Analysis on the Feasibility of Landsat 8 Imagery for Water Quality Parameters Assessment in an Oligotrophic Mediterranean Lake

V. Markogianni, D. Kalivas, G. Petropoulos, E. Dimitriou

***Abstract*—**Lake water quality monitoring in combination with the use of earth observation products constitutes a major component in many water quality monitoring programs. Landsat 8 images of Trichonis Lake (Greece) acquired on 30/10/2013 and 30/08/2014 were used in order to explore the possibility of Landsat 8 to estimate water quality parameters and particularly CDOM absorption at specific wavelengths, chlorophyll-*a* and nutrient concentrations in this oligotrophic freshwater body, characterized by inexistent quantitative, temporal and spatial variability. Water samples have been collected at 22 different stations, on late August of 2014 and the satellite image of the same date was used to statistically correlate the *in-situ* measurements with various combinations of Landsat 8 bands in order to develop algorithms that best describe those relationships and calculate accurately the aforementioned water quality components. Optimal models were applied to the image of late October of 2013 and the validation of the results was conducted through their comparison with the respective available *in-situ* data of 2013. Initial results indicated the limited ability of the Landsat 8 sensor to accurately estimate water quality components in an oligotrophic waterbody. As resulted by the validation process, ammonium concentrations were proved to be the most accurately estimated component (R = 0.7), followed by chl-*a* concentration (R = 0.5) and the CDOM absorption at 420 nm (R = 0.3). *In-situ* nitrate, nitrite, phosphate and total nitrogen concentrations of 2014 were measured as lower than the detection limit of the instrument used, hence no statistical elaboration was conducted. On the other hand, multiple linear regression among reflectance measures and total phosphorus concentrations resulted in low and statistical insignificant correlations. Our results were concurrent with other studies in international literature, indicating that estimations for eutrophic and mesotrophic lakes are more accurate than oligotrophic, owing to the lack of suspended particles that are detectable by satellite sensors. Nevertheless, although those predictive models, developed and applied to Trichonis oligotrophic lake are less accurate, may still be useful indicators of its water quality deterioration.

***Keywords*—**Landsat 8, oligotrophic lake, remote sensing, water quality.

I. Introduction

WATER is essential for the survival of all living organisms. Part of this resource is stored in lakes and reservoirs, which are freshwater resources used to satisfy environmental and human requirements. Unfortunately, their water quality is chemically deteriorated, and water managers/ scientists need new means for observing water quality [1].

The continuous monitoring of large water bodies is a complex task, since it demands frequent and detailed data collection and interpretation efforts. Only intensive sampling efforts can fully capture the spatial and temporal variability of a multitude of key indicators. This leads to a necessary compromise between the number of sampling stations and the need of maintaining costs within reasonable limits [2] in [3].

Satellite remote sensing is a powerful supportive tool for assessing of spatial and temporal variations in water quality [4]-[6] in [1]. Remote sensing technologies enable researchers to acquire a unique, holistic perspective of the ecosystems. From the vantage point of space, satellite data become an invaluable tool in support of wetland management. This is of especial importance in the context of the increasingly strict environmental regulations approved by governments worldwide (e.g. Water Framework Directive and the European Marine Strategy Framework Directive) [7].

Since the European Commission Water Framework Directive (EC, 2000) was promulgated, Member States have started to develop lake ecological status assessment systems, and finished setting TP and Chl-*a* as reference conditions for European lakes in different lake types and ecoregions [8]-[10] in [11]. In particular, the use of multi-spectral sensors makes possible to measure many of the parameters required by law [3]. Apart from the law-required components, the major factors which can influence the quality of inland water bodies are the suspended sediments (turbidity), phytoplankton and cyanobacteria (i.e., chlorophylls, carotenoids), dissolved organic matter (DOM), organic and inorganic nutrients, pesticides, metals, thermal releases, macrophytic algae, pathogens and oils. The above mentioned factors affect the optical properties of waters (except for nutrients) thus directly changing the signal acquired by optical sensors over water bodies. The parameters which can be directly quantified using remote sensing techniques are the suspended particulate matter

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(SPM), which is placed in suspension by wind-wave stirring of shallow waters and can be a tracer for inflowing pollutants [12], the phytoplankton mainly as chlorophyll-*a* (chl-*a*) or phycocyanin (PC), that can be used to indicate the trophic level, to evaluate the presence of potentially toxic algal blooms and as a proxy of phytoplankton biomass [13], [14], the coloured DOM (CDOM), which is investigated because of its role in protecting aquatic biota from ultraviolet solar radiation and its influence on specifically heterotrophic bacterial productivity in the water column, indicative of the shift from net autotrophy to net heterotrophy [15], [16].

