Annals of Valahia University of Targoviste. Geographical Series (2017), **17**(1): 83-89
DOI: 10.1515/avutgs-2017-0008
ISSN (Print): 2393-1485, ISSN (Online): 2393-1493

A LANDSAT 8 OLI SATELLITE DATA-BASED ASSESSMENT OF SPATIO-TEMPORAL VARIATIONS OF LAKE SEVAN PHYTOPLANKTON BIOMASS

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Abstract

The Sevan is one of the world's largest highland lakes and the largest drinking water reservoir to the South Caucasus. An intensive drop in the level of the lake that occurred over the last decades of the 20th century has brought to eutrophication. The 2000s were marked by an increase in the level of the lake and development of fish farming. To assess possible effect of these processes on water quality, creating a state-of-the-art water quality monitoring system is required. Traditional approaches to monitoring aquatic systems are often time-consuming, expensive and non-continuous. Thus, remote sensing technologies are crucial in quantitatively monitoring the status of water quality due to the rapidity, cyclicity, large-scale and low-cost. The aim of this work was to evaluate potential applications of the Landsat 8 Operational Land Imager (OLI) to study the spatio-temporal phytoplankton biomass changes. In this study phytoplankton biomasses are used as a water quality indicator, because phytoplankton communities are sensitive to changes in their environment and directly correlated with eutrophication. We used Landsat 8 OLI (30 m spatial resolution, May, Aug, Sep 2016) images converted to the bottom of atmosphere (BOA) reflectance by performing standard preprocessing steps (radiometric and atmospheric correction, sun glint removal etc.). The nonlinear regression model was developed using Landsat 8 (May 2016) coastal blue, blue, green, red, NIR bands, their ratios (blue/red, red/green, red/blue etc.) and in situ measurements (R^2=0.7, $p<0.05$) performed by the Scientific Center of Zoology and Hydroecology of NAS RA in May 2016. Model was applied to the OLI images received for August and September 2016. The data obtained through the model shows that in May the quantity of phytoplankton mostly varies from 0.2 to 0.6g/m^3. In August vs. May a sharp increase in the quantity of phytoplankton around 1-5 g/m^3 is observable. In September, very high contents of phytoplankton are observed for almost entire surface of the lake. Preliminary collation between data generated with help of the model and in-situ measurements allows to conclude that the RS model for phytoplankton biomass estimation showed reasonable results, but further validation is necessary.

Keywords: Remote sensing, Water quality, Phytoplankton biomass, Highland lake, Lake Sevan

1. INTRODUCTION

Freshwater lakes known as a valuable water source for recreational, industrial, water supply etc. use, have a significant role in economic activities of a man. Commonly, man-made intervention triggers environmental changes which in turn adversely impact the quality of lake waters, this being one of grave concerns on a global scale (Brivio et al., 2001).

The Sevan is one of the world's largest highland freshwater lakes and the largest drinking water reservoir to the South Caucasus. The lake has a significant role in the economy of Armenia. The overuse of the Sevan water in the 20th century brought to dramatic drop in the lake level - by almost 20 m - and consequently to reduction of its surface area. The 21th century has been marked by an increase in the level of Lake Sevan water (some 2 m) and a steady inundation of near-shore areas, both forested and man-altered. Over the last decades such processes have provoked an increase in trophic level of the lake finally making it highly eutrophic (Babayan et al., 2006; Heblinski et al., 2011).

It is known that the underlying lymnological parameter for assessing lake water quality is trophic condition or eutrophication of a lake. A widely applicable indicator when assessing the degree of eutrophication is phytoplankton biomass. Therefore, proper decisions regarding recovery of ecosystem services and functions should be made based on a proper understanding of time and space dynamics of phytoplankton to be achieved through continuous monitoring (Dalu et al., 2015; Rakocevic-Nedovic and Hollert 2005).

