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Estimating Chlorophyll-A Concentration in a Freshwater Lake Using Landsat 8 Imagery

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Abstract
Numerous studies suggest that chlorophyll-*a* in waters can be measured using Landsat TM/ETM imagery but the feasibility of newly launched Landsat 8 with Operational Land Imager (OLI) on board is still being tested. Jordan Lake is one of the most eutrophic reservoirs in North Carolina, U.S and there is a great need to monitor the spatial distribution of chlorophyll-*a* in this freshwater lake for better water quality management. The purpose of this study was to examine the applicability of using Landsat 8 imagery to estimate and map chlorophyll-*a* concentration in Jordan Lake. In this study, the relationship between the reflectance value of an individual OLI band and *in situ* chlorophyll-*a* concentration was examined to identify bands sensitive to chlorophyll-*a*. We also investigated the performance of ratio-based spectral indices to retrieve chlorophyll-*a* concentrations in Jordan Lake. Two optimal linear equations were developed to model the relationship between ratio-based spectral index and *in situ* chlorophyll-*a* concentration in Jordan Lake for different seasons. There was a significant correlation between the spectral index derived from Landsat 8 imagery and chlorophyll-*a* concentration for Jordan Lake in summer and fall 2013. Spatial distribution of chlorophyll-*a* concentration in the Jordan Lake was successfully mapped using Landsat 8 imagery for two seasons in 2013. Despite the limitation of this work, our findings suggest that Landsat 8 imagery can be used to estimate chlorophyll-*a* concentration in fresh waters and it is promising to estimate and map chlorophyll-*a* concentration in freshwater lakes.
Keywords: Chlorophyll-*a*, Spectral index

1. Introduction

Numerous studies suggest that chlorophyll-*a* in waters can be measured using Landsat TM/ETM imagery (Keiner and Yan, 1998; Giardino, 2001; Zhang et al., 2002; Erkkilä and Kalliola, 2004; Hellweger, 2004; Sudheer et al., 2006, Kabbara et al., 2008; Kulkarni, 2011; Nazeer and Ncichol, 2016). Han and Jordan (2005) discovered strong correlation between the ratio of Band1/Band3 and *in situ* chlorophyll-*a* concentration in the Pensacola Bay on the Gulf of Mexico. Kabbara et al. (2008) reported that there were significant correlations (R^2 = 0.719 - 0.7234) between the surface chlorophyll-a concentrations and spectral indices based on the combination of blue/green or blue/red band. Lim et al. (2009) revealed the correlation coefficient of 0.8259 between the predicted and the measured chlorophyll-*a* values. Kulkarni (2011) stated that chlorophyll-*a* could be retrieved using models based on the red or green band and the model with the green band value showed the highest correlation (R=0.864) with chlorophyll-*a* content in waters. Torbick et al. (2013) concluded that there was a strong correlation (R^2 = 0.65-0.81) between band ratio radiance and water quality indicators including Sechhi depth (SD), chlorophyll-*a*, green biovolume, total phosphorus (TP), and total nitrogen (TN). The correlation coefficient of green and blue ratio and chlorophyll-*a* (0.89) was obtained by Nazeer and Nichol (2016). These results suggested that chlorophyll-*a* in waters could be effectively retrieved from the Landsat TM/ETM imagery using appropriate algorithms.

There have been a few studies that involve the use of Landsat 8 since its launching in Feb 2013. Yunus et al. (2015) employed spectral indices derived from reflectance data of Landsat 8 imagery to retrieve the chlorophyll-*a* in Tokyo Bay and obtained R^2=0.63 for the correlation between the blue and green band ratio and *in situ* chlorophyll-*a* with p-value<0.05. Lim and Choi (2015) discovered that band 5 reflectance value from Landsat 8 images was significantly correlated with suspended solid (SS) (R= -0.74) and chlorophyll-*a* (R = -0.71). Watanabe et al. (2015) examined various indices derived from OLI bands and found that NIR-Red, NIR-Green and NIR-Blue ratios performed well (R^2 greater than 0.70) to retrieve chlorophyll-*a*. These results suggested that OLI bands were sensitive enough to detect Chlorophyll-*a* and derived spectral indices could be used for estimating chlorophyll-*a* concentration in various waters.

