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Comparative analysis of remote sensing techniques to estimate and map floating algae in the northern part of the gulf of Evoikos in Greece

Abstract

Various types of floating algae have been reported in the northern part of Evoikos gulf during June and July 2017. Floating algae is a highly adaptable, to different environments, single celled organism more complex than bacteria and is able to photosynthesize. Algae is an indicator of water pollution and is caused by a combination of biotic and abiotic parameters such as the richness in nutrients in a certain area, their ability to absorb light and the high water temperature and pH. Algal blooms are divided in two categories, the Harmful Algal Bloom (HAB) and the Macroalgal Bloom (MAB). In case of Evoikos gulf the floating algae can be classified as MAB. Detection and mapping of floating algae is necessary for both environmental and economic implications because eutrophication is linked with the MABs which affects not only the aquatic life but the fishing based economy of the gulf. Many algorithms and methodologies exist (e.g. Kahru's model, the Meris Terrestrial Chlorophyll Index – MCI etc.) in remote sensing with the most common being color indexes such as FAI (Floating Algae Index). This paper uses collectively satellite images from sensors Landsat 8 OLI/TIRS and Sentinel – 2A, who have different spatial resolutions, 30x30 meters and 10x10 meters respectively, but they have similar spectral bands. The methodologies applied are Hu's Floating Algae Index (FAI), the newly developed Surface Algal Bloom Index (SABI) and object oriented image analysis using semi-automatic algorithms in order to model the spatial distribution of the algal blooms. Also, the Normalized Difference Vegetation Index (NDVI) was calculated. The data were statistically analyzed and are highly correlated in each sensor. NDVI was set as an independent variable and FAI and SABI as dependents. All the results were visualized in maps and diagrams for better understanding of the differences between indexes, methodologies and sensors. The aim of this paper is to compare methods and data to find which parameters (sensor, bands etc.) affect the quality of the final result and which is the most suitable method in each case.

Key words

Floating algae, Spectral Indices, Semi – automatic algorithm, correlation

Introduction

A common and growing environmental problem in the aquatic ecosystem is the existence of surface algal blooms. Algae are a highly adaptive plant - like group of photosynthetic micro – organisms, more complex than bacteria but single celled, found in oceans, lakes and ponds. They can be grown almost anywhere, even in fresh and salt water, and do not require fertile land or food crops for their development (Demirbas, 2011), only sunlight or any source of energy, water (H_2O), carbon dioxide (CO_2) and inorganic nutrients. Algal bloom is the massive accumulation of planar cyanobacteria in the surface water layer and it's divided in two categories, the Harmful Algal Bloom (HAB) and the Macroalgal Bloom (MAB). The increasing development of HABs (and MABs) reflects the advanced state of eutrophication in the aquatic eco – system caused by urban, agricultural, and industrial sewage (El-Alem et al, 2012).

When algae covers the water surface, it prevents oxygenation and causes a lack of light in the bottom, resulting in the reduction of both photosynthetic and non-photosynthetic organisms (Han & Liu, 2014). Nevertheless, algae are important for biological monitoring since they respond immediately to both qualitative and quantitative composition of species in a wide range of water situations due to changes in water chemistry (Gokce, 2016). Also, they can function as indicators of organic environmental pollution (bio – pollution), therefore their monitoring is essential for the detection of the water quality along the shoreline and within the surrounding watershed. Algal monitoring is carried out with in situ sampling, but the sampling analysis is a highly expensive process.

Remote sensing offers the possibility to monitor surface algal blooms spatially and temporally in large areas, fast and with low cost. Chlorophyll – A, the photosynthetic pigment found in algae, is light absorbent and can be estimated using satellite datasets. Satellite sensors that provide data in visible and near infrared (NIR) wavelengths can be used to estimate Chlorophyll-A concentration (Chl-a) based on its high absorption of the blue and red part of the spectrum, and its high reflectance of the green and NIR bands (El – Alem et al, 2012). So, many semi analytical algorithms and spectral indices for estimating Chlorophyll-A's (Chl-a) concentration have been applied, such as Hu's (2009) Floating Algae Index (FAI), the semi – analytical Kahru model (Kahru et al, 2004) and the Merris Terrestrial Chlorophyll Index (Gower et al, 2005).

