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Article in International Journal of Remote Sensing - January 2018
DOI: 10.1080/01431161.2017.1421796

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To link to this article: https://doi.org/10.1080/01431161.2017.1421796

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Shallow water bathymetry mapping using Support Vector Machine (SVM) technique and multispectral imagery

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ABSTRACT
Satellite imagery along with image processing techniques prove to be efficient tools for bathymetry retrieval as they provide time and cost-effective alternatives to traditional methods of water depth estimation. In this article, a nonlinear machine learning technique of Support Vector Machine (SVM) is used to derive shallow water bathymetry data along Sint Maarten Island and Ameland Inlet, The Netherlands, by combining echo-sounding measurements and the reflectance of blue, green, or red bands of Landsat Enhanced Thematic Mapper Plus (Landsat 7 ETM+) and Landsat 8 Operational Land Imager (OLI) imagery with 30 m spatial resolution. In the analysis, 80% of data points of the echo-sounding measurements are used for training and the remaining 20% data points are used for testing. The model utilizes the radial basis kernel function (nonlinear) and the other training factors such as the smoothing parameter, penalty parameter $C$, and insensitivity zone $\varepsilon$ are selected and tuned based on the learning (i.e. training) process. The overall errors during test phases for Sint Maarten Island (1–15 m) and Ameland Inlet (1.00–3.50 m) are 8.26% and 14.43%, respectively, reflecting that the model produces significant estimations for the shallow depths ranges, considered in this study. The results obtained are also compared statistically with those estimated from the widely used linear transform model and ratio transform model, which establish a linear relationship between the water depth and band reflectances. Based on the results, it is evident that SVM provides a comparable or better performance for shallow depth ranges and can be used effectively for deriving accurate and updated medium resolution bathymetric maps.

1. Introduction
Near-shore bathymetry is one of the most important input requirements of any coastal numerical model (Roelvink and Reniers 2011). Remote sensing (RS) plays an important role in hydro-informatics (Mynett and Vojinovic 2009; Vojinovic 2015), and the ability to
derive bathymetry using RS techniques is a topic of growing interest in coastal monitoring and research, especially given the high global demand for climate change impact assessments on coasts (Ranasinghe 2016). This is primarily because conventional methods for acquiring in situ measurements such as ship-based echo-sounding and lidar-based techniques prove to be time consuming and expensive.

RS exploits the fact that different wavelengths of the light spectrum are attenuated by varying degrees and hence can be used to derive bathymetry information at varying spatial and temporal scales. Several algorithms have been proposed for bathymetry estimation using optical RS by utilizing either analytical or empirical methods. Analytical methods are based on the optical properties of water such as attenuation, backscattering, so on, which are mainly characterized by the propagation of light in the water column. Empirical methods, on the other hand, establish a mathematical relationship between the remotely sensed digital numbers (DNs)/radiance/reflectance of the waterbody with the depth at few sampled locations. One of the initial attempts to estimate water depth from RS was done by Lyzenga (1978) utilizing a combination of aerial multispectral data and radiometric techniques. A commonly used analytical model, based on flow radiative transfer model, was developed by Spitzer and Dirks (1986) to estimate shallow water depths. Other analytical approaches have been suggested by Benny and Dawson (1983) and Philpot (1989).

Empirical methods have also been used extensively for shallow water bathymetry estimations. The most popular approach is the linear band method, which was proposed by Lyzenga (1981; 1985) assumes that the bottom reflected reflectance is a linear function of the bottom reflectance and an exponential function of the water depth. This model was further modified by Conger et al. (2006), and they suggested an approach that involves rotating the ln-transformed colour bands against a bathymetry band to de-correlate the former from depths in optically shallow water. Other widely used algorithms are those proposed by Jupp (1988) and Stumpf, Holderied, and Sinclair (2003). The Jupp’s method has three parts (i) calculation of depth of penetration (DOP) zones (ii) interpolation of depths within the DOP zone and (iii) the calibration of depths within the DOP zones. Stumpf, Holderied, and Sinclair (2003) proposed a linear ratio model contrary to the linear band algorithm which is successful in deriving depths even greater than 25 m in case of clear waters. It is further suggested that the ratio transform model addresses relevant issues pertaining to application of passive RS for shallow water bathymetry retrieval, such as, it does not require subtraction of dark water pixels and requires fewer empirical coefficients for the solution which makes its application relatively easier and more robust.

The advancement of RS technology has enabled the expansion of these methodologies to satellite data with improved spatial and spectral resolution such as IKONOS, Quickbird, and Worldview-2 (Su, Liu, and Heyman 2008; Lyons, Phinn, and Roelfsema 2011; Bramante, Raju, and Min 2011). Furthermore, in recent times, few researchers have attempted to improve the accuracy of bathymetry retrieval by utilizing RS data sets along with machine learning (ML) approaches. Gholamalifard et al. (2013) tested three different algorithms: single band algorithm, principal component analysis, and multilayer perceptron (MLP, back propagation), for bathymetry estimation in the Southern Caspian Sea, Iran. Liu et al. (2015) investigated
the potential of two artificial neural network models, MLP and general regression neural network (GRNN) for bathymetry estimation by utilizing IKONOS and Landsat imageries for their case studies. It is evident that optical RS-based analysis is widely considered as an efficient alternative to field observations; however, their usage is greatly limited due to water turbidity and reflectance penetration.