Current *in situ* chlorophyll-*a* monitoring in U.S. lakes is limited in spatial coverage and resolution due to high cost of data collection and laboratory analysis. The water quality data collected from fewer fixed sampling stations in a lake usually does not represent the condition of an entire water body for a big lake. The cost of conducting extensive water quality sampling has been an obstacle to water quality monitoring and management in big lakes. Satellite-based monitoring could serve as an effective alternative for water quality monitoring in big lakes. This is because satellite-based remote sensing provides not only a larger spatial coverage but also more cost-effective observation on spatial pattern and gradient of chlorophyll-*a* in a lake than traditional water quality sampling. While some satellite imagery from sensors, such as the Hyperion, Medium Resolution Imaging Spectrometer (MERIS), or Moderate Resolution Imaging Spectroradiometer (MODIS), offers higher spectral resolution but is not suitable for water quality monitoring in lakes due to a low spatial resolution (pixel size>=250 m), Landsat 8 imagery has a better spatial resolution (pixel size=30 m) to enable obtaining water quality data at a high spatial resolution. This is very helpful to fully understand the status of water quality for the entire water body in a lake. It is also beneficial to study potential algal bloom problems due to excessive nutrients in many U.S. freshwater lakes.

The purpose of this study was to examine the applicability of using Landsat 8 imagery to estimate and map chlorophyll-*a* concentration in a U.S. freshwater lake (Jordan Lake) which has a nutrient over-enrichment problem and occasionally experiences algal blooms. In this study, the relationship between the reflectance value of an individual OLI band and *in situ* chlorophyll-*a* concentration was examined to identify bands sensitive to chlorophyll-*a*. We also investigated the performance of ratio-based spectral indices to retrieve chlorophyll-*a* concentrations in Jordan Lake. This would help determine the feasibility of measuring chlorophyll-*a* in fresh waters using satellite-based remote sensing.

2. Material and Methods

2.1 Study area

Jordan Lake is located on the Haw River and New Hope Creek, in the Cape Fear River Basin in the eastern Piedmont region of North Carolina, U.S. (Figure 1). It is a reservoir created by the U.S. Army Corps of Engineers in 1982 and covers an area of 56.4 km^2 with mean depth of 4.3 m (NC DWQ, 2007a). It serves as a major drinking water supply for its surrounding cities and towns such as Chapel Hill, Cary and Apex. The Jordan Reservoir watershed is mainly located within the Carolina Slate Belt and Triassic Basins which consist of volcanic and/or sedimentary rocks. Major land use and cover in the watershed are 18% urban, 20% agriculture, and 56% forest. But cities around Jordan Lake including Cary and Apex have experienced significant urban development in recent decade.