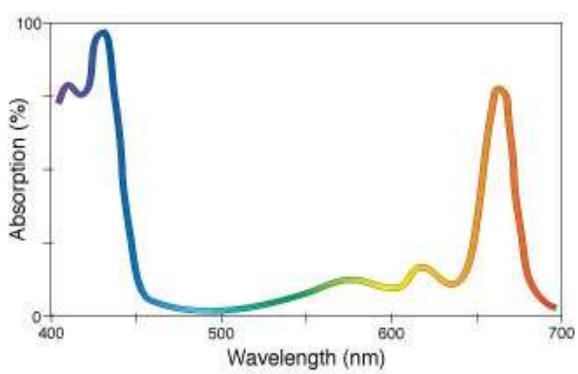

Figure 1: Absorption spectrum of Chlorophyll - A (https://www.giss.nasa.gov/research/features/201311_kiang/)

In this paper four different methods are applied to estimate the concentration of Chlorophyll – A, on Landsat 8 imagery. The methods used are indices NDVI (Normalized Difference

Vegetation Index) and FAI (Floating Algae Index), the empirical algorithm SABI (Surface Algal Bloom Index), and a proposed a semi – automatic algorithm based on the Object Image Analysis (OBIA). The results were statistically analyzed using simple linear regression to examine the correlation between the indices and the proposed algorithm. Also, additional Sentinel – 2A datasets were used to cross - calibrate the results between sensors.

Dataset & methodology

The study area is the Northern Part of Evoikos Gulf in Greece (Longitude 23° 26' 31.09", Latitude E 38° 35' 33.8" N). North Evoikos is a semi-bay of 390 km^2, formed by the eastern coasts of Fthiotida and Viotia and the western coasts of Evia. It connects with the West Aegean Sea through the Oreon Channel and the South Evian via the straits of Euripus. The eastern coastline includes low hills and gulfs such as Maliakos and Atalanti Bay. The depth of the gulf is relatively small 10-100 m, with a maximum depth of 430 m (Chrysogelos, 2005). The gulf is a graben which was formed during the Quaternary from the action of normal NW-SE to WNW-ESE and it has intense tectonic activity. The most impressive active fault, is the fault of Atalanti with well-known seismic activity (Papaioanou et al, 2004; Pavlides et al, 2014).

In the area of the gulf, a large number of human activities is gathered (cities and industries) such as various forms of fishing, like fish farming and coastal fishing, crops and touristic activities. The existence of all those activities makes the management and protection of the area complex (Chrysogelos, 2005). Many sewages caused from all those activities end up in the gulf, therefore the result is the lack of oxygen and the increased concentrations of silicates, nitrates and phosphates. According to Water Framework Directive (WFD), the waters of Evoikos are characterized as "coastal waters" of moderate quality.

