Thomas Thébault
Earth Observation Department
UiT Tromsø, Norway
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# Applying the Radar Statistical Reconnaissance Method to Sea Ice: Surface Property Insights from CryoSat-2 Radar Altimetry

## Abstract

This study explores the application of the Radar Statistical Reconnaissance (RSR) method to analyze sea ice surface properties using radar altimetry data obtained from the CryoSat-2 mission, equipped with advanced radar technology. By examining the surface echo power of radar signals reflected from the surface, we derive coherent and incoherent power with the RSR method. These observations offer crucial insights into the near surface sea ice properties, such as surface roughness and local heterogeneity of sea ice types. The findings enhance our understanding of sea ice dynamics and contribute to refining climate models, ultimately improving projections of sea ice behavior in response to ongoing climate change. This research underscores the importance of utilizing satellite radar altimetry to monitor and assess the changes in sea ice properties, which are vital for accurate climate modeling and prediction.

**Key Words:** Sea Ice, Surface Roughness, Radar Altimetry, RSR Method

## Introduction

The polar regions are undergoing rapid and unprecedented transformations due to climate change, with sea ice serving as both a critical indicator and a driver of global environmental shifts. As sea ice extent and thickness decline, the need for precise, large-scale monitoring of its physical properties—such as surface roughness, snow cover, and internal heterogeneity—has become increasingly urgent. These properties govern the energy exchange between the ocean and atmosphere, influencing weather patterns, ocean circulation, and global climate systems.

The Radar Statistical Reconnaissance (RSR) method, originally developed to identify landing zones on Mars by analyzing surface roughness (Grima et al., 2014), has since been adapted to Earth's cryosphere. Recent studies successfully applied RSR to characterize surface roughness and dielectric properties of the Greenland Ice Sheet (Scanlan et al., 2023, 2025), demonstrating its potential for terrestrial research.

Building on these advancements, this study explores the application of the RSR method to sea ice, a dynamic and heterogeneous surface that poses unique challenges for remote sensing. By analyzing radar altimetry data from CryoSat-2, we derive coherent and incoherent power components of the surface echo, which provide critical information about near-surface sea ice properties, including roughness and local heterogeneity.

## The RSR Method over sea ice

### Data Used

The data used is extracted from the CryoSat-2 mission, equipped with several tools. This study focuses on the Synthetic Aperture Radar (SAR) product. The data is available in different levels of pre-processing from the ESA. Here, the FBR

(Full Bit Rate) and the L1B products are used.

The SAR sends a burst of 64 pulses (Ku-band radar, RF peak power = 25W) on each observed point with an interval of 50μs to process them by exploiting the frequency shift caused by the Doppler effect (Fig1). This waveform is available in the L1B product for each measured point along the track, with a spacing of 80m between bursts (~85Hz). In the FBR product, we can access the 64 echoes for each measured points, free of any pre-processing operations.

All those products are available in netCDF files, free to access.

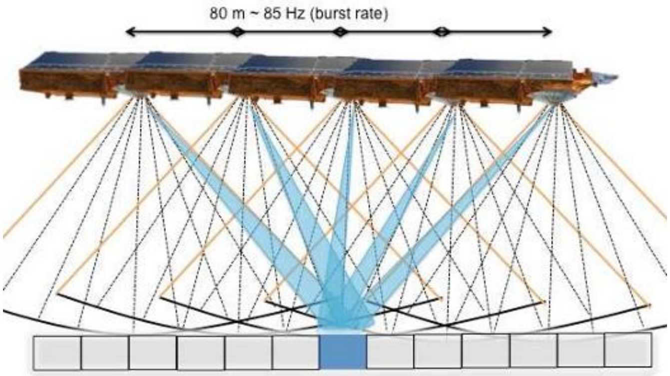



**Figure 1 :** Geometry of multi-looking [1]

In most of the following computations, all the data available over a month is used, covering all of the arctic ocean (Fig2)

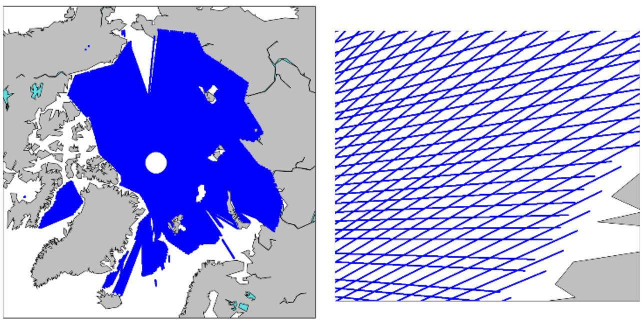


**Figure 2 :** Cryosat-2 coverage of the Arctic Ocean

## First attempt : with the SARAL 1B product

In this first attempt to apply the RSR method, we chose to work with the L1B product, which is already calibrated and had an operation of noise reduction.

