Sentinel 2 tools for monitoring and detecting the eutrophication status of freshwater lakes, the case of Lake Siutghiol

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Abstract. Inland lakes, and especially those in areas with anthropogenic activity, are prone to the tendency to move towards a eutrophic state due to nutrients. This manifestation, which affects the inland lakes, has lately become a global ecological problem. The associated ecosystems will suffer effects, including the deterioration of biodiversity, closely related to the decrease in oxygen in the water and algal blooms. Traditional methods are limited, difficult, time-consuming, and in some cases impossible, so an alternative that is taking shape is remote sensing (using data from satellites such as Sentinel-2 and Landsat), which allows rapid and extensive monitoring of lakes or areas of interest. The assessment of the eutrophication state by analysing several categories of parameters: bio-physical parameters, climatic and hydrodynamic parameters, and advanced spectral can make up for the lack of data obtained by local measurements. Each country considers certain aspects and establishes a series of parameters that characterize the state of the ecosystems. In the case of lakes, for example, the concentration of chlorophyll a, total nitrogen, total phosphorus, and turbidity can be considered as bio-physical parameters (alternatively, you can opt for the depth determined using the Secchi disk). Nitrogen and phosphorus from various sources are considered the nutrients that dictate the ecosystem's response, but a direct method of detection using satellite data is not possible. Factors that depend on the climate of the location, the hydrographic basin that develops, and the ecosystem can be considered to understand the phenomena that lead to the evolution in that area. For the satellite data, several indices have been identified that depend on the spectral bands or the ratios between these bands, such as NDVI for vegetated areas, NDWI for wetlands or bodies of water. If the water quality or eutrophication status is to be determined, it is necessary to determine the concentrations of chlorophyll A, total nitrogen, total phosphorus and the turbidity of the water. The work establishes a series of methods and identifies the appropriate tools for monitoring and detecting the eutrophic state of shallow lakes, such as the Siutghiol lagoon.

Keywords: Sentinel 2, algal bloom, chlorophyl-a, turbidity, machine learning.

1. Introduction

Eutrophication is caused by the excessive accumulation of nutrients, especially nitrogen (N) and phosphorus (P), from various sources, which can be agricultural, industrial, and urban areas. As an immediate effect, we are talking about a massive algal bloom, changes in the transparency of the water, a decrease in the concentration of dissolved oxygen, and thus a deterioration of aquatic biodiversity (Schindler, 1974).

The classical methods, based on the local measurement of the concentrations of parameters directly related to the eutrophication state, chlorophyll-A, nitrogen concentration, phosphorus, and turbidity, provide accurate data that can be used in establishing the eutrophication state. The major disadvantage of these methods is the fact that they are spatially limited, the sample collection points are small, and from a temporal point of view, the analysis of the samples is time-consuming. By developing remote sensing and identifying methods that could monitor aquatic ecosystems, it has been possible to develop new methods that provide an immediate perspective on the state of the lakes. Satellite platforms such as Sentinel-2 and Landsat provide high-resolution data, which is essential for detecting eutrophication indicators over large areas (Guansan et al., 2025).

The present study traces the link between the values of the indices calculated from the Sentinel 2 bands in different locations around the Siutghiol Lake. In the first stage, the actual status of the indices defined for Sentinel 2 was analysed, and their connection with the parameters of interest was examined. It is also envisaged to correlate these values with the values of the parameters experimentally determined in accessible points distributed around Lake Siutghiol. Among the parameters determined from the measurements are chlorophyll-A, turbidity, total nitrogen, and total phosphorus. For the first two parameters, there is a correlation with satellite data, and estimation models developed using machine-learning algorithms; for the last two, on the other hand, there is no such clear correlation; they are only attempts based on limited experiments (Guansan et al., 2025).

The climatic and hydrodynamic parameters give us a more complex understanding of the dynamics of the lake, and the study will also integrate meteorological data such as wind speed, wind direction, and atmospheric pressure. These factors play a crucial role in the processes of water mixing, sediment resuspension, and spatial distribution of algae, directly influencing the optical parameters detected by the satellite (Jensen, 2007).

Advanced spectral indices are used to enhance the accuracy of analysis; we will evaluate the effectiveness of several remote sensing indices. Specific indices such as MCI (Maximum Chlorophyll Index), FAI (Floating Algae Index), and FVI (Floating Vegetation Index) have recently been developed to detect floating algae and aquatic vegetation. The values of these indices can be interpreted and used in the precise detection of algal blooms even in small and complex lakes (Hu, 2009; Kokolakis et. al., 2025). The possibility of detecting anomalies present in water quality is given by the WAI index, developed and tested for complex geographical environments (Wei et al., 2024).

A dynamic and detailed assessment of the eutrophication status of lakes, essential for making informed decisions to protect water resources, can be implemented using this framework that we will develop to overcome the limitations of conventional methods.

The choice of Lake Siutghiol for the study is because the ecosystem in the area has been disturbed for a very long time, possibly over 50 years, by states of eutrophication. The geomorphological characteristics of this freshwater lake are the area of 19 km² and the average depth of about 2.5 meters, the maximum being almost 19m near Ovidiu Island, a 2 ha limestone island located in the western area of the lake.

The eutrophication of Lake Siutghiol is a complex phenomenon, influenced by natural factors and, especially, by anthropogenic pressure. Like other lakes in the area, Siutghiol has undergone significant hydrological and geological changes. A 2024 study points out that the situation of the lake is influenced by urban development and artificial water sewerage (Skolka 2024). These interventions, along with the development of tourism and overfishing, have begun to put pressure on the ecosystem. Eutrophication has intensified due to pollution coming from various sources, including sewage discharges, sewage water leakage, and waste. In conclusion, although Lake Siutghiol is an ecosystem of major ecological and tourist importance, recent history shows an increased vulnerability to anthropogenic pressure and climate change, which contributes to the eutrophication process. Since 2000, Siutghiol has been included in the European network of protected areas Natura 2000 due to the presence in the area of a variety of bird and fish species (ROSPA0057).

