





Synergistic Monitoring of Sea Ice from Multi-sensors (ID: 57889)

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Outline

- I. Introduction
- II. Main results
- **III.Cooperation**
- **IV.Young scientists and Publications V.Next planning**





I. Introduction

Objective

Upgrade and develop methodologies to retrieve quantitative sea ice information including measurements of thickness, drift, concentration, and detection of icebergs. > Satellite data: Sentinels, ALOS-1/2, SMOS, CryoSAT-2, CFOSAT; HY-2, GF series

Arctic, Antarctic and regional sites with seasonal ice cover

Dragon-2 5290	Dragon-3 10501	Dragon-4 32292,Part I	Dragon-5 57889
Only SAR Types	SAR + Optical Types, thickness, drift	Altimeter + SAR Thickness, deformation/drift	Multiple data More ice parameters
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Team Composition

European Partners

- Prof. Dr. Wolfgang Dierking (PI) University in Tromsø, Norway; Alfred Wegener Institute Helmholtz Center for Polar and Marine Research, Germany.
- Dr. Marko Mäkynen and Dr. Juha Karvonen Finnish Meteorological Institute, Finland
- Dr. Rasmus Tonboe Technical University of Denmark, Denmark

Chinese Partners

- Dr. Xi Zhang (PI) First Institute of Oceanography, Ministry of Natural Resources
- Dr. Li-jian Shi, Tao Zeng and Qian Feng National Satellite Ocean Application Service
- Dr. Jie Liu and Zhi Yuan Institute of Spacecraft System Engineering, China Academy of Space Technology
- Dr. Xiao-yi Shen Nanjing University
- Dr. Zhen-yu Liu South-Central Minzu University
- Dr. Mei-jie Liu Qingdao University







II. Main Results

- 1. Sea ice classification with multi-frequency SAR data during freezing and melting period
- 2. Sea ice surface and bottom morphology observation with SAR data
- 3. Sea ice drift detection with FY-3D microwave radiometer data
- 4. Snow depth retrieval over sea ice using microwave radiometer data
- 5. Analysis of decadal changes of ice in the Bohai Sea with GOCI data





1. Sea ice classification during melting period with SAR data

Objective

- > Current studies primarily focus on SAR sea ice classification during the freezing-up period
- > Surface meltwater can affect the identification of sea ice types.
- > The use of SAR for type identification during melting ice may be a problem.





Assessment of sea ice classification capabilities during melting period using airborne multi-frequency PoISAR data.





- Airborne Multi-frequency PolSAR data
- > Time(UTC): 2022-02-27 06:22:54
- Frequency: L/S/C
- Resoultion: 1/1/0.5 m
- Flight altitude: 4710 m
- Incidence angle: 31°~34°
- > Temperatures: 6~10°C
- > Wind speed: 3~8 m/s













Sentinel-2 MSI data

121°56'0"E 122°0'0"E



121°56'0"E 122°0'0"E UC Time: 2022-02-27 02:36:39 4-hour ahead of SAR data Visual interpretation







Method

The sea ice type discrimination ability of 51 polarization features in 3 bands was evaluated

The target	Freeman-Durden decomposition	Surface Scattering (P_S) , Double Bounce Scattering (P_D) , Volume Scattering (P_V)			
decomposition based scattering model	Yamaguchi decomposition	Surface Scattering (P_S) , Double Bounce Scattering (P_D) , Volume Scattering (P_V) , Helix Scattering (P_h)			
$H/A/\overline{lpha}$ decomposition	Eigenvalue(λ_1, λ_2 scattering en Anisotropy(λ_1, λ_2 Single bounce Double bounce Polarization fractio vegetation in approximation ($\overline{\alpha}$) Covariance f	, λ_3), Eigenvector (P_1 , P_2 , P_3), Polarization ntropy(H), Eigen component (β , δ , γ), 4, A_{12}), Shannon entropy(SE , SE_P , SE_I), e eigenvalues relative difference($SERD$), e eigenvalues relative difference($DERD$), on (PF), Polarimetric asymmetry (PA), Radar dex (RVI), Pedestal height (PH), Alpha), Consistency correlation coefficient(CCC), matrix diagonal elements (C_{11} , C_{22} , C_{33})			
Other parameters	Span o Polarizatio	of coherency matrix T3(Span), on correlation coefficient($\rho_{12}, \rho_{13}, \rho_{23}$)			

