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Bathymetric Modeling from Satellite Imagery via Single Band Algorithm (SBA) and Principal Components Analysis (PCA) in Southern Caspian Sea

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ABSTRACT: Remotely sensed imagery is proving to be a useful tool to estimate water depths in coastal zones. Bathymetric algorithms attempt to isolate water attenuation and hence depth from other factors by using different combinations of spectral bands. In this research, images of absolute bathymetry using two different but related methods in a region in the southern Caspian Sea coasts has been produced. The first method used a Single Band Algorithm (SBA) and assumed a constant water attenuation coefficient throughout the blue band. The second method used Principal Components Analysis (PCA) to adjust for varying water attenuation coefficients without additional ground truth data. PCA method (r=-0.672394) appears to match our control points slightly better than single band algorithm (r=-0.645404). It is clear that both methods can be used as rough estimates of bathymetry for many coastal zone studies in the southern Caspian Sea such as near shore fisheries, coastal erosion, water quality, recreation siting and so forth. The presented methodology can be considered as the first step toward mapping bathymetry in the southern Caspian Sea. Further research must investigate the determination of the nonlinear optimization techniques as well as the assessment of these models' performance in the study area.

Key words: Bathymetry, Satellite Imagery, Single Band Algorithm (SBA), Principal Components Analysis (PCA), Caspian Sea

INTRODUCTION

Remotely sensed imagery is proving to be a useful tool to estimate water depths in coastal zones around the world. Procedures have been developed that isolate solar reflectance due to water depth from other factors (Kumar and Jayappa, 2009; Ehsani and Quiel, 2010; Zhang *et al.*, 2010; Siddiqui, 2011; Odindi and Mhangara, 2012; Kowkabi *et al.*, 2013; Mahmoodzadeh, 2007). For instance, Lyzenga (1978) proposed a modified exponential depth model for clear shallow waters, ignoring the internal reflection in the water column; Louchard *et al.* (2003) used radiative transfer calculations to generate a spectral library of remote sensing reflectance to classify obtained reflectance according to bottom type and water depth; Leu and Chang (2005) used two dimensional wave spectrums to estimate water depths based on the principle that while waves propagate toward shoreline, these wave lengths decrease due to decrements in water depth; Fonstad and Marcus (2005) combined remote sensing imagery and open channel flow principals to estimate water depths in clear rivers; Ceyhun and Yalçýn (2010) proposed Artificial Neural Networks (ANN) to estimate water depths in shallow waters. ANNs allows considering nonlinear multi-parameter relationship between reflectance from different spectral bands and water depths. These algorithms attempt to isolate water attenuation and hence depth from other factors by using different combinations of spectral bands. These multiple band techniques depend upon large amounts of ground truth data and a fine enough resolution to discriminate bottom types; they are also limited to the sensitivity to attenuation of the longest wavelengths used. These procedures are invaluable to Iranian coastal zone research because these areas

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have not been extensively surveyed and are changing rapidly. In fact, we have a little ground truth knowledge as to the depth or bottom type in the southern Caspian Sea. Also unfortunately, in this research, we had access only to those satellite images with a resolution that made it difficult to discriminate sea bottom types. On the other hand, many coastal zone studies in the southern Caspian Sea, such as those examining near-shore fisheries, coastal erosion, water quality, or recreation siting, are only concerned with areas of shallow water and would benefit from easily updated bathymetric estimates. In this research we calculated bathymetry for a region in the north of Iran along the southern coasts of the Sea within–Mazandaran Province.

The procedure uses an algorithm for transforming a single band of information into an index of water depth that can then be calibrated to known depths. The algorithm (Stoffle and Halmo, 1991) is one of a family of algorithms that have been used to estimate bathymetry (Lyzenga, 1985; Paredes and Spero, 1983). These algorithms are based on the fact that radiance is, to varying degrees, attenuated by the water column. The degree of attenuation coefficient is a function of wavelength, sea bottom types, and water column properties. However, when there is only one band available, meaning the shortest wavelength in the visible spectrum (blue), its best to try and take full advantage of its water penetrating properties. For these reasons we use a Single Band Algorithm (SBA) which assumes a constant attenuation coefficient and requires the least amount of ancillary information. The second procedure utilizes several bands of imagery and Principal Components Analysis (PCA). This method is analogous to a Multi-Band Algorithm that accounts for varying attenuation coefficients for different bottom types as it calculates water depth, unlike the Single Band Algorithm (Van Hengel and Spitzer, 1991).

