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ORIGINAL ARTICLE

Multitemporal Mapping of Chlorophyll–α in Lake Karla from High Resolution Multispectral Satellite data

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Abstract With the aquatic environments being excessively stressed by human activities, the need for monitoring critical quality parameters continuously and at large spatial scales is greater than ever. To this end, the goal of this study was to exploit remote sensing data for water quality estimation towards the development of a long-term monitoring protocol for aquatic systems. High resolution, multitemporal data were employed along with in-situ measurements for key water quality parameters. After establishing relations between the satellite and in-situ data, multitemporal geospatial maps of Lake Karla were produced and validated, indicating that the observed chlorophyll-α is fluctuating throughout the year. In particular, a high correlation rate ($r^2 > 89$ %) for *Chl-a* was derived through a linear regression model while certain mismatches occurred due to frequent cyanobacterial blooms that were mainly observed in the quite shallow parts of the lake. Moreover, the spatiotemporal analysis revealed a gradual slight decline in average chlorophyll-α concentrations from the beginning of 2011 and onward. The lake regions which were affected the most were the shallow ones, so it is necessary to better distribute the sampling locations within the lake in order to better quantify the fluctuations of water quality parameters. By exploiting high resolution satellite imagery, the proposed methodology implements a low-cost water monitoring system which enables the frequent update of important water quality parameters of any relevant geo-database, towards the efficient development of water management plan for protection and restoration of sensitive aquatic ecosystems.

Keywords Landsat · Earth observation · Monitoring · Chlorophyll–α · Shallow Lake · Water quality

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1 Introduction

Currently, the need to protect the aquatic environment by monitoring critical parameters is greater than ever (Tsakiris 2015). Thus, reliable and low cost monitoring methods and techniques are becoming more essential. The most commonly used approach to assess water quality in aquatic systems is through in-situ water sampling and physico-chemical and biological analyses (Heddam 2016). This process, while quite satisfactory in terms of accuracy, is relatively expensive and limited in terms of spatial-temporal sampling distribution. An accurate representation of the physical processes taking place in a complex aquatic ecosystem requires frequent sampling. Moreover, in-situ field measurements cannot provide the spatial distribution in real time due to their limited resources, weather conditions and the remoteness of an aquatic system (Tebbs et al. 2015). On the other hand, remote sensing data and techniques have shown great potentials towards the efficient and accurate estimation of key water quality parameters for inland water systems.

In this study, the main focus is on shallow inland aquatic ecosystems, in which the physical processes taking place are extremely sensitive to small changes in water balance. Reviewing past literature, Wrigley and Horne (1974) were among the first to use multi-temporal, multi-sensor data to estimate the lake eutrophication phenomenon. Several research efforts have been reported in the literature which employ remote sensing approaches to estimate water quality parameters in lakes (Gons et al. 2008; Matthews et al. 2010; Lesht et al. 2013; Nobuhle et al. 2014), rivers (Olmanson et al. 2013), marine environment (Meguro et al. 2004) or artificial reservoirs (Nellis et al. 1998), with promising results. These studies were mainly focusing on the retrieval of specific water quality parameters such as: chlorophyll-α (Pozdnyakov et al. 2005; Giardino et al. 2007; Bresciani et al. 2011), dissolved organic matter (Kutser et al. 2005; Brezonik et al. 2015), turbidity (Chen et al. 2007), water clarity –the opposite of turbidity- (Olmanson et al. 2008; McCullough et al. 2012), and cyanobacteria (Dash et al. 2011; Matthews et al. 2012).