2. Materials and methods

2.1. Bio-physical parameters: Chlorophyll-a and turbidity

These parameters are interconnected and crucial for assessing the optical state of the water. Chlorophyll-a is an indicator of phytoplankton biomass, which absorbs blue and red light and reflects it back into the green band and the red-edge (the transition region from red to near-infrared). Turbidity, caused by suspended particles, increases reflectance especially in red and near-infrared bands. Alternatively, the estimated depth can be used using the Secchi disk (SDD), which measures the transparency of the water, and is directly influenced by chlorophyll-a concentration and turbidity. A shallow Secchi depth indicates low transparency, often associated with eutrophication.

Also, for the estimation of chlorophyll-a and turbidity, semi-empirical models and machine learning algorithms are used that correlate spectral reflectance with the values measured in situ. A recent study used deep learning algorithms to estimate chlorophyll-a and turbidity concentrations in satellite data, achieving higher accuracy than traditional methods (Zhang et al., 2024).

The Secchi depth estimate (SDD) is often estimated by its correlation with turbidity and light absorption, parameters that can be derived from satellite data. For example, a regression model can use the reflectance in the green and red bands to predict the Secchi depth. A 2025 study proposed an innovative method, using data from very high-resolution satellites to estimate the depth of Secchi in small and complex lakes (Olson et al., 2025).

Other bio-physical parameters are total nitrogen (TN) and total phosphorus (TP), which are dissolved nutrients, so they cannot be detected directly, but are estimated by indirect methods using machine learning (ML) algorithms. Predictive models such as Random Forest (RF) or Extreme Gradient Boosting (XGBoost) are trained with an in-situ dataset and satellite parameters (chlorophyll-a, turbidity, SDD, temperature, spectral indices). These models identify complex correlations to estimate TN and TP concentrations with high accuracy. A recent study showed that adding Secchi depth to the training dataset significantly improved the prediction accuracy for total phosphorus (Qin et al., 2025).

Conductivity and pH are the parameters that are obtained indirectly, through correlations with the variables detectable by remote sensing. Current research focuses on the development of predictive models that use optical (turbidity, chlorophyll-a) and environmental parameters to infer pH and conductivity values. For example, an elevated pH is often a consequence of intense photosynthesis, which can be detected by high concentrations of chlorophyll-a. A study published in 2024 proposed a new index to detect water quality abnormalities that may be associated with variations in pH and conductivity (Wei et al., 2024).

2.2. Meteorological parameters: temperature, wind speed and direction, pressure

These parameters are obtained from specialized satellites and are essential to understand water dynamics and algae distribution. The data can be retrieved from historical databases, such as e.g. meteostat, openweather, etc. This information is also included in the data cubes of the spectral data saved for the processing level 2 of the Sentinel 2 satellite.

If an analysis of the water surface temperature (LST) from satellite data is desired, this can be obtained from satellite data in the thermal infrared band. A recent study from 2025 showed a positive correlation between water temperature and total phosphorus concentrations in lakes in China, indicating the crucial role of temperature in eutrophication processes (Wang et al., 2025).

For wind speed and direction, satellite-mounted katathermometers can be used, which measure the roughness of the water surface. A recent study explored the use of LIDAR and RADAR technologies to obtain 3D wind profiles, a major evolution in remote sensing (Li et. al., 2025).

Atmospheric pressure is obtained from satellite data by integration into numerical forecast models, which combine information from multiple sources.

2.3. Spectral indices

Spectral indices are mathematical formulas that combine reflectance values from different spectral bands to highlight a specific surface feature. NDVI, NDWI, NDTCI, NDTI are classic indices and continue to be widely used, but they are often improved. For example, modified versions of NDWI have been proposed to better differentiate water from other elements (Zhang et al., 2025).

The NDVI index quantifies the presence of vegetation in the studied area, tracking the normalized difference between the scattering of NIR radiation by green leaves and the absorption of radiation from the spectral zone associated with red color by chlorophyll (SentinelHub, 2025).

$$NDVI = Index(NIR, RED) = \frac{NIR - RED}{NIR + RED} \tag{1}$$

In the case of the Sentinel 2 satellite, this relationship becomes:

$$NDVI = Index(B08, B04) = \frac{B08 - B04}{B08 + B04} \tag{2}$$

The calculated values will be in the range [-1, 1], values that can be interpreted according to the table below (Table 1).

Table 1. Interpretation of NDVI values

Interval NDVI	Meaning
Negative values	Water
-0.1 and 0.1	Rocks, sand or snow
0.2 and 0.4	Bushes, grass
Close to 1	Dense vegetation, forests

Alternatively, this index can be used in areas with water to track the presence of green algae, thus B08 (NIR) is the spectral band, where algal reflectance is high and B04 (Red) is the spectral band where chlorophyll absorption is maximum and reflectance is low. The interpretation of the result in this case becomes: for positive values (close to 1) a high probability of the presence of floating algae is indicated, suggesting an algal bloom. For negative values (close to -1) we have clean water, without a significant concentration of algae. This index is useful for quickly identifying areas with algal blooms and monitoring their expansion and evolution over time. However, it is important to note that, as with the other indices, a calibration with field data will provide a much more accurate quantitative estimate of algal biomass.

Another classic index, often used in satellite data processing algorithms, is the NDWI (Normalized Difference Water Index), which can be calculated by two methods, depending on the purpose. The first method uses the NIR band, respectively SWIR proposed by Gao in 1996 to monitor the water content of leaves/vegetation, respectively the method proposed by McFeeters, 1996 to track changes in water areas (ponds, lakes, etc.).

$$NDWI = Index(GREEN, NIR) = \frac{GREEN - NIR}{GREEN + NIR} \tag{3}$$

In the case of the Sentinel 2 satellite, this relationship becomes:

$$NDWI = Index(B03, B08) = \frac{B03 - B08}{B03 + B08} \tag{4}$$

The values calculated from the range [-1, 1], show the areas with water, for positive values, respectively without water in the case of negative values. Thus, many of the processing scripts present on the Sentinel Hub use this index to detect water holes in the studied area.