The present research involves retrieval of satellite-derived bathymetry (SDB) for near-shore regions using an ML approach called Support Vector Machine (SVM). SVM is a data-driven technique which keeps the training error fixed (i.e. within given boundaries) and minimizes the confidence interval, that is, it matches the machine capacity to data complexity (Vojinovic, Kecman, and Babovic 2003; Vojinovic 2007). SVM mainly uses data to find the approximating function or the separation boundary, the former being the case for the present study. The SVM model demonstrated here is developed by Vojinovic et al. (2013) and as such has been applied to Landsat Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) data for the Dutch territory of Sint Maarten Island and the Ameland Inlet in the Dutch Wadden Sea. The study also includes a comparison of the results obtained using SVM with two other established models; the linear transform (Lyzenga 1981; Lyzenga 1985) and the ratio transform (Stumpf, Holderied, and Sinclair 2003) algorithms.

The primary objective of this study is to provide an efficient method for deriving bathymetric data from satellite images. The SDB maps generated have a medium spatial resolution of 30 m and can easily be used to provide inexpensive (Landsat data sets are freely available) and high density data in raster format or converted to ASCII format for further utilization in numerical models for coastal research. The technique can also be utilized in studies related to coastal management especially near harbours; ports, so on, where shallow depths can present risks to shipping and navigation; near shoals and banks where rapid changes due to sedimentation, erosion, and scoring of channels can lead to alteration in the bottom topography. This approach can be considered as a rapid and economical alternative for bathymetry estimation at higher temporal resolutions.

2. Study area

2.1. Sint Maarten Island

The study area (Figure 1) consists of the Dutch territory of Sint Maarten Island (SM), which is located at 63° W and 18° N. The southwest side of Sint Maarten is mainly exposed to deep water waves and the wave energy reaching this coast mainly consists of ocean swells from the Caribbean Sea, or the Atlantic, mixed intermittently with local winds (Netherlands Antilles Meteorological Service 1981). In addition, the island experiences an insignificant tidal difference of the order less than 10 cm (Vojinovic et al. 2013). Extensive shallow platforms border the eastern side of the island wherein the 30 m depth contour is located approximately 5 km from the shore (Boon and Green 1988). SM is impacted by the North Atlantic hurricane season from 1 June to 30 November, with the hurricanes being the strongest in the months of September and October (Vojinovic and Van Teeffelen 2007). Negligible scientific information regarding the water quality is available in this location. However, as
can be seen in Figure 1(a), clear waters dominate most parts of this region that facilitate reef formation, except along certain bays dominated by human activities leading to slight increase in turbidity.

### 2.2. The Ameland Inlet

This study area is located in the north of The Netherlands at 53° N and 5° E and is one of the tidal inlets connecting the Dutch Wadden Sea to the North Sea. The Ameland Inlet (Figure 2) is characterized by a highly complex and dynamic geometry. The inlet water motion and the morphology are strongly governed by offshore waves and tidal forcing. Along the Dutch coast, the tidal waves propagate from southwest to northeast and have a semi-diurnal character with a mean tidal range of approximately 2 m. The average significant height is about 1 m (Cheung, Gerritsen, and Cleveringa 2007) with the dominant wave direction being from northwest. A combined effect of tidal and wave-induced currents causes a complex interaction leading to huge sediment influxes (Jirka and Uijttewaal 2004) and a net easterly sediment transport between the barrier islands/inlets systems (Dissanayake 2011). The approximate Secchi depths observed in this region ranges between 0.00 and 3.50 m.
3. Data and Methodology

3.1. Data

3.1.1. In situ measurements
In order to tune the satellite images to depths, bathymetric information procured using an echo-sounder during the period between 31 January 2011 and 8 February 2011 in the case of Sint Maarten Island as well as 20 May 2014 and 4 June 2014 for Ameland Inlet are used. For the present study, XY positions from the survey data for Sint Maarten Island and Ameland Inlet are projected using UTM Zone 20 and 31, respectively. The depths (Z) are tide adjusted and reduced to mean sea level (MSL) (Pacheco et al. 2015).

3.1.2. RS data sets
The satellite data sets from Landsat 7 ETM+ in the case of Sint Maarten Island and Landsat 8 OLI for Ameland Inlet are used for the estimation of bathymetry in this study. The data are downloaded from the public domain data sets of United States Geological Survey, USGS.

