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A Review of Advancements and Applications of Satellite-Derived Bathymetry

Aigerim Kalybekova[1, 2,*]

Abstract

Satellite-derived bathymetry (SDB) has revolutionized underwater mapping by using remote sensing techniques to estimate water depth with high spatial coverage and cost-effectiveness. This paper reviews the evolution of bathymetric methods from traditional ruler-based measurements to modern acoustic and satellite-based approaches. Different remote sensing technologies, including Light Detection and Ranging (LiDAR), multispectral, and altimetric bathymetry, are reviewed, emphasizing their advantages and limitations. The performance of SDB in various environments, including coastal zones, coral reefs, inland water bodies, and glacial regions, is analyzed, with a focus on how water transparency, spectral band selection, and machine learning techniques impact accuracy. Additionally, new deep learning models, including convolutional neural networks (CNNs) and U-Net architectures, are explored in terms of their potential to enhance bathymetric mapping. Although SDB provides significant advances in mapping capabilities, challenges, such as optical limitations in turbid waters and seasonal variability, require hybrid approaches that combine multiple sensing modalities. This study emphasizes the role of artificial intelligence in refining bathymetric estimates and highlights future research directions, including the combination of hyperspectral imagery and radar.

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1. Introduction

Bathymetry, the science of mapping the sea floor, has undergone significant evolution from mechanical depth measurements to modern satellite technologies. The needs of navigation, underwater communication infrastructure, marine geology, and environmental monitoring have driven its development. Historically, bathymetric studies relied on primitive methods, such as sounding poles and lead lines, which later evolved into echo-sounding and remote sensing. Today, bathymetry utilizes satellite radar, laser scanning (LiDAR), and gravimetry methods to provide global seafloor mapping.[1,2]

1.1 Evolution of bathymetric methods

1.1.1 Manual methods (19th century – early 20th century)

The first systematic bathymetric survey began in the 19th century using the "line and weight" method. Significant contributions were made by the studies of British navigators James Clark Ross (1840) and Matthew Fontaine Maury (1849), who created the first depth chart of the Atlantic Ocean.[3] These studies provided the first insights into underwater topography and laid the foundation for further development. The lead-line method enabled accurate depth measurements at specific points, but it was extremely slow and dependent on weather conditions. Additionally, errors arose due to currents that could alter the rope’s position. The advancement of technology led to the development of piano-wire sounding systems, designed by William Thomson in the 1870s, which accelerated measurements and reduced errors compared to traditional rope-based methods.[3,4]

Later, in the 1870s, a measurement method using metal wire was developed (Lord Kelvin's project), which significantly improved the accuracy and speed of operations.[3] However, despite the progress, this method remained limited in coverage and required significant time. The wire-sounding method allowed data collection at greater depths and with less error than traditional rope measurements. Subsequently, this method was improved by Henry Sigsbee, who developed the Sigsbee Sounding Machine, which was actively used in the early 20th century for deep-sea research.[5]

Additionally, during this period, large-scale ocean studies

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[1] *Department of Mechanics, Al-Farabi Kazakh National University, Almaty, 050040, Kazakhstan*
[2] *Institute of Ionosphere, Almaty, 050020, Kazakhstan*
**Email:* aigerimkalybekova8@gmail.com (A. Kalybekova)

were conducted. For example, the HMS Challenger expedition (1872-1876) played a key role in the development of bathymetry, collecting over 360 deep-sea measurements and confirming the existence of the Mid-Atlantic Ridge. Similar studies were conducted by the National Oceanic and Atmospheric Administration (NOAA) in the United States, resulting in a deeper understanding of the seafloor's structure.[6] These methods enabled the creation of the first detailed maps of the continental shelf and the discovery of major underwater formations, such as the Mid-Atlantic Ridge. In 1905, the first General Bathymetric Chart of the Oceans (GEBCO) was published, marking a significant milestone in the study of underwater topography.[3]

1.1.2 Development of acoustic methods (20th century)

The development of hydroacoustic technologies began in the 1920s with the introduction of single-beam echo sounders, which were used in NOAA expeditions. These devices enabled accurate measurements of seafloor topography along individual profiles. However, their main drawback was the lack of a complete picture of the seafloor between the ship tracks.[3]

Single-beam echo sounders (SBES) represent an early form of acoustic seafloor mapping. They operate by emitting a single acoustic pulse, which reflects off the seafloor and is received back, allowing depth measurement at a single point. SBES were widely used in the mid-20th century and remain relevant for studies of small water bodies and rivers. However, they have limitations in terms of area coverage and data accuracy.[7,8]

Multibeam echo sounders (MBES) emerged in the second half of the 20th century, marking a significant advancement over SBES. They use multiple acoustic beams, enabling the simultaneous scanning of extensive areas of the seafloor and providing more accurate and detailed maps. MBES are widely used for deep-sea research, seafloor mapping, and the assessment of underwater geomorphological structures.[8]

From the 1950s to the 1980s, MBES were developed, providing wide-area coverage of the seafloor, which enabled detailed studies of continental slopes, oceanic ridges, and deep-sea basins. During the same period, side-scan sonars (SSS) became widely used, offering the capability for high-resolution structural analysis of the seafloor.[2]

1.2 Modern bathymetric methods

At the end of the 20th and the beginning of the 21st century, bathymetric research began to incorporate remote sensing methods. LiDAR bathymetry utilizes green-spectrum lasers, enabling depth measurements in clear waters up to 70 meters.[9] Satellite altimetry uses gravimetric methods and sea surface height measurements to calculate ocean depths. Optical methods for analyzing the spectral characteristics of reflected sunlight are used in shallow water areas. [1,9]

LiDAR bathymetry uses a green laser with a wavelength of 532 nm, which can penetrate water, making it particularly effective for mapping shallow areas, rivers, and coastal regions. Unlike acoustic methods such as echolocation, LiDAR bathymetry allows for the simultaneous measurement of both the seafloor and adjacent land areas, providing a comprehensive landscape view.[9] The key applications of LiDAR bathymetry include:

- Monitoring coastal zones and shoreline dynamics.[10]
- Mapping river channels and assessing hydrological parameters.[11]
- Analyzing erosion processes, sediment deposition, and river channel changes.[9]
- Creating high-precision flood models and forecasting floods.[10]

1.3 Transition to satellite technology

Before the advent of satellite methods, bathymetric maps were created exclusively through ship-based surveys, making them costly and labor-intensive. In the late 20th century, the transition to Satellite-Derived Bathymetry (SDB) was achieved with the launch of specialized missions, including SEASAT (1978), the first satellite to use radar for ocean monitoring. TOPEX/Poseidon (1992), satellite altimetry that provided high-precision sea level measurements.[12] CryoSat, Jason, SWOT (21st century) – modern satellite platforms used for global monitoring of ocean depths and gravitational anomalies.[2]

The use of satellite data in bathymetry has become a significant step in global ocean monitoring, as traditional methods, such as echolocation, require substantial resources and have limited coverage. Satellite altimetry enables the global reconstruction of the seabed by utilizing gravity anomaly data obtained through radar altimeters. These data allow for the mapping of deep-sea regions where ship-based measurements are rare or unavailable.[13] Fig. 1 shows the typical workflow used to estimate underwater depth using satellite images. This process, called SDB, combines image processing, modeling, and validation.

