Implementation of Smart Buoys and Satellite-Based Systems for the Remote Monitoring of Harmful Algae Bloom in Inland Waters

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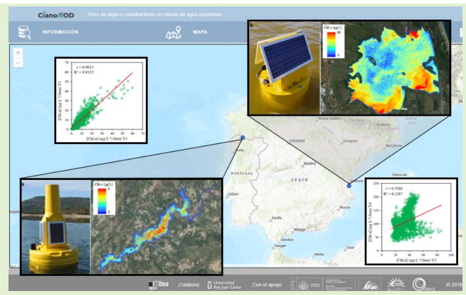

***Abstract*—The deployment of Remote Monitoring Systems (RMS) based on Internet of Things (IoT) technologies and data management in the cloud is a cutting-edge solution for water management agencies to track harmful algae blooms (HABs). However, each environment presents different intrinsic characteristics, hence the reliability and representativeness of collected data may vary according to the selected RMS architecture. This study aims to implement the same RMS in two different water bodies in Spain: the freshwater As Conchas reservoir and the shallow L'Albufera brackish water lagoon. We firstly evaluate the pros and cons of current technologies available on the market and then we select an RMS based on a combination of plug-and-play (YSI-based) and customisable solutions (Libelium-based). The deployment of nodes on buoys allows big data collection from different areas of water bodies, their continuous transfer and storage on a web server, and their subsequent visualisation on the web interface in real time. Secondly, in order to know whether the selected RMS architecture and monitored environment influence the representativeness of the collected data, we perform a Pearson correlation test between the deployed nodes and satellite images. The results point out that the more heterogeneous the environment is, the more nodes must be deployed in different areas for a longer time to obtain a realistic view of the water body status. Therefore, this study provides critical and empirical data to implement a profitable and effective real-time monitoring system in other HAB-affected areas.**

***Index Terms*— Harmful algae blooms (HAB), Internet of Things (IoT), remote monitoring system (RMS), nodes, sensors, satellite.**

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I. Introduction

CLIMATE change and water pollution due to urban, agricultural and industrial developments have impacted inland water bodies worldwide. Today, one of the most worrying troubles are harmful algae blooms (HAB) [1], which is a persistent problem induced by rising temperatures and overabundance of key nutrients, such as nitrogen (N) and phosphorus (P) [2], [3]. Algae proliferation on surface water triggers poor transparency, which affects the trophic chain by preventing benthic photosynthetic organisms from developing. Besides, damage to the ecosystem increases when bloom collapses and dies as the excessive consumption of dissolved oxygen by bacterial decomposers may result in aquatic animal death by asphyxia. The HAB dominated by cyanobacteria are a particular concern. These microorganisms are photosynthetic bacteria, also known as blue-green algae, and many of the most frequent species can produce toxins that are highly poisonous for animals and human beings [4]. When a toxic HAB appears, the authorities must set up exhaustive vigilance programmes and restrict water uses [5]. Consequently, affected areas often suffer vast economic losses in public health, fisheries, tourism and water management terms, which range from hundreds to billions of dollars, according to evaluations made in Europe, North America and Australia [6], [7].

Toxic cyanobacterial blooms are widespread in water bodies worldwide [8]. In Spain, about 35-48% of reservoirs are impacted by cyanobacterial blooms [9]. For instance, the As Conchas reservoir, located in the "Baixa Limia-Serra do Xurés" Natural Park (The Miño-Sil River Basin District in Galicia, NW Spain), undergoes intense eutrophication. Public reports by the Spanish Ministry have shown that the worse water quality in the As Conchas reservoir is due to not only poor sewage water purification at the head of the Limia River, but also to very diffuse agro-livestock contamination on the Limia plain. Consequently, the cyanobacterial concentration has nearly exceeded alert level 2 according to World Health Organization (WHO) guidelines [5], which implies several cuts in the water supply to the population and restricting recreational activities in aquatic areas. Likewise, the shallow L'Albufera Lagoon in Valencia (E Spain) is a characteristic wetland of Mediterranean coastal environments that is also impacted by HABs. Human activities exert significant pressures on this lagoon as most incoming water is traditionally regulated by rice cultivation requirements and leftover sewage water discharges [10]. The occurrence of cyanobacteria at the shallow L'Albufera Lagoon follows a spatial-temporal pattern related to seasonality and strong anthropic pressure, which make it a highly eutrophic lagoon whose recovery to an optimal state is difficult [11].