In case of Sint Maarten Island the Landsat 7 ETM + data of 14 January 2011 are used for bathymetry estimation. The Landsat 7 satellite is equipped with ETM+ which is the successor of Thematic Mapper (TM). The observation bands are essentially the same seven bands as TM with a spatial resolution of 30 m, with an additional panchromatic band of 8, and 15 m resolution. Although these images are accurately calibrated and geolocated, their major drawback is the appearance of gaps in the form of alternating wedges that increase in width from the centre to the edge of a scene, caused due to the failure of the scan line corrector (SLC). The maximum width of these data gaps is approximately equal to one full scan line or about 390 to 450 m. This causes an estimated

Figure 2. Study area (a) rectangular box showing location of Ameland Inlet and (b) near-shore bathymetry using echo-sounding measurements.
loss of about 22% of the scene, although about 22 km of the middle of the scene has the same quality of data as that of the previous (SLC-on) Landsat 7 imagery. For this study, the focal analysis tool of ERDAS Imagine 10 software is used to fill the gaps by utilizing the mean intensity values from the nearby pixels within a $3 \times 3$ window.

In the case of Ameland Inlet, the Landsat 8 OLI data for 9 March 2014 is used, which is a moderate resolution satellite imagery consisting of 11 spectral bands. The spatial resolutions of the bands 1–7 and 9 are 30 m, 15 m for band 8, and 100 m for bands 10 and 11. The Landsat 8 OLI has a particularly relevant band 1, which is used for coastal and aerosol studies.

The data sets are chosen based on their temporal proximity to the dates of the in situ measurements for these regions, as well as availability of cloud-free data. The selection of the best spectral bands for analysis is mainly governed by the penetrating capability of the bands as well as the aquatic environment under consideration. In general, short wavelength bands like blue and green are generally preferred for bathymetry estimation due to their strong penetration capabilities. However, in case of turbid waters, the optimum wavelength shifts to longer radiation and the water depth is strongly correlated with the red band (George 1997). Thus, the best bands are selected for application of the bathymetry algorithms based on a correlation analysis taking into account the individual band reflectances and the depths.

3.2. Methodology

The methodology of analysing the satellite imageries involves a four stage process, as schematically shown in Figure 3.

3.2.1. Pre-processing of satellite images

The pre-processing of satellite data sets is an important pre-requisite for any RS-based analysis. This is specifically important to eliminate the atmospheric effects, unwanted path radiance, unnecessary sea surface reflectance as well as distortion of the image. All the pre-processing steps in this study are carried out using the ENVI 5.1 software.

Radiometric Calibration and atmospheric correction: Calibrating imagery is essential to convert the raw image DNs to spectral radiance and subsequently to top of the atmosphere (ToA) reflectance. Here, the ENVI Radiometric Calibration tool is used for converting the DN values to radiance and ToA reflectance for both Landsat 7 ETM+ and Landsat 8 OLI based on the information available in the .MTL file associated with the downloaded data.

Moreover, the radiation recorded at satellite sensor maybe influenced by a range of effects when it passes through the atmosphere. Atmospheric properties such as aerosols, suspended sediment particles of dust, water vapour and water droplets may alter the transmittance. Hence, atmospheric correction becomes an imperative step before application of any algorithm.

In this analysis the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module of ENVI is used to eliminate the atmospheric errors in the satellite images. The FLAASH algorithm derives its physics-based mathematics from Moderate Resolution Atmospheric Transmission (MODTRAN4) that corrects wavelengths in the visible through near-infrared (NIR) and shortwave infrared regions (SWIR), up to 3 μm.
The input image for FLAASH is a radiometrically calibrated radiance image in band interleaved-by-line (BIL) format. The module further takes into consideration the date of acquisition, time as well as the sensor altitude for further correction of the image. The tool uses a dark pixel reflectance ratio method (Kaufman et al. 1997) to retrieve the aerosol amount and estimate the average scene visibility. For atmospheric correction one of the standard MODTRAN model atmospheres is chosen according to the expected surface temperature of the RS scene. After the images are atmospherically corrected, they are rescaled to reflectance values ranging from 0 to 1 using the band math tool in ENVI.

3.2.2. Spatial sub-setting – land/water separation

The geo-referenced images of Landsat ETM+ and OLI are further processed for spatial sub-setting to remove land pixels from the images. The NIR and MIR (mid infra-red) corresponds to regions of the electromagnetic radiation spectrum which are very sensitive to identifying land-water boundaries. In this case band 4 (NIR, 0.77–0.90 μm) and band 6 (SWIR, 1.57–1.65 μm) are used for Landsat 7 ETM+ and Landsat 8 OLI, respectively. The threshold values for water features are examined and defined for the final sub-setting of the images. In case of Sint Maarten Island a reflectance threshold of 0.06 is used and for the Ameland Inlet imagery a value of 0.20 is used for subsetting.

3.2.3. Bathymetry estimation

After pre-processing of satellite data sets and land/water separation, it is essential to identify the extinction depth, that is, the optical depth beyond which there is no evident
relationship between the depth and the reflectance. Here, for Sint Maarten Island, a depth value of 22.04 m (complete range) is considered as the extinction depth. On the other hand, based on the available Secchi depth information, an optical depth limit of 3.50 m is used for Ameland Inlet. For both the case studies, the bathymetry estimation has been restricted to these depths.