Traditional methods of measurement (field measurements) of lake water quality and determination of quality-impacting factors assure credibility of data, but are time consuming and expensive and, above all, do not give a spatial picture to underpin lake water quality assessment and monitoring. This problem is solved in the result of simultaneous use of traditional field measurements and up-to-date remote sensing (RS) methods (Brivio et al., 2001). The latter help both collect rapid, temporal and synoptic data regarding water bodies and implement a spatio–temporal assessment of phytoplankton abundance in water ecosystems (Dalu et al., 2015; Watanabe et al. 2015).

Presently widely applicable operational spacecraft RS system intended for lake water assessment is considered to be Landsat since it acquires spectral data within optical and thermal regions of electromagnetic spectrum and its spatial resolution is quite sufficient for monitoring inland water bodies (Brivio et al., 2001; Dalu et al., 2015; Lim and Choi 2015; Watanabe et al. 2015).

Detection of phytoplankton by means of RS is possible due to spectral variations of phytoplankton pigment absorption. In this research, phytoplankton abundance was determined through a statistical approach - the most widely used technique for establishing a correlation between spectral data and phytoplankton abundance. However, the use of RS is somewhat limited, major limitations being cloudiness, presence of sun glints, high levels of aerosols in atmosphere. Besides, the fact that satellite signal originates in the surface layer commonly makes it impossible to investigate sub-surface phytoplankton abundance **(**Brivio et al., 2001; Joint and Groom 2000).

The accepted practice in a RS spatio-temporal assessment of phytoplankton is to use chlorophyil-a as a proxy indicator (Montes-Hugo et al., 2005; Joint and Groom 2000; Dalu et al., 2015; Brivio et al., 2001; Matthews et al., 2012; Watanabe et al. 2015), nonetheless we made an attempt to do such research using a total phytoplankton biomass (PB) instead. So, the research goal was to assess spatio–temporal variations of Lake Sevan phytoplankton employing Landsat 8 OLI/TIRS multispectral satellite imagery.

2. STUDY SITE

Lake Sevan is located in Gegharkoonik marz (province) of Armenia (40°23´N, 45°21´E) (Fig. 1). Mean lakeshore temperature varies from 6°C in January to 16°C in July, mean annual temperature is 5°C. The amount of annual precipitation is 340-720 mm. Morphologically Lake Sevan consists of the Minor Sevan (up to 90m) and the relatively swallow Major Sevan (up to 40 m deep). Lake Sevan is fed by 28 rivers and water streams**,** the only river flowing out of the lake being the Hrazdan. The lake mirror lies at the altitude ≈1900 m a.s.l., its surface area approximates to 1260 sq.km (Heblinski et al., 2011; Babayan et al., 2006).

