MONITORING WATER QUALITY PARAMETERS OF LAKE KORONIA BY MEANS OF LONG TIME-SERIES MULTISPECTRAL SATELLITE IMAGES

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ABSTRACT

In this study, a comprehensive 30-year (1984–2016) water quality parameter database for Lake Koronia – one of the most important Ramsar wetlands of Greece – was compiled from Landsat imagery. The reliability of the data was evaluated by comparing water Quality Element (QE) values computed from Landsat data against *in situ* data. Water quality algorithms developed from previous studies, specifically for the determination of Water Temperature and pH, were applied to Landsat images. In addition, Water Depth, as along with the distribution of floating vegetation and cyanobacterial blooms, were mapped. The performed comprehensive analysis posed certain questions regarding the applicability of single empirical models across multi-temporal, multi-sensor datasets, towards the accurate prediction of key water quality indicators for shallow inland systems. Overall, this assessment demonstrates that despite some limitations, satellite imagery can provide an accurate means of obtaining comprehensive spatial and temporal coverage of key water quality characteristics.

Keywords: Lake Koronia, Landsat, water quality, Water Framework Directive

Received 20 March 2017; Accepted 14 September 2017; Published online 4 October 2017

1. Introduction

Both natural and artificial lakes supply over 90% of Earth's liquid surface freshwater, facilitating human activities and economic development, while serving as essential habitats for a large variety of biota. Lake ecological status affects their value as drinking water reservoirs for irrigation, fishery and recreation. For this reason, the alleviation of the degradation of surface and ground waters was one of the main objectives outlined in the Water Framework Directive (WFD, 2000/60/E.C.). WFD aims at protecting surface waters of Member-States and ensuring that there shall be no further deterioration in water quality, structure and function of aquatic ecosystems. Concerning lake ecosystems, the WFD specifies Quality Elements (QE, Annex V) for the classification of ecological status, which include biological and hydro-morphological elements, as well as ancillary chemical and physico-chemical information.

In many cases, lake water quality data either do not exist or are very limited. Only a small percentage of lakes are regularly monitored by *in situ* measurements and, as a result, historical water quality data are sparse, sporadically collected or non-consistent for most lakes. Nevertheless, a fundamental part of this "missing" information has been recorded in the historical archives of satellite imagery, enabling the extraction of some historical water quality information over lakes, which have never been retrieved before.

Coupled with advanced processing methods and improved sensor capabilities, an increasing development in remote sensing of lake quality parameters has been observed during the last decades (Dekker and Seyhan 1988; Fuller and Minnerick 2007; Bresciani et al. 2011). Satellite remote sensing can be used to map and monitor QE, with the aim of reconstructing their historical variation and assessing their distribution and patterns.

Inland natural waters are complex physical–chemical–biological systems, including living and non-living elements that may be present in aqueous solutions or in aqueous suspensions (Younos & Parece 2015). Lake water contains numerous dissolved mineral salts and organic substances, suspensions of solid organic and inorganic particles, including various live microorganisms, as well as gas bubbles and oil droplets. The water components participate directly in the interactions with solar radiation in that they absorb or scatter photons. Also, they may participate in diverse geochemical and biological functions, for example, in photosynthesis, which regulates the circulation of matter in these ecosystems and affects the concentrations of most of the optically active water components. Four components of aquatic ecosystems are the major cause of light absorption in natural waters (Kirk 2013): a) Water, b) Photosynthetic biota (phytoplankton and Macrophytes), c) Tripton, and d) Dissolved pigments. Remote sensing sensors measure the water leaving radiance (*Lu*), which is the upwelling radiance emerging from the water surface, as well as the radiance derived from scattering processes in the atmosphere. The estimation of water quality derived from remote sensing measurements is based on water quality parameters that have an effect on water-leaving radiance. The absorption and scattering

https://doi.org/10.14712/23361980.2017.14
Perivolioti, T.-M. – Mouratidis, A. – Bobori, D. – Doxani, G. – Terzopoulos, D. (2017): Monitoring water quality parameters of Lake Koronia by means of long time-series multispectral satellite images
AUC Geographica, 52, No. 2, pp. 176–188

properties of the medium are described by its inherent optical properties (IOPs).

As some of the lake QE can be determined using remote sensing with a reasonable accuracy, remote sensing techniques may be integrated in the monitoring programs defined by the WFD (Giardino et al. 2007).

The aim of this study was to reconstruct/create a historical lake water quality parameter profile, by adopting a remote sensing time-series approach. The purpose was to monitor lake QE, such as Water Temperature and pH, using multispectral Landsat images from 1984 to 2016. In addition, Water Depth, as well as the distribution of floating vegetation and cyanobacterial blooms were mapped. The remote sensing data were Landsat-5/TM (Thematic Mapper), Landsat-7/ETM (Enhanced Thematic Mapper), Landsat-8/OLI (Operational Land Imager) and Landsat-8/TIRS (Thermal Infrared Sensor) images. The investigation took place over a Ramsar-protected ecosystem, i.e. Lake Koronia, Greece.

Along with mapping the temporal and spatial QE variability of lake Koronia for the past three decades, the results are expected to contribute to: (a) the definition of optimal image processing routines for QE estimation and external calibration procedures based on multispectral satellite images and *in situ* measurements, (b) the assessment of the correlation of water quality parameters with Landsat bands (c) the establishment of procedures that shall allow the compatibility of past satellite information with water quality information derived from future Sentinel-2 data.

2. Study area

Lake Koronia (40°41′N, 23°09″E) is the one of two lakes composing the Mygdonia Basin. It is situated 30 km north-east from Thessaloniki (Figure 1), Central Macedonia, northern Greece. Koronia is an elliptic-shaped, shallow, polymictic lake, with a surface of 29 km^2.

The wetland of Lake Koronia has a tremendous ecological importance, which has been worldwide recognized. Namely, it is protected by the Directives 79/409/EEC and 92/43/EC, the RAMSAR Convention and is categorized as a Natura 2000 site. It used to be one of the four largest lakes in Greece, occupying an area of 46.2 km^2, but in recent years, due to low precipitation and the water over-consumption, it has become an intermittent lake. Hence, Lake Koronia has highly variable hydrologic conditions. This leads to rapid changes in physical and chemical conditions in the lake water column. The regular dry out and re-filling of the lake creates an extreme state of flux which prevents the establishment of stable states observed in more typical lakes (Zalidis et al. 2014).