A number of satellite sensors have been used for the study of surface water quality [17]-[21]. References [17] and [22] have recently provided a detailed review of remote sensing instruments which can be used to assess water quality in inland and near-coastal waters. Medium spatial resolution multi-spectral sensor such as Advanced Land Imager (ALI) (30 m), Advanced Land Observation Satellite (ALOS) (10 m), SPOT-5 (10 m) and Landsat provide images in the visible and near-infrared wavelengths; compared to the higher spatial resolution sensors, these sensors are characterized by a higher radiometric performance which contributes to a more accurate assessment of the concentrations of quality parameters over water. On May 30, 2013, data from the Landsat-8 satellite (launched on 11 February, 2013) became available allowing the continuance of studies on water quality of lakes [16].

Although Landsat sensors were not designed for aquatic applications [22], [23], we find numerous examples of applications of Landsat images for estimating and/or monitoring lake water quality. Several studies have proposed reliable algorithms between Landsat data and water quality parameters, including chlorophyll; phytoplankton and PC concentrations [24]-[30], water clarity [31]-[35], CDOM [24], [36], [37], blooms of cyanobacteria [28], macrophyte [38] and total suspended sediments [39]-[43]. Few studies, though, have attempted to monitor and model nutrient data, since those data do not have optical properties and the regression models yielded statistically insignificant results [44]-[46] in [47]. In particular, [44] used Landsat TM imagery to attempt to predict nitrogen and phosphorus concentrations in Tiahu Lake, China with some successful results for phosphorus and less successful results for nitrogen [47].

In general, the aforementioned studies considerably increase knowledge of water quality and most of their developed algorithms are commonly based on empirical relationships using classical simple linear regression models between remotely sensed reflectance values and measurements collected simultaneously in the field.

In contrast to the clear oceanic waters (case-1 waters), retrieval problems of some water quality parameters have arisen for coastal and inland waters (case-2 waters) [48]. Monitoring of water quality parameters in case 2 waters is not an easy task due to runoff and discharges from rivers/streams, which add to the complexity of the water constituent retrieval process. Inflows from streams introduce different organic/ inorganic particles, known as total suspended solids (TSS). As opposed to particles, Chlorophyll-*a* and particularly CDOM are absorbing components of water with CDOM absorbing the greatest in short wavelengths (350–440 nm) and Chlorophyll-*a* representing two absorption peaks in the blue and the red regions of the spectrum (nm) [49]. Whereas Chl-*a* in case-1 waters can be accurately estimated on the basis of the pigment's absorption peak in the blue, in oligotrophic case-2 waters, estimation on the basis of the Chl-*a* absorption peak in the red can be no alternative due to the overwhelming absorption by water of the red and near-infrared (NIR) wavelength bands [48].

As well, lake water clarity can be estimated more accurately in eutrophic and mesotrophic than oligotrophic lakes, due to the absence of suspended particles in oligotrophic lakes that are evident by satellite sensors [50]. In oligotrophic lakes, water clarity is primarily controlled by the concentration of coloured organic matter (dissolved organic carbon DOC) [51]-[54] in [55], which, in turn, affects a wide range of chemical, physical and biological processes. These include thermal structure, light transmission for photosynthesis, attenuation of damaging levels of ultraviolet light, vertical distribution of plants and animals, as well as the form and availability of toxic metals [53], [56]-[60] in [55]. This study presents the analysis of the quite recently launched Landsat 8 OLI imagery in combination with simultaneous field data to conduct basic spatial assessment of various water quality parameters in a natural lake. The main objective is to develop predictive algorithms and determine chlorophyll-*a* concentration (Chl-*a*), CDOM absorption at 420 and 440 nm ($a_{cdom}(420)$; $a_{cdom}(440)$) and nutrient concentrations in the deep oligotrophic Lake Trichonida (Greece), using multiple linear regression. Selected optimal algorithms were applied to another L8 image of different date but with available *in-situ* Chl-*a*, nutrient and CDOM absorption data, in order to validate the results. Satellite derived values were compared to *in-situ* ones and the initial results indicated the weakness (depending on the parameter) of the L8 imagery for accurately assessing the concentrations of the above mentioned optically-active water quality components in an oligotrophic lake, characterized by particularly low concentration values and the absence of strong spatial and temporal variability.

II. Methodology

A. Study Area

Trichonis Lake is the largest natural freshwater body in Greece and it is subjected to pollution from several unnatural activities, especially from intensive farming practices, urban sewages, grazing and small industries. Even though large quantities of fertilizers are applied in the lake’s catchment, the trophic status of the lake is oligotrophic to oligomesotrophic [61]-[63]. Trichonis Lake is a deep freshwater body which has a surface area of 97 km^2, a maximum depth of 58 m and a potential water volume of approximately 2.8x109 m^3 (Fig.1) [64].

