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Exploring global remote sensing products for water quality assessment: Lake Nicaragua case study

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ABSTRACT

This study explores the applicability of 13 globally-derived Chlorophyll-a (CHL) products from optical satellite remote sensing to support local water quality management in Lake Nicaragua. The temporal and spatial consistency between the products was analyzed, as well as their agreement with in-situ data collected from 2011 to 2016. The Climate Change Initiative (CCI) CHL product was identified as the most stable and reliable, suggesting its suitability for monitoring Lake Nicaragua. However, the correlation of this product with in-situ measurements was weak, attributed to the sparse and inconsistent nature of the available in-situ water quality data. The hotspots analysis identified critical areas around urban and agricultural zones with high CHL concentrations, providing valuable insights for targeted management interventions. This study emphasizes the need for improved global to local remote sensing strategies, including the selection of the appropriate algorithms for the region, continuous calibration and validation with in-situ data, and the development of a robust, publicly accessible local water quality database that includes both in-situ and remote sensing data, to support effective monitoring for local water management.

1. Introduction

Rivers and lakes provide vital ecosystem services and play a pivotal role in the functioning of socio-ecological systems. However, the escalating influence of climate change, large urbanization, industrialization, and shifting land use patterns on these fresh water resources, have heightened concerns about water quality degradation (Vasistha and Ganguly, 2020). Several studies show evidence that nutrient loads are increasingly higher in lakes (Adrian et al., 2009; Agramont et al., 2022), causing (hyper)eutrophic conditions that consequently affect biodiversity and the socioenvironmental services that these lakes can provide (Bhateria and Jain, 2016). Given lakes' swift responsiveness to climatic shifts and basin alterations, it becomes imperative to characterize and improve water quality, especially amidst significant global changes (Adrian et al., 2009; Vasistha and Ganguly, 2020). However, these efforts are limited due to lack of information regarding the water quality status of many lakes, especially in the Global South (Damania et al., 2019; Hestir

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et al., 2015; World Bank, 2013).

Conventional water quality field-based monitoring practices, such as gathering samples to be analyzed in labs, face challenges in providing comprehensive and systematic data due to logistical, operational, and budgetary constraints. In-situ measurements, while offering precision, are labor-intensive, not spatially representative and time-consuming, limiting their scalability for extensive water quality assessments (Barreneche et al., 2023; Hestir et al., 2015), and fixed stations for automated in-situ measurements are not present everywhere, due to investment, communications and safety constraints (Barreneche et al., 2023). Such difficulties are even more amplified in countries where the allocation of resources for such matters is not always a priority and where access to reliable data remains a persistent challenge (Damania et al., 2019). These limitations underscore the critical necessity of a complementary use of remote sensing with a robust in-situ database to have spatio-temporally efficient analyses that are continually validated to guarantee their reliability.

The integration of remote sensing into water quality assessments offers a paradigm shift. Remote sensing provides a synoptic view, historical context, and aids in pinpointing critical sampling locations for its ability to spot changing areas with high concentrations of parameters that alter the optical properties of the water bodies, thus, addressing the limitations of traditional in-situ measurements (Gholizadeh et al., 2016; Mouw et al., 2015). Remote sensing can be useful in identifying source-impact relationships in water quality (Baltodano et al., 2022). Thus, the synergy between remote sensing and traditional monitoring methods emerges as a powerful approach for a more comprehensive understanding of water quality dynamics.

Remote sensing technologies facilitate the monitoring of diverse water quality parameters, including suspended sediments, CHL, turbidity, and water temperature (Gholizadeh et al., 2016). However, challenges arise, particularly in discerning CHL in turbid waters due to the optical complexity of suspended particles, emphasizing the need for a multi-parameter or multi-sensor approach in remote sensing assessments (Gholizadeh et al., 2016). These approaches can help address such challenges by providing spectral diversity, different spatial and temporal resolutions, multiple polarizations and angles and algorithm flexibility (Wang et al., 2022). Understanding these parameters is crucial not only for evaluating water quality but also for comprehending the ecological dynamics of aquatic ecosystems and their influence over the local communities.

Global water quality products hold the potential to contribute significantly to environmental monitoring, ecosystem health assessments, and water resource management (Copernicus GLS, 2019; De Keukelaere et al., 2022; ESA, 2018; NASA, 2020). Their spatial and temporal coverage could allow for a nuanced examination of changes over time, with the potential of providing valuable insights for sustainable water management practices.

The landscape of water quality monitoring derived from remote sensing involves a diverse array of studies, each contributing to our understanding of remote sensing capabilities. For instance, a recent study by Barreneche et al. (2023) analyzed the accuracy of a specific combination of three sensors, three atmospheric correction methods, and seventeen CHL estimation models. Their focus was

