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Title: Arctic sea ice radar freeboard retrieval from ERS-2 using altimetry : Toward sea ice thickness observation from 1995 to 2021

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Anonymous referee n°3 - global comments

First, I would like to express my apologies to the authors for taking this long to provide my review due to personal reasons. Nonetheless, I was asked to still provide it also in the light of the two already published referee comments. This in mind, I will focus on aspects I do not see covered yet or extend on raised issues as I see fit with a focus on the “calibration” using a neural network. I provide general comments first with some additional specific comments at the end.

The authors present in their study their way of generating a new dataset of altimetry-based freeboard data with ERS-2 data incorporated for the first time. This is a great achievement in itself and definitely justifies publication. Furthermore, the authors put substantial effort in validating their results against several different types of validation data. ERS data in general is a great challenge to work with and there is a reason why not many people are actually working on the task to make use of them over sea ice.

However, as also pointed out in the very detailed review by Robbie Mallet, who went to great lengths to analyze the results and underlying data, it appears the chosen methodology does not really work the way the authors or at least any potential reader would expect it. There appears to be strong evidence that the large mix of input data to the neural network along side the ERS freeboard estimates dominate the outcome. Hence, the NN did not learn what was expected but something else. While this is not necessarily bad, it is a fundamental problem of the presented study, as in my opinion, this is can be seen as grist to the mills of all machine learning or artificial intelligence sceptics. It should clearly be stated what the impact of each dataset is on the resulting product or rather that its apparently not the input raw freeboard. Potentially, the product could even e generated without the raw freeboard? This really should be clarified upfront and likely further investigated by the authors before publication.

Answer to Anonymous referee n°3 - global comments

We would like to thank the reviewer for his careful reading of the manuscript and for the relevant remarks that have helped to improve the quality of the manuscript. In order to fit with your comments, we have made a revision of the manuscript that should have corrected the textual issues and well improved the readability of the document. We hope that these modifications will meet your requirements. Please find below the details on how your specific comments have been taken into account.

As the referee n°3 seems to have the same concerns as referee n°2 with some conclusions taken from the other referee’s review, we propose the same global answer as for referee n°2.

In our understanding, the main concern of the reviewer is : "To what extent can we claim that the resulting product is a corrected or calibrated retrieval when it doesn’t reflect the variability in the raw, retracked values ? " Expressed in other word, the referee states that "nothing of the original radar freeboard measurement remains in the corrected value" and that is an issue.

First, we would like to indicate that referee n°2’s detailed analysis on the correlations between raw freeboard and calibrated radar freeboard have pointed out difficulties that have motivated the calibrations (past studies) and thereafter the use of a neural network.

