ASSESSMENT OF GENETIC ALGORTHIM IN DEVELOPING BATHYMETRY USING MULTISPECTRAL LANDSAT IMAGES

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ABSTRACT: Bathymetry is required for coastal zone management; hence, it is important to be evaluated properly. Also, bathymetry is highly dynamic in nearshore zone, so, it needs continuous monitoring. The conventional method for bathymetry retrieval is based on sounding that requires intensive time, cost and calm sea conditions. Recently, remote sensing is commonly used to map the shallow water bathymetry since it is frequently captured. Adding up, satellite images may be attained freely with quietly high resolution like Landsat images; 30 m spatial resolution. Consequently, there is intensive research directed to correlate the reflectance/radiance to the water depths. Variable models either linear or nonlinear were developed while in this research, a nonlinear technique, Genetic Algorithm (GA), is introduced. GA was applied on data from multispectral Landsat images. Landsat images were geo-referenced, radiometrically calibrated and atmospherically corrected to attain the reflectance of different bands. GA was utilized to derive the bathymetry for a coastal stretch along the Egyptian Northern Coast (NC). Several trials have been investigated using a reflectance of a single band and a combination of bands, i.e., blue, green and red bands of Landsat 8. Bathymetry measurements at the study site have been used to calibrate the different models/trials. 70% of the data has been assigned to the training of models and the rest has been utilized in the testing process. Comparison of linear model, ratio transform model and GA has been performed. GA showed a comparable performance for estimating shallow water depths; R-squared= 0.95 and RMSE=0.59 m; while enhancements of the derived bathymetry can be achieved by clustering water depths with different assigned GA equations.

Keywords: Remote sensing, Satellite derived bathymetry, Egyptian Northern Coast.

INTRODUCTION

The seas cover about 70% of the earth's surface; they constitute a valuable resource supporting the economy for most of nations. Therefore, a proper management of coastal zone is crucial. Either monitoring of coastal ecosystem or planning and design of projects in the nearshore zone needs information about sea bottom topography.

Bathymetric data is an essential requirement in coastal environment for different reasons. Since it may be used for navigation purpose, monitoring the temporal morphological changes and for coastal zone management. Moreover, bathymetry is a basic input for numerical modeling.

The conventional technique for bathymetric data retrieval is via sounding either using single or multi beam. The advantages, for deep waters it provides high vertical accuracy measures. In addition, the single beam echo sounder represents a feasible alternative for producing sea bottom maps at lower cost. However, echo-sounding is quite expensive, time consuming and require intensive labor and suitable sea conditions. Also, sometimes shallow water, rocky areas or regions of coral reefs cannot be accessible. The economic designations lower the ability for bathymetric data update and the frequent monitoring process of coastal zone.

Recently, remote sensing is commonly used to map the water bathymetry. The wave lengths of emitted light penetrate water with varying degree. The light is attenuated exponentially with water depth. Hence, the shallower and clear water provide a good seabed reflectance with limited amount of light absorption.

Several attempts have been introduced for bathymetry estimation from remote sensing. Each algorithm proposed to correlate the remotely sensed seabed reflectance with the real water depths measured at particular locations. The most popular approach is the linear model of (Lyzenga 1981), (Lyzenga 1985). The main assumption is that the sea bed reflectance is exponentially related to water depth. Two bands or more may be used to formulate the reflectance/depth relationship by multivariate linear regression. Another widely used algorithm is provided by (JUPP 1988). The methodology has three consecutive steps: defining Depth of Penetration (DOP) zones, interpolation of depths within each zone and calibration of depths within these zones. Alternatively, (Stumpf et al. 2003) proposed the ratio transform model for estimating water depths with fewer calibration parameters.

Currently, more research is directed to improve the accuracy of the satellite derived bathymetry (SDB) especially by the freely available data set of Landsat.

The modifications concentrated on proposing machine learning and artificial intelligence techniques for

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bathymetry retrieval. (Gholamalifard et al. 2013) applied three Machine Learning (ML) techniques: Single Band Algorithm (SBA), Principal Component Analysis (PCA), and Multi-Layer Perceptron (MLP) neural network in the Southern Caspian Sea, Iran. The best performance is regarded to neural network, SBA provided a medium accuracy and PCA failed to present an acceptable correlation.