### *Pre-processing*

From the CryoSat dataset, we extract unscaled waveforms and the coefficients needed to convert them in relative power values (uncalibrated). After scaling the echoes, we can derive the maximum power received (Fig3)

1. The leading edge is defined as the position of the maximum integrated echo amplitude gradient [2]
2. The peak surface echo power is the maximum measured power within a window following the position of the leading edge. This window is 5% as long as the received window.

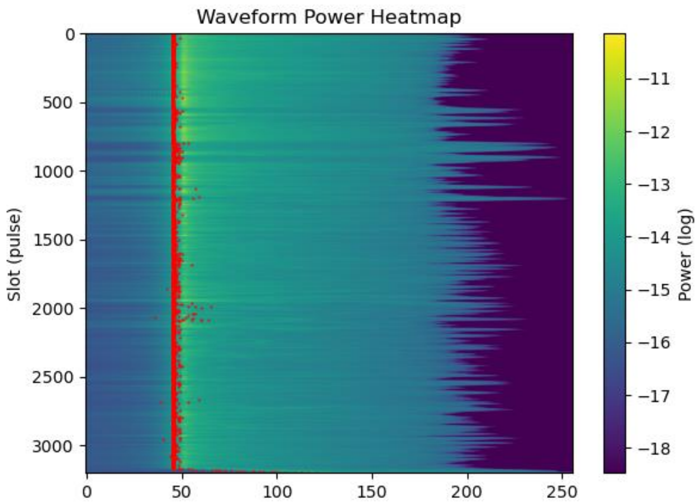



**Figure 3 :** Waveform Power Heatmap. Each line represents a waveform, with here approximately 3200 waveforms in one track. The red dots indicate the leading edges position derived from the data. The colors represent the power on a log scale

### *The RSR Method implementation*

The Radar Statistical Reconnaissance (RSR) method is a powerful tool for characterizing surface properties using radar data. This method has been successfully applied in various planetary and terrestrial contexts to derive surface roughness and permittivity information, which are crucial for landing site selection and surface characterization (Grima et al. ,2014 [6]).

The RSR method involves fitting the power distribution to a Homodyned-K (HK) distribution, to extract the coherent and incoherent components of the surface signal. The HK distribution is particularly valuable in radar altimetry for its ability to accurately model the statistical characteristics of backscattered signals from the surface. This compound distribution combines the square root of a gamma distribution with a Gaussian distribution, capturing both coherent and diffuse components of the signal. The coherent component represents the specular reflection from relatively flat surfaces, while the incoherent component accounts for the diffuse scattering from rough surfaces.

This method is applied with the rsr python package [5].

After having pre-processed all the data from a whole month, the power distribution fitting is applied on the 1000 closest measures from the target point (Fig4), from which are removed the highest values (corresponding to the tail of the distribution) and the leads (Fig5, using data from a previous J.C. Landy study [8]). To remove the tail, several algorithms have been tried :

V1 - Save only the measured powers under 0.5e-12 W among the 1000 closest points around the target point.

V2 – Save only the 900 lowest measured powers among the 1000 closest

V3 – Split the powers measured from the 1000 closest points in 100 bins and delete the tail, defined as the part of the histogram for which the height of the bins is less than 2.5% of the peak. Repeat recursively on the data that passed the filter (Usually, it takes around 4 recursions to be stable)

V4 - Same, but with a "tail threshold" of 5% (then, it takes around 8 recursions)

The lead filter was only applied to versions 1 and 3.

