remote sensing

Editorial

Editorial for Special Issue: "Monitoring Terrestrial Water Resource Using Multiple Satellite Sensors"

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1. Introduction

In the past few decades, with the advent of climate change, population growth, agricultural irrigation, and industrial development, there have been increasing demands for water resources across the globe, especially in widely distributed arid areas or densely populated areas [1]. In order to better implement water resource management in the future, it is necessary to accurately evaluate terrestrial water resources (such as lakes, reservoirs, ponds, rivers, and snow cover) and track their temporal changes over time. It is also necessary for us to focus on certain water-related extreme events (e.g., rainfall, flooding, and storms), which are highly associated with terrestrial water resources. In addition, apart from inland water bodies, it is crucial to pay attention to the ocean, which is actually the largest water body in the world. However, due to the high cost of traditional in situ measurement, the distribution of gauging stations around the world is very sparse spatially, especially in remote and less populated areas, largely limiting our capacity for monitoring and understanding global surface water.

Compared with traditional approaches, emerging satellite technologies (such as satellite altimeters, gravity satellites, optical remote sensing, and microwave remote sensing) exhibit significant advantages, such as relatively low costs, large spatial coverage, long-term temporal span, and repeatable observations [2–5]. As a result, satellite technology is becoming a powerful tool for monitoring and assessing terrestrial water resources at various temporal scales, from regional to global [6–14]. Furthermore, remote-sensing-derived results in inland and coastal water areas can not only benefit process-based modeling and factor analysis, but also guide water resource prediction, planning, management, sustainable development, and related policy-making [15–25].

This Special Issue, "Monitoring Terrestrial Water Resource Using Multiple Satellite Sensors", contains various topics on water resource monitoring in both inland and coastal areas using different satellite sensors, such as shallow water bathymetry estimation, water body extraction, river channel mapping, flood disaster mapping (including flooding area, water level, and flooding water depth), lake dynamics monitoring, lake scale water balance analysis, and coastal wetland dynamics monitoring. Considering the purpose of the 15 studies included in this Special Issue and the satellite sensors used, the former can be divided into two categories: water-related area mapping derived from satellite imagery and water-related elevation estimation derived from satellite altimeter data.

Moreover, these studies in our Special Issue mainly focus on the development of a surface water information acquisition method based on the use of specific satellite sensors (such as satellite altimeters and satellite imagery). From the satellite sensor perspective, studies in our Special Issue can be divided into two parts, which are detailed in the following sections.

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2. Water-Related Area Mapping Derived from Satellite Imagery

In the past few decades, surface water mapping has been conducted in a broad range of applications using satellite imagery, such as multispectral imagery and SAR imagery. The work of Yu et al. [26] introduces a novel boundary-guided semantic context network (BGSNet) with which to extract water bodies. The researchers tested their method on Qinghai–Tibet Plateau Lake (QTPL) and Land-cOVEr Domain Adaptive semantic segmentation (LoveDA) datasets, and the results show that BGSNet has an overall accuracy of 98.97% on the QTPL dataset and that of 95.70% on the LoveDA dataset. Wu et al. [27] proposed a remote-sensing-based method for mapping channel activity using the MNDWI index combined with the Otsu method based on the Google Earth Engine (GEE) platform, applying the method with the Lower Yellow River as a case study. Lyu et al. [28] developed a MSAFNet (multiscale successive attention fusion network) model for extracting water bodies from remote sensing images; they tested their method on the Qinghai–Tibet Plateau Lake (QTPL) and the Land-cOVEr Domain Adaptive semantic segmentation (LoveDA) datasets and achieved a high mapping accuracy (i.e., overall accuracy of 98.97% on the QTPL dataset and 95.87% on the LoveDA dataset). Lu et al. [29] proposed a model for extracting river networks by combining DEM, a Landsat-derived global surface water occurrence (GSWO) dataset, and Sentinel-2 imagery, and they applied the model to conduct a case study across the Danjiangkou Reservoir Area, finding results consistent with the actual river network. Wang et al. [30] investigated the spatial–temporal variation in water coverages in the sub-lakes of Poyang Lake in accordance with multi-source remote sensing imagery (Landsat 8 data, MODIS data, GF-1 data, and GlobeLand30 data) by using the MNDWI (modified normalized difference water index) and the ISODATA (iterative self-organizing data analysis technique algorithm), achieving a good accuracy value of 97%.