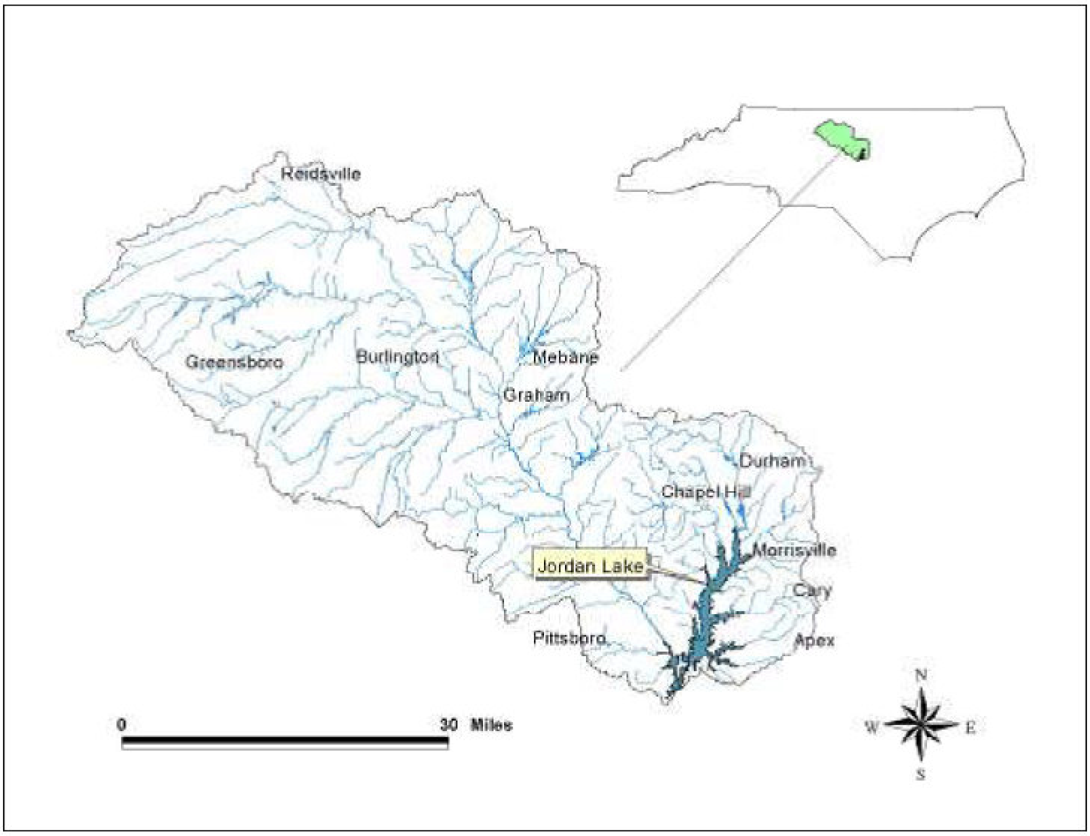

Figure 1. Location of Jordan Lake, NC, U.S

Jordan Lake is one of the most eutrophic reservoirs in North Carolina. Based on NC Division of Water

Quality (DWQ) monitoring, the Upper New Hope Creek Arm of Jordan Lake is listed as an impaired water in North Carolina's 2002 303(d) list because of exceedances of the chlorophyll-*a* water quality standard. In 2006, the Lower New Hope and Haw River Arms of Jordan Lake were also added into the 303(d) list for chlorophyll-*a* exceedances (NC DWQ, 2007b). Measurements in 2011 showed that annual mean concentration of chlorophyll-*a* for each station of Upper New Hope Creek Arm was larger than 40 µg/l, the North Carolina fresh water quality standard for chlorophyll-*a* in Class C waters.

2.2 Water quality sampling stations

Since 2009 Jordan Lake has been sampled monthly by DWQ, twice per month during May through September, and monthly during cooler periods. The coordinates of water quality sampling stations are shown in Table 1. Chemical samples are collected from the photic zone and analyzed for total phosphorus (TP), total nitrogen (TN), ammonia (NH_3), nitrate + nitrite (NO_3+NO_2), total Kjeldahl nitrogen (TKN), turbidity, and chlorophyll-*a* (Chl-*a*). In summer and fall 2013, about twenty water quality sampling stations were set up in Jordan Lake and they were sampled for the water quality indicators mentioned above.

2.3 Landsat 8 data

Landsat 8 was launched on February 11, 2013 and is equipped with two scientific instruments—the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) with a spatial resolution of 30 meters (visible, NIR, SWIR), 100 meters (thermal) and 15 meters (panchromatic). It revisits the same location on earth surface every 16 days thus has an advantage in monitoring water quality of big lakes in NC, U.S. In this study, Landsat OLI data (path 16, row 35) and *in situ* Chlorophyll-*a* data cover a time period from May to December, 2013(Table 2). Two OLI reflectance images (partially shown in Figure 2) were downloaded from "Earth Explorer" web site managed by The United States Geological Survey (USGS). The *in situ* chlorophyll-*a* data for days within satellite observation date ± 2 days were acquired from the U.S. EPA STORE web site for all water quality sampling stations in Jordan Lake.

Table 1. Coordinates of water quality sampling stations in Jordan Lake

FID	Station_ID	Longitude	Latitude
1	CPF055C	-79.079	35.69131
2	CPF055C1	-79.082	35.69883
3	CPF055C2	-79.0761	35.69554
4	CPF055C3	-79.083	35.69322
5	CPF055C4	-79.0756	35.68988
6	CPF055C5	-79.0841	35.6867
7	CPF055C6	-79.078	35.68225
8	CPF055D	-79.0772	35.6725
9	CPF055E	-79.07	35.65995
10	CPF081A1C	-78.9868	35.81622
11	CPF086C	-78.9974	35.82151
12	CPF086CUPS	-79.001	35.837
13	CPF086F	-79.0076	35.79494
14	CPF087B3	-79.026	35.76522
15	CPF087D	-79.0243	35.7384
16	CPF0880A	-79.0436	35.69647
17	CPFMC01	-78.9998	35.83199
18	CPFMC02	-78.9991	35.82752
19	CPFMC03	-79.0002	35.81717
20	CPFMC04	-78.9934	35.81718

Table 2. Metadata for Landsat 8 imagery and *in-situ* chlorophyll-*a* data used in this study.