MATERIALS & METHODS

The different stages of methodology have been shown in Fig. 1. Data provided for this research include: Visible blue, green and red bands of TM Landsat Image (Data: 2010/06/04); A boolean image in which water has a value of one; A vector polygon of the known deep-water area (greater than 100 m) in the imagery; vector and value point file of the locations of known depths. Time and space of the coincident pairs of satellite and in situ data, called matchups, are the basis for methodology. Therefore, 24 sampling points were determined according to stratified random sampling scheme across imagery (Fig 2.) of which 12 points (depth lesser than 40m) were used for bathymetric algorithms. Stratified random sampling scheme is usually preferred since it combines the best qualities of the unbiased character of the random sampling scheme with an even geographic coverage of the systematic scheme.The term stratified in stratified random means that it is spatially stratified according to a systematic division of the area into rectangular regions. The Speedtech SM-5 Depthmate portable sounder used for concurrent sonar depth measurements. This unique pocket-sized depth sounder is very accurate and of very high quality and is useful for boating, fishing, scuba diving, coastal survey, and scientific work. The position of locations was recorded using Garmin 62S Global Positioning System (GPS) receiver.

Clearly, without much knowledge of the area, it is difficult to even separate the water areas from land in the Landsat imagery. Therefore, to get a better idea of the area, we combined information from the blue, green and red bands to produce a natural color composite image with original values and stretched saturation points and 2.5 as the percent to be saturated (Fig. 2).

There are two very important procedures that must be undertaken prior to bathymetric analysis. First the image must be geometrically registered so that corresponding pixels in the entire image refer to exactly the same place on the ground. Resampling or rubber sheeting is used with a set of control points to make image sets match a base map. The second pre-processing procedure involves the correction of the imagery to remove random noise and stripping. Both the single band algorithm and the PCA method are sensitive to random noise and striping within the raw imagery. Therefore, the image has been enhanced with a low-pass (mean) filter.

The algorithm is as follows (Stoffle and Halmo, 1991):

$$\mathrm{Z} = \frac{-1}{2\kappa}\ln(V - Vs) + \frac{1}{2\kappa}(\ln Vo)$$

Where, Z = depth; V = observed signal radiance; Vs = portion of signal resulting from scattering of radiation in the atmosphere, water column and water surface; κ = water attenuation coefficient; Vo = sensitivity factor consisting of contributions from solar irradiance at the surface, the bottom reflectance, atmospheric transmission, and sensor equipment.

It assumes that the actual observed radiance (V) varies exponentially with water depth, after the portion of the signal due to scattering (VS) is removed, radiance is logarithmically transformed to a linear function of depth. The result can then be put back into the equation. The equation now takes the form of *depth* =