(Liu et al. 2017) used two bathymetric data set to test several types of artificial neural network models, multilayer perceptron (MLP) and general regression neural network (GRNN) as a predictor of bathymetric data from IKONOS and Landsat moderate imageries. Both neural network models achieved superior accuracy compared to other prediction models such as inversion model and regression tree. The MLP was quite satisfactory in performance more than GRNN.

(Mohamed et al. 2017) assessed the performance of various bathymetry retrieval models by application to a low turbidity deep water area, a highly turbid unstable area and a coral reef area. These models are the ensemble regression tree fitting using Bagging (BAG), ensemble regression tree fitting with Least Squares Boosting (LSB) and Support Vector Regression (SVR). The best results were attained by BAG regression compared with the conventional algorithms. (Misra et al. 2018) investigated the validity of a nonlinear machine learning approach called Support Vector Machine (SVM) to compose the shallow water bathymetry data. Comparison of SVM with other linear models evidenced that it is better perform. (Makboul et al. 2018) assumed a nonlinear 3rd order polynomial relationship between each individual band logarithm and actual water depth. The green band of Landsat 8 revealed a comparable estimation of bathymetric data. (Shen et al. 2018) attempted to perform some improvement to Lyzenga's model by developing generalized additive models. The enhanced models account for the nonlinear behavior between water depths and band reflectance's of multispectral imagery data. Based on the previous research, remote sensing can be considered as an efficient alternative to hydrographic survey using different algorithm.

The present research targets retrieval of SDB for nearshore regions using genetic algorithm (GA). GA is an optimization technique that adapt optimal solutions of nonlinear, nonconvex and multimodal problems, (Gobeyn et al. 2017). The concept of GA is based on both biological evolution and natural genetics. The algorithm helps in combining the involved variables in a defined problem with boundary conditions to develop an objective function. This function can be evaluated by calculating its fitness using a relevant chosen statistic. The proposed GA here has been applied to a certain site of the Northern Coast (NC) of Egypt using Landsat 8 Operational Land Imager (OLI) data. The aim was to attain the most representative objective function that can be used for bathymetry mapping and asses its performance. So, GA tested the ability of two or more bands combination in order to formulate a calibrated bathymetry. To assess the performance of GA, a comparison was considered with the linear transform model and the ratio transform algorithm.

The research aims to find an alternating efficient, rapid and cheap method for driving bathymetry maps with high temporal resolutions. Such technique may be used effectively in coastal zone management and support the decision makers. Especially in case of sensitive areas exposed to short term/rapid morphology changes.

STUDY AREA

As shown in Fig. 1, the studied coastal stretch is located at the Northern Coast (NC), Egypt. It extends 17

Fig. 1 Study area location and field measurements

km along-shore, starting from Badr village in the West (29°10′15″E 30°49′36″N) to Marabella resort in the East (29°20′11″E 30°52′38″N).

The maximum wave height is close to 5 m and about 40% of approaching waves do not exceed 0.5 m. The highest waves come from the NNW and WNW directions. This area is exposed to a limited portion of waves from N to ENE sector. The water level fluctuation is not small while the tidal range is less than 0.5 m. The water is extremely clear at this region and no coral reefs formation. There is a slight increase in turbidity and that backs to the flat beach conditions and sea grass existence.

METHODOLOGY

The methodology of bathymetry deriving is expanded in four main partitions; data collection, satellite image processing, bathymetry estimation and the statistical analysis. Data collection includes field data of water depths and the available Land Sat images. The Landsat data is corrected through the image processing stage. Bathymetry estimation involves the application of various algorithms to the study area. Each algorithm is evaluated separately and then compared with the others using some descriptive statistics in a statistical analysis stage.

(1) Data Collection

- *Field data*

Bathymetry estimation is based on calibrating the available remotely sensed data using real water depths. Commonly, a group of scattered points through of the area of concern with known depth are used. The source of calibration data may differ as the availability and consequently, the accuracy will be affected. Nautical charts, hydrographic charts, (Jagalingam et al. 2015), Light Detection and Ranging (LiDAR) data, (Pacheco et al. 2014) or survey data may be an option.

In current study, field measurements using single beam echo-sounder during the day of 25 December 2017 were acquired. The survey is extended 1.3 km cross shore and covers an approximate area of 22 km2. The echo-sounder observations gathered depths of 2588 points spaced roughly 25 m. The collected water depths are varying from 0.7 m to 11.8 m.