The NDCI is the index that allows the monitoring of chlorophyll content in turbid waters (Mishra et. al., 2012) and can be calculated using the following relationships,

$$NDCI = Index(REDEDGE1, RED) = \frac{REDEDGE1 - RED}{REDEDGE1 + RED} \tag{5}$$

In the case of the Sentinel 2 satellite, this relationship becomes:

$$NDCI = Index(B05, B04) = \frac{B05 - B04}{B05 + B04} \tag{6}$$

Extreme negative values of this index will show clean waters, without the presence of algae. A value between -0.3 and 1 will indicate the presence of algal biomass, with algal blooms being indicated by a value between 0.5 and 1.

Regarding the monitoring of water turbidity, another index was proposed, namely NDTI or Normalized Difference Turbidity Index (J.P. Lacaux et. al) given by,

$$NDTI = Index(RED,\ GREEN) = \frac{RED - GREEN}{RED + GREEN} \tag{7}$$

where RED and GREEN were reversed, starting from the premise that the radiometric responses in the red band are much higher than those in the green band, based on the conclusions of (Campbell, J. B. (1996) and Verbyla, D. L. (1995)). For Sentinel 2, the above relationship becomes,

$$NDTI = Index(B04, B03) = \frac{B04 - B03}{B04 + B03} \tag{8}$$

The NDTI index has values between -1 and +1, and their interpretation is a high turbidity of the water for positive values (close to +1), respectively clear water, with low turbidity for negative values (close to -1). This happens because cloudy water reflects more in the red band than in the green one. The higher the value, the more pronounced the turbidity. Clean water absorbs more in the red band and reflects more in the green band. It is important to note that NDTI values are relative. They do not directly represent specific units of measurement of turbidity (such as NTU - nephelometric turbidity units). To obtain an accurate estimate of turbidity, NDTI values must be calibrated with field (in-situ) data, i.e. turbidity measurements collected directly from the water at the same time as the acquisition of satellite images.

MPH, MCI, FAI, FVI, FUI are specific indices to detect various types of algae. The general calculation formula for these indices can be written,

$$IndexName = R_{BC} - R_{BI} - (R_{BS} - R_{BI}) \times \frac{\lambda_{BS} - \lambda_{BI}}{\lambda_{BC} - \lambda_{BI}} \tag{9}$$

R – is the reflectance of the band, λ – the wavelength of the band, BI – the lower band, BC – the central band, BS – the upper band

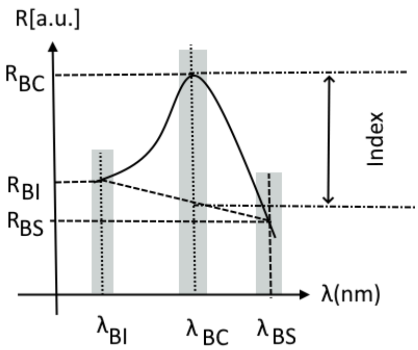

Figure 1. Graphical representation for the calculation of a specific general index

MCI, or Maximum Chlorophyll Index (Gower et al., 2008), is a remote sensing index used to detect and estimate the concentration of chlorophyll-A in lake water, a key measure of eutrophication. It is particularly useful in turbid (with high turbidity) and eutrophic waters, where other indices may be less effective. MCI is based on the concept of spectral "line height". Specifically, it measures the difference between the reflectance of a spectral band (usually the one in the red-edge region, i.e. the red-infrared edge) and a baseline drawn between two other spectral bands. This reference line is intended to compensate for the effects of reflectance of water and other components, thereby isolating the specific chlorophyll-a signal. For the Sentinel-2 satellite, the formula for MCI uses the spectral bands: B05 (705 nm) - the central band, where chlorophyll reaches a maximum reflectance, B04 (665 nm) - the reference band with maximum chlorophyll absorption, and B06 (740 nm) - another infrared reference band, thus the above formula becomes,

$$MCI = B05 - B04 - (B06 - B04) \times \frac{740 - 665}{705 - 665} \quad (10)$$

Unlike NDCI, which uses a normalized band ratio, MCI is more robust in the case of waters with high turbidity. In such waters, reflectance in the infrared region (NIR) can be influenced by sediment particles, but MCI is less sensitive to this effect. Therefore, MCI can provide a more accurate estimate of chlorophyll-a concentration in lakes with an advanced level of eutrophication, where algal blooms are dense and the water turbidity is higher.

MCI was originally developed for the MERIS satellite but has been successfully adapted for the Sentinel-2 data, due to its similar spectral bands, suitable for monitoring water quality. An additional correction factor was added later for the Sentinel 2 tapes, the above formula being filled in at,

$$MCI = B05 - k \cdot \left(B04 - (B06 - B04) \times \frac{740 - 665}{705 - 665}\right) \quad (11)$$

where k=1,005. Depending on the Sentinel product, L1C or L2A, an additional mask should be applied to band 7 to obtain correct results, i.e. at 50 units of radiance for L1C and 0.017 radiance for L2A.

The Floating Algae Index (FAI) is an index designed to detect floating algae on the surface of the water. FAI (Floating Algae Index) is a robust index for the detection of surface algae, being often mentioned in recent studies (Hu, 2009). It works by creating a spectral baseline to eliminate the effects of water and atmosphere and highlight the algae signal, which has a high reflectance in the near-infrared (NIR) band. For Sentinel-2, the bands used are, NIR (near-infrared) i.e. band B08 (with a wavelength of about 842 nm), Red (red), band 4 (with a wavelength of about 665 nm) and SWIR2 (shortwave infrared), band 12 (with a wavelength of about 2190 nm). Thus, the FAI formula adapted for Sentinel-2 is:

$$FAI = B08 - \left(B04 + (B12 - B04) \times \frac{842 - 665}{2190 - 665}\right) \quad (12)$$

This formula is effective because the floating algae reflects strongly in the B8 band, while the water absorbs almost completely in the B12 band. Linearization of the signal by creating a baseline between B4 and B12 allows the isolation of spectral anomalies caused by algae.

