applied sciences

MDPI

Article

Advances in the Monitoring of Algal Blooms by Remote Sensing: A Bibliometric Analysis

Maria-Teresa Sebastiá-Frasquet [1,*], Jesús-A Aguilar-Maldonado [1], Iván Herrero-Durá [2], Eduardo Santamaría-del-Ángel [3], Sergio Morell-Monzó [1] and Javier Estornell [4]

1 Instituto de Investigación para la Gestión Integrada de Zonas Costeras, Universitat Politècnica de València, C/Paraninfo, 1, 46730 Grau de Gandia, Spain; jesusaguilarmaldonado@gmail.com (J.-A.A.-M.); sermomon@doctor.upv.es (S.M.-M.)
2 KFB Acoustics Sp. z o. o. Mydlana 7, 51-502 Wrocław, Poland; i.herrero-dura@kfb-acoustics.com
3 Facultad de Ciencias Marinas, Universidad Autónoma de Baja California, Ensenada 22860, Mexico; santamaria@uabc.edu.mx
4 Geo-Environmental Cartography and Remote Sensing Group, Universitat Politècnica de València, Camí de Vera s/n, 46022 Valencia, Spain; jaescre@cgf.upv.es
* Correspondence: mtsebastia@hma.upv.es

Received: 20 September 2020; Accepted: 4 November 2020; Published: 6 November 2020

check for updates

Abstract: Since remote sensing of ocean colour began in 1978, several ocean-colour sensors have been launched to measure ocean properties. These measures have been applied to study water quality, and they specifically can be used to study algal blooms. Blooms are a natural phenomenon that, due to anthropogenic activities, appear to have increased in frequency, intensity, and geographic distribution. This paper aims to provide a systematic analysis of research on remote sensing of algal blooms during 1999–2019 via bibliometric technique. This study aims to reveal the limitations of current studies to analyse climatic variability effect. A total of 1292 peer-reviewed articles published between January 1999 and December 2019 were collected. We read all the literature individually to build a database. The number of publications increased since 2004 and reached the maximum value of 128 in 2014. The publications originated from 47 countries, but the number of papers published from the top 10 countries accounted for 77% of the total publications. To be able to distinguish between climate variability and changes of anthropogenic origin for a specific variable is necessary to define the baseline. However, long-term monitoring programs of phytoplankton are very scarce; only 1% of the articles included in this study analysed at least three decades and most of the existing algal blooms studies are based on sporadic sampling and short-term research programs.

Keywords: phytoplankton; ocean colour; chlorophyll a; SeaWiFS; CZCS; MODIS; MERIS; VIIRS; Sentinel; GOCI

1. Introduction

Remote sensing of ocean colour began in 1978 with the launch of NASA's Coastal Zone Colour Scanner (CZCS). Since then, several new ocean-colour sensors have been launched and more are planned for the near future by various space agencies. Several water properties can be derived from remote sensing imagery, e.g., sea surface temperature (SST), chlorophyll-*a*, turbidity, and optical properties. These properties are applied to study different water quality issues and marine environmental management [1,2]. Among them, phytoplankton blooms, also known as algal blooms, are of significant relevance [3,4]. An algal bloom can be defined as the rapid growth of one or more species leading to an increase in the species' biomass resulting from favourable environmental conditions [5,6]. However, there is not a unique threshold that defines what can be considered a bloom [7]. To define a bloom, it is key to know the standard values and seasonal patterns at a specific site, so a bloom can be defined as a deviation to higher values than those [8]. Unusual high phytoplankton biomass values can be very different between sites, from concentrations of a few hundreds to millions of cells per millilitre, depending on the causative species [6,8]. Different adjectives have been used to characterize the degree of the negative impact of these blooms according to their characteristics and those of the causative species, such as toxic, noxious, or harmful [9], which can cause negative impacts to other aquatic organisms and on the ecosystem and human health, and they are often divided into toxic versus high-biomass blooms [10]. Harmful blooms causing mass mortality of organisms during a long lasting phytoplankton bloom may be a result of three main factors: (1) Asphyxia caused by saturation of the microalgae in the water and/or mechanical asphyxia caused by clogging of the fish gills. (2) Asphyxia caused by hyper-eutrophication of the system creating anoxic-hypoxic conditions in the water column. (3) Poisoning of organisms because of consuming or bioaccumulating toxins produced by certain phytoplankton species [11–14]. The most common and repetitive blooms occurring at present cannot automatically be labelled as harmful algae blooms (HABs).

Identifying phytoplankton blooms has been the target of extensive research [15]. Blooms in a strict sense are a natural phenomenon that has occurred throughout recorded history. However, due to anthropogenic activities, blooms appear to have increased in frequency, intensity, and geographic distribution [16]. Climatic variability plays a key role in factors like wind-driven upwelling and thermal stratification, which largely influence phytoplankton abundance and composition. Nowadays, it is hypothesised that climate change will have a direct effect on those factors and modify future scenarios for algal blooms [17]. Ocean colour is recognised as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS) [18,19].

To interpret the effect of different oceanographic factors, it is necessary to establish continuous monitoring programs for the variables that may be more sensitive. These programs must generate time series long enough to be able to differentiate natural variations from those of anthropogenic origin [20]. Data can be obtained from in situ monitoring, but, in recent years, remote sensing technologies have emerged as an adequate tool for providing a synoptic view of extensive ocean or coastal areas, effective in complementing in situ sampling programs [21–24]. Time series derived from ocean-colour data, at the global scale and at high spatial resolution, are key to studying phytoplankton variability at seasonal and inter-annual scales [19]. But even satellite data will require decades of observations before the signal of climate change is noticed over large regions of the ocean [25].

There are two types of orbits for Earth observation satellites, polar orbiting and geostationary, with different revisit time, and while polar-orbiting satellites typically have a revisit time of 2–3 days, geostationary satellites operate in time scales of hours, which is key to be able to capture diurnal variation in phytoplankton abundance and productivity. South Korea's (GOCI) instrument on board the COMS-1 satellite, launched on 26 June 2010, is the first ocean-colour sensor in a geostationary orbit. The important factors to consider when designing an observation strategy and a detection technique are the scales of variability for these algal blooms [26]. Blooms usually have spatially distinct patchy distributions that should also be considered to select the suitable spatial scale of satellite sensors [23]. Data from remote sensing monitoring can inform decision-makers where to apply their sampling effort to verify the presence of a bloom [27]. Sample measurements at the spatial and temporal scale that are made possible with satellite imagery are not possible with in situ observations [28].

Bibliometrics is a useful tool for quantitatively evaluating the present situation and development of scientific production in specific study fields that has been applied in various fields [29–31]. This paper aims to provide a systematic analysis of research on remote sensing of phytoplankton blooms during 1999–2019 via bibliometric technique. This study aims to reveal the limitations of current remote sensing of phytoplankton bloom studies to analyse the climatic variability effect and propose suggestions for the direction of future research.

2. Materials and Methods

2.1. Data Source

The data were retrieved from the Science Citation Index (SCI), the Clarivate Analytics' Web of Science. It is one the most used data source for bibliometric studies [29–31]. The search was restricted to the core collection. The retrieval strategy was TS = (bloom * AND (remote sens * OR satellite *)). TS herein means topic. The used of the asterisk in this search ensures the inclusion of all the possible variants such as bloom, blooms, blooming, remote sensing, remote sensed, remote sensors, satellite, and satellites to avoid missing results. The search was restricted to articles published in English. This search returned 2173 peer-reviewed articles.

Data cleaning was performed removing irrelevant publications through initial screening of the title, abstract, and keywords. Due to the difficulties in identifying the needed information, in some cases, it was necessary to read the methodology section. Finally, we collected 1292 peer-reviewed articles.

2.2. Data Analysis

We read all the literature individually to build a database according to the following criteria for further analysis. The database included the following information: title, publication year, author country, journal, research area, study duration, water type (ocean, coastal, inland), satellite, bloom type (phytoplankton in general or specific such us cyanobacteria, dinoflagellate, diatom, etc., at species level when known), studied variable, algorithm (generic or empiric for a specific area or type of bloom), and citation count (until December 2019). Information on the article country was only selected based on the first author. Also, information was gathered about monitoring programs if the study was done in the context of one. Finally, we searched if climate change was a topic of study of either oceanographic phenomenon dependent on clime.