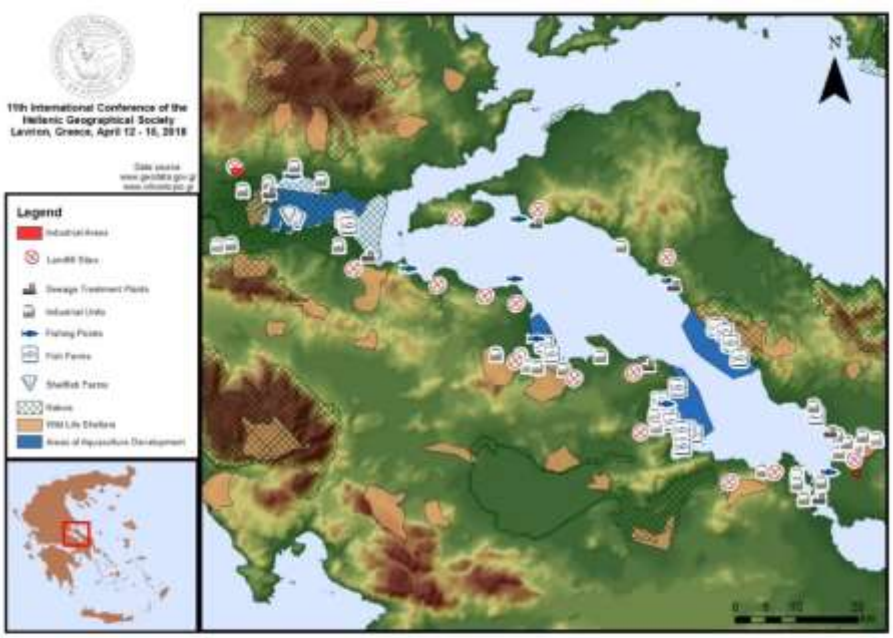

Figure 2: Map of the study area and the surrounding activities (10 km)

On early June and mid – July of 2017, a layer of green floating algae was reported in the area of the gulf. Green algae is classified as HAB and its sign of eutrophication. The source of the bloom is considered to be the mining factory of Larimna. The floating HABs can easily be recognized via satellite data with simple ocean color indices. The monitoring of the algal layer is essential, so to estimate and map it, satellite images derived from Landsat 8 – OLI TIRS and Sentinel 2A were used. The dataset consists of 6 Landsat 8 images, one before the algal bloom surfaced (11-05-2017), 4 during the bloom (12-06-2017, 28-06-2017, 14-07-2017 and 30-7-2017) and one when it weakened (15-8-20017) and a Sentinel – 2 image, during the bloom (28-8-2017). Originally, the Sentinel dataset consisted of 11 images who were merged into 3 mosaics according to the date, they were acquired, but the last two mosaics (28-7-2017 and 17-8-2017) were rejected due to heavy cloudiness which caused enormous data loss.

Figure 3: HABs in the Northern Part of Evoikos Gulf (https://tvstar.gr/fthiotida-articles/88030-to-plagkton-pnigei-maliako-kai-evvoiko-video ; http://el-vima.blogspot.gr/2017/06/)

The images were downloaded from the United Stated Geological Survey's website (http://earthexplorer.usgs.gov/) and were free of charge. Their format was Level 1 – High Quality Terrain Product, so they already include radiometric and geometric corrections, orthorectifiation and spatial registration on the global reference system. The Sentinel – 2 dataset, was also downloaded from the same website in order to have imagery with the same pre – processing level. The bands used were the BLUE, GREEN, RED, NIR and SWIR – 1 bands in Landsat 8 and the BLUE, GREEN, RED, Narrow NIR and SWIR – 1 bands in Sentinel – 2. Then, the images were subset into the study area and were atmospherically corrected (atmospheric scattering), using thresholds from the histogram of the RED band, to remove the clouds. Moreover, the land was masked using the NIR band's histogram, because the pixel value of the water is distinguishable from the land's (Katsara et al, 2016).

Table 1: The characteristics of the stacked bands of both Sensors (http://www.gisagmaps.com/landsat-8-sentinel-2-bands/)

	Wavelength (μm)		**Central wavelength (μm)**		**Bandwidth**		**Resolution**	
	Landsat 8	**Sentinel 2**	**Landsat 8**	**Sentinel 2**	**Landsat 8**	**Sentinel 2**	**Landsat 8**	**Sentinel 2**
BLUE	0.452 - 0.512	0.439 – 0.532	0.482	0.490	0.060	0.096	30	10
GREEN	0.533 - 0.590	0.537 – 0.582	0.562	0.560	0.057	0.045	30	10
RED	0.636 - 0.673	0.646 – 0.685	0.654	0.665	0.037	0.039	30	10
NIR	0.851 - 0.879	0.848 – 0.881	0.865	0.865	0.028	0.033	30	10
SWIR - 1	1.566 - 1.651	1.539 – 1.681	1.609	1.610	0.085	0.142	30	20

The indices used to estimate the concentration of the algal bloom are the Floating Algae Index (FAI), the Surface Algal Bloom Index (SABI) and the Normalized Difference Vegetation INDEX (NDVI). FAI is a simple ocean color index developed by Hu (2009) and is suitable for mapping algae in various aquatic environments using satellite data from any satellite equipped with RED, NIR and SWIR bands. The advantage of FAI is that the index is less sensitive to observational changes (e.g. solar/viewing geometry and sun glint) than other indices (Oyama et al, 2015). On the other hand, SABI is an empirical algorithm specifically modelled to adapt to marine habitants (Alawadi, 2010). SABI was proposed by Alawadi (2010) for the delineation of the spatial distributions of floating algae. Both, indices are used in water surfaces, on the contrary with NDVI, which is used to map changes in the vegetation. Therefore, the NDVI by Rouse et al (1973) was used in order to check it's capability to detect coastal vegetation changes, such as algal blooms.