Overall, Lake Koronia faces a number of serious environmental issues and water management problems, which cause changes to this unique and invaluable ecosystem. The degradation of Lake Koronia is caused, mainly, by inflow pollutants (municipal, industrial, agricultural) and by the overpumping of water for irrigation. The surface water of the lake as well as the groundwater cannot sustain the unsystematic economic growth of the area resulting in water depletion, negative water balance, environmental degradation and very serious economic problems (Mylopoulos et al. 2007).

The water quality of Lake Koronia is monitored by the Management Authority of Lakes Koronia-Volvi (M.A.L.K.V.), which was established in 2002 under Law 3044.

3. Data and Methodology

3.1 Lake reference data

The spatial and temporal resolution of *in situ* data that have been collected over Lake Koronia during the past decades is limited. For the purposes of this study, *in situ* measurements were performed at three sampling stations in Lake Koronia on 30 November 2015. The location of the sampling points was selected taking into account the adequate spatial coverage of the lake. Two sampling stations were located in medium depth points (Station 1, Station 2) and one sampling station was located in the deepest point (DP) of Lake Koronia (Figure 1).

For the determination of the sampling station coordinates, a handheld Garmin GPSMap76S receiver was used. Concerning the reduction of the location error, the coordinates were determined three times per sampling point and the average value was considered.

The QE Water Temperature (°C), pH and Water Depth (m) were measured just below the lake surface. Oxi 3205, WTW, Dissolved Oxygen (D.O.) meter, including integrated temperature sensor, was used to perform Temperature measurements. For pH measurements a pH meter 3110, WTW was used.

In addition to the field data that were collected on 30 November, *in situ* data of the parameters Temperature and pH, were provided by the M.A.L.K.V. These parameters were monitored monthly from two sampling stations (Akti Analipsis, Vasiloudi) (Figure 1) and as a consequence there was an adequate database of *in situ* estimation that could be used for satellite data calibration/validation. The data that were provided by the M.A.L.K.V. correspond to the period from 27/4/2009 to 2/11/2014. Due to the absence of *in situ* measurements of the QE Secchi Disk Depth and Chl*a*, field data available from relevant publications were used (Michaloudi et al. 2009; Michaloudi et al. 2012; Moustaka-Gouni et al. 2012). Michaloudi et al. (2009) and Michaloudi et al. (2012) present values of physical and chemical parameters in water samples from the deepest point of Lake Koronia during the period from March 2003 to December 2004. Moustaka-Gouni et al. (2012) present phytoplankton data that were collected in years 2003–2007 and 2009–2011.

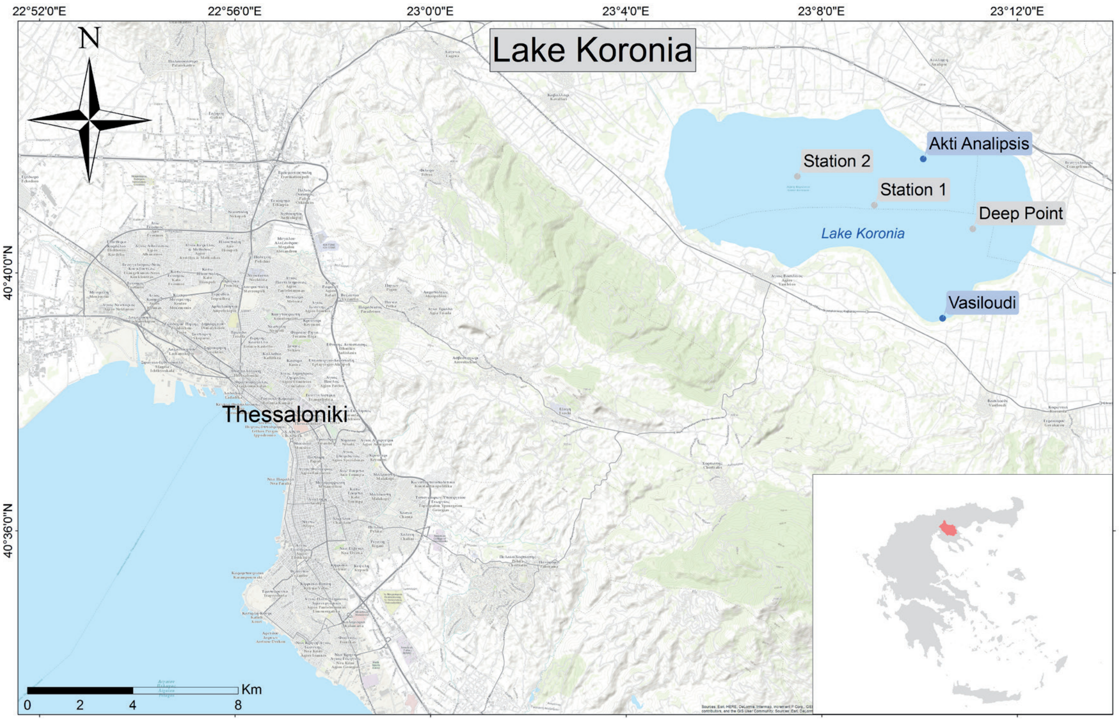

Fig. 1 Map of Lake Koronia and the locations of the M.A.L.K.V. sampling stations (Blue), as well as the sampling points used in sampling procedures on November 30 (Grey), in Lake Koronia.

Field data collected within one day of the satellite overpass yield the best calibration results, while the larger number of field measurements with a longer time window offsets some of the loss of correlation (Kloiber et al. 2002). All field data used in this study were collected within ± 1 day of a Landsat image acquisition date. The *in situ* data collection on 30 November 2015 was carried out during (within few hours from) the Landsat-8 overpass.

3.2 Satellite data

The satellite data (Level 1T) of Landsat-5/TM, Landsat-7/ETM+, Landsat-8/OLI and Landsat-8/TIRS were used, as these provide the longest consistent temporal record of space-based surface observations. Typically, only two Landsat scenes were required to cover lake Koronia (path/row: 184/32,183/32). Appropriate satellite data were identified using EOLI-SA and USGS Global Visualization Viewer. EOLI-SA's satellite data were provided by ESA (ID: 31068). A total of 715 multispectral satellite images were selected, spanning the period from 1984 to 2016 and fulfilling the following criteria: (a) less than 70% overall cloud coverage and (b) low cloud coverage over the study area.

3.3 Image pre-processing

Digital Numbers (DNs) from image data were converted to spectral radiance (L_λ) and top-of-atmosphere (TOA) reflectance (ρ_P) (Chander and Markham 2003; Zanter 2015).

