Assessment of Phytoplankton Biomass and Diversity in Northeast Brazil via Satellite Ocean Color Observation

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Abstract

The study investigates the distribution and seasonal dynamics of phytoplankton communities in Northeast Brazil using ocean color data obtained through satellite remote sensing (RS). This unprecedented approach for the region assesses the biomass and composition of phytoplankton, which is crucial for understanding the responses of the marine ecosystem to environmental changes and impacts on biogeochemical cycles. The research uses in situ data from oceanographic campaigns (MARSEAL, ABRACOS and SWOT) and satellite data from sources such as OC-CCI (multi-mission), GlobColour (multi-mission) and Sentinel-3 OLCI (single sensor). These datasets allow for the analysis of chlorophyll-a (chl *a*), phytoplankton functional types (PFTs) and phytoplankton size classes (PSCs), with a focus on in situ sampling periods. For chl *a*, the correlation observed between the *in situ* data from the campaigns and the OC-CCI satellite data was explained by some statistical descriptors with the coefficient of determination (R^2) explaining approximately 34% of the variation in the in situ samples, with a root mean square deviation (RMSD) of around 0.2926 and mean absolute percentage deviation (MAPD) and mean bias error (MBE) values of -18.7361% and -2.3454%, respectively. As for the *in situ* data for the accessory pigment 19'Hexfucoxanthin (19HF) from the ABRACOS campaigns, which was correlated with the satellite data from the model by El Hourany et al. (2019), the R^2, RMSD, MAPD and MBE were 58%, 0.1815, -4.528% and 0.5411%, respectively.

1. Introduction

Phytoplankton is responsible for about 50% of global primary production (Field, 1998; Häder & Gao, 2015; Carvalho et al., 2017), a process by which nutrients are assimilated and inorganic carbon is converted into organic carbon (Kemp et al., 1997), removing between 5-12 Gt C y^{-1} of carbon from the atmosphere and making it available to consumers such as zooplankton (Ducklow & Doney, 2013; Karlusich et al., 2020). Furthermore, this planktonic compartment is central to several biogeochemical cycles such as those of nitrogen and phosphorus (Naselli-Flores & Padisak, 2023). As a result, phytoplankton organisms play a fundamental role in the functioning of marine ecosystems (Abreu et al., 2010). Various biological, environmental, and anthropogenic factors influence the phytoplankton community structure. These factors include rainfall, tide level changes, fluctuations in herbivory rates, and competition among species (Parizzi, 2014). Among nthropogenic factors include the release of untreated domestic and industrial sewage into water bodies, which, in addition to other problems with the water body's bathing water, has a direct impact on phytoplankton organisms, as this discharge raises the levels of nutrients that previously did not exist and can encourage eutrophication events and even an increase in harmful algae (Pan & Rao, 1997).

To assess the impacts of biological, environmental, and anthropogenic factors on the community, we can evaluate phytoplankton biomass, which can be estimated using chlorophyll *a* (chl *a*), a pigment common to most phytoplankton organisms except for the cyanobacteria genus *Prochlorococcus*, which predominantly uses divinyl chl *a* as its photosynthetic pigment (Gonzalez-Rodriguez et al., 2017). Estimating biomass in a region (using chl a as a proxy) allows us to evaluate the availability of organic matter for subsequent trophic levels (Passavante and Feitosa, 1989), as well as measure biological

production, facilitating the rational use of ecosystems and the development of remediation strategies when necessary (Fonseca et al., 2002).

The study of the spatiotemporal dynamics of phytoplankton biomass represents an essential first step in understanding this community. However, it is also fundamental to understand its taxonomic diversity and other functional factors such as size classes (Alvain et al., 2008; Bricaud et al., 2012). While other understandings regarding biomass require elucidation, the study of phytoplankton biomass provides crucial information for understanding the structure and functioning of ecosystems. It is also relevant for assessing the impact of climate modulation on marine biodiversity (Henson et al., 2021) and its effects on oceanic biogeochemical cycles (Falkowski et al., 2003).
Over the years, studies of phytoplankton organisms have evolved significantly. Approaches range from plankton net tows for visualization and identification under a microscope, which remain the most common and accessible methods, to the use of more modern and specific techniques such as high-performance liquid chromatography (HPLC) and flow cytometry. These methods define organisms based on autofluorescence and light scattering properties, alongside molecular methods used to elucidate phylogenetic relationships (IOCCG, 2014). Microscopy has the advantage of requiring low investment compared to other methods, but it is limited due to the lack of experts in phytoplankton taxonomy. The HPLC technique is automatic and precise, but it lacks *in situ* tools and is very expensive. Flow cytometry has available *in situ* tools, but the instruments are expensive and delicate and require a specialized user. As for molecular methods, taxa can be selected with a high degree of specificity, but the development of methods and tests are time-consuming and exceedingly expensive (IOCCG, 2014).