Recently, Majozi et al. (2014) determined spectral diffuse attenuation coefficient in a water column in order to map the eutrophic depth in Lake Naivasha, Kenya using Medium Resolution Imaging Spectrometer (MERIS) data. Also, Jay and Guillaume (2014) proposed a statistical method to map water column characteristics, including depth and water quality parameters, using hyperspectral remote sensing data. Their analysis obtained reliable estimations of water quality with respect to depth, especially in shallow aquatic systems. Palmer et al. (2015) were able to map phytoplankton phenology in Lake Balaton, Hungary, by using a 10-year set of MERIS observations. Luo et al. (2016)) applied remote sensing techniques using HJ-CCD and Landsat TM imagery, in order to monitor seasonal and inter-annual variations and the dynamics of aquatic vegetation types in Taihu Lake, China. Matthews et al. (2010) also used MERIS imagery in order to evaluate the performance of empirical and semi-analytical algorithms in the hypertrophic lake Zeekoevlei, in Cape Town. Wilkie et al. (2015) applied a model in Lake Balaton, Hungary, in order to produce a calibrated log(chlorophyll-α) spatial map from remote-sensing data and in-lake laboratory-analyzed data, using statistical downscaling. The results were promising in the majority of cases.

In addition, one should consider the current availability of open/free, high resolution, multispectral satellite data like Landsat 8 (with 30 m/15 m spatial resolution) and Sentinel-2 (with 20 m/10 m spatial resolution). Therefore, the main challenge is to exploit such data, develop and validate low-cost but reliable monitoring systems. Such tools will not only provide the opportunity to analyze data from satellite images and extract information on a regular basis, but will also have the ability to export information from images corresponding to prior years, when sampling in a particular aquatic system has not been conducted in the past (Zheng and Yuanling 2011).

Regarding the necessity to establish innovative approaches for the protection, restoration and monitoring of aquatic ecosystems in all member states, this was mainly imposed by the 2000/60/EC Water Framework Directive (WFD), requiring regular monitoring of water quality for all water bodies within a river basin. Remote sensing techniques have already provided evidence for the accurate estimation of water quality indicators such as chlorophyll-α, turbidity and dissolved organic matter, leading to a representative assessment of aquatic ecosystem environmental status (Giardino et al. 2001; Gons et al. 2002; Koponen et al. 2002; Brezonik et al. 2005; Wang et al. 2006; Hellweger et al. 2007). Regarding the European Policy Framework, there is solid acknowledgment of earth observation capabilities since satellite based water quality services can serve as a harmonized measure of several relevant water quality parameters, such as turbidity, suspended matter, organic absorption and chlorophyll concentration, and the ratio of green algae and blue algae, which are already used as proxies for the ecological status defined in the WFD.

The aim of this study was to develop and validate a predictive relationship between physicochemical in-situ measurements, with emphasis on chlorophyll-α, and satellite data. Therefore, advanced remote sensing methods were employed for water quality estimation through the development of a long-term monitoring protocol for aquatic systems of high interest.

2 Area of Study, Materials and Method

The proposed methodology focuses on inland aquatic systems, and specifically, the emphasis is given in shallow lakes due to the lack of strong vertical stratification, as the water quality characteristics could be described as homogeneous in depth. The implementation of this analysis was performed in Lake Karla, Greece, which is located in the lowest part of Thessaly plain, and up to 1962, when it was dried, it was considered to be one of the most important wetlands in Greece. Watershed surface runoff and floodwaters of Pinios River were the main freshwater suppliers of Lake Karla. In 1962, a complete drying of the lake took place, in order to provide additional agricultural area.

The decision to restore part of the former lake was taken in the early 80s, but the construction works began a few years later. The rehabilitation of the former lake Karla has been funded by the Operational Program ‘Environment’, which was approved by the European Commission for the period 2000–2006. The plans dictate that the restored lake should meet the goals of flood protection, wetlands conservation, fulfillment of irrigation needs and the need for drinking water supply. The new reconstructed Lake Karla lies between latitude 39°26’49″ to 39°32’03′ N and longitude

22°46’47″ to 23°51’50″ E, and has a surface area of 38 km^2, while its perimeter is 30.55 km. The hydrological basin of Lake Karla has a total area of 1171 km^2, of which more than 600 km^2 comprise a southern flat plain, while the eastern part is surrounded by mountains and hills. It is mainly characterized by its shallow depth, with a maximum water depth of 4.5 m and a mean depth of 2 m (Fig. 1). Nowadays, its main sources of freshwater are surface runoff from the drainage area, direct precipitation and overflow from Pinios River. However, the obtained water quantities are considered limited, resulting in severe water quality and quantity problems affecting primarily the biodiversity of the lake (Mellios et al. 2015).