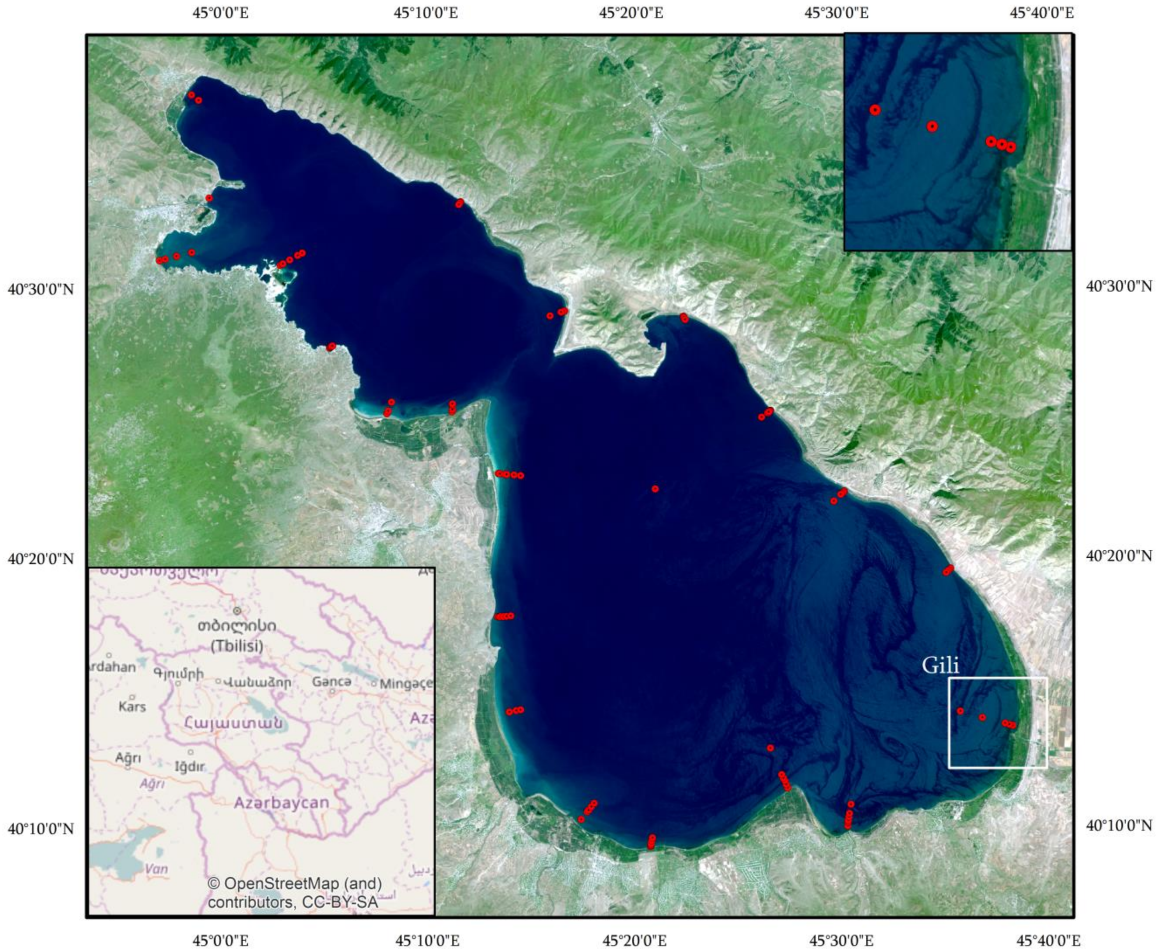

Figure 1. The study site and sampling network

3. MATERIALS AND METHODS

3.1. Data acquisition and pre-processing

Field Data: Lake Sevan phytoplankton abundance data for May 2016 were provided by the Scientific Center of Zoology and Hydroecology NAS RA. Sampling was done from 109 locations throughout the lake (Fig. 1). The collected samples were then analyzed to determine total contents of diatomites, blue-green, green and yellow-green algae. The data were filtered to remove sites located on cloudy sections of satellite images (n=48), to then conduct statistical preprocessing i.e. outlier detection and elimination. The sample follows a Normal distribution (H0). Descriptive statistics of the PB data are the following (g/m^3): N=50, Min=0.05, Max=1.52, Mean=0.56, SD=0.44 (where SD is standard deviation).

Remote Sensing Data: Sensors intended for investigating water bodies must have a broader SNR (signal to noise ratio) than earth resource sensors, due to the low values of the water-leaving radiances. Unlike previous Landsat TM and ETM+ images intended mainly for a land surface research, a Landsat 8 sensor has the improved SNR ratio that will enable better characterization of land cover, particularly over water. In any case, images should be used only after adequate preprocessing (Acharya et al., 2016; Brivio et al., 2001; Salama et al., 2009; Matthews et al., 2012). Both scattering and absorption of light - induced by molecules, aerosols and gaseous constituents in atmosphere - adversely influence surface reflectance information captured by sensors. Moreover, water-leaving radiance from the sensor as compared to atmospheric path radiance is very low (Maul 1985), therefore it is necessary to do atmospheric correction. This research employed the ATCOR atmospheric correction model. A sun glint removal model used in his research was that suggested by Hedley (2005). This method suggests that brightness in NIR band consists of sun glint alone, whereas in visible region the latter is linearly dependent on brightness in the NIR band (Hedley et al., 2005). Spatial transform was performed using low pass convolution filtering (3x3 kernel size) (Schowengerdt 2006).

