Journal of Geomatics and Environmental Research, Vol. 7, No. 1, Dec. 2024
ISSN 2682-681X (Paper) ISSN 2705-4241 (Online) |
http://unilorinjoger.com

VALIDATING THE REMOTE SENSING APPROACH TO THE BATHYMETRIC SURVEY OF TAGWAI DAM

Baba, Mahmud, Adeleke, Abdulrahman, Zita, Nanpond ., and Opaluwa, Yusuf Drisu

Department of Surveying and Geoinformatics, Federal University of Technology Minna
Corresponding Email: Adelekeabdul87@gmail.com

ABSTRACT

Remotely sensed image data are considered attractive for bathymetry applications as they provide a timely and less cost-effective solution to ocean depth estimation. The research uses a remote sensing technique to present an estimate of the depth (bathymetric survey) of Tagwai Dam. In this research work, sentinel-1 image data was used, having undergone the pre-processing stages, to derive the depth, and three spectral bands, blue spectrum (450-520nm), green spectrum (530-590nm) and NIR spectrum (850-880nm) were utilized to carry out this task. Stumpf's (Sfs) Model of depth estimation was implored. The highest depth recorded by the Sf's algorithm was 17.352m as against the highest depth recorded by echo (Ec) sounding equipment 20.800m, which happens to be the referenced observation. Statistical tools were used to compute the Root Mean Square Error (RMSE), the standard error of the estimate (SEE), and the Correlation Analyses Index (CAI) between the Sf's algorithm and the Ec sounder. The RMSE incurred was 3.324, the SEE was 0.4901, while the correlation analyses index R was about 95%, which shows a high level of closeness between both approaches. However, the results also indicate that the rate of growth of sediment accumulation over time is alarming, as it gradually reduces the capacity of the dam. Hence, the authority involved should, as a matter of urgency, carry out an overhaul of sediment removal to preserve the life span of the dam.

Keywords: *Stumpf's Model, Echo-sounder, Monitoring seafloor, Marine Navigation System*

1.0 Introduction

Accurate and precise bathymetric measurements are considered of fundamental importance in monitoring seafloor and producing nautical charts in support of marine navigation systems. Until recently, bathymetric surveying has been mainly based on conventional ship-borne echo-sounding operations, which seem to be costly and time-consuming (Lyzenger 1985). However, the remote sensing approach has shown high reliability in terms of retrieving bathymetry data (Chukwuma and Dupe, 2016). Traditional bathymetric acquisition methods can generate accurate point measurements or depth profiles along transects but are constrained by their inefficiency, logistical expenses, and inaccessibility to operate in remote areas (Jawaks *et al.*, 2015; Sun *et al.*, 2023; Tang and Mahmud, 2021). Although the conventional shipborne approach of ocean depth estimation is still the most used and this is because of its high accuracy bathymetry data. The limited coverage, time, and high cost of operation remain the primary concern for the surveying industry players. In shallow-depth water areas, ship-borne soundings commonly use a single-beam echo Sounder System (SBES), which in return generates a

low spatial resolution and encounters high operational risk due to limited navigation space (Najhah *et al.*, 2017).
Considering the limitation of ship borne acquisition, remotely sensed data technique through space borne acquisition has been accepted as an alternative method of the bathymetric data acquisition especially for the shallow water area. However, Light Detection and Ranging (LiDAR), an airborne bathymetric acquisition technique has been routinely deployed in some countries for seafloor mapping within shallow coastal waters (Su *et al.*, 2008). Indeed, LiDAR has produced reliable bathymetric data, which, in certain conditions, can meet the International Hydrographic Organization (IHO) Special Order survey (Pe'eri *et al.,* 2014). However, apart from its inability to operate in water bodies having high levels of turbidity, the common concern for some service providers when operating aircraft in the enclosed maritime region like Nigeria is the permits for airborne operations, especially in porous regions (States) where insecurity challenges are on the rise. All the perilous issues, coupled with the unavailability of the equipment, have influenced the operational cost of a LiDAR system in this region, making it extremely high. Especially when the project requires more frequent flyovers (Minghelli *et al.,* 2009: Pe'eri *et al.,* 2014).
Hence, with more new satellites being launched and new sensors being developed every year, a significant number of research works have been conducted to assess and analyze the satellite-derived bathymetric (SDB) acquisition techniques (Bramante *et al.,* 2013). Unsurprisingly, this contemporary remote sensing technology is considered a promising technology and an attractive option for seafloor mapping, especially in shallow water environments. The Stumpf model provides a distinct advantage over other satellite-based bathymetric approaches by utilizing a logarithmic band ratio technique, which significantly reduces the influence of varying bottom types and water column conditions (Hao Quang *et al.*, 2024).
Unlike traditional linear or single-band models that are highly sensitive to substrate reflectance and turbidity, the Stumpf model calculates depth using the natural logarithm of the ratio between two spectral bands, typically blue and green (Casal *et al.,* 2019; Azzam and Susilo, 2023). One of the key advantages of Stumpf's model is its simplicity, which is characterized by a limited number of parameters, making it a more straightforward and easily applicable approach (Nagahisarchoghaei *et al.,* 2023). This method enhances the stability and accuracy of depth estimations across diverse aquatic environments (Stumpf *et al.,* 2003). Additionally, it requires minimal field calibration, making it more practical and cost-effective for large-scale or remote applications (Viaña-Borja, *et al.*, 2025; Ashphaqet *et al*., 2021). Its flexibility across different satellite platforms, such as Landsat and Sentinel image datasets, further strengthens its applicability compared to more complex or sensor-specific models. This study builds upon the established accuracy of satellite-derived bathymetry approaches and aims to further validate the remote sensing method for depth estimation using Stumpf's model. Specifically, this research seeks to verify the accuracy of Stumpf's (Sf's) model-based depth estimations through a comparative analysis with echo (Ec) sounding measurements,

