Mapping Arctic Sea Ice Surface Roughness with Multi-angle Imaging SpectroRadiometery

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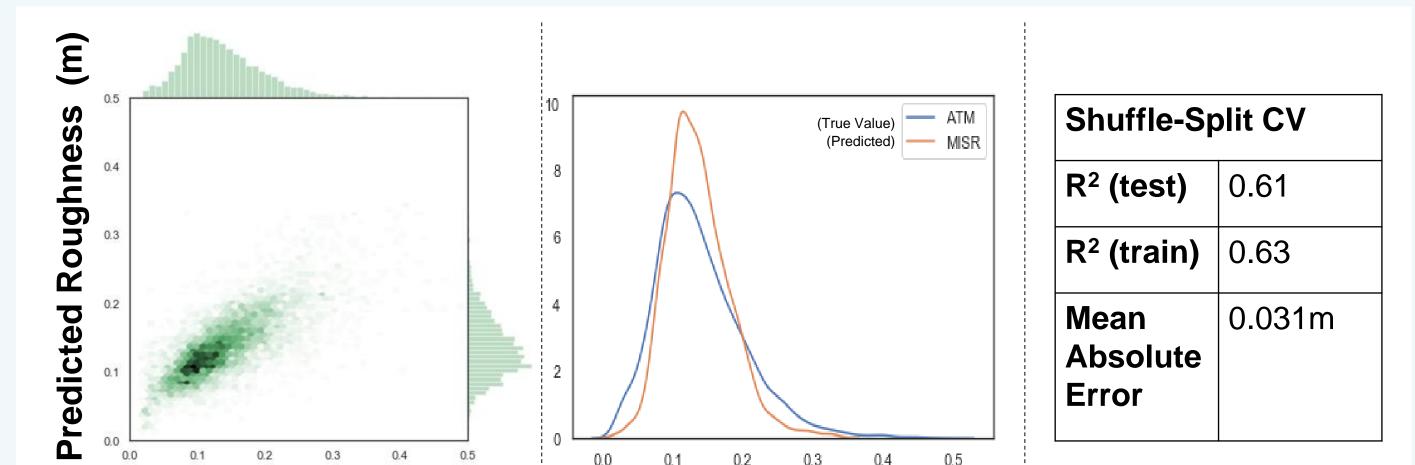
1) Motivation

2) Background

- Surface Roughness, defined as the standard deviation of elevations within an footprint minimized to a best fit plane, is a crucial parameter in many climate and oceanographic studies, constraining momentum transfer between the atmosphere and ocean, providing preconditioning for summer melt pond extent, while also closely related to ice age.
- High resolution roughness estimates from airborne laser measurements are limited in spatial and temporal coverage. Pan-Arctic satellite roughness have remained elusive and do not extended over multi-decadal time-scales.

4) Validation

 Model performance is initially assessed using an 80:20 random permutation 'shufflesplit, cross-validation.





