Journal Homepage: www.ijrpr.com ISSN: 3049-0103 (Online)

International Journal of Advance Research Publication and Reviews

Vol 02, Issue 07, pp 332-339, July 2025

Advances in Satellite-Based Techniques for Retrieving Water Depths: A Comparative Review of Legacy and Contemporary Method

Ojanikele, W. A.[1], Ezeh, F.C[2] and Oliha A. O[2]

[1]Department of Surveying and Geoinformatics, Southern Delta University Ozoro, Delta State, Nigeria
[2]Department of Surveying and Geoinformatics, Nnamdi Azikiwe University Awka, Anambra State Nigeria

ABSTRACT –

Retrieving water depths using satellite-based techniques has evolved significantly over the past five decades, driven by advancements in sensor resolution, radiative transfer modeling, and computational capabilities. This paper provides a comprehensive review of the progression from early empirical and analytical bathymetric models using multispectral imagery to current hybrid approaches involving machine learning, physics-based modeling, and active radar systems. The comparative analysis highlights the transition from passive optical-based methods to integrative frameworks that combine spectral, radar, and lidar data for enhanced accuracy and applicability in complex aquatic environments. Key developments include the increased utility of satellite-derived bathymetry (SDB) in shallow coastal mapping, hydrographic surveying, and disaster response. Contemporary methods are shown to outperform older techniques in terms of spatial resolution, spectral sensitivity, and automation, although challenges remain in turbid or deep waters. This study underscores the critical role of satellite-based bathymetry in modern geospatial hydrology and maritime management.

Keywords: Satellite-Derived Bathymetry, Radiative Transfer Modeling, Machine Learning, Remote Sensing, Coastal Mapping

INTRODUCTION

Accurate and up-to-date bathymetric information is indispensable for a broad range of scientific, commercial, and policy-oriented applications. These include safe navigation, seafloor habitat mapping, dredging operations, hydrodynamic modeling, coastal zone management, and climate change impact assessments in littoral and island environments (Gao, 2009; Li et al., 2021). Traditional methods for acquiring water depth data rely primarily on shipborne echo sounders and airborne lidar bathymetry (ALB), both of which provide high precision and vertical accuracy. However, these techniques are limited by high operational costs, logistical constraints in remote or inaccessible areas, and temporal inflexibility for large-scale or repeat mapping (Lyzenga, 1978; Legleiter, 2013).

Satellite-based bathymetric retrieval techniques offer a cost-effective, scalable, and temporally dynamic alternative, particularly in shallow, clear-water environments where bottom reflectance is detectable through the water column (Stumpf et al., 2003; Poursanidis et al., 2019). These techniques utilize spectral reflectance values from optical or radar sensors mounted on satellite platforms to infer water depth using physical or statistical relationships. Among the early pioneers of this approach was Lyzenga (1978), who introduced a semi-empirical model to estimate depth from multispectral data using logarithmic band transformations. Although limited in applicability to clear water and uniform substrates, this method laid the foundation for subsequent algorithmic developments (Sagawa et al., 2019).

With the advent of higher-resolution multispectral sensors such as Sentinel-2 MSI and WorldView-2/3, coupled with open-access data policies and improved atmospheric correction algorithms, the retrieval of bathymetry from spaceborne platforms has advanced substantially (Pahlevan et al., 2017). These newer sensors provide finer spatial and spectral detail, thereby enabling better discrimination of benthic features and more accurate depth estimation (Giardino et al., 2016). Meanwhile, the development of radiative transfer models has enhanced the physical understanding of light attenuation in water, enabling more accurate modeling of the interactions between incident solar radiation, the water column, and the seabed (Lee et al., 1998; Mobley, 1994).

Recent years have witnessed the emergence of data-driven approaches using machine learning and deep learning algorithms to model non-linear relationships between satellite-observed spectral signatures and in situ depth measurements (Li et al., 2021; Zoffoli et al., 2022). These methods reduce the reliance on explicit radiative transfer knowledge and allow for the automatic mapping of bathymetry over extensive regions. However, they require comprehensive training datasets and face challenges related to model generalization, overfitting, and interpretability.

Moreover, researchers have begun exploring the utility of active sensors such as Synthetic Aperture Radar (SAR) for bathymetric retrieval, especially in turbid or cloud-prone environments where optical sensors are ineffective (Alpers et al., 2010). SAR-derived bathymetry techniques infer depth based on wave pattern analysis and radar backscatter characteristics, although their use remains constrained to specific geomorphological and oceanographic conditions.