thereby assessing the reliability and efficacy of this remote sensing approach for bathymetric mapping.

2.0 Study Area

Tagwai Dam is situated in the Chanchaga Local Government Area (LGA) of Niger State, Nigeria. Geographically, the dam lies within the coordinates of 09° 37' 00" N to 09° 33' 00" N latitude and 06° 39' 00" E to 06° 42' 00" E longitude, corresponding to the Nigerian sheet 142 North Western (Minna). The study area is drained by two major rivers, River Jidua and River Lumo, which serve as the primary sources of water for the dam. According to the 2006 census, the population of Chanchaga LGA is approximately 138,434 inhabitants, with most residents belonging to the Nupe and Gbagyi tribes (Niger State Government, 2013). The topography of the area is characterized by low-lying terrain and a prominent ridge in the northeastern sector of the dam, with a hill elevation exceeding 913 feet above sea level and steep side slopes, as observed during fieldwork and confirmed by GPS data (2006).

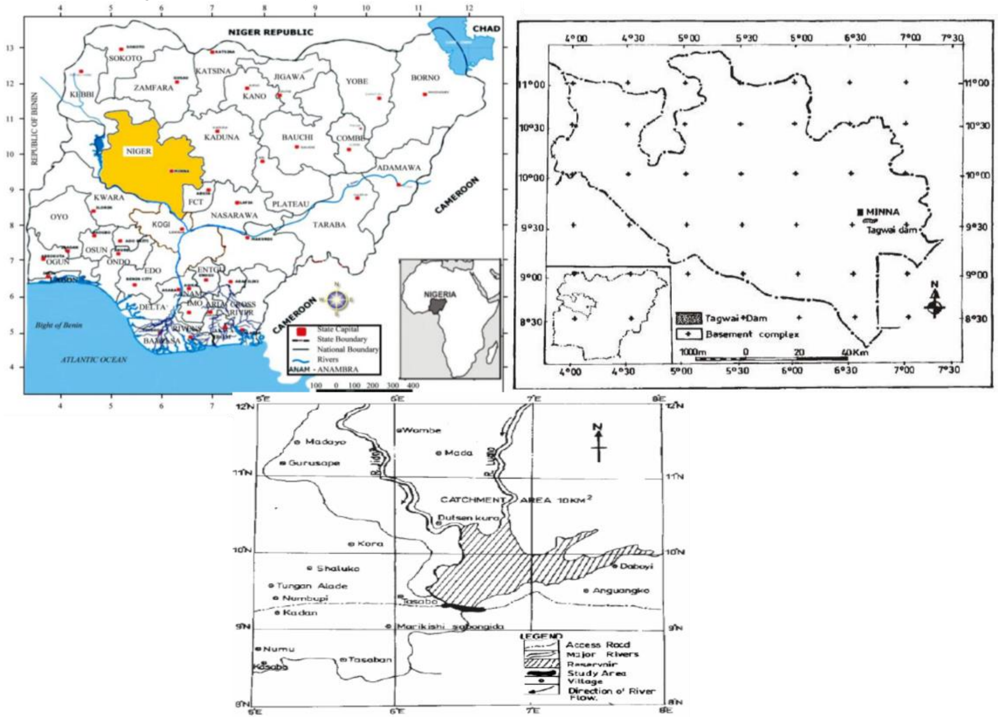

Figure 1. The Study Area

3.0 Methods

3.1 Data Acquisition

The Sentinel-1 multispectral image data was downloaded from an open access hub via httpps://scihub.copernicus.eu. The satellite image used has 10m spatial resolution. The three spectral bands used are blue spectrum (450-520nm), green spectrum (530-590nm), and near infrared (NIR) spectrum (850-880nm) were utilized. The blue spectrum and green spectrum were used in the derivation of the SDB algorithms, this is because both bands have higher penetration strength on clean water (Green *et al.*, 2000). Whereas the near-IR (NIR) and green band were used to carry out the normalized difference water index (NDWI), it's effective in separating water body from land surfaces (McFeeters, 1996). Equation (1) shows the formula for the estimation of NDWI is:

$$NDWI = \frac{G-NIR}{G+NIR} \qquad 1$$

Where;
G; Indicate green spectrum while NIR depicts near infrared spectrum