Image Date	Image ID	Date for *in situ* Chl-*a* Data Collection
July 30, 2013	LC80160352013214-SC20160101142745	Aug 2, 2013
November 6, 2013	LC80160352013310-SC20160101142702	November 5, 2013

Figure 2. Two Landsat images (left: July 30, 2012; right: Nov 6, 2013) used in this study

2.4 Image processing

Two Landsat 8 images examined were for July 30 and November 6, 2013 (Table 2) respectively. They were processed using QUick Atmospheric Correction (QUAC) Module in the ENVI software package. QUAC determines atmospheric compensation parameters directly from the information contained within the scene (observed pixel spectra) without ancillary information and it allows the retrieval of reasonably accurate reflectance spectra.

After the atmospheric correction, band ratios for different band combinations such as b2/b1 were calculated for five bands from band 1 to band 5 using ENVI for each Landsat OLI image. Two Middle infrared bands (OLI6 and OLI7) were not included in the computation and later analysis due to their lower sensitivity to chlorophyll-*a* concentration in water. Rationing technique was used for this study since it is often used to suppress illumination differences attributable to surface albedo, look angle, and topographic effects (Avery and Berlin 1992). In this technique, the DN value of one band is divided by the value of another band. Band ratio is one of spectral indices widely used for many remote sensing studies, especially in retrieving chlorophyll-*a* from waters.

Once computations were finished for each corrected OLI image, the reflectance of each OLI band and all derived spectral ratio indices were exported into ArcMap Then “Extract values to point” tool in ArcMap was used to extract values of reflectance and band ratios for the correspondent water quality sampling stations in Jordan Lake.

2.5 Correlation testing

In this study, the linear correlation between *in situ* chlorophyll-*a* concentration and reflectance value of OLI band1-5 /band ratios was examined for each OLI image. First, chlorophyll-*a* concentration and extracted value of reflectance/ band ratio were paired for each station in the Excel spreadsheet. Then the correction coefficient was calculated in Excel and tested for statistical significance at a 95% confidence level (critical value = 0.468). For a band or band ratio, if its correlation coefficient was lower than the threshold value there would be no significant correlation for that band or band ratio. Also the correlation coefficient values were compared with each other and ranked for each date (July 30 and November 6, 2013).

2.6 Regression analysis and mapping of chlorophyll-a

The spectral ratio index providing the strongest correlation with *in situ* chlorophyll-*a* was selected as an optimal spectral index to map chlorophyll-*a* in Jordan Lake for each date mentioned above. The regression analysis was first conducted for the optimal spectral index and *in situ* chlorophyll-*a* concentration. Root mean square error

(RMSE) was then calculated for the chlorophyll-*a* estimation from the image of July and November 2013. After that, two linear equations generated from the regression analysis were used to produce the chlorophyll-*a* maps for Jordan Lake in July and November 2013.

3. Results and Discussion

3.1 Correlations between spectral index and in situ chlorophyll-a concentration

Correlations between spectral index and *in situ* chlorophyll-a concentration are summarized in Table 3 and Table 4. These tables show that OLI bands and spectral indices displayed differential sensitivity to chlorophyll-*a*.

Table 3. Correlation coefficients between spectral index and chlorophyll-*a* concentration in July 2013

Spectral Index	Correlation Coefficient
b1	-0.0391
b2	0.0154
b3	0.4114
b4	0.3798
b5	0.1440
b2/b1	0.2541
b3/b1	0.8151*
b3/b2	0.7573*
b4/b1	0.7301*
b4/b2	0.7646*
b4/b3	0.0641
b5/b1	0.2919
b5/b2	0.2194
b5/b3	-0.1962
b5/b4	-0.1897

Critical Value = 0.468 at 95% confidence level
*Significant at 95% confidence level

