Response to Referee #2

In this document, we outline our responses to comments from the referee, including modifications that we intend to make to the manuscript where necessary.

Referee comments are shown in black and our responses in blue.

The manuscript is well written and clearly structured, and it presents a promising high-resolution freeboard retrieval method using ICESat-2 ATL03 photon data. The results show improved performance relative to existing ICESat-2 products, and the method may also increase the usability of weak-beam observations for sea-ice freeboard retrieval. However, some methodological details require further clarification. In particular, the machine-learning workflow should be described in more detail, especially the link between GMM clustering, Sentinel-2-based human interpretation, and RF classification. In addition, the diversity of the Sentinel-2/ICESat-2 coincident cases should be better documented, including their seasonal coverage and time offsets, to support the claimed year-round applicability of the method.

We appreciate the reviewer's positive assessment and constructive suggestions that improve the clarity of the work.

Specific comments:

P6, L168: Because both the GMM clustering and the Sentinel-2-based manual interpretation rely on the 25 coincident scenes, the authors should show how these scenes are distributed across months/seasons and surface conditions. A table summarizing the acquisition dates, Sentinel-2–ICESat-2 time offsets, beam types, and assigned surface classes would help assess whether the training data adequately support the claimed year-round applicability of the classifier.

We will add a new table (table 1) in the Appendix to document the 25 Sentinel-2/ICESat-2 coincident scenes. The table will include the Sentinel-2 and ICESat-2 acquisition dates, the time offset between the two observations. All six ICESat-2 beams, including three strong beams and three weak beams, were used in the training data set.

table 1 Available coincident pairs between Sentinel-2 and ICESat-2.

No.	ICESat-2	Sentinel-2	Acquisition date	Δ Time (minute)
1.	ATL03_20190712224936_02270404_006_02	S2_20190712T222111_20190712T222106_T13XDL	2019-07-12	28

2.	ATL03_20190526002946_08820304_006_02	S2_20190525T221109_20190525T221104_T13XEK	2019-05-26	94
3.	ATL03_20190622105707_13010304_006_02	S2_20190622T103631_20190622T103627_T44XMQ	2019-06-22	20
4.	ATL03_20190805215948_05930404_006_02	S2_20190805T220101_20190805T220056_T11XMK	2019-08-05	01
5.	ATL03_20200327220004_00210703_006_01	S2_20200327T220119_20200327T220223_T09XWH	2020-03-27	01
6.	ATL03_20200410204349_02340703_006_02	S2_20200410T205021_20200410T205019_T11XMG	2020-04-10	06
7.	ATL03_20200314145921_12050603_006_01	S2_20200314T150909_20200314T150906_T28XEN	2020-03-14	09
8.	ATL03_20200322082530_13230603_006_01	S2_20200322T083621_20200322T083621_T43XEJ	2020-03-22	10
9.	ATL03_20210704231644_01731204_006_01	S2_20210704T232129_20210704T232125_T10XEQ	2021-07-04	04
10.	ATL03_20210704231644_01731204_006_01	S2_20210704T232129_20210704T232125_T11XML	2021-07-04	04
11.	ATL03_20210711140000_02741204_006_01	S2_20210711T135731_20210711T135734_T31XFL	2021-07-11	02
12.	ATL03_20210624163315_00161204_006_01	S2_20210624T163839_20210624T163900_T28XES	2021-06-24	05

13.	ATL03_20220416233410_03801504_006_02	S2_20220416T234129_20220416T234130_T09XWM	2022-04-16	07
14.	ATL03_20220510145813_07411505_006_01	S2_20220510T145749_20220510T145752_T28XDM	2022-05-10	00
15.	ATL03_20220402135041_01601504_006_02	S2_20220402T135729_20220402T135727_T35XNL	2022-04-02	06
16.	ATL03_20220521101556_09061505_006_01	S2_20220521T101601_20220521T101603_T39XVJ	2022-05-21	00
17.	ATL03_20220423155204_04821504_006_02	S2_20220423T155831_20220423T155825_T28XES	2022-04-23	06
18.	ATL03_20220414225057_03491504_006_02	S2_20220414T230119_20220414T230114_T12XVR	2022-04-14	10
19.	ATL03_20220424231746_05021504_006_02	S2_20220424T230109_20220424T230111_T10XDR	2022-04-24	16
20.	ATL03_20220424135203_04961504_006_02	S2_20220424T134731_20220424T134731_T33XWL	2022-04-24	04
21.	ATL03_20230821234625_09592004_007_01	S2_20230822T002159_20230822T002154_T11XML	2023-08-21	30
22.	ATL03_20230908222151_12332004_006_02	S2_20230908T225121_20230908T225116_T11XNK	2023-09-08	29
23.	ATL03_20230821093750_09502004_006_02	S2_20230821T100601_20230821T100600_T45XWM	2023-08-21	28

