Journal of Scientometric Research, 2026; 15(1):294-309.
https://www.jscires.org

Research Article

Scientometric Trends in Harmful Algal Bloom Prediction: Integrating Optical Remote Sensing and Mathematical Models (2000-2024)

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ABSTRACT

Harmful Algal Blooms (HABs) pose a significant threat to the environment, economy, and public health, producing toxins, reducing biodiversity, causing decomposition, and, in some cases, generating vector-borne diseases. The early detection of HABs using predictive models remains a challenge. This study fills a gap in the literature by performing a scientometric analysis of 155 unique scientific articles published between 2000 and 2024, focusing on the prediction of HABs using mathematical models in conjunction with optical detection methods. The articles were obtained from Scopus and Web of Science and unified using a semi-automated process that included text mining and DOI-based web scraping with CrossRef API. The search strategy was structured into three thematic axes: Harmful Algal Blooms (HABs), mathematical modelling, and optical detection methods. Using tools such as Bibliometrix and ScientoPy, the analysis revealed a 29.20% increase in publications between 2018 and 2023, indicating growing scientific interest. The United States led research productivity (36.69%) and citations (51.1%). Three main research trends were identified: authorship patterns, national-level contributions, and emerging issues in the field. These results underscore the increasing integration of remote sensing and predictive modelling in HAB monitoring, highlighting areas for future research.

Keywords: Harmful Algal Blooms (HABs), Mathematical modelling, Optical satellite detection, Remote sensing, Scientometric analysis.

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Received: 16-01-2026;
Revised: 02-03-2026;
Accepted: 21-04-2026.

INTRODUCTION

The prediction of Harmful Algal Blooms (HABs) has become increasingly relevant in environmental research because of their ecological and social impact. In this context, scientometric analysis allows us to identify patterns of scientific production, influential authors, and knowledge gaps in these interrelated fields. This study sought to map and characterize the evolution of scientific production on Harmful Algal Blooms (HABs) from an integrated perspective, using prediction models based on optical variables, many of which are derived from satellite remote sensing platforms. By structuring the analysis into three thematic areas: Harmful Algal Blooms (HABs), optical sensing, and predictive modelling, we fill the gap in scientometric reviews that focus on the convergence of these domains.

Harmful Algal Blooms (HABs) arise from nutrient pollution in marine and freshwater ecosystems and significantly affect aquatic life and human health. These blooms produce toxins that are harmful to aquatic organisms, including fish, shellfish, and marine mammals. In addition, the breakdown of these blooms depletes oxygen levels in the water, leading to eutrophication. This drives the need for effective monitoring and predictive tools. Owing to these serious consequences, regulatory bodies, such as the U.S. Environmental Protection Agency, have implemented guidelines to monitor and control algal blooms (Stroski *et al*., 2024). In response to these challenges, various monitoring techniques and predictive models have been developed to address these issues. Satellite remote sensing has become an essential tool because of its ability to track the spatial and temporal distribution of harmful algal blooms (Gupta *et al*., 2023). Consequently, numerous strategies have been proposed in recent years to improve the accuracy and efficiency of bloom monitoring and

DOI: 10.5530/jscires.20260590

prediction techniques to mitigate environmental impacts and protect public health.

Mathematical modelling is a crucial method for forecasting Harmful Algal Blooms (HABs) and has been extensively explored in recent years (Yussof *et al.*, 2022). The methodologies used for predictive modelling of HABs include statistical analysis, Machine Learning (ML), and dynamic modelling. For example, statistical techniques can efficiently process environmental data to generate early warnings (Yan *et al.*, 2024), and machine learning applications have shown that variables such as precipitation, water temperature, and salinity significantly influence the growth of harmful algal blooms (Jang *et al.*, 2024). Consequently, there has been an increase in publications on these techniques, complicating the identification of recent contributions to the field. Therefore, a comprehensive review that articulates the evolution of HABs and the modelling techniques used for their prediction is warranted. Unlike traditional reviews, scientometrics adopts a quantitative approach that provides an objective perspective on the scientific dynamics and future directions of this field.

To our knowledge, there are several reviews of the literature on Harmful Algal Blooms (HABs) and predictive models; however, there is a notable absence of quantitative approaches in these reviews. Many existing reviews have adopted a qualitative approach, manually selecting articles to build theoretical frameworks for identifying variables influencing the proliferation of harmful algal blooms or for developing mitigation strategies (Shimasaki *et al.*, 2021; Summers and Ryder, 2023; Yan, Kamanmalek *et al.*, 2024). In addition, these reviews often focus on specific elements or areas (Fernandes-Salvador *et al.*, 2021). We found only one article that performed a quantitative analysis (meta-analysis) and focused only on remote sensing (Khan *et al.*, 2021). Therefore, this study is the first scientometric study to focus on the integration of HABs with prediction-oriented mathematical modelling.

Methodologically, this study performed a scientometric analysis, which is a valuable approach for mapping and identifying knowledge gaps in specific fields. A search equation was simultaneously structured and applied to the Web of Science and Scopus databases, highlighting one of the unique values of this study. Scientometric analyses are typically limited to a single database because of the challenges associated with integrating multiple data sources into the existing software systems. We identified 155 papers in both databases, which allowed us to examine the temporal evolution, production by country, key authors, and most influential journals. In addition, this analysis was complemented by examining thematic trends using the Tree of Science (ToS) algorithm, which has been successfully implemented in previous reviews in various fields (Botero *et al.*, 2023; Grisales *et al.*, 2023; Vivares *et al.*, 2022).

The present study focuses on publications at the intersection of harmful algal bloom prediction, mathematical modelling, and optical detection methods. This scope was defined to examine the evolution of a specific interdisciplinary niche within the broader HAB literature.

The results made it possible to identify three stages in the evolution of scientific production: establishment, dynamic growth, and accelerated growth, each characterized by specific patterns, which are discussed in detail in the following subsections. At the national level, the United States leads in both the volume of publications and their reception within the scientific community (citations) and in the participation of its researchers in collaborative efforts with scientists from other countries. The application of the Tree of Science (ToS) algorithm made it possible to identify three thematic trends that articulate recent advances and perspectives in the research field. These findings underscore the value and novelty of this study, which is discussed in detail throughout the paper. The second section presents the methodology applied; the third, the results obtained through the analysis of trends and thematic content; and the fourth presents the main conclusions, together with the bibliographic references.

METHODOLOGY

Datasets retrieval and analysis

Scientometric analysis is crucial for constructing maps and identifying knowledge gaps in a specific field (Aguirre and Paredes Cuervo, 2023). This study aims to provide a scientometric description of the scientific literature on HABs concerning prediction using mathematical modelling through optical variables. The search strategy was structured around three thematic areas (Table 1): HAB-related terminology, modelling and forecasting terminology, and optical detection terminology. This design was intended to prioritize specificity toward the intersection of HAB prediction, modelling, and optical detection rather than exhaustive coverage of the broader HAB domain. Various date ranges are applicable for this type of analysis (Sun *et al.*, 2024); however, the period from 2000 to the present was selected to better understand the scientific output, as the scientific surge was enabled by Internet access (Yu *et al.*, 2024). The total result, after merging data from the Web of Science (WoS) and Scopus, was 155 unique articles across both databases, which constituted the final corpus for the scientometric analysis.

