Satellite-Derived Bathymetry Modelling in Shallow Water: A Case Study of Lighthouse Creek, Lagos

Dupe N. OLAYINKA and Chukwuma J. OKOLIE, Nigeria

Keywords: Bathymetry, Satellite-Derived Bathymetry, Shallow Water, Echo-Sounding, Least Squares

Summary

There is great demand for accurate and high-resolution seafloor topography data. However, present availability of such data remains spatially incomplete and limited. Bathymetry in shallow water areas are the most costly and challenging for ship-based bathymetric surveys and this zone is where remote sensing typically outperforms traditional methods. Specific uses of satellite-derived bathymetry include characterisation of the underwater environment and monitoring seafloor changes that have occurred since the last hydrographic survey was done. The obvious advantages over conventional echo sounding methods include the wide data availability, synoptic surface coverage, and high spatial resolution. Bathymetric models are very important in studying the underwater bottom morphology. The limitations of earlier models inspired Stumpf et al (2003) to develop an alternative model for transforming the reflectance in an attempt to determine the depth.
A bathymetric survey by acoustic method was carried out at Lighthouse Creek, Lagos to extract reference data for evaluating the remotely sensed bathymetry from a time series of Landsat imagery (2002, 2006 and 2015). To derive depths from the imageries, they were first pre-processed and atmospherically corrected. Next, the optic depth limit for inferring bathymetry (the extinction depth) was determined ($\sim 5m$). The final bathymetry was obtained after applying corrections from tidal prediction values connected by a shape preserving interpolant. The standard errors in the estimated depths were 0.29m for 2002, 0.31m for 2006 and 0.27m for 2015. The absolute differences between the actual depths and estimated depths at these points ranged from 0.1 – 0.49m. In a final step, we evaluated and modelled the image spectral contribution to the estimated bathymetry by the application of a least squares solution to derive a linear mathematical model. This was done to evaluate the contribution of the significant Blue, Green and NIR bands in the depth estimation. Accuracy tests of Stumpf's model and validation of the subsequent linear model to relate bathymetry with the spectral bands of Landsat showed very good performance.

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1. INTRODUCTION

Bathymetry (the measurement of the depths of water bodies from the water surface) is the marine equivalent to topography. Bathymetric surveys are generally conducted with a transducer which transmits a sound pulse from the water surface (usually attached to a boat) and records that same signal when it bounces from the bottom of the water body. An echo sounder attached to the transducer filters and records the travel time of the pulse. At the same time that the pulse occurs, a GPS unit can record the location of the reading. After many of these readings are taken, corrections are made based on fluctuations in the water surface elevation that may have occurred during the survey. There is great demand for accurate and high-resolution seafloor topography data. However, present availability of such data remains spatially incomplete and limited. Traditional bathymetric charts are based on individual soundings accumulated during decades of ship-borne surveying operations. Ship-borne surveys with single- or multi-beam echo sounders can operate to depths in excess of 500m by sensing and tracking acoustic pulses. Single-beam SONAR (Sound Navigation and Ranging) systems have been used since the 1950s by survey vessels to measure water depths along transect lines, but these lines are generally sparsely distributed. Since the 1980s, more accurate multi-beam echo sounders have been widely used in bathymetric surveys. However, ship-borne surveys are time consuming, costly, particularly in relatively shallow coastal waters where survey swaths are narrow (Su et al, 2008). Also, it may not be feasible to survey shallower waters because of sound saturation and/or inaccessibility of survey vessels. In sufficiently shallow and clear waters, the magnitude and spectral quality of light reflected from the seafloor can be interpreted from remotely sensed ocean colour. Using passive ocean colour, bathymetry has been mapped with high spatial resolution from aircrafts (Dierssen et al, 2003) to regional and global scales from satellites orbiting the earth.

Moreover, bathymetry in particular can change rapidly in response to storm surges, sea level rise, changes in river conditions, and engineering activity such as dredging. Because of the expense and time involved with traditional, though very accurate, bathymetric methods, remote sensing imagery-derived measurement is often used as a technique for in-fill or rapid response to bathymetry-changing events. While imagery-based bathymetry has been in use for many decades, the techniques and imaging platforms have both evolved and improved over the years. It should be noted however that no single technique is ideal for measuring the diversity and complexity of the underwater landscape because limitations are inherent in all these methods. The preference for each method is usually determined in terms of scale of feature observed, accuracy, and water depth that can be sensed.
Landsat imagery, with its high spectral capability, revisit time, and global coverage, is an important step forward in updating underwater morphology maps and extending them into less well-known coastal and inland waters. The generation of bathymetric maps is founded on analytical modelling

based on the manner of light penetration and propagation through the water column in visible bands of Landsat imagery. The use of satellites for bathymetry is very effective and cost-efficient when compared to acoustic methods. This is largely because ocean colour sensors are already up in space for oceanographic research with data freely available (McClain, 2009). However, one cannot overlook the problems of cloud cover masking the ocean colour and the fact that only a little percentage of the incident light reaching the ocean is reflected back to a satellite (Figure 1). The atmosphere is filled up with gases and aerosols which also reflect sunlight back to the sensor. Therefore, remotely sensed images have to be atmospherically corrected to obtain an accurate water-leaving radiance required for estimating shallow water bathymetry. If too much signal is removed from the atmospheric correction, the ocean will appear too dark and bathymetry can be overestimated and vice-versa (Dierssen et al, 2011). Bathymetry estimated with optical remote sensing methods are generally not accurate enough for navigational purposes, but provide much better results than gravimetric measurements over shallow basins and the spectral information can also provide an estimate of the seafloor composition (Dierssen et al, 2011).