With a different approach to studying phytoplankton, satellite ocean color observation is a unique tool for analyzing phytoplankton dynamics across a wide range of scales, both spatial (from a few kilometers to global patterns) and temporal (daily, seasonal, and annual variations). Since the late 1970s, sensors coupled with satellites have been developed to observe ocean color and from that infer conclusions about the optical properties of the water and the phytoplankton community. In this sense, the Coastal Zone Color Scanner (CZCS) aboard the Nimbus-7 satellite was the first satellite ocean color sensor, being operational from 1979-1986 and allowing the estimation of phytoplankton pigment concentrations in the global ocean, which was essential for understanding phytoplankton biomass patterns and inevitably served to improve sensors developed later (Blondeau-Patissier et al., 2014; Oziel et al., 2022).

Phytoplankton biomass is the main parameter estimated from ocean color observation by remote sensing (O'Reilly et al., 2019); however, numerous efforts have been made in recent decades to go beyond this information (IOCCG, 2014), developing methods to represent the structure of the phytoplankton community through the description of phytoplankton functional types (PFTs), conceptual groupings of phytoplankton species that have a common ecological functionality, for example, size classes (PSCs), pico-, nano-, and microphytoplankton (Mouw et al., 2017; IOCCG, 2014), or accessory pigment composition, such as fucoxanthin (fuco) and peridinin (Peri) (El Hourany et al., 2019). Such information derives from ocean color observation due to a variety of direct and indirect effects of phytoplankton composition on marine optical properties such as absorption and scattering properties, marine reflectance (IOCCG, 2014).
Performance evaluation of different algorithms derived from ocean color observation is highly important as regional influences directly affect algorithm performance (Seegers et al., 2018). So far, no assessment of the performance of methods used to estimate phytoplankton diversity from space has been conducted in northeastern Brazil (NE). This study will represent a necessary first step to evaluate the relevance of existing methods and select the most suitable products to provide a first description of phytoplankton diversity on a regional scale. Furthermore, this proposal is important to establish a new research field in Pernambuco and NE, contributing to the development of new disciplines and filling scientific, technological, and methodological gaps.

2. Materials and Methods

2.1 Study Area Characterization

The study used *in situ* data collected in the coastal and oceanic region of NE comprising the states of Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Sergipe and Bahia. The area features a narrow continental shelf, up to 40 km wide, with depths ranging from 40 to 80 m, and a continental slope ranging between 1,600 and 3,600 m. Further offshore, the geomorphology includes a chain of seamounts with heights ranging from 20 to 250 m, the Fernando de Noronha Ridge, which encompasses the Rocas Atoll and the Fernando de Noronha Archipelago (Figure 1).

In the basin of the states of Sergipe (SE) and Alagoas (AL) within the Environmental Characterization Project of the Sergipe and Alagoas Basins (MARSEAL), this area continental shelf varies in width, with a range of 20 km in the southern part of SE and 38

km in AL (Moreira et al., 2019). In the region, we can find the third largest drainage basin in Brazil, the São Francisco River basin, with a net flow of 1758 m³/s (Marques et al., 2002; Medeiros, 2003). The area is highly oligotrophic due to the influence of the South Equatorial Current, which transports warm and nutrient-poor waters (Ekau and Knoppers, 1999).

In the Acoustics along the BRAzilian CoaSt (ABRACOS) campaign region, the geomorphology is characterized by a chain of seamounts (ranging from 20 to 250 m in height), the Fernando de Noronha Ridge which includes the oceanic island of Rocas Atoll and the Fernando de Noronha Archipelago (Castello, 2010; Kikuchi, 2002). This area is further influenced by the central and southern branches of the South Equatorial Current and the South Equatorial Subcurrent, forming the South Equatorial Current System (Dossa et al., 2021).