Modern satellite missions, such as GeoSat and ERS-1, have demonstrated a high correlation between gravity anomaly measurements and seafloor topography, enabling the creation of more accurate depth models. However, the resolution of satellite data depends on the characteristics of altimetric systems. The latest technologies, including Delay-Doppler altimeters, significantly improve measurement accuracy and expand the applications of satellite bathymetry.[13,14]

Satellite bathymetry is particularly in demand for global monitoring programs, such as seafloor tectonic activity studies, mapping underwater ridges, and detecting potentially hazardous underwater objects. Additionally, this data is used to improve tsunami forecasting and climate change modeling, as a detailed understanding of seafloor topography helps simulate wave propagation and ocean currents.[15]

1.4 Limitations of satellite bathymetry

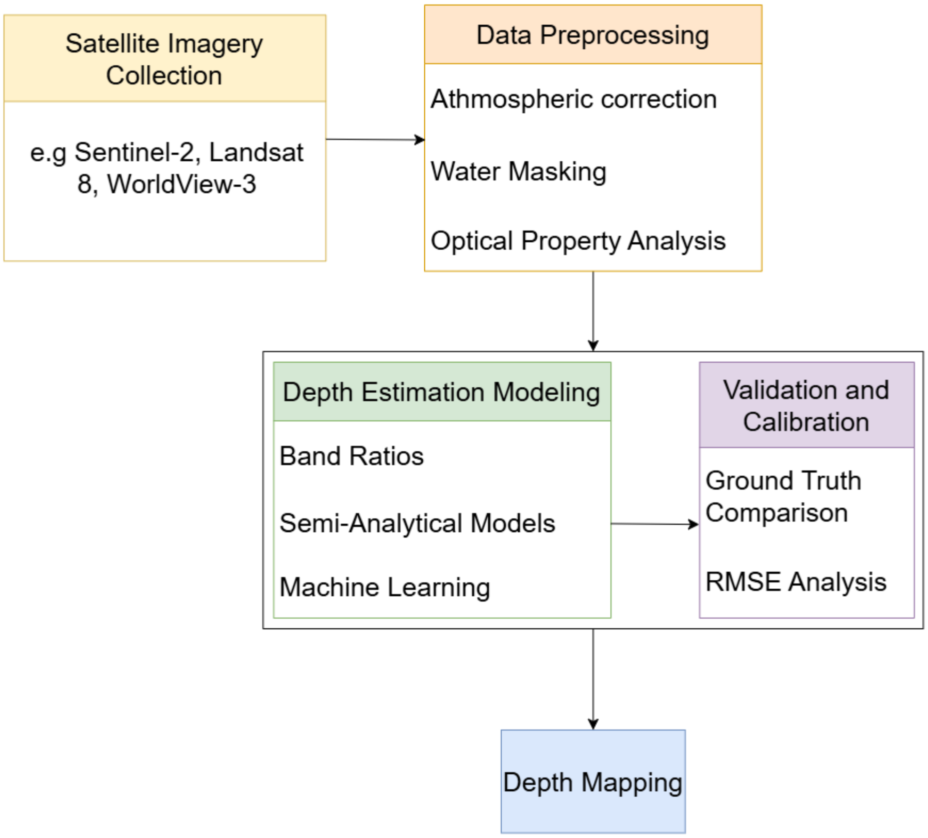

Fig. 1: Workflow of satellite-derived bathymetry processing, from raw satellite imagery acquisition to final bathymetric map generation.

Although satellite altimetry provides global coverage, its resolution remains limited. The primary sources of error stem from the influence of ocean waves, which smooth the signal, reducing the accuracy of depth determination. For a long time, the main limitation was the insufficient density of measurements. Only after high-resolution data from ERS-1 and Geosat became available did it become possible to conduct detailed studies of the ocean floor with a resolution of 20-30 km.[16]

Data filtering methods are important in improving the accuracy of satellite bathymetry. Global gravity models, derived from satellite altimetry data, are optimized for deep-sea regions where wave influence is minimal. However, in coastal areas, the accuracy of such methods decreases, necessitating their integration with local measurements obtained using shipborne echo sounders.[16] The historical development of bathymetry demonstrates a transition from mechanical measurement methods to high-precision satellite technologies. A comparative overview of these bathymetric methods, including their periods of use, advantages, and limitations, is presented in Table 1. In the future, the integration of satellite data with autonomous underwater drones and artificial intelligence methods will significantly enhance the capabilities of seabed exploration and improve the accuracy of bathymetric mapping.[1,2,9]

Another important issue is that SDB models often rely on ground truth data that's very limited in location or time. This makes it tough to generalize findings across different regions. Many studies are still based on site-specific models without strong external validation, which limits how widely the results can be applied. To fix this, future research should focus on using independent testing datasets, trying models across different environments, and clearly reporting uncertainty metrics. Strengthening reproducibility and standardization is key if we want to shift SDB from purely academic studies to practical, real-world coastal and marine management.

2. Optical properties of water

Satellite bathymetry is based on a detailed analysis of the interaction of sunlight with the water environment. The primary optical properties of water—transparency, absorption, and scattering—have a substantial impact on the characteristics of the reflected signal used for depth estimation. Absorption and scattering of light in the aquatic medium are determined by its physical and chemical characteristics. The spectral properties of reflected radiation depend on the wavelength and the nature of the interaction with surface materials, which affects the accuracy of remote sensing methods.[17-19]

Table 1: Comparison of bathymetry methods.

Method	Period	Description	Advantages	Limitations
Lead sounding	19th century	A weight on a rope was lowered to the bottom, and the length of the rope was measured.	Simplicity, low cost	Slow process, low accuracy
Wire lead	1870s	Use of metal wire instead of rope.	Reduced error, faster measurement	Still limited by currents and weather conditions
Sigsbee machine	Early 20th century	Automated depth sounding with a wire mechanism.	Faster measurements, improved accuracy	Requires mechanical maintenance
Single-beam echo sounder (SBES)	1920s	Measures the time it takes for a sound wave to travel to the seabed and back.	High accuracy, capability to measure great depths	Covers a narrow strip of the seabed
Multibeam echo sounder (MBES)	1950s	Measures depth over a wide swath beneath a vessel.	3D seafloor maps, high accuracy	High-cost, complex data processing
Laser bathymetry (LiDAR)	Late 20th century	Uses green-spectrum laser radiation to measure depth.	High detail, suitable for shallow water mapping	Limited by water turbidity, high cost
Satellite altimetry	1980s	Uses radar to measure the ocean surface height.	Global coverage, regular data updates	Low resolution, dependent on gravity models
Satellite-derived bathymetry (SDB)	21st century	Estimates depths based on spectral analysis of water surfaces.	Enables rapid analysis of large areas	Sensitive to water turbidity, requires calibration

2.1 Water clarity and light reflection

The water’s optical properties are influenced by various factors, including suspended particles, dissolved organic matter, and chlorophyll concentration. These elements affect both absorption and scattering, leading to variations in the reflected light signal (Fig. 2). Water clarity is influenced by environmental factors such as erosion, pollution, and organic matter, which impact the performance of optical and LiDAR-based models. The Secchi disk depth (SD or ZSD) is commonly used to measure water transparency, providing a direct estimate of the light penetration limit. The diffuse attenuation coefficient (Kd), which quantifies the decrease in light intensity with depth, is another key metric. Lower Kd values correspond to clearer waters where Lidar beams and optical signals penetrate deeper and yield more accurate depth estimations.[20]

However, the effectiveness of these systems drops in turbid environments due to increased backscatter noise, necessitating advanced waveform analysis algorithms to distinguish true bottom reflections from noise. Reduced water clarity limits light penetration, and in turbid water, the speed of light decreases, reducing the ability to reach greater depths.[20,21] In optical models, seasonal variations in turbidity and watercolor influence model accuracy. For instance, studies have shown that bathymetric accuracy improves during periods of lower turbidity and clearer water conditions. During high-turbidity

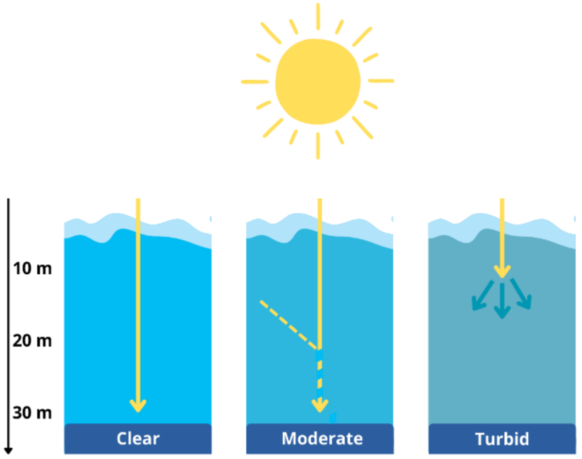

Fig. 2: Light penetration and scattering behavior in different water types.

periods, errors in depth estimation can exceed 0.3 m, while in clearer conditions, they are reduced to approximately 0.05 m.[22]

Turbidity, caused by suspended particles, organic matter, and phytoplankton, is a significant factor leading to the underestimation of water depth in SDB models. High turbidity increases backscatter from suspended sediments, reducing the ability to distinguish between water column reflectance and bottom reflectance. This effect leads to depth overestimation in shallow regions and increases noise in deeper waters.[23] Studies indicate that SDB performs best in waters with moderate turbidity (*e.g.*, SSC < 15 mg/L), while accuracy decreases sharply in environments with higher suspended sediment loads, particularly for depths beyond 5 meters.[21] Variations in water quality across study areas further increase errors, particularly when using empirical models that assume homogeneous water properties.