The following aspects were analysed intensively: (1) core journals, (2) geographic distribution of author country, (3) geographic distribution of studied area, (4) citation counts, (5) satellite use evolution, and (6) study period.

To evaluate academic influence, we calculated a citation index (C.I.) based on citations per publication according to next equation:

$$C.I. = \frac{total\ citations\ in\ December\ 2019}{(2020 - publication\ year)}. \tag{1}$$

C.I. equals to total citations in December 2019 for publication of 2019.

Publications were classified as described in Table 1:

Table 1. Citation index values.

	Citation Index Value
null relevance	0–0.49
low relevance	0.50–0.99
medium relevance	1.00–2.00
high relevance	2.00–4.00
very high relevance	>4.00

3. Results

3.1. Number of Publications (Country)

A total of 1292 peer-reviewed articles on remote sensing of phytoplankton blooms published between January 1999 and December 2019 were collected. Information on the article country was only selected based on the first author.

The number of publications increased since 2004 and reached the maximum value of 128 in 2014 after two years of lower production (Figure 1). The publications originated from 47 countries; the United States (US) had the largest number of publications (total of 373 papers), followed by China (209), the United Kingdom (95), India (73), Canada (57), Japan (57), France (45), South Korea (45), Australia (37), Italy (37), and Spain (37) (Figure 2). The number of papers published from the top 10 countries accounted for 77% of the total publications. We must notice that there are many publications developed during a doctoral or post-doctoral stay of the first author in another country, this is especially important for many Chinese studies that were developed in USA research teams.

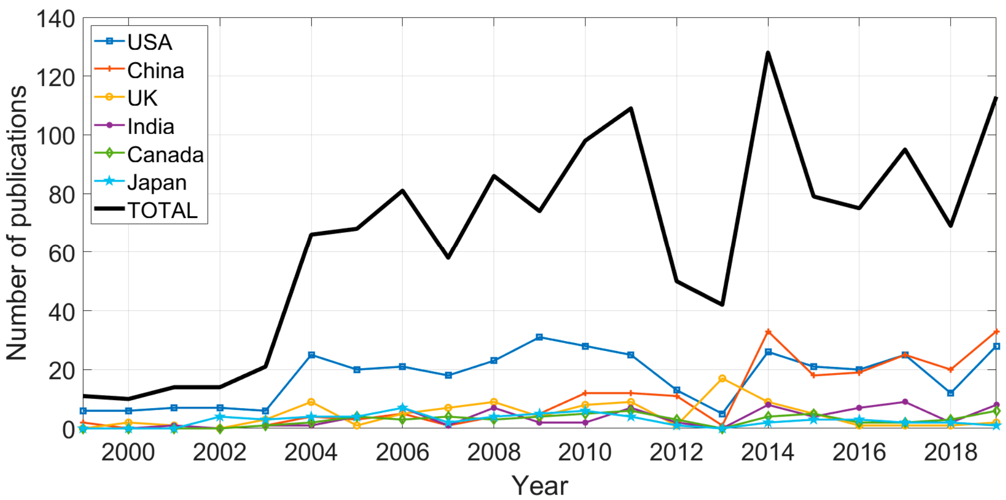

Figure 1. Temporal evolution of peer reviewed articles published according to countries. Information on the article country was only selected based on the first author.

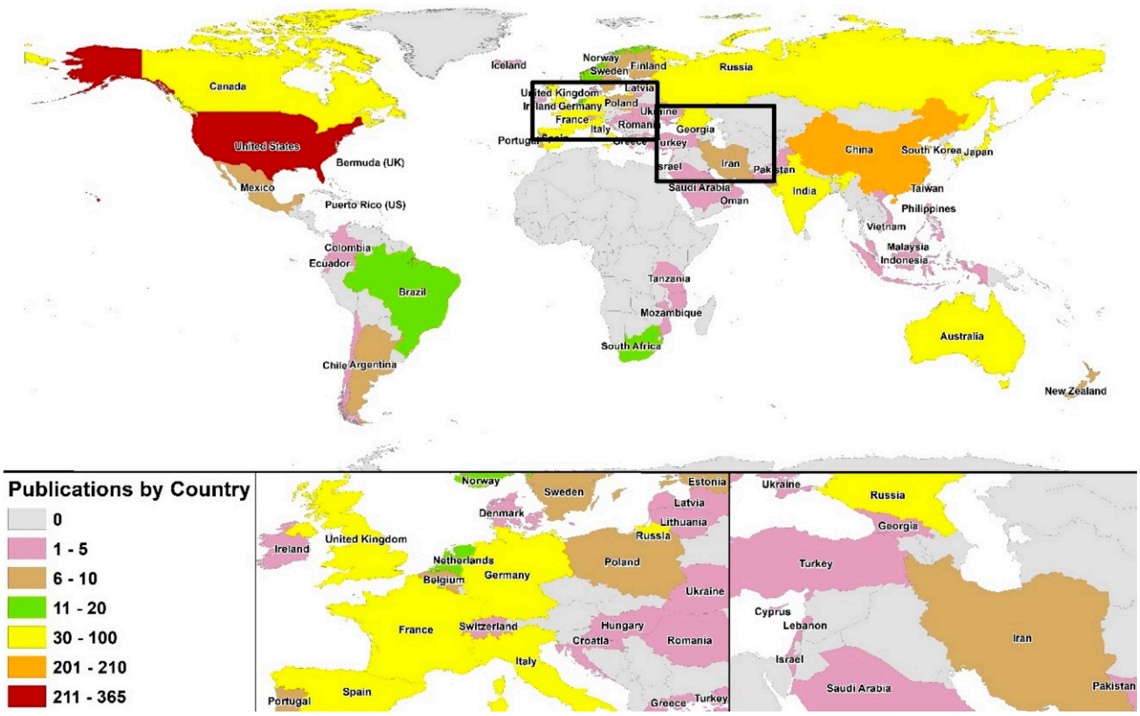

Figure 2. Planisphere with countries number of publications. Information on the article country was only selected based on the first author.

3.2. Number of Publications (Study Area)

The study area for the detection of phytoplankton blooms could be associated with the country for the first author or for the other/s. In Figure 3, the number of publications for each study area is summarised. Only study areas with at least two publications were represented; study areas with only one publication were not represented for map clarity. We used the ecoregions shapefile provided by Spalding et al. [32] to separate coastal and open ocean environments. The Marine Ecoregions of the World (MEOW) is a bioregionalization of coastal and shelf areas, and ecoregions are its smallest-scale units. Spalding et al. [32] suggest that the most appropriate outer boundary for coastal and shelf realms, provinces, and ecoregions is the 200-m isobath, which is a widely used proxy for the shelf. Coastal environments are 60% of the total represented studies, open ocean 25%, and inland environments 14%. So, the most studied along the entire study period are coastal environments.