Data preparation

Scopus and Web of Science (WoS) export bibliographic records in different formats; therefore, record integration required a semi-automated harmonization process (Xu *et al.*, 2024). Bibliographic fields were standardized across databases to facilitate comparison among titles, authors, sources, publication years, and DOI metadata. Duplicate detection was conducted primarily through DOI matching whenever DOI information was available. In records with missing or inconsistent DOI metadata, comparison relied on title, source, and publication year. Text mining was applied to Scopus references to extract bibliographic elements, whereas DOI information from WoS supported complementary lookup through the CrossRef API. Tools such as Bibliometrix and ScientoPy support this type of scientometric data processing (Derviş, 2020; Ruiz-Rosero *et al.*, 2019). This workflow yielded a final corpus of 155 unique records and supported the preparation of the Excel file used to generate tables and figures (Figure 1). Similar semi-automated integration strategies have been implemented in previous scientometric studies (Ariza-Colpas *et al.*, 2024; Botero *et al.*, 2023; Robledo *et al.*, 2023). The resulting dataset was used as the analytical corpus for the scientometric procedures described below.

Analysis methods

The analysis was divided into two sections: the first section provides a general mapping, while the second offers a closer examination of the most significant theoretical contributions within the thematic sub-areas.

Scientific Production

The analysis of scientific production adopts a methodology that transitions from a broad to a specific focus. It begins with a general analysis of scientific output from 2000 to 2023 using indicators such as the total citations received per year and overall production from the two databases. This is followed by a country-level analysis examining three variables: productivity, impact, and quality, and a network analysis of international collaborations based on author affiliations. Subsequent analyses targeted the journals in which the thematic articles were published. Initially, a table featuring the top ten journals by output was generated, followed by a citation network to identify the themes of the three most significant journal groups. The final stage involved an analysis of the most productive authors and their scientific collaboration. The personal networks of each author were merged to map the academic and social structures in this field. Such analyses provide deeper insights into the dynamics of scientific collaboration among authors (Hurtado-Marín *et al.*, 2021; Robledo *et al.*, 2023). Generally, the process described above offers a comprehensive understanding of the dynamics within a field of knowledge, enabling new researchers to quickly gain a broad overview of the field (Azizan, 2024; Rezazadegan *et al.*, 2024).

Tree of Science

The ToS algorithm categorizes academic documents into roots, trunks, and branches within citation networks (Robledo *et al.*, 2022; Valencia-Hernandez *et al.*, 2020; Zuluaga *et al.*, 2022). This classification system swiftly identifies theoretical contributions and elucidates their connections to the literature. ToS has been applied in various fields, including tourism (Ariza-Colpas *et al.*, 2023), engineering (Urina-Triana *et al.*, 2024), environmental studies (Aguirre and Paredes Cuervo, 2023), and business management (Duque *et al.*, 2023). A detailed discussion of the initial adoption process by researchers is provided by Duque *et al.* (2023). In this study, Tree of Science was used as a complementary citation-based interpretive tool to organize foundational, structural, and emerging contributions within the selected corpus. Because its outputs depend on citation structure, the method is best understood as a complementary approach to thematic interpretation rather than as a substitute for other science-mapping techniques.

RESULTS

Scientometric Analysis

Scientific production

Periodic reviews of scientific research on specific topics are essential because they document the key developments in the field. Figure 2 provides a detailed analysis of the annual scientific output of harmful algal blooms from 2000 to 2023. The analysis indicated an annual growth rate of 13.39% and continuous evolution over the years, with a notable increase in the last two periods. A slight predominance in publication volume is evident in the Web of Science (WoS) (yellow bars) (104 publications) compared to 89 publications recorded in Scopus (green bars). The examination of scientific production delineates three main phases: establishment, dynamic growth, and accelerated growth, which are described in detail in the following sections.

During the establishment period (2000-2007), an annual growth rate of 0.00% was recorded. Although there were no scientific publications in Web of Science (WoS) on algal blooms in the early years, both databases recorded the same number of publications during this period. Notably, a peak in the total number of citations occurred in 2003, largely attributed to the influential work 'Harmful algal blooms: causes, impacts, and detection' by Sellner *et al.* (2003). This review article contributes significantly to the understanding and visibility of the field by reviewing the causes, impacts, and detection methods of HABs. The causes include eutrophication, climate change, and pollution, which cause the death of fish and other aquatic organisms, contamination of shellfish, deterioration of water quality, and affect the economy. Among the detection methods, they emphasized satellite monitoring, water sampling and biosensors.

During the dynamic growth period (2008-2017), a significant increase in article production was observed across both databases, with an annual growth rate of 19.58%. This surge intensified in 2011 and 2015, with 2015 marking a second significant peak in the total number of citations. A large portion of these citations can be attributed to the research conducted by Wells *et al.* (2015), which focused on the impact of climate change on HABs in oceans. This study underscores the importance of predictive models in anticipating these changes and discusses the dual role

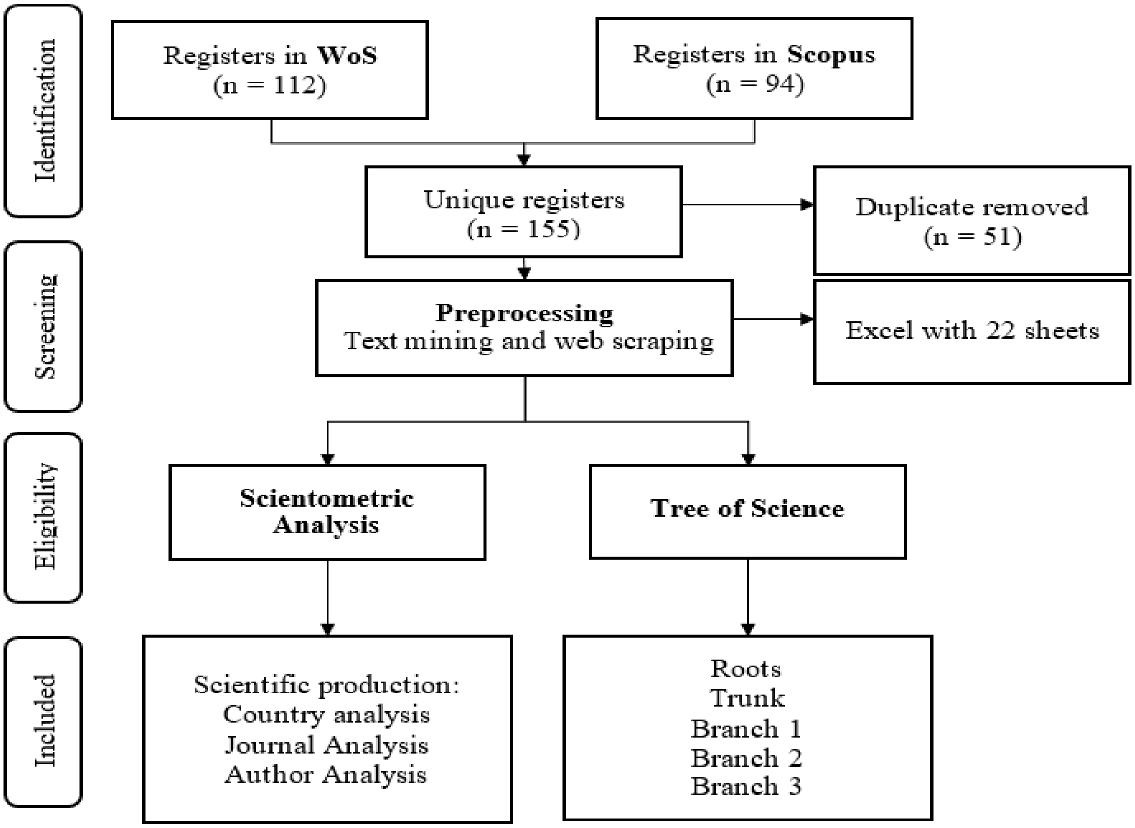

Figure 1: Flowchart of Methodology for Literature Review and Analysis on Harmful Algal Bloom Research.

of stratification in intensifying or restricting HABs. This upward trend in publication volume is notably linked to articles published in the journals 'Harmful Algae' (7 articles) and 'Remote Sens. Environ.' (4 articles).

