



Year-Round High-Resolution Sea Ice Freeboard Retrieval Using ICESat-2 ATL03 Photon Data

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- 15 **Abstract.** Arctic sea ice freeboard is critical for estimating ice thickness and characterizing surface morphology, yet it remains poorly constrained, especially during melt seasons due to limitations in conventional altimetry products. The ICESat-2 ATL07 product retrieves surface heights at variable along-track segment lengths (10 – 200 m) and identifies floes and leads using fixed thresholds (photon rate, background rate and the width of height distribution) to support freeboard estimation, which smooths small-scale features and reduces reliability over sea ice surface with complex spatial variations or affected by melting.
- 20 To address these challenges, we present a year-round, high-resolution (5 m) freeboard retrieval method (HRFM) based directly on ICESat-2 ATL03 photon data. A two-stage denoising strategy is implemented to robustly extract signal photons, while a machine-learning classifier, trained on 25 coincident Sentinel-2 images, discriminates between sea ice, thin ice, and leads across seasons. Identified lead segments provide local sea surface references from which freeboard is estimated. Validation against Airborne Topographic Mapper (ATM) data shows that HRFM reduces the surface-height root-mean-square error
- 25 (*RMSE*) for strong beams from 0.12 m (ATL07) to 0.08 m (by 33%), while weak-beam retrievals achieve comparable accuracy. HRFM better preserves ridge-related heights that are underestimated by ATL07. The classification attains a precision of 0.96 and a recall of 0.95 for lead detection, supporting reliable freeboard estimation. After applying the method at a pan-Arctic scale, the spatial patterns of retrieved freeboard are consistent with the ICESat-2 ATL20 product, but with seasonal mean differences reaching up to 0.04 m. By improving both topographic fidelity and lead detection, HRFM mitigates common
- 30 limitations of ICESat-2 sea ice products and enables high-resolution freeboard estimates across seasons.



1 Introduction

Arctic sea ice plays a pivotal role in regulating exchanges of heat (Aylmer et al., 2024), momentum (Muilwijk et al., 2024), and water vapor (Ridley et al., 2023) between the atmosphere and oceans, with impacts spanning local processes to the global climate system (Sun et al., 2018). Changes in sea ice thickness are widely recognized as a key indicator of climate change (Stroeve and Notz, 2018), influencing Earth surface energy balance (Von Schuckmann et al., 2023; Zhou et al., 2025), ocean–atmosphere interactions (McPhee, 2008; Timmermans and Marshall, 2020), high-latitude biodiversity (Macias-Fauria and Post, 2018; Pratte et al., 2019), and Arctic shipping operations (Shu et al., 2024). Sea ice freeboard, defined as the height of the ice surface above the local sea level, is a fundamental parameter for estimating ice thickness from satellite altimeters (Kacimi and Kwok, 2024), for characterizing surface roughness relevant to stress and momentum transfer (Krumpen et al., 2025; Mchedlishvili et al., 2023), as well as for parameterizing mechanical interactions between sea ice and ships or platforms (Lund et al., 2025). Despite its importance for quantifying ice mass balance and improving sea ice forecasts (Liu et al., 2025; Song et al., 2024), obtaining sustained, high-resolution, and year-round spaceborne observations of freeboard remain challenging largely due to limitations in current altimetric retrieval frameworks to robustly obtain sea surface levels and ice surface heights, particularly across the pan-Arctic and throughout the seasonal cycle.

Satellite altimeters retrieve freeboard as the difference between the measured ice surface height and the local sea level inferred from leads or open water (Laxon et al., 2013; Quartly et al., 2019). Consequently, the accuracy of freeboard estimation depends mainly on two key processes: precise surface height retrieval and robust surface type classification. Earlier lidar and radar missions, such as ICESat (Ice, Cloud, and land Elevation Satellite; Schutz et al., 2005) and CryoSat-2 (Wingham et al., 2006), provided valuable insights into sea ice freeboard and thickness (Kurtz and Markus, 2012; Landy et al., 2022). Notably, recent advances in lead detection using machine learning applied to CryoSat-2 data have enabled the first year-round *radar freeboard* products (Dawson et al., 2022; Landy et al., 2022), underscoring the importance of improved surface-type classification for extending the year-round applicability of altimetric freeboard retrievals. Launched in 2018, ICESat-2 (IS-2) represents a major advance in ice surface altimetry. Equipped with the Advanced Topographic Laser Altimeter System (ATLAS), a photon-counting lidar, IS-2 reduced the along-track footprint from ~170 m (ICESat) to ~0.7 m, improving elevation precision and the capacity to resolve small-scale surface roughness (Markus et al., 2017; Ricker et al., 2023) and thereby supporting more accurate surface-type classification. The ATLAS acquires data via six beams organized into three pairs, each consisting of one strong beam and one weak beam with a 4:1 transmit-energy ratio. While this configuration enhances spatial coverage, the lower signal-to-noise ratio of the weak beam poses challenges for data processing. The ATL03 product supplies geolocated photon clouds and constitutes the raw observational source from which all higher-level IS-2 products are derived (Neumann et al., 2019). Operating at a 532 nm wavelength, IS-2 measurements primarily reflect from the air-snow interface; Thus, the derived freeboard is typically defined as the total snow + ice freeboard (Kacimi and Kwok, 2022; Magruder et al., 2025).



Among the IS-2 products, ATL07 provides sea ice (snow-including) surface heights and types through a two-step retrieval procedure and a fixed-threshold classification, applied to photon-aggregated segments containing ~150 photons (Kwok et al., 2023). As the only publicly available IS-2 sea ice product, ATL07 has been used in retrievals of sea ice freeboard, sea ice thickness/volume, ice-atmosphere drag coefficients, and linear ice fraction (Buckley et al., 2025; Koo et al., 2025; Kortum et al., 2025; Kwok et al., 2021; Mchedlishvili et al., 2023; Petty et al., 2020). Nevertheless, several limitations associated with its surface-height retrieval and surface-type classification approach constrain its performance, particularly for high-resolution retrievals and robust seasonal applications (Petty et al., 2020, 2023; Ricker et al., 2023). First, the ATL07 signal extraction is susceptible to detector after-pulses during saturation events, which frequently occur over specular leads, occasionally inducing biases in surface height (Farrell et al., 2020). Second, the variable segment lengths (10–200 m for strong beams; 40–800 m for weak beams) smooth fine-scale ice morphology, resulting in underestimation of freeboards, surface roughness, and ridge heights (Duncan and Farrell, 2022; Ricker et al., 2023). Third, the fixed-threshold classification is sensitive to surface heterogeneity during the melt season (Tilling et al., 2020), when melt ponds and wet snow diminish the contrast in radiometric signatures, increasing lead misclassification (Kwok et al., 2016; Liu et al., 2025). Since freeboard retrieval relies on accurate identification of leads to estimate local sea level, such misclassifications propagate directly into systematic freeboard uncertainties. Furthermore, IS-2 weak-beam observations have so far been utilized and evaluated less extensively for freeboard retrieval owing to their lower transmitted energy, although they have been applied successfully to determine dust-storm heights and to derive terrain profiles in mountainous regions (Dandabathula et al., 2025; Zhang et al., 2021). Theoretically, the IS-2 weak-beam observations can increase the actual area of sensed sea ice (Ricker et al., 2023).

Notably, recent research has increasingly focused on developing specialized algorithms that use raw ATL03 photon data. In terms of the height retrieval, the University of Maryland Ridge Detection Algorithm (UMD-RDA) improves ridge identification from ATL03 (Duncan and Farrell, 2022; Farrell et al., 2020), but does not provide the surface type classification required for freeboard estimation. While upcoming updates to the ATL07 product aim to adopt 10-m fixed-length segments and non-Gaussian distributions (Wimert et al., 2025), they still rely on the original classification approach. Specialized melt-season algorithms, such as DDA-Bifurcate-Sea-ice, have succeeded in detecting melt ponds on multi-year ice (Buckley et al., 2023; Herzfeld et al., 2023) but do not distinguish between ice floes and leads. Furthermore, for surface-type classification, machine-learning classifiers have improved lead detection (Koo et al., 2023; Liu et al., 2025), but they remain structurally tied to ATL07's preprocessing frameworks, which precludes direct application to ATL03 photon data. While substantial progress has been made, existing efforts typically target individual subtasks rather than integrating them within a photon-level processing pipeline. Without a unified photon-level approach, uncertainties propagate across steps and the methodology becomes difficult to generalize across varying seasonal states and surface regimes. Consequently, high-resolution freeboard retrieval that is reliable year-round and transferable across surface types and beam types remains challenging.

In this study, we introduce the High-Resolution Freeboard Method (HRFM), a framework that retrieves sea ice freeboard directly from ATL03 photon data and maintains consistent performance for both strong and weak beams throughout the year. HRFM incorporates two key advances to address the aforementioned limitations: 1) A refined surface height retrieval



algorithm employing a two-stage denoising strategy, combining Kernel Density Estimation (KDE) with adaptive histogram-based filtering. This approach enables robust signal extraction at the native 0.7-m photon scale, preserving fine-scale morphology even under high solar background and during melt-season ice conditions. 2) A machine-learning surface-type classifier trained on 25 coincident Sentinel-2 scenes acquired in winter and summer, spanning $\sim 200\,000\text{ km}^2$ and encompassing both multi-year and first-year ice under level and deformed conditions. This classifier ensures seasonally consistent lead identification, which is critical for accurate local sea-level estimates. By integrating these components, HRFM provides along-track freeboard estimates at 5-m intervals and gridded freeboard fields across seasons.

The structure of this study is as follows: The datasets and methods are described in **Sect. 2** and **Sect. 3**, respectively. **Section 4** presents the retrieval results and validation. **Section 5** discusses the results, and Sect. 6 summarizes the main conclusions.

2 Data

This study focuses on the pan-Arctic sea ice region, defined by areas where monthly sea ice concentration (SIC) exceeds 50%. This threshold was applied to exclude most isolated ice features near the ice edge, as they can contaminate the signal and significantly degrade satellite retrievals of sea ice freeboard, owing to strong ice and oceanic dynamics (Kwok et al., 2023).

The pink line denotes the 50 % SIC contour, derived from the mean April SIC for 2019–2023 (**Fig. 1**).

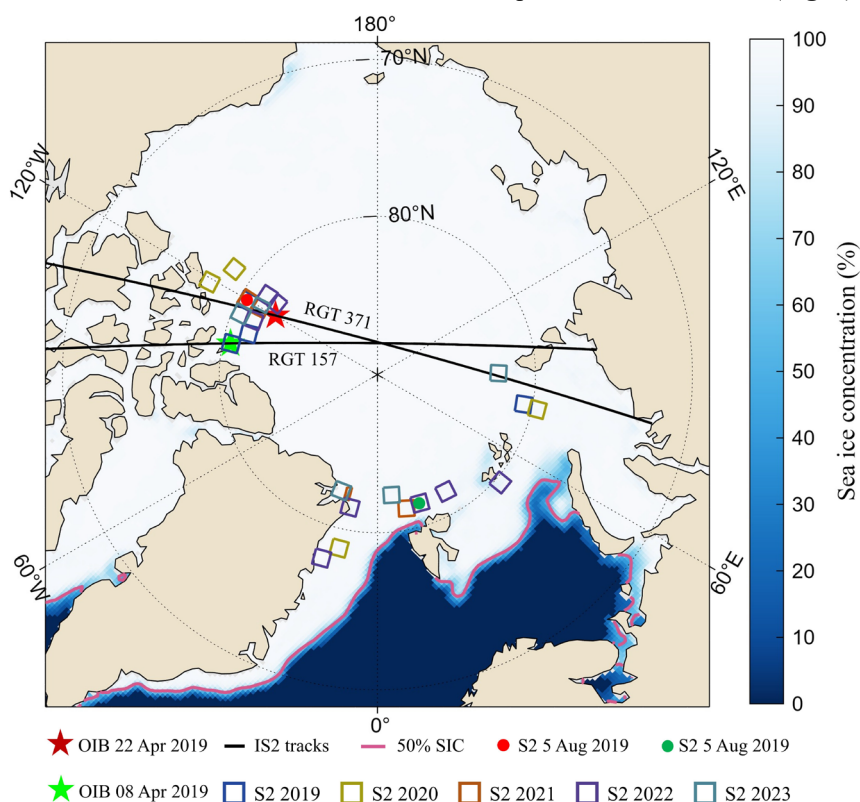




Figure 1: Overview of the study area and multi-source datasets. The background shading shows April monthly SIC obtained in 2019 – 2023 from the NOAA Climate Data Record (CDR). The pink contour represents the multi-year mean April 50% SIC. The black lines mark ICESat-2 Reference Ground Track (RGT) 371 and 157, with the red and green stars indicating the location of coincident Airborne Topographic Mapper (ATM) measurements. Colored squares denote Sentinel-2 (S2) images that spatially coincide with ICESat-2 profiles, obtained from years of 2019 – 2023. Red and Green dots show the positions of the Sentinel-2 images detailed in Sect. 3.2.1

2.1 ICESat-2 data

IS-2 provides a suite of sea ice products derived from its photon-counting lidar observations. The processing workflow begins with geolocated photon clouds (ATL03), progresses to segment-level surface heights and classifications (ATL07) and along-track freeboard estimates (ATL10), and culminates in gridded monthly freeboard product (ATL20). In this study, our HRFM utilizes ATL03 Version 06 as the primary input to retrieve surface height, surface type, and freeboard (**Sect. 3**). ATL07 Version 06 and ATL20 Version 05 are used for comparison and evaluation purposes (**Sect. 4**). Although the newer release ATL07 Version 07 introduces fixed 10 m segment lengths, it was experimental and limited to strong-beam observations during the study period. Therefore, to ensure a consistent and comprehensive evaluation across strong and weak beams, we use ATL07 V06 as the comparison reference unless otherwise specified.

2.1.1 ATL03 global geolocated photon data

The ATL03 product provides geolocated, time-tagged photon events detected by ATLAS (Neumann et al., 2023). Each photon is associated with its latitude, longitude, ellipsoidal height, photon confidence label, background rate estimates, and geophysical corrections, including those for tidal, atmospheric and inverse barometer effects, all referenced to the WGS-84 ellipsoid. In our HRFM, these corrections are applied to derive the corrected height for each photon.

2.1.2 ATL07 sea ice height

The ATL07 product provides sea ice surface heights and surface-type classifications derived from ATL03 photon data (Kwok et al., 2023) for estimating sea ice freeboard. In this product, raw photons are aggregated into adaptive segments containing approximately 150-photons, resulting in variable along-track lengths ranging from ~10–200 m for strong beams to ~40–800 m for weak beams (Kwok et al., 2019b). Surface height estimation involves a two-stage trimming process: 1) removing photons outside a fixed height window (–2.0 m to 3.5 m), and 2) excluding photons beyond two standard deviations of the remaining photons. A dual-Gaussian distribution is then assumed to fit the trimmed histograms to derive the segment's surface height (Kwok et al., 2023).

Surface type is classified using empirical thresholds based on photon rate, background rate, and the width of the height distribution, informed by Multiple Altimeter Beam Experimental Lidar (MABEL) measurements and post-launch IS-2 assessments (Petty et al., 2021; Kwok et al., 2016). Classified categories include (-1) unknown surface type, (0) cloud covered, (1) non-lead snow/ice surface, (2-5) specular lead, and (6-9) dark lead, denoted by the *height_segment_type* flag. Specular (dark) lead segments are leads with high (low) photon rates. To mitigate uncertainties in radiometric classification, ATL07



145 applies a post-classification height filter utilizing neighboring specular lead segments within a 10-km window. A candidate lead's height must lie between the minimum of the specular lead heights (h_{sl_min}) and the larger of (i) the 2nd percentile of specular lead heights, or (ii) $h_{sl_min} + 2\sigma$, where $\sigma = 0.02\text{--}0.03$ m is the expected surface-height uncertainty over specular-lead segments. Segments meeting both classification and height-filter criteria are flagged as $ssh_flag = 1$, designating them as sea surface segments for ATL10 and ATL20 freeboard estimations.

150 2.1.3 ATL20 gridded sea ice Freeboard

The ATL20 product provides a basin-scale perspective of Arctic sea ice freeboard, offering daily and monthly composites on a $25\text{ km} \times 25\text{ km}$ polar stereographic grid. These gridded fields are derived from along-track ATL10 freeboard estimates exclusively using strong-beam observations (Kwok et al., 2023). To ensure data quality and minimize coastal or open-ocean contamination, ATL20 applies a strict mask, retaining grid cells only where the SIC exceeds 50% and the distance from the coastline is at least 25 km. In this study, monthly freeboard fields derived from HRFM are compared with the ATL20 product for the period from October 2021 to September 2022 to evaluate their basin-scale spatial consistency.