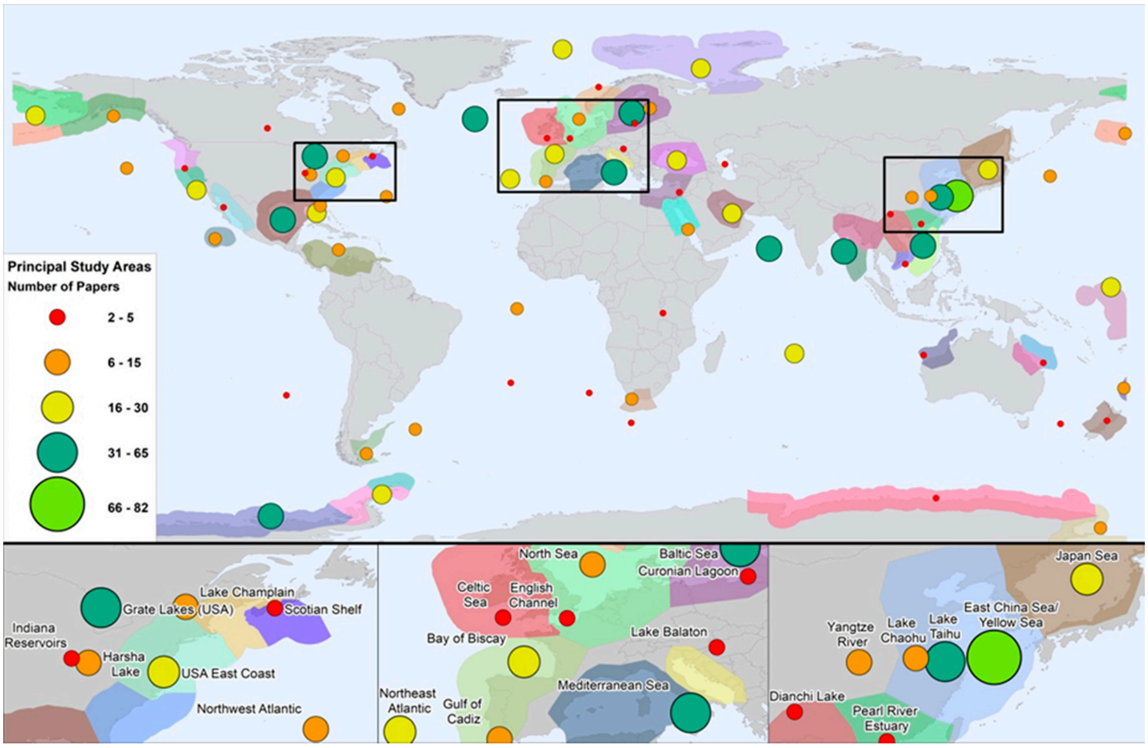

Figure 3. Planisphere with number of publications for each study area. The 200-m isobath of ecoregions is used for separating coastal and open ocean environments according to [32]. The ecoregions legend is presented in a separate figure (Figure 4).

Globally, the areas with the most concentrated studies are the East China sea and the Yellow sea with 82 peer reviewed articles. It was followed by the next 10 areas: Baltic sea (54), Lake Taihu (52), South China sea (48), North Atlantic (47), Great Lakes (42), Arabian sea (41), Mediterranean sea (40), Gulf of Mexico (39), Bay of Bengal (32), and Southern ocean (32).

Most studies focus on three areas, North America, Europe, and East Asia, while other areas have nearly no studies (Africa and South America).

In Figure 5, we classified study areas into marine or inland waters; marine waters included coastal and offshore waters. We observed that marine studies were dominant along the entire study period, but since 2010, there is an increasing trend in inland water studies. Lake Taihu (China) and the Great Lakes (USA) were the most studied inland waters.

Marine Ecoregions Of the World (MEOW)	Papers		
Agulhas Bank	3	Gulf of Maine/Bay of Fundy	13
Aleutian Islands	14	Gulf of Mexico	39
Amundsen/Bellingshausen Sea	32	Gulf of Tonkin	10
Antarctic Peninsula	10	Kermadec Island	12
Arabian (Persian) Gulf	22	Mediterranean Sea	40
Baltic Sea	60	North Sea	10
Black Sea	20	North and East Barents Sea	18
Caribbean Sea	7	Northern California	24
Carolinian	11	Northern and Central Red Sea	6
Celtic Seas	4	Oregon, Washington, Vancouver Coast and Shelf	5
Central New Zealand	3	Patagonian Shelf	14
Central and Southern Great Barrier Reef	3	Revillagigedos	8
Coral Sea	2	Ross Sea	13
Cortezian	4	Scotian Shelf	4
East Antarctic Wilkes Land	4	Sea of Japan/East Sea	28
East China and Yellow Sea	82	South China Sea Oceanic Islands	38
Eastern Bering Sea	17	South European Atlantic Shelf	23
Exmouth to Broome	3	South Shetland Islands	6
Floridian	23	Southern China	5
Gilbert/Ellis Islands	16	Southern Norway	3
Gulf of Alaska	11	Southern Vietnam	3
		Virginian	15

Figure 4. Ecoregions according to [32] and number of published papers in each ecoregion.

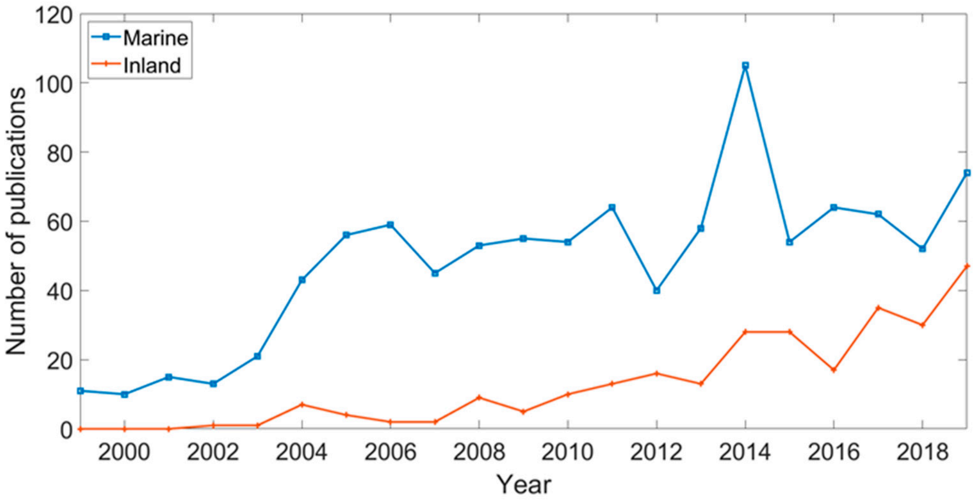

Figure 5. Temporal evolution of number of peer reviewed articles published divided in marine and inland waters. Seven publications were developed in both type of waters and were not included.

3.3. Journal Distribution and Academic Influence

The following tables show the ranking of the top 10 journals that publish peer-reviewed articles on remote sensing of phytoplankton blooms according to the total number of published articles (Table 2) and total citations (Table 3). There is an evident dominance of USA journals regarding publication of this research topic, with 6 journals. The other 4 journals are European (England, Netherlands, Switzerland, and Germany).

Although both tables may look similar, they share only six journals. Four of the journals with the most published articles (Table 2) do not reach a high enough number of total citations to be included in the ranking of the top 10 journals according to total citations (Table 3). These journals are Remote Sensing of Environment, Journal of Marine Systems, and Harmful Algae.

Table 2. Ranking of the top 10 journals according to number of published articles.

Position	Journal	Total Articles (%)	Total Citations (%)	IF 2019	Country
1	Journal of Geophysical Research: Oceans	8.08	13.70	3.559	USA
2	Remote Sensing of Environment	6.87	1.47	9.085	USA
3	International Journal of Remote Sensing	5.50	3.69	2.976	England
4	Deep-Sea Research: Part II	4.53	8.41	2.697	USA
5	Geophysical Research Letters	4.28	7.22	4.497	USA
6	Continental Shelf Research	3.80	4.15	2.424	England
7	Journal of Marine Systems	3.72	3.58	2.528	Netherlands
8	Remote Sensing	3.40	1.34	4.509	Switzerland
9	Harmful Algae	2.83	3.36	3.707	USA
10	Deep-Sea Research: Part I	2.43	3.61	2.606	USA
	Total	45.44	50.53		

Table 3. Ranking of the top 10 journals according to total citations.

Position	Journal	Total Citations (%)	Total Articles (%)	IF 2019	Country
1	Journal of Geophysical Research: Oceans	13.70	8.08	3.559	USA
2	Deep-Sea Research: Part II	8.41	4.53	2.697	USA
3	Geophysical Research Letters	7.22	4.28	4.497	USA
4	Global Biogeochemical Cycles	5.21	1.46	4.608	USA
5	Nature	4.23	0.16	42.778	England
6	Continental Shelf Research	4.15	3.80	2.424	England
7	Marine Ecology Progress Series	3.99	1.70	2.326	Germany
8	Limnology and Oceanography	3.80	1.94	3.778	USA
9	International Journal of Remote Sensing	3.69	5.50	2.976	England
10	Deep-Sea Research: Part I	3.61	2.43	2.606	USA
	Total	58.01	33.88		

The remote sensing of phytoplankton blooms literature originated from 219 journals. The ten journals with the highest number of publications (Table 2) accounted for 45.44% of the total number of papers. Among these, 118 journals had only one publication on this topic each, which accounted for 53.9% of all the journals. Overall, 177 journals had less than five publications, which accounted for 80.8% of all the journals and 22.5% of the total number of papers.