- *Remote sensing data*

The digital images provided by Landsat were commonly used to derive shallow water bathymetry. The Landsat was established by the U.S. Geological Survey (USGS) to routinely gather land imagery from space. Eight satellites were launched to remotely collect the data around the Earth. The Landsat 8 satellite orbited at 705 kilometers, and carries Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). OLI and TIRS images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. The ultra-blue Band 1 is useful for coastal and aerosol studies. Band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. Thermal bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi). A satellite image from Landsat 8 OLI data sets was used in this study. The image was captured at date 25 June 2017. It was chosen based on the full coverage of proposed site, the temporal proximity to the survey dates and the minimum cloud cover.

(2) Image Processing

The processing of satellite images is a preliminary step before execution any analysis of data. The objective is to eliminate the atmospheric effects, unwanted path radiance, unnecessary sea surface reflectance as well as any distortion of the image. Generally, the processing scheme is divided in to three major parts; image rectification, radiometric calibration, atmospheric correction.

Regarding image rectification, the Landsat images were firstly geo-referenced using a sufficient number of ground control points referred to WGS84 datum and UTM zone 35. Radiometric calibration is essential to convert the raw image Digital Numbers (DNs) to spectral radiance and then to Top of Atmosphere (TOA) reflectance. 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 vapor and water droplets may alter the transmittance. Hence, atmospheric correction becomes an imperative step before application of any algorithm.

In this study, all the processing steps are carried out using ENVI 5.1 software. The ENVI Radiometric Calibration tool is used for converting the DN values to radiance and TOA reflectance based on the information available in the MTL file associated with the downloaded data. 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. One of the standard MODTRAN models 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) Bathymetry Estimation

This section presents two of the widely used models for bathymetry extraction in addition to the proposed GA. As several bands data exist, and each model is demonstrated by two or three bands; it is important to investigate which bands will be useful for bathymetric data retrieval. Conceptually, the selection of the best spectral bands for analysis is mainly governed by the penetrating capability as well as the aquatic environment under consideration. In general, short wavelength bands such as blue and green are generally preferred for bathymetry developing due to their strong penetration proficiency.

- Linear transform algorithm

(Lyzenga 1981), (Lyzenga 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 model by (Lyzenga 1985) is formulated as follows:

$$Z = a_{\circ} + a_i X_i + a_j X_j \tag{1}$$

where,

$$X_i = Ln(R_{w,i} - R_{dp,i}) \tag{2}$$

$$X_j = Ln(R_{w,j} - R_{dp,j}) \tag{3}$$

$a_{\circ}$, a_i and a_j = coefficients determined through multiple regression using known depths and the corresponding reflectance.

$R_{w,i}$ and $R_{w,j}$ = Observed reflectance in bands i and j.

$R_{dp,i}$ and $R_{dp,j}$ = Reflectance of dark water pixel in bands i and j.

If imagery has already been atmospherically corrected then, $X_i = Ln\ (R_{ac,i})$ and $X_j = Ln\ (R_{ac,j})$. As $R_{ac,i}$ and $R_{ac,j}$ are the corrected reflectances, (Green et al. 2000).

This model is not restricted to only two bands. (Pacheco et al. 2014) utilized the three bands of coastal aerosol, blue and green in bathymetry estimation.

- Ratio transform algorithm

(Stumpf et al. 2003) presented the ratio transform model for shallow water bathymetry retrieval. This model basically depends 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. The model structure is expressed as follows:

$$Z = m_1 \frac{Ln(nR_{w,i})}{Ln(nR_{w,j})} - m_0 \tag{4}$$

where,

Z is the water depth.

m_1 is a tunable constant to scale the ratio to depth.

m_0 is the depth offset.

$R_{w,i}$ and $R_{w,j}$ are the reflectance of bands i and j.

n is a fixed constant for all areas.

The value of n is chosen to assure that both the logarithms will be positive under any condition and that the ratio will produce a linear response with depth. Generally, the reflectances of blue and green bands are used to express the model ratio.