2.2 Sentinel-2 data

To construct a robust training data set for the machine-learning surface-type classifier, we selected Sentinel-2A and -2B scenes near-coincident with IS-2 overpasses during 2019 – 2023. A maximum time offset of 30 min was applied to minimize misregistration due to sea ice advection, while retaining a sufficient number of coincident observations. Assuming a typical sea ice drift speed of $\sim 0.05\text{--}0.1$ m/s, a 30-min offset corresponds to an advective displacement of approximately 150 m, which is negligible relative to the spatial extent of a single Sentinel-2 scene ($\sim 290\text{ km} \times 290\text{ km}$) and is easy to align them manually based on correspondence between surface optical features and IS-2 photon returns. Because of Sentinel-2's orbital inclination, coincident acquisitions are limited to latitudes south of 82° N.

165 From an initial pool of 822 overlapping scenes spanning 416 IS-2 tracks, we applied a stringent quality-control procedure. Each scene was manually interpreted using true-color imagery to identify surface types. Leads were distinguished from ice floes based on their characteristic elongated morphology and low reflectance in the visible bands. After extensive manual review, 25 scenes (corresponding to 25 IS-2 overpasses) were retained as the training and validation dataset. The retained scenes cover a wide range of Arctic regions ($\sim 200\,000\text{ km}^2$), sea ice types, surface-roughness conditions, and seasons, supporting the classifier's applicability (locations marked in Fig. 1).

2.3 ATM data

The performance of HRFM in retrieving high-resolution along-track heights is also evaluated using coincident observations from the Airborne Topographic Mapper (ATM), collected during a dedicated IS-2 underflights of NASA's Operation IceBridge (OIB) on April 2019 (Kwok et al., 2019a). The ATM utilizes a conically scanning green laser lidar (532 nm) that



175 produces footprints approximately 1 m in diameter with a vertical precision of ~ 0.03 m (Krabill et al., 2002). We used ATM
 profiles from two underflights acquired within ~ 38 min of coincident IS-2 tracks. There are ~ 149 km of along-track overlap
 below IS-2 reference ground track (RGT) 157 and ~ 187 km of along-track overlap below IS-2 RGT 371 (green and red stars
 in **Fig. 1**). These dense, independent elevation surveys provide the primary reference for assessing the accuracy of HRFM-
 derived surface heights and the preservation of fine-scale sea ice features.

180 3 Method

This section details the implementation of the HRFM applied to ATL03 data. As illustrated in the schematic workflow in **Fig.**
2, the method consists of two main components. The first is a high-resolution surface height retrieval, which begins with a
 two-stage denoising procedure that removes background and after-pulse photons while preserving morphology-related photons
 as faithfully as possible. The filtered signal photons are subsequently used to estimate surface heights within fixed-length 5-m
 185 segments. The second component is a machine-learning surface-type classifier that discriminates between ice floes and leads,
 facilitating the estimation of reference sea level required for freeboard retrieval.

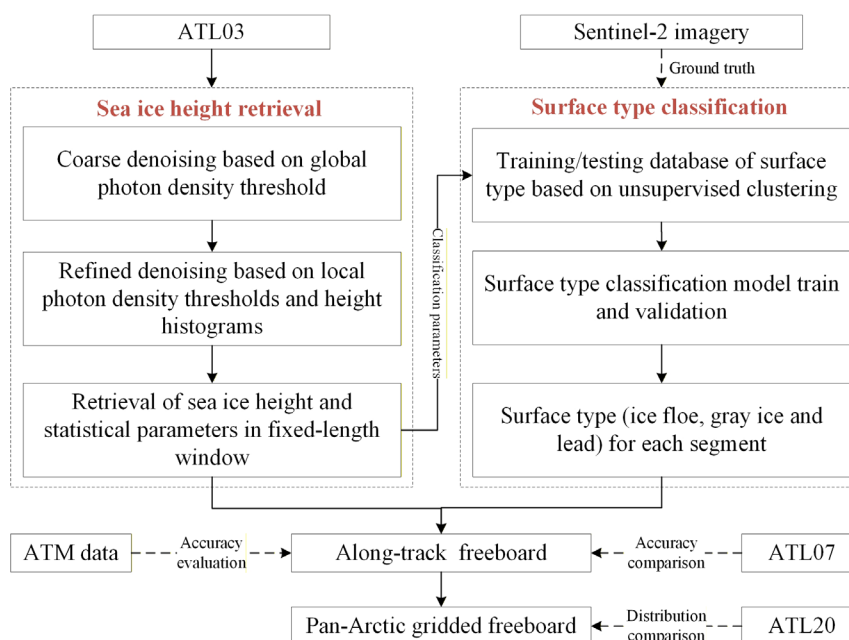


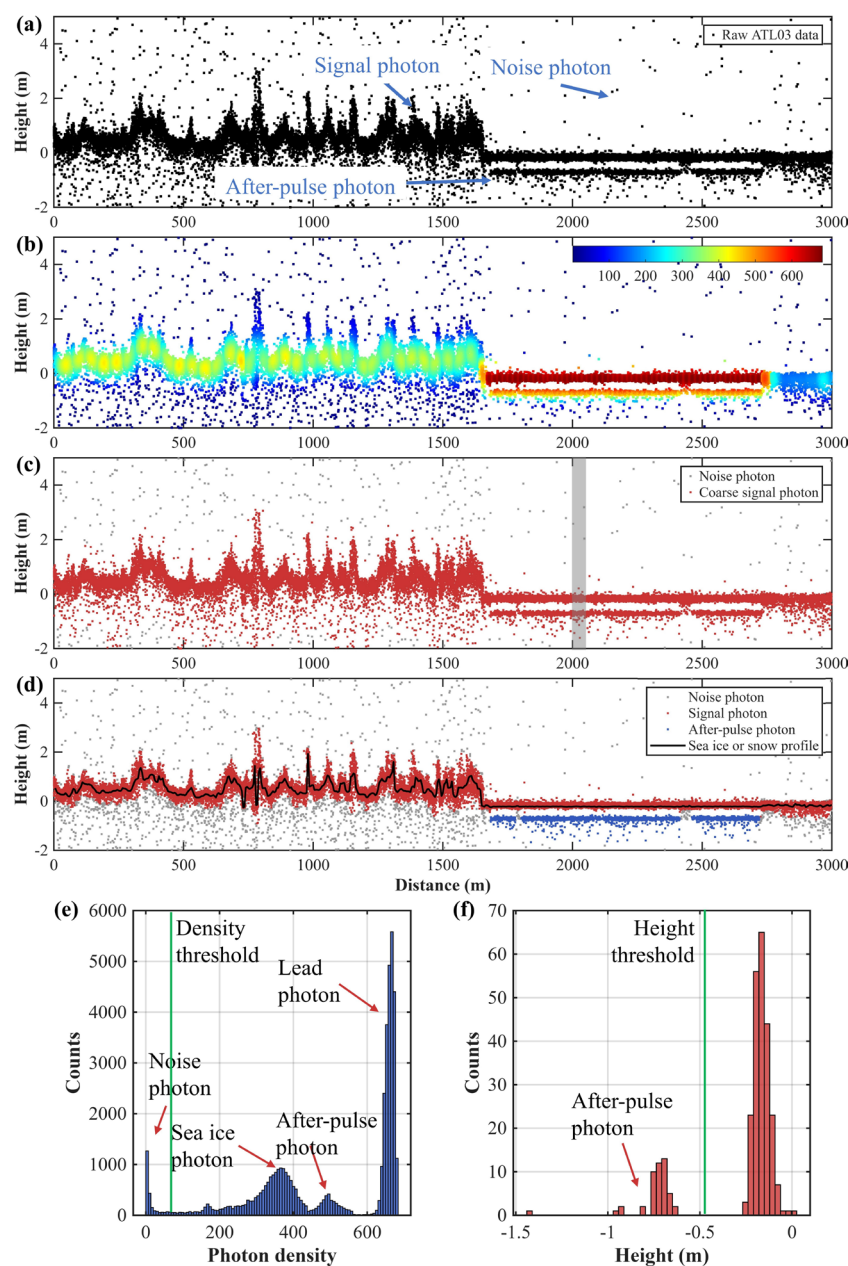
Figure 2: The flowchart of HRFM.

190 Compared to the ATL07 algorithm, HRFM provides two major advancements. First, photon-density information is
 incorporated into both surface-height retrieval and surface-type classification, improving robustness under challenging
 conditions, including ATLAS detector saturation and footprints affected by melt ponds. This improves the retention of sea ice
 morphology-related photons, particularly over ridges, narrow leads, and melt ponds, and yields more accurate surface height
 estimates and denser freeboard sampling. This improvement is especially pronounced for weak beams, where lower transmitted



energy and reduced signal-to-noise ratios often degrade ATL07 retrieval performance. Second, HRFM employs a machine-learning classifier trained from coincident Sentinel-2 imagery, rather than the empirical thresholds used in ATL07. This approach provides more reliable and seasonally consistent discrimination of sea ice features, particularly during the melt season when surface radiometric contrast is reduced. This facilitates the continuous and stable acquisition of reference sea level.

3.1 Surface height retrieval





200 **Figure 3: Sequential processing steps for retrieving sea ice surface height from the middle strong beam of**
ATL03_20190526002946_08820304_006_02 obtained from the Lincoln Sea of the Arctic Ocean. (a) Raw ATL03 data converted into
along-track distance–height coordinates. (b) KDE-estimated photon density (the color bar indicates photon density). (c) Coarse
signal photons. (d) Refined signal photons, together with the detected after-pulse photons and the sea ice or snow surface profile
 205 **retrieved at 5-m horizontal resolution. (e) Histogram of photon density corresponding to panel (b). The green vertical line indicates**
the density threshold used to separate noise photons from coarse signal photon. (f) Height histogram of coarse signal photons within
the grey-shaded region in panel (c). The green vertical line denotes the height threshold applied to distinguish after-pulse photons
from surface signal photons.

As illustrated in **Fig. 3a**, accurate surface height retrieval from ATL03 data requires the separation of signal photons (surface) from noise photons (background) originating from solar background, atmospheric scattering, and detector noise.
 210 HRFM implements a two-stage denoising strategy, consisting of coarse and refined denoising, to extract the final set of signal photons. The resulting signal photon set forms the basis for surface height retrieval at fixed 5-m segments.

3.1.1 Coarse denoising

To remove large-scale background noise, ATL03 raw photons are first divided into 3-km along-track segments. Their heights are referenced to the DTU21 Mean Sea Surface (MSS) model (Andersen et al., 2023) to remove geoid trends. Photon density
 215 is calculated using a KDE approach. For each photon p , the density D_p is defined as:

$$D_p = \sum_{i=1}^n K(d_{pi}), \quad (1)$$

where n is the number of photons within a predefined search region, d_{pi} is the distance between photon p and neighbor photon i , and K is kernel function (Chu et al., 2017):

$$K(d_{pi}) = \frac{3}{4} \max(0, 1 - d_{pi}^2). \quad (2)$$

220 Since ATL03 photons show much stronger clustering in the horizontal direction than in the vertical direction, distances are computed within an anisotropic elliptical search region:

$$d_{pi} = \sqrt{\frac{\Delta x_{pi}^2}{a^2} + \frac{\Delta h_{pi}^2}{1}}, \quad (3)$$

where Δx_{pi} and Δh_{pi} represent the distances between the two photons in the horizontal and vertical directions, respectively. The horizontal scaling parameter a is set to 25 for strong beams and 100 for weak beams. This process is used to increase the
 225 weight of photons in the horizontal direction, thereby preserving the along-track resolution and improving signal-photon extraction (Lu et al., 2025).

Photon densities vary along track due to differences in surface types and beam types (**Fig. 3b**, **Fig. A1b**, and **Fig. A2b**). To determine a segment-specific threshold that removes noise while retaining morphology-related photons (e.g. ridges or melt ponds), we examine the photon-density distribution within each 3-km segment. The resulting density histogram typically



230 shows a multi-modal structure (**Fig. 3e, Fig. A1e, and Fig. A2e**) corresponding to various ground object features: 1) a narrow low-density peak representing noise photons, 2) a broad intermediate-density peak corresponding to sea ice photons, 3) a smaller secondary peak linked to after-pulse photons or weak subsurface scattering, and 4) a high-density peak associated with specular leads.

We fit the noise and sea ice peaks using a two-component Gaussian mixture model (GMM). The intersection of the two
235 fitted components defines the segment-specific density threshold (green lines in **Fig. 3e, Fig. A1e, and Fig. A2e**). Photons with densities exceeding this threshold are retained as coarse signal photons (**Fig. 3c, Fig. A1c, and Fig. A2c**). However, some after-pulse photons and subsurface returns can overlap in density with the sea ice signal; therefore, a second local refinement step is required.

3.1.2 Refined denoising

240 Refined denoising is performed within local 10-m windows to remove residual noise photons. This adaptive process is triggered by the ATLAS detector saturation state, which is assessed via the signal photon rate (coarse signal photons per transmitted pulse). Based on ATLAS instrument characterization, detector saturation is identified when the photon rate exceeds 16 photons per pulse for strong beams or 4 photons per pulse for weak beams.

Under saturation conditions, after-pulse echoes appear at fixed vertical offsets below the true surface, typically ~0.45 m and
245 ~0.9 m (Lu et al., 2021). Density alone cannot reliably distinguish these photons. Therefore, a 0.1-m height interval histogram is constructed for each saturated window (**Fig. 3f and Fig. A1f**), and the primary peak is taken as the physical surface. Photons situated more than 0.3 m below this peak are classified as after-pulses and subsequently removed (green lines in **Fig. 3f and Fig. A1f**).

In the absence of saturation, remaining noise photons are removed using a locally adaptive density threshold. The threshold
250 is set to the 10th percentile of coarse signal photon densities within the window. Only photons exceeding this threshold are retained as refined signal photons. Together, the coarse and refined denoising stages isolate the signal photons, as illustrated in **Fig. 3d, Fig. A1d, and Fig. A2d**.

3.1.3 Sea ice surface height Estimation

Following refined denoising, surface heights are estimated from the optimized signal photon set. Although the surface heights
255 are resolved at the native resolution of ATL03 data (~0.7 m), classification and freeboard retrieval require statistical segment-level estimates. Therefore, the along-track surface height profile is partitioned into fixed 5-m segments after trade-off analyses between spatial resolution and height precision. For each segment, the surface height is defined as the KDE-density-weighted mean of all refined signal photon heights (black lines in **Fig. 3d and Fig. A1d**):

$$H_{seg} = \frac{\sum_{i=1}^N D_i \cdot h_i}{\sum_{i=1}^N D_i}, \quad (4)$$



260 where h_i and D_i are the geophysical corrected height and KDE-derived density of the i -th photon, respectively. Geophysical corrections (e.g. atmospheric delays and tides) are applied.

To support the subsequent machine-learning classification, we extract four statistical features for each segment: 1) Photon rate: the number of refined signal photons per transmitted pulse within a 5 m segment (a proxy for relative surface brightness). 2) Background rate: the mean ATL03 background rate for all photons in the segment, indicative of scattered sunlight at the
 265 laser wavelength. The background rate is normalized to a solar elevation angle of 20° , as is applied in ATL07 (Kwok et al., 2023). 3) Height standard deviation (STD): the spread of refined signal photon heights over the segment, representing small-scale surface roughness. and 4) Mean photon density: the average KDE-derived photon density (not available in ATL07).

Furthermore, segments impacted by melt ponds are identified by adapting the bimodal height distribution analysis proposed by Herzfeld et al. (2023). A segment is flagged as melt-pond affected when (1) the photon rate remains below the saturation
 270 threshold and (2) the height histogram is bimodal, indicating returns from both the pond surface and the pond bottom (Fig. A2). While these subsurface returns can be preserved for potential depth retrieval applications (Buckley et al., 2023; Herzfeld et al., 2023), these segments are excluded from the freeboard estimation to avoid downward bias.

3.2 Surface type classification

Accurate surface type classification is a prerequisite for reliable freeboard retrieval, as the local reference sea level is
 275 determined exclusively from identified lead segments. In this section, we first analyze two representative winter and summer scenes, using coincident Sentinel-2 imagery to examine the variability of the four HRFM classification parameters across various surface types. We then describe the construction of a labeled training dataset based on unsupervised clustering and visual interpretation. Finally, we introduce the machine learning classifier employed in HRFM to discriminate between floe- and lead-dominated segments.