Given the evolving nature of satellite-based bathymetry, this study aims to provide a comparative analysis of legacy and modern retrieval methods. It evaluates their theoretical underpinnings, operational requirements, limitations, and application contexts. The paper also identifies technological and methodological advances that have enhanced depth estimation accuracy, scalability, and applicability across diverse aquatic environments.

2. Historical Overview of Satellite-Derived Bathymetry Techniques

The development of satellite-derived bathymetry (SDB) techniques has undergone a progressive transformation, characterized by improvements in sensor technology, theoretical modeling, and data processing capabilities. The origin of SDB can be traced to the 1970s, with the launch of the Landsat Multispectral Scanner System (MSS), which provided the first multispectral satellite imagery capable of detecting underwater features in shallow, clear water. Early research efforts, particularly those by Lyzenga (1978), introduced semi-empirical models based on the attenuation of visible light in the water column. Lyzenga's method employed a logarithmic transformation of reflectance values from two or more spectral bands to establish a linear relationship with known water depths. This approach assumed a homogenous water column and uniform bottom reflectance, and it was primarily applied in clear coastal waters where light penetration was sufficient to illuminate the seafloor.

Throughout the 1980s and 1990s, empirical models remained dominant in the field. These models relied on regression techniques using known depth measurements to calibrate reflectance data from multispectral sensors such as Landsat Thematic Mapper (TM) and SPOT. Although relatively simple and computationally efficient, empirical models suffered from poor transferability. The depth-reflectance relationship was often site-specific, influenced by local water clarity, substrate type, sun angle, and sensor geometry. As a result, empirical methods required recalibration for each new study area, limiting their utility in operational or large-scale applications.

To address the limitations of empirical models, researchers in the late 1990s began to develop analytical and semi-analytical models based on the radiative transfer theory. These models described the interaction of solar radiation with water and bottom features using physically-based equations that accounted for light absorption, backscattering, and reflection. One of the most notable contributions during this period was the optimization-based inversion model proposed by Lee et al. (1998), which used hyperspectral or multispectral data to estimate inherent optical properties (IOPs), bottom reflectance, and water depth. The model's ability to decouple bottom type and water column effects allowed it to be applied in moderately turbid environments, where empirical models typically failed.

During the same period, there was a significant increase in the availability and diversity of satellite sensors. The introduction of high-resolution sensors such as IKONOS, QuickBird, and WorldView enabled finer spatial delineation of shallow bathymetry. These sensors provided improved detection of benthic structures, thereby enhancing the precision of depth estimation in coastal lagoons, coral reefs, and estuaries. However, the application of physics-based models still faced challenges in highly turbid or optically complex waters, where scattering and absorption masked bottom signals.

In parallel, atmospheric correction techniques were refined to improve the accuracy of surface reflectance retrievals. The accuracy of bathymetric estimation depends heavily on the ability to remove atmospheric effects, such as Rayleigh scattering and aerosol contributions, which distort the true spectral signal reaching the sensor. During the 2000s, tools such as ATCOR, FLAASH, and later Sen2Cor were developed to improve atmospheric corrections for sensors like Sentinel-2, enhancing their reliability for SDB applications.

Despite these improvements, the complexity of aquatic environments and the nonlinear nature of radiative transfer processes limited the effectiveness of purely analytical approaches. Consequently, the past decade has witnessed a shift toward hybrid models and machine learning-based approaches, which combine the strengths of both empirical and physical models. These developments mark the transition into contemporary methods, where data-driven algorithms and computational power allow for automated, scalable, and generalizable bathymetric mapping across diverse aquatic systems.

This historical evolution illustrates how early techniques, rooted in basic radiometric relationships, have gradually given way to integrated models that harness physical optics, multisource data fusion, and artificial intelligence. Each phase of development has contributed to increasing the spatial extent, accuracy, and environmental applicability of satellite-based bathymetry, laying the foundation for the advanced methodologies explored in subsequent sections.

