Leveraging Polarized Ku- and C-band Radar Backscatter Time Series for Sea Ice Thickness Prediction using Random Forest

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Abstract

Arctic sea ice thickness has been declining over recent decades due to climate change, making accurate prediction increasingly critical for environmental monitoring and climate modeling. Microwave remote sensing combined with machine learning has emerged as a promising approach for estimating sea ice thickness. This study investigates the prediction of lab-grown sea ice thickness (27-47 cm), using time-series backscatter data collected from surface-based Ku- and C-band scatterometers in three polarizations (VV, HH, and HV). A Random Forest model was applied to the time series, incorporating Normalized Radar Cross-Section (NRCS) values and statistical features (mean and standard deviation) across various temporal variables (lead and lag times). The model achieved high prediction accuracy, with the lowest error recorded at RMSE = 0.03 cm. Feature importance analysis using the Permutation Importance method revealed that co-polarized C-band features (C-VV and C-HH) were the most determining parameters in predicting sea ice thickness. These findings underscore the potential of integrating microwave remote sensing with Random Forest models to enhance sea ice thickness prediction and provide valuable insights for future research and real-time monitoring in Arctic regions.

1. Introduction

Sea ice in the Arctic is critical in the Earth’s climate regulating by reflecting solar radiation back into space and helping to maintain global temperature balance (Cohen et al., 2020). Recent decades have seen significant declines in sea ice extent and thickness due to climate change (Steiner et al., 2021). Reductions in thickness are especially critical because thinner ice allows greater heat exchange between the ocean and atmosphere, absorbs more solar energy, alters ocean circulation through freshwater input (Stössel, 1997), and threatens the stability of Arctic ecosystems (Steiner et al., 2021). These rapid changes underscore the need for improved monitoring and prediction of polar sea ice thickness.

Microwave remote sensing technologies have facilitated monitoring of sea ice conditions because they provide frequent, all-weather, long term coverage of the polar regions (Kwok, 2018). For measuring sea ice extent, passive microwave sensors are more common; however, measuring sea ice thickness requires different sensor types, including satellite altimetry, synthetic aperture radar (SAR), and surface-based or airborne microwave instruments, which provide complementary information about ice volume and structure (Sandven et al., 2023).

While monitoring sea ice using satellite observations is conventional (Leppäranta et al., 2020), surface-based sensors (scatterometers) can be complementary to satellite-based data, providing ground-truth measurements and detailed local measurements of sea ice (Dadjoo and Isleifson, 2025c). Normalized Radar Cross Section (NRCS), is the common output of both scatterometers and conventional satellite platforms (Isleifson et al., 2018). Analyzing NRCS values in relation to environmental and physical parameters can significantly enhance understanding of sea ice formation and evolution and provide valuable insights into the tracking of thickness trends over time (Dadjoo and Isleifson, 2025b).

In recent years, Machine Learning (ML) algorithms have been increasingly applied in sea ice studies, driven by significant advancements in computational hardware and software capabilities (Li et al., 2024b). ML algorithms have enabled researchers to process large volumes of geophysical data efficiently and uncover complex patterns related to sea ice thickness (Leppäranta et al., 2020). Compared to traditional physical models, which rely heavily on solving complex equations, ML approaches offer a more flexible and data-driven alternative (Li et al., 2024b). As statistical methods, ML algorithms can learn from time series observations and, with a well-trained model, simplify the prediction of sea ice thickness. Their ability to capture nonlinear relationships and adapt to diverse environmental inputs has made them superior in many cases, offering improved accuracy in sea ice thickness estimation (Dadjoo and Isleifson, 2025c).

This study presents a focused assessment of the predictive capability of surface-based radar observations, Ku- and C-band NRCS values, for estimating sea ice thickness without relying on additional physical or environmental inputs including temperature, humidity, wind speed, salinity, or snow depth. To compensate for the absence of these environmental parameters, statistical features (mean and standard deviation) were calculated in multiple temporal window sizes to support the ML model in maintaining predictive accuracy. Moreover, the model was assessed based on the resulting model performance in various amounts of temporal variables (lead and lag times) to identify the optimal configuration, and the radar parameters were subsequently ranked according to their relative influence on sea ice thickness prediction.