280 3.2.1 Variability of classification parameters

To characterize the response of the four HRFM classification parameters across diverse surface types, we analyze two representative IS-2/Sentinel-2 coincident scenes: a winter case (April 2022, Fig. 4) and a summer case featuring melt ponds (August 2019, Fig. 5). Each scene contains a strong/weak beam pair (gt3l and gt3r) to evaluate beam-dependent sensitivity. Based on the coincident Sentinel-2 imagery, the winter scene suggests snow-covered sea ice, thin young ice with little or no
 285 snow cover, and open-water leads (Fig. 4a) whereas the summer scene is characterized by a mixture of open water, melt ponds, bare ice, and residual deteriorated snow (Fig. 5a).

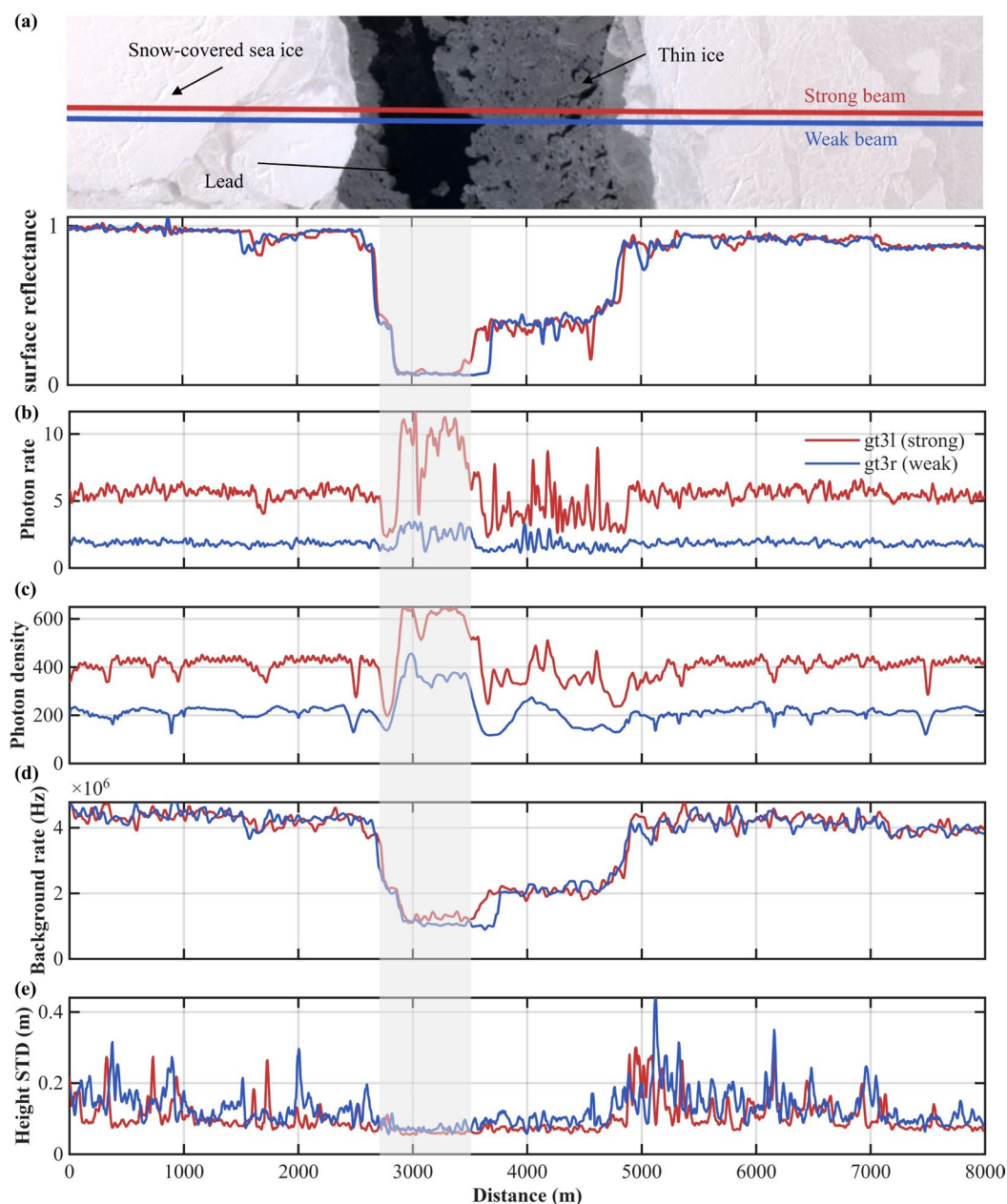


Figure 4: Winter case with an along-track profile of approximately 8 km acquired on 24 April 2022. (a) Sentinel-2 RGB imagery (green dot in Fig. 1) overlaid with ICESat-2 gt3l (strong beam, red) and gt3r (weak beam, blue), with surface reflectance derived from the RGB bands of the Sentinel-2 image from nearest neighbor pixels to the ICESat-2 segments. (b) Photon rate, (c) photon density, (d) background rate, and (d) height standard deviation (STD) along track. The gray-shaded region indicates the open-water lead area.

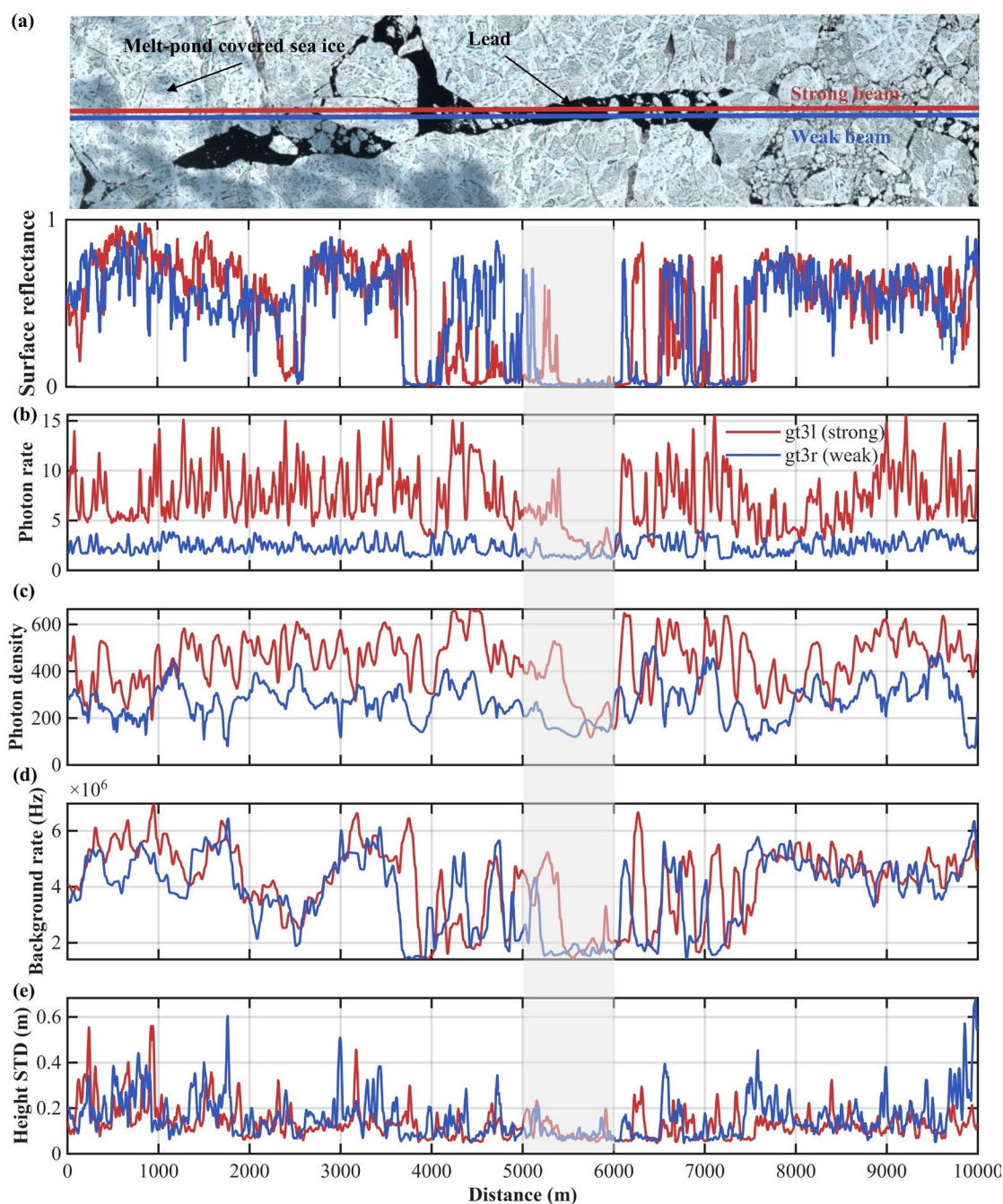


Figure 5: As in Fig. 4, but It's a 10-km profile observed on 5 August 2019 (red dot in Fig. 1).

295 In the April (winter) scene, photon rate (Fig. 4b) and photon density (Fig. 4c) generally scale with surface RGB reflectance over snow-covered and thin ice, yielding relatively stable along-track values. In contrast, pronounced and localized spikes are consistently observed over leads, where photon rates and photon densities often exceed those over adjacent snow-covered ice.



These enhancements result from strong specular reflections off smooth open-water or newly formed thin-ice surfaces, which concentrate a large fraction of the emitted laser energy back toward the receiver despite the low reflectance of water (**Fig. 4a**).
 However, in the August (summer) scene, specular returns occur with higher frequency due to the widespread presence of melt ponds and narrow leads, resulting in substantially increased along-track variability in both photon rate (**Fig. 5b**) and photon density (**Fig. 5c**). Notably, the wide (~1000 m) open-water lead, indicated by the gray shaded region at 5 – 6 km in **Fig. 5**, shows simultaneously low photon rate and photon density, unlike the winter case, suggesting a rougher (likely wind-roughened) water surface that scatters energy away from the receiver. This may be related to stronger wind-driven surface waves in summer open water relative to winter conditions (Liu et al., 2016) or the absence of new ice formation in leads compared to the winter case where new ice forms rapidly and truly open water will rarely be present. Across both scenes, weak beams exhibit a reduced dynamic range and diminished contrast, complicating the discrimination between classes. **Fig. A4** shows the monthly distributions of photon rate and photon density across the annual cycle, further indicating their seasonal difference.

The background rate is predominantly influenced by solar illumination geometry and surface reflection. Its along-track variation closely tracks the intensities in Sentinel-2 RGB imagery and is nearly identical between strong and weak beams (**Fig. 4d** and **Fig. 5d**), reflecting their shared dependence on solar background. Background rates are highest over bright snow-covered ice (4–5 MHz), intermediate over gray ice (2–3 MHz), and lowest over dark open-water leads (1–2 MHz), qualitatively matching the strong albedo contrast from snow-covered sea ice (~0.7–0.8) to open water in leads (~0.1–0.2) (Light et al., 2022). In the summer scene, background rate variations increase because melt ponds, bare ice, and wet snow mix over much shorter spatial scales with high spatial heterogeneity in the proportion among components within a single segment.

The height standard deviation reflects local surface roughness and shows a smaller dynamic range than the other parameters (**Fig. 4e** and **Fig. 5e**). It is higher and more spatially variable over deformed, snow-covered ice, but reduced over thin ice and leads, consistent with their smoother surface conditions.

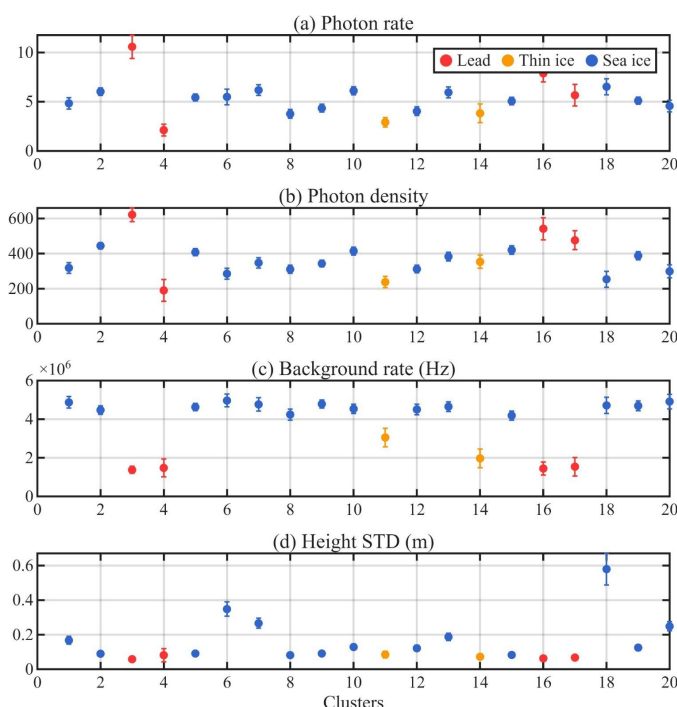
In summary, while these four parameters provide complementary information for distinguishing sea ice from leads, consistent with early airborne photon-counting lidar studies (Kwok et al., 2016), their responses are highly sensitive to seasonal transitions, beam energy, and wind-induced roughness of open water surfaces, and ice types or ages. This complex, nonlinear overlap in feature space motivates the use of a supervised, data-driven classifier to achieve robust and seasonally consistent surface type discrimination.

3.2.2 Training dataset generation

To develop a robust machine-learning surface type classifier, a high-quality training dataset was constructed using coincident Sentinel-2 imagery as the ground truth. Given that HRFM generates thousands of 5-m segments per overlapping scene, direct manual annotation is impractical. Following the strategy previously developed for improving ATL07 classification (Liu et al., 2025), we combined unsupervised clustering with visual interpretation to generate the training dataset.

For each coincident IS-2/Sentinel-2 scene, HRFM segments were grouped into 20 clusters using a GMM applied to the four classification parameters of photon rate, background rate, height standard deviation, and photon density. This clustering step

collapses vast segment populations into a limited number of statistically consistent groups, thereby reducing annotation effort while enhancing labeling robustness. Strong and weak beams were clustered independently because of their different photon statistics.



335 **Figure 6** Mean values and standard deviations of four classification parameters for clusters derived from ICESat-2 observations on 24 April 2022 (the winter case). Panels show (a) photon rate, (b) photon density, (c) background rate, and (d) height standard deviation. The surface types are color-coded: lead (red), thin ice (yellow), and sea ice (blue).

Since the unsupervised clustering itself does not reveal surface type, each cluster was assigned a label using Sentinel-2 RGB imagery. Following the same visual interpretation criteria and alignment method for Sentinel-2 and IS-2 as in our earlier
 340 ATL07 work (Liu et al., 2025), the clusters were manually assigned to three surface types: sea ice, thin ice (gray ice), and leads. **Figure 6** illustrates the mean values and standard deviations of the classification parameters for clusters derived from a representative strong-beam data on 24 April 2022. The clusters align with the expected parameter behaviors summarized in Sect. 3.2.1, indicating that they map consistently onto physical surface types. Sea ice clusters are characterized by high background photon rates and larger height standard deviations. Thin-ice clusters exhibit intermediate photon rates, photon
 345 densities, and background rates, with moderate height variability. Lead clusters are distinguished by either extreme high (specular) or low (dark) photon rates and densities, accompanied by low background rates and height standard deviations. This labeling process was applied consistently to 25 coincident Sentinel-2/IS-2 scenes shown in **Fig. 1**, representing a wide distribution across the Arctic and a multi-year temporal spread (2019–2023). The final aggregated dataset comprises 1,029,289 labeled strong-beam segments and 1,023,895 labeled weak-beam segments, providing a substantial and diverse foundation for
 350 training the machine-learning classifier.



3.2.3 Training of machine learning classifier

With the labeled training dataset established, a supervised Random Forest (RF) classifier is employed to assign surface types to each HRFM segment. Consisting of an ensemble of decision trees, the RF algorithm is well-suited for this application due to its ability to capture complex, non-linear relationships among physical parameters without requiring feature normalization (Breiman, 2001). RF is computationally efficient and has been widely adopted in studies on sea ice classification (Fredensborg Hansen et al., 2021; Mugunthan et al., 2023; Shen et al., 2017). Furthermore, the ensemble-averaging nature of RF could mitigate sensitivity to mislabeling within the training data, which is unavoidable when surface labels are derived from visual interpretation of statistically aggregated clusters of samples from optical imagery.

The RF classifier was configured with 200 decision trees and a maximum tree depth of 20 to ensure a balance between model complexity and computational efficiency. Separate models were trained for strong and weak beams to account for their distinct signal-to-noise ratios and dynamic ranges. The classification relies on the four primary features: photon rate, background rate, height standard deviation, and mean photon density. Previous studies indicated that photon rate and mean photon density provide the highest discriminative power for detecting specular leads, while background rate is crucial for separating thin ice from snow-covered ice (Koo et al., 2023; Kwok et al., 2016; Liu et al., 2025).