Attempts to obtain Surface Reflectance from the initial DN values were made using software developed specifically for this purpose, i.e. LEDAPS (Masek et al. 2013) for Landsat-5 and -7 images. However, a strong discordance of the processed images was observed when compared against *in situ* data and this observation resulted in the exclusion of the surface reflectance products for further calculations, in favor of TOA-reflectance values, which were derived solely by algorithmic processes developed by the authors, according to the officially designated mathematical models previously mentioned.

3.3.1 Geometric correction

Two cloud-free Landsat/TM images (path: 183/184), were geometrically corrected using a) Ground Control Points/GCPs, which were available from Mouratidis et al. (2010) and b) a processed 3-arcsecond SRTM (Data Version 4.1) DEM, available from CGIAR-CSI (Jarvis et al. 2006). The GCPs were collected in 2008 (Mouratidis et al. 2010). With the intention of facilitating GCP identification, the selected Landsat/TM images were acquired in 2008 as well. The selected images had minimum or no cloud coverage. To obtain adequate accuracy during geometric correction, GCPs were evenly distributed in the image. The process was concluded, when accuracy better than 0.5 pixel (15 m) had been achieved. These two orthorectified Landsat/TM images were subsequently used, in order to georeference, via an automatic image-to-image co-registration, some of the other downloaded Landsat images which were characterized by geolocation errors of several km.

3.3.2 Area of Interest

All Landsat images were cropped, setting as Area of Interest (AOI) a rectangle area surrounding Lake Koronia and considering its maximum extend, as depicted on topographical maps of the '70s and '80s (Hellenic Military Geographical Service/HMGS, scale 1:50,000). The selected AOI was chosen to be as small as possible, in order to facilitate further processing of the long time-series. Images, in which the boundary of the Lake was not clearly visible, were excluded from further processing.

3.3.3 Water-only image

Subsequently, water-only images were created, in order to delineate the water body and extract water features. In addition, water-only data were used for the creation of pixel level condition maps of Lake Koronia. In order to extract a water-only image from each AOI Landsat image subset, from 1984 to 2016, a function was developed in MATLAB. Firstly, a broad separation of lake water from land areas was performed using Normalized Difference Water Index (NDWI) (McFeeters 1996):

$$\frac{\mathrm{GREEN} - \mathrm{NIR}}{\mathrm{GREEN} + \mathrm{NIR}}$$

where GREEN is the band that includes reflected green light and NIR is the reflected near-infrared radiation. Positive values pertain to water features and zero or negative values to vegetation and soil.

As the optical properties of Lake Koronia vary both temporally and spatially, the water extraction cannot be based on one standardized cut-off value/threshold (usually value 0 for NDWI). Consequently, the isolation of water pixels was accomplished by performing k-means unsupervised classification, to all NDWI Landsat images. In order to avoid the inclusion of separate water areas on the same image, which may not belong to Lake Koronia, but are probably randomly distributed small-scale water occurrences on the images, a neighbor expansion method was implemented using MATLAB. By employing k-means classification, the cut-off value for each NDWI image was fluctuating around zero (but not being necessarily exactly equal to zero) – thus taking into account the variation of the optical properties of Lake Koronia. Furthermore, the neighbor expansion method that resembles a typical Floodfill algorithm (Godse and Godse 2008) was used to isolate the main body of Lake Koronia, before the next processing step.

3.4 Water quality parameters extraction from multispectral satellite data

The estimation of lake QE was based on the application of an empirical or statistical approach for remote sensing data analysis. Algorithms, statistically modelling relations between combinations of spectral bands and measured water QE, as well as procedures developed from previous studies, were applied to radiometrically calibrated pixels of Lake Koronia.

Parameters such as pH, Water Temperature, Lake Coverage, Water Depth were selected as primary representative characteristics of the status of Lake Koronia. The selection of the parameters was based on their contribution as key-variables to lake water quality.

Temperature was estimated from all Landsat images, using the respective thermal bands and applying the calibration methods described in NASA (1999), Chander and Markham (2003) and Zanter (2015). Linear regression analysis was performed for the complete, unified time series of the temperatures of Lake Koronia.

In order to measure the pH of Lake Koronia the following formula was used (Khattab and Merkel 2014):

$$\mathrm{pH} = 9.738 - 0.084 \cdot \mathrm{SWIR}$$

where SWIR corresponds to the DN value of the shortwave infrared band.

Furthermore, the distribution of aquatic vegetation and Cyanobacterial blooms was mapped. Pixels were classified into four groups: (a) floating vegetation, (b) submerged vegetation, (c) lake water and (d) Cyanobacterial bloom zones. For the separation of the "mask pixels" into four classes, a three-step process was followed. Firstly, water pixels and vegetation pixels were distinguished using Floating Algae Index (FAI), modified for Landsat images (Oyama et al. 2015):

$$\mathrm{FAI} = R_{rc,B4} - \left[R_{rc,B3} + (R_{rc,B5} - R_{rc,B3}) \cdot \frac{(\lambda_{B4} - \lambda_{B3})}{(\lambda_{B5} - \lambda_{B3})}\right]$$

where λ_{Bi} is the center wavelength for the i-th band of Landsat-5.

FAI pixels were sorted according to class value size using k-means classification. The pixels in the class with higher FAI values were classified as vegetation.

Afterwards, vegetation pixels, which were distinguished using FAI, were separated into submerged and floating vegetation, using the blue/green band ratio (Cho 2007). Since the presence of vegetation in water alters the relationship between depth and reflectance in blue and green bands, it was experimentally shown that a ratio between bands Blue and Green provided the highest degree of correlation with vegetation cover in shallow waters. Vegetation pixels were separated into two classes, using k-means classification. Lower Blue/Green reflectance ratio pixel values were classified as SAV, while higher values where categorized as floating vegetation.