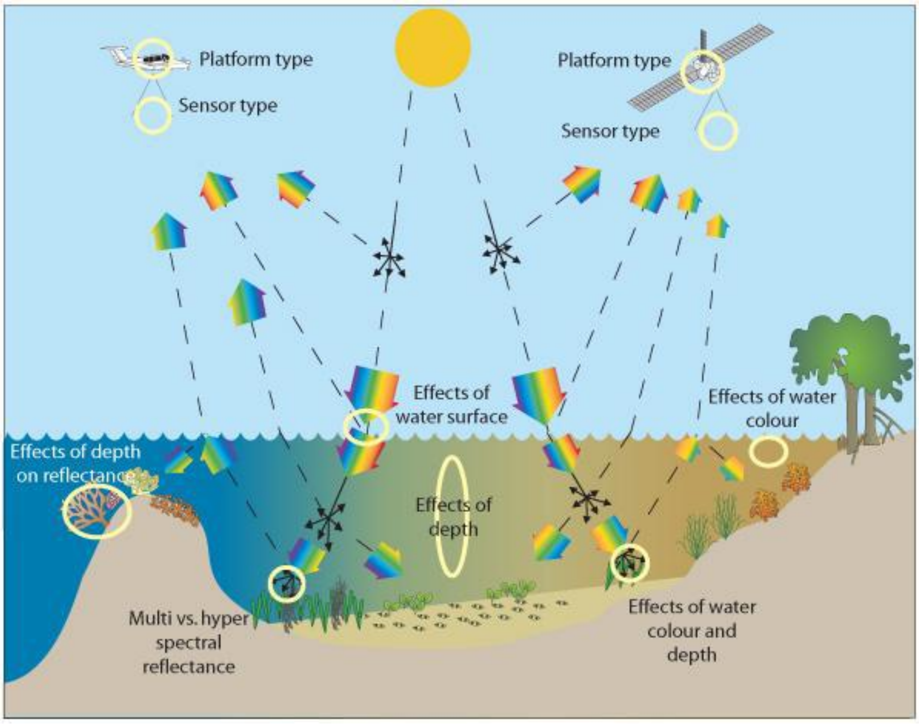

Figure 1: Schematic illustrating the path of the sunlight signal, interacting with the atmosphere, water column and seafloor, and finally being measured by a space-borne or airborne sensor (EOMAP, 2013)

1.1 Bathymetric Inversion Model for Optical Remote Sensing

The fundamental principle behind using remote sensing to map bathymetry is that different wavelengths of light will penetrate water to a varying degree. When light passes through water it becomes attenuated by interaction with the water column. The intensity of light remaining (I_d) after passage length p through water, is given by (Stumpf et al, 2003):

$$I_d = I_0 e^{-pk} \quad \text{Eq. 1}$$

Where, I_0 – intensity of the incident light, and
k – attenuation coefficient which varies with wavelength

The longer wave length of light has a higher attenuation coefficient than shorter ones. Therefore, the blue light can penetrate much deeper in the water than the red. For clear water, the blue light can penetrate 30m deep, but red and near-infrared can penetrate 5m and 0.5m only, respectively (Green et al, 2000 cited in Nga and Nga, 2007). Therefore, on the same band, the higher DN (digital number) value a pixel has the deeper water column is. The intensity of light can be quickly attenuated by interaction with suspended materials such as sediments, phytoplankton and dissolved organic compounds. In highly turbid waters, the depth of attenuation of the blue light can be sub-meters.

The standard bathymetry algorithm has a theoretical derivation (Lyzenga, 1978 cited in Stumpf et al, 2003) but also incorporates empirical tuning as an inherent part of the depth estimation process. Lyzenga (1978) failed to account for any heterogeneity in water column properties across an image. Although later updated, Lyzenga's (1985) method was limited in that it was unable to accurately model variable bottom types with various albedos. It therefore proved inaccurate for calculating water depth since the bottom albedos varied significantly (Green et al, 2000). These limitations inspired Stumpf et al (2003) to develop an alternative model for transforming the reflectance in an attempt to determine the depth utilizing Equation 2. The principle behind Stumpf et al's method is the absorption degrees of different bands with different wavelengths where each band attenuates at a different degree while the energy penetrated the water. Thus, the band with the higher absorption degree decreases consistently faster while the depth increases. As the ratio increases so does the depth increase. Stumpf et al (2003) went further to remove the effects of varying albedo where both bands have a similar effect. The ratio between these bands was affected by the increase in depth more than the varying bottom albedo. As shown in Equation 2, this algorithm requires only two tunable parameters which could be computed using the linear regression method between the ratio result and ground truth (Alsubaie, 2012).

Stumpf's ratio algorithm was compared with a standard linear transform using IKONOS satellite imagery as opposed to LIDAR bathymetry. The coefficients (m_1,m_0) were tuned manually to a few depths from a nautical chart in order to compute the ratio algorithm. The linear algorithm was tuned using multiple linear regressions against the LIDAR data. Stumpf et al (2003) found that both algorithms are equivalent over variable bottom type albedo and retrieve bathymetry in water depths less than 10–15m. However, while the linear transform does not distinguish depths greater than 15m, ratio transforms can also be applied to low-albedo water. Stumpf et al (2003) thereafter posited that that this method was robust and works well over variable bottom types. It also accounts better for water turbidity:

$$Z = m_1 \frac{\ln\left(nR_w(\lambda_i)\right)}{\ln\left(nR_w(\lambda_j)\right)} - m_0 \quad \text{Eq. 2}$$

Where m_1 (gain) is a tunable constant to scale the ratio to depth, n is a fixed constant for all areas to assume that the algorithm is positive, and m_0 is the offset for a depth of 0m where ($Z = 0$). R_w is the reflectance of water, and ($\lambda_{i,j}$) are two different bands. The fixed value of n in Eq. 2 is chosen to assure both that the logarithm will be positive under any condition and that the ratio will produce a linear response with depth.

