Analysis of long-term satellite products for the Essential Climate Variable 'Lakes' in the LTER framework

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Abstract.

Lakes are integrators of environmental and climatic changes occurring within their contributing basins. Understanding the complex behaviour of lakes in a dynamic environment is essential for effective management of water resources and mitigation of climate change effects. The Lakes CCI project is a multi-disciplinary ESA (European Space Agency) funded project that aims to use satellite Earth Observation data to create the largest and longest possible global record of the five climate variables of lakes: lake water level, extent, temperature, surface-leaving reflectance and ice cover. The phase 1 version of the database covers 250 lakes distributed globally, while the phase 2 version is expected to expand to 2000 lakes. The temporal coverage varies depending on the parameter, with data ranging from 1992 to 2019. The potential of the dataset is explored for two Italian lakes and one Swedish lake: i) Trasimeno, a shallow eutrophic lake, ii) Garda, a deep subalpine oligotrophic lake, and iii) Erken, a shallow meso-eutrophic lake. These areas are a specific case study of the lakes CCI project included in the Long-Term Ecosystem Research (LTER) network. The obtained satellite products will be compared and integrated with the corresponding *in situ* data in the LTER dataset. Time-series of satellite data are then explored to examine trends in the context of key meteo-climatic variables, comparing the effects of climate change in the two different geographic areas of northern and southern Europe.

Keywords: Chorophyll-a; Turbidity; Lake Surface water temperature; satellite data; Lake Trasimeno; Lake Garda; Lake Erken

1. Lake Trasimeno ECV and trends: methodology and assessment

For Lake Trasimeno, lake surface water temperature (LSWT) and chlorophyll-a (Chl-a) (derived from water-leaving reflectance data from MERIS and OLCI sensors) were extracted from the CCI Lakes database version 1.0, the dataset for LSWT dates from 1993 while that for Chl-a starts in 2002. Daily climatic data (wind vectors for speed and direction, 2 m air temperature, total precipitation, and the sum of rainfall for the preceding seven days) were obtained from ERA5, the fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis for the global climate and weather (https://cds.climate.copernicus.eu/cdsapp#!/home). Lake level at S. Savino station was obtained from the regional authority (Umbrian Regional Hydrographic Service; https://annali.regione.umbria.it/#). Daily values of the North Atlantic Oscillation (NAO) were obtained from NOAA-CPC (https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml).
Non-Parametric Multiplicative Regression (NPMR) and Google AI (Artificial Intelligence) models were used to analyse the data. In order to understand the factors influencing the dynamics of Chl-a in Lake Trasimeno, we first carried out a NPMR

including the variables day of year (DOY), year, lake level, LSWT, wind vectors, the NAO, and the sum of the antecedent rain for 7 days (Table 1). The best model had an xR^2 of 0.62 and included DOY, year, lake level, and the NAO; however, the NAO was interchangeable with LSWT (Table 1). The sensitivity value provides an indication of the importance of the variables in the models.

Table 1. Results of NPMR (Nonparametric Multiplicative Regression) models for Chlorophyll-a (adapted from [1]). xR^2 = cross-validated R^2; Ave. size = Average neighborhood size; Tol. = Tolerance; Sen. = Sensitivity; NAO = North Atlantic Oscillation; Level =lake level; LSWT = lake surface water temperature.

	Model 1 (NAO)	**Model 2 (LSWT)**
xR²	0.62	0.62
Ave size	99.1	98.7
Variable 1	DOY	DOY
Tol.	18.3	18.3
Sen.	0.338	0.331
Variable 2	year	year
Tol.	1.2	1.2
Sen.	0.065	0.064
Variable 3	Level	Level
Tol.	0.7	0.6
Sen.	0.014	0.017
Variable 4	NAO	LSWT
Tol.	3.3	13
Sen.	0.004	0.006
p	0.045	0.045