To ensure robust generalization across diverse spatial and seasonal conditions, we implemented a Leave-One-Group-Out (LOGO) cross-validation strategy. In each iteration, data from one entire coincident IS-2/Sentinel-2 pass was held out for testing, while the remaining 24 scenes were used for training. This rigorous approach prevents spatial autocorrelation from overinflating accuracy estimates and ensures the model can handle unseen geographical regions.

The trained classifier assigns a surface type of sea ice, thin ice, or lead to every HRFM segment. Segments previously identified as melt-pond influenced (details in Sect. 3.1.3) are excluded prior to classification to avoid ambiguity during the melt season.

3.3 Sea ice freeboard estimation

Following the retrieval of surface heights and surface-type classifications, HRFM derives freeboard at two spatial scales: along-track freeboard and monthly gridded fields.

(1) Along-track freeboard calculation

The along-track freeboard is computed by subtracting a local reference sea level from the heights of identified sea ice segments. As the establishment of an optimal reference sea level is not the primary focus of this study, a pragmatic and efficient approach is adopted. Specifically, all lead segments identified within a 10-km along-track window are aggregated to estimate the local sea surface height. To mitigate the influence of spurious detections, lead elevations falling outside three standard deviations of the window mean are excluded. The mean height of the remaining lead samples is then taken as the reference sea level for that window. In 10-km windows where no valid lead detections are available, the reference sea level is estimated by linear interpolation between the neighboring 10-km windows to ensure continuity.

(2) Gridded monthly freeboard



To generate composite maps of the Arctic freeboard and facilitate direct comparison with the ATL20 product, monthly gridded freeboard fields are generated on a 25-km polar stereographic grid (EPSG:3411). All along-track freeboard observations acquired within a given month are projected onto this grid. For each grid cell, the freeboard value is computed as a distance-weighted average of all contributing observations. Grid cells with no valid observations during the month are left empty.

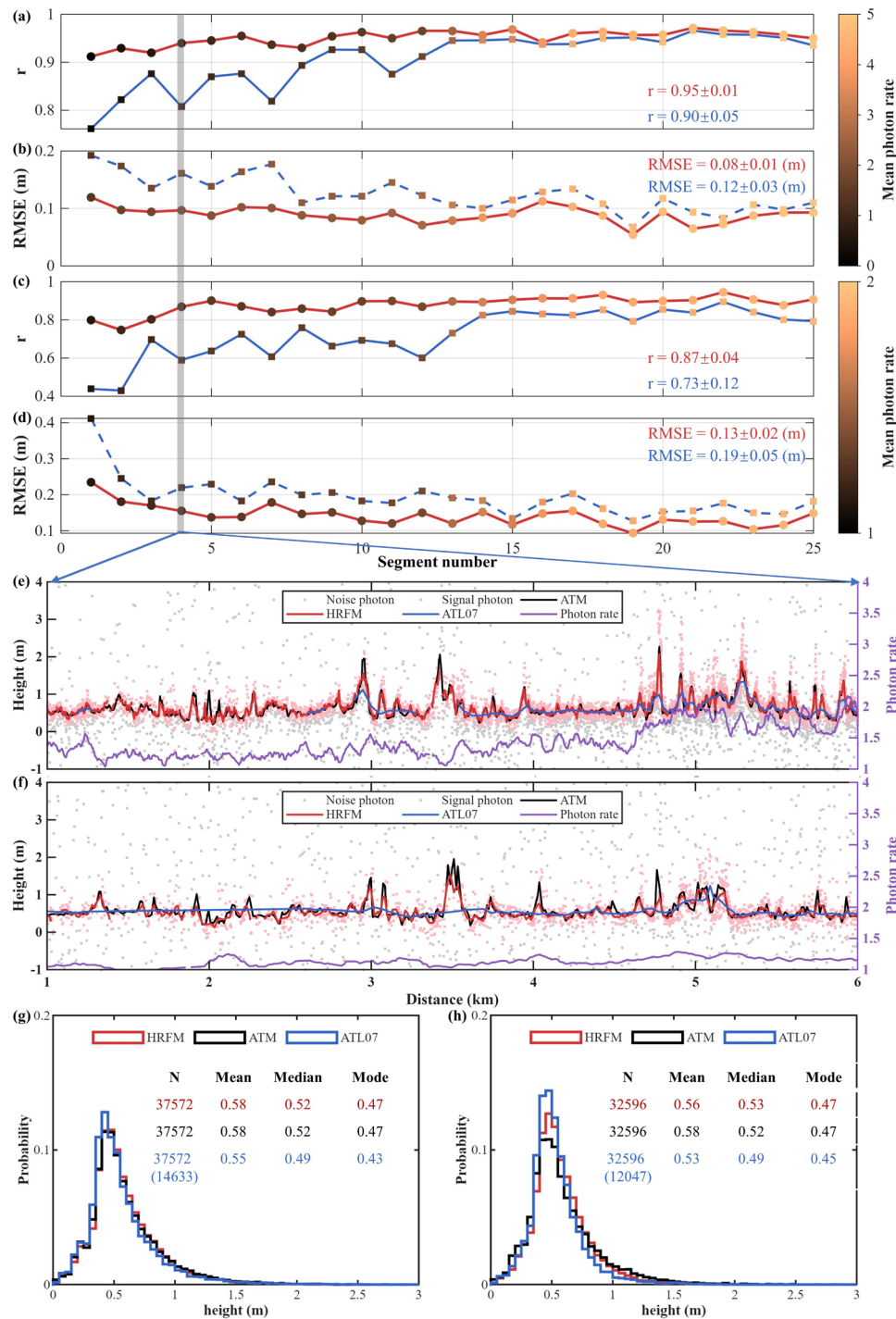
4 Results

4.1 Surface height evaluation and comparison

To quantitatively evaluate the surface height retrieval performance of HRFM and compare it with ATL07, ATM heights within ~ 10 km segments are averaged within the spatial extent corresponding to HRFM and ATL07 segments, following the approach of Kwok et al. (2019a). The averaged ATM heights associated with ATL07 segments are subsequently resampled to the HRFM segment spacing to facilitate a consistent comparison and to illustrate the resolution differences between the two products.

Fig. 7a and **b** summarize the correlation coefficient (r) and root-mean-square error (RMSE) between ATM observations and IS-2 surface heights (HRFM and ATL07) for the strong (gt2l) and weak (gt2r) beams on 22 April 2019, across the twenty-five segments ordered by mean photon rate. The validation results of 08 April 2019 are provided in **Fig. A3**. For both beams, HRFM shows consistently higher correlations with ATM (0.95 ± 0.01 for strong beam and 0.87 ± 0.04 for weak beam) than ATL07 (0.90 ± 0.05 and 0.73 ± 0.12 , respectively). Correspondingly, HRFM achieves lower RMSE values of 0.08 ± 0.01 m and 0.13 ± 0.02 m, representing reductions relative to ATL07 (0.12 ± 0.03 m and 0.19 ± 0.05 m). The improvement is evident in segments with lower photon rates (e.g., Segments 1 to 14). It indicates the robustness of HRFM's photon extraction strategy under low signal-to-noise conditions, particularly for the weak beam.

The along-track profiles for a representative case (segment 4) are shown in **Fig. 7e** and **f** for the strong and weak beams, respectively. HRFM closely follows the ATM profile, capturing the fine-scale height variability associated with ice ridges and surface roughness. In contrast, ATL07 produces smoother profiles that fail to resolve peak ridge heights and exhibits intermittent data gaps, most notably for the weak beam. **Fig. 7g** and **h** present the distributions of surface height estimates from HRFM, ATL07, and ATM aggregated over all twenty-five segments. The aggregated distributions further confirm that HRFM distributions align more closely with ATM in mean, median, and mode. In comparison, the ATL07 distributions are shifted towards lower heights, with mean, median, and mode surface heights that are approximately 0.02 – 0.04 m lower than those of the ATM, which is consistent with previous studies (Duncan and Farrell, 2022; Kwok et al., 2019a; Ricker et al., 2023). By refining the signal photon extraction and operating at a higher effective resolution, HRFM preserves a larger fraction of observations associated with individual ridges, resulting in a surface height distribution that better represents the observed variability. As indicated by the sample counts shown in parentheses, HRFM retains twice as many valid surface samples as ATL07 across the examined segments.



415 **Figure 7: Evaluation of HRFM and ATL07 surface height retrievals against ATM heights obtained on 22 April 2019. (a) and (b) Correlation coefficient (r) and root-mean-square error (RMSE) between HRFM (red) and ATL07 (blue) against ATM for strong beam. (c) and (d) The same statistics for weak beams. The color scale indicates the mean photon rate for each segment. (e) and (f)**



Surface height profiles of segment 4 for strong and weak beams, respectively, including ATM heights (black), HRFM heights (red), ATL07 heights (blue), HRFM-identified signal (pink) and noise (gray) photons, and the corresponding photon rate (purple). (g) and (h) The distributions of surface height estimate for all 25 segments for strong and weak beams, respectively, with the number of observations (N), mean, median, and mode indicated for each dataset. Numbers in parentheses denote the original number of ATL07 samples.

Table 1 summarizes the modal values of surface height distributions for HRFM, ATL07, and ATM derived from the upper 3%, 5%, and 10% of heights for both strong and weak beams, together with their pairwise differences. The differences between the HRFM and ATM modes remain small (-0.02 to $+0.03$ m) and show no dependence on percentile or beam type. In contrast, ATL07 underestimates surface height modes relative to ATM, with negative ATL07 – ATM differences observed in all cases. This underestimation increases is markedly amplified for weak beams, reaching -0.19 to -0.23 m at the 3–10% levels. These results further demonstrate that smoother surface retrieval produced by ATL07 leads to an underestimation of ridge-related surface height extremes, with downstream implications for the estimations of sea ice surface roughness and associated processes such as atmospheric form drag, wind stress, and ice–structure interactions (e.g., Krumpen et al., 2025; Mchedlishvili et al., 2023; Muilwijk et al., 2024).

Table 1 Modal surface height values (unit: m) derived from the upper 3%, 5%, and 10% of the height distributions for HRFM, ATL07, and ATM from strong and weak beams. Values in parentheses indicate the number of valid observations (N).

Percentile	Strong beam			Weak beam		
	3%	5%	10%	3%	5%	10%
HRFM_mode	1.39 (N=1102)	1.21 (N=1837)	1.02 (N=3674)	1.36 (N=837)	1.20 (N=1395)	1.01 (N=2791)
ATL07_mode	1.35 (N=439)	1.17 (N=732)	0.97 (N=1463)	1.11 (N=361)	0.97 (N=602)	0.82 (N=1205)
ATM_mode	1.37 (N=1102)	1.23 (N=1837)	1.0 (N=3674)	1.33 (N=837)	1.20 (N=1395)	1.01 (N=2791)
HRFM-ATL07	0.04	0.04	0.05	0.25	0.23	0.19
HRFM-ATM	0.02	-0.02	-0.01	0.03	0.00	0.00
ATL07-ATM	-0.02	-0.05	-0.06	-0.22	-0.23	-0.19

While the ATM comparison provides a quantitative validation of HRFM surface height retrieval over thick, consolidated ice, it should be noted that ATM observations are primarily obtained from the regions north of Greenland, where is characterized by high surface roughness and infrequent open-water leads. To further assess the impact of signal photon extraction on surface height estimation under flat-surface conditions, we examine two cases with open-water lead derived from IS-2 observations.

Fig. 8a and c visualize the signal photon extractions and surface height retrievals for the selected leads. HRFM effectively distinguishes between noise (gray), signal (pink), and after-pulse (orange) photons and therefore produces stable surface heights (red lines). In contrast, the ATL07 signal selection envelope (green dashed lines) incorporates a significant fraction of

subsurface scattering and after-pulse photons. This leads to physically inconsistent height fluctuations in the ATL07 profile (blue lines). Given that open-water leads should exhibit a flat surface, the downward spikes and increased variability in ATL07 are results of poor signal-noise separation related to after-pulse photons rather than true topographic features. The height distributions (Fig. 8b and d) further quantify this discrepancy. While HRFM yields unimodal distributions with well-defined peaks, ATL07 exhibits bimodal distributions. The primary ATL07 mode is shifted downward by approximately 0.05 – 0.10 m due to the inclusion of after-pulse photons. Consequently, the mean ATL07 height is 0.03 – 0.04 m lower than the HRFM estimate. Crucially, these low-value signals do not represent the physical water surface; rather, they would introduce a negative bias in reference sea level estimates. If uncorrected, this systematic underestimation of lead heights would lead to an overestimation of sea ice freeboard by ~0.03 – 0.04 m, ultimately propagating errors into the calculation of sea ice thickness.

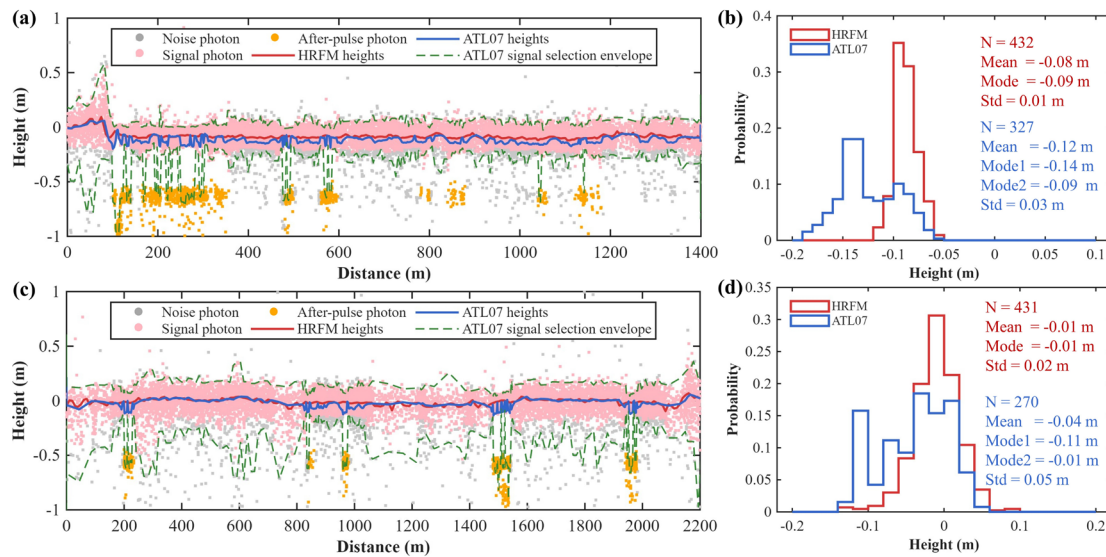


Figure 8: Surface height retrieval over open-water leads and comparison between HRFM and ATL07 for ATL03_20220424135203_04961504_006 and ATL03_20220510145813_07411505_006. (a, c) Along-track photon clouds and surface height retrievals for two open-water lead regions. Gray, pink and orange points denote noise, signal, and after-pulse photons identified by HRFM. Green dashed lines indicate the upper and lower height bounds used in the ATL07 signal photon selection algorithm. Red lines show HRFM surface heights, while blue lines represent ATL07 surface heights. (b, d) Probability distributions of surface height estimates derived from HRFM (red) and ATL07 (blue).

4.2 Surface type classification validation and comparison

Figure 9 provides a qualitative validation of HRFM surface-type classification using coincident Sentinel-2 imagery as an independent reference, together with a direct comparison to ATL07 across a range of observation conditions. For ATL07, two surface-type flags are considered: *height_segment_type* and *ssh_flag* (described in Sect. 2.1.2).