2. MATERIALS AND METHODS

A bathymetric survey was conducted at the study site with an echo sounder to extract reference data for evaluating the remotely sensed bathymetry from a time series of Landsat imagery. Then we evaluated and modelled the image spectral contribution to the estimated bathymetry by the application of a least squares solution to derive a linear mathematical model. Specialist software used include HYPACK, ArcInfo and Matlab.

2.1 Study Site

Lighthouse Creek (Figure 2) is located to the west of the Commodore channel in the vicinity of Lagos harbour just by the entrance to Badagry Creek in Lagos state, South-Western Nigeria. It lies beside the West mole wharf and the Atlas Cove Oil Terminal. The creek is relatively shallow with depths ranging from about 0.1 – 6m. The 2km wide Lagos harbour located in Lagos state, Nigeria, is Nigeria's most important seaport. It receives inland waters from the Lagos Lagoon and from Badagry Creek in the west and provides the only opening to the sea for nine lagoons of South-Western Nigeria (Onyema, 2009). The tidal regime in this area is semi-diurnal with tidal heights that decrease inland from the Lagos harbour into the Lagos lagoon system.

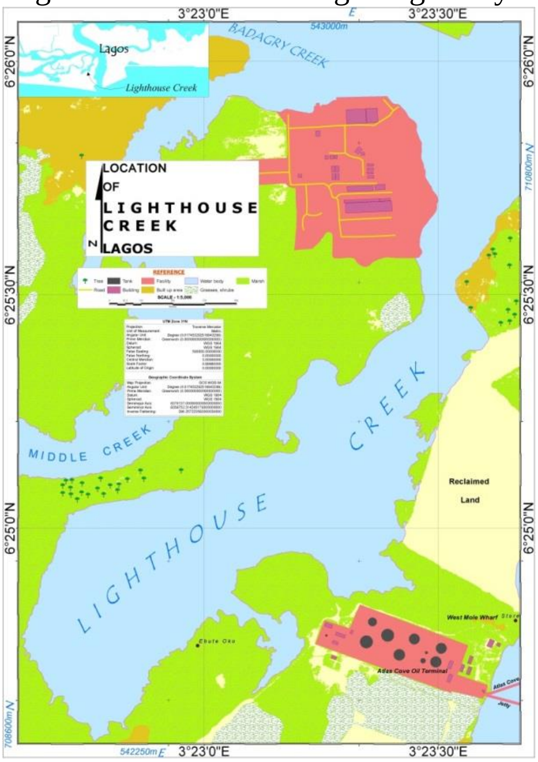

Figure 2: Location map of Lighthouse Creek, Lagos

2.2 Data

The datasets used are listed in Table 1. The selection process for acquiring the Landsat images to be used was based on the condition of the image with the cloud-free ones given higher priority. Tidal prediction tables were acquired from the Nigerian Navy Hydrographic Office (NNHO) for interpolating correction values from the tidal curves. All Landsat scene acquisition times were converted to GMT + 1 (Table 2) by the addition of 1 hour before referencing their corresponding tidal values.

Table 1: Datasets Used

Data	**Publisher/ Source**	**Year**
Lighthouse Creek Bathymetry	Primary Field data acquisition	2015
Hydrographic Chart (for reconnaissance)	Lagos Channel Management (LCM)	2014
Landsat Imageries	US Geological Surveys (USGS)	2002, 2006, 2015
Tidal Predictions	Nigerian Navy Hydrographic Office (NNHO)	2002, 2006, 2015

Table 2: Landsat Datasets

Landsat Data	**Path/Row (WRS-2)**	**Acquisition Date (DD-MM-YYYY)**	**Acquisition Time (GMT +1)**
Landsat 7 ETM+	191/55	28-12-02	10:51:17
		07-12-06	10:53:04
Landsat 8 OLI	191/55	06-01-15	11:02:59

2.3 Survey Procedure

A South SDE28 digital recorder (Figure 3) with an over-the-side mounted transducer shoe was used for the survey. The transducer was installed rigidly and side mounted on the survey vessel.

Figure 3: Bathymetric survey with echo sounder

The transducer shoe was sufficiently deep and well positioned not to experience turbulence and aeration from the vessel during data acquisition. All positions were referenced to WGS84 UTM Zone 31N. Tidal correction from tide prediction tables of Lagos Bar was applied. Depths were recorded in meters, with decimeter precision. The positioning method used for the survey was a Garmin receiver (accuracy <10m) interfaced with the in-built GPS of the echo sounder to form a GPS system. This GPS pairing/interfacing computed vessel positions from direct satellite observations. The computer received GPS derived coordinates in WGS84 from the GPS system to output the final grid coordinates in Universal Transverse Mercator system. The accuracy of the GPS system ensured good correlation of the horizontal positions of the sounded depths with their corresponding positions on the Landsat imagery.

The navigation system software provided display presentations suitable for navigating sounding and cross lines and included a visual aid. Figure 4 shows the produced bathymetric chart of the area.