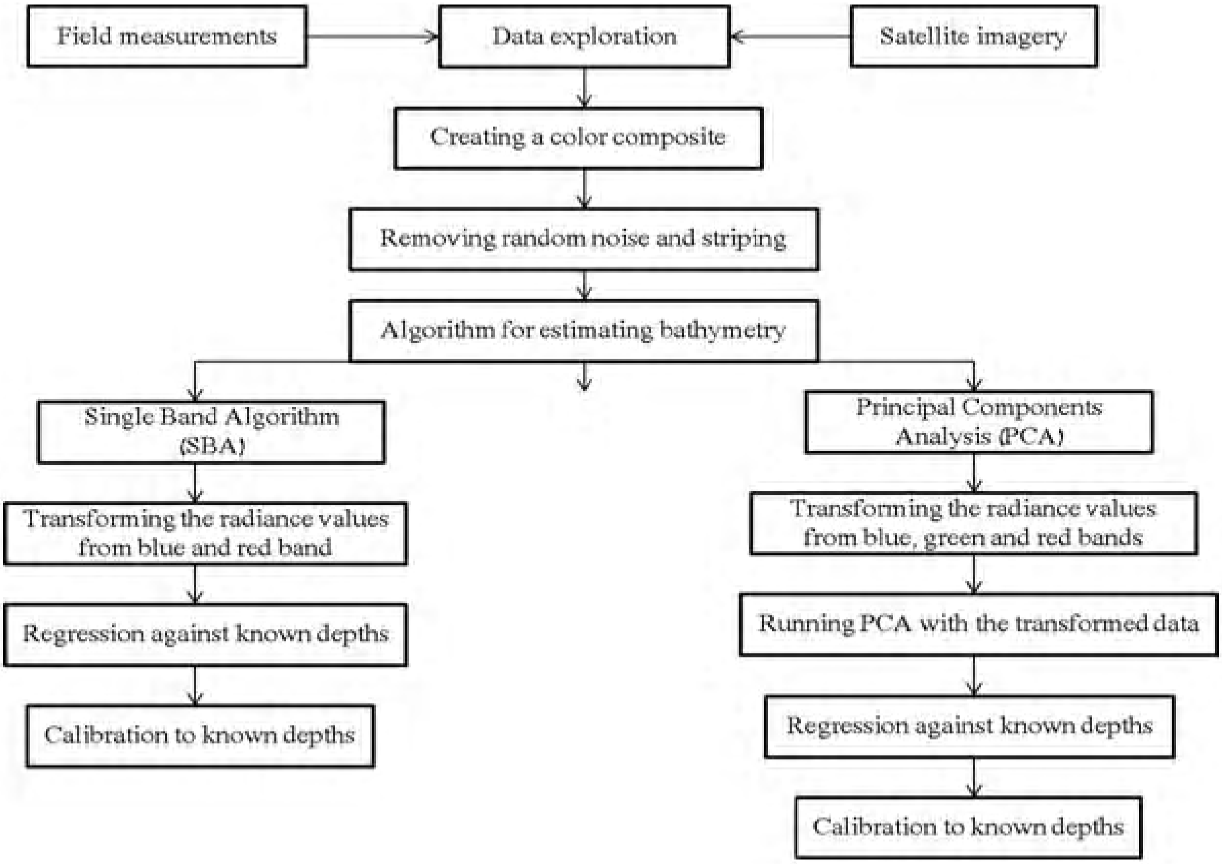

Fig.1. Stages of the methodology

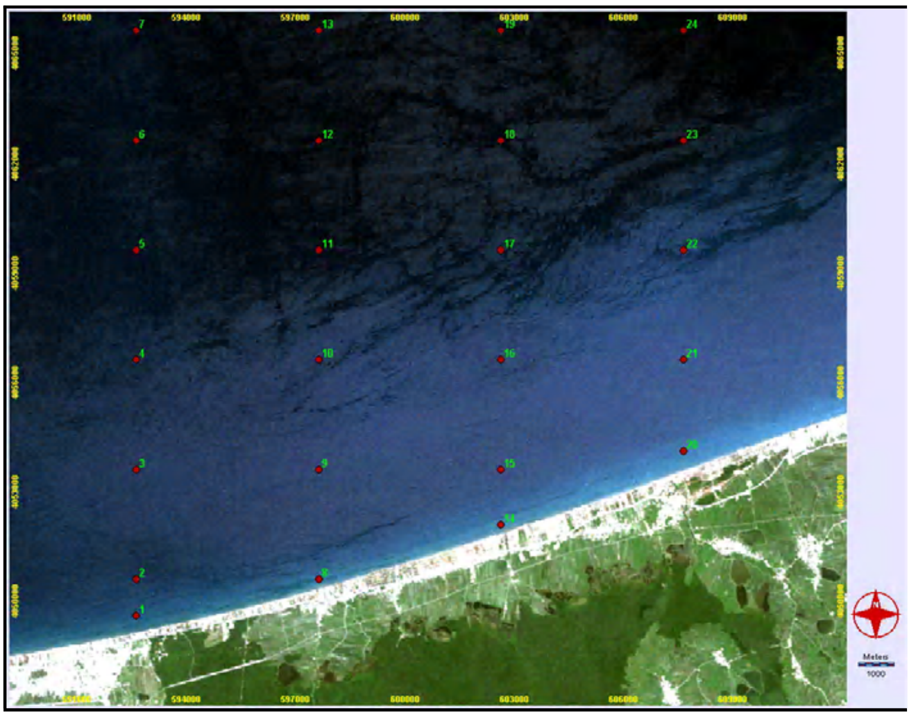

Fig. 2. Natural color composite and sampling stations in the study area

slope (X) + constant. The line this equation describes is the best fit of a simple linear regression using known variable. The slope of this line is related to the water attenuation coefficient such that $\text{slope} = \frac{-1}{2\kappa}$, and the constant value is given by $\text{constant} = \frac{1}{2\kappa}(\ln Vo)$.

By first calculating the transformed radiance values and then regressing them against control points of known depth, all of the variables in the above equation and estimate of the bathymetry are calculated.

The transformed radiance values were calculated by taking the values from blue band, subtracting VS, and then taking the natural log of the result. VS was estimated from the spectral properties of the deepest water in image; known to be at a depth greater than 100 m. A polygon file was provided that outlined the known deep water area to estimate VS. Assuming that such deep water should have virtually zero radiance values in the blue band, any reflectance registered must be due to scattering. Then, the average value of the pixels that lied in known deep water was taken and one standard deviation was subtracted.

This step is to actually run a linear regression between the transformed blue band and the file of known depth measurements provided through sea sampling. There were 24 locations scattered across imagery where depth is known (Fig. 2). This procedure provided all the information needed to calibrate the transformed radiance values to water depth using the original algorithm. It then calibrated to actual water depth by regression analysis.

This next section will demonstrate the second method to estimate bathymetry: Principal Components Analysis (PCA). Principal Components Analysis (PCA) is related to Factor Analysis and can be used to transform a set of image bands such that the new bands (called *components*) are uncorrelated with one another *and* are ordered in terms of the amount of image variation they explain (Eastman, 2012).The input images into the PCA are the TM imagery transformed, just as in the algorithm method. While the algorithm method assumes that the transformed blue band corresponds directly to water depth, PCA assumes that the first component from an analysis using all three bands (transformed) will correspond to water depth. It is the first component that can be calibrated to known water depths. Because the PCA requires that input files be of a byte/binary format, transformed blue, green and red bands stretched to a value range of 0 - 255. Then, to make analysis more accurate, the land areas were masked for all three stretched images and the results used as the input files for the PCA.The first component was produced using forward T-Mode PCA showing the sources of variation in the data set. PCA method assumes that change in depth explains the most variance and other factors, such as a changing bottom type, will be secondary sources of variation (Khan, *et al.*, 1992). Values at the first component image for the known site locations were extracted. Knowing the slope and constant values from the regression, it was easy to calibrate the transformed data to depth. Finally, the first component was calibrated with known depths.