Using the exact same processing chain as for CryoSat-2 (with a TFMRA-50 retracker), the Envisat, and ERS radar freeboard estimates are very different to what we are supposed to observe in terms of magnitude and spatial patterns. Indeed, LRM waveforms are strongly impacted by the size of the footprint which is much larger in LRM than in SAR Mode ($\sim$ 180 km^2 to $\sim$ 5 km^2 [Stammer et al, 2018]). This is the main cause for the misfit between Envisat and CS-2 radar freeboards. In order to deal with this issue, differences between CS-2 and Envisat have been analyzed, please see Guerreiro et al. 2017, Paul et al. 2018 and Tilling et al. 2019 for a complete overview. As mentioned in the manuscript, the first two studies point out that the radar freeboard differences between the two altimeters are correlated (not especially linearly correlated) to the sea ice roughness, characterized by the waveform backscatter, the leading edge width or the pulse peakiness. The third study identified a link between the misfit and the distance between floes and leads.
The optimal solution would be to find a theoretical model, such as the Brown's model over open ocean, to represent the radar response over sea ice in order to correctly retrack the waveform. Despite significant progress in SAR mode (SAMOSA+, LARM, etc.), these models are not yet able to represent all the complexity of this response even in SARM. For instance, they are not able to represent snow penetration effects (i.e. volume backscatter effects). Moreover, in LRM, no study reports relevant retracked height over sea ice floes with a physical retracker and the complexity of the response is still poorly understood. The objective of this paper is neither to model any effect of the ice surface condition, nor to understand its influence on the FBr but rather to reconstruct the best possible ERS-2 radar freeboard with our actual knowledge consistently with Envisat and CS-2 ones. To do so, roughness or more globally sea ice surface state proxies are used to post-correct the estimated radar freeboard using as a reference Envisat previously calibrated on CS-2. Our study is based on the principle that the radar freeboard computed with a TFMRA50 from LRM waveforms is strongly polluted by the surface roughness. Then, we propose to calibrate LRM radar freeboard on CS-2 using some parameters characterizing the sea ice surface roughness. The same methodology is applied to calibrate ERS-2 radar freeboard on a CryoSat-2 like radar freeboard from Envisat. Thereafter, some other parameters such as the ice concentration or the sea ice age were added to improve and consolidate the learning of the NN so to reach a better match with CS-2 (in the case of Envisat and Envisat calibrated for ERS-2).
Unlike the review suggests, we would like to specify that the sea ice age is not directly used in the regression, we use a MYI fraction. The way this fraction is calculated has been developed in the manuscript, but it is not discrete values, as it is considered by the reviewer. Also, we would like to specify that correlations calculated with a variable that takes only two values can not be relevant.

To illustrate that the calibration is based on the PP and the LES, Figure 1 shows radar freeboard for April 2011 for CS-2, for Envisat with the calibration presented in the manuscript and one with another model trained only with the raw freeboard, the Pulse Peakiness and the Leading edge slope. It shows that these three parameters are sufficient to represent the magnitude and the patterns we are supposed to see in the Arctic. The other parameters help the calibration to get closer to CS-2 radar freeboard and bring more spatial variability.

The correction we have to process is strongly non-linear, so this is the reason why we have chosen a neural network approach, which has the specificity to handle well with non linearities. Then, correlation between parameters based on linear approximation are not representative of the dependencies between parameters (inputs/output) in the neural network. Indeed, it is much more complicated to estimate the relative importance of each parameter in a regression, and it is not given by the correlations between the inputs and the predicted value. As it has been already mentioned, the main reason is that the relations that have been established by the neural network are not linear, while the correlation only evaluate whether the variables are related by a linear relation. Figure 2 shows the "partial dependencies" which refers to an illustration (statistically computed) of the relations between each input parameters (x-axis) and the predicted value (y-axis). It also illustrates the relative importance of each parameter: a parameter with no influence would have a horizontal curve as a mean state but it is not a quantitative approach. Partial dependency plots should be interpreted with caution, it refers to the mean state of statistical computation, depends on a discretization choice and values of input parameters have been standardized (mean = 0 and Standard deviation=1). The Figure 2 presents 2 panels, one for Envisat calibration (left) and one for ERS-2 calibration (right). Nevertheless, we can say that curves are not linear, no input is unused or with a very low influence, we can also note that LES and PP have the largest influence on the predicted radar freeboard.