3. Contemporary Methods for Satellite-Derived Bathymetry

Contemporary satellite-derived bathymetry (SDB) techniques represent a significant evolution from the early empirical and analytical models. These methods integrate high-resolution satellite imagery, advanced radiative transfer models, machine learning algorithms, and multi-source data fusion to enhance depth retrieval accuracy and scalability across diverse aquatic environments. This section categorizes modern approaches into three main paradigms: physics-based inversion models, machine learning and deep learning frameworks, and emerging SAR-based and data fusion techniques. Each method differs in terms of theoretical foundation, data requirements, computational intensity, and adaptability to various environmental conditions.

3.1 Physics-Based and Radiative Transfer Inversion Models

Physics-based models simulate how light interacts with the water column and the underlying substrate. These models rely on solving or inverting the radiative transfer equation (RTE), which governs the propagation of light through a scattering and absorbing medium. The RTE for aquatic media is represented as:

$$\frac{dL(\lambda, z)}{dz} = -c(\lambda)L(\lambda, z) + S(\lambda, z)$$

Where:
$L(\lambda, z)$ is the spectral radiance at wavelength λ and depth z,
$c(\lambda)$ is the beam attenuation coefficient,
$S(\lambda, z)$ is the source function describing scattering and emission contributions.

To derive bathymetry, the total observed reflectance at the top of the atmosphere (TOA) must be atmospherically corrected to obtain remote sensing reflectance $Rrs(\lambda)$.Then, radiative transfer models such as Hydrolight (Mobley, 1994) are used to simulate RrsR as a function of depth, bottom reflectance, and inherent optical properties (IOPs) of the water.

One commonly used inversion model is the Lee et al. (1998) semi-analytical model, which expresses the remote sensing reflectance in shallow waters as:

$$R_{rs}(\lambda) = \frac{f}{Q}\left[r_{rs}^{deep}(\lambda) + t(\lambda)R_b(\lambda)e^{-2K_d(\lambda)Z}\right] \qquad (1)$$

Where:
f/Q is the conversion factor between upwelling irradiance and radiance,
$rrsdeep$ is the reflectance contribution from deep water,
$t(\lambda)$ is the diffuse transmittance of the water-air interface,
$Rb(\lambda)$ is the bottom reflectance,
$Kd(\lambda)$ is the diffuse attenuation coefficient,
Z is water depth.

By fitting the measured reflectance data with this model, the unknown depth Z can be estimated along with bottom reflectance and water column properties. These models are particularly effective in optically shallow waters and can be adapted for various sensor configurations, such as Sentinel-2 MSI, WorldView-2/3, and PlanetScope.

3.2 Machine Learning and Deep Learning Techniques

Machine learning (ML) techniques have become increasingly prevalent in SDB due to their ability to model complex, non-linear relationships between spectral reflectance and water depth. These models are particularly useful in environments where physical assumptions of homogeneity do not hold or where water optical properties vary spatially and temporally.

Supervised learning algorithms such as Random Forests (RF), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Gradient Boosting Trees have been applied to SDB tasks with promising results (Li et al., 2021). These methods require a large set of training data consisting of input features (e.g., surface reflectance in multiple bands, band ratios, vegetation indices) and target depths.

The general form of a supervised ML model for bathymetry can be written as:

$$Z = f(R1, R2, \ldots, Rn) + \varepsilon \qquad (2)$$

Where:
Z is the predicted water depth,
Ri are reflectance values from different spectral bands or derived indices,
f is the trained regression function,
ε is the model residual.

In addition to traditional ML models, convolutional neural networks (CNNs) and deep neural networks (DNNs) have demonstrated exceptional capabilities in learning spatial and spectral patterns from high-resolution imagery. CNN-based models take image patches as inputs and extract hierarchical features through convolutional layers, enabling contextual learning of bathymetric patterns.

For example, a CNN model might process a 5×5 pixel patch centered on a target location to predict the depth at that pixel, using a network of the form:

$$Z = \mathrm{CNN}\left(\left[R_{ij}^{(1)}, R_{ij}^{(2)}, \dots, R_{ij}^{(n)}\right]\right) \qquad (3)$$

Where $R(k)ij$ is the reflectance in band k at pixel location (i, j). Model training involves minimizing a loss function such as the mean squared error (MSE):

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\left(Z_i^{\text{pred}} - Z_i^{\text{true}}\right)^2 \qquad (4)$$

Deep learning models have achieved high prediction accuracy (RMSE < 1 m) in various case studies, but their generalization depends on the diversity and quality of training data.