A significant hydrogeologic aspect of Trichonis lake’s catchment is that groundwater inflows to the lake during the dry periods are considerably high, which enhances the water abstraction potential for anthropogenic activities [65].

Trichonis Lake’s catchment is a 399 km^2 semi-mountainous area in Western Greece (Fig. 1). The regional climate is characterized as semi-arid to arid Mediterranean with an average annual rainfall of 936 mm and an average annual temperature of 17 ^{0}C which fluctuates by 19 ^{0}C annually [66].

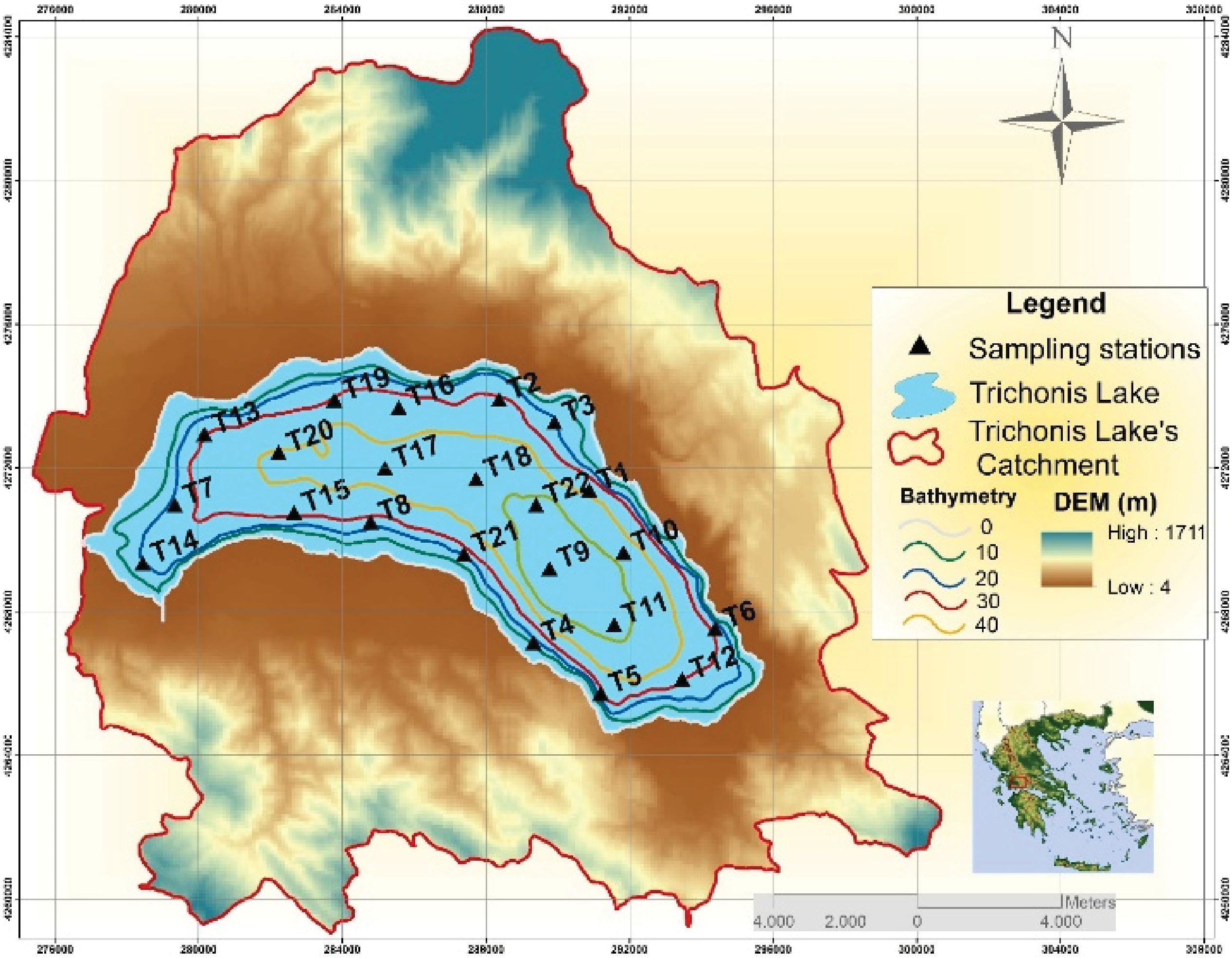

Fig. 1 Trichonis Lake's catchment and bathymetry and chl-*a, CDOM* and nutrients' sampling stations of 30-31/10/2013 and 30/08/2014

B. Water Sampling

Since the timing of field observations and satellite overpass is often considered to be critically important, [67], [68] in [69], water samplings were conducted the same date as the satellite overpass. A total of 22 water samples were collected across the lake Trichonis's surface (5-10 cm) with NIO samplers of 1.5 l capacity in 29-30/10/2013 and 30/08/2014. Following collection, the water samples for nutrient analysis were preserved by the addition of $HgCl_2$ and then were filtered and analyzed for nutrients' concentrations. Samples were filtered through 0.45 μm cellulose acetate filters that had been pre-cleaned with 10% hydrochloric acid (pH = 2) followed by rinsing with Milli-Q water.