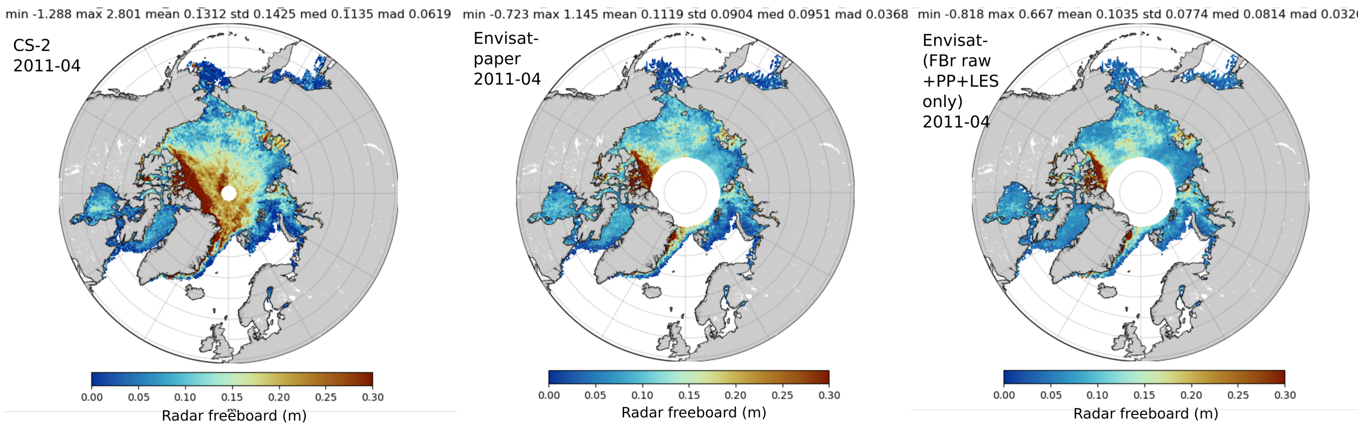


Figure 1. Radar freeboard from CS-2 (left), Envisat calibrated presented in the paper (middle) and Envisat using only the raw freeboard+LES+PP (right)

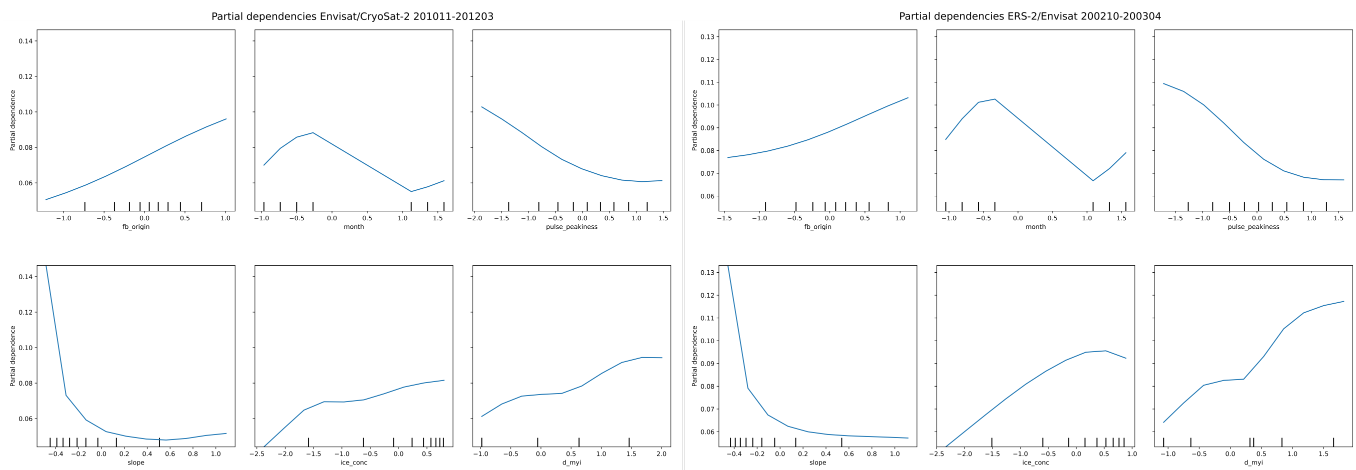


Figure 2. Partial dependencies plots for Envisat and ERS-2 calibration, from top left to top right, inputs are, the raw radar freeboard, the month, the pulse peakiness, the Leading edge slope, the concentration and the f_{MYI}.