The Geometric correction was implemented by rectifying set of ground control points derived from large-scale topographic maps of the study area and then transformed to the Universal Transverse Mercator projection with the WGS84 datum. The ground control points were carefully selected and fine-tuned to manage the final error down to below half of the image pixel while the radiometric correction aimed at converting digital number (DN) to radiance values in the image data. This will improve the reflective properties of the image data. According to Hedeyet, (2023), this technique firstly converts the DN value to the atmospheric radiance using equation 2.

$$L\lambda = \frac{SR_k \ *DN}{DN_{max}} \qquad 2$$

Where;
SR_k the saturated radiance of Kth band, DN is the digital number, and DN_{max} is the maximum possible value of a pixel. Figure 2. depicts the methodology flow of the research

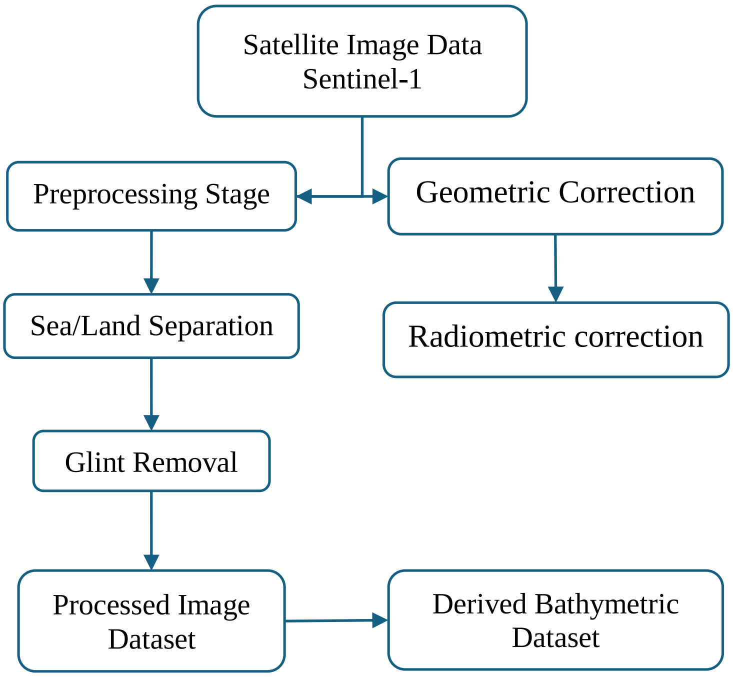

Figure 2: Methodology Flow

Journal of Geomatics and Environmental Research, Vol. 7, No. 1, Dec. 2024
ISSN 2682-681X (Paper) ISSN 2705-4241 (Online) |
http://unilorinjoger.com

The sun glint effect on the image data was corrected by dividing the digital number values in the image data by the sine of the solar elevation angle (Hedeyet, 2023). Equation 3 shows the correction model.

$$DN_{corr} = \frac{DN}{sin\ a} \qquad 3$$

Where;
DN_{corr}: corrected digital numbers of values
$\sin a$: Solar elevation angle

3.2 Water Depth Extraction Model

Stumpf (2003) has designed a ratio transformation method for shallow water bathymetry estimation. This model is principally based on the concept that light weakens exponentially at water depths shows an albedo effect on the substrate and will be minimized using two bands (green and blue) to obtain water depth. Thus, according to this model, different spectral bands will weaken at different depth levels. Therefore, the ratio between the two spectral bands will vary in obtaining water depth data. Equation 4 below expresses Stumpf's model.

$$Z = m_1 \frac{Ln\left(nR_w(\lambda_i)\right)}{Ln\left(nR_w(\lambda_j)\right)} - m_0 \qquad 4$$