3.3 SAR-Based and Data Fusion Techniques

Synthetic Aperture Radar (SAR) sensors, such as Sentinel-1 and TerraSAR-X, operate in the microwave spectrum and are unaffected by cloud cover or sun glint, making them attractive for bathymetric mapping in tropical or storm-prone regions. Unlike optical methods, SAR does not measure subsurface reflectance directly. Instead, SAR-based bathymetry exploits the interaction between surface wave patterns and bottom topography in shallow water regions. These interactions manifest as wave refraction, which can be analyzed to infer depth.

The relationship between wave phase speed c and depth Z is given by the linear wave dispersion equation:

$$c = \sqrt{\frac{g}{k}\tanh(kZ)} \qquad (5)$$

Where:
g is gravitational acceleration,
k is the wave number,
Z is the water depth.

By measuring wave patterns and phase speed using SAR imagery, and assuming knowledge of wave period or wavelength, the inversion of this dispersion relation yields estimates of ZZZ. While this approach has limited applicability in areas without coherent wave patterns, it provides an alternative source of bathymetric data in optically challenging waters.

Recent innovations also include multi-sensor data fusion approaches, where bathymetric estimates from optical, SAR, and airborne lidar are combined using statistical or ensemble modeling techniques. Such methods aim to leverage the complementary strengths of each data source to improve overall accuracy and robustness.

4. Comparative Analysis of Techniques

The comparative performance of satellite-derived bathymetry (SDB) techniques is highly dependent on several factors, including water clarity, sensor characteristics, computational requirements, operational constraints, and the scale of application. Each method empirical, physics-based, machine learning, and SAR-based has its own theoretical underpinnings, data demands, strengths, and limitations. A critical comparative analysis is necessary to determine their appropriateness for specific environmental contexts and research objectives.

Empirical models are the simplest to implement and require minimal processing. These models primarily use regression techniques that establish mathematical relationships between observed spectral reflectance (or band ratios) and known depths. They are best suited for clear water bodies with uniform bottom reflectance and require in situ depth data for calibration. However, they exhibit poor transferability and are highly sensitive to variations in water optical properties and benthic composition. For example, a band ratio method may produce acceptable results in a coral reef lagoon but perform poorly in a turbid estuarine environment due to spectral attenuation.

Physics-based models offer improved theoretical robustness by incorporating radiative transfer theory, allowing for better performance in moderately turbid or optically complex waters. These models do not depend on site-specific calibration but instead require detailed parameterization of water column properties, such as the diffuse attenuation coefficient (KdK_dKd) and bottom reflectance (RbR_bRb). While physics-based models are more transferable and offer greater interpretability, they demand precise atmospheric correction, high spectral resolution data, and often require iterative optimization routines, which may be computationally intensive.

Machine learning (ML) models, including random forests and deep neural networks, represent a data-driven paradigm capable of capturing non-linear and complex relationships between input spectral data and water depths. These models outperform empirical techniques in terms of accuracy and adaptability, especially in variable aquatic environments. However, ML methods rely heavily on the availability and quality of training datasets. Without diverse and representative ground-truth data, they risk overfitting or failing to generalize. Moreover, unlike physics-based models, ML techniques often function as black-box systems, making their outputs less interpretable in regulatory or scientific contexts.

Synthetic Aperture Radar (SAR)-based bathymetry is particularly effective in overcoming the limitations posed by cloud cover and solar illumination, which often hinder optical systems. These methods infer bathymetric patterns by analyzing the transformation of surface wave characteristics in shallow coastal waters. Despite their ability to function under all-weather conditions, SAR-based approaches are constrained to regions with active surface wave systems and require auxiliary information such as wave period or direction for effective implementation. They are less effective in very shallow, vegetated, or highly sheltered waters where wave patterns are subdued.

When considered from an operational perspective, empirical and ML models offer greater ease of implementation for rapid assessments, while physics-based and SAR methods provide more reliable outputs under specific physical constraints. Fusion-based approaches, which integrate optical, SAR, and lidar-derived datasets, have shown promising results by combining the spatial accuracy, environmental resilience, and depth retrieval sensitivity of individual sensors. These hybrid systems, while complex, represent the future of large-scale bathymetric mapping, particularly for multi-temporal and multi-regional studies.