2.1 In-situ, Ground-truth Data

Field monitoring studies have been conducted from 2011 to 2014 and data acquired has been presented in previous studies (Sidiropoulos et al. 2012; Chamoglou et al. 2014). Moreover, field data sets were also obtained from the Management Body of Lake Karla database (www.fdkarlas.gr), along with observed events in macroscopic scale (massive fish kills, rainfalls, inputs etc.). Data involve mainly abiotic parameters such as pH, conductivity, D.O., inorganic nitrogen compounds (NH_4 and NO_3), total phosphorus and also chlorophyll-α, as an indirect index of algal biomass. Conductivity, pH and D.O. concentrations were measured in-situ by electrode probes (YSI, USA), while concentrations of nutrients and chlorophyll-α were determined based on laboratory analyses. Moreover, multitemporal, multispectral, remote sensing Landsat data have been exploited towards the establishment of a standardized, cost-effective, monitoring process of key water quality parameters. Based on concurrent field and satellite data acquisition campaigns, multiple in-situ, analytical, hyperspectral and satellite observations were processed and fused towards the establishment of concrete regression models between remote observations and physico-chemical measurements.

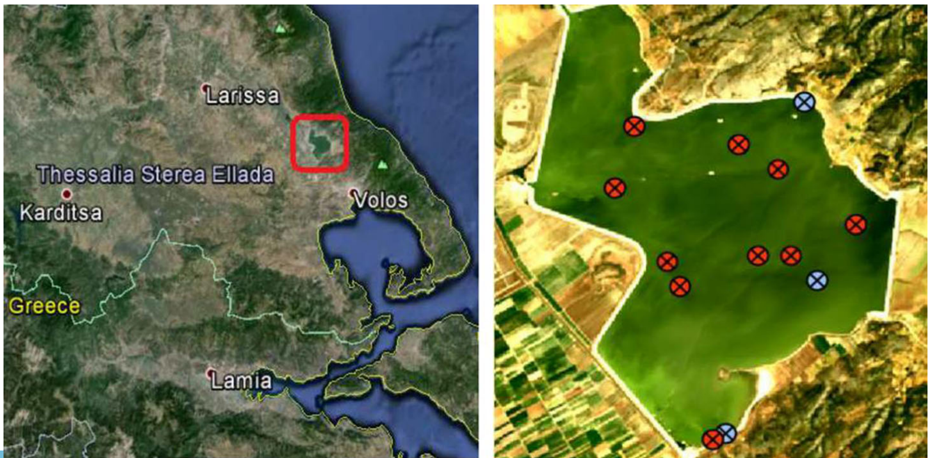

Fig. 1 Lake Karla is located in central Greece (*left*). In-situ sampling locations (*right*): permanent (in *blue* colour) and non-permanent (*red* colour) (Source: Google maps & USGS respectively)

2.2 Remote Sensing Data

One of the main approaches used in the water quality estimation, also implemented in the current paper, is the creation of empirical algorithms, thus, relating satellite imagery data with water quality parameters, a process which is rather field-dependent (Giardino et al. 2007). In other words, it is a form of data fusion, as it combines information from different sources (Wilkie et al. 2015). For the purposes of this analysis, remote sensing data were obtained from Landsat 7 (L7) and Landsat 8 (L8) imagery acquired from 2011 to 2014 (Table 1). The data were acquired from the U.S. Geological Survey (USGS) free of charge. Radiometric and atmospheric corrections were consequently performed on the remote sensing data, as specified by standard protocols.