Finally, aquatic Macrophytes and cyanobacterial blooms were detected using the Normalized Difference Water Index $(\mathrm{NDWI})_{4,5}$ (Oyama et al. 2015).

$$\mathrm{NDWI}_{4,5} \frac{(\rho_{NIR} - \rho_{SWIR})}{(\rho_{NIR} - \rho_{SWIR})}$$

where $(\rho_{NIR}, \rho_{SWIR})$ is the reflectance of near-infrared and short-wave infrared bands

An $\mathrm{NDWI}_{4,5}$ threshold of 0.63 is shown to syccessfully detect aquatic Macrophytes when their concentration in

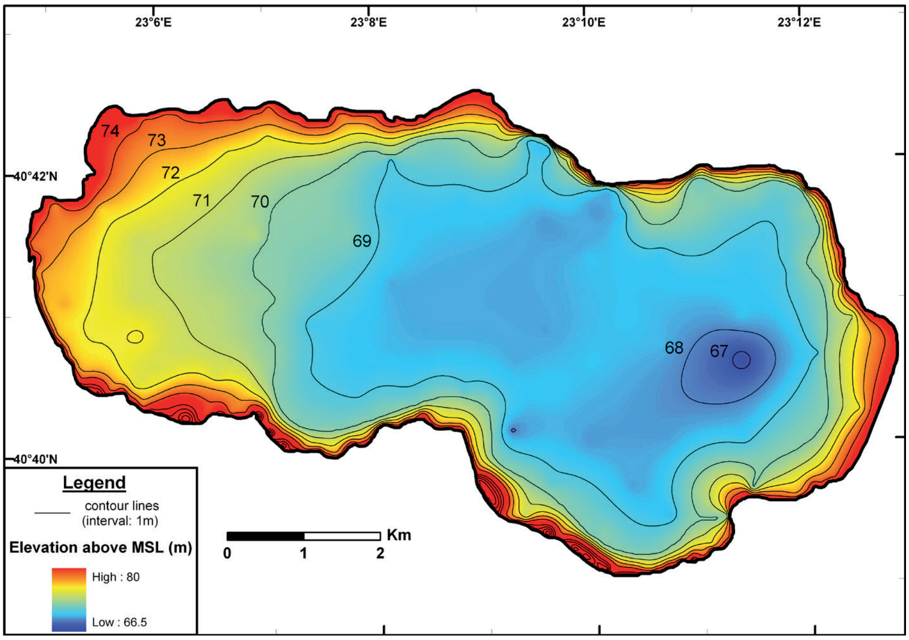

Fig. 2 Digital elevation model of the Lake Koronia bottom.

the lake is larger than 10% (Oyama et al. 2015). Consequently, the floating vegetation pixels were separated in two classes using k-means classification with respect to $NDWI_{4,5}$ values. The class with values larger than 0.63 corresponds to Cyanobacterial blooms, whereas the class with lower values corresponds to aquatic Macrophytes.

An analytic band-ratio depth model was determined by following the model described in Stumpf et al. (2003). Electromagnetic radiation intensity is attenuated exponentially as a function of optical depth along the emission path, as well as the wavelength of the radiation. Different wavelengths are attenuated at different levels, as a result of variable water absorption. As a consequence, it is expected that the ratio of the logarithms of reflectance in two different bands shall vary linearly with depth over water. This provides a method for the calculation of the lakebed terrain.

The logarithmic ratio used to study the bathymetric characteristics of Lake Koronia was blue/red. The ratio values were calculated for the pixels of the water area of Lake Koronia (22/5/1986) and a digital elevation model (Figure 2) of the lake bottom, created from 1:50,000 scaled maps of the HMGS from the ’70s, was used to extract bathymetric data for the same pixels. A linear model was fitted in value pairs of reflectance logarithm ratios and depths, and the model parameters were recorded. The model was applied on the same satellite image to map the reliability of the model with respect to the original depths. The errors were found to lie within reasonable ranges, in comparison, for example, to Tang and Pradhan (2015).

The QE variations over the sampling stations in pairs of time-series from *in situ* data and data derived from Landsat satellites were calculated. The satellite-derived values were calculated as 3 × 3 averages over the stations’ matching pixels.

4. Results and Discussion

4.1 Satellite data validation using *in situ* measurements

The values of the hydromorphological and physico-chemical parameters, measured on 30 November, 2015 at three sampling stations are given in Table 1. No significant deviations were observed between the values at the three sampling stations for most of the parameters. This could be attributed to the relatively intense weather conditions at the time of the sampling, which were characterized by relatively strong winds and water currents, causing significant relocations of large water masses, thus smoothing out the parameter variations over the lake area.

These values appear to have large deviations from the corresponding parameter values calculated from the Landsat-8 satellite image of the same day (Table 2). This was, in part, expected, due to the very prominent cloud artifact coverage of the image during the day of overpass. Furthermore, it should be noted that this disagreement between the values may be coincidental, owing to a multitude of sources of error in both the *in situ* and the satellite data and processing procedures, and that a larger number of both *in situ* and satellite measurements have to be available to avoid circumstantial inaccuracies. Comparison of a larger data series should enable the delineation of a more definitive, reliable and conclusive picture of the relation between pH values acquired through these different methodologies. Apart from that, it was impossible to calculate temperature data because the TIRS instrument of the Landsat-8 satellite was not functional during that time period, since on November 1, 2015, the Thermal Infrared Sensor (TIRS) experienced an anomalous condition related to the instrument’s ability to accurately measure the location of the Scene Select Mechanism (SSM).

Tab. 1 Physical and chemical composition of *in situ* water samples (Station 1, Station 2, Deep Point) from Lake Koronia on 30 November 2015.

		Sampling Station		
Parameters	**Units**	**Station 1**	**Station 2**	**DP**
pH		8.54	8.54	8.52
Temperature	°C	11.1	11.1	11.3
Water Depth	m	2.3	2.1	2.2

Tab. 2 Comparison between *in situ* and satellite-derived data for pH.

	Sampling Station					
	Station 1		Station 2		DP	
Parameters	*In situ*	Satellite measurements	*In situ*	Satellite measurements	*In situ*	Satellite measurements
pH	8.54	5.4	8.54	5.8	8.52	5.81

Fig. 3 pH (1) and Water Temperature (2) variations over the two sampling stations (Vasiloudi, Akti Analipsis) in pairs of time-series (2009–2014) from *in situ* data and data derived from suitable radiometric calibration of the thermal bands of the Landsat satellites.

Figure 3 depicts the temperature and pH variations over the sampling station Akti Analipsis in pairs of time-series from *in situ* data, provided by Management Authority of Lakes Koronia-Volvi, and data derived from suitable radiometric calibration of the suitable bands of the corresponding Landsat satellites. In the case of Landsat-5/TM data, the pH values appear to deviate no more than 1 pH unit. The same limitations with above also apply for this parameter, which means that when the lake water level was relatively low, the station pixels typically refer to dry land, rendering the parameter calculation equations invalid.

In the case of Landsat-7 SLC OFF, the data appears to be scrambled and misleading. This is because, frequently, every few consecutive satellite images, the scan lines of invalid data cover the sampling station pixels, resulting in invalid measurements. The deviations could, also, be attributed to shortcomings of the derived parameter model equation. In the case of Landsat-8, the temporal overlap between the *in situ* and the satellite image derived data is even smaller in duration, primarily because the Landsat-8 mission is very recent in comparison to the data available from the sampling stations. The inconsistency of the data could be, too, attributed to the fact the water level of the lake was lower, often forcing the calculation to take place over very shallow waters.