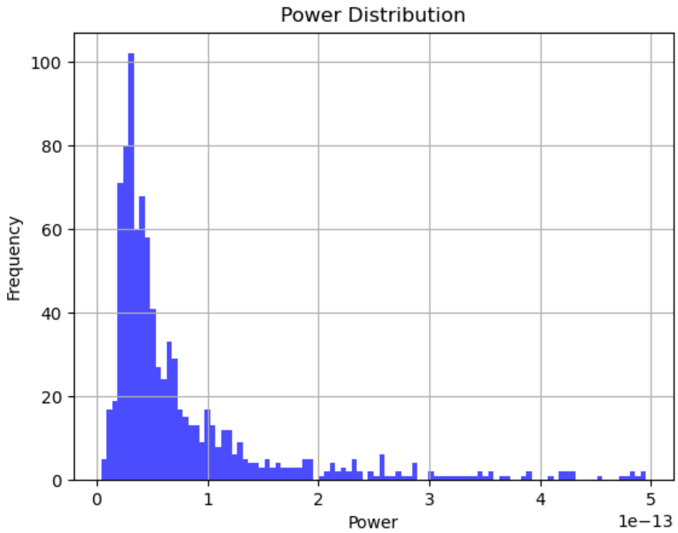



**Figure 4 :** Example of power distribution (W) around a target point

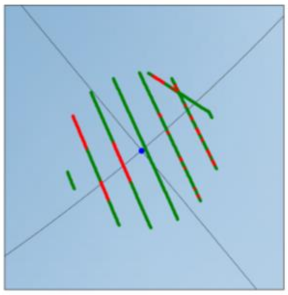


**Figure 5 :** Example of the 1000 closest measured points chosen (green) around a target point (here in February 2018, lat 82°, lon 40°), avoiding the leads (red)

### *Results*

Figure 6 plots the results from the RSR method application.

While the correlation coefficient, which expresses how well the HK model fits the power distribution, is not high enough (in Scanlan [2], all targets with a coefficient bellow 0.96 are removed), the estimated values for Pn and Pc are relatively similar depending on the filter chosen (excepted for Pc on the points 0 and 3). To get a greater quality result, the following attempt focus on the FBR product.

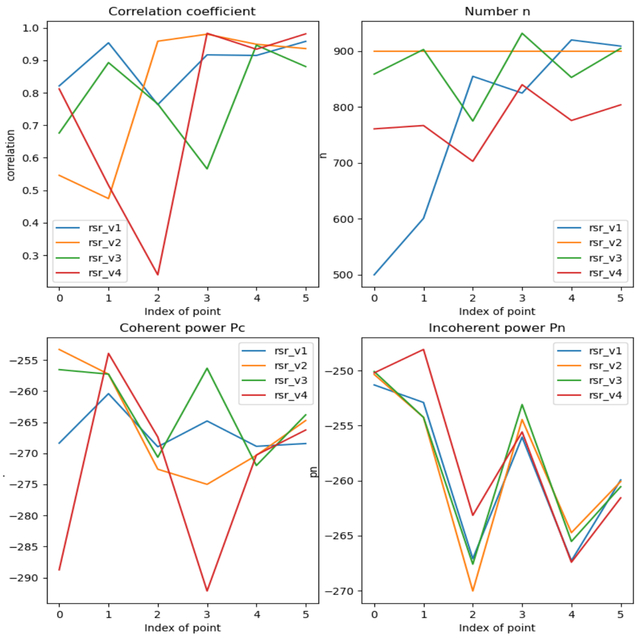



**Figure 6 :** Correlation coefficient, number n of measures fitted by the RSR method, Coherent power Pc and Non-coherent power Pn vs. the 6 studied points (feb 2018, (lat,lon) resp. (80,35), (80,75), (82,40), (82,80), (85, 30), (85,70)), with different filtering method

## Second attempt : with the SARAL FBR product

### *FFT on the complex signal*

To extract the peak power from each individual radar echo in the CryoSat FBR dataset, range compression is performed [4], using a Fast Fourier Transform (FFT). Each echo is a complex signal (I and Q channels) representing the radar return sampled in the time domain. These echoes contain energy reflected from a distributed surface, but in their raw form, the signal is not yet localized in the range (distance) direction.

An FFT is applied to convert the time-domain signal into the frequency domain, which encodes the range information corresponding to specific frequencies (delays) of the chirp signal. Prior to analyzing the results, a shift is applied to center the zero-frequency component, which rearranges the output so that the main peak appears in the center of the spectrum. The squared magnitude of the complex FFT output is eventually computed to obtain the power waveform.

### *Peak surface echo power*

Just like with the data from the L1B product, we extract the peak surface echo power from each waveform, after deriving the leading edge.

### *Calibration and corrections*

Several corrections are applied on the power extracted, to counteract both atmospheric and instrumental attenuations.

