Turnitin Empirical Modeling Of The Distribution Of Chlorophyll-A In Riam Kanan Reservoir

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Empirical modeling of the distribution of chlorophyll-a in riam kanan reservoir

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Abstract. Monitoring inland water quality through remote sensing is an alternative method. Broad remote sensing image coverage has the potential to increase the scope of monitoring. Remote sensing imagery is very suitable for monitoring in the Riam Kanan Reservoir which has a normal water level of 3200 Ha. Community activities for fisheries and tourism have the potential to increase nutrients and water fertility. The impact is in the form of an explosion of algal micro population which has a negative effect on the aquatic ecosystem and the surrounding population. Landsat 8 OLI was used in this study to determine the level of chlorophyll-a content in reservoir waters. Empirical modeling is a method for modeling the distribution of chlorophylla content utilizing the results of field measurements. Through this method also can be known which spectral band has an influence in monitoring the chlorophyll-a so that it can be seen the level of water fertility in the Riam Kanan reservoir.

1. Introduction

Inland waters, especially lakes and reservoirs, have an important role in the environment. These terrestrial waters become a habitat for various species and have a role in the hydrological, nutrient, and carbon cycle [1]. Freshwater ecosystems separated from the oceans provide benefits to humans around them [2]. Utilization includes drinking water, irrigation, energy generation, transportation, fisheries, and recreation [3]. Human activities in the use and exploitation of excessive water can lead to stress for the species in it and threaten the ecological function of the waters [4]. Stress triggers in aquatic species include eutrophication, contamination of inorganic and organic materials, morphological changes, and the effects of climate change such as acidification or increased water temperature [5,6].

One of the organisms that play an important role in inland aquatic ecosystems is phytoplankton [7]. Phytoplankton in aquatic ecosystems acts as a converter of inorganic substances into organic substances through the process of photosynthesis, which can then determine the productivity of the waters [8]. The Chl-a content in phytoplankton can be used as an indicator of the high and low productivity of water [9]. The content of photosynthetic pigments (especially Chl-a) in sample water describes the phytoplankton biomass in water. Chl-a is a pigment that is always found in phytoplankton and all autotrophic organisms and is a pigment that is directly involved (active pigment) in the photosynthetic process [10]. Therefore, Chl-a is usually used to assess trophic levels of lakes [11], and also to measure water quality.

Measurement of water quality and the factors that affect the surface of the lake require in situ measurements or water sampling for laboratory analysis. While the point sampling method provides accurate results, it is time-consuming and costly and more importantly, it does not provide the spatial picture required for assessing and monitoring lake water quality. Synoptic coverage is needed to determine sample collection locations when the distribution of chlorophyll on the surface is uneven [12]. Remote sensing images can provide a suitable method for integrating limnological data collected from in situ measurements with the reflected values of various wavelengths. The use of remote sensing imagery for observing water quality, especially for the study and mapping of land water quality has been widely used [13–16]. The Landsat-8 OLI application in this study is aimed at meeting these needs.

2. Methods

Landsat 8 OLI-TIRS level 1T imagery is the image used for this water quality study. The conversion of the image to the TOA reflectance value is carried out based on an algorithm issued by the United States Geological Survey (USGS) [17]. Relative atmospheric correction with the application of the dark object subtraction (DOS) method to produce images with surface reflectance values [18]. The image masking process for land and water areas is based on the range of pixel values in waters and land also by utilizing the range of values from the NDVI (Normalized Difference Vegetation Index) transformation. The masking process involves near-infrared bands because there is a high possibility of mud contained in the waters so that it is identified as land when using a visible band [19]. The masked image is then used for extraction as a tentative map for sampling. Data extraction was carried out through digital image processing using spectral transformation using the band ratio method. The band ratio method uses an algorithm to highlight the appearance of chlorophyll-a that has been produced by previous studies by modifying the band according to the band from Landsat-8 OLI [20]:

$$\ln (\text{Chl})\text{-a} = 9.82(\text{TM1}-\text{TM3})/\text{TM2} \qquad (1)$$

Where:

ln (Chl)	= Natural logarithm of Chl-a
TM1	= Landsat-5 TM band 1 reflectance value
TM2	= Landsat-5 TM band 2 reflectance value
TM3	= Landsat-5 TM band 3 reflectance value

The content value of each parameter in the field is tested for accuracy with the band ratio image results. Based on the accuracy test, a regression test was carried out between the content value in the field and the image value for empirical spatial modeling to obtain a modeling map for chlorophyll-a content in the Riam Kanan reservoir. In addition to using the resulting band ratio image between trophic status parameters, the image with a single band is also used to be correlated and regressed with parameter values in the field.

3. Results and Discussion

Empirical modeling is done by utilizing statistical analysis between the pixel value of the image on the tentative parameter map and the results of field measurements. The statistical analysis used is a linear regression analysis. The results of sampling in the field were then tested in the laboratory for chlorophyll-a parameters. The results of parameter measurements in the laboratory and in the field are then converted into natural logarithms. The distribution of each sample is subjected to a sample normality test and then a correlation between the sample value and the pixel value is carried out.