The models for Chl-a concentration were most influenced by the time variable (87% of feature importance), followed by the NAO variable (4% of feature importance). In fact, in Lake Trasimeno the Chl-a dynamics show a summer bloom that starts consistently in July and typically peaks in early September, while when there is a positive NAO, associated with high pressure and a warm, sunny weather, it leads to an increase in Chl-a concentrations, as confirmed by the NPMR and this is mostly important during early to mid-September. Regional climate indices, as well as the more obvious nutrient drivers of phytoplankton blooms, should therefore be considered in the management of the lake. However, the relative role of these parameters and other factors in influencing Chl-a is difficult to apportion because they are seasonally correlated. Analyzing phytoplankton phenology, it is interesting to note that a longer warmer season, typically beginning early in the year, leads to a shorter duration of blooms, possibly due to seasonal nutrient restriction and possibly increased of co-precipitation of phosphorous and calcite.

In addition to the data provided by the datasets described above, an *in situ* WISPstation sensor was also used to provide information on chlorophyll-a and phycocyanin concentrations in near real time (every 15 minutes). Comparison of the high-frequency

WISPstation data (2018-2020) with the CCI dataset allows detailed cross-validation, revealing that rapid fluctuations in the satellite records were supported by in situ data which might otherwise have been interpreted as noise. In addition, using phycocyanin results from the WISPstation showed, in near real-time, how cyanophytes played a key role in the sudden increases and decreases in Chl-a in mid- and late summer (Fig. 1). The coupling of climate indices, satellite data and near-real-time Chl-a concentrations allowed for a greater understanding and improved state of knowledge of the conditions and changes in water quality in Lake Trasimeno and its relationship with climate change.

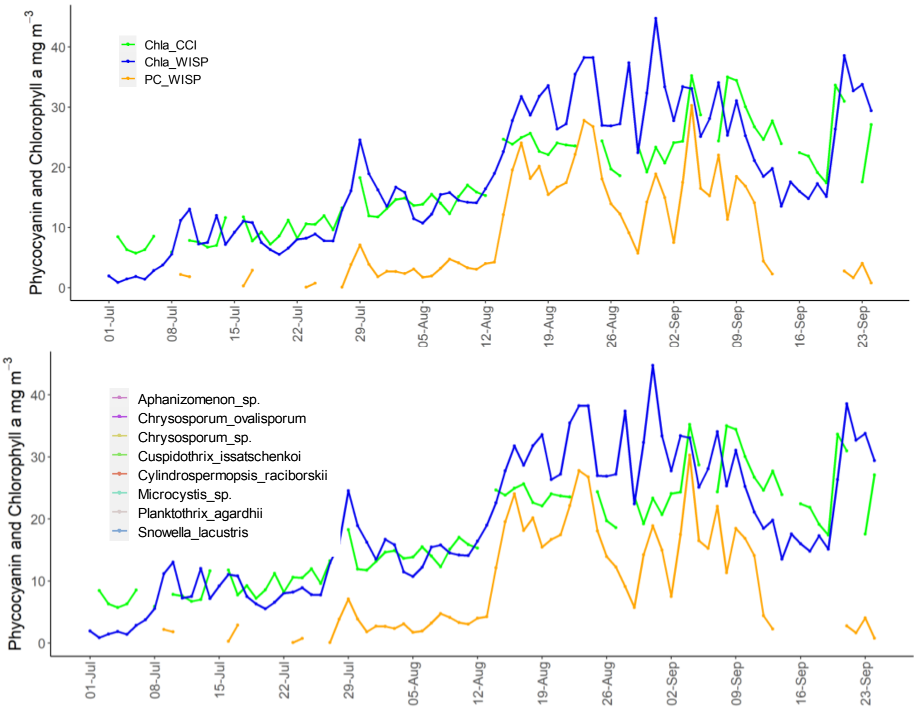

Fig. 1. In the upper graph estimates of Chl-a from the CCI project (Chla_CCI), and Chl-a (Chla_WISP) and phycocyanin (PC_WISP) estimated from Wispstation data in 2019. In the lower graph the cyanobacteria species biovolume (modified from [1]).

