

Article

A Segmented Adaptive Filtering Method for Nearshore Bathymetry Using ICESat-2 Dataset

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Highlights

What are the main findings?

- A novel segmented adaptive filtering bathymetry method was proposed for high-precision nearshore bathymetry using ICESat-2 data.
- Extensive experiments across different coastal sites (Qilanyu Islands and West Island) demonstrate that our method achieves high accuracy, with a root mean square error (RMSE) as low as 0.37 m and a coefficient of determination (R^2) of 0.98 when validated against airborne LiDAR bathymetry.

What is the implication of the main finding?

- The proposed method provides a fully automated, accurate, and reliable solution for nearshore bathymetric mapping from space, effectively overcoming the challenges of varying environmental conditions and photon density.
- This study confirms the significant potential of ICESat-2's ATLAS data for underwater bathymetry, paving the way for its broader application in coastal zone management and marine geospatial research.
- The high-accuracy results coupled with robust performance across different regions demonstrate the method's strong potential for enabling operational, large-scale bathymetric surveys.

Abstract

Equipped with an Advanced Topographic Laser Altimeter System (ATLAS), ICESat-2 (Ice, Cloud and land Elevation Satellite-2) is a photon-counting laser altimetry mission with strong potential for nearshore bathymetry. In this study, a novel filtering and bathymetric method termed a segmented adaptive filtering bathymetry has been proposed. Sea-surface photons are identified from peaks in the elevation-density histogram, enabling separation of surface and seafloor photons. The seafloor photons are then partitioned into along-track segments, where seafloor signal photons are extracted using an adaptive elliptical kernel whose parameters and orientation are determined from local density patterns and seafloor slope. The seafloor profile is obtained by polynomial fitting, and nearshore depth is estimated from the elevations of the surface and seafloor signal photons. To ensure and improve the accuracy and reliability of the proposed method, ICESat-2 data from Qilanyu Islands at the South China Sea and West Island at the Florida Keys of the United States were



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adopted to perform experiments. Furthermore, the bathymetric results obtained by ICESat-2 datasets at different experimental areas were compared with the reference bathymetry obtained by the airborne light detection and ranging (LiDAR) bathymetry (ALB) system. Finally, the bathymetric accuracy validation and assessment were performed. The highest accuracy of root mean square error (RMSE) and coefficient of determination (R^2) has reached 0.37 m and 98%, respectively. The accuracy validation of bathymetric results at different study areas demonstrated that the method proposed in this study can automatically and effectively achieve high-precision nearshore bathymetry and topographic surveys.

Keywords: ATLAS; ICESat-2; photon counting; filter kernel; nearshore bathymetry

1. Introduction

Islands and reefs play a pivotal role in the global ecosystem and support a wide range of human activities [1]. Accurate nearshore bathymetry and underwater topography are therefore critical for marine resource management, coastal ecological protection, benthic habitat assessment, and navigational safety [2,3]. However, the shallow-water zones around islands and reefs are often characterized by complex terrain and highly dynamic environmental conditions, posing substantial challenges for bathymetric surveying and mapping [4]. Conventional methods, including shipborne single- and multibeam sonar systems, airborne LiDAR bathymetry (ALB), and satellite-derived bathymetry (SDB), often struggle to deliver simultaneous, high-precision coverage across such regions [5,6]. As a result, bathymetric products derived from these methods frequently fall short of practical requirements in terms of accuracy, efficiency, and reliability [7].

Launched by NASA in September 2018, the Ice, Cloud, and land Elevation Satellite-2 (ICESat-2) represents the first spaceborne photon-counting LiDAR mission. Equipped with the Advanced Topographic Laser Altimeter System (ATLAS), ICESat-2 was designed to provide highly accurate measurements of Earth's surface elevation, offering an innovative active remote sensing capability for characterizing surface and topographic properties [8–11]. Primary observational targets of ICESat-2 include land ice, sea ice, cloud tops, forest canopies, terrestrial topography, and sea surface height [12–14]. The ATLAS instrument emits three green laser beams at 532 nm (left, center, and right) along the ground track, with a cross-track spacing of 3.3 km between adjacent beams. Each beam operates at a pulse repetition frequency of 10 kHz, producing footprints approximately 17 m in diameter and an along-track sampling interval of 0.7 m [15,16]. By leveraging photon-counting technology, ATLAS achieves lower energy consumption, higher pulse repetition rates, and reduced beam divergence compared to conventional full-waveform LiDAR systems [11]. As a result, ATLAS offers superior measurement precision [17]. Moreover, the 532 nm green laser wavelength exhibits strong water-penetrating capability, endowing ATLAS with considerable potential for nearshore bathymetric applications [18].

Previous ICESat-2 nearshore bathymetry studies have proposed a variety of photon-filtering algorithms, which can be broadly grouped into image-based, density-clustering, and tree-structure approaches [19]. Image-based methods typically rasterize photon point clouds into 2D grids and then apply edge detection or segmentation (e.g., Canny or Chan–Vese) with subsequent smoothing to suppress noise [20,21]. Although effective in reducing noise, such methods often suffer from loss of valid signal photons during rasterization and subsequent inverse transformation, thereby compromising filtering accuracy. Density-clustering methods exploit the spatial aggregation of signal photons (e.g., DBSCAN or OPTICS) to separate signals from background noise [22–24]. A common limitation is

that their parameters are often difficult to adapt to spatially varying photon density and depth-dependent attenuation, leading to degraded performance under heterogeneous spatiotemporal photon distributions. Tree structure-based methods, in contrast, operate under the assumption of photon sparsity and utilize spatial partitioning to separate signal from noise. A representative approach employs quadtree decomposition, recursively subdividing each spatial region into four quadrants until each contains no more than one photon [25,26]. This process constructs a hierarchical quadtree structure that facilitates noise suppression [18,23]. Furthermore, the Otsu thresholding method has been integrated with elevation and quadtree depth histograms to determine depth-dependent thresholds for underwater signal extraction. Nevertheless, the use of fixed thresholds in such frameworks often leads to unstable detection performance and reduced accuracy when photon density and distribution vary significantly across different environments [19].

To overcome these limitations, this study proposes a novel piecewise adaptive photon filtering method for the accurate extraction of seafloor signal photons and high-precision nearshore bathymetry. The method incorporates two key innovations. First, an adaptive elliptic filter kernel is dynamically adjusted in size and orientation based on local photon density distribution and underlying seafloor topographic trends, enabling precise identification of signal photons at both the water-surface and seafloor. Second, a piecewise fitting strategy is introduced to refine the detected signal photons, thereby enhancing detection accuracy and robustness. Additionally, a refraction correction model is applied to each identified seafloor photon to compensate for optical displacement caused by light refraction at the air–water interface, further improving bathymetric fidelity. To evaluate the performance of the proposed method, experiments were conducted using ICESat-2 data acquired over two distinct study areas: Qilianyu Islands in the South China Sea and West Island in the Florida Keys, USA. These sites exhibit contrasting photon density regimes, allowing for comprehensive validation. The derived bathymetric results were compared against reference datasets obtained from airborne LiDAR bathymetry (ALB) surveys to assess accuracy and reliability.

2. Materials

2.1. Study Area

This study focuses on two geographically distinct regions, as illustrated in Figure 1. The first site is located at Key West, part of the Florida Keys, United States; the second is situated at Qilianyu Islands, within the Xisha Islands of the South China Sea. Key West is a coral island measuring approximately 7.2 km in length and 3.2 km in width, with a mean elevation of only 2.1 m above sea level. As the southernmost city and island in the Florida Keys, it encompasses a total land area of 19.2 km². The Qilianyu Islands are positioned in the northeastern sector of the Xuande Islands group, which constitutes part of the Xisha Islands (approximately 16°55′N, 112°12′E). The archipelago comprises seven small islands: Zhaoshu Island, Beidao, Zhongdao, Nandao, Beisha Island, Zhongsha Island, and Nansha Island. Each of these islands has an individual area of approximately 0.4 km².

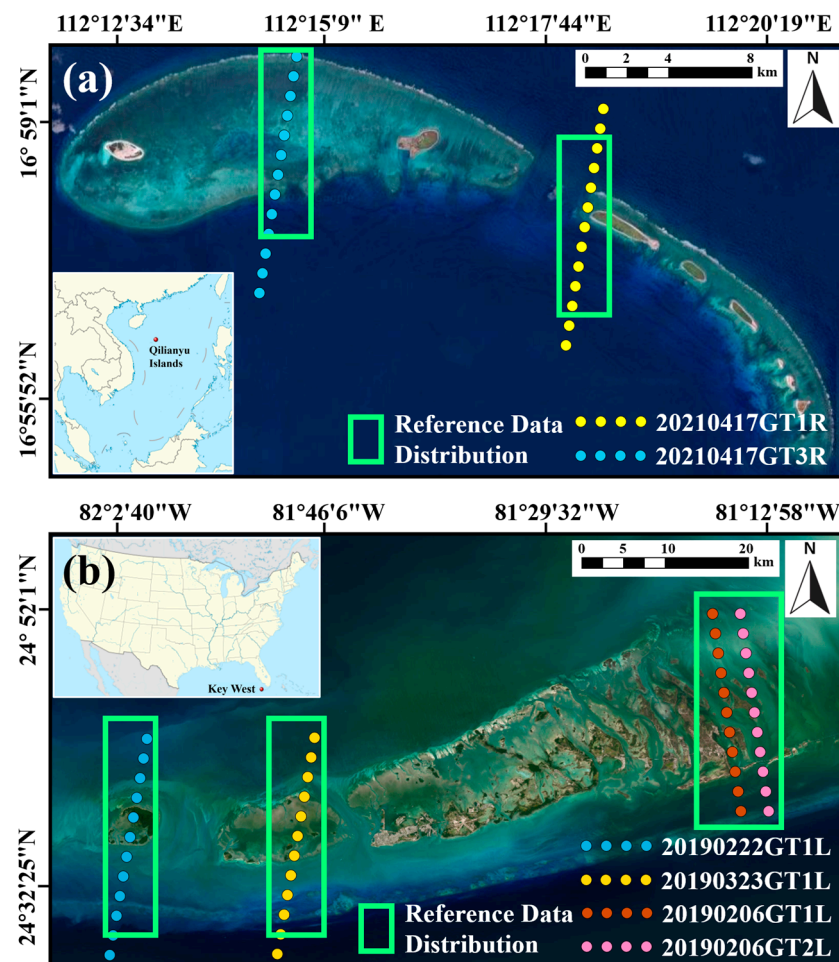


Figure 1. Location of research areas and data distribution. The dotted lines of different colors represent different track distributions of ATLAS datasets obtained at study area of Qilanyu Islands (a) and Key West (b).