Statistical analysis: To develop an RS model of determination and spatio-temporal assessment of PB in Lake Sevan water, multiple linear and nonlinear regression models were used. Models quality assessment was done using RMSE (Root Mean Square Error), R^2 and RPD (Ratio of Performance of Deviation).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i^{predicted} - x_i^{measured}\right)^2} \qquad (1)$$

$$RPD = \frac{SD}{RMSE} \qquad (2)$$

where SD is the standard deviation of measured values.

4. RESULTS AND DISCUSSION

To derive phytoplankton abundance from RS data multiple linear (eq. 3) and nonlinear (eq. 4) regression models were developed using Landsat 8 (May 2016) coastal blue, blue, green, red, NIR bands, their ratios (blue/red, red/green, red/blue etc.) and in situ measurements. We selected bands and ratios most widely used in determination of PB (Brivio et al., 2001; Dalu et al., 2015; Matthews et al., 2012; Montes-Hugo et al., 2005; 0).

$$\boldsymbol{PB} = 0.87 + 41.5 * \boldsymbol{Coastal\ blue} + 131.1 * \boldsymbol{Blue} - 17.8 * \boldsymbol{Green} - 204.05 * \boldsymbol{Red} + 10.4 * \boldsymbol{NIR} - 0.95 * \boldsymbol{Blue/Red} + 0.21 * \boldsymbol{Blue/Gren} + 0.11 * \boldsymbol{Green/Red} + 2.12 * \boldsymbol{Red/Blue} - 3.73 * \boldsymbol{Red/Green} \qquad (3)$$

$$\boldsymbol{PB} = 435 + 1162 * \boldsymbol{Coastal\ Blue} - 4329.35 * \boldsymbol{Blue} + 3063.4 * \boldsymbol{Green} - 2419 * \boldsymbol{Red} + 105.22 * \boldsymbol{NIR} + 0.79 * (\boldsymbol{Blue/Red}) - 122.03 * (\boldsymbol{Blue/Green}) - 77.95 * (\boldsymbol{Green/Red}) - 308.5 * (\boldsymbol{Red/Blue}) - 303 * (\boldsymbol{Red/Green}) - 17858.23 * \boldsymbol{Coastal\ Blue} + 59246.5 * \boldsymbol{Blue}^2 - 27821.33 * \boldsymbol{Green}^2 + 36393.6 * \boldsymbol{Red}^2 - 1774 * \boldsymbol{NIR}^2 + 0.812 * (\boldsymbol{Blue/Red})^2 + 30.23 * (\boldsymbol{Blue/Green})^2 + 5.2 * (\boldsymbol{Green/Red})^2 + 165.88 * (\boldsymbol{Red/Blue})^2 + 277.7 * (\boldsymbol{Red/Green})^2 \qquad (4)$$

As seen from Fig. 2, a nonlinear regression model has a relatively low RMSE (0.23), high R^2 (0.71) and RPD (1.9) as compared to those of a linear regression model RMSE=0.31, R^2=0.45, RPD=1.4. Therefore, for a purpose of spatial prediction and mapping of phytoplankton abundance through RS data we used a nonlinear regression model.