For decades, water management agencies have made many efforts to track HAB dynamics by manual water sampling [12]. However, their variable distribution over space and time requires monitoring with a very fine spatial-temporal resolution, which limits manual long-term monitoring techniques because they are time-consuming and expensive to analyse in a laboratory [13]. As an alternative or auxiliary technology, remote monitoring techniques based on the Internet of Things (IoT) have emerged to provide continuous (real-time) and autonomous surveillance. These second-generation systems employ advanced sensors that allow the detection of key parameters related to HAB; *e.g.* photosynthetic pigments, nutrients load, pH, temperature, dissolved oxygen, electric conductivity, etc. [13]. Current advances in wireless communications permit sensors to communicate with one and other and with users, which helps to make decisions supported by real-time data [14], [15]. Accordingly, IoT-based solutions have led to more studies that use nodes deployed *in situ* [16], [17] and sensors aboard satellites [18], [19] for the spatial-temporal monitoring of HABs in freshwater, brackish water and marine environments [20]–[22].

Modern monitoring programmes are beginning to include these technologies worldwide [23]–[25], and some initiatives propose using the big data collected to develop algorithms to foresee HABs in any lake on the earth [16], [26]. However, these emerging tools are in their very early development stage and some relevant issues still constrain their applicability by many water management agencies. For instance, there is no standard method or decision protocol to choose the right monitoring system architecture depending on the intrinsic characteristics of environments (salinity, size, depth, hydrodynamics, anthropogenic pressure, etc.). Because of this, many Remote Monitoring System (RMS) architectures are chosen for price, technical knowledge for handling or the availability of the sensing parameters offered by manufacturers. Instead they overlook the fact that the reliability and representativeness of the collected data may vary according to the number of nodes deployed per area, the selected parameters to be measured, the surroundings and depths where sensors are placed, among others [27]–[29]. This, together with the many studies that collect the data by developing their own nodes [17], [30], [31], makes comparisons between monitoring systems difficult and, therefore, big data collection may be rendered ineffective for HABs estimations.

In this study we implement an RMS based on IoT technologies which, combined with satellite imagery, track HAB in two Spanish water bodies with different characteristics: the freshwater As Conchas Reservoir (Galicia) and the brackish water shallow L'Albufera Lagoon (Valencia). Readers will find herein the RMS architecture selection for nodes and their deployment *in situ*, the satellite images acquisition system and the development of a multiplatform web application for on-line data visualisation. Based on this, the aim of this paper is twofold: to firstly provide critical and empirical data based on market availabilities to replicate a continuous, real-time and remote monitoring platform in other HAB-affected areas; to secondly, test whether the same RMS architecture is adequate for monitoring different environments. To this end, we analyse the correlation of the data collected by the different nodes deployed in various areas of the water body and their variation depending on the measured parameter and monitored environment. Therefore, this study provides relevant information for water management agencies to choose the right monitoring system architecture, and thus paves the path to effective big data collection based on the IoT.

II. System Architecture and Implementation

Briefly, an RMS can be defined as a set of nodes with sensing and computing capabilities that allow data transfer to a central server, usually via wireless communication. This technology has its limitations, such as its inability to control the environment or other restrictions related to topological, power use and computing capabilities [32]. For continuous water monitoring, nodes must be installed on a floating platform or buoy (Fig. 1), withstand adverse environmental conditions (resist water, sun exposure, robustness against wind and waves, wildlife impact), be energetically autonomous and have enough communication coverage for data transfer. They must also be scalable and adaptable to the requirements (size, volume, depth, etc.) present at different locations. Gradual system deterioration caused by natural fouling or possible acts of vandalism must also be considered. Nonetheless, when the deployed RMS possesses the aforementioned characteristics, big data are collected with minimal human intervention, which provides a cost-effective solution for diverse IoT-based environmental monitoring applications.