A specific quantity of water samples for chlorophyll-a (usually 1 L) was filtered through Whatman GF/F filters immediately after collection. These filters were maintained in a dry and dark environment at −15 °C and then transferred to HCMR laboratories for further analysis.

Water samples for CDOM absorption were filtered through 0.22 μm polycarbonate filter immediately after sampling. Filtered water was transferred into acid-cleaned (HCL 10%, 12 h) glass bottles and stored in the dark at ~-20 °C. Before measurement, the samples were allowed to stand until reaching room temperature.

C. Chemical Analyses

Concentrations of nutrients (NO_3^-, NO_2^-, NH_4^+, and PO_4^{3-}) were determined in the soluble fraction using an ion analyser Metrohm, the automatic analyzer Radiometer and the photometer Merck Nova 400. The chlorophyll-a concentrations were determined with a TURNER 00-AU- 10U fluorometer according to the method of [70], modified by [71]. CDOM absorption spectra were obtained between 250 and 700 nm at 1 nm increments using a dual beam UV-visible spectrophotometer (Perkin Elmer, Lambda 25) equipped with 5 cm quartz cells and referenced to Milli-Q water. A baseline correction was applied by subtracting the average sample absorbance between 690 and 700 nm from the entire spectrum. In addition, a blank scan containing Milli-Q water was subtracted from each spectrum. Absorption units were converted to absorption coefficients using the relationship:

$$a(\lambda) = 2.303 * \mathrm{A}(\lambda) / l \qquad (1)$$

where $\alpha(\lambda)$ = absorption coefficient (m^{-1}) , $A(\lambda)$ = absorbance, l = cell's light pathlength (m).

D.Satellite Data and Pre-Processing

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images consist of 9 spectral bands with a medium spatial resolution (30 meters) for Bands 1 to 7 and 9. The ultra-blue Band 1 is advantageous for coastal and aerosol research. Furthermore, Band 9 is expendient for cirrus cloud observation. The resolution for Band 8 (panchromatic) is 15 meters (Table I) [72]. Two Landsat 8 OLI images of Lake Trichonis (Path 184, Row 33) of 30 October 2013 and 30 August 2014 were used for this study. According to the large size of the Trichonis Lake, the number of sampling stations (22) were considered to be adequate for monitoring variability of CDOM, chl-*a* and nutrient concentrations. The satellite images were acquired from the USGS (United States Geological Survey) Data Centre (http://glovis.usgs.gov/).

The image processing was completed in ENVI software (EXELIS Visual Information Solutions, Version 5.1) while further data elaboration and analysis were conducted in ESRI's software (ArcGIS v. 10.1). Prior to applying the atmospheric correction, the satellite scenes underwent radiometric and geometric corrections.

Each band for both Landsat 8 images was radiometrically and geometrically corrected (using GCP). After conducting an assessment of geometric accuracy for the two images with our Global Position System measurements (coordinate data) taken in the study area, the geometrical accuracy was determined to be less than one half pixel (<15 m). Finally, each band was converted to top-of-atmosphere reflectance with sun angle correction using radiometric calibration coefficients provided in the metadata file to normalize the images for comparison between different days. For atmospheric correction, dark object subtraction (DOS) technique was used, which takes the minimum value in each band and removes it from each pixel [28], [73], [74]. Although this method was used very often in the past, it still constitutes a simple and reliable manner to exclude the atmospheric bias from the image.

E. Development of Models Relating Landsat 8 and Water Quality Data

Numerous studies have investigated single bands, band combinations and band ratios to estimate mainly chl-*a* concentration, CDOM absorption and to a lesser extent nutrient concentrations in freshwater bodies [1], [26], [27], [29], [36], [47]. Multiple linear regression was used in this study to develop relationships between remotely sensed reflectance data (independent) and chl-*a*, CDOM and nutrient values (dependant).

