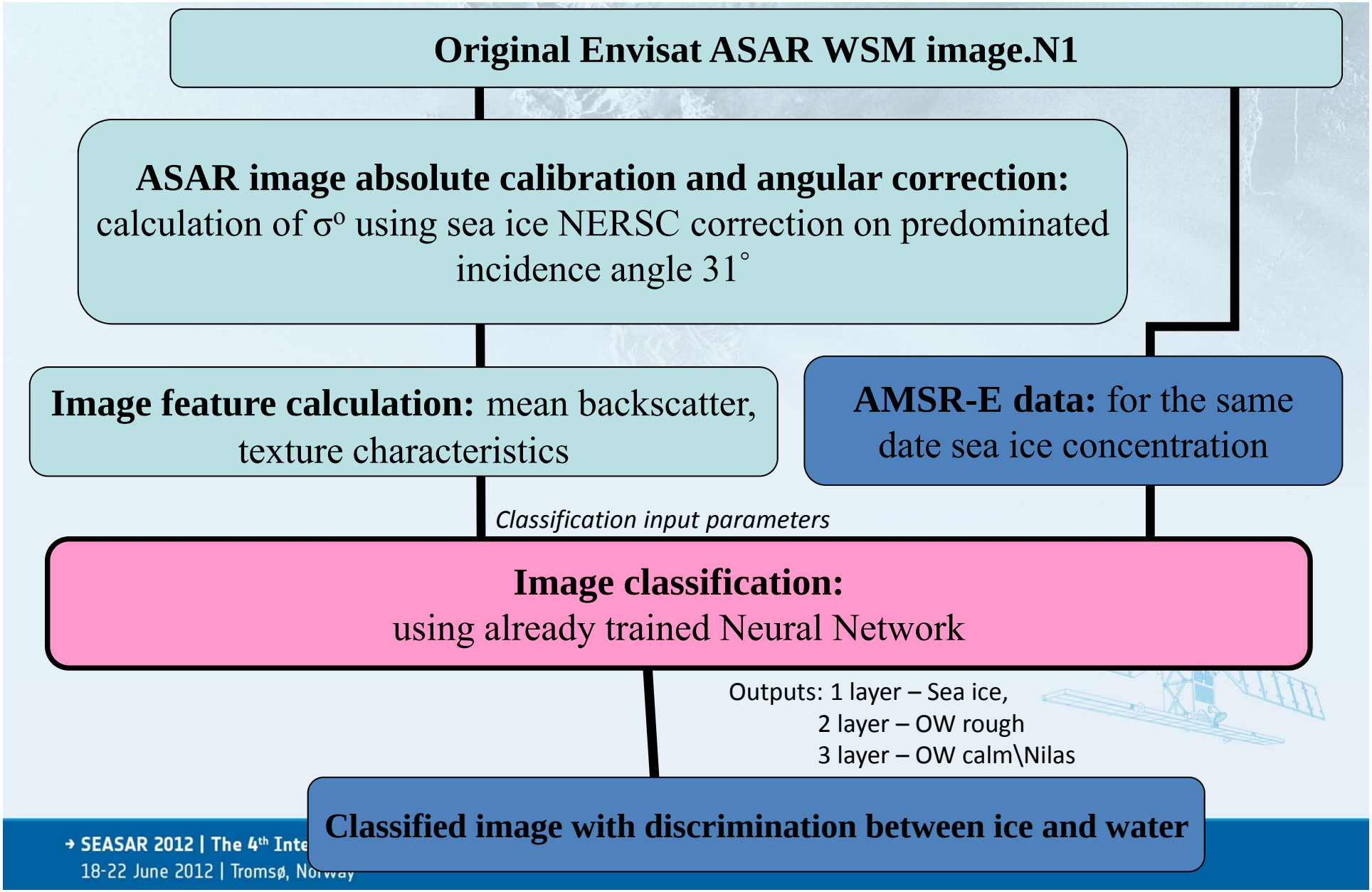
09 February 2011

Ice chart from met.no | SAR image | SAR ice-water discrimination | Difference

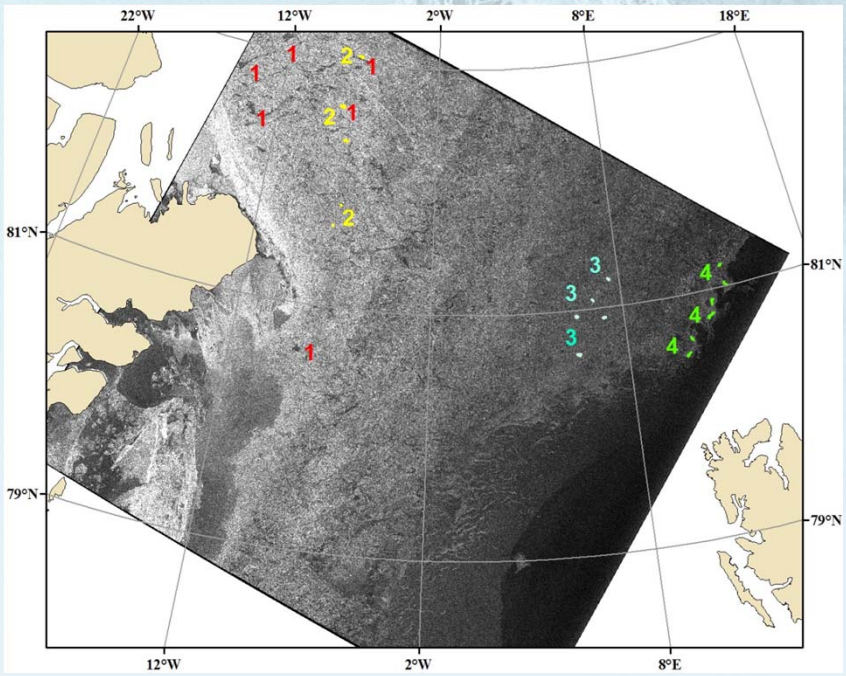


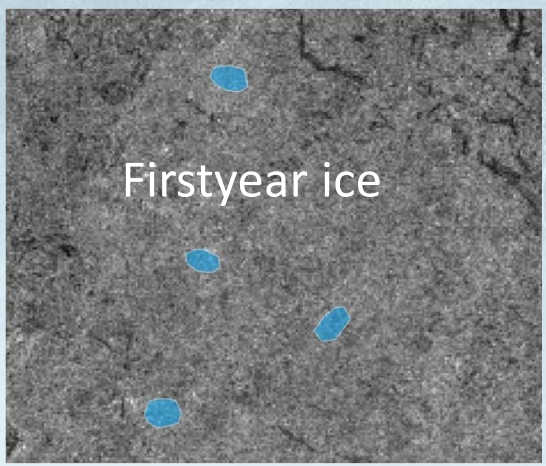

| | | |
|---|---|---|
| **MET.no ice chart**<br>**Brown: sea ice (concentration values from 15 to 100 %)**<br>**Green: OW (concentration from 0 to 15%)**<br>**White: outside the SAR coverage or the test area** | **Neural net classification result:**<br>**Brown: sea ice**<br>**Yellow: OW** | **Validation:**<br>**light blue: no difference (zero)**<br>**dark blue: OW in ice chart, sea Ice in NN**<br>**Yellow: Sea Ice in ice chart , OW in NN** |

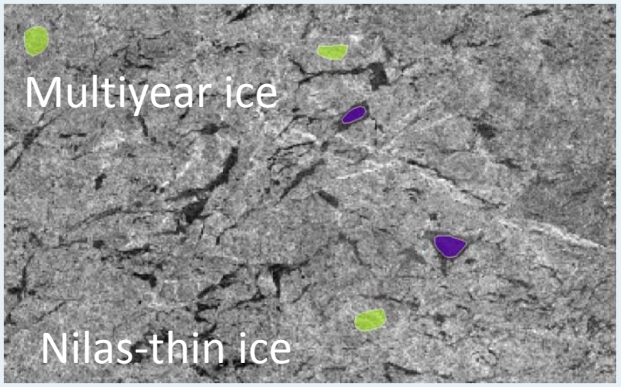
# The processing algorithm for sea ice/open water for discrimination