The question of the non-linearity is central in our study but also in referee n°2's analysis. But, since the correction is not linear at all, the largest raw radar freeboard is not necessarily the largest corrected freeboard, just as it is not the largest raw freeboard that will benefit from the largest correction. The raw radar freeboard, even noisy, still gives information on how the altimeter perceives the surface and how much it should be corrected, which remains an important information. We expect that the raw freeboard define the space and time variability of the calibrated radar freeboard over the whole period but this is hard to show since we don't have any reference of the expected variability of the SIT/FBr/FB during 1995-2010. To enhance the fact that the raw radar freeboard impacts the corrected radar freeboard, figure 3 shows the relative difference between the predicted FBr of the NN presented in the paper and one from a NN trained without the raw FBr for April 2011. It shows that for a large part of the basin, the difference of FBr is up to 25% of the predicted radar freeboard.

Finally, it's important to keep in mind that we have trained the neural network to reach the best score i.e. the best coefficient of determination (compared to CS-2 for Envisat and to Envisat corrected for ERS-2). Choosing the best NN, means choosing the combination of hyperparameters and even the choice of input parameters that gives the best scores. This means that the

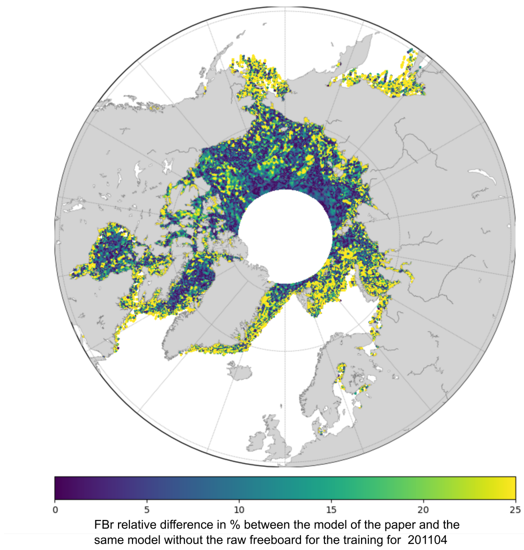


Figure 3. Relative difference in % between the corrected freeboard of our study and one with the same NN trained without the raw freeboard

fraction of MYI allows to better fit CS-2 radar freeboard, that's why we keep it. However, it's even expected to find a good correlation between the sea ice age and the sea ice freeboard because, in average, older ice will be thicker.

To sum up, the purpose of this paper is to retrieve a consistent radar freeboard estimation for ERS-2 using the current knowledge on LRM waveforms over sea ice. Because LRM waveforms are highly impacted by the surface state and poorly understood over sea ice, raw freeboard have to be calibrated. Two calibrations need to be implemented to get consistent ERS-2 radar freeboard, first Envisat against CS-2 and then ERS-2 against Envisat calibrated radar freeboard. The calibration is first based on surface roughness proxy because evident link have been emphasized with the size of the correction (previous studies) and secondly on auxiliary data that were used to reach better fit with CS-2. The calibrated radar freeboard is partly driven by the raw radar freeboard, both parameters are not linear correlated as it would say that the calibration did not perform well. The "age" or in our case the MYI fraction is not the key input for the NN training. Furthermore, 'ice with a higher-than-average raw FBr in a given month" can not necessarily "end up with a higher than average corrected FBr value" as the calibration is not linear.

Unfortunately, the impact of each parameter could be a dedicated study and it would not be the purpose of this study.

In this document, the referee's comments are in bold type, the answers are in italic type, and the corrections to the revised manuscript are in normal type.

L257: One could doubt the idea to use this kind of freeboards as an input in the first place. Wouldn't it make a difference to choose a more appropriate retracker threshold for leads in LRM waveforms like 90/95%? This might not solve the problem with regional patterns but would likely eliminate the negative freeboards and deliver a better initial state.