2.2. ATLAS Dataset

The Advanced Topographic Laser Altimeter System (ATLAS) aboard ICESat-2 splits each of its three primary laser beams into two sub-beams, one of which carries approximately four times the pulse energy of the other. In this study, we employed the ATL03 data product—the standard global geolocated photon dataset from ATLAS—which is freely available for download via the NASA Earthdata Search platform (<https://search.earthdata.nasa.gov/search>, accessed on 5 February 2025). ATL03 provides precise geolocation information for each detected photon, including latitude, longitude, elevation, acquisition time, and along-track distance. All photon coordinates are referenced to the World Geodetic System 1984 (WGS84) ellipsoid [27]. The ATL03 product has been corrected for geophysical effects such as atmospheric delay, solid Earth tides, and system directivity bias, and photon confidence filtering has been achieved by removing photons labeled as noise (level 0) using the `signal_conf_ph` parameters provided in the ATL03 product prior to segmented adaptive filtering. When a laser pulse intersects the air–water interface, a fraction of photons penetrates the surface and propagates toward the seafloor. Due to refraction at the interface, both the direction and speed of the transmitted photons are altered: the incident angle changes according to Snell’s law, and the reduced speed of light in water introduces a vertical displacement in the apparent photon return location. This results in a spatially distorted distribution of underwater signal photons [28,29]. Conse-

quently, correcting for water column effects—particularly refraction-induced geometric displacement—is essential for achieving high-fidelity nearshore bathymetric retrievals.

As summarized in Table 1, the study areas and corresponding ICESat-2 overpass dates are detailed. A total of two ground tracks intersected the Qilianyu Islands, while four tracks covered Key West, as shown in Figure 1a,b, respectively. From the ATL03 data, we extracted the latitude, longitude, elevation, along-track distance, and signal confidence level for each photon along these trajectories. These parameters formed the basis for subsequent filtering, refraction correction, and bathymetric estimation procedures.

Table 1. Distribution information for the ATLAS datasets in the study sites.

Study Area	ATLAS Dataset	Trajectory Used	Time	Geodetic Coordinate Distribution (Latitude, Longitude)
Qilianyu Islands	20210417	GT1R	00:22	16.9620, 112.3028–16.9769, 112.3043
	20210417	GT3R	00:22	16.9660, 112.2430–17.0019, 112.2467
Key West Islands	20190222	GT1L	02:51	24.4500, −82.1534–24.4769, −82.1505
	20190323	GT1L	01:27	24.4400, −81.9284–24.4699, −81.9252
	20190206	GT1L	15:19	24.5630, −81.3142–24.6799, −81.3268
	20190206	GT2L	15:19	24.5720, −81.2835–24.7129, −81.2987

2.3. Reference Dataset

The depth reference data for the Qilianyu Islands region were acquired on 17 April 2021, using the airborne LiDAR system Mapper5000, The Shanghai Institute of Optics and Fine Mechanics of the Chinese Academy of Sciences, Shanghai, China. This system operates at a pulse repetition rate of 5 kHz, and its coordinate system is referenced to the WGS84 ellipsoid [30]. The corresponding measurement accuracy of the nearshore bathymetry achieved a root mean square error (RMSE) of 0.23 m. For the Key West area, the reference dataset was collected on 23 March 2019, by the airborne LiDAR bathymetry (ALB) system equipped with the RIEGL VQ-880-G Series sensor, which provides a bathymetric accuracy of 0.20 m RMSE. Reference datasets in the two study areas are represented by green rectangles in Figure 1. To validate the bathymetric accuracy of ICESat-2, an interpolation-based comparison was performed by searching for reference data within a spherical radius of 2.5 m centered on each ICESat-2-derived bathymetric point. Local water levels may fluctuate due to tidal influences, which can typically introduce decimeter- to meter-level deviations in bathymetric results. To address this, the present study utilized the NAO.99b tidal model to simulate tidal variations throughout the entire data acquisition period. The initial tidal simulation provided tidal height data at fifteen-minute intervals, which were then interpolated to minute-level resolution using a bilinear interpolation method. Based on this processing, the ICESat-2-derived water depth data were uniformly corrected to align with the acquisition time of the ALB data, effectively reducing the impact of tidal fluctuations on bathymetric accuracy [31].

3. Methods

In the nearshore bathymetry process using the proposed method, the original photon dataset is first categorized into water-surface and underwater photons based on the elevation histogram of detected photons. To enhance adaptability to spatially varying photon densities, the dataset is partitioned into multiple intervals along the track direction. Subsequently, an elliptical filtering kernel is constructed, and its parameters are adaptively determined to enable high-precision detection of both water-surface and seafloor signal

photons. Using the identified seafloor signal photons, a refinement step is applied through piecewise polynomial fitting, which facilitates accurate reconstruction of the seafloor topography and sea surface wave profile, from which the final bathymetric results are derived. Furthermore, a refraction correction is applied to each seafloor signal photon to compensate for water column-induced coordinate displacement, thereby improving overall bathymetric accuracy. In general, the proposed method comprises three main components: (1) separation of water-surface and seafloor photons coupled with adaptive signal-photon filtering; (2) refinement of signal photons and derivation of the seafloor topographic curve; and (3) refraction correction for water column effects.

3.1. Separating Water-Surface and Water-Bottom Photons and Adaptive Signal-Photon Filtering

(1) Separating water-surface and water-bottom photons

The original data are projected into a two-dimensional space of elevation and orbital distance. Along the track direction, the photon set is adaptively divided into a series of segments based on a fixed photon count. Specifically, each segment contains 6000 photons, and the segment boundaries are indicated by blue dashed lines in Figure 2. This segmentation strategy partitions the photon data into along-track segments with the same photon counts, such that all subsequent filtering and signal extraction steps are conducted within individual segments rather than on the entire photon dataset. As a result, the computational burden is reduced and the overall processing efficiency of the algorithm is significantly improved.

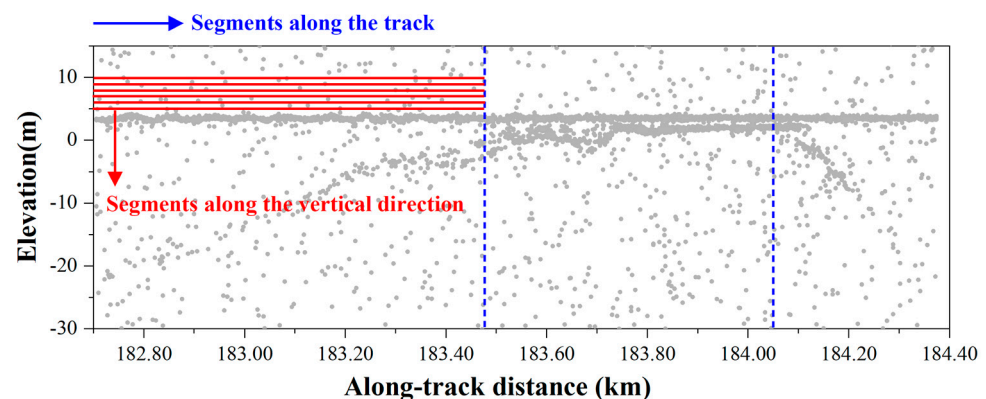


Figure 2. Photon segmentation along the track and elevation direction. Blue dashed lines denote along-track segments defined by a fixed photon count, while red rectangles indicate windows along the elevation direction with a height of Δh .

Within each along-track segment, the original photon data are further divided into a series of windows along the elevation direction, as illustrated by the red rectangle in Figure 2. The number of windows along the elevation direction is calculated using Equation (1), where H_i denotes the elevation of photons, Δh represents the height of the window, and M denotes the total number of windows along the elevation direction within each along-track segment. In this study, Δh is set to 0.1 m based on empirical considerations, to meet the requirement for accurate determination of the sea surface elevation in subsequent processing.

$$M = \frac{\max(H_i) - \min(H_i)}{\Delta h} \quad (1)$$

Within each window, the number of photons is counted for constructing the histogram distribution of photon quantity, represented in Figure 3. A normal distribution curve was used to fit the relationship between the elevation and the number of photons of the windows, and the resulting fitting curve is formulated as expressed in Equation (2). where

A represents the number of photons in the window with the highest photon count, h_{max} denotes the elevation of that window, and σ is the standard deviation of normal distribution. The sea surface photon area can then be determined with the top and bottom elevation boundaries set to twice the standard deviation of the normal distribution.

$$f(x) = A * \exp\left(-\frac{(x - h_{max})^2}{2\sigma^2}\right) \quad (2)$$

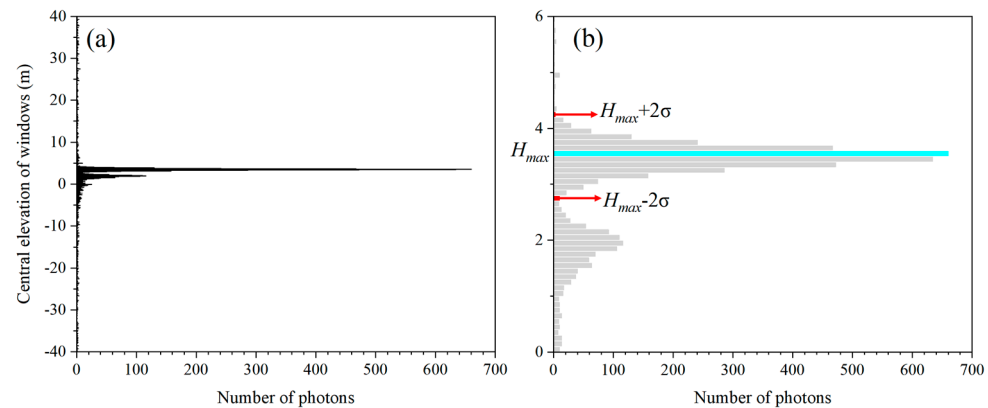


Figure 3. Identification and detection of the boundary between sea-surface and sea-bottom photons. The photon-density histogram in different segments is shown in (a), and the local magnification of the photon-density histogram near the sea surface is shown in (b).