In the Sentinel Hub platform, a specialized index is defined, called MPH or Maximum Peak Heigh Bloom Index, developed to indicate the presence of algal blooms. It detects the height of the peak in the spectrum between 705 and 740 nm, like MCI, but also tracks changes in the FAI. The principle is to select, for the water areas in the investigated region, the predominant index (MCI or FAI).

The Floating Vegetation Index (FVI) was developed by Gao and Li (2018) to detect algae and other types of floating vegetation using spectral channels in the near-infrared (NIR) region. The index is based on a linear baseline method to eliminate the water signal and highlight the specific reflectance of the vegetation. The FVI formula is:

$$FVI = R_{1.07} - \left(R_{1.0} + (R_{1.24} - R_{1.0}) \times \frac{\lambda_{1.07} - \lambda_{1.0}}{\lambda_{1.24} - \lambda_{1.0}}\right) \quad (13)$$

where: R represents reflectance at a given wavelength, λ represents wavelength (in micrometers). This formula was originally designed for hyperspectral data, which have very narrow and specific bands. Since multispectral satellites like Sentinel-2 do not have bands centered exactly at 1.0, 1.07 and 1.24

µm, its direct implementation on this data is difficult. A formula adapted for Sentinel 2 could consider the reflectance in the B8A band (865 nm), and the range between B08 (842 nm) and B09 (945 nm).

$$FVI = B8A - \left(B08 + (B09 - B08) \times \frac{865 - 842}{945 - 842}\right) \quad (13)$$

FUI (Forel-Ule Index), although older, is used in new approaches to characterize water color, a visual indicator of eutrophication status (Wang et al., 2021), but presents difficulties in use due to the calibration operation that must be performed based on a relevant number of samples taken under different conditions.

Remote sensing satellites can be used to calculate these spectral indices. They represent the most important category of instruments, providing multispectral and hyperspectral data. They are essential for large-scale and long-term monitoring. Sentinel-2 is part of the European Copernicus program and is one of the most widely used satellites for monitoring water quality. It has a high spatial resolution and a high viewing frequency, making it ideal for detecting chlorophyll-A (Chl-A) concentration, a key indicator of eutrophication, as well as water turbidity. Landsat is a mission with a series of satellites, operated by NASA, and provides a long history of data (since 1970), allowing the analysis of eutrophication trends over the decades. MODIS (Moderate Resolution Imaging Spectroradiometer), although it has a lower spatial resolution, offers a very high temporal resolution, being excellent for detecting rapid events such as algal blooms.

3. Results and discussions

To estimate the values of the indices presented earlier, public data available on online platforms such as CDSE and UGSG can be used. To simplify the data processing process, the use of data from the satellites of the Sentinel 2 mission was particularly chosen, as seen in the materials and methods section where the formulas are adapted for the bands available at the MSI sensor in Sentinel 2.

The Copernicus Data Space Ecosystem is an integrated and unified platform, developed under the aegis of the European Commission, which facilitates access to data collected by Copernicus satellites. Its main objective is to provide a single point of access to a huge amount of remote sensing data (over 30 petabytes), services and processing tools, transforming raw data into useful information for a wide range of fields, from environmental monitoring to civil security.

Copernicus Browser is the visual and user-friendly interface of this ecosystem. It is a free tool that allows users to explore, view, and download high-resolution satellite imagery without the need for advanced programming or processing knowledge. Users can search for images based on criteria such as geographic location, date, satellite type (e.g., Sentinel-1, Sentinel-2, Sentinel-3) and apply various basic processing, such as combining spectral bands to create false-color images or calculating indices such as NDVI and NDWI.

ESA's SNAP (Sentinel Application Platform) is a free and open-source software platform developed by the European Space Agency (ESA) for the processing and analysis of Earth observation data, in particular for the Copernicus Sentinel satellites. SNAP 12 represents a recent version of this platform, which comes with significant improvements in workflows for SAR (synthetic aperture radar), optical and atmospheric data processing. Its key features include extensibility and portability, multi-mission processing (it focuses on Sentinel-1, Sentinel-2, and Sentinel-3 data, but also supports a variety of other data formats from third-party missions), Graphical Interface, and Command Line (Graph Processing Framework - GPF).

The case study was carried out following the values of the 7-point indices (Fig. 1) around the lake, where sampling was initiated to determine the necessary parameters to establish the eutrophication state of the lake (chlorophyll-a, total nitrogen, total phosphorus, cyanobacteria, pH, conductivity, turbidity, temperature).

Label	Lon/Lat
P1	28.602640378026393 44.23384641627766
P2	28.574270473914464 44.2499963029106
P3	28.599908502179314 44.28088041067822
P4	28.6163314196362 44.28109930396021
P5	28.61820062035677 44.2487520891683
P6	28.624667170900278 44.219760532048916
P7	28.617798613038833 44.21580665660868

Figure 2. Location of the measuring points (RGB image from 01.01.2025 in the ESA SNAP 12)

3.1. Maximum Peak Height

For the early analysis, we used an elevated index, available in the Sentinel Hub, namely Maximum Peak Height (MPH) or Bloom Index. It is designed to detect and quantify algal blooms in surface waters, a direct indicator of eutrophication. Visualizing the evolution of the eutrophication phenomenon over an extended period can be done in Copernicus Browser by constructing a timelapse with the MPH images obtained.