Based on the results of the accuracy test, it is known that from the three bands, it is found that the red band has higher accuracy than the other bands from the Landsat 8 OLI image. The red band has a higher value due to the alleged development of phytoplankton species that are more sensitive to red wavelengths such as Cyanophyceae which have myxoxanthophyll pigments [21]. More laboratory tests are needed to determine the types of species that thrive in reservoir waters.

Table 1. Accuracy test

Parameter	RMSE
Klorofil-a	0.156848

Then in the results of linear regression statistical data analysis, it can be seen that there is a low coefficient of determination between the results of the field data for chlorophyll-a and the reflectance value in the green band of the Landsat-8 OLI image. This is possible because reservoir water has been mixed with rainwater. Apart from this, it is also possible because the peak period of microalgae productivity has passed in the reservoir waters.

Table 2. Linier Regression test

Regression Statistics	
Multiple R	0.510323
R Square Adjusted	0.260429
R	
Square	0.203539
Standard Error	2.472351
Observations	16

Based on the results of the linear regression analysis, the coefficient of determination (R2) was 0.260429. This value was obtained because there was quite a distance between the coverage time of the images used (November, 27 2019) and the time of sampling in the field (December, 14 2019). The equations obtained from the results of the linear regression analysis are:

$$\text{Chlophyll-a} = -20.146379+(163.6131 \times \text{band } 4) \quad (2)$$

The equation results from linear regression analysis are then applied to the image for further digital transformation to obtain the extraction of the chlorophyll-a value from the Landsat 8 OLI image as shown in Figure 1.

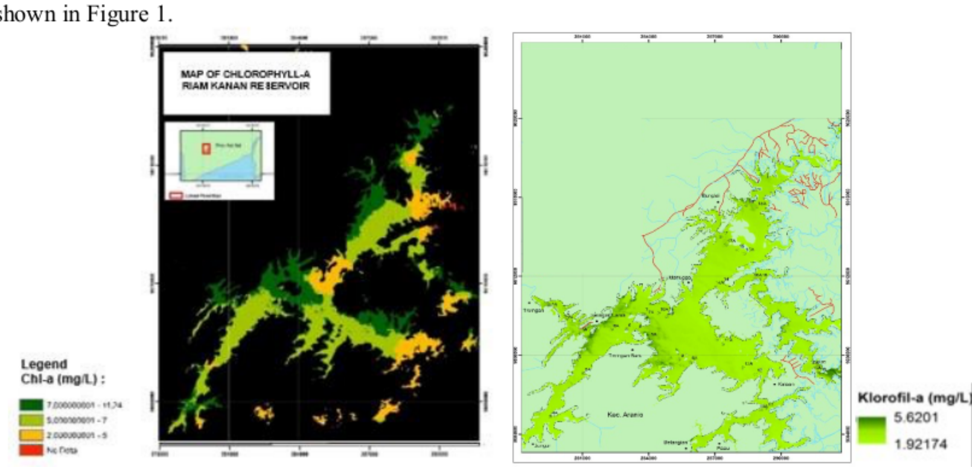

Figure 1. Distribution of chlorophyll-a in Riam Kanan Reservoir 2020 (left) and 2016 [22] (right)

Based on the results of the spectral transformation, it can be seen that the chlorophyll-a concentration tends to be higher in the reservoir curves. This is due to the lack of influence of currents on the physical and biological contents of the waters [22]. The inlet area is also an area that has high Chl-a content. Compared to the chlorophyll-a measurement in 2016 there was an increase in the concentration and amount of chlorophyll-a content. in the 2020 measurement. The increase in tourism activity which increases motor boat waste and floating net cages increases the chlorophyll-a content and other chemical contents. The potential for a harmful micro algae bloom is a risk that can arise in the following years

The regression value is very low because of a long time of image coverage and field sampling. The long time span between the images used and the sampling (2 weeks) allows the mixing of new materials and elements from both the inlet and from the surface runoff of the reservoir edges [23,24]. This mixing process allows a change in the value of chlorophyll-a content in the reservoir area plus the sampling time has entered the beginning of the rainy season at that time. The elements that have just entered contain a lot of mud and material from the land which also stirs the reservoir waters. Reduction in the number of microalgae can occur when new material enters the water, along with an increase in reservoir volume [23].

4. Conclusion

Based on the results of linear regression analysis, it is known that generally, the water conditions in the Riam Kanan reservoir have increased the level of chlorophyll-a content. This increase has the potential to pose a threat to increasing water fertility as well as decreasing water quality. It is also feared that the increase in fertility could trigger an explosion in the microalgae population which will be very dangerous for the ecological conditions in the reservoir area.

Through the methods and processes used in the study, it is also known that the use of the band ratio does not always have a high correlation in certain water areas. The value of surface reflectance in the image is also known to have a similarity in value to the value of trophic parameter content in the field. So that the use of the band ratio is enough to be used as an approach to the initial estimation of sampling each parameter in the field.

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