Separability Index

Euclidean distance

$$D = \frac{|m_1 - m_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}}$$

K-S distance

$$\mathbf{d}_{n} = \mathbf{d}_{\kappa}(\mathbf{F}_{n}, \mathbf{F}_{0}) = \sup_{\mathbf{x}} \left| \mathbf{F}_{n}(\mathbf{x}) - \mathbf{F}_{0}(\mathbf{x}) \right|$$
$$= \max_{i} \left(\max(\mathbf{F}_{0}(\mathbf{x}_{(i)}) - \frac{i-1}{n}, \frac{i}{n} - \mathbf{F}_{0}(\mathbf{x}_{(i)}) \right)$$





L-band

											1
	OW-Gi	OW-GiW	OW-Gw	OW-GwW	Gi-GiW	Gi-Gw	Gi-GwW	GiW-Gw	GiW-GwW	Gw-GwW	Ice Type
SE	0.26	1.54	3. 57	2.88	1.79	3.26	2. 53	5. 42	5.06	1.16	2.75
SE_I	0. 33	0.84	2. 39	1.77	1.35	2. 42	1.74	3.75	3. 28	1.11	1.90
Span	0. 28	0.78	2.09	1.61	1.17	2.00	1.49	3.13	2.80	0.84	1.62
ā	0. 61	0.64	2.06	1.05	1.80	1.87	0.68	3.63	1.80	0.65	1.48
λ_2	0.13	1.07	1.58	1.81	1.17	1.56	1.78	1.66	2.02	0.72	1.35
Н	0. 26	0.60	1.47	1.27	0.44	2.15	1.93	2.62	2.42	0.28	1.34
λ3	0. 24	1.42	1.55	1.57	1.04	1.54	1.50	1.60	1.72	1.04	1. 32
SE_P	0. 24	0.56	1. 51	1.26	0.38	2. 11	1.83	2. 42	2.16	0. 39	1. 29
α_{l}	0.65	0.47	2.07	0.82	1.75	1.82	0.50	2.87	1.18	0.71	1.29
λ_I	0.17	0.64	1.52	1.24	1.05	1.49	1.21	1.81	2.17	0.93	1. 22
P _{V_FREEMAN}	0.16	1.24	1.42	1.32	1.05	1.44	1.36	1.49	1.58	1.01	1.21
p1	0. 29	0.58	1.27	1.13	0. 45	1.93	1.77	2.30	2.14	0.14	1.20



SE: ED=2.75

Clear differences between sea ice types

RVI: ED=1.10

OW and Gi are easily confused

- > Shannon entropy has the highest ice type discrimination ability.
- > Good discrimination ability among sea ice types.
- Poor discrimination in OW-Gi separation and Gw-GwW separation.





S-band

[OW-Gi	OW-GiW	OW-Gw	OW-GwW	Gi-GiW	Gi-Gw	Gi-GwW	GiW-Gw	GiW-GwW	Gw-GwW	Ice Type
SE	1.80	2.49	3. 25	4. 27	0.94	1.96	3. 24	1.07	2. 12	0. 79	2. 19
SE	1.38	2.29	2.96	4.00	1.22	2.07	3. 48	0. 81	1. 92	0. 99	2. 11
Span	1.67	2.35	2. 98	3.95	0.84	1.69	2.77	0. 92	1. 85	0. 69	1.97
Pv_freeman	1.49	2.19	1.95	2.95	1.03	1.49	2.48	1.01	1.96	0.72	1.73
λ_1	1.77	2.18	1.83	2.63	0.72	1.34	2.12	1.05	1.79	0. 52	1. 59
λ_2	1. 22	1.81	1.96	2.72	0.89	1.48	2.30	0. 93	1.79	0.80	1. 59
λ	1.78	2. 21	1.82	2.63	0.67	1.33	2.09	1.06	1.79	0.50	1. 59
$P_{V_Yamaguchi}$	1.18	1.67	1.73	2. 43	0.68	1.38	2.04	1.08	1.71	0. 43	1. 43
λ_3	0. 21	1.56	1. 32	2. 51	1.53	1.27	2.50	0. 18	1.38	1.07	1. 35



perform similarly

SE₁: ED=2.19

Except for Gw-GwW, other sea ice types vary significantly

β: ED=0.83

OW and GI

- Intensity component of shannon entropy has the highest ice type discrimination ability.
- Good discrimination ability between OW and sea ice.
- > Poor discrimination in GiW-Gw separation and Gw-GwW separation.