2.2 Spectral bands and depth estimation

Different spectrum channels are used to estimate depth in turbid water conditions, including the blue and green channels.[24,25] In clear waters, the blue band is preferred for bathymetry retrieval due to its greater penetration into the water column. However, in waters with high concentrations of dissolved organic matter (CDOM), the optimal bands shift to longer wavelengths, such as the green and yellow spectral regions, to account for increased absorption and scattering effects.[26] In areas of low water clarity, spectral ratio models can help to estimate underwater topography, such as log-transformed band ratio models or other relative bathymetric models.[21]

Longwave infrared channels are sensitive to changes in turbidity levels because their ability to penetrate water decreases more rapidly with increasing depth.[21] These channels provide valuable information on suspended particle concentrations, which directly affects the accuracy of data extracted from satellite images. Additionally, near-infrared (NIR) bands are generally excluded due to their rapid attenuation in water and the increased noise they introduce in in-depth estimation.[24]

2.3 Modeling approaches for optical correction

Empirical and physically based models each handle turbidity in different ways. The linear band model employs multiple linear regression across spectral bands, accounting for some variability in water quality and achieving the lowest root mean square error (RMSE) (0.48 m) in turbid conditions.[27] The linear ratio model uses the ratio of two bands to estimate depth but has higher errors (RMSE 0.56 m) due to its sensitivity to suspended sediment backscatter.[28] Look-up table (LUT) classification methods produce the highest RMSE (0.64 m) and are the most affected by turbidity.[29]

Further analysis highlights the importance of turbidity correction in enhancing bathymetric accuracy. Zhang *et al.*[30] developed a regression model using MODIS bands, which compensates for the influence of suspended sediment by incorporating a correction factor. The most accurate model is expressed as Eq. (1):

$$D = -7.833 + 0.0326 \times \left(\frac{M3}{M2 \times M5}\right) \quad (1)$$

where D represents depth (in meters), and $M2$, $M3$, and $M5$ are the reflectance values from corresponding MODIS bands.[30] This correction significantly reduces errors from 3.26 m to 1.52 m in absolute terms or from 39% to 24% in relative terms, making it suitable for depths between 5 and 20 m in turbid environments. However, the model assumes a uniform vertical distribution of suspended sediments, which may not reflect real-world variability, particularly where sediments accumulate near the seabed.

Hybrid models that integrate empirical methods with analytical approaches, such as semi-analytical algorithms, have shown promise in addressing the complexities of varying water transparency and chlorophyll levels. These models apply physical principles of light attenuation while incorporating statistical adjustments for site-specific conditions. This combination enables more robust performance across diverse water conditions, thereby reducing the sensitivity of depth retrieval to variations in suspended particles.[26]

Advanced methods, such as multi-temporal compositing, combine data from multiple observations to reduce the influence of transient turbidity and enhance model performance. This technique has demonstrated success in reducing noise and enhancing depth accuracy, particularly in dynamic coastal regions. In tests across seven different coastal environments ranging from the Caribbean to the U.S. east coast, multi-temporal compositing achieved median absolute errors (MedAE) between 0.31 and 1.31 m for depths ranging from 0 to 30 m, significantly improving on single-scene methods.[23] This approach overcomes the limitations of conventional scene selection by addressing the spatial and temporal heterogeneity of turbidity patterns.

3. Satellite sensors and platforms for SDB applications

Accurate and efficient satellite SDB relies on a variety of satellite platforms equipped with multispectral and active sensors. Different platforms are used based on their spectral capabilities, spatial resolution, temporal coverage, and ability to penetrate water columns.

3.1 Overview of satellite platforms for bathymetry

Landsat 8 and Sentinel-2 are the most widely used optical satellites for SDB due to their free and open access, global coverage, and consistent temporal resolution. Landsat 8, launched in 2013, features two main instruments: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The OLI provides a spatial resolution of 30 m for visible and near-infrared bands, including a coastal aerosol band (433-453 nm) designed explicitly for water studies. With a revisit period of 16 days, it enables frequent monitoring of coastal regions and effectively maps shallow waters up to a depth of 12 m. However, its coarser resolution limits precision in highly dynamic or narrow coastal areas.[31-33]

Sentinel-2, a component of the European Space Agency's Copernicus program, comprises two satellites, Sentinel-2A and Sentinel-2B, launched in 2015 and 2017, respectively. These satellites offer a spatial resolution of 10 m for visible and near-infrared bands, with 13 spectral bands spanning from coastal aerosol to shortwave infrared regions. The constellation's revisit frequency is notably 5 days, making it beneficial for monitoring dynamic coastal changes.[34] Sentinel-2 is favored for complex coastal morphologies and shallow reefs due to better resolution and temporal frequency. Moreover, its integration with Google Earth Engine facilitates rapid, large-scale bathymetric estimation through automated processing and cloud-based analysis.[33]

WorldView satellites, particularly WorldView-3 and WorldView-4, represent the next generation of commercial satellite imagery, providing spatial resolutions as fine as 0.3 meters and a revisit frequency of approximately 1 day for off-nadir observations. These satellites capture high-resolution imagery across 16 spectral bands, including the visible, near-infrared, and shortwave-infrared regions, which enhances their capacity for detailed bathymetric and environmental analyses, providing spatial resolutions as fine as 0.3 meters.[35] These satellites capture high-resolution imagery across multiple spectral bands, including the visible and near-infrared spectrum, which are essential for effective SDB applications. The advanced capabilities of WorldView satellites facilitate more accurate depth estimations in shallow coastal waters. However, the availability of WorldView data often comes at a higher cost, which may limit accessibility for some users.[36,37]

PlanetScope satellites offer a significantly higher spatial resolution of 3 meters, providing four spectral bands (red, green, blue, and near-infrared) and a revisit frequency of approximately one day. This enables more precise detection of fine-scale underwater features compared to Landsat's 30 meters. With the capability to capture daily imagery, PlanetScope is particularly useful for monitoring dynamic coastal environments where rapid changes occur. However, PlanetScope's commercial nature and associated costs can restrict access to some research applications.[38]

In contrast to these passive optical platforms, ICESat-2, launched by National Aeronautics and Space Administration (NASA) in 2018, employs the Advanced Topographic Laser Altimeter System (ATLAS) for photon-counting lidar measurements. This platform accurately measures water depth by detecting photon returns through the water column. While its coverage is confined to specific tracks, it provides critical validation for passive optical methods and retrieves depths in challenging scenarios. ICESat-2 can detect the seafloor at depths up to approximately 40 m in clear waters.[39]

The Pleiades constellation, particularly when operating in persistent video mode, can capture image sequences that allow for wave-derived bathymetry through spatiotemporal cross-correlation methods. This approach enables accurate bathymetric mapping in regions where other methods struggle, with depth estimates reaching up to 35 m under optimal conditions.[40] Additionally, the fusion of Pleiades-1 passive multispectral imagery with ICESat-2 data has produced very high-resolution bathymetric models (0.5 m) with a vertical accuracy of 0.89 m, demonstrating the potential of integrating active and passive remote sensing techniques for comprehensive coastal monitoring.[33]

3.2 Comparison of sensor characteristics and performance

Landsat 8 and Sentinel-2 provide moderate-resolution data suitable for large-scale bathymetric mapping, while ICESat-2 offers high vertical accuracy but limited spatial coverage. Sentinel-2 is more effective in resolving fine-scale bathymetry in complex environments due to its higher spatial resolution and frequent revisit times.[41] In contrast, the photon-counting lidar on ICESat-2 is less affected by atmospheric and water column noise, offering more precise depth estimates in areas where optical methods struggle.[42] ICESat-2 also complements passive sensors by providing high-accuracy bathymetric points for model training, reducing the reliance on field-based depth measurements.[43]

WorldView-2, Pleiades, and PlanetScope deliver the highest spatial resolution, enabling the detailed mapping of small-scale features, such as coral reefs and narrow inlets. The Pleiades persistent mode can capture dynamic coastal changes through wave characteristics analysis, improving bathymetric accuracy in areas with complex seafloor structures.[40] Gradient boosting methods further refine these estimates by using Sentinel-2 data to address light attenuation and scattering challenges in turbid environments.[44] The WorldView-3 sensor offers increased radiometric sensitivity and expanded band coverage, thereby enhancing bathymetric retrieval accuracy in challenging optical conditions.[35]

3.3 Summary of satellite platforms performance in SDB

Satellite-derived bathymetry, made possible through platforms such as Sentinel-2, Landsat, Pleiades, WorldView, and PlanetScope, has transformed coastal monitoring.[41] Fig. 3 illustrates the comparison of spatial resolution, temporal resolution, and maximum measurable depth for the six key SDB platforms.