Depth retrieval algorithms: The following section describes the principles of the three bathymetry algorithms applied in this study.

(1) Linear transform algorithm:

Lyzenga (1981, 1985) suggested that the errors resulting from different bottom types could be corrected by using two bands provided that the ratio of the bottom reflectance between the two bands for all bottom types is constant over the scene. The proposed model is (Lyzenga 1985)

\[ Z = a_0 + a_i X_i + a_j X_j; \]  

where

\[ X_i = \ln \left( \frac{R_{w, i}}{R_{dp, i}} \right), \]  

\[ X_j = \ln \left( \frac{R_{w, j}}{R_{dp, j}} \right), \]

\[ a_0, a_i, a_j = \text{coefficients determined through multiple regression using known depths and the corresponding reflectances, } R_{w, i}, R_{w, j} = \text{observed reflectance in bands } i \text{ and } j, \text{ and } R_{dp, i}, R_{dp, j} = \text{reflectance of dark water pixel in bands } i \text{ and } j. \] If imagery has already been atmospherically corrected then, \[ X_i = \ln \left( \frac{R_{ac, i}}{R_{ac, j}} \right), \]

Lyzenga, Malinas, and Tanis (2006) finally gave the \( n \)-band model as

\[ Z = a_0 + \sum_{i=1}^{n} a_i X_i, \]  

where, \( X_i \) is same as above.

(2) Ratio transform method:

Stumpf, Holderied, and Sinclair (2003) devised a ratio transform method for shallow water bathymetry estimation. This model is principally based on the concept that light attenuates exponentially with depth and suggests that the effects of substrate albedo are minimized using two bands to derive depths. According to this model, different spectral bands attenuate at different rates, and hence the ratio between two spectral bands will vary with depth. The model is expressed mathematically as follows:

\[ Z = m_1 \frac{\ln(nR_w(\lambda_i))}{\ln(nR_w(\lambda_j))} - m_0, \]
where, $Z$ is depth, $m_1$ is a tunable constant to scale the ratio to depth, $R_{W}$ is observed reflectance in bands $i$ and $j$ of wavelengths $\lambda$, $n$ is a fixed value, and $m_0$ is the offset.

Generally, for this model the reflectance from blue and green bands are used to express the ratio defined in Equation (5).

(3) Support Vector Machines:

Although, Stumpf, Holderied, and Sinclair (2003) suggests a linear model, in practice the relationship between the ratio and the water depths may not always be linearly dependent. Hence, it is best captured by exploring a nonlinear function ($f$) to map the bathymetry, by further refining the equation as

$$Z = f\left(\frac{\ln(nR_W(\lambda_i))}{\ln(nR_W(\lambda_j))}\right).$$

(6)

The main aim of this article is to establish this function using the data-driven ML approach SVM (Vojinovic et al. 2013). An ML approach generally refers to an algorithm that estimates unknown values by mapping a system’s input and output using available data. The learning task applied here is based on regression, wherein the task involves prediction of real values associated with input data points. For this model the input is the same ratio as is used for the application of the Stumpf model, but the function is defined by SVM.

The SVM model used here performs learning by solving a quadratic programming problem and the code has been implemented using a combination of Borland Delphi and C programming languages (Vojinovic and Kecman 2004).

The regression used in SVM can be expressed using the following notation:

$$E = \sum_{i=1}^{p} L_{si} + \lambda \| \mathbf{Pf} \|^2 = \sum_{i=1}^{p} L_{si} + \Omega(h, I).$$

(7)

The above formula is a common expression of error or cost function (in some literature it is also referred to as risk) for SVM. It contains two terms, the first term minimizes the empirical risk (approximation or training error, or discrepancy between the data and the approximating function) and the second term enforces the smoothness of that function (Vapnik 1998).

Hence, $E$ is commonly referred in the literature as a cost or generalization error (or even risk) function to measure model’s performance, goodness of fit; $L_{si}$ denotes the closeness to data, that is, the sum of differences between the measurements and model outputs calculated in the training phase; $p$ refers to the size of measurements/training data; $\mathbf{Pf}$ denotes the capacity of SVM, that is, it controls the parameters for minimizing $E$; $\Omega$ is the VC (Vapnik and Chervonenkis) function (also called as confidence term or confidence interval) and relates to the smoothness of approximation; $\lambda$ denotes the regularization parameter (i.e. the Lagrange multiplier); $h$ is the VC dimension; and $I$ refers to the number of support vectors.