Briefly as mentioned, there are two main assumptions in the presented methodology:

1) The Single Band Algorithm (SBA) assumes that the transformed blue band corresponds directly to water depth, while PCA assumes that the first component using all three transformed bands corresponds to water depth.

2) Assuming that known deep water (greater than 100 m) should have virtually zero radiance values in the blue band, any reflectance registered must be due to scattering.

RESULTS & DISCUSSION

Natural color composite (Fig. 2.) suffices to point out a few coastal features of the image. Just beyond the land is the sea, shown in various shades of blue. The lighter the shade of blue, the shallower the water is for estimating Vs, the mean value of known deep water is 72.18962 for blue band, 25.51753 for green band and 20.14141 for red band. The standard deviation is 1.0356, 0.7331 and 0.8294 respectively. Then, the estimated value of VS is 71.15402, 24.78443 and 19.31201 respectively. The difference between the original band and the transformed band is striking (Fig 3. & 4).

After regressing the transformed blue band and known depths, we got a slope = -89.336279, a constant value = 207.682598, and a correlation coefficient (r) = -0.645405 (Fig. 5.). Then, plugging in the values of *k* and *VO*, the map of water depth was produced (Fig. 6). Regressing the first component of PCA and known depths, found the slope = - 1.136398, the constant = 230.870964, and the correlation coefficient (r) = -0.672394 (Fig 7.). Then, the map of water depth was produced (Fig. 8).

Neither the composite image nor any of the original bands could be used as an index to depth without some further processing. Other factors such as sea-bottom type and ocean surface scattering contribute to variance in reflectance value and need to be accounted for before any imagery can be considered an index of water depth.While the composite image