(2) Adaptive signal-photon filtering

To account for spatial density variations among photons and adapt to seafloor topography trends, an elliptic filtering kernel is employed. The orientation of the ellipse is automatically adjusted based on water depth and seafloor topography to improve detection accuracy, as illustrated by Figure 4. The major and minor half-axes denoted as a and b of the elliptic filter are calculated by Equation (3), where R_{ab} is the ratio of the along-track length to the elevation difference, reflecting the stretching degree of photon distribution and thereby adaptively adjusting the size of the elliptic filtering kernel. $d_{\Delta n}$ is the along-track length of each vertical segment, and h_{dif} is the corresponding maximum elevation difference in photons within each segment. ε is the adaptive filtering parameter, derived from the neighborhood radius in the DBSCAN algorithm. This parameter is computed as follows: for each segment, the k -nearest neighbor distance ($k = 4$) of all photon points is calculated, the distances are sorted, a k -distance curve is plotted, and the distance corresponding to the curve's inflection point is selected as the adaptive filtering parameter ε for that segment.

$$\begin{cases} R_{ab} = \frac{d_{\Delta n}}{h_{dif}} \\ b = \varepsilon \\ a = b \times R_{ab} \end{cases} \quad (3)$$

Further, the elliptic filter kernel is expressed by Equation (4). The distance between any two photons of p and q is denoted by $dist(p, q, \theta)$. Symbols of d_p and d_q are the distances in the along-track and elevation directions, ΔD and ΔH are the distances calculated by d_p and d_q . The symbol of θ means the direction angle of the elliptic filter kernel and can be obtained by the optimal fitting slope that is calculated by the linear fitting of photons within the circle with the major half-axis as the radius. For the elliptic filter kernel, the adaptive change in direction angle with the seafloor topography trend, shown by different

red elliptic filters in Figure 4, can effectively improve the accuracy and reliability of signal photon detection.

$$\begin{cases} \text{dist}(p, q, \theta) = \left[\frac{\Delta D^2}{a^2} + \frac{\Delta H^2}{b^2} \right]^{\frac{1}{2}} \\ \Delta D = \cos\theta(d_p - d_q) + \sin\theta(h_p - h_q) \\ \Delta H = \sin\theta(d_p - d_q) - \cos\theta(h_p - h_q) \end{cases} \quad (4)$$

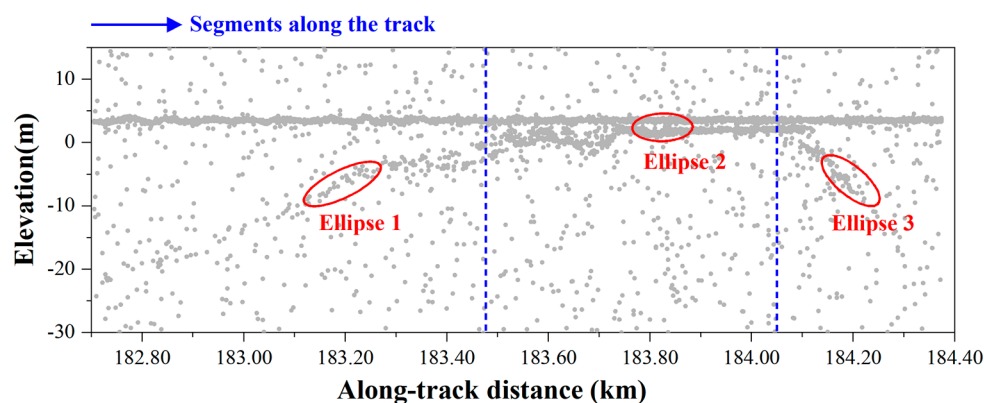


Figure 4. Adaptively adjusting the size and direction of the elliptic filter kernel was constructed to accurately detect the signal photon at the sea-surface and sea-bottom. Ellipse1, ellipse2, and ellipse3 represent the size and direction of the filter kernel at different moments.

Furthermore, to achieve adaptive filtering, the minimum point threshold $MinPts$ must be dynamically determined for each segment to judge whether photons within the ellipse form a signal cluster. The evaluation threshold $\overline{pho}$ is calculated according to Equation (5), where $N_{\Delta n}$ is the total number of photons in the current slice unit, and M is the number of windows divided along the elevation direction. The original photon data is divided into a series of spatial horizontal windows, as shown by the red rectangle in Figure 1, where H_i is the elevation of each photon and Δh is the height of the horizontal window. If the number of photons in a window is greater than or equal to $\overline{pho}$, the window is considered to contain both signal and noise photons; if the number is less than $\overline{pho}$, the window is regarded as a pure noise window. Based on this, the total number of photons in all windows containing signal and noise, N_1 , the total number of photons in all pure noise windows, N_2 , the number of windows containing both signal and noise, M_1 , and the number of pure noise windows, M_2 , can be counted.

$$\overline{pho} = \frac{N_{\Delta n}}{M} \quad (5)$$

Based on the above parameters, the expected total number of photons N_{sn} and the expected number of noise photons N_{no} within the ellipse can be calculated according to Equation (6):

$$\begin{cases} N_{sn} = \pi R_{ab} \varepsilon^2 \cdot \frac{N_1}{\Delta h \cdot d_{\Delta n} \cdot M_1} \\ N_{no} = \pi R_{ab} \varepsilon^2 \cdot \frac{N_2}{\Delta h \cdot d_{\Delta n} \cdot M_2} \end{cases} \quad (6)$$

According to the DBSCAN clustering principle, $MinPts$ should be set as the threshold to distinguish signal from noise. This paper adopts Equation (7) to effectively differentiate signal clusters from noise:

$$MinPts = \frac{(N_{sn} - N_{no}) + \ln(M)}{\ln(N_{sn}/N_{no})} \quad (7)$$

For a photon point p , the number of all photon points within its elliptical neighborhood (i.e., inside the ellipse centered at point p with semi-major axis a , semi-minor axis b , and

direction angle θ) is calculated. If this number reaches the adaptively computed minimum point threshold $MinPts$, point p is judged as a core point; otherwise, it is regarded as noise.

3.2. Refining the Signal Photon and Obtaining Seafloor Topographical Curve

To enhance the detection accuracy of seafloor signal photons, the signal photons are divided into a series of intervals along the track direction, with each interval denoted as Δd . Based on empirical considerations, Δd is set to 200 m in this study. The segmentation of the along-track intervals is illustrated by the dashed lines in Figure 5a.

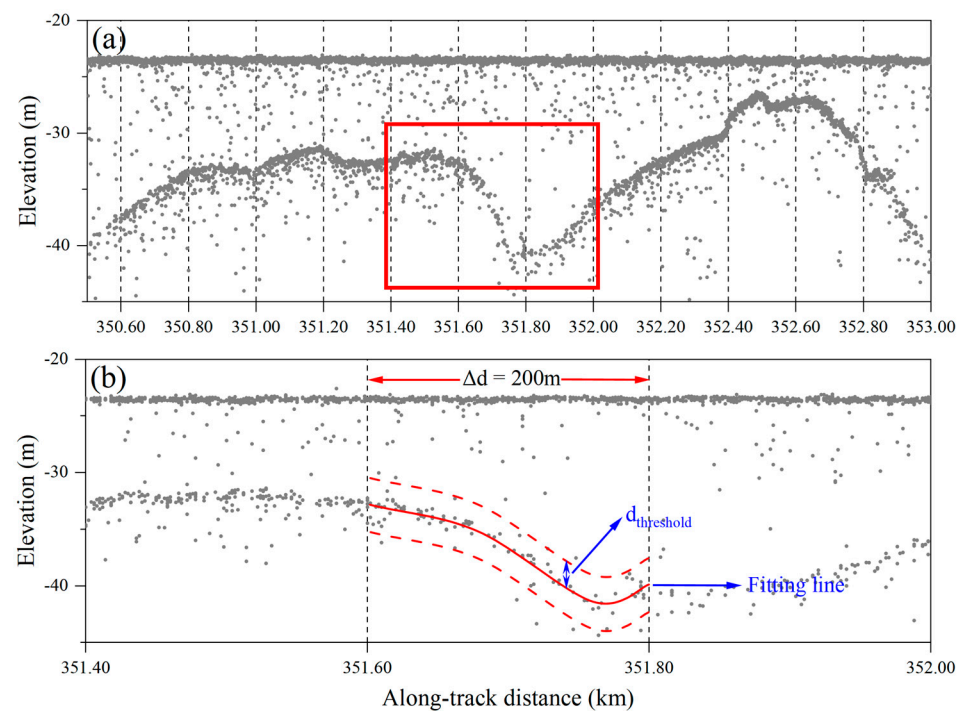


Figure 5. Piecewise polynomial fitting to refine signal photons at the seafloor. (a) Segmentation of the signal photons into along-track intervals. (b) Refinement of signal photons using a cubic polynomial curve fitting within each interval.

A curve fitting algorithm is adopted to further refine the results of signal photons, as expressed by Equation (8). The symbol of h means the elevation and d is its distance along the track. Cubic polynomial coefficients of a_0 , a_1 , a_2 and a_3 , can be calculated and determined based on the sample points by the least squares method.

$$h = a_3d^3 + a_2d^2 + a_1d + a_0 \quad (8)$$

Additionally, the residual distances d_{plu} between the photons and the fitted curve is calculated, as expressed by Equation (9). Then twice the standard deviation of d_{plu} was defined as $d_{threshold}$. When the distance is less than $d_{threshold}$, the corresponding photon is considered the final seafloor signal photon, which is represented by Figure 5b.

$$d_{plu} = h_u - (a_3d_u^3 + a_2d_u^2 + a_1d_u + a_0) \quad (9)$$

Through this process, the signal photon on the seafloor is refined and some missing signal photons can also be detected and added into signal photon. After processing all the intervals, signal photons on the seafloor can be determined. Finally, continuous seafloor topography and bathymetric data are obtained by using the B-spline model [32].

3.3. Achieving Refraction Correction of the Water Column

As a laser pulse passes through the air/ocean interface, its direction and speed of transmission are altered by the water column, resulting in the coordinate displacement and bathymetric error [33]. Therefore, the refraction correction of the water column is necessary and crucial for ensuring and improving the bathymetric accuracy. According to Snell's law, both horizontal and vertical errors occur in the geographical locations recorded in ATL03, causing photon positions to appear deeper than the actual measured values and farther from the lowest point [34]. Based on Snell's law and the transmission path of seafloor photons, the geometric relationship between the intersection point of the sea-air interface and the position of seafloor photons was constructed to formulate the model of refraction correction, as shown in Figure 6. The refractive index of water in air and seawater and photon velocity are shown by Equation (10).

$$n_w = \frac{C_a \cdot t/2}{C_w \cdot t/2} = \frac{\sin \alpha}{\sin \beta} = \frac{L}{R} \quad (10)$$

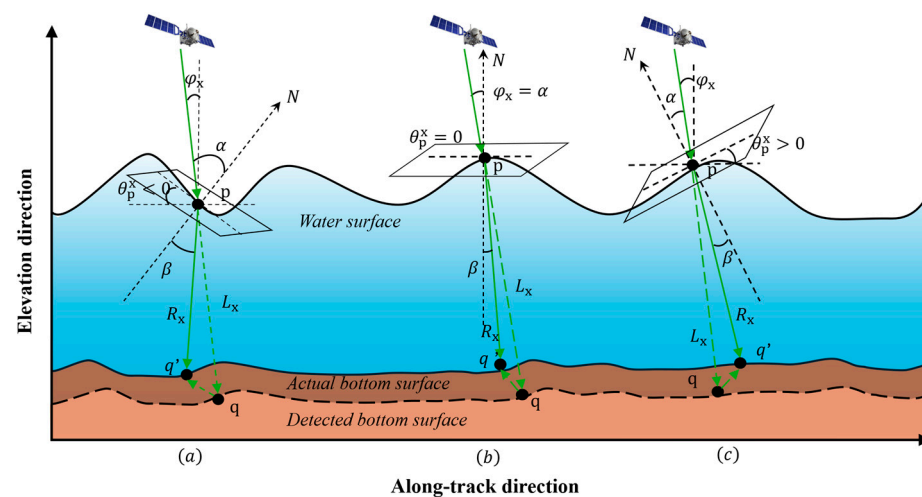


Figure 6. Relationship between water refraction and the geometric correlation among the laser pulse, sea wave, and seafloor photon. The black points on the diagram indicate where the laser pulse intersects with the air/sea interface. The green, orange, and blue lines with arrows indicate the original laser path, refracted laser path, and refraction displacement, respectively. (a–c) are schematic diagrams of different incident angles and their corresponding refraction corrections.