Finally, the accelerated growth period (2018-2023) exhibits a marked upward trend, with a growth rate of 29.20% and a reduction in the number of publications from Scopus compared to WoS, with the latter leading in this period. Notably, 2021 saw the highest number of publications; however, unlike previous periods, there was no trend of significant peaks in the total citations. This can be partially attributed to the recency of the publications, which may not have had sufficient time to accumulate a comparable number of citations. Accordingly, citation-based comparisons for the most recent period should be interpreted with caution. However, Huang *et al.* (2020) analyzed the magnitude and factors influencing HABs in China and observed a decreasing trend from 2006 to 2013, followed by a slight increase until 2018. This could be studied using machine learning models, such as the General Regression Neural Network (GRNN), which allows the identification of water quality patterns, while mapping HABs and their associated factors helps design nationwide management strategies to mitigate eutrophication. Taken together, these three phases suggest not only growth in publication output, but also a gradual transition from detection-oriented studies toward more integrated predictive frameworks, particularly those incorporating machine-learning approaches after 2018.

Country Analysis

Table 2 presents metrics on studies conducted on harmful algal blooms in 10 countries, relating to the percentage of production, impact (number of citations), and quality (Scimago SJR quartiles). The United States is the leading country in terms of productivity and impact. In terms of productivity, it achieves 36.69% of publications, followed by China with 23.08%. In terms of impact, measured by citations received, the United States accounts for 51.1% of citations, whereas China accounts for only 13%. Regarding the quality associated with the quartiles in which publications are ranked, the trend continues with the USA and China maintaining the first and second positions, respectively, for the first two quartiles; however, this pattern shifts for the third quartile, where China records a point above that of the USA. Research on harmful algal blooms has gradually gained prominence in countries such as Japan, the United Kingdom, and Spain, owing to the specific needs of each country. The United Kingdom and Spain occupy the third and fourth positions in terms of the highest number of citations, despite being below Japan in terms of scientific production on harmful algal blooms. From a scientometric perspective, this distribution suggests a strong concentration of visibility and influence in a limited number of national research systems, while collaboration patterns indicate that connectivity also contributes to the structure of the field.

A supplementary analysis of countries revealed that researchers from the USA generated the most international collaborative relationships (Figure 3). Khan *et al.* (2021) illustrated collaborative ties between researchers at the State University of New York (USA) and Memorial University of Newfoundland (Canada), who conducted a meta-analysis on the proliferation of harmful algal blooms and identified five research gaps. While the USA's leadership is partly due to the volume of publications, it is noteworthy that other countries, such as the Netherlands and Germany, although not in the top 10 by publication volume, act as catalysts within the scientific community through the relationships they establish in the network. An example of this is the work of Qian *et al.* (2024), which involved collaboration among researchers from Germany, the Netherlands, and China to develop an intelligent early warning system for the proliferation of harmful algal blooms using big data and deep learning models tested in Taihu Lake, China.

Figure also indicates that international relationships still have substantial room for growth in contributing to the consolidation of the scientific community, as the number of nodes in the network exceeds the number of links generated between countries for almost every year of the study period. Furthermore, the collaborative networks facilitated the identification of five communities (clusters) led by the USA, China, Japan, the United Kingdom, and a separate cluster comprising Serbia and Greece. The latter community is not integrated with the others, a phenomenon illustrated by Minic *et al.* (2015).

Journal Analysis

Table 3 displays the ten journals with the highest scientific output on harmful algal blooms, including metrics such as the impact factor, H-index, and Scimago quartile ranking. Predominantly, journals on this topic are ranked in the first quartile, indicating their high relevance, with the exception of 'Proceedings of SPIE - The International Society for Optical Engineering.' 'Harmful Algae' leads in publication volume, boasting an impact factor of 1.94 and an H-index of 114. The most cited article in this journal is by Professor Mark L. Wells, who discussed the global impacts of climate change on marine planktonic systems and how this could exacerbate the frequency and severity of harmful algal blooms (Wells *et al.*, 2015). Machine learning techniques have become increasingly important for the study of algal proliferation. In one of the journal's most recent studies, Cao proposed and applied an integrated CNN-LSTM model to predict the area of harmful algal blooms (CyanoHABs) in Taihu Lake, China. This model utilized time-series data spanning 20 years and MODIS imagery from 2000 to 2019. The integrated CNN-LSTM model demonstrated superior predictions in both the training and test datasets compared to the standalone CNN and LSTM models (Cao *et al.*, 2022).

The Sci. Total Environ. and Front. Mar. Sci were the next most prolific journals. Both journals exhibit similar publication volumes in the Web of Science (WoS) and Scopus databases and are ranked within the same quartile. However, the impact factor and H-index of Sci. Total Environ. are higher. A recent study published in this journal assessed the community structure