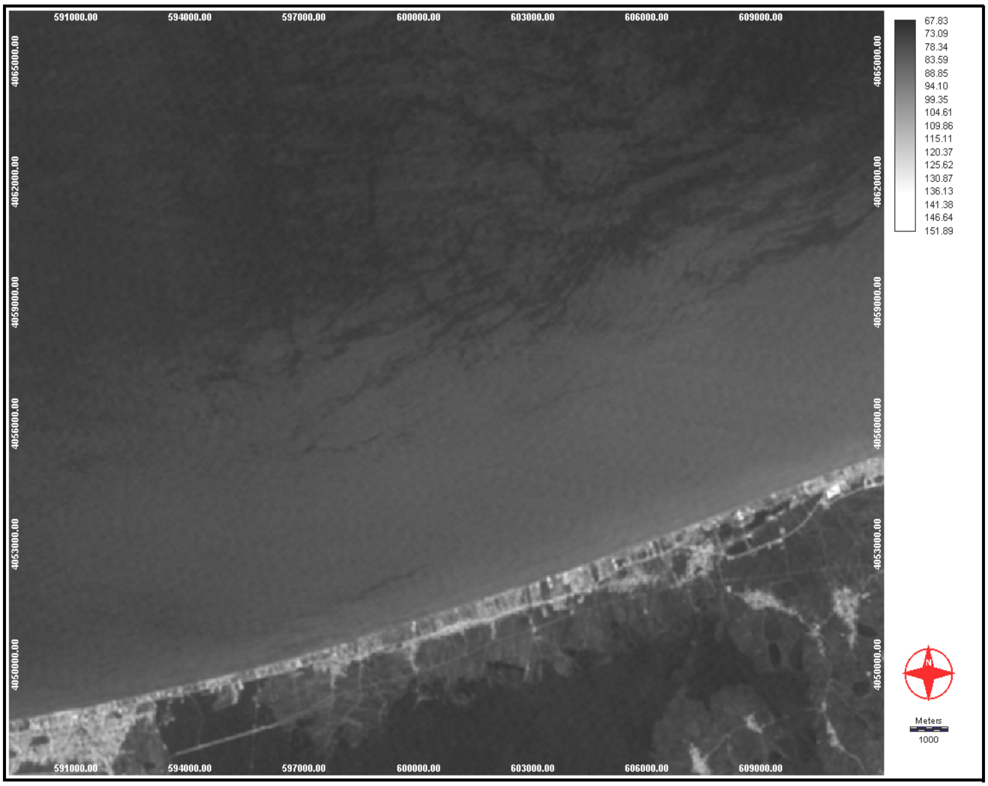

Fig. 3. The original blue band of TM landsat imagery

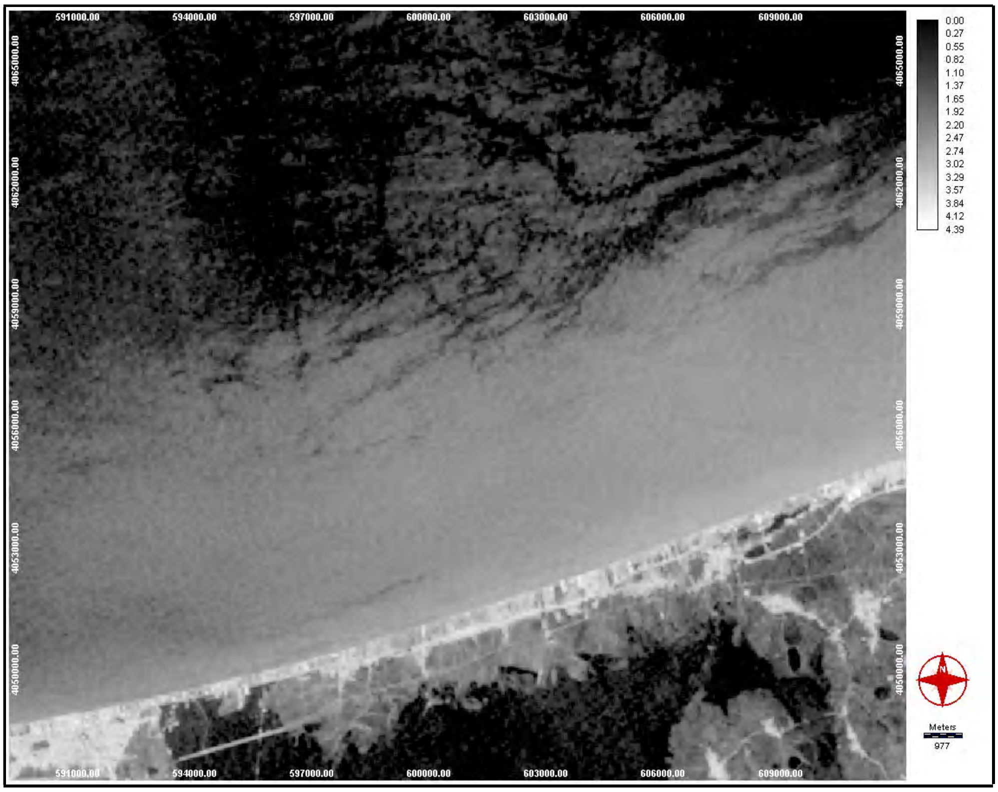

Fig. 4. The transformed blue band (ln (V-Vs)

