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ESTIMATION OF DEPTH OF RIVER BY BATHYMETRY OF SATELLITE IMAGES

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Abstract - The collection of bathymetric data is crucial for examining the river environment, watershed hydrological response, and river hydraulics. However, traditional field surveys for acquiring such data are costly and time-consuming, and may be hindered by inaccessibility to partially or completely submerged riverbeds. To supplement these surveys, remote sensing methods offer new possibilities. The objective of this research is to showcase how satellite imagery can be utilized to approximate the depth of water in a river. Specifically, the study focuses on the shallow portion of the Mula-Mutha River situated near Pune, utilizing four spectral bands of high-resolution multispectral satellite imagery (red, green, blue, and near-infrared) with minimal cloud interference and adequate light penetration. Furthermore, correlation analysis between frequency bands and field measurements has been conducted at numerous survey sites.

Key Words: Satellite imagery, Bathymetry, Image processing, Machine learning

1.INTRODUCTION

The analysis of the underwater topography or bathymetry of water bodies like rivers, streams, seas, and lakes is crucial for predicting shorelines, seabed depth, and managing flood protection and vessel operations. The objective of this is to create a prototype using machine learning and deep learning techniques that can perform bathymetry on a large scale. Bathymetry, which refers to the study of the floors or beds of water bodies, is an important area of research that has various applications in hydrology, water resource management, shipping operations, and flood management. Traditional approaches to collecting bathymetry data, such as field surveys, can be time-consuming and expensive. Furthermore, inaccessible riverbeds can make field surveys challenging to conduct in many cases. Remote sensing techniques, such as satellite image processing, provide new ways to supplement traditional field surveys. Satellite imagery offers a unique opportunity to obtain information about the depth and shape of underwater land, enabling us to estimate river water depth and map the underwater features of rivers. Satellite image processing for bathymetry of rivers has become an area of interest in recent years due to its potential to provide large-scale, high-resolution, and accurate depth estimation with minimal cost and time. High-resolution, multispectral satellite imagery is now available., which can penetrate the water body with favorable conditions of sunlight, has opened up new possibilities for researchers to explore this area.This study aims to demonstrate the estimation of river water depth using satellite images and to develop a method for mapping the underwater features of rivers.

2. EXISTING WORK

Hojat Ghorbanidehno [1] discussed the importance of river bathymetry and the difficulty of obtaining direct measurements of depth. However, indirect measurements can be obtained using physics-based inverse modeling techniques. A new deep learning framework is developed and applied to three problems of identifying river bathymetry by combining connected principal component analysis (PCA) and DNN.

Tatsuyuki Sagawa [2] proposed a method to create a general depth estimation model, a shallow water bathymetric mapping approach was developed using Random Forest learning and multitemporal satellite imagery. The research looked at 135, Landsat-8 images and extensive training bathymetric data from five different regions. Satellite bathymetry (SDB) accuracy was tested against reference bathymetric data.

Motoharu Sonogashira [3] performed deep learning-based image super-resolution experiments to improve resolution of bathymetric data. By implementing this technique, the quantity of sea areas or points that require measurement is decreased, leading to the swift and detailed mapping of the seabed and the creation of high-resolution bathymetric maps of the encompassing regio.

Manuel Erena [4] emphasized that the applicability and utility of bathymetric information is:The effectiveness of the approach is heavily reliant on the standard and spatial precision of the data, in addition to the configuration of the model network. He proposed using various remote sensing tools to obtain extensive inland bathymetric information and one approach is to obtain coastal water masses with progressively enhanced spatial resolution.

Jiaxin Wan [5] concluded that coastal bathymetry is an important parameter in coastal research and management. Previous research has shown the importance of obtaining high resolution coastal bathymetric data. The study found that the combination of high-resolution multispectral imagery with appropriate algorithms could generate accurate near-shore bathymetric data.

3. METHODOLOGY

In this paper, the conventional least squares regression analysis to resolve the gradient of a line is not used. This is because the choice of dependent variable band can significantly impact the outcome. Instead of measuring the root mean square error of the regression line along the dependent variable, the approach used here selects the slice with the smallest root mean square error. The regression line is then positioned accordingly. The following equation illustrates this approach:

$ki/kj = a+\sqrt{(a\ 2+1)}$

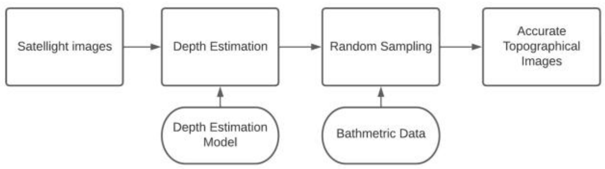

Fig 1.Block Diagram.