TABLE I
LANDSAT 8 BANDS, WAVELENGTH AND THEIR RESOLUTION

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Ultra Blue (coastal/aerosol)	0.435 - 0.451	30
Band 2 - Blue	0.452 - 0.512	30
Band 3 - Green	0.533 - 0.590	30
Band 4 - Red	0.636 - 0.673	30
Band 5 - NIR	0.851 - 0.879	30
Band 6 - Shortwave Infrared (SWIR) 1	1.566 - 1.651	30
Band 7 - Shortwave Infrared (SWIR) 2	2.107 - 2.294	30
Band 8 - Panchromatic	0.503 - 0.676	15
Band 9 - Cirrus	1.363 - 1.384	30
Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
Band 11- Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

Initially, attempts were made to find combinations, transformations, or logarithmic transformations of Landsat 8 OLI bands which would provide more information about the under study parameters in the lake than only one band. Such combinations are: ratios of B1/B2, B1/B3, B2/B3, B1/B4, B1/B5, B4/B1, B3/B1, B3/B2, B2/B1, B2/B4, B2/B5, B3/B5, B4/B2, B3/B4, B4/B3, and B5/B4; multiplications of B1*B4 and B2*B4; math combinations of B3-B2, B3-B4, (B1-B3)/B2, (B2+B3)/2, (B1+B2)/2, (B2-B4)/(B2+B4), (B2-B3)/(B2+B3), aver(B2,B4), (B2-B4)/B3, (B2+B4)/2, (B3+B4)/2, (B2/B4)/2, B2/(B1+B2+B3) and (B1-B4)/(B3-B4) and the logarithmic (and natural logarithmic) transformations of log(B1/B2), log(B1/B3), log(B1/B4), log(B2/B3), log(B2/B4), logB2/logB3, logB2/logB4, logB3/logB4, ln(B2/B4), ln(B4/B2), ln(B3/B4), ln(B4/B3). Subsequently, pixel values of each transformed image were retrieved from those regions where the 22 sampling stations are located. The transformed variables were denoted as log(Chl-*a*), ln($a_{CDOM(420)}$) and ln(acdom440).

The first criterion taken into account in order to select the best predictive model was the calculation of the predictor importance conducted in IBM SPSS software Statistics v. 23.0. The predictor importance chart contributes to indicating the relative importance of each predictor in estimating the model, it does not relate to model accuracy but to the importance of each predictor in making a prediction. (IBM SPSS, Statistics Base 23). Subsequently, after having selected the predictors with the highest importance for each under study water quality parameter, they were further elaborated in a series of stepwise and backward linear regressions. Criteria of multicollinearity and acceptable values of tolerance factor, variance inflation factor (VIF) and condition indices (CI) were applied to a subset of strategic models to further help compare them and select more straightforward models versus models with higher accuracy (higher R) but more complexity to pick an optimal one to assess water-quality attributes across Trichonis Lake. Then, the optimal predictive models developed based on field sampling of 30 August 2014 and satellite image L8 of the same date, were applied to the Landsat image of 30/10/2013 (L8) in order to assess and validate their efficiency by comparing the resulting estimates with the respective available in situ measurements. Those in situ data were collected in 29 and 30 October 2013 at the same sampling stations (Fig. 1).

III. Results

A. Statistical Summary of Trichonis lake's In-Situ Measurements and Water Quality Classification

In situ dataset of both sampling campaigns covered wide ranges of water quality key indicators: chlorophyll-a (chl-*a*), a $a_{CDOM(420)}$, $a_{CDOM(440)}$, total phosphorus, total nitrogen, nitrate, nitrite, phosphate and ammonium concentrations. In-situ nitrate, nitrite, phosphate and total nitrogen concentrations of 2014 were measured as lower than the detection limit of the instrument used, hence no statistical elaboration was conducted. Data distributions for the rest parameters were skewed with mostly low values and without extremely high values or outliers (Table II). In general, most values of all parameters of 2013 were measured slightly higher than the values of 2014, without indicating great differences or existence of water quality deterioration in 2013.

TABLE II
Descriptive Statistics of *In Situ* Data of 2013 and 2014

	N	Minimum		Maximum		Mean		Std. Deviation		Skewness			
										Statistic		Std. Error	
		2013	2014	2013	2014	2013	2014	2013	2014	2013	2014	2013	2014
Chl*a* (μg/l)	22	.5	0.2	1.4	.88	1.07	.39	.22	.14	-.51	2.15	.49	.49
a_{cdom}(420)	22	.1	.08	.4	.4	.19	.22	.09	.09	1.35	.46	.49	.49
a_{cdom}(440)	22	.07	.06	.33	.38	.16	.18	.07	.09	1.34	.97	.49	.49
TP (mg/l)	22	.03	.01	.08	.06	.04	.02	.013	.012	1.2	1.9	.49	.49
NH_4^+ (mg/l)	22	.02	.01	.06	.09	.03	.03	.01	.02	2.1	1.99	.49	.49