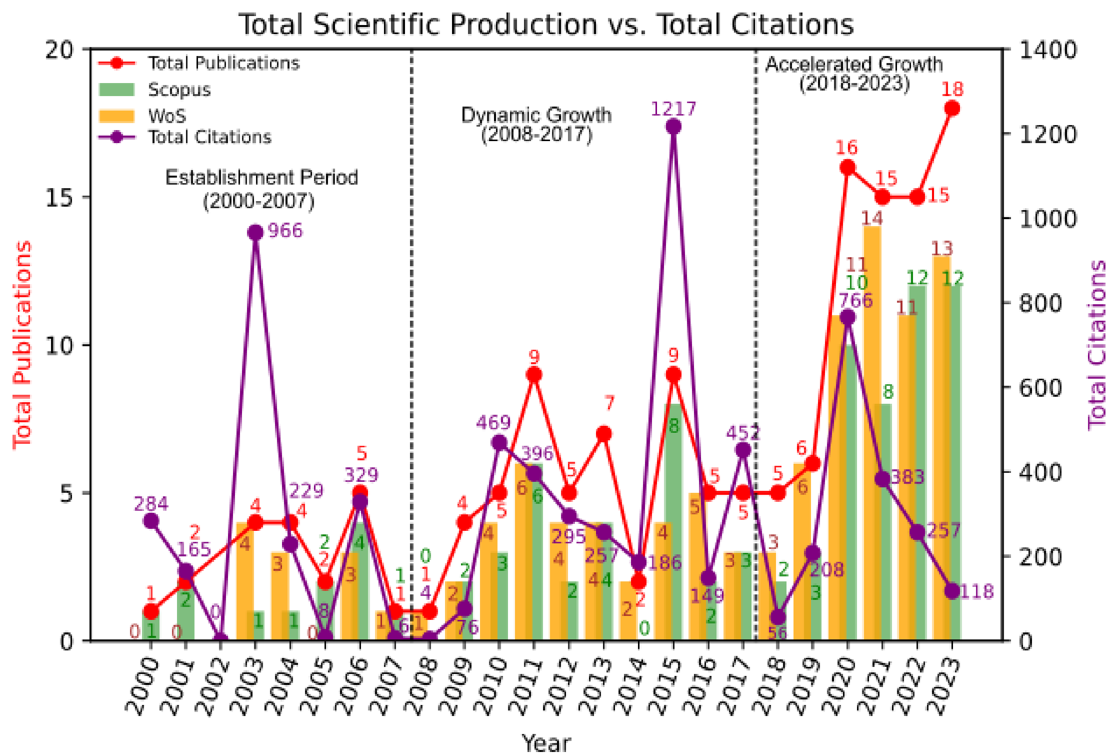

Figure 2: Trends in Scientific Publications and Citations on Harmful Algal Blooms from 2000 to 2023.

of bacteria in full-scale biological filtration systems during severe and mild harmful algal bloom outbreaks, offering deeper insights into the structure, function, and assembly of bacterial communities in response to harmful algae (Jeon *et al.*, 2023). In conclusion, Table underscores the significance of studying algal proliferation, as reflected by the high metric values of the listed journals and the volume of publications therein.

To construct Figure 4, journals from the references were used to create citation networks. This network delineates thematic clusters among journals. For instance, the first cluster focuses on the application of remote sensing technologies for the early detection of HABs using satellites and predictive algorithms (Davidson *et al.*, 2021; Lin *et al.*, 2021; Mardones *et al.*, 2023). The second cluster focuses on impact studies and management, such as the effects on aquaculture and fisheries industries, and discusses management strategies and prediction methods (Chang *et al.*, 2022; Kim *et al.*, 2022; Zhou *et al.*, 2022). The third group involves sophisticated modelling techniques with multi-algorithm approaches and the integration of various data sources to forecast early detection (Cao *et al.*, 2022; Guan *et al.*, 2022; Yan *et al.*, 2024).

Author Collaboration Network

Table 4 lists the most prolific authors of harmful algal bloom research. Professor Richard P. Stumpf stands out for his extensive publication record on the subject and holds the highest H-index. In 2012, Stumpf *et al.* published a pivotal study on harmful algal blooms in the western basin of Lake Erie, where they uncovered significant spatial variability in microcystin concentrations at the edges of the blooms (Stumpf *et al.*, 2012). This finding poses significant challenges for spatial assessments and suggests that predictive models must incorporate heterogeneity to accurately estimate microcystin concentrations. The second most cited researcher is Professor Jaeyoung Kim, who published an analysis in 2022 on the effects of removing the Singok Weir hydraulic structure in the Han River estuary, examining its impact on water quality and harmful algal blooms (Kim *et al.*, 2022). This study establishes a direct link between the removal of hydraulic infrastructure and variations in algal blooms, highlighting the influence of these changes on the water quality. The observed correlation between the number of publications and the quality of research, measured by the H-index, underscores researchers' contributions to advancing knowledge of harmful algal blooms.

Figure 5 illustrates the personal (ego network) of scientific collaboration among the most productive authors. The results revealed two components, one significantly larger (pink) than the other (green), indicating that the authors maintained collaborative social connections even if they were not working directly together. For instance, the first group has six subgroups, one of which demonstrates scientific collaboration among authors, such as Professor Gary J. Kirkpatrick, Gustavo A. Carvalho, and Viva F. Banzón (Carvalho *et al.*, 2011; Craig *et al.*, 2006). On the other hand, Professor Richard P. McCormick, Richard P. Stumpf, and Michelle C. Tomlinson serve as connectors linking other research groups (Chaffin *et al.*, 2021; El-Habashi *et al.*, 2017). An intriguing aspect of the network is that Professor Rose Ann Cattolico is disconnected from the social network of the first group, which can be attributed to her research focus on the psychological aspects of changes in HABs (Bearon *et al.*, 2004; Tobin *et al.*, 2013).

Tree of Science

Roots

Articles that form the roots are those that initially established the field of study in harmful algal bloom research. Notably, while the Tree of Science (ToS) algorithm primarily utilizes data from the Web of Science and Scopus, its network analysis capabilities allow it to identify significant works that may not be present in these databases or that do not exactly match the search terms or the focused search period. One such seminal work, conducted in 1996 by researchers Ricardo M. Letelier and Mark R. Abbott (Letelier and Abbott, 1996), explored algorithms for measuring passive chlorophyll fluorescence using the MODIS spectroradiometer, concluding that it can detect chlorophyll concentrations as low as 0.5 mg/m³ under optimal conditions.

Tester and Stumpf (1998) discussed how remote sensing, utilizing wind data, sea surface temperatures, and ocean color, can be used to predict phytoplankton blooms by incorporating real-time data and new sensors. Their study highlights how models derived from

Table 1: Search Parameters for Literature on Modeling and Monitoring of Harmful Algal Blooms in Web of Science and Scopus, 2000-2024.

Parameter	Web of Science	Scopus
Range	2000-2024	
Date	6-June-2024	
Document Type	Article, Review, Conference, Data Paper, Proceeding Papers	
Words	Title:("blue-green algae" OR "harmful algae*") AND Title-Abstract-Keywords: ("modelling*" OR "model*" OR "forecast*" OR "predict*" OR "algorithm*" OR "network*" OR "simulation" OR "numeric*") AND Title-Abstract-Keywords: (optica* OR spectral OR photometric OR light OR luminescent OR fluorescent OR fluorescence OR absorption OR emission OR reflectance OR transmittance OR scattering OR refractive OR radiative).	
Results	112	94
Total (WoS+Scopus)		155