In July 2013, there was no significant correlation between reflectance value and *in situ* chlorophyll-*a* concentration for all OLI bands from band 1 to 5. Band 3 (Green) and 4 (Red) were more sensitive than band 1 (Coastal aerosol), 2 (Blue) and 5 (Near Infrared). There was a significant correlation between spectral indices including b3/b1, b3/b2, b4/b1, and b4/b2 and *in situ* chlorophyll-*a* concentration; the spectral ratio index b3 (Green) /b1 (Blue) had the highest correlation with *in situ* chlorophyll-*a*. The rest of the spectral indices did not show sensitivity to chlorophyll-*a* concentration in July 2013. Previous studies show that the Blue-Green ratio was sensitive to chlorophyll-*a* concentration (Yunus et al., 2015). Our result confirmed this finding from the literature.

In Nov 2013, there was also a significant correlation between reflectance value and *in situ* chlorophyll-*a* concentration for all OLI bands from band 1 to 5. Band 5 (Near Infrared) and 3 (Green) were slightly more sensitive than band 1 (Coastal aerosol), 2 (Blue) and 4 (Red). Lim and Choi (2015) discovered that band 5 (Near Infrared) was highly sensitive to chlorophyll-*a* (R = -0.71). Our examination of band sensitivity also showed that band 5 was very sensitive to chlorophyll-*a.* But it was not clear that all OLI bands were sensitive to chlorophyll-*a* in Nov 2013. There was a significant correlation between spectral indices including b4/b3, b5/b3, and b5/b4 and *in situ* chlorophyll-*a* concentration; the spectral ratio index b5 (Near Infrared) /b3 (Green) had the highest correlation with *in situ* chlorophyll-*a*. The remaining spectral indices were not sensitive to chlorophyll-*a* in November 2013. Watanabe et al (2015) found that NIR-Red, NIR-Green and NIR-Blue ratios had an R^2 greater than 0.70 with *in situ* chlorophyll-*a* concentration. Our results were similar to their findings except the NIR-Blue ratio. The higher sensitivity in NIR-Red and NIR-Green may be due the fact there is a positive reflectivity of chlorophyll-*a* in the NIR and an inverse behavior in the visible band such as red (Rundquist et al. 1996, Pepe et al. 2001).

Table 4. Correlation coefficients between spectral index and chlorophyll-*a* concentration in November 2013

Spectral Index	Correlation Coefficient
b1	0.8002*
b2	0.8073*
b3	0.8103*
b4	0.8087*
b5	0.8122*
b2/b1	-0.2520
b3/b1	-0.2525
b3/b2	-0.3911
b4/b1	-0.2114
b4/b2	-0.2975
b4/b3	0.6287*
b5/b1	0.0616
b5/b2	0.3389
b5/b3	0.7269*
b5/b4	0.7213*

Critical Value=0.468 at 95% confidence level
*Significant at 95% confidence level

There was a difference in the sensitivity of a band and spectral ratio index between July and November, 2013. This difference is likely caused by a variation in the spectral characteristics of water bodies in different seasons. Seasonal variation in chlorophyll-*a* might be a factor in the spectral difference in water bodies. Many studies suggest that the best spectral indices for retrieving chlorophyll-*a* may be dependent on the spectral characteristics of the waters investigated, and possibly even the time it was investigated (Jacques et al., 1998; Tilstone et al., 2012). This is because inland waters are optically complex and their reflectance is determined by the combined effects of absorption and scattering by phytoplankton particles, inorganic and organic particles, and colored dissolved organic matter (Gurlin et al., 2011). It was found that different phytoplankton species dominated in different seasons in Jordan Lake (Shahady et al. 1994). A variation in species type/composition in different seasons might lead to a variation in spectral characteristics of water bodies. Thus spectral differences in water bodies may cause a shift or change at bands/band combinations sensitive to chlorophyll-*a* in different seasons.