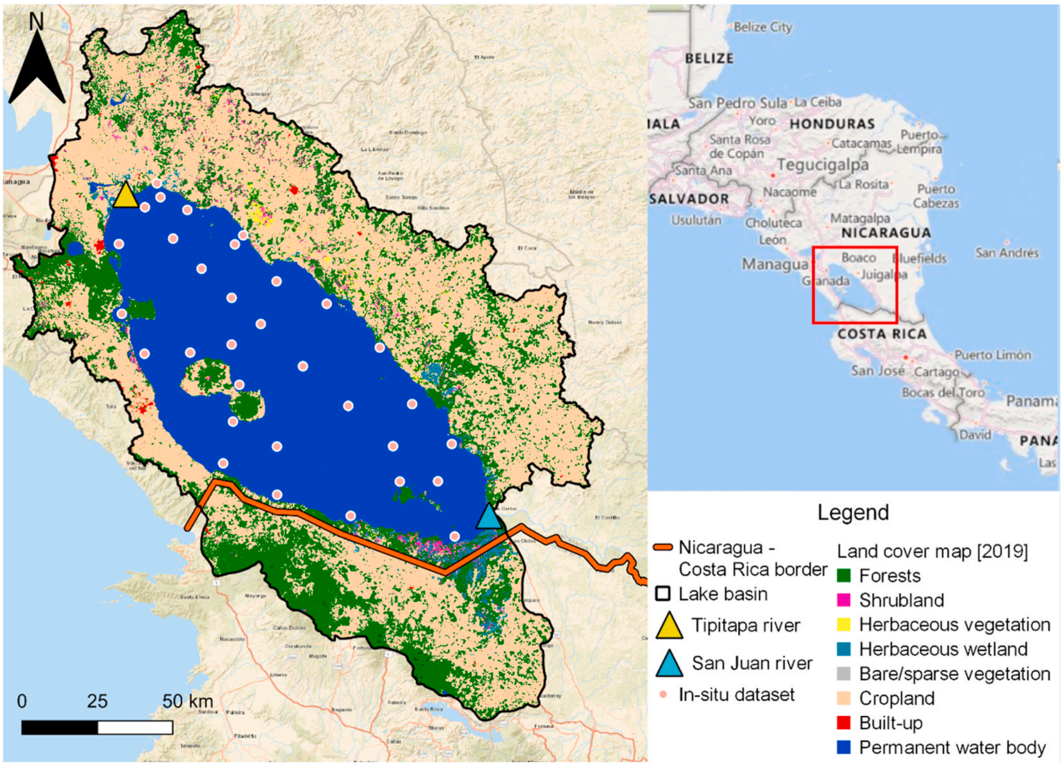

Fig. 1. Lake Nicaragua basin and its land cover distribution. Source: (Buchhorn et al., 2020).

on Uruguay's inland and coastal waters, aiming to identify the best-practice algorithms for CHL estimation, which emphasizes the need for tailored approaches in different geographical contexts. In the context of phytoplankton CHL concentration, Werther et al. (2022) characterized remote sensing product uncertainties across 13 existing algorithms. This analysis used an in-situ dataset of water constituent concentrations and inherent optical properties (IOPs) collected from 53 lakes and reservoirs. Similarly, Sent et al. (2021) did a comparison of different atmospheric correction and water quality retrieval algorithms over the Sado Estuary in Portugal, highlighting the importance of this comparison to determine the best processing combination per case study in order to establish an effective monitoring of the area. Conclusively, these work emphasized the need for a better understanding of algorithmic performance across different water bodies.

While comparing the performance of different algorithms for the estimation of water quality parameters has already been carried out in many studies (Barreneche et al., 2023; Gidudu et al., 2021; Wang and Chen, 2024; Werther et al., 2022), the intercomparison between publicly available global water quality products is still limited within literature, as well as their validation with in-situ data to assess correspondence in magnitudes and, temporal and spatial behavior. Without such comparisons and analysis, it is challenging to determine which remote sensing global products are suitable for monitoring water quality in specific local scales, which is the unexamined aspect explored in this study.

This study aims to conduct an analysis of globally-derived water quality parameters obtained through satellite remote sensing. The focus is on evaluating their spatial and temporal agreements to understand their reliability. Consequently, these will be assessed against in-situ data, with the overarching goal of understanding these global water products and how they can be employed as a practical tool for the effective water quality management of Lake Nicaragua. This would offer multifold benefits, such as cost-effective water quality monitoring for the whole lake surface, support local decision-making, and for policy accountability of future actions targeting the local water quality challenges, among others. These findings may be one more step in bridging the water quality data gap and support local environmental decision-making.

2. Materials and methods

2.1. Case study

Lake Nicaragua (also known as Lake Cocibolca) covers an area of 8200 km^2 which makes it the largest freshwater lake in the Central American region and the second-largest in Latin America (World Bank, 2013). Lake Nicaragua includes roughly 15 percent of Nicaragua's territory and while its basin is shared between Nicaragua and Costa Rica, the lake is located entirely within Nicaraguan territory as it can be seen in Fig. 1. The basin spans an area of about 15550 km^2, involving two countries and thirty municipalities across seven departments, adding layers of complexity to its management (Flores Meza et al., 2009; Vammen et al., 2006; World Bank, 2013).

The hydrological dynamics of the lake are significantly influenced by annual rainfall variations ranging from 1500 to 6000 mm (OAS, 2005; World Bank, 2013). The seasons are similar to those of the rest of the country, with the months between December and April as the dry season and the months between May and November as the wet season (Montenegro-Guillén, 2005). This tropical lake is characterized by its shallowness as 60% of the lake has a depth of less than 9 m, 37% between 9 and 15 m while certain areas have a maximum depth of 40 m (Vammen et al., 2019). The basin's topography, with more than 20 percent of the area with slope gradients exceeding 30%, increases the risk of soil erosion and sediment runoff into the lake, contributing to its overall vulnerability (World Bank, 2013).

The lake faces numerous pressures from natural phenomena and anthropogenic activities, notably from agriculture, urbanization, and tourism, which have led to significant land cover change, deforestation, and increased sediment yields (Buchhorn et al., 2020; Global Forest Watch, 2020; MARENA, 2018; Vammen and Peña, 2022; World Bank, 2013).

Agricultural areas are the main land cover class as it can be seen in Fig. 1, which contribute to the lake's nutrient influx caused by agricultural runoff. This, combined with the abovementioned pressures, exacerbate the lake's vulnerability to eutrophication, leading to increased phytoplankton biomass, algae blooms, and water turbidity. The absence of frequent water quality monitoring and data availability complicates the understanding and management of these impacts, highlighting the lake's fragility and the urgent need for a systematic monitoring approach (Montenegro-Guillén, 2005; Vammen et al., 2006; World Bank, 2013).

Limited local resources and technical capabilities are significant constraints, and the necessity for frequent monitoring makes remote sensing a vital tool for overcoming these challenges. Remote sensing holds the potential to contribute a cost-effective systematic way to monitor the lake's water quality, enabling the detection of eutrophication trends and contributing to a more precise understanding of nutrient sources and their impacts (OAS, 2005; Vammen et al., 2019, 2006; World Bank, 2013). The case of Lake Nicaragua can be instrumental to understand the critical role of remote sensing in addressing water quality monitoring challenges and to support local management in environments with complex biophysical characteristics and limited in-situ monitoring resources. On the other hand, it is also a useful case to demonstrate whether the evaluation of these remote sensing derived products can be adequately performed even with such a scanty in-situ database.