As shown in Fig. 3, ICESat-2 offers the greatest maximum depth but a much lower temporal resolution (91 days), whereas Sentinel-2 and PlanetScope provide daily revisits at the expense of lower depth penetration. Landsat 8 strikes a balance between revisit and depth, while WorldView-3 and Pleiades-1, though highly precise in spatial resolution, are commercial platforms with varying revisit rates. WorldView-3 offers advanced imaging capabilities and high-resolution data for shallow-water mapping but requires calibration and favorable water conditions for optimal performance. Combining satellite imagery with traditional survey methods

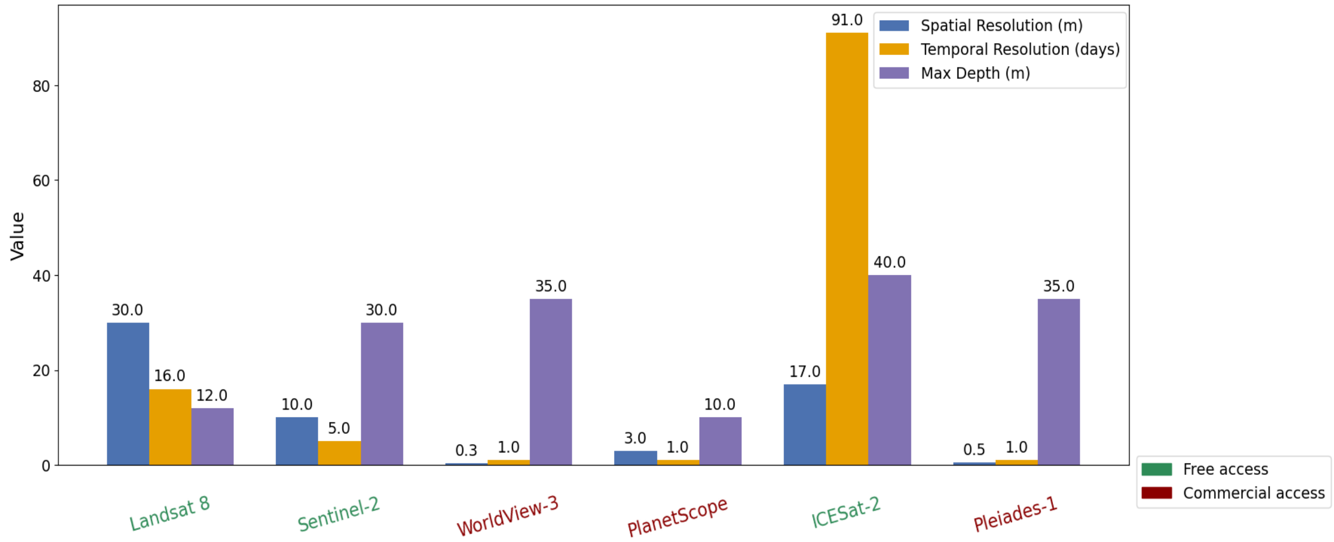

Fig. 3: Comparison of spatial resolution, temporal (revisit) resolution and maximum depth detection for six satellite platforms.

enhances the accuracy and comprehensiveness of bathymetric assessments. Future research will focus on refining algorithms and integrating diverse datasets to improve accuracy.

Even though SDB has come a long way, one big challenge remains. There's still no standard way of doing things. Different satellite platforms, like Sentinel-2, WorldView-3, and ICESat-2, have their own spatial resolutions, spectral bands, and revisit times, which makes it hard to get consistent results across different studies. On top of that, differences in how researchers handle atmospheric correction, turbidity filtering, and depth retrieval add even more variation.

Some efforts are being made to create cross-platform calibration methods, such as using standardized reference sites and combining data from multiple sensors. However, so far, there's no universally accepted approach, especially for areas where the water is turbid and optically complex. To move forward, the SDB community needs benchmark datasets with reliable ground truth measurements, and studies should use common performance metrics like RMSE, MAE, and relative error. This will help make SDB results more transparent, comparable, and useful for scientific and operational work.

4. Applications and use cases of SDB

A global overview of key case studies is shown in Fig. 4, highlighting where coastal, reef, inland and glacial SDB applications have been successfully implemented.

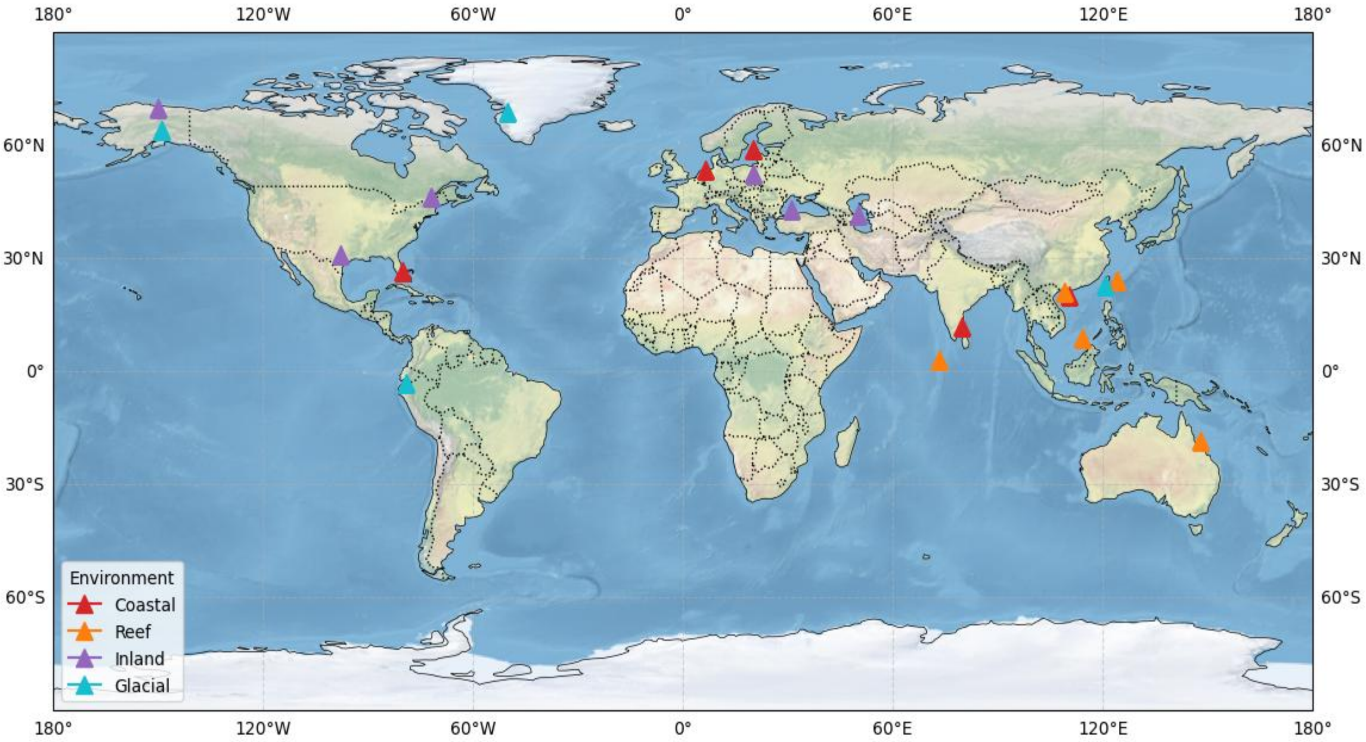

Fig. 4: Geographic distribution of key SDB studies across different environments.