After converting peak surface echo power from counts to dB, those gains (available on the netCDF Cryosat files) are added :

- Static gain : *tot_gain_ch1_85_ku*, the total fixed instrument gain
- Dynamic gain : the sum of *agc_1_85_ku*, *agc_2_85_ku*, and *instr_cor_gain_tx_rx_85_ku*, the 2 steps of gain command and the instrument gain correction

The three previous steps (FFT, peak surface echo power extraction and calibration) are applied on every burst measured from a whole month, excluding the ones located on leads.

### *The RSR method implementation*

For each target, the RSR method is applied on the power received from the 1000 closest measured points. As we previously extracted from each of those measured points the peak surface echo power of the 64 pulses, the fitting is then computed over a distribution of 64 000 powers (Fig 8.b & 9.b).

*Application on the whole Arctic ocean*

This method is applied to a grid of targets covering all the observed Arctic Ocean, with a minimum latitude of 72°. The grid has a step of 10km and includes around 75 000 targets. The following figures plot the results obtained for November 2017.

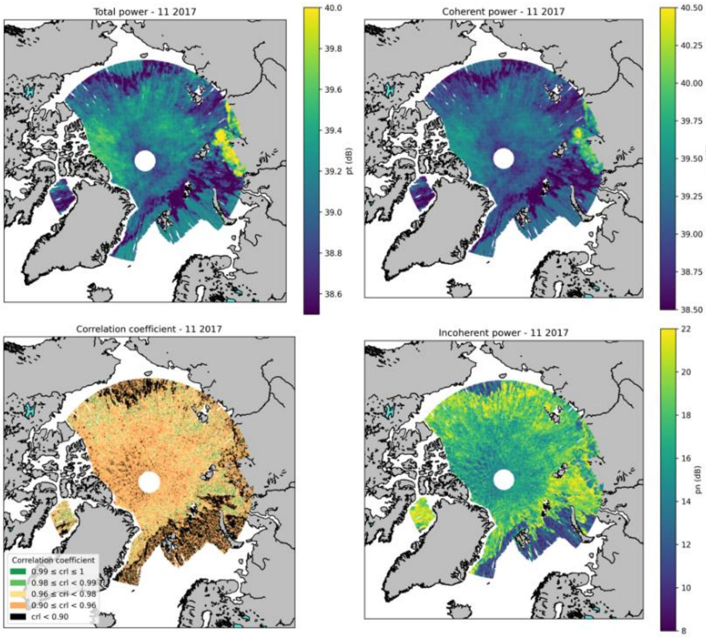



**Figure 7 :** Heat maps of total power, coherent power, incoherent power (dB) and correlation coefficient obtained with the first computation of the RSR method over the Arctic Ocean, with the data from Nov 2017.

The total power, incoherent power and coherent power maps are relevant, as continuous areas in the values computed are observed.

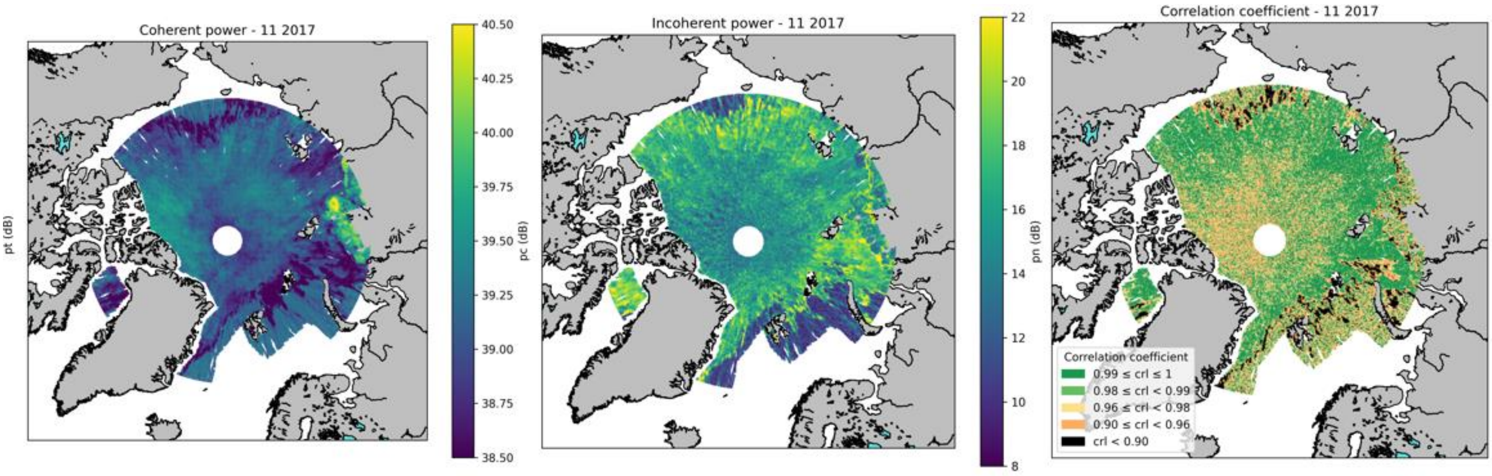
For most targets, the correlation coefficient is above 0.9 but lower than 0.98. This results from a poor fit of the HK model to the power distributions. In the rsr python package [5], the fitting is computed by the lmfit package, with the Levenberg-Marquardt minimization algorithm. After several experiments using other methods, it has been observed that the least squares minimization algorithm offers better results (Fig 8.b & 9.b)