The regression models tested were ones with chlorophyll-*a* (again logarithmically transformed) as the dependent variable and band ratio as the independent variable. Table 5 shows that there was a strong correlation (R^2=0.7252) between the logarithm of chlorophyll-*a* concentration and the spectral ratio index (b3/b1) in July 2013. This suggests that chlorophyll-a concentration can be estimated using a ratio index with high accuracy (RMSE=1.2 μg/l). In November 2013 there was a medium correlation (R2=0.4751) between the logarithm of chlorophyll-a concentration and the spectral ratio index (b5/b3). This indicate that chlorophyll-a concentration can be estimated using a ratio index with good accuracy (RMSE=1.3 μg/l). It was found that the correlation between the spectral index and chlorophyll-a was lower in fall than in summer. This is because some thin clouds covered the upper part of Jordan Lake on November image and that part of Jordan Lake is clearer on July image (Figure 2). The thin clouds can partially obscure light transmission and cause some bias on radiance readings of OLI bands. As the result, the derived spectral index was affected and the correlation between the spectral index and chlorophyll-*a* concentration was also compromised. This is one of well-known issues for satellite-based remote sensing studies. In summary, chlorophyll-*a* concentration in Jordan Lake could be estimated using a different spectral ratio index in different seasons with good accuracy. Further studies are needed to explore mapping chlorophyll-*a* in other seasons including spring and winter seasons.

Table 5. Regression results for July and November 2013

Month	Spectral Index	Equation	R^2	RMSE(μg/l)
July	b3/b1	LogChl=7.7555*log(b3/b1)+1.1738	0.7252	1.2
November	b5/b3	LogChl=0.7354*log(b5/b3)+1.5972	0.4751	1.3

LogChl: Logarithm of chlorophyll-*a* concentration

3.2 Spatial distribution of chlorophyll-a concentration in Jordan Lake

Two chlorophyll-*a* maps for the Jordan Lake were created using the optimal spectral ratio index in July (summer) and November (fall). The results are shown in Figure 3 and 4. In both seasons high chlorophyll-*a* concentrations were observed at locations along the bank of Jordan Lake. This is reasonable since a large portion of water pollutants (nutrients) in Jordan Lake come from land surface runoff. There will be more nutrients and thus high chlorophyll-*a* concentration at locations closer to the lake bank. Also, in both seasons higher chlorophyll-*a* concentrations were observed in upper streams of Jordan Lake including New Hope and Morgan creeks. This demonstrates that nutrients in Jordan Lake mainly come from watersheds linked to New Hope and Morgan creeks and a watershed management approach is needed to reduce nutrient loading to Jordan Lake. Additionally, higher chlorophyll-*a* concentrations were found in summer than in fall in most locations of Jordan Lake. This indicates most nutrients in Jordan Lake are attributed to those upper streams which were polluted by urban runoff from nearby cities/towns including Chapel Hill, Durham and fast-growing Cary. This is because fertilizer applications to lawns occur more often in spring than other seasons and residues are likely to be washed to the streams during summer.

Due to the availability of paired cloud-free images and *in situ* chlorophyll-*a* data, the correlation between spectral index and *in situ* chlorophyll-*a* concentration was examined only for two seasons: summer and fall in 2013. There might be a different relationship between spectral index and *in situ* chlorophyll-*a* concentration in other seasons in Jordan Lake. Also a different linear equation might be needed for a lake in different location. This is because there is a variation in species type/composition in different seasons/locations, leading to inherent variability of the bio-optical constituents. Thus there might be a shift or change at bands/band combinations sensitive to chlorophyll-*a* in different seasons and locations. For future studies, Landsat 8 images in spring and winter need to be examined to understand the impact of seasonality on spectral characteristic of waters in Jordan Lake and its relation to chlorophyll-*a* concentration. There is also a need to explore Landsat 8 images in multiple years to check the reliability of relationship between spectral characteristic and chlorophyll-*a* in waters in Jordan Lake. Additionally, it is necessary to test the two linear chlorophyll-*a* retrieval equations developed in this study in other freshwater lakes in order to determine their applicability. Nevertheless, this work demonstrated that there is a significant correlation between spectral indices derived from Landsat 8 imagery and *in situ* chlorophyll-*a* concentration and it is very promising to estimate and map chlorophyll-*a* concentration in freshwater lakes. The method developed from this study could be applied to other lakes in the state of North Carolina and other states in U.S.