C-band

	OW-Gi	OW-GiW	OW-Gw	OW-GwW	Gi-GiW	Gi-Gw	Gi-GwW	GiW-Gw	GiW-GwW	Gw-GwW	Ice Type
SE	3.96	4. 39	4.46	6.67	0. 42	0.86	3. 18	0.52	2.88	1.87	2.92
SE	4.14	4. 81	4.28	6.90	0.60	0.68	3.00	0.20	2.56	1.73	2.89
Span	3. 92	4. 54	4.05	6. 42	0.55	0.63	2.68	0.18	2.25	1.58	2.68
λ_3	1.76	1.76	1.73	2.40	0.22	0.95	2.06	0.80	1.99	1.51	1.52
Pv_freeman	1.69	1.72	1.69	2.37	0.30	0.90	2.01	0.67	1.90	1.47	1.47
α	1.18	0.19	2.23	2.10	1.24	1.42	1.17	2. 41	2.36	0. 42	1.47
λ_2	1.66	1.87	1.23	2.67	0.21	0.62	2. 23	0.51	2.15	1.55	1.47
$P_{V_Yamaguchi}$	1.59	1.67	1.70	2.17	0.21	0. 91	1.85	0.75	1.79	1.38	1.40
λ_1	1.74	2.28	0.89	2.64	0.63	0. 38	2.02	0.12	1.70	1.14	1.35
λ	1.72	2.27	0.86	2.65	0.65	0. 38	2.04	0.11	1.70	1.12	1.35
α1	0.84	0.00	2.30	1.51	0.92	1.70	1.00	2.40	1.56	0. 44	1.27
C ₂₂	1.49	1.58	1.39	1.83	0.25	0.75	1.56	0.60	1.49	1.14	1.21



and sea ice

PF: ED=0.55

SE: ED=2.92

Clear contrast between OW

Almost indistinguishable between sea ice types.

- > Shannon entropy has the highest ice type discrimination ability.
- Good discrimination ability between OW and sea ice.
- Poor discrimination in Gi-GiW separation and Gi-Gw separation.





Sea ice classification based on multi-band and multi-polarization features

- Extracting polarization features using multiple polarization decomposition methods
- Constructing a feature set based on separability index.
- Combining recursive feature elimination with various classifiers to discuss and obtain the optimal feature set.









Proposed method

	•							
	OW	Gi	Giw	Gw	GwW			
ow	5250176	6199	7009	2526	10			
Gi	31086	956218	78045	30439	27974			
Giw	15138	37394	1104166	0	43807			
Gw	2982	38471	0	787046	4309			
GwW	48	6423	924	94268	475342			
Uers acc	99.70	85.09	91.98	94.51	82.38			
Overall acc/Kappa	95.26%/0.9222							



PCNN

	OW	Gi	Giw	Gw	GwW			
ow	5255513	9649	10555	1045	10			
Gi	28226	871390	103412	38002	21304			
Giw	412	75157	1074227	7	81564			
Gw	15815	76717	29	746596	34223			
GwW	94	11792	1921	128629	414341			
Uers acc	99.60%	82.03%	87.24%	85.55%	74.42%			
Overall acc/Kappa	92.91%/0.8837							





Operational sea ice mapping combining C- and L-band SAR imagery

- European ice services, Canadian ice service, and International Ice Patrol judged the gain of using L-band SAR images in addition to C-band data (ESA-funded project supported by JAXA and the International Ice Charting Working Group)
- > Automatic classification of combined C- and L-band data were tested.
- > Alignment of L- and C-band images acquired at different times was investigated.
- Gain of using L-band in addition:
- + earlier detection of fractures and of fast ice breakup
- + easier first-year / multi-year ice discrimination during the melt season
- + better discrimination of thin and thick ice
- + L-band is less sensitive to wind and sea state (=> iceberg detection)
- + Icebergs inside sea ice are easier to detect





- 2. Sea ice surface and bottom morphology observation with SAR data
 Objective
 - > Does a correlation exist between sea ice surface deformation and bottom morphology?
 - > Is it possible to use SAR to invert sea ice surface deformation?
 - > Can SAR backscattering be correlated with the bottom morphology of ice?



Answering the above questions is very useful for sea ice thickness retrieval from SAR.





Data

- Test site: Labrador coast
- > Time: 19–20 March 2011
- In situ: Airborne HEM data
- SAR: RADARSAT-2 Quad-Pol data



RADARSAT-2 PolSAR data were acquired nearly coincident with the airborne survey flights, with a maximum time difference of 4 hours.