Table 2: The formula and the range of each spectral index

Index	Equation	Range
FAI	RNIR – RNIR' $RNIR' = (R_{RED} + (R_{SWIR} - R_{RED}) * \frac{\lambda_{NIR}-\lambda_{RED}}{\lambda_{SWIR}-\lambda_{RED}})$, RNIR = the baseline reflectance in the NIR band derived from a linear interpolation between the RED and SWIR Bands λ = central wavelength in nm	[-1,1], -1 is dry land, 0 is clear water and 1 algal bloom
SABI	$\frac{NIR - RED}{BLUE + GREEN}$	Same range as FAI
NDVI	$\frac{NIR - RED}{NIR + RED}$	[-1,1], -1 is water, 0 is dry land and 1 healthy vegetation

A semi-automatic algorithm (eCognition ruleset) was developed in order to detect areas with high concentration of algae. Due to the existence of algae in shallow areas and their spatial relationship to the already present seagrass meadows, a pixel based analysis would require a lot of time and effort, especially when creating training points or training areas for the classifier. Thus an object-based analysis of the images was chosen. Landsat-8 images used in the algorithm were first pre-processed in a different way than the others, according to the following order:

- Images were atmospherically corrected using the FLAASH (fast line of sight Atmospheric Analysis of Hypercubes) tool.
- To each image was a mask applied (exported using the Worldview-2 Water Index), covering land portions.
- New Regions of Interest (ROIs) were exported in order to study the designated area and also to obtain Images of a more compact size.

The image taken in June (when the Algae were then segmentated into objects (groups of pixels) with a scale of 100. The goal was to obtain 3 different (e.g. easily distinguishable) object classes. The 3 classes of objects created were: Deep Sea, Shallow Areas and Vegetation. The class "Vegetation" includes both sub-classes "Algae" and "Seagrass" which in many cases were spatially identical (a mix in the same pixel (mixel), a mix in smaller objects and as a result hardly distinguishable) and had similar layer characteristics. For the sake of simplicity and due to the study focusing on the areas with Algae blooms, the semi-automatic algorithm can distinguish

Shallow Areas from Vegetation but there were cases where Seagrass meadows were wrongly interpreted as Shallow Areas. Landsat-8 bands used were Coastal, Blue, Green, Red and SWIR. Layer values with arithmetic combinations and standard deviation values of those bands were compared for the division of the objects like follows:

1. Assign Class “Deep Sea” to:
   Category “Unclassified objects” with B/G > = 1.1 && Standard Deviation Red > 30
2. Assign Class “Shallow Areas” to:
   Category “Unclassified Objects” with (B*G)/R > = 100 && Mean Green > 170
3. Assign Class “Vegetation” to:
   Category “Unclassified Objects” with Mean Green > 70

The order in which the above mentioned rules were applied, was critical since after every successful classification the classifying tool (e.g the ruleset) is set to search for new unclassified objects. This means that when trying to execute the rules in a different order the result would not be the desired one. In order to test the functionality of the ruleset it was executed on images taken at an earlier and a later time in comparison to the one taken in June.

Finally, the results derived from the indices were statistically analyzed and graphically visualized in order to check the covariance between them. To achieve that, 40 points were randomly generated in the gulf and in each point the value of the corresponding pixel was assigned. The values were exported in an .xls table to complete the analysis. For the cross – calibration between sensors, the statistical method used was the simple linear regression.