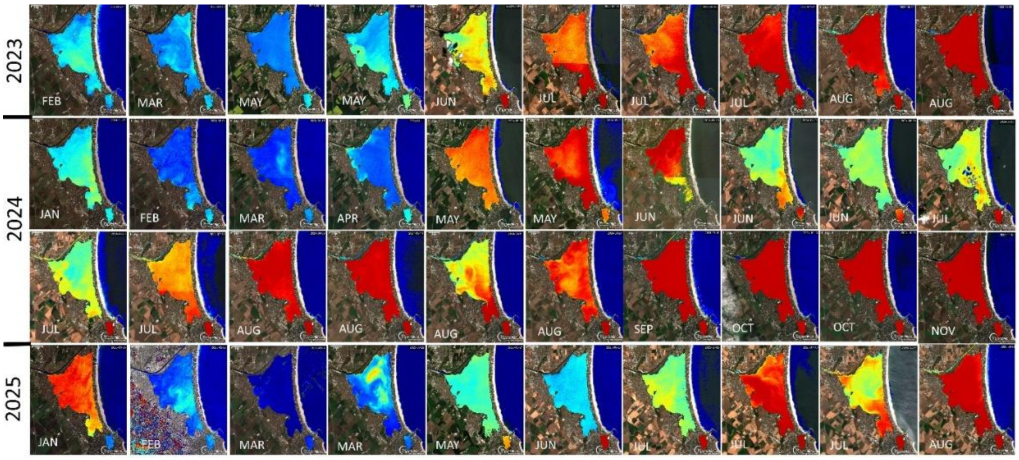

Figure 3. Evolution of the Maximum Peak Height Bloom Index for 2023-2025

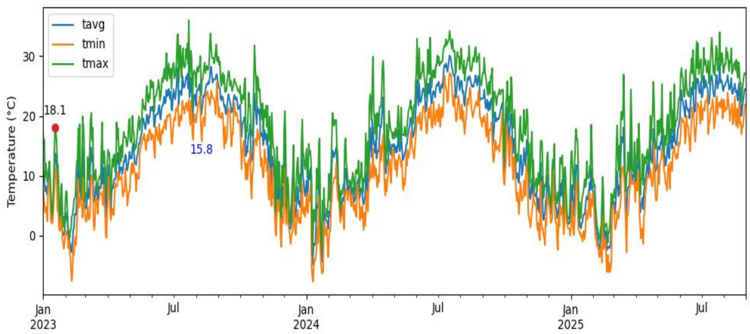

Figure 4. Monthly average, maximum and minimum temperature values in the period 2023-2025

In February 2023, an increase in MPH is observed due to the high temperatures in January, which reached values of 18°C on 18.01.2023, gradually decreasing towards normal values for that period. The 5 days in which temperatures remained above 10°C led to the activation of the ecosystem. In March, there is also an increase in the MPH index, with temperatures at the end of February approaching 20°C. Starting in May, the trend of increasing temperatures is normal, and the increase of the MPH index is observed, reaching saturation in July, which is maintained until the end of the year, with a short pause at the end of August (Figure 5). This decrease is probably due to the minimum temperatures between 8 and 11 August, which reached 15°C.

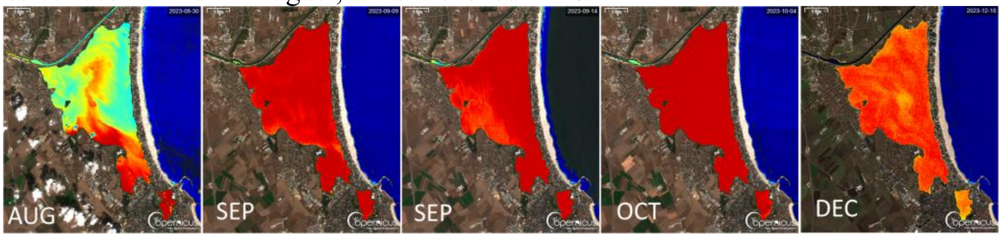

Figure 5. August-September-October- -December 2023

In the year 2024, there are two periods in which MPH reaches saturation. The first shorter duration in May-June, respectively the second starting from August until the end of the year. This can be associated with minimum temperatures reaching 12°C on May 29, 2024, respectively maintaining saturation due to the positive temperatures at the end of the year. At the beginning of 2025, the decrease in the MPH index is observed in February, because temperatures drop below zero degrees at the end of January. A temporary increase in the index occurs in May, but is blocked by low temperatures, it returns to a significant increase in July, respectively in August it reaches saturation.

3.2. Sentinel Product Processing

The analysed period is January – August 2025. Data from Sentinel 2 Level 2A products were processed using the Snap 12 application, selecting the available values from the MSI sensor bands. These values were then grouped and used to calculate the values of the indices, respectively to plot the temporal evolution of the indices, as can be seen below in figures (6-12 and 14-20). The processing was done in Jupyter Notebook using the pandas and matplotlib packages for visualization.

3.3. Normalized indices

The first index analysed is NDVI, the results obtained in the points of interest are shown in the figure below.

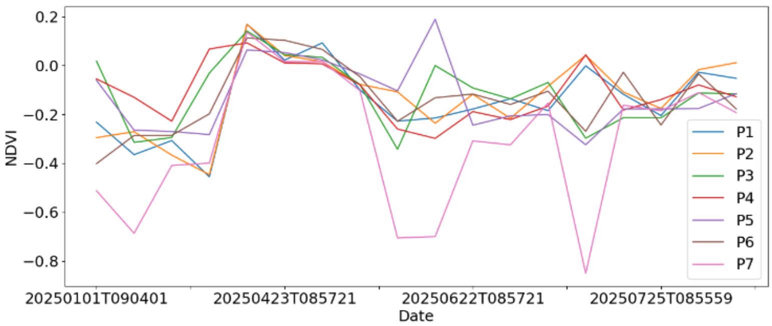

Figure 6. Evolution of the NDVI index in the analysed period January – August 2025

The evolution of the NDVI generally shows a variation close to 0, except for the P7 point, where the values in January, June and July are close to -0.7÷ -0.8. The negative value, close to -1, can be attributed to the fact that the selected measurement points are near the shore, and thus there is a possibility that the sand or rocks at the bottom of the water influence this index.