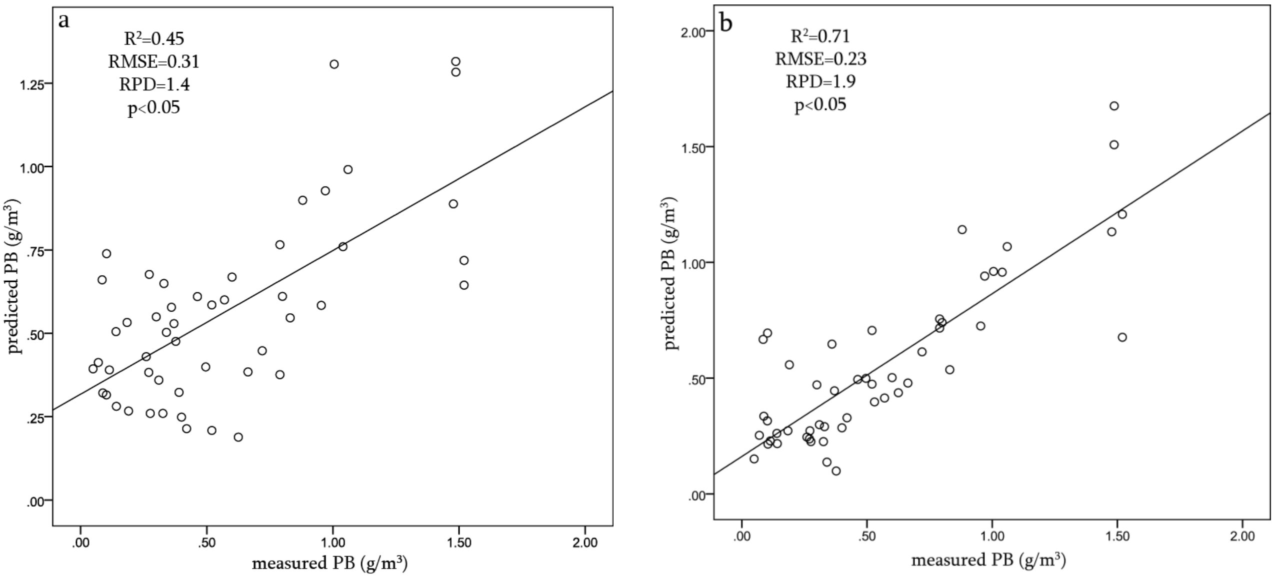

Figure 2. Correlation between measured and predicted PB data: a) a multiple linear regression model, b) a multiple nonlinear regression model.