Additionally, some studies have focused on surface water dynamics monitoring by using multi-temporal remote sensing imagery. For example, Wang et al. [31] utilized a 0.5 m resolution remote sensing image of Yiwu city in the Chinese province of Zhejiang to develop a river skeleton line extraction model based on both the DeepLabv3+ deep learning model and the conventional visual interpretation method, which consumes less than 1% of the memory of the classical method (i.e., Zhang and Suen [32] developed raster-based skeleton line extraction algorithms) and improves the computational efficiency by more than 10-fold. Sun et al. [33] used multi-temporal Landsat imagery to obtain the lake shoreline of Hulun Lake in various years to further estimate lake water storage changes and analyze water balance. Zhang et al. [34] conducted monitoring of mangrove wetland change dynamics across the Sundarbans using all available Landsat image time series on the Google Earth Engine platform, and observed a net mangrove loss of 8507.9 ha from 1988 to 2022.

3. Water-Related Elevation Estimation Derived from Satellite Altimeter Data

Apart from the type of surface water (lake, pond, river, or other water bodies), the water-related elevation information (water depth, bathymetry, elevations of water level, and snow cover) is also essential for inland and coastal water areas. Traditional satellite imagery is unable to provide elevation information. Fortunately, the recent ICESat-2 (Ice, Cloud, and Land Elevation Satellite-2) satellite exhibits great potential for detecting land surface, water surface, and underwater topography, providing elevation information, such as water level, water depth, and snow surface elevation. Zhang et al. [35] proposed a ICESat-2 bathymetric photon extraction model based on a pre-pruning quadtree isolation (PQI) method, which was experimented in Culebra, Puerto Rico, and achieved a 92.71% F1 score. Gao et al. [36] assessed the ICESat-2's horizontal accuracy using a two-dimensional affine transformation model matching method based on high-accuracy terrains, which shows the great potential of ICESat-2 for evaluating water resource changes induced by snow melt under global warming. Xie et al. [37] proposed a denoising method (i.e., fine denoising of underwater point cloud data using single-photon point cloud filtering based on improved local distance statistics (LDSBM)) for ICESat-2/ATLAS photon data in nearshore areas, providing coastal bathymetry information. Yang et al. [38] developed a method of correcting forward-scattering-induced bathymetric bias for ICESat-2 data that presents an empirical formula that corrects the ICESat-2 bathymetric bias in deep water (>20 m) from more than 50 cm to less than 13 cm and significantly improves the accuracy of extracted bathymetry.

However, ICESat-2 can only provide elevation information along satellite trajectories. Thus, some researchers have attempted to conduct studies using aa fusion of ICESat-2 and satellite imagery to further produce a spatially continuous map. Jia et al. [39] developed a method to obtain a bathymetry map by fusing ICESat-2-derived bathymetry water depth information and Sentinel-2-derived multispectral information via bathymetric empirical models, and achieved an accuracy of about 1m. Bernardis et al. [40] also combined ICESat-2 and Sentinel-2 data to map the bathymetry in the Sardinia and Venice Lagoon areas along the coastline, and found their results agreed well with the updated and reliable data from BathyDataBase of the Italian Hydrographic Institute. Cao et al. [41] took the flood event in Huoqiu County in 2020 as an example, and integrated ICESat-2-derived water levels and the Sentinel-2-derived flooding extent to estimate the lake storage volumes during the flooding events, showing that it can provide valuable information for flood control and disaster reduction.

4. Conclusions

In this Special Issue, the studies included mainly address the challenges of surface water related 3D information acquisition by fusing multi-source satellite remote sensing data. To be specific, many traditional studies have used satellite imagery to track horizontal surface water information (i.e., water-related area mapping derived from satellite imagery), such as water extent, water area, and the land–water boundary positions of lakes, rivers, and coastal zones. However, these studies have missed important vertical information on surface water (i.e., water-related elevation estimation derived from satellite altimeter data), such as water level, water depth, and bathymetry. In reality, vertical information is very essential for further quantitatively investigating 3D information on surface water, such as water volume and discharge in inland and coastal areas, which can further be linked to various natural factors and human activities. Several studies in our Special Issue propose a method to extract the water level, water depth, and bathymetric information from noisy ICESat-2 data, and further combine horizontal surface water information derived from satellite imagery to conduct 3D monitoring for Earth surface water. In summary, our Special Issue focuses on the challenges of 3D terrestrial water resource monitoring via satellite observation.