High correlation rates were established between satellite and in-situ sampling data. Linear regression equations were created by correlating ground-truth data with corresponding reflectance values acquired from the equivalent point in the satellite imagery. Multiple combinations of the spectral bands were used. Meanwhile, the bands of the hyperspectral data were converted to correspond to the satellite's, so that both datasets were comparable, in order to examine the consistency of the equations among the datasets. The model which yielded the best results was the first one. Therefore, its equations which yielded the highest correlations per key water quality parameter were implemented on the satellite imagery, creating multi-temporal geospatial maps with the estimated concentrations per date. The maps were consequently evaluated using the remaining ground truth data and, when needed, the appropriate feedback was carried out before the creation of the final product (Fig. 2).

3 Results and Discussion

3.1 Quantitative Evaluation of Remote Sensing Products

Preliminary results of the present analysis showed that water quality indicators such as chlorophyll-α, dissolved oxygen, conductivity, ammonium and pH, were strongly correlated ($r^2 > 0.80$) with Landsat band ratios, while total phosphorus and nitrates yielded lower correlations ($r^2 = \sim 0.55$). Nonetheless, while NH_4 showed strong correlations, when the equations were applied on the Landsat imagery, the results were quite dissimilar to the sampling, thus proving it to be a rather sensitive parameter. However, it should also be considered that the ground-truth data were collected from point locations, while a Landsat pixel is equivalent to an area of 30 × 30 meters.

In particular, results for chlorophyll-α demonstrated satisfying correlations for L7 ($r^2 = 89.80$ %) and L8 ($r^2 = 78.06$ %), while, when compared with the in-situ ground-truth data, the calculated chlorophyll-α levels were slightly overestimated with L7 data and slightly underestimated with L8 data. The reliability of the developed model is boosted by the fact that the calibration and validation data series consist of multiple images per year, for a time period of 4 years (approx. 30 maps), resulting in ameliorating the compatibility process, whereas in a number of similar approaches reported in the literature, the data series validation was limited to few satellite images (Koponen et al. 2002). A significant number of earth observations are in good

Table 1 Satellite data employed and acquisition dates

Year	2011									2012						
Date	Feb 12	April 24	June 20	June 27	July 13	Jul 22	Aug 14	Aug 23	Sept 15	Mar 25	Apr 19	May 5	June 22	July 15	Sept 1	Oct 3
Satellite	Landsat 7															

Year	2013						2014									
Date	May 15	June 16	June 17	June 24	July 10	July 11	Aug 11	Feb 12	Mar 16	Mar 23	May 10	May 26	June 11	Aug 14	Aug 23	Sept 24
Satellite	Landsat 7		Landsat 8			1.7	Landsat 8									

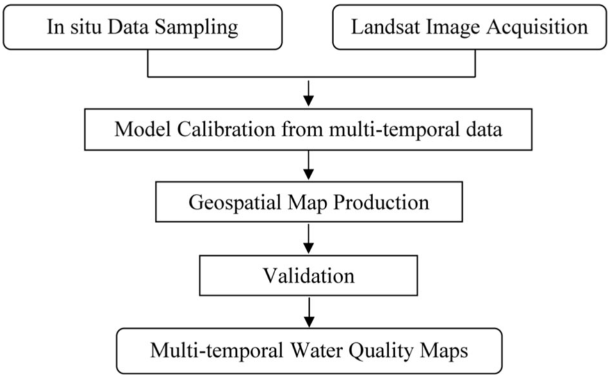

Fig. 2 The flowchart of the developed mapping procedure

agreement with water quality field data over many time periods, demonstrating that the developed model is able to produce reliable water quality maps for Lake Karla (Table 2).