3.1 Land and Water Separation

The ability of light to penetrate decreases as the wavelength increases, and the Near Infrared (NIR) band is unable to penetrate deep into water due to strong absorption. Additionally, vegetation and soil strongly reflect NIR radiation, resulting in a visible distinction between land and water bodies in NIR band images and a significant difference in DN (digital number) values. The histogram of NIR band DN values displays two peaks, representing water pixels and land pixels, respectively. This threshold value is used to exclude points corresponding to land, resulting in an array of solely water body pixels for additional processing.

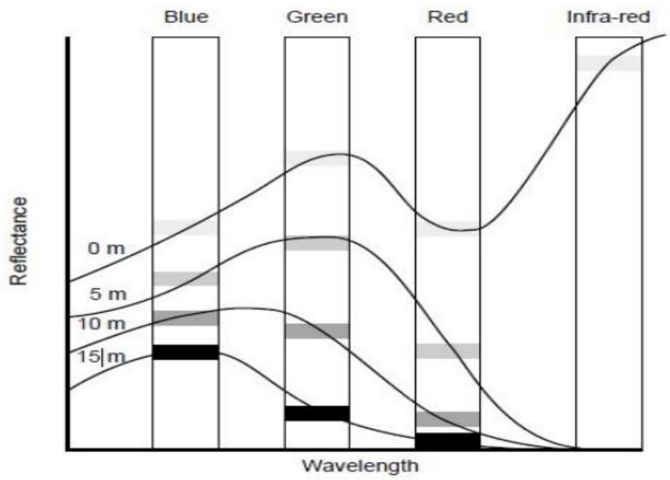

Fig 2.Trend of reflectance of bands with depth

3.2 Water Column Correction

Attenuation is a phenomenon whereby the intensity of light passing through water decreases exponentially as depth increases, which affects remotely sensed data from aquatic environments. In the visible spectrum, the degree of attenuation varies depending on the wavelength of electromagnetic radiation, with longer-wavelength red light attenuating faster than shorter-wavelength blue light. The separability of habitat spectra decreases as depth increases. Despite the same substratum, the spectral signature of sand at 2 meters depth can differ significantly from that at 10-20 meters depth. In fact, at 20 meters, the spectral signature of sand may resemble that of seagrass at 3 meters.

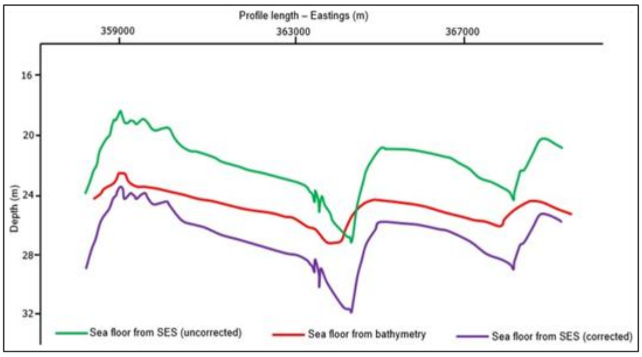

Fig 3.Correction of the Water Column

3.3 Effect of variable depth

To eliminate the effect of depth on bottom reflectance, the following steps would be necessary:To comprehend the attenuation characteristics of the water column, it is crucial to acquire a depth measurement for each pixel in an image. However, generating precise digital elevation models of deep waters can be a challenging task, particularly in coral reef systems where the accuracy of charts is frequently uncertain.. As a compromise, Lyzenga [6] suggested a straightforward method to account for the variable depth effect when mapping bottom features through the creation of a 'depth invariant bottom index' using pairs of spectral bands instead of attempting to predict seabed reflectance. Approach involves the removal of atmospheric scattering and external reflection from the water surface by subtracting the average radiance of a significant number of 'deep water' pixels from all other pixels in each band. Additionally, this technique is based on the concept of 'dark pixel subtraction:

Atmospheric corrected radiance = Li - Lsi

Where Li represents the pixel radiance in band i and Lsi represents the deep water average radiance in band i.