In order to classify the water quality of Trichonis lake, the EPA classification system was used [75]. According to this scheme, the classification of lake water quality is based on the total phosphorus concentration, water transparency and trophic index (Trophic State Index—TSI). Trophic index TSI is calculated for each classification quality parameter as follows [76]:

$$TSI(SD) = 60 - 14.41 * \ln(SD) \tag{2}$$

$$TSI(Chl-a) = 9.81 * \ln(Chl-a) + 30.6 \tag{3}$$

$$TSI(TP) = 14.42 * \ln(TP) + 4.15 \tag{4}$$

where SD is the Secchi disk (m) and Chl-*a* and TP (μg/l) are the concentrations of chlorophyll-*a* and total phosphorus, respectively. In the context of this study, there are no available data of Secchi disk. Therefore, it should be noted that this water quality classification effort is developed in order to better understand the prevailing conditions during the sampling periods and not to definitely classify the water quality of the Trichonis Lake. Taking into account the concentrations of total phosphorus and chlorophyll-*a* and the estimated average Trophic Index (TSI) of both the sampling campaigns, Trichonis Lake is characterized as oligotrophic to oligomesotrophic in 2013 and oligotrophic in 2014 (Table III).

TABLE III
EPA classification system and estimated TSI for Trichonis Lake

Date	TSI (TP)	TSI (Chl-*a*)	TSI average	Classification
2013	57.4	31.26	44.3	oligotrophic to oligomesotrophic
2014	47.35	21.36	34.4	oligotrophic

B. Predictive Algorithms

To develop predictive Chl-*a*, $a_{CDOM(420)}$, $a_{CDOM(440)}$ and nutrient algorithms, we established different regression models and MLR relating *in situ* data and reflectance values of the selected bands and band combinations. Several regressions resulted in unsuccessful results accompanied by statistically insignificant correlations. Taking into account certain aforementioned statistical indices, optimal models were recorded for each studied water quality parameter (Table IV). MLR model including the spatial correlation structure and involving Landsat8 bands 2 (blue), 3 (green) and 4 (red) proved to be the most suitable for predicting CDOM absorption at 420 nm in Trichonis Lake. Correlation coefficient equals to 0.48 while Durbin-Watson value indicates independence of residuals. The optimal estimating model of ammonium concentration includes the bands 1 (ultra-blue), 3 (green), and 4 (red), while the value of the correlation coefficient is equal to 0.26. Collinearity statistics (Tolerance and VIF) of the coefficients are 1, excluding the possibility of multicollinearity. Concerning the chl-*a* predictive model, coefficients B2/(B1+B2+B3) and (B1+B2)/2 (Table IV) were used presenting acceptable multicollinearity statistics with values of tolerance and VIF 0.96 and 1.04, respectively.

TABLE IV
Water Quality Parameters' Predictive Models Summary

Model	R	R^2	Std. Error of the Estimate	R^2 Change	Durbin-Watson
$acdom420 = -2.195 - (859.4 * B3) + (3426.1 * B4) - 497.51 * [(B2 + B4)/2]$	0.48	0.23	0.08	0.23	1.75
$NH4+ = -0.32 + 0.14 * [(B1 - B4)/(B3 - B4)]$	0.26	0.07	0.02	0.7	2.33
$CHL - a = -38.62 + 92.05 * [(B2/(B1 + B2 + B3)] + 2239.7 * [(B1 + B2)/2]$	0.44	0.19	0.13	0.19	2.5

C. Algorithm Validation

In order to explore the reliability of the final predictive models, regressions between Landsat 8-estimates of Chl-*a*, $a_{CDOM(420)}$ and ammonium concentrations in Trichonis Lake versus respective in-situ measurements of 2013 were calculated

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(Fig. 2). Several models (linear, logarithmic, quadratic, cubic, power and exponential) have been applied in order to detect the best potential agreement between the observed and satellite-estimated values with the cubic model presenting the highest correlation coefficients for all parameters (Table V). Nevertheless, the moderate fit between in-situ and predicted water quality parameters by each selected MLR indicated the moderate and low predictive capacity of these models. In particular, the highest correlation coefficient concerning the chl-*a* estimation was equal to 0.45 with standard error of estimates equal to 0.21 μg/l. Following, correlation coefficients of $a_{CDOM(420)}$ and ammonium concentrations were calculated 0.3 and 0.7 with standard error of estimates 0.17 m^{-1} and 0.004 mg/l, respectively (Table V).