In the future, newly released satellite data, such as SWOT (surface water and ocean topography) should be included to enhance our ability to acquire information on the world's inland areas, coastal areas, and oceans. SWOT was designed to collect detailed measurements of how water bodies on Earth change over time. Despite this, it is very hard to continuously monitor surface water by solely using satellite remote sensing data, owing to the satellite revisit period and the influence of clouds/shadows. As is widely known, surface water exhibits large dynamics induced by various factors across different spatial and temporal scales, such as reservoir regulation, extreme precipitation, and flooding. Hence, it is highly encouraged that researchers consider combining satellite observation (which is data-driven) and model simulation (which is model-driven) to better monitor terrestrial water resources, improving our understanding of the water cycle, and guiding policy making on sustainable water resource management.

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List of Contributions:

1. Yu, J.; Cai, Y.; Lyu, X.; Xu, Z.; Wang, X.; Fang, Y.; Jiang, W.; Li, X. Boundary-Guided Semantic Context Network for Water Body Extraction from Remote Sensing Images. *Remote. Sens.* **2023**, *15*, 4325. https://doi.org/10.3390/rs15174325.
2. Wu, T.; Xu, Z.; Chen, R.; Wang, S.; Li, T. Channel Activity Remote Sensing Retrieval Model: A Case Study of the Lower Yellow River. *Remote. Sens.* **2023**, *15*, 3636. https://doi.org/10.3390/rs15143636.
3. Lyu, X.; Jiang, W.; Li, X.; Fang, Y.; Xu, Z.; Wang, X. MSAFNet: Multiscale Successive Attention Fusion Network for Water Body Extraction of Remote Sensing Images. *Remote. Sens.* **2023**, *15*, 3121. https://doi.org/10.3390/rs15123121.
4. Lu, L.; Wang, L.; Yang, Q.; Zhao, P.; Du, Y.; Xiao, F.; Ling, F. Extracting a Connected River Network from DEM by Incorporating Surface River Occurrence Data and Sentinel-2 Imagery in the Danjiangkou Reservoir Area. *Remote. Sens.* **2023**, *15*, 1014. https://doi.org/10.3390/rs15041014.
5. Wang, H.; Shen, D.; Chen, W.; Liu, Y.; Xu, Y.; Tan, D. Run-Length-Based River Skeleton Line Extraction from High-Resolution Remote Sensed Image. *Remote. Sens.* **2022**, *14*, 5852. https://doi.org/10.3390/rs14225852.
6. Wang, C.; Xie, W.; Li, T.; Wu, G.; Wu, Y.; Wang, Q.; Xu, Z.; Song, H.; Yang, Y.; Pan, X. Analysis of Spatial and Temporal Variation in Water Coverage in the Sub-Lakes of Poyang Lake Based on Multi-Source Remote Sensing. *Remote. Sens.* **2023**, *15*, 2788. https://doi.org/10.3390/rs15112788.
7. Sun, B.; Yang, Z.; Zhao, S.; Shi, X.; Liu, Y.; Ji, G.; Huotari, J. Water Balance Analysis of Hulun Lake, a Semi-Arid UNESCO Wetland, Using Multi-Source Data. *Remote. Sens.* **2023**, *15*, 2028. https://doi.org/10.3390/rs15082028.
8. Zhang, Z.; Ahmed, R.; Zhang, Q.; Li, Y.; Li, Y. Monitoring of 35-Year Mangrove Wetland Change Dynamics and Agents in the Sundarbans Using Temporal Consistency Checking. *Remote. Sens.* **2023**, *15*, 625. https://doi.org/10.3390/rs15030625.
9. Zhang, G.; Xing, S.; Xu, Q.; Li, P.; Wang, D. A Pre-Pruning Quadtree Isolation Method with Changing Threshold for ICESat-2 Bathymetric Photon Extraction. *Remote. Sens.* **2023**, *15*, 1629. https://doi.org/10.3390/rs15061629.
10. Gao, M.; Xing, S.; Zhang, G.; Zhang, X.; Li, P. Assessment of ICESat-2's Horizontal Accuracy Using an Iterative Matching Method Based on High-Accuracy Terrains. *Remote. Sens.* **2023**, *15*, 2236. https://doi.org/10.3390/rs15092236.
11. Xie, J.; Zhong, J.; Mo, F.; Liu, R.; Li, X.; Yang, X.; Zeng, J. Denoising and Accuracy Evaluation of ICESat-2/ATLAS Photon Data for Nearshore Waters Based on Improved Local Distance Statistics. *Remote. Sens.* **2023**, *15*, 2828. https://doi.org/10.3390/rs15112828.
12. Yang, J.; Ma, Y.; Zheng, H.; Gu, Y.; Zhou, H.; Li, S. Analysis and Correction of Water Forward-Scattering-Induced Bathymetric Bias for Spaceborne Photon-Counting Lidar. *Remote. Sens.* **2023**, *15*, 931. https://doi.org/10.3390/rs15040931.
13. Jia, D.; Li, Y.; He, X.; Yang, Z.; Wu, Y.; Wu, T.; Xu, N. Methods to Improve the Accuracy and Robustness of Satellite-Derived Bathymetry through Processing of Optically Deep Waters. *Remote. Sens.* **2023**, *15*, 5406. https://doi.org/10.3390/rs15225406.
14. Bernardis, M.; Nardini, R.; Apicella, L.; Demarte, M.; Guideri, M.; Federici, B.; Quarati, A.; De Martino, M. Use of ICEsat-2 and Sentinel-2 Open Data for the Derivation of Bathymetry in Shallow Waters: Case Studies in Sardinia and in the Venice Lagoon. *Remote. Sens.* **2023**, *15*, 2944. https://doi.org/10.3390/rs15112944.
15. Cao, Y.; Wang, M.; Yao, J.; Mo, F.; Zhu, H.; Hu, L.; Zhai, H. Stereoscopic Monitoring Methods for Flood Disasters Based on ICESat-2 and Sentinel-2 Data. *Remote. Sens.* **2023**, *15*, 3015. https://doi.org/10.3390/rs15123015.