2. Lake Garda ECVs and trends: methodology and assessment

Lake Garda with the other lakes in the subalpine region of Northern Italy have experienced an increase in water temperature, with warmer winters leading to more stable water stratification and an alteration of the mixing regime due to climate change. The time series of satellite Chl-a concentration was obtained from four optical sensors MERIS, OLI, MSI and OLCI covering a time span of 16 years (2003-2018) providing a high temporal and spatial resolution. Some evidence for a change in phenology of the phytoplankton was found in a shift in timing of the traditional Chl-a peak. The pattern changed from a concave shape (spring peak, clear phase, summer/autumn peak) to a convex shape (dominant summer concentrations) i.e., there was a shift from spring and summer/autumn blooms towards more intense summer blooms after 2015. In addition, there was a tendency for this shift to be interspersed with a period of lower Chl-a (Fig. 2). We tested for a trend using Theil-Sen function, accounting for seasonal variation and interpolating missing data, and found evidence for a significant decline in Chl-a in Lake Garda from 2003 to 2018 (Fig. 2).

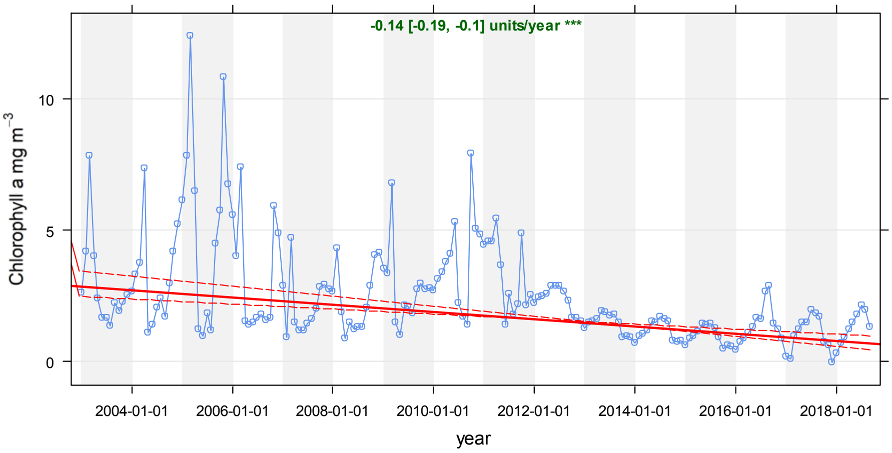

Fig. 2. Lake Garda, chlorophyll-a TheilSen trend with removal of seasonal variation and interpolation of missing data. The solid red line shows the trend and the dashed red lines show the 95% confidence intervals. The slope value is -0.14 mg m^{-3} / year, with 95% confidence intervals of -0.19; -0.1 mg m^{-3} / year, from 2003 to 2018.

To test for a change in seasonal pattern we fitted a second-order polynomial to Chl-a for each year between April and October. The coefficient of the squared term was then assessed to see if it was changing from positive (a concave pattern) to negative (indicating a convex pattern) over time. A significant negative trend for Garda was found with a slope of -0.032 ($p \leq 0.05$). To explore the drivers of this change we used NPMR which resulted in a model for Chl-a with a xR^2 of 0.58 ($p \leq 0.05$) and included the variables time, air temperature and winter (DJF) air temperature. In Lake Garda, the winter temperature had the highest sensitivity value (0.31) compared to time (0.04) and air temperature (0.25).
The decline and alteration of the seasonal pattern of Chl-a peaks is probably caused by the cascading effects of increasing winter temperatures and reduced winter turnover, which exerts a significant control on nutrient dynamics. Future trends will depend on climate change and interdecadal climatic factors.