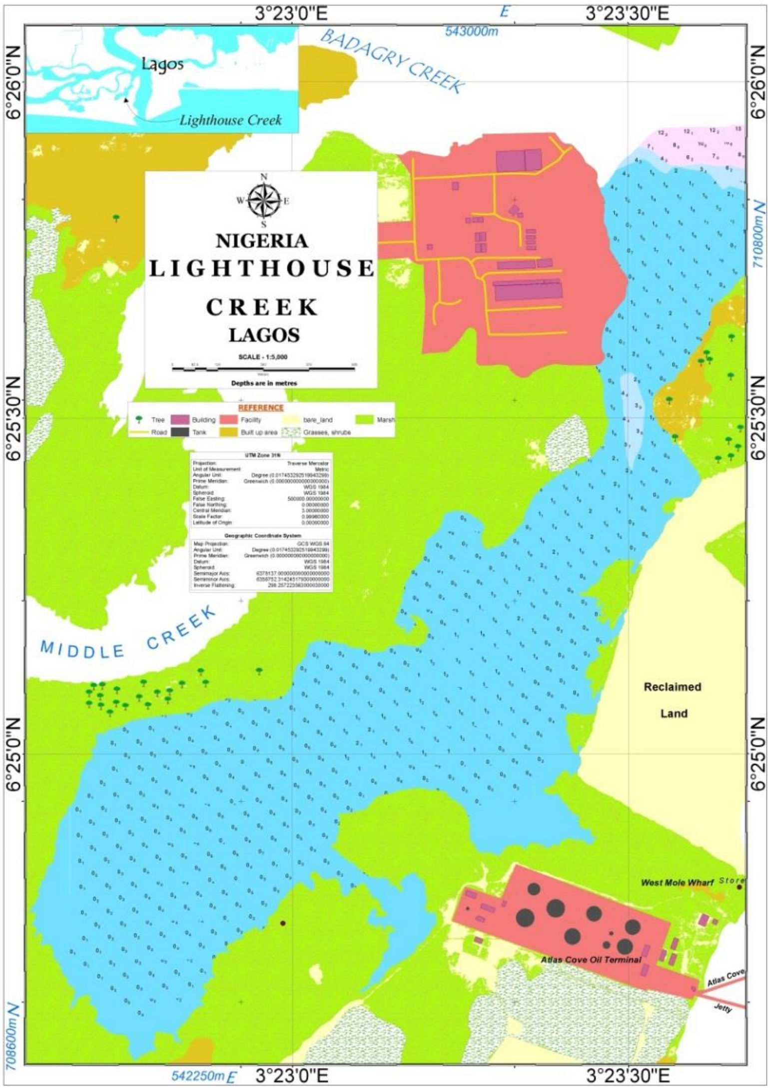

Figure 4: Bathymetric chart of Lighthouse Creek, Lagos from field survey

2.4 Depth Estimation from Imagery

The spectral information of the Blue, Green and Near infrared (NIR) bands are considered significant for this process. It was not necessary to convert the Landsat 8 pixel values to surface reflectance as the former could be used directly. First, threshold values at the land/water boundary (shown in profile graphs, Figure 5 - 7) were used to separate water from the land. The smooth sections with low values represent water, whereas the fluctuation high value areas represent land. Most of the cloud cover was removed in this phase. Next, a low-pass preset focal filter was performed to smooth the rasters and reduce the significance of anomalous cells. NoData values were assigned to cells with values higher than the previously calculated water threshold value. The practical approach put forward by Hedley et al (2005) was used to implement correction for sun glint and cloud cover which is a serious confounding factor for remote sensing in shallow water areas. The step was used to correct radiometric contribution from low altitude clouds and glint from the Blue and Green bands. To do this, a narrow polygon was created over the NIR layer to cover the dark areas in the water. This polygon constituted a mask layer. The cells of the Blue, Green and NIR bands corresponding to the areas defined by the mask were extracted. **N**ext, two sets of scatter plots were created for each image (Blue vs NIR and Green vs NIR). The slope of the trend line for the blue and green layers was calculated and inputted into Hedley et al's algorithm.

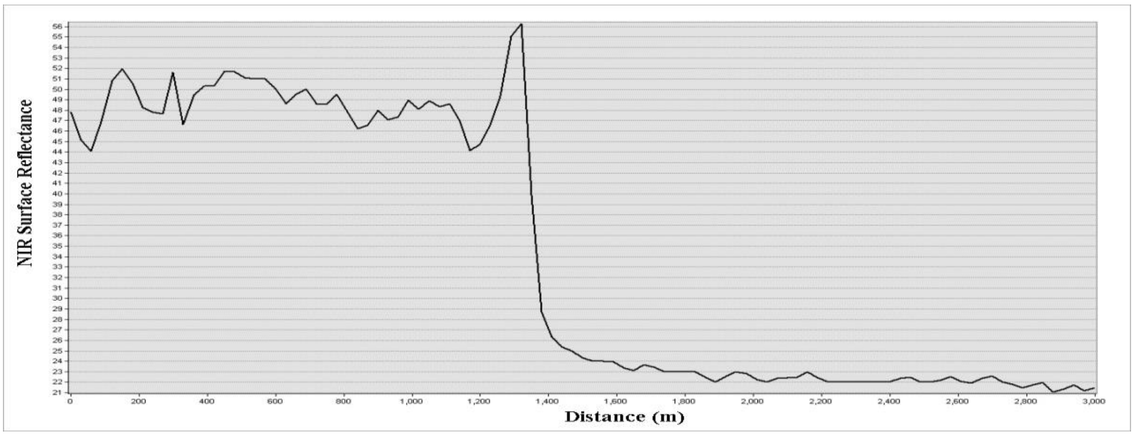

Figure 5: Profile graph for Landsat 7 NIR Band 4 – 2002 (Path/Row – 191/55)