It is also possible that, because the original equations were developed using Landsat-5 data, discrepancies arise from slight differences in the corresponding sensors of Landsat-7 and Landsat-8 satellites.

The only significant match between *in situ* and satellite-derived temperature values occurred for the sampling station of Akti Analipsis, when using thermal band radiation data from Landsat-5/TM thermal and Landsat-7/ETM+VCID-2 bands. The irregular (negative) values in the figures for the cases of Landsat-7 are attributed to the cases where the sampling station pixels are at a location with invalid satellite data, due to the Landsat-7 SLC malfunction.

The mismatch between the time-series values of Landsat-8 and the *in situ* data could be because of stray light. Since the launch of Landsat-8 in 2013, thermal energy from outside the normal field of view (stray light) has affected the data collected in TIRS Bands 10 and 11. This stray light increases the reported temperature by up to four degrees Kelvin (K) in Band 10 and up to eight K in Band 11. This can vary throughout each scene and depends upon radiance outside the instrument field of view, which users cannot correct in the Landsat Level 1 data product. Band 11 is significantly more contaminated by stray light than Band 10. It is recommended that users refrain from using Band 11 data in quantitative analysis including use of Band 11 in split-window surface temperature retrieval algorithms.

4.2 pH

Figure 4 depicts the time-series of satellite-derived average pH values of Lake Koronia. It is easy to distinguish an overall drop in pH in the case of Landsat-5 data over the period of approximately mid-1988 until the early 1990. Similar periods can be seen in Landsat-8 data. The Landsat-8 data appear to be out of place, with relatively unrealistic pH values. This observation once again validates the suspicion that the pH equation favours data from the Landsat-5 satellite. Although Landsat-7 SLC-ON derived data also appear realistic in relation to well-known *in situ* data over the area, data derived from Landsat-7 SLC-OFF images appear to produce distorted pH values. This can be attributed to both the Scan Line Corrector malfunction (as the designated point pixels may contain invalid data in many cases) and the presumed higher "affinity" of the equation model to Landsat-5 data.

Elevated pH values arise when the photosynthetic activity is very high (Scheffer 2004). Three major processes that affect the pH are photosynthesis, respiration, and nitrogen assimilation. The effects of photosynthesis and respiration on the pH depend largely on the carbonate–bicarbonate–carbon dioxide equilibrium (Lampert and Sommer 2007).

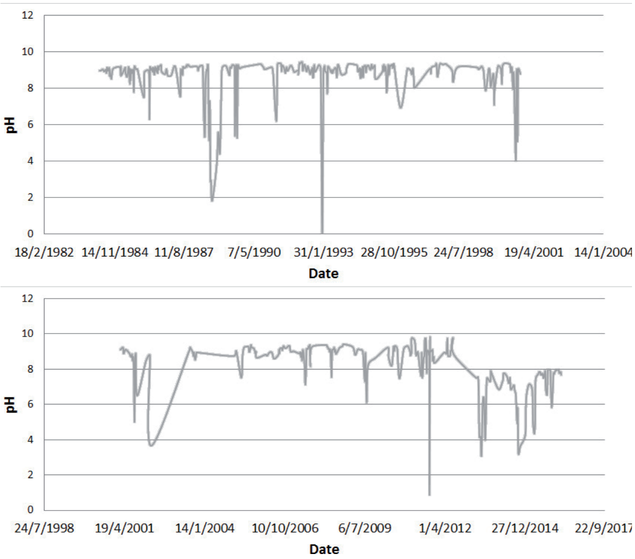

Fig. 4 The average pH values of Lake Koronia derived from Landsat images (1984–2016).

4.3 Temperature

Water surface temperature is the result of the energy balance at the water surface and heat transport mechanisms within the water body. Therefore, knowledge of it is required to characterize processes at the water surface. Figure 5 presents the average temperature time-series of Lake Koronia from satellite image derived data over a period of about 30 years. The seasonal pattern is clearly visible on the charts, with peak temperatures occurring during the summer seasons and minimums in winter seasons.

The temperature of the lake's water presented wide fluctuations over the course of the years, with values in the expected range, from a few degrees under 0 °C up to 25 °C, or even 30 °C. Meterological and climatic factors, including air temperature, cloud cover, and solar radiation, in addition to geomorphometric factors, such as lake surface area and depth, influence surface water temperatures in Lake Koronia. A statistically significant increase trend is observed in the temperature of Lake Koronia in the time interval between 1984 and 2016. The increase corresponds to a coefficient of 0.000422 (+/− 0.00022) per day ($p = 0.00015$), which is equivalent to an increase of about 1.54 (+/− 0.8) °C per 10-years. This can be attributed to the effects of the reduction, up to 90%, of Lake Koronia water volume (Mylopoulos et al. 2007).

A comparison of the Temperature values with data from Bobori (2001) shows a relatively fair accuracy, well within the limits of one standard deviation. In specific, the temperature from 5 stations in a period of two full years (of irregular observations), namely 1989 and 1990, from Bobori (2001) results in an average Temperature value of 16.90 ± 8.2 °C, whereas the corresponding overall average of the lake in the same time period in the current study results in a value of 14.78 ± 8.1 °C.

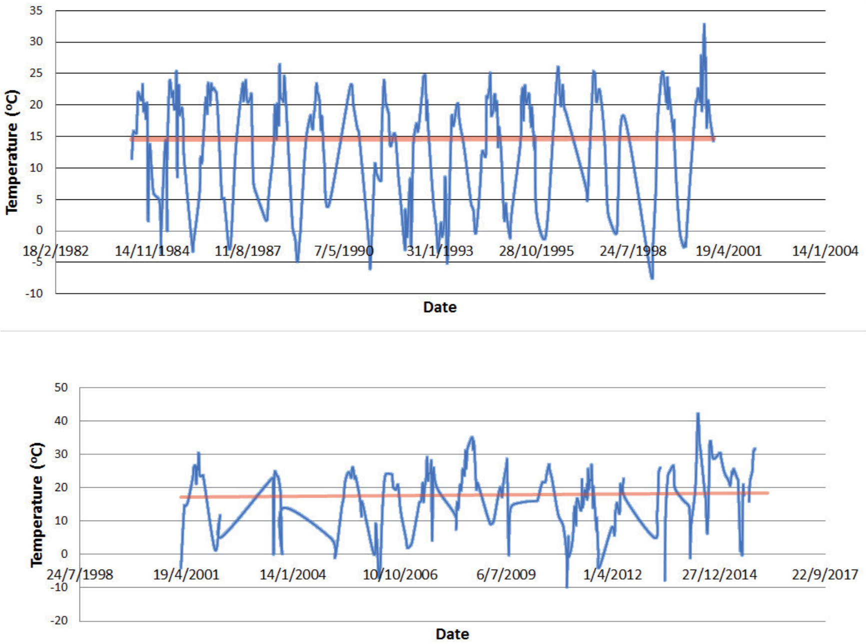

Fig. 5 The average temperature values of Lake Koronia derived from Landsat images (1984–2016).