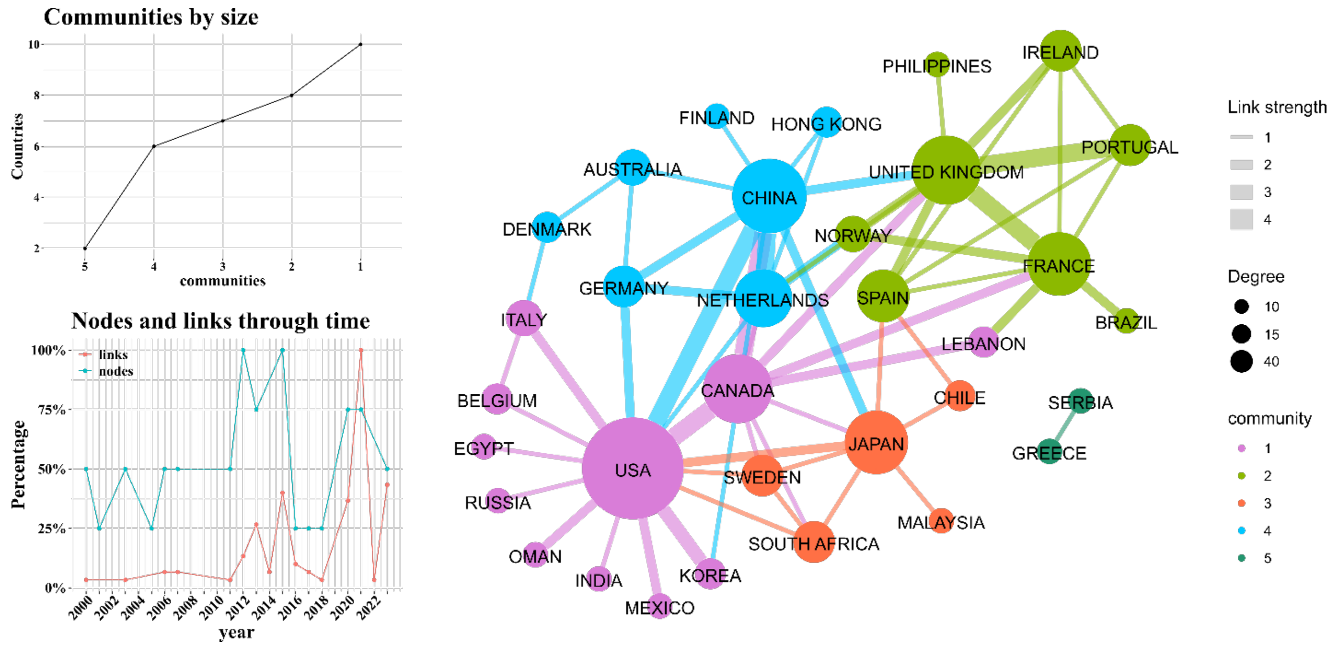

Figure 3: Network Analysis of Global Research Collaborations on Harmful Algal Blooms by Country.

Table 2: Global Distribution of Research Production and Citation Impact on Harmful Algal Blooms by Country and Quartile.

Country	Production		Citation		Q1	Q2	Q3	Q4
USA	62	36.69%	2879	51.1%	39	9	0	0
China	39	23.08%	772	13.7%	34	3	1	0
Japan	8	4.73%	259	4.6%	6	1	0	0
United Kingdom	8	4.73%	332	5.89%	6	0	0	0
Spain	7	4.14%	271	4.81%	4	2	0	0
Australia	5	2.96%	70	1.24%	3	1	0	0
Canada	4	2.37%	208	3.69%	4	0	0	0
Italy	4	2.37%	62	1.1%	3	1	0	0
Korea	4	2.37%	87	1.54%	3	0	0	0
India	3	1.78%	3	0.05%	2	0	0	1

these data help identify conditions conducive to phytoplankton growth ('Phytoplankton blooms and remote sensing: What is the potential for early warning'). Anderson *et al.* (2002) provided a regional and global review of the current state of knowledge on Harmful Algal Blooms (HABs), addressing the uncertainties that require further research, the global issues related to these blooms, their connection to eutrophication accelerated by anthropogenic activities, and how nutrient contributions affect the toxicity and impact of these algae. Hu *et al.* (2005) introduced a method to detect and track red tides using MODIS fluorescence data, which has been crucial for monitoring water quality along the southwest Florida coast.

Tomlinson *et al.* (2009) conducted innovative research, as they successfully identified blooms of the dinoflagellate Karenia brevis with high spatial and temporal resolution in the Gulf of Mexico. This was achieved using ocean color data obtained from remote sensors, focusing on the backscattering properties of particles rather than the absorption properties of cellular pigments. Overall, the network analysis performed using the Tree of Science (ToS) algorithm allows us to conclude that the referenced works were pivotal in establishing a scientific foundation for the phenomenon studied in this study.

Trunk

Studies that provide structural support to the field are located in the trunks. Harmful Algal Blooms (HABs) have garnered increasing interest owing to their significant ecological and economic impacts, as massive proliferation can drastically alter aquatic ecosystems, affecting biodiversity and water quality. In Asian countries, there has been particular interest due to the adverse effects on one of their major commercial activities: fishing. The 2006 study by Ahn *et al.* (2006) addressed the detection of HAB occurrences in Korean waters using satellites and MODIS data. Through this monitoring, they identified the presence of chlorophyll-a, which is an indicator of algal biomass, in the water. The analysis determined that blooms of Cochlodinium Polykrikoides resulted in significant economic losses due to fish mortality during the summer and autumn seasons.

Similarly, Siswanto *et al*. (2013) conducted a study on the detection of HABs using remote sensors, specifically targeting the dinoflagellate Karenia mikimotoi in the Seto Inland Sea in Japan. Their results demonstrated that this method is effective as a detection technique and is a valuable tool for managing the environment. In the same vein, the work by Hu *et al*. (2015) compares sensors for the detection of HABs in their study titled 'A Harmful Algal Bloom of Karenia Brevis in the Northeastern Gulf of Mexico Revealed by MODIS and VIIRS: A Comparison.' This study focused on the detection of HABs in waters rich in Colored Dissolved Organic Matter (CDOM). It was observed that, unlike VIIRS, MODIS can detect patches of Karenia brevis blooms due to its fluorescence capabilities.

HABs are not exclusively caused by algae but also by toxic dinoflagellates. In the research led by Kurekin *et al*. (2014), a satellite-based discrimination study was conducted to differentiate between two types of harmful blooms in European coastal waters: Karenia mikimotoi (dinoflagellate) and Phaeocystis (marine phytoplanktonic algae). This study utilized water radiance analysis and other optical properties of water. The findings accurately identified that 89% of Phaeocystis globosa blooms occur in the southern North Sea, while 88% of Karenia mikimotoi blooms are found in the English Channel.

In 2020, Smith and Bernard (2020) presented a cost-effective method for monitoring HABs in aquaculture in southern Benguela, South Africa, using satellite observations. Its potential lies in risk management and support for preventive decision-making in the aquaculture industry, thereby avoiding economic losses by identifying and classifying different types of phytoplankton from space, such as diatoms, including the potentially toxic Pseudo-nitzschia, and dinoflagellates, which are responsible for most blooms in the region. Additionally, satellite data from the Copernicus Sentinel-2 and Sentinel-3 programs were used to monitor HABs in Chile during the COVID-19 lockdown. Moving to the American continent, Rodríguez-Benito *et al*. (2020) focused their research on the detection of a dinoflagellate bloom that caused mass salmon mortality in Chile. Their study demonstrated how satellite technology enables monitoring despite restrictions on *in situ* sampling, highlighting the importance of remote sensing in early warning models.

In another study on HABs using satellite technology, Caballero *et al*. (2020) employed Sentinel-2A/B from the Copernicus program, along with *in situ* data, to monitor small harmful algal blooms in complex coastal waters. The Atmospheric Correction for OLI 'lite' (ACOLITE) processor and Normalized Difference Chlorophyll Index (NDCI) were used to map blooms at a spatial resolution of 10 m. The results demonstrated superior continuous monitoring capabilities compared with Landsat-8 and Sentinel-3.

