Response to CC1

A Framework for Automated Supraglacial Lake Detection and Depth Retrieval in ICESat-2 Photon Data Across the Greenland and Antarctic Ice Sheets

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Comments from the reviewers are given in black.
Our responses are given in red.
Quotes from the submitted manuscript are given in bold red.
Proposed amendments or additions to the revised manuscript are given in blue in the Times New Roman font.

References that were already included in the original manuscript are cited in-text only, in the same format as in the submitted manuscript. New references are added to the end of this document in full.

Community Comment 1 (Bert Wouters)

CC1: 'Comment on egusphere-2024-1156', Bert Wouters, 26 Jun 2024
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Notes:
- *B. Wouters, H.A. Fricker and P. Arndt are all co-authors of Fricker et al. (2021);*
- *P. Arndt was a referee for Datta and Wouters (2021).*

I agree with the two other reviewers that this is a well-written and important contribution, presenting an elegant method to derive supraglacial lake bathymetry. Nevertheless, I would like to comment on the two statements below, in the Introduction and Summary sections:

- L47-53: *Previous ICESat-2 studies have been limited to applying depth estimation methods to a handful of manually picked lakes or data granules, with no clear pathway to large-scale computational implementation across the ATL03 data catalog, which comprises hundreds of terabytes of unstructured point cloud data (Neumann et al., 2023b). To address this challenge, we have created a fully automated and scalable algorithm for lake detection and depth determination from ICESat-2 data.*
- L646-651: *ICESat-2 data had not previously been used at scale for this purpose because its photon-level product comprises hundreds of terabytes of unstructured point cloud data along spatially discrete ground tracks, which makes it difficult to integrate the data with spatially continuous data in existing workflows. To address this challenge, we have presented the fully automated, two-step FLUID/SuRRF algorithm for the detection and depth determination of supraglacial lakes on the ice

sheets in ICESat-2 photon data, and proposed a computational framework that allows for its large-scale implementation across any desired ice sheet drainage basins and melt seasons.

Whereas it is true that other methods have not been used at such a large scale as in the manuscript, the Watta algorithm (Datta and Wouters, 2021) is fully automated (i.e. it detects potential lake locations based on a flatness criterion and then estimates the bathymetry, similar to the framework presented in this manuscript) and it is designed to be run in parallel, allowing large-scale application at any location or time period. The reason Watta hasn't been applied at large scale is a lack of computational infrastructure.

It would be nice to acknowledge that the automated and scalable nature of the method, while advantageous, is not a unique selling point. This doesn't take away that there is plenty of novelty in the manuscript to merit publication. Emphasizing these specific innovations would strengthen the manuscript, in my view.

Thanks very much Bert for your positive and constructive comment, and for bringing this particular issue to our attention. First off, we would like to express our appreciation for the scientific contributions that you made in Datta and Wouters (2021) and acknowledge that the results you published had a large impact on motivating our own study and informing our opinion that it is crucial to retrieve and publicly share as many ICESat-2 water depth estimates as possible, to improve our ability to continuously monitor supraglacial meltwater volumes across the ice sheets. We explain this in the later paragraphs.

Thank you for pointing out that automation and scalability are selling points that are not unique to our algorithm. We agree that this should be pointed out in the manuscript. We will explain that other automated and scalable algorithms exist for this purpose, and that the new contribution of our study is the fact that in addition to developing another such algorithm, we also propose a computational framework for applying it at ice-sheet-wide scale and then demonstrate that it works in practice.

For completeness, we would like to note here that in our own experience, the task of computationally scaling up FLUID-SuRRF was hugely more time- and work-intensive than developing the initial algorithm. At the time, we already considered it to be automated because it ran smoothly on a few dozen granules that we had used to develop empirical thresholds and tune parameters. It is amazing that multiple automated and scalable algorithms have been proposed for this purpose, and in Fricker et al. (2021) we pointed out that ensemble estimates from various different algorithms outperformed any single algorithm on the small number of lakes presented in that case study. However, just because such automated and theoretically scalable algorithms exist, does not mean that it is easy at all to use them to generate large, comprehensive data products. This is why we spent three years since the initial algorithm was presented in Fricker et al. (2021) working on actually implementing FLUID-SuRRF at scale.

We would like to make it clear we are in no way trying to diminish the scientific significance of Watta. In Datta and Wouters (2021) you are showing many other significant and very impressive scientific results that go well beyond what we are presenting in our manuscript. In fact, our own study is largely motivated by the fact that you successfully demonstrated that depths and volumes of supraglacial lakes can be accurately estimated by combining along-track depth measurements from Watta/ICESat-2 with concurrent imagery from various passive optical sensors. As we explain in the manuscript, this is absolutely necessary for using ICESat-2 to improve estimates for continuously monitoring melt lake volumes through space and time. In Datta and Wouters (2021), you use imagery to extrapolate depths along ICESat-2 segments to the full lake basins that these segments intersect. You convincingly showed that this indeed works very well, and these results inspired us to attempt to go one step further: To be able to use ICESat-2 to empirically estimate depths/volumes of supraglacial lakes in locations and at times where/when ICESat-2 measurements *are not directly available*, it is necessary to rely on statistical methods that can generalize the depth-reflectance relationship for a particular passive optical sensor independently of the availability training data that is closeby in space and time. For this to work, the data that are used to train statistical learning models capable of multiple non-linear regression for representing this depth-reflectance relationship need to adequately cover the parameter space defined by the combination of predictors that are included.