4.1 SDB in coastal zones

The continental shelf and coastal regions are highly dynamic environments where satellite-derived bathymetry plays a crucial role in monitoring seabed topography and shoreline changes. These areas are particularly vulnerable to natural processes such as tides, currents, and storms, as well as anthropogenic activities, including port construction, resource extraction, and dredging. Satellite-based observations provide a cost-effective and large-scale method for assessing these changes, enabling better decision-making in marine spatial planning and environmental management.[30,32,45]

However, several challenges limit the accuracy of SDB in coastal areas. Depth variability in shallow waters is influenced by sandbanks, underwater dunes, and sediment transport, which complicates the interpretation of satellite data. Tidal fluctuations and strong coastal currents cause temporary changes in water levels, potentially introducing discrepancies in depth estimations. Additionally, high water turbidity and suspended particle concentration significantly reduce the effectiveness of optical remote sensing methods, leading to errors in depth retrieval. Despite these limitations, SDB has been successfully implemented in various coastal regions around the world, each with unique environmental and geomorphological challenges.[46]

One key application of SDB is the multi-temporal monitoring of nearshore morphology. A notable example is the Puducherry coast in India, where a beach nourishment project was carried out to combat erosion. The SDB-derived bathymetric maps showed significant shoreline changes, with accretion occurring north of the pier and overall stabilization of the coastline.[47] This case highlights how SDB can effectively track sediment transport in rapidly changing coastal environments. Similarly, in South Florida, USA, SDB has been used to monitor the nearshore bathymetry of areas such as West Palm Beach and Key West. These sites exhibit varying levels of turbidity and water transparency; however, Sentinel-2 imagery enabled accurate bathymetric assessments, with median absolute errors as low as 0.22 m in the clear waters of the Dry Tortugas.[48] The Florida study further noted the advantage of Sentinel-2’s 5-day revisit, suggesting that continuous SDB monitoring could support operational coastal management and hazard assessment in remote or dynamic areas. These results demonstrate SDB’s effectiveness in a subtropical coastal setting and its potential for routine use by agencies.

In Europe, the Pan-European Satellite-Derived Coastal Bathymetry project identified critical gaps in bathymetric data availability across the continent. Countries bordering the North Sea and the Mediterranean, where sediment transport and tidal dynamics play a key role in coastal morphology, have benefited from satellite-based monitoring. SDB has been particularly effective in tracking changes in dynamic coastal systems such as the Wadden Sea, a UNESCO World Heritage site, where sediment deposition and shifting tidal channels present ongoing challenges for navigation and habitat conservation.[49] Additionally, in the Baltic Sea, where ice cover and seasonal variations influence bathymetry, SDB provides a cost-effective means of mapping seabed changes over time.

A recent study applied SDB using the gradient boosting machine (GBM) algorithm to estimate water depth in Nanshan Port, Hainan Province, China. This area, a key maritime hub in Southeast Asia, presents challenges due to its turbid waters and active coastal development. The study demonstrated that GBM-based SDB successfully extracted depth information in these challenging conditions, outperforming traditional bathymetric retrieval models.[44] Another significant advancement in machine learning-based SDB was demonstrated by Al Najar *et al*.,[50] who developed two novel deep-learning models for bathymetry estimation. These methods leverage satellite wave observations and convolutional neural networks (CNNs) to reconstruct nearshore bathymetry. Their approach significantly improves accuracy and computational efficiency, with a tested RMSE of ~3 m down to 70 m depth. This highlights the potential of machine learning-enhanced SDB in complex coastal environments where conventional methods struggle due to variable optical properties.[44,50]

4.2 SDB in coral reef environments

Beyond traditional applications in coastal zones, SDB has been increasingly employed in coral reef environments. In the Indo-Pacific region, including areas such as the Great Barrier Reef in Australia and the Maldives, SDB has played a crucial role in mapping shallow reef structures and detecting degradation over time. The ability to track coral growth, bleaching events, and reef sedimentation has allowed conservationists to develop targeted protection strategies. High-resolution optical satellite data, such as those from Pleiades-1 and WorldView-3, have enabled researchers to produce accurate reef bathymetric models.[33, 51]

In the South China Sea, the Weizhou Island coral reef has been mapped using multispectral satellite images, demonstrating the effectiveness of SDB in high-latitude coral environments. Using the Quasi-Analytical Algorithm (QAA), researchers derived bathymetry independent of auxiliary data, achieving RMSEs of 1.01 m (ZY-3 satellite) and 0.77 m (WorldView-3 satellite).[52] These results highlight the adaptability of SDB in complex reef environments, where traditional methods struggle due to the presence of shallow waters and high turbidity.

Paringit and Nadaoka investigated the simultaneous estimation of benthic fractional cover and shallow-water bathymetry in coral reef areas using high-resolution satellite images. Their approach, which integrated spectral unmixing with radiative transfer modeling, allowed for accurate mapping of both seabed composition and depth in reef environments. This methodology, tested in Ishigaki Island, Japan, demonstrated that SDB could estimate depths with an RMSE of 0.45 m in depths up to 20 m.[53]

Recent advances in deep learning have further enhanced coral reef mapping capabilities. Chen *et al*.[54] introduced a bathymetry-assisted deep neural network for coral reef benthic habitat classification. Using a multi-task learning framework, this approach integrated bathymetry data to improve the accuracy of coral reef classification, demonstrating that bathymetry features contribute valuable structural information for reef mapping. This method was tested on 10 coral reefs in the Spratly Islands, China, showing an improvement of 22.54 % in mIoU compared to traditional classification approaches. These findings highlight the importance of bathymetry in not only reef depth estimation but also in ecological monitoring and habitat assessment.

The integration of SDB with other remote sensing technologies, such as ICESat-2 LiDAR, has further improved depth retrieval in complex reef environments. By combining multispectral satellite imagery with LiDAR altimetry data, researchers have developed highly accurate bathymetric models that enhance coral reef conservation efforts.[33] This hybrid approach is particularly useful in tracking the degradation of reefs caused by climate change and anthropogenic activities.

4.3 SDB in inland water bodies

SDB has also been applied in inland water bodies, including lakes, reservoirs, and rivers. These environments are critical for water resource management, hydrology, and climate change studies. Accessibility issues and the dynamic nature of water levels often hinder traditional bathymetric surveys in inland waters. SDB offers a viable alternative by leveraging optical and radar satellite data to estimate depth variations over time.

A significant application of SDB in inland water bodies involves estimating volume variations. Schwatke *et al*.[55] developed a novel approach to estimate volume changes in small lakes and reservoirs by combining satellite altimetry-derived water levels with surface area measurements from optical imagery. Their study focused on 28 lakes and reservoirs in Texas, where volume variations were computed using a modified Strahler hypsometry model. The results showed strong correlations (0.80–0.99) with in-situ volume measurements, and the relative errors in volume estimations ranged from 2.8% to 14.9%. This approach demonstrates how SDB can be integrated with altimetric data to improve volume estimation in water bodies that lack in situ measurements.

In addition, SDB has been used to study internal waves in enclosed inland seas such as the Black Sea and Caspian Sea. Lavrova and Mityagina utilized synthetic aperture radar (SAR) imagery to investigate internal waves, which can impact hydrodynamics and sediment transport in these non-tidal seas.[56] Their study identified key generation mechanisms, including riverine freshwater intrusions and coastal upwelling relaxation, which create hydrological fronts capable of generating internal waves. In the Caspian Sea, the study highlighted the role of seiches, standing wave oscillations, which interact with bathymetry and influence sediment redistribution. These findings suggest that SDB can be an important tool for understanding inland water dynamics, particularly in large inland seas where conventional bathymetric surveys are limited.[56]

Recent advancements in high-resolution SDB techniques have enabled the mapping of shallow and ultra-shallow inland water bodies using multispectral satellite imagery. Kulbacki *et al*.[57] demonstrated the feasibility of using PlanetScope satellite imagery to retrieve bathymetry in optically complex inland waters. Their study focused on two bays of Dabie Lake in Poland, where regression models were developed using spectral bands and in-situ reference data collected via unmanned surface vessels (USVs). The study highlighted that the best penetration capability was achieved using the green and yellow bands, with regression models achieving root mean square errors in the centimeter range in certain cases. These findings reinforce the potential of SDB for monitoring bathymetric changes in small inland water bodies with fine-scale accuracy.[57]

Further, Saylam *et al*.[20] assessed bathymetry in shallow water bodies of the Alaskan North Slope by integrating airborne LiDAR bathymetry with multiband satellite imagery. Their study emphasized the importance of water clarity in determining SDB performance, identifying significant variations in bathymetric accuracy depending on turbidity conditions. The research demonstrated how ALB (Airborne LiDAR Bathymetry) and SDB can be combined to improve depth estimation in periglacial lake environments, where traditional surveys are difficult due to seasonal ice cover and remote locations.[20]

Salavitabar *et al*.[58] applied SDB techniques to map river bathymetry in the Nicolet River, Quebec, Canada. Their study leveraged WorldView-3 multispectral imagery to retrieve river depths without requiring field calibration data. The study introduced a ratio-based method using the red and green bands, showing that depth estimates correlated well with field measurements. This application highlights the feasibility of SDB for monitoring river geomorphology, sediment transport, and restoration efforts in fluvial systems.