The motivation for this radar-only approach is rooted in operational robustness and data availability in some Arctic environments, where ancillary parameters are sparse, discontinuous, or model-derived coming with uncertainties. Radar backscatter measurements are directly observed, continuously available under all weather and illumination conditions, and are known to be sensitive to key ice growth processes, including changes in surface roughness and dielectric properties associated with thermodynamic thickening (Nghiem et al., 1997b; Isleifson et al., 2023a). By applying a Random Forest model, as one of the advanced and efficient ML models, to a time series of Ku- and C-band NRCS measurements, this study establishes a streamlined predictive framework that minimizes data dependency while retaining physically meaningful sensitivity to ice thickness evolution. This experimental setup is particularly well suited for autonomous monitoring systems and long-term deployments in data-limited Arctic regions, where radar observations may represent the most reliable and consistent source of information.

As reported in the literature, C-band scatterometer has been used for monitoring of the growth of thin sea ice alongside physical variables (e.g. temperature and salinity) (Kwok et al., 1995). C-band NRCS values in various polarizations have been used to carry out a multivariate thin sea ice thickness prediction and as determining features in the predicting process, leading to a high accuracy (Dadjoo and Isleifson, 2025c).

Scatterometers have been widely applied in sea ice research across a range of applications. In particular, C-band systems have been examined for their ability to analyze the impact of frost flowers on radar backscattering (Isleifson et al., 2014; Nghiem et al., 1997a), recognizing frost flowers electromagnetic properties (Nghiem et al., 1997a). More recent investigations have integrated data from Ku- and C-band scatterometers, LiDAR, and drone-based platforms, to analyze thin sea ice with various surface coverage such as snow and frost flowers (Isleifson et al., 2023a). In addition, radar altimetry has been applied operating in Ka- and Ku-bands to estimate the sea ice thickness with snow layers (Stroeve et al., 2020). These efforts also highlight the role of snow properties, including salinity and depth, in modulating radar backscatter signals over sea ice (Tonboe et al., 2021).

A range of machine learning approaches has been applied in sea ice thickness studies, with commonly used methods including Neural Networks, Tree-based, and Deep Learning models (Li et al., 2024b). Among these, Neural Networks have been widely utilized across different data sources and applications. For instance, they have been employed with polarimetric SAR observations to estimate ice thickness (Kwok et al., 1995), and have also been used with in situ measurements to analyze variations in Arctic sea ice thickness (Belchansky et al., 2008). In addition, hybrid frameworks combining Neural Networks with optimization techniques such as genetic algorithms have been developed (Lin and Yang, 2012). Other studies have integrated L-band microwave radiometry and environmental variables within Neural Network models to estimate a range of sea ice thickness conditions (Herbert et al., 2021). Decision Tree methods, in contrast, are more often applied within integrated or multi-step approaches. For example, Decision Tree models have been used to identify leads in CryoSat-2 data, contributing to improved accuracy in sea ice thickness retrievals within these regions (Lee et al., 2016).

Random Forest models consist of several decision trees, and they mainly achieve higher accuracy in their estimations comparing to single trees (Breiman, 2001). These models have been applied in sea ice thickness estimation across diverse datasets and input configurations (Li et al., 2024a). Applications further include the prediction of Arctic thin sea ice thickness using passive microwave remote sensing (the SMOS satellite) (Hernández-Macià et al., 2024). In addition, Random Forest models have been employed to derive sea ice thickness from polarimetric features obtained from Sentinel-1 data (Shamshiri et al., 2022). Time series approaches integrating both physical and radar-derived variables have also been explored for multivariate thin sea ice thickness prediction (Dadjoo and Isleifson, 2025b). More broadly, their performance has been systematically evaluated in terms of efficiency and accuracy for sea ice thickness estimation tasks (Dadjoo and Isleifson, 2025c).