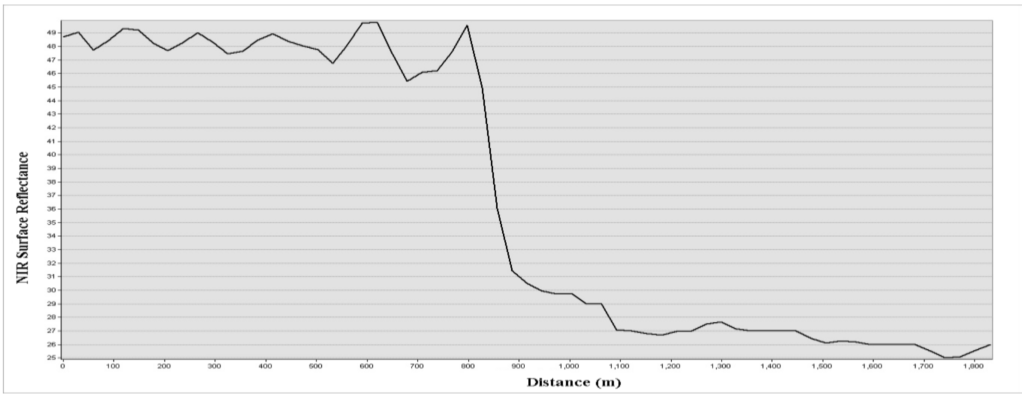

Figure 6: Profile graph for Landsat 7 NIR Band 4 – 2006 (Path/Row – 191/55)

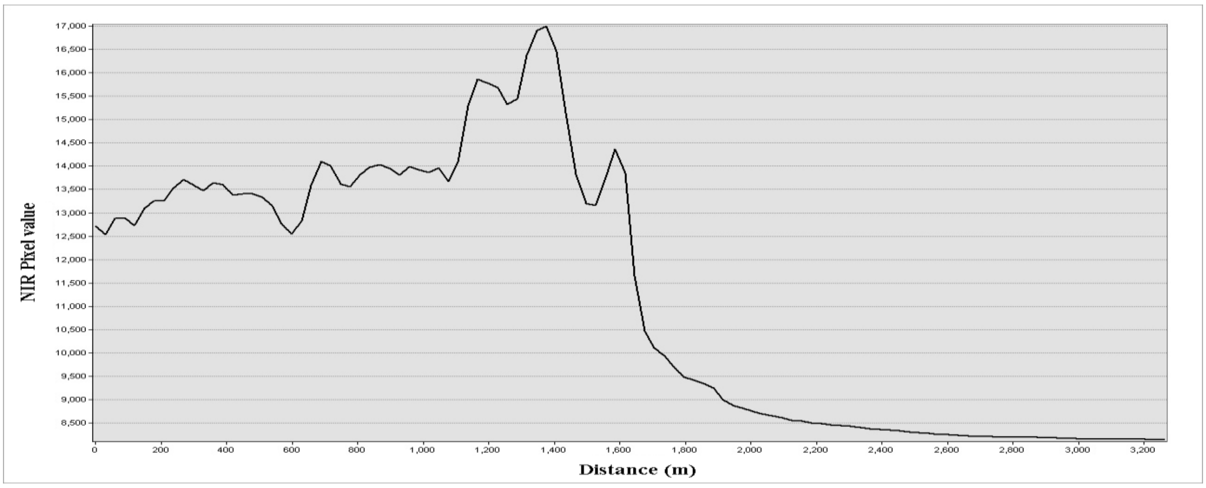

Figure 7: Profile graph for Landsat 8 NIR Band 6 – 2015 (Path/Row – 191/55)

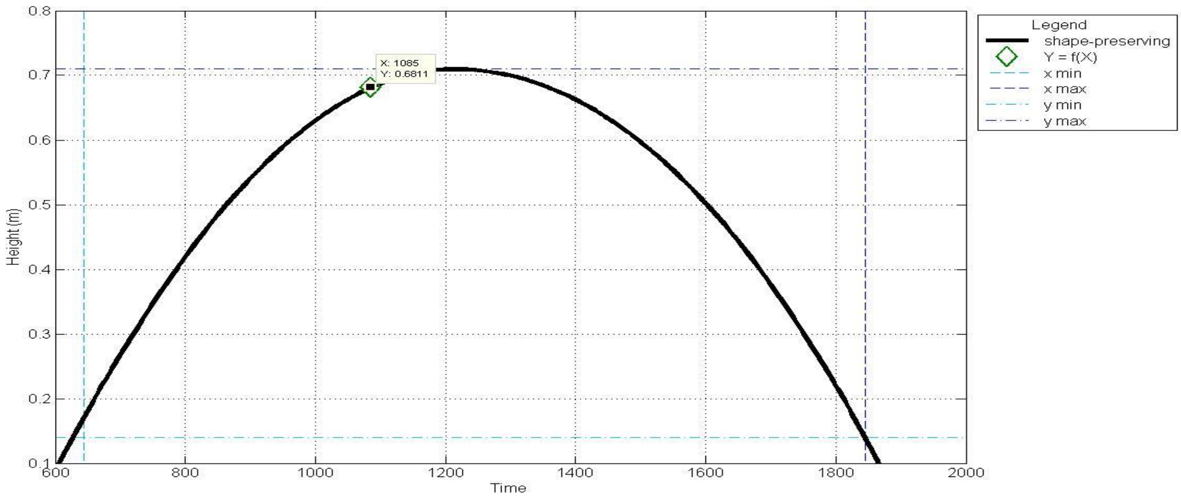

Figure 8: Tidal prediction curve for Lighthouse Creek (28-12-2002)

Figure 9: Tidal prediction curve for Lighthouse Creek (07-12-2006)

Next, the optic depth limit for inferring bathymetry (the extinction depth) was determined to be $\sim 5m$. It was observed that beyond this depth, there was a change in angle and less correlation between the soundings and algorithm values [$\ln\left(nR_w(\lambda_i)\right)/\ln\left(nR_w(\lambda_j)\right)$]. Next, the gain ($m_1$) and offset ($m_0$) for referencing the algorithm to the chart datum were determined through vertical referencing. In a final step, the bathymetry was calculated using the Stumpf et al (2003) algorithm. The final bathymetry was gotten after corrections gotten from tidal prediction values connected by a shape preserving interpolant (Figures 8 – 10) were applied.