References

1. Pekel, J.F.; Cottam, A.; Gorelick, N.; Belward, A.S. High-resolution mapping of global surface water and its long-term changes. *Nature* **2016**, *540*, 418–422. [CrossRef]
2. Pi, X.; Luo, Q.; Feng, L.; Xu, Y.; Tang, J.; Liang, X.; Ma, E.; Cheng, R.; Fensholt, R.; Brandt, M.; et al. Mapping global lake dynamics reveals the emerging roles of small lakes. *Nat. Commun.* **2022**, *13*, 5777. [CrossRef]
3. Xu, N.; Lu, H.; Li, W.; Gong, P. Natural lakes dominate global water storage variability. *Sci. Bull.* **2024**, *69*, 1016–1019. [CrossRef]
4. Alsdorf, D.E.; Rodríguez, E.; Lettenmaier, D.P. Measuring surface water from space. *Rev. Geophys.* **2007**, *45*, RG2002. [CrossRef]

5. Pickens, A.H.; Hansen, M.C.; Hancher, M.; Stehman, S.V.; Tyukavina, A.; Potapov, P.; Marroquin, B.; Sherani, Z. Mapping and sampling to characterize global inland water dynamics from 1999 to 2018 with full Landsat time-series. *Remote Sens. Environ.* **2020**, *243*, 111792. [CrossRef]
6. Wang, J.; Song, C.; Reager, J.T.; Yao, F.; Famiglietti, J.S.; Sheng, Y.; MacDonald, G.M.; Brun, F.; Schmied, H.M.; Marston, R.A.; et al. Recent global decline in endorheic basin water storages. *Nat. Geosci.* **2018**, *11*, 926–932. [CrossRef]
7. Ma, Y.; Xu, N.; Sun, J.; Wang, X.H.; Yang, F.; Li, S. Estimating water levels and volumes of lakes dated back to the 1980s using Landsat imagery and photon-counting lidar datasets. *Remote Sens. Environ.* **2019**, *232*, 111287. [CrossRef]
8. Xu, N.; Ma, Y.; Wei, Z.; Huang, C.; Li, G.; Zheng, H.; Wang, X.H. Satellite observed recent rising water levels of global lakes and reservoirs. *Environ. Res. Lett.* **2022**, *17*, 074013. [CrossRef]
9. Luo, S.; Song, C.; Ke, L.; Zhan, P.; Fan, C.; Liu, K.; Chen, T.; Wang, J.; Zhu, J. Satellite laser altimetry reveals a net water mass gain in global lakes with spatial heterogeneity in the early 21st century. *Geophys. Res. Lett.* **2022**, *49*, e2021GL096676. [CrossRef]
10. Xu, N.; Ma, Y.; Zhang, W.; Wang, X.H. Surface-water-level changes during 2003–2019 in Australia revealed by ICESat/ICESat-2 altimetry and Landsat imagery. *IEEE Geosci. Remote Sens. Lett.* **2020**, *18*, 1129–1133. [CrossRef]
11. Zhang, G.; Chen, W.; Xie, H. Tibetan Plateau's lake level and volume changes from NASA's ICESat/ICESat-2 and Landsat Missions. *Geophys. Res. Lett.* **2019**, *46*, 13107–13118. [CrossRef]
12. Zhao, Y.; Jiang, L.; Zhang, X.; Liu, J. Tracking river's pulse from space: A global analysis of river stage fluctuations. *Geophys. Res. Lett.* **2023**, *50*, e2023GL106399. [CrossRef]
13. Gou, J.; Soja, B. Global high-resolution total water storage anomalies from self-supervised data assimilation using deep learning algorithms. *Nat. Water* **2024**, *2*, 139–150. [CrossRef]
14. Li, X.; Long, D.; Scanlon, B.R.; Mann, M.E.; Li, X.; Tian, F.; Sun, Z.; Wang, G. Climate change threatens terrestrial water storage over the Tibetan Plateau. *Nat. Clim. Chang.* **2022**, *12*, 801–807. [CrossRef]
15. Coppo Frias, M.; Liu, S.; Mo, X.; Nielsen, K.; Ranndal, H.; Jiang, L.; Ma, J.; Bauer-Gottwein, P. River hydraulic modeling with ICESat-2 land and water surface elevation. *Hydrol. Earth Syst. Sci.* **2023**, *27*, 1011–1032. [CrossRef]
16. Chawla, I.; Karthikeyan, L.; Mishra, A.K. A review of remote sensing applications for water security: Quantity, quality, and extremes. *J. Hydrol.* **2020**, *585*, 124826. [CrossRef]