The intensity of light decreases exponentially with depth in relatively clear water. By applying natural logarithms to the values of light intensity (radiance), a linear relationship with depth is established, represented by the symbol "ln". If Xi represents the transformed radiance of a pixel in band i, then this step can be expressed in the following manner. As the depth increases, the transformed values of radiance will decrease linearly. In mathematical notation, this transformation can be denoted as follows:

$$X_i = \ln(L_i - L_{si})$$

The intensity of light attenuation in water for that spectral band is described by the irradiance diffuse attenuation coefficient (abbreviated k). The following equation relates it to radiance and depth, this equation involves a constant term represented by, bottom reflectance denoted by "r", and depth indicated by "z":

$$L_i = L_{si} + a.r.e^{-2 k_i z}$$

The equation for generating a bottom type reflectance image, which was the intended parameter to be estimated, was manipulated in theory. However, the presence of numerous unknown variables, such as the value of constant "a", the attenuation coefficient for each band, and the water depth for each pixel, makes it a challenging task, this technique is not practical. Lyzenga's approach, on the other hand, circumvents this issue by employing data from multiple bands and does not necessitate the direct computation of these parameters. The attenuation coefficient ratio between two spectral bands is all that is required. Many of these unknowns are eliminated by using ratios, which can be calculated from the imagery.

If radiance values for a different type of ocean floor were included in the graph, a comparable line would result, but the difference between the data points would only be in terms of depth. Due to the dissimilarity in the reflectance of the second type of ocean floor as compared to the first one, the placement of a new line would be either above or below the current line. For instance, if the first line was created using sand, which reflects light highly, and the second line was produced using seagrass, In case the second line represents an area with lower reflectance, it would be situated below the sand line. It is noteworthy that the slope of both lines will be identical, as the ratio of attenuation coefficients k_i/k_j is determined solely by the wavelength of the light bands and the clarity of the water. The mathematical formula for the depth-invariant index is straightforward and it is based on the straight line equation:

$$y = p + q.x$$

Where p is the y-intercept and q is the y-x regression gradient. The y-intercept is obtained by rearranging the equation:

$$p = y - q.x$$

$$\text{Depth invariant index} = \ln(L_i - L_{si}) - [(k_i/k_j).\ln(L_j - L_{sj})]$$

For every spectral band, a solitary depth-invariant bottom band is generated. When the satellite imagery includes numerous bands that possess strong water penetration capabilities, it is possible to develop several depth-invariant bands. During image processing or visual examination, the depth-invariant bands can be utilized rather than the original bands. The blue and green bands were preferred due to their ability to penetrate the water deeply and produce a more distinct depiction of the substrate features.

3.4 Modules used

3.4.1 PyQt5

PyQt5 is a Python binding for the Qt toolkit, which is a cross-platform GUI toolkit widely used in industry for developing graphical user interfaces. PyQt5 provides Python bindings for the Qt5 framework, allowing developers to create desktop applications with a modern UI, high performance, and great compatibility with multiple platforms.

3.4.2 NumPy

NumPy is a Python library that caters to scientific computing needs and facilitates the handling of multi-dimensional arrays, mathematical functions, and linear algebra operations. It is one of the most widely used libraries in scientific computing and data analysis.

3.4.3 Rasterio

Rasterio is a Python library that specializes in handling geospatial raster datasets for the purpose of reading and writing. It is built on top of the GDAL (Geospatial Data Abstraction Library) and numpy libraries, making it a powerful and efficient tool for working with geospatial data in Python.

3.4.4 MatPlotLib

Matplotlib is a widely-used Python library that facilitates the production of static, animated, and interactive data visualizations. It is constructed on top of the NumPy library and offers a diverse array of instruments for generating exceptional-quality plots, charts, and graphs.

3.4.5 SkLearn

Sklearn, commonly referred to as Scikit-learn, is a well-known Python library utilized for machine learning, equipped with a plethora of data mining, data analysis, and predictive modeling tools. It is constructed on top of NumPy and SciPy, providing significant efficiency and potency in handling vast datasets.