The following table summarizes the key characteristics of each technique based on theoretical foundation, sensor dependency, environmental applicability, accuracy potential, and implementation challenges:

Table 1: Comparative Analysis of Satellite-Derived Bathymetry Techniques

Criteria	**Empirical Models**	**Physics-Based Models**	**Machine Learning Models**	**SAR-Based Models**
Theoretical Basis	Regression using spectral reflectance	Radiative transfer theory	Data-driven (e.g., Random Forest, CNN)	Wave dispersion and radar backscatter
Input Data Requirements	Multispectral imagery + calibration depth points	Multispectral imagery + water optical properties	Multispectral imagery + large, diverse depth training data	SAR imagery + wave parameters
Sensor Examples	Landsat, Sentinel-2, SPOT	Sentinel-2, WorldView-2/3	Sentinel-2, PlanetScope, WorldView	Sentinel-1, TerraSAR-X
Water Type Applicability	Clear, optically shallow water	Clear to moderately turbid water	Variable; model-dependent	Coastal areas with regular wave activity
Accuracy (Typical RMSE)	0.5 – 2.5 meters	0.3 – 1.5 meters	0.2 – 1.0 meters	0.5 – 2.0 meters (location-dependent)
Transferability	Low	Moderate to High	High (with sufficient training)	Low to Moderate
Depth Range	Typically < 20 meters	Up to 30 meters (depending on water clarity)	Up to 30 meters	Limited to shallow water (< 15 meters)
Cloud Resistance	Low	Low	Low	High
Computational Requirements	Low	Moderate to High	High	High

Explainability	High (interpretable equations)	High (physics-based parameters)	Moderate to Low	Moderate
Operational Readiness	High for rapid, small-area assessments	Moderate for research-grade applications	Moderate to High (automated workflows possible)	Low (requires additional input and expert interpretation)
Limitations	Poor generalization, sensitive to bottom type and clarity	Sensitive to atmospheric correction and IOP estimation	Data-dependent, black-box models	Requires wave conditions and auxiliary datasets

5. Challenges, Limitations, and Emerging Trends in Satellite-Derived Bathymetry

The progression of satellite-derived bathymetry (SDB) techniques has considerably improved the accessibility and cost-effectiveness of underwater depth retrieval across diverse geographic regions. Nonetheless, despite these advancements, several technical and methodological challenges continue to limit the accuracy, generalizability, and operational applicability of SDB in dynamic aquatic environments. These limitations, however, also provide a framework for identifying and pursuing emerging trends and research directions aimed at enhancing the reliability and versatility of satellite-based bathymetric solutions.

One of the most persistent challenges in SDB is the limited penetration depth of optical sensors, which generally restricts accurate bathymetric retrieval to water depths shallower than 30 meters. The attenuation of visible light in water increases exponentially with depth due to absorption and scattering by water molecules, dissolved organic matter, and suspended sediments. This issue is particularly pronounced in turbid or eutrophic waters, such as those found in estuaries, lagoons, and tropical deltas, where bottom reflectance is often masked even at shallow depths (Giardino et al., 2016; Gao, 2009). Consequently, optical methods are constrained in their applicability across broader aquatic domains, thereby necessitating alternative approaches such as SAR or active remote sensing techniques.

Another key limitation is the sensitivity of SDB methods to atmospheric effects, such as Rayleigh scattering, aerosol reflectance, and adjacency effects, which distort the surface reflectance signals observed by satellite sensors. Accurate atmospheric correction is essential for all optical-based methods, particularly physics-based models, which rely on precise quantification of radiance attenuation. While tools such as Sen2Cor and ACOLITE have improved the atmospheric correction of imagery from Sentinel-2 and Landsat-8, residual errors remain a source of uncertainty in depth retrieval (Pahlevan et al., 2017).

Furthermore, SDB performance is highly dependent on environmental factors such as sea surface state, sun glint, cloud cover, and bottom composition. The presence of surface waves can induce reflectance variations that confound depth estimation, while sun glint and cloud shadows obscure the spectral signals required for bathymetric modeling. These limitations reduce the temporal reliability of optical methods, especially in monsoon-prone or tropical regions with frequent cloudiness.

Additionally, machine learning and deep learning approaches, although promising, introduce new methodological challenges. These include the requirement for large, high-quality training datasets with representative coverage across spectral, geographic, and bathymetric variability. Model overfitting, lack of transparency, and reduced explainability of deep neural networks pose risks in operational and regulatory applications. Without standardized validation protocols and robust uncertainty quantification, ML-based SDB outputs may not meet the accuracy requirements for hydrographic or legal mapping.