"Journal of Geophysical Research: Oceans" is the journal with more published articles and is the most cited journal with 13.7% of the total citations. "Remote Sensing" is the second journal in number of published articles, but is not among the top ten most cited journals. "Global Biochemical Cycles," which is not one of the top ten publishing journals (only 1.46% of total analysed articles), accounts for 5.21% of total citations and is the fourth most cited journal. This happens similarly with "Nature," which is the fifth most cited journal thanks mainly to only two papers with 1089 and 200 citations, respectively, both published about the Southern Ocean in 2000.

The calculation of the Citation Index showed that 26% of the papers had null or low relevance, meaning a low citation number, while 51% had high or very high relevance. Relevance was similar for marine and inland studies.

3.4. Number of Publications (Sensor)

The number of publications for each satellite must have taken into account the launching and operating dates. Table 4 summarizes the most commonly used sensors, both for historical satellites (no longer working) and for current satellites (still in operation) (more information can be found at https://ioccg.org/resources/missions-instruments/).

Table 4. Summary of historical satellites operating data and current satellites launch data. Adapted from: https://ioccg.org/resources/missions-instruments/.

	Sensor	Agency	Satellite	Operating Data or Launch Data
Historical	CZCS	NASA (USA)	Nimbus-7 (USA)	24/10/78–22/6/86
	MERIS	ESA (Europe)	ENVISAT (Europe)	1/3/02–9/5/12
	OCM	ISRO (India)	IRS-P4 (India)	26/5/99–8/8/10
	OCTS	NASDA (Japan)	ADEOS (Japan)	17/8/96–29/6/97
	SeaWiFS	NASA (USA)	OrbView-2 (USA)	01/08/97–14/02/11
Current	GOCI	KARI/KIOST (South Korea)	COMS	26 June 2010
	MODIS-Aqua	NASA (USA)	Aqua (EOS-PM1)	4 May 2002
	MODIS-Terra	NASA (USA)	Terra (EOS-AM1)	18 Dec 1999
	MSI	ESA (Europe)	Sentinel-2A	23 June 2015
	MSI	ESA (Europe)	Sentinel-2B	7 March 2017
	OCM-2	ISRO (India)	Oceansat-2 (India)	23 Sept 2009
	OLCI	ESA/EUMETSAT	Sentinel 3A	16 Feb 2016
	OLCI	ESA/EUMETSAT	Sentinel 3B	25 April 2018
	VIIRS	NOAA (USA)	Suomi NPP	28 Oct 2011
	VIIRS	NOAA/NASA (USA)	JPSS-1/NOAA-20	18 Nov 2017

The SeaWiFS (Sea-viewing Wide Field-of-view Sensor) operated from 1997 to 2011, and it was the most used sensor in phytoplankton blooms publications from 2000 to 2015 (Figure 6). SeaWiFS was used in 49% of the studies, either as a unique sensor or included in multisensor studies. MODIS (Moderate Resolution Imaging Spectroradiometer) usage analysis encompasses MODIS Aqua and MODIS Terra. MODIS was the second most used satellite from 2005 to 2017, and it was used in 27% of the analysed studies. Other satellites include: OCM (Ocean Colour Monitor) (32 studies), LANDSAT (25 studies), OCTS (Ocean Colour Temperature Scanner) (14 studies), CZCS (Coastal Zone Colour Scanner Experiment) (14 studies), GOCI (Geostationary Ocean Color Imager) (13 studies), and other sensors that were applied in ten or less studies (Figure 6 "other satellites").

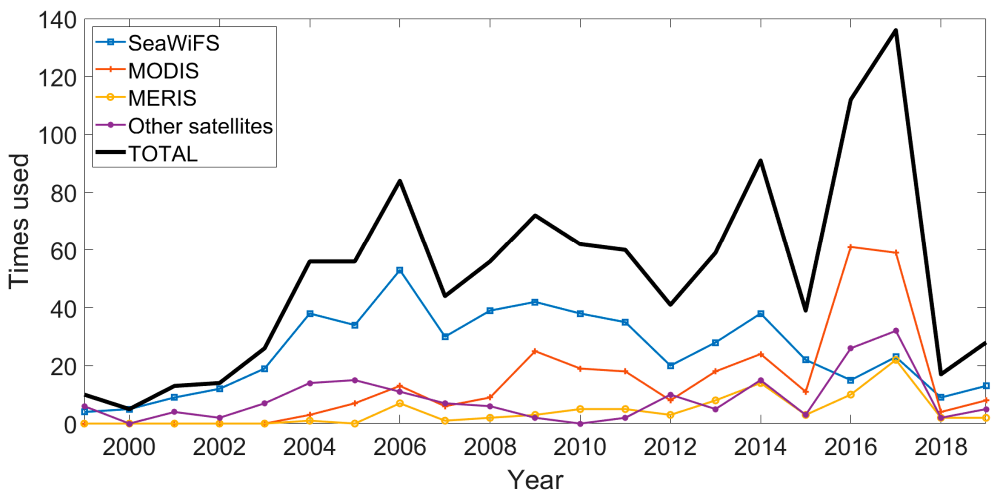

Figure 6. Temporal evolution of peer reviewed articles published according to sensor.

3.5. Study Period

To be able to detect a bloom, it is necessary to determine the baseline condition of any phytoplankton property to detect deviations from the baseline taking into account climatic variability [15]. The baseline can be calculated from a compilation of years of historical data that define an average of past performance, or from a rapid measurement of current production before initiating a change [15]. Keeping that in mind, we analysed the study period of each study, and Table 5 summarizes the results. Most of the analysed publications conducted short time studies, under a year (43%), usually focused on a specific bloom event. Only 1% of publications studied a period longer than 30 years.

Table 5. Duration of study period.

Study Period (Years)	Percentage of Publications (%)
≤1	43
≤5	19
>5	18
≤10	19
>30	1

4. Discussion

Aquatic ecosystems are very dynamic, especially coastal ecosystems, which implies great variability. Phytoplankton is a variable that is subject to changes that can be influenced by anthropogenic or climatic variables. Among climatic phenomenon or variables that can have an effect on phytoplankton abundance and composition, we have found studies of dust storms [33], medicanes [34], typhoon-induced upwellings [35], El Niño [36–38], or Indian Ocean Dipole [39], among others, but the variation scale is different, and it can range from seasonal to decadal [20]. However, most studies analyse point situations or compare two-point situations [40].

According to several indices, the El Niño and La Niña phase of the 1997–1998 ENSO was one of the strongest on record and several studies analysed its influence on phytoplankton blooms [34–36]. However, most studies analysed short time series, such a period of 3 to 4 years (including the year before and the year after) [39,40] or a year of coverage (October 1997 to September 1998) [23].