During our experiment we tested more than 140 spectral band combinations of Landsat 7/8 against in-situ data. The ones which yielded the best results were used in the creation of the maps. The main remote sensing indices that yielded robust results were (R835, R660), (R835, R2220), (R835, R1650), (R485, R560, R660, R835), (R560, R835) for L7 and (R655, R560), (R480, R560, R655), (R560, R865),

Table 2 Compatibility between field and satellite data based on a qualitative evaluation. Quantitatively the threshold (regarding r^2) were approximately set to Yes: >80 % & No: <80 %. Mismatches were due to frequent cyanobacterial blooms and observed mainly on the quite shallow parts of the lake

Acquisition date	Compatibility of field and satellite data
12 Feb. 2011	Yes
24 Apr 2011	Yes
20 Jun 2011	No
13 Jul 2011	No
14 Aug 2011	Yes
23 Aug 2011	No
15 Sept 2011	Yes
25 Mar 2011	Yes
22 Jun 2012	Yes
15 Jul 2012	No
1 Sept 2012	Yes
3 Oct 2012	No
15 May 2013	Yes
16 Jun 2013	Yes
11 Jul 2013	Yes
23 Mar 2014	Yes
11 Jun 2014	No

Table 3 Sensor-specific band combination and established correlation for Chl-α estimation

Landsat 7 Band combinations	r^2	Landsat 8 Band combinations	r^2
R835/R660	89.80	R560-R865	78.06
(R835/R660) + R1650	89.60	R480-R560	76.65
R835/R2220	82.49	R560-R480	76.65
R835/(R485 + R560 + R660)	82.21	R440-R560	72.90

(R865, R1690), (R480, R560), (R440, R560) for L8 (Table 3). The final equations used for the derivation of chl-α maps from satellite data were the following:

$$y = 391.3413\left(R835 \big/ R660\right) - 138.9378(L7\ \text{data}) \quad (1)$$

$$y = 127.2997(R655/R560) - 49142(L8\ \text{data}) \quad (2)$$

3.2 Multi-temporal Evaluation of Delivered Geospatial Maps

An attempt to produce multi-temporal geospatial maps in Lake Karla was performed based on the developed model, since chlorophyll-α is a phyto pigment present in all algal groups in freshwaters. Chlorophyll-α shows distinct absorption maxima in the blue wavelength range at 440 nm and in the red wavelength range at 678 nm, leaving a green reflectance maximum, due to cell internal scattering processes (i.e., biomass). Chlorophyll-α forms a good descriptor for primary productivity and could be linearly related to biomass. Moreover, the excessive algal growth is observed as the main symptom of eutrophication, but at the same time algal biomass dynamics is an essential tool for eutrophication management. Remote sensing data analysis showed that chlorophyll-α concentrations displayed a wide variance in field measurements (from 16 to 400 mg/cm^3), indicating, generally, high values during summer months, while the same pattern is also obvious from the geospatial chlorophyll-α concentration distribution in the lake, confirming its eutrophic to hypertrophic status according to the OECD (1982) and TSI Carlson (1977) classification schemes.

Deviations from this pattern are mainly due to the conditions during the time of measurements (time-specific events) and also the spatial characteristics of the lake (site-specific). For example, the organic load inflows through the main ditches that are affecting the north-western and the eastern part of the lake, could be justified by produced maps, depicting chlorophyll-α concentrations on June 17th, June 24th and July 11th of 2013. Unfortunately, oligo-trophic values were not measured in Lake Karla and cannot be compared with the corresponding satellite data.

On the other hand, meso-trophic values were well correlated (February and April 2014), while extreme in-situ values corresponding to strong hypertrophic conditions (> 200 mg/m^3) were underestimated in some occasions, concluding that new classification schemes should be applied for heavily modified reservoirs with high nutrient loads such as Lake Karla (Fig. 3).