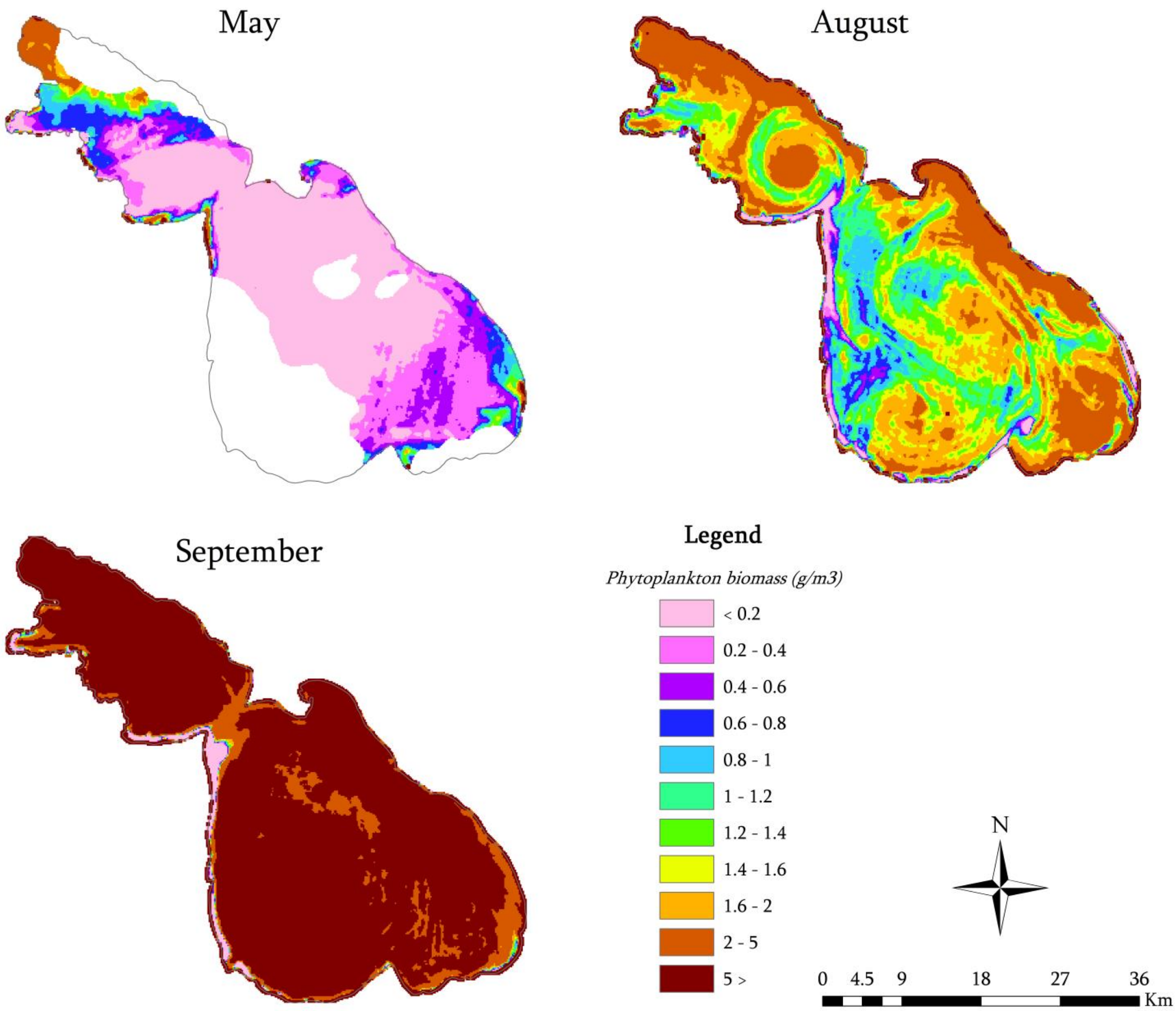

Figure 3. A spatio-temporal distribution of phytoplankton in Lake Sevan water according to a Landsat 8 OLI/TIRS satellite image.

Model was applied to the OLI images received for August and September 2016 (Fig. 3). The data obtained through the model shows that in May the quantity of phytoplankton mostly varies from 0.2 to 0.6g/m^3. High contents of phytoplankton are observed particularly for Lake Sevan southeast (River Masrik mouth) and central western coastal sections 1.2-5g/m^3 (River Gavaraget mouth). In August vs. May a sharp increase in the quantity of phytoplankton around 1-5 g/m^3 is observable. Maximal contents are detected in the northeast and southeast sections of the lake. In contrast to the high contents of phytoplankton detected for the central coastal sections of the west shore of the lake in May, relatively low contents are detected in August <0.2 g/m^3. In September, very high contents of phytoplankton are observed for almost entire surface of the lake. Hence, the quantity of PB steadily increases and reaches its maximum in September, while phytoplankton accumulations are observable mainly in the southeast, northeast and northwest coastal sections.

5. CONCLUSION

The results obtained from this research have indicated that it is possible to determine spatio–temporal distribution of phytoplankton throughout Lake Sevan based on RS and particularly Landsat 8 OLI/TIRS data. A multiple nonlinear regression model is more effective as compared to a multiple linear regression model. However, the empiric character of the proposed algorithm narrows its applicability depending on specific range of phytoplankton abundance, different locations and seasons. It is suggested that specific per month algorithms of phytoplankton determination be developed and a field data set improved as well.

ACKNOWLEDGEMENT

The authors would like to express their sincere thanks to Scientific Center of Zoology and Hydroecology of NAS RA and Foundation for Restoration of Sevan Trout Stocks and Development for Aquaculture (FRSTSDA) for supporting field works and providing some of in-situ data.

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