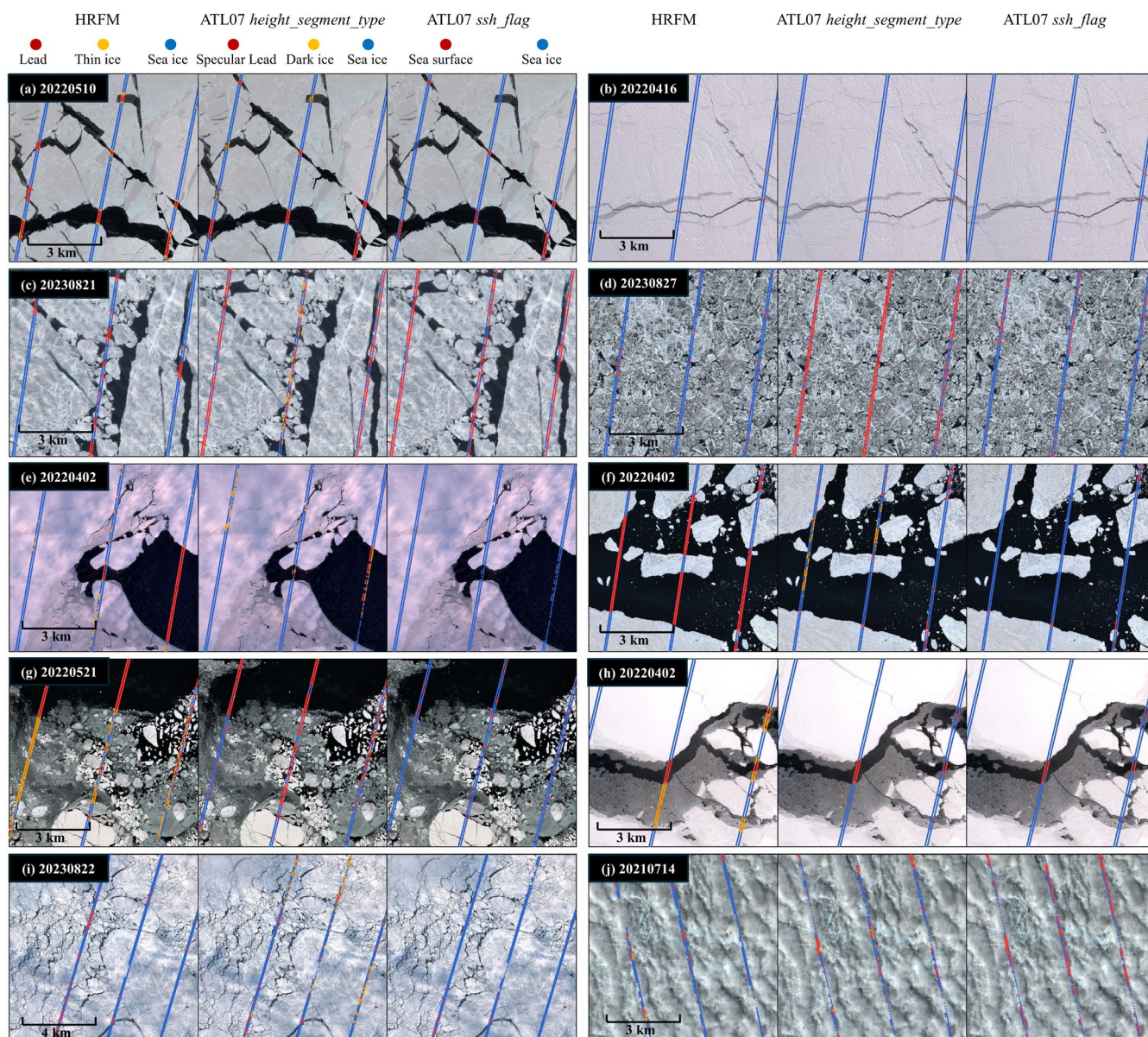


Figure 9: Comparison of surface type classification from HRFM and ATL07 in (a, b) winter cases, (c, d) summer melt-season cases, (e, f) large-lead cases, (g-h) gray-ice cases, (i, j) cloud-cover cases. The HRFM classification results are from Leave-One-Group-Out (LOGO) tests. Background images are coincident Sentinel-2 optical images acquired within 30 minutes of the ICESat-2 tracks. The ICESat-2 footprint size is not to scale.

Under favorable winter conditions (Fig. 9a and b), the HRFM and ATL07 classifications are consistent with the Sentinel-2 imagery for both strong and weak beams. Both methods detect major leads (~1 km scale) and narrow cracks (< 50 m), and there are no apparent differences between beam types. This indicates that classification is not limited by beam energy.



470 In contrast, the differences between HRFM and ATL07 become more evident under challenging surface conditions. During summer (**Fig. 9c** and **d**), widespread melt ponds increase photon rates (**Fig. 5b**) and photon densities (**Fig. 5c**), reducing the contrast between open water and melt-pond-covered ice. The fixed-threshold algorithm used in ATL07, originally tuned for winter conditions, associates high photon rates with open water and therefore misclassifies segments of melt-pond-covered ice as leads. This could result in some sea ice heights being included in the reference sea level, which would lead to a low bias in
 475 freeboard estimates. In these cases, HRFM more consistently distinguishes true open-water leads from melt-pond-covered ice, producing surface-type labels that agree more closely with Sentinel-2 imagery.

Fig. 9e and **f** illustrate additional limitations of ATL07 related to dark leads. Large leads with low albedo and wind-roughened surfaces often exhibit reduced specular returns and lower photon rates and photon densities (**Fig. 5**), leading ATL07 to label portions of open water as dark leads or sea ice. As dark-lead segments are excluded from the reference sea level in
 480 ATL07, their omission reduces the number of valid open-water samples available for sea surface height determination. This thereby could increase uncertainty in the reference sea level and reduce freeboard accuracy. In contrast, HRFM successfully identifies these segments as leads, particularly for large leads where specular returns are sparse.

Beyond lead detection, **Fig. 9g** and **h** demonstrate HRFM's ability to distinguish thin (gray) ice as separate surface class during winter. Although ATL07 reliably separates open water as specular or dark leads, it does not explicitly distinguish
 485 thin/gray ice from thicker snow-covered ice and therefore tends to merge most thin-ice surfaces into the general "sea ice" category. HRFM more consistently separates gray ice from both thick ice and open water, enabling a finer partitioning of surface types. This distinction is relevant not only for classification and freeboard retrieval, but also for a better understanding of energy exchange, since thin ice supports larger turbulent (over surface) and conductive heat fluxes (through it) than thick ice (Uhlíková et al., 2024).

490 Finally, **Fig. 9i** and **j** illustrate the impact of cloud conditions on surface-type classification. Under optically thin clouds (**Fig. 9i**), ATL07 occasionally misclassifies portions of sea ice as dark leads, as reported by Kwok et al. (2021). Under optically thick clouds (**Fig. 9j**), cloud scattering reduces the effective surface return (lower photon rate) and can distort the estimated classification parameters, leading to missing observations and misclassification in both HRFM and ATL07. To mitigate this effect in subsequent freeboard retrieval, HRFM lead segments with fewer than 10 valid signal photons and a height standard
 495 deviation exceeding 0.8 m are excluded.

Table 2 summarizes the LOGO cross-validation results for the HRFM surface-type classification. Statistics are obtained separately for strong and weak beams, including overall accuracy, precision, and recall values. Here, precision value quantifies false positives, defined as the fraction of correctly classified segments among all segments assigned to a class, whereas recall value quantifies false negatives, defined as the fraction of correctly classified segments among all reference segments of that
 500 class.

For both beam types, HRFM achieves high overall accuracy, with 0.98 for strong beams and 0.97 for weak beams. For strong beams, sea ice is classified with 0.99 precision and 0.99 recall, while leads reach 0.96 precision and 0.95 recall. For weak beams, sea ice remains robust (0.98 precision and 0.99 recall), whereas lead performance is slightly reduced (0.94



precision and 0.91 recall), consistent with weaker photon statistics and lower signal-to-noise ratios that can blur the separation between open water and low-reflectance ice surfaces.

Table 2 Confusion matrices and classification accuracy statistics for the HRFM surface-type classifier based on leave-one-group-out (LOGO) cross-validation over the track with a total length of ~10,000 km

Strong beam		Ground truth from Sentinel-2				Precision
		Sea ice	Lead	Thin ice	All	
HRFM surface type	Sea ice	902,888	1,787	10,056	914,731	0.99
	Lead	166	90,149	3,665	93,980	0.96
	Thin ice	3,464	3,194	13,920	20,578	0.67
	All	906,518	95,130	27,641	1,029,289	
Recall		0.99	0.95	0.50		0.98

Weak beam		Ground truth from Sentinel-2				Precision
		Sea ice	Lead	Thin ice	All	
HRFM surface type	Sea ice	904,947	3,410	12,341	920,698	0.98
	Lead	730	78,172	4,509	83,411	0.94
	Thin ice	3,224	3,970	12,592	19,786	0.64
	All	908,901	85,552	29,442	1,023,895	
Recall		0.99	0.91	0.43		0.97

Classification uncertainty is larger for thin ice. Precision and recall for gray ice are 0.67 and 0.50 for strong beams and decrease to 0.64 and 0.43 for weak beams. This is expected because thin ice represents a transitional surface state: its photon rate, background rate, height standard deviation and photon density often fall between those of snow-covered ice and leads, leading to overlapping feature distributions and increased confusion. In addition, gray-ice labeling from Sentinel-2 imagery is intrinsically less certain than identifying open water or bright snow-covered ice, which propagates into the reference labels and limits achievable class separability.

To isolate the performance most directly affecting freeboard retrieval, we also evaluated a two-class setting in which thin ice is merged into sea ice. Overall accuracy increases to 0.99 for strong beams and 0.99 for weak beams (Table A1), indicating that most errors in the three-class problem arise from ambiguity within ice subclasses rather than from confusion between ice and lead. Overall, HRFM produces consistent surface-type labels along both strong and weak beams across a range of conditions, supporting reliable identification of lead segments that define the local reference sea level used for freeboard estimation.



520 4.3 Year-round sea ice freeboard

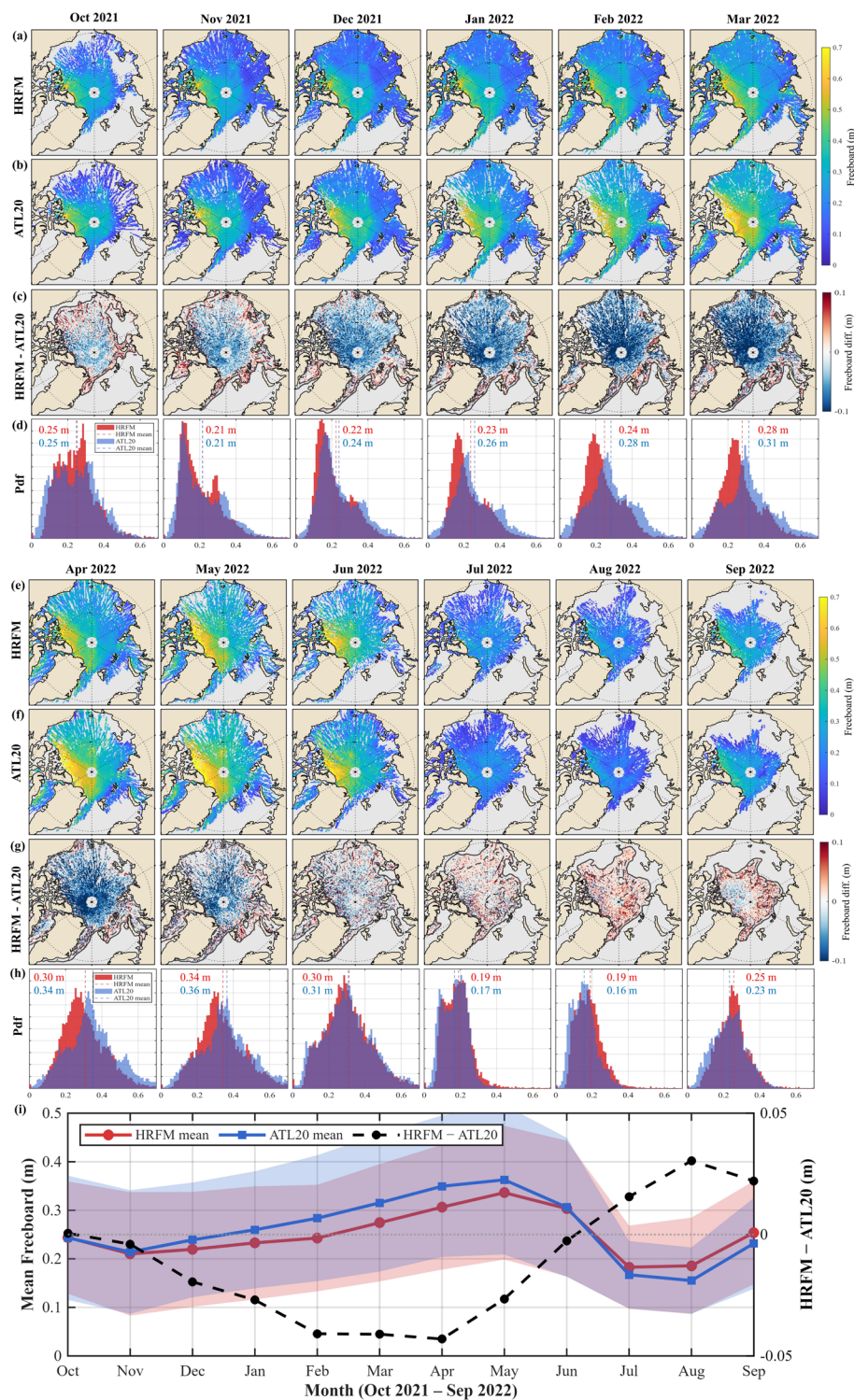




Figure 10: Monthly gridded freeboard from October 2021 to September 2022. (a, e) Monthly mean laser freeboard estimated using the proposed HRFM method. (b, f) Corresponding monthly mean freeboard from the ATL20 product. (c, g) Spatial differences between the two products (HRFM – ATL20). (d, h) Histograms of gridded freeboard for HRFM (red) and ATL20 (blue), with dashed vertical lines indicating the respective monthly means. (i) Time series of monthly mean freeboards from HRFM (red) and ATL20 (blue), with shaded areas representing ± 1 standard deviation around the mean, and the corresponding mean difference (HRFM – ATL20, dashed black line).

The gridded freeboard estimates from HRFM and the official ATL20 product from October 2021 to September 2022 are compared in **Fig. 10**. Standard deviation of freeboards in each monthly grid cell is shown in **Fig. A5**. Utilizing data from the central strong beam, HRFM provides year-round freeboard estimates over most of the Arctic Ocean, with broader spatial coverage than ATL20 in several months. Both products display highly consistent Arctic-wide spatial distribution patterns (**Fig. 10a–b, e–f**), characterized by increasing freeboard from the central Arctic toward the marginal seas and persistently high values north of Greenland and the Canadian Arctic Archipelago, closely associated with the presence of older sea ice and thicker snow cover in these areas. The histograms of gridded freeboard (**Fig. 10d and h**) further illustrate the statistical consistency between the two products.

The spatial distribution of freeboard differences (HRFM – ATL20) reveals two distinct patterns related to zones of SIC (**Fig. 10c and g**). Positive differences are mainly observed in low-SIC regions ($<90\%$), whereas negative differences dominate in high-SIC areas ($>90\%$). In the low-SIC regions, it's observed that the conservative lead detection algorithm employed by ATL07 frequently fails to identify true open-water leads within large and dynamically evolving leads (**Fig. 9e–g**). Given that the dynamic interaction between the ocean and fragmented ice floes often introduces surface variations, such as waves or swells (Bateson et al., 2020), within expansive leads, the limited sampling of lead heights may fail to capture a statistically representative reference sea level, leading to substantial estimation uncertainties. Therefore, the HRFM's ability to identify a greater number of lead segments could result in differences between the HRFM and ATL20 freeboards in low SIC areas. Conversely, in compacted high-SIC areas dominated by thick ice, leads are sparse. As noted by Petty et al. (2021), there are fewer specular leads available from the ATL07 product in these regions compared to more seasonal ice regions, which can lead to the freeboard difference between the ATL07-based ATL20 product and our HRFM.

The seasonal evolution of basin-averaged freeboard (**Fig. 10i**) further shows a contrast between the two products. HRFM yields lower freeboard estimates than ATL20 during the cold season from October to May, while producing higher values during the melt season from June to September. These differences likely arise from a combination of factors related to surface-height retrieval, lead detection, and reference sea-level construction. During winter, narrow and smooth leads are more susceptible to ATLAS detector saturation, which can generate after-pulse photons below the true water surface (**Fig. 8**). HRFM explicitly identifies and removes such after-pulse returns, whereas residual noise photons may remain in the ATL07 surface-height retrieval. This effect may bias lead surface heights low and consequently lead to higher freeboard estimates in ATL20 during the freezing. In addition, differences in lead detection methods influence the representativeness of the reference sea level: the conservative threshold-based ATL07 approach identifies a relatively limited subset of available leads, whereas HRFM detects a substantially a larger population of lead segments, potentially yielding a more spatially representative local sea-level estimate. During the melt season, melt-pond-covered ice becomes more prevalent, increasing the likelihood that



ATL07 misclassifies such surfaces as open-water leads (**Fig. 9c, d**). This misclassification may bias the reference sea surface upward and reduce the derived freeboard therefore potentially leading to an underestimation of sea ice thickness or sea ice melt during summer. In contrast, HRFM more consistently separates true open-water leads from pond-covered ice through its machine-learning surface-type classifier. It can therefore be expected to help improve the accuracy of estimates of summer sea ice melt rates using the data derived by the HRFM (Wang et al., 2025). The combined effects of improved surface-height retrieval and surface-type classification on along-track freeboard estimation are further examined in Sect. 5.2.