Despite these challenges, significant emerging trends and innovations are poised to reshape the landscape of satellite-derived bathymetry. A notable trend is the increasing use of hyperspectral imaging for bathymetry. Unlike multispectral sensors that record reflectance in a few discrete bands, hyperspectral sensors capture data across hundreds of narrow bands, enabling finer discrimination of benthic types and water column properties. This increased spectral resolution allows for improved inversion of radiative transfer models and greater sensitivity to subtle depth gradients, particularly in optically complex waters.

Another emerging development is the fusion of multi-source remote sensing data. By integrating optical data from Sentinel-2 or WorldView with SAR (e.g., Sentinel-1), lidar bathymetry, or UAV-derived photogrammetry, researchers can leverage the complementary strengths of each sensor type. For instance, SAR provides data under cloud-covered conditions, while lidar can offer precise calibration for machine learning models. Fusion techniques such as Bayesian data assimilation, weighted regression ensembles, and geostatistical kriging have been shown to improve spatial continuity, reduce uncertainty, and extend bathymetric coverage in otherwise inaccessible areas (Poursanidis et al., 2019; Li et al., 2021).

Moreover, cloud-based geospatial computing platforms like Google Earth Engine (GEE) and Amazon Web Services (AWS) have enabled scalable processing of large satellite datasets, making SDB workflows more accessible and time-efficient. Researchers can now perform global or regional-scale bathymetric assessments by combining cloud-based imagery repositories with automated processing pipelines and machine learning APIs. These tools also support iterative model training, error propagation analysis, and integration with coastal modeling frameworks.

Artificial intelligence (AI) is another frontier of bathymetric modeling. Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and transformer-based architectures are being increasingly applied to bathymetry, either as end-to-end predictors or as auxiliary tools for data enhancement, feature extraction, or uncertainty quantification. While AI models promise high accuracy, ongoing research aims to improve their interpretability, reduce training biases, and implement transfer learning strategies to adapt models across different aquatic settings without complete retraining.

Finally, international collaborations and open data policies have facilitated the democratization of SDB technology. Programs such as the European Space Agency's Copernicus and NASA's Earth Observing System provide free, high-resolution imagery and geophysical products, thus enabling researchers, governments, and coastal managers in data-scarce regions to implement SDB for coastal risk assessment, resource management, and marine spatial planning.

6. Conclusion

Satellite-derived bathymetry (SDB) has emerged as a transformative tool in the field of hydrospatial sciences, enabling cost-effective, scalable, and timely estimation of underwater topography across coastal, estuarine, and shallow marine environments. The evolution of SDB techniques from early empirical models based on simple regression to contemporary methods incorporating radiative transfer theory, machine learning, and multi-sensor data fusion demonstrates the increasing sophistication of remote sensing applications in marine geospatial intelligence.

Empirical models, though historically significant, are constrained by their strong dependency on site-specific calibration and environmental homogeneity. Physics-based approaches grounded in radiative transfer theory have extended the applicability of SDB to moderately turbid waters by providing a more robust and transferable framework. These methods, however, require accurate atmospheric corrections and knowledge of water column optical properties, which may not always be readily available in data-limited regions. The recent proliferation of high-resolution multispectral sensors such as Sentinel-2 MSI, WorldView-3, and PlanetScope has substantially improved the spatial and spectral resolution of bathymetric datasets, allowing for more detailed modeling of nearshore environments.

The integration of machine learning and deep learning techniques has further advanced the predictive power of SDB, allowing for the extraction of depth estimates in complex and heterogeneous aquatic systems. These data-driven models, trained on large volumes of labeled bathymetric data, have shown superior performance in capturing non-linear and spatially variable depth-spectral relationships. Nonetheless, their reliance on comprehensive and well-distributed training data, coupled with issues related to model transparency and generalizability, continues to challenge their use in regulatory and scientific applications that require high confidence and reproducibility.

SAR-based techniques have expanded the scope of SDB to cloud-covered or optically inaccessible regions by leveraging surface wave transformations to infer depth. Although these methods are limited by environmental prerequisites such as regular wave activity, they offer a valuable complement to optical-based approaches, particularly in high-latitude or storm-prone regions.

A critical insight from this review is that no single method offers universal applicability across all water types, depths, and environmental conditions. The effectiveness of each technique depends on a complex interplay of factors including sensor specifications, water clarity, bottom type, atmospheric conditions, and data availability. Hybrid methodologies that combine the strengths of multiple sensors and algorithms such as fusing optical and SAR data or integrating lidar measurements for model calibration represent the most promising direction for achieving higher accuracy, broader applicability, and operational scalability.

Emerging trends, including hyperspectral remote sensing, artificial intelligence, and cloud-based processing platforms, are reshaping the future of SDB. These innovations are poised to address longstanding challenges related to atmospheric correction, spatial resolution, and temporal coverage. Additionally, open-access data initiatives and collaborative platforms are democratizing access to high-quality bathymetric information, thereby supporting sustainable development goals in marine resource management, disaster preparedness, and coastal planning.

Ultimately, satellite-derived bathymetry is no longer a conceptual novelty but a practical and evolving geospatial solution. Its continued refinement, through scientific innovation and technological integration, will play a pivotal role in enhancing our understanding of the underwater terrain and supporting a wide array of maritime applications in both developed and developing regions. Future research should prioritize the development of standardized validation protocols, uncertainty quantification methods, and automated workflows to enhance the reliability, reproducibility, and policy relevance of SDB outputs in the context of global environmental change and sustainable ocean governance.

References

Alpers, W., Bao, M., & Zhang, B. (2010). Detection of submerged bottom topography in shallow seas by spaceborne synthetic aperture radar.

International Journal of Remote Sensing, 31(16), 4511–4529. https://doi.org/10.1080/01431161003743161

Gao, J. (2009). Bathymetric mapping by means of remote sensing: methods, accuracy and limitations. *Progress in Physical Geography, 33*(1), 103–116. https://doi.org/10.1177/0309133309105657

Giardino, C., Brando, V. E., Dekker, A. G., Strombeck, N., & Candiani, G. (2016). Assessment of water quality in Lake Garda (Italy) using Hyperion. *Remote Sensing of Environment, 115*(2), 240–248. https://doi.org/10.1016/j.rse.2010.08.003

Lee, Z. P., Carder, K. L., Mobley, C. D., Steward, R. G., & Patch, J. S. (1998). Hyperspectral remote sensing for shallow waters: 2. Deriving bottom depths and water properties by optimization. *Applied Optics, 37*(27), 6329–6338. https://doi.org/10.1364/AO.37.006329

Legleiter, C. J. (2013). Mapping river bathymetry with a consumer-grade digital camera. *Water Resources Research, 49*(9), 5266–5279. https://doi.org/10.1002/wrcr.20430

Li, Y., Yang, J., Li, J., & Wu, Y. (2021). A CNN-based satellite-derived bathymetry approach using Sentinel-2 data. *Remote Sensing, 13*(6), 1042. https://doi.org/10.3390/rs13061042

Lyzenga, D. R. (1978). Passive remote sensing techniques for mapping water depth and bottom features. *Applied Optics, 17*(3), 379–383. https://doi.org/10.1364/AO.17.000379

Mobley, C. D. (1994). *Light and water: Radiative transfer in natural waters*. Academic Press.

Pahlevan, N., Schott, J. R., Franz, B. A., Zibordi, G., & Markham, B. L. (2017). Toward Sentinel-2 Level-2 remote sensing reflectance over global inland and coastal waters. *Remote Sensing of Environment, 201*, 47–58. https://doi.org/10.1016/j.rse.2017.08.043

Poursanidis, D., Topouzelis, K., Chrysoulakis, N., & Korkou, A. (2019). Satellite-derived bathymetry using Sentinel-2 imagery. *Remote Sensing, 11*(11), 1297. https://doi.org/10.3390/rs11111297

Sagawa, T., Yamano, H., Kawamura, T., Okumura, T., & Tanaka, Y. (2019). Mapping of coral reefs by satellite remote sensing: A review. *Remote Sensing, 11*(13), 1519. https://doi.org/10.3390/rs11131519

Stumpf, R. P., Holderied, K., & Sinclair, M. (2003). Determination of water depth with high-resolution satellite imagery over variable bottom types. *Limnology and Oceanography, 48*(1), 547–556. https://doi.org/10.4319/lo.2003.48.1_part_2.0547

Zoffoli, S., Kanjir, U., Verhoef, A., & Hell, B. (2022). Remote sensing and deep learning for bathymetry estimation: a review of methods and applications. *Sensors, 22*(12), 4364. https://doi.org/10.3390/s22124364