Although Random Forest has been employed in sea ice thickness estimation, there exists a research gap in utilizing radar-derived polarimetric parameters exclusively, combined with varying amounts of previous observations (lag time), to predict future sea ice thickness (lead time) within a time series via Random Forest. However, the application of lag and lead times in Random Forest has been demonstrated in other areas of sea ice research. For instance, Chen et al. (2023) predicted sea ice extent using lag times of 6 and 12 months and lead times of 1 to 3 months, based on monthly ERA5 reanalysis data and sea ice extent records from the National Snow and Ice Data Center (NSIDC). Their model achieved high predictive accuracy, with a R^2 score of 0.99, underscoring the effectiveness of incorporating temporal dependencies in sea ice forecasting. As another example, Palerme and Müller (2021) developed the calibration method using random forest algorithms to improve 10-day sea ice drift forecasts, leveraging buoy and SAR observations. Lead times (1 to 10 days) were used to evaluate forecast accuracy, showing a decrease in performance with longer lead times, while lag times (previous data) helped incorporate historical observations to train the models effectively.

In recent years, Deep Learning approaches, representing advanced multi-layered machine learning architectures, have demonstrated strong performance in sea ice thickness estimation (Li et al., 2024b). Notable studies include the application of Fully Connected Neural Networks using input variables including passive radar observations, and physical parameters (Herbert et al., 2021). Other developments involve the design of ensembled Convolutional Neural Networks (CNNs) (Chi and Kim, 2021), as well as self-attention-based CNN models for daily Arctic winter predictions (Liang et al., 2023). In addition, Deep Learning frameworks have been combined with Bayesian inference techniques and extended through temporal architectures such as various RNN models (Liu et al., 2023). Despite these advancements and improvements in estimation accuracy, the performance of Deep Learning models remains strongly dependent on the availability of large and high-quality datasets.

Overall, although previous research studied sea ice thickness prediction using radar-environmental parameters and ML algorithms, there remains a lack of comprehensive and targeted studies focused on developing highly efficient ML models specifically using surface-based microwave backscattering data. The main objective of this study is investigating the feasibility of predicting sea ice thickness solely from radar-derived NRCS values without relying on additional physical or environmental parameters typically involved in ice formation and thickening processes. While the inclusion of environmental parameters improved performance in specific settings (Dadjoo and Isleifson, 2025c), isolating the contribution of C-band NRCS provides a critical baseline for understanding the standalone information content of radar backscatter in sea ice thickness estimation, and it would be applicable in harsh or far Arctic environments, where environmental parameters are sparse and/or uncertain.

Although this study deliberately avoids the use of environmental parameters, their absence is compensated through temporal feature engineering applied to the radar observations. Specifically, sliding time windows of varying lengths are used to compute statistical descriptors, including the mean and standard deviation of NRCS values. These features enable the model to capture both short-term variability and longer-term trends in radar backscatter associated with thermodynamic ice growth and changes in dielectric properties. This strategy reduces sensitivity to short-term noise allowing the Random Forest model to extract temporal context that would otherwise be provided by environmental inputs. As a result, the approach maintains a radar-only configuration while retaining sensitivity to key processes governing sea ice thickness evolution. Using a time series dataset containing NRCS values at Ku- and C-band frequencies in VV, HH, and HV polarizations, a Random Forest model has been applied to the dataset with various temporal window sizes and variables to establish an optimal predictive framework. Subsequently, using the optimal case, the radar parameters were ranked to identify the most/least influential parameters in the predictions.

2. Data and Methods

2.1 Study Site and Data Preparation

The used data in this paper was recorded from 12-20 February, 2021, at an outdoor research site, Sea-ice Environmental Research Facility (SERF), at the University of Manitoba (Dadjoo and Isleifson, 2025a). SERF has a sensor-equipped pool with dimension of $9.1 \times 18.2 \times 2.45$ m (Isleifson et al., 2023a). Two polarimetric scatterometers in Ku- and C-band (with center frequencies of 17.2 and 5.5 GHz, respectively), and azimuth angle of 30°, measured the microwave scattering response of the grown sea ice in the pool. More detailed description of the scatterometers can be found in Isleifson et al. (2023b). As reported in the literature, thin sea ice growth can be represented more clearly using lower incidence angles (Isleifson et al., 2018).Hence, only the NRCS measurements of the 25° incidence angle was used in this paper. Figure 1 demonstrates the picture of the study site prior to the start of the experiment.