Results

The statistical results show high correlation between the indices in each image but the covariance between them is relatively low, this is due to the different spectral values which compose each index. However, the relation between the cross - calibrated results (Landsat 8 – Sentinel 2) is not significant. Sentinel’s – 2 pixels depict the 1/3 of the area, pictured in a Landsat 8 pixel. To have more significant statistical result, the Sentinel imagery’s pixels should be grouped and that will cause data loss.

As far as the validity of the produced ruleset is concerned, the most noticeable feature was that the classification results were different (as expected) in images taken weeks before and after the peak of the algal bloom. The classifier did not detect areas with high concentration of Algae (or even Seagrass) characterizing them all as Shallow Areas. The reason behind this is that the layer values vary from image to image due to the dynamic nature of the aquatic scenery. Another important fact which affects the end results is the decline of the algal blooms in July and their close-to-absent state during the month of September.

In conclusion features that can be used in order to export a new ruleset which will detect not only the algae parts in the Gulfs but also differentiate them from Seagrass, are the shape characteristics of the objects created together with their texture, their already processed layer values and finally their relations to super or sub objects (when classifying an image in multiple layers). A fully automated ruleset is being developed which is expected to produce the result of the manual classification, as shown in Figure 28.

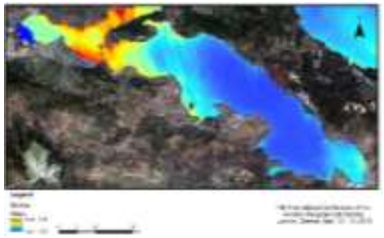

Figure 4: FAI (Landsat – 8, 11-05-2017)

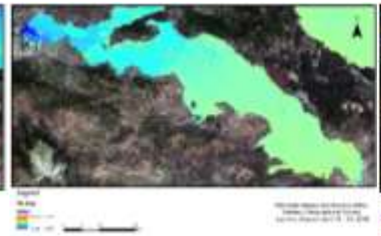

Figure 5: FAI (Landsat – 8, 12-06-201

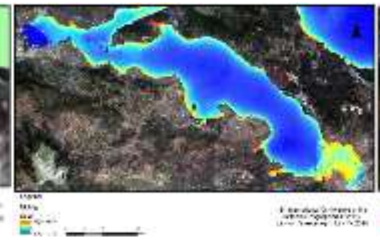

Figure 6: FAI (Landsat – 8, 28-06-2017)

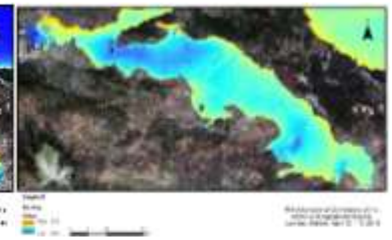

Figure 7: FAI (Landsat – 8, 14-07-2017)

Figure 8: FAI (Landsat – 8, 30-07-2017)

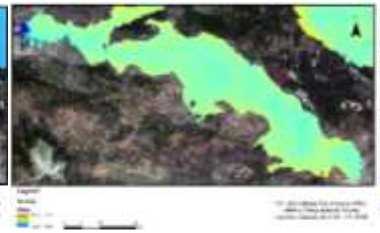

Figure 9: FAI (Landsat – 8, 15-08-2017)

Figure 10: FAI (Sentinel -2, 28-06-2017)

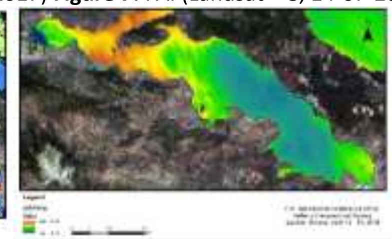

Figure 10: SABI (Landsat – 8, 11-05-2017)

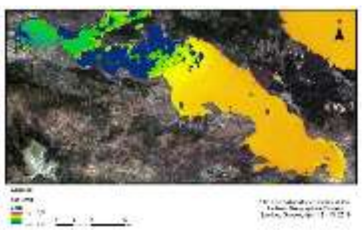

Figure 11: SABI (Landsat – 8, 12-06-2017)

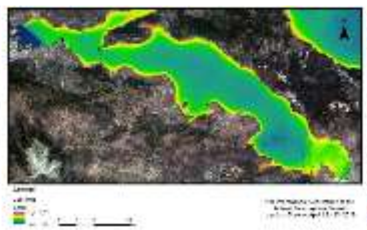

Figure 12: SABI (Landsat – 8, 28-06-2017)