There is growing interest regarding the impacts of future climate change on blooms, either in marine waters [41,42] or in inland waters [43–46]. However, few studies have assessed decadal trends in variables such as surface temperature that may be altering the growth of blooming species [41,42]. Several studies analysed two decades. Sharma et al. [41] analysed a time series over the 1997–2010 period in the warm oceans (region with average SST > 15 °C that includes tropical and subtropical biomes). Griffith et al. [42] studied satellite-based sea surface temperature records since 1982. Sayers et al. [43] studied the Western Basin of Lake Erie for the 20-year period from 1998 to 2017. Zong et al. [44] studied cyanobacterial blooms from 1990 to 2016 in 30 large lakes and 10 reservoirs. However, publications analysing three decades are only 1% of the articles included in this study and are very scarce. For instance, Ho et al. [45] used three decades of high-resolution Landsat 5 satellite imagery to investigate long-term trends in summertime near-surface phytoplankton blooms for 71 large lakes. These studies and others suggest that warming temperatures have and will support an expansion of some types of blooms. However, other variables must be taken into account from an historical perspective, such as fertilizer use, increased wastewater treatment, etc., which are sources of nutrients that are another important driver of algal blooms. Nevertheless, Ho et al. [45] found that lakes with a decrease in bloom intensity warmed less compared to lakes with an increase in blooms, suggesting that lake warming could counteract management efforts to ameliorate eutrophication. The increasing frequency and severity of blooms in recreational waters (lakes and coastal waters) and water supply reservoirs is a concern to public health and a significant threat to the environment, and bloom monitoring is necessary for early warning and treatment [47,48]. The major concern is with cyanobacteria-dominated HABs [49]. We observed in Figure 5 an increasing trend in inland water studies since 2010. This trend can be due to the increasing awareness on eutrophication problems of these water bodies, but it has been made possible thanks to the recent advancements in high spatio-temporal resolution sensors [47]. The greatest efforts of monitoring programs go to the freshwater resource, that is in inland waters, recognizing freshwater as a first-class ecosystem service [23]. The Medium Resolution Imaging Spectrometer (MERIS) on board the European Space Agency (ESA) ENVISAT platform already provided better capability for monitoring inland water systems from 2002 until 2012 than previous sensors (e.g., MERIS spatial resolution was 300 m and SeaWiFS was 1100 m, and MERIS had 15 spectral bands and SeaWiFS 8 bands) [47]. More recent sensors, such as the OLCI (Ocean and Land Color Instrument) on board the Sentinel-3, have a number of improvements when compared to MERIS, including an increase from 15 to 21 spectral bands, improved signal-to-noise ratio (SNR), global spatial resolution of 300 m at full resolution, and improved coverage [47].

To be able to distinguish between climate variability and changes of anthropogenic origin for a specific variable is necessary to define the baseline. The baseline can be defined as the mean value of the studied variable over which fluctuations can occur within an interval that contains most observed cases [50,51]. Based on this concept we can calculate simple anomalies, simple standardised anomalies, or climatic anomalies [51]. Values above the baseline are described as positive anomalies (increase) and values below as negative anomalies (decrease). In the climatic anomalies, the average value of the variable is replaced by the 12 monthly averages that constitute the climatology of the variable. Both simple anomalies and climatological anomalies are defined locally. Its definition is valid only for the place where the data series used to define it is available. As the time series is longer, the definition of the baseline will be more precise, and the extreme values will be highlighted in a better way. The anomalies methodology has been widely applied for the study of oceanographic processes [52–55]. To apply this methodology, it is essential to establish continuous monitoring programs. However, if monitoring programs measuring a simple variable continuously such as temperature are scarce [51], long-term monitoring programs of phytoplankton are even scarcer.

According to our database results, most of the existing algal blooms studies globally are based on sporadic sampling and short-term research programs. Sporadic sampling is usually done in the context of monitoring programs that only take samples when there is a noticeable change in the sea colour or when dead fish appear, and samples are taken to characterize the event. This has been noticed by Band-Schmidt et al. [56] in Mexico, but our results show that it happens the same around the world. Only a few programs are based on an ongoing monitoring strategy that could allow the building of a good quality baseline if maintained on time (e.g., HELCOM in the Baltic sea WWW.HELCOM.FI/ENVIRONMENT/ALGALBLOOMS.HTML [57]; Coastal Intensive Site Network (CISNet) program around the U.S. marine and Great Lakes coasts [58]; Water Framework Directive monitoring https://ec.europa.eu/environment/water/water-framework/index_en.html).

The scarcity of in situ monitoring programs is worst in non-developed countries, probably due to economic constraints and lack of individual training. In our results (Figure 3), we observe that South America and Africa have nearly no studied areas. Even if remote sensing images are mostly free, in situ remote sensing is expensive and poses a limitation for non-developed countries. It is important to say that remote sensing and in situ sampling are complementary techniques and deriving results only from remote sensing can lead to wrong conclusions.

Finally, to be able to detect algal blooms with remote sensing, some considerations about the bloom's characteristics must be considered: patchy distribution, duration, and depth, because there can be limitations. A patchy distribution of blooms is quite common and sensors with a spatial resolution of 4, 9, and 25 km may not be enough [27]. The duration is quite variable, from days to weeks is the most common, but it can last even months [59]. The frequency of passage of the satellites depends on their orbit (polar or geostationary) and on the latitude of the area to be studied, and may vary between several daily passes and several days between passes (the lower the latitude, the lower the frequency).

This added to the cloudy characteristics of some areas can prevent detection of short duration blooms. This disadvantage can be overcome using a multisensor approach. However, according to our research, the multisensor approach is still the minority [60–62]. It is important to highlight the effort undertaken by the European Space Agency (ESA) that launched its Climate Change Initiative (CCI) in 2010 [63]. This initiative was dedicated to producing climate-quality data for Essential Climate Variables (ECVs), and among them were ocean colour variables [63]. To be able to apply the multisensor approach, data from multiple sensors must be merged to create a single time series, and inter-sensor biases must be corrected to avoid introducing artefacts in the time series [19]. The CCI obtained a time series for the period 1997 to 2018 using data from the MERIS sensor of the European Space Agency, the SeaWiFS and MODIS-Aqua sensors from the National Aeronautics and Space Administration (USA), and VIIRS (Visible and Infrared Imaging Radiometer Suite) from the National Oceanic and Atmospheric Administration (USA) [19]. To achieve this, all radiometric products band-shifted to a common set of bands corresponding to SeaWiFS and corrected for inter-sensor bias [15].

The focus of the CCI is on open-ocean (case-1) waters [19]. Remote sensing reflectance (R_{RS}) is the standard product provided by space agencies. To obtain chlorophyll-*a* (Chl-*a*), which is the most common variable used to track changes in phytoplankton, several algorithms and quasi-analytical methods are applied to R_{RS} [26,64]. However, it has been proven that R_{RS} in the blue-green spectrum is likely to have a stronger and earlier climate-change-driven signal than Chl-*a* [19]. This is because R_{RS} integrates not only changes in-water Chl-*a*, but also in other optically important constituents (e.g., Coloured Dissolved Organic Matter (CDOM) [19]). This is key for optically complex waters (case-2). During events of HABs, water discolouration can be due to CDOM accumulated from decaying cells; then R_{RS} will be more appropriate than Chl-*a* algorithms. According to our results, approximately 70% of the reviewed studies focused on detecting high Chl-*a* levels that can not necessarily be classified as HABs (e.g., do not cause mortality events) and do not report the causative species. The studies that identified at least the causative group or species are in the minority. Among the bloom forming species studied, we can cite the dinoflagellates *Karenia brevis, Karenia mikimotoi*, *Alexandrium fundyense, Cochlodinium polykrikoides, Prorocentrum donghaiense, Prorocentrum minimum, Noctiluca miliaris, Alexandrium minutum, Alexandrium catenella, and Alexandrium taylori*; the diatoms *Pseudo-nitzschia, Rhizosolenia* spp., and *Rhizosolenia imbricata*; the cyanobacteria *Microcystis* spp., *Trichodesmium erythraeum, Trichodesmium* spp. *Synechococcus, Nodularia spumigena, Anabaena circinalis*, and *Aphanizomenon flos-aquae* sp.; and the haptohytes *Emiliania huxleyi, Phaeocystis globose*, and *Phaeocystis pouchetii*. Even if some of these species can be toxin producers, only a few studies analysed the toxin concentration in water samples [65–70]. These studies involved inland waters or coastal waters with shellfish farming [70].

Regarding bloom depth, for a phytoplanktonic bloom to be detected by remote sensors it must be in the first optical depth [71]. Most of the publications read in this research do not specify phytoplankton bloom depth, which we think is important data to mention in the research description.