The project Surface Water and Ocean Topography (SWOT) took place in the southernmost part of Bahia (BA) around the Abrolhos Marine National Park, which covers 46,000 km² within the continental shelf, characterized by mangroves, coral reefs, and rhodolith banks (Moura et al., 2021). The Abrolhos shelf is influenced by Tropical Water (TW) and South Atlantic Central Water (CSAW) (Castro Filho and Miranda, 1998).

2.2 *In situ Data*

The *in situ* data used were collected during oceanographic campaigns of the MARSEAL during the raining season (MARSEAL_A1) (May-June 2014) and the dry season (MARSEAL_A2) (December 2014 to January 2015), coordinated by PETROBRAS/CENPES aboard of the R/V Seward Johnson, ABRACOS aboard the R/V ANTEA, which was divided into two campaigns, ABRACOS 1 (A1) (August-September 2015) (Bertrand, 2015) and ABRACOS 2 (A2) (April-May 2017) (Bertrand, 2017), and SWOT during the rainy season (SWOT_1) (May 2023) and the dry season (SWOT_2) (September 2023) aboard the R/V Ciências do Mar IV.

In the MARSEAL and SWOT campaigns, chl *a* data were obtained through spectrophotometer analysis, allowing for the quantification of total biomass and biomass of the fraction > 20 µm. During the ABRACOS campaigns, data were obtained through High Performance Liquid Chromatography (HPLC), providing information on chl *a* and accessory pigments indicating different phytoplankton groups, such as Bacillariophyceae (fuco) and Dinophyceae (Peri).

During MARSEAL, it was observed that picophytoplankton and nanophytoplankton (fraction <20 µm) strongly dominated the community (>70%), which is a strong indicator of the oligotrophic nature of the area (Weber and Weber, 1998; Sabetta et al., 2008). As for ABRACOS, as described by Farias et al. (2022), it was observed that picophytoplankton and nanophytoplankton (fraction <20 µm) strongly dominated the community (>80%), regardless of the season and sampling depth.

Medeiros et al. 2023 observed chl *a* values for the Abrolhos Archipelago region ranging from 0.058 to 1.034 mg m³, with an average value of 0.525 (± 0.26) mg m³. These values are characteristic of oligotrophic waters.

2.3 Satellite Ocean Color Data

The ocean color data consist of a dataset used to evaluate chl *a*, PFTs, and PSCs results, focusing on the time period corresponding to *in situ* sampling. In this case, daily data (e.g.,

GlobColour, Ocean Color Climate Change Initiative (OC-CCI), and Sentinel 3 OLCI) were considered, and extractions around each sampling point were conducted to perform a "matchup exercise" (which involves assessing the performance of satellite products and associated uncertainties using *in situ* data).

The homogeneity criteria for the matchup took into account the coefficient of variation (CV) < 0.2, and at least 5 valid pixels in the 3x3 window that was created around each point in the image from the satellite. In practice, various methods currently available for assessing phytoplankton biomass (e.g., OC4 algorithm for chl *a*; O'Reilly et al., 2019), PFTs (PHYSAT, Alvain et al., 2005, Machine learning-based approaches; Xi et al., 2020), PSCs (Kostadinov et al., 2022, Xi et al., 2020, Ciotti et al., 2006), and accessory pigments of phytoplankton (El Hourany et al., 2019) were considered.

The OC-CCI uses data from five sensors: the Sea-viewing Wide Field-of-view Sensor (SeaWiFS), the Moderate Resolution Imaging Spectroradiometer on board the Aqua Earth Observing System (MODIS-Aqua), Medium Resolution Imaging Spectrometer (MERIS), Visible Infrared Imaging Radiometer Suite (VIIRS) and the Ocean and Land Colour Instrument Sentinel-3A (OLCI-S3A) (Colella et al. 2021).

2.4 Statistical Methods

The comparison between *in situ* observations and satellite estimates followed standardized protocols to validate ocean color data. A subset of pixels around the sampling points was extracted, and quality criteria were applied to verify the consistency between observations. The "matchup" data set was used to analyze the performance of the assessed methods and calculate statistical descriptors such as root mean square deviation (RMSD), mean absolute percentage deviation (MAPD), mean bias error (MBE), and coefficient of determination (R^2) to select the best satellite product.