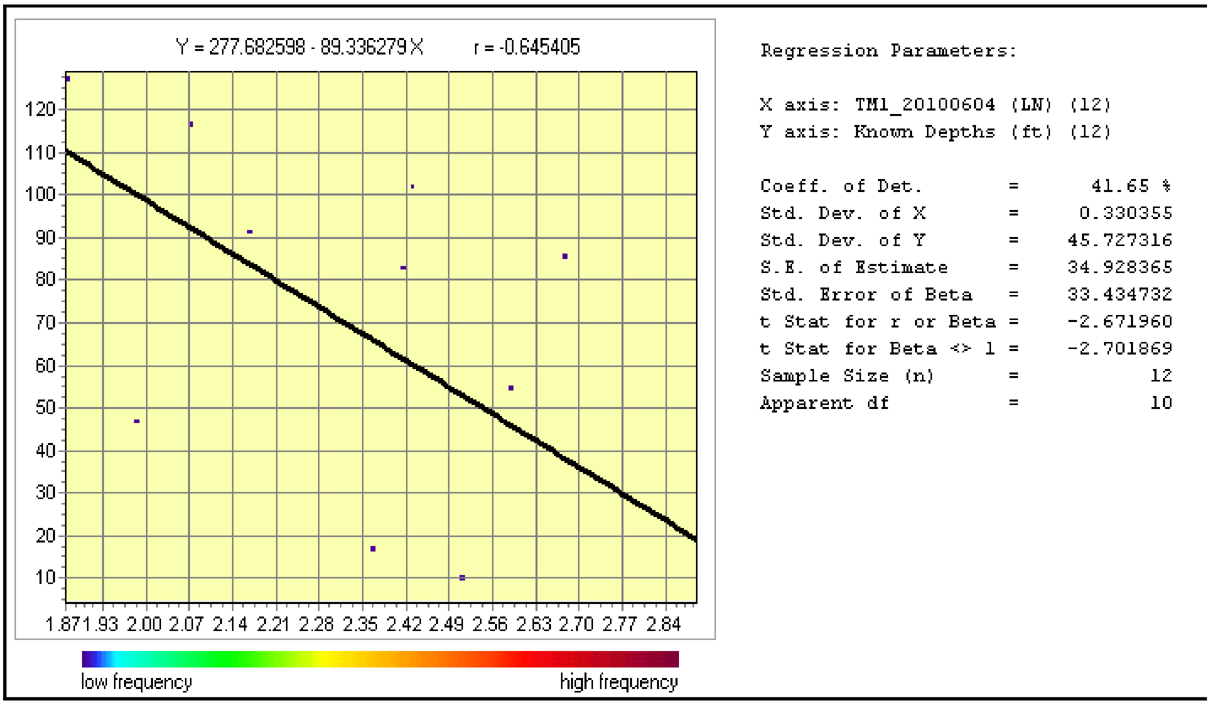

Fig. 5. Regression of transformed blue band against known depths

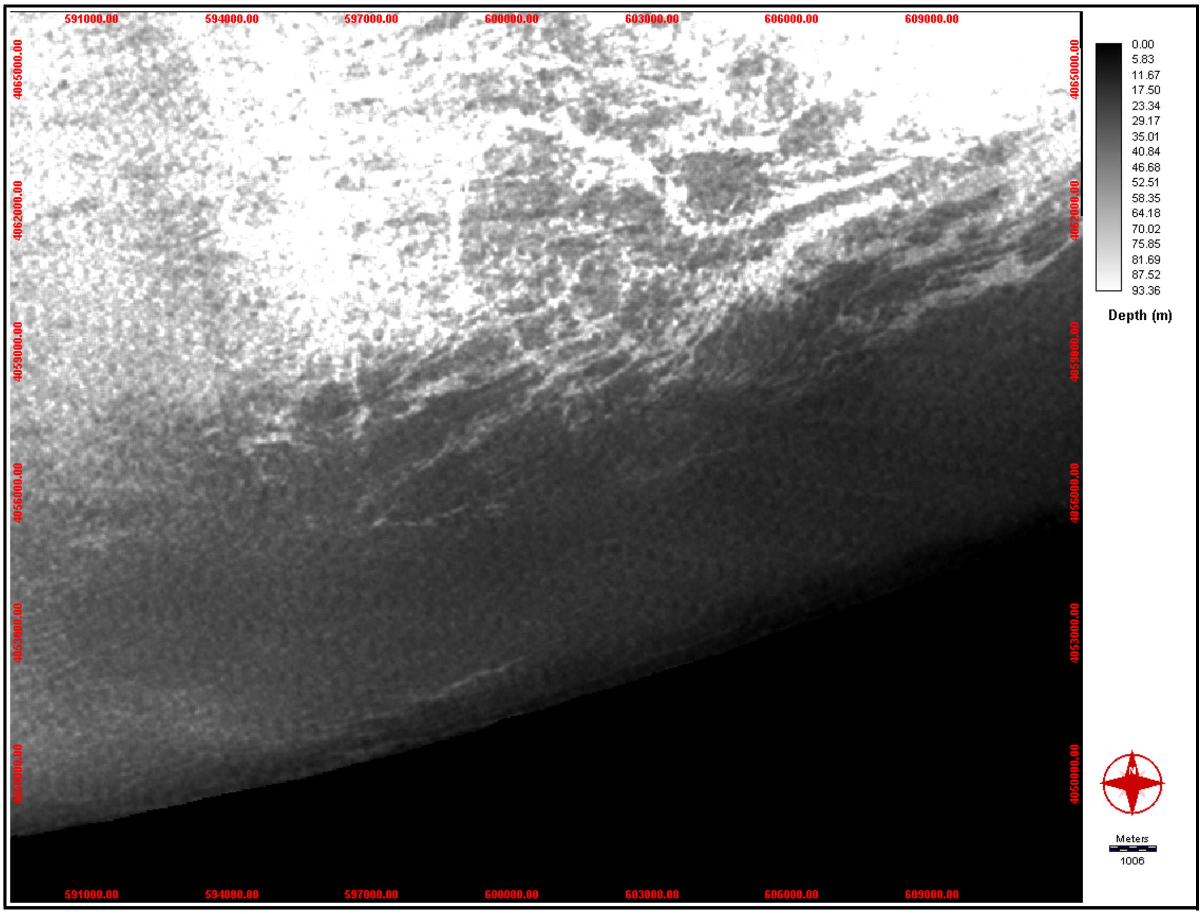

Fig. 6.The map of water depth produced by single band algorithm (SBA)