5. Conclusions

This study aimed to provide a systematic analysis of research on remote sensing of phytoplankton blooms during 1999–2019 via bibliometric technique. We built a database that included 1292 peer-reviewed articles. The number of publications increased since 2004 and originated from 47 countries, clearly dominated by the United States and followed by China. Coastal environments are 60% of total analysed studies, open ocean 25%, and inland environments 14%. Thus, coastal environments are the most studied along the entire study period. SeaWiFS was the most used sensor in phytoplankton blooms publications from 2000 to 2015 (49% of the studies), either as unique sensor or included in multisensor studies. MODIS (including MODIS Aqua and MODIS Terra) was the second most used satellite from 2005 to 2017 (27% of the analysed studies). Ocean colour is recognised as an Essential Climate Variable by the Global Climate Observing System, but most of the analysed publications conducted short time studies, and only 1% of publications studied a period longer than 30 years. It is important to highlight the CCI initiative that obtained a time series for the period 1997 to

2018 using a multisensor approach merging data from MERIS, SeaWiFS, MODIS-Aqua, and VIIRS. This type of approach and a consistent field database for validation are key to elucidate climate change effects on phytoplankton dynamics. The recent advancements in high spatio-temporal resolution sensors allow us to have a better knowledge of small water bodies such as inland waters (e.g., reservoirs) and to identify blooms with the typical patchy distribution. Though the use of Chl-*a* algorithms is very common, we encourage the use of R_{RS}, especially in optically complex waters. According to our results, most of the reviewed studies focused on detecting high Chl-*a* levels, which can not necessarily be classified as HABs and do not report the causative species. Toxin concentration in water is only measured on a few studies and link to the anthropic use of water bodies (e.g., reservoirs for freshwater supply or coastal water with shellfish farming).

Author Contributions: Conceptualization, M.-T.S.-F., J.-A.A.-M. and I.H.-D.; Formal analysis, M.-T.S.-F., J.-A.A.-M., I.H.-D., E.S.-d.-Á., S.M.-M. and J.E.; Investigation, M.-T.S.-F., J.-A.A.-M., I.H.-D., E.S.-d.-Á., S.M.-M. and J.E.; Methodology, M.-T.S.-F., J.-A.A.-M. and I.H.-D.; Software, J.-A.A.-M., I.H.-D. and S.M.-M.; Supervision, M.-T.S.-F.; Validation, E.S.-d.-Á. and J.E.; Visualization, J.-A.A.-M., I.H.-D., E.S.-d.-Á., S.M.-M. and J.E.; Writing—original draft, M.-T.S.-F., J.-A.A.-M. and E.S.-d.-Á.; Writing—review & editing, M.-T.S.-F., E.S.-d.-Á. and J.E. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Welch, H.; Brodie, S.; Jacox, M.; Robinson, D.; Wilson, C.; Bograd, S.; Oliver, M.; Hazen, E. Considerations for transferring an operational dynamic ocean management tool between ocean color products. *Remote. Sens. Environ.* **2020**, *242*, 111753. [CrossRef]
2. El Mahrad, B.; Newton, A.; Icely, J.; Kacimi, I.; Abalansa, S.; Snoussi, M. Contribution of Remote Sensing Technologies to a Holistic Coastal and Marine Environmental Management Framework: A Review. *Remote Sens.* **2020**, *12*, 2313. [CrossRef]
3. Ershadifar, H.; Koochaknejad, E.; Ghazilou, A.; Kor, K.; Negarestan, H.; Baskaleh, G. Response of phytoplankton assemblages to variations in environmental parameters in a subtropical bay (Chabahar Bay, Iran): Harmful algal blooms and coastal hypoxia. *Reg. Stud. Mar. Sci.* **2020**, *39*, 101421. [CrossRef]
4. Hayashida, H.; Matear, R.J.; Strutton, P.G. Background nutrient concentration determines phytoplankton bloom response to marine heatwaves. *Glob. Chang. Biol.* **2020**, *26*, 4800–4811. [CrossRef] [PubMed]
5. Richardson, K. Harmful or Exceptional Phytoplankton Blooms in the Marine Ecosystem. *Adv. Mar. Biol.* **1997**, *31*, 301–385.
6. Gokul, E.A.; Shanmugam, P. An optical system for detecting and describing major algal blooms in coastal and oceanic waters around India. *J. Geophys. Res. Oceans* **2016**, *121*, 4097–4127. [CrossRef]
7. Carstensen, J.; Klais, R.; Cloern, J.E. Phytoplankton blooms in estuarine and coastal waters: Seasonal patterns and key species. *Estuar. Coast. Shelf Sci.* **2015**, *162*, 98–109. [CrossRef]
8. Aguilar-Maldonado, J.A.; Santamaria-Del-Angel, E.; Gonzalez-Silvera, A.; Cervantes, O.; Sebastiá-Frasquet, M.-T. Mapping Satellite Inherent Optical Properties Index in Coastal Waters of the Yucatán Peninsula (Mexico). *Sustainability* **2018**, *10*, 1894. [CrossRef]
9. Kudela, R.M.; Bickel, A.; Carter, M.L.; Howard, M.D.; Rosenfeld, L. The monitoring of harmful algal blooms through ocean observing: The development of the California Harmful Algal Bloom Monitoring and Alert Program. In *Coastal Ocean Observing Systems*; Academic Press: Cambridge, MA, USA, 2015; pp. 58–75.
10. Smayda, T.J. What is a bloom? A commentary. *Limnol. Oceanogr.* **1997**, *42*, 1132–1136. [CrossRef]
11. Hallegraeff, G.M.; Anderson, D.M.; Cembella, A.D. *Manual on Harmful Marine Microalgae: Monographs on Oceanographic Methodology*; UNESCO: Paris, France, 2004; 53p.
12. Hallegraeff, G.M.; Blackbum, S.I.; Bolch, C.J.; Lewis, R.J. (Eds.) Harmful Algal Blooms 2000. In Proceedings of the Ninth International Conference on Harmful Algal Blooms, Hobart, Australia, 7–11 February 2000.
13. Anderson, D.M. Red tides. *Sci. Am.* **1994**, *271*, 52–58. [CrossRef] [PubMed]
14. Anderson, D.M. *The Ecology and Oceanography of Harmful Algal Blooms Multidisciplinary Approaches to Research and Management*; IOC Technical Series 74; UNESCO: Paris, France, 2007.