3. Lake Erken ECVs and trends: methodology and assessment

For Lake Erken, time series of satellite data on four parameters that can be estimated by remote sensing (LSWT, Lake Ice Cover (LIC), Chl-a and Turbidity) were extracted using the MERIS and MODIS sensors for data from 2002 to 2015, while the OLCI sensor was used for data from 2016 to 2020 (extracted from the CCI Lakes database

version 1.0). As in the two previous cases, the daily climate data (wind vectors for speed and direction, air temperature at 2 m, total precipitation and sum of precipitation of the previous seven days) were obtained from ERA5, and the daily values of the North Atlantic Oscillation (NAO) were obtained from NOAA-CPC.
For the past 30 years, a substantial environmental monitoring programme has been underway that includes manual and automatic high-frequency measurements of physical and chemical water parameters as well as plankton composition. Lake Erken is one of the very few lakes in Northern Europe that has a long history of monitoring and through the integration of remote sensing data it is possible to study and monitor water quality in response to climate change more effectively and efficiently, as well as identify any extreme events.
The non-parametric Theil-Sen Estimates test was used to analyse the data. The test for LSWT and LIC did not show significant trends, and the two variables were significantly negatively correlated (r=-0.5). Instead, a significant negative trend over time was found for Turbidity (Fig. 3). Moreover, the seasonal analysis shown a significant decrease in turbidity in the summer. Turbidity was also positively correlated with air (r=0.59) and water (r=0.61) temperatures. The time series indicated a significant increase in Chl-a (Fig. 4) and air temperature, specifically Chl-a increased in spring and summer, while air temperature increased significantly in summer and winter. Indeed, thermal stratification and the mixing process, influenced by the change in temperature, appear as a primary response that subsequently determines the phytoplankton's exposure time to light and the nutrient concentrations in the epilimnion, ultimately influencing phytoplankton development. The seasonal succession pattern of phytoplankton in Lake Erken is characterised by two chlorophyll peaks occurring in spring and autumn (dominated by diatoms), interspersed with a summer bloom. A regular bloom of the colonial cyanobacterium *Gloeotrichia echinulata* occurs between mid-July and early August, and these algae migrate rapidly to the surface when strong vertical stratification is present [3]. Under these conditions, where a large portion of the lake's chlorophyll is present in the upper layers of the water column, it provides an interesting test for the application of remote sensing methods.
Our results can be integrated with previous studies on the effects of climate change on the phytoplankton community and timing of blooms. For example [4] reported significant variation of spring diatom communities and period of growth driven by warmer winters.

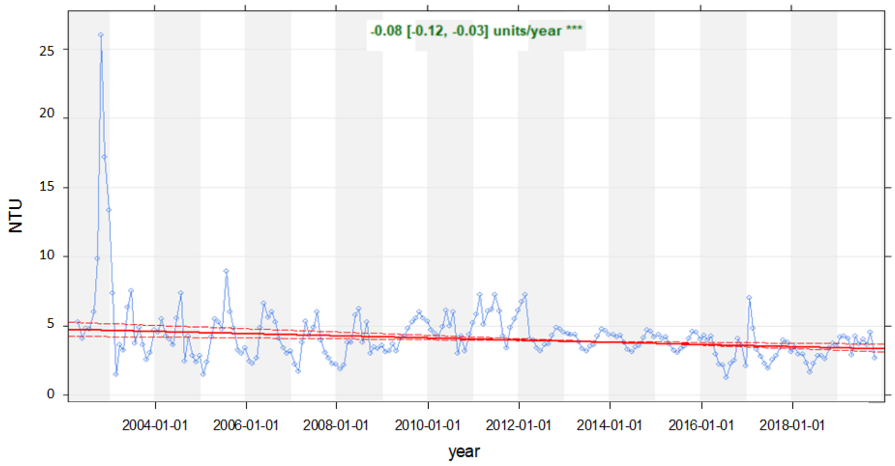

Fig. 3. Lake Erken, Turbidity (NTU) TheilSen trend with removal of seasonal variation and interpolation of missing data. The solid red line shows the trend and the dashed red lines show the 95% confidence intervals. The slope value is -0.08 NTU / year, with 95% confidence intervals of -0.12; -0.03 mg m^{-3} / year, from 2003 to 2018.