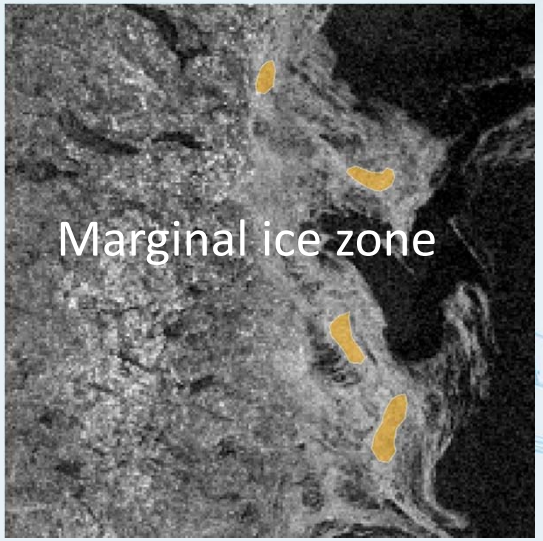


# Classification of Radarsat-2 dual-pol images for the Fram Strait (23 February 2012 Image)

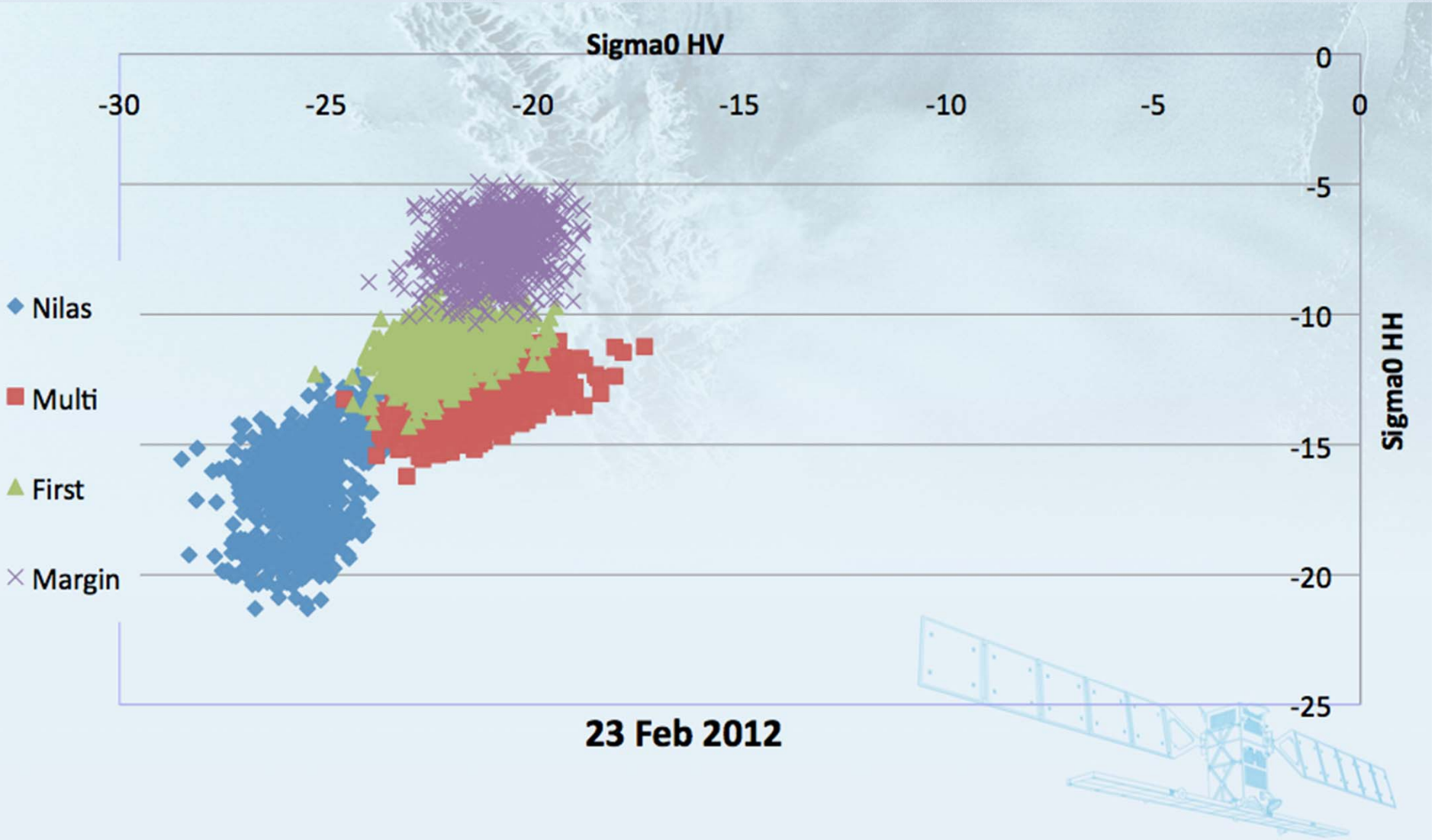


# Sigma-0 for four ice types in the Radatsat dual-pol image
(23 February 2012 Image)



# Concluding remarks

- The purpose of sea ice classification needs to be defined. Different users have different needs
- Neural Network classification can be adapted to specific ice conditions by improved training and be applied to complex ice conditions
- Bayesian classification is simpler, but fully adequate when ice conditions are not too complicated
- Validation is always a bottleneck, improvements depends on access to relevant non-satellite data
- Use of dual-pol SAR data will in principle improve ice classification, but systematic studies are needed to improve algorithms
- Automated processing and retrieval systems are needed to be able to utilize the quantities of SAR data available for sea ice monitoring and other applications