2.2. In-situ dataset

The in-situ data used were collected through sampling campaigns between 2011 and 2016 by different entities, among them the National Central University, National Autonomous University of Nicaragua through the Center for Aquatic Resources Research of Nicaragua (CIRA, for its acronym in Spanish), and the Wisconsin Department of Natural Resources to monitor water quality at 34 unique points located throughout the lake. The parameters measured included: CHL, Secchi Disk Depth, Total Phosphorus and Total Nitrogen. The complete data can be found in Chang et al. (2017). In Table 1 an overview of the total measurements is shown, it is worth mentioning that the temporal distribution of the samples is not optimal, since sampling was not carried out regularly throughout the years, nor every site was sampled with the same frequency throughout the months. Nevertheless, this is the only openly available water quality information that can be used for analyses to date. Sampling was greater during the dry season of the year, predominantly in 2015 and 2016, whereas in 2013 no sampling record could be found. The dataset consists of a total of 34 unique points distributed over the lake, of which 26% were sampled only once, 38% were sampled twice, and 21% and 15% were sampled thrice and 4 times respectively.

Although the available in-situ data was not optimal due to the spatial and temporal gaps in the measurements, an effort was made to extract as much information as possible. These interpretations were always made knowing the limitations that could be encountered (discussed further in section 4), as is the case in most data-poor regions (Damania et al., 2019). However, this research seeks to give visibility to the fact that while the potential of remote sensing is great, a minimum of in-situ knowledge is needed to determine its optimal use.

2.3. Global water quality products

In this study we focus on the intercomparison of global water quality products that have been derived based on satellite remote sensing, by applying generally different methodologies. These sources are namely NASA Ocean Color, Copernicus Global Land Service (GLS), Terrascope (Belgian Copernicus Collaborative Ground Segment) and ESA's Climate Change Initiative Lakes (CCI Lakes). Within these global product sources, a distinction is then made according to the satellite/sensor combination used to generate each product.

The water quality parameter studied was CHL. Eutrophication is one of the most important water quality problems affecting water bodies, and especially lakes. As a representative indicator of eutrophication, CHL concentration has always been a key indicator monitored by environmental managers (Wang and Chen, 2024). As an optically active constituent, CHL is one of the most frequently derived water quality parameters monitored by remote sensing. A summary containing general data for each CHL product by source can be seen in Table 2.

The Copernicus GLS products on Table 2 are an indication of CHL concentrations that were derived from the Trophic State Index (TSI) according to the conversion tables found in Simis et al. (2020). Whilst the existence of additional water quality parameters found in these sources is acknowledged, our study is limited to the analysis of CHL due to the available in-situ dataset. In our study, a deliberate preference was made to use Level 3 satellite imagery rather than Level 2 products because of several compelling advantages that align with the goals of an initial exploration of the readily-available choices water managers have for this regions. Level 3 imagery, while temporally and spatially aggregated, provides greater consistency and coverage, crucial for capturing large-scale trends in the environment and minimizing the noise and gaps that are often present in Level 2 data (Balsamo et al., 2018; Kratzer et al., 2019; Martin et al., 2019). This aggregation is especially beneficial in regions with frequent cloud cover, such as Lake Nicaragua, where Level 3 composites ensure more complete and representative data sets. In addition, Level 3 products are validated and corrected for atmospheric interferences, which reduces errors and biases that could be introduced by performing the retrieval ourselves due to the lack of knowledge of the properties and dynamics of the lake (which atmospheric correction and water quality algorithm retrievals to use). The use of Level 3 data is further justified in contexts where in-situ measurements are scarce or logistically challenging, as these products offer a robust alternative that complements the limited actual field data, improving the overall accuracy and scope of our study (Damania et al., 2019; Gholizadeh et al., 2016; Kratzer et al., 2019).

It is important to emphasize that CHL products are made available in a variety of formats and delivery ways. In section *3.3* we discuss the complexity involved when these products are proposed to practitioners. As for the different ways to access each of the products, these are following described in Table 3.

To reduce the bias in the calculations due to cloud cover on some dates, a mask was applied to only select products with valid pixel values over 80% of the lake area. For this purpose, the shapefile of Lake Nicaragua available in HydroLAKES (https://www.hydrosheds.org/products/hydrolakes) was used.

A summary table containing the different algorithms applied to each product and the technical specifications per source can be found in Annex 1.

2.4. Remote sensing and in-situ data comparison

As the in-situ data consist of coordinates along the lake that were collected over the years, spatial and temporal matching was performed to facilitate comparison. Comparison between in-situ data and remote sensing products was only performed when there was a 3-day window between field measurement and availability of the remote sensing product as the methodology followed by Beltrán-Abaunza et al. (2017) and Fuentes-Yaco et al. (2005). For each in-situ data point, a 3-day window of comparison was determined, and as the temporal resolution of the global products differed between them, the match-up was determined as follows: 1) For Ocean Color and GLS, the intervals of the 8-day and 10-day composites were defined, identifying which composites overlapped with the in-situ comparison window. If two composites overlapped, both were used for comparison by assigning a weighted value, 2)

Table 1
In-situ data distribution over the season/years (number of total measurements).

	Year	2011	2012	2014	2015	2016	Total
Season	Dry	7	7	–	40	7	61
	Wet	–	–	9	–	6	15
	Total	7	7	9	40	13	76

Table 2
Global remote sensing-based water quality products characteristics.

Source	Sensor/Satellite	Code	Data Availability	Spatial resolution	Temporal resolution
NASA Ocean Color	MODIS/Aqua	MODISa_OC	2002–2023	4 km	8-day composite
	MERIS/ENVISAT	MERIS_OC	2002–2012	4 km	
	VIIRS/NOAA-20	VIIRSn_OC	2017–2023	4 km	
	OLCI/Sentinel-3a	S3A_OC	2016–2023	4 km	
	OLCI/Sentinel-3b	S3B_OC	2018–2023	4 km	
	SeaWIFS/SeaStar	SeaWIFS_OC	1997–2010	9 km	
	VIIRS/SuomiNPP	VIIRSs_OC	2011–2023	4 km	
	MODIS/Terra	MODISt_OC	1999–2023	4 km	
Terrascope	MSI/Sentinel 2-a	S2A_T	2015–2023	20 m	5 days
	MSI/Sentinel 2-b	S2B_T	2017–2023	20 m	
Copernicus GLS	*MERIS/ENVISAT*	*MERIS_G*	*2002–2012*	*300 m*	*10-day composite*
	OLCI/Sentinel-3a-b	*OLCI_G*	*2016–2023*	*300 m*	
ESA CCI Lakes	MERIS, MODIS, OLCI/ ENVISAT, Aqua, Sentinel-3a-b	CCI	2002–2020	1 km	Daily

Table 3
Procedure for acquiring CHL products per source.