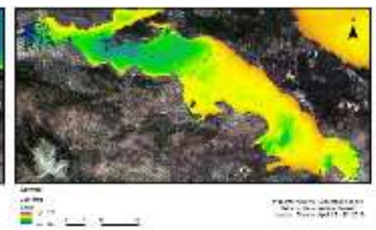

Figure 13: SABI (Landsat – 8, 14-07-2017)

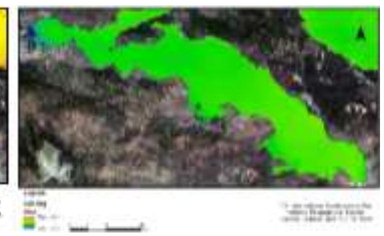

Figure 14: SABI (Landsat – 8, 30-07-2017)

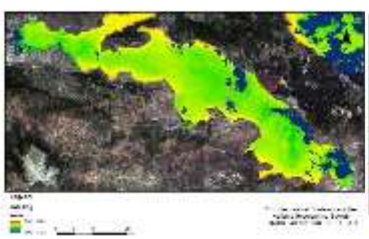

Figure 15: SABI (Landsat – 8, 15-08-2017)

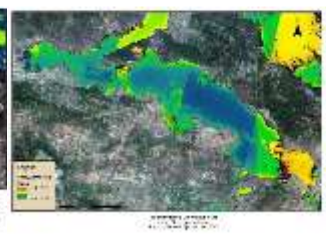

Figure 16: SABI (Sentinel -2, 28-06-2017)

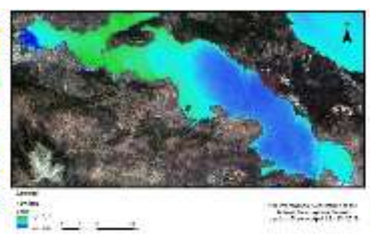

Figure 17: NDVI (Landsat – 8, 11-05-2017)

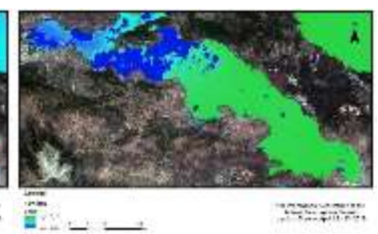

Figure 18: NDVI (Landsat – 8, 12-06-2017)

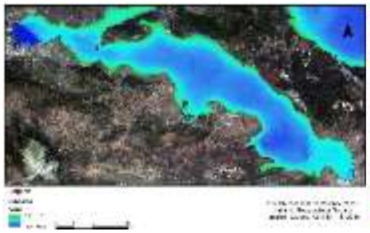

Figure 19: NDVI (Landsat – 8, 28-06-2017)

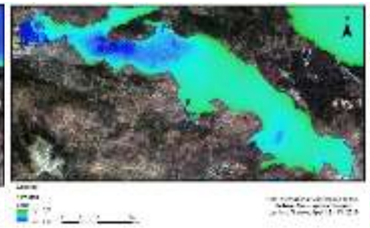

Figure 20: NDVI (Landsat – 8, 14-07-2017)

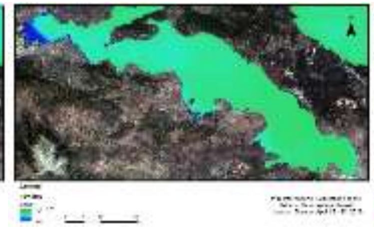

Figure 21: NDVI (Landsat – 8, 30-07-2017)

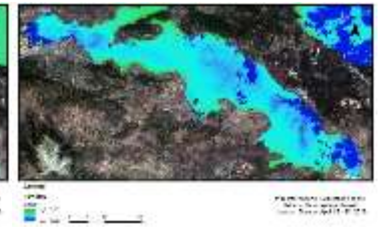

Figure 22: NDVI (Landsat – 8, 15-08-2017)