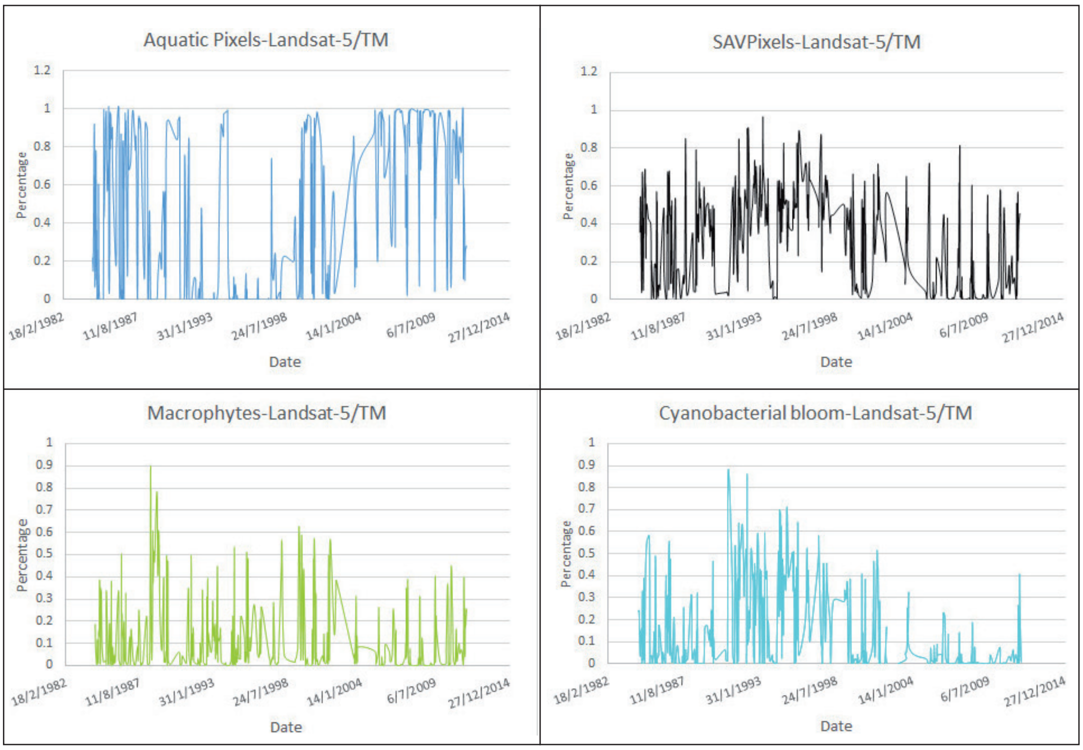

Fig. 6 The percentages of various coverage types (water, Submerged Aquatic Vegetation, Macrophytes, Cyanobacterial Blooms) of Lake Koronia surface derived from Landsat-5/TM images (1984–2011).

Furthermore, an investigation of Temperature data from Michaloudi et al. (2012) also reveals a fair accordance. An indicative example from Michaloudi et al. (2012) shows an average Temperature value of 24.1 °C in August and September 2003. The Temperature data of the present study resulted in an average Temperature value of 21.84 ± 2.35 °C during the same period.

4.4 Lake Coverage

Figure 6 depicts the time-series of the lake pixels as classified into water, SAV, Macrophytes and Cyanobacterial blooms. The data are presented in percentage of pixels of each class with respect to the total of the lake pixels. In general, a strong temporal variation in the 4 categories is apparent from all charts. There are extended time

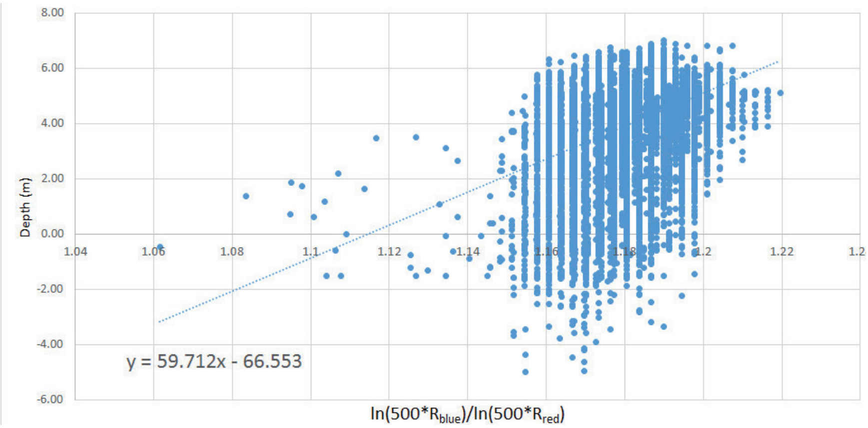

Fig. 7 Water Depth model of Lake Koronia (22/5/1986).

periods, during which the lake was increasingly covered with either Macrophytes, or Cyanobacterial blooms. An interesting observation is that pixel Macrophytes and Cyanobacteria never appear to covary. This contravariance between the two coverage types can be explained as the two organism species are antagonistic in nature. In the later years, the lake appears to have relatively clear water, with a notable exception between approximately August, 2014 to May, 2015, when there was an increase in Macrophytes coverage and Submerged Aquatic Vegetation. Similar observations can be made from the charts for earlier time periods.

4.5 Water Depth

The data plotted are logarithmic ratios (X-axis) against depth values over pixels (Y-axis) (Figure 7). The data pairs used for the fit are about 50,000, which is a very large amount of data for this kind of statistical calculations. Although this can strongly bias the data, it appears on the plot that there is an even balancing-out of relative outliers. The expected trend is effectively captured and the resulting equation can be seen on the plot.

