Detection of Surface Water Bodies and Cyanobacterial Blooms using Satellite based Remote Sensing

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Abstract: **For many environmental applications, accurate surface water maps are crucial. It is possible to construct surface water maps by merging data from multiple sources. Due to sensor limitations, complex land cover, geography, and atmospheric conditions, accurate surface water estimation using satellite imagery is still a difficult undertaking. In this study, Sentinel 1 images from Google Earth Engine (GEE) was used to derive a high-resolution water mask. To overcome the limitation of visible satellite images which is the presence of clouds, on this research was focused on using Synthetic-Aperture Radar (SAR) sensors, like Sentinel-1, which penetrate clouds and permitting to get a view of the earth surface, even when clouds are presence. To validate the proposed method, it was applied to three study cases which are located in different climate zones in Sri Lanka. In the meanwhile, this research implemented a time series of Sentinel 2 satellite images from GEE to monitor the distribution of cyanobacterial blooms on those lakes. Recent years have seen an increase in the frequency and severity of cyanobacteria in recreational lakes and reservoirs, which has become a serious concern for the public's health and a serious environmental danger. Monitoring cyanobacterial blooms serves as the foundation for early detection and treatment. Therefore, the results of this study could be used as a benchmark for future environmental monitoring and management of these Sri Lankan lakes and reservoirs.**

Keywords: **Synthetic-Aperture Radar, Water Mask, Cyanobacterial Blooms, Satellite Images, Google Earth Engine, Vegetation Index**

I. INTRODUCTION

A. *Surface Water Detection*

Surface water refers to water found in wetlands, rivers, lakes, and the ocean that is located close to the surface of the planet. Due to the ocean's size and salinity, smaller water bodies are typically included in the definition instead of the ocean. Surface waters are important freshwater resources for both humans and ecosystems. Mainly lakes and reservoirs act as climate regulators and Carbon cycling. It provides water for multiple human practices, from drinking water to recreation, and they support a high level of biodiversity as well as agriculture. For many environmental applications, including flood forecasting and warning, agricultural and urban water management, and modelling the transport of contaminants in water bodies, high-resolution extents of surface water form and dynamics are essential limitations [1]. Since water absorbs the majority of radiation above the near infrared wavelength, water may be distinguished from other objects in satellite images. A spectral index can be used to distinguish between clear water and water that indicates the slope of the water spectral curve, such as the Normalized Difference Water Index (NDWI) [2].

Over the past few decades, there has been a lot of research on surface water detection using water indices. It functions by using mathematical ratios between two or more spectral bands of a multispectral satellite image, allowing the discovery of thresholds that differentiate features that are located near water from those that are not. The vegetation index was utilized in certain research to detect water and floods, while the Tasseled Cap Wetness (TCW) was used in early studies to distinguish between water and non-water surfaces [8]. It has been suggested to use the Normalized Difference Vegetation Index (NDVI) [9]. Normalized Difference Water Index (NDWI) and Modified NDWI are more practical indexes (MNDWI). The first ten years of the twenty-first century saw widespread application of NDWI [10].

The main limitation of visible satellite images is the presence of clouds. Synthetic-Aperture Radar(SAR) sensors, like Sentinel-1, use radar waves, which penetrate clouds, permitting to get a view of the earth surface, even when clouds are present. To overcome the above limitation this research was focused on the Synthetic Aperture Radar Water Body Classification.

B. *Detection of Cyanobacterial Blooms*

High population densities are always present near freshwater sources, which promotes activities that heighten artificial eutrophication and even widespread cyanobacterial flowering[3]. Ecosystems and human health are both threatened by the growth of cyanobacteria. The severity and intensity of cyanobacterial blooms produced in lakes, reservoirs, rivers, and marine ecosystems have grown during the past few decades as a result of climate change and human activity [4]. The technique developed in this study to identify cyanobacterial bloom regions using Sentinel 2 data can also be successfully used to water bodies in Sri Lanka.

II. METHODOLOGY

A. The Technology

A computer platform called Google Earth Engine (GEE) enables customers to perform geospatial analyses on Google infrastructure. There are numerous applications for the platform. A web-based IDE for writing and executing scripts is called Code Editor. Anyone can browse data catalogs and carry out elementary analyses using Explorer, a simple web application. Wrappers for the Web API in Python and JavaScript are provided by the client library [5]. The general procedure of the GEE was depicted in Figure 1.