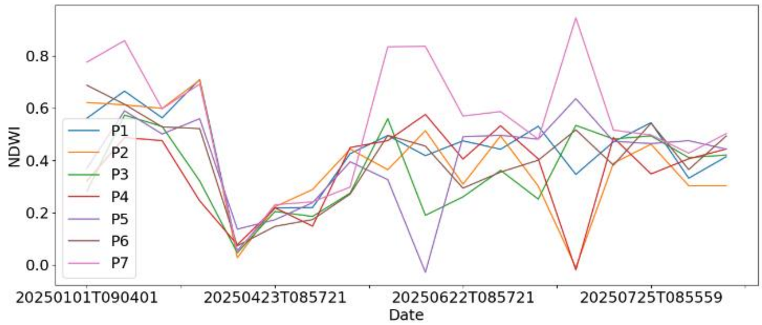

Figure 7. Evolution of the NDWI index in the analysed period January – August 2025

In the case of the NDWI index, the P7 point goes out of trend again for the months of January, June and July, with a strong deviation reaching values between 0.7÷0.8, the interpretation of this value would be cleaner water than in other points. In April, we have a value close to zero at all points. There are 3 more values close to zero, namely in the P5 measurement point in June, respectively in the P2 and P4 points in July. Overall, the value of this index is around 0.4, which shows that in the water there are elements that disturb the radiation reflected for the bands used in the calculation.

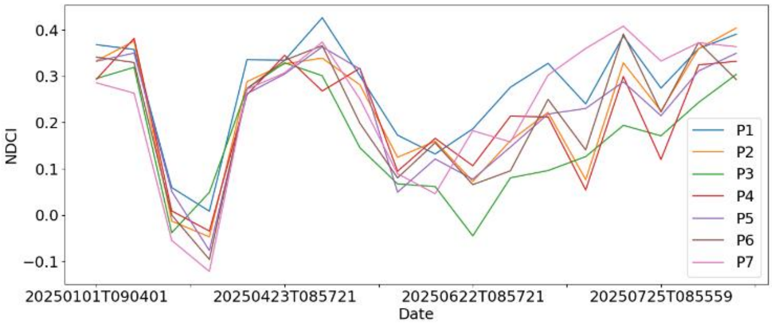

Figure 8. Evolution of the NDCI index in the analyzed period January – August 2025

We also have an interesting trend in the case of NDCI, where a decrease close to zero (P1, P2, P3, P4) and below zero (P5, P6, P7) is observed for February. The range of values for this index could be considered between 0.3 and 0.4, a range observed in January, March, April and August, respectively. At point P3 there is a decrease below zero in June, but after the decrease in May the trend is upward, with fluctuations for certain points (P1, P2, P4, P6) or for July we have a fluctuation for all points. These fluctuations may be determined by the minimum values of the temperatures in July that reach 17°C on 10.07.2025, respectively 17.9°C on 18.07.2025

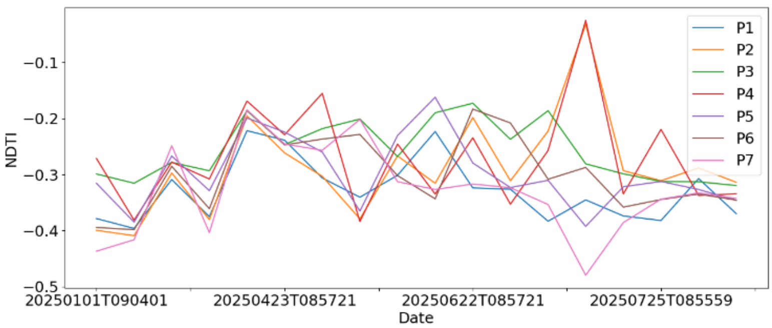

Figure 9. Evolution of the NDTI index in the analysed period January – August 2025

The change in the NDTI index is between -0.2 and -0.4. There are two exceptions, with values approaching zero, for points P2 and P4 at the beginning of July. At the same time, at point P7 at the same time, the value of the index drops to -0.5. Again, fluctuations of values are observed over time.

3.4. Special indices: MCI, FAI, FVI

We evaluate first special indices, MCI, that are direct related to presence of chlorophyl-A in water, and the values calculated from Sentinel 2 L2A product are shown in Fig. 10.

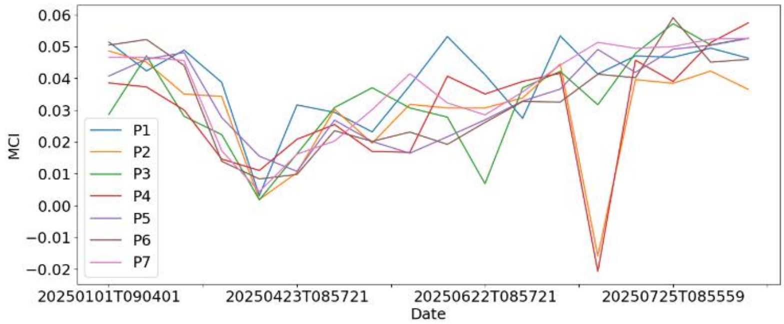

Figure 10. Evolution of the MCI index in the analysed period January – August 2025

A drop in February is visible on data, due to drop in the temperature. Also, there are some points July and August that shown a drop in Chlorophyll-A concentration, this behaviour can be corelated to evolution on NDTI.

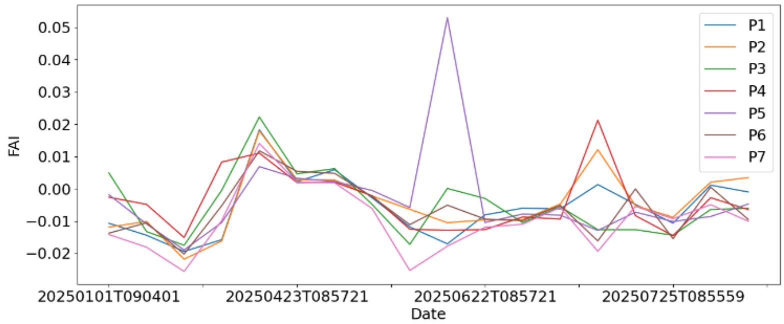

Figure 11. Evolution of the FAI index in the analysed period January – August 2025

Again. we observed that same points of measurement exhibit the same evolution, FAI mean the presence of algae at water surface.