Multispectral satellite images also enable water bodies to be monitored by measuring reflectance of water at different wavelengths and delivering data about environmental colours [33]. The colour of bloom-forming algae and cyanobacteria depends on the pigments they contain and their absorption or reflectance at different wavelengths [34]. For instance, Chlorophyll-a (Chl-a), the most dominant pigment in algae, is strongly reflected on the green spectrum, which the human eye captures as green. Otherwise, cyanobacteria also produce Phycocyanin (Phy), which reflects more intensely on the cyan and green spectrum and appears as a variation in blue or turquoise [35]. By processing this type of images, different indices can be calculated as specific indicators, which is extremely useful for detecting various types of HAB. To date, several indices have been applied, such as the Harmful Algae Bloom Index (HABi), developed by the company EOMAP (Earth Observation and Environmental Services), which specialises in detecting blue algae containing Phy pigments; the Red-Tide Index (RI), which tracks the reflectance of Carotenoid pigments [19]. Satellite-based remote sensing can offer daily/weekly temporal and large spatial resolution and, thus, supplement the RMS deployed *in situ* (Fig. 2). However, interferences with cloud cover and low light penetration in the water column may limit HAB monitoring by this technology [36].

Finally, given the need to gain ubiquitous access to the collected data, a data management system is required as an integral part of the IoT-based solution (Fig. 2). This could involve software that allows the received data to be collected and stored in a database and a web interface for data viewing and post-processing purposes. For a HAB monitoring platform, it is advisable that the RMS system exhibits a modular design to manage several databases from different locations and to access them simultaneously from distinct devices [24]. It would also be desirable for the system to allow the database to be replicated in several remote servers by adding backup capabilities to the system and allowing remote collaboration between different users and sites.

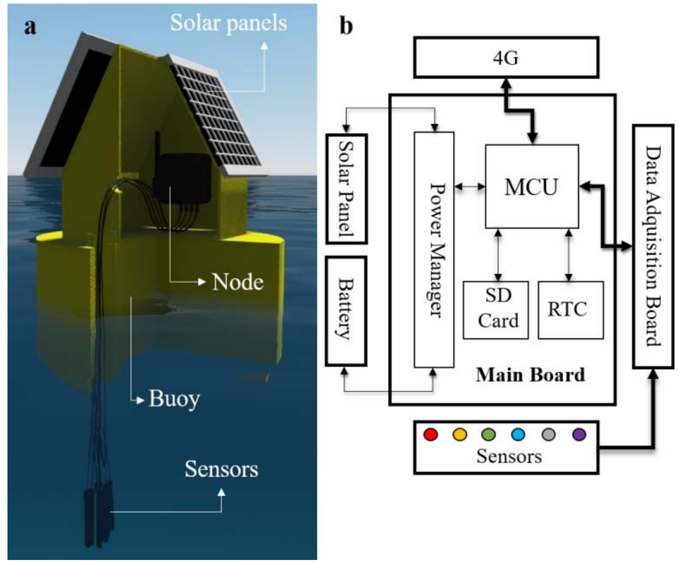

Fig. 1. (a) Structure of a smart buoy: Solar panel, node based on Libelium technologies, sensors and buoy. (b) Block diagram of a node showing the interconnection among Sensors, Data Acquisition Board, Main Board and Wireless Transceiver Device (4G). Main Board includes a Microcontroller Unit (MCU), Real Time Clock (RTC), SD Card for data saving and a Power Manager for controlling energy suppliers.

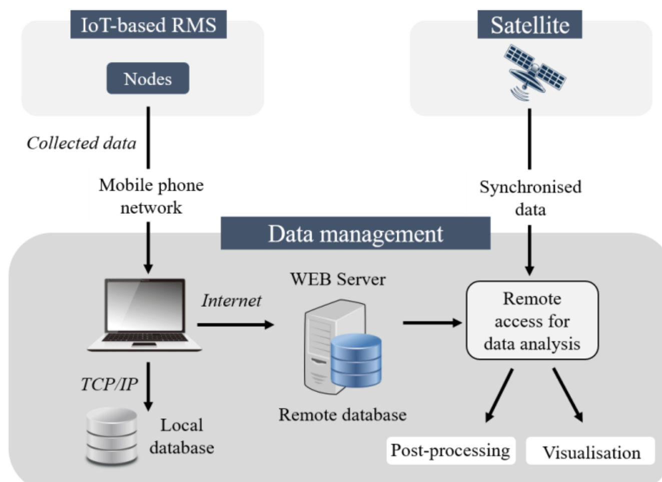

Fig. 2. RMS architecture. Big Data collection by the nodes deployed *in situ*, images acquired by on-board satellite sensors, and subsequent data management in the cloud.