Source	Procedure
NASA Ocean Color	File format: NetCDF The Level-3 (compositing) product library was browsed, which is available for different compositing periods to counteract data gaps that can be caused by, for example, clouds, sun glint, inter-orbit gaps, ice, low light, etc. The 8-day composite was selected to facilitate comparison with the other products, at the maximum spatial resolution possible (4 km for all, with the exception of SeaWiFS which was 9 km). Data were extracted in mapped format using coordinates 12.2, 11, −86 and −84.7 for north, south, west and east, respectively. https://oceancolor.gsfc.nasa.gov/l3/
Copernicus Global Land Service (GLS)	File format: NetCDF In the 'Water' and subsequent 'Lake Water Quality' tab of the service's website, the 300 m spatial resolution for the study area was selected. The coordinates mentioned in the previous paragraph were used to refine the search, the start and end dates were selected (longest time period allowed), and all the files available for download were selected. https://land.copernicus.eu/global/index.html
Terrascope	File format: TIFF Terrascope provides global products on-demand only. To access these Level-2W products (single scene product), a request was made to process the algorithms for the Sentinel-2 tiles corresponding to Lake Nicaragua, namely 16 PFU, 16PFT and 16PGT. Once processed, the virtual machine provided by Terrascope was used to access the data, which consisted of raster files at 20 m spatial resolution. V120 (De Keukelaere et al., 2022) was used. https://docs.terrascope.be/#/DataProducts/Sentinel-2/WaterQual/WaterQuality
ESA Climate Change Initiative (CCI)	File format: NetCDF The codes available in the project's GitHub were used, which exist specifically to aid the access and download process, the code 'lakes_cci_download1lake_by_id.ipynb' was used to download products based on the lake identifier, in this case study, Lake Nicaragua has id 21 and short name GLWD00000021 in the CCI database. Dates were adjusted according to first and last based on availability and project coverage. https://github.com/cci-lakes/lakes_cci_tools

For Terrascope and CCI, the match-up was only performed if the RS image was taken on the same date as the in-situ measurement or within the 3-day window. Correlation and residual plots were generated to better visualize the performance of each product in estimating in-situ concentrations from the pixel-by-pixel comparison. The residual plot was employed as it helps understand how far off the in-situ predictions are from the satellite-observed values, as well as for pattern identification and homoscedasticity/heteroscedasticity checks that would help identify constancy of the variance (Law and Jackson, 2017).

Statistical analyses such as mean absolute error (MAE), root mean square error (RMSE), percent bias (PBIAS), correlation coefficient (r), and the coefficient of determination (R^2) were used to obtain results regarding the overall agreement and discrepancies between the datasets. The spatial and temporal distribution of the global products were taken into account to estimate which one yielded data that were closest to those of the in-situ dataset.

2.5. Spatial and temporal analysis

In this study a deliberate decision was made not to employ spatial resampling techniques when comparing the datasets. As our focus was to determine the spatial dynamics including the sensors' characteristics and whether the CHL spatial dynamic was similar among them, it was considered counterproductive to perform resampling. On the contrary, it was preferred to preserve the inherent characteristics and spatial details of each original product. The only aggregation made in terms of temporal scale was according to the weeks corresponding to the dry and wet seasons, allowing a better visualization of the variations in the statistics. Out of the 52 weeks per year, weeks 1–15 and 42–52 correspond to the dry season, whereas weeks 16–41 cover the wet season according to (Montenegro-Guillén, 2005; Vammen et al., 2006, 2019; Vammen and Peña, 2022).

To compare how these products agreed with each other spatially, an additional analysis consisted of performing a comparison of the entire time series by applying a threshold of 25 mg/m^3, which is the minimum concentration to consider the water body as hypereutrophic (Kerekes and Kerekes, 1982). For each product, the threshold was applied and if at least 80% of the images met this criterion in the same pixel, it was flagged (resulting images can be found in Annex 2). Once this resulting composite image per product was obtained, the comparison of all the products was made, applying the same 80% criterion. A final figure was obtained, showing the