In our study, the refractive index n_w of water is 1.341; this value corresponds to the refractive index of the 532 nm laser wavelength of the ICESat-2/ATLAS under typical seawater conditions, and has been used by Parrish et al. as a constant correction parameter in several major ICESat-2 bathymetry studies [35]. The symbols α and β represent the incident and refraction angles, respectively. Additionally, C_a and C_w denote the velocities of the laser in air and seawater. The symbols L and R represent the transmission distances of photons on the seafloor before and after refraction correction.

The instantaneous sea-wave profile is reconstructed by the extracted sea surface signal photons and the weighted cubic polynomial model (PWCP). For each seafloor photon, six surrounding sea-surface photons are selected to solve the polynomial parameters via least squares, enabling precise determination of the air/sea intersection point and local wave slope. Using the reconstructed local sea-wave profile and geometric relationship of water refraction, the incident angle, α , of a certain seafloor photon can be calculated via the pointing

angle, φ_x , and the slope angle, θ_x^p , which is expressed as Equation (11) for the three different angle ranges, such as $\theta_x^p \in (0, \varphi_x)$, $\theta_x^p \in (\varphi_x, 90^\circ + \varphi_x)$, and $\theta_x^p \in (90^\circ + \varphi_x, 180^\circ)$.

$$\begin{cases} a = \varphi_x - \theta_x^p, \theta_x^p \in (0, \varphi_x) \\ a = \theta_x^p - \varphi_x, \theta_x^p \in (\varphi_x, 90^\circ + \varphi_x) \\ a = 180^\circ - \theta_x^p + \varphi_x, \theta_x^p \in (90^\circ + \varphi_x, 180^\circ) \end{cases} \quad (11)$$

Subsequently, the corresponding refraction angle, β , is acquired with the incident angle, α , and the refractive index of air and seawater, represented by Equation (12).

$$\beta = \sin^{-1}\left(\frac{n_a}{n_w} \cdot \sin \alpha\right), (\beta \geq 0) \quad (12)$$

Finally, the displacement of seafloor photons caused by water refraction is derived and formulated using Equations (13)–(16) for the three different cases, where Δx and Δz represent the displacement in the x and z directions. The symbol h_q denotes the elevation difference between intersection point p, where air meets sea, and its corresponding photon, q, located on the seafloor.

$$L_x = \frac{h_q}{\cos \varphi_x} \quad (13)$$

$$\begin{cases} \Delta x = R_x \cdot \sin(\theta_x^p + \beta) - L_x \cdot \sin \varphi_x = L_x \cdot [\sin(\theta_x^p + \beta) \cdot \frac{1}{n_w} - \sin \varphi_x] \\ \Delta z = L_x \cdot \cos \varphi_x - R_x \cdot \cos(\theta_x^p + \beta) = L_x \cdot [\cos \varphi_x - \cos(\theta_x^p + \beta) \cdot \frac{1}{n_w}] \end{cases}, \theta_x^p \in (0, \varphi_x) \quad (14)$$

$$\begin{cases} \Delta x = R_x \cdot \sin(\theta_x^p - \beta) - L_x \cdot \sin \varphi_x = L_x \cdot [\sin(\theta_x^p - \beta) \cdot \frac{1}{n_w} - \sin \varphi_x] \\ \Delta z = L_x \cdot \cos \varphi_x - R_x \cdot \cos(\theta_x^p - \beta) = L_x \cdot [\cos \varphi_x - \cos(\theta_x^p - \beta) \cdot \frac{1}{n_w}] \end{cases}, \theta_x^p \in (\varphi_x, 90^\circ + \varphi_x) \quad (15)$$

$$\begin{cases} \Delta x = R_x \cdot \sin(\theta_x^p + \beta - 180^\circ) - L_x \cdot \sin \varphi_x = -L_x \cdot [\sin(\theta_x^p + \beta) \cdot \frac{1}{n_w} + \sin \varphi_x] \\ \Delta z = L_x \cdot \cos \varphi_x - R_x \cdot \cos(180^\circ - \theta_x^p - \beta) = L_x \cdot [\cos \varphi_x + \cos(\theta_x^p + \beta) \cdot \frac{1}{n_w}] \end{cases}, \theta_x^p \in (90^\circ + \varphi_x, 180^\circ) \quad (16)$$

4. Results

4.1. Results of Signal-Photon Extraction at Sea-Surface and Sea-Bottom

In the Qilianyu Islands study area, signal-photon extractions were performed using the ICESat-2 ATL03 datasets 20210417GT1R and 20210417GT3R. Figure 7a,b illustrate the corresponding ground tracks overlaid on satellite imagery. Both datasets were acquired at 00:22:25 local time on 17 April 2021. As shown in Figure 7c,d, the detected sea-surface and seafloor signal photons are marked in blue and red, respectively, while gray points denote the raw ATL03 photons. The results indicate that the track traverses a deep-water zone, crosses a shallow-water region, and then re-enters deep water. Consistent with the satellite imagery, the spatial pattern of the extracted seafloor signal photons (red) closely follows the underlying seafloor topography.

In the Key West study area, four ICESat-2 ATL03 datasets were used to detect signal photons at the sea surface and seafloor. The ground tracks of 20190222GT1L and 20190323GT1L crossed the western part of Key West (Figure 8a,b) and were acquired at 02:51:57 local time on 22 February 2019, and at 01:27:59 local time on 23 March 2019, respectively. The corresponding detection results are shown in Figure 8c,d. In addition, the tracks of 20190206GT1L and 20190206GT2L traversed the eastern part of Key West (Figure 9a,b), with ICESat-2 overpassing the region at 15:39:37 local time on 6 February 2019. As illustrated in Figure 9c,d, the detected sea-surface and seafloor signal photons are marked in blue and red, respectively. Overall, the spatial pattern of the extracted seafloor signal photons shows strong consistency with terrain features visible in the satellite imagery.

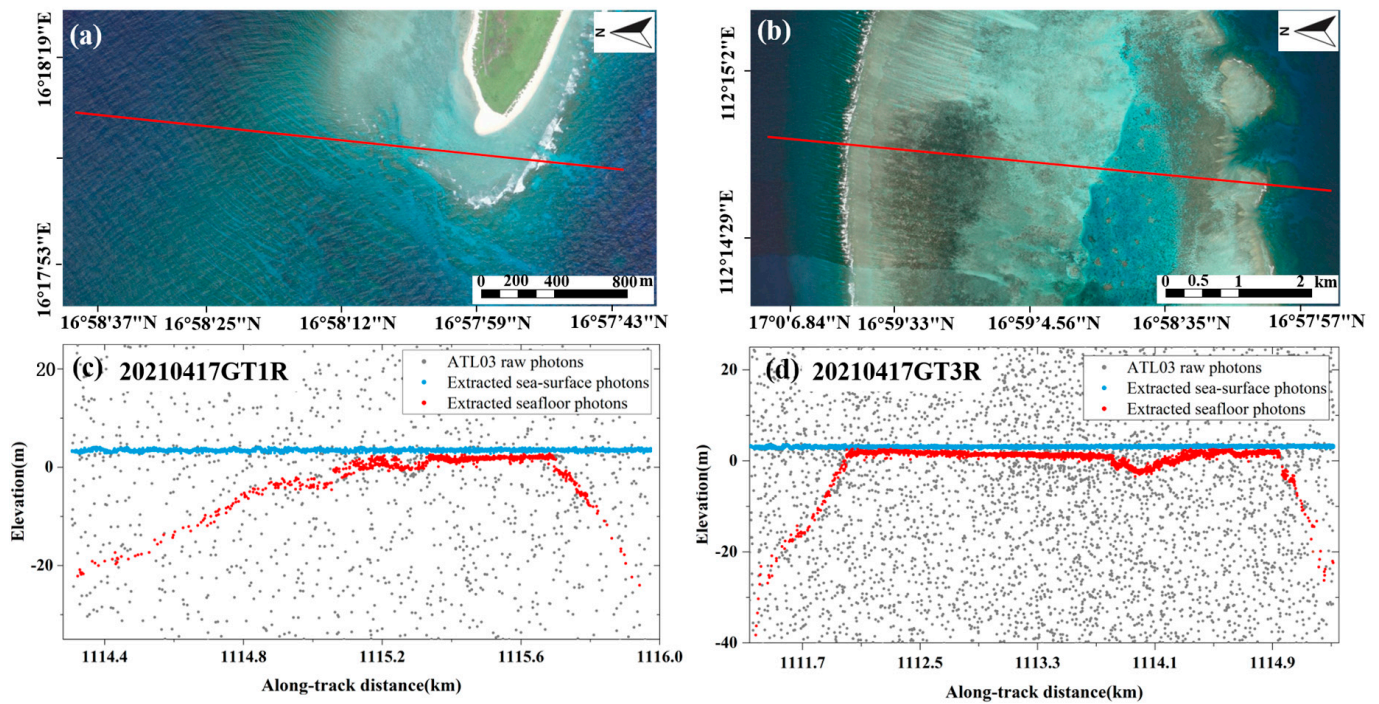


Figure 7. Ground tracks covering the satellite images at Qilanyu Island (a,b). Results of automatic separation and extraction of water-surface and water-bottom signals in datasets (c,d).