Airborne HEM data can provide sea ice surface and bottom morphology

HEM	Data	Accuracy		───► Primary magnetic field
Laser altimeter	Height of the snow surface	±1.5 cm		Secondary magnetic field
		±1.5 cm		Laser altimeter
Ground-penetrating radar	Snow depth	±5cm	Transmitter coil	Receiver coil
Ice-plus-snow thicl	kness = EM - Laser			
Sea-ice thickness	= EM - Laser – GPR			
> Surface Morpholog	gy extracting from Lase	er		Eddy currents
Bottom Morpholog	y extracting from EM			Ice Sea water





The parameters of surface and bottom morphology

Seven parameters are employed to describe both surface and bottom deformation

 $\sigma_{h} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(h_{i} - \bar{h}\right)^{2}} \qquad \sigma_{r} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n-1} (S_{i} - \bar{S})^{2}}$ (1) Root-mean-square height (σ_h) 2 Height skewness (h_{sk}) $h_{sk} = \frac{1}{n\sigma_{sk}} \sum_{i=1}^{n} (h_i - \bar{h})^3 \qquad R_{sk} = \frac{1}{(n-1)\sigma^3} \sum_{i=1}^{n-1} (S_i - \bar{S})^3$ 3 Height kurtosis (h_{ku}) (4) Average slope (S) $h_{ku} = \frac{1}{n\sigma_{i}} \sum_{i=1}^{n} (h_{i} - \bar{h})^{4}, \sigma_{h} = Srms \quad R_{ku} = \frac{1}{(n-1)\sigma^{4}} \sum_{i=1}^{n-1} (S_{i} - \bar{S})^{4}$ 5 Root-mean-square slope (σ_r) (6) Slope skewness (R_{sk}) $\bar{S} = \frac{1}{n-1} \sum_{i=1}^{n-1} S_i, S_i = \left| \frac{h_{i+1} - h_i}{x_{i+1} - x_i} \right|$ **7** Slope kurtosis (R_{ku})





- Correlation analysis between PoISAR feature and ice surface roughness
- > Only Root-mean-square height has a strong correlation with polarization features.
- 9 polarization features have correlations with sea ice surface Root-mean-square height exceeding 0.6.

0.9

0.8

0.7

0.6

0.5

0.4

0.3

0.2

0.1

> The HV to HH ratio has the highest correlation coefficient (R=0.688).



	σ_h	hsk	hku	\overline{S}	σ_r	σ_{sk}	σ_{ku}
σ_{VV}	-9.21	0.100	0.095	-0.180	-0.156	0.049	0.042
σνн	0.167	0.059	0.024	0.196	0.146	-0.082	-0.103
о нн	-0.431	0.056	0.074	-0.409	-0.366	0.125	0.139
A	-0.367	0.077	0.090	-0.332	-0.269	0.156	0.158
A12	-0.550	-0.039	0.016	-0.551	-0.476	0.133	0.179
PA	-0.261	-0.080	-0.040	-0.286	-0.261	0.024	0.064
(1-H)(1-A)	-0.455	-0.048	0.002	-0.458	-0.395	0.099	0.142
(1-H)A	-0.602	0.029	0.071	-0.579	-0.493	0.195	0.228
H(1-A)	0.668	-0.033	-0.081	0.639	0.535	-0.213	-0.247
Н	0.631	0.019	-0.038	0.622	0.533	-0.17	-0.218
SE	-0.288	0.110	0.094	-0.013	-0.013	0.036	0.019
SE_I	-0.052	0.101	0.107	-0.247	-0.213	0.100	0.102
SE_P	0.636	0.017	-0.039	0.625	0.538	-0.174	-0.224
λ,	-0.407	0.069	0.084	-0.369	-0.325	0.112	0.123
λ_2	0.008	0.120	0.089	0.058	0.048	0.012	-0.016
λ3	0.167	0.072	0.041	0.196	0.155	-0.063	-0.087
PH	0.684	-0.023	-0.076	0.660	0.551	-0.208	-0.244
PF	-0.683	0.023	0.076	-0.658	-0.551	0.210	0.246
ρ ₁₂	-0.167	-0.022	-0.033	-0.165	-0.155	-0.037	-0.053
ρ ₁₃	-0.520	-0.057	-0.003	-0.526	-0.463	0.106	0.157
ρ ₂₃	-0.120	-0.103	-0.109	-0.114	-0.135	-0.111	-0.095
RVI	0.683	-0.023	-0.076	0.658	0.551	-0.210	-0.246
SERD	-1.603	0.033	0.087	-0.641	-0.53	0.213	0.245





Correlation analysis between sea ice surface roughness and bottom roughness

> The first-order roughness parameters have the strongest correlation

between ice surface and bottom roughness.