24.	ATL03_20230827145527_10452004_006_02	S2_20230827T152811_20230827T152812_T31XEM	2023-08-27	30
25.	ATL03_20230831162132_11072004_006_02	S2_20230831T164851_20230831T164845_T27XWM	2023-08-31	27

Figure 2: As I understand the workflow, the authors first grouped HRFM segments into 20 GMM clusters and then manually assigned these clusters to three surface classes using Sentinel-2 imagery. However, this important step is not easy to follow from Fig. 2. I suggest revising the flowchart so that the intermediate GMM clustering step and the subsequent human interpretation/manual class assignment based on Sentinel-2 imagery are shown more explicitly. This would make the training-data generation procedure clearer to readers.

We will revise Fig. 2 accordingly to make the training-data generation workflow clearer.

P11, L280: More detail is needed on how transitional or ambiguous classes were handled during the Sentinel-2-based manual labeling, especially for thin ice, dark leads, and melt-pond-covered ice. This subjectivity may affect the RF training labels and should be discussed as a source of uncertainty.

We will clarify the treatment of transitional and ambiguous surface classes in the revised manuscript. In Sect. 3.2.1, we will expand the discussion of the variability of classification parameters and describe the characteristic overlap among thin ice, dark leads, and melt-pond-covered ice. In Sect. 3.2.2, we will provide a more detailed description of how the Sentinel-2-assisted manual labeling was performed for these ambiguous cases

Figure 10 shows systematic seasonal differences between HRFM and ATL20, with HRFM generally lower during the cold season and higher during the melt season. The manuscript attributes these differences to surface-height retrieval, lead detection, and reference sea-level construction, but the explanation would be stronger if supported by more quantitative evidence. For example, monthly differences in the number of detected lead segments, reference sea-level estimates.

We have discussed the potential sources of the freeboard differences in Sect. 5.2, including the differences between HRFM and ATL07, which provides the input data for ATL20, in surface-height retrieval, surface classification, and reference sea-level construction, as well as their combined impacts on freeboard estimates.

We will add available quantitative evidence where possible to better support this interpretation. However, a full decomposition of the HRFM–ATL20 differences is limited by product availability, because ATL20 does not provide key intermediate variables such as detected lead segments and reference sea-level estimates. We will clarify this limitation in the revised manuscript.

Table 2 shows that a non-negligible number of thin-ice segments are classified as leads, particularly for weak beams. Since HRFM uses identified lead segments to estimate the local sea-surface reference, misclassified thin ice could bias the reference sea level and propagate into the freeboard estimates. This issue is only indirectly discussed through the low thin-ice classification performance, but its potential impact on freeboard retrieval should be addressed more explicitly.

Although our analysis indicates that ICESat-2 has some potential to identify thin-ice surfaces, the classification uncertainty for thin ice remains relatively high. Therefore, the thin-ice category is currently treated as 'experimental' class and is not used as an independent class in the final freeboard retrieval. We will clarify this point in the revised manuscript.

For the final HRFM freeboard estimation, we use a binary sea-ice/lead classification, in which thin ice is merged into the sea-ice class. The binary classification performance is reported in Table A1 of the original manuscript. For the strong beam, the precision/recall values are 0.99/0.99 for sea ice and 0.96/0.95 for leads. For the weak beam, the corresponding values are 0.99/0.99 for sea ice and 0.95/0.91 for leads. We agree that any remaining misclassification of thin ice or sea ice as leads could affect the local sea-surface reference and propagate into the freeboard estimates. We will therefore make the role of the binary classifier clearer and explicitly discuss the residual thin-ice/lead ambiguity as a source of uncertainty in the revised manuscript.

Minor comments:

Figure 2: Please show the RF classifier more explicitly in the workflow after the GMM clustering and manual labeling steps.

Figure 4 caption: (d) height standard deviation (STD) à (e) height standard deviation.

Please clarify whether “thin ice” and “gray ice” refer to the same class and use the terminology consistently throughout the manuscript.

We will revise these points following the reviewer’s suggestions.