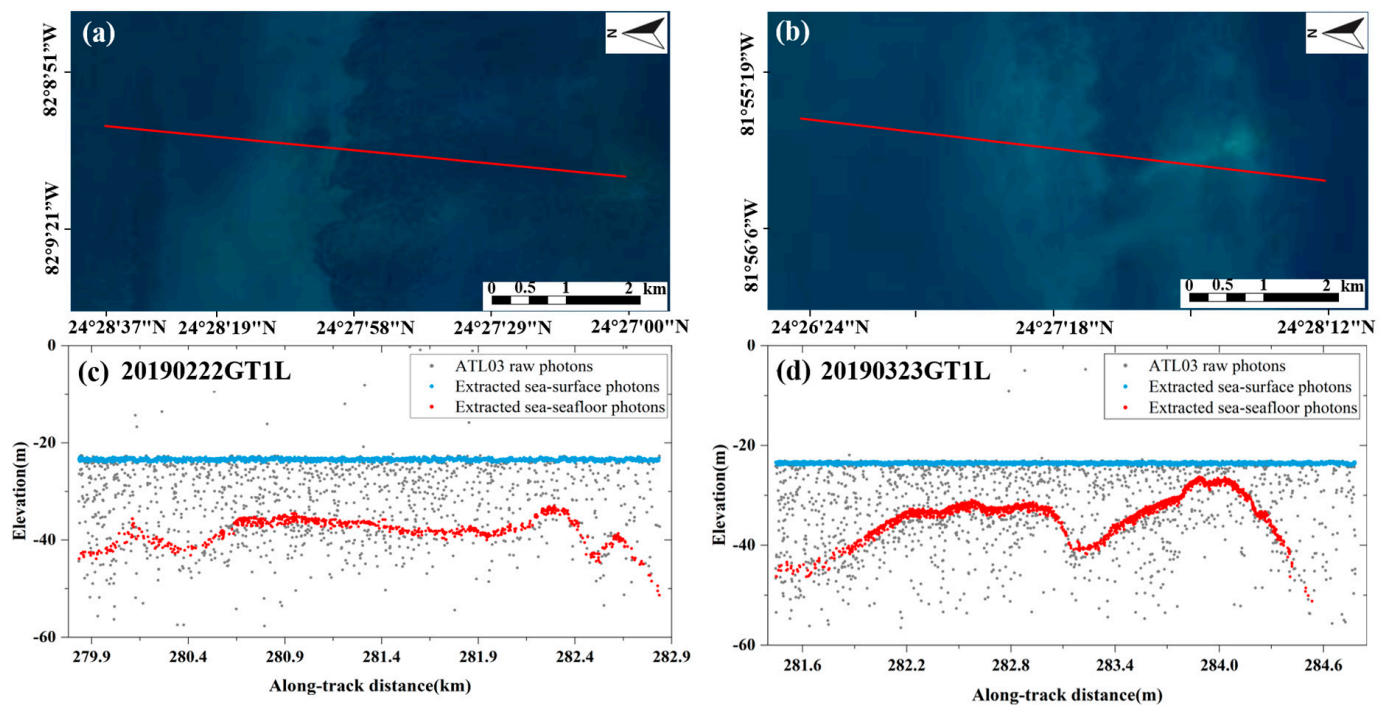


Figure 8. Ground tracks of 20190222GT1L and 20190323GT1L covering the satellite images at Key West (a,b). Results of automatic separation and extraction of water-surface and water-bottom signals in datasets (c,d).

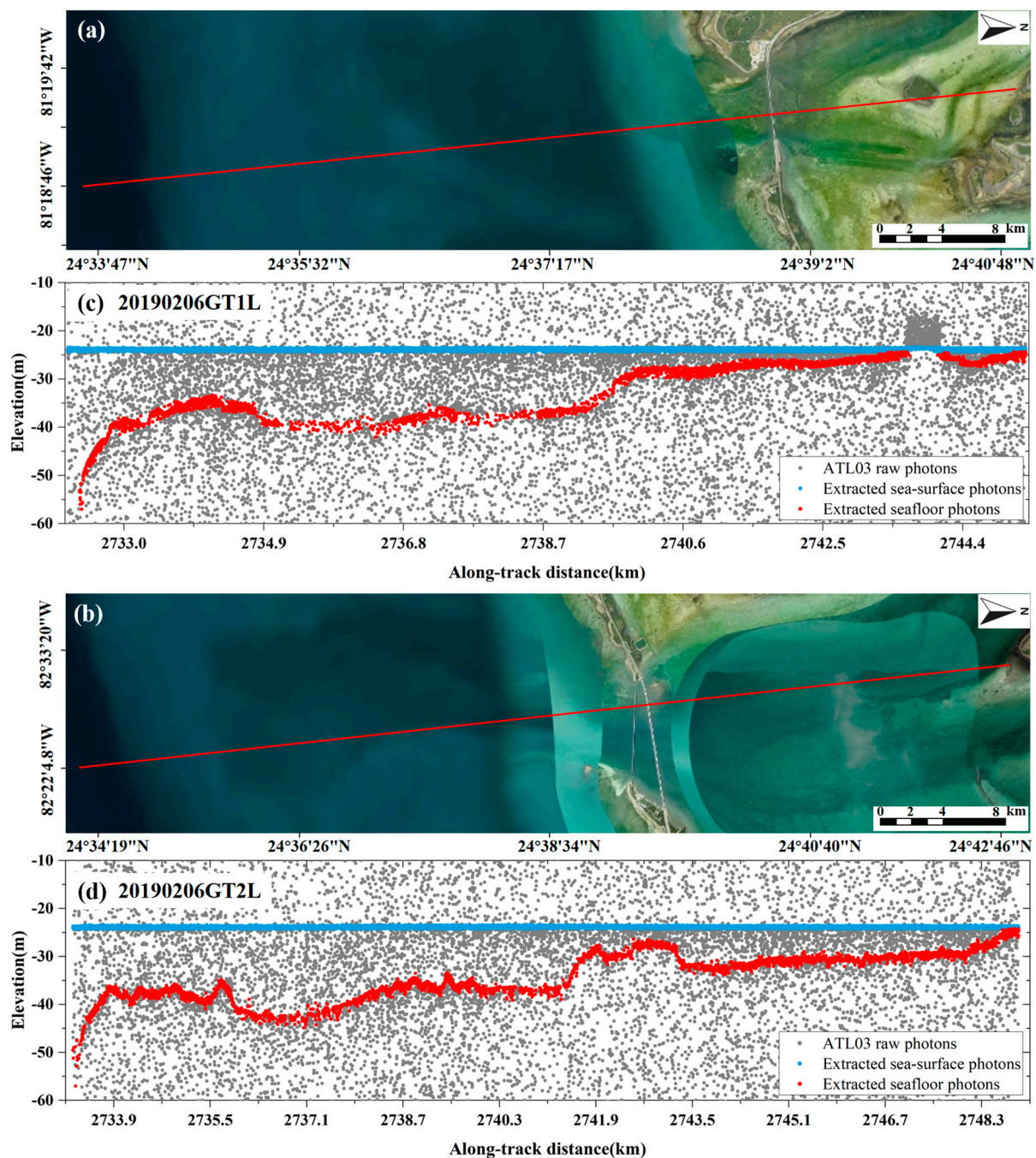


Figure 9. ICESat-2 bathymetric data processing and results at Key West. (a) Ground track of dataset 20190206GT1L overlaid on satellite imagery. (b) Ground track of dataset 20190206GT2L overlaid on satellite imagery. (c) Results of the automatic separation and extraction of water-surface and bottom signals for dataset 20190206GT1L. (d) Results of the automatic separation and extraction of water-surface and bottom signals for dataset 20190206GT2L.

4.2. Refraction Correction of Water Column

Refraction correction was applied to the seafloor signal photons detected in the six datasets, and the results are shown in Figure 10. Red and green points indicate the seafloor signal photons before and after refraction correction, respectively, while blue points denote the sea-surface signal photons. Continuous seafloor topography before and after correction was fitted using a B-spline model and is plotted in red and green, respectively; the fitted sea-surface wave curve is shown in blue.

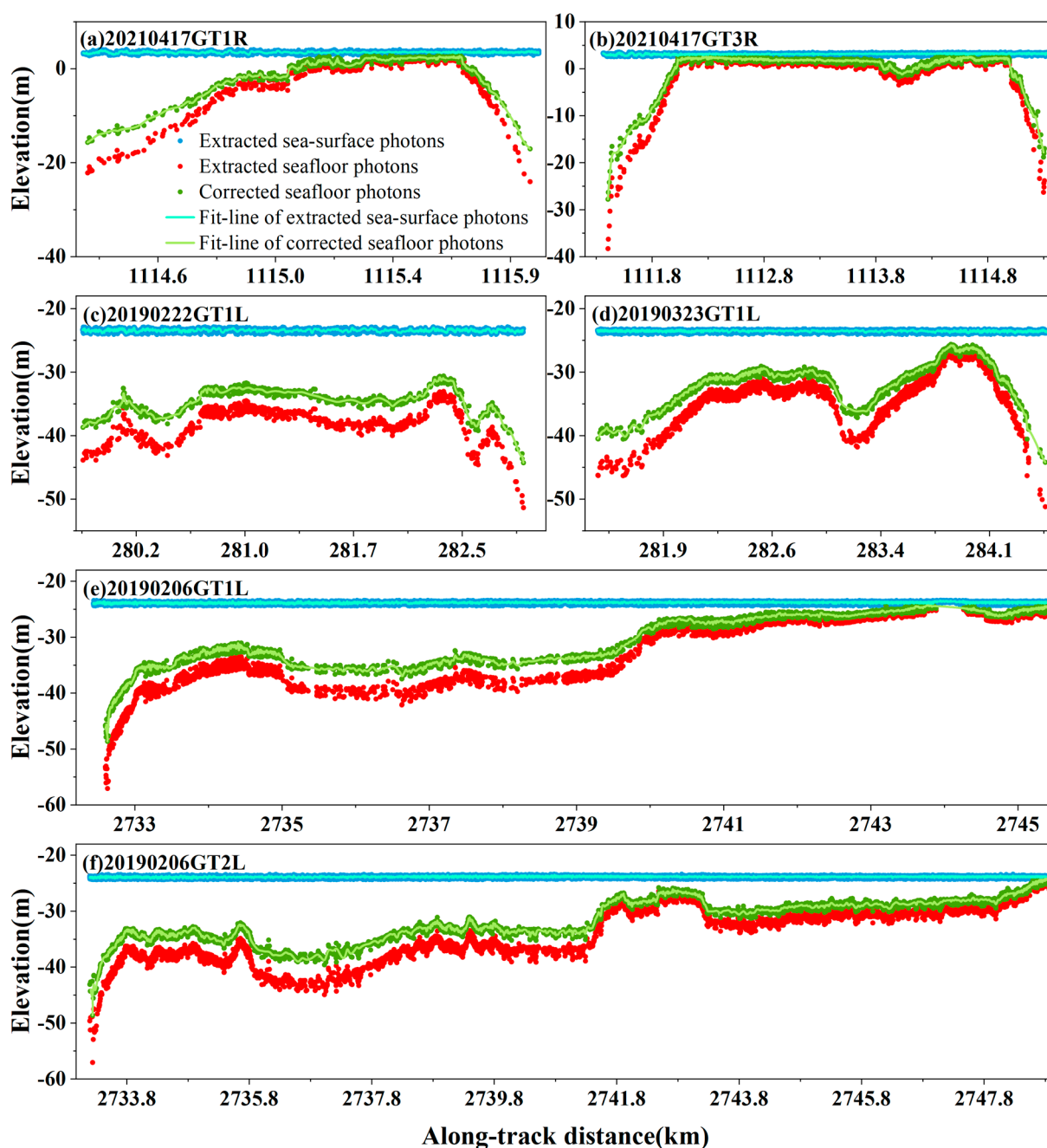


Figure 10. Refraction correction results of six datasets at two study areas. The six subfigures (a–f) correspond to the ground tracks 20210417GT1R, 20210417GT3R, 20190222GT1L, 20190323GT1L, 20190206GT1L and 20190206GT2L. Water-surface photon curve was represented in blue color. Water-bottom photon curves before and after refraction correction were shown in red and green, respectively.