15. Aguilar-Maldonado, J.A.; Santamaria-Del-Angel, E.; Gonzalez-Silvera, A.; Cervantes, O.; López, L.M.; Gutiérrez-Magness, A.; Cerdeira-Estrada, S.; Sebastiá-Frasquet, M.-T. Identification of Phytoplankton Blooms under the Index of Inherent Optical Properties (IOP Index) in Optically Complex Waters. *Water* **2018**, *10*, 129. [CrossRef]
16. Paerl, H.W.; Paul, V.J. Climate change: Links to global expansion of harmful cyanobacteria. *Water Res.* **2012**, *46*, 1349–1363. [CrossRef]
17. Liu, X.; Xiao, W.; Landry, M.R.; Chiang, K.-P.; Wang, L.; Huang, B. Responses of Phytoplankton Communities to Environmental Variability in the East China Sea. *Ecosystems* **2016**, *19*, 832–849. [CrossRef]
18. GCOS. Systematic Observation Requirements from Satellite-Based Data Products for Climate 2011 Update. In *Supplemental Details to the Satellite-Based Component of the "Implementation Plan for the Global Observing System for Climate in Support of the UNFCCC"*; Technical Report, No. 154; World Meteorological Organisation (WMO): Geneva, Switzerland, 2011.
19. Sathyendranath, S.; Brewin, R.J.; Brockmann, C.; Brotas, V.; Calton, B.; Chuprin, A.; Cipollini, P.; Couto, A.B.; Dingle, J.; Doerffer, R.; et al. An Ocean-Colour Time Series for Use in Climate Studies: The Experience of the Ocean-Colour Climate Change Initiative (OC-CCI). *Sensors* **2019**, *19*, 4285. [CrossRef]
20. Santamaría-del-Angel, E.; Sebastia-Frasquet, M.T.; Millán-Nuñez, R.; González-Silvera, A.; Cajal-Medrano, R. Anthropocentric bias in management policies. Are we efficiently monitoring our ecosystem. In *Coastal Ecosystems: Experiences and Recommendations for Environmental Monitoring Programs*; Sebastiá-Frasquet, M.T., Ed.; Nova Science Publishers: New York, NY, USA, 2015; Chapter 1; pp. 1–12. ISBN 978-1-63482-189-6i.
21. Aguilar-Maldonado, J.A.; Santamaria-Del-Angel, E.; Gonzalez-Silvera, A.; Sebastiá-Frasquet, M.-T. Detection of Phytoplankton Temporal Anomalies Based on Satellite Inherent Optical Properties: A Tool for Monitoring Phytoplankton Blooms. *Sensors* **2019**, *19*, 3339. [CrossRef] [PubMed]
22. Blondeau-Patissier, D.; Gower, J.F.; Dekker, A.G.; Phinn, S.; Brando, V.E. A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans. *Prog. Oceanogr.* **2014**, *123*, 123–144. [CrossRef]
23. IOCCG. *Earth Observations in Support of Global Water Quality Monitoring*; Greb, S., Dekker, A., Binding, C., Eds.; IOCCG Report Series, No. 17; International Ocean Colour Coordinating Group: Dartmouth, NS, Canada, 2018.
24. IOCCG. *Synergy between Ocean Colour and Biogeochemical/Ecosystem Models*; Dutkiewicz, S., Ed.; IOCCG Report Series, No. 19; International Ocean Colour Coordinating Group: Dartmouth, NS, Canada, 2020.
25. Von Schuckmann, K.; Le Traon, P.-Y.; Alvarez-Fanjul, E.; Axell, L.; Balmaseda, M.; Breivik, L.-A.; Brewin, R.J.W.; Bricaud, C.; Drevillon, M.; Drillet, Y.; et al. The Copernicus Marine Environment Monitoring Service Ocean State Report. *J. Oper. Oceanogr.* **2016**, *9*, s235–s320. [CrossRef]
26. Dutkiewicz, S.; Hickman, A.E.; Jahn, O.; Henson, S.; Beaulieu, C.; Monier, E. Ocean colour signature of climate change. *Nat. Commun.* **2019**, *10*, 1–13. [CrossRef] [PubMed]
27. Santamaría-del-Angel, E.; Soto, I.; Millán-Nuñez, R.; González-Silvera, A.; Wolny, J.; Cerdeira-Estrada, S.; Cajal-Medrano, R.; Muller-Karger, F.; Cannizzaro, J.; Padilla-Rosas, Y.X.S.; et al. Phytoplankton Blooms: New Initiative Using Marine Optics as a Basis for Monitoring Programs. In *Coastal Ecosystems: Experiences and Recommendations for Environmental Monitoring Programs*; Sebastiá-Frasquet, M.T., Ed.; Nova Science Publishers: New York, NY, USA, 2015; Chapter 4; pp. 57–88. ISBN 978-1-63482-189-6i.
28. IOCCG. *Uncertainties in Ocean Colour Remote Sensing*; Mélin, F., Ed.; IOCCG Report Series, No. 18; International Ocean Colour Coordinating Group: Dartmouth, NS, Canada, 2019.
29. Xu, X.; Chen, M.; Yang, G.; Jiang, B.; Zhang, J. Wetland ecosystem services research: A critical review. *Glob. Ecol. Conserv.* **2020**, *22*, e01027. [CrossRef]
30. Ma, Q.; Zhang, Y. Global Research Trends and Hotspots on Submarine Groundwater Discharge (SGD): A Bibliometric Analysis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 830. [CrossRef]
31. Díez-Herrero, A.; Garrote, J. Flood Risk Analysis and Assessment, Applications and Uncertainties: A Bibliometric Review. *Water* **2020**, *12*, 2050. [CrossRef]
32. Spalding, M.D.; Fox, H.E.; Allen, G.R.; Davidson, N.; Ferdaña, Z.A.; Finlayson, M.; Halpern, B.S.; Jorge, M.A.; Lombana, A.; Lourie, S.A.; et al. Marine Ecoregions of the World: A Bioregionalization of Coastal and Shelf Areas. *Bioscience* **2007**, *57*, 573–583. [CrossRef]
33. Bali, K.; Mishra, A.K.; Singh, S.; Chandra, S.; Lehahn, Y. Impact of dust storm on phytoplankton bloom over the Arabian Sea: A case study during March 2012. *Environ. Sci. Pollut. Res.* **2019**, *26*, 11940–11950. [CrossRef]

34. Kotta, D.; Kitsiou, D. Medicanes Triggering Chlorophyll Increase. *J. Mar. Sci. Eng.* **2019**, *7*, 75. [CrossRef]
35. Aoki, K.; Kuroda, H.; Setou, T.; Okazaki, M.; Yamatogi, T.; Hirae, S.; Ishida, N.; Yoshida, K.; Mitoya, Y. Exceptional red-tide of fish-killing dinoflagellate Karenia mikimotoi promoted by typhoon-induced upwelling. *Estuar. Coast. Shelf Sci.* **2019**, *219*, 14–23. [CrossRef]
36. Murtugudde, R.G.; Signorini, S.R.; Christian, J.R.; Busalacchi, A.J.; McClain, C.R.; Picaut, J. Ocean color variability of the tropical Indo-Pacific basin observed by SeaWiFS during 1997–1998. *J. Geophys. Res. Oceans* **1999**, *104*, 18351–18366. [CrossRef]
37. Kahru, M.; Mitchell, B.G. Influence of the 1997–1998 El Niño on the surface chlorophyll in the California Current. *Geophys. Res. Lett.* **2000**, *27*, 2937–2940. [CrossRef]
38. Yoder, J.; Kennelly, M.A. Seasonal and ENSO variability in global ocean phytoplankton chlorophyll derived from 4 years of SeaWiFS measurements. *Glob. Biogeochem. Cycles* **2003**, *17*, 17. [CrossRef]
39. Setiawan, R.Y.; Wirasatriya, A.; Hernawan, U.; Leung, S.; Iskandar, I. Spatio-temporal variability of surface chlorophyll-a in the Halmahera Sea and its relation to ENSO and the Indian Ocean Dipole. *Int. J. Remote Sens.* **2019**, *41*, 284–299. [CrossRef]
40. Chiswell, S.M.; Safi, A.K.; Sander, S.G.; Strzepek, R.; Ellwood, M.J.; Milne, A.; Boyd, P.W. Exploring mechanisms for spring bloom evolution: Contrasting 2008 and 2012 blooms in the southwest Pacific Ocean. *J. Plankton Res.* **2018**, *41*, 329–348. [CrossRef]
41. Sharma, P.; Marinov, I.; Cabré, A.; Kostadinov, T.; Singh, A. Increasing Biomass in the Warm Oceans: Unexpected New Insights from SeaWiFS. *Geophys. Res. Lett.* **2019**, *46*, 3900–3910. [CrossRef]
42. Griffith, A.W.; Doherty, O.M.; Gobler, C.J. Ocean warming along temperate western boundaries of the Northern Hemisphere promotes an expansion of *Cochlodinium polykrikoides* blooms. *Proc. R. Soc. B* **2019**, *286*, 0340. [CrossRef]
43. Hansen, C.H.; Burian, S.J.; Dennison, P.E.; Williams, G.P. Evaluating historical trends and influences of meteorological and seasonal climate conditions on lake chlorophyll a using remote sensing. *Lake Reserv. Manag.* **2019**, *36*, 45–63. [CrossRef]
44. Zong, J.-M.; Wang, X.-X.; Zhong, Q.-Y.; Xiao, X.; Xiao, X.; Zhao, B. Increasing Outbreak of Cyanobacterial Blooms in Large Lakes and Reservoirs under Pressures from Climate Change and Anthropogenic Interferences in the Middle–Lower Yangtze River Basin. *Remote Sens.* **2019**, *11*, 1754. [CrossRef]
45. Ho, J.C.; Michalak, A.M.; Pahlevan, N. Widespread global increase in intense lake phytoplankton blooms since the 1980s. *Nat. Cell Biol.* **2019**, *574*, 667–670. [CrossRef]
46. Sayers, M.J.; Grimm, A.G.; Shuchman, R.A.; Bosse, K.R.; Fahnenstiel, G.L.; Ruberg, S.A.; Leshkevich, G.A. Satellite monitoring of harmful algal blooms in the Western Basin of Lake Erie: A 20-year time-series. *J. Great Lakes Res.* **2019**, *45*, 508–521. [CrossRef]
47. Kravitz, J.; Matthews, M.; Bernard, S.; Griffith, D. Application of Sentinel 3 OLCI for chl-a retrieval over small inland water targets: Successes and challenges. *Remote Sens. Environ.* **2020**, *237*, 111562. [CrossRef]
48. Nguyen, H.-Q.; Ha, N.-T.; Pham, T.-L. Inland harmful cyanobacterial bloom prediction in the eutrophic Tri An Reservoir using satellite band ratio and machine learning approaches. *Environ. Sci. Pollut. Res.* **2020**, *27*, 9135–9151. [CrossRef]
49. Binding, C.; Greenberg, T.; McCullough, G.; Watson, S.; Page, E. An analysis of satellite-derived chlorophyll and algal bloom indices on Lake Winnipeg. *J. Great Lakes Res.* **2018**, *44*, 436–446. [CrossRef]
50. Jiang, W.; Li, J.; Wang, Z. Determination of global mean sea surface WHU2000 using multi-satellite altimetric data. *Chin. Sci. Bull.* **2002**, *47*, 1664–1668. [CrossRef]
51. Santamaría-del-Ángel, E.; Sebastia-Frasquet, M.T.; González-Silvera, A.; Aguilar-Maldonado, J.; Mercado-Santana, A.; Herrera-Carmona, J.C. Uso Potential Use of Standardized Anomalies in the Interpretation of Global Oceanographic Phenomena at Local Scales. In *Tópicos de Agenda para la Sostenibilidad de Costas y Mares Mexicanos*; Rivera-Arriaga, E., Sánchez-Gil, Y.P., Gutiérrez, J., Eds.; Universidad Autónoma de Campeche: Campeche, Mexico, 2019; pp. 193–212.
52. Bost, C.-A.; Cotté, C.; Terray, P.; Barbraud, C.; Bon, C.; Delord, K.; Gimenez, O.; Handrich, Y.; Naito, Y.; Guinet, C.; et al. Large-scale climatic anomalies affect marine predator foraging behaviour and demography. *Nat. Commun.* **2015**, *6*, 8220. [CrossRef]
53. Cavole, L.; Oceanography, S.I.O.; Demko, A.; Diner, R.; Giddings, A.; Koester, I.; Pagniello, C.; Paulsen, M.-L.; Ramirez-Valdez, A.; Schwenck, S.; et al. Biological Impacts of the 2013–2015 Warm-Water Anomaly in the Northeast Pacific: Winners, Losers, and the Future. *Oceanography* **2016**, *29*, 273–285. [CrossRef]