- Genetic algorithm

The steps of the proposed GA were summarized as follows:

1. Randomly generate an initial population of equations. The population size (N) is a user defined number input (N = 10000 in this study). It is adopted so that enhance the ability of obtaining good results and avoid time consuming in computations. The demonstrated methodology to build the chromosome of each individual in population was by composing a random structured string from bands as variables and other additional parameters.

$$Z = (F_1.\ R_{w,i}).\ (F_2.\ R_{w,j}).\ (F_3.\ R_{w,k}) \pm Const \tag{5}$$

where,

Z is the predicted water depth.

($R_{w,i}$, $R_{w,j}$, and $R_{w,k}$) are the scaled band reflectances.

(F_1, F_2, and F_3) are factors computed by GA.

Dot stands for an operator (+, -, /, *, log, sin, exp …etc.).

Const is addition or subtraction part adapted by GA.

2. Evaluate each element in population by calculating its fitness by such a relevant statistic. The fitness function used in this study is the Root Mean Square Error (RMSE). The calculation of RMSE is implemented using bands reflectance of Landsat multispectral data and the collected field measurements of water depths.

3. The 50% of the population with highest score of fitness are arranged in pairs and selected for reproducing the new generation. Equations with higher fitness values have higher probability to be chosen as first generation parents. Each pair of parents will produce two off-springs to initiate a new generation. Firstly, off-springs are identical to parents. Then, off-springs are exposed to two different processes called cross over and mutation.

4. Cross over will be applied through the generated off-springs by replacing two variables from ($R_{w,i}$, $R_{w,j}$, or $R_{w,k}$) randomly between each couple of parents.

5. a limited portion of off-springs are exposed to mutation according to an assigned uniform probability. The scheme is executed by randomly replacing a single operator, factor or constant in an off-spring equation.

6. This algorithm will be repeated till a fixed number of iterations is maintained or a required fitness criterion is met.

(4) Analysis of Results

In order to evaluate the accuracy of the used model, some descriptive statistical parameters are used. The parameters are defined as follows:

$$Bias\ (Z_p, Z_m) = Mean(Z_p) - Mean(Z_m) \tag{6}$$

$$RMSE(Z_p, Z_m) = \sqrt{\sum_1^N (Z_p - Z_m)^2 / N} \quad (7)$$

$$MAE(Z_p, Z_m) = \frac{1}{N} \sum_I^N |Z_p - Z_m| \quad (8)$$

$$R^2 = \left[\sum_1^N (Z_m - Z_p)^2 / \sum_1^N (Z_m - Mean(Z_m))^2 \right] \quad (9)$$

where,
Z_p is the predicted depth from satellite imagery.
Z_m is the measured depth in field.
N is the number of field measurements.

CASE STUDY

Field measurements were divided into training data and testing data. Both training and testing terms are important in such methodology. Training is a basically expresses the model calibration and commonly utilized in machine learning techniques. However, in the testing phase a percentage of data set test the model validity and accuracy. In the present study, about 70% of the collected data points are used as training for depth retrieval algorithms and the rest are assigned for testing/ validation.

Table 1 Statistics of field data for training and testing

Phase	No. of points	Min. depth (m)	Max. depth (m)	Avg. depth (m)
Training	1857	0.71	11.70	7.93
Testing	731	0.70	11.94	8.05

(1) Linear Transform Model

The depth calculation for this model can be performed using two or more bands. To select the best bands to contribute, the correlation between every band scaled reflectances and the corresponding measured depths were investigated separately. As we have Landsat 8 OLI, the commonly used bands in bathymetry estimation are; coastal blue (B_1), blue (B_2), green (B_3) and the red band (B_4) due to their shorter wave lengths. The estimated R-squared values for B_1, B_2, B_3 and B_4 were found as 0.79, 0.81, 0.87 and 0.49 respectively.

Hence, the most significant band is the green and the red band can be assumed less effective than the others. Furthermore, all of the first three bands evidenced that there is a good relationship with the real depths. So, here, two trials were examined for bathymetry estimation using B1, B2 and B3. A trial was implemented using two bands (B2 & B3) and another one utilized three bands (B1 & B2 & B3). The forms of the two resulting equations were found as:

$$Z = 1.89 + 6.98\, Ln(R_2) - 10.82\, Ln(R_3) \quad (10)$$

$$Z = 0.79 + 5.72\, Ln(R_1) + 1.88\, Ln(R_2) - 10.63\, Ln(R_3) \quad (11)$$

Finally, the two linear models were assessed and compared with each other to propose the best performed relation.