Following the tree analogy, it is now pertinent to explain the three most relevant thematic subareas identified in this study, which are classified as branches according to the metaphor: These areas were identified through the citation network and the application of the Blondel *et al*. (2008) algorithm, which was integrated into the ToS algorithm. Figure 6 summarizes the identified network and highlights three areas with word clouds representing each theme. The thematic structure derived from ToS should therefore be understood as an interpretive organization of the selected citation network. In general, Branch 1 was distinct from the other two, which shared similarities and were closely related to each other. The following is a detailed description of each branch as part of a comprehensive analysis.

BRANCHES

Branch 1 - Integrating Omics Data and Climate Models to Understand and Predict the Impact of Climate Change on Harmful Algal Bloom Dynamics

The most frequently identified theme in this branch was the evaluation of the effects of climate change on the proliferation of

Table 3: Journal Metrics in Harmful Algal Bloom Research: Comparison of Impact Factor, H-Index, and Quartile Rankings.

Journal	Wos	Scopus	Impact Factor	H Index	Quantile
Harmful Algae	14	8	1.94	114	Q1
Sci. Total Environ.	6	5	2	353	Q1
Front. Mar. Sci.	6	4	0.91	101	Q1
Remote Sensing	6	0	1.09	193	Q1
Remote Sens. Environ.	5	2	4.31	350	Q1
Environ. Sci. Technol.	0	4	3.52	480	Q1
Mar. Pollut. Bull.	3	2	1.45	229	Q1
Proc. SPIE.	0	3	0.15	193	-
Prog. Oceanogr.	2	2	1.3	151	Q1
Scientific Reports	3	0	0.9	315	Q1

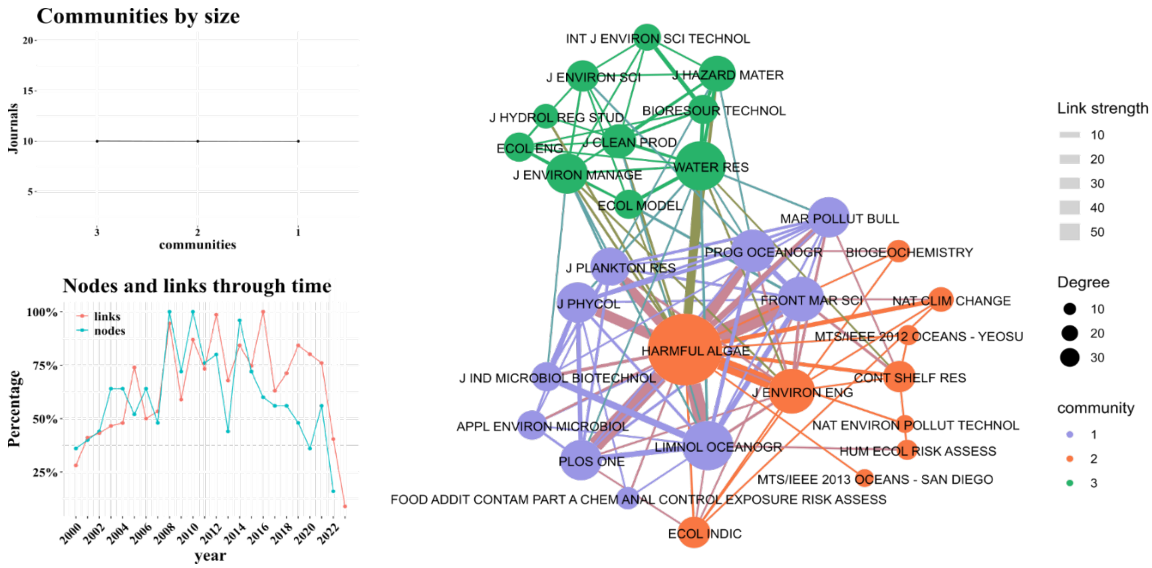

Figure 4: Citation Network Analysis of Journals on Harmful Algal Bloom Research: Community Dynamics and Influence Over Time.

Harmful Algal Blooms (HABs). Glibert (2020) analyzed the effects of eutrophication and climate change on harmful algae. The study was based on climate projections suggesting global warming above 1.5ºC, coupled with increasing population, food demand, and fuel consumption, which results in greater pollution. This study emphasizes the complex, subtle, and unexpected effects on the physiology of both harmful and non-harmful algae. To address this issue, Professor Gwenn M.M. Hennon explored how current omics datasets (genomics, transcriptomics, proteomics, and metabolomics) can be incorporated into numerical predictive models to improve predictions of the effects of climate change on HAB dynamics, highlighting promising avenues for integrating this technology (Hennon and Dyhrman, 2020).

Given that climate change is a major factor in evaluating algal proliferation, one of the initial studies was conducted by Professor David Ralston, who evaluated HAB modelling in the context of climate change and classified these models into statistical, process-based, and hybrid types. His work details that statistical models are mainly used for short-term forecasting and management but are less effective for long-term use. In these cases, process-based models are used, which increase system complexity and calibration requirements. However, modelling the future response of HABs to climate change remains an emerging field of study (Ralston and Moore, 2020).

The use of mathematical tools and Machine Learning (ML) has advanced significantly, incorporating new variables that enhance our understanding of algal proliferation phenomena. The most recent work by Yan *et al.*, (2024) provides a comprehensive view of HABs by examining the chemical, physical, biological, and climatological factors influencing their occurrence. This study also analyzed various predictive modelling methods used to understand and forecast HABs. This emphasizes the importance of integrating diverse predictive modelling approaches to improve the understanding and prediction of HAB events. While process-based models offer detailed insights into HAB dynamics, statistical-empirical and machine learning models provide predictive capabilities that complement experimental research. By combining these methodologies, researchers can improve prediction accuracy, address extrapolation issues, and develop effective strategies for managing and mitigating the harmful effects of HABs in coastal areas. Challenges and limitations include the need for historical data for ML models, the long development time for process-based models, and the requirement for precise expression of vital HAB processes.

A common parameter for predicting harmful algal blooms is the availability of long-term data. Professor Vera L. Trainer's work provides a solid foundation for how time series, including phytoplankton records, dinoflagellate cyst records, Continuous Plankton Recorder surveys, and toxin records in shellfish, can identify extreme events that significantly deviate from long-term averages. This study highlights that these extreme climatic events can simulate future conditions and offer a "rehearsal" for understanding the future frequency, intensity, and geographic extent of HABs (Trainer *et al.*, 2020).

The implementation of predictive models serves a greater purpose beyond research, and a monitoring tool is necessary to fully leverage scientific findings. An important work emphasizing this point was conducted by Professor Weibing Guan, who discussed the monitoring, modelling, and forecasting of HABs in Chinese seas. This study covers various methods and technologies used to study the processes involved in the formation and dissipation of HABs, such as field data collection, statistical analysis, Lagrangian models, and ecosystem modelling. This underscores the importance of interdisciplinary approaches, advanced modelling tools, and data-driven analyses to improve our understanding of HABs and early warning systems in marine environments (Guan *et al.*, 2022).

Table 4: Top Researchers in Harmful Algal Bloom Studies: Article Production, Scopus H-Index, and Affiliations.