Figure 8 depicts the error map of the extracted bathymetric model referred to in the previous two figures. The values of the lake pixels are calculated as the differences between the pixel 'actual' depth (from the DEM) and the depth calculated using the equation extracted from the log-ratio fitted model. It is encouraging to observe the fair accuracy of the model, as well as the very important pattern of higher errors close to the shores. The latter observation was expected and provides a validation of the model and is attributed to the much smaller difference in electromagnetic radiation attenuation between the two different wavelength bands of blue and red when the 'travelled' water column thickness is smaller. When light travels a larger distance in water, the much higher absorbance of the red band wavelengths in comparison to blue absorbance, due to much faster exponential attenuation of red radiation, creates much more acute differences in the distribution of ratio values, resulting in a higher sensitivity for the model. In simple words, the model can capture a depth difference of 0.5 m between two points much more accurately in deeper waters than in shallower. Furthermore, in shallow waters, the recorded reflectance values are also significantly altered by the optical properties of the bottom of the lake.

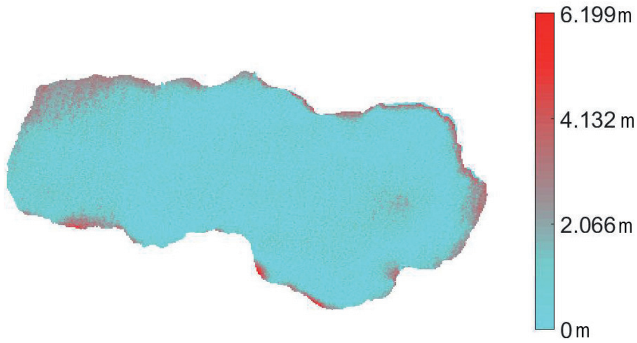

Fig. 8 The residuals (m) of the lake depth model of 22/5/1986 compared against the bathymetry derived from the used DEM.

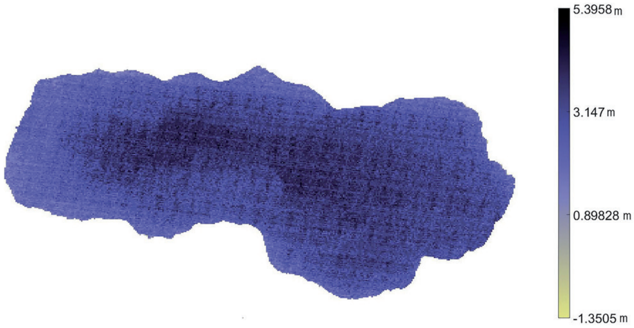

Fig. 9 Lake Koronia Depth (m) (30/7/1988).

Figure 9 depicts the application of the derived bathymetric model over the lake at a later date, but still relatively close to the date of the satellite image used to estimate the model. In time, it is expected that the bottom of the lake undergoes significant changes in its morphology, due to mass (and biomass) deposition and other reasons. This fact alone is enough to render the bathymetric model valid for a limited time period spanning the temporal proximity of the date of retrieval of the data used for the model fitting. The result appears to provide a bathymetric map of the lake with a fairly satisfactory accuracy, as seen in comparison to the lake bottom DEM used for the extraction of the model.

5. Conclusions

5.1 General Remarks

Prior to presenting the conclusions of this study, it ought to be noted that the mathematical foundations underlying the mechanics of the models adopted do not bear the same integrity in all cases of parameters, and a similar observation can be made for the physical foundations to an even higher degree. It is nevertheless important to be cautiously optimistic in view of the vast availability and potential of satellite data. Apart from the physics behind the studied parameters, moderation should also guide the statistical interpretations, in the sense that there is not always a clear and definitive meaning behind an apparent correlation. Therefore, the results of this study are in no way conclusive, and extensive cross-validation is necessary prior to adopting a model for wider application.
In this context, the conclusions of this paper are subsequently discussed along two axes, i.e. (a) with respect to the feasibility of extracting reliable water quality parameter values from satellite imagery and (b) regarding the evolution of Lake Koronia, based on the creation and analysis of QE time-series from satellite data.

5.2 Model Assessment and Parameter Calculation Feasibility

The notion of feasibility as used henceforth refers to the physical possibility of exploiting the satellite imagery data to obtain a deterministic relation between the optical properties of water and a specific parameter. It is clear that this cannot always be the case. Whenever this is not the case, a relation may still be obtainable but is nevertheless not expected to carry a deterministic meaning, rather it may be valid for purely statistical reasons. Such relations are not expected to be reliable in the long term, in contrast to deterministic ones for feasible parameters. Empirical models specific for the calculation of feasible quality parameters have long term use, while empirical models related with not feasible parameters should be calibrated/validated using *in situ* measurements when the optical properties of the lake change.

Water temperature can be considered as a feasible parameter, as it is directly related to thermal radiation.

A deviation of the pH of water from its neutral value in a natural system is always brought about by the existence of one or more substances, acidic or basic in chemical nature. Each substance may have a specific light absorption spectrum, different to that of another one. Should the spectra have a high degree of overlap, the results on optical properties and reflectance of the various wavelengths are expected to be cumulative, creating a specific optical signature determinable by reflectance. However, this is not always the case. Therefore, the cumulative optical signature will necessarily depend on the concentrations of the strongest of acids or bases that are dissolved in the water and, simultaneously, have dominant EMR absorbance spectra (strong absorption or reflection at various wavelengths). EMR absorbance spectra of such substances may have very diverse presentations. As a result, a significant problem is that the water in natural systems is only slightly acidic or alkaline, which means that small changes in pH may be associated with large changes in optical properties. This renders pH determination a rather precarious methodology. In a simple example, two acid substances with very different absorption spectra might, in suitable concentrations, alter pH in the exact same way in a water solution. Any model "trained" to identify the pH based on EMR reflectance of water in the setting of one substance will fail when the pH change is due to the other substance, due to much different reflectance values. Therefore, pH is hereby considered not feasible as a satellite-image derivable parameter. It must be mentioned, however, that there are cases of natural water bodies that are affected by, more-or-less, the same substances over relatively medium-sized time periods of up to a few decades. Therefore, relatively small pH variations can actually be effectively captured by a model exploiting the reflectance properties of water, as long as the dissolved substance profile does not change significantly in composition.

The Lake Coverage from various types of aquatic vegetation and organisms is based on justified scientific evidence. The physical basis is connected to the natural pigmentation from molecules residing within the various different organisms, such as chlorophyll in aquatic vegetation or phycobiliproteins, such as phycocyanin and phycoerythrin in cyanobacteria. The light absorbance spectra of these pigments are well documented and reflectance in the suitable wavelengths, as well as various band combinations, correlate well with the concentration of vegetation or cyanobacteria. Thus, the lake Coverage is hereby considered a feasible determination.