Empirical retracker with a threshold of 90/95% can be a risky strategy. The error on the range would vary a lot according to the sampling, randomly up to a gate ($\sim$ 47cm). Using a 50% ensure the stability of the range (Poisson et al 2018 fig.9) even if we know we have a bias. Laforge et al 2020 shows that over leads comparing to physical retracker, the SLA bias is constant for altimeters in SARM, nevertheless this conclusion is also relevant for LRM as peaky waveforms are similar over leads. We *prefer to correct a bias than a random error, as we don't usually have a lot of measurement over leads. As suggesting for Jack Landy's review, we propose the following modification:*

In LRM, most of this error comes from a constant bias on the Sea Level Anomaly

replaced by

Negative radar freeboards are mainly due to the retracker choice. Indeed, a TFMRA50 is used to retrack height on both leads and floes, this introduces a bias on the height over the leads. The TFMRA threshold to retrack heights over leads should be closer to 80% and because we use a threshold of 50% that corresponds to the position of the retrack point for ocean surfaces, not specular ones (Poisson et al 2018), the leads are measured higher than they are and even higher than the floes. The SLA bias (in leads) is evaluated constant for SARM altimeter in the study of Laforge et al 2020, this conclusion is also relevant for LRM altimeters as waveforms over the leads are peaky and similar from a lead to an other.

This positive constant bias over the leads results to a negative bias on the radar freeboard. To avoid this bias, the retracker threshold could be adapted for leads or the SLA could be calibrated on CryoSat-2 one. Nevertheless, a threshold of 50% ensure the stability of the range (Poisson et al 2018, Fig.9)) contrary to higher threshold (80%-95%) that could lead up to 47 cm of random error on the SLA. A TFMRA at 50 % for both leads and floes is preferred in this study as a constant bias is easier to correct than an undetermined random error.

On a very general note: What are the improvements over Guerreiro et al (2017)? What justifies the use of a neural network instead of simply extending this methodology? As it had a more direct link to the actual measurements of the instrument? (as suggested also by the authors in L258-260)

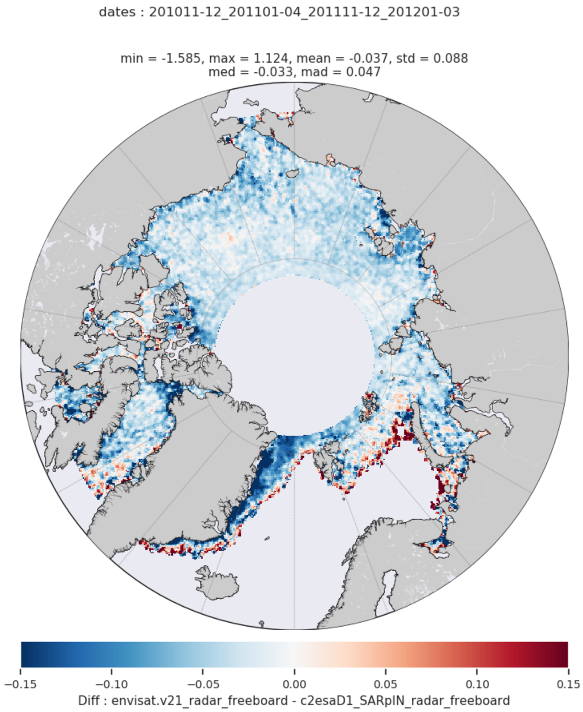
Figure 4 shows comparisons between Envisat-G radar freeboard from Guerreiro et al 2017, Envisat-B from this study compared to CryoSat-2 TFMRA50 radar freeboard. Maps present the mean radar freeboard difference between Envisat and CS-2 for the 12 months of the mission overlap period. These maps reveal that the first radar freeboard estimates were underestimated over the entire basin and especially in thick ice area. The correlation is much higher for Envisat-B radar freeboard. Compared to CryoSat-2, the improvement is evident with the method developed in this study. This study also reveals two modes of radar freeboard that could correspond to MYI/FYI.