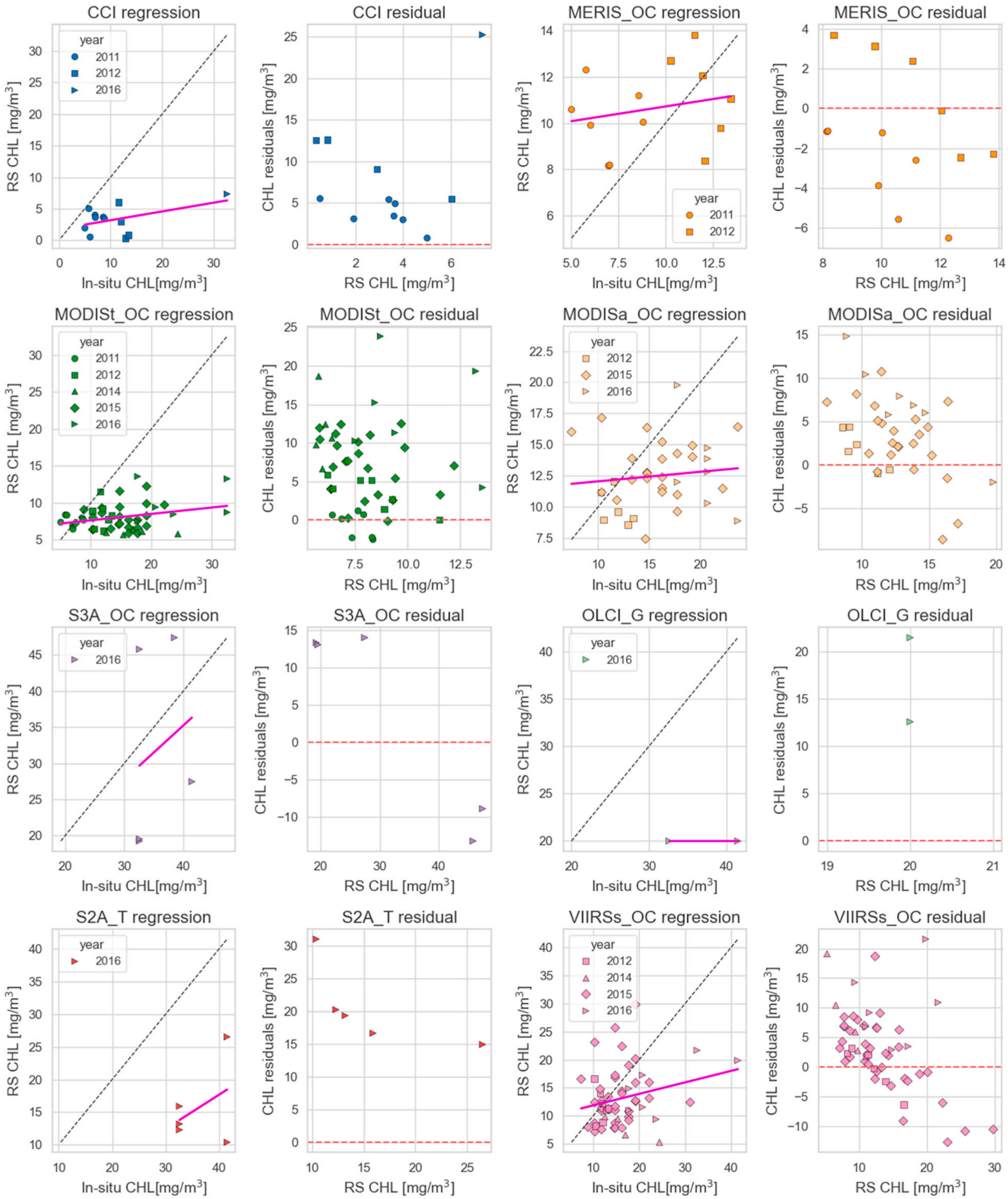

Fig. 2. Correlation plot of in-situ vs RS values and residual plot for all products.

pixels in which values equal to or greater than 25 mg/m^3 predominate in all products over time. Subsequently, regions presenting a visible clustering of these pixels were delimited and identified as "hotspots". By extracting the mean values by product for the entire study period per hotspot, it was possible to determine their trend through the Mann-Kendall test using the pyMannKendall Python package (Hussain and Mahmud, 2019).

3. Results and discussion

3.1. In-situ vs. remote sensing data

When performing the comparison of remote sensing (RS) data with in-situ samples, only eight of the thirteen products had data that overlapped. Furthermore, Fig. 2 shows the correlations by RS product and also the residuals in comparison with in-situ values.

The comparison with the RS data seen in Fig. 2 shows that the correlation is not so strong with any of the products. Once again it is observed that the measurements with lower concentrations correspond to the first years of sampling, and the opposite, higher concentrations for the last years of measurements. There are more outliers and a wider range of derived values as the magnitudes of the in-situ concentration increase, which suggests that after a certain threshold, the sensors or the algorithms that have been used are not capable of yielding accurate results, which may be due to the fact that the optical properties of the water vary greatly as their divergent optical constituents (Kahru et al., 2012). The residual plots in Fig. 2 do not have a random distribution around zero without an apparent pattern, instead, all show a descending behavior, indicating heteroscedasticity. Such systematic pattern which suggests difficulties of accurate measurements when the concentrations tend to be very low or very high. Products such as CCI, S2A_T and OLCI_G have a tendency to underestimate the CHL concentrations, whereas the rest of the products have errors in both directions (both under and overestimation). This inability to correctly predict low or high CHL concentrations may be due to several limitations, such as atmospheric correction, algorithm selection, spatial and temporal resolution and aggregation, and most importantly, the few in-situ data that was used to perform this comparison.

A total of 177 comparisons could be made from the pixel-by-pixel comparison, the products with the most match ups being VIIRSs_OC, MODISt_OC and MODISa_OC with 55, 49 and 36 respectively. This was followed by MERIS_OC, CCI, S2A_T, S3A_OC and OLCI_G with 13, 12, 5, 5 and 2 respectively. The average number of match ups per coordinate was 5, with certain locations having a maximum of 13 match ups and others with a minimum of 1. Similarly, the year with the most comparable measurements was 2015 with 84, followed by 2016, 2012, 2011 and 2014 with 33, 30, 21 and 9 respectively.

Upon reviewing the metrics calculated for each product in Table 4, it can be confirmed that the overall performance is low for all products, being the CCI the one with low to moderate values as far as correlation coefficient is concerned. Although this product is not the one with the lowest errors and biases of all, this may be due to the sensitivity of MAE, RMSE and PBIAS to extreme values and outliers, while r and R^2 tend to be less sensitive to these values. Since CCI considers OWT for algorithm application, while its atmospheric correction is validated with multiple in-situ databases of both concentration and surface reflectance, it can be less affected by the sudden spikes in concentration reported by other products. As Yang et al. (2022) states, it is essential to recognize that remote sensing, while broadening the observational scope, only achieves optimal precision when combined with traditional in-situ methods for the development of algorithms or for validation purposes.

3.2. Spatial and temporal analysis

With the aim to identify the spatial agreement level between products in terms of high concentration zones and their dynamics over time, the filtering methodology using the 25 mg/m^3 threshold was applied as stated in section *2.5*. The resulting hotspots can be found in Fig. 3.

Right away it is noticeable how the areas with high concentrations over the years are located near the larger cities with more tourism taking place. In the delimited hotspots, similar concentration changes could be observed with maximums reaching 100 mg/m^3 in the years with exceptionally high values (2000–2006 in Fig. 4) to current values of 16 mg/m^3 on average. In Fig. 3 it is also wished to highlight the wastewater treatment plants that have been inaugurated after 2006, that possibly contributed to positively reduce the organic load coming from the cities, thus leading to the improvement of the CHL concentrations.

In order to further examine the temporal dynamics of these hotspots, the Mann-Kendall trend test was conducted, for which the averages within each hotspot were compared for each time step (resulting graphs can be found in Annex 3), and Table 5 shows the summary of the results obtained.

The values in Table 5 are divided by hotspot and by product, giving two values resulting from the Mann-Kendall trend test that are

Table 4
Performance metrics of in-situ vs. RS comparison by product. Values in bold represent the best performance, while the values in italics represent the worst performance.