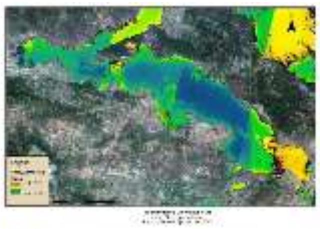

Figure 23: NDVI (Sentinel -2, 28-06-2017)

Figure 24: Segmentation Base

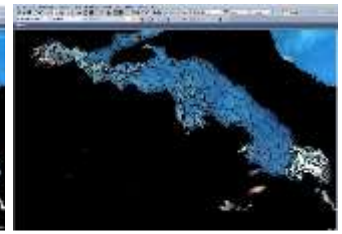

Figure 25: Segmentation

Figure 26: Success

Figure 27: Before the bloom

Figure 28: Manual Classification result

Figure 29: Indices' covariance (11-05-2017)

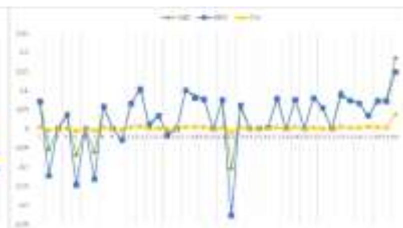

Figure 30: Indices' covariance (12-06-2017)

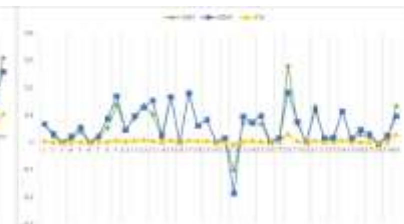

Figure 31: Indices' covariance (28-06-2017)

Figure 32: Indices' covariance (14-07-2017)

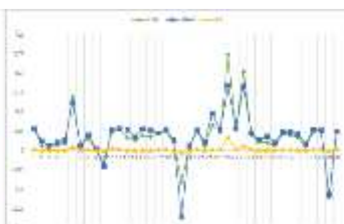

Figure 33: Indices' covariance (30-07-2017)

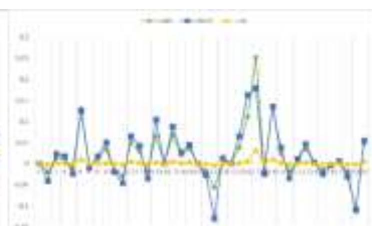

Figure 34: Indices' covariance (15-08-2017)

Figure 35: Indices' covariance (28-06-2017,S2)

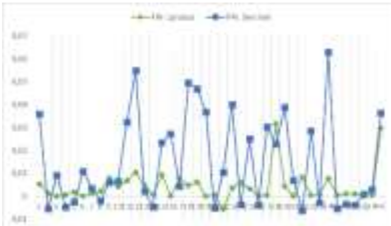

Figure 36: Sentinel 2 ~ Landsat 8 (FAI)

Figure 37: Sentinel 2 ~ Landsat 8 (NDVI)

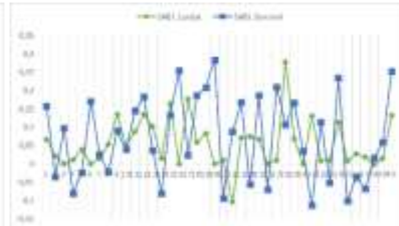

Figure 38: Sentinel 2 ~ Landsat 8 (SABI)

Conclusions & Discussion

Floating algae can function as an indicator of water pollution so the estimation and mapping of an algal bloom is essential. Remote sensing is useful and allows to study the marine environment and coastal zones, fast and in large areas. The methodologies applied in this paper are common and very effective with accurate results but it's necessary for the results to be more realistic to complement the satellite's data with in situ measurements.

Sentinel – 2 has higher spatial resolution than Landsat 8, so it was expected for the results not to have a significant statistical relationship. Landsat's pixel size is larger, so the values are three times larger than Sentinel's. The algorithm was used only in Landsat dataset in order to check its validity and because the mosaics need an entirely different process. Also, the classification and the results derived from the indices can't be statistically correlated only visually due to the fact that the comparison between pixels and objects is not possible because a portion of pixel can be in one segment and the other in another.

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