A. Node Alternatives

Modern devices for HAB monitoring are normally divided into physical and chemical sensors [32]. The number of measurable parameters often depends on the available ports at each node, the load capacity of a buoy, as well as other restrictions; *e.g.* costs or suitability of commercially available sensor devices (range, accuracy, resolution, etc).

Optical sensors, also called fluorometers, of Chl-a and Phy are normally mandatory because they allow the monitoring of algae and cyanobacteria as these photosynthetic pigments are frequently considered to be a proxy of phytoplankton biomass [37]. Likewise, optical turbidity sensors are commonplace for environmental water quality monitoring as they reflect content substances in water, including pigments, suspended organic matter, microorganisms, etc. [38]. Optical sensors exhibit a high-accuracy and low-calibration drift, but at a high cost. One major drawback is that they acquire information from their close surroundings, which means that the deployment area must be correctly selected. Instead their use is significant when combined with satellite images.

Indirect parameters come into play for monitoring HAB outbreaks at a lower cost than optical sensors, but at higher calibration frequencies and replacement rates. A temperature sensor is widely used because temperature has an strong effect on HAB dynamics and distribution [39]. Even intense light absorption by photosynthetic microorganisms can locally increase water temperature [40]. This is a thermistor and many commercial brands offer this sensor combined with electrodes to detect the electrical conductivity of water. The latter can be an interesting incorporation because electrical conductivity is related to rainfall and flushing events, and can be associated with certain toxic species [41]. The pH sensor, mostly measured by ion-selective glass combined electrodes, is also commonplace because it is responsive to changes in photosynthetic activity as a consequence of phytoplankton growth [42]. Another sensor capable of measuring microbial activity is the Oxydo Reduction Potential (ORP) sensing electrode [43]. This sensor is a platinum electrode whose potential is to read the sample oxidation, which may indicate algae decomposition [44]. Other widely employed electrochemical sensors for water quality analyses are those based on ion-selective electrode (ISE) membranes. They are cost-effective, but are subject to poor stability and a short lifespan due to fouling [45]. ISE membranes-based sensors have been developed for dissolved oxygen detection, which is a critical component of any healthy aquatic system [46], but modern optical options are also available. ISE membrane-based sensors can also measure essential nutrients for HABs promotions, such as nitrate (N-source) and orthophosphate (P-source). However, inherited problems of ISE membrane technologies and further limitations in other commercial alternatives, such as using chemical reagents-based sensors for orthophosphate detection [47], can restrict their use for long-term monitoring.

Once sensors measure water samples, collected data must be stored in a datalogger and sent to the data management system by wireless communication. Today's wireless communication technologies market offers several suitable alternatives, such as ZigBee, GSM, GPRS, Bluetooth, Long Range Wide Area Network (LoRa) and SigFox. They differ in frequency bands, data rate, range capability, network topology and energy use term [14], and the most appropriate technology depends on each specific location, requirement and application.

Of all the different available commercial node alternatives on the market, multiparametric probes from the YSI, Hydrolab or Manta+ manufacturers are some of the most extended. These commercial systems can be implemented using fully functional proprietary solutions (plug-and-play), but also involve a high cost and very few customisation options. Alternatively, customisable commercial solutions, such as Libelium Waspmote [48], have appeared to offer *ad-hoc* solutions with open software. Differences in costs between plug-and-play and customisable nodes are not negligible as they are around 10-fold lower with Libelium Waspmote. Conversely, although the variety of sensing parameters in Libelium Waspmote is miscellaneous, they do not currently offer optical sensors for Chl-a and Phy detection, but multiparametric probes do. Notwithstanding, the set of available IoT-based options in Libelium is still growing, as shown by recent hybrid alternatives that combine custom-made dataloggers with multiparametric probes.

B. Node Selection and Deployment

In this study we select a combination of plug-and-play and customisable technologies for the RMS architecture implemented in the As Conchas reservoir and the shallow L'Albufera Lagoon. Tables I and II show the selected technologies and the available information for the characteristics of the sensors procured. Early in 2020, two multiparametric probes based on YSI technologies, two customised nodes based-on Libelium Waspmote and one Libelium weather station were deployed in each water body (Fig. 3). The system was set up to take measurements every 15 min, and a periodic maintenance of the installed sensors was carried out following the manufacturer's recommendations for cleaning, calibration and replacement rates.