The multi-temporal satellite data analysis performed in Lake Karla indicated that the observed chlorophyll-α fluctuates throughout the year. The spatio-temporal analysis revealed

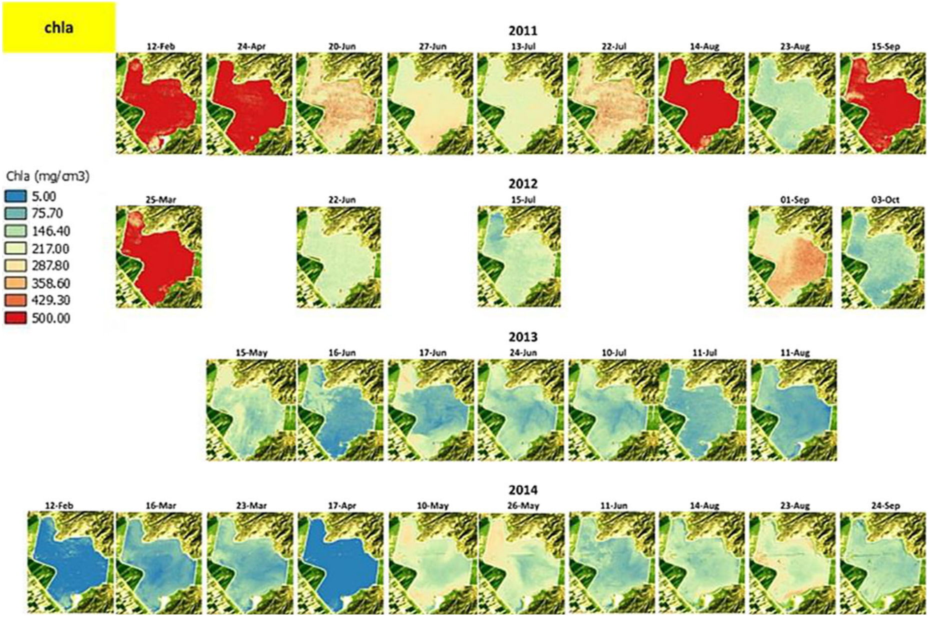

Fig. 3 Chlorophyll-α multi-temporal geospatial maps for Lake Karla

a gradual slight decline in average chlorophyll-α concentrations from the beginning of 2011 and onward. The areas of the lake that were affected to a greater extent are the shallow ones. After the precipitation periods, a slight improvement could be observed, in terms of chl-α, explaining a consequent improvement of the turbid conditions. It is worth mentioning that throughout almost the entire monitoring period (2011–2014) the only freshwater sources in the lake were the precipitation and the surface runoff, while the retention time was almost infinite since there was not any outflow except evaporation. Along with the decrease in mean chlorophyll-α levels, a similar gradual decrease was also detected on the peak concentration levels, as well.

The established relation between remote sensing and in-situ field data was based on linear regression models with high correlation rates (i.e., $r^2 > 89$ % for chl-α), while certain mismatches occurred due to frequent cyanobacterial blooms and were mainly observed on the quite shallow parts of the lake. In particular, cyanobacterial blooms are very common in Lake Karla persisting from early spring to mid autumn (Papadimitriou et al. 2013). The findings of this analysis are in accordance with those of Kutser (2004), according to whom a large uncertainty associated to chlorophyll-α detection occurs during cyanobacterial blooms, leading to over/underestimation of remote satellite observations. Cyanobacteria are strongly affected by weather conditions regulating their buoyancy and forming also dense scums just below water surface or on the surface, thus resulting in rough chlorophyll-α assessment.

4 Conclusions

Multi-temporal, multispectral, remote sensing Landsat data have been exploited towards the establishment of a standardized, cost-effective, monitoring process of key water quality parameters in shallow lake ecosystems. Landsat 7 and Landsat 8 satellite data, along with hyperspectral and ground truth data, covering a time period of 4 years, were processed and fused under a quantitative evaluation framework. The results were quite promising, as concrete prediction models were created for chlorophyll-α. While the results are rather satisfying, the need for better distributed sampling stations is pointed out, as the current ones do not provide a view on the fluctuations throughout the entire water body of Lake Karla. By using satellite imagery, this methodology presents a low-cost water monitoring system that could provide a frequently updated water quality parameters geo-database, eventually leading to an efficient development of water management plan for protection and restoration of sensitive aquatic ecosystems.

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