54. Findell, K.L.; Delworth, T.L. Impact of Common Sea Surface Temperature Anomalies on Global Drought and Pluvial Frequency. *J. Clim.* **2010**, *23*, 485–503. [CrossRef]
55. Mkrtchyan, F.A.; Varotsos, C.A. A New Monitoring System for the Surface Marine Anomalies. *Water Air Soil Pollut.* **2018**, *229*, 273. [CrossRef]
56. Band-Schmidt, C.J.; Bustillos-Guzmán, J.J.; López-Cortés, D.J.; Núñez-Vázquez, E.; Hernández-Sandoval, F.E. The current status of the study of harmful algal blooms in Mexico. *Hidrobiológica* **2011**, *21*, 381–413.
57. Kutser, T. Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing. *Limnol. Oceanogr.* **2004**, *49*, 2179–2189. [CrossRef]
58. Summers, K.; Robertson, A.; Levinson, B. Development of the Coastal Intensive Site Network (CISNET). *Environ. Monit. Assess.* **2000**, *64*, 379–390. [CrossRef]
59. Lewitus, A.J.; Horner, R.A.; Caron, D.A.; Mendoza, E.G.; Hickey, B.M.; Hunter, M.; Huppert, D.D.; Kudela, R.M.; Langlois, G.W.; Largier, J.L.; et al. Harmful algal blooms along the North American west coast region: History, trends, causes, and impacts. *Harmful Algae* **2012**, *19*, 133–159. [CrossRef]
60. Carranza, M.M.; Gille, S.T.; Piola, A.R.; Charo, M.; Romero, S.I. Wind modulation of upwelling at the shelf-break front off Patagonia: Observational evidence. *J. Geophys. Res. Oceans* **2017**, *122*, 2401–2421. [CrossRef]
61. He, Q.; Zhan, H.; Shuai, Y.; Cai, S.; Li, Q.P.; Huang, G.; Li, J. Phytoplankton bloom triggered by an anticyclonic eddy: The combined effect of eddy-Ekman pumping and winter mixing. *J. Geophys. Res. Oceans* **2017**, *122*, 4886–4901. [CrossRef]
62. Huang, L.; Zhao, H.; Pan, J.; Devlin, A. Remote sensing observations of phytoplankton increases triggered by successive typhoons. *Front. Earth Sci.* **2016**, *11*, 601–608. [CrossRef]
63. Plummer, S.; LeComte, P.; Doherty, M. The ESA Climate Change Initiative (CCI): A European contribution to the generation of the Global Climate Observing System. *Remote Sens. Environ.* **2017**, *203*, 2–8. [CrossRef]
64. Maritorena, S.; Siegel, D.A.; Peterson, A. Optimization of a semi-analytical ocean color model for global scale applications. *Appl. Opt.* **2002**, *41*, 2705–2714. [CrossRef]
65. Zhang, F.; Hu, C.; Shum, C.K.; Liang, S.; Lee, J. Satellite Remote Sensing of Drinking Water Intakes in Lake Erie for Cyanobacteria Population Using Two MODIS-Based Indicators as a Potential Tool for Toxin Tracking. *Front. Mar. Sci.* **2017**, *4*, 124. [CrossRef]
66. Gorham, T.; Jia, Y.; Shum, C.; Lee, J. Ten-year survey of cyanobacterial blooms in Ohio's waterbodies using satellite remote sensing. *Harmful Algae* **2017**, *66*, 13–19. [CrossRef] [PubMed]
67. Pitcher, G.C.; Foord, C.J.; Macey, B.M.; Mansfield, L.; Mouton, A.; Smith, M.E.; Osmond, S.J.; Van Der Molen, L. Devastating farmed abalone mortalities attributed to yessotoxin-producing dinoflagellates. *Harmful Algae* **2019**, *81*, 30–41. [CrossRef]
68. Chaffin, J.D.; Mishra, S.; Kane, D.D.; Bade, D.L.; Stanislawczyk, K.; Slodysko, K.N.; Jones, K.W.; Parker, E.M.; Fox, E.L. Cyanobacterial blooms in the central basin of Lake Erie: Potentials for cyanotoxins and environmental drivers. *J. Great Lakes Res.* **2019**, *45*, 277–289. [CrossRef]
69. Esposito, G.; Teta, R.; Marrone, R.; De Sterlich, C.; Casazza, M.; Anastasio, A.; Lega, M.; Costantino, V. A Fast Detection Strategy for Cyanobacterial blooms and associated cyanotoxins (FDSCC) reveals the occurrence of lyngbyatoxin a in campania (South Italy). *Chemosphere* **2019**, *225*, 342–351. [CrossRef]
70. Torres Palenzuela, J.M.; González Vilas, L.; Bellas, F.M.; Garet, E.; González-Fernández, Á.; Spyrakos, E. *Pseudo-nitzschia* Blooms in a Coastal Upwelling System: Remote Sensing Detection, Toxicity and Environmental Variables. *Water* **2019**, *11*, 1954. [CrossRef]
71. Castillo-Ramírez, A.; Santamaría-Del-Ángel, E.; González-Silvera, A.; Frouin, R.; Sebastiá-Frasquet, M.-T.; Tan, J.; Lopez-Calderon, J.; Sánchez-Velasco, L.; Enríquez-Paredes, L. A New Algorithm to Estimate Diffuse Attenuation Coefficient from Secchi Disk Depth. *J. Mar. Sci. Eng.* **2020**, *8*, 558. [CrossRef]

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.