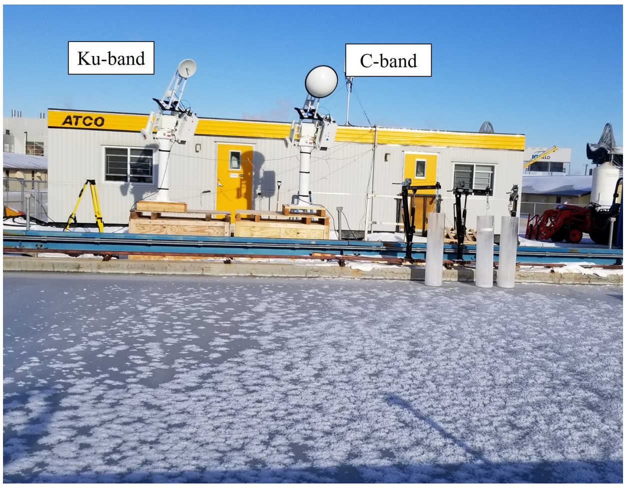


Figure 1. Study site and scatterometers configuration. The image was taken on 12 February 2021 at 10:00. The height of the scatterometers was 2.4 m above the surface and frost flowers with maximum height of 1.5 cm covered sea ice.

Although the original dataset (Dadjoo and Isleifson, 2025a), contains various physical and radar features, only the six radar-related features (NRCS values of Ku- and C-band in three polarizations) have been used in this study to meet the research objective. The experiment lasted about 186 hours and yielded 1511 recorded timestamps, with a temporal resolution of approximately 15 minutes. Considering 1511 timestamps (as rows), the six NRCS values (dB), two columns for mean and standard deviation of the NRCS values, one column for time, and one column for sea ice thickness (cm), the time series contained 1511 rows and 8 columns (Figure 2).

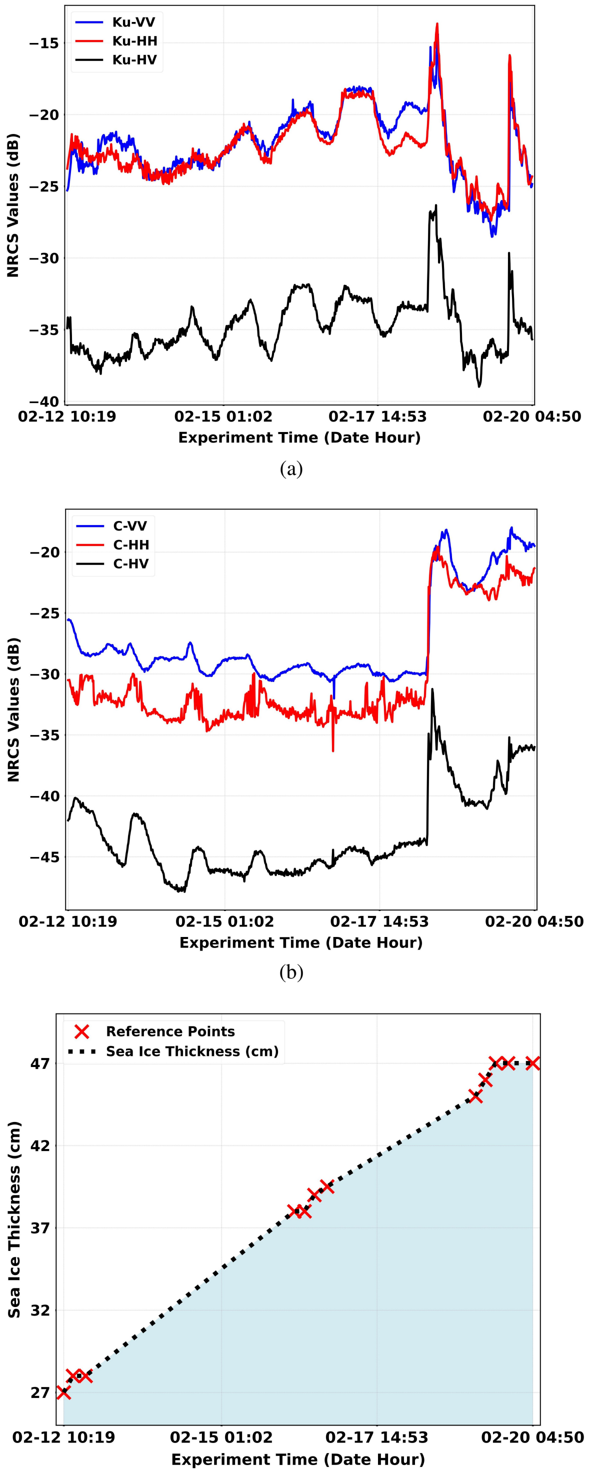
At the early stages of the experiment, sparse frost flowers were observed covering the ice surface (Figures 2(a) and 2(b)), reaching a maximum height of 1.5 cm. Subsequently, two layers of snow were accumulated (using a snow making machine) on the ice on February 18 and 19, with a combined maximum depth of 4 cm. The impact of these snowfalls on NRCS values is evident in Figure 2, where sudden spikes appear toward the end of the time series in both Ku- and C-band data. The presence of frost flowers followed by snow cover makes this dataset a representation of the complex environmental conditions of Arctic sea ice.