Sl. No.	Researcher	Total Articles*	Scopus h-Index	Affiliation
1	Stumpf R	7	48	National Oceanic and Atmospheric Administration, Washington, D.C., United States
2	Miller P	6	39	Plymouth Marine Laboratory, Plymouth, United Kingdom
3	Kim J	5	5	Chungnam National University, Daejeon, South Korea
4	Kirkpatrick G	5	29	Mote Marine Laboratory and Aquarium, Sarasota, United States
5	Tomlinson M	5	16	NOAA National Ocean Service, Silver Spring, United States
6	Zhang C	5	24	Northeast Normal University, Changchun, China
7	Banzon V	4	29	NOAA/National Centers for Environmental Information, Asheville, United States
8	Baringer W	4	4	Rosenstiel School of Marine and Atmospheric Science, Miami, United States
9	Carvalho G	4	2	Rosenstiel School of Marine and Atmospheric Science, Miami, United States
0	Cattolico R	4	24	University of Washington, Burn, United States

Branch 2 - Evolution of Satellite Monitoring Techniques for Harmful Algal Blooms: From Remote Sensing Integration to Advanced Discriminant Analysis

This branch explores methodological advances in the techniques for monitoring and detecting Harmful Algal Blooms (HABs) using satellites. In 2012, a significant milestone was achieved by a paper (Shen *et al*., 2012) that reviewed the feasibility of various satellite data and algorithms for the remote sensing of HABs. This study proposes an integrative framework that combines physiological ecology with remote sensing technologies, highlighting the importance of satellites in enhancing the tracking of harmful algal blooms. A year later, in 2013, another relevant technique emerged with the use of Linear Discriminant Analysis (LDA) in a study (Kurekin *et al*., 2014). This methodology allowed for the classification of pixels in MODIS and MERIS images, thereby improving the precision of HAB detection in European waters.

In 2016, a significant advancement was made with a study on the West Florida Shelf (El-habashi *et al*., 2016) that employed Neural Networks (NN) to process observations from the Visible Infrared Imaging Radiometer Suite (VIIRS). This adaptation compensated for the lack of a specific fluorescence channel and recovered phytoplankton absorption, demonstrating advanced capability for tracking and validating harmful algal blooms. Concurrently, Ghanea *et al*. (2016) examined the biophysical properties of water during a red tide outbreak using MODIS measurements to monitor oceanographic phenomena.

In the satellite detection of harmful algal blooms, significant gaps have been identified in atmospheric correction methods, analytical models, machine learning algorithms, and the use of cloud-computing platforms (Khan *et al*., 2021). Recent research has made significant strides in addressing these gaps. Ocean color satellite images have been used in the southern Benguela region, demonstrating the practical utility of these data for efficient Harmful Algal Bloom (HAB) detection (Smith and Bernard, 2020). Additionally, there is a trend toward integrating various data sources to improve detection accuracy (Bu *et al*., 2023). A recent study highlighted that incorporating a second Geostationary Ocean Color Imager (GOCI-II) could significantly optimize ocean monitoring (Jing *et al*., 2024). This approach, along with the use of cloud computing platforms, has the potential to overcome the current limitations of HAB detection and management, offering more integrated and effective solutions.

A common theme among the reviewed articles is the significant contribution of advances in remote sensing methods for Harmful Algal Blooms (HABs) in developing roadmaps to address issues associated with these proliferations. These studies emphasize how satellite remote sensing techniques, such as ocean color imagery, Neural Networks (NN), and Linear Discriminant Analysis (LDA), have enabled more precise and efficient detection of HABs, facilitating the real-time identification and monitoring of these events. These advancements not only enhance our understanding of oceanographic phenomena but also provide practical tools for managing and mitigating the environmental and economic impacts caused by harmful algal blooms.

Branch 3 - Advancements in Lake-Based Monitoring and Prediction of Harmful Algal Blooms: Integrating Environmental Factors and Remote Sensing Technologies

This branch encompasses a diverse array of research, much of which has been conducted in lakes, as these ecosystems are ideal for studying HABs by observing various variables and phenomena.

In one study (Chen *et al*., 2021), two sibling lakes, Hulun Lake in northeastern China and Buir Lake shared by China and Mongolia, were examined owing to their varying degrees of exposure to HABs. The study found that nutrient limitation affects algal proliferation in both lakes, with Buir Lake exhibiting perennial flow, whereas Hulun Lake became an internally draining lake, leading to the accumulation of Total Nitrogen (TN) and Total Phosphorus (TP). This study underscored the critical role of substantial nutrient load increases and the need for further research and policy development in this area. Another study (Ma *et al*., 2021) proposed a multi-source remote sensing approach for monitoring HABs in Chaohu Lake, China, identifying the months of occurrence and peak periods. Higher temperatures and light rainfall favored the occurrence of HABs, with wind being the primary factor driving their growth.

Studies on lakes have also addressed the cyanobacterial perspective. For instance, Lake Erie (Boegehold *et al*., 2023), situated between Canada and the USA, frequently experiences cyanobacterial HABs. Monitoring over several years included observations of physicochemical properties, nutrient fractions, phytoplankton pigments, microcystins, and optical properties of the water, resulting in an open-access dataset for the scientific community to develop models and algorithms to better understand the water quality dynamics that influence HABs. Another study (Cao *et al*., 2022) developed a Convolutional Neural Network-based model to predict CyanoHAB areas in Taihu Lake, China, using 20 years of data. Temperature, relative humidity, wind speed, and precipitation were closely related to CyanoHAB outbreaks in the lake.

A significant finding from lake studies is that the succession of cyanobacterial harmful algal blooms (CyanoHABs) is regulated by co-occurring microbes. For example, research on Harsha Lake, USA (Wang *et al*., 2021), demonstrated that, in addition to environmental conditions and the inherent traits of specific cyanobacterial species, CyanoHAB development and succession are regulated by concurrent microorganisms.

Moreover, the cyanobacterial perspective has enabled researchers to develop infrastructure for the detection and monitoring of HABs. One study (Mishra *et al*., 2020) introduced "CyanoTRACKER," a multi-cloud cyber infrastructure integrating community reports (social cloud), remote sensing data (sensor cloud), and digital image analysis (computing cloud) to detect and differentiate between regular algal blooms and CyanoHABs. The CyanoTRACKER components include a reporting website, a mobile application, and a remotely deployable, solar-powered automated hyperspectral sensor (CyanoSense). The twin Sentinel-2 satellite mission of the Copernicus program (Rodríguez-Benito *et al*., 2020) is also noteworthy, although the scope of this article does not allow for a detailed discussion of the extensive scientific and technological infrastructure resulting from these investigations.