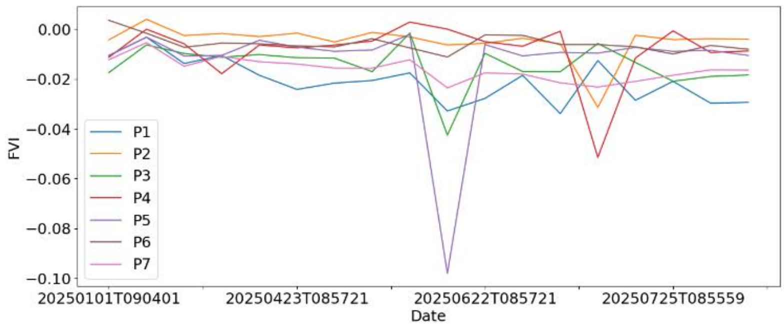

Figure 12. Evolution of the FVI index in the analysed period January – August 2025

3.5. Correlations

To connect indexes, we calculate the corresponding correlations between normalized indices and special indices.

Table 2. Correlation between calculated parameters

	NDVI	NDWI	NDCI	NDTI	MCI	FAI	FVI
NDVI	1.000000	-0.939611	0.310955	0.569310	-0.498761	0.821462	-0.179600
NDWI	-0.939611	1.000000	-0.150482	-0.795197	0.638446	-0.837820	0.247257
NDCI	0.310955	-0.150482	1.000000	-0.279894	0.244883	0.291810	0.040409
NDTI	0.569310	-0.795197	-0.279894	1.000000	-0.629634	0.497209	-0.223716
MCI	-0.498761	0.638446	0.244883	-0.629634	1.000000	-0.602042	0.062050
FAI	0.821462	-0.837820	0.291810	0.497209	-0.602042	1.000000	-0.452811
FVI	-0.179600	0.247257	0.040409	-0.223716	0.062050	-0.452811	1.000000

The NDVI index is inversely correlated with the evolution of the NDWI, MCI parameters, respectively directly correlated with NDCI, NDTI and FAI. The NDWI index is inversely correlated with NDVI, NDTI and FAI, respectively directly correlated with MCI. For NDCI we have an inverse correlation with NDTI, respectively a direct correlation with NDVI. The NDTI index correlates inversely with NDWI, NDCI, MCI, respectively directly with NDVI and FAI. MCI is inversely correlated with NDVI, NDTI and FAI, respectively directly correlated with NDWI. For the FAI index we have an inverse correlation with the NDWI, MCI and FVI indices, respectively a direct correlation with NDVI and NDTI. The FVI index correlates inversely with the FAI.

In all other cases, the values sound below a threshold and we can consider the indices uncorrelated.

3.6. Extended analysis

For this analysis, 87 points were selected evenly distributed in the lake area, so that the selected area would not be covered by clouds during the period selected for analysis.

Figure 13. Siutghiol points for extended analysis

As in previous section, the calculated parameters were added to a graph to estimate the overall behaviour of indices. Figure 14 to 20 are shown below, and calculated correlations in Table 3.

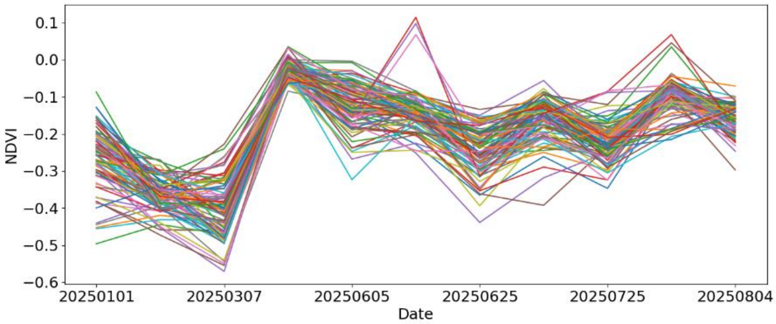

Figure 14. Evolution of the NDVI index in the analysed period January – August 2025

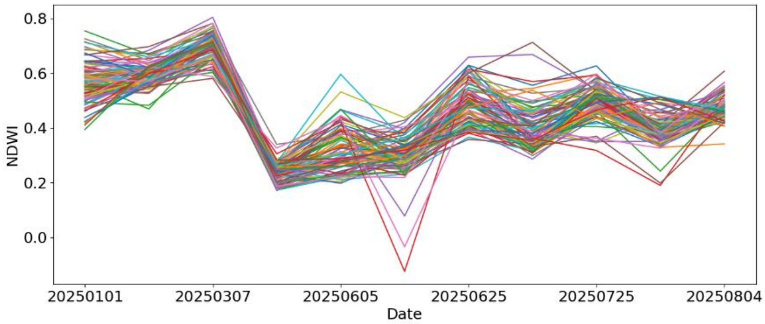

Figure 15. Evolution of the NDWI index in the analysed period January – August 2025

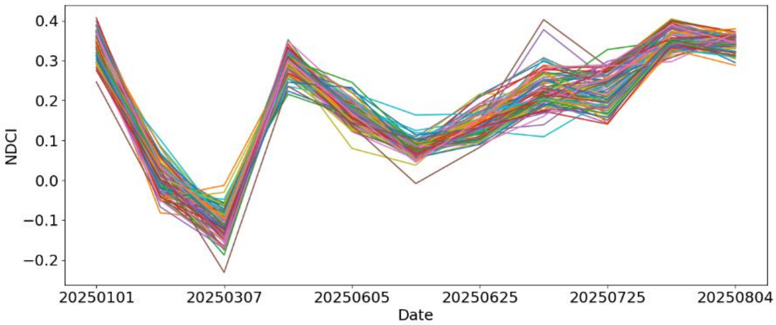

Figure 16. Evolution of the NDCI index in the analysed period January – August 2025

