Journal Pre-proof

Review of near-shore satellite derived bathymetry: classification and account of five decades of coastal bathymetry research

Mohammad Ashphaq , Pankaj K Srivastava , D Mitra

PII: S2468-0133(21)00021-8
DOI: https://doi.org/10.1016/j.joes.2021.02.006
Reference: JOES 210

To appear in: *Journal of Ocean Engineering and Science*

Received date: 22 October 2020
Revised date: 24 February 2021
Accepted date: 27 February 2021

Highlights

- Application of Satellite Derived Bathymetry Surveying as an alternate to overcome Complexity of Hydrographic Surveying and other Bathymetric techniques
- Account of Satellite derived bathymetry for five decades and its systematic Classification scheme grounded in research philosophy
- SDB Approaches, models, methods and techniques along with chronological development of SDB Algorithms, Application studies, their accuracy and errors in retrieval
- A matrix of prerequisite satellite data, in-situ data resolution, methods and algorithms of SDB based on level of accuracy needs to be achieved for future researchers.
- Operationalisation of satellite SDB products in coastal water

Review of near-shore satellite derived bathymetry: classification and account of five decades of coastal bathymetry research

Mohammad Ashphaq[1,*], Pankaj K Srivastava[2], D Mitra[3]

1. National Hydrographic Office, Dehradun

2. University of Petroleum & Energy Studies (UPES), Dehradun

3. Indian Institute of Remote Sensing, Dehradun

* Correspondence: ashphaq.md824@nic.in

ABSTRACT

The number of civilian, commercial and military applications are dependant on accurate knowledge of bathymetry of coastal regions. Conventionally, hydrographic surveying methods are used for bathymetric surveys carried by ship-based acoustic systems, but needs high-cost resources. Space technology has provided a cost-effective alternate means for charting near shore and inaccessible waters. The optical satellite data have capabilities to offer alternate solution in near-shore region, which has been researched for past 50 years, using evolving algorithms to estimate Satellite Derived Bathymetry (SDB). However, there is no agreement on use of terms like approach, model, method and techniques, which have been used varyingly and interchangeably as per context of SDB research. This paper suggests a classification scheme for SDB algorithms which is also applicable to other Marine Remote Sensing studies.

In this paper, based on literature available on SDB for the past five decades, an insight on SDB classification has been offered grounded in research philosophy. The SDB Approaches, models, methods and techniques have been elaborated with chronological development, along with SDB studies based on them, their accuracy and errors in SDB retrieval. We have suggested a matrix of prerequisite satellite data, in-situ data resolution, methods and algorithms of SDB based on level of accuracy needs to be achieved, which will guide future researchers to select one as per their context of research.

Keywords: Satellite Derived Bathymetry, Hydrography, Bio-optical Model, Physio-optical Model

Abbreviations: ANN-Artificial Neural Network; AOP-Apparent Optical Property; Chl-Chlorophyll; AUV-Autonomous Underwater Vehicle; CDOM-Colored Dissolved Organic Matter; IOCCG-International Ocean Colour Coordinating Group; IHO-International Hydrographic Office; HS-hyper-spectral; IOP-Inherent Optical Properties; LUT-Look-Up-Table; MLR-Multiple Linear Regression; ML-Machine Learning; MS-Multi-Spectral; MBES-Multi Beam Eacho-Sounder; NIR-Near-Infrared; PCA-Principal Component Analysis; RS-Remote Sensing; RT-Radiative Transfer; SA-Semi-Analytical; SBES-Single Beam Echo-Sounder; Semi-Empirical-SE; QA-Quasi-Analytical

Acknowledgement: The authors would to thank the Dr. Richard P. Stumpf, NOAA, National Ocean Service, for their comments that have improved the presented SDB classification scheme.

1. INTRODUCTION

The importance of accurate knowledge of bathymetry is manifested in its application areas, which includes, marine navigation, harbours, submarine pipelines & cables laying, etc. Bathymetric surveys use traditional methods of collecting data mostly by acoustic echo sounding technique. The acoustic echo-sounding is done by two different methods; Single Beam Echo Sounding (SBES) which provides less coverage and spatial data resolution, and Multi Beam Echo Sounding (MBES) which provides better coverage and depict underwater topography by complete insonification of the area. The sensor development was further advanced by evolving depth profilers, current profilers, bio-optical sensors, etc. further increasing the accuracy of data collection.

Recently, various modern techniques have been adopted to determine the bathymetry of the ocean, this includes LIDAR operated from aerial platforms, use of Remotely Operated Vehicles (ROV’s) & Autonomous Underwater Vehicles (AUV’s) for effective determination of depth in coastal waters. The cost of operation for Hydrographic surveying is very high, which restricts repetitive and frequent survey in any area of interest. Besides, in shallow waters regions the scanning width of the echosounders becomes narrow limiting coverage. Some remote and difficult areas such as massive hidden reefs, creeks and estuaries, tides bores and surge areas are so complex to undertake hydrographic surveys due to risk of life of men and loss of materials. The remote and autonomous technologies like ROV & AUV are also very expensive for its high purchasing and maintenance costs. It needs huge resources to undertake frequent hydrographic surveys in countries like India having coastline of more than 7500 kms. This has led researchers, way back since the 1970's to search for alternative methods to bathymetric surveying. One of the practical solutions to assess dynamic changes in the vast coastal region with reasonable accuracy was provided by space technology.

The objective of the paper is to critically analyse the relevance and shortcomings of SDB algorithm development over the past five decades. Algorithms have been categorized into empirical, semi empirical, quasi analytical, analytical on the basis of statistical, bio-optical and physical optical properties. This paper aims to establish the suitability of algorithms in varying coastal depths.

1.1 Satellite Derived Bathymetry Methods

The viable alternatives researched for the past five decades is SDB, which effectively provides a key solution to coastal regions characterized by swift seabed changes and complex areas. However, these methods have potential to generate results, relatively based on existing ins-situ bathymetric data. The SDB Method was developed based on the theory of underwater reflectance, underwater optics, and algorithms to derive SDB using optical remote sensing data (Polcyn, 1969 & Colleagues). Simultaneously other groups of researchers focused on other methods to derive SDB, using Satellite Altimetry data (Haxby et al., 1983; Dixon et al., 1983) and SAR data (Alpers, & Hennings, 1984).

Synthetic Aperture Radar (SAR) data is used to estimate coastal bathymetry in site specific conditions like high energetic wave area with several limiting factors such as the intensity of the swells, relationship between swell and sea waves. Although SAR data has moderate resolution and coverage, it is complex to derive the required input parameter and implement an algorithm. This technique is unreliable in shallow coastal waters (Wiehle, Pleskachevsky, & Gebhardt, 2019). Another group of researchers has used satellite altimeter measurements along with sparse in-situ bathymetry to derive a low-resolution bathymetry of the seafloor. The satellite altimetry data has comparatively very low accuracy and resolution to have utility in coastal regions (Smith & Sandwell, 2004). Thus, the only option that assures feasibility to provide alternatives to bathymetric surveying with similar accuracy level, but low cost is multispectral optical data (especially Multispectral). Availability of high resolution optical data and improvement in algorithms has led to significant improvement in mapping of seabed topography. The optical data has been used for the past 50 years by different researchers, using evolving algorithms. The existing bathymetry techniques are summarized below in table 1 representing sensible depth, accuracy, strength and limitations of each technique.

Table 1: Summary of Bathymetry (Modified after Jawak, Vadlamani, & Luis, 2015)

Method	System	Sensible depth	Accuracy	Affecting factors	Strengths	Limitations	Applications
Ship based Systems Echo Sounders	**Singlebeam ES**	Shallow to deep	High	Single Footprint	Highly reliable Wide depth range	Expensive, High cost of operation	Diverse environments as per the IHO Standards
	Multibeam ES	Shallow to deep	Very high	Swath, Heave	High Precision Wide depth range	Expensive High cost of operation	Diverse environments with Very High Resolution
Non-imaging Active RS	**LiDAR**	Up to 70 m	Very high	Water clarity, bottom material, surface state, background light	Wide depth range; concurrent measurement not essential	Expensive Limited swath width	Clear waters with Very High Resolution
	Radar Altimetry	Beyond 40 km From the coast	Very Low	Elastic thickness Of lithosphere and/or Crustal thickness, sediments	Global coverage, needs Only simple altimetry with no iono / troposphere measurement	Possible over a limited Wavelength band	Coarse bathymetry Derivation in open ocean Deep seas & Oceans with accuracy of ± 50 m
Imaging Active RS	**Microwave / SAR Spaceborne**	Shallow to deep	Low	Image resolution slicks, fronts, weather condition (eg, waves)	Over large areas Not subject to cloud cover	Complex and Not so accurate	Open, coastal and oceanic waters but Unreliable, Low accuracy
Imaging Passive RS	**Optical – analytical**	Up to 30 m	High	Water quality, atmospheric conditions	Based on physical Process, Accurate	Complex as several input parameters required Concurrent sea truth essential	Turbid and shallow inland waters, estuary and river Nearshore and coastal waters Theoretically, the 0.48–0.60 μm radiation is able to penetrate clear, calm sea water up to 20 m.
	Optical – empirical	Up to 30 m	Varying	Atmospheric calibration, water turbidity Bottom reflectance	Simple to implement Accurate at certain depth	Limited depth Accuracy lower at a depth Concurrent sea truth essential	
	Video	Tidal	High	Image resolution	Able to reveal minor	Restrictive area,	Shallow water with

		height			bathymetric change	Bathymetry along profiles	vegetation; accuracy not yet established

1.2 Optical SDB

The optical SDB derivations rely on reflected radiant energy of EMR in the visible spectrum, intensity of which decays gradually with depth due to IOP's of the water column in the coastal region. The various confounding factors that limit radiance are induced by signal attenuation by atmosphere, water column properties, nature of seabed, and depth of water. The core doctrine of remote sensing methods is to identify most of unknown parameters with the help of coarsely collected known parameters from field observation. Thus, the depth of water can be resolved by finding values for the few unknown parameters. Polcyn & Rollin, (1969) used a semi analytical method, using optical bandwidth to derive SDB. Polcyn et al., (1970) developed an algorithm based on a ratio of reflectance in two spectral bands in the visible spectrum, to determine shallow water depth. The further segregation of the methodology was continued to focus on reducing the number of unknown parameters, which paves way for empirical methods, which has continued in SDB research for almost two decades. Challenging few of the tacit assumptions of empirical approach and excluded water column properties which predominantly influence water leaving reflectance, Lee et al., (1998) proposed SA methodology to derive not only bathymetry but also various IOPs. The last decade of SDB research was dedicated to correlating IOPs to bathymetry and water column parameters. The huge database of marine IOP's and ancillary oceanographic observation drove the enthusiasm of synthesizing the data, and LUT techniques were developed in the last decade. Further, development in huge data storage and processing capabilities by advanced computers introduced several ML algorithms and automation in applying SDB algorithms.

1.3 SDB Algorithms

The five decades of SDB literature has been classified majorly on the basis of method used for estimation of coefficients for SDB derivation into analytical, SA and empirical methods (Jawak, Vadlamani, & Luis, 2015; Misra et al., 2018; Traganos et al., 2018). Other few referred the same studies into the category of statistical and Physics-based methods (Dekker et al., 2011). Wherein, the majority of studies referred methods employed e.g. statistical, empirical, ML, etc. as the basis of classification. In addition, same studies have been referred varyingly among above either of classification as per context of research. The SDB researchers who are mostly from technical backgrounds used the terms like approach, method, technique, tools, & model frequently and interchangeably without understanding the philosophical worldview of these terminologies. Although, there is vast difference in these terms, none has got any advantage on other, but relates to altogether different objectives, have discrete meanings and should be used suitably. For systematic classification of any subject matter, there should be focus on details of subject and consensus among stakeholders on the appropriate practice of terms. In this paper, based on literature available on SDB for the past five decades, an insight on SDB classification has been offered grounded in research philosophy.

1.3.1 Proposed Classification of SDB

Anthony, (1963) has differentiated use of terms Approach, Method, and Technique in language learning theories. The term *Approach* is defined as the basic philosophy or belief regarding a specified subject oriented in a direction to solve a problem based on a set of assumptions originating from an assemblage of theories, and concepts (Hofler 1983; Andiappan & Kin, 2020). In SDB literature, two approaches are majorly cited; first is *Statistical Approach* which refers to identifying relationship between remote sensing spectral data and bathymetry without any deliberation on physics of light propagation in water and water column properties, and other is *Physics-Based Approach* emphasizing on propagation of light in the water and its attenuation due to water constituents and environmental parameters. A *Model* defines a theoretical framework or the general strategy to resolve a problem. The synonyms like Methodology or framework are often used interchangeably to understand a model as a system of methods applied with specific set rules. More the rationality in determination of a model, more precise method can be preferred. The RT Physics based approach of SDB can be categorized into *Bio-optical model* and *Physio-optical model* where Bio-optical model is based on assumption that optical properties of water are principally controlled by the biological materials in the water column, mainly phytoplankton and its derivatives (Smith and Baker 1977) and Physio-optical model which explains remote sensing reflectance as a function of water quality, water depth, and bottom reflectance by a forward-model which when inverted gives depth estimation (Lee et al., 1999; Hedley et al., 2009).

A *Method* describes a practical solution to be implemented in order to solve the problem. The *Statistical approach* is straightforward and can be executed by *Empirical Methods* which includes several statistical techniques. Wherein, both the Bio-optical model and Physio-optical model can be executed via *Semi-Empirical (SE)*, and *Analytical methods*. SE methods are based on explicit assumption of RT of light and its attenuation in propagating medium and uses statistical calibration of transformed to field data. Analytical methods are referred to algorithms grounded in physics of RT of light within a water body purely on the basis of water constituents Bio-physio-optical properties. However, the analytical method has been considered as an acrimonious mathematical problem, complex to execute practically (Mouw et al., 2015; Werdell et al., 2018). These limitations and complexities related to analytical methods have been addressed by few theoretical assumptions, based on which Analytical methods were bifurcated into *Semi-Analytical* (SA) and *Quasi Analytical* (QA) methods. SA methods have been pioneered by Lee et al., (1998;1999) who modified (Maritorena, Morel, & Gentili, 1994; Mobley, 1994) analytical RT equation to to derive water column optical properties, depth, and seafloor reflectance based on water's absorption and backscatter properties of the light using spectral matching technique without any need of field data. Wherein, QA method was developed by Lee, Carder, & Arnone, (2002) to derive total absorption α (which can be further decomposed to absorption coefficients of phytoplankton α_{ϕ} and gelbstoff α_g) and backscattering coefficients b_b, based on relationships between remote sensing reflectance and IOPs of the water by applying radiative RT equation.

The *Technique* refers to a sequence of actions to be executed to observe and measure the phenomena, and also involves data collection, processing and analysis of result (Andiappan & Kin, 2020). However, it's not necessary that every problem will be resolved within each class, thus suggesting a 'Hybrid' (either Approach, Model, Method or Technique). Thus, the

SDB studies have been proposed to be classified in the scheme as shown in the figure 1 elaborating the relationship of these above concepts in respect of SDB.

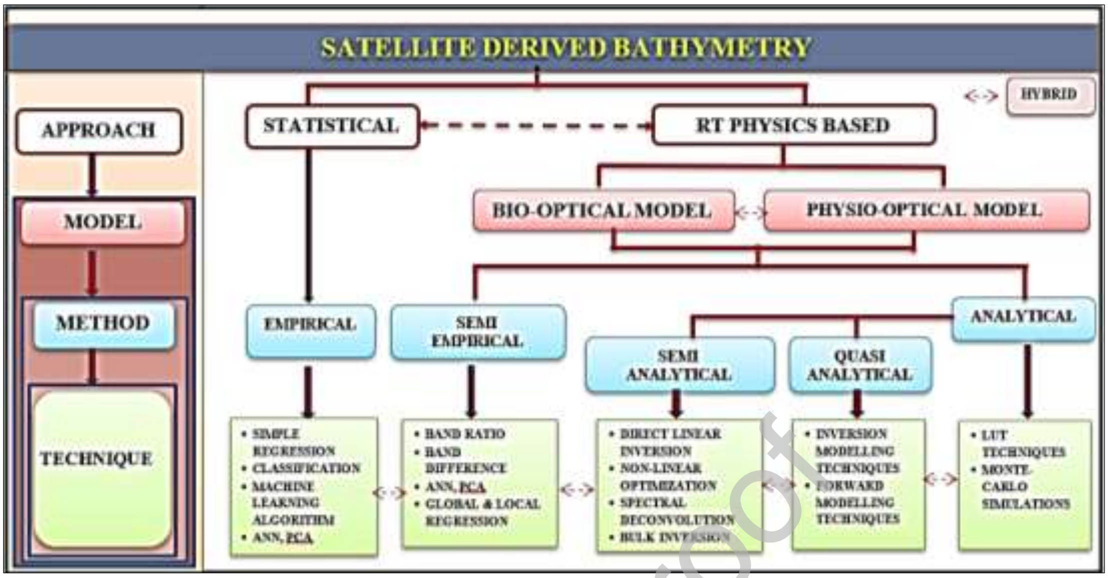

Figure 1: Conceptual Framework for SDB Classification

2. APPROACHES IN OPTICAL SDB

2.1 Statistical Approaches

The primary aim of the statistical approach is to derive estimates usually the coefficient of determination for the same image on which they are derived based on statistical relationship. There is no consideration for any spectral, radiometric or environmental parameter in this relationship. The statistical approach employs empirical methods (discussed in section 4.1) and the accuracy depends on the data on which statistical coefficients are derived or the physical model it was trained upon. The statistical approach should not be confused with statistical analysis (calculation of statistical indices such as Root Mean Square Error, Mean Absolute Error, etc. between in-situ and derived data) of result, errors, and uncertainty in derivation of result in various studies.

The major advantages of statistical approach are that they are easy to apply, tools are readily available to process & analyse data, and recent developments in advanced ML techniques enhanced the efficiency to process huge in-situ data. The limitations are requirement of in-situ data, specific adaptation to the same image & same site, difficult to transfer to other sites (Dörnhöfer & Oppelt, 2016). However, few of the studies have employed ‘spatial transfer’ (application of the statistical empirical method to a nearby site) and ‘temporal transfer’ (application of the statistical empirical model to acquisitions on same site but different dates) to SDB studies (Danilo & Melgani, 2019).

2.2 RT Physics-Based Approaches

The Physics-Based Approaches relies on the physics of exponential attenuation of light with depth in the water column and its reflection from either water column or from the seabed (Bramante, Raju, & Sin, 2013). Generally, the bands with the lowest level of light absorption

(Blue & Green) are used for SDB. The physics-based approaches estimate and explain the physical properties of spectral, water column, and environmental parameters, e.g. Chl concentration, TSM, Detritus concentration, spectral shape, absorption & backscattering coefficients, and water depth (Brando et al., 2009; Lee et al., 1999). The inherent strength of the physics-based approaches is in the estimation of the physical parameters affecting spectral observations with or without in-situ data. However, the RT Physics based approaches have been referred as the difficult mathematical problems, complex to implement pragmatically (Mouw et al., 2015). Besides, RT Physics based approaches need detailed theoretical knowledge about the under-consideration parameters to explain the modelled relationship. RT physics-based approaches are thus only advocated when there exists a strong understanding of the physical and biological processes in the water.

Theoretically, the physics-based approach for SDB has been developed using Beer's Law to model radiant intensities that are scattered and absorbed by water. Since then a number of different techniques under the label of either Physics-based model or Bio-optical model has been developed to estimate SDB.

Models in RT Physics-Based Approach

The physics-based approaches are applied under the two varying but complementary assumptions about the reflectance data. The first is referred as Bio-optical model as its is based on assumption that optical properties of water are principally controlled by the biological materials in the water column, mainly phytoplankton and its derivatives (Smith and Baker 1977) and later is called Physio-optical Model which explains remote sensing reflectance as a function of water quality, water depth, and bottom reflectance by a forward-model which when inverted gives depth estimation (Lee et al., 1999; Hedley et al., 2009).

2.2.1 Physio-Optical Models

Lord Rayleigh (1899) discovered that the molecular scattering in the atmosphere results from diffuse reflection and transmission of sunlight. However, a solution to Rayleigh's problem was suggested by Chandrasekhar (1950) in his book RT (Suomi & Haar, 1970). Chandrasekhar described 'RT' as a mathematical solution to the equation of transfer of radiation in a medium which absorbs, emits, and scatters them. In remote sensing science, the RT theory provided rationale for causality between observations received at sensors and physical processes that generated the signal, thus becoming the most efficient tool for precise retrievals of earth and atmospheric properties from satellite data. The RT theories have been varyingly studied for scattering behaviour in different mediums of transmission, and representation of RT equations in solution methods applied in atmospheric corrections, air aerosol & cloud studies, water bodies, vegetation, etc. A specific formula of the RT in a medium which is absorbing and scattering is given by the classical RT equation (cf Jerlov, 1976; Bukata et al., 1995) as follows:

$$\frac{\mathrm{dL}(\lambda, \mathrm{z}, \theta, \phi)}{dr} = -c\ (\lambda, \mathrm{z})\ L(\lambda, \mathrm{z}, \theta, \phi) + L^{*}(\lambda, \mathrm{z}, \theta, \phi) + L_{S}^{*}(\lambda, \lambda', \mathrm{z}, \theta, \phi) \ldots \ldots \ldots (1)$$

Where, dL - change of radiance, λ – wavelength, $-c\ (\lambda, \mathrm{z})\ L(\lambda, \mathrm{z}, \theta, \phi)$ - represents loss by attenuation, $L^{*}(\lambda, \mathrm{z}, \theta, \phi) -$ gain by elastic scattering traveling a small distance dr in a medium at depth z in the direction (θ; ϕ), and $L_S^*(\lambda, \lambda', z, \theta, \phi)$ - gain by luminescence. Thus, RTE is an integration-differential problem complex to be solved analytically, therefore application specific methods are adapted to derive the illumination geometry, relevant shape, consistency and composition of the considered medium.

2.2.2 Bio-Optical Models

Smith and Baker (1977) used the term 'Bio-Optical' refer to the optical state of water, which is mainly dependent on optical properties of the biological materials (Chl, phytoplankton, etc.) in the water column. Since then, the term has been used widely and inconsistently in specifying bio-optical models (Ogashawara, 2015). Bio-optical models are based on radiometric quantities (IOPs and AOPs), like downwelling & upwelling spectral irradiance and the absorption and scattering properties of elements in the water column. These spectral characteristics may be determined at the level of a single cell (using physical structure such as cell size, distribution size, chemical composition, etc.), and extended to a population of such cells numerically (Morel, 2001). The first bio-optical model using Monte Carlo simulation of the RT equations to develop relationships between AOPs and IOPs of sea water. The basic RT equation has been suggested by (Gordon, 1973) is presented in simple form as below,

$$R_{rs}(\lambda) = F[IOPs\ (\lambda) \quad \ldots\ldots\ldots (2) \text{ or}$$

$$R_{rs}(\lambda) = G(\lambda)\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)} \quad \ldots\ldots\ldots (3)$$

where the G(λ) coefficients represent the combined influence of illumination conditions and geometry, sea surface properties, and the shape of the marine VSF (Common methods for estimating the G(λ) functions include Gordon et al. (1988), where G1(λ) and G2(λ) are spectrally fixed as 0.0949 and 0.0794 (see Lee et al. (2002, 2011)). a and b_b (both expressed in units of m^{-1}) are the bulk absorption and backscattering coefficients, respectively, and are expressed as the sum of the contributions from each Optically Active Substances (OAC) as follows (Mobley, 1994),

$$R_{rs}(\lambda) = G(\lambda)\ \frac{b_{bw}(\lambda) + b_{bp}(\lambda)}{a_w(\lambda) + a_{ph}(\lambda) + a_{dg}(\lambda) + b_{bw}(\lambda) + b_{bp}(\lambda)} \quad \ldots\ldots\ldots (4)$$

According to Morel, (2001), the Bio-optical model is classified in two categories; (1) Models for Individual Particle / Population of Particles: These models aim at deriving information about the bio-physical processes (optics of individual cells, or ultimately whole populations) in the water from relationships between remote sensing data and optically active constituents (Chl in case 1 water and organic sediments, CDOM, mineral, etc in case 2 water) and thus supports the second category of bio-optical models, (2) Modelling the Optical Properties of Ocean Waters in Relation to their Biological State based on *IOP* (absorption coefficient and scattering coefficient*) and AOP* (Downwelling irradiance & Irradiance reflectance). Bio-Optical models are primarily based on ocean color theories related with concentration and distribution of Chl and phytoplankton. Based on the quantification of IOPs, these bio-optical models are usually referred as analytical models (Mobley, 2001). Although bio-optical models have been classified differently based on their formulation and goals (Odermatt et al., 2012), the major classification is into four general categories as *Semi-Empirical (SE), Semi-Analytical* (SA) and *Quasi Analytical* (QA), and analytical methods (Ogashawara, 2015).

3. INTRODUCTION TO SDB METHODS

Wherein, both the Bio-optical model and Physio-optical model can be executed via *SE* and *Analytical methods*. SE methods are based on explicit assumption of RT of light and its attenuation in propagating medium and uses statistical calibration of transformed to field data. Analytical methods are referred to algorithms grounded in physics of RT of light within a water body purely on the basis of water constituents Bio-physio-optical properties. However, the analytical method has been considered as an acrimonious mathematical problem, complex to execute practically (Mouw et al., 2015; Werdell et al., 2018). These limitations and complexities related to analytical methods have been addressed by few theoretical assumptions, based on which Analytical methods were bifurcated into SA and QA Methods. SA methods have been pioneered by Lee et al., (1998;1999) who modified (Maritorena, Morel, & Gentili, 1994; Mobley, 1994) analytical RT equation to to derive water column optical properties, depth, and seafloor reflectance based on water's absorption and backscatter properties of the light using spectral matching technique without any need of field data. Wherein, QA method was developed by Lee, Carder, & Arnone, (2002) to derive total absorption α (which can be further decomposed to absorption coefficients of phytoplankton α_{ϕ} and gelbstoff α_g) and backscattering coefficients b_b, based on relationships between remote sensing reflectance and IOPs of the water by applying radiative RT equation.

3.1 Empirical SDB

Empirical methods purely rely on the statistical estimators derived from in-situ data. The empirical algorithm is developed using a training dataset of in-situ observation and the reflectance of suitable bands from satellite imagery. Empirical method uses statistical techniques, like linear & non-linear regression, neural networks, maximum likelihood, least squares, etc. to estimate the highest degree of relationship between reflectance of selected band and parameter of interest without any concern for physio-optical properties (IOPs or AOPs). These algorithms provide the advantage of processing huge amounts of data, simply and rapidly. Matthews, (2011) reviewed several empirical studies on remote sensing in coastal water and concluded that accepting a considerable degree of error, a great amount of valuable knowledge can be obtained using empirical methods. The assumption of optically homogeneous environments in a single scene makes empirical algorithms site-specific and time-dependent. However, empirical methods using ML and multi temporal data have helped overcome these limitations (Salameh et al., 2019). Important empirical method-based techniques in SDB studies are discussed below.

3.1.1 Empirical SDB Techniques

The empirical methods mostly employ regression tools for data analysis using spectral values of a single/multiple bands with in-situ data to calculate the regression coefficients. The various techniques of regression applied in SDB studies includes; simple step-wise regression (Chen & Zhu, 2015; Doxani et al., 2012), MLR & nonlinear regression (Manessa et al., 2017); Linear regression with principal components (Mishra et al., 2004); geographically-weighted regression (Poliyapram et al., 2017) & second order polynomial regression (Hamylton, Hedley, & Beaman, 2015); least-square regression (Su, Liu, & Heyman, 2008); cluster-based regression (Geyman & Maloof, 2019), etc. Although regression techniques have been considered the most practical solution to huge data analysis, they may cause algorithms to fail in the area of varied seabed (Doxani et al. 2012). Gao, (2009) described that the regression coefficients deteriorate in mixed bottom types; hence a separate regression algorithm may be constructed for each different bottom type which includes nature of bottom and vegetation at the site.

The classification techniques supervised/unsupervised are also used either alone to classify bathymetry and bottom in the satellite imagery or in combination with SE method prior to applying band ratio algorithms. Clark, Fay, & Walker, (1988) used clustered image by supervised statistical clustering and the maximum likelihood classifier before applying a band ratio algorithm. The core assumption in supervised classification is that bathymetry, or seabed, has spectral signatures to be differentiated within an image. The classified image is then calibrated according to statistical parameters related to bathymetry from training areas (Liceaga-Correa & Euan-Avila, 2002). The Unsupervised classification is classified in broad classes of relatively similar radiometric reflectance and then these classes are used to create regions, to be regressed against the bathymetric calibration data (Collet, Rostaing, & Bouthemyb, 2000; Liceaga-Correa & Euan-Avila, 2002; Mavraeidopoulos et al., 2019). Several unsupervised classification techniques like, K-Mean unsupervised classification (Geyman & Maloof, 2019; Halls & Costin, 2016); Iso Cluster Unsupervised Classification (Poursanidis et al., 2019) have been used in SDB studies concluding effectiveness of classification of pixels into subgroups prior applying SDB algorithm.

The other techniques include PCA by adopting the first component using all three bands (transformed) that will correlate to water depth (Gholamalifard et al., 2013). Mohamed et al., (2016) used the PCA for detecting SDB, where principal components of the log transformed reflectance was linearly correlated with in-situ water depths, achieved better SDB estimation. The few studies also used Maximum Likelihood algorithms to determine SDB and seabed classification (Andrew et al., 1988; Liceaga-Correa & Euan-Avila, 2002; Zhou, 2011). Jay & Guillaume, (2014) have proposed a non-stationary maximum likelihood estimation technique for SDB and water quality from HS data for better results.

Besides, there are several other statistical and image based techniques like object-based image analysis (OBIA) used in SDB (Eugenio, Marcello, & Martin, 2015; Hedley et al., 2018). Few of the empirical SDB studies, satellite data used, depth range in the area, and results are shown in figure 2 below.

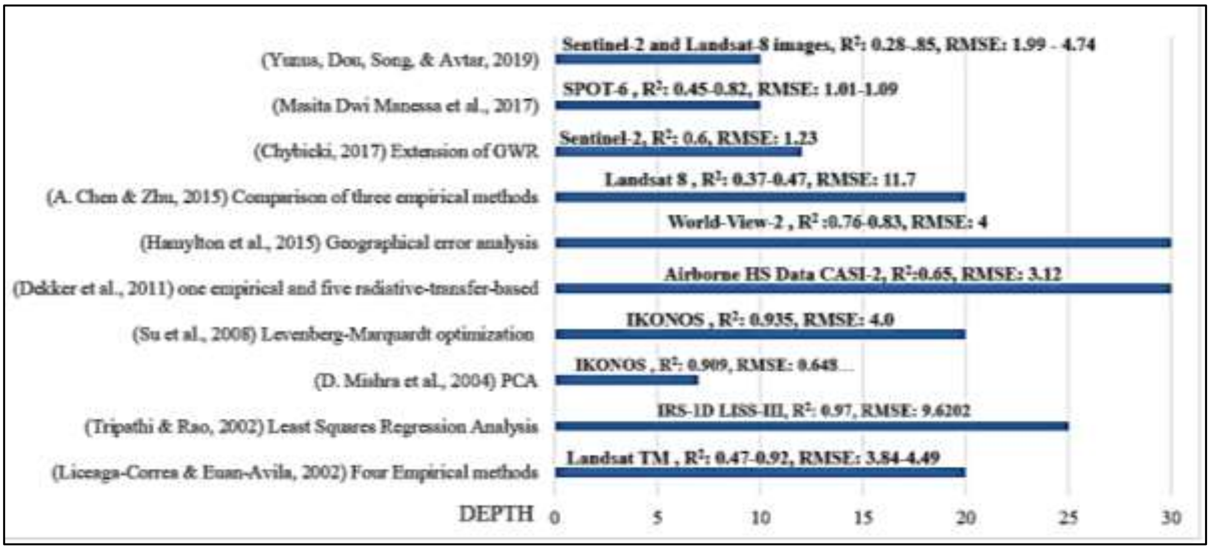

Figure 2: Empirical SDB Studies

The few empirical studies have considered the effect of a few confounding factors in SDB retrieval. Tripathi & Rao, (2002) studied influence of turbidity on bathymetry using IRS-1D LISS-III Band 1 (0.52–0.59 nm) and suggested a correcting factor Turbidity Influence Factor (TIF) to minimise the error. Author applied Least Squares Regression technique between band 1 reflectance and bathymetry up to 25 m resulting in a very high R^2 0.97 when TIF was utilized but RMSE of predicted SDB was substantially high. Mishra et al., (2004) studied bathymetry in different but uniform bottom types (seagrass, coral, and sand) in Honduras for depth of 7 m using PCA on IKONOS data achieving R^2 = 0.90 and standard error of 0.64 m.

The few studies have compared techniques to determine the best suited algorithm established till date of study for their study site. The four empirical methods; a linear regression model using the first principal component, a MLR, a two-step non-supervised classification with MLR, and a supervised classification has been compared using Landsat TM data in Alacranes Reef of Gulf of Mexico for depth of 20 m and the RMSE were estimated 4.14 m, 3.84 m, 3.83 m and 4.49 m respectively, concluding two step non supervised method produced the lowest overall RMSE (Liceaga-Correa & Euan-Avila, 2002). Chen & Zhu, (2015) has also compared three empirical methods primary component analysis, independent component analysis, and Log ratio transform to retrieve SDB at Pratas Island using Landsat 8, where result shown regression was not robust due to vast outliers.

Overall, it can be concluded from the empirical studies that SDB derived by various researchers have shown more than 60% of the validation points have a RMSE lower than 1 m but other predicted data have large errors and few of them are having RMSE up to the depth range of the area. This has been a definite reason that empirical methods have been used limitedly to derive SDB. Moreover, based on studies in the turbid region, it is suggested that the empirical methods may be used very cautiously in coastal turbid water as it results in higher errors.

3.1.2 Machine Learning SDB

ML is becoming a widely accepted research tool for researchers in GIS and remote sensing studies offering a greater flexibility in techniques to process huge amounts of data. ML has gained wide acceptance in remote sensing studies especially processing longitudinal high-resolution satellite data and or with high resolution in-situ data. The Ceyhun & Yalçın, (2010) was pioneer study in applying ML to SDB, used ANN algorithm to Aster and Quickbird satellite data in Foca, Izmir Turkey for the depth of 45 m and has derived fairly accurate SDB estimates having determination coefficient 0.80. Eugenio et al., (2015) used the SVM algorithm on World-View 2 data at Canary Islands coastal areas for depth of 0-30 m, and achieved a result of R^2 between 0.93 and 0.94 and RMSE between 1.20 and 1.94 m. Kibele & Shears, (2016) used a non-parametric nearest neighbor regression for WorldView- 2 and World-View-3 imagery in Cape Rodney, New Zealand and compared result with Lyzenga Depth Estimation and proved KNN method has outperform the Lyzenga's algorithm. An ANN algorithm was applied to IRS-P6 LISS-IV at turbid water of Bhopal City Lower Lake for a depth of 0-12 m achieving R^2 of 0.9514 and RMSE 1.618 m, proved ANN techniques possibly, can be used without refining for environmental factors like bottom material and vegetation (Patel, Katiyar, & Prasad, 2016). The few of the studies on SDB using ML algorithms have been shown below with details of algorithm and accuracy achieved.

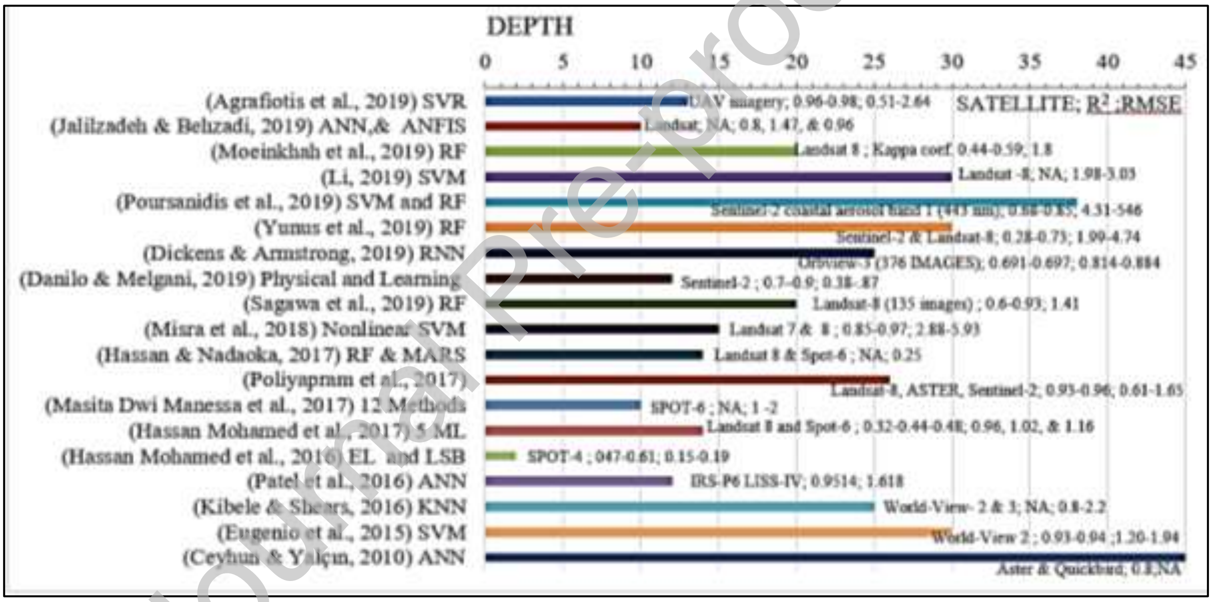

Figure 3: SDB using ML algorithms

Hassan et al., (2017) has compared SDB derived from five ML algorithms; ensemble regression tree-fitting algorithm using bagging (BAG), ensemble regression tree-fitting algorithm of least squares boosting (LSB), and support vector regression (SVR) the neural network (NN) and the Lyzenga generalised linear model (GLM) using Landsat 8 and Spot-6 data at three different sites for depth range 0-10.5 m (Alexandria port, Egypt), 0-6 m (Lake Nubia), and 0-14m (Ishigaki Island, Japan) and found BAG algorithm produced the most accurate result. Misra et al., (2018) used Nonlinear SVM in shallow water using Landsat 7 & 8 at Maarten Is., Netherlands for depth 1– 15 m. The SVM provided better performance of R^2 0.73 in for shallow turbid water. The another note worthy study by Sagawa et al., (2019) who used Random Forest Method on multi-temporal Landsat data (135 scenes) in five test areas, for depth range of 0 to 20 m and found RMSE in the final derived SDB in the five test areas was about 1.41 m. However, SDB estimated was in the various shallow water regions under highly transparent conditions. Dickens & Armstrong, (2019) employed RNN on Orbview-3 multi-temporal images (376 images) at three different sites for depth range of 0- 25 m, and found R^2 between 0.69 concluding even deep learning techniques derived SDB do not meet the IHO bathymetry standards. Moein et al., (2019) utilized RF Algorithm using Landsat 8 data for depths 0 – 20 m, and explained that the best combination of bands for SDB was the band combination (1–2–3–4), with RMSE and MAE was 1.253 and 0.766, in depth of 0 to 5 m. However, beyond 10 m onward, the measurement error increased exponentially.

Thus, it can be concluded that ML algorithms have proven superiority over traditional empirical techniques. The most commonly used methods, SVM and RF produces SDB results for depth up to 10 m significantly, but hereinafter error increases exponentially. Besides, a very few have attempted SDB in turbid water. The ML is one of the emerging areas in SDB studies and has a vast potential to develop operational SDB models.

3.2 Semi-Empirical SDB

The various researchers have attempted to explore analytic solutions to SDB, however their efforts till earlier part of 1990's was to correlate image pixel values with simultaneously collected in-situ bathymetric data without much deliberation on other atmospheric, water column and environmental parameters. The underlying assumption of band ratio (especially blue and green bands) as substitute to attenuation coefficients helped to retrieve SDB to the accuracy level of about 70 percent without much ground data (Polcyn, 1969 and colleagues; Benny & Dawson, 1983; Paredes & Spero, 1983). Parallelly, few other researchers suggested that, even only single band can account for exponential decay of light in the water if used log linear transformation of difference between actual radiance value of pixel to the deep-water radiance of pixel in the same image (Lyzenga, 1978; Warne, 1978). Log linear transformation was further extended to dual-band ((Clark et al., 1987; Lyzenga, 1985) and multiband (Lyzenga et al., 2006) channels for better accuracy of SDB. The modified log ratio transformation for dual-band was suggested by (Stumpf, Holderied, & Sinclair, 2003), further modified to use with a combination of several other bands (Kabiri, 2017). The RT approach enhanced the potential to use MS data for SDB estimation by its explicit assumption (wherein, in empirical methods assumption is implicit) in the equation where either *Band Ratio techniques* or *Linear Regression Techniques* was utilized for addressing the exponential attenuation of light in the water and thus reduced the number of unknown parameters.

3.2.1 Band Ratio SDB

According to Lambert-Beer law Transmittance T of absorbing medium is expressed as T = exp (- αz). A collimated beam propagating vertically downwards with negligible scattering at depth z can be expressed as,

$$\frac{\ln E_0(\mathrm{z})}{\ln E_0(0)} = -az \dots\dots\dots\dots\dots(5)$$

where $E_0(z)$ is scalar irradiance and given as,

$$E_0(\mathrm{z}) = \iint_{4\square} \mathrm{L}(\mathrm{z}, \theta, \phi)\mathrm{dw} \dots\dots\dots..(6)$$

Where, z-depth, θ - Zenith angle, ϕ -Azimuthal angle, dw- differential solid angle and $E_0(0)$ is $E_0(z)$ at surface of water z = 0. The pioneer study on SDB by (Polcyn & Rollin, 1969) was based on exponential attenuation theory of light which explains radiant intensities are scattered and absorbed by water according to Beer's Law and is given by,

$$\mathrm{Iz} = \mathrm{I_o}\ \mathrm{e}^{-\alpha z} \ldots\ldots\ldots\ldots (7)$$

where $\mathrm{I_z}$ = intensity after: traveling a distance z; $\mathrm{I_o}$ = intensity at the surface; z = distance traversed in the water; α = total attenuation coefficient, or extinction coefficient, with units of reciprocal length and $\alpha = \alpha_s + \alpha_\alpha$ (where α_s = scattering coefficient of the medium and its suspended particles α_α = absorption coefficient α); Both the scattering and the absorption coefficient are wavelength dependent. Polcyn & Rollin, (1969) derived electrical signal V received at a satellite sensor for power P areas where bottom type and water clarity are uniform is given as,

$$V = \mathrm{K\rho H e}^{-\alpha\,(\cos^{-1}\theta\,+\,\cos^{-1}\phi\,)\,z} \ldots\ldots\ldots (8)$$

Where, V = signal in channel of bandwidth$\Delta\lambda$; ρ = reflectance of bottom material in that wavelength interval; H = irradiance of the sun at the water surface; α = water extinction coefficient; z = depth of the water; θ = known angle of incidence; ϕ = viewer observation angle; K = function of other known quantities, i.e., of receiver size, FoV (field of view), responsivities, transmission (atmosphere), and optics.

Based on assumption that one band is decayed in water more rapidly than other and total attenuation coefficient derived from ratio of two attenuating signals, the depth z has been inverted from equation (3) as follows.

$$z = \frac{1}{f(\theta,\phi)(\alpha_{\lambda 2} - \alpha_{\lambda 1})}\ ln\frac{V_{\lambda 1}\,K_{\lambda 2}\,\rho_{\lambda 2}\,H_{\lambda 2}}{V_{\lambda 2}\,K_{\lambda 1}\,\rho_{\lambda 1}H_{\lambda 1}} \qquad \ldots\ldots\ldots (9)$$

The Band Ratio Technique has been used for almost a decade to derive unknown attenuation coefficient based on ratio of two bands, being all other parameters known from satellite data to estimate depth. This technique helped determine bands useful in SDB and maximum derivable depth up to 5 m with low accuracy. However, ratio technique was enhanced by (Stumpf et al., 2003) who suggested ratio of the attenuation of two bands (than using albedo) as different spectral bands attenuate at different rates. The algorithms derived is as given by,

$$z = m_1\,\frac{ln(nR_w\,(\lambda_j))}{\ln(nR_w\,(\lambda_i))} - m_0 \quad \ldots\ldots\ldots (10)$$

where, Z - depth, n - constant to ensure the ratio remains positive under all values, Rw is observed reflectance in band, and m_0 is the offset and m_1 is a gain. Stumpf et al., (2003) is one of the most utilized algorithms in SDB applied studies.

The SDB Algorithms based on Band Ratio techniques initiated by Polcyn, & Rollin, (1969) using 18 band MS data collected by airborne sensor at Gulf of Maine achieved depth of 13 ft or less which improved to 20 ft by Polcyn et al., (1970) using MS Scanner in Caesar Creek, Florida. Polcyn & Lyzenga, (1973) used Band 4 and 5 of ERTS-1 MSS data taken on

October 10, 1972 for developing a mathematical method for SDB showing correlation of depth measurements to 5 meters in Little Bahama Bank. This study proved that Band *4 (*.5-.6) clearly shows underwater features, and band 5 (.6-.7) shows some of the shallower areas, wherein band 6 and 7 of ERTS-I satellite data show no underwater features. Paredes & Spero, (1983) extended generalized ratio assumption to the multiband on the tacit assumption that attenuation is constant over the scene. Stumpf et al., (2003) developed a semi empirical solution using a ratio of reflectance with only two parameters and can also be applied to low-albedo features. This ratio transform technique of SDB has proven more robust, can retrieve depths to 25 & shows stability and has normalized rms error up to 30% up to 25 m depth. However, technique is effective only in clear and transparent water. This technique has been further extended to include the effect of turbidity and chlorophyll on SDB estimation (Caballero, Stumpf, & Meredith, 2019).

3.2.2 Linear Band SDB

Lyzenga (1978) modified the ratio technique to develop a more generic set of Shallow Water Radiance data and developed algorithms for water depth and bottom features from single band exponential depth dependence using the log linear transformation. This technique has an explanation for unpredictability in bottom type by using multiple spectral bands. A variable, Xj, has been defined for each of the N bands (for details, refer Lyzenga, 1978, p. 383)

$$z = h_0 - \sum_{J=1}^{N} h_j \; X_j \; \ldots\ldots\ldots. \; (11)$$

Where, Xi = In(Li – Lsi); Lsi - deep-water radiance and Li- above-surface reflectance; h_j and h_0 Derived from regression of radiance and in-situ data. Deep-water reflectance was assumed to account for reflection from sea surface, volume scattering in the water column and sun-glint effects, and atmospheric scattering. This led the development of Linear Band technique (Lyzenga, 1978) which is one of the most widely utilized techniques in SDB studies, as it only needs in-situ data for calibration of technique. The various other algorithms were developed concurrently using linear transformation technique (Benny & Dawson, 1983; Warne, 1978; Jupp, 1989).

Warne, (1978) used single band linear technique using Landsat data in Australia for the depth of 0-30 m, proved Landsat may derive SDB up to 20 metres with an accuracy of 10 % . Lyzenga, (1981) assuming the water optical properties to be uniform over a given scene used Landsat and Airborne MS data at North Cat Cay in the Bahamas and found this technique gives accurate results to a depth of 15 m in clear water. Lyzenga, (1985) used hybrid airborne sensor which incorporates both a lidar system and a passive MS to derive SDB in 2 sites Bahama Islands for depth 0-10 m and found RMSE 0.928 m for depth 8-10 m. Lyzenga continued his efforts in improving SDB and proposed multi band linear technique (Lyzenga et al., 2006). The algorithm based on this technique corrects variations in both attenuation and bottom using a linear combination of the log-transformed radiances mostly in the blue & green bands. This model is applicable to areas of uniform water optical properties and bottom reflectance. It also accounts for the sun glint, gives operational flexibility, better discrimination of bottom, improved performance through the use more than two bands.

3.3 Analytical SDB

Analytical methods are grounded on physics of RT of light within a water body purely on the basis of physical properties of water constituents such as attenuation, backscattering, & absorption. According to Gordon & Morel, (1983), the analytical methods directly utilizes the RT theory, and describes the absorption and backscattering coefficients as the constituents of the water. Gordon, (1973) formulated theory find an analytic expression of reflectance in oceanic water using RT, as a function where w_o is the ratio of the scattering coefficient b to c, and the scattering phase function by using a Monte Carlo simulation that included all orders of multiple scattering and interface reflection. Gordon & Mccluney, (1975) expressed the radiance $N_z(\mu')$ as,

$$N_z(\mu') = \frac{4H_0}{n(n+1)^2} \; \frac{\mathrm{T}(\mu,\mu')}{1+\mu} \; P(-\mu) \frac{\mathrm{w}_0}{1-\mathrm{w}_0 F} \; X\{1-\exp[-zc(1-\mathrm{w}_0 F)(1+\mu)/\mu]\} \ldots (12)$$

where n - refractive index of water; $\mathrm{T}(\mu,\mu')$ - Fresnel transmittance; $P(-\mu)$ - phase function for scattering; $\mu^2 = 1 - n^2(1-\mu'^2)$ – Snell's law. Author concluded that spectral radiance $L_t(\lambda)$ received at the sensor can be appraised by RT equation which will provide optical properties and therefore the constituent concentrations (with few simplifying assumptions) by solving the inverse problem (Gordon & Morel, 1983). This RT equation has been modified by several others for deriving solutions to light and water problems (Mobley, 1994; Mobley et al., 1993). Albert & Mobley, (2003) has further improved the method by derivation of total Analytical solution for the irradiance reflectance and remote sensing reflectance for deep and shallow water applications. The remote sensing reflectance R_{rs} has been expressed with a similar approximation as the irradiance reflectance, but with an additional dependence on the subsurface viewing angle θ_v.

$$R_{rs} = R_{rs,\infty}\left(1 - A1\exp\left\{-\left[k_0\frac{\cos\theta_v}{\cos\theta_s} + (1+x)^{k_i,w}\left(1+\frac{k_2,w}{\cos\theta_s}\right)\right]\frac{\alpha+b_b}{\cos\theta_v}z_B\right\}\right) + A_2\frac{R_B}{\pi}\exp\left\{-\left[k_0\frac{\cos\theta_v}{\cos\theta_s} + (1+x)^{k_i,B}\left(1+\frac{k_2,B}{\cos\theta_s}\right)\right]\frac{\alpha+b_b}{\cos\theta_v}z_B\right\} \ldots\ldots\ldots\ldots\ldots(13)$$

The analytical methods give highly accurate results, but are very complex to execute as it needs the input of several in-situ parameters related to the optical properties of water column and the seabed (Albert & Mobley, 2003; Jawak, Vadlamani, & Luis, 2015; Liu, Islam, & Gao, 2003). The measured optical properties and constituent concentrations in water are physically related to the reflectance spectra applying RT models which are then inverted through regression, curve fitting, neural networks, or matrix inversion, etc. The analytical implementation is more accurate, and can yield highly accurate bathymetric information. Methods retrieve water depth and bottom type simultaneously (Bramante et al., 2013; Hamylton, Hedley, & Beaman, 2015; Hedley et al., 2018; Olayinka & Knudby, 2019).

The implementation of analytical methods also needs a precise input of a set of parameters related to atmospheric effect. Even the small errors in atmospheric correction induces larger errors in retrieval, as the water leaving radiance only amounts to 10 percent of total signal and remaining 90 percent accounts for atmospheric effects (Caballero et al., 2019). Another limitation of analytic approach is simultaneous collection of field data to image acquisition (satellite pass) for modelling accurate water constituents in coastal dynamic water. Analytical methods are computationally complex and execution is difficult as there are no atmospheric correction methods that provide accurate water reflectance for shallow and/or optically complex coastal waters.

In analytical method, RT equation is principally solved using three techniques, first forward modelling, inverse modelling techniques or look-up tables (LUT) based on forward & Inverse modelling techniques or combination of any of three (Hodúl, Bird, Knudby, & Chénier, 2018). An analytical method forward-model a range of probable R_{rs} as a function of constituents of water, bathymetry, and seabed reflectance which is then inverted to derive water constituents and bathymetry by recognizing the modelled R_{rs} which resembles most closely to the observed R_{rs} in each pixel (Hedley et al., 2009).

3.3.1 Forward & Inversion Modelled SDB

Analytical method Forward modelling techniques are used majorly to serve three functions; explain, predict or model inversion of problem in consideration. Models explain relationships between physical parameters and remote sensing parameters or derived parameters like AOPs/IOPs. Model simulations are used to explain certain phenomena from actual satellite images. Certain phenomena observed in the actual data but can't be explained through the model, provides the prospect to modify the model to predict the phenomena more precisely (Verhoef, 1998). However, retrieval of any constituent parameter needs inversion of the forward model.

In Analytical methods, Inversion Modelling to RTE is applied to estimate input parameters used in the model using detected remote sensing data. However, its implementation is subject to a number of known & unknown parameters and available bands in remote sensing data. Moreover, execution of model inversion needs extensive computational efforts, and several iterations on the forward model to arrive at a solution (Verhoef, 1998). Inversion techniques mostly simulate spectral signatures, and a set of constant as well as variable model parameters related to IOPs and AOPs. The variable parameters are revised iteratively till the variance between modelled and actual image spectral signatures reach to a lowest. The result of inverse modelling provides data retrieval of water constituents, bathymetry, and seabed substrates. Inversion techniques have grown rapidly for water constituent's retrieval in marine remote sensing (Hedley et al., 2009). The inversion techniques have been applied varyingly in SDB literature, e.g. linear inversion, non-linear inversion, adaptive inversion, log-linear inversion, log-ratio inversion, etc.

3.3.2 Look-Up Tables (LUT) SDB

LUT technique refers to a large database containing spectral signatures, known constituent concentrations' water leaving radiance, IOPs, bathymetry, and seabed properties. The spectral signatures of satellite image and LUT database are assessed to find the nearest match for all the parameters under consideration (Dekker et al., 2011). The analytical method applied to RTE by Mobley, (1994) resulted in the first LUT technique 'Hydrolight' using forward modelling of remote sensing reflectance (Mobley et al., 2005). The spectral matching

LUT algorithm of Mobley et al. (2005) is also referred as Comprehensive Reflectance Inversion based on Spectrum matching and Table Look up (CRISTAL) developed for concurrent retrieval of bathymetry, benthic substrate, and IOPs (Dekker et al. 2011). The other technique ALUT has been developed by (Hedley, Roelfsema, & Phinn, 2009). SDB studies based on LUT techniques show SDB has been derived up to the depth of 30 m significantly.

Hedley, Roelfsema, & Phinn, (2009) presented an Adaptive Look-Up Tree (ALUT) that evenly distributes the discretization error of tabulated reflectance in the spectral space as a function representing the shape of the spectral reflectance using 17-Band CASI HS image (430 –710 nm) in Heron Reef, Australia for depth 0-20 m with R^2 0.91. Bramante, Raju, & Sin, (2013) compared conventional SDB and LUT techniques using MS data of Worldview-2 in Singapore's turbid shallow coastal waters for depth 0-4 m. LUT classification provided a precision of 0.64 m, but was limited by a training set that did not fully represent variance in water column and benthic properties. Hedley et al., (2018) used Sentinel-2 and Landsat 8 in Australia for depth up to 30 m and found depths were well estimated to around 15 m with R^2 value of 0.89, showing with accurate atmospheric correction, SDB can be estimated up to 15 m, where optical conditions are favourable. LUT techniques have been effectively used for SDB estimation and water constituent determination, however the result of derivation depends on precision of LUT database, whether it contains IOP/AOP, benthic substrate spectral signature and bathymetry as in the geographical area of the imagery. Maritorena, Morel, & Gentili, (1994) suggested that the safe use of analytical algorithms demands validation of the underlying approximations and quantification of their impact. The authors used a dual method of comparison; first, the analytical solution compared with precise solution derived via Monte Carlo simulations of the RT and the second spectral reflectance (in variable depth and bottom) has been compared to field data.

Although substantial efforts have been placed on the development of analytical methods for deriving marine IOPs from the sensor radiance, these methods cannot be exactly reduced to an analytical equation. The similar view was expressed by (Mouw et al., 2015) referring analytical methods as basically an acrimonious mathematical problem which needs continual development to translate from laboratory-based practice to in field methods. These limitations and complexities related to analytical methods have been addressed by few theoretical assumptions, based on which Analytical methods were bifurcated into SA and QA Methods.

3.4 Semi Analytical SDB

Most of the literature on SDB prior to 1998 refers to SE methods as SA methods. However, SA methods have been pioneered by Lee et al., (1998;1999) who modified (Maritorena et al., 1994; Mobley, 1994) analytical RT equation to derive water column optical properties, depth, and seafloor reflectance. This method is developed based on water's absorption and backscatter properties of the light using spectral matching Levenberg-Marquardt optimization algorithm. It needs the HS data, to optimize water parameters to match the spectral signatures in the HS dataset. This method does not require field data for calibration (Lee, Carder, & Arnone, 2002) and derived algorithms can be applied to different waters with better predictive accuracy than empirical algorithms (Sathyendranath, 2000). The semi analytic method gained wide popularity in various marine studies which includes water column properties & bathymetry. This method was originally developed for HS data, however, it can even be applied to MS data with substantial results (Dekker et al., 2011). The more specific derivation for SDB in shallow water was established by Lee et al., (1999), using HS remote sensing data using by optimization technique for nadir-viewing Rrs is expressed as,

$$R_{rs} = \frac{0.5 r_{rs}}{1 - 1.5 r_{rs}} \text{ where } r_{rs} = r_{rs}^{c} + r_{rs}^{B}$$

$$r_{rs} \approx r_{rs}^{dp}\left(1 - \exp\left\{-\left[\frac{1}{\cos(\theta_w)} + \frac{D_u^C}{\cos(\theta)}\right] kH\right\}\right) + \frac{1}{\pi}\rho \exp\left\{-\left[\frac{1}{\cos(\theta_w)} + \frac{D_u^B}{\cos(\theta)}\right] kH\right\} \ldots (14)$$

Where, ρ (λ)is the bottom albedo; H is the bottom depth; θ_w is the subsurface solar zenith angle; θ is the subsurface viewing angle from nadir; r_{rs} – subsurface remote-sensing reflectance; r_{rs}^{dp} – remote-sensing reflectance for optically deep water $r_{rs}^{dp} \approx (0.084 + 0.170u)u$; optical path-elongation factors for scattered photons from the water column $D_u^C \approx 1.03(1 + 2.4u)^{0.5}$ and bottom $D_u^B \approx 1.04(1 + 5.4u)^{0.5}$; $u = b_b / (\alpha + b_b)$; $k = \alpha + b_b$; ($b_b = b_{bw} + b_{bp}$) & ($\alpha = \alpha_w + \alpha_\phi + \alpha_g$). This equation was modified as explicit functions of P, G, X, B, and H (i.e. 5 unknowns in via spectral optimization, derived from modelled and measured Rrs without any field data) and their values that fits the modelled R_{rs} are considered as the solutions as below;

$$R_{rs}(\lambda_n) = F(\alpha_w(\lambda_n), b_{bw}(\lambda_n), P, G, X, B, H) \ldots\ldots (15)$$

$$P = 0.05\left(\frac{R_{rs}(440)}{R_{rs}(550)}\right)^{-1.7} \quad G = 1.5\,P \quad X = 8\,R_{rs}(660) \quad B = 4\,R_{rs}(490) \quad H = \frac{1}{6P}$$

Where, where P, G, X, and H respectively represent the water column phytoplankton, coloured dissolved organic matter (CDOM), particulate backscatter and depth.

The inversion of the above equation was used to derive SDB with computer simulated data with accuracy of 5% for a range of 2 – 20 m, and for field data, it was accurate to within 11% for a depth range of 0.8–25 m. The semi-analytic method proposed by Lee et al., 1999 was used widely in marine remote sensing studies especially for constituent's retrieval (Bramante et al., 2013). Most of these SDB studies have emphasized the advantages of HS data in coastal shallow water (Gould, Arnone, & Sydor, 2001; Lee & Carder, 2002; Wettle & Brando, 2006).

McKinna et al., (2015) elaborated that a typical SA method to retrieve IOP from remote sensing reflectance based on spectral matching follows three steps; (1) The forward modelling is used to analytically approximate the modelled remote sensing reflectance, to the observed one, (2) spectral shapes of unknown parameters are modelled using exponential or power law functions, and (3) The spectral IOPs magnitude in the forward model are then iteratively adjusted by an inverse solution. Werdell et al., (2018) suggested that the solution techniques based on SA can be categorized in four broad groups; (i) Nonlinear Spectral Optimization e.g. Levenberg Marquardt technique (Maritorena et al., 2002; McKinna et al., 2015) , (ii) Direct Linear Inversion e.g. Linear matrix inversion, (iii) spectral deconvolution in which spectral shapes are assigned Step-wise algebraically and (iv) bulk inversion which determine IOPs at each wavelength independently.

The few of the techniques used to derive SDB based on SA includes; (Lee, et al., 1999) as HS Optimization Process Exemplar (HOPE); SA Model for Unmixing and Concentration Assessment (SAMBUCA) is a extension of the work of Lee et al. (1999) by including a more than one substrates type (Brando et al., 2009); Bottom reflectance un-mixing computation of the environment model (BRUCE) based on Lee et al. (1999) with a modification to the bottom reflectance parameterization by (Klonowski et al. 2007); Shallow Water Inversion Model by (McKinna et al., 2015), SWAM (Shallow Water SA Model) ESA's SNAP toolbox (Hedley et al., 2018) and many such other techniques discussion of which is beyond purview of this review. The SDB studies based on SA based algorithms is shown below with details of data used, depth range in the area and result derived.

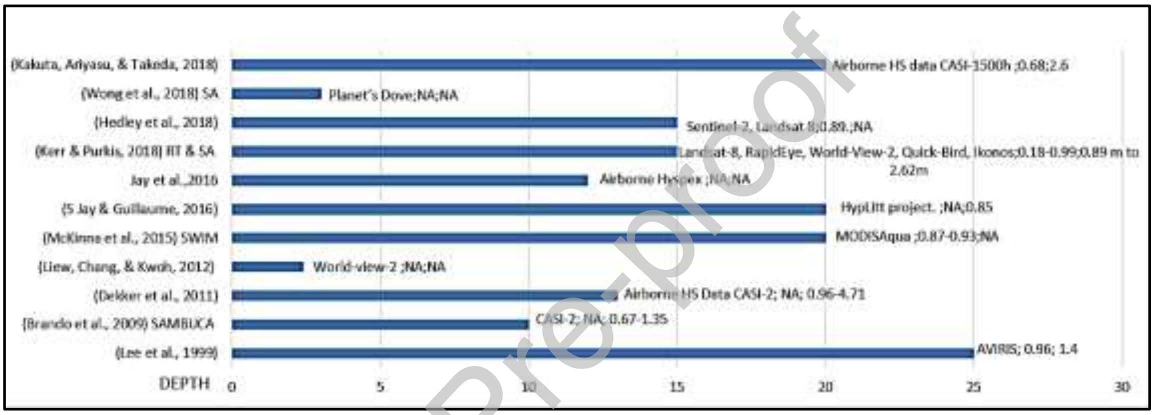

Figure 4: SDB Studies based on SA based Techniques

Lee & Carder, (2000) suggested that their SA model may retrieve SDB with accuracy R2 = 0.96, (for n = 37), however, the discrepancies are increased with turbidity. Brando et al., (2009) developed SA technique called SAMBUCA based on optimization of Lee et al. (1999), was applied to airborne HS data CASI-2 in Moreton Bay, Australia for depth 0-10 m. The results indicated better output in shallow clear water (RMSE 0.67 m) than optically deep water (RMSE 1.35 m). Dekker et al., (2011) compared five SA algorithms namely; HOPE, BRUCE, SAMBUCA, CRISTAL, and ALLUT using Airborne HS Data of CASI-2 at Lee Stocking Is. in the Bahamas and Moreton Bay in eastern Australia for depth range of 0-13 m. The retrieval of RMS error was lowest for BRUCE method, although all techniques estimate SDB and benthic substrate types. Liew, Chang, & Kwoh, (2012) investigated the sensitivity and limitations of WorldView-2 data for SDB retrieval in turbid coastal waters using SA at Singapore Strait. The study concluded the utility of Red and Yellow bands for SDB in turbid water, however the maximum depth of SDB was low to about 2.4 m.

The various SDB studies cited above have suggested that depth can be retrieved up to 15 to 20 m using SA algorithms. Few studies elaborated SDB retrieval even without any field data. This advantage may be helpful in ensuring data production at any site and over a longitudinal period.

3.5 Quasi Analytical (QA) SDB

Lee, Carder, & Arnone, (2002) developed a multiband QA method to derive total absorption α (which can be further decomposed to absorption coefficients of phytoplankton α_ϕ and gelbstoff α_g) and backscattering coefficients b_b, based on relationships between remote sensing reflectance and IOPs of the water by applying radiative RT equation. QA method is near-analytical in nature and can be applied to both HS and MS data. The study also advocated that QA methods retrieval have its accuracy comparable to that of optimization with calculation efficiency like empirical methods. In QA methods, $b_b(\lambda)$ is computed based on the RT expression of (Gordon and Morel, 1983) using remote sensing Reflectance with 555 nm as the Reference Wavelength. The QA Method based techniques were used in SDB by (Zhou, 2011) using EO-1 HS data; estimate bathymetry and benthic habitats using MS imagery (Eugenio et al., 2015; Huang et al., 2017); comparison with SA method in SDB derivation (McKinna et al., 2015); without any field data (Chen, Yang, Xu, & Huang, 2019).

4. DISCUSSIONS AND ANALYSIS

The importance of remote sensing data in the SDB studies have been brought by growing interest of industries as well as academia in various forums, Technical Working Groups and regional Hydrographic commissions meetings of IHO. Besides, there is also a surge in remote sensing studies related to Hydrographic Surveying like coastal processes like erosion, accretion & coastline changes along with SDB. The main hurdle in synthesizing the existing knowledge on SDB is found to be congested by interchanging and variably used concepts related to execution of methodology to derive SDB. Therefore, at foremost an attempt has been made to propose a classification scheme rooted in philosophy of research and a suitable classification as provided in Figure 1 has been attempted based on literature.

This study has analysed more than 150 papers exclusively on SDB with the ultimate purpose of classifying the literature in systematic classification, so that the future studies will have clarity of concepts and terms used in SDB. While classifying the SDB studies, this study also aimed at identifying the gap areas and challenges in each sub domain of classification. Based on proposed classification, existing SDB studies have been categorized in relevant sections and discussed the notable studies, data used, study site & depth range in the area and result achieved. The four themes emerged from literature segregated with respect to chronological improvement in Sensors, Algorithms, Hybridization, and Accuracy achieved in SDB for the purpose of analysis.

4.1 Improvements in Sensors

SDB started with aircraft based multispectral instruments that had 18 channels of spectral range 0.3 and 15 μ of which 12 channels were in visible spectrum. This study founds best spectral bandwidth for shallow water observation ranges from 0.55 to 0.58 μ green-region, wherein 0.62 to 0.66 μ red-region for shallowest depths, although blue region 0.40 to 0.44 μ has lower scattering of light than other bands. Moving further, Polcyn et al., (1970) developed an algorithm based on a ratio of reflectance in two spectral bands in the visible spectrum, to determine shallow water depth. However, the accuracy of technique was true for only the depth is about 4 ft (actual depths in the site 17—20 feet). Again, Polcyn & Lyzenga, (1973) demonstrated the ERTS-I bands 4, 5, and 6 data can be used for bathymetry estimation improving results for SDB up to 05 meters. The contemporary researchers used

ERTS-I and SKYLAB imagery for classifying coastal zones into deep and sediment laden shallow water (Klemas, Bartlett, & Rogers, 1975). This decade established the demand of remote sensing data in SDB and marine studies which drove the enhancement in sensors and instruments onboard satellites to acquire MS and HS data. The MS data offers the advantage of being relatively low cost, easier processing, and spatially synoptic. Along with Open-source Landsat series and Sentinel-2, other commercial satellites like GeoEye, Quickbird, Ikonos, World View, Pleiades, Spot- 6, RapidEye, Planet Dove, etc. offers very high spatial resolution data to derive SDB. In the last few decades, a number of studies have also used HS data in SDB. The figure below shows the number of papers included in this review for the last five decades and satellite data available for SDB.

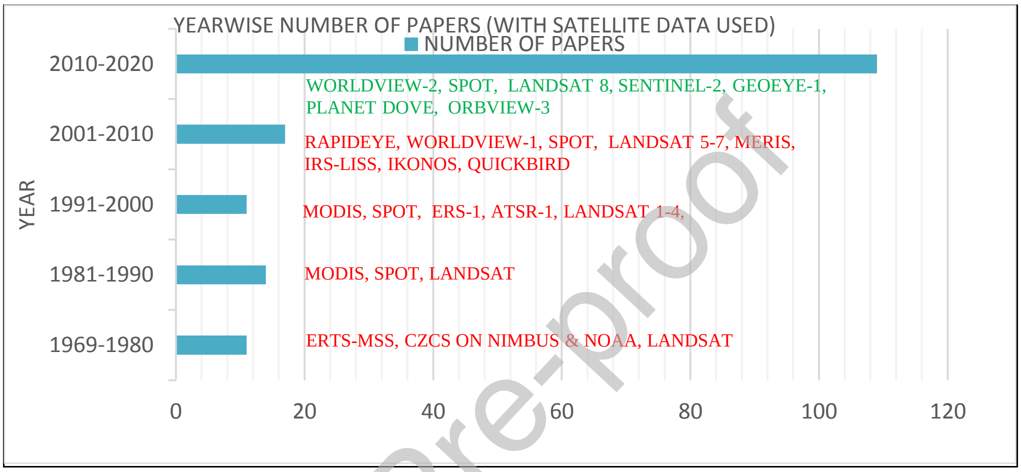

Figure 5: Graph of year-wise studies on SDB with satellite data

Minghelli-Roman et al., (2009) compared MS data derived from QUICKBIRD, & Landsat and HS data of CASI, CHRIS-PROBA, HYPERION & MERIS using single SDB technique in single geographical site to identify best set of satellite image parameters to estimate SDB. Author elaborated on features like; available spectral resolution, spatial resolution, S/N ratio, and image quantization) and concluded that no sensor seems perfect to SDB.

The open source data of Landsat and Sentinel-2 is widely used by SDB researchers. The Sentinel-2 MSI data is acquired 12 bit and level 2 products (refers to ortho-image Bottom of Atmosphere corrected reflectance imagery) are processed to 16 bits, having SNR ranging from 154 to 174 for 10 m spatial resolution bands. The legacy data of Landsat mission is 8-bit, wherein the Landsat-8 OLI is acquired 12 bit and processed to 16-bit for level 1 products (refers to Radiometrically calibrated and orthorectified imagery). However, the SNR for bands varies for range 145-361. Thus, Landsat is having more advantage in coastal regions for better SNR as in coastal areas low is the backscattering intensity, but its resolution is insufficient in creeks & estuaries. The higher SNR values of the sensor (more than 500) should be preferred for SDB. The more the SNR, the better the resolution, hence a high resolution should be preferred in shallow water whereas lower resolutions for deep water. In the last decade few of the satellites like GeoEye, worldview-3, CartoSat-3 and others have achieved resolution in decimetres, wherein for general SDB below a meter resolution is actually not required. The SNR can be improved by an increase in bandwidth and equally addressing the trade-off between bandwidth and error of estimation. The more intervening variable in water demands radiance may be coded to the minimum 12-bit so as to have adequate radiometric levels in water. Besides, based on SDB studies it's worth advocating that HS data has an edge over MS data in SDB derivation, and has at par accuracy of optimized algorithms.

The figure 6 and 7 below depict ML SDB and Empirical SDB for mentioned studies. The best results achieved by the researchers in the last few years with their accuracy and root mean squared errors for each satellite data are only used for depiction.

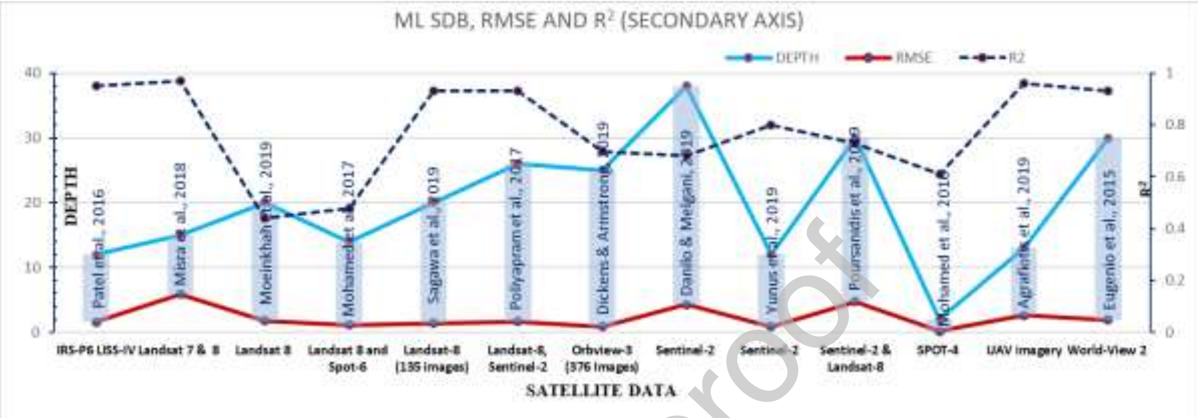

Figure 6: Machine Learning SDB studies with Satellite, RMSE and R^2

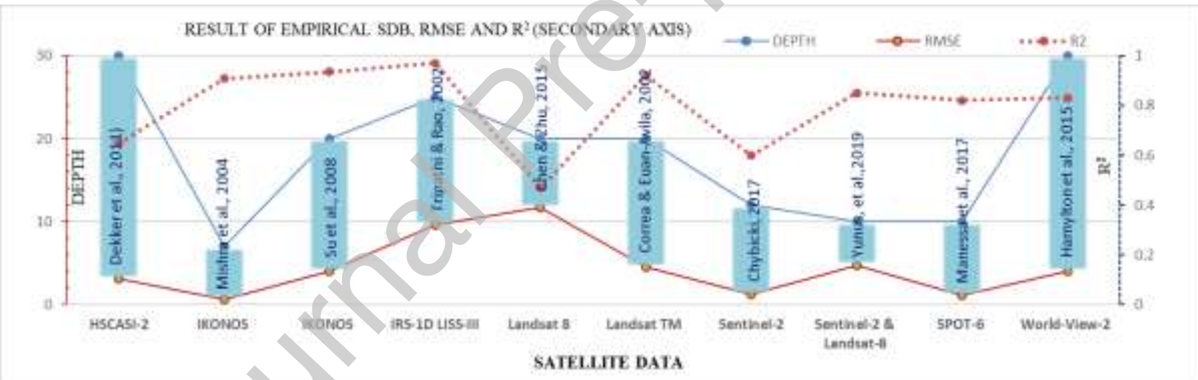

Figure 7: Empirical SDB studies with Satellite, RMSE and R^2

4.2 Improvements in SDB Algorithms

The theory building of empirical method in SDB is mostly accredited group of researchers at the Environmental Research Institute, Michigan (Polcyn and colleagues) among these researchers, Lyzenga, (1975, 1978) who introduced the log-linear semi-empirical method on single band image for detecting SDB. Lyzenga's research continued for three decades in improving his technique for multiband images by proposing log-linear correlation between multiband and water depth values (Lyzenga et al., 2006). Another Semi-empirical method which conceptualized (difference in attenuation of different bands in water can be used for SDB) on band ratios, developed by (Stumpf et al., 2003) is also used widely in SDB research. The chronological order of development of dominant SDB algorithms commonly used are; Linear Band technique of Lyzenga (1978); Benny and Dawson (1983); Flow Radiative Transfer technique of Spitzer & Dirks, (1986); Depth of Penetration Zone Model of Jupp, (1988); Philpot, (1989) & Band Ratio technique of Stumpf et al. (2003).

These algorithms have been kept evolving for three decades along with improvements in sensor resolution. The enhanced spectral capabilities lead researchers to reflect about other intervening atmospheric and environmental variables confounding water leaving radiance. The advanced computing capabilities and vast data storage in acquisition devices gave a push to several RT based Atmospheric & water column corrections. Generally, the limitations in SDB retrieval were attributed to water turbidity and sub-bottom benthos or vegetation which impacts signal attenuation. The last decade has seen surge of studies focusing environmental variables like benthos and turbidity confounding in SDB retrieval (Bramante et al., 2013; Caballero & Stumpf, 2020; Caballero et al., 2019; Sánchez-Carneroab et al., 2014).

The major change in paradigm of SDB has been noticed in the last five years research trends where the majority of studies were using ML algorithms. Several studies have advocated ML over tradition techniques providing better results of SDB (Li, 2019; Mohamed & Nadaoka, 2017). Sagawa et al., (2019) reported RMSE of 1.41 m for depths range 0 to 20 m in highly clear water & transparent conditions using cloud-based ML implementation strategy using Google Earth Engine (cloud-based GIS) GEE and suggested Amazon Web Services (AWS) where huge amount of data may be processed without actually downloading that data may also be used. The several ML algorithms like SVM, CNN, RF, etc. are considered to be useful for SDB Estimation. The figure below shows recent different ML algorithms with depth, accuracy and RMS error applied to SDB.

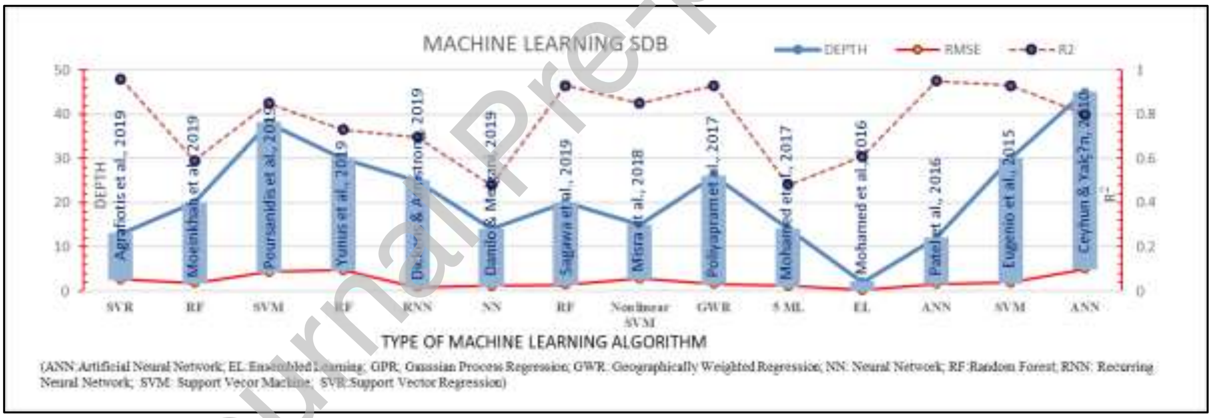

Figure 8: Methods-wise Depth, RMSE and R^2 of Machine Learning SDB

Therefore, it can be concluded that ML has provided advantage over conventional SDB algorithms by offering superior flexibility, and availability of suitable, & customized programmable algorithms to process large amounts of training data. However, none of the studies has declared that derived SDB meets the IHO criteria for charting (Dickens & Armstrong, 2019). Favoretto et al., (2017) & Kerr & Purkis, (2018) elaborated SDB retrieval even without any field data, which may be considered a breakthrough in SDB research if validated at several other sites. Favoretto et al., (2017) proposed 'Self-calibrated Spectral Supervised Shallow-water Modeler' technique to derive coastal bathymetry without any field data with Landsat-8 images and achieved accuracy of an average r^2 =0.90, and a low RMSE = 1.47 m for SDB vs in-situ depths. Wherein, Kerr & Purkis, (2018) performed study in Case 1 waters dominated by phytoplankton by applying forward modelling of band-ratios.

4.3 Advantage of Hybrid Approach/ Model/ Method/Technique/data

The hybrid refers to the combination of any two or more approaches or models or method or techniques or fusion of any among them to derive SDB. The several hybrid approach in SDB derivation has been proposed, and validated. Mavraeidopoulos et al., (2019) proposed hybrid bio-optical transformation for SDB using both empirical method and SA method for Sentinel-2 MS data. Chénier, Faucher, & Ahola, 2018) have used optical and Synthetic Aperture Radar data to derive SDB. Brando et al., (2009) utilized a hybrid technique that combines the spectral matching technique and the least squares relation. Dekker et al., (2011) used nonlinear spectrum matching and SA method and spectrum matching in precomputed database LUT to develop ALLUT (Adaptive Linearized Look-Up Trees). Jay & Guillaume, (2016) have developed a hybrid method based on Maximum Likelihood function based on a statistical approach and a RT approach-based model. Kerr & Purkis, (2018) used a hybrid of the RT and statistical approach to generate DTM from derived SDB. Danilo & Melgani, (2019) used a fusion of a physical wave model and statistical technique (Gaussian Process Regression) in an unsupervised learning to derive a novel SDB algorithm. Thus, it can be predicted that the next decade of SDB research will be primarily focused on such hybrid frameworks to estimate SDB with or without any field data for calibration.

4.4 Improvement in Accuracy of SDB Retrieval

The result from almost all the SDB studies in each section has provided accuracy of study either in terms of RMSE or coefficient of determination. The reported accuracy by various SDB studies has been found predisposed towards publishing better results either by hiding the depth range in which result was comparatively very low or using choice of error criterion least questionable. Majority of studies have used the criterion of reporting the accuracy in terms of RMSE or the validation with test data in terms of coefficient of determination. The depth ranges up to 5 m have categorically got a lower RMSE and value of R^2 high enough to appreciate the result as they have achieved better results than Bathymetric surveying. The accuracy of SDB retrieval decreases as the depth increases beyond 5 m and thereafter the reliability of retrieved depth is beyond the confidence level to assure mariner of navigation safety. If vis-à-vis comparison is made between techniques, and methods; almost all the techniques have reported similar results that SDB retrieval is accurate up to 70 % depending on the site of study. The figure 9 below represents SDB accuracy comparison between empirical, ML and SA Algorithms and the figure 10 represents comparison of errors (RMSE) between Empirical, ML and SA method. The best results achieved by each study employing one of the three methods and worst RMSE results have been used as data to depict the figure 9 and figure 10 below.

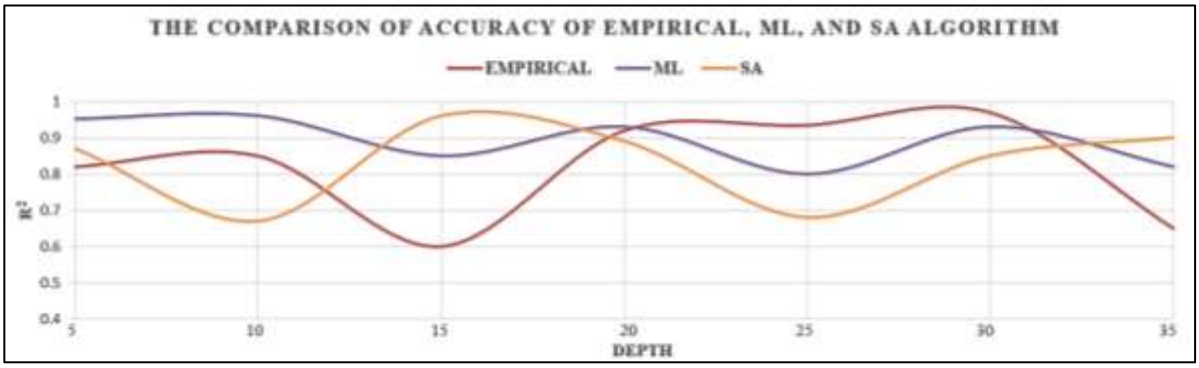

Figure 9: SDB Accuracy (R^2) comparison between Empirical, ML and SA Algorithms

The comparison of methods implies the better performance of ML up to the depth of 20 m, however, empirical methods have shown significantly better performance for depth of 20 m to 30 m (which performed fairly low below depth of 20 m), beyond 30 m the accuracy declines sharply.

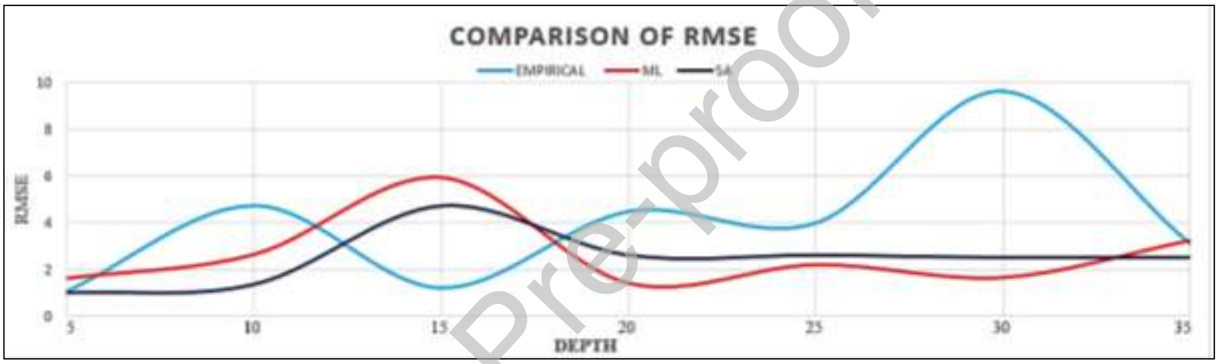

Figure 10: Comparison of Errors (RMSE) between Empirical, ML and SA

The comparison of errors between the methods implies the better performance of SA and ML algorithms. The errors up to the depth of 15 m are almost similar for these two methods. However, empirical methods show higher errors in retrieval beyond depth of 25 m.

The major factors confounding factors in SDB estimation such as turbidity, benthos and its classification, have been studied since past few years. Still, few other factors which inhibit acoustic waves like salinity, temperature, etc. are yet to be considered in SDB. The most of the SDB studies have been carried in clear transparent water, however the regions having rich sediments laden creeks and channels are yet far away from scope of SDB studies. The future SDB research will have to discover solutions for sites having highly turbid areas, or variable bottom types using all contemporary available data and techniques.

The table 2 provides a matrix for future researchers of SDB. This matrix provides information on required satellite resolution, in-situ data, methods & algorithms for SDB based on level of accuracy required. The table 2 should be used in supplement to table 1 to select methods of SDB as per demand of study and resources available. The study sites have been categorized in shallow water clear and shallow water turbid up to depth of 30 m and shallow turbid estuarine water less than 15 m depth. The accuracy needs to be achieved, the spatial resolution of satellite data and in-situ bathymetric data has been categorized into three categories of Low (more than 300 m), medium (300-10 m) and High (less than 5 m) classes. The preferred methods and algorithms are denoted for required accuracy and available resources along with studies that may be referred as ready reckoner for further research. Caballero, Stumpf, & Meredith, (2019) have extended Stumpf et al., (2003) developed a ratio transform technique of SDB to include the effect of turbidity and chlorophyll on SDB estimation for depths range of 0–18 m in South Florida and reported very low errors. The IHO-IOC GEBCO Cookbook is ready to use SDB reconnaissance tool which provides quick steps to derive SDB using Landsat-8 data in ArcGIS. The Semi-Analytical studies of McKinna et al., (2015) and Lee et al., (1999) provide detailed description of all the parameters required to be studied in conjunction with SDB. The table 2 also denotes the open sources to bathymetric data for researchers using IHO Data Centre for Digital Bathymetry (DCDB) which provides crowd-source bathy data for most of the coastal regions.

Table 2: Matrix of SDB Technique selection

Depth region	**Accuracy required**	**Satellite resolution**	**In-situ resolution**	**Preferred method**	**Preferred Algorithms**	**Refer Studies**	**Data Resources**	
							Satellite	BathyData
Shallow Turbid < 30 m	L	L	L	●Empirical Methods ● Semi-Empirical	● Regression, ● Band Ratio ● Classification ● ML	● (Caballero et al., 2019; South Florida); ● (Hernandez & Armstrong, 2016; Puerto Rico)	**Low:** MODIS, MERIS SENTINEL 3	**Low:** SBES GEBCO DCDB#
	M	M, H	M, H					
	H	-	-	-	● Not Achievable			
Shallow clear < 30 m	L	M	M	●Empirical Methods ● Semi-Empirical ● QAA ● SA*	● Regression ● Band Ratio ● Band Diff. ● ML ● Forward/ inverse modelling ● Optimization	● IHO Cookbook (Pe'eri, Azuike, & Parrish, 2013; US, Nigeria, and Belize) ● (Sagawa et al., 2019; Japan, USA, Puerto Rico, Japan, Vanuatu) ● (Masita Dwi Manessa et al., 2017;Indonesia)	**Medium:** LANDSAT SENTINEL 2 SPOT, ASTER	**Medium** LIDAR
	M	M	H					
	H	H	H*					
Shallow turbid, Creek & Estuaries < 15 m	L	M	M	● Analytical Methods* ● SA*	● ML if High resolution in-situ data available ANN, Deep Learning ● Forward/inverse modelling	● SAA SWIM (McKinna et al., 2015, GBR, Australia) ● SA Optimization (Lee et al., 1999, Florida) ● (Dekker et al., 2011, Australia & Bahamas)	**High:** IKONOS QUICKBIRD WORLDVIEW RAPIDEYE CARTOSAT	**High:** MBES SSS Depth-Profiler
	M	H	H					
	H	H	H*					
Shallow	L	M, H	No In-situ data	QAA	4SM Method by Favoretto et al., (2017), California; and Kerr & Purkis, (2018), 5 Sites in caribbean for depth up to 15 m, RMSE 2-5 m			
L:Low (>300m), M:Medium (300-10m), H:High (<5m) ; * indicates Water Quality Parameters -Required; GEBCO (General Bathymetric Chart of Ocean) & DCDB (Data Centre for Digital Bathymetry) are open source bathy database of IHO. # For Indian Coast data Refer Sindhu et al., (2007).								

5. CONCLUSION

SDB has become very popular to the scientific community because of its synoptic coverage and getting information of inaccessible regions. Passive sensors are most popular for SDB but late active sensors are also being used for SDB by various researchers. In this paper, we have discussed mainly the passive sensors. Comparative analysis of optical SDB within and between the methods for the last 5 decades has been done. Although, the comparison was constrained by parameters or site-specific environmental variables which were inconsistent. The variable depths in the study area, different resolution of sensors, and dynamics of coastal IOPs were few of the hindrances in comparative analysis. We have also emphasized the areas where challenges, and apparent knowledge gaps exist for further research in the SDB domain. The contemporary surge in SDB studies is especially focusing on shallow water depth estimation where numerous challenges are posed due to the dynamic nature of confounding variables in developing operational models for coastal regions.

The current studies on SDB are focused on efficacy to provide operational products wherein future lies in real-time operational use in ports, harbours, channels, creeks, etc. The present limitations of best-fit sensors for precise data acquisition in shallow waters of coastal regions is already under deliberation by some space agencies. Cloud based and web-based platforms are available to overcome challenges of high-end data processing capabilities to process huge amounts of data even without downloading it. The hybrid approach definitely provides an edge to think beyond the horizon of traditional algorithms. Few of the constraints, like turbidity, Chlorophyll, and other parameters in the dynamic nature of water column properties poses a major challenge, yet unresolved in SDB literature for the past so many years, and need a relook with advanced data and models. This provides wide opportunity to researchers in the field of SDB to explore the relationship of dynamic parameters in the water column with satellite bathymetry.

We have provided a matrix of SDB method selection based on the review of existing knowledge in the field. This matrix may help future researchers to determine the way ahead for SDB study as per the requirement of study area. The matrix of prerequisite satellite data, in-situ data resolution, methods and algorithms of SDB for the level of accuracy needed, as per the context of research is ready reckoner for practitioners in the field. The future work of the authors is focused on SDB by utilizing a hybrid of statistical and RT based approach with huge in-situ data of water constituents by executing ML algorithms.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

6. REFERENCES

Agrafiotis, P., Skarlatos, D., Georgopoulos, A., & Karantzalos, K. (2019). Shallow water bathymetry mapping from uav imagery based on machine learning. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci*, *XLII*.

Albert, A., & Mobley, C. D. (2003). An analytical model for subsurface irradiance and remote sensing reflectance in deep and shallow case-2 waters. *OPTICS EXPRESS*, *11*(22), 2873–2890.

Andrew, B., Stephen, P., Martinez, B., Richard, T., Joy, T., Maria, K., … Haimbach, P. (1988). Adaptive estimation of water depth using multispectral remote sensing Andrew. *OCEAN OPTICS*, *IX*, 222–228.

Bagheri, S., Stein, M., & Dios, R. (1998). Utility of hyperspectral data for bathymetric mapping in a turbid estuary. *International Journal of Remote Sensing*, *19*(6), 1179–1188. https://doi.org/10.1080/014311698215676

Benny, A. H. H., Dawson, G. J. J., & Benny, A. H. H. (1983). Satellite Imagery as an Aid to Bathymetric Charting in the Red Sea Satellite Imagery as an Aid to Bathymetric Charting in the Red Sea. *The Cartographic Journal*, *20*(1), 5–16. https://doi.org/10.1179/caj.1983.20.1.5

Bierwirth, P. N., Lee, T. J., & Burne, R. V. (1993). Shallow Sea-Floor Reflectance and Water Depth Derived by Unmixing Multispectral Imagery *. *Photogrammetric Engineering & Remote Sensing*, *59*(3), 331–338.

Bramante, J. F., Raju, D. K., & Sin, T. M. (2013). Multispectral derivation of bathymetry in Singapore 's shallow , turbid waters. *International Journal of Remote Sensing*, *34*(6), 2070–2088. https://doi.org/10.1080/01431161.2012.734934

Brando, V. E., Anstee, J. M., Wettle, M., Dekker, A. G., Phinn, S. R., & Roelfsema, C. (2009). A physics based retrieval and quality assessment of bathymetry from suboptimal hyperspectral data. *Remote Sensing of Environment*, *113*(4), 755–770. https://doi.org/10.1016/j.rse.2008.12.003

Caballero, I., & Stumpf, R. P. (2020). Towards Routine Mapping of Shallow Bathymetry in Environments with Variable Turbidity : Contribution of Sentinel-2A / B Satellites Mission. *Remote Sensing*, *12*(451). https://doi.org/10.3390/rs12030451

Caballero, I., Stumpf, R. P., & Meredith, A. (2019). Preliminary Assessment of Turbidity and Chlorophyll Impact on Bathymetry Derived from Sentinel-2A and Sentinel-3A Satellites in South Florida. *Remote Sensing*, *11*(645), 1–20. https://doi.org/10.3390/rs11060645

Ceyhun, Ö., & Yalçın, A. (2010). Remote sensing of water depths in shallow waters via artificial neural networks. *Estuarine, Coastal and Shelf Science*, *89*, 89–96. https://doi.org/10.1016/j.ecss.2010.05.015

Chen, A., & Zhu, B. (2015). Comparison of three empirical methods for water depth mapping with case study of Pratas Island. *Remote Sensing of the Environment: 19th National Symposium on Remote Sensing of China*. https://doi.org/10.1117/12.2204945

Chen, B., Yang, Y., Xu, D., & Huang, E. (2019). ISPRS Journal of Photogrammetry and Remote Sensing A dual band algorithm for shallow water depth retrieval from high spatial resolution imagery with no ground truth. *ISPRS Journal of Photogrammetry and Remote Sensing*, *151*(February), 1–13. https://doi.org/10.1016/j.isprsjprs.2019.02.012

Chénier, R., Faucher, M.-A., & Ahola, R. (2018). Satellite-Derived Bathymetry for Improving Canadian Hydrographic Service Charts. *International Journal of Geo-Information*, *7*(306), 2–15. https://doi.org/10.3390/ijgi7080306

Chybicki, A. (2017). Three-dimensional geographically weighted inverse regression (3GWR) model for satellite derived bathymetry using Sentinel-2 observations. *Marine Geodesy*, *0419*(September). https://doi.org/10.1080/01490419.2017.1373173

Clark, R. K., Fay, T. H., & Walker, C. L. (1987). Bathymetry calculations with Landsat 4 TM imagery under a generalized ratio assumption. *Applied Optics*, *26*(19), 4036–4038.

Clark, R. K., Fay, T. H., & Walker, C. L. W. C. L. (1988). Bathymetry using Thematic Mapper Imagery. *SPIE Ocean Optics*, *Vol. 925*(IX), 229–231.

Collet, C., Rostaing, P., & Bouthemyb, P. (2000). Spot satellite data analysis for bathymetric mapping. *IEEE*, 464–467.

Collings, S., Botha, E. J., Anstee, J., & Campbell, N. (2018). Depth from Satellite Images : Depth Retrieval Using a Stereo and Radiative Transfer-Based Hybrid Method. *Remote Sensing*, *10*(1247), 1–23. https://doi.org/10.3390/rs10081247

Danilo, C., & Melgani, F. (2019). High-Coverage Satellite-Based Coastal Bathymetry through a Fusion of Physical and Learning Methods. *Remote Sensing*, *11*(376), 1–16. https://doi.org/10.3390/rs11040376

Dekker, A. G., Phinn, S. R., Anstee, J., Bissett, P., Brando, V. E., Casey, B., … Chris, R. (2011). OCEANOGRAPHY : METHODS Intercomparison of shallow water bathymetry , hydro-optics , and benthos mapping techniques in Australian and Caribbean coastal. *LIMNOLOGY and OCEANOGRAPHY: METHODS*, *9*, 396–425.

Dickens, K., & Armstrong, A. (2019). Application of Machine Learning in Satellite Derived Bathymetry and Coastline Detection. *SMU Data Science Review*, *2*(1).

Doxani, G., Papadopoulou, M., Lafazani, P., & Pikridas, C. (2012). Shallow-water bathymetry over variable bottom types using multispectral worldview-2 image. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XXXIX*(September 2012), 159–164.

Eugenio, F., Marcello, J., & Martin, J. (2015). High-Resolution Maps of Bathymetry and Benthic Habitats in Shallow-Water Environments Using Multispectral Remote Sensing Imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *53*(7), 3539–3549. https://doi.org/10.1109/TGRS.2014.2377300

Gabr, B., Ahmed, M., & Marmoush, Y. (2020). PlanetScope and Landsat 8 Imageries for Bathymetry Mapping. *Journal of Marine Science and Engineering*, *8*(143), 2–17.

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

Geyman, E. C., & Maloof, A. C. (2019). A Simple Method for Extracting Water Depth From Multispectral Satellite Imagery in Regions of Variable Bottom Type Earth and Space Science. *Earth and Space Science*, *6*, 527–537. https://doi.org/10.1029/2018EA000539

Gholamalifard, M., Esmaili Sari, A., Abkar, A., & Naimi, B. (2013). Bathymetric Modeling from Satellite Imagery via Single Band Algorithm (SBA) and Principal Components Analysis (PCA) in Southern Caspian Sea. *Int. J. Environ. Res*, *7*(4), 877–886.

Giardino, C., Candiani, G., Bresciani, M., Lee, Z., Gagliano, S., & Pepe, M. (2012). BOMBER: A tool for estimating water quality and bottom properties from remote sensing images. *Computers and Geosciences*, *45*, 313–318. https://doi.org/10.1016/j.cageo.2011.11.022

Gordon, H. R. (1973). Simple Calculation of the Diffuse Reflectance of the Ocean. *Applied Optics*, *12*(12), 2803–2804.

Gordon, H. R., & Mccluney, W. R. (1975). Estimation of the Depth of Sunlight Penetration in the Sea for Remote Sensing. *Applied Optics*, *14*(2), 413–416.

Gordon, H. R., & Morel, A. Y. (1983). Coastal and Estuarine Studies of Ocean Color for Interpretation of Satellite. *BOOK*.

Gould, R. W. J., Arnone, R. A., & Sydor, M. (2001). Absorption, Scattering, and Remote-Sensing

Reflectance Relationships in Coastal Waters: Testing aNew Inversion Algorithm. *Journal of Coastal Research*, *17*(2), 328–341.

Halls, J., & Costin, K. (2016). Submerged and Emergent Land Cover and Bathymetric Mapping of Estuarine Habitats Using WorldView-2 and LiDAR Imagery. *Remote Sensing*, *8*. https://doi.org/10.3390/rs8090718

Hamylton, S. M., Hedley, J. D., & Beaman, R. J. (2015). Derivation of High-Resolution Bathymetry from Multispectral Satellite Imagery : A Comparison of Empirical and Optimisation Methods through Geographical Error Analysis. *Remote Sensing*, *7*, 16257–16273. https://doi.org/10.3390/rs71215829

Hassan, H. M., & Nadaoka, K. (2017). Assessment of machine learning approaches for bathymetry mapping in shallow water environments using multispectral satellite images. *International Journal of GeoInformatics*, *13*(2).

Hedley, J. D., Roelfsema, C., Brando, V., Giardino, C., Kutser, T., Phinn, S., … Koetz, B. (2018). Remote Sensing of Environment Coral reef applications of Sentinel-2 : Coverage , characteristics , bathymetry and benthic mapping with comparison to Landsat 8. *Remote Sensing of Environment*, *216*(April), 598–614. https://doi.org/10.1016/j.rse.2018.07.014

Hedley, J., Roelfsema, C., & Phinn, S. R. (2009). Efficient radiative transfer model inversion for remote sensing applications. *Remote Sensing of Environment*, *113*(11), 2527–2532. https://doi.org/10.1016/j.rse.2009.07.008

Hernandez, W. J., & Armstrong, R. A. (2016). Deriving Bathymetry from Multispectral Remote Sensing Data. *Journal of Marine Science and Engineering*, *4*(8). https://doi.org/10.3390/jmse4010008

Hodúl, M., Bird, S., Knudby, A., & Chénier, R. (2018). Satellite derived photogrammetric bathymetry. *ISPRS Journal of Photogrammetry and Remote Sensing*, *142*(June), 268–277. https://doi.org/10.1016/j.isprsjprs.2018.06.015

Huang, R., Yu, K., Wang, Y., Wang, J., Mu, L., & Wang, W. (2017). Bathymetry of the Coral Reefs of Weizhou Island Based on Multispectral Satellite Images. *Remote Sensing*, *9*(750), 1–25. https://doi.org/10.3390/rs9070750

Jalilzadeh, A., & Behzadi, S. (2019). Machine Learning Method for Predicting the Depth of Shallow Lakes Using Multi - Band Remote Sensing Images. *Journal of Soft Computing in Civil Engineering*, *2*, 54–64.

Jawak, S. D., Vadlamani, S. S., & Luis, A. J. (2015). A Synoptic Review on Deriving Bathymetry Information Using Remote Sensing Technologies : Models , Methods and Comparisons. *Advances in Remote Sensing*, *4*, 147–162.

Jay, S, & Guillaume, M. (2016). Regularized estimation of bathymetry and water quality using hyperspectral remote sensing. *International Journal of Remote Sensing*, *37*(2), 263–289.

Jay, Sylvain, & Guillaume, M. (2014). A novel maximum likelihood based method for mapping depth and water quality from hyperspectral remote-sensing data. *Remote Sensing of Environment*, *147*, 121–132. https://doi.org/10.1016/j.rse.2014.01.026

Jil, W., Civco, D. L., & Kennard, W. C. (1992). Satellite Remote Bathymetry : A New Mechanism for modelling. *Photogrammetric Engineering & Remote Sensing*, *58*(5), 545–549.

Kabiri, K. (2017). Discovering Optimum Method To Extract Depth Information For Nearshore Coastal Waters From Sentinel-2a Imagery- Case Study : Nayband Bay, Iran. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII*(October), 7–10. https://doi.org/10.5194/isprs-archives-XLII-4-W4-105-2017

Kakuta, S., Ariyasu, E., & Takeda, T. (2018). Shallow water bathymetry mapping using hyperspectral data. *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, 1539–1542.

Kerr, J. M., & Purkis, S. (2018). An algorithm for optically-deriving water depth from multispectral imagery in coral reef landscapes in the absence of ground-truth data. *Remote Sensing of Environment*, *210*(March), 307–324. https://doi.org/10.1016/j.rse.2018.03.024

Kibele, J., & Shears, N. T. (2016). Non-Parametric Empirical Depth Regression for Bathymetric Mapping in Coastal Waters. *IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing*, *2*(Fig 1), 1–9.

Klemas, V., Bartlett, D., & Rogers, R. (1975). Coastal Zone Classification from Satellite Imagery. *Photogrammetric Engineering & Remote Sensing*, 499–513.

Klonowski, W. M., Fearns, P. R. C. S., & Lynch, M. J. (2007). *Retrieving key benthic cover types and bathymetry from hyperspectral imagery*. *1*(December), 1–21. https://doi.org/10.1117/1.2816113

Lee, Z., & Carder, K. L. (2000). Hyperspectral remote sensing of shallow water environments: A REVIEW. *Proceedings of SPIE, 4154*, 83–94.

Lee, Z., & Carder, K. L. (2002). Effect of spectral band numbers on the retrieval of water column and bottom properties from ocean color data. *Applied Optics*, *41*(12), 2191–2201.

Lee, Z., Carder, K. L., & Arnone, R. A. (2002). Deriving inherent optical properties from water color : a multiband quasi-analytical algorithm for optically deep waters. *Applied Optics*, *41*(27), 23–30.

Lee, Z., Carder, K. L., Mobley, C. D., Steward, R. G., & Patch, J. S. (1999). Hyperspectral remote sensing for shallow waters : 2 . Deriving bottom depths and water properties by optimization. *Applied Optics*, *38*(18), 3831–3843.

Li, S. (2019). A method of Remote Sensing Water Bathymetry based on Support Vector Machine. *2019 International Conference on Communications, Information System and Computer Engineering (CISCE)*, 451–455. https://doi.org/10.1109/CISCE.2019.00105

Liceaga-Correa, M. A., & Euan-Avila, J. I. (2002). Assessment of coral reef bathymetric mapping using visible Landsat Thematic Mapper data. *International Journal of Remote Sensing*, *23*(I), 3–14.

Liew, S. C., Chang, C. W., & Kwoh, L. K. (2012). Sensitivity analysis in the retrieval of turbid coastal water bathymetry using worldview-2 satellite data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXIX*(September), 13–16.

Liu, Y., Islam, A., & Gao, J. (2003). Quantification of shallow water quality parameters by means of remote sensing. *Progress in Physical Geography, 1*, 24–43.

Loureiro, C., Pacheco, A., Horta, J., Loureiro, C., Ferreira, Ó., Pacheco, A., … Ferreira, Ó. (2015). monitoring in shallow waters Retrieval of nearshore bathymetry from Landsat 8 images : a tool for coastal monitoring in shallow waters. *Remote Sensing of Environment*, *March*(March). https://doi.org/10.1016/j.rse.2014.12.004

Lyzenga, D. R. (1978). Passive remote sensing techniques for mapping water depth and bottom features. *Applied Optics*, *17*(3), 379–383.

Lyzenga, D. R. (1985). Shallow-water bathymetry using combined lidar and passive multispectral scanner data. *International Journal of Remote Sensing*, *6*(1), 115–125.

Lyzenga, D. R., Malinas, N. P., & Tanis, F. J. (2006). Multispectral Bathymetry Using a Simple Physically Based Algorithm. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, *44*(8), 2251–2259.

Lyzenga, D. (1981). Remote sensing of bottom reflectance and water attenuation parameters in shallow water using aircraft and Landsat data. *International Journal of Remote Sensing*, *2*(1), 71–82. https://doi.org/10.1016/j.geomorph.2019.02.017

Maritorena, S., Morel, A., & Gentili, B. (1994). Diffise reflectance of oceanic shallow waters : Influence of water depth and bottom albedo. *Limnol. Oceanogr.*, *39*(7), 1689–1703.

Masita Dwi Manessa, M., Haidar, M., Hastuti, M., Kresnawati, D. K. K., Dwi, M., Manessa, M., … Sensing, R. (2017). Determination of the best methodology for bathymetry mapping using spot 6 imagery : a study of 12 empirical. *International Journal of Remote Sensing and Earth Sciences*, *14*(2), 127–136.

Mavraeidopoulos, A. K., Oikonomou, E., Palikaris, A., & Poulos, S. (2019). A Hybrid Bio-Optical Transformation for Satellite Bathymetry Modeling Using Sentinel-2 Imagery. *Remote Sensing*, *11*, 1–16.

McKinna, L. I. W., Fearns, P. R. C., Weeks, S. J., Werdell, P. J., Reichstetter, M., Franz, B. A., … Feldman, G. C. (2015). A semianalytical ocean color inversion algorithm with explicit water column depth and substrate reflectance parameterization. *JOURNAL OF GEOPHYSICAL RESEARCH:Oceans*, *120*, 1741–1770. https://doi.org/10.1002/2014JC010224.Received

Minghelli-Roman, A., Goreac, A., Mathieu, S., Spigai, M., & P. Gouton. (2009). Comparison of bathymetric estimation using different satellite images in coastal sea waters. *International Journal of Remote Sensing*, *30*(21), 37–41. https://doi.org/10.1080/01431160902729580

Mishra, D., Narumalani, S., Lawson, M., & Rundquist, D. (2004). Bathymetric mapping using IKONOS multispectral data. *GIScience and Remote Sensing*, *41*(4), 301–321.

Mishra, D. R., & Gould, R. W. (2016). Preface : Remote Sensing in Coastal Environments. *Remote Sensing*, *8*(665), 1–6. https://doi.org/10.3390/rs8080665

Mishra, D. R., Ogashawara, I., & Gitelson, A. A. (2017). Bio-optical Modeling and Remote Sensing of Inland Waters. *BOOK*, 1–324.

Misra, A., Vojinovic, Z., Ramakrishnan, B., & Luijendijk, A. (2018). Shallow water bathymetry mapping using Support Vector Machine (SVM) technique and multispectral imagery Shallow water bathymetry mapping using Support Vector Machine (SVM) technique and multispectral imagery. *International Journal of Remote Sensing*, *00*(00), 1–20. https://doi.org/10.1080/01431161.2017.1421796

Mobley, C. D. (1994). Light and Water Radiative Transfer in natural Waters. *Book*.

Mobley, C. D., Gentili, B., Gordon, H. R., Jin, Z., Kattawar, G. W., Morel, A., … Stavn, R. H. (1993). Comparison of numerical models for computing underwater light fields. *Applied Optics*, *32*(36), 7484–7504.

Moeinkhah, A., Shakiba, A., & Azarakhsh, Z. (2019). Assessment of Regression and Classification Methods Using Remote Sensing Technology for Detection of Coastal Depth (Case Study of Bushehr Port and Kharg Island). *Journal of the Indian Society of Remote Sensing*, *0123456789*. https://doi.org/10.1007/s12524-019-00959-x

Mohamed, H, & Nadaoka, K. (2017). assessment of machine learning approaches for Bathymetry Mapping in shallow water environment using MS images. *International Journal of GeoInformatics*, *13*(2).

Mohamed, Hassan, Negm, A., Zahran, M., & Saavedra, O. C. (2016). Bathymetry Determination from High Resolution Satellite Imagery Using Ensemble Learning Algorithms in Shallow Lakes : Case Study El-Burullus Lake. *International Journal of Environmental Science and Development*, *7*(4), 295–301. https://doi.org/10.7763/IJESD.2016.V7.787

Mohamed, Hassan, Salah, M., & Nadaoka, K. (2017). Assessment of proposed approaches for bathymetry calculations using multispectral satellite images in shallow coastal / lake areas : a comparison of five models. *Arabian Journal of Geosciences*, 1–17. https://doi.org/10.1007/s12517-016-2803-1

Morel, A. (2001). Bio-optical models. *BOOK-SECTION*, 317–326. https://doi.org/10.1006/rwos.2001.0407

Mouw, C. B., Greb, S., Aurin, D., DiGiacomo, P. M., Lee, Z., Twardowski, M., … Craig, S. E. (2015). Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions. *Remote Sensing of Environment*, *160*, 15–30. https://doi.org/10.1016/j.rse.2015.02.001

Noujas, V., Kankara, R. S., & Selvan, S. C. (2019). Shoreline management plan for embayed beaches : A case study at Vengurla , west coast of India. *Ocean and Coastal Management*, *170*(January), 51–59. https://doi.org/10.1016/j.ocecoaman.2019.01.001

Odermatt, D., Gitelson, A., Brando, V. E., & Schaepman, M. (2012). Review of constituent retrieval in optically deep and complex waters from satellite imagery. *Remote Sensing of Environment*, *118*, 116–126. https://doi.org/10.1016/j.rse.2011.11.013

Olayinka, I. C., & Knudby, A. (2019). Satellite-derived bathymetry using a radiative transfer-based method : A comparison of different atmospheric correction methods. *MTS*.

Pan, Z., Glennie, C., Fernandez-diaz, J. C., Starek, M., Pan, Z., Glennie, C., … Starek, M. (2016). Comparison of bathymetry and seagrass mapping with hyperspectral imagery and airborne bathymetric lidar in a shallow estuarine environment. *International Journal of Remote Sensing*, *1161*(March), 516–536. https://doi.org/10.1080/01431161.2015.1131869

Paredes, J. M., & Spero, R. E. (1983). Water depth mapping from passive remote sensing data under a generalized ratio assumption. *Applied Optics*, *22*(8), 1134–1135.

Patel, A., Katiyar, S. K., & Prasad, V. (2016). Bathymetric Mapping of Bhopal City Lower Lake Using IRS-P6 : LISS-4 Imagery and Artificial Neural Network Technique. *Journal of the Indian Society of Remote Sensing*, *44*, 605–616. https://doi.org/10.1007/s12524-015-0523-8

Polcyn, F C, Brown, W. L., & Sattinger, I. J. (1970). THE MEASUREMENTS OF WATER DEPTH BY REMOTE SENSING TECHNIQUES. *Spacecraft Oceanography Project*.

Polcyn, Fabian C, & Lyzenga, D. R. (1973). CALCULATIONS OF WATER DEPTH FROM ERTS-MSS DATA. *Ntrs.Nasa.Gov*, 1433–1441.

Polcyn, Fabian C, & Rollin, R. A. (1969). Remote sensing techniques for the location and measurement of shallow-water features. *Spacecraft Oceanography Project*, 1–80.

Poliyapram, V., Raghavan, V., Metz, M., Delucchi, L., & Masumoto, S. (2017). Implementation of Algorithm for Satellite-Derived Bathymetry Using Open Source GIS and Evaluation for Tsunami Simulation. *International Journal of Geo-Information*, *6*(89), 1–17. https://doi.org/10.3390/ijgi6030089

Poursanidis, D., Traganos, D., Reinartz, P., & Chrysoulakis, N. (2019). On the use of Sentinel-2 for coastal habitat mapping and satellite-derived bathymetry estimation using downscaled coastal aerosol band. *Int J Appl Earth Obs Geoinformation*, *80*(March), 58–70. https://doi.org/10.1016/j.jag.2019.03.012

Sagawa, T., Yamashita, Y., Okumura, T., & Yamanokuchi, T. (2019). Satellite Derived Bathymetry Using Machine Learning and Multi-Temporal Satellite Images. *Remote Sensing*, *11*(1155), 2–19.

Sam, L., Prusty, G., & Gahlot, N. (2017). Evaluation of optical remote sensing-based shallow water bathymetry for recursive mapping. *Geocarto International*, *6049*(March), 1–17. https://doi.org/10.1080/10106049.2017.1299800

Sánchez-Carneroab, N., Ojeda-Zujarb, J., Rodríguez-Pérezc, D., & J.Marquez-Perezb. (2014). Assessment of different models for bathymetry calculation using SPOT multispectral images in a high-turbidity area : the mouth of the Guadiana Estuary. *International Journal of Remote Sensing*, *35*(2), 493–514. https://doi.org/10.1080/01431161.2013.871402

Sathyendranath, S. (2000). Reports of the International Ocean-Colour Coordinating Group Remote Sensing of Ocean Colour in Coastal , and Other Optically-Complex , Waters. *IOCCG 2000*.

Spitzer, D., & Dirks, R. W. J. (1986). Shallow water bathymetry and bottom classification by means of the Landsat and SPOT optical scanners. *SPIE*, *660*, 136–138.

Stumpf, R. P., Holderied, K., & Sinclair, M. (2003). Determination of water depth with high-resolution satellite imagery over variable bottom types. *Limnol. Oceanogr.*, *48*, 547–556.

Su, H., Liu, H., & Heyman, W. D. (2008). Automated Derivation of Bathymetric Information from Multi-Spectral Satellite Imagery Using a Non-Linear Inversion Model. *Marine Geodesy*, *31*, 281–298. https://doi.org/10.1080/01490410802466652

Tripathi, N. K., & Rao, A. M. (2002). Bathymetric mapping in Kakinada Bay , India , using IRS-1D LISS-III data. *International Journal of Remote Sensing*, *23*(6), 1013–1025. https://doi.org/10.1080/01431160110075785

Verhoef, W. (1998). *Theory of radiative transfer models applied in optical remote sensing of vegetation canopies*.

Warne, D K. (1978). Landsat as an Aid in the Preparation of Hydrographic Charts. *Photogrammetric Engineering and Remote Sensing*, *44*(8), 1011–1016.

Werdell, P. J., Mckinna, L. I. W., Boss, E., Ackleson, S. G., Craig, S. E., Gregg, W. W., … Zhang, X. (2018). An overview of approaches and challenges for retrieving marine inherent optical properties from ocean color remote sensing. *Progress in Oceanography*, *160*(January), 186–212. https://doi.org/10.1016/j.pocean.2018.01.001

Wettle, M., & Brando, V. E. (2006). SAMBUCA Semi-Analytical Model for Bathymetry, Un-mixing, and Concentration Assessment. *Report*, (July).

Wezernak, C. T., Lyzenga, D. R., & Polcyn, F. C. (1975). Report: Remote Sensing studies in the newyork bight. *NOAA Technical Report*.

Wong, E. W., Wong, J. M. C., & Liew, S. C. (2018). Operational derivation of water quality , water depth and sea bottom type from remote sensing satellite data. *IEEE IGARSS*, 953–956.

Yunus, A. P., Dou, J., Song, X., & Avtar, R. (2019). Improved Bathymetric Mapping of Coastal and Lake Environments Using Sentinel-2 and Landsat-8 Images. *Sensors*, *19*(2788).

Zhou, X., Marani, M., Albertson, J. D., & Silvestri, S. (2017). Hyperspectral and Multispectral Retrieval of Suspended Sediment in Shallow Coastal Waters Using Semi-Analytical and Empirical Methods. *Remote Sensing*, *9*(393), 1–28. https://doi.org/10.3390/rs9040393