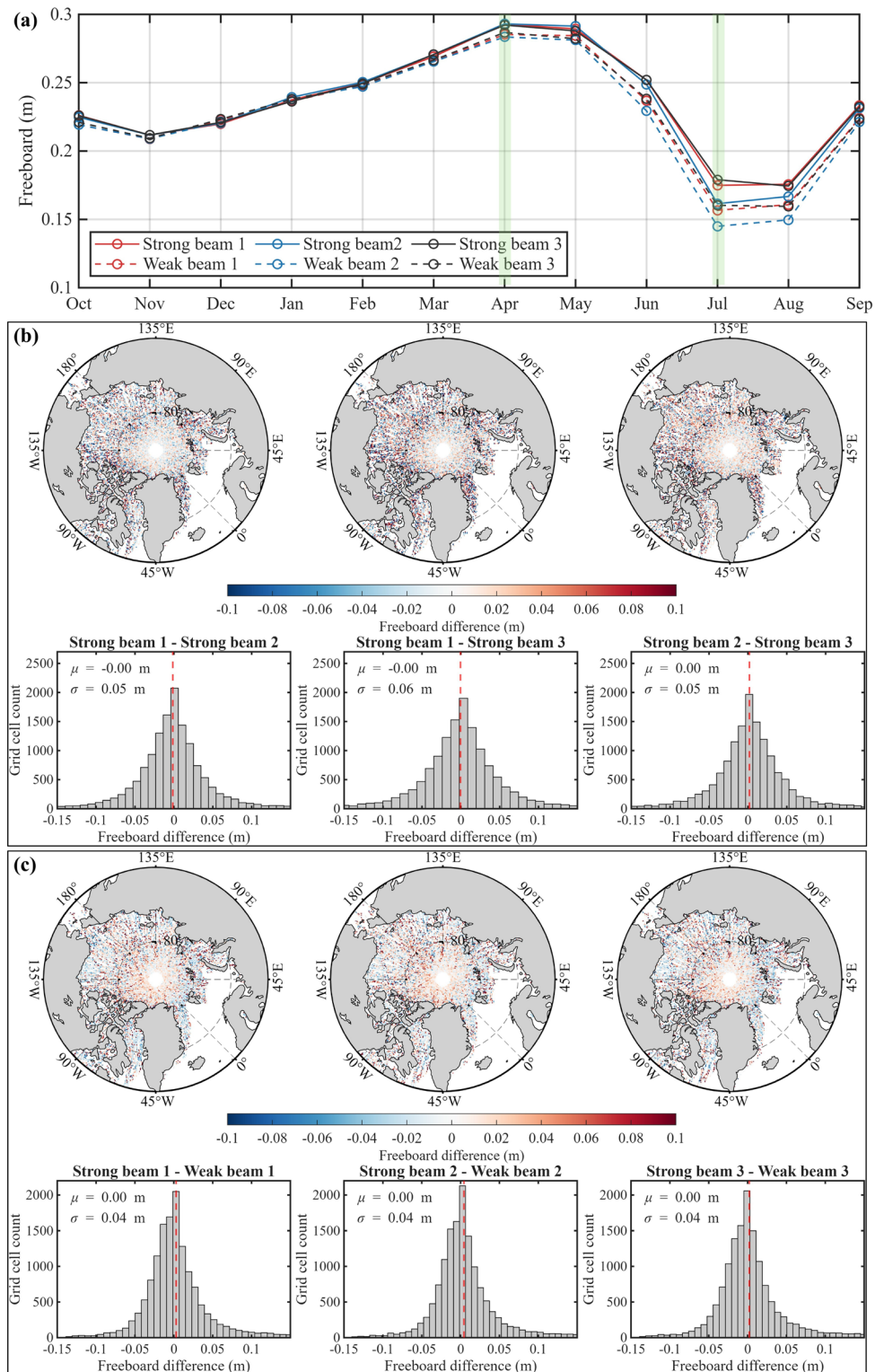
Although HRFM demonstrates improved performance in along-track surface-height retrieval and surface-type classification relative to ATL07, systematic differences remain between gridded HRFM freeboards and the ATL20 product. It should be noted that differences in reference sea-level construction and gridding methods may also contribute to the observed discrepancies at the grid scale. The observed differences provide a valuable insight into how surface-height retrieval and lead detection strategies influence basin-scale freeboard estimates.

5 Discussion

5.1 Inter-beam consistency and weak-beam performance

IS-2 utilizes a multibeam configuration consisting of three strong-weak beam pairs. The weak beams—transmitting approximately 25% of the energy of the strong beams—have been underutilized in sea ice studies due to their lower signal-to-noise ratio (SNR). A primary objective of this study is to evaluate whether the proposed High-Resolution Fitting Method (HRFM) can enhance freeboard retrieval under low-SNR conditions and enable weak beams to achieve performance comparable to that of strong beams, thereby increasing effective sampling density and spatial coverage. In addition, previous studies have reported inter-beam range biases in IS-2 observations, including centimeter-level differences among strong beams in Arctic sea surface height anomaly retrievals (Bagnardi et al., 2021) and ice-sheet elevation measurements (Brunt et al., 2021), with persistent biases associated with strong beam 1. Such inter-beam inconsistencies raise concerns about the joint use of six beams for freeboard estimation.

To evaluate inter-beam consistency and weak-beam performance in freeboard retrieval, we calculate the monthly mean freeboard using six different beams respectively (**Fig. 11**). The monthly mean freeboard derived from each of the six beams reveals high inter-beam consistency throughout the year, particularly during the freezing months (October to May), where the differences among all six beams remain below 0.01 m (**Fig. 11a**). During the summer melt months, however, a slight deviation is observed between strong beams and weak beams. The middle beams (Strong beam 2 and weak beam 2) exhibit a maximum deviation of approximately 0.02 m compared to the outer beams, which may be attributed to the increased complexity of surface conditions, lower transmitted energy level (~80% of outer beams) and decreased valid observations due to clouds compared to winter.





590 **Figure 11: Beam comparison. (a) Monthly mean freeboard from October 2021 to September 2022 for the three strong beams (solid lines) and the corresponding weak beams (dashed lines). Shaded vertical bands highlight the representative spring (April) and summer (July) periods discussed in the text. (b) Spatial distribution of gridded freeboard differences among strong beams for April (Strong beam 1 – Strong beam 2, Strong beam 1 – Strong beam 3, and Strong beam 2 – Strong beam 3), together with histograms. The mean (μ) and standard deviation (σ) of each distribution are indicated. (c) Same as (b), but for differences between corresponding strong–weak beam pairs (Strong beam 1 – Weak beam 1, Strong beam 2 – Weak beam 2, and Strong beam 3 – Weak beam 3).**
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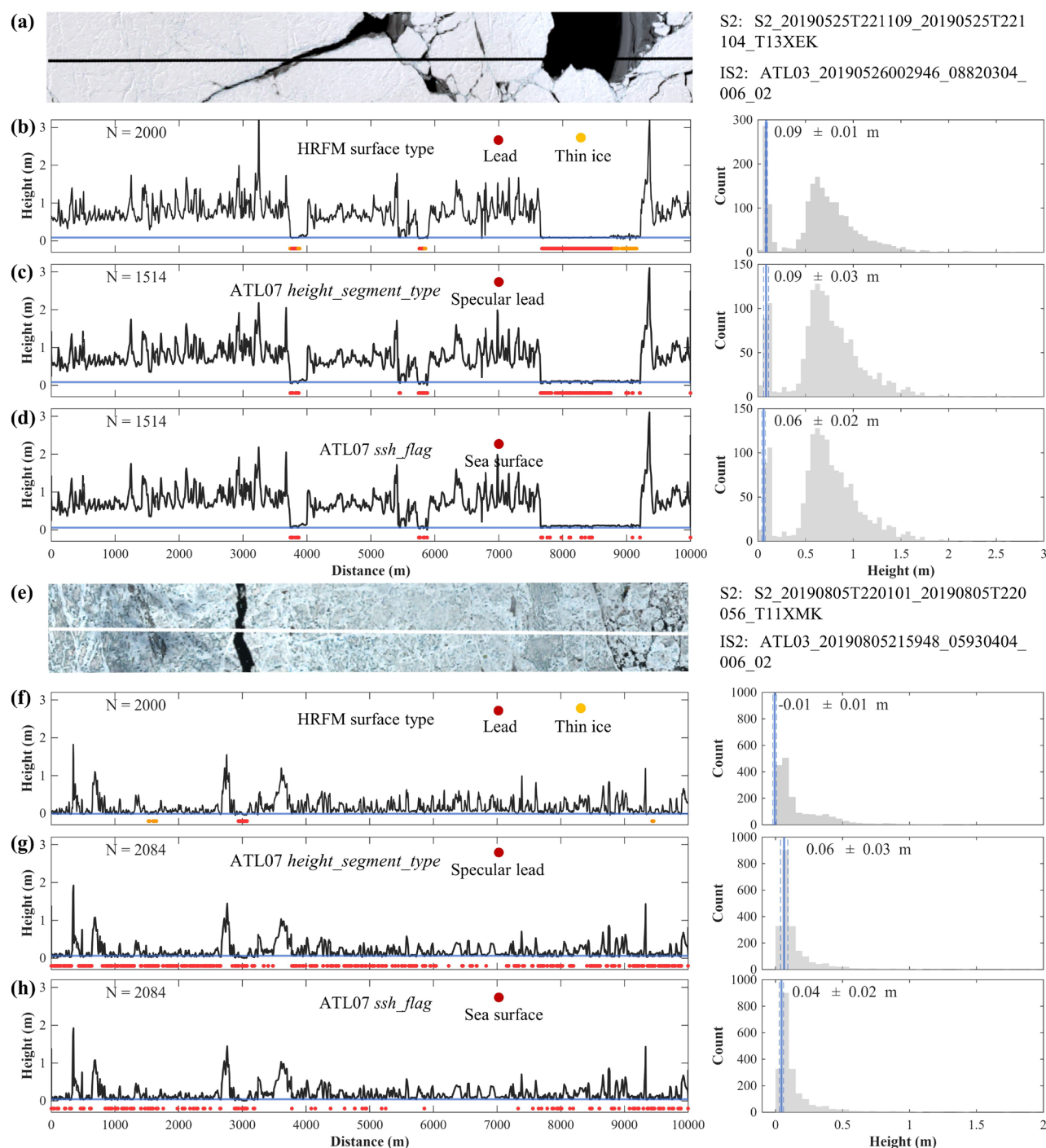
We show the spatial distributions and histograms of intercomparisons among the three strong beams (**Fig. 11b** and **Fig. A6a**) and differences between corresponding strong-weak beam pairs (**Fig. 11c** and **Fig. A6b**) for April 2022 and July 2022 (Green bar in **Fig. 11a**). The differences among the three strong beams and the three strong-weak beam pairs show no evident regional patterns across the Arctic basin. The histograms for April 2022 show that the differences among the strong beams and the strong-weak pairs are normally distributed around a mean of 0.00 m with a standard deviation (σ) ranging from 0.04 to 0.06 m. It is notable that the standard deviations on the differences are lower between the weak beams than the strong beams, potentially owing to the lower sensitivity of the weak beams to heterogeneous surface conditions. The histograms for July 2022 show that a mean offset of -0.01 to -0.02 m is associated with the middle beam (Strong beam 2) when compared to Strong beam 1 and Strong beam 3 and that weak beams exhibit a bias of approximately -0.02 m relative to their corresponding strong beams.
 600
 605

The limited impact of inter-beam range bias on our freeboard estimates is likely related to the differential nature of freeboard retrieval. Freeboard is derived as the relative height between the ice surface and a locally determined sea-surface reference along the same beam, which largely cancels beam-dependent absolute range offsets. By stabilizing surface height retrieval and lead identification under low-photon conditions, HRFM further reduces sensitivity to energy discrepancies between strong and weak beams, allowing weak beams to achieve freeboard estimates that are statistically consistent with those from strong beams.
 610

These results demonstrate that HRFM elevates weak beams from an auxiliary role to fully usable contributors in freeboard estimation. Weak-beam freeboards not only achieve accuracy comparable to strong beams but also generate spatially coherent freeboard maps independently. This enhanced inter-beam consistency implies that future IS-2 sea ice freeboard and thickness products could benefit from jointly exploiting all six ATLAS beams, increasing effective sampling density, improving spatial coverage, and reducing gridded uncertainty, particularly in regions and seasons where observations are otherwise sparse (Ricker et al., 2023).
 615

5.2 Potential sources of freeboard difference

The seasonally contrasting freeboard differences between HRFM and ATL20 primarily originate from differences in surface-height estimation, surface-type classification, and the construction of the reference sea level. Two examples (from winter and summer conditions) in **Fig. 12** present how to determine the reference sea level using the surface height and surface type from HRFM and ATL07 (including *height_segment_type* and *ssh_flag*). The reference sea level is the mean height of lead segments for HRFM, specular lead segments for ATL07 *height_segment_type* and sea surface segments for ATL07 *ssh_flag*. Above the reference level (blue line) is the freeboard of the floating ice cover.
 620



625 **Figure 12: The determination of reference sea level in 10-km segments for freeboard estimation combining surface heights and surface-type classification. Two examples from (a-d) 26 May 2019 and (e-h) 05 August 2019. (a, e) Coincident sentinel-2 images with IS-2 tracks in black and white. Surface heights and surface-type classifications from HRFM (b and f), ATL07 *height_segment_type***



(c and g), and ATL07 *ssh_flag* (d and h) are used to obtain the reference sea levels (blue lines), respectively. N is the number of height-segments in each 10-km. Quantity on right panel shows the calculated reference sea level (mean and standard deviation).

630 For the winter example, HRFM provides surface-type classifications that are more consistent with Sentinel-2 imagery than those from ATL07, together with a more stable surface-height retrieval over lead regions (**Fig. 12b**). As shown by the height distributions on the right-hand side of **Fig. 12**, the HRFM-derived reference sea level is 0.09 ± 0.01 m, indicating that the retained lead segments form a compact and internally consistent sea-surface sample. When the ATL07 *height_segment_type* classification is used, the reference sea level is close to 0.09 m, but exhibits a larger standard deviation (0.03 m). This larger
 635 standard deviation reflects the inclusion of lead segments whose surface heights are locally underestimated, partly due to residual after-pulse photons that are not fully removed in the ATL07 processing chain, as illustrated in **Fig. 8**. The ATL07 *ssh_flag* represents an additional height-based filtering applied to the *height_segment_type* surface types (Sect. 2.1.2). This filtering preferentially retains lower-height specular lead segments, while discarding a large fraction of valid lead segments (**Fig. 12c and d**). Consequently, the number of retained sea-surface samples is markedly reduced, and the resulting reference
 640 sea level decreases to 0.06 ± 0.02 m, which is lower than both the HRFM- and *height_segment_type* - based estimates. This downward shift in the reference sea level explains why ATL07-based freeboard estimates (ATL20) tend to be higher than HRFM during winter conditions.

Under summer melt conditions, the dominant source of differences shifts from height filtering to surface-type misclassification. Extensive melt ponds reduce the contrast of classification features and cause ATL07 *height_segment_type*
 645 to misclassify large fractions of melt-pond-affected sea ice as leads (**Fig. 12g**). Consequently, the reference sea level derived from *height_segment_type* is elevated to 0.06 ± 0.03 m, compared to the HRFM reference sea level of about -0.01 ± 0.01 m. Although the *ssh_flag* filtering removes some high-height segments and lowers the reference sea level to 0.04 ± 0.02 m (**Fig. 12h**), a number of misclassified sea ice segments remain. These residual errors continue to bias the ATL07-based reference sea level upward relative to HRFM, leading to systematically lower freeboard estimates in summer.

650 The plots in **Fig. 13** best show the difference of reference sea level determination between HRFM and ATL07 during winter and summer examples. **Fig. 13a and b** show the relevant statistics from fifty 10-km segments in the May 26, 2019 and August 05, 2019 tracks, respectively. HRFM estimates are generally higher than ATL07 in winter but lower in summer. Crucially, HRFM exhibits a smaller standard deviation in identified lead heights compared to ATL07, suggesting that HRFM achieves lower uncertainty by effectively filtering outliers in the lead detection process. It is noteworthy that during the summer melt
 655 season, the height range of lead segments expands for all methods due to the challenging surface-type classification.

Taken together, these differences in reference sea-level estimation might lead to the observed seasonal reversal in HRFM–ATL20 freeboard differences: HRFM freeboards are generally lower than ATL20 during winter, when ATL07 filtering removes many valid lead samples, but higher during summer, when melt-pond-affected ice is erroneously included in the reference sea-surface estimate. Similar winter–summer contrasts have been reported by Koo et al. (2023) in Antarctic sea ice
 660 freeboard, and are also consistent with recent findings by Petty et al. (2025), who showed that IS-2–derived sea ice thickness tends to be higher than CryoSat-2 estimates, with lower winter freeboards yielding improved inter-sensor consistency.