TABLE V
MODELS SUMMARY FOR WATER QUALITY PARAMETERS' PREDICTIVE MODELS VALIDATION

Chl-*a*	R	R^2	Adjusted R Square	Std. Error of the Estimate
linear	0.200	0.040	-,017	,220
logarithmic	0.223	0.05	-0.006	0.218
quadratic	0.440	0.194	0.093	0.207
cubic	0.447	0.199	0.099	0.207
power	0.226	0.051	-0.005	0.094
exponential	0.202	0.041	-0.016	0.095
$a_{cdom}420$	R	R^2	Adjusted R Square	Std. Error of the Estimate
linear	0.11	0.012	-0.037	0.162
logarithmic	0.131	0.017	-0.032	0.162
quadratic	0.196	0.038	-0.063	0.164
cubic	0.258	0.067	-0.089	0.166
power	0.136	0.018	-0.031	0.106
exponential	0.118	0.014	-0.035	0.106
NH_4^+ (mg/l)	R	R^2	Adjusted R Square	Std. Error of the Estimate
linear	0.325	0.106	0.061	0.005
logarithmic	0.252	0.064	0.017	0.006
quadratic	0.611	0.374	0.308	0.005
cubic	0.689	0.474	0.387	0.004
power	0.421	0.177	0.136	0.379
exponential	0.505	0.255	0.217	0.360

IV. DISCUSSION AND CONCLUSIONS

Remote sensing provides suitable information concerning water quality and aquatic systems management. In this study, we demonstrated the limited feasibility of Landsat 8 OLI imagery in combination with in situ water quality parameters' concentrations to identify relevant algorithms for water quality characterization in an oligotrophic waterbody, Trichonis reservoir.

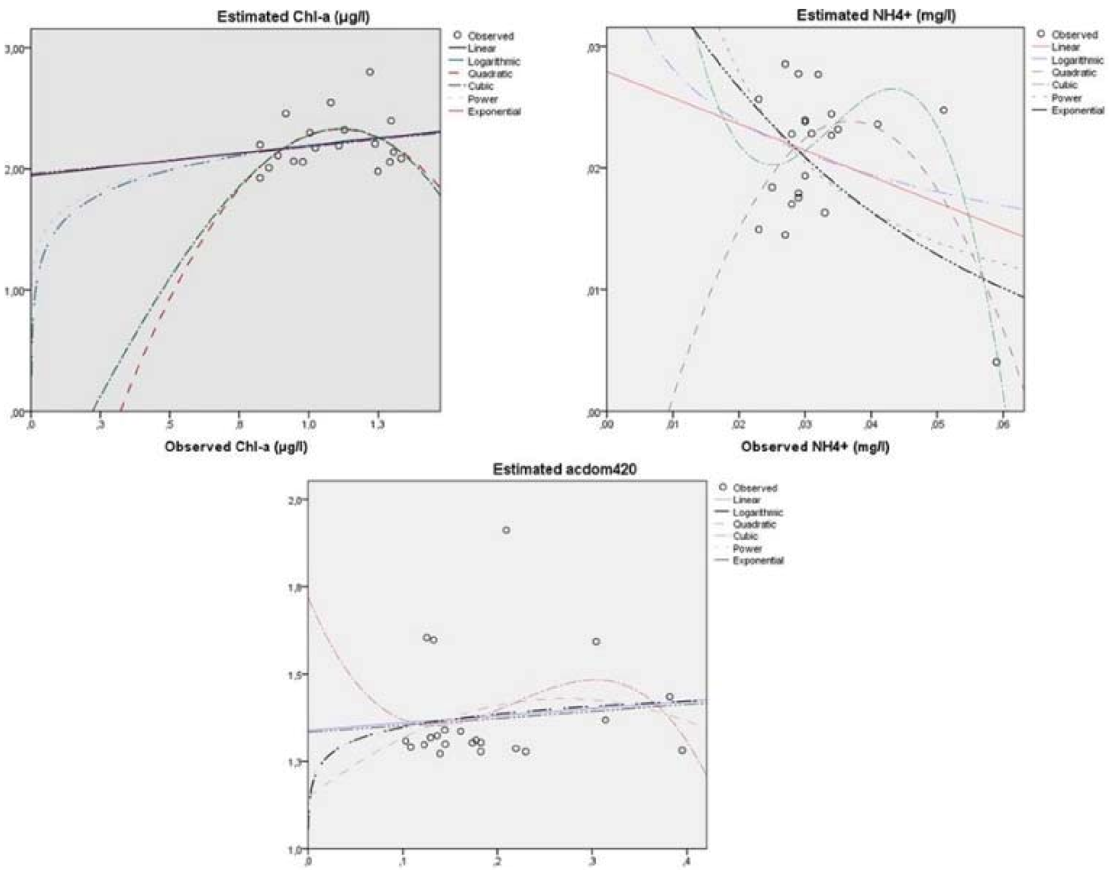

Fig. 2 Scatterplots among observed and satellite-derived data

Water samples from Trichonis Lake were analyzed twice in 2013 and 2014 regarding its concentrations of chl-*a*, ammonium and CDOM concentration, which then was determined as the absorption at 420 nm, $a_{CDOM(420)}$, extrapolated from the absorption spectra. According to lab measurements, Trichonis Lake is not only characterized as an oligotrophic lake but also illustrates a relatively low quantitative, temporal and spatial variability.