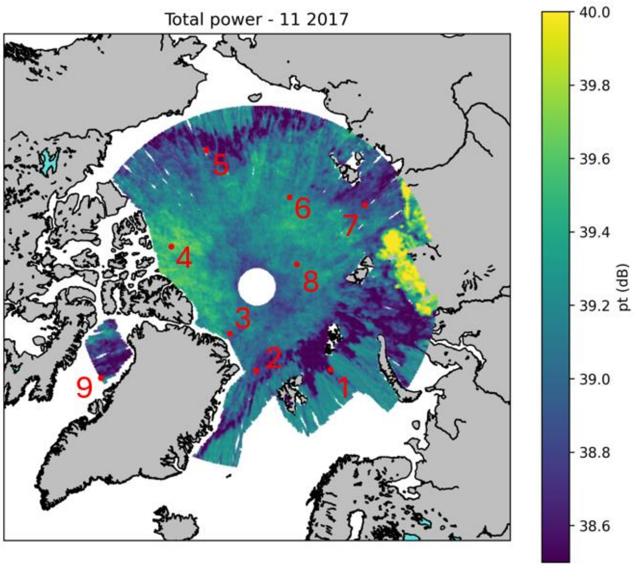
Thus, the RSR method has been applied with the least-squares method, on the Nov 2017 and Feb 2018 data (Fig 8.a & 9.a).

As a first observation, the correlation coefficient is sometimes lower than 0.9, for instance on the edge of the sea ice. We can indeed find in those location several surface types coexisting : ocean and sea ice. This results in a power distribution with a double peak (e.g. 9th distribution of Fig8.b), and a HK fitting being irrelevant. Additionally areas with low correlation coefficient moves toward lower latitudes from November to February, as the ice front is shifting.

However, the incoherent power map is surprising, as we expected a lower value on first-year ice (e.g. target n°7) than on rougher multi-year ice (e.g. target n°4), because a younger flatter ice is expected to reflect almost perfectly the radar pulse. Here, the power distribution for target 7 is wider than that for target 4, reflecting greater variability in surface echo power—an indication of increased surface roughness and less predictable backscattering. Also, the total power map surprisingly matches exactly the opposite of the $\sigma^0$ map (Fig10) : a error in my implementation [9] may explain this feature. In another hand, we can see that we receive more total power and less incoherent power from the ocean water (Fig 8.a, on the south of targets n° 1 and 2), which is relevant as water is quite flat. Thus, the reverse matching of Pt and $\sigma^0$ can maybe be explained by influence of snow (its depth or density) or melting ice.