17. Kavvada, A.; Metternicht, G.; Kerblat, F.; Mudau, N.; Haldorson, M.; Laldaparsad, S.; Friedl, L.; Held, A.; Chuvieco, E. Towards delivering on the sustainable development goals using earth observations. *Remote Sens. Environ.* **2020**, *247*, 111930. [CrossRef]
18. Yang, W.; Long, D.; Scanlon, B.R.; Burek, P.; Zhang, C.; Han, Z.; Butler, J.J., Jr.; Pan, Y.; Lei, X.; Wada, Y. Human intervention will stabilize groundwater storage across the North China Plain. *Water Resour. Res.* **2022**, *58*, e2021WR030884. [CrossRef]
19. Li, Y.; Zhao, G.; Allen, G.H.; Gao, H. Diminishing storage returns of reservoir construction. *Nat. Commun.* **2023**, *14*, 3203. [CrossRef]
20. Rao, D.P. A remote sensing-based integrated approach for sustainable development of land water resources. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **2001**, *31*, 207–215. [CrossRef]
21. Sawaya, K.E.; Olmanson, L.G.; Heinert, N.J.; Brezonik, P.L.; Bauer, M.E. Extending satellite remote sensing to local scales: Land and water resource monitoring using high-resolution imagery. *Remote Sens. Environ.* **2003**, *88*, 144–156. [CrossRef]
22. Jiang, R.; Lu, H.; Yang, K.; Chen, D.; Zhou, J.; Yamazaki, D.; Pan, M.; Li, W.; Xu, N.; Yang, Y.; et al. Substantial increase in future fluvial flood risk projected in China's major urban agglomerations. *Commun. Earth Environ.* **2023**, *4*, 389. [CrossRef]
23. Xu, N.; Gong, P. Significant coastline changes in China during 1991–2015 tracked by Landsat data. *Sci. Bull.* **2018**, *63*, 883–886. [CrossRef]
24. Mentaschi, L.; Vousdoukas, M.I.; Pekel, J.F.; Voukouvalas, E.; Feyen, L. Global long-term observations of coastal erosion and accretion. *Sci. Rep.* **2018**, *8*, 12876. [CrossRef]
25. Jiang, S.; Xu, N.; Li, Z.; Huang, C. Satellite derived coastal reclamation expansion in China since the 21st century. *Glob. Ecol. Conserv.* **2021**, *30*, e01797. [CrossRef]
26. Yu, J.; Cai, Y.; Lyu, X.; Xu, Z.; Wang, X.; Fang, Y.; Jiang, W.; Li, X. Boundary-guided semantic context network for water body extraction from remote sensing images. *Remote Sens.* **2023**, *15*, 4325. [CrossRef]
27. Wu, T.; Xu, Z.; Chen, R.; Wang, S.; Li, T. Channel Activity Remote Sensing Retrieval Model: A Case Study of the Lower Yellow River. *Remote Sens.* **2023**, *15*, 3636. [CrossRef]
28. Lyu, X.; Jiang, W.; Li, X.; Fang, Y.; Xu, Z.; Wang, X. MSAFNet: Multiscale Successive Attention Fusion Network for Water Body Extraction of Remote Sensing Images. *Remote Sens.* **2023**, *15*, 3121. [CrossRef]
29. Lu, L.; Wang, L.; Yang, Q.; Zhao, P.; Du, Y.; Xiao, F.; Ling, F. Extracting a Connected River Network from DEM by Incorporating Surface River Occurrence Data and Sentinel-2 Imagery in the Danjiangkou Reservoir Area. *Remote Sens.* **2023**, *15*, 1014. [CrossRef]
30. Wang, H.; Shen, D.; Chen, W.; Liu, Y.; Xu, Y.; Tan, D. Run-Length-Based River Skeleton Line Extraction from High-Resolution Remote Sensed Image. *Remote Sens.* **2022**, *14*, 5852. [CrossRef]
31. Wang, C.; Xie, W.; Li, T.; Wu, G.; Wu, Y.; Wang, Q.; Xu, Z.; Song, H.; Yang, Y.; Pan, X. Analysis of Spatial and Temporal Variation in Water Coverage in the Sub-Lakes of Poyang Lake Based on Multi-Source Remote Sensing. *Remote Sens.* **2023**, *15*, 2788. [CrossRef]
32. Zhang, T.; Suen, C. A Fast Parallel Algorithm for Thinning Digital Patterns. *Commun. ACM* **1984**, *27*, 236–239. [CrossRef]
33. Sun, B.; Yang, Z.; Zhao, S.; Shi, X.; Liu, Y.; Ji, G.; Huotari, J. Water Balance Analysis of Hulun Lake, a Semi-Arid UNESCO Wetland, Using Multi-Source Data. *Remote Sens.* **2023**, *15*, 2028. [CrossRef]