3. Discussion and Results

3.1 Chlorophyll *a*

A linear regression of *in situ* chl *a* with satellite-measured (OC-CCI and GlobColour 4Km) chl *a* was made. For the OC-CCI, the R^2 explained approximately 34% of the variation in the *in situ* samples, with an RMSD of around 0.29, and MAPD and MBE values of -18.73% and -2.34%, respectively. For GlobColour, the R^2 explained approximately 32% of the variation in the *in situ* samples, with an RMSD of around 0.31, and MAPD and MBE values of -23.1% and 64.37%, respectively.

Sathyendranath et al. (2019) evaluated the performance of OC-CCI against global *in situ* data. Compared to the present study, the RMSD was very close with a value of 0.30. As for R^2, the value was 0.81. On the other hand, the MBE of our study was quite low compared to the cited study with the lowest value being -0.0409 for. In the study we are comparing for the OC-CCI, the lowest data value (N) was 6049, while ours was 44. Coppini et al. (2013), evaluating the performance of GlobColour in the Mediterranean Sea, obtained values similar to our study for R^2 and intercept, being 0.31 and -0.41, respectively. The authors compared the performance of GlobColour in the Mediterranean Sea with a regional model focused on the area, Med Regional SeaWiFS RANMyOcean (Med Reg) and it was observed that Med Reg obtained better results and this was pointed out as an advantage of using regionalized algorithms to specific regions.

It was found that OC-CCI offers greater spatial coverage and better performance in long-term applications while GlobColour provides an integration of more satellite sensors (Moradi, 2021). In general, performance was reasonable, with dispersion due to differences in the *in situ* methods used in the campaigns. There was an overestimation in the chl *a* found for lower values, this has already been observed for the OC-CCI (Moradi, 2021) and an alternative to resolve this is to use the optical water types (OWT) to identify the classes where there is a failure in said sensor (Cui et al., 2020). The data set for the region needs to be more robust so that the results are also robust, since the number of data (n sample) interferes with the conclusions of the most adapted algorithm.

3.2 Accessory pigments

Regarding accessory pigments, the algorithm by El Hourany et al.(2019) was tested for 6 accessory pigments that are present in the *in situ* HPLC data set of A1 and A2 (Zeaxanthin (zea), Peri, Fuco, 19'Butanoyloxyfucoxanthin (19BF), 19'Hexfucoxanthin (19HF) and Chlorophyll b (chl *b*)) and below it is possible to observe some results. In Figure 3a, the *in situ* data for the dinoflagellate's diagnostic pigment peri from campaigns A1 and A2 exhibit a strong correlation with satellite data processed using the algorithm developed by El Hourany et al. (2019) for GlobColour data. Peri is one of the 10 pigments reliably estimated in El Hourany et al. (2019), where self-organizing maps (SOMs), unsupervised neural classifiers applied in remote sensing, were utilized. In this instance, the R^2 explains approximately 44% of the variation in the *in situ* samples, with an RMSD around 0.32, and MAPD and MBE values of -7.06% and 11.45%, respectively. El Hourany et al. (2019) used R^2 and RMSD as statistical metrics and found values of 80% and 0.01 for peri, respectively.

Figure 3b shows the relationship between *in situ* data and the haptophyte diagnostic pigment, 19HF, for the same campaigns. Here, R^2 explains approximately 58% of the variation in *in situ* samples, with RMSD around 0.18, and MAPD and MBE values of -4.52% and 54%, respectively. In one of the metrics used El Hourany et al. (2019) found the same value for R^2 and the RMSD was 0.03. Figure 3c illustrates the relationship between *in situ* data and cyanobacteria diagnostic pigment, (zea), for the same campaigns. In this case, R^2 explains approximately 33% of the variation in *in situ* samples, with RMSD around 0.36, and MAPD and MBE values of -23.92% and 29.92%, respectively. El Hourany et al. (2019) found a maximum R^2 value for zea of 79% and the RMSD was 0.02.