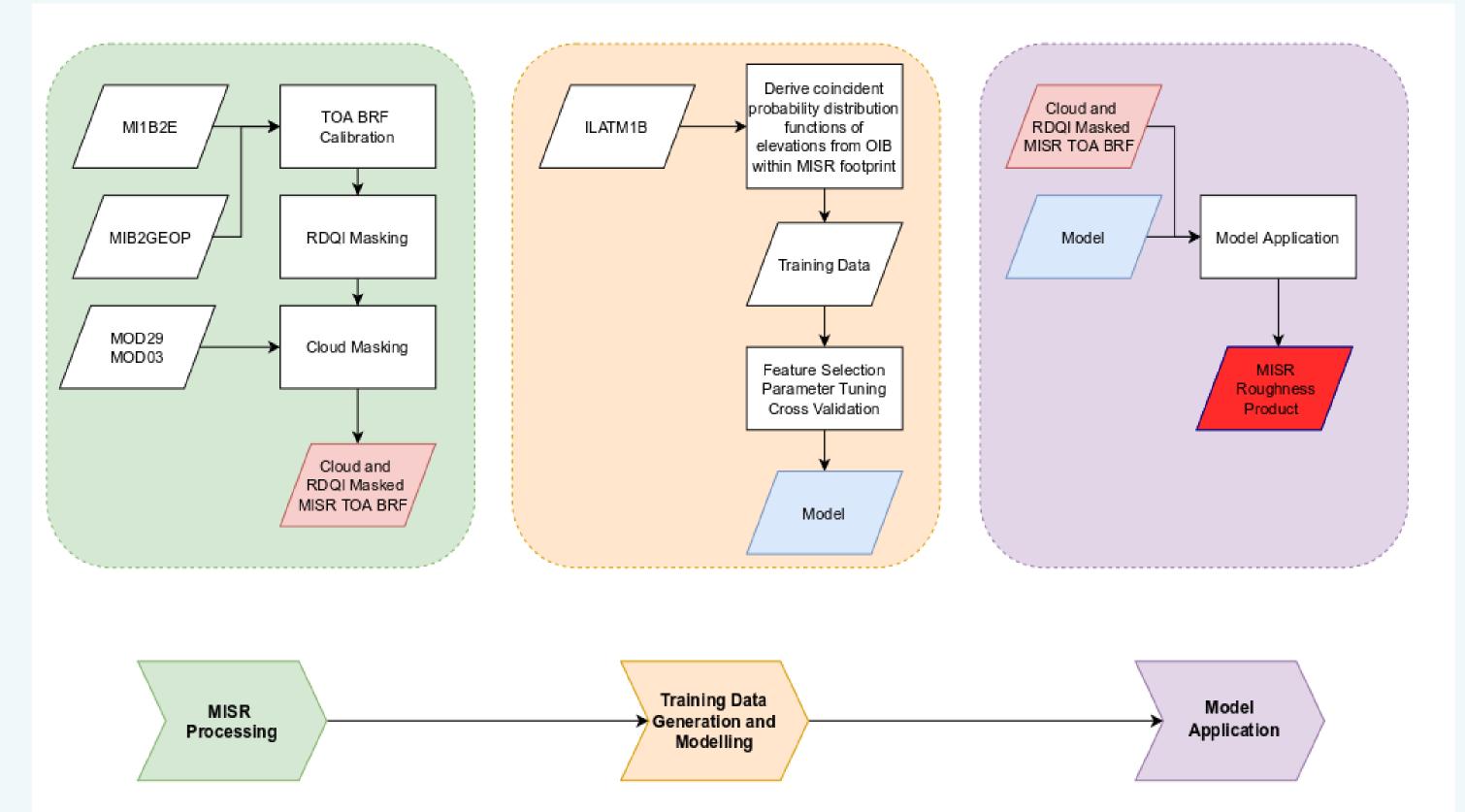
The Multi-angle Imaging SpectroRadiometery (MISR) instrument provides near simultaneous retrieval of images at nine camera angles; use of angular reflectance signatures to derive surface roughness has proven successful on continental ice (Nolin *et al., 2002*) using a combination of aftward and forward images known as the NDAI (Normalized Difference Angular Index)

$$NDAI = \frac{Aft - Fore}{Aft + Fore}$$

The NDAI is highly empirical; over sea ice it is not possible to make direct comparisons with NDAIs retrieved between different scenes.

3) Methodology

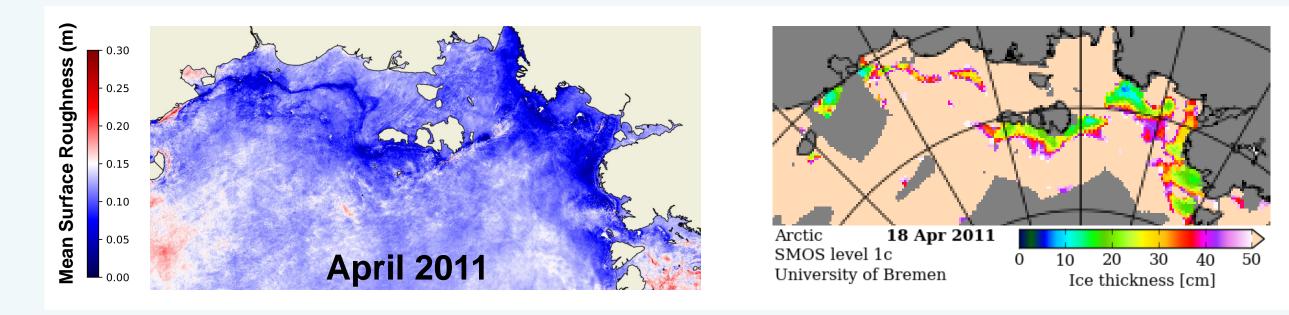
The objective is to generate a training data set of coincident angular reflectance signatures (from MISR) and roughness measurements (using LiDAR from IceBridge ATM, Airborne Topographic Mapper). This is then applied to a machine learning regression scheme to provide a mapping from specular anisotropy as sampled from MISR to surface roughness. Model performance is assessed, then is applied to individual swaths that can be stacked, generating pan-Arctic roughness maps.