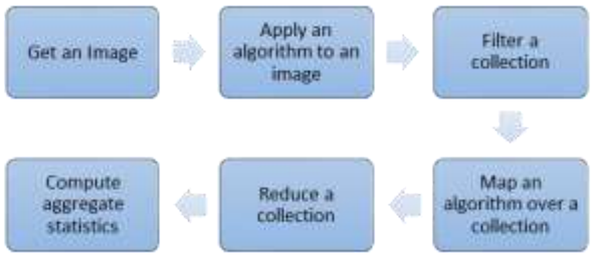

Fig. 1 General process of the Google earth engine

B. Synthetic Aperture Radar Water Body Classification

The following Figure 2 displayed the process of SAR water body classification method.

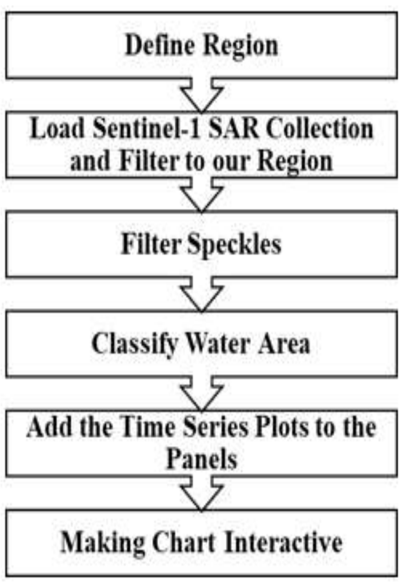

Fig. 2 The Block diagram of the SAR water body classification process

1) Load Sentinel-1 SAR Collection and Filter to Specific Region: Radar waves are used by SAR instruments like Sentinel-1. Radar can view the surface of the Earth even when there are clouds since its waves can penetrate through them. Radar signals from satellites are sent at an angle to the earth to enable SAR (ie, obliquely, not directly below). The satellite measures the amount of backscatter coming back to the satellite after the signal strikes the ground and scatters. The surface's roughness has a role in determining the quantity of backscatter, with smoother surfaces producing less of it. On comparably dispersed ground surfaces, large flat surfaces, like water, scatter little and stand out as dark spots.

2) Filter Speckles: Speckle noise commonly found in SAR images that lowers the image quality. Small bright spots can be seen if zoom in on a portion of the water in the image. T These dots make the image difficult to classify because these bright spots are classified as land. Speckle can be handled in a number of ways. The focal median filter was applied by a relatively straightforward procedure. This filter computes the median value after examining each pixel and its neighbors. Map this central focus procedure to each and every image in the collection afterward.

3) *Classify Water Area:* Accordingly, classify the water pixels in the SAR image. Water was identified using a simple threshold approach. Since water looks darker than land, choose a backscatter threshold and classified all pixels below that threshold as water. This threshold was based solely on heuristics. Adjusting the threshold can see how the classification changes. The optimal threshold can be determined by comparing to a training dataset or using more robust statistical techniques.

4) *Making Chart Interactive:* Functionality was added to a chart by creating a callback function that fires when the user clicks on a data point in the chart. Next, the function adds the SAR image corresponding to the clicked data point and the classified water area to the map. It also displays the date of the currently selected image and adds a label to the map that updates dynamically when a new image is selected.

C. Cyanobacterial Blooms Detection

The two commonly used vegetation indices (VIs), one for water-related spectral indices and one for algae-related spectral indices, were computed from Sentinel 2 data. To detect surface water bodies, the Normalized Difference Water Index (NDWI) [2] is sensitive. Originally designed for use in MODIS, the Float Algal Index (FAI) [6] is a specially developed index for spotting cyanobacterial blooms. It may also be derived from the reflectance of the RED, NIR, and SWIR bands of Sentinel 2 images. [7]. Oyama et al. [3] found that an algorithm combining FAI and NDWI calculated by bands RED and SWIR1 can effectively identify cyanobacterial bloom regions when FAI> 0.05.

$$NDWI = \frac{X_{green} - X_{nir}}{X_{green} + X_{nir}} \qquad (1)$$

$$FAI = \rho_{NIR} - \{\rho_{red} + (\rho_{SWIR1} - \rho_{red}) \times \frac{865-655}{1610-655}\} \qquad (2)$$

III. RESULTS AND DISSCUSSION

Three study cases that are situated in various climate zones in Sri Lanka are used to the approach as stated in section B under methodology to validate its accuracy. The findings are assessed and interpreted.

A. Results of SAR water body classification

The time series plots of three different lakes in different climate zones in Sri Lanka were showed under Figure 3, Figure 4 and Figure 5.