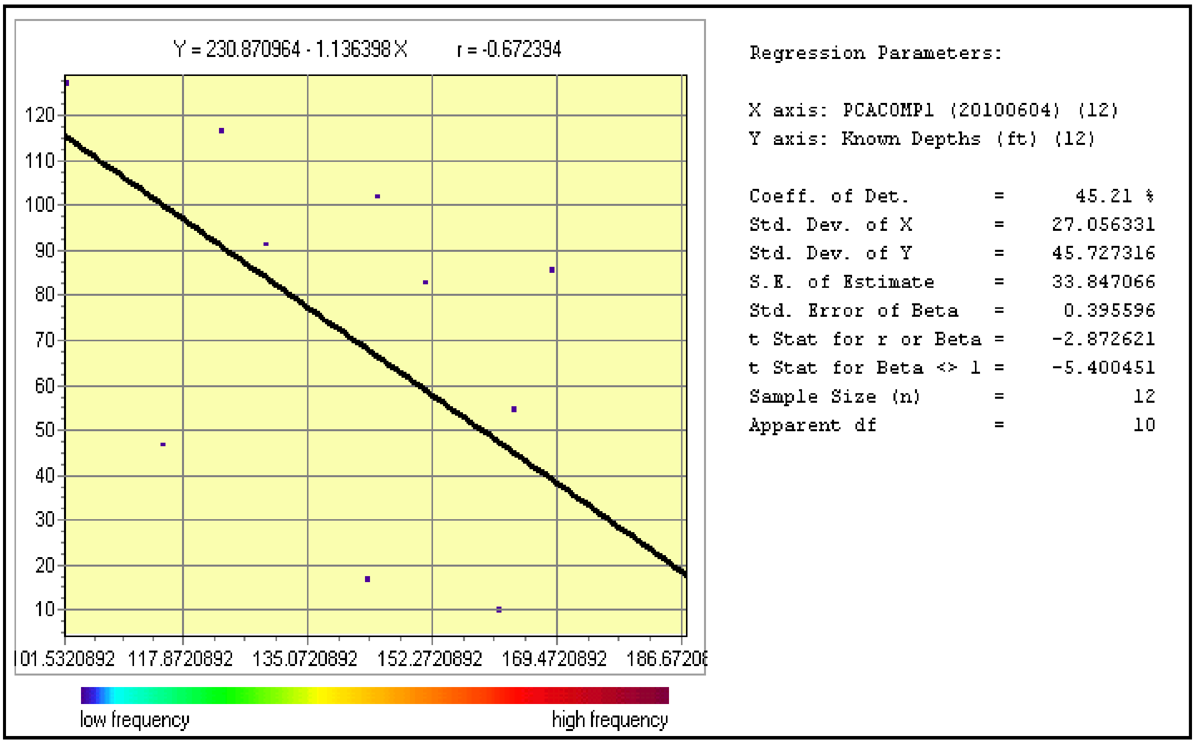

Fig. 7. Regression of first component of PCA against known depths

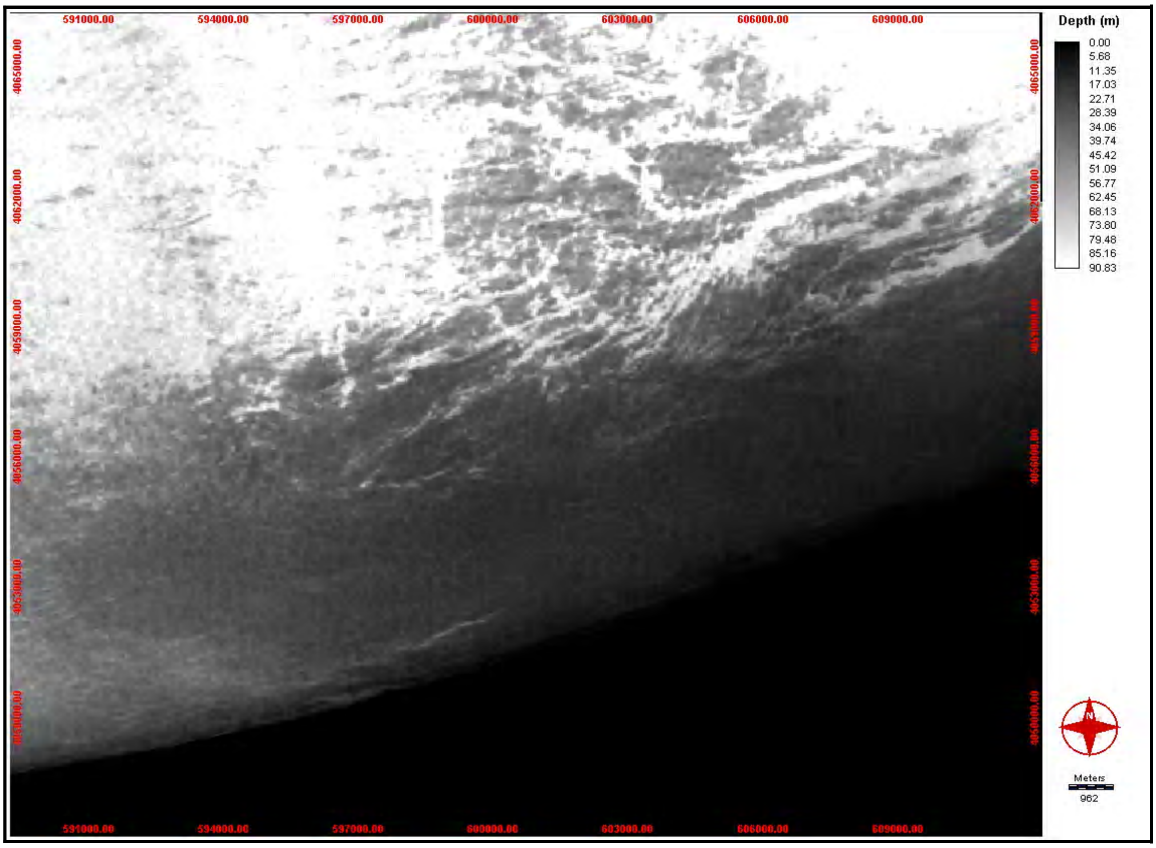

Fig. 8. The map of water depth produced by Principal Components Analysis (PCA)