Actual Roughness (m)

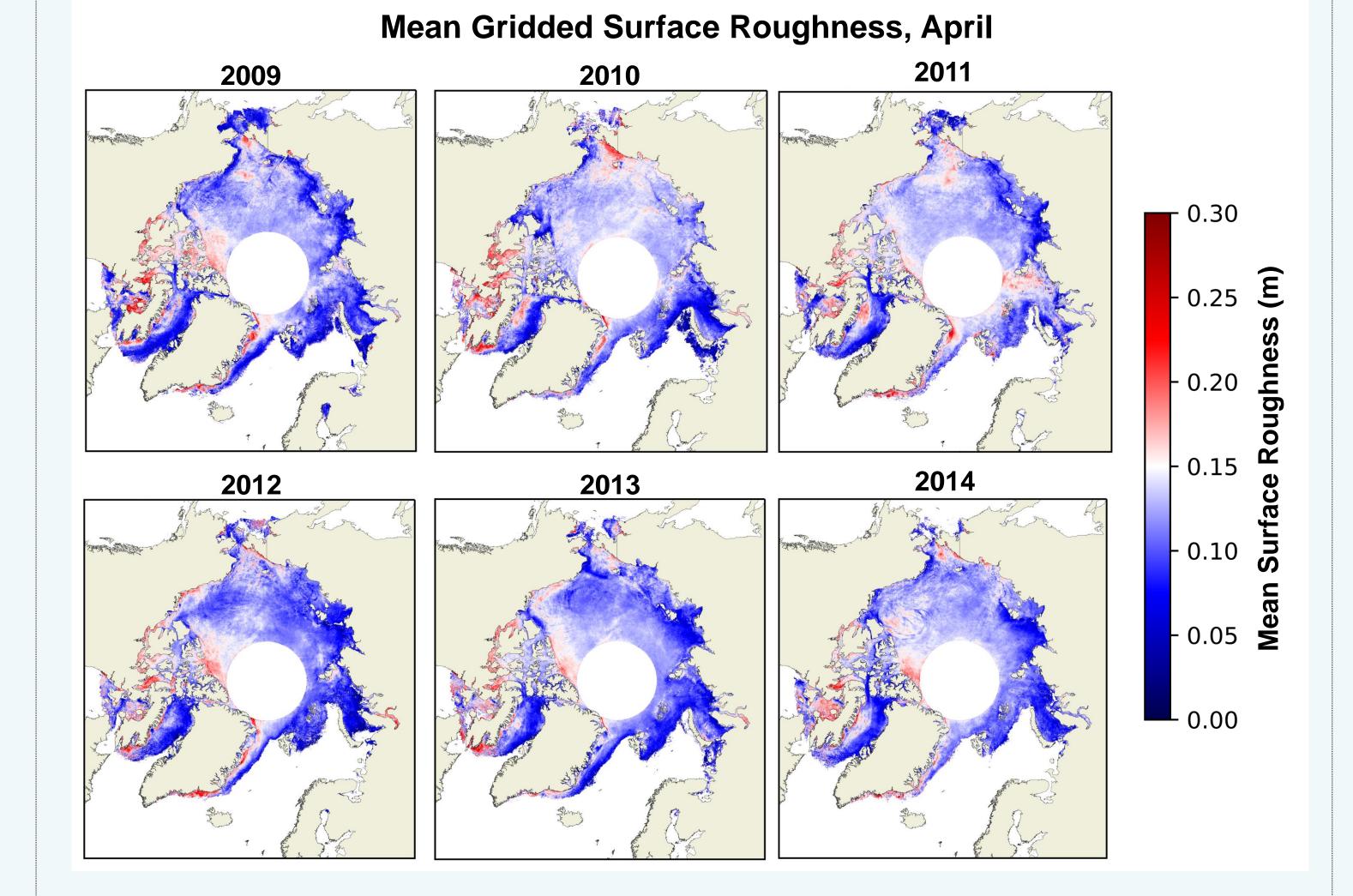
Roughness (m)

Convergent R² scores for the training and testing datasets, and MAE approaching the machine error of the ATM are good indicators that overfitting has been avoided through appropriate hyperparameter tuning. Future work will look at nested cross validation. Monthly Gridded Mean roughness maps exhibit good qualitative agreement with SMOS Ice Thickness (*Huntemann et al., 2014;* shown below, right for the Laptev Sea and East Siberian Sea) and with ASCAT backscatter maps.



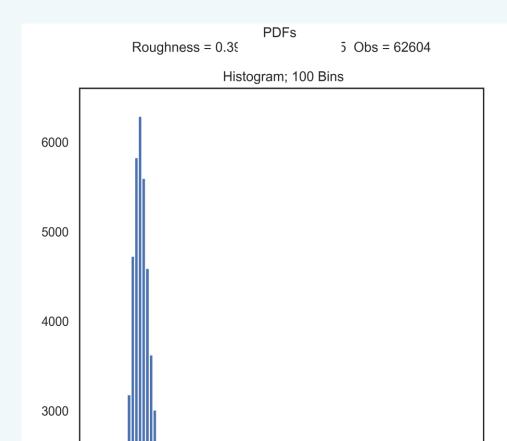
5) Time Series Analysis

A six year time series for April surface roughness is displayed below.

