

## Response to the reviewer comments

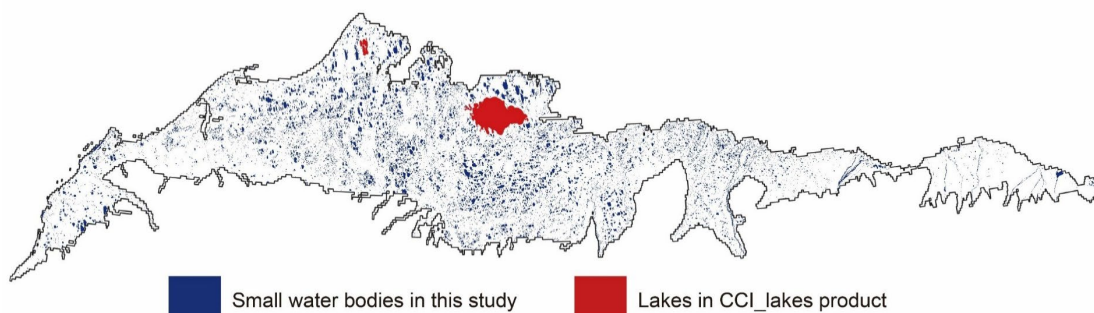
### Reviewer #1

The manuscript is a valuable contribution to the delineation of lake ice/water cover using SAR imagery. Although coverage is limited to the ACP, the algorithm shows promise for application to broader areas across the northern hemisphere. The data provides advantages over optical imagery as expected of active microwave. The comparison to DW is a provides suitable validation for the ice fraction product. There are some minor comments that would be good to address. Overall, the manuscript quality is very high but there a few key points that should be addressed.

Thank you for your thorough evaluation and valuable suggestions. We have revised the manuscript accordingly.

There is clear indication that this product could be extended to be an operational product. Was there a reason that other operational products were not compared? For example, the CCI lakes lake ice cover product is available at roughly a 1km resolution and covers some of the lakes in the study area. A comparison to the CCI product would be beneficial due to the similarity between methods, both use a random forest algorithm to classify ice cover.

Thank you for the comment. The Lakes Essential Climate Variable products (Lakes\_cci project; <https://climate.esa.int/en/projects/lakes/data/>) have a spatial resolution of approximately 1 km, and focus on relatively large lakes. Accordingly, the CCI Lakes product has almost no spatial overlap with our data set, which focused on the small water bodies within the ACP study region (Fig. R1).



**Figure R1**

Spatial distributions of small water bodies focused in this study and the lakes in the CCI product (<https://climate.esa.int/en/projects/lakes/data/>) within the ACP study region.

Considering the complementary nature of the two data sets, we added the following in the Discussion:

*Line 433-435: In addition, our dataset of small water bodies can be merged with operational products that focus on relatively large lakes, such as the ESA Lakes\_cci (Carrea et al., 2024). The complementary datasets allow for comprehensive assessment of water bodies across a wide range of sizes.*