Trees are characterized by branching, and similarly, not all studies in this branch of the Tree of Science (ToS) are based on lake studies, as HABs occur in various ecosystems, each with different intrinsic characteristics (Moron-Lopez *et al*., 2021). This includes environments such as drinking-water production. For instance,

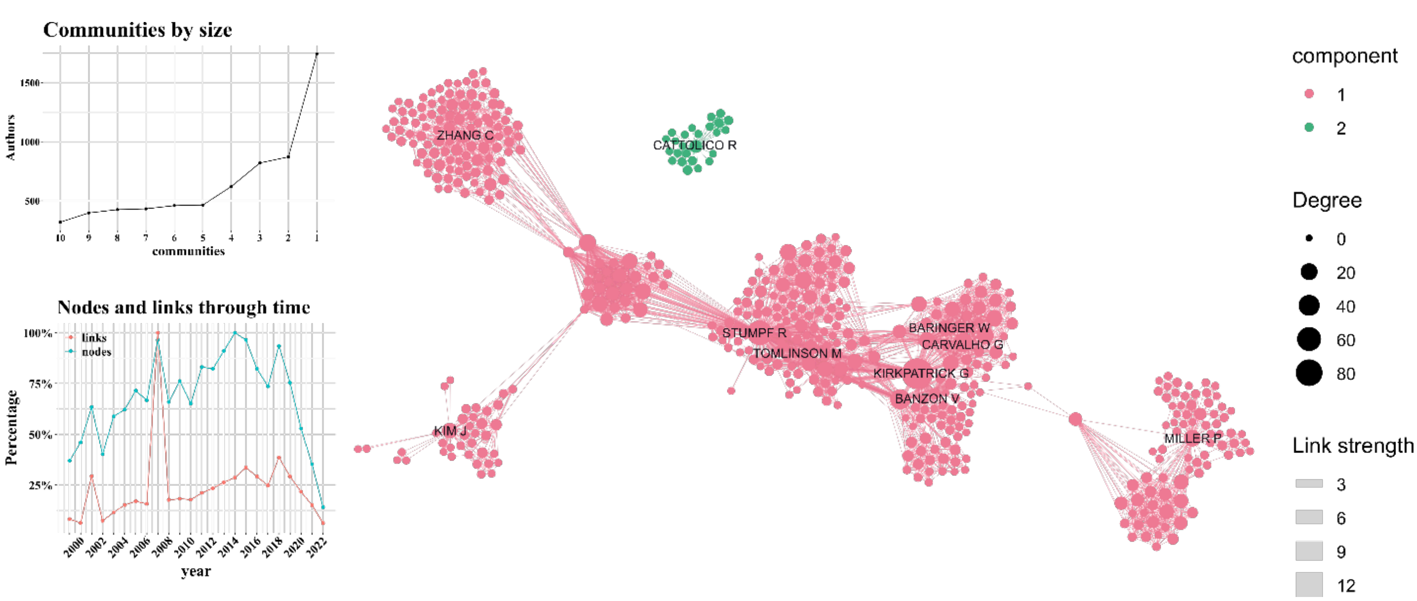

Figure 5: Collaborative Network Analysis of Leading Researchers in Environmental Science.

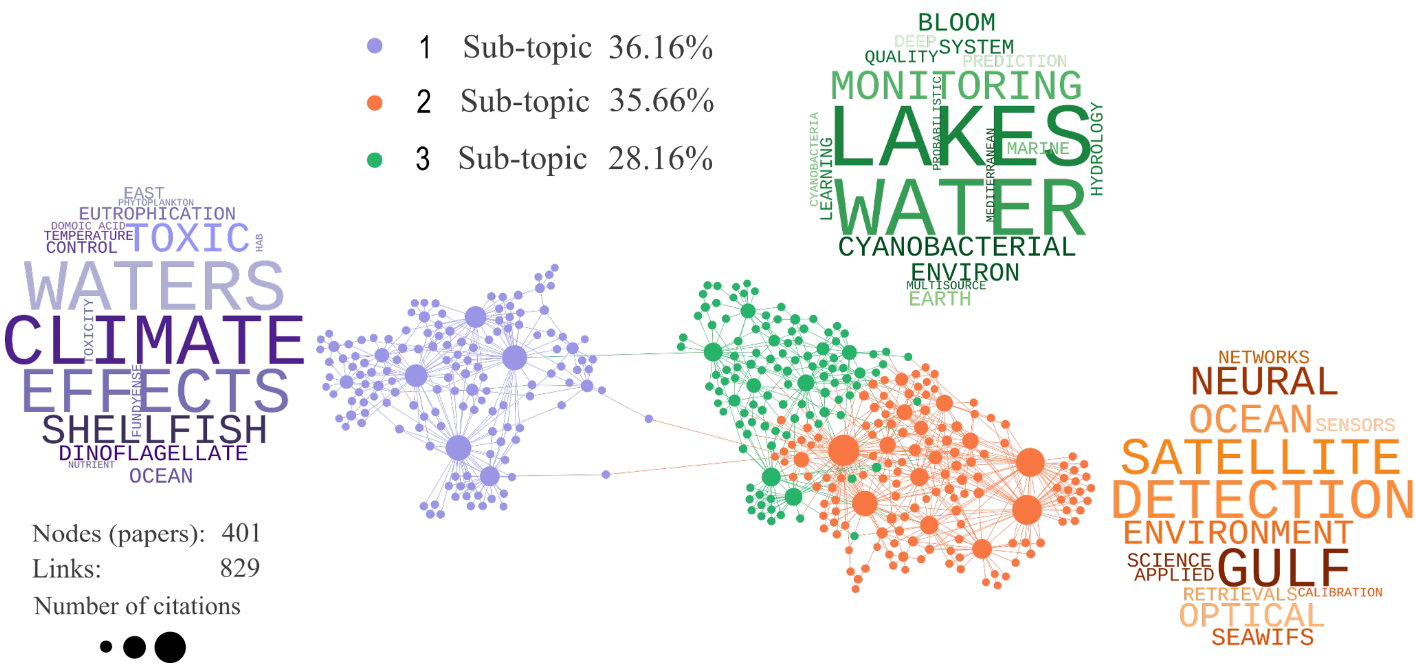

Figure 6: Citation Network and Thematic Analysis of Research on Harmful Algal Blooms: A Focus on Marine, Lake, and Remote Sensing Studies.

Jeon *et al.* (2023) agree that HABs in freshwater environments are increasing in frequency and severity, posing risks to potable water supplies. However, the potential impact of HAB-affected water on granular media filtration systems has not been extensively studied. They found that bacterial diversity in Biologically Active Filters (BAFs) significantly decreased during severe HABs owing to the predominance of bacteria associated with blooms (e.g., Spingopyxis, Porphyrobacter, and Sphingomonas).

CONCLUSION

Studies on HABs are crucial because these blooms can devastate aquatic ecosystems, causing high mortality rates in fish and marine mammals. This study presents a scientometric analysis of HABs, focusing on predictive models that use optical measurements. The results indicate rapid growth in the academic literature, with a 29.20% increase between 2018 and 2023, highlighting the growing importance of this research in recent years. In terms of country-specific analysis, the United States leads in production, with 36.69% of the total publications and an impressive 51.1% of the total citations. The two journals with the highest output on this topic are Harmful Algae and Science of the Environment. Notably, nine of the ten journals publishing on HABs are ranked in the highest quartile (Q1), reflecting the significance and quality of the research. The author analysis reveals a well-established and connected academic community fostered by collaborative efforts.

The analysis using the ToS algorithm identified three major sub-areas (branches based on the tree analogy). The first is integration of omics data and climate models to understand and predict the impact of climate change on harmful algal bloom dynamics. The second is the Evolution of Satellite Monitoring Techniques for Harmful Algal Blooms: From Remote Sensing Integration to Advanced Discriminant Analysis, and the third is Advancements in Lake-Based Monitoring and Prediction of Harmful Algal Blooms: Integrating Environmental Factors and Remote Sensing Technologies.

The interