Arctic Sea Ice Recognition Based on CFOSAT SWIM Data at Multiple Small Incidence Angles

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Sea ice plays an important role in global climate change, shipping, navigation and the extraction of natural resources, and influences the detection of other ocean phenomena; for example, sea wave retrieval requires the removal of sea ice 'pollution'. The Surface Wave Investigation and Monitoring instrument (SWIM) on the China-France Oceanography Satellite (CFOSAT) is a new type of sensor with a small incidence angle detection mode that is different from traditional remote sensors. Sea ice monitoring at small incidence angles has rarely been studied. Therefore, this research focuses on sea ice monitoring in the Arctic based on SWIM data from October 2019 to April 2021. Sea ice type is the key parameter of Arctic Sea ice monitoring.

Data

1. SWIM

The Chinese-French Oceanic Satellite (CFOSAT) was successfully launched on October 29, 2018, which was developed by CNSA and CNES.

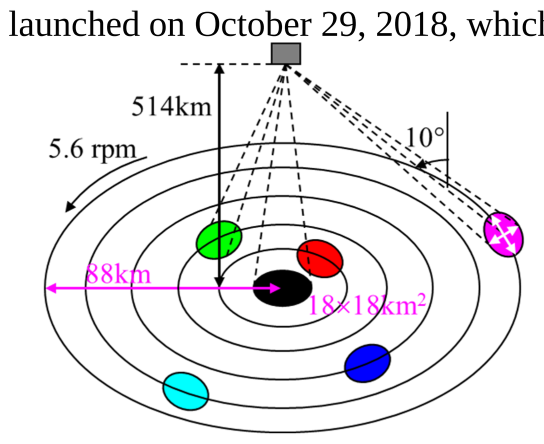
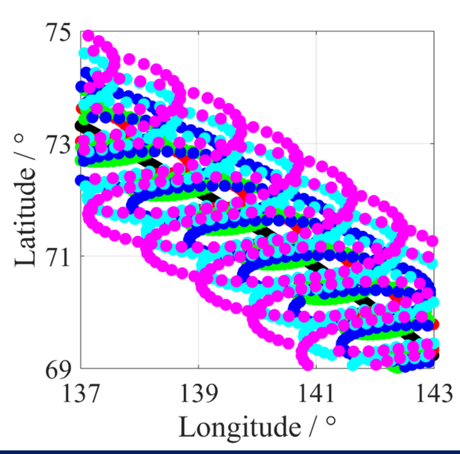


Fig.1 SWIM detection schematics for six incidence beams.



2. AARI (Arctic and Antarctic Research Institute)

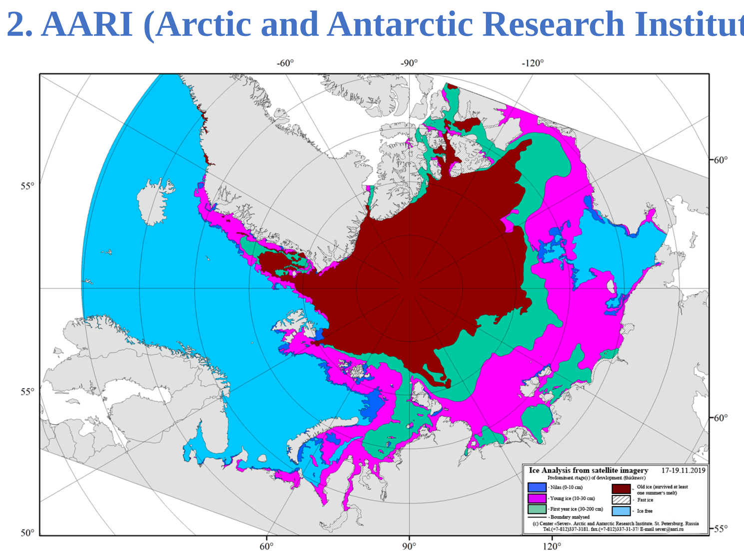


Fig.2 AARI products

3. NSIDC (National Snow and Ice Data Center)

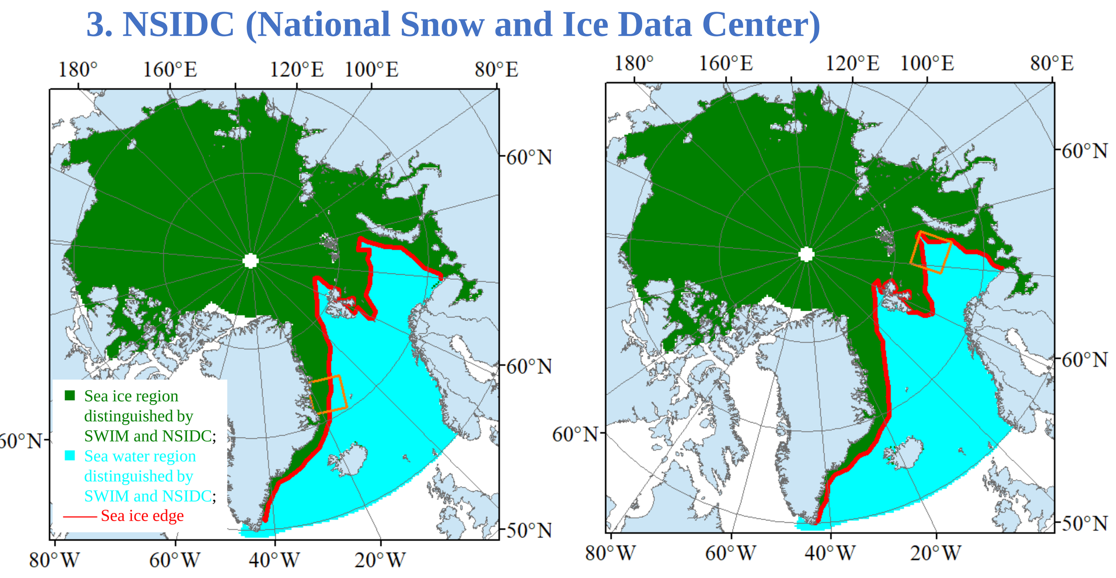


Fig.3 NSIDC products

4. Sentinal-1

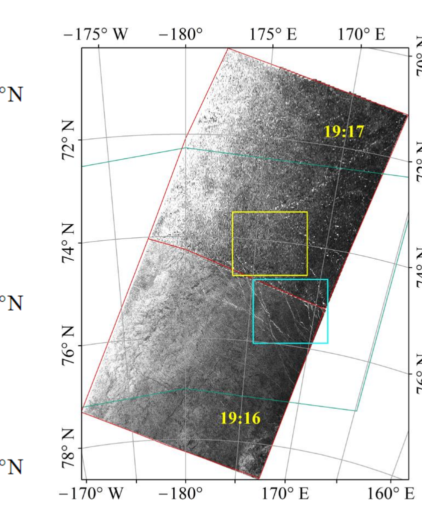


Fig.4 Sentinel-1 SAR image

Methods and Results

Sea ice classification

1. Extraction of SWIM Waveform Features

- MAX $P_{max_\theta} = max(P_{i_\theta})$
- BSP $BSP_\theta = \sqrt{\frac{\sum_{i=1}^{n_\theta} P_{i_\theta}^4}{\sum_{i=1}^{n_\theta} P_{i_\theta}^2}}, \theta = 0°$ $BSP_\theta = \frac{\sum_{i=1}^{n_\theta} P_{i_\theta}}{n_\theta}, \theta = 2° \sim 10°$
- PP $PP_\theta = \frac{P_{max_\theta}}{\sum_{i=1}^{n_\theta} P_{i_\theta}} \times n_\theta$
- SSD $SSD_\theta = \sqrt{\frac{\sum_{i=1}^{n_\theta} (P_{i_\theta} - \bar{P}_\theta)^2}{n_\theta}}$
- LEW $A_{1\theta} = P_{max_\theta} \cdot 0.95, A_{2\theta} = P_{max_\theta} \cdot 0.05, LEW = Bin(A_{1\theta}) - Bin(A_{2\theta})$
- TEW $A_{1\theta} = P_{max_\theta} \cdot 0.05, A_{2\theta} = P_{max_\theta} \cdot 0.95, TEW = Bin(A_{1\theta}) - Bin(A_{2\theta})$

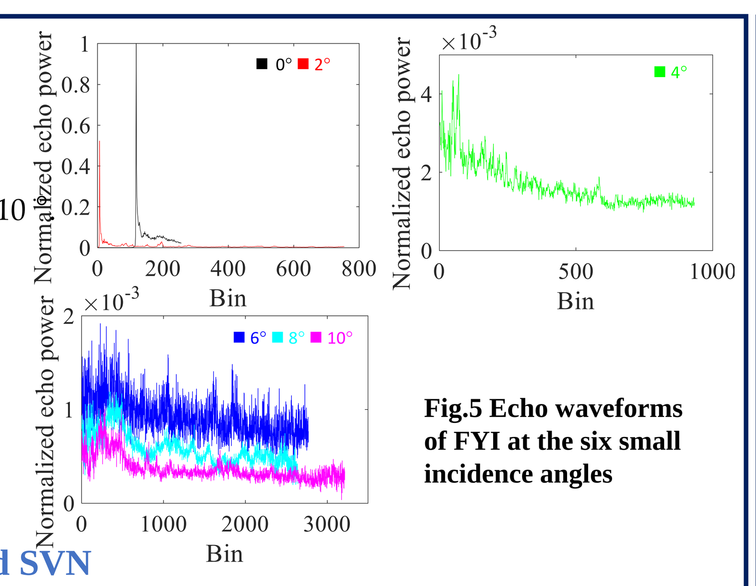


Fig.5 Echo waveforms of FYI at the six small incidence angles

2. Kolmogorov-Smirnov distance

The K-S distance is defined as: $D = \max|S_2(x) - S_1(x)|$,

It can have values between 0 and 1, which can be divided into four levels. The values of $0.5 \leq D < 0.7$ represent some discrimination capability for the corresponding waveform feature; values of $0.7 \leq D < 0.9$ mean good separability, values greater than or equal to 0.9 express very good separability, and values less than 0.5 express little separability.

3. KNN and SVN

Classification methods using KNN and SVM are tested with different settings. The KNN method is chosen to distinguish sea ice types and sea water based on multifeature combinations. The KNN setting includes the Euclidean distance and k equal to 11. Multifeature combinations at small incidence angles with the KNN method are studied for sea ice classification. The highest overall accuracy is up to 81% at 2°.

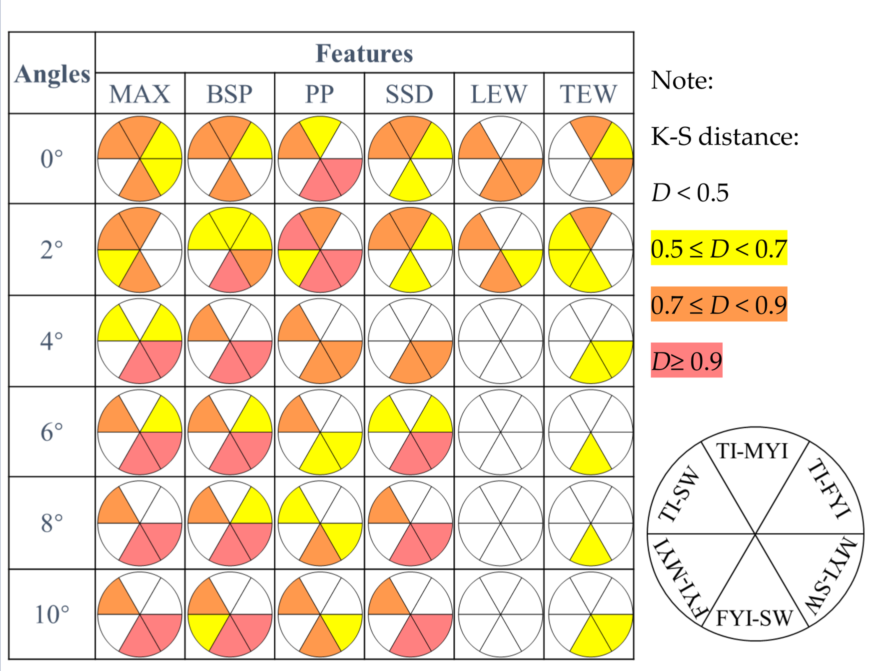
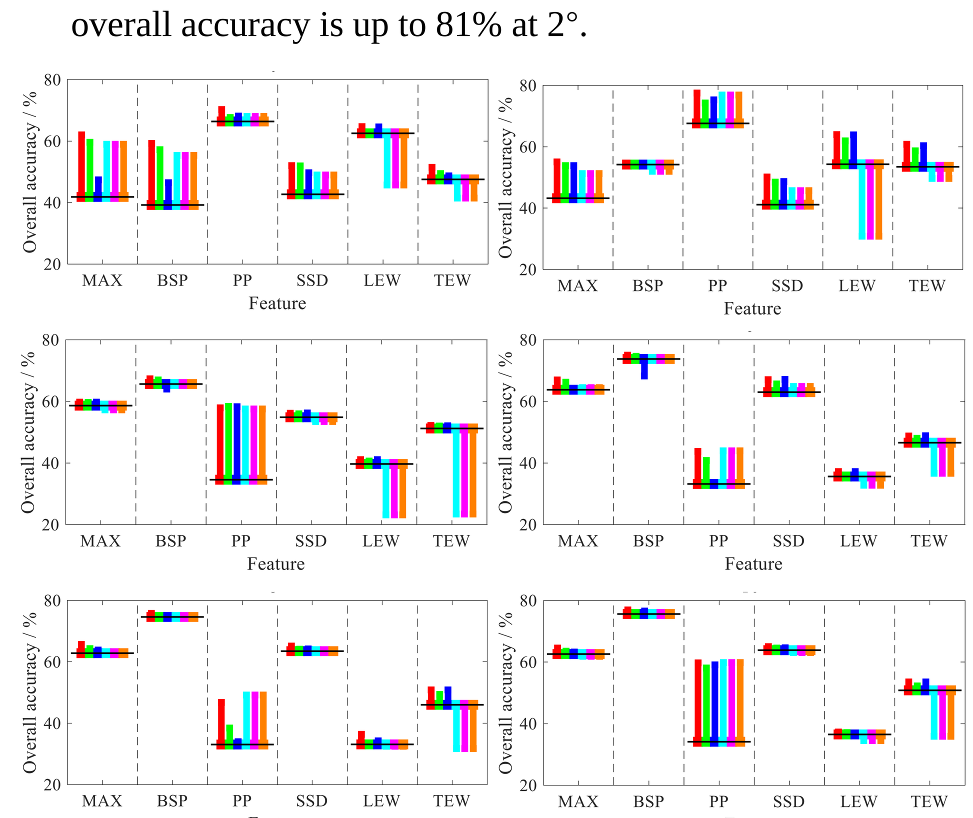


Fig.6 K-S distances between sea ice types and sea water using single features



— Linear, ■ Gaussian, ■ Polynomial (q = 2), ■ Polynomial (q = 3), ■ Euclidean, ■ Manhattan, ■ Mahalanobis.

Fig.7 Overall accuracies of single features of KNN and SVM settings

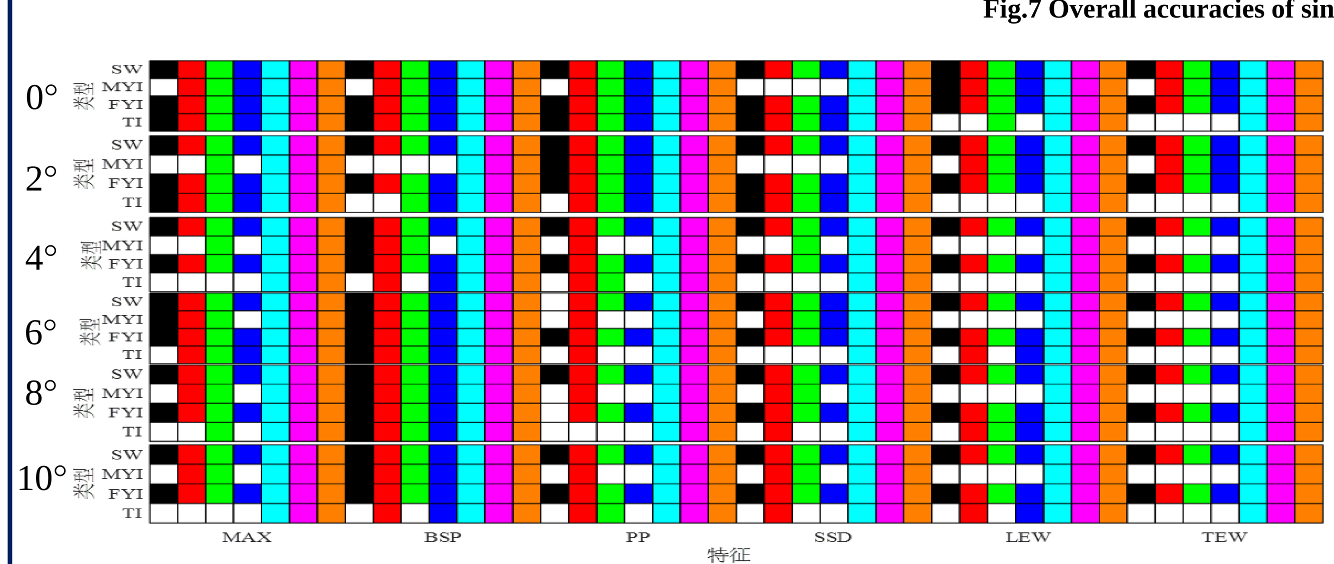


Fig.8 Recognition rates of a single feature of the KNN and SVM settings

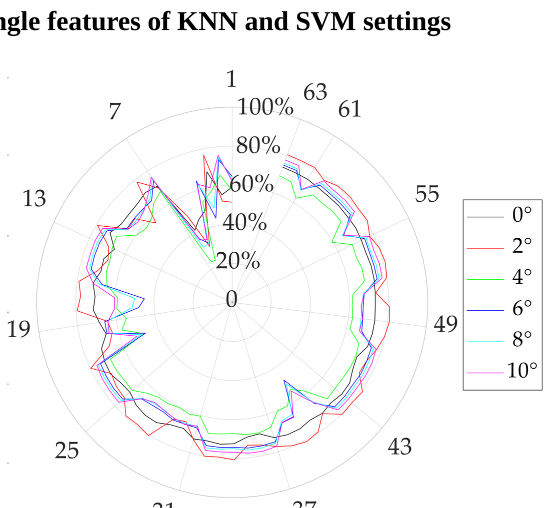


Fig.9 Overall accuracies of multifeature combinations

Sea ice and sea water recognition

1. Extraction of SWIM Waveform Features

In the discussion of the previous study, we add six features to recognize sea ice and sea water. MED is the medium of power.

- MED $MED_\theta = medium(P_{i_\theta})$
- MEA $MEA_\theta = \frac{\sum_{i_\theta=1}^{n_\theta} P_{i_\theta}}{n_\theta}$
- OCOG $OCOG_\theta = \sqrt{\frac{\sum_{i_\theta=1}^{n_\theta} P_{i_\theta}^4}{\sum_{i_\theta=1}^{n_\theta} P_{i_\theta}^2}}$
- IMP $IMP = \frac{n_\theta}{\sum_{i_\theta=1}^{n_\theta} P_{i_\theta}} \cdot 2 \cdot 10^{-13}$
- LES $LES_\theta = \frac{MAX_\theta}{LEW_\theta}$
- TES $TES_\theta = \frac{MAX_\theta}{TEW_\theta}$

MIMs of feature pairs larger than 0.65

Angle	0°	2°	4°	6°	8°	10°
Feature pair	{OCOG – MAX} {SSD – MAX} {SSD – OCOG}	{OCOG – MAX} {SSD – MAX} {SSD – OCOG}	{OCOG – MAX} {MEA – MED}	{OCOG – MAX} {MEA – MED}	{MEA – MED}	{MEA – MED}

CPD and MIM are applied to analyze SWIM waveforms using the eleven features at six small incidence angles.

Cumulative probability distribution (CPD) illustrates the distribution ranges and probabilities of feature values for sea ice and sea water at six incidence angles. The CPDs reveal that the distributions of the features at 0–10° for sea ice and sea water are different.

Mutual information measures (MIM) the mutual dependence of two discrete random variables. Eleven features can be used to establish 66 feature pairs. Larger MIMs of feature pairs imply higher redundancy or relevance, and MIMs larger than 0.65 indicate strong correlations.

CPDs of the features obviously different between sea ice and sea water

Angle	0°	2°	4°	6°	8°	10°
Feature	PP	PP	MED	MED	MED	MED
	LEW	LEW	MEA	MEA	MEA	MEA

2. Optimal classier-feature assembly

Based on our previous study focused on sea ice type classification, the optimal classifier is selected, that is the KNN classifier with Euclidean distance and k = 11. The eleven features can construct 2047 feature combinations at each incidence angle. These feature combinations are input to the optimal classifier, then their F1 scores and overall accuracies are shown in Fig.10. The highest overall accuracy reaches 97.1%.

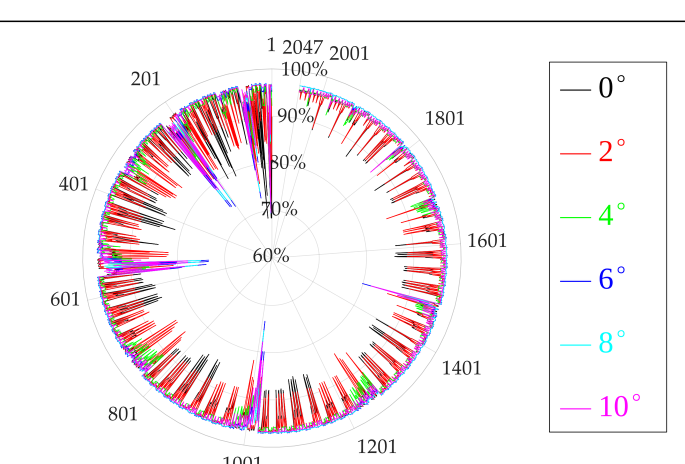


Fig.10 Overall accuracies

3. Application analysis of optimal classer-feature assembly

- ***Sea ice recognition accuracies in three stages of sea ice development***

The Arctic ice year were expressed three stages of sea ice development. The overall accuracies of sea ice recognition using the optimal classier–feature assemblies in Stages 1–3 are higher than 90%. Sea ice development obviously affects the accuracy of the proposed approach. The invariant distribution of sea ice contributes to high overall accuracy. As a result, the optimal classifier–feature assembly can be used to provide sea ice recognition results with high accuracy, and sea ice can then be removed from SWIM sea wave products. Moreover, SWIM can be a valid data source for operational sea ice monitoring.

- ***Sea ice edge extraction***

According to the sea ice recognition results based on SWIM data, sea ice extents and edges can be extracted and compared with Sentinel-1 SAR images and NSIDC sea ice products. SWIM sea ice extents are consistent with those of NSIDC sea ice products at a high level of precision (the highest is up to 98.2%). And, SWIM provides a good one-day product of sea ice edges.

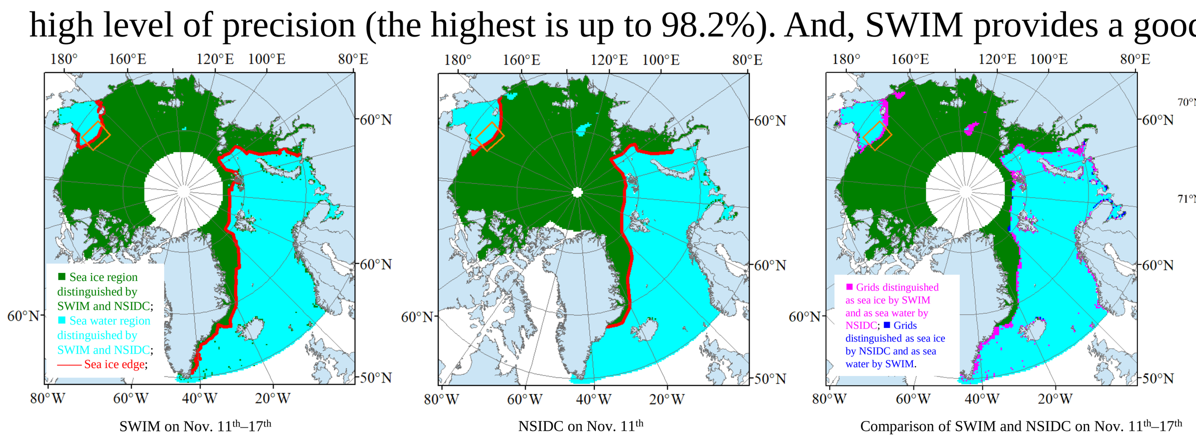


Fig.11 Comparison of sea ice extents and edges between SWIM and NSIDC.

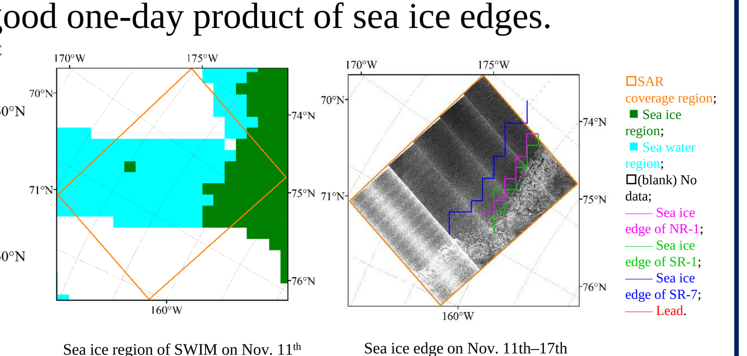


Fig.12 Sea ice edges based on SWIM and NSIDC data with synchronous sentinel-1 SAR images

Conclusion

For the new detection mode of SWIM, our research focuses on sea ice classification an recognition, classifier selection and setting, analysis of multifeature combinations, and application of the optimal classier–feature assemblies. Sea ice classification results based on multifeature combinations at small incidence angles with the KNN method(the Euclidean distance and k equal to 11) show that the highest overall accuracy is up to 81% at 2°, and the lowest is approximately 70% at 4°. The top multifeature combinations with the KNN method are applied for sea ice classification in the local regions, and the results are analyzed and compared with Sentinel-1 SAR images. It is concluded that optimal multifeature combinations with the KNN method are effective in sea ice classification. Further more, we develop a method to distinguish between sea ice and sea water. Six features are added, then the different feature combinations are input the same optimal-classifier. The results illustrate that the highest overall accuracy at each incidence angle is greater than 96% and can reach 97.1%. Sea ice and sea water can be effectively distinguished using the optimal feature assemblies, thus meeting the requirements for SWIM-based sea wave retrieval. Consequently, sea ice extents and edges can be extracted from these SWIM results with high accuracy, which can provide new data for operational sea ice monitoring.