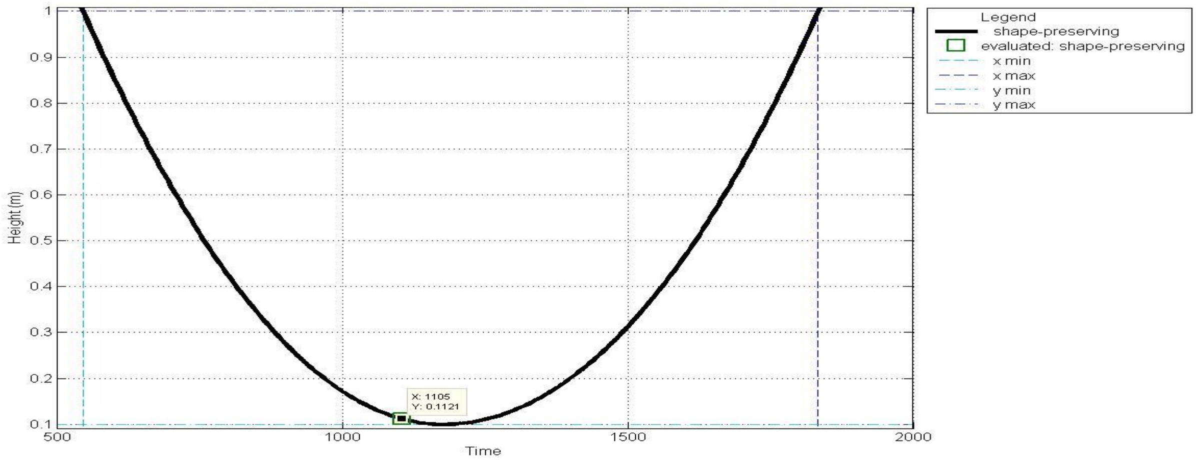

Figure 10: Tidal prediction curve for Lighthouse Creek (06-01-2015)

The estimated bathymetry was tested against control points of known depth which were determined from the bathymetric survey. After sequential statistical evaluations and filtering of outliers, 67 points for 2002, 82 points for 2006 and 91 points for 2015 (Tables 3 – 5) were arrived at. Goodness of fit statistics show strong agreement between estimated and known depths. Evaluation of Coefficient of determination (R^2) yielded 0.9639 for 2002, 0.9576 for 2006 and 0.9560 for 2015. Root mean squared error (RMSE) was 0.2944m, 0.3103m and 0.2671m respectively for the same periods. The standard errors in the estimated depths were gotten as 0.29m for 2002, 0.31m for 2006 and 0.27m for 2015. Table 6 summarises the fitness statistics.

Table 3: Comparison of Estimated and Actual Depths at Lighthouse Creek - 2002

	Estimated Depth (m)	**Actual Depth (m)**	**Error (m)**
Count	67		
Minimum	0.25	0.19	-0.5
Maximum	6.78	6.41	0.5
Mean	1.95	1.9	-0.05
Standard Deviation	1.54	1.53	0.29
Variance	2.37	2.33	0.09
Standard Error	0.29		

In Figures 11 – 13, the estimated depths were plotted against the known depths. The dotted red lines represent the limits of 90% confidence interval of estimated individual values. Estimated depths are on y axis. The absolute differences between the actual depths and estimated depths at these points ranges from 0.1 – 0.49m

Table 4: Comparison of Estimated and Actual Depths at Lighthouse Creek - 2006

	Estimated Depth (m)	Actual Depth (m)	Error (m)
Count	82		
Minimum	0.43	0.25	-0.49
Maximum	6.6	6.41	0.5
Mean	2.14	2.06	-0.08
Standard Deviation	1.48	1.48	0.31
Variance	2.2	2.2	0.1
Standard Error	0.31		

Table 5: Comparison of Estimated and Actual Depths at Lighthouse Creek - 2015

	Estimated Depth (m)	Actual Depth (m)	Error (m)
Count	91		
Minimum	0.12	0.17	-0.49
Maximum	5.39	5.82	0.49
Mean	1.86	1.86	-0.01
Standard Deviation	1.27	1.29	0.27
Variance	1.6	1.65	0.07
Standard Error	0.27		

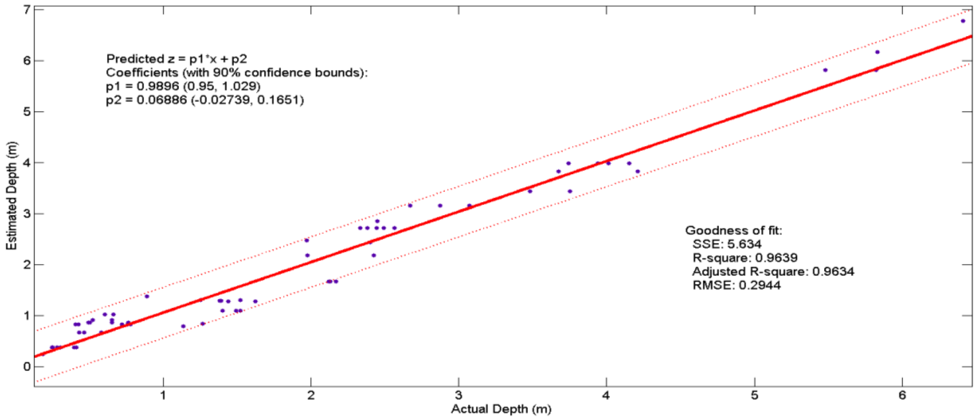

Figure 11: The graphic expression of 90% confidence zone for depth comparison at Lighthouse Creek - 2002