Multiple linear regressions were conducted among available data and the majority of models were characterized by insignificant statistical correlations. Optimal models were selected based on statistical criteria and indices but presented low coefficients and unsuccessful results. The selected predictive model of chl-*a* concentration involves the combination of ultra-blue (B1), blue (B2) and green (B3) OLI bands of Landsat 8 satellite sensor. These results are in accordance with those of [77], who attempted to map OLI's spectroradiometric sensitivity to changes in optically active components (OACs), such as Chl-*a*, for a nominal solar zenith angle $\theta s=40^o$, (solar zenith angle in our study equals to $\theta s=35^o$). According to [77], the blue band (B2) shows the highest sensitivity to changes in chl-*a*, in particular on average for changes greater than 0.5 μg/l. This implies difficulties in detecting changes smaller than 0.5 units of chl-*a* on the focal plane using this single band. While the Ultra Blue (B1) and the green bands (B3), on average, exhibit similar sensitivity to the changes in chl-*a*, the B1 band is slightly better for waters with low chl-*a* concentrations.

At the same study [77], the detection limits associated with CDOM absorption at 440 nm were explored. While our study resulted in a predictive model for CDOM absorption at 420 nm combining the blue, green and red bands, [77] found out that in waters with relatively low CDOM concentrations, ($a_{CDOM(440)}<0.5$ m^{-1}), the blue and the green bands exhibit the highest sensitivity whereas the red band was found insensitive to the changes in CDOM absorption. In general it was found that OLI is, on average, sensitive to changes in chl-*a* and CDOM absorption larger than 0.5 μg/l and 0.1 m^{-1}, respectively. Although actual retrievals can be improved by the use of multiple bands, the fact that in our case detected changes in chl-*a* concentrations and to a lesser extent in CDOM absorption are marginally equal to the aforementioned threshold values, could be the main reason of not managing high-precision assessment results. Furthermore, [49] applied a physics-based approach to fully examine the potential of OLI in terms of its enhanced features in a water constituent retrieval framework. Based on their observations they concluded that the disparity between the response functions of OLI is more noticeable in turbid waters than in clearer waters when mapping CDOM absorption. Development of reliable methods to retrieve CDOM information from spectral reflectance data is difficult. Indeed, among the major water quality variables measurable by remote sensing (e.g., suspended solids, chlorophyll, Secchi depth), for several reasons CDOM may be the most difficult to measure accurately in inland waters. CDOM absorbs but does not scatter or reflect light while it has no absorbance troughs or peaks, such as are found for plant pigments; instead light absorption by CDOM follows a simple quasi-exponential decrease with increasing wavelength. There are no wavelength bands in the visible spectrum uniquely associated with CDOM that can be used for measurement purposes. Thus, measurement of low to moderate levels of CDOM in optically complex Case-2 waters is especially difficult because light scattering by these particles dominates their reflectance spectra [36].

Predicting ammonium concentration in inland waters can be a hard task since very few studies have attempted to monitor data with non-optical properties, such as nutrient concentrations. Furthermore, not many previous studies have been able to provide total nitrogen models with statistically significant results or reasonable adjusted R^2 values [47]. Our research resulted in the ammonium predictive model incorporating ultra-blue, green and red bands yielding a regression coefficient equal to 0.7, regarding the validation process. Similar results, regarding the utilized wavelengths, presented [45] and [47], who detected the strongest correlation among total nitrogen and Landsat TM bands 1 (blue) and 2 (green). [44] predicted total nitrogen concentrations with Landsat TM bands 1 (blue), 2 (green), 3 (red), and 4 (NIR), however these results were not very successful ($R^2 = 0.24$) [47].

[47] also supported that Landsat band ranges can be the most significant for nutrient predictions in eutrophic lakes, but except for Landsat sensor, [78] in [48] attempted to estimate chl-*a* concentration by using MERIS images and they concluded that the application of MERIS FLH algorithms in oligotrophic waters may indeed be precluded because of too low signal to noise ratio.

From a management perspective, in particular eutrophic and mesotrophic lakes are of greater interest owing to their susceptibility to development-related eutrophication [23]. In the context of this research effort, it has been proved that greater assessment accuracy was especially hindered from the extremely low concentrations which strongly characterize Trichonis lake and the lack of any value differentiation among the sampling stations. Nevertheless, although some model predictions applied to oligotrophic lakes are less accurate [23], these models increase knowledge of their water quality and may be particularly useful indicators of their water quality deterioration.

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