- > The correlation between sea ice surface and bottom roughness weakens
 - for higher-order roughness parameters.







Correlation analysis between sea ice surface roughness and ice thickness

The highest correlation between sea ice surface roughness and thickness is found at the average slope.

> There is no correlation between height kurtosis and sea ice thickness.







- Correlation analysis between sea ice bottom roughness and ice thickness
- In comparison to the sea ice surface roughness, the bottom roughness values are larger and rougher.
- Similar with ice surface, the average slope has the highest correlation coefficient between sea ice bottom roughness and ice thickness.
- > The slope skewness is the lowest.







Correlation analysis between sea ice bottom roughness and ice thickness







3. Sea ice drift extraction with FY-3D microwave radiometer data

Objective

- > Developing a sea ice drift extraction method suitable for the FY-3D microwave radiometer.
- Evaluation with IABP buoy data, and the consistency between SSMIS, and AMSR2 sea-ice drift products.
- > Analysis effects of different time intervals, frequencies, and SICs on the accuracy of ice drift.
- Data

Auxiliary data

- FY-3D Microwave radiation imager
- > DMSP SSMIS
- > GCOM-W1 AMSR2

- NSIDC sea ice concentration: used for quality control
- IABP buoy: used to validation results





Methodology

A CMCC-based approach is used to generate sea ice drift products from gridded vertically and horizontally polarized Tb data from FY-3, HY-2, SSMIS, and AMSR2 radiometers.



- Daily Tb data were merged, and the 37 GHz and 89 GHz data were gridded into 25 × 25 km and 12.5 × 12.5 km grid.
- 2 Laplacian filtering was applied to reduce data noise, and exclude areas with SIC<15%.</p>
- \bigcirc CMCC with an 11 \times 11 pixel slide window was used to retrieve sea ice drift.
- A fusion method was used to average the Hand V- polarized sea ice drift vector results.





Effect of time interval on the accuracy of sea ice drift retrieval

Validation and comparison with IABP buoy data

Satellite	F	Y-3D	S	SMIS	A	AMSR2	
DMCE	Speed	Direction	Speed	Direction	Speed	Direction	
NVISE	(cm/s)	(degree)	(cm/s)	(degree)	(cm/s)	(degree)	
3 d	1.34	7.98	0.92	6.83	0.73	6.49	
6 d	0.77	6.49	0.52	5.56	0.51	5.36	
14 d	0.45	6.03	0.33	4.45	0.32	4.48	
Satellite	F	TY-3D	S	SMIS	AI	MSR2	
Satellite RE (%)	F Speed	TY-3D Direction	Speed	SMIS Direction	AN Speed	MSR2 Direction	
Satellite RE (%) 3 d	F Speed 7.21	TY-3D Direction 7.80	Speed 4.00	SMIS Direction 10.83	AN Speed 3.70	MSR2 Direction 5.30	
Satellite RE (%) 3 d 6 d	F Speed 7.21 4.38	TY-3D Direction 7.80 9.23	Speed 4.00 2.37	SMIS Direction 10.83 8.50	AN Speed 3.70 2.42	MSR2 Direction 5.30 8.32	

- > Longer time intervals are associated with higher accuracy.
- However, considering the effect of the spatial and temporal resolution, an interval of 6 days is a good compromise.







Comparison of product accuracy at different frequency

Validation and comparison with IABP buoy data, the time interval is 6 d.

Satellite	FY-3D		S	SMIS	AMSR2		
RMSE	Speed (cm/s)	Direction (degree)	Speed (cm/s)	Direction (degree)	Speed (cm/s)	Direction (degree)	
37 GHz (January to February)	0.75	6.68	0.59	6.29	0.49	5.88	
37 GHz (March to April)	0.77	6.42	0.51	5.56	0.51	5.36	
89 GHz (January to February)	0.58	5.99	0.51	6.92	0.50	6.03	
89 GHz (March to April)	0.70	7.13	0.49	5.85	0.53	6.14	

- \succ For FY-3, the accuracy was higher at 89 GHz than at 37 GHz.
- \succ For SSMIS and AMSR2, the accuracy was slightly lower at 89 GHz.
- The low accuracy of the 37 GHz FY-3 product was probably related to outliers in the Tb data between orbits.