1) Wet Zone:

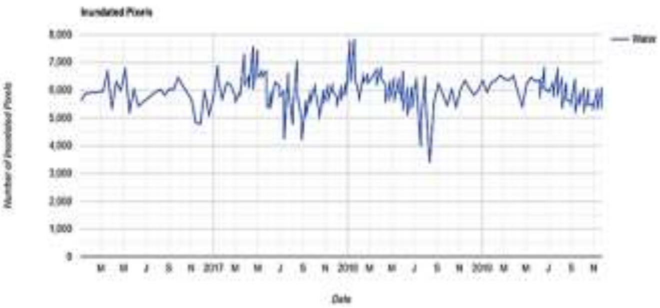

Fig. 3 Time series plot of Gregory lake surface water area

2) Semi-Arid Zone:

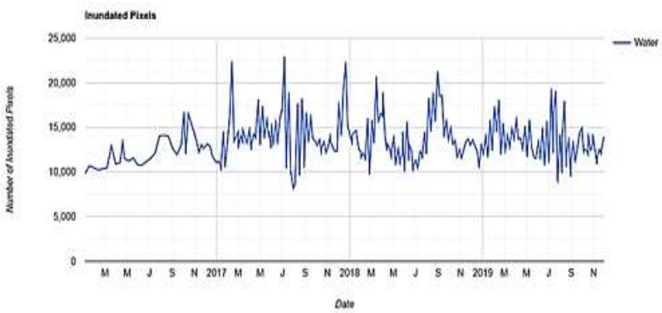

Fig. 4 Time series plot of Tissa lake surface water area

3) Dry Zone:

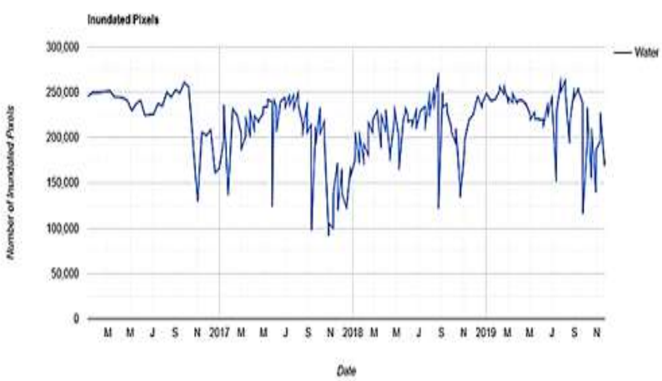

Fig.5 Time series plot of Kaudulla lake surface water area

B. Validation

Data extracted from the above method was compared to data obtained using multispectral satellite images (NDWI) (Figure 6) and with the ground data (Figure 7) and comparison was done using time series plots (8, 9 and 10). Additionally, correlation between the NDWI approach and ground data as well as the SAR classification method and ground data was performed (Figure 11) and (Figure 12).

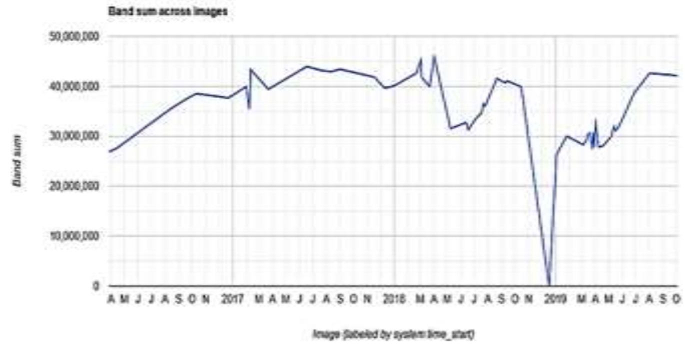

Fig. 6 Time series plot using multispectral satellite images of Kaudulla Lake.