2.2 Methodology

Due to some inconsistency in time intervals of the recorded parameters, any time points without value (NaN values) were considered as data gaps, and in the pre-processing phase these cells in the raw data were filled using linear interpolation. In this study, a multivariate predictor approach was used (Breiman, 2001). The ice thickness and the other six NRCS values were considered as the target and features, respectively. To capture local trends and variability in each feature over time, the mean and standard deviation of the six features were calculated using a rolling window approach with various sizes of 8, 24, 48, and 96, which were then added as new features to the dataset. To capture local trends and variability in each feature over time, the mean and standard deviation of the six features were calculated using a rolling window approach with various sizes of 8, 24, 48, and 96, which were then added as new features to the dataset. Given the ∼15-minute interval of the measurements, these window sizes correspond to temporal aggregations of approximately 2, 6, 12, and 24 hours, respectively.

To capture temporal dependencies and predict future sea ice thickness, lag and lead time values were included to the model processing. Lag times represented past values of each feature (Surakhi et al., 2021) and were created using time shifts of 8, 24, 48, and 96 steps. This allowed the model to learn from historical patterns and trends in the data. Lead times, on the other hand, were applied to the target (sea ice thickness) to define the prediction horizon (Palerme and Müller, 2021). By shifting the target forward in time using lead intervals of 8, 24, 48, and 96 steps, the model was trained to predict sea ice thickness at specified future points. Using consistent window sizes, lag and lead times enabled Random Forest to effectively model the time-dependent nature of sea ice thickness using radar features.

As the parameters were in various ranges, and to avoid the effect of very small or large numbers on the analysis, min-max scaling method was used to normalize both features and the target so that the results (Starovoitov and Golub, 2021). Then, based on trial and error, 80% of the data samples were considered as the training and the remaining samples (20%) were considered as



(a) (b) (c)

Figure 2. Scatterometer data; (a) Ku-band and (b) C-band NRCS measurements; and (c) ice thickness graph. The cross markers on dotted line show in-situ measurements from physical sampling. Shaded area demonstrates the accumulated sea ice over time.

the testing subsets. This split was done randomly. Due to applying lag, lead, and rolling window processes, the original dataset containing 1511 was reduced in size. Specifically, rolling mean and standard deviation calculations with a window size of 96 and lag time of 96 removed the first 96 rows. Additionally, shifting the target by a lead time of 96 excludes the last 96 rows from the dataset. As a result, the number of usable rows after these calculations and shifts was reduced to 1319. Since the dataset was split into training and testing sets using an 80/20 ratio, the test set consisted of 263 samples. This reduction in sample size was a necessary trade-off to ensure that the model was trained on temporally consistent and statistically enriched features, which are critical for capturing the underlying patterns in sea ice thickness prediction.