Where:
Z = Bathymetry depth; m_1, m_1 = Regression coefficient value; $Rw(\lambda i)$= reflectance value of blue band; and $Rw(\lambda j)$ = reflectance value of green band.
The stumpf's band ratio was justified by comparing the wavelength of three bands (red, green and blue) of the source image data. Green/red, Blue/red and Blue/Green, the most correlated outcome from the band's combination was used as the predicted (SDB) depth of the dam.
The predicted SDB data was validated using the echo-sounding data. According to Kasvi *et al. (*2019), the sounding technique is more accurate for ocean depth determination, especially in both shallow and deep oceans. Statistical templates such as the RMSE (Root mean squared error) method and SEE (standard error of estimate) on each depth data to obtain the accuracy level of each algorithm (Mateo-Pérez *et al.*, 2021). Equations 5 and 6 depict the formular for RMSE and SE.

$$RMSE = \sqrt{\sum(Z_{sat} - Z_{obs})^2} \qquad 5$$

$$SEE = \sqrt{\frac{\sum(\hat{y}-y)^2}{n-2}} \qquad 6$$

Where:
Z_{sat}:$\hat{y}$; predicted observation
Z_{obs}: y : Referenced observation
n: Number of observations
The RMSE compares the predicted value with the observed value to measure how much error is between the two data sets. The smaller the RMSE value, the closer the predicted (SDB) depth values are to the observed values Echo (Ec) sounder. SEE measures how far

the predicted value deviated from a known observation. That is, the distance between the predicted valve and the referenced, it shows the average mean (error) of each point of the measurement between the predicted (SDB) and the referenced observation Ec sounding depth.

4.0 Results and Discussion

4.1 Depth Estimation Using Stumpf's (Sf's) Model (Band Transform Ratio)

Figures 3, 3.1, and 3.2 depict the scattered regression plot of the image bands used for SDB depth estimation. The three bands (Blue, Green, and Red) were considered, and the highly correlated bands' combination served as the predicted SDB depth.