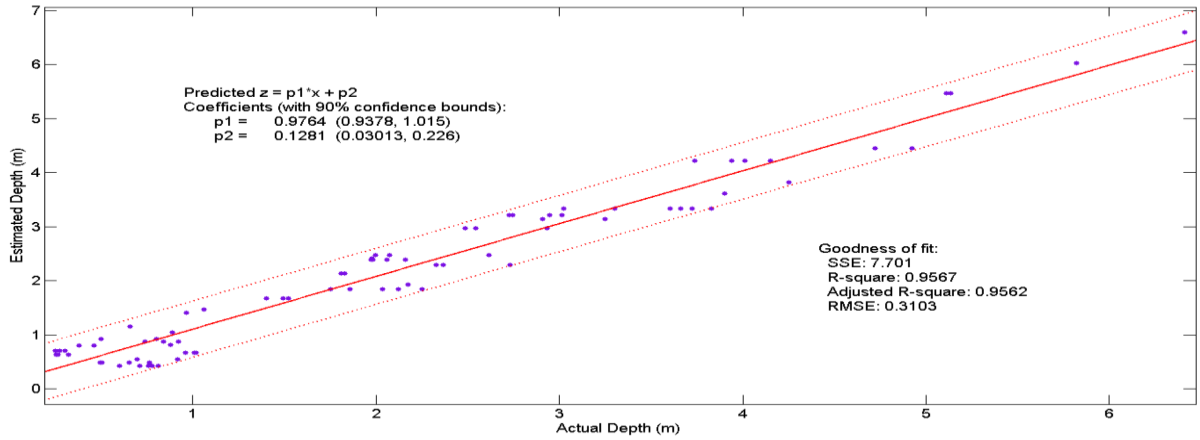

Figure 12: The graphic expression of 90% confidence zone for depth comparison at Lighthouse Creek - 2006

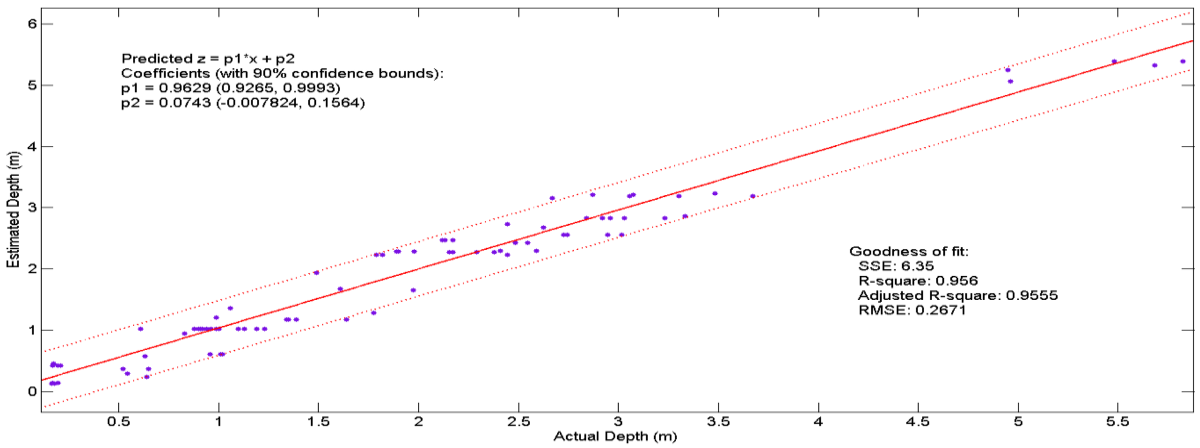

Figure 13: The graphic expression of 90% confidence zone for depth comparison at Lighthouse Creek – 2015

Table 6: Goodness of Fit statistics

Landsat Derived Bathymetry	**Coefficient of Determination (R^2)**	**Root Mean Squared Error (RMSE)**
2002	0.9639	0.2944
2006	0.9576	0.3103
2015	0.956	0.2671

3. LINEAR MODEL FOR DEPTH ESTIMATION

This was done to evaluate the contribution of the significant Blue, Green and NIR bands in the depth estimation. To derive the model, a least squares solution was used to describe the functional relationship between the estimated depths and actual depths of 149 control points.

The derived model is:

$$z = 15.9616 - 0.2598X_1 + 0.2925X_2 - 0.3614X_3 \qquad \text{Eq. 3}$$

Where,

z = the estimated depth

X_1, X_2, X_3 = the corresponding pixel values of Blue, Green and NIR bands

A testing of the model on 142 points of known depths was considered satisfactory for the test points that lied inside the zone of confidence interval of the estimated individual values. A number of 11 points lie outside the zone while 131, that is 92% of the total, lie inside it. The absolute differences between known depths and estimated depths at these points vary from 0.01 m to 0.50 m (Figure 14). The estimated zone depths vary from 0.17m to 2.40m. The covariance matrix of adjusted parameters yielded variances of 0.0030 (S.D = 0.055), 0.0051 (S.D = 0.071) and 0.0062 (S.D = 0.079) for the three coefficients respectively. The results of accuracy tests indicates a very sufficient performance of the model (R^2 = 0.8034, RMSE = 0.249).