Overall, El Hourany et al. (2019) found that their model was efficient for all pigments used with $R^2 > 0.75$ and an average RMSE = 0.016 mg/m³. Farias et al. (2022) observed in the area that for the phytoplankton groups that can be quantified by the amount of accessory pigments, the distribution of pigments showed higher concentrations of Cyanophyceae (zea) in the surface layer, regardless of region and season, and an increase in the accessory pigments of three phytoplankton groups, Bacillariophyceae (fuco), Dinophyceae (peri) and Chlorophyceae (chlorophyll b, neoxanthin, violaxanthin) in the fall in all regions, indicating a structural change in the community between seasons. This was the first time that the method of El Hourany et al. (2019) was evaluated in Northeast Brazil. This algorithm can provide valuable information for assessing and diagnosing the distribution of the main phytoplankton groups, as it seems to work effectively for certain groups, for example for

dinoflagellates, as an exactly equal R² was observed for one of the metrics used in the El Hourany et al. (2019) neural network.

The *in situ* data set used in this work was nowhere near the data set that generated the SOMs and this reinforces the need to have a robust data set so that more robust analyses can be carried out. The limitation in relation to zea can be attributed to the low chlorophyll values characteristic of these groups, which consist of cyanobacteria, organisms with small cell sizes and, consequently, low chl *a* content characteristic of oligotrophic regions.

4. Conclusion

This study represents the first evaluation of ocean color algorithms for the NE region, and while the results for chlorophyll a are considered reasonable, some dispersion and underestimation were observed.

The study of accessory pigments used the A1 and A2 datasets, which are the first *in situ* HPLC data available for the region. This approach is valuable as it quantifies accessory pigments in addition to chlorophyll *a*, which is important for understanding phytoplankton community composition. Future studies using this methodology are promising and crucial for gaining a better understanding of phytoplankton community structure.

Subsequently, methods such as those of Brewin et al. (2010) and Hirata et al. (2011), which are simpler and use empirical relationships involving chl *a*, will be evaluated in the Northeast of Brazil. This step is crucial because it marks the beginning of the use of satellite data for time series, seasonality, trends and climate modulation.

Methods that evaluate phytoplankton groups based on accessory pigments such as that of El Hourany et al. (2019) are promising and show that it is necessary to evaluate other methods that already exist or that may emerge in order to assess which are most suitable for the region. Finally, satellite images derived from sensors that evaluate phytoplankton will be analyzed to have a better representation of phytoplankton biomass and community composition dynamics on the NE shelf of Brazil.
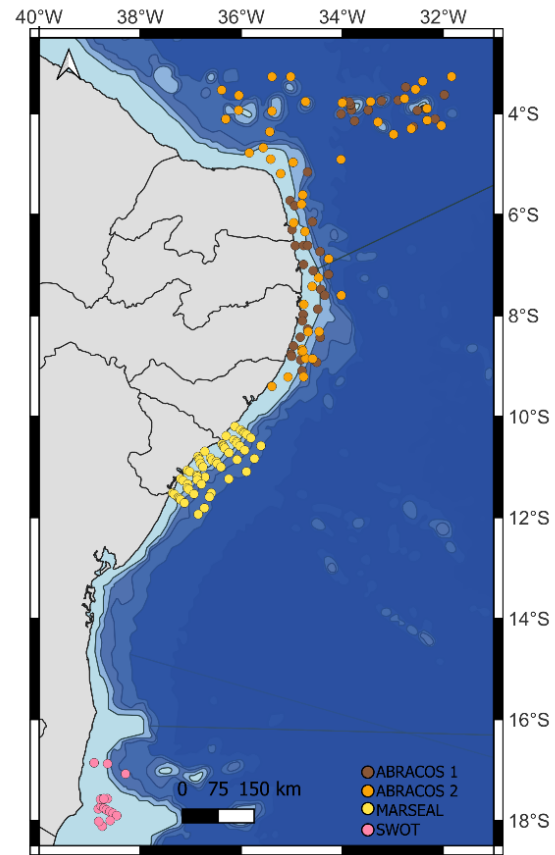