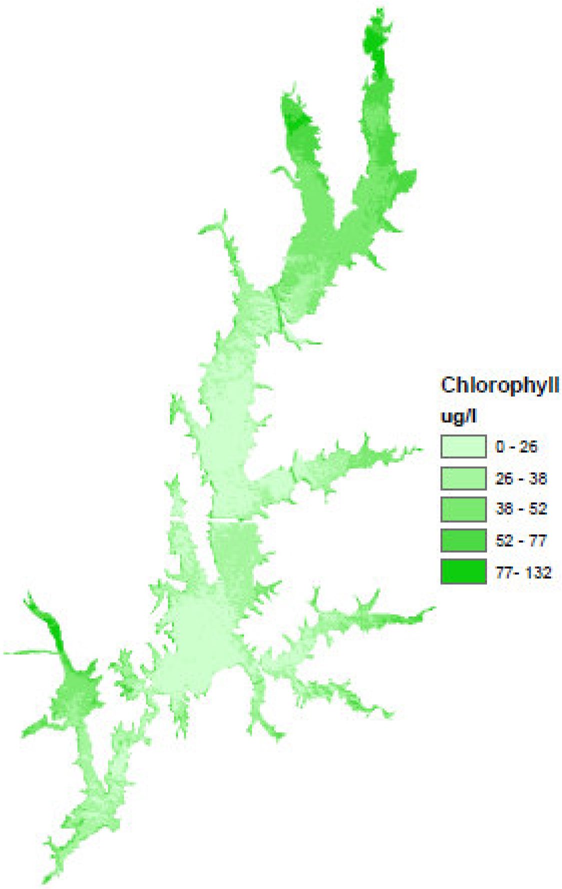

Figure 3. Map of chlorophyll-*a* concentration in July 2013.

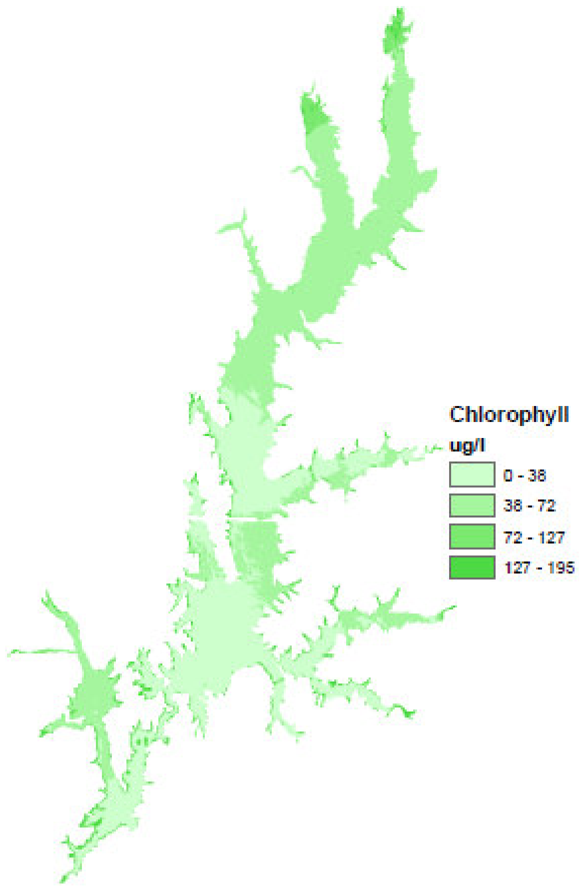

Figure 4. Map of chlorophyll-*a* concentration in November 2013.

4. Conclusion

This study developed a methodology to estimate and map chlorophyll-*a* concentration by using Landsat 8 imagery. There was a significant correlation between a spectral ratio index derived from Landsat 8 imagery and chlorophyll-*a* concentration in Jordan Lake in summer and fall 2013. Two different linear equations were established for summer and fall, all of which showed good accuracy when correlating with the *in situ* chlorophyll-*a* measurements. The spatial distribution of chlorophyll-*a* concentration in Jordan Lake was successfully mapped using Landsat 8 imagery and it could be useful for analyzing the chlorophyll-*a* sources, as well as the transport processes. However, the results of this study were limited by number of Landsat 8 images analyzed and more efforts should be done in the analysis of more images in other seasons and different lakes in order to fully explore the relationship between spectral characteristic and chlorophyll-*a* in lake waters. Despite the limitation of this work, our findings suggest that Landsat 8 imagery can be used to estimate chlorophyll-*a* concentration in fresh waters and thus it is promising to map chlorophyll-*a* concentration in fresh lakes.

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