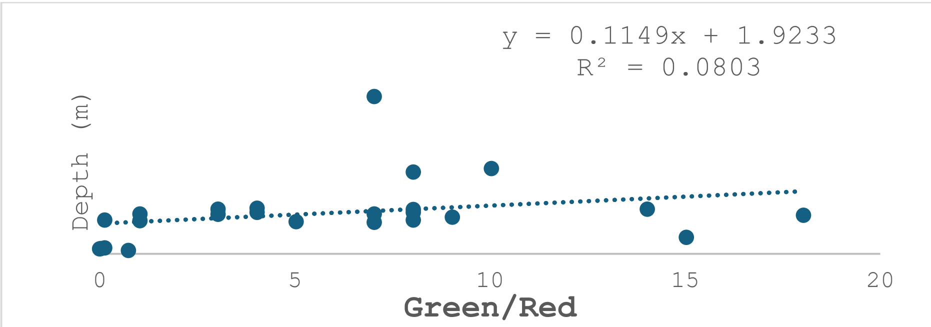

Figure 3. Regression Analyses of Band Combination

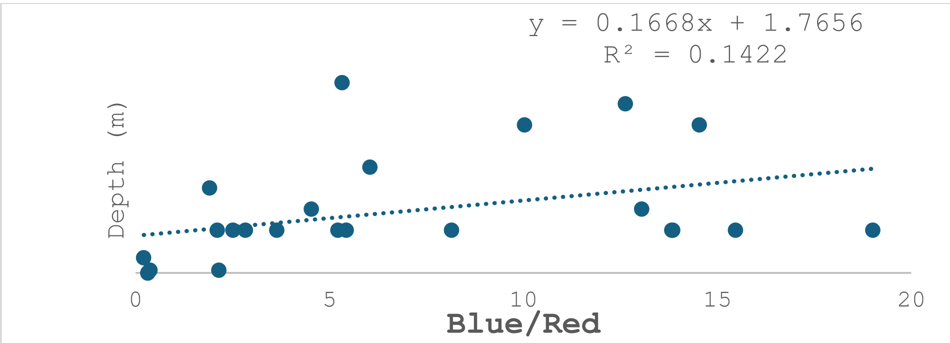

Figure 3.1 Regression Analyses of Band Combination

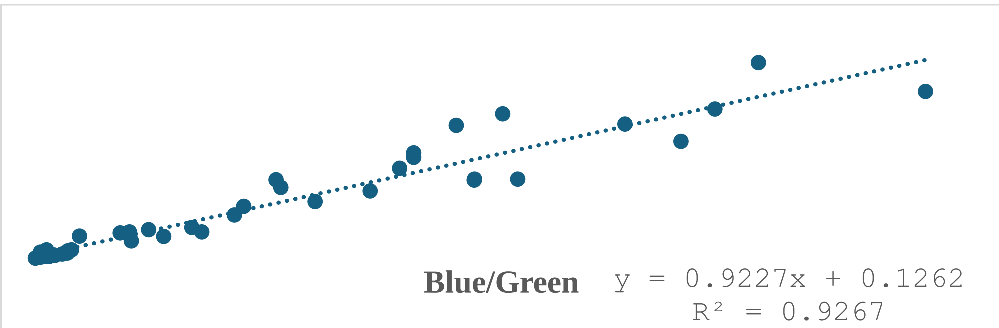

Figure 3.2. Regression Analyses of Band Combination

Table 1. Bands Combination from the Image Data

Band Ratio	R^2	R	Slope
Green/Red	0.0803	0.2834	1.9233
Blue/Red	0.1422	0.3771	1.7656
Green/Blue	0.9267	0.9627	1.1262

The regression test results presented in Table 1 reveal significant differences in the values obtained from various band combination ratios. Notably, the Blue/Red, Green/Red, and Blue/Green band combinations yielded correlation index values (R) of 0.377, 0.283, and 0.9627, respectively. These findings suggest that the red band spectrum is characterized by weak water penetration and its less effective in estimating water depth. In contrast, the blue and green bands, with their higher penetration strength, exhibit a strong correlation, making them more suitable for predicting water depth in clean waters over longer distances (Chénier *et al.*, 2018). Consequently, the Blue/Green band ratio was selected as the optimal predictor for estimating the Satellite derived bathymetry (SDB) of the dam. Figure 4 depicts the depth variation of the dam.

The model uses the division between observed reflectance log values to estimate water depth (Geyman and Maloof, 2019). Stumpf's model was chosen amidst other models in this research project due to it simplifies principles and its ability to estimate water depth even in a turbid water body, with an appreciable accuracy. The processed image data revealed a significant range of depths within the study area. The maximum depth recorded was approximately 17.352 meters, while the minimum depth was as shallow as 0.013 meters, indicating a substantial variation in water depth across the region.

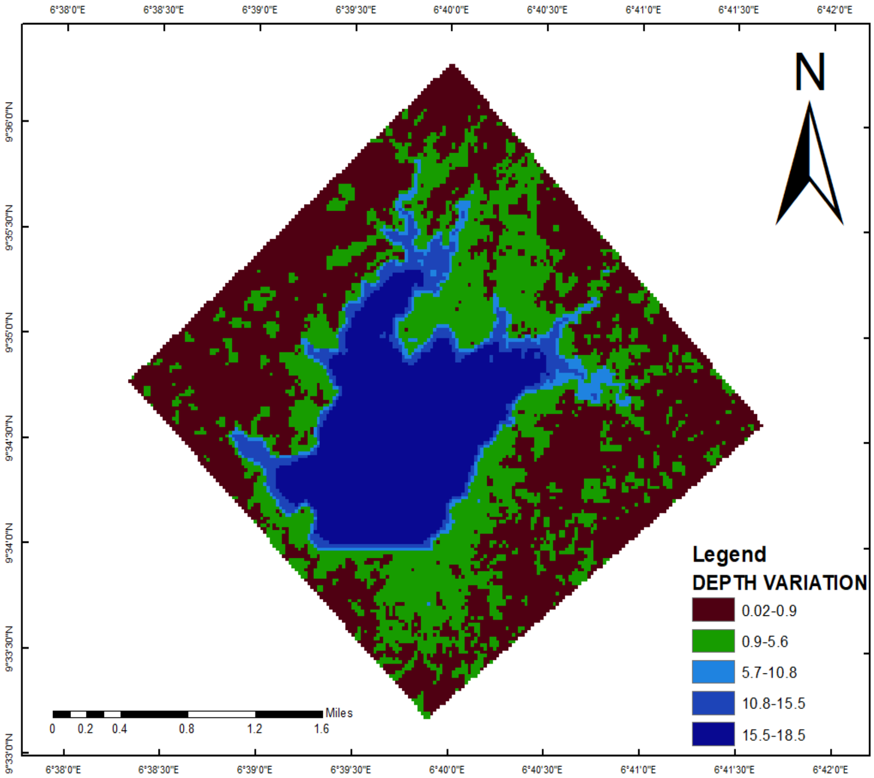

Figure 4. Depth Variation of Tagwai Dam

Figure 4 illustrates the spatial variation in depth across Tagwai Dam. The color-coded representation reveals that areas with high depths are denoted by dark blue, while light blue signifies regions with average depths. In contrast, green indicates areas with lower depths and negative anomalies. Notably, the dam entrance is experiencing sedimentation, with significant mud accumulation, while the perimeter embankment is overgrown with vegetation, indicating neglect by the agency or ministry in charge of overseeing the maintenance of the Dam. Furthermore, the occurrence of negative depth values can be attributed to sudden changes in surface reflectance, resulting from differences in the microwave pulse signals emitted by the satellite sensor.