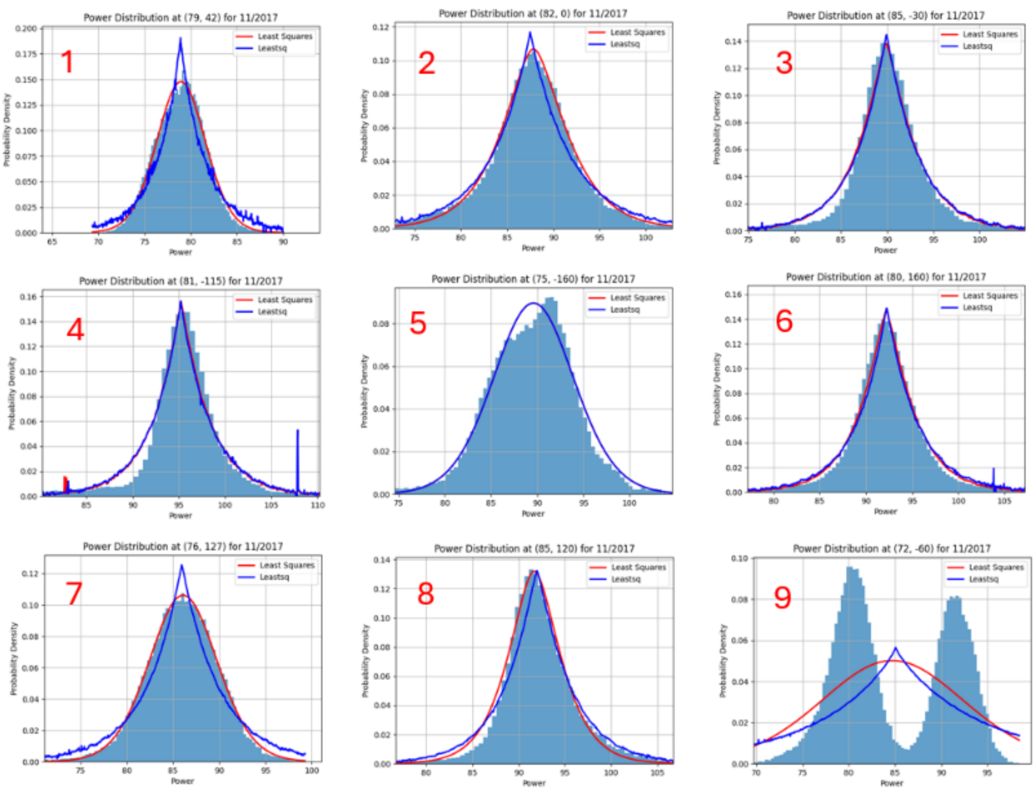
Despite those unexpected results, this study proves that the RSR method can be applied to sea ice : the power distributions are relevant after filtering the leads and can fit a HK model, and the computed coherent and incoherent power maps are promising.