The As Conchas reservoir roughly contains 80 Hm3 and its depth varies between 15 m and 32 m in central reservoir areas. YSI multiparametric probes were deployed in the area using

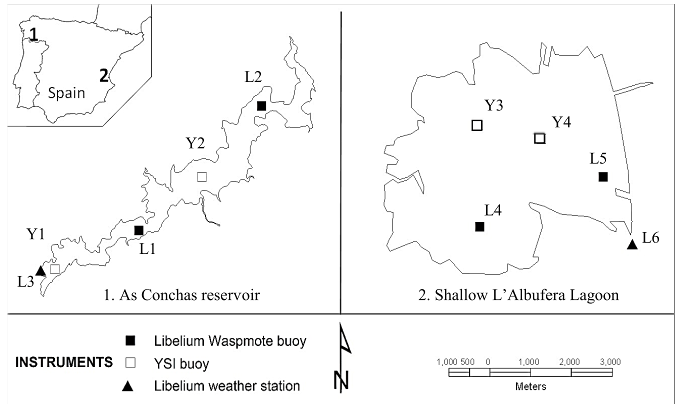

Fig. 3. Deployment of buoys containing nodes in (1) As Conchas Reservoir (Galicia, Spain) and (2) L'Albufera shallow lagoon (Valencia, Spain).

TABLE I
SELECTED TECHNOLOGIES CHARACTERISTICS

YSI (plug-and-play)	Libelium Waspmote (customisable)
Datalogger	**Datalogger**
Strom-3	Waspmote-4G
Serial communication: RS-485, RS-232 and SDI-12. GSM communication	Protocols: TCP/UDP, HTTP, FTP. GSM communication
Battery	**Battery**
12V rechargeable	4.2V Li-ion rechargeable
Solar panel	**Solar panel**
Nominal Peak Power (Wp) 30W Nominal Voltage (Vmp): 17.5V Nominal Current (Imp): 1.72A	Nominal Peak Power (Wp) 3.5W Nominal Voltage (Vmp): 7.0V Nominal Current (Imp): 0.5A
Node	**Node**
EXO 3 multiparametric probe	Smart Water Sensor Board & Smart Agriculture 3.0 Sensor Board
Available Sensor Ports: 5	Available Sensor Ports: 6

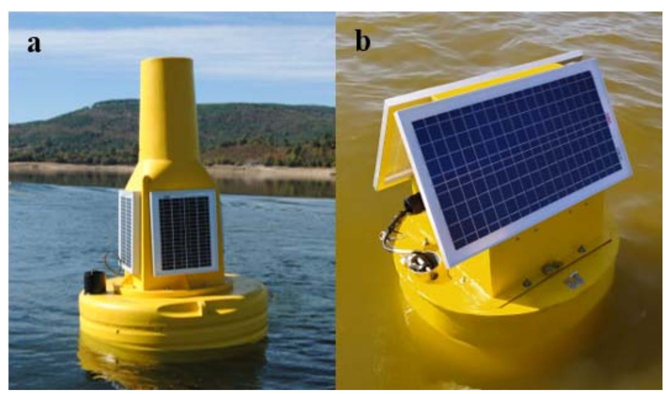

Fig. 4. (a) Plug-and-play buoy containing YSI multiparametric probes and (b) customised buoy containing Libelium Waspmote sensing nodes.

two commercial EM1250 buoys (Xylem Analytics) (Fig. 4a), while Libelium Waspmotes were deployed by two custom-made buoys (Fig. 4b). Buoys were anchored to the bottom at fixed coordinates in different reservoir areas (Fig. 3) and annual swings ranging from 10 m to 11 m were considered. The shallow L'Albufera Lagoon has a minimal volume of 17.2 Hm3 and a maximum one of 27 Hm3 depending on water volume contributions, and its average depth is 0.9 m [11]. Given its shallow depth, all the nodes were deployed using custom-made buoys (Fig. 4b) to avoid sensors coming close to sediment after considering minimal swings. The weather