In the model tuning stage, 200 trees and random state of 42 (reproducibility) were set as the hyperparameters of Random Forest. After training the model using the training data, its performance was assessed using RMSE on the testing subset providing the predictions error. Then, to visualize the performance, predictions were plotted versus actual values.

Moreover, feature importance in the prediction process was evaluated using the Permutation Importance method. This approach randomly shuffles the values of each feature, thereby breaking the relationship between the feature and the target variable while preserving the feature’s original distribution. If permuting a feature leads to a significant decline in model performance, the feature is considered important for the model’s predictions (Altmann et al., 2010). A positive importance score indicates that shuffling the feature degrades model accuracy, confirming its relevance. In contrast, near-zero or negative scores suggest that the model performs similarly or even better when the feature is shuffled, implying that the feature may be uninformative or contributing noise (Breiman, 2001).

3. Results and Discussion

Using the dataset described in Section 2.1 containing time series of Ku- and C-band NRCS values, sea ice thickness in the range of 27-47 cm was predicted in various lag and lead times. The objective of this analysis was to identify the optimal lag and lead configurations by comparing the resulting RMSE values. Then, using the optimal configuration, predicted and actual sea ice thicknesses were compared to investigate the performance of the model.

3.1 Temporal Effects on Prediction Accuracy

Various combinations of temporal parameters including lead, lag times and window sizes, were investigated to evaluate the sensitivity of the model to these parameters. Lag time indicates the number of previous time steps used as input features, while lead time denotes how far into the future the model is trying to predict. Figure 3 illustrates a comprehensive heatmap of RMSE values generated by the Random Forest model, showing its performance in predicting sea ice thickness across a range of lead, lag and window sizes configurations.

According to Figure 3, the results show a general tendency for RMSE to decrease as lead time increases, particularly in configurations using larger window sizes. For example, in the case of window size 96, the RMSE was 0.26 for a lead time of 24, but dropped significantly to 0.03 for a lead time of 96. This suggests that the model is capable of capturing stable long-term patterns, and that longer lead times may not necessarily degrade predictive accuracy when the input features are sufficiently smoothed. However, this trend is not consistent across all configurations. In some cases, such as with window size 24, longer lag times (e.g., lag 96) resulted in higher RMSE values

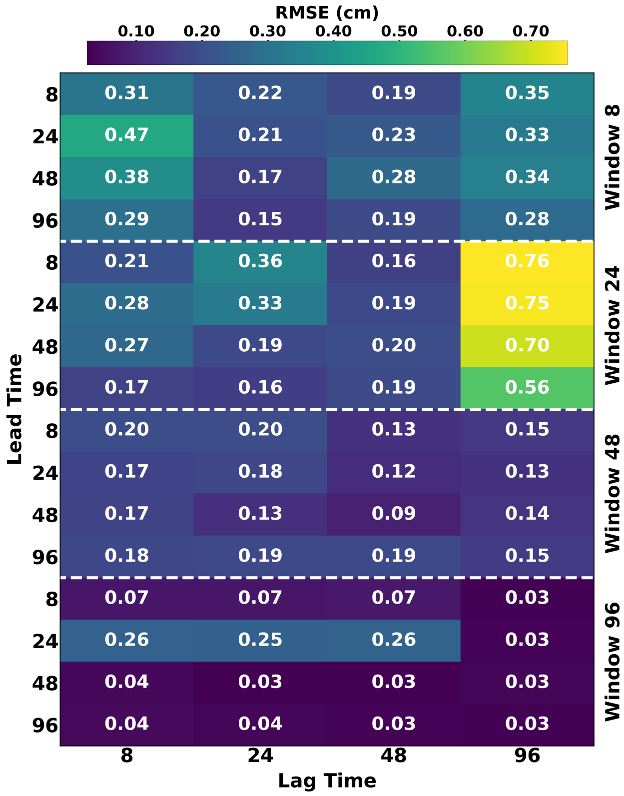


Figure 3. RMSE values of sea ice thickness prediction using various lag, lead and window sizes.

compared to shorter lag times, indicating that the interaction between lag, lead, and window size can be complex and data-dependent.