The surface difference will be positive if the reflected signal was on water surface while negative, if reflected signal (wave) was on earth surface. According to Muhammed *et al.*, (2018), Tagwai earth dam from its original design construction, it is built to house about 28.3million m^3 of water, design depth was about 25m, and a longitudinal length was about 18km. The aforementioned give more evidence that the dam is not well taking care of. And this account for the reduction in depth recorded by Stumpf's model in the research work. The predicted SDB measurements by the stumpf's model revealed a maximum depth of 17.352m at the centre of the dam and a minimum depth of 0.013m.

Journal of Geomatics and Environmental Research, Vol. 7, No. 1, Dec. 2024
ISSN 2682-681X (Paper) ISSN 2705-4241 (Online) |
http://unilorinjoger.com

4.2 Validation of Stumpf's Model Using Echo-Sounding Approach

The bathymetric data for Tagwai Reservoir were meticulously collected using a single-beam echo-sounder, specifically the Echo Map 50s, mounted on a manned vessel. The data were acquired at 25m interval strips and 50m interval cross-sections to ensure comprehensive coverage of the reservoir. To accurately position the dam shoreline, a differential global positioning system (Hi-Target V30) was employed. The resulting sounding data revealed a maximum depth of 20.800m and a minimum depth of 0.051m. All spatial data were referenced to the Minna Zone 32 projection system, which is based on Clark's 1880 ellipsoidal parameter. This ensures that the bathymetric data are accurately georeferenced and can be integrated with other spatial datasets. Figure 5, and 6 depicts the graphical overlay of the SDB and the echo sound (Ecs) data and the depth variations between the SDB and the reference observations.

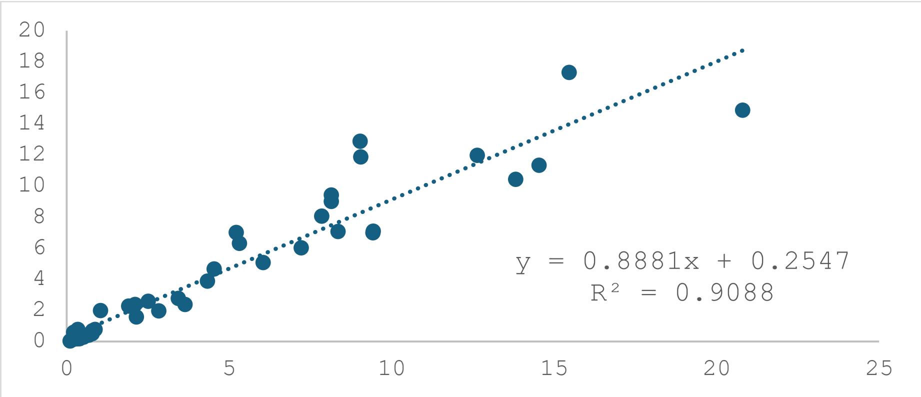

Figure 5: Regression of the Echo sounding depth and the predicted SDB depth

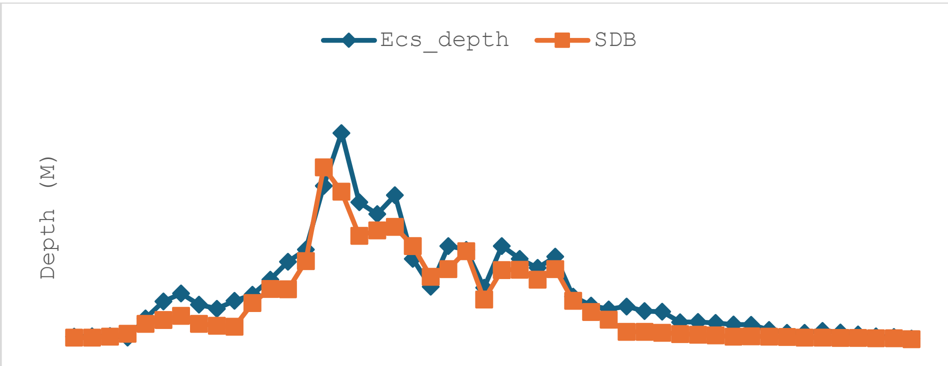

Figure 6: Depth Variation of Echo sounding Data and the predicted SDB Dataset.