(2) Ratio Transform Method

In this model, the scaled reflectances of blue and green bands (B_2 & B_3) are used as common for bathymetry estimation. A simple linear regression is carried out using measured depths and the ratio of reflectance's logarithms to calculate the model parameters (m0, m1). The factor n is adopted to achieve the best correlation (n=35) and the equation is finally deformed as follows:

$$Z = 21.37 * \frac{Ln(35 * R_2)}{Ln(35 * R_3)} - 18.51 \quad (12)$$

(3) Genetic Algorithm

Based on the correlation of bands to the actual depths, the bands B_1, B_2 and B_3 were employed to compose an alternative nonlinear equation to either ratio transform model or linear model. In GA, a population of equations were initially formulated in random way and then evaluated by RMSE as an objective function. After a frequent application of the two consecutive processes; cross over and mutations; the RMSE was optimized to minimum. Finally, the algorithm suggested the best performing equation as:

$$Z = \frac{(4.99 * R_1)}{\sqrt{(2.67 * R_2) * SIN(1.53 * R_3)}} - 0.31 \quad (13)$$

RESULTS AND DISSCUSION

The testing data correlation were displayed for each algorithm as in fig. 2. All models achieved high values of R-squared values; 0.95 (ratio transform) and 0.94 (the others). In shallower depths, GA predictions overestimated the water depth and in contrary the linear model produced an underestimation of results while the ratio transform was more compensated. For other regions, GA and ratio transform model results are more concentrated about the best fit linear trend. However, the predicted depths of linear model were significantly deviated; they have the lowest RMSE even though the R-squared score was roughly similar to the other models.

As shown in table 2, regarding RMSE and MAE, the ratio transform model was the best by retrieving the lowest estimate. Either linear models or GA also provided a good accuracy with insignificant variability to the ratio transform. The bias of means between measured and predicted depths was observed as negligible for all algorithms. During transitions between training and testing phases, the linear model resulted in a higher difference in RMSE and MAE, nevertheless, GA and ratio transform model were more consistent.

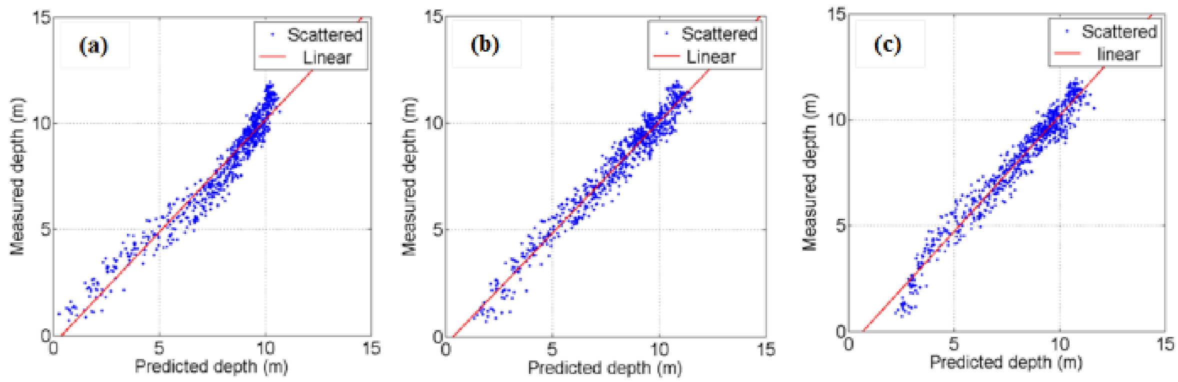

Fig. 2 Correlation between observed and predicted depths for testing data (a) linear model; (b) ratio transform model; (c) GA

Table 2 Comparison of SDB models results by statistical analysis for training and testing data

Method	R-Squared		RMSE (m)		MAE (m)		Bias (m)	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Ratio transform	0.95	0.96	0.54	0.54	0.41	0.44	3.914E-05	4.07E-04
Linear (Two bands)	0.94	0.93	0.61	0.70	0.37	0.57	6.679E-10	6.43E-02
Linear (Three bands)	0.94	0.93	0.60	0.68	0.36	0.55	7.717E-10	6.21E-02
Genetic Algorithm	0.94	0.95	0.59	0.59	0.44	0.48	3.083E-05	3.35E-02

The depths were gathered into four classes to partially calculate RMSE and evaluate the performance of each model in all the different zones. As in fig. 3, for depths from 0 to 3m, GA maintained the higher RMSE value (1.30 m) followed by the ratio transform (0.86 m) and the linear model was the best performed (0.63 m). But generally, in all the remaining depth clusters, the linear model was not better than the other two models.