In regression-based SVM, the learning problem is pre-defined as the learning machine is given training data from which it attempts to learn the input-output relationship. The training vectors are mapped into a higher dimensional space by using a nonlinear kernel.
function. In this model, different kernel functions can be utilized; however, here the radial basis function (RBF) kernel has been used which is expressed as follows:

$$K(x_i, x_j) = \exp\left(-\phi \|x_i - x_j\|^2\right), \phi > 0.$$  \hspace{1cm} (8)

where, $\phi$ is the Gaussian function $x_i, x_j$ are feature vectors.

The other parameters that need to be selected during the learning process are the ‘shape’, that is, the smoothing parameter in the kernel function (variance of the Gaussian RBF kernel), $C$, that is, the penalty parameter that determines the trade-off between the training error and the Vapnik–Chervonenkis dimension of the model and the insensitivity $\epsilon$. Increasing the value of $C$ results in larger weights by virtue of assignment of higher penalty to errors. On the other hand, $\epsilon$ decreases the number of support vectors resulting in data compression. Further, an increase in $\epsilon$ has a smoothing effect on noisy data and implies a reduction in the accuracy of approximation (Vojinovic et al. 2013).

4. Results and discussion

Optical RS-based bathymetry is primarily based on the principle that the radiative energy is a function of reflected energy from the bottom and is therefore a robust indicator of water depth (Gao 2009). As mentioned earlier, bathymetric models can be analytical, semi-analytical or empirical. In the present study, empirical modelling using three different methodologies is carried out on Landsat 7 ETM+ and Landsat 8 OLI imageries for Sint Maarten Island and Ameland Inlet, respectively to estimate shallow water bathymetry.

4.1. Application of depth retrieval algorithms

For both the data sets, 80% of the data points, obtained from the echo-sounding measurements, are used for training and the remaining 20% data points are used for testing (Table 1).

This ratio is commonly used for ML studies and hence has been applied for training and testing all the bathymetry models considered in this study. Also, the same set of training and testing data are used to test each of the algorithms in order to ensure better comparison in their accuracies. It is to be noted here that although the in situ measurements are referenced to MSL and tide corrected the satellite images are procured at a particular date and time. Hence, a corresponding tide offset is applied to the final SDB obtained for both the region. Moreover, for pixels with more than one measurement, a single mean value of the echo-sounder data is calculated.

4.1.1. Linear transform model

The methodology used here is an adapted version of the liner transform algorithm developed by Lyzenga (1978, 1981, 1985) and utilizes the atmospheric corrected log linearized reflectances of selected bands regressed against depths available at select locations. The optimal wavelengths can be determined by measuring the spectrum at different depths and selecting the most sensitive bands to bathymetry.
In order to select the best bands and apply the linear transform model, the correlation between the individual bands reflectances with the depth range were checked. According to Lyzenga (1978, 1985) and Stumpf, Holderied, and Sinclair (2003), utilizing two or more bands for bathymetry estimation can aid in correcting for bottom albedo. Hence, blue, green, and red bands with 30 m resolution are adopted in this algorithm, for both the data sets. In case of SM, the blue and green bands show a coefficient of determination ($R^2$) of 0.96 and 0.93 respectively. The red band shows a relatively less correlation ($R^2 = 0.55$) with the depths. Nevertheless, it has been included in the study, to account for turbidity at certain locations (bays) along the coastal extent considered for this analysis. In case of Landsat 8 OLI, it is observed that the $R^2$ between the depths and the band reflectance is good for all the four bands; blue, green, red and coastal blue range between 0.93–0.96. However, the coastal blue band (0.43–0.45 $\mu m$) is not included in this study as it is spectrally similar to the blue band (0.45–0.51 $\mu m$). Here, the red band shows a very significant relationship ($R^2 = 0.93$) with the depth and hence it is included for the analysis. Since, depths are highly correlated with the red band (0.63–0.67 $\mu m$) in case of turbid waters, this analysis also helps to highlight that the clarity of water at Sint Maarten Island is better than that of Ameland Inlet.

Further, multiple regression is carried out using the training data and the corresponding reflectances for both the data sets. For Sint Maarten Island, the analysis yielded the regression coefficients: $-6.89$, $14.53$, $0.91$, which are further used to derive the bathymetry. On comparison of the predicted depth values with the observed depth values an $R^2$ of 0.95 is obtained (Figure 4 (a)). The coefficients derived for Ameland Inlet are $-33.44$, $41.68$, $-1.71$, and the resulting coefficient of determination between observed and estimated depth values is 0.79 (Figure 4 (b)).

### 4.1.2. Ratio transform method

This methodology uses a simple linear relationship between the ratio of reflectances in the blue-green bands and depths. This model assumes that the changes in bottom reflectance is either equal in both bands or affects the ratio insignificantly and hence ensures a relatively constant ratio over variable bottom types and depths.

A linear regression analysis is carried out using depth values from 1.00 to 22.04 m between the echo-sounding measurements and the reflectance ratio of Landsat ETM+ data for Sint Maarten Island. Subsequently the gain and offset values, derived to be 39.21 and $-48.09$ respectively, are used to obtain the bathymetry. An $R^2$ of 0.73 is
obtained between the observed and estimated depth values (Figure 4 (c)). For Landsat 8 OLI data set of Ameland Inlet, the linear regression yields the gain and offset values of 75.19 and −89.78, respectively and the corresponding coefficient of determination obtained is 0.77 (Figure 4 (d)).