A comparative analysis of the satellite-predicted depth measurements and the referenced observational data revealed a remarkably high correlation index, indicating a closeness of approximately 95%. As presented in Table 2, the degree of accuracy between the predicted (SDB) and the referenced observation is noteworthy. The standard error estimated from the comparison was found to be minimal, further underscoring the high level of agreement between the two datasets. Moreover, the root means square error (RMSE) of 3.3241 suggests that the satellite-predicted depth measurements are in close agreement with the referenced observational data, thereby validating the accuracy of the predictive model.

Table 2. Depth Errors Analyses

Statistics	Ecs	SDB
RMSE	3.3241	
SEE	0.4901	
Correlation index	1	0.9533

5.0 Conclusion

The Sf's algorithm has demonstrated a high level of reliability in its results, notwithstanding the challenging conditions of high turbidity in the dam during data acquisition. The algorithm's performance has also validated the robustness of the linear model incorporated within it. The predicted depth measurements revealed a maximum depth of 17.352m at the middle center of the reservoir, with other depths ranging below this value. A comparison with the echo-sounder instrument's measurements showed a maximum depth of 20.800m, resulting in a difference of 2.475m. This discrepancy can be attributed to sediment accumulation at the dam floor, which may have affected the accuracy of the predicted depths. Nevertheless, the model performed well, as the difference between the predicted and measured depths was within an acceptable range. Most importantly the trend of depth variation was highly correlated (see figure 6), it has further validated the reliability of stumpf's model

A statistical assessment of the predicted measurements and referenced data revealed a remarkably high correlation coefficient of approximately 95%, indicating a strong agreement between the two datasets. Furthermore, the Root Mean Square Error (RMSE) and Standard Error of Estimate (SEE) were found to be minimal, providing additional evidence of the reliability and accuracy of the model used. However, to achieve even higher accuracy, it is essential to utilize high-resolution image datasets. Notably, the results also suggest that sediment accumulation is gradually reducing the water-holding capacity of the dam, as evidenced by the discrepancy between the computed and designed depths. This finding underscores the urgent need for the responsible authorities to undertake a comprehensive cleaning and removal of suspended particles and sediments from the dam, to maintain its optimal functionality and prevent further degradation.

Reference

Abdullah Azzam, A & Susilo, S. B. (2023). Estimating bathymetry using sentinel-2a for shallow-waters mapping: a case study in Kelapa Dua Island., IO Web of Conferences 106, 04001., /doi.org/10.1051/bioconf/202410604001

Ashphaq, M., Srivastava, P. K., & Mitra, D. (2021). Review of near-shore satellite derived bathymetry: Classification and account of five decades of coastal bathymetry research, *Journal of Ocean Engineering and Science*, 6(4), 340-359, Doi.org/10.1016/j.joes.2021.02.006.

Bramante, J. F., Raju, D. K. & Sin, T. M. (2013). Multispectral Derivation of Bathymetry in Singapore's Shallow, Turbid Waters. *International Journal of Remote Sensing*, 34:6, 2070-2088.

Casal, G., Harris, P., Monteys, X., Hedley, J., Cahalane, C., & McCarthy, T. (2019). Understanding satellite-derived bathymetry using Sentinel 2 imagery and spatial prediction models. *GIScience & Remote Sensing*, *57*(3), 271–286. https://doi.org/10.1080/15481603.2019.1685198

Chénier, R., Faucher, M.A., & Ahola, R. (2018). Satellite-Derived Bathymetry for Improving Canadian Hydrographic Service Charts. *ISPRS International Journal of Geo-Information*, 7(8), p.306. doi: 10.3390/ijgi7080306.

Chukwuma, J. O., & Dupe, N. O. D. (2016). Satellite derived bathymetric modelling in shallow water. A case study of light house creek, Lagos

Geyman, E. C., & Maloof, A.C. (2019). A Simple Method for Extracting Water Depth from Multispectral Imagery in Regions of Variable Botton Type. *Earth and space science*., 6(3). Doi.org/10.1029/2018EA000539.

Green, E. P., Clark, C. D. & Edwards, A. J. (2000). Image Classification and Habitat Mapping. In Remote Sensing Handbook for Tropical Coastal Management, A.J. Edwards (Ed.), pp. 141–154 (Paris: UNESCO).