TABLE II
INSTALLED SENSORS CHARACTERISTICS

	Sensors	Range	Accuracy	Resolution
YSI buoys	Chl-a (Total algae sensor)	0 – 400 μg·L^{-1} Chl; 0 – 100 RFU	LOD: 0.03 μg·L^{-1} Chl	0.01 μg·L^{-1} Chl; 0.01 RFU
	Phy (Total algae sensor)	0 – 100 μg·L^{-1} Phy; 0 – 100 RFU	LOD: 0.07 μg·L^{-1} Phy	0.01 μg·L^{-1} Chl; 0.01 RFU
	Conductivity	0 – 200 mS· cm^{-1}	0 to 100: ±0.5%; 100 to 200: ±1%	0.0001 to 0.01 mS· cm^{-1}
	pH	0 – 14 u	±0.1 u within ±10℃; ±0.2 u for entire T^a range	0.01 u
	Nitrate (ISE)	0 – 200 mg·L^{-1}	±10% or 2 mg·L^{-1}	0.01 mg·L^{-1}
Libelium buoys	Conductivity	Not available	Not available	Not available
	Temperature	0 – 100°C	DIN EN 60751	Not available
	pH	0 – 14 u	Up to 0.01 u	Up to 0.01 u
Libelium weather st.	Solar radiation	Range 410 – 655 nm	±5%	0 – 800 mV (ADC 16-bit, 3V)
	Anemometer	0 – 240 km·h^{-1}	Not available	Not available
	Pluviometer	Not available	Not available	Not available
	Wind Vane	0 – 360º	22.5°	0.28 mm

stations were installed in dam facilities and park management agencies' facilities (Fig. 3), respectively.

C. Satellite Image Acquisition System

Sentinel-2 is an Earth Observation mission that comprises a constellation of two twin satellites, Sentinel-2A and Sentinel-2B, from European Space Agency's (ESA) Copernicus Programme. This is oriented to provide surface reflectance images in 13 spectral channels from 443 nm to 2190 nm (central wavelength) with the Sentinel Application Platform (SNAP). The mission's novel imager can capture water quality parameters, such as the surface concentration of chlorophylls, water turbidity (or water clarity) and environmental levels of health and pollution [36]. Sentinel-2 optical imagery is used in this work for the systematic revisits made over the same area in inland water bodies at a high spatial resolution (10 m to 60 m). The selected images were calibrated by the C2RCC semi-analytical algorithm for atmospheric correction. This algorithm possesses a set of tools capable of reducing the atmospheric path radiance required to estimate the Chl-a concentration from the Sentinel-2 satellite images [49].

D. Data Management System

The data management system is based on a software that collects and stores big data from nodes in a database in real-time. It consists of a web interface with different modules, including data management functions (Fig. 2). The system was developed with the Spring Source Platform through the MVC (Model-View-Controller) architecture pattern. Programming was developed in Java using: Spring Security modules to provide the server with security; Spring Data for simplified data access; and Spring Boot as a development framework combined with Maven and Thymeleaf as a template engine for HTML5, CSS and JavaScript files, which form the web application design (front-end). Data persistence was guaranteed with JPA and Hibernate, which allow to interact with the database. The TCP/IP protocol was employed to receive the binary communication frames from each deployed sensing node.

An external database server was also implemented. MySQL Server 5.7.29 was used as a server in an Ubuntu 18.04 LTS (Long Time Service) machine. A Python code was developed to introduce the data saved before the platform was launched into the database. Formats JSON and CSV were used by administrators and customers to download the data from the database. In fact, access to database content was secured with HTTPS and secure authentication. Different user profiles were defined: Administrator, with full access to all the data and permission to manage user profiles; Customers, with full access to data and some configuration options for a specific location; the public profile, which was able to access open information, but not to download data. This monitoring platform was installed at the IMDEA Water Institute facilities and data can be consulted on the website: www.cianomod.es. Spanish was used as the native language as this system attempts to meet the needs of water bodies in Spanish regions.

III. SYSTEM TEST

The monitoring website allows access to geolocated data online with a latency to transmit the data from sensors to the server of 45 $\pm$ 6 sec. After 6 months of implementing the same RMS architecture at each water body, different outcomes were attained. All the nodes ran well at the As Conchas reservoir, while those deployed at the shallow L'Albufera Lagoon considerably deteriorated, particularly the nodes belonging to Libelium technologies. Likewise, the lifespan of the ISE membranes-based sensors installed on the YSI multiparametric probes (*i.e.* nitrate sensor) was significantly shorter in the L'Albufera Lagoon than in the As Conchas reservoir. The most adverse conditions at the L'Albufera Lagoon, such as the proximity of sensors to sediment, hypereutrophic water, penetrating fouling, higher salinity, etc., may explain the worse response of some sensors in that environment.