The model fitting of Water Depth on reflectance data is based on the different properties of the absorption spectrum of clear water in different wavelengths. An important problem arising in this calculation is the maximum depth that can be captured from a model, and the prerequisite that the water be clear. These two facts need to be suitably verified to an adequate degree in order for the model to be able to provide bathymetric data of usable accuracy. Since the mechanics of the model are very vividly explained and consolidated in (Stumpf et al. 2003), the approximation of bathymetric from satellite-image derived data is hereby considered a feasible process with trustworthy results. It must be stated in this point as well that a bathymetric model of whichever, relatively shallow overall, water body is only valid as long as the water remains relatively clear and the surface of the bottom is not heavily affected and deformed. Furthermore, it is clear from the fact that the final model is a single linear equation that acute simplification of reality occurs in the end product (the equation of the log-ratio model). As a result, the model should only be considered a preliminary compaction of bathymetric information, valid for a few years or even decades in the case of clear water and relatively undeformable lakebed.

As concluded by scrutinizing the content of the corresponding articles in literature, the primary concern of this study is to capture possible trends and correlations between a parameter and variations in one or more bands or mathematical band combinations from satellite images of the Landsat satellite missions. It appears that the TOA reflectance (or surface reflectance) is not the only favored measurement for the modeling, as a significant number of papers make extensive use of DN values from raw satellite images.

Although a number of models, such as those applied for the estimation of pH, appear to provide realistic results, it must be noted that there is an irregular intrinsic scaling between DN values from different bands. This can be ascertained by closely following the radiometric calibration procedure, during which DN values are converted to radiances using a pre-designated linear transformation, with different coefficients for each band, as given in the satellite image accompanying metadata files. Because DN values of a band are rescaled and compacted in integer values, the DN pixel value distribution over a specific band does not accurately reflect the actual variation of the optical properties for the various land covers, as does the distribution of true TOA- or surface reflectance values. Because the transformation between DN and radiance values is linear, this turns out to be a minor problem when fitting linear models of parameters on DN values. However, the final statistical coefficients cannot be physically interpreted. It is, of course, clear, that the scaling difference between DN values and radiance values becomes a problem when fitting a nonlinear model on DN values, rather than radiances.

DN values do not directly correspond to a physical quantity and being favorable when probing for a realistic correlation between pixel values from a specific band of a satellite image and the values of a specific parameter appears rather counterintuitive to the author. The statistical basis is even further distorted, when the correlation model involves more than one band from DN pixel values, because DN pixel values follow different scaling for different bands. In spite of all that, however, a number of research articles use DN values, probably because they are easier to access, without having to follow a number of cumbersome preprocessing steps. The corresponding models appear to capture the relation between the DN values and certain parameters with satisfactory accuracy. It is important to state that the equations of these models do not have clear natural interpretations; rather they reflect the variation of patterns exhibited by the data used. On the other hand, models based on reflectance values, such as the aquatic vegetation classification, are more realistic and exhibit a straightforward dependence on certain natural properties of the parameters involved. It can be stated, for example, that the TOA- (or surface) reflectance of a specific piece of land cover (within a pixel) with respect to EMR of a specific wavelength (e.g. TIRS, or VCID bands) is directly associated with some natural properties (correspondingly, the average temperature) of the same piece of land.

The successful retrieval of water quality information from Landsat data depends on the quality of *in situ* measurements that will be used for data calibration/validation. The *in situ* samples collected should be as fully representative as possible of the whole site to be characterized and all precautions should be taken to ensure, as far as possible, that the samples do not undergo any changes in the interval between sampling and analysis. Before any sampling project is devised, it is very important to define the lake structure and to establish the objectives since these are the major factors in determining the position of sampling sites, frequency of sampling, duration of sampling, sampling procedures, subsequent treatment of samples, and analytical requirements. Extensive field data are required in order to enable an accurate comparison of satellite data with actual ground data. One of the very first problems is the spatial divergence between the *in situ* measurements and the satellite remotely sensed data. In order to solve this problem it was suggested to realize limnological transects, where possible, instead of point stations. Another problem is the temporal congruity among all the *in situ* measurements. Sampling *in situ* is a long process and a time gap of several hours may exist between sampling stations. On the contrary, the remotely sensed data collection is instantaneous. A partial solution for the problem was pointed and consisted in organizing more boat-stations, displaced at different locations, and again sampling transects. The recording of some additional, complementary to the *in situ*, data, such as weather conditions and wind speed may be useful for the interpretation of the results derived from satellite data.

5.3 The evolution of Lake Koronia

The extreme hydrologic variability of Lake Koronia makes it difficult to predict future trends in the QE values and complicates the development of management strategies that may lead to a healthy and sustainable ecosystem.

The values of the various QE determined in this study by analyzing satellite image data of (Landsat-5/TM, -7/ETM+, -8/OLI) are relatively close to reality for the feasible parameters in general, and clearly appear to follow the patterns of their actual variations in time. In the case of non-feasible parameters, short-term periods of accordance between satellite-derived and *in situ* data have been sporadically observed, although general variation trends are missed in the long term. All parameter models perform more accurately on average, rather than in a point-wise (pixel) approach, mostly because of the inconsistencies in image clarity over specific fixed pixels, which invalidate intermediate images of a timeline and, therefore, values of a time-series.

In the present study, the decrease of the measurement accuracy was caused by:
- Atmospheric effects
- Sensor accuracy: <5%
- Sensor failure (e.g. TIRS)
- Models evaluated in other lakes
- Unclear relationship between parameter and optical properties of the water
- Use of DNs in estimating QE
- Low water level of lake Koronia

Genuine outlier values do occur, however, and may be important indicators of changes in water quality.

As lake ecosystems have integral evolutionary characteristics, parameters (QE) are also interdependent and not fully independent of each other. For a deeper understanding, a more extensive statistical correlation analysis between different time-series would be of utmost importance, in order to monitor the co-evolution and identify highly-specific relevant trends in co-variation. In order to provide a more functional satellite-data facility for the monitoring of, including but not limited to, Lake Koronia, a larger volume of *in situ* measurement data with high consistency would be necessary in order to formulate new models and algorithms based on data extracted from satellite images. In that case M.A.L.K.V will be able to have multiple QE measurements with only a few *in situ* measurements.

Acknowledgements

Satellite data were provided by the European Space Agency (ESA), after the submission of a proposal (ID: 31068). Presentation of the preliminary results of this study during the ESA Living Planet Symposium 2016 held in Prague, Czechia, was made possible through a European Commission student grant. The assistance of the Management Authority of Lakes Koronia-Volvi in the field operation is greatly appreciated.

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