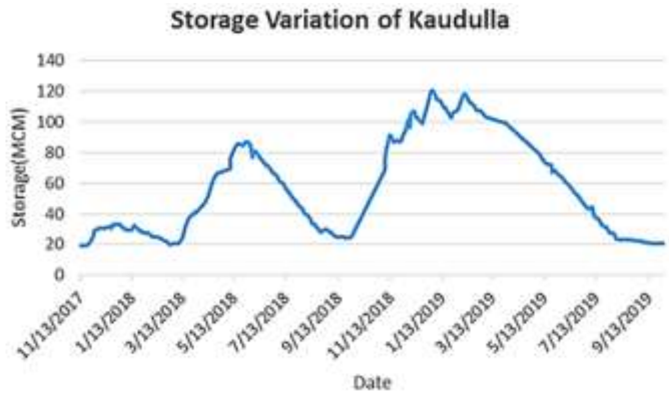

Fig. 7 Ground data of the Kaudulla Lake

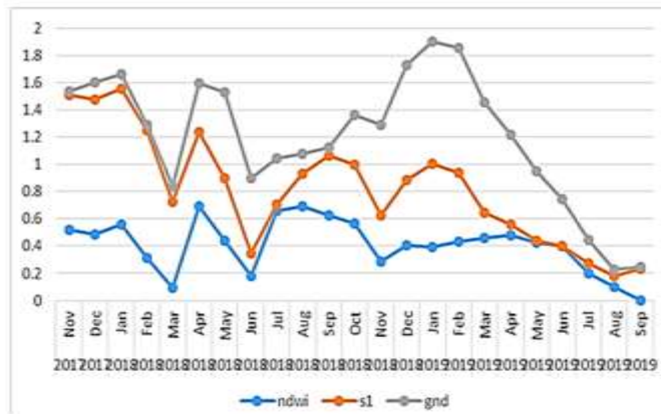

Fig. 8 Comparison between SAR classification method NDWI and ground data of Kaudulla Lake

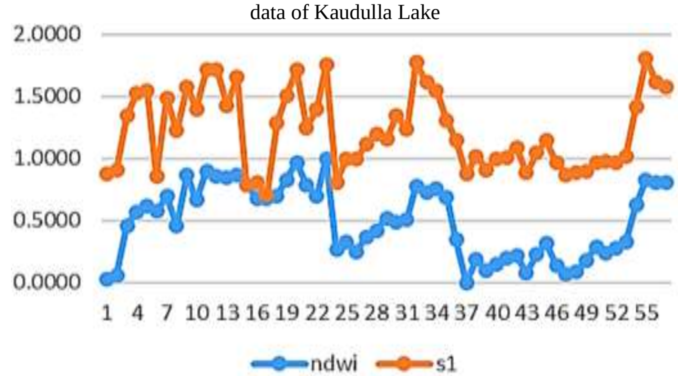

Fig. 9 Comparison between SAR classification method and using NDWI of Kaudulla Lake