In order to know whether the measurements of each parameter varied depending on the monitored area per water body, a Pearson correlation test was performed by using the big data collected from March to September 2020. To reduce correlation errors due to spurious measurement peaks or missing data, data were filtered by a median every 2 h (for every 8 data). Given the inconsistency of the collected data for nitrate in both water bodies, and the erratic data of buoy L5 at the L'Albufera Lagoon (Fig. 3), they were not considered for this assessment. The results showed that the correlations among nodes differed depending on both parameters and monitored environment. For instance, temperature sensor measurements were highly correlated between nodes in both water bodies, and the same occurred between pH sensors (Tables S1 and S2). In contrast, the correlation of the electric conductivity data was very low to moderate in the As Conchas reservoir, but it was highly correlated at the L'Albufera Lagoon (Tables S1 and S2). These differences could be due to the variation in depths

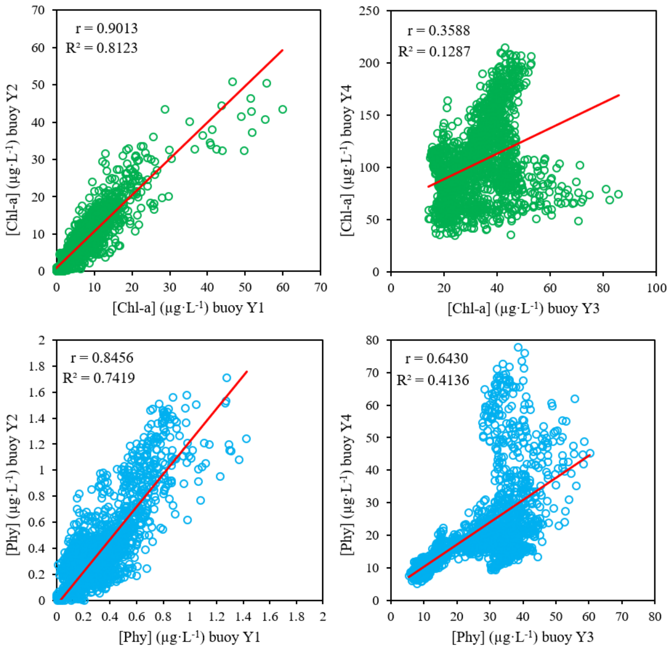

Fig. 5. Scatter plot showing the Pearson correlation between the YSI multiparamteric probes measurements in the As Conchas reservoir (left plots) and the shallow L'Albufera Lagoon (right plots) for Chl-a (upper plots) and Phy (botton plots) concentration.

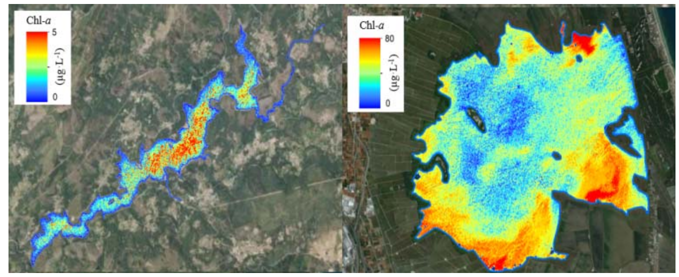

Fig. 6. The Chl-a concentration (μg·L^{-1}) derived from Sentinel-2 satellite images using the C2RCC algorithm. Left: the As Conchas Reservoir (Galicia, Spain); right: the shallow L'Albufera Lagoon (Valencia, Spain).

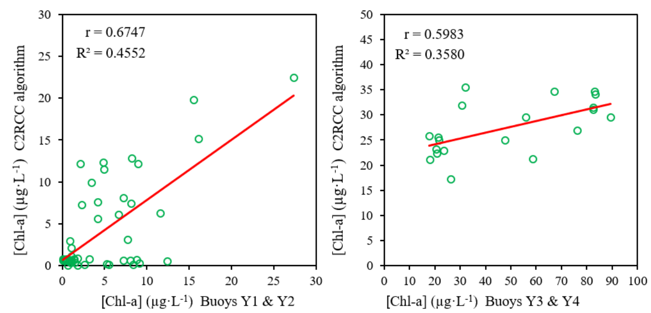

Fig. 7. Scatter plot showing the correlation between the Chl-a concentrations measured *in situ* with buoys and those deriving from the C2RCC algorithm satellite images in the As Conchas reservoir (left plot) and the L'Albufera Lagoon (right plot).