Intercomparison and consistency analysis of satellite-derived sea ice drift





The effect of sea ice concentration on sea ice drift

- There is a negative correlation between ice speed differences and sea ice concentration.
- Speed differences are notably high for all products at concentrations of 80–90%, but they decrease at concentrations exceeding 90%.
- The smallest differences in drift speeds are observed between those retrieved from SSMIS and AMSR2.
- For concentrations below 70%, differences between drift speeds retrieved from FY-3 and those from AMSR2 remain small, but they become relatively large at concentrations of 70–90%.









- Our results showed that the four microwave radiometers provided relatively consistent measurements of sea ice drift.
- The largest differences were concentrated at the ice edge and between eastern Iceland and western Russia.





- 4. Snow depth retrieval over sea ice using microwave radiometer data
 Objective
 - > Snow over sea ice controls energy budgets and affects sea ice growth and melting.
 - Passive microwave radiometers can be used for basin-scale snow depth estimation at a daily scale.
 - The Antarctic sea ice surface is covered by a thick layer of snow, and high-frequency signals of radiometer cannot completely penetrate the snow-load.
 - The existing algorithm tends to underestimate the snow depth by approximately half of its actual value.

A new snow depth retrieval model was developed using low-frequency Tbs.





Data

- > AMSR-E (2002-2011)
- > AMSR2 (2011-2012)



AMSR-E



AMSR2

Auxiliary data

- > Airborne OIB snow depth data
- > ASPeCt shipboard observation data
- > AADC in situ data





Spatial and temporal distribution of OIB data

Spatial and temporal distribution of AADC and ASPeCt data





Methodology

- The vertical polarization GR at 19 and 37 GHz are commonly used to estimate of snow depth.
- > 19 and 37 GHz, high-frequency, hardly penetrate snow load.
- 7 GHz, low-frequency, can penetrate snow cover at greater depth.



$$GR(37/19) = \frac{Tb_{37} - Tb_{19} - k_1(1 - C)}{Tb_{37} + Tb_{19} - k_2(1 - C)}$$
$$k_1 = Tb_{37,OW} - Tb_{19,OW} \quad k_2 = Tb_{37,OW} + Tb_{19,OW}$$
$$SD (cm) = a + b \cdot GR(37/19)$$

$$SD_{GR(37/7)}(cm) = 26.7 - 411 \cdot GR(37/7)$$

GR	RMSD (cm)	Correlation coefficient	Number of grid cells
GR(37/24)	9.22	-0.61	740
GR(37/19)	9.11	-0.62	
GR(37/11)	8.95	-0.64	
GR(37/7)	8.92	-0.64	
GR(24/19)	9.21	-0.61	
GR(24/11)	9.03	-0.63	
GR(24/7)	9.14	-0.62	
GR(19/11)	9.15	-0.62	
GR(19/7)	9.46	-0.58	
GR(11/7)	10.62	-0.41	
$\frac{GR(37/19)+GR(19/10)}{2}$	8.96	-0.64	





Self-evaluation of the proposed method

The regression coefficients of snow depth estimation equations based on OIB snow depth data in different years

Year	Intercept	Slope	Number of grid number
2009	25.4	-417	161
2010	27.2	-445	88
2012	28.3	-349	147
2013	23.8	-707	40
2014	25.4	-394	103
2016	27.3	-474	134
2017	33.8	-176	68
Apply all data	26.7	-411	740

No obvious interannual variations could be found for either the slope or the intercept values.

The comparisons between the OIB snow depth and the snow depth estimates from our method and the Comiso method

				Correlation
	MD (CIII)	MAD (CIII)		coefficient
Proposed	-1.55	6.84	9.23	0.62
Comiso	-19.15	19.15	21.26	0.60

The proposed method has a good result
 by compared with OIB snow depth.





Comparison to AADC and ASPeCt data

	Comparison to AADC data		Comparison to ASPeCt data		
	Proposed method	Comiso method	Proposed method	Comiso method	
MD (cm)	5.64	-14.47	8.62 (8.94)	-9.96 (-10.16)	
MAD (cm)	10.77	17.08	13.80 (13.91)	13.11 (13.20)	
RMSD (cm)	13.79	19.49	16.85 (16.85)	17.61 (17.61)	
Correlation coefficient	0.42	0.40	0.13 (0.13)	0.19 (0.19)	
Number of grid cells	15	15	264 (257)	273 (257)	
(a) 7.0 6.0 5.0 4.0 4.0 3.0 2.0 5.0 3.0 2.0	Snow depth different Proposed method	(b) ^{7.0} 6.0 - ASPeCt 4.0 2.0		Snow depth differences: Comiso method- ASPeC	
^{1.0} 0.0 Proposed	method was b	etter during sp	ring, summer a	ind autumn	
-0.6 -0.4 -0.2 0.0 0.2 0.4 Snow depth difference (m)	0.6	-0.6 -0.4	-0.2 0.0 0.2 0.4 Snow depth difference (m)	0.6	