		Match ups	MAE	RMSE	PBIAS	r	R^2
Product	CCI	12	7,60	9,92	*64,09*	**0,48**	**0,23**
	MERIS_OC	13	**2,77**	**3,27**	−25,78	0,21	0,04
	MODISa_OC	36	4,60	5,67	15,74	*0,11*	*0,01*
	MODISt_OC	49	7,02	8,83	36,53	0,27	0,07
	S3A_OC	5	12,49	12,63	**10,16**	0,23	0,05
	OLCI_G	2	17,00	17,57	45,16	-	-
	S2A_T	5	*20,45*	*21,21*	56,76	0,40	0,16
	VIIRSs_OC	55	5,72	7,50	12,23	0,25	0,06

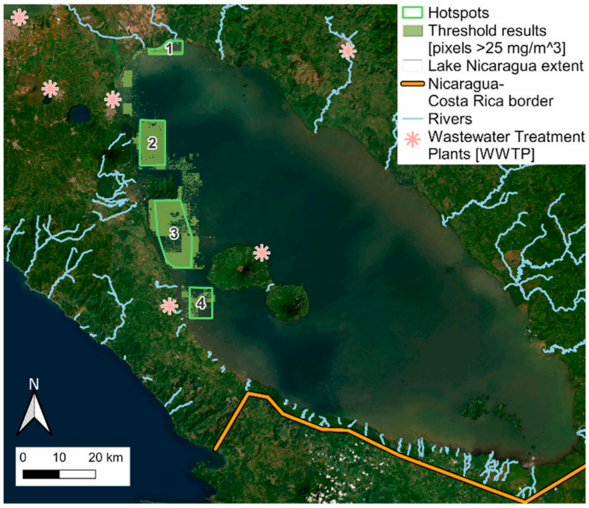

Fig. 3. Geographical location of the selected high concentration hotspots.

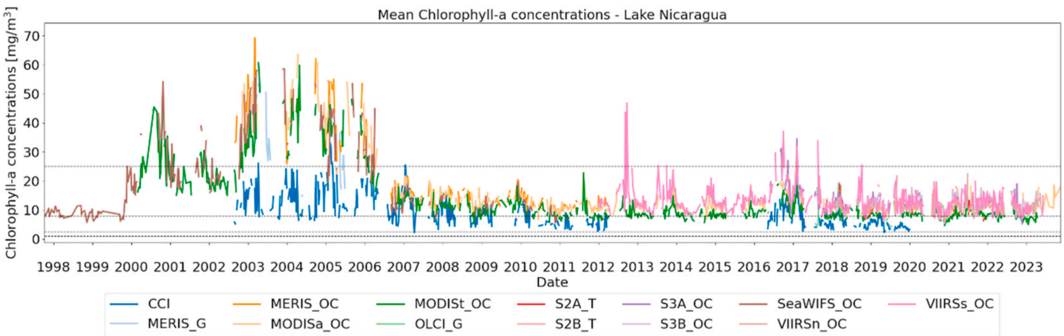

Fig. 4. Weekly mean CHL over Lake Nicaragua for the entire study period per product. Dashed lines indicate concentrations corresponding to Ultraoligotrophic (<1 mg/m^3), Oligotrophic (1–2.5 mg/m^3), Mesotrophic (2.5–8 mg/m^3), Eutrophic (8–25 mg/m^3) and Hypereutrophic (>25 mg/m^3) conditions according to the OECD (Kerekes and Kerekes, 1982).

of great importance. On the left is the p-value, which indicates whether there is ($p \leq 0.05$) or not ($p > 0.05$) a significant trend. High p-values suggest that any observed trend is probably due to random variation rather than a true underlying trend. The gray circle icons indicate no trend, while the green circles indicate a significant trend. The products that did not exhibit a significant trend coincided with those whose number of observations was low, i.e., those that had lower coverage throughout the study period (as can be seen in the graphs in Annex 3), as opposed to those that consistently had p-values of less than 0.05, which showed a longer time series. Longer time series generally provide more reliable and statistically robust results, increasing the likelihood of detecting true underlying trends in the data. On the other hand, we have the S-statistic values, which when positive indicate a positive trend, while negative values indicate a negative trend. The magnitude of this value is a reflection of the strength of the trend, with higher absolute values indicating stronger trends. The values that are highlighted with gray are those where there was no trend, if the symbol is red, it indicates a negative trend, while the green sign indicates the opposite. For each hotspot the value with the highest magnitude was indicated in italics, which always corresponded to MODISt_OC, that showed the longest time series of all the products analyzed. Most of the products displayed negative trends, indicating that the concentrations in these hotspots have decreased over time. This probably has to do with the inclusion of the extremely high values from the 2000–2006 period in the calculations. VIIRSn_OC was one of the products that showed slightly positive trends, despite only being present from 2017 onwards. Certainly, these values should continue to be monitored over time, in order to understand the temporal and spatial dynamics of the lake.

As for the temporal analysis, Fig. 4 shows the behavior of these over the years, only considering the masked scenes with more than 80% of pixel coverage over the lake area. CHL data are available from the late 1990s up to this day, which is very valuable in terms of gaining an understanding of the dynamics within the lake both temporally and spatially. Between the years 2000–2006, Fig. 4 reveals very high concentrations for all products analyzed, possibly related to the high number of algal blooms and fish kills that were reported during those years (Vammen et al., 2006; World Bank, 2013).

However, a very marked difference can clearly be observed between the magnitudes estimated by MERIS_G, MERIS_OC, MODISa_OC, MODISt_OC and those of CCI. CCI seems to be the product that consistently estimates the lowest concentrations for the whole

Table 5
Mann-Kendall test results per hotspot and product. Values on the left correspond to p-values whereas those on the right indicate the S-statistic.