**Added reference:**

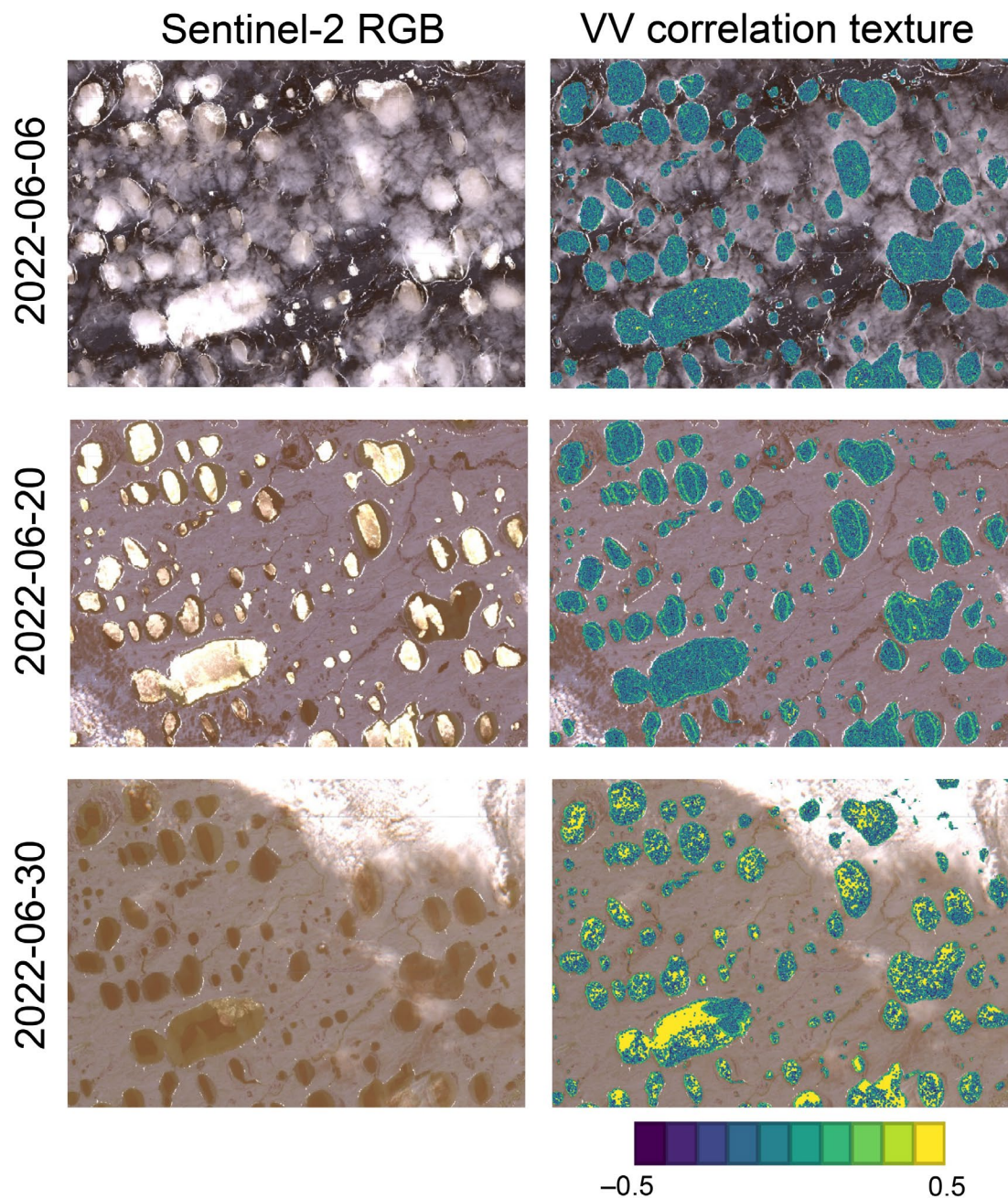
Carrea, L., Crétaux, J.-F., Liu, X., Wu, Y., Bergé-Nguyen, M., Calmettes, B., Duguay, C., Jiang, D., Merchant, C. J., Mueller, D., Selmes, N., Simis, S., Spyrakos, E., Stelzer, K., Warren, M., Yesou, H., and Zhang, D.: ESA Lakes Climate Change Initiative (Lakes\_cci): Lake products, Version 2.1, <https://doi.org/10.5285/7FC9DF8070D34CACAB8092E45EF276F1>, 2024.

Another question for the authors relates to the choice of texture as a variable for the classifier. The citation provided was conducted for sea ice, however, to the reviewers knowledge no formal exploration of texture has been done for lake ice. Did the authors conduct any investigation into texture values for lake ice? For example, does the texture provide any context for heterogenous surfaces during freeze-up? break-up? Was an investigation done into the temporal evolution of the texture pattern?

As suggested, we examined texture patterns and used the VV correlation texture as an example to illustrate the temporal evolution of texture during the ice break-up period (Fig. S1 in the Supplementary Materials).

For the selected area, the VV correlation texture exhibited a noisy spatial pattern at the onset of ice melt (first row of Fig. S1). The irregular spatial correlations among adjacent pixels indicated heterogeneous snow and ice conditions, likely associated with variations in surface roughness, snow wetness, and ice thickness during this transitional phase. As melting progressed, elevated correlation values emerged along the ice-water boundary (second row of Fig. S1), reflecting spatially consistent backscatter from ice slush or saturated, rough ice surfaces within the ice-water transition zone. This pronounced texture signal provided direct spatial evidence for delineating ice-water boundaries. In the late stage of break-up, open water areas exhibited high correlation values, consistent with the relatively homogeneous surface structure of calm water (third row of Fig. S1).