As mentioned in the manuscript, the use of a neural network is justified by the non-linearities that exist between inputs and output, especially since it is not necessary to make any assumptions about the nature of the relations. The calibration can be seen as a usual regression in the continuity Guerreiro et al, 2017 with additional inputs to increase the match with SARM radar freeboard.

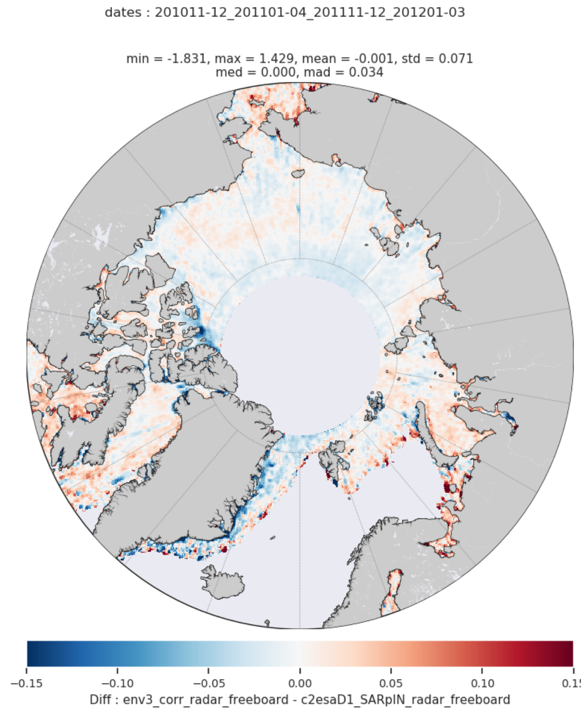
L277: Out of curiosity, did the authors test various setups and this architecture of the NN showed the best results? How was it evaluated and what different setups were used? Things like the number of layers, number of neurons per layer, activation functions etc. come to mind and all the mentioned specifics come without references or justification! For example, there are pretty much no modern studies on ML/AI that do not use some sort of ReLU activation functions, why do the author use a Sigmoid? Some elaboration on this might be informative to the readers as well and also provide a broader background also to non-ML enthusiasts in the sea-ice community.

Yes, a lot of setups has been tested. As already mentioned in the manuscript, the hyperparameters which also included the architecture (number of neurons and layers) have been choosing by gridding, e.g. by testing a large amount of combination. It was evaluated by cross validation, training 5 times the same setup on different training sets (randomly chosen) and test on the remaining 10% testing dataset (each time different). The best statistics on the ensemble of the 5 five scores were used to evaluate a combination. However, models with 102 neurons per layer instead of 100 were not significantly different.

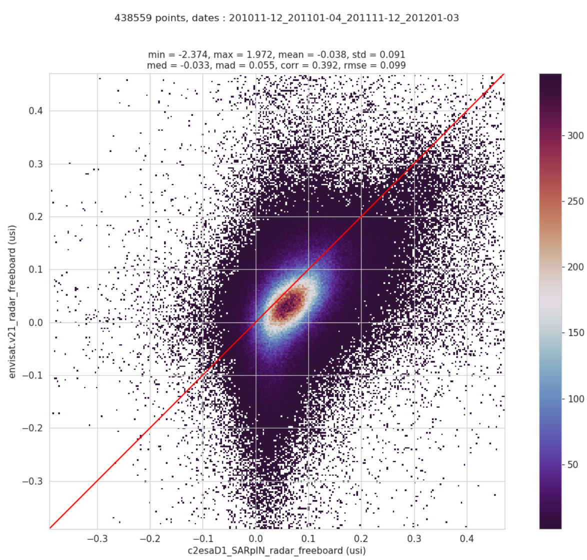
The tuning of hyperparameters has been made by experimenting, that the reason why there are no references, if you mean referencing other geophysical studies, it will have no sens as the tuning is really specific to the study. Activation function relies