and wide swings in volume that the As Conchas reservoir presents, which causes variable proximity of some sensors to sediment, while the characteristics of the shallow L'Albufera Lagoon led to more homogeneous changes in electric conductivity among nodes. The correlation outcomes between optical sensors were also diverse. The Chl-a measurements were highly correlated between nodes in As Conchas, but poorly correlated at L'Albufera (Fig. 5). Similar results were observed for the Phy data in both environments (Fig. 5). Altogether, these results suggest that the representativeness of the collected data was subjected to the parameter type and water body's heterogeneity and, therefore, we agree with other studies which highlighted that not all RMS architectures would be effective for monitoring any water body [29].

To verify the previous observation, an assessment of the distribution of the algae bloom over space and time was performed by satellite imagery. To do so, 44 Sentinel-2 images were processed to produce detailed maps of the Chl-a concentrations in both water bodies (Fig. 6). In each image, 9 pixels data of 20 m were taken from around the coordinates of each deployed node. As far as our data show, Chl-a accumulated in patches in different areas of the water bodies (Fig. 6). This is particularly relevant for the L'Albufera Lagoon, where the largest differences in Chl-a concentrations were recorded.

In order to validate these estimations, the satellite imagery data were compared to the optical measurements taken by *in situ* nodes. The results showed that satellite estimations correlated moderately with the nodes in both environments (Fig. 7, Tables S3 and S4). In the As Conchas reservoir, a mean difference of 0.6 μg·L^{-1}, with a root-mean-square error (RMSE) from ~0.1 μg·L^{-1} to 27,6 μg·L^{-1}, was obtained for the entire Chl-a concentrations range. At the L'Albufera Lagoon, it was 20.7 μg·L^{-1}, with RMSE going from ~0.1 μg·L^{-1} to 89.4 μg·L^{-1}. These results show that, as the Chl-a concentration increased, the differences between the values measured *in situ* and those deriving from the satellite images were bigger. One reason for this could be that when dealing with turbid waters, the C2RCC algorithm does not properly adjust due to high suspended sediment loads [50]. Therefore, larger data sets are needed to better adjust the calibration parameters in the C2RCC processing algorithm [51], [52] and, thus, unequivocally confirm the satellite estimations.

Overall, these results support previous observations [27], [29] and point out that the more heterogeneous the environment is, the more nodes must be deployed in different areas and for longer time to obtain a realistic view of the water body status. As the optical sensors onboard of plug-and-play technologies are expensive, but essential for HAB growth estimations, the deployment of RMS by combining plug-and-play and customisable technologies could allow more sampling points at a lower cost. Thereby, the development of models based on variables of homogeneous distribution measured from many areas, combined with a few deployed optical sensors for algae quantification, could be an alternative to foresee HABs in a cost-effective manner. Likewise, combining the nodes deployed *in situ* with satellite imagery for data validation purposes could provide a robust and effective monitoring system architecture for many water management agencies to track HABs in inland water.

IV. Conclusion

The RMS allowed big data collection from two different environments, data transfer to a data management system on the cloud and their subsequent visualisation on the web interface in real time. The Pearson correlation tests suggested that the multiple nodes deployed in different areas are necessary to obtain a realistic view of the water body status. This could be particularly important for monitoring HABs in heterogenic water bodies with high anthropogenic pressure, where algae biomass could accumulate in patches that difficult to track by single nodes. If the high prices of nodes limit this approach, a combination of plug-and-play (*e.g.* YSI) and customisable (*e.g.* Libelium Waspmote) technologies could be a cost-effective solution. Satellite imagery could allow the suitability of deployed RMS architecture to be validated by analysing the spatial-temporal distribution of the algae bloom in such an environment. Therefore, this study provides critical and empirical data for water management agencies to implement a profitable and effective monitoring system to track HAB in inland water bodies.

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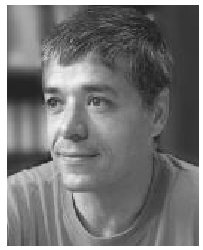

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