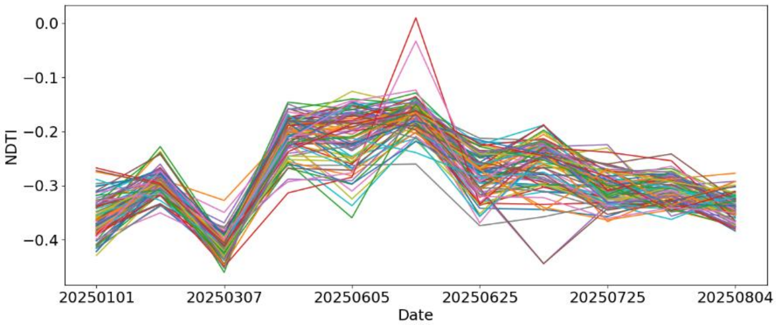

Figure 17. Evolution of the NDTI index in the analysed period January – August 2025

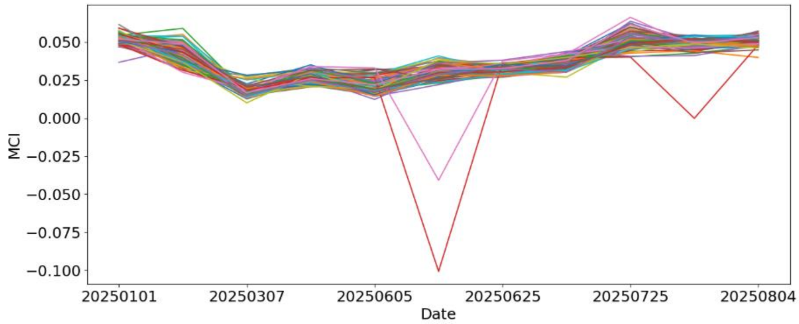

Figure 18. Evolution of the MCI index in the analysed period January – August 2025

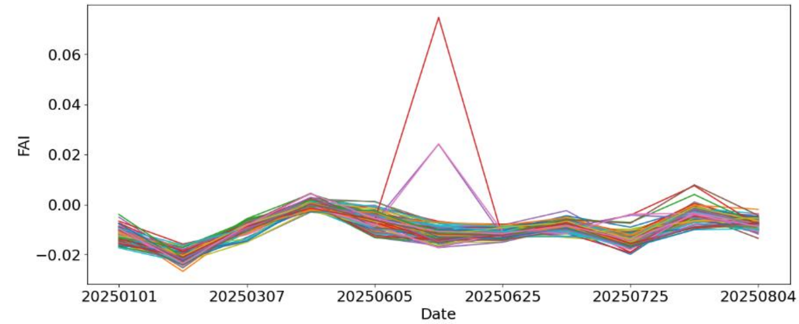

Figure 19. Evolution of the FAI index in the analysed period January – August 2025

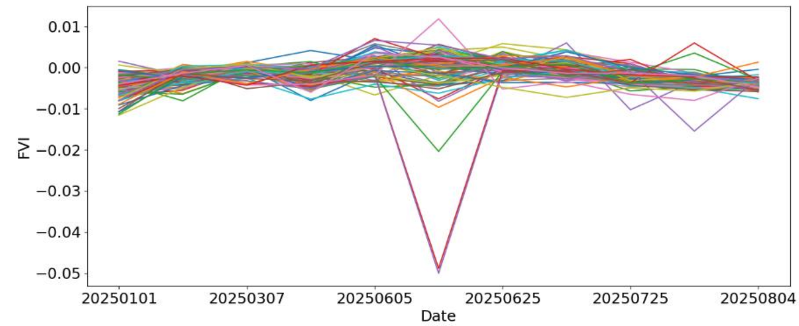

Figure 20. Evolution of the FVI index in the analysed period January – August 2025

Table 3. Correlation between calculated parameters

	NDVI	**NDWI**	**NDCI**	**NDTI**	**MCI**	**FAI**	**FVI**
NDVI	1.000000	-0.931724	0.591755	0.627887	-0.049652	0.709327	-0.123698
NDWI	-0.931724	1.000000	-0.374241	-0.860704	0.222214	-0.601464	-0.006673
NDCI	0.591755	-0.374241	1.000000	0.031840	0.568266	0.371900	-0.238167
NDTI	0.627887	-0.860704	0.031840	1.000000	-0.309324	0.226495	0.194504
MCI	-0.049652	0.222214	0.568266	-0.309324	1.000000	-0.410902	-0.259116
FAI	0.709327	-0.601464	0.371900	0.226495	-0.410902	1.000000	-0.291122
FVI	-0.123698	-0.006673	-0.238167	0.194504	-0.259116	-0.291122	1.000000

4. Conclusions

Preliminary analysis of the use of satellite data in monitoring and establishing the eutrophic status of a lake shows that there is the possibility of quickly using the tools already developed, possibly for other investigations. A handy solution is the Copernicus browser that allows access to Sentinel 2 data, and its processing to immediately visualize the values of interest. The ESA Snap method is useful when data extraction operations are required, for the analysis of values at a point.

The paper highlighted a correlation in the evolution of the normalized indices, respectively of the special ones, which are related to the monitored parameters. Thus, a qualitative analysis can be carried out quickly, followed by a quantitative analysis if necessary.

The Maximum Peak Height Bloom Index (MPH) combined with the temporal analysis in the Copernicus Browser can be used to identify the dynamics of algal blooms. FAI and FVI complete the study to identify chlorophyll sources. Evalscript (javascript implemented on Copernicus browser API) can be successfully used both in the browser/web page (e.g. Copernicus Browser) and in specific codes (e.g. python) to extract data of interest.

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