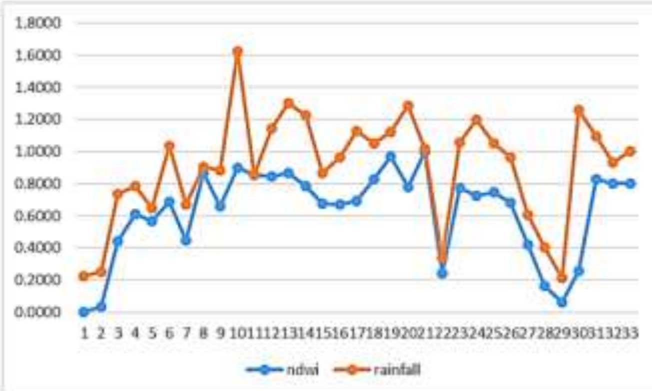

Fig. 10 Comparison between rainfall data and NDWI data in Kaudulla Lake

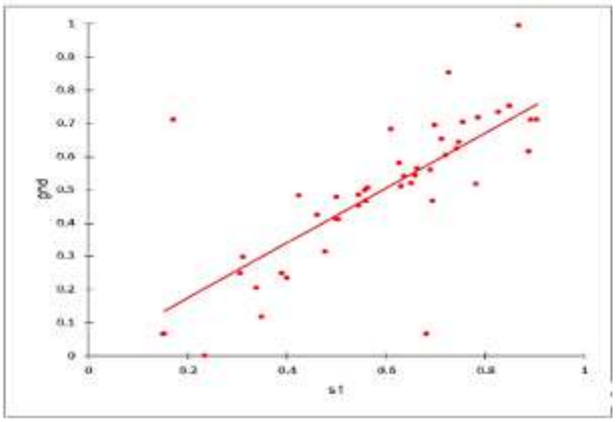

Fig. 11 Correlation between SAR classification method and ground data

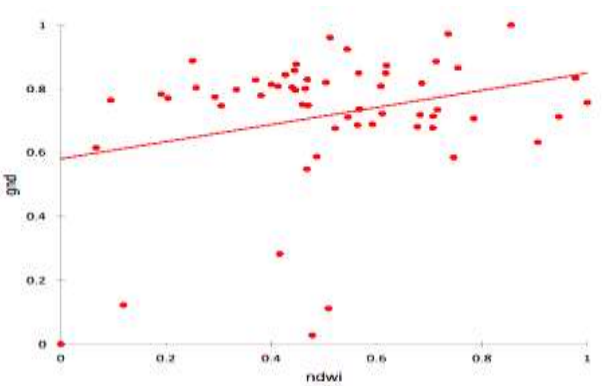

Fig. 12 Correlation between NDWI classification method and ground data

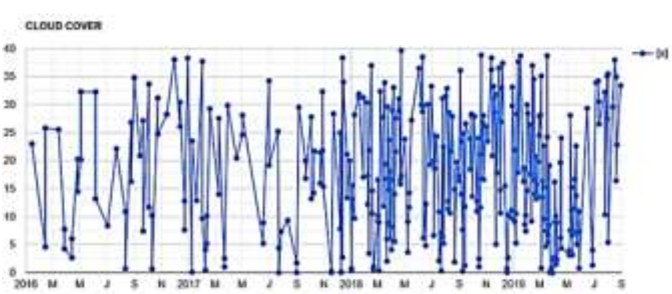

Fig. 13 Cloud cover data of Sentinel 2- Multispectral satellite (Kaudulla)

C. Results of cyanobacterial blooms distribution

Three research cases, each in a different climate zone in Sri Lanka, are applied using the approach as mentioned in section C of the methodology (Figure 14, 15 and 16).

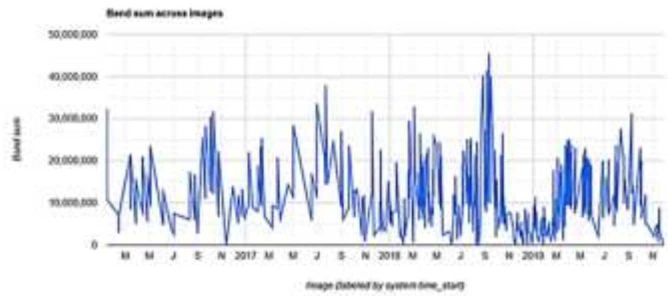

Fig. 14 Cyanobacteria distribution of Kaudulla Lake

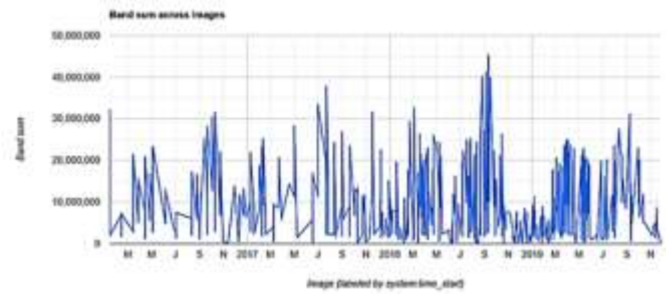

Fig. 15 Cyanobacteria distribution of Tissa Lake

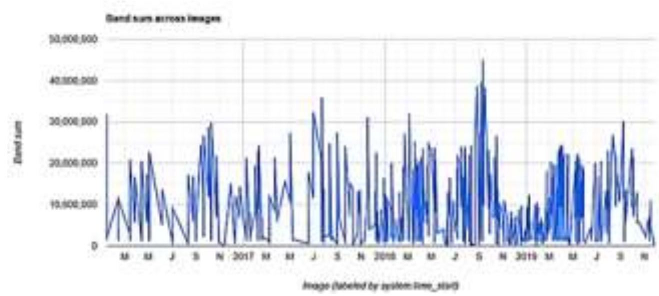

Fig. 16 Cyanobacteria distribution of Gregary Lake

IV. DISCUSSION

Remotely sensed data covers a wide area of the earth and it can be obtained with frequently, repeated passing changes over one day to several days at the same place. Therefore can take advantage of these satellite imagery features of several areas for monitoring different phenomena to detect large-scale spatial scales and their variations observable in soil or water. In this study, mostly focused on the creating water mask using Synthetic Aperture Radar Water Body Classification method and also it illustrate that the algorithm produced to distinguish a cyanobacterial bloom region from Sentinel 2 data can also be well applied to water bodies in Sri Lanka. Accurate information about reservoirs is an important task for monitoring and forecasting water quality and assessing water resources for human consumption and agriculture. The objective of this project is to model and estimate specific water quality metrics from satellite images in order to monitor water quality in the future.

V. CONCLUSION

This research created an approach for identifying the surface water features in both clear and cloudy conditions, utilizing Sentinel 1 satellite data (Synthetic Aperture Radar), based on previously done research and current concepts from many domains. To investigate the geographical distributions of cyanobacterial blooms during the past eight years in big lakes in Sri Lanka that are situated in three different climate zones, Sentinel 2 images were processed using the GEE platform utilizing FAI and NDWI.

The conclusions may therefore be used as a benchmark for ongoing environmental surveillance and management of these lakes and reservoirs.

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