Hao Quang, N., Banno, M., & Ha, N. T. (2024). Satellite derived bathymetry using empirical and machine learning approaches: a case study in the highly dynamic coastal water. *Coastal Engineering Journal*, 1–20. Doi.org/10.1080/21664250.2024.2445418

Hedeyat I. S. (2023), Radiometric Correction of Remote Sensing Image, Jahangirnagar University. Doi. 10.13140/Rg2.2.14013.84960

Jawak, S, D., Somashekhar, S., V, Alvarinho & Luis, J. (2015). A Synoptic Review on Deriving Bathymetry Information. *Using Remote Sensing Technologies*: Models, Methods and Comparisons.DOI: 10.4236/ars.2015.42013

Kasvi, E., Salmela, J., Lotsari, E., Kumpula, T., S. N. & Lane, S. N. (2019) Comparison Of Remote Sensing Based Approaches For Mapping Bathymetry Of Shallow, Clear Water Rivers. *Geomorphology*. V(333), 15Pg 180-197. doi.org/10.1016/j.geomorph.2019.02.017

Lyzenga, D. R. (1985). Shallow-Water Bathymetry Using Combined Lidar and Passive Multispectral Scanner Data. *International Journal of Remote Sensing*, 6:1, 115-125.

Mateo-Pérez, V., Corral-Bobadilla, M., Ortega-Fernández, F. & Rodríguez-Montequín, V., 2021. Determination of water depth in ports using satellite data based on machine learning algorithms. *Energies*, 14(9), p.2486. doi: 10.3390/en14092486.

Mcfeeter (1996). The use of Normalised Difference water index (NDWI) in the delineation of open water feature. *International Journal of Remote Sensing*. Doi. Org/10.1080/01431169608948714

Minghelli, A., Goreac, A., Mathieu, S., & Spigai, M. (2009). Comparison of Bathymetric Estimation Using Different Satellite Image in Coastal Sea Water. *International Journal of Remote Sensing*. 30(21)5737-5750., Doi: 10.1080/014311609022950

Muhammed H. M., Ibrahim, B. U., Balogu D. O., Isah, M. C., & Musa A. I. (2018). Assessment of the Water Quality Parameters of Tagwai Reservoir, Nigeria., *International Journal of Oceanography & Aquaculture*., (2)5.

Nagahisarchoghaei, M., Nur, N., Cummins, L., Nur, N., Karimi, M. M., Nandanwar, S., Bhattacharyya, S., & Rahimi, S. (2023). An Empirical Survey on Explainable AI Technologies: Recent Trends, Use-Cases, and Categories from Technical and Application Perspectives. *Electronics*, *12*(5), 1092. Doi.org/10.3390/electronics12051092

Najhah, Md-S., Mohammed R. M., & Rozaimi Che-H. (2017). Satellite bathymetry accuracy assessment on depth derivation algorithm for shallow water area. *Remote Sensing and Spatial Information Scienc*e. Doi. Org/10.5195/issprs-archive

NGS. (2013). Niger State Government, fact and figures. /https://nairametrics.com/wp-content/uploads/2013/05/Facts-and-Figures-about-Niger-State1.pdf

Pe'eri, S., Parrish, C., Azuike, C., Alexander, L. & Armstrong, A. (2014). Satellite Remote Sensing as Reconnaissance Tool for Assessing Nautical Chart Adequacy and Completeness. *Marine Geodesy*, 37, 293–314.

Stumpf, R. P., Holderied K. & Sinclair, M. (2003) Determination of Water Depth with High Resolution Satellite Imagery over Variable Bottom Types. *Limnology and Oceanography*, 48, 547-556. Doi.org/10.4319/lo.2003.48.1_part_2.0547

Su, H., Liu, H. & Heyman, W. D. (2008). Automated Derivation of Bathymetric Information from Multi-Spectral Satellite Imagery Using a Non-Linear Inversion Model. *Marine \Geodesy*, 31, 281-298.

Sun, S., Chen, Y., Mu, L., Le, Y., & Zhao, H. (2023). Improving Shallow Water Bathymetry Inversion through Nonlinear Transformation and Deep Convolutional Neural Networks. *Remote Sensing*, *15*(17), 4247. https://doi.org/10.3390/rs15174247

Tang, K. K. W., & Mahmud, M. R. (2021). The Accuracy of Satellite Derived Bathymetry in Coastal and Shallow Water Zone. *International Journal of Built Environment and Sustainability*, *8*(3), 1–8. https://doi.org/10.11113/ijbes.v8.n3.681

Viaña-Borja, S.P., González-Villanueva, R., Alejo, I. Stumpf, R.P. Navarro, G.& Caballero, I. (2025). Satellite-derived bathymetry using Sentinel-2 in mesotidal coasts, *Coastal Engineering.* 195. Doi.org/10.1016/j.coastaleng.2024.104644