Overall, the VV correlation texture evolved with the changing ice/water conditions and their spatial patterns, thereby providing support for the machine-learning-based classification.



**Figure S1**

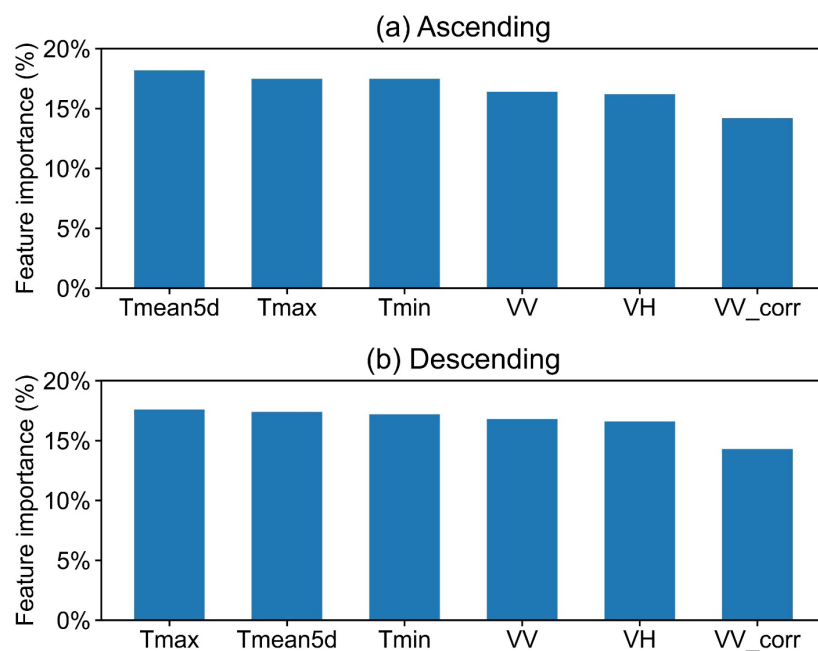
The texture derived from SAR imagery provides spatial information for distinguishing lake ice and open water, illustrated here using a selected area within the study region. The figure shows three stages of lake ice break-up: (1) the early stage (first row, 6 June 2022), (2) the rapid melt stage (second row, 20 June 2022), and (3) the late stage (third row, 30 June 2022). For each row, the two panels from left to right represent the Sentinel-2 RGB image, and the correlation texture computed from the VV band.

We added the following clarification in the manuscript:

*Line 201-203: For example, VV\_corr texture information is indicative of ice and water conditions (e.g., ice patches, open water patches, and ice-water boundaries) during the break-up period (Fig. S1), and thus supports the machine-learning based classification.*

There is no variable importance analysis provided - was this conducted? It would be of interest to users to see how the valuable the different variables were in the random forest classifier. The classifier used both SAR parameters and temperature variables, how does the model rate these? The concern here being that the classifier is being driven by temperature rather than SAR/EO data which is the original goal.

We conducted analysis on variable importance and provided Fig. S3 in the Supplementary Materials. Both temperature-based and radar-based features are important, with comparable contributions to the predictions (Fig. S3). For example, in the descending-orbit model, Tmax accounts for 17.6% while VV accounts for 16.8%, and in the ascending-orbit model, Tmean5d accounts for 18.2% while VV accounts for 16.8%, and in the ascending-orbit model, Tmean5d accounts for 18.2% while VV accounts for 16.4% (Fig. S3). The temperature variables provide regional temperature distributions and seasonal context, whereas the SAR variables provide the direct observations crucial for distinguishing pixel-level ice conditions.



**Figure S3**

Feature importance of the random forest classifiers trained with ascending-pass data (a) and descending-pass data (b).

We added the following in the manuscript:

**Line 289-291:** *Both temperature-based and radar-based features are important, with comparable contributions to the predictions (Fig. S3). The temperature variables provide regional temperature distributions and seasonal context, whereas the SAR variables provide the direct observations crucial for distinguishing pixel-level ice conditions.*