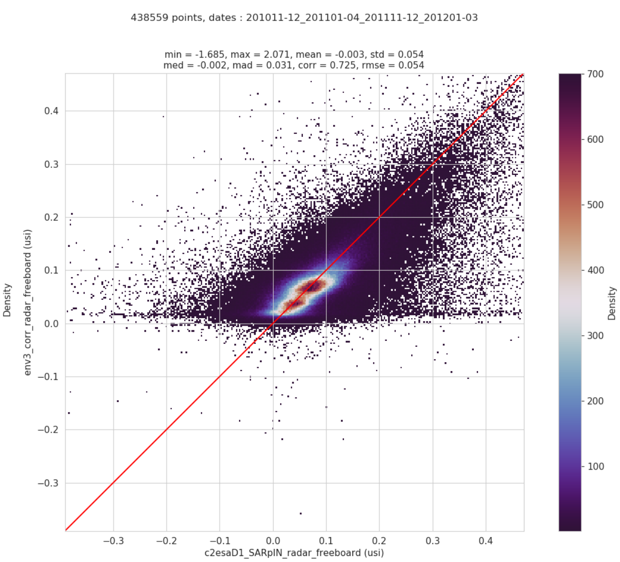
(a) Mean difference Envisat-G - CS-2



(b) Mean difference Envisat-B - CS-2



(c) Envisat-G vs CS-2



(d) Envisat-B vs CS-2

Figure 4. Comparison of Envisat-G (Guerreiro et al, 2017) and Envisat-B (Bocquet et al, 2022) with CryoSat-2 for the missions overlap period

on the type of value of the output data and ReLu function does not allow negative values, which could occur here. We propose the following modifications:

The neural network is a multilayer perceptron regressor (MLP) composed of 5 hidden layers, each composed of 100 neurons. The activation function used is a sigmoid. Hyper-parameters have been tuned by dichotomy by choosing at each step the hyper-parameter combination with the highest mean score (average score made on 5 models) on the test sample. The score used for this regression is the Pearson correlation coefficient. To determine the most suitable hyper-parameter combination, the dataset is randomly split into a training and a testing dataset, corresponding respectively to 90% and 10% of the initial dataset. To avoid overfitting, we use early stopping to interrupt the training when the score is not improving anymore. Once the hyper-parameter combination is set, the MLP is trained with the whole dataset. The NN trained is then applied to the LRM monthly grids to obtain a monthly LRM-corrected radar freeboard.

replaced by:

The neural network used is a multilayer perceptron (MLP). Both calibrations have been processed with Scikit learn [Pedregosa et al, 2011]. The MLP is composed of 5 hidden layers, each composed of 100 neurons. The choice of hyperparameters : number of neurons, the learning rate, the regularization term, batch size, activation functions, solver for the weights optimization, have been done using gridding methodology, e.g. testing combinations and take the one that give best score. The evaluation criterion, called the score, is chosen as the determination coefficient. Models are trained on 90% of the dataset and tested on the remaining 10%, the splitting in random. During the tuning step, models are cross validated, it means that they are each trained 5 times with the same combination of hyperparameters but without the same train/test dataset, the 5 scores are then analyzed to determine the best combination. Cross validation give a better idea of the model performance as the dependence to the training dataset is limited. The activation function for the hidden layers neurons is a sigmoid, motivated by possible negative radar freeboard values and the optimizer is and ADAM [Kigma et Ba, 2014]. Moreover, in order to avoid over-fitting, an early stopping criterion is used to stop the model training as soon as the score is not improved during 10 consecutive iterations, with a defined tolerance.

Finally, once the hyperparameters combination is set, the MLP is trained on the whole dataset to provide the calibration function. The trained model is then applied to the LRM monthly grids to obtain a monthly LRM-corrected radar freeboard.

L279: The authors should clarify hyper parameters to the non-AI/ML expert readers. Without any reference I fear this is a lot to ask from potential readers of a non-AI journal. Additionally, what optimizer did the authors use as this can also have a substantial impact on the training process and the model performance and is totally unmentioned in the current version of the manuscript.