If instead we attempted to train a model to learn the relationship between Sentinel-2 reflectance and water depth from the lake segments provided in Datta and Wouters (2021), the training data would be limited to estimates based on five ICESat-2 tracks from five different dates, all of which cluster closely together near Sermeq Kujalleq and Sarqardliup Sermia. This means that we would sample associated Sentinel-2 data from only a handful of satellite overpasses, which would likely be acquired under similar conditions (e.g., sun angles). If we now show the model unseen Sentinel-2 data that originated under different conditions and ask it to estimate water depth, it will likely not be able to extrapolate well. Since ICESat-2 observations are fundamentally quite sparse, we believe that it is necessary to obtain as many ICESat-2 depth estimates from different locations and times to be able to effectively use ICESat-2 to improve monitoring of meltwater volumes across the ice sheets: in this case, we argue that "more data is always better". We hope that this explains why we considered it to be so important to take on the task to scale up ICESat-2 lake detection on depth determination algorithms, and to share the resulting data.

For reference, see Domingos (2012) for an explanation of how more data usually improves statistical / machine learning models. This article also mentions the need for models to generalize, as well as the benefits of using ensemble methods. While somewhat outdated for such a fast-moving field, the article does a great job at explaining the fundamental principles.

We propose the following changes:

- It seems that we have not detailed our motivation for large-scale extraction of ICESat-2 melt lake depths (based on promising recent results from combining ICESat-2 depths with imagery / fundamental principles of statistical learning) clearly enough. We therefore propose to rewrite the corresponding section in the introduction in its own paragraph:
  "While ICESat-2 data alone cannot be used to continuously monitor melt lake volumes, several case studies have shown that ICESat-2 depth measurements can be used to constrain parameters in models that estimate lake volumes from satellite imagery (Datta and Wouters, 2021; Leeuwen, 2023; Lutz et al., 2024). For instance, Datta and Wouters demonstrated that it is possible to accurately extrapolate depths along ICESat-2's ground track segments to the full lake basins that these segments intersect. To be able to use ICESat-2 to improve depth estimates of supraglacial lakes in locations where (and at times when) ICESat-2 measurements are not directly available, it will be necessary to rely on statistical methods that can generalize the relationship between water depth and reflectance for a particular passive optical sensor under a wide variety of conditions and independently of the availability training data that is close-by in space and time (Hastie et al., 2009). For this to work effectively, the data that are used to train statistical learning models capable of multiple non-linear regression for representing a complex depth-reflectance relationship need to adequately cover the parameter space defined by the combination of predictors that are included (Markham and Rakes, 1998; Wang et al., 2022). Since ICESat-2 observations of melt lakes are relatively sparse, it is therefore crucial to to obtain as many ICESat-2 depth estimates as possible from different locations and times (and thus under a wide variety of environmental conditions) to be able to effectively use ICESat-2 to improve monitoring of meltwater volumes across the ice sheets. This suggests that large-scale extraction of accurate supraglacial lake depths from a wide range of ICESat-2 photon-level data in combination with concurrent optical satellite imagery can provide a labeled training data set enabling the application of machine learning methods (e.g., Leeuwen, 2023) capable of generating a well-constrained data-driven model for ice-sheet-wide lake volume estimation (Melling et al., 2023)."

- L47-53: We had to restructure the entire paragraph to make sure we are not misleading the reader by making it sound like automation and scalability are unique selling points of our algorithm. Here are our proposed changes:
  "While automated and scalable algorithms for lake detection and depth retrieval in ATL03 photon data have been proposed (e.g., Datta and Wouters, 2021; Xiao et al., 2023), in practice no previous ICESat-2 studies have applied supraglacial lake depth estimation methods to more than a handful of manually picked lake segments or data granules, or presented a straightforward pathway to large-scale computational implementation across the ATL03 data catalog, which comprises hundreds of terabytes of unstructured point cloud data (Neumann et al., 2023b). To address this challenge, we present a framework for ice-sheet-wide implementation of our own fully automated and scalable algorithm for along-track lake segment detection and depth determination from ICESat-2 data. Here, we present this algorithm, apply it to two entire drainage basins in Greenland and Antarctica (Sect. 3.5, Fig. 2) using distributed high-throughput computing, and demonstrate its performance for two full melt seasons."

- L646-651: We believe that by now it should be sufficiently clear to the reader that other automated and scalable algorithms do exist, but have not been applied at scale. However, we propose to switch the sentence structure to make it more clear that we are "addressing this challenge" primarily by taking on the actual implementation rather than by proposing an additional automated algorithm:
  "ICESat-2 data had not previously been used at scale for this purpose because its photon-level product comprises hundreds of terabytes of unstructured point cloud data along spatially discrete ground tracks, which makes it difficult to integrate the data with spatially continuous data in existing workflows. To address this challenge, we have proposed a computational framework that allows users to detect lake segments and determine their water depths across all available ICESat-2 data for any desired ice sheet drainage basins and melt seasons. Using distributed high-throughput computing, this framework applies the fully automated, two-step FLUID/SuRRF algorithm to large numbers of ICESat-2 ATL03 photon data granules in parallel. To test our method, we applied FLUID-SuRRF to all available ICESat-2 data over two drainage basins, one on the Antarctic Ice Sheet and one on the Greenland Ice Sheet, for a high-melt and a low-melt summer."

References:

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