For more visualization of results, the reflectance of each model outcome on morphology may be alternatively an appropriate tool for each model assessment. Two profiles as shown in the plan with the actual bathymetry, fig. 4, were selected at two separate locations within the testing data. As in fig. 5, for this particular case, GA profiles were found luckily coincided with the measured ones. While the linear model profiles had a magnificent variation and the ratio transform profiles were a medium case.

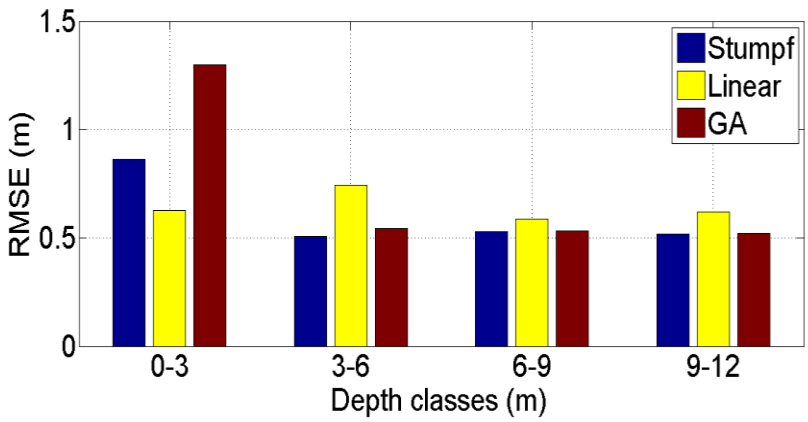

Fig. 3 The variation of RMSE with the different water depth clusters

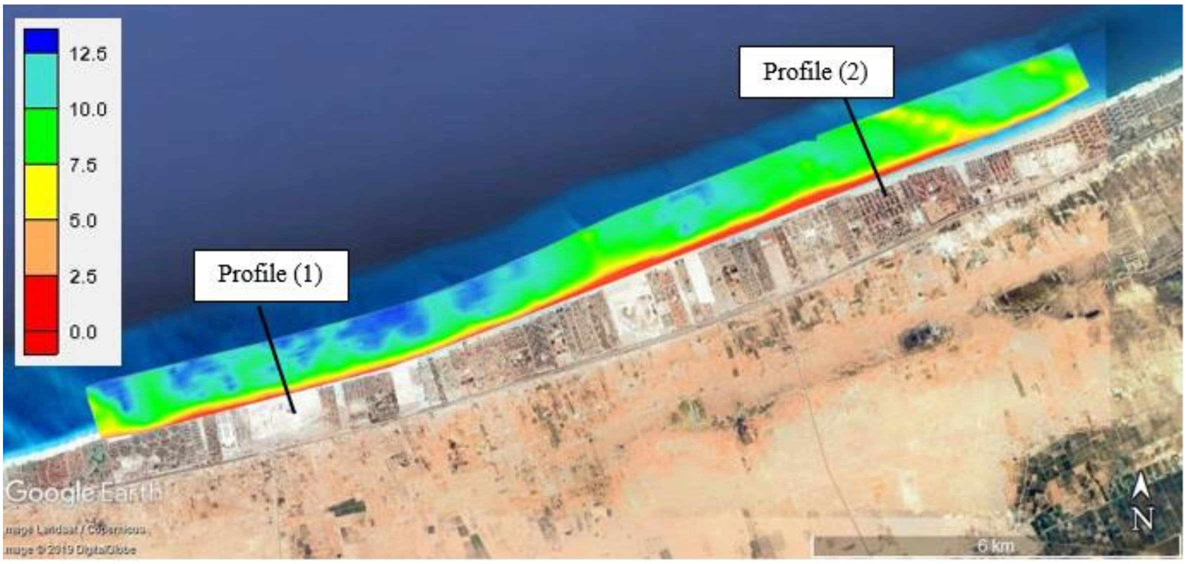

Fig. 4 Location of the two selected profiles on the actual bathymetric map

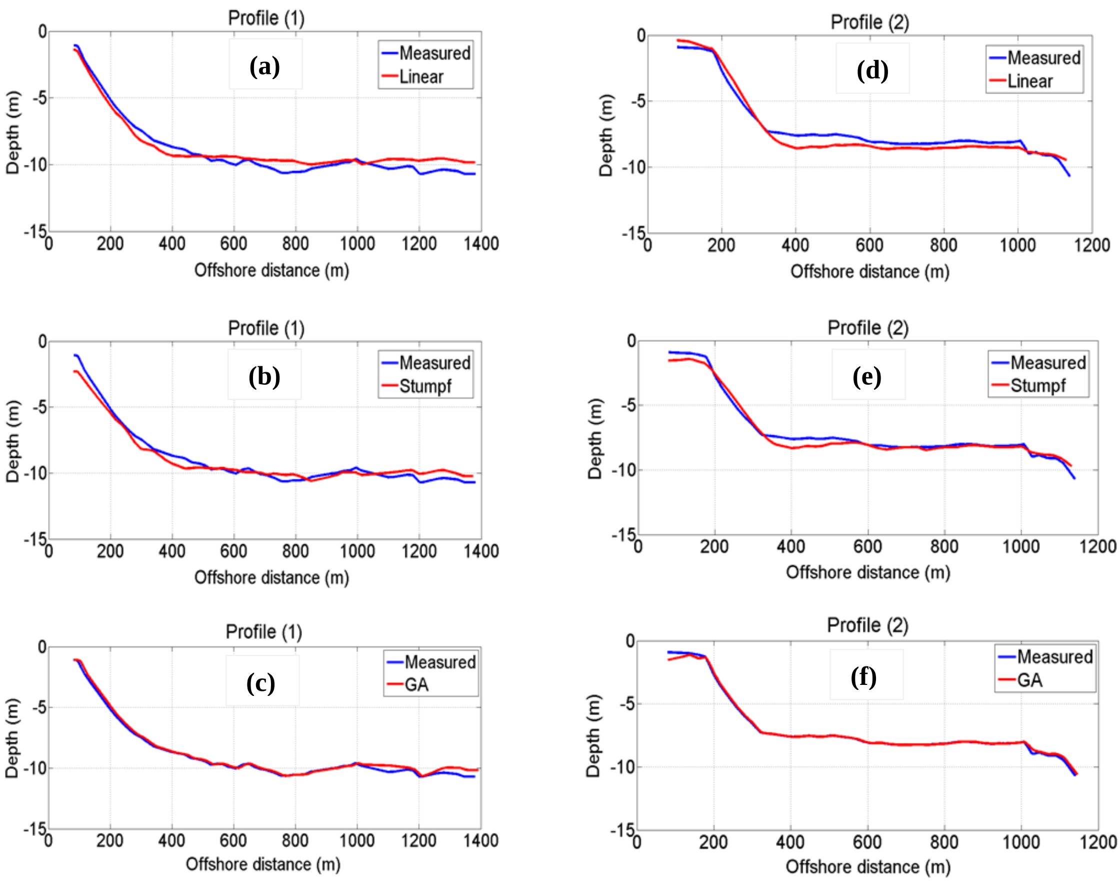

Fig. 5 Comparison of beach profiles of SDB models with the field measurements(a) profile 1 from linear model; (b) profile 1 from ratio transform model; (c) profile 1 from GA; (d) profile 2 from linear model; (e) profile 2 from ratio transform model; (f) profile 2 from GA

CONCLUSION

This paper involved an application of GA to develop a bathymetry by using multispectral Landsat-8 satellite data. The GA performance was assessed by an integrated comparison with the widely used methods such as linear and ratio transform models. The statistical analysis showed a comparable potentiality to the GA, i.e. RMSE=0.68, 0.54 and 0.59 for linear, ratio transform and GA respectively. Although, GA conducted a relatively high RMSE in the shallower depths close to the shoreline, the overall accuracy was satisfactory. Moreover, a better enhancement for GA may be attained by clustering depths and deriving a group of nonlinear equations instead of one. The availability of Landsat data and the SDB algorithms is beneficial for monitoring the temporal morphology changes along the coast.

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