34. Zhang, Z.; Ahmed, M.R.; Zhang, Q.; Li, Y.; Li, Y. Monitoring of 35-year mangrove wetland change dynamics and agents in the sundarbans using temporal consistency checking. *Remote Sens.* **2023**, *15*, 625. [CrossRef]
35. Zhang, G.; Xing, S.; Xu, Q.; Li, P.; Wang, D. A pre-pruning quadtree isolation method with changing threshold for ICESat-2 bathymetric photon extraction. *Remote Sens.* **2023**, *15*, 1629. [CrossRef]
36. Gao, M.; Xing, S.; Zhang, G.; Zhang, X.; Li, P. Assessment of ICESat-2's Horizontal Accuracy Using an Iterative Matching Method Based on High-Accuracy Terrains. *Remote Sens.* **2023**, *15*, 2236. [CrossRef]
37. Xie, J.; Zhong, J.; Mo, F.; Liu, R.; Li, X.; Yang, X.; Zeng, J. Denoising and Accuracy Evaluation of ICESat-2/ATLAS Photon Data for Nearshore Waters Based on Improved Local Distance Statistics. *Remote Sens.* **2023**, *15*, 2828. [CrossRef]
38. Yang, J.; Ma, Y.; Zheng, H.; Gu, Y.; Zhou, H.; Li, S. Analysis and Correction of Water Forward-Scattering-Induced Bathymetric Bias for Spaceborne Photon-Counting Lidar. *Remote Sens.* **2023**, *15*, 931. [CrossRef]
39. Jia, D.; Li, Y.; He, X.; Yang, Z.; Wu, Y.; Wu, T.; Xu, N. Methods to Improve the Accuracy and Robustness of Satellite-Derived Bathymetry through Processing of Optically Deep Waters. *Remote Sens.* **2023**, *15*, 5406. [CrossRef]
40. Bernardis, M.; Nardini, R.; Apicella, L.; Demarte, M.; Guideri, M.; Federici, B.; Quarati, A.; De Martino, M. Use of ICEsat-2 and Sentinel-2 Open Data for the Derivation of Bathymetry in Shallow Waters: Case Studies in Sardinia and in the Venice Lagoon. *Remote Sens.* **2023**, *15*, 2944. [CrossRef]
41. Cao, Y.; Wang, M.; Yao, J.; Mo, F.; Zhu, H.; Hu, L.; Zhai, H. Stereoscopic Monitoring Methods for Flood Disasters Based on ICESat-2 and Sentinel-2 Data. *Remote Sens.* **2023**, *15*, 3015. [CrossRef]