The uncertainty from estimation methods

Considering the sources of uncertainty: brightness temperatures, model coefficients, et al.

$$\sigma_{\rm SD} = \sqrt{\left(\frac{\partial \rm SD}{\partial a}\right)^2 (\sigma_a)^2 + \left(\frac{\partial \rm SD}{\partial b}\right)^2 \sigma_b^2 + b^2 \sigma_{\rm GR}^2}$$

$$\sigma_{GR} = \sqrt{G_1^2 \sigma_{Tb_{v1}}^2 + G_2^2 \sigma_{Tb_{v2}}^2 + G_3^2 \sigma_{k_1}^2 + G_4^2 \sigma_{k_2}^2 + G_5^2 \sigma_c^2}$$

- > The uncertainty of proposed method: 0~50 cm
- The uncertainty is large in the marginal zone and small in the interior; while is large in summer and small in winter.







Data access

Antarctic Sea Ice Surface Snow Thickness Dataset (2002-2020), published in the National

 Tibetan Plateau Science Data Center
 https://doi.org/10.11888/Snow.tpdc.271653



Shen, X., Ke, C.-Q., et al. (2022). A new digital elevation model (DEM) dataset of the entire Antarctic continent derived from ICESat-2, *Earth Syst. Sci. Data*, 14, 3075–3089, https://doi.org/10.5194/essd-14-3075-2022.





- 5. Analysis of decadal changes of sea ice in the Bohai Sea with GOCI data
 - Objective
 - The region surrounding the Bohai Sea is a important strategic economical circle.
 - Sea ice seriously impacts ports, shipping,
 fishers, and marine operations around the
 Bohai Sea.
 - > Sea ice monitoring is an important task.



A long-term analysis helps us understand sea ice changes and climate change.





GOCI Data

- Satellite: Communication Ocean and Meteorological Satellite, Korea
- Launch: June 2010, Korea
- > Orbit: Geostationary Orbit
- Spatial resolution: 500 m
- > Imaging Time: 00:15 (UTC) \sim 07:45
 - (UTC), 8 images a daytime
- >Band: 8 bands (6 visible, 2 NIR)



GOCI data can provide hourly sea ice observations with 500 m resolution.





Sea ice parameters extraction







Decadal changes of sea ice area



Annual maximum sea ice area -1214.1 km²/year







Decadal changes of sea ice thickness

Annual average sea ice thickness -0.30 cm/year



Annual maximum sea ice thickness

-0.56 cm/year







Decadal changes of sea ice drift



The frequency of sea ice drift direction

- SW, largest proportion;
- NE, small proportion;
- NW and SE: little proportion;



The interannual characteristics is not obvious.





Sea ice prediction models based on decadal statistics

- > Cumulative negative temperature is key to predict the change of sea ice.
- > We analyze the correlation between cumulative negative air temperature-

Days with ice area and ice thickness.













Sea ice thick prediction model



Growth period **Development period** All periods Melting period $H = -0.017t_{AT} - 0.29v_{wind} + 0.56$ $H = -0.041t_{AT} - 0.1v_{wind} + 8.38$ $H = -0.048t_{AT} - 0.26v_{wind} + 0.76$ 0.25 Predicted thickness/m 0.25 0.25 0.25 Predicted thickness/m Predicted thickness/m Ξ 0.2 Predicted thickness/n 0.15 0.1 c.c.=0.5074 c.c.=0.5028 0.05 0.05 c.c.=0.5735 c.c.=0.4663 0.05 0.05 MRE=0.0687 MRE=0.0345 MRE=0.0524 MRE=0.0586 0.05 0.1 0.15 0.2 0.25 0.3 0.05 0.1 0.15 0.2 0.25 0.3 0.05 0.1 0.15 0.2 0.25 0.3 Measured thickness/m Measured thickness/m Measured thickness/m 0.05 0.1 0.15 0.2 0.25 0.3 Measured thickness/m





Sea ice drift prediction model (Neglecting the influence of internal ice stresses)



- The model is simple and needs to be improved
- Wind and current data are from ECMWF ERA5