The ability of SDB to capture lake volume fluctuations is crucial for understanding hydrological responses to climate change. Many reservoirs worldwide experience seasonal and long-term fluctuations in water levels due to variations in precipitation, dam operations, and human consumption. In regions where water levels fluctuate significantly, such as the Great Lakes in North America and Lake Victoria in Africa, SDB offers a practical solution for monitoring depth changes without the need for extensive field campaigns. Moreover, its integration with hydrological models enhances the prediction of water availability in drought-prone regions.[55]

However, challenges remain in applying SDB in turbid inland waters. Sediment-rich rivers and lakes, such as the Amazon River basin and the Mekong Delta, pose difficulties for optical depth retrieval. Water quality parameters, including chlorophyll concentration and dissolved organic matter, affect spectral reflectance and introduce uncertainties in bathymetric calculations. In such environments, combining SDB with radar altimetry and in situ calibration data improves accuracy.[20,55-58]

4.4 SDB in alpine, glacial, and polar water bodies

Mountainous, glacial, and polar environments present unique challenges for bathymetric mapping due to steep terrain, extreme climatic conditions, and variable sediment loads. Traditional bathymetric surveys in these regions are often hindered by difficult access and highly dynamic water bodies. Recent advancements in remote sensing, unmanned aerial vehicle (UAV)-based methodologies, and spectral data fusion have enabled more effective monitoring of bathymetry in high-altitude rivers, glacial lakes, and Arctic ice sheet meltwater reservoirs.[59-65]

A notable application of SDB in alpine regions is the bathymetric modeling of high-altitude tropical lakes in Ecuador, as demonstrated by Vázquez *et al*.[60] Their study focused on 119 lakes in the Cajas National Park, where bathymetric data were collected using a low-cost fishing echo sounder and processed with multiple interpolation techniques. The study found that methods such as Kriging, natural neighbor, and TIN performed best, though no single method consistently outperformed the others. By integrating the interpolated bathymetric data into a digital elevation model (DEM), researchers developed an enhanced dataset for improved hydrological and ecological management of these fragile mountain lakes.[60]

On the Tibetan Plateau, Song *et al*.[64] reviewed the use of remote sensing for monitoring alpine lake water environment changes. The study highlighted the impact of climate change on lake expansion, glacial melt, and hydrological balance in the high-altitude lakes of the TP. They emphasized the need for multi-source satellite data fusion to improve the accuracy of lake volume estimations in this region. This work aligns with findings from Ecuadorian mountain lakes, reinforcing the importance of using SDB techniques to track long-term hydrological and geomorphological changes in alpine environments.

Similarly, Lee *et al*.[59] used UAV-mounted multispectral imaging combined with machine learning techniques to estimate bathymetry in Taiwan's Chishan River Basin. Their Gene-Expression Programming (GEP) model achieved RMSE of 0.195 m, outperforming traditional regression-based models. UAV-SDB proved particularly effective for shallow, rapidly changing mountain rivers, where conventional survey methods face significant limitations. This approach is particularly relevant for mountainous river systems, where high sediment transport and hydrodynamic variability pose challenges for traditional bathymetric retrieval.

In the Arctic region, SDB has been applied to supraglacial lakes on the Greenland Ice Sheet (GrIS), which are critical indicators of climate change. Lv *et al*.[61] combined ICESat-2 altimetry data with Sentinel-2 spectral stratification to estimate the bathymetry of four lakes on the Greenland Ice Sheet. Their approach improved the accuracy of depth inversion compared to traditional models, reducing RMSE by up to 13.0% and MAE by 14.0%. Furthermore, a long-term study by Lv *et al*.[62] extended this work by analyzing five years (2019-2023) of bathymetric changes in supraglacial lakes on the GrIS. The study employed log-ratio and BP neural network models, demonstrating a significant correlation between supraglacial lake volume and rising Arctic temperatures. Legleiter *et al*.[65] further validated the potential of satellite-based SDB by combining field depth measurements with WorldView-2 imagery to assess supraglacial meltwater storage. Their findings highlight the importance of integrating multi-year remote sensing data for tracking climate-induced changes in glacier meltwater storage.[62,65]

Compared to traditional acoustic and LiDAR-based methods, SDB techniques, such as those derived from UAVs and satellites, offer advantages in narrow, shallow, and rapidly evolving river and lake systems. However, optical SDB techniques remain limited by turbidity, sediment concentration, and seasonal hydrological variations, making data fusion approaches necessary. The use of multi-sensor integration and machine learning has the potential to enhance retrieval accuracy, particularly in complex environments where traditional methods fail. Nevertheless, further refinement in spectral correction methods and atmospheric interference models is required to improve SDB reliability across varying climatic and hydrological conditions. Continued development in high-resolution satellite constellations and deep learning-driven inversion techniques will be crucial in overcoming the existing limitations of SDB in alpine, glacial, and polar regions. With increasing climate variability, ensuring accurate and continuous monitoring of these water bodies is vital for understanding their role in global hydrological cycles and climate feedback mechanisms.[59-62,64,65]

4.5 Limitations of SDB in different geographic zones

Despite its advantages, SDB has several limitations that vary across different geographic zones. In coastal environments, factors such as water turbidity, sediment transport, and dynamic wave conditions introduce uncertainty in depth retrieval, particularly in areas with high concentrations of suspended particles.[44,48] In turbid estuarine and deltaic regions, optical SDB techniques struggle due to the reduced penetration of light, making complementary methods such as wave-based inversion or LiDAR integration necessary.[49,66] Similar issues arise in inland water bodies, where sediment-laden rivers such as the Amazon, Mississippi, and Mekong exhibit high turbidity that reduces the effectiveness of optical depth retrieval.[55] Additionally, the presence of dissolved organic matter and chlorophyll can alter spectral reflectance, further complicating bathymetric estimations.[20,56-58] Seasonal variations in water levels and flow dynamics, particularly in floodplains and reservoirs, create discrepancies in bathymetric estimations if temporal resolution is insufficient. Studies have shown that integrating SDB with satellite altimetry or Airborne LiDAR Bathymetry (ALB) improves accuracy in these challenging environments.[20,55,58]

Similar to coastal and inland waters, coral reef environments present additional complexities due to the intricate structure of reef systems, which causes variations in light reflection and absorption. The presence of living coral, algae, and benthic habitat variations can result in inaccurate SDB estimates unless additional calibration data or deep learning enhancements are applied.[52,54,67] Seasonal fluctuations also play a role in coral reef environments, requiring frequent updates to bathymetric models to ensure reliability. However, Sentinel-2, while highly effective for coastal zones and reef monitoring, does not cover approximately 12% of the world's coral reefs, limiting its applicability in some areas.[67]

In mountainous and glacial environments, SDB faces further limitations related to extreme seasonal changes, steep terrain, and variable sediment transport. In high-altitude lakes, such as those on the Tibetan Plateau and in the Ecuadorian Andes, the effectiveness of SDB is restricted by frequent cloud cover, rapid hydrological shifts, and the presence of glacial meltwater, which introduces fine sediment that complicates optical retrieval.[60,64] Additionally, mountainous rivers, particularly those influenced by high sediment loads and rapid hydrodynamic changes, present challenges for conventional SDB methods. UAV-based multispectral imaging has been explored as an alternative, yet its accuracy is highly dependent on atmospheric conditions and the stability of the water column.[59]

In polar regions, SDB is further constrained by persistent ice cover, extreme seasonal variability in solar illumination, and cloud interference, all of which impact the retrieval of optical satellite depth. The availability of cloud-free satellite imagery remains a significant challenge for bathymetric mapping in Arctic and Antarctic waters, necessitating the use of alternative sensing techniques such as ICESat-2 altimetry or radar-based bathymetric estimations.[66] Furthermore, studies on supraglacial lakes on the Greenland Ice Sheet have demonstrated that while combining optical satellite data with ICESat-2 depth profiles improves accuracy, the presence of snow, ice, and meltwater dynamics still introduces variability in bathymetric assessments.[61] A study on Alaska's North Slope also highlighted that even multi-temporal SDB approaches struggle with the rapid morphological changes induced by ice melt and sediment redistribution.[68] As shown in Fig. 5, the RMSE values vary across different environments, with the lowest errors in coastal zones and higher errors in glacial/polar regions.