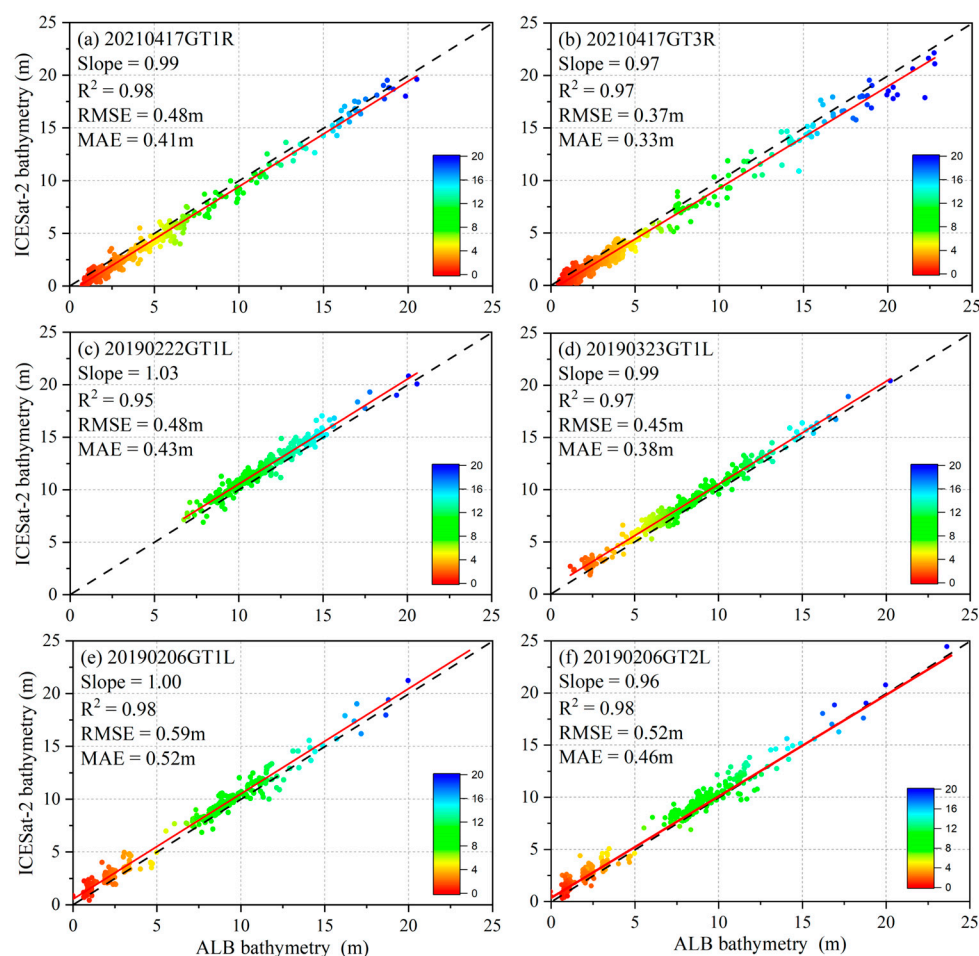
Table 2 summarizes the minimum and maximum water depths and the corresponding depth-displacement deviations (before and after refraction correction) for the six datasets from the Qilanyu Islands and Key West study areas. After correction, the minimum water depth is 0.32 m (20190206GT2L) and the maximum reaches 30.91 m (20210417GT3R). The associated depth-displacement ranges from 0.06 m to 10.51 m, indicating that refraction-induced displacement increases with water depth. In nearshore bathymetry, such displacement can vary from centimeters to meters and therefore should be corrected to ensure accurate depth retrieval.

Table 2. Comparison of bathymetric results before and after refraction correction for six datasets from study areas.

ATLAS Data	Depth Before Correction (m)		Depth After Correction (m)		Depth Displacement (m)	
	Min	Max	Min	Max	Min	Max
20210417GT1R	0.72	27.49	0.62	20.52	0.08	6.97
20210417GT3R	0.57	41.42	0.43	30.91	0.14	10.51
20190222GT1L	9.57	27.91	7.15	20.83	2.43	7.08
20190323GT1L	2.76	27.66	2.06	20.64	0.70	7.02
20190206GT1L	0.55	33.23	0.49	24.80	0.06	8.43
20190206GT2L	0.44	33.18	0.32	24.77	0.12	8.41

4.3. Accuracy Verification of Bathymetric Results

To validate the bathymetric accuracy of the proposed method, bathymetry derived from six ATL03 datasets was systematically compared with reference bathymetry from airborne laser bathymetry (ALB). In the Qilanyu Islands study area, RMSE values of 0.48 m and 0.37 m were achieved for 20210417GT1R and 20210417GT3R, with corresponding MAEs of 0.41 m and 0.33 m. The coefficients of determination (R^2) reached 0.98 and 0.97, and the regression slopes were 0.99 and 0.97, respectively (Figure 11a,b).

**Figure 11.** Accuracy and validation of ICESat-2 bathymetric results relative to ALB data, which was assessed by slope, R^2 , RMSE, and MAE. The six subfigures (a–f) correspond to the ground tracks 20210417GT1R, 20210417GT3R, 20190222GT1L, 20190323GT1L, 20190206GT1L and 20190206GT2L.

In the Key West study area, the four ATL03 datasets (20190222GT1L, 20190323GT1L, 20190206GT1L, and 20190206GT2L) yielded RMSEs of 0.48 m, 0.45 m, 0.59 m, and 0.52 m, with MAEs of 0.43 m, 0.38 m, 0.52 m, and 0.46 m, respectively. The corresponding regression slopes were 1.03, 0.99, 1.00, and 0.96. The highest R^2 (0.98) was obtained for the 20190206GT1L/20190206GT2L datasets. Among all evaluated datasets, 20210417GT3R (Qilanyu Islands) achieved the best overall performance, with an RMSE of 0.37 m and an MAE of 0.33 m. Overall, these results demonstrate that the proposed method provides accurate and consistent bathymetry when validated against ALB reference data across different regions and acquisition conditions.

To further evaluate the performance of the proposed method under different water depth conditions, an accuracy analysis was conducted by grouping the bathymetric results into five depth intervals (0–2 m, 2–5 m, 5–10 m, 10–15 m, and >15 m). As shown in Figure 12, the highest RMSE and MAE values are observed in the extremely shallow-water range (0–2 m), which can be mainly attributed to strong surface effects, bottom heterogeneity, and increased photon interference in nearshore environments. In contrast, the bathymetric accuracy within the 2–15 m depth range remains relatively stable and achieves the lowest RMSE and MAE values across most datasets, representing the optimal operating depth interval for the proposed method in coastal bathymetric applications. With further increases in water depth (>15 m), both RMSE and MAE exhibit a moderate degradation trend, primarily due to reduced signal-to-noise ratios caused by water-column scattering.

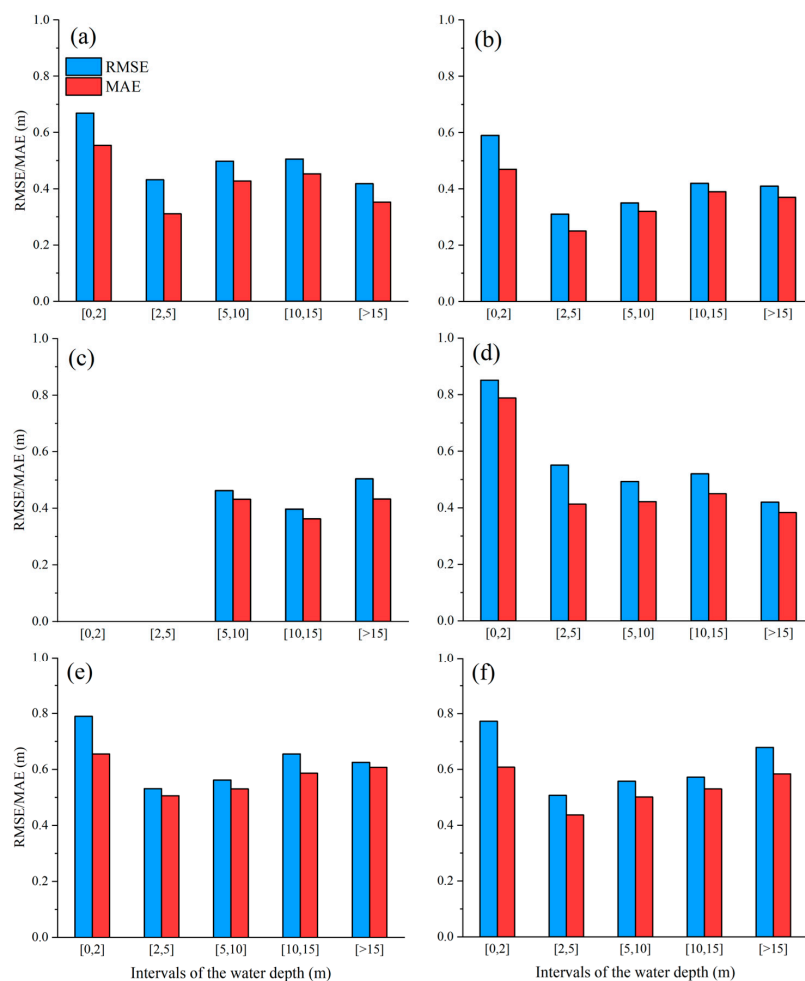


Figure 12. RMSE and MAE of bathymetric results at different water depth ranges for six ATL03 datasets. The six subfigures (a–f) correspond to the ground tracks 20210417GT1R, 20210417GT3R, 20190222GT1L, 20190323GT1L, 20190206GT1L and 20190206GT2L.

It should be noted that bathymetric accuracy in extremely shallow waters is inherently more challenging. In nearshore regions, strong bottom reflectance, wave-induced surface roughness, and whitecap effects can significantly interfere with photon returns, often leading to increased uncertainty in depth estimation. Consequently, relatively higher RMSE and MAE values observed in the 0–2 m depth interval were expected and reflect the intrinsic limitations of shallow-water bathymetry rather than deficiencies of the proposed method. In areas with steep seafloor slopes, rapid depth variations typically degrade retrieval accuracy. Moreover, the absence of abrupt error escalation across depth gradients indicates reduced sensitivity to variations in water quality and bottom complexity, supporting the applicability of the method across diverse coastal and island-reef environments.