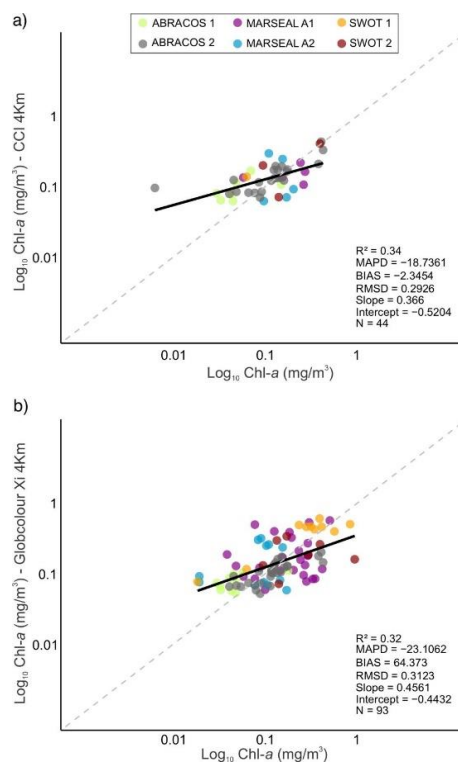*Figure 1: Sampling area of in situ data on the Brazil northeast, campaigns ABRACOS 1 and ABRACOS 2, MARSEAL, and SWOT.*

Figure 2: Linear regression between the in situ chlorophyll a concentrations of the campaigns and the chlorophyll a values observed by the OC-CCI and GlobColour, both with a resolution of 4km.
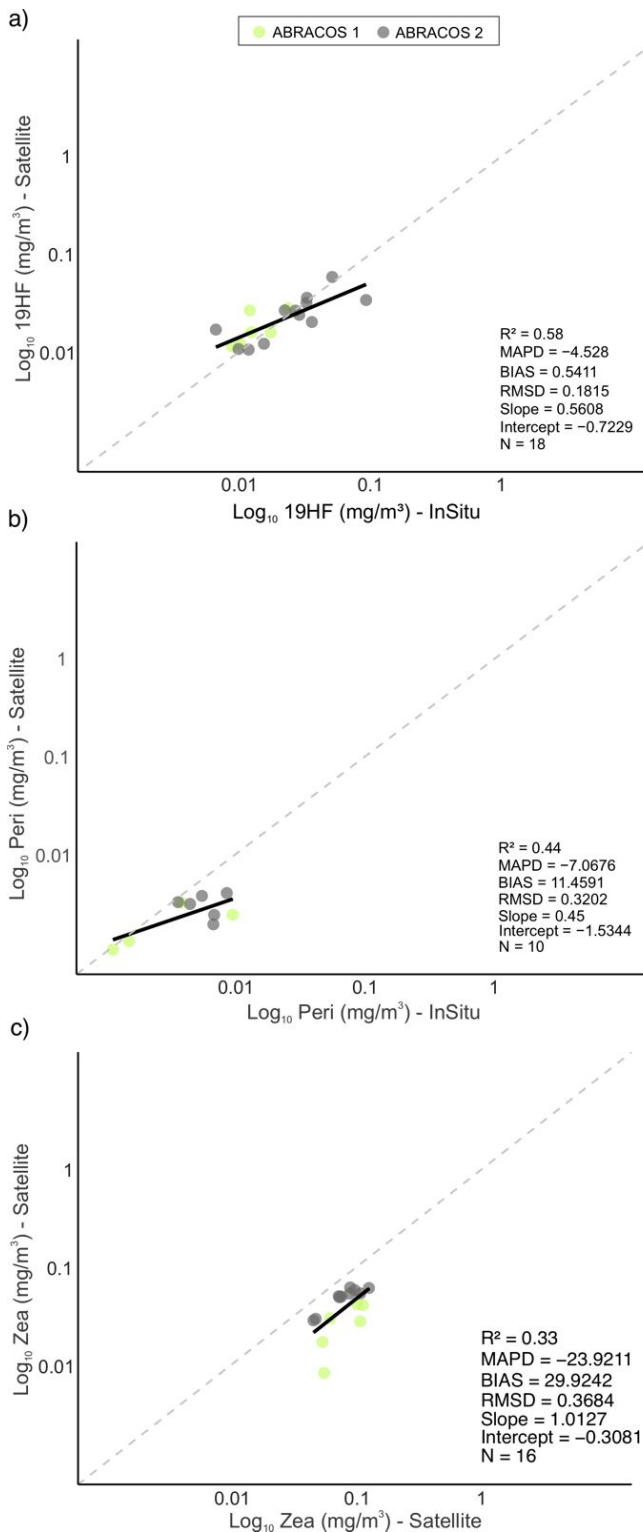
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Figure 3: Linear regression between the in situ 19HF, Peridinin and Zeaxanthin concentrations from the ABRACOS 1 and ABRACOS 2 campaigns and the satellite-observed values using the El Hourany et al. (2019) algorithm.

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