A particularly important observation is that most of the highest RMSE values occurred when the window size was smaller than the lag time. For instance, using a window size of 24 with a lag time of 96 produced some of the worst RMSE values across all tested combinations. This suggests that when a model is configured to use a large amount of historical data, it is essential to apply a window size that is at least equal to the lag time. Doing so ensures that the rolling statistical features can effectively smooth the input data, reducing the impact of noise and fluctuations. This is especially relevant in the context of NRCS data, which is subject to significant variability due to environmental and physical factors such as wind, humidity, and temperature (Isleifson et al., 2023a). The use of rolling mean and standard deviation features helps mitigate this issue by stabilizing the input data, thereby enabling the model to better learn and predict sea ice thickness.

The best overall performance was achieved with window size 96, where the RMSE reached a minimum of 0.03 across a majority of parameter combinations. This result highlights the dominant role of window size in shaping model accuracy. Not only did the larger window size improve prediction quality, but it also appeared to reduce the model's sensitivity to variations in lag and lead time. This suggests that with an appropriately chosen window size, the model can maintain stable and reliable performance across a wide range of lead and lag times. Such robustness is particularly valuable for operational applications, where flexibility in prediction timing is often required. Overall, the heatmap provides strong evidence that window size is a critical factor in NRCS-based sea ice thickness prediction, and that its proper tuning can significantly enhance model performance and stability.

The use of rolling window statistics in this study is consistent with established time-series feature engineering practices, where moving window descriptors such as the mean and standard deviation are commonly employed to capture temporal context in machine learning models (Wang et al., 2022; Mojtahedi et al., 2025).

3.2 Predicted Versus Actual Thickness Comparison

In Section 3.1, the lowest RMSE values, indicating the highest prediction accuracy, were mostly associated with a window size of 96, particularly when both lag and lead times were set to 96. In this section, a comparison between predicted and actual sea ice thickness values was conducted using this configuration, which achieved an RMSE of 0.03 cm. Figure 4 shows the results of this comparison. This figure compares the predicted sea ice thickness values with the corresponding actual measurements for the test subset, plotted along the vertical and horizontal axes, respectively. The dashed diagonal line represents the ideal relationship, where predictions perfectly coincide with observations. The concentration of data points tightly aligned with this reference line demonstrates strong agreement between predicted and observed values. This is supported by the low RMSE value of 0.03 cm.

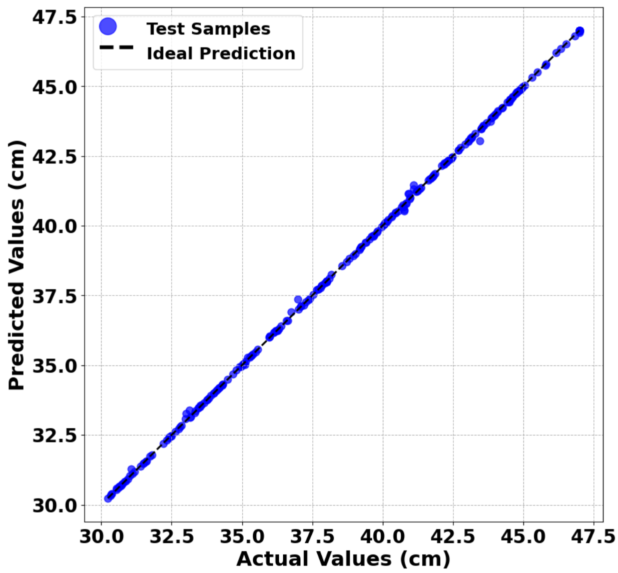


Figure 4. Comparison of actual and predicted sea ice thickness values obtained using lead, lag times and a window size of 96 (RMSE = 0.03 cm). Each blue marker corresponds to an individual sample from the test dataset (263 samples). The black dashed diagonal line indicates the ideal relationship.