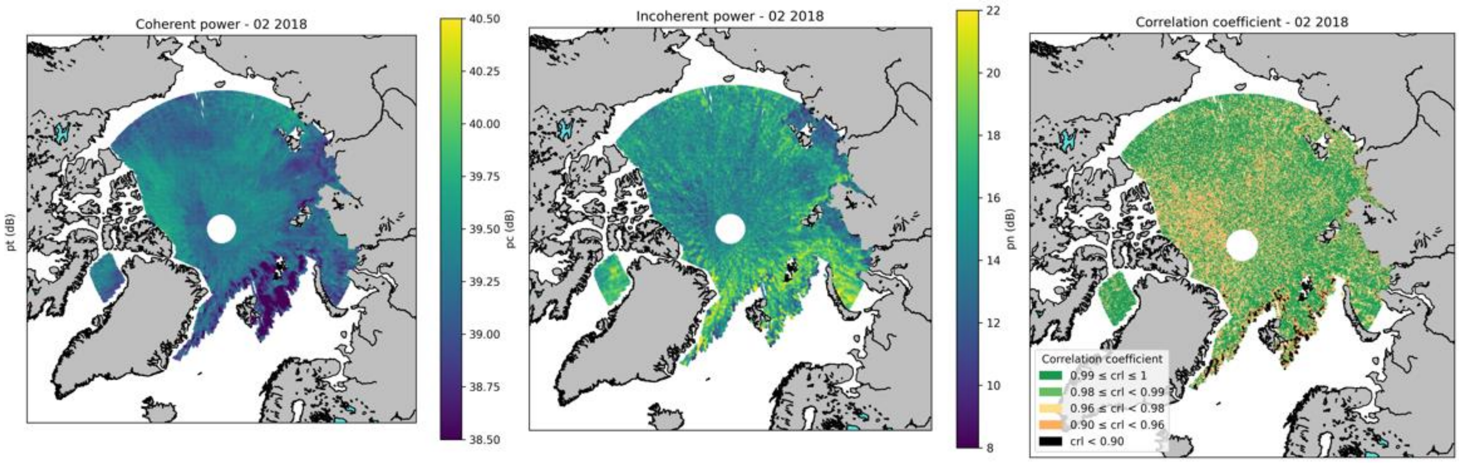


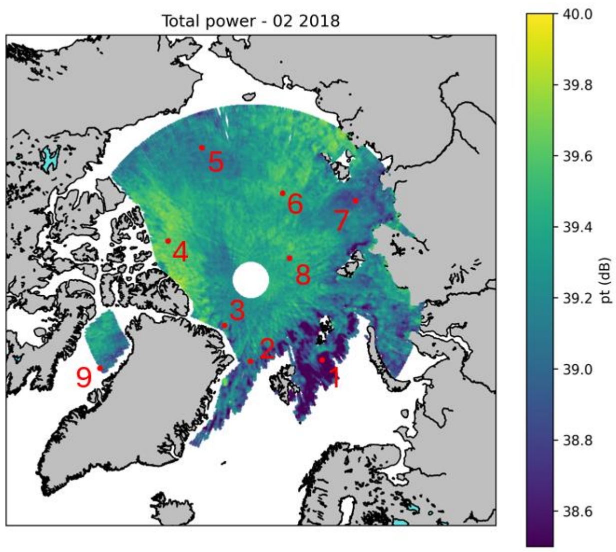




↑ **Figure 8.a :** Heat maps of total power, coherent power, incoherent power (dB) and correlation coefficient over the Arctic Ocean with the data from Nov 2017, obtained with the RSR method using the Least Squares minimization algorithm.

↓ **Figure 8.b :** Power distribution (dB) of the 64 000 surface echo powers picked around 9 targets indicated in figure 8.a, for which the fitting with a HK model has been computed with the Levenberg-Marquardt algorithm (blue) and with the least squares algorithm (red)

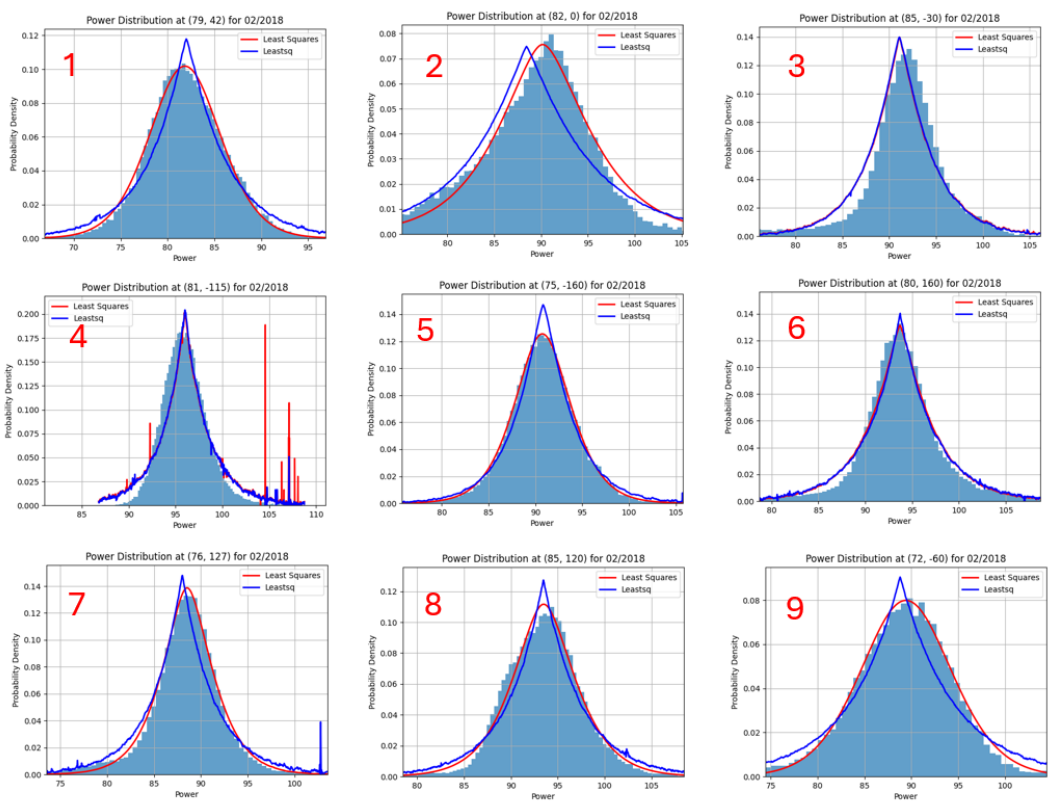





↑ **Figure 9.a :** Heat maps of total power, coherent power, incoherent power (dB) and correlation coefficient over the Arctic Ocean with the data from Feb 2018, obtained with the RSR method using the Least Squares minimization algorithm.