4.1.3. Support Vector Machine
In case of Sint Maarten Island, the C parameter, the ε values are 100 and 3.50, respectively. The total number of support vectors chosen is 22.79% of the entire training data.

Figure 4. Correlation between observed depths and predicted depths obtained for (a) Sint Maarten Island (1.00–22.04 m) using linear transform model; (b) Ameland Inlet (1.00–3.50 m) using linear transform model; (c) Sint Maarten Island (1.00–22.04 m) using ratio transform model; (d) Ameland Inlet (1.00–3.50 m) using ratio transform model; (e) Sint Maarten Island (1.00–22.04 m) using SVM model; and (f) Ameland Inlet (1.00–3.50 m) using SVM model.
set. The training error is 24.53 which is less than the test error, that is 24.74. The predicted values of the water depths are in close agreement with that of the in situ measurement, as can be seen in Figure 4 (e), with a $R^2$ value of 0.77.

To obtain the bathymetry map of Ameland Inlet, the SVM Model is run with values of $C$ and $\varepsilon$ as 100 and 0.50, respectively. With a total number of chosen support vectors of about 16.19% of the entire training data set, the test error is 14.43, which is less than the training error of 14.65. The coefficient of determination $R^2$ of 0.79 is obtained between the observed and predicted values (Figure 4 (f)).

### 4.2. Statistical and visual comparison of results obtained from the above methodologies

In order to compare the accuracy of the three methodologies, three descriptive statistical parameters along with correlation coefficient $r$ and mean absolute error (MAE) are used. The parameters are defined as follows:

1. $\text{Bias}(Z_{\text{sat}}, Z_{\text{echo}}) = \text{mean}(Z_{\text{sat}}) - \text{mean}(Z_{\text{echo}})$,
2. $\text{DifMedian}(Z_{\text{sat}}, Z_{\text{echo}}) = \text{median}(Z_{\text{sat}}) - \text{median}(Z_{\text{echo}})$,
3. $\text{RMSE}(Z_{\text{sat}}, Z_{\text{echo}}) = \sqrt{\text{Var}_{\text{sat}} + (\text{Bias}(Z_{\text{sat}}, Z_{\text{echo}}))^2}$,
4. $\text{MAE}(Z_{\text{sat}}, Z_{\text{echo}}) = \frac{1}{N} \sum_{i=1}^{N} |Z_{\text{sat}} - Z_{\text{echo}}|$, where $N$ is the number of observations.

In case of Sint Maarten Island (Table 2), statistically, there is a considerable improvement in the estimated depths for SVM as compared to both the linear model and ratio model, especially in terms of RMSE and MAE values. It is observed that the $R^2$ value obtained is very strong in case of the linear transform model whereas is lower in case of both, the ratio transform model as well as SVM. This is mainly because empirically driven models take into account the local set of conditions of the study area. For Sint Maarten Island, a longer stretch of coastline with varying degree of turbidity has been considered and tuned using a smaller training set. Considering Lyzenga model utilizes three parameters (blue, green and red bands) to represent the depth values it shows stronger association in terms of the correlation as compared to the other two models which use only two bands (blue and green) as a ratio. Also, it can be seen that the overall RMSE and MAE values for SM are very high. These results clearly highlight the limitation of optical RS for bathymetry estimation. Theoretically the radiation from 0.48 to 0.60 $\mu$m can penetrate clear and calm ocean water only up to 15–20 m (Gao 2009) with the best detectability occurring at approximately 10 m (Bagheri, Stein, and Dios 1998). According to Muirhead and Cracknell (1986) the discernible depth rarely exceeds 20 m and associated uncertainties can be larger than 4–5 m. Therefore, in the case of Sint

### Table 2. Error statistics obtained by comparing predicted and observed value of depths in metres for Sint Maarten Island (1.00–22.04 m) using test data set.

<table>
<thead>
<tr>
<th>Method</th>
<th>Bias (m)</th>
<th>Dif median (m)</th>
<th>$r$</th>
<th>RMSE (m)</th>
<th>Mean absolute error (MAE) (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear transform algorithm</td>
<td>−5.68</td>
<td>−5.91</td>
<td>0.97</td>
<td>5.93</td>
<td>5.69</td>
</tr>
<tr>
<td>Ratio transform algorithm</td>
<td>0.13</td>
<td>−2.61</td>
<td>0.85</td>
<td>3.12</td>
<td>2.61</td>
</tr>
<tr>
<td>Support Vector Machine (SVM)</td>
<td>−0.16</td>
<td>−3.16</td>
<td>0.88</td>
<td>2.88</td>
<td>2.39</td>
</tr>
</tbody>
</table>
Maarten Island the large errors can be clearly attributed to the fact that a longer range of depth values from 1.00 to 22.04 m is considered for the analysis. In order to further verify the inference that the accuracy of bathymetry estimation improves in the case of shallow depths, an additional analysis is performed for this region taking into consideration depth ranges from 1 to 15 m. Considering that most shallow water studies generally involve depth ranges from 1 to 15 m, this range has been used for further analysis.