Table 1. Comparison of known and estimated depths in sampling stations

Site Number	Known Depths (m)	Single Band Algorithm Depths (m)	PCA Depths (m)
1	5.1	21.1872559	21.8136082
2	14.5	32.9526062	35.4711456
3	28.5	27.4562817	28.6756268
4	39.3	36.3829384	42.0433426
5	55.6	57.1423111	68.2472000
6	78	85.6041641	87.2884369
7	123.3	78.6175537	84.0651398
8	3	16.7989140	13.1144505
9	25.5	19.6530323	18.1056118
10	36	30.2919750	31.7064552
11	50.3	91.3507996	89.8670807
12	75	93.3568344	90.8340759
13	129.84	93.3568344	90.8340759
14	1.4	6.3055778	0.7950491
15	16.9	14.4409237	12.0341311
16	31.6	19.3552551	21.0993919
17	44.6	51.5325050	47.6814842
18	69.7	93.3568344	90.8340759
19	139.97	83.0925980	84.0615311
20	1.3	5.3559709	1.9841952
21	26.3	21.7871132	23.4779615
22	37.1	35.8685379	40.2580681
23	59.4	93.3568344	90.8340759
24	100.07	93.3568344	90.8340759
		r = -0.645405	r = -0.672394

gives us a general picture of the area in question, it cannot be used as an index of water depth. The change in radiance in the composite, or in any of the three raw bands, is due not just to changes in water depth but to changes in sea bottom type, interference from wave action and atmosphere, water quality, etc. Classification of these images into categories representing depth would be hard task waiting to be addressed in later studies.

In transformed blue band, changes in the reflectance values of off-shore pixels are seen that appear to correspond to depth or perhaps to changes in sea-bottom types. This variation was not as visible in the non-transformed imagery.

Using single band method, for which we assume a simple linear relationship between the transformed radiances of the blue band and water depth, we needed only to know the slope and constant values. However, Calculating ê and Vo may be necessary in other more complex equations to calculate depth.However, while this and other algorithms that account for bottom type are dependent upon extensive ground truth information, the PCA method produce a depth dependent variable (independent of bottom type) without ground truth data. The first component of PCA, using the three TM bands of imagery, should approximate relative water depth given the assumption that depth explains most of the variance between two or more bands of information.

Generally, it is difficult to tell which method provides the best estimation of water depth. The Table 1 shows known depths against the estimated values from single band algorithm and PCA.

According to the results, the PCA method appears to match our control points slightly better than the single band algorithm. Comparing estimations reveals discrepancies in both methods. It is clear that both methods can be used as rough estimates of bathymetry and that these and similar methods might prove useful in situations where little or no ground truth information is available. However, it is vital that we look upon such estimates as only the first step toward mapping bathymetry for a given area.

Accurately rating either method would require further ground truth information and analytical algorithms instead of empirical algorithms.

CONCLUSION

The first method used a single band algorithm and assumed a constant water attenuation coefficient throughout the blue band. To assume otherwise would have required more ground truth knowledge about bottom type than was not available. When such data is available, there are a number of algorithms that might be used to effectively isolate changes in depth from changes in other factors. When not available, the single band method works well as a rough estimate of bathymetry as our analysis has shown. The second method used Principal Components Analysis (PCA) in an attempt to adjust for varying water attenuation coefficients without additional ground truth data. This procedure is based on the assumption that the first component result of PCA, which explains most of the variance in the data set, will be a depth-dependent variable that is independent of other sources of variation such as bottom type. After producing the first component image and calibrating it to known depths, we compared the results to the algorithm method.

Apart from the presented methodology, nonlinear optimization techniques and other machine learning methods such as Artificial Neural Networks (ANNs) provide an interesting alternative to examine complex coastal waters and to handle multivariate data. Models based on these methods determine the output values (e.g., the bathymetric values) from input data (e.g., water reflectance at various wavelengths) through nonlinear multidimensional parametric functions. The determination of the model parameters, as well as the assessment of the model performance rely on a reference data set and are suggested as an applicable research topic in the southern Caspian Sea. In any method we must be aware of the possibility for error at each of the steps involved and continually question our results. While the dynamic nature of the coast makes precision in bathymetric estimation difficult (e.g. tides, waves, lack of ground truth information), it also makes such analyses essential if we are to have recent and/or time series data for the coastal zone.

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