5. Discussion

5.1. Refraction Correction and Bathymetric Accuracy

Consistent with Figure 10 and Table 2, the refraction-induced depth displacement increases with water depth, confirming that neglecting refraction can introduce non-negligible bias in nearshore bathymetry using ATLAS data. Across the six datasets, the displacement-to-depth ratio remains on the order of one quarter (24.71–26.15%), with an average of 25.43%, indicating that refraction correction is necessary not only in deeper waters but also for shallow-water retrievals when high accuracy is required. The minimum and maximum displacements span 0.06 m (20190206GT1L) to 10.51 m (20210417GT3R), further highlighting the depth-dependent impact of refraction.

As shown in Figure 11, bathymetric accuracy improves after refraction correction, with RMSE values generally around 0.5 m. The best overall performance is achieved for 20210417GT3R in the Qilianyu Islands (RMSE = 0.37 m), while the best Key West result reaches an RMSE of 0.45 m; across all six datasets, the mean RMSE is 0.48 m. The coefficient of determination remains high (average $R^2 = 0.97$), with the maximum R^2 of 0.98 observed for 20210417GT1R, 20190206GT1L, and 20190206GT2L, indicating strong consistency with the ALB reference. Notably, the maximum water depth approaches ~31 m in the Qilianyu Islands, demonstrating that the proposed workflow can maintain stable performance across a relatively wide depth range. Variations in accuracy among datasets are primarily attributable to short-term sea-surface wave conditions, which perturb the instantaneous surface elevation used for depth estimation, while the overall results suggest relatively uniform and robust nearshore bathymetry performance with ATLAS data and the proposed method.

5.2. Signal-Photon Detection Capability

The signal-photon extraction performance of the proposed method is evaluated using the counts and proportions of sea-surface photons, seafloor photons, and noise photons for each dataset (Table 3). Because the total photon number varies with acquisition time, location, and environmental conditions, we report percentages in addition to absolute counts. For example, the Key West dataset 20190206GT1L covers an along-track span of 13 km and contains the largest number of photons (64,099), whereas 20190206GT2L spans only 3 km with 5953 photons. Among all datasets, 20190222GT1L exhibits the highest proportion of sea-surface photons (68.4%).

Table 3. Number and percentage of different types of photons extracted in each dataset.

ATLAS Dataset	Total Number of Raw Photons	Number of Sea-Surface Photons	Percentage of Sea-Surface Photons to the Raw Photons	Number of Seafloor Photons	Percentage of Seafloor Photons to the Raw Photons	Number of Noise Photons	Percentage of Noise Photons to the Raw Photons
20210417GT1R	6200	3297	53.2%	1190	19.2%	1713	27.6%
20210417GT3R	21,114	9814	46.5%	6154	29.1%	5146	24.4%
20190222GT1L	5953	4071	68.4%	695	11.7%	1187	19.9%
20190323GT1L	11,251	7358	65.4%	2486	22.1%	1407	12.5%
20190206GT1L	64,099	34,651	54.1%	6907	10.7%	22,541	35.2%
20190206GT2L	55,573	28,878	52.0%	6188	11.1%	20,507	36.9%

Across all six datasets, sea-surface photons consistently account for a larger fraction than seafloor and noise photons (Table 3), which is physically expected because most ATLAS photons are returned from the air–sea interface [11]. The noise in photon-counting lidar data mainly arises from background solar illumination, dark current, shot noise, and thermal noise [36,37]. Notably, the two daytime Key West datasets (20190206GT1L and 20190206GT2L) show higher noise fractions (35.2% and 36.9%) than the four nighttime datasets (all < 30%), indicating the dominant contribution of solar background during daylight acquisitions. This effect is also evident in absolute counts: the daytime tracks contain 20,507 and 22,541 noise photons, exceeding the maximum observed in any nighttime track (5146), even when total photon counts are comparable. Together, these statistics confirm that the elevated noise floor is strongly associated with daylight acquisition conditions.

5.3. Comparison of Results with Other Methods

To further demonstrate the advantages of the proposed method, we conducted comparative experiments against AVEBM and adaptive DBSCAN (A-DBSCAN) for sea-surface and seafloor signal-photon extraction [38,39]. Codes for both algorithms are available in the Supplementary Materials. Results on four Key West datasets are presented in Figures 13 and 14. Overall, AVEBM can recover a rough seafloor pattern that is generally consistent with the underlying topography; in Figure 13, the extracted sea-surface and seafloor photons are marked by blue and red points, respectively. For a closer inspection, zoomed-in views of AVEBM and the proposed method are provided in the second and third columns. The comparisons show that the proposed method yields more accurate and more complete surface and seafloor signal photons under varying photon-density conditions. For example, in Figure 13a, AVEBM fails to remove some underwater noise photons, resulting in false detections. In Figure 13b–d, AVEBM misses a portion of the seafloor signal photons, producing discontinuities in the extracted seafloor profile. This limitation becomes more pronounced in deeper water and steep-slope regions.

Additionally, the percentages of different photon types extracted by AVEBM are calculated and presented in Table 4. For dataset 20190222GT1L, the proportion of seafloor signal photons is 15.6%, which represents an increase of 3.9% compared to the result obtained with our method (as reported in Table 3). This overestimation is consistent with the misclassification of underwater noise photons as signal photons, as illustrated in Figure 13a. For the other three datasets—20190323GT1L, 20190206GT1L, and 20190206GT2L—the proportions of seafloor signal photons are consistently lower than those achieved by our method. Specifically, the seafloor signal-photon percentages are 20.9%, 7.4%, and 9.2%, respectively, corresponding to decreases of 1.2%, 3.3%, and 1.9% relative to our method. Correspondingly, the noise photon percentages extracted by AVEBM are 13.6%, 38.8%, and 40.2%, which represent increases of 1.1%, 3.6%, and 3.3% compared to our method. As revealed in Figure 13b–d, this under-detection of true signal photons results in omissions during the extraction process.

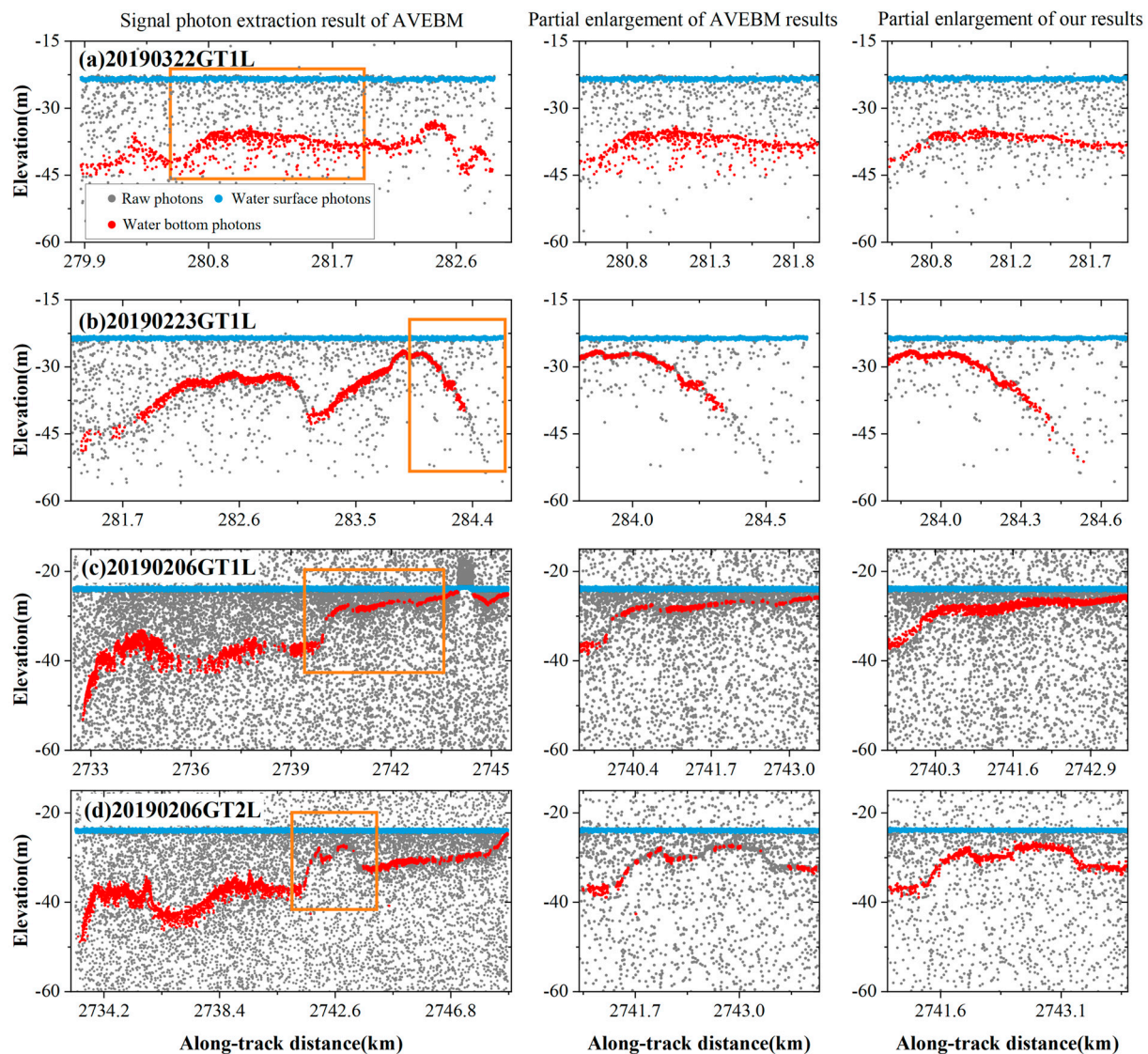


Figure 13. Comparison of signal-photon results and local amplifications, detected by AVEBM and our method.

Furthermore, adaptive DBSCAN (A-DBSCAN) was applied to extract sea-surface and seafloor signal photons, and its results were compared with those of AVEBM and the proposed method. As shown in Figure 14, A-DBSCAN misclassifies a considerable number of noise photons as signals in both shallow and deep water, which can degrade bathymetric accuracy. This behavior is largely attributable to its limited ability to adapt the clustering parameters to depth-dependent photon attenuation and spatially varying photon density associated with seafloor topography. In low-density regions (e.g., Figure 14c), A-DBSCAN fails to fully recover seafloor signal photons, whereas in higher-density regions, it is more prone to false detections, as illustrated in Figure 14a,b,d. In contrast, the proposed method achieves more reliable signal photon detection by adaptively adjusting to photon-density variations across different nearshore environments (Figures 4 and 7–9).

Finally, the percentages of different photon types extracted by A-DBSCAN are also calculated and listed in Table 5. The percentage of seafloor signal photons extracted from dataset 20210417GT1R is 18.6%, which is 0.6% lower than that achieved by our method. For datasets 20190222GT1L, 20190323GT1L, and 20210417GT3R, the seafloor signal-photon percentages are 11.8%, 22.6%, and 29.5%, respectively, representing increases of 0.1%, 0.5%, and 0.4% compared to our method. By comparing the detection results of the different

methods shown in Figures 7–9, 12 and 13, it is demonstrated that the method proposed in this study exhibits superior adaptability to varying photon-density distributions. Owing to its higher accuracy in signal photon detection, the resulting bathymetric accuracy can be effectively ensured and further improved across diverse water environments.