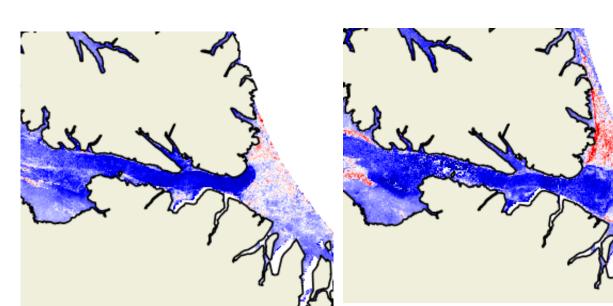


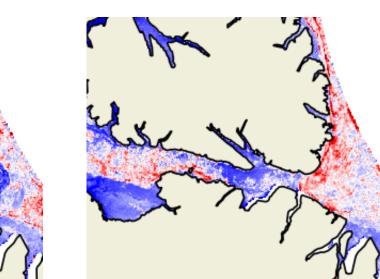
Cloud masking of scenes that include sea ice with high accuracy remains a substantial open problem for imagery from the MISR satellite. We exploit the inherent time located orbital path geometry of all satellites on the Terra platform and implement the MOD35 cloud mask from Terra MODIS. This cloud mask uses more bands over a wider window resulting in an accuracy in excess of 90%.

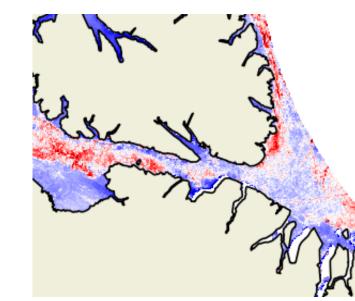
In order to derive roughness measurements from IceBridge over a spatially coherent footprint with the 1.1km resolution from MISR, probability distribution functions of coincident elevation measurements are generated, and the standard deviation calculated. An example of the elevation point cloud for a MISR Pixel (below) and the corresponding probability distribution function (right) is provided. Only the derived roughness is used for modelling.

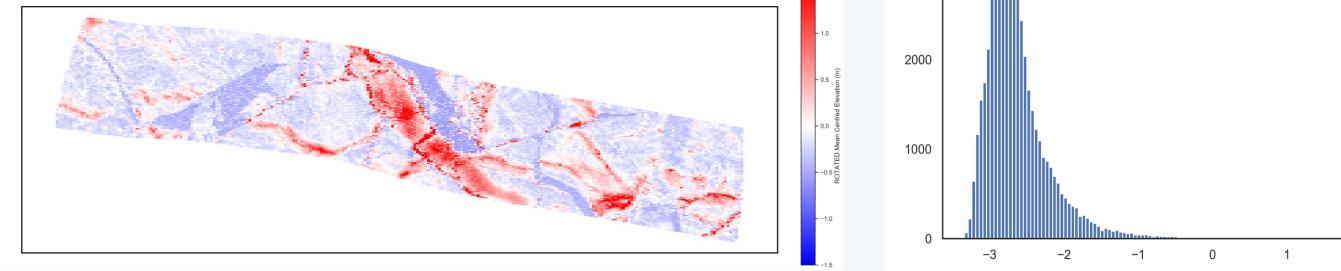


This product is particularly adept at distinguishing newly formed sea ice, and thus is a good tool for visualizing polynyas. Below we present a surface roughness time series of the North Water Polynya, note the development of northern ice arches in 2009 and 2010, and southern ice arches in 2011 and 2012.









The training dataset is filtered to remove data that is of poor quality (such as low shot density of elevation measurements) and, after applying a feature subset using nested cross-validation, is modelled using support vector regression with a radial basis function kernel. Grid-Search cross-validation is used to tune the hyperparameters.

April 2009	April 2010	

April 2011

April 2012

6) Conclusions

- We present a new sea ice surface roughness product from calibration of LiDAR elevation measurements from the ATM with angular reflectance signatures from MISR
 Monthly Gridded Mean roughness maps exhibit good qualitative agreement with SMOS Ice Thickness, and with ASCAT backscatter maps.
- This product is particularly adept at distinguishing newly formed sea ice, and thus is a good tool for visualizing polynyas.

References

Huntemann, M., Heygster, G., Kaleschke, L., Krumpen, T., Mäkynen, M., and Drusch, M.: Empirical sea ice thickness retrieval during the freeze-up period from SMOS high incident angle observations, The Cryosphere, 8, 439-451, doi:10.5194/tc-8-439-2014, 2014. Nolin, A.W., Fetterer, F.M. and Scambos, T.A., 2002. Surface roughness characterizations of sea ice and ice sheets: Case studies with MISR data. IEEE transactions on Geoscience and Remote Sensing, 40(7), pp.1605-1615.