3.3 Features Ranking

Using the Permutation Importance method, the NRCS values from Ku- and C-band scatterometers were ranked based on their importance to sea ice thickness prediction (Table 1). The results show that the C-band in VV polarization is the most important feature, with an importance score of 0.1166, significantly outperforming all other features. C-HH and C-HV follow with importance scores of 0.0385 and 0.0139, respectively, further highlighting the dominant role of C-band data in the model’s predictive performance. In contrast, Ku-band features contribute minimally, with Ku-VV scoring only 0.0045, and Ku-HH and Ku-HV showing negligible importance (0.0025 and 0.0001, respectively). The superior performance of the C-band observed in this study may be attributed to its heightened sensitivity to the transition from frost flowers to snow-covered sea ice, as reflected in the NRCS values. Similar findings were reported by Isleifson et al. (2023a), demonstrated the effectiveness of the C-band in detecting changes in sea ice surfaces, particularly the transition from frost flower-covered ice to snow-covered ice.

Ranking	Feature	Importance
1	C-VV	0.1166
2	C-HH	0.0385
3	C-HV	0.0139
4	Ku-VV	0.0045
5	Ku-HH	0.0025
6	Ku-HV	0.0001

Table 1. Feature ranking using Permutation Importance method.

According to Table 1, VV and HH polarizations are more effective than HV in both C- and Ku-band because co-polarized signals (VV, HH) are more sensitive to surface roughness, which are directly related to ice thickness. In contrast, HV backscatter is weaker and more affected by depolarization, making it less reliable for thickness estimation (Isleifson et al., 2023a).

4. Conclusions

Accurate prediction of sea ice thickness is increasingly vital for climate monitoring and Arctic operations. This study demonstrated the effectiveness of integrating surface-based microwave remote sensing with machine learning to predict the thickness of the lab-grown sea ice (with thickness range of 27-47 cm). Using time-series NRCS measurements from Ku- and C-band scatterometers across VV, HH, and HV polarizations, a Random Forest model was trained under various temporal configurations. The highest prediction accuracy (RMSE = 0.03 cm) was achieved using a temporal window size of 96 with equal lag and lead times, highlighting the importance of temporal aggregation and smoothing in enhancing model performance.

An important outcome of this work is the demonstration that accurate sea ice thickness prediction can be achieved using radar backscatter observations alone, without the explicit inclusion of physical or environmental parameters. This was made possible through targeted feature engineering applied to the NRCS time series, whereby statistical descriptors such as the mean and standard deviation were computed over multiple temporal window sizes and combined with lead and lag times.

Feature importance analysis revealed that C-band NRCS in VV polarization was the dominant contributor to thickness prediction, followed by C-HH and C-HV, while Ku-band features contributed minimally. This behavior is attributed to the longer wavelength and greater penetration depth of C-band, which makes it more sensitive to ice growth processes within the investigated thickness range. The superior performance of co-polarized channels compared to HV further reflects their stronger response to surface roughness and volume scattering mechanisms associated with ice thickening.

Beyond the laboratory setting, these results demonstrate the potential of a radar-only, data-efficient framework for sea ice thickness estimation in data-sparse Arctic environments, where ancillary environmental parameters are unavailable or unreliable. The proposed methodology is well suited for surface-based monitoring systems and shows promise for transferability to satellite-based C-band radar observations, supporting real-time sea ice thickness monitoring.

Although this study is based on surface-based radar observations, the findings provide valuable guidance for satellite-based applications. While satellite SAR systems face limitations related to spatial resolution and revisit time, the proposed NRCS-only framework relies on temporal backscatter patterns and statistical feature engineering rather than instantaneous measurements. This design enhances robustness to reduced temporal sampling and supports transferability to C-band satellite observations, with surface-based results serving as a benchmark for assessing performance under satellite constraints. Future work should focus on extending this framework to a broader range of ice thicknesses and ice types to ensure robustness and applicability across diverse Arctic environments. In addition, further investigations incorporating advanced polarimetric parameters, such as co-polarization ratios, cross-polarization ratios, and polarimetric decomposition features are recommended to evaluate their potential for providing enhanced sensitivity to ice structure and for further improving prediction accuracy. Expanding the analysis to include different machine learning models will also enable performance comparisons and support the broader application of advanced machine learning models in sea ice thickness studies.

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