Product	Hotspot 1		Hotspot 2		Hotspot 3		Hotspot 4	
CCI	1E-14	-3367	4E-13	-3088	1E-08	-2556	5E-13	-3267
MERIS_G	0,62	-13	0,71	-10	0,51	-17	0,97	2
MERIS_OC	0,00	-1581	4E-15	-2074	2E-16	-2614	7E-10	-1323
MODISa_OC	7E-10	-5834	3E-13	-7659	1E-12	-7447	9E-15	-8123
MODISt_OC	0E+00	*-12613*	0E+00	*-12966*	0E+00	*-13301*	0E+00	*-12492*
OLCI_G	0,03	-86	0,03	-90	0,56	-23	0,94	-4
S2A_T	0,11	-173	0,44	-85	0,81	-27	0,82	-25
S2B_T	0,29	-46	0,44	-34	0,69	-18	0,50	-30
S3A_OC	7E-05	-818	8E-04	-702	0,01	-580	3E-04	-711
S3B_OC	0,32	-130	0,40	-113	0,68	-60	0,81	-32
SeaWIFS_OC	0,59	122	0,44	-257	0,29	-402	0,84	34
VIIRSn_OC	0,60	-92	0,03	401	0,05	352	0,84	37
VIIRSs_OC	0,99	-9	1,00	3	0,35	-475	0,86	87

study period, this may be due to its processing chain which involves an atmospheric correction that has been validated with multiple in-situ databases of both concentration and surface reflectance, also, this product makes a distinction from the OWT for the application of the algorithms, reasons why it usually tends to underestimate some water quality parameters (Simis et al., 2023). While there are some fluctuations between the magnitudes calculated by the different products, there is a certain degree of agreement between them over the years, with CCI being the one with consistent lower values than others. All products have magnitudes of CHL that correspond to the eutrophic condition with concentrations between 8 and 25 mg/m^3, highlighting the water quality issue in the lake.

In Fig. 5 the weekly means were split into seasons, to better visualize whether there were strong changes in behavior between products depending on the time of the year. As a result, CHL concentrations are slightly higher in the dry season compared to the wet

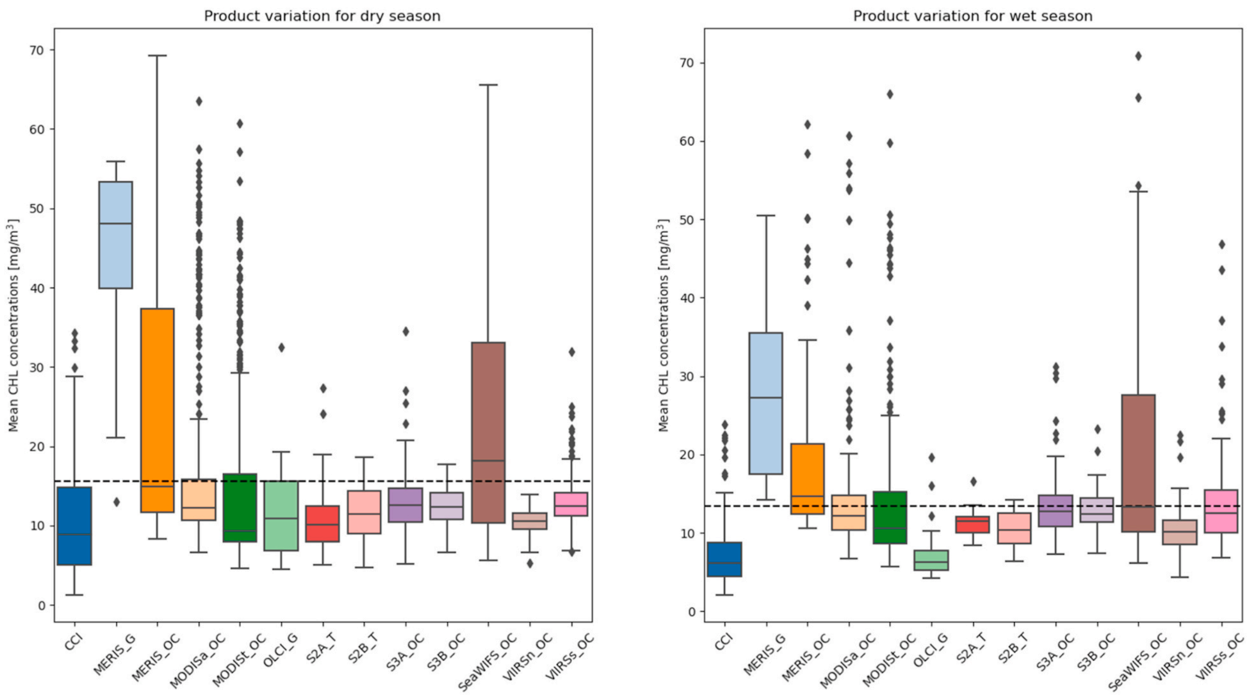

Fig. 5. Product variation for dry season (left) and wet season (right) over entire study period.

season, with the average for the seasons being 15.54 mg/m^3 and 13.39 mg/m^3, respectively. Similarly, a certain stability is observed in the products and in the magnitudes in the dry season, with very few outliers. The dry season exhibits slightly elevated mean CHL concentrations across most products compared to the wet season, which may indicate a seasonal surge in algal biomass. On the other hand, in the wet season, which can be seen in Fig. 5 (right), there are more outliers between products and lower concentrations overall.

Notably, MERIS_G, MODISt_OC, and S3B_OC demonstrate considerable variability with their expansive interquartile ranges (IQRs), suggesting that these sensors capture a broad spectrum of CHL variability, potentially reflecting the high variability of CHL of the years in which they compiled data or varying algorithm performance. The consistent presence of upper outliers, might point to episodic algal blooms, consistent overestimation of concentrations or sensor sensitivity to specific chlorophyll-rich conditions. Conversely, products like CCI and SeaWiFS_OC showcase tighter IQRs, indicating more stable CHL readings, which may be advantageous for studies in need of consistent temporal monitoring. The skewness towards higher values in some products highlights the need for careful consideration of product-specific biases when interpreting CHL data, that can be related to the sensor, to the algorithms or to the spatial and temporal aggregations in which they are generated. The selection of remote sensing products for water quality monitoring should thus consider not only the central tendency and variability of CHL concentrations but also the frequency and impact of extreme values, as these can significantly influence ecological assessments and algorithm validations.