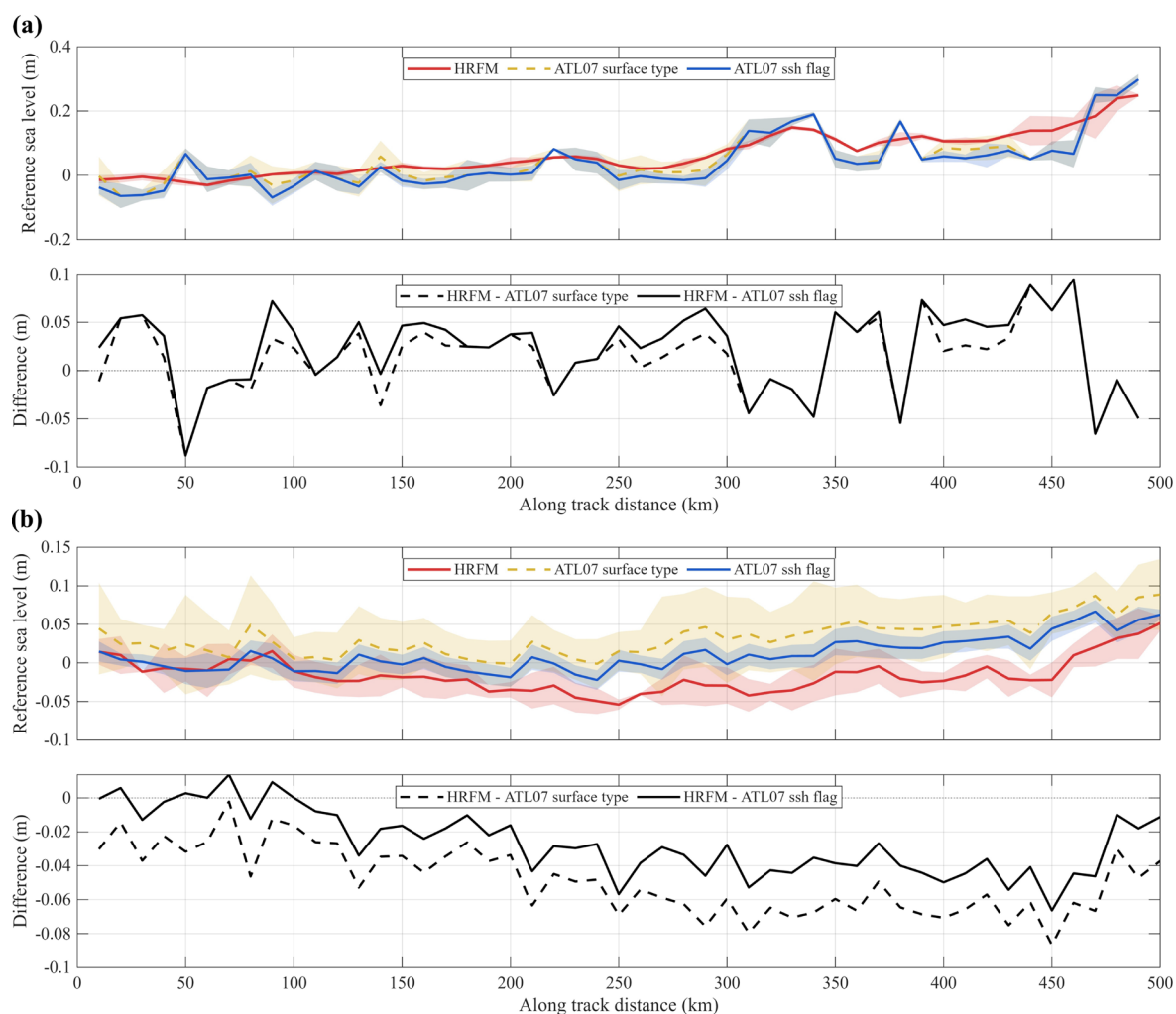


Figure 13: Determination of reference sea levels along fifty consecutive 10-km segments for ICESat-2 ground tracks acquired on (a) 26 May 2019 and (b) 05 August 2019. The upper panels show the reference sea levels derived from HRFM (red solid line), ATL07 surface_type (yellow dashed line), and ATL07 ssh_flag (blue solid line), with shaded envelopes indicating ± 1 standard deviation. The lower panels present the corresponding differences between HRFM and the two ATL07-based reference sea levels.

5.3 Possible limitations and future work

Despite the improved performance of HRFM in along-track surface-height retrieval, surface-type classification, and inter-beam consistency, several limitations remain and should be considered when interpreting the results of this study.

First, independent validation of gridded freeboard estimates at basin scale remains limited. While comparisons with ATM profiles provide robust validation over thick, consolidated ice, comparable independent observations are scarce for summer conditions and for large spatial scales (Saylam et al., 2025). Consequently, the absolute accuracy of gridded HRFM freeboards

cannot yet be conclusively quantified. Future efforts combining airborne campaigns, autonomous platforms, and coordinated satellite observations will be essential for evaluating grid-scale freeboard products, particularly during the melt season.

675 Second, HRFM relies on the supervised machine-learning classifier trained using coincident optical imagery. While the leave-one-group-out cross-validation results demonstrate stable performance across beam types, surface conditions, and seasons, generalization to a broader range of atmospheric and illumination conditions remains an important consideration. Background photon rates are strongly correlated with solar elevation and can vary by orders of magnitude under low solar angles. Although surface-type classification could get noisier, Background rate was excluded as a classification feature when
 680 the solar elevation angle is below 15°, following established practices (Kwok et al., 2016, 2023). Future work could address this limitation by incorporating a larger and more diverse training dataset and by exploring classification models that exploit along-track contextual information from multiple adjacent segments, rather than relying solely on features derived from individual signal segments. Such approaches may help reconcile robustness under low background conditions with improved separability of surface types, thereby further strengthening year-round surface-type classification and freeboard retrieval.

685 **6 Conclusion**

In this study, we developed and implemented the High-Resolution Freeboard Method (HRFM), a novel processing framework designed to optimize ICESat-2 ATL03 data for year-round, high-resolution sea ice monitoring. By improving signal photon extraction, surface-height retrieval, and surface-type classification, HRFM addresses several long-standing challenges in laser altimetry, including signal denoising in complex environments, weak-beam underutilization, and melt-pond interference.

690 HRFM employs a two-stage denoising strategy to extract signal photons associated with fine-scale ice morphology, including ridges, leads, and melt ponds, allowing along-track surface heights to be resolved at 5-m intervals. Validation against airborne ATM data demonstrates that HRFM achieves a lower RMSE (0.08 ± 0.01 m) and higher correlation ($r=0.95$) than the ATL07 product, while better preserving small-scale surface variability. Notably, HRFM successfully minimizes height fluctuations over specular leads typically caused by detector saturation.

695 Melt ponds forming on sea ice surfaces during summer are a major obstacle to robust year-round freeboard retrieval, as they weaken classification contrast and challenge conventional threshold-based schemes. HRFM addresses this issue using a machine-learning-based surface-type classifier trained with 25 coincident optical images, comprising approximately two million ICESat-2 segments across all seasons. HRFM successfully separates true open-water leads from sea ice and melt ponds in summer and identifies thin gray ice as a distinct class in winter. This refined classification (overall accuracy > 0.98) ensures
 700 a more stable and consistent reference sea level.

Comparative analysis with the ATL20 product shows that while HRFM freeboard maps maintain consistent large-scale spatial patterns, they exhibit seasonal mean differences of up to ± 0.04 m. HRFM yields lower freeboard estimates in winter by retaining more valid lead samples and removing after-pulse photons, but produces higher freeboard estimates in summer by effectively excluding misclassified melt ponds in the determination of reference sea level.



705 An additional contribution of HRFM is the enhanced performance of weak beams, which yield freeboard estimates statistically consistent with those from strong beams. This capability might enable the joint utilization of all six ICESat-2 beams, increasing the actual area of sensed sea ice and reducing uncertainties in gridded freeboard products. Our ongoing work aims to extend HRFM to long-term ICESat-2 observations to construct continuous, cross-season records of sea ice freeboard and thickness, providing a high-fidelity dataset for sea ice forecasting and climate change investigations in the Arctic.

710 **Authorship contribution**

Wenxuan Liu: Conceptualization, Data curation, Methodology, Validation, Writing – original draft, Visualization.

Ruibo Lei: Supervision, Writing – review & editing, Funding acquisition

Taoyong Jin: Supervision, Writing – review & editing,

Heyang Sun: Data curation, Writing – review & editing,

715 **Michel Tsamados:** Writing – review & editing.

Isolde A. Glissenaar: Data curation, Writing – review & editing.

Jack C. Landy: Writing – review & editing.

Yi Zhou: Writing – review & editing.

Data availability statement

720 The ICESat-2 ATL03 (geolocated photon), ATL07 (sea ice height and type), ATL20 (gridded freeboard), ATM, and sea ice concentration data are available through the National Snow and Ice Data Center (<https://nsidc.org/data/atl03/versions/6>, <https://nsidc.org/data/atl07/versions/6>, <https://nsidc.org/data/atl20/versions/5>), <https://nsidc.org/data/ilatm1b>, and <https://nsidc.org/data/g02202/versions/6>, respectively). The Sentinel-2 imagery was derived from Google Earth Engine at <https://developers.google.com/earth-engine/datasets/catalog/sentinel-2>. The HRFM-derived monthly sea ice freeboard can be
725 accessed from Zenodo at <https://doi.org/10.5281/zenodo.18452459>.

Declaration of Competing Interest

At least one of the (co-)authors is a member of the editorial board of *The Cryosphere*.

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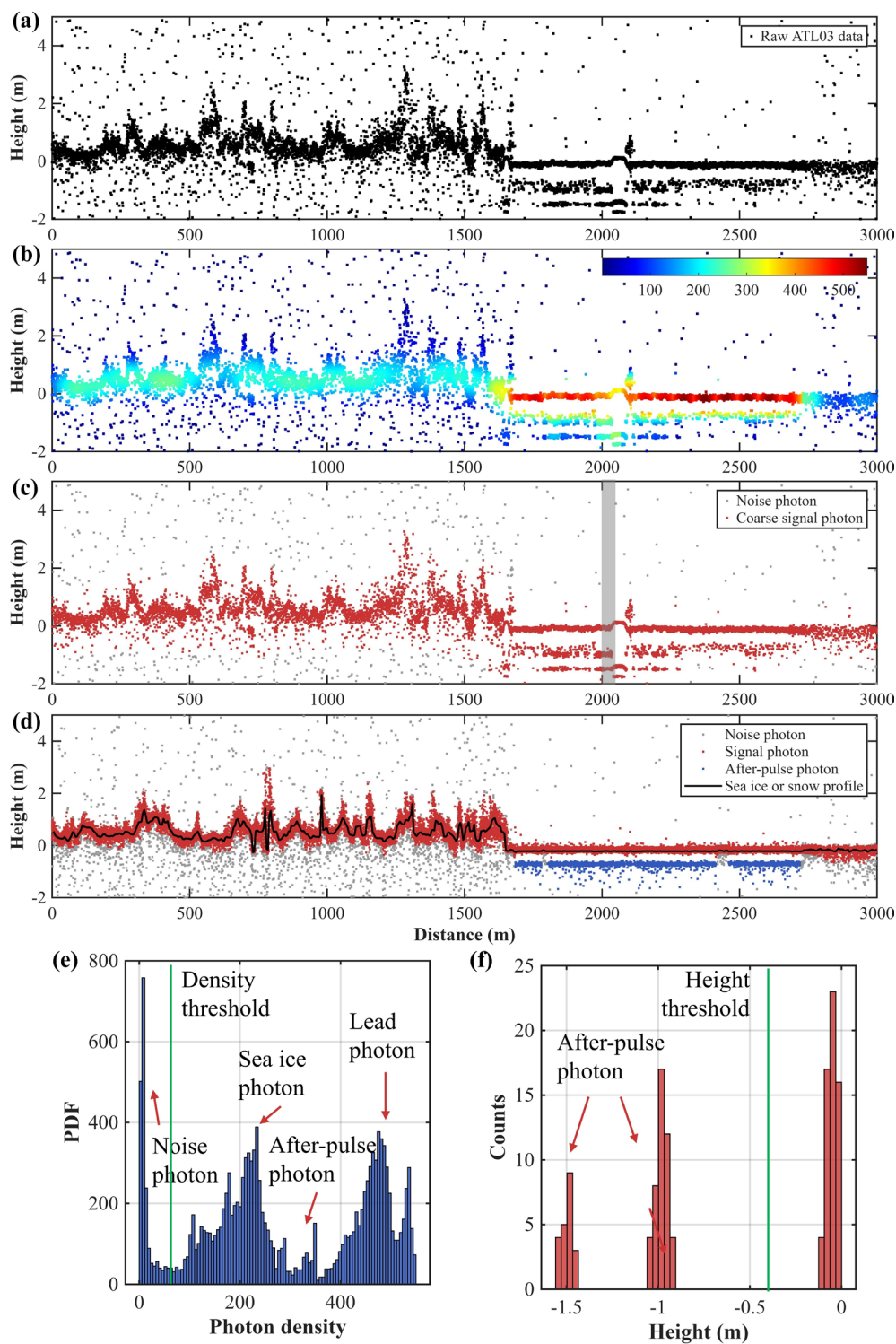
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Appendix A

Table A1 Confusion matrices and classification accuracy statistics for the HRFM surface-type classifier based on leave-one-group-out (LOGO) cross-validation, when thin-ice type is merged into sea-ice type

Strong beam			Ground truth from Sentinel-2			Precision
			Sea ice	Lead	All	
HRFM type	surface	Sea ice	930768	5315	936083	0.99
		Lead	3391	89815	93206	0.96
		All	934159	95130	1029289	
Recall			0.99	0.95		0.99
Weak beam			Ground truth from Sentinel-2			Precision
			Sea ice	Lead	All	
HRFM type	surface	Sea ice	933895	8044	941939	0.99
		Lead	4448	77508	81956	0.95
		All	938343	85552	1023895	
Recall			0.99	0.91		0.99



935 Figure A1 As in Fig. 3, but for weak beam.

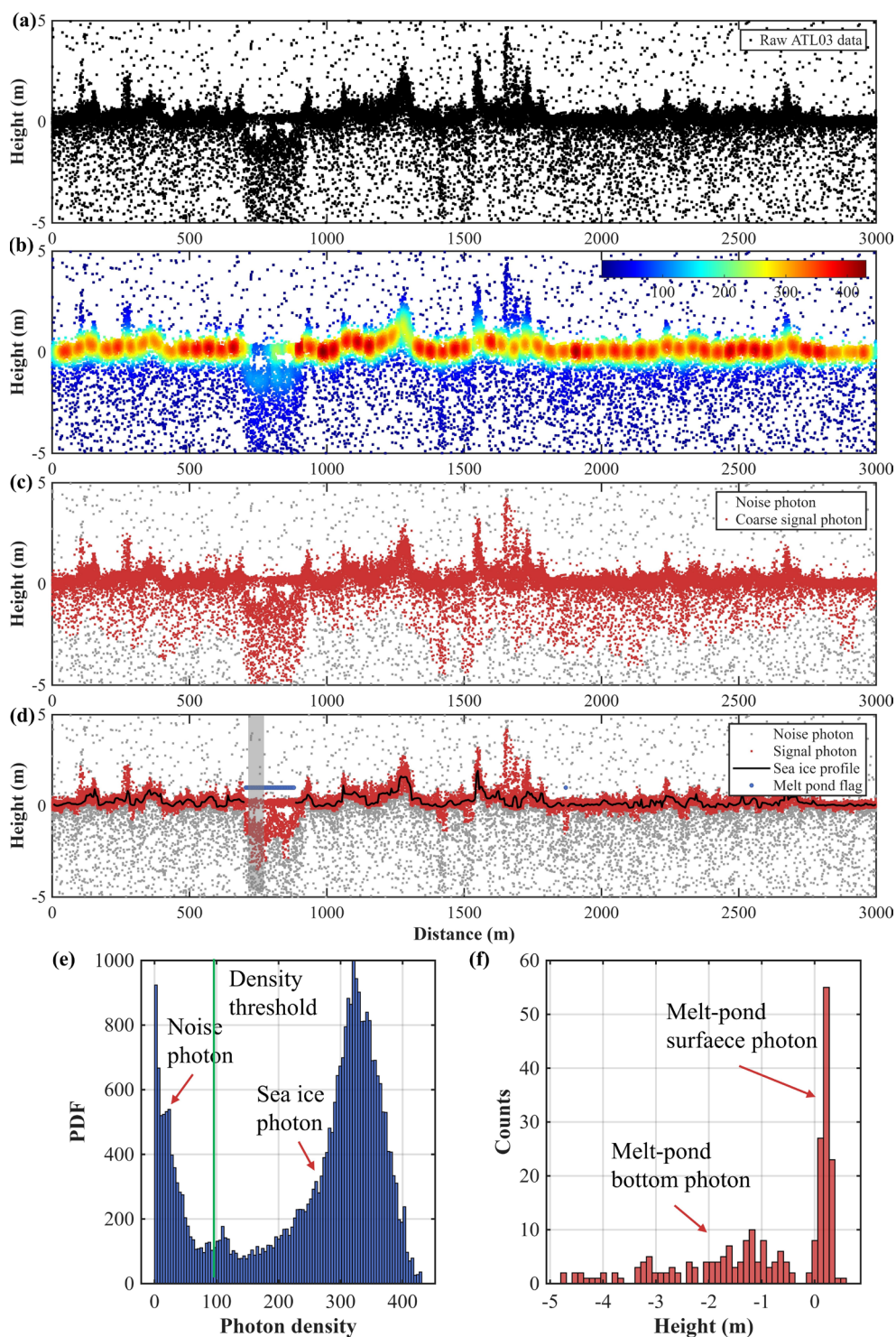


Figure A2 As in Fig. 3, but for a melt pond example.