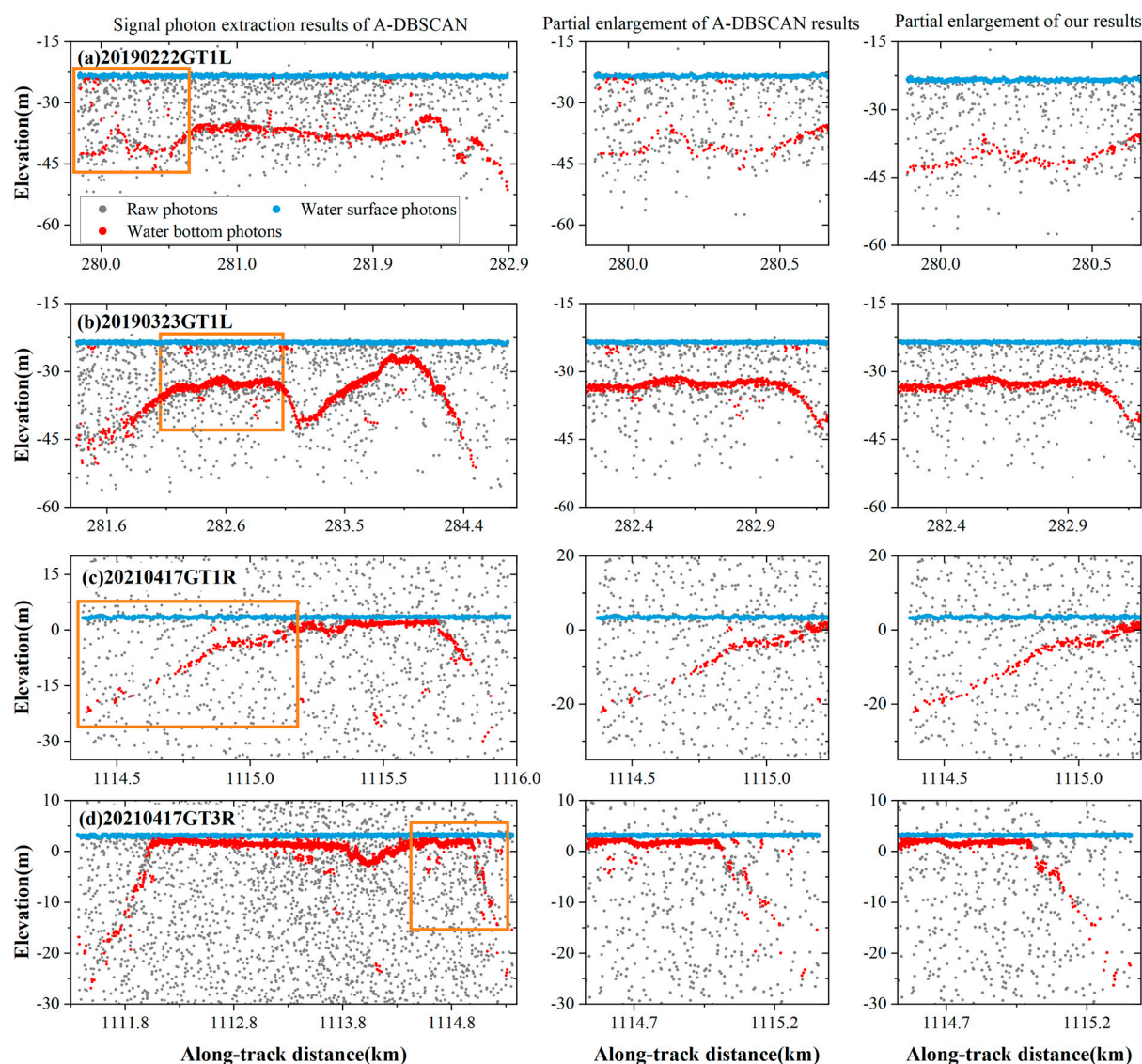


Figure 14. Comparison of signal-photon results and local amplifications, detected by A-DBSCAN and our method.

Table 4. Number and percentage of different types of photons extracted by AVEBM.

ATLAS Dataset	Total Number of Raw Photons	Number of Sea-Surface Photons	Percentage of Sea-Surface Photons to the Raw Photons	Number of Seafloor Photons	Percentage of Seafloor Photons to the Raw Photons	Number of Noise Photons	Percentage of Noise Photons to the Raw Photons
20190222GT1L	5953	3856	64.8%	930	15.6%	1167	19.6%
20190323GT1L	11,251	7370	65.5%	2345	20.9%	1536	13.6%
20190206GT1L	64,099	34,457	53.8%	4788	7.4%	24,854	38.8%
20190206GT2L	55,573	28,147	50.6%	5070	9.2%	22,356	40.2%

Table 5. Number and percentage of different types of photons extracted by A-DBSCAN.

ATLAS Dataset	Total Number of Raw Photons	Number of Sea-Surface Photons	Percentage of Sea-Surface Photons to the Raw Photons	Number of Seafloor Photons	Percentage of Seafloor Photons to the Raw Photons	Number of Noise Photons	Percentage of Noise Photons to the Raw Photons
20190222GT1L	5953	4046	68.0%	702	11.8%	1205	20.2%
20190323GT1L	11,251	7355	65.4%	2545	22.6%	1351	12.0%
20210417GT1R	6200	3248	52.4%	1153	18.6%	1799	29.0%
20210417GT3R	21,114	9836	46.6%	6230	29.5%	5048	23.9%

To further evaluate the accuracy of the proposed method, two datasets acquired at Key West (20190222GT1L and 20190323GT1L) are used to statistically assess the bathymetric accuracy of four methods: AVEBM, the adaptive DBSCAN method, the Quasi Full Waveform-based Bathymetric Extraction Method for ICESat-2 Photon Counting Data (QFW-BEM) [40], and the adaptive-bandwidth mean shift filtering method (AFMF) [41]. The bathymetric accuracy results are represented by the slope, R^2 , and RMSE values in Table 6.

Table 6. Bathymetric accuracy comparison of five methods on two Key West ATL03 datasets (slope, R^2 , and RMSE).

ATLAS Dataset	AVEBM			A-DBSCAN			QFW-BEM			AFMF			The Proposed Method		
	Slope	R^2	RMSE (m)	Slope	R^2	RMSE (m)	Slope	R^2	RMSE (m)	Slope	R^2	RMSE (m)	Slope	R^2	RMSE (m)
20190222GT1L	1.08	0.88	0.74	0.93	0.91	0.68	1.06	0.92	0.64	0.95	0.93	0.57	1.03	0.95	0.48
20190323GT1L	0.89	0.90	0.69	0.93	0.92	0.65	1.03	0.92	0.64	1.05	0.94	0.52	0.99	0.97	0.45

As shown in Table 6, the bathymetry estimates produced by the proposed method exhibit strong agreement with the validation data and outperform the other methods in terms of overall accuracy. For dataset 20190222GT1L, AVEBM and A-DBSCAN yield slopes of 1.08 and 0.93, respectively, with relatively large RMSE values (0.74 m and 0.68 m), indicating larger deviations from the reference. QFW-BEM and AFMF perform better, with RMSE values of 0.64 m and 0.57 m; however, their highest R^2 reaches only 0.93, which remains lower than that achieved by the proposed method. For dataset 20190323GT1L, the proposed method achieves a slope of 0.99, an R^2 of 0.97, and an RMSE of 0.45 m, indicating closer agreement with the ideal slope of 1.0, stronger correlation, and reduced error relative to the competing approaches. Overall, across both datasets, the proposed method consistently attains slopes closest to 1, the highest R^2 values, and the lowest RMSE, demonstrating its high accuracy for nearshore shallow-water bathymetry.

In addition, the method proposed in this study offers excellent computational efficiency while maintaining high accuracy. On a standard desktop (Intel Core i7 processor, 16 GB memory), the entire process takes less than 2 min to process an ICESat-2 track of data, as shown in Table 3. The 20190206GT1L orbit, which processes the largest number of photons (approximately 64,099 photons), takes about 110 s, while the 20190222GT1L orbit (approximately 5953 photons), which processes fewer photons, takes only about 25 s. This efficiency is mainly attributed to the segmentation strategy, which reduces global complexity, and the adaptive calculation of the elliptic filter kernel parameters that avoid time-consuming iterative searches. Compared to deep learning methods that require complex training, this method achieves a good balance between efficiency and accuracy.

5.4. Limitations and Potential Improvements

Although the proposed method demonstrates robust performance across diverse coastal environments, several potential limitations should be acknowledged. First, under

conditions of extremely low photon density, such as deeper waters or highly turbid environments, the signal-to-noise ratio may be reduced, which can adversely affect photon classification and subsequent bathymetric estimation accuracy. In such cases, sparse signal photons may limit the effectiveness of local statistical filtering strategies. Second, in areas characterized by severe seafloor terrain fluctuations, rapid depth variations within short spatial distances may challenge the adaptive elliptic filtering process. Although the proposed method adjusts the elliptic kernel according to local photon distributions, abrupt terrain changes may introduce a potential lag in kernel adaptation, leading to locally increased uncertainty. To further enhance the robustness of the method, future work may explore integrating machine learning techniques to improve the adaptive adjustment of elliptic kernel parameters, as well as introducing multi-scale filtering strategies to better accommodate complex seafloor terrain. These improvements are expected to extend the applicability of the proposed framework under more challenging environmental conditions.

6. Conclusions

This study presents a novel segmented adaptive photon filtering method for accurate nearshore bathymetry using ICESat-2 ATLAS data. The proposed approach effectively addresses the critical challenge of automatically and precisely identifying water-surface and seafloor signal photons under diverse environmental conditions. By adaptively adjusting the size and orientation of an elliptical filtering kernel in response to local photon density variations and seafloor topography, the method achieves robust signal extraction. Further refinement through segmented polynomial fitting enhances detection accuracy and reliability, while a dedicated refraction correction model compensates for water-column-induced photon displacement, significantly improving bathymetric precision. Comprehensive validation using multiple ATLAS datasets from distinct study areas demonstrates the high performance of the method, yielding optimal statistical metrics of slope = 1.00, coefficient of determination (R^2) = 0.98, and root mean square error (RMSE) = 0.37 m. Comparative analysis with existing methods confirms the superior detection reliability and generalizability of our approach across varied coastal environments. Future work will extend the application of ATLAS data to further explore the potential of spaceborne photon-counting LiDAR for underwater topographic mapping and nearshore bathymetric surveying in diverse marine settings.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18040568/s1>.

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