3.3. Applicability and relevance for water local management

The integration of remote sensing data into local water quality monitoring of Lake Nicaragua offers a potential transformative approach to sustainable water resource management. However, based on the results obtained, adequate in-situ data is of vital importance for the validation and selection of the algorithms to be used. For instance, the identification of CHL hotspots using satellite imagery may enable policy makers to identify areas most in need of intervention, thus optimizing resource allocation in the basin. In addition, the cost-effectiveness of remote sensing compared to full traditional in-situ sampling offers a compelling advantage. By reducing the need for extensive in-situ sampling, remote sensing allows for more frequent and widespread monitoring, ensuring that emerging water quality problems are addressed promptly. This technology fosters the development of potential early warning of algal blooms that can lead to massive fish kills, significantly mitigating large-scale ecological and economic damage. Consequently, the results of this study reflects on the potential role of remote sensing in the development of informed and effective water management strategies that are both proactive and sensitive to the dynamic conditions of Lake Nicaragua.

However, it should be emphasized that to ensure a good use and exploitation of remote sensing for water quality monitoring, several considerations must be taken into account, among them the selection of appropriate algorithms depending on the water body to be studied, and for this, periodic in-situ measurements of water quality and water reflectance are essential. Likewise, trained and well-equipped personnel are required to handle this type of data formats in order to derive reliable and accurate information from them and to interpret them in the correct way. Providing free access to the data is also essential for the purpose of promoting research and to avoid duplication of efforts. This research focused on the analysis of global CHL products, however, more water quality parameters and water quantity related variables can be obtained by remote sensing. Relevant projects such as Water-ForCE (https://waterforce.eu/es) have conducted extensive work on the availability of remote sensing data for water management, and documents such as Baltodano and van Griensven (2023) list several ways in which this data is already being actively employed in water management in different countries. Whilst the database that was available is less than optimal. By stressing the potential of its combination with remote sensing, we can suggest that water managers and monitoring agencies may be able to plan monitoring campaigns in the future that can be effectively compared with satellite imagery (matching dates and times with satellite overpass, complementing with water surface reflectance measurements, etc.).

Furthermore, the strategic use of remote sensing data can contribute significantly to the sustainability of water management by supporting educational campaigns and public awareness initiatives related to the local water quality state. By visualizing the spatial distribution of pollutants and identifying trends over time, stakeholders can better understand the impact of human activities on the system. Such awareness may promote community engagement and fosters collaborative water conservation efforts. In addition, the ability of remote sensing to provide consistent and replicable data can supports the evaluation of management interventions over time, allowing for the refinement of strategies to meet the evolving challenges of preserving water quality in Lake Nicaragua.

4. Limitations

While this study makes an initial effort to evaluate global satellite-based products as a potential complement to in situ water quality monitoring, there is still room for improvement. First, we recognize the limited in-situ data that was used to evaluate these products; an extensive dataset might yield better and different correlation results. Likewise, we have worked with products for which algorithms were already implemented, and while the literature recognizes the importance of region-specific processing, this could not be carried out due to limited data available. In the future, the ideal scenario would be to have sampling campaigns that would allow discerning between algorithms and applying the suitable ones for the specific region depending on the optical water properties. An additional limitation in using global products is that many sources generate these data at coarse spatial resolutions since they are mainly used to monitor the oceans (Ocean Color), whereas processing of the satellite information in-house would allow to preserve the high spatial resolution that many satellites/sensors have (e.g. Sentinels) as in source Terrascope (20m spatial resolution). Lastly, a thorough and complete in-situ dataset would also allow the assessment of different water quality parameters leading to more robust conclusions regarding the status of the lake's waters.

5. Conclusions

This study consisted of the intercomparison of 13 different CHL products derived from remote sensing between 1997 to date, and their validation with available in-situ data from 2011 to 2016. Upon validation of the products with the few in-situ data that were available, the best correlation results were found with CCI, yet the correlation was not strong. This is attributed to the fact that the in-situ data were few and inconsistent. We believe that better and more in-situ data could provide a stronger and more reliable analysis. In reviewing the residuals from this same correlation analysis, certain behavior in the RS values was identified, indicating heteroscedasticity, which depict difficulties in replicating in-situ values when CHL concentrations are either too low or too high, which is a problem that has been encountered and shared in the literature.

Further analyses were carried out, both temporal and spatial, to determine whether the products yielded similar outcomes. The spatial analysis allowed for the detection of hotspots with consistently high CHL concentrations (>25 mg/m^3) throughout the study period. The hotspots were particularly located in the northern part of the lake, near urban and agricultural zones like Granada and the Tipitapa river inflow. These regions showed a general decline in CHL levels since 2006, likely due to improved wastewater treatment, yet they remain eutrophic. Temporally, a period was identified between the early 2000s and 2006 in which all products reported very high CHL concentrations, coinciding with algal blooms and massive fish kills reported in national news with no official report listing any particular cause. After 2006, the levels of CHL in the lake have remained rather stable, albeit remaining within values that categorize the lake as eutrophic. Differentiation was also made between the dry and wet seasons, with the dry season having a slightly higher mean of 15.54 mg/m^3 and the wet season 13.39 mg/m^3.

Global remote sensing products can be a valuable monitoring tool for local water managers, however, certain efforts must be made initially to identify the optimal combination of sensors and algorithms for the particular region represented in this study. Such efforts consist of measurement campaigns with a certain periodicity of in-situ water quality but also surface water reflectance. This study can be used as a guide as to which areas should be prioritized for monitoring in order to work on a water quality database that is robust and open to the public. Meanwhile, we consider that even with low correlation, the CCI product is the most reliable for Lake Nicaragua, being the one that takes into account the properties of the OWT, however, the data available today are until 2020, therefore, continuity is expected.

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Ethical statement

We declare that all ethical practices have been followed in relation to the development, writing, and publication of the article titled: **"Exploring Global Remote Sensing Products for Water Quality Assessment: Lake Nicaragua case study"** submitted for review on the **Remote Sensing Applications: Society and Environment** journal on April 15th, 2024

CRediT authorship contribution statement

Analy Baltodano: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Afnan Agramont:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Katoria Lekarkar:** Visualization, Methodology, Formal analysis. **Evangelos Spyrakos:** Writing – review & editing, Supervision, Formal analysis. **Ils Reusen:** Writing – review & editing, Supervision. **Ann van Griensven:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Ann van Griensven reports financial support was provided by Research Foundation Flanders. Analy Baltodano reports financial support was provided by AXA Research Fund. Afnan Agramont reports financial support was provided by VLIR-UOS. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2024.101331.

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