We hope that the previous comment will give an element of answer. The optimizer used is an adam, according to your comment, this information has been added.

L280: It is not clear to me how these 5 models are differing from each other? By slightly different choices on the learning rate? Please elaborate!

They are differing from their training dataset as it has been randomly split each of the 5 times. 5 models are used to make the cross validation. We also hope that the modification of the paragraph L277-285 help the reader and has clarified this part of the manuscript.

L282: Common practice would be a split around 80/20% or 75/25%, how do the authors justify such a small test-set size? This could result in a quite non-representative test dataset in the end.

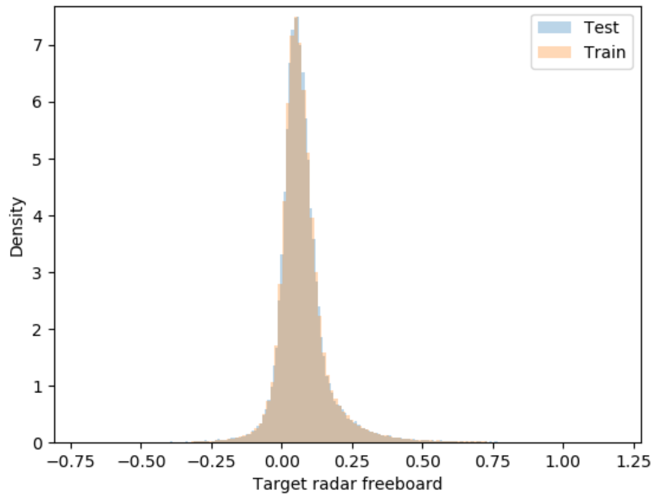


Figure 5. Probability density function of target radar freeboard for Envisat calibration for Test (blue) and Train (orange) dataset

This split can be justified by the fact that the dataset is quite important, with about 600000 values for Envisat calibration and about 300000 values for ERS-2 calibration. Figure 5 shows the probability density of the target radar freeboard for Envisat calibration for both test and train sample. Densities are identical for both datasets, this supports the fact that this splitting, in our case, leads to a representative test dataset.

Answers to referee 3 : specific comments

L118 & 122: the (Lindsay and Schweiger, 2013) reference should not be in parenthesis.

This point has been corrected.

L126: I think these PP thresholds should be mentioned here in a Table or within the text.

The following table has been added in appendix (Table A1).

L284: This should be 'the trained NN' not the 'the NN trained'.

This comment has been taken into account.

Table 1. Pulse peakiness thresholds for lead/floe classification

Mission (RA mode)	PP lead threshold	PP floe threshold
CryoSat-2 (SAR)	0.3*	0.1*
Envisat (LRM)	0.3*	0.1*
ERS-2 (LRM)	0.2839	0.1328

* [Guerreiro et al, 2017]

L286: I might just have missed it (sorry then) but what is the SARM abbreviation?

Indeed, this acronym was missing in the list of acronyms. SARM refers to 'Synthetic Aperture Radar Mode' to be consistent with LRM 'Low resolution Mode'. This point has been taken into account.

Figure 6: This definitely needs a much larger figure caption!

We do agree with that comment, the following modification has been done:

Summary diagram of the uncertainty budget from along track to the propagation by the neural network.
replaced by:
Summary diagram of uncertainty budget during along track, gridding and calibration steps. Top left panel corresponds to the along track to grid uncertainty budget. Top right panel defines the notations, for the Monte Carlo procedure : Ω for the Neural Network input parameters, Γ for the Neural Network output parameter (radar freeboard) with σ_Ω and σ_Γ, the corresponding uncertainties. The middle panel corresponds to the training of M models with noisy inputs and outputs. Bottom panel show the predictions of the N noisy input with the M trained neural network. γ is the predicted radar freeboard estimation for one pixel of the MxN predictions. M=100, N=200.

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