Statistics of the training and test data sets are given in Table 3.

In case of linear transform model the regression coefficients $-10.58$, $14.38$, $0.77$ are used to derive the bathymetry, which results in a strong $R^2$ of $0.97$ on comparison of the predicted depth values with the observed depth values. The application of the Stumpf model yields the gain and offset values of $28.23$ and $-35.77$, respectively, and in this case, a correlation of $0.92$ is obtained between the observed and estimated depth values. Finally, for the application of SVM, the $C$ parameter, the $\varepsilon$ value are $1000$ and $0.80$, respectively. $20.38\%$ of the entire data set are selected as support vectors which results in a training error of $8.08$, less than the test error which is $8.26$. A very good performance of SVM is observed with a $R^2$ value of $0.97$.

It is evident in Table 4 that the RMSE and MAE values have decreased for all the algorithms’ in comparison to those obtained for the depth ranges of $1.00$–$22.04$ m, improving the accuracy of bathymetry estimation significantly. Hence, it can be confirmed that the inclusion of deeper depths for bathymetry estimation significantly reduces the accuracy of the predictions in case of optical-based RS. In the case of Ameland Inlet (Table 5) significantly accurate bathymetry estimations are achieved in case of all the three algorithms with the RMSE values ranging between $0.34$ and $0.35$.

In terms of evaluation of the relative performance of all the three algorithms, it can be strongly suggested that SVM method proves to be very efficient in bathymetry estimation in case of varying environmental factors (turbidity) and depth ranges. According to available previous literature the linear transform model performs better than the ratio model at shallow water depths (Jawak and Luis 2015; Lyons, Phinn, and Roelfsema 2011). This is also observed when depths between $1$–$15$ m and $1.00$–$3.50$ m are considered for Sint Maarten Island and Ameland Inlet, respectively. However, it is argued that the ratio transform model is a more robust methodology, especially for varying bottom types and greater depth ranges, in comparison to the standard linear transform algorithm (Stumpf, Holderied, and Sinclair 2003), which proves to be valid when the depth from $1.00$ to $22.04$ m is considered for Sint Maarten Island, where the ratio model performs better than the Lyzenga by decreasing the RMSE from $5.93$ to $3.12$ m, and SVM further reducing it to $2.88$ m. The nonlinear SVM model used in the present study is proposed.

### Table 3. Statistics of the training and test data sets for Sint Maarten Island (1–15 m).

<table>
<thead>
<tr>
<th></th>
<th>Training Phase</th>
<th>Testing Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of data points</td>
<td>Minimum depth (m)</td>
</tr>
<tr>
<td>Sint Maarten Island</td>
<td>1099</td>
<td>1.26</td>
</tr>
</tbody>
</table>
as an improvement to the linear ratio model and it can be clearly observed that it outperforms the ratio model in case of both the study regions and all depth ranges. In comparison to the results obtained through the Lyzenga model for shallow depths, SVM produces comparable or better results in terms of the $R^2$, RMSE and MAE values. Additionally, it is to be noted that SVM produces more accurate results than those obtained from previously conducted ML-based bathymetric studies. Gholamalifard et al. (2013) used Landsat 5 TM along with MLP-ANNs method and produced depth estimates with a $R^2$ value of 0.8836. Liu et al. (2015) used MLP and GRNN for bathymetry estimation (depths 1–18 m) on Landsat ETM and reported a RMSE of 2.33 and 2.24 m as well as $R^2$ of 0.80 for both cases, respectively. Their results improved further on applying the two methods on IKONOS image with RMSEs decreasing to 1.26 and $R^2$ increasing to 0.96 for both MLP and GRNN. In the present study, for both Sint Maarten Island and Ameland Inlet, SVM produces very low RMSE values of 0.69 m and 0.34 m respectively, when shallow water depths are considered for the analysis.

Considering the RMSEs for the depth range from 1.00 to 22.04 m in the case of Sint Maarten Island is very high, the results cannot be used to derive operational maps. However, when the sensible depth of 1–15 m is used for analysis the resulting bathymetric products are comparable with acceptable accuracy and can be further utilized as an input to numerical models or for geomorphological studies (Figure 5).

For the case study of Ameland Inlet, it can be seen that the Lyzenga model tends to over-estimate in the depth ranges of 0.00–1.50 m (Figure 6 (b)). These depths are captured in the case of both the ratio models (Figure 6 (c, d)). However, visually, the main limitation in the case of SDBs generated using ratios is that they are relatively noisier than those derived by the linear transform algorithm. This is mainly because, as ratio combinations inherently magnify small differences more than a linear combination, they correspondingly lead to an increase in error variability (Stumpf, Holderied, and Sinclair 2003). Furthermore, it can be observed that none of these models are able to capture the siltation feature in this area. This highlights an important limitation of optical RS, which tends to fail in the case of highly turbid

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**Table 4.** Error statistics obtained by comparing predicted and observed value of depths in metres for Sint Maarten Island (1–15 m) using test data set.