4. RESULTS AND DISCUSSIONS

These studies show that it is possible to estimate emissivity parameters in deep water, leading to depth models similar to those obtained in river water at several meters depth. There is a long history of using multispectral satellite imagery processing for bathymetric research (SDB) in which Lorenzo Rossi, Irene Mammi, and Filippo Pelliccia [7] created drone-derived multispectral bathymetry. High-Resolution Bathymetry by Motoharu Sonogashira, Michihiro Shonai, and Masaaki Iiyama [3]. Using image super-resolution based on deep learning, the number of water regions or points to be surveyed could be greatly reduced to map the seabed and create high resolution maps on a global scale for bathymetric maps of resolution. The optical river bathymetry by Carl J. Legleiter [8] is shown in Figure 4. Mahmoud Al Najar, Grégoire Thoumyre, Erwin W.J. Satellite [9] Bathymetry Bergsma and Rafael Almar, presented the first use of deep learning for bathymetric estimation using wave physics. Hojat Ghorbanidehno, Jonghyun Lee, Matthew Farthing, and Tyler [1] introduced a data-based inverse modeling method that can be utilized for large-scale river analysis even with limited data and computation resources. They resolved the Bathymetry problem consisting of three major components that performed key tasks in bathymetry estimation. Finally, Xinji Island Shallow Water Bathymetry mapping Jiaxin Wan and Yi Ma's [5] Multispectral Satellite Imagery using Deep Learning described a proposed method for creating measurements with more detailed morphological information than ordinary kriging data points. The methods reviewed found that the combination of high-resolution multispectral imagery using different bands added with machine learning, regression techniques and appropriate algorithms could be used to generate an accurate topographical map of the river for bathymetry.

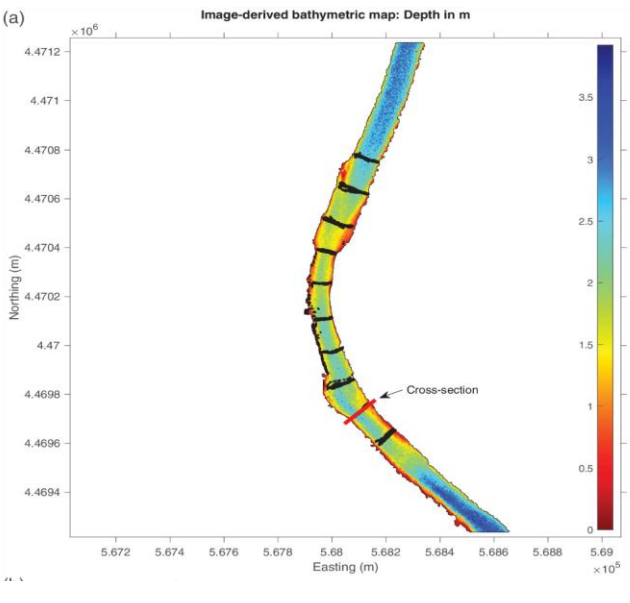

Fig 4. Bathymetry of river [8]

5. FUTURE WORK

The application of deep learning to satellite bathymetry is demonstrated for the first time in this study using a synthetic case. The next step will be to create a supervised dataset of real-world data to train and test the NHO model using transfer learning techniques. Shows that the model can estimate bathymetry from synthetic satellite images using the appropriate network architecture and loss function. In addition, the deep learning-based image super-resolution used increases the resolution of bathymetric data up to. Further research may involve analyzing the performance of other maritime domains and -specific sensors, as well as fine-tuning network parameters using new training samples to improve its accuracy. These efforts will increase the availability of bathymetric data for seabed models for which current data is insufficient and improve the efficiency of the proposed learning-based methods

6. CONCLUSION

Previous attempts to use machine learning algorithms for bathymetry have been hampered by lack of data or difficulties in processing high-dimensional data. However, greater accuracy can be achieved by using a larger, higher quality dataset. Recent results showed that estimating radiative parameters in deep water was feasible, and the resulting depth models were comparable in accuracy to models previously obtained at depths of several meters in river water. The use of several machine learning models can greatly decrease the number of areas or points that require surveying, resulting in a faster generation of comprehensive seafloor maps and high-quality bathymetric maps. This approach enhances overall efficiency. The improved accuracy can be used in a variety of applications such as dam operations, disaster relief, humanitarian relief work, near-shore computing, and overseas cargo transportation.

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