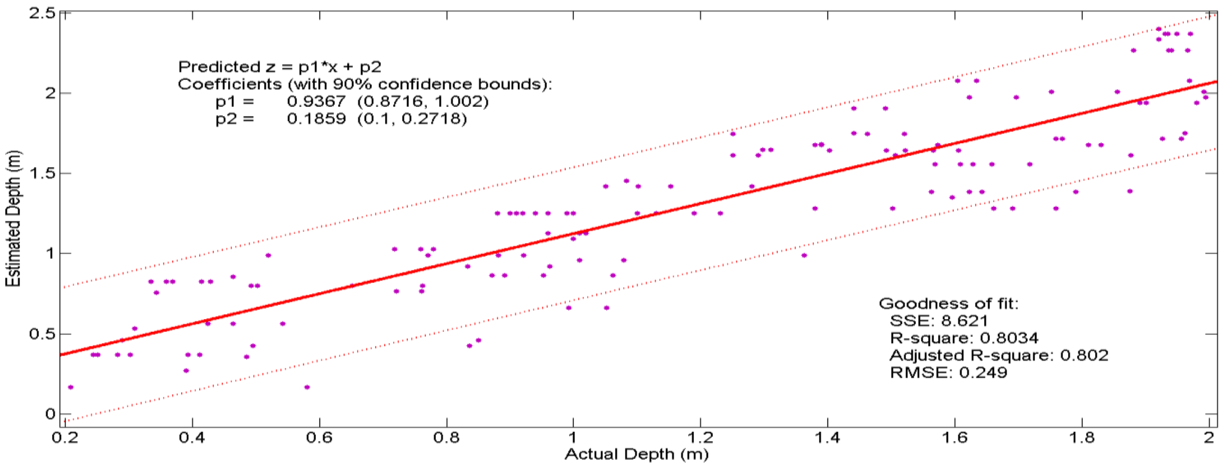

Figure 14: The graphic expression of 90% confidence zone for depth estimation from model

4. CONCLUSION

More studies continue to show that bathymetry can be estimated from optical multispectral imagery. Various inversion models have been developed to convert image pixel information into depth estimates. The non-linear bathymetric inversion model by Stumpf et al (2003) was tested in our study after pre-processing and atmospheric correction was applied to the imageries. Results of accuracy assessment show good correlation between Landsat derived depths and known depths from the sounding. Our comparisons show that the overall performance of the inversion model over our test site was satisfactory with no significant difference in correlation between epochs considered. Further, a linear mathematical model to describe the relationship between significant spectral band properties (independent variables) and the estimated depths (dependent variable) was determined by a computationally rigorous least squares solution. The outcomes of the analysis indicated that the model provided very good results. While the dynamic nature of the underwater environment seriously impacts the accuracy of bathymetric estimation, it still offers us a viable interim solution for areas where there is inadequate hydrographic data and scarce resources for extensive surveys using other higher accuracy methods. The only caveat is that remotely sensed images need to be carefully calibrated to ensure the accuracy of extracted depth information.

5. RECOMMENDATIONS

Recommendations for improved results are:

- The spectral behaviour of optical image bands in the zones beyond the extinction depth should be further investigated and modelled with an appropriate fitting curve.
- Further extensive assessments of Stumpf's model with various benthic environments are needed in order to determine its robustness.
- Other empirical models to account for turbidity and other extraneous variables underwater which could explain the outcomes of erroneous and outlier depth estimates should be incorporated.

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BIOGRAPHICAL NOTES

Dr. Dupe N. Olayinka obtained a Doctorate degree from Lancaster University, UK with specialization in Environmental and Flood Modelling under the Schlumberger Foundation (Faculty for the Future) for Women in Science and Engineering. She was the University of Lagos Scholar in 1998 having graduated with First Class (Honours) in Surveying from the University of Lagos. She also graduated with Distinction in her Master of Science (Surveying and Geoinformatics). Dr. Olayinka is a Lecturer in the Department of Surveying and Geoinformatics. She is a full member of the Nigerian Institution of Surveyors; Member, African Association of Remote Sensing of the Environment (AARSE); Member, EIS-Africa and an Associate Member of Institute of Civil Engineers (British Hydrological Society), UK. Dr. Olayinka is a Registered Surveyor (2003). She has over 33 publications to her credit and has attended several conferences both in Nigeria and abroad.

Mr Chukwuma J. Okolie has a Master of Science, M.Sc. (Distinction) in Surveying and Geoinformatics from the University of Lagos. His M.Sc. thesis comparatively assessed Satellite Derived Bathymetry and conventional Echo Sounding for nine (9) rivers and creeks along Nigeria's coastline. Mr Okolie provides training services in GIS and Remote Sensing to Government Agencies and the Private Sector. He has over 6 publications to his credit both locally and internationally. In 2010, he was a Research Assistant on 'A Study of Spatial Changes in the Wetlands of Lagos Lagoon', a Central Research Committee (University of Lagos) funded research. He has a wide range of experience in Digital Mapping Projects and GIS/Remote Sensing Consultancy services. Mr. Okolie personally supervised the production of numerous digital and topographic maps at various scales on behalf of the Office of the Surveyor General of the Federation (OSGOF) and is actively involved in several research interests.

CONTACTS

Dr. Dupe Nihinlola OLAYINKA
University of Lagos
Department of Surveying and Geoinformatics
Faculty of Engineering
Lagos, Nigeria
Tel. +234-811-111-2569
Email: dsaka@unilag.edu.ng
Web site: www.unilag.edu.ng

Mr Chukwuma John Okolie

University of Lagos
Department of Surveying and Geoinformatics
Faculty of Engineering
Lagos, Nigeria
Tel. +234-803-133-2527
Email: mrjohnokolie@gmail.com