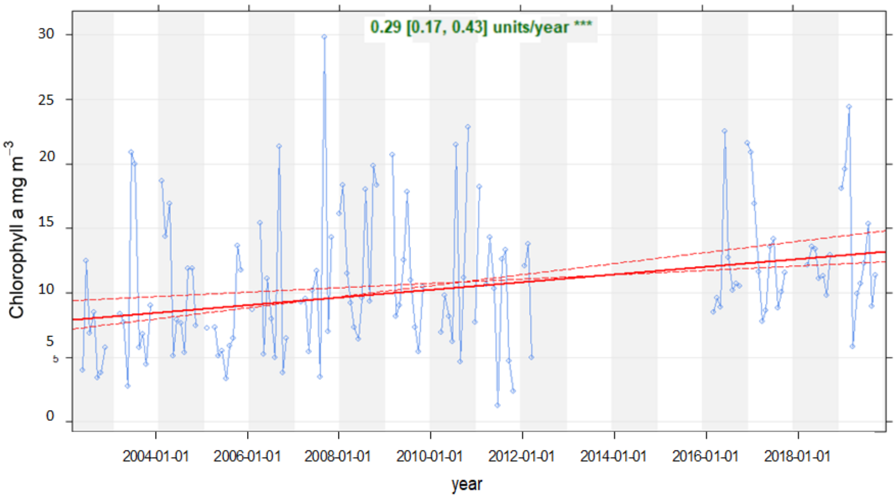

Fig. 4. Lake Erken, chlorophyll-a (Chl-a; mg m^{-3}) TheilSen trend with a gap from 2012-2016 (end of mission Envisat, start of mission Sentinel-3). The solid red line shows the trend and the dashed red lines show the 95% confidence intervals. The slope value is 0.29 mg m^{-3} / year, with 95% confidence intervals of 0.17; 0.43 mg m^{-3} / year, from 2003 to 2018.

4. Conclusions

Lakes are special and complex ecosystems because they are influenced by many variables and have diverse catchment and lake characteristics and climate. This complexity means that the study of a lake cannot be achieved by approaching it with a single discipline. The study of a lake must therefore be approached in an interdisciplinary manner, i.e. taking into account a broad suite of information, synthesizing the surrounding environment, the effect of hydrodynamics and meteorological conditions. For these reasons, remote sensing is an ideal complementary technique for studying lakes.

This study showed changes in the parameters that can be estimated by remote sensing, including significant alteration to chlorophyll-a concentrations in the lakes under study. Another aspect highlighted in the study is the variation in response to climate change in lakes in different geographical regions and with different trophic and morphological characteristics, comparing northern Europe with southern Europe.

The comparison between lakes distributed in different regions of Europe has made it possible to highlight trends and phenomena with respect to the responses of the lakes to climate change. For example, the examination of the time series of chlorophyll-a in Garda indicated the potential influence of warmer winters reducing lake overturn leading to lower nutrient entrainment to the upper layers which thereby alters the phenology, especially reducing the spring bloom. The cause of the lack of vertical mixing of lakes is attributed to long-term climate change and fluctuations in large-scale regional climate factors such as the North Atlantic Oscillation (NAO), and in particular the East Atlantic (EA) pattern during winter. These large-scale climate movements control the climate in Europe, especially in the north, and undergo oscillations every 10 years.

In contrast, a long-term positive trend was detected for Lake Erken. On the other hand, in Lake Trasimeno the algal bloom pattern remained unchanged but warmer summers increased concentrations of Chl-a but the trend towards longer warmer seasons is likely to generally reduce bloom duration in summer/autumn through earlier exhaustion of nutrients.

In conclusion, the integration between the data obtained with remote sensing and the *in situ* data made it possible to study and monitor the quality of the water in an effective and efficient way and to identify any changing phenomena, their influence on water quality as well as exploring the main drivers.

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