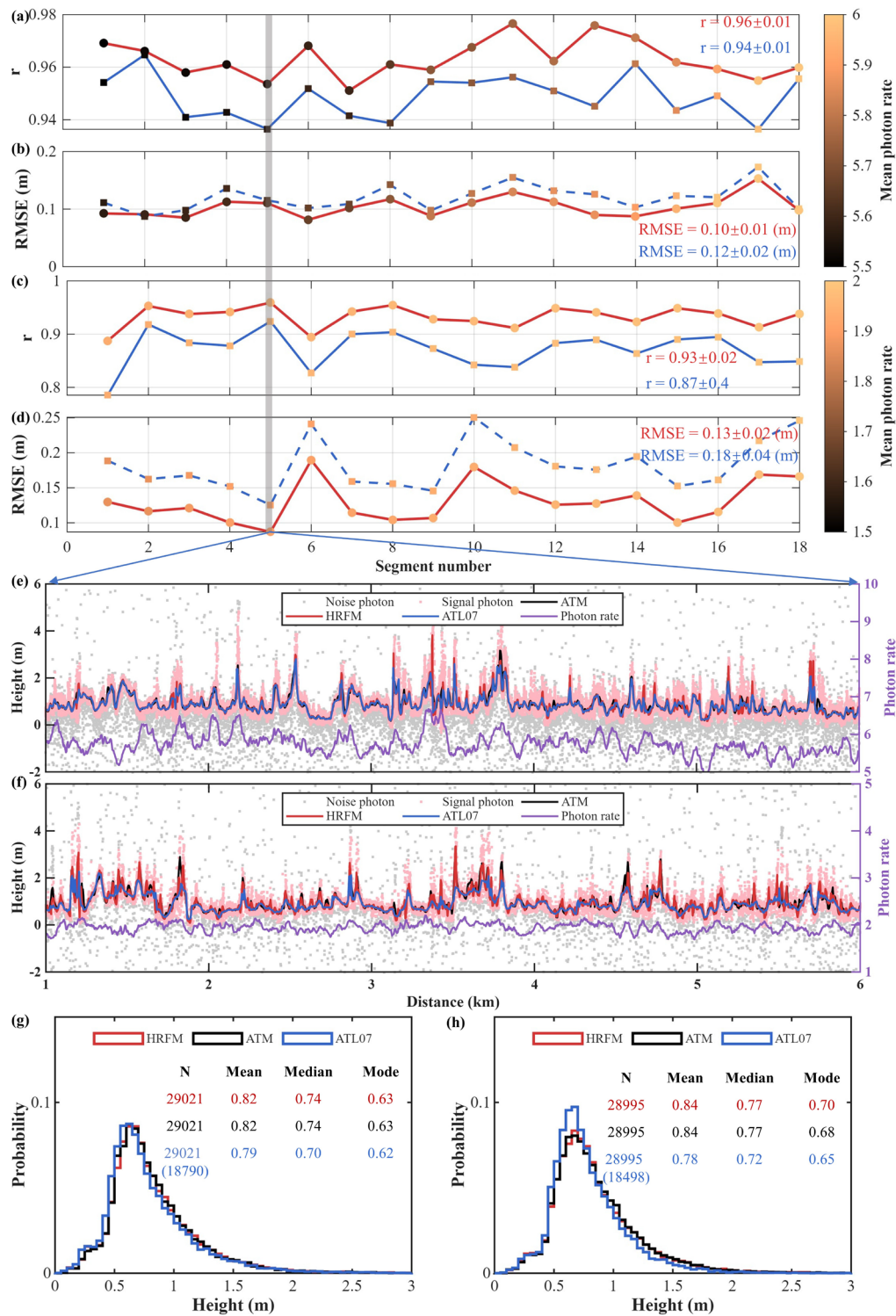


Figure A3 As in Fig. 7, but for 08 April 2019

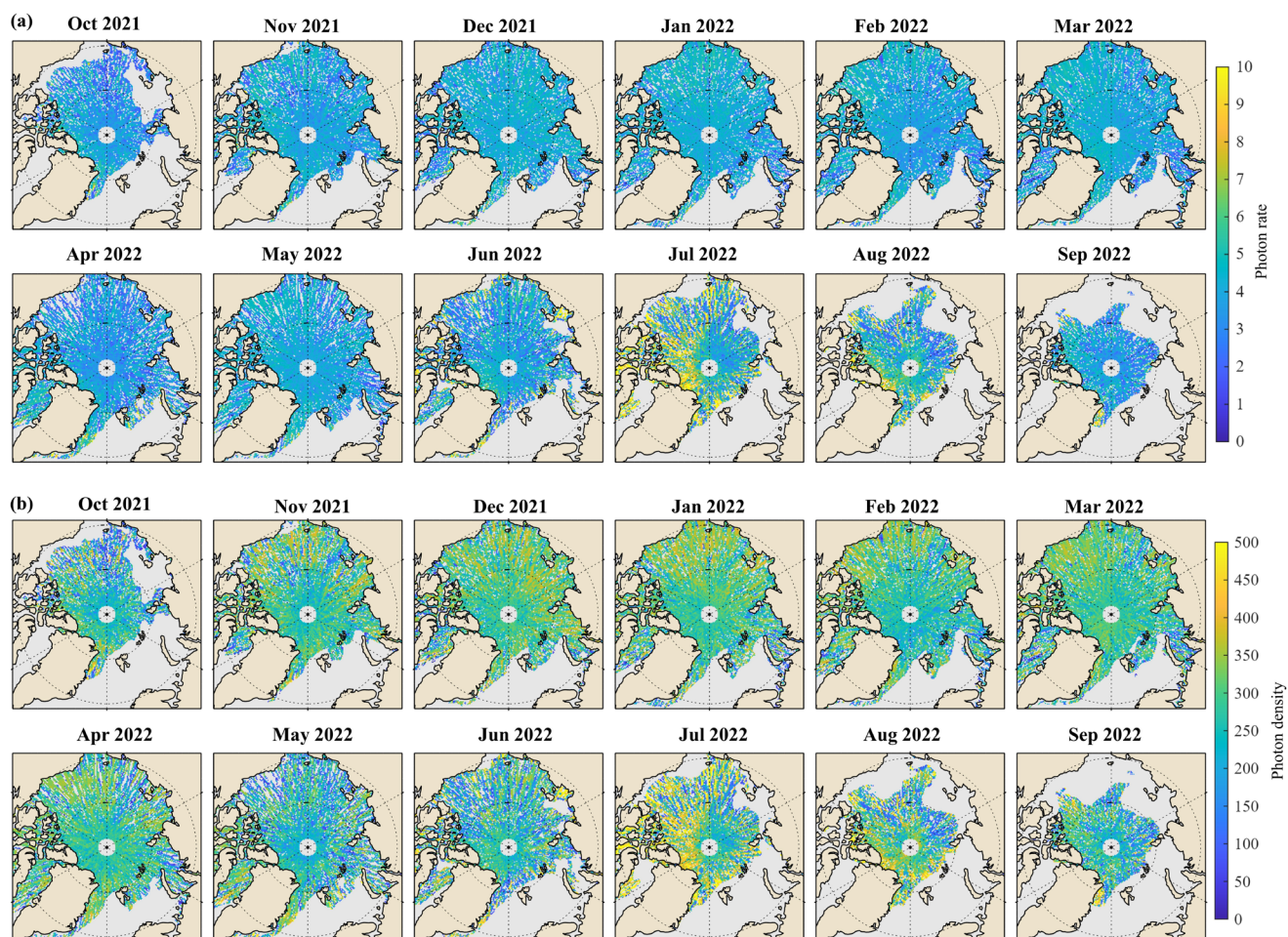


Figure A4 Monthly (a) photon rate and (b) photon density.

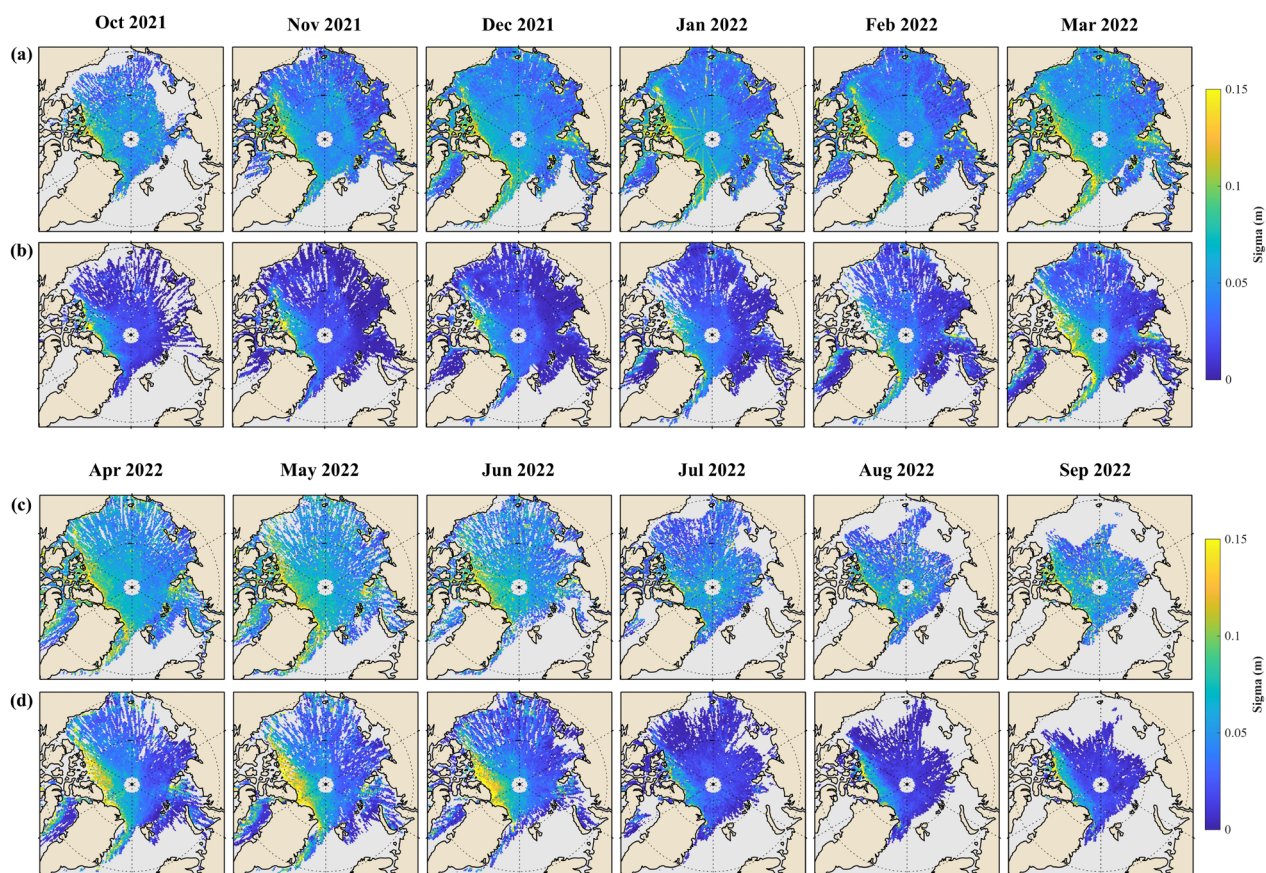
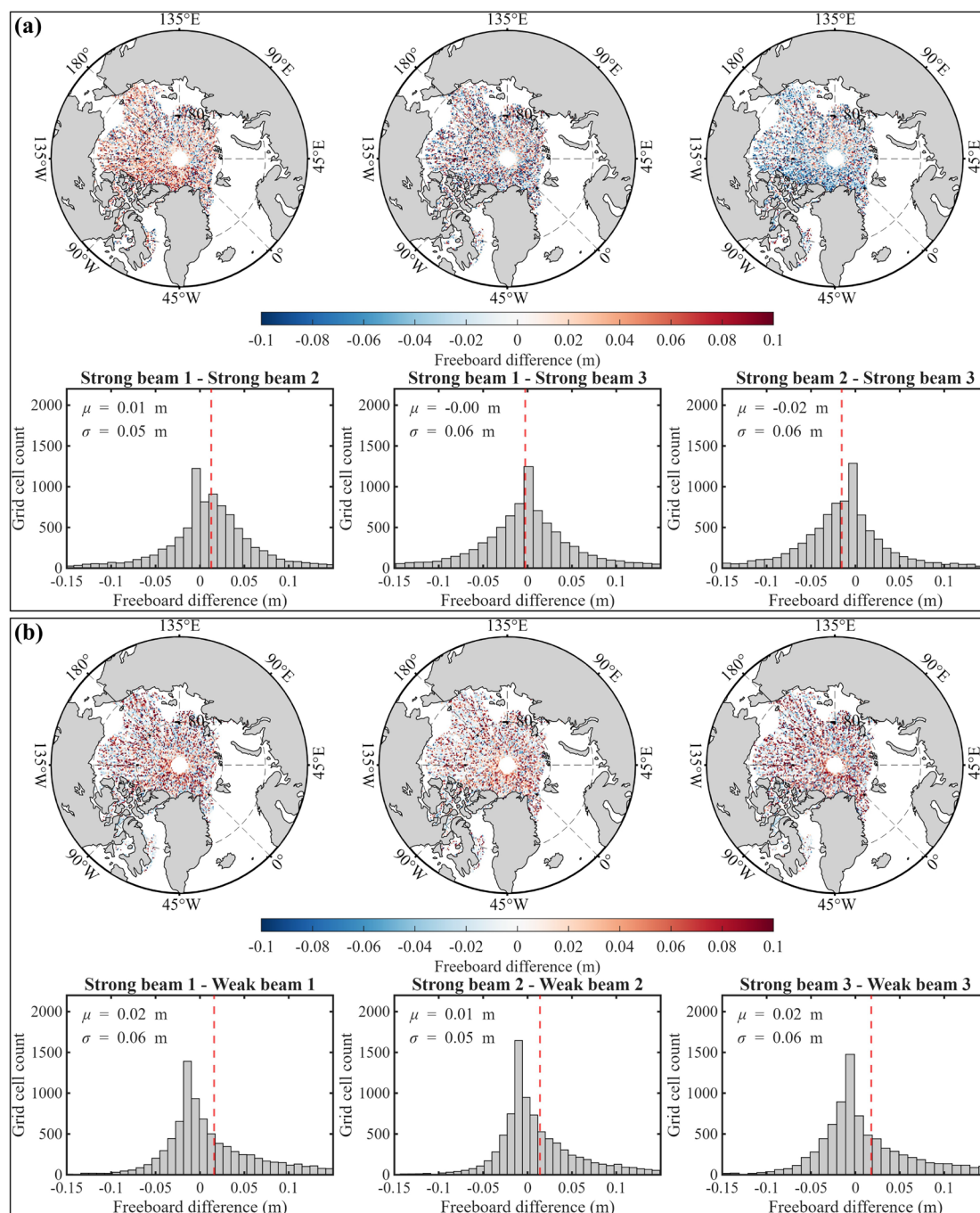


Figure A5 Standard deviation of freeboards in each monthly grid cell for HRFM (a, c) and ATL20 (b, d).



945 Figure A6 As in Fig. 11, but for July 2022.