EO Data Delivery



Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert "ftp"

ESA Third Party Missions	No. Scenes	ESA Third Party Missions	No. Scenes	Chinese EO data	No. Scenes
1. ALOS PALSAR	6	1. Sentinel-1	45	1. HY-2B	2018~2023
2. RadarSAT-2	16	2. Sentinel-3 SLAT	2017~2023	2. GF-3	45
3. Cosmo-SkyMed	6	3. CryoSat-2	2017~2023	3. FY-3C	2019~2023
4.		4.		4.	
5.		5.		5.	
6.		6.		6.	
Total:		Total:		Total:	
Issues: Iceberg detection, University in Tromsø/Norway: ESA-Agreement with JAXA: PALSAR-2 FB and WB images since April 2019 (not specifically via Dragon)		Issues: Iceberg detection, University in Tromsø/Norway: S1 and S2 images via Science Hub since April 2019 (not specifically via Dragon)		Issues:	





III. Cooperation

- > FIO, AWI, FMI, and NSOAS continue to develop sea ice thickness retrieval algorithms.
- NSOAS, FMI and DMI develop sea ice concentration estimation and SIC noise reduction algorithms.
- Joint effort by AWI/UiT, FIO, FMI, and SCMU is in preparation to deal with the detection of icebergs in sea ice.
- Cooperations with ice services world-wide (e.g. Denmark, Norway, Sweden, Canada, US, Argentina), plus Chalmers Technical University in Gothenburg, Sweden.
- The work of sea ice thickness detection work was selected for China-EU Space Science and Technology Cooperation Briefing.





International Glaciological Society

Arctic thin ice detection using AMSR2 and FY-3C MWRI radiometer data

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IV. Young scientists and Publications

Name	Institution	Poster title	Contribution
Laust Færch	UiT The Arctic University of Norway	Variations of Signature Contrast Between Icebergs and Sea Ice Dependent on Ice Conditions and Radar Parameters	lceberg
Xiao-yi Shen	Nanjing University	An Observation of Arctic Melt Ponds Based on Sentinel-2 and ICESat-2	Melt ponds
Wen-shuo Zhu	Shandong University of Science and Technology	Comparison of Doppler-Derived Sea Ice Radial Surface Velocity Measurement Methods from Sentinel-1A IW data	Sea ice drift
Jun-hui Zhu	Shandong University of Science and Technology	Enhanced-resolution reconstruction for the China-France Oceanography Satellite scatterometer	Sea ice drift
Ran Yan	Qingdao University	Sea Ice Parameter Retrieval In The Bohai Sea Using GOCI Data From 2011-2020	Ice concentration, thickness, drift
Wen-long Bi	Qingdao University	Inversion Of Sea Ice Concentration And Thickness In The Yellow Sea And Bohai Sea Based On HY-1C Data	Ice concentration, thickness





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- ③ Dierking W. et al., "Synergistic used of L- and C-band SAR satellites for sea ice monitoring", IGARSS 2021.
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- (5) Shi L., et al., Sea Ice Concentration Products over Polar Regions with Chinese FY3C/MWRI Data. Remote Sens. 2021, 13, 2174.
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- ⑦ Dong Z. et al., A Suitable Retrieval Algorithm of Arctic Snow Depths with AMSR-2 and Its Application to Sea Ice Thicknesses of Cryosat-2 Data. Remote Sensing, 2022, 14, 1041.
 ⑧ Wu S, Shi L, Zou B, et al. Daily Sea Ice Concentration Product over Polar Regions Based on Brightness Temperature Data from the HY-2B SMR Sensor. Remote Sensing, 2023, 15(6): 1692.





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- 14 Xiaoyi Shen et al. Snow depth product over Antarctic sea ice from 2002 to 2020 using multisource passive microwave radiometers. Earth System Science Data, 2022, 14(2): 619-636.
- (15) Xiaoyi Shen et al. Assessment of Arctic sea ice thickness estimates from ICESat-2 using IceBird airborne measurements. IEEE Transactions on Geoscience and Remote Sensing, 2021, 59(5): 3764-3775.
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V. Next planning

- Iceberg detection: improvement of algorithms, comparison and selection of optimal one(s), collection of data for validation, validation, building semi-operational environment (the key work of Sino-European joint effort).
- Sea ice drift: develop algorithm for Chinese HY-2 radiometer and for alignment of C- and L-band images (at AWI and University in Tromsø)
- Sea ice thickness: Altimeter + SAR to improve the spatial resolution of sea ice thickness product.