↓ **Figure 9.b :** Power distribution (dB) of the 64 000 surface echo powers picked around 9 targets indicated in figure 9.a, for which the fitting with a HK model has been computed with the Levenberg-Marquardt algorithm (blue) and with the least squares algorithm (red)



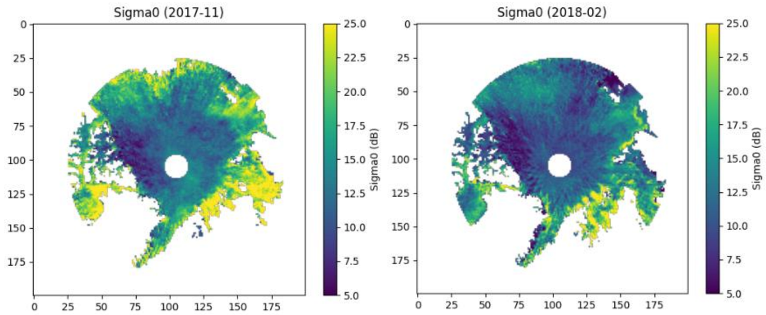



**Figure 10 :** Heat maps of $\sigma^0$ (dB) over the Arctic Ocean in Nov 2017 and Feb 2018, plotted from a previous J.C. Landy study [7].

## Further studies

### Geophysical properties

By inverting the results form the RSR method, it has been possible to estimate some physical properties of the Greenland ice sheet surface, such as dielectric permittivity or ice density, using empirical models [2].

To do the same on sea ice, reformulated models for Pc and Pn would be required, as well as calibration to in situ reference sites

### Extracting tendances and correlations

By fitting the Pc and Pn distributions computed over several months with observed snow densities, melting and freezing periods or ice thickness, it may be possible to correlate these physical trends with our remote sensing data.

The results obtained in this first attempt to apply the RSR method to sea ice are not conclusive, as they don't fit our expectations, for the reasons previously explained. A complete revision of my code may be relevant, as well as evaluating the influence of snow on the RSR results.

## Conclusion

This study demonstrates the feasibility of applying the Radar Statistical Reconnaissance (RSR) method to sea ice, using radar altimetry data from the CryoSat-2 mission. By analyzing coherent and incoherent power components of radar echoes, we gained valuable insights into near-surface sea ice properties, including roughness and heterogeneity. While the results highlight the method's potential, they also reveal challenges, such as unexpected incoherent power distributions and discrepancies with theoretical expectations, which warrant further investigation.

By addressing these challenges, the RSR method could become a robust tool for monitoring sea ice properties, ultimately contributing to more accurate climate projections and a deeper understanding of polar environmental changes. Future collaborations with field campaigns and interdisciplinary studies might be interesting to unlock the full potential of this approach.

## Acknowledgments

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## References

[1] CryoSat-2 Product Handbook, Baseline E 1.0 — Draft C, ESA.

[2] Scanlan, K. M., Rutishauser, A., & Simonsen, S. B. (2023). Observing the near-surface properties of the Greenland ice sheet. Geophysical Research Letters, 50, e2022GL101702. https://doi.org/10.1029/2022GL101702

[3] Scanlan, K. M., Rutishauser, A., & Simonsen, S. B. (2025). Greenland Ice Sheet surface roughness from Ku- and Ka-band radar altimetry surface echo strengths. The Cryosphere, 19, 1221–1239, 2025 https://doi.org/10.5194/tc-19-1221-2025

[4] Guidelines for the SAR (Delay-Doppler) L1b Processing, ESA, 2013

[5] github.com/cgrima/rsr

[6] Grima et al., Elsevier, Planetary landing-zone reconnaissance using ice-penetrating radar data: Concept validation in Antarctica (2014)

[7] Sea ice thickness observations derived from CryoSat-2 using the UiT Arctic University of Norway processing chain, jack.c.landy@uit.no

[8] Arctic CryoSat-2 Along-Track Data Baseline E, jack.c.landy@uit.no

[9] github.com/ThomasTBO/rsr_sea_ice