Despite these limitations, advances in multi-sensor integration, deep learning, and improved atmospheric correction techniques continue to enhance the applicability of SDB across diverse environments. The combination of optical, LiDAR, and radar-based methods offers a promising path forward, particularly in regions where individual techniques encounter environmental constraints. Future research should focus on refining these hybrid approaches to ensure more consistent and reliable bathymetric estimations across varying climatic and hydrological conditions.

4.6 Comparison of SDB in shallow and deep waters

SDB exhibits distinct performance characteristics depending on the depth of the water body. Optical penetration limits,

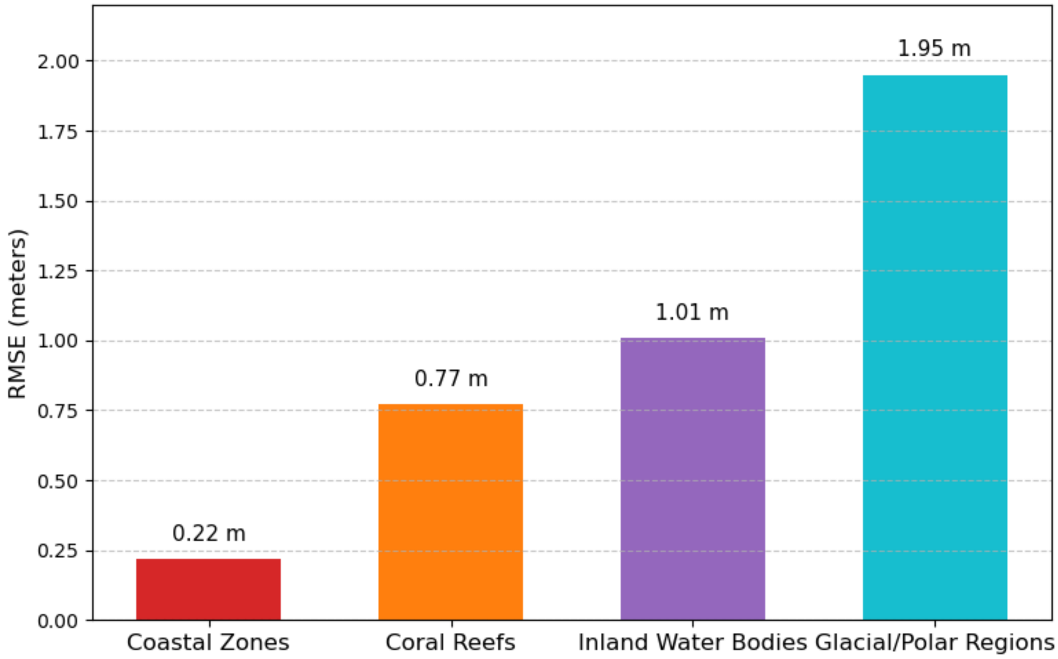

Fig. 5: Comparison of SDB performance across different environments (RMSE values).

sensor capabilities, and environmental factors, including turbidity, sediment transport, and bottom reflectance, influence the effectiveness of SDB in shallow and deep waters.

In shallow waters, SDB is generally more accurate because light can penetrate the water column and reach the seafloor. Methods such as spectral band ratio techniques, empirical regression models, and machine learning-based inversion models are frequently used to derive bathymetry in depths up to approximately 30 meters. Optical-based approaches, particularly those using high-resolution sensors such as Sentinel-2 and Landsat-8, excel in clear water environments with minimal turbidity. However, shallow waters often present challenges such as sediment suspension, tidal influences, and dynamic seabed changes, which can introduce noise into SDB-derived depth estimates.[48,52]

Recent accuracy assessments of SDB in shallow waters highlight the variability of results based on algorithm selection and environmental conditions. A study comparing the performance of Stumpf's log-ratio model and Lyzenga's log-linear model in Malaysian waters found that Stumpf's model achieved an RMSE of 1.432 m. In contrast, Lyzenga's model had an RMSE of 1.728 m after calibration.[69] These results indicate that SDB accuracy can vary significantly depending on the model used, necessitating proper calibration to reduce errors. Furthermore, the study confirmed that shallow water accuracy is affected by turbidity, atmospheric correction, and sensor resolution, with increased errors observed in depths less than 5 meters due to sediment resuspension and bottom reflectance variability.

Another study conducted along the coast of Misano Adriatico, Italy, assessed the contribution of multispectral satellite imagery to mapping shallow-water bathymetry. The study found that depth retrieval accuracy is highly dependent on water clarity, with performance degrading in areas with higher levels of dissolved organic matter and suspended sediments.[70] This further supports the need for adaptive correction techniques to improve SDB reliability in shallow coastal waters.

In contrast, deep waters pose significant challenges for SDB, as the penetration of light diminishes rapidly beyond 30–40 meters, rendering traditional optical techniques ineffective. Alternative methods, such as radar altimetry, wave kinematics inversion, and semi-empirical modeling, are required for deep-water bathymetric mapping.[66] Optical models become unreliable in optically deep waters, where sun glint effects, depth-induced spectral distortions, and inconsistencies in reference depth selection degrade accuracy. However, recent advancements in sun glint correction and multi-source data fusion have demonstrated improvements in deep-water SDB accuracy, with an approximately 0.6-meter reduction in RMSE in validation tests.[71]

The methodological differences between shallow and deep-water SDB highlight the need for tailored approaches based on depth constraints. Shallow-water SDB typically relies on spectral band processing and machine learning models, whereas deep-water SDB integrates radar and altimetry data to compensate for the limitations of optical observations. High-resolution satellite imagery is particularly useful in shallow-water applications, whereas deeper waters require the fusion of active and passive remote sensing techniques.[71,72]

Practically, SDB is widely used in shallow waters for coastal management, navigation safety, and habitat mapping. In contrast, deep-water SDB is crucial for applications such as continental shelf mapping, studies of submarine geomorphology, and tsunami hazard modeling. The combination of optical, LiDAR, and radar-based approaches presents a promising solution to overcome depth-related limitations, ensuring the continued development of SDB methodologies for a broader range of marine environments.

5. Machine learning applications in SDB

Given the challenges inherent in SDB, such as optical limitations, variable water transparency, and the need for accurate depth estimation, machine learning (ML) techniques have emerged as a new tool to improve bathymetric mapping. ML has been widely used to enhance accuracy in various domains, including remote sensing, hydrological modeling, and environmental monitoring, demonstrating its ability to process complex and high-dimensional datasets effectively.[73-80] By using large-scale remote sensing datasets, ML models improve the accuracy of depth estimation by identifying complex patterns in spectral data that traditional empirical methods are not able to detect.

Random forest (RF) has been widely applied in bathymetric estimation due to its robustness against overfitting and its capability to handle high-dimensional data.[81,82] Studies have demonstrated that RF models trained on ICESat-2 and Sentinel-2 datasets have achieved RMSE values below 1.5 meters, making them highly effective for coastal bathymetry estimation.[34] In South-West Florida, RF models were tested using multiple Sentinel-2 images, showing improvements in depth accuracy with RMSE values dropping below 8% of the total depth range. The study also demonstrated that the reflectance-based feature selection improved the reliability of the model for bathymetric mapping under different water conditions.[83] Another study explored the application of RF in a multi-temporal setting using Landsat-8 imagery, where the model demonstrated improved generalization capabilities, achieving RMSE values of approximately 1.41 m for depths of up to 20 m. The multi-temporal approach enabled the model to learn seasonal variations in water properties, resulting in more stable depth predictions.[84] In another instance, RF was applied to bathymetric mapping in seaports, where it was integrated with sonar data. This approach reduced error margins by incorporating in situ depth measurements, highlighting RF's adaptability in combining heterogeneous datasets for high-precision maritime mapping.[85]

In addition to RF, active-passive fusion approaches have further refined ML-based bathymetric mapping. One study demonstrated that integrating Sentinel-2 imagery with ICESat-2 bathymetric measurements improved model accuracy in reef environments. Specifically, multilayer perceptron (MLP) and k-nearest neighbor (KNN) models were tested,[86-88] with RMSE values as low as 1.034 meters. The study found that MLP was particularly effective in areas where optical complexity was high, while KNN performed well in regions with relatively homogenous seabed conditions.[89] Similar approaches have been tested in shallow coastal waters, where random forests, gradient boosting, and support vector machines consistently outperformed traditional empirical methods. In these studies, RF models achieved RMSE values of approximately 1.2 meters across different shallow water environments, emphasizing their adaptability.[90]

Support vector machine (SVM) has also been widely used for SDB, particularly in environments with significant optical variability.[91] A study comparing SVM and RF models found that SVM performed better in areas where bottom reflectance varied sharply due to mixed sediment compositions. The model, when integrated with ICESat-2 and Sentinel-2 datasets, improved bathymetric estimations by leveraging spectral reflectance properties and optimizing feature selection techniques.[92] A variant of SVM, support vector regression (SVR), was explicitly tested for nearshore bathymetry, where water clarity conditions fluctuate due to tides and wave action. SVR models achieved RMSE values below 1.5 meters in such challenging environments, outperforming traditional regression models in handling highly dynamic conditions.[93] These findings suggest that SVM and SVR are particularly effective for sites where spectral reflectance varies significantly due to the presence of sediments, algae, or coral formations.

Ensemble learning approaches have further strengthened machine learning applications in SDB.[89,93,94] These methods have demonstrated superior performance in handling complex seabed compositions and variable water conditions, particularly in regions with high turbidity. A study on reef bathymetry applications found that ensemble models improved spatial consistency across coral-dominated seafloors, reducing RMSE values and increasing robustness.[89] These findings highlight the advantage of ensemble models in integrating multiple weak learners to improve overall predictive accuracy.

Gaussian process regression (GPR) has also been explored in bathymetric mapping, particularly in data-limited environments.[95] Along the Indian coastline, GPR outperformed traditional regression techniques, achieving an R^2 value of 0.97 while providing uncertainty quantification, a crucial aspect for decision-making in coastal management applications. The study noted that GPR was particularly beneficial in cases where bathymetric training data were sparse, as the model was able to generalize well across different water types.[96]

Adaptive clustering methods,[97] such as Adaptive EllipseDBSCAN (AE-DBSCAN),[98] have further enhanced ML-based SDB applications. AE-DBSCAN dynamically adjusts clustering parameters based on the complexity of underwater terrain, refining data preprocessing for ML training. A study applying AE-DBSCAN to ICESat-2 datasets demonstrated that it improved depth predictions in complex coastal terrains where abrupt bathymetric changes occur.[34] These advancements in ML-based SDB significantly reduce reliance on in situ measurements while increasing predictive accuracy, particularly in optically complex coastal waters.[99]

6. Deep learning applications in SDB

Deep learning (DL) has emerged as a powerful tool in SDB, leveraging large-scale remote sensing data to extract spatial and spectral patterns associated with water depth automatically. Unlike traditional ML models, which require extensive feature engineering, DL models learn hierarchical representations of features, making them highly effective for depth estimation.[34]

6.1 CNNs for bathymetric estimation

Among the most widely used deep learning architectures for SDB, CNNs have demonstrated strong capabilities in extracting spatial patterns from remote sensing imagery, significantly improving depth estimation accuracy.[99,100] Studies have shown that CNN-based models trained on Sentinel-2 and Landsat-8 imagery outperform empirical and machine learning approaches, particularly in complex optical environments.[34] A study applied CNNs to Sentinel-2 imagery to estimate water depths in nearshore environments, where it achieved RMSE values ranging from 1.3 to 1.94 meters, highlighting CNNs' effectiveness in handling spectral and spatial variations.[101]

Further advancements in CNNs include their integration with multi-temporal Sentinel-2 imagery. A study found that CNNs trained on multi-date images performed better than those trained on single-date images, reducing RMSE errors and increasing the stability of depth estimations under variable atmospheric and water clarity conditions.[101] Additionally, CNNs have been used in hybrid models that incorporate LiDAR data from ICESat-2 to enhance prediction accuracy, particularly in turbid coastal environments.[102]

6.2 U-Net and segmentation-based architectures

U-Net, initially designed for medical image segmentation, has been adapted for bathymetric mapping due to its ability to efficiently capture spatial hierarchies.[103] A study using U-Net trained on a combination of optical and LiDAR datasets showed significantly lower RMSE values compared to traditional regression models,[104] demonstrating the architecture's suitability for complex seafloor topographies.[96] The integration of multi-scale feature extraction techniques further improved accuracy, particularly in environments with highly variable seabed compositions.

Another adaptation of U-Net has been the DeepUNet model, which incorporates additional edge-detection filters and convolutional layers to enhance bathymetric estimation in shallow-water environments. DeepUNet has proven particularly effective in mapping depth variations around coral reefs and estuarine regions, where seabed heterogeneity complicates depth retrieval from optical imagery alone.[105]

Wilson *et al*. (2020) explored SegNet,[106,107] a deep CNN architecture, to frame bathymetric mapping as a pixel-wise classification problem.[108] Using Sentinel-2 imagery and depth measurements from Humminbird™ sonar data, the model was trained to generate bathymetric maps with an F1-score of 0.734 and an AUC of 0.82. SegNet's performance demonstrated its effectiveness in generating pixel-wise depth classifications from high-resolution satellite data.

6.3 Deep belief networks and data perturbation methods

Deep belief networks (DBNs) have been successfully applied to bathymetric mapping, particularly in challenging shallow-water environments.[109] The DBN with Data Perturbation (DBN-DP) method has been introduced to enhance estimation robustness by introducing controlled noise into the training data, thereby significantly improving accuracy in areas with high optical complexity.[110] The DBN-DP model achieved RMSE values as low as 1.53 meters and a mean relative error (MRE) of 12.8%, outperforming traditional DBN and Backpropagation (BP) methods.

6.4 Transformer-based models for bathymetry mapping

Transformer architectures have recently been applied to SDB, leveraging self-attention mechanisms to analyze spatial and spectral dependencies across entire images. Unlike CNNs, which rely on localized receptive fields, Transformers capture long-range contextual information, improving depth estimation in diverse water conditions.[102]

A study comparing Vision Transformers (ViTs) with CNN-based models for bathymetry estimation found that ViTs performed better in environments with significant water column effects.[111] Hybrid Transformer-CNN models have also been tested, demonstrating improved feature extraction and depth prediction accuracy, particularly in coastal areas with dynamic sediment transport.[93]

These advancements in deep learning for SDB underscore the growing role of neural networks in enhancing bathymetric mapping. Future research is expected to focus on refining these models by integrating additional sensor modalities, such as hyperspectral imaging and SAR, further advancing the field of satellite-derived bathymetry.

7. Conclusion

The development of satellite-derived bathymetry represents a significant advancement in seafloor mapping, offering a cost-effective and large-scale alternative to traditional shipborne surveys. The integration of optical, LiDAR, and radar-based techniques has improved depth estimation across diverse aquatic environments, yet challenges remain in achieving high accuracy in turbid and optically complex waters. Advances in machine learning and deep learning have shown promise in refining bathymetric retrievals, particularly in coastal and coral reef environments where seabed heterogeneity complicates depth estimation. Future research should focus on enhancing the integration of multi-sensor data, improving atmospheric and turbidity correction models, and leveraging artificial intelligence for adaptive depth estimation algorithms. The continued development of high-resolution satellite missions, such as ICESat-2 and Sentinel-2, combined with data fusion techniques, will further strengthen the reliability and applicability of SDB. Addressing these challenges will enable more precise bathymetric mapping for applications in coastal management, marine conservation, and climate change monitoring, ultimately contributing to a more comprehensive understanding of global underwater topography.

Looking ahead, some exciting new technologies are likely to take SDB even further. Hyperspectral satellites like PRISMA and EnMAP offer hundreds of bands, letting scientists better distinguish between different water and seafloor types. There's also a lot of interest in quantum sensing, which could one day provide extremely sensitive measurements of the ocean floor. Plus, new satellite constellations and AI-powered underwater vehicles might soon allow real-time updates of bathymetric maps. When combined with deep learning models and advanced data fusion techniques, these tools could make it possible to generate global, high-resolution seafloor maps — even in complicated and remote areas.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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