<table>
<thead>
<tr>
<th>Method</th>
<th>Bias (m)</th>
<th>Dif median (m)</th>
<th>$r$</th>
<th>RMSE (m)</th>
<th>MAE (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear transform algorithm</td>
<td>0.02</td>
<td>−0.03</td>
<td>0.99</td>
<td>0.65</td>
<td>0.45</td>
</tr>
<tr>
<td>Ratio transform algorithm</td>
<td>0.07</td>
<td>−1.18</td>
<td>0.96</td>
<td>1.08</td>
<td>0.88</td>
</tr>
<tr>
<td>SVM</td>
<td>−0.01</td>
<td>−0.30</td>
<td>0.99</td>
<td>0.69</td>
<td>0.52</td>
</tr>
</tbody>
</table>

**Table 5.** Error statistics obtained by comparing predicted and observed value of depths in metres for Ameland Inlet (1.00–3.50 m) using test data set.

<table>
<thead>
<tr>
<th>Method</th>
<th>Bias (m)</th>
<th>Dif median (m)</th>
<th>$r$</th>
<th>RMSE (m)</th>
<th>MAE (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear transform algorithm</td>
<td>−0.08</td>
<td>−0.43</td>
<td>0.89</td>
<td>0.34</td>
<td>0.27</td>
</tr>
<tr>
<td>Ratio transform algorithm</td>
<td>−0.08</td>
<td>−0.44</td>
<td>0.87</td>
<td>0.35</td>
<td>0.28</td>
</tr>
<tr>
<td>SVM</td>
<td>−0.95</td>
<td>−0.51</td>
<td>0.89</td>
<td>0.34</td>
<td>0.27</td>
</tr>
</tbody>
</table>
locations such as Ameland Inlet, which is governed by complex tidal and sediment dynamics.

In terms of implementation, according to Stumpf, Holderied, and Sinclair (2003) the ratio based approach has a number of advantages over the linear transform method. Firstly, contrary to Lyzenga method, the ratio models (both linear ratio transform and SVM) do not necessarily require atmospheric correction like dark pixel subtraction or FLAASH, which expands their utility over larger number of benthic habitats. Also, they are more stable over broader geographic types and have superior depth penetration. Secondly, based on the number of bands used, the linear transform model requires more variables in terms of atmospheric corrected reflectances as well as coefficients contrary to the Stumpf model which requires only the ratio of blue to green bands and two other coefficients from linear regression and the SVM model which only requires the ratio as an input, thus making the ratio models, especially SVM more easy to implement. Finally, the main advantage of SVM over the linear ratio model is that it capable of predicting depths even in the case of nonlinear data sets which demonstrates it versatility for estimation of shallow water bathymetry.

5. Conclusion

Bathymetry data is a fundamental input for any coastal research that aims to understand the coastal processes of a particular region. In this study, a nonlinear ML approach called SVM is suggested as a possible improvement to the linear approaches widely used for shallow water bathymetry estimation. The statistical and visual evaluations obtained for
the two selected study areas demonstrate the capabilities of the SVM method for estimation of near-shore depths provided that clear satellite images (i.e. clear of clouds and clarity of water) are available. The low RMSE and MAE values obtained for both Sint Maarten Island and Ameland Inlet highlight the accuracy of the derived bathymetries. The SDBs generated through this method have a strong potential to complement survey data in a more cost effective and efficient way as they are not restricted by boats, aircraft or other survey systems. Moreover, the availability of satellite data at a high temporal resolution of satellite return periods of about 2 weeks makes it an extremely beneficial tool from the viewpoint of continuous coastal monitoring. The method presented here can therefore be used to derive quick and updated bathymetry information which can be further used as an input to numerical modelling studies for better understanding of coastal dynamics and management. The future scope of this study will be to find solutions for depth estimations in the case of highly turbid areas, or those with variable bottom data types, by exploiting multi-spectral imageries with higher spatial and spectral resolution.

Acknowledgments

The authors would like to thank Council of Scientific & Industrial Research – CSIR for providing the funding for Ms Ankita Misra, who is CSIR-Senior Research Fellow (SRF) at Indian Institute of Technology-Bombay, Mumbai, India. This work has been carried out as a part of her doctoral research. RR is supported by the AXA Research fund and the Deltares Harbour, Coastal and Offshore engineering Research Programme ‘Bouwen aan de Kust.’
Conflict of interest

The authors clearly declare that they have no conflict of interest and informed consent was obtained from all the individual participants and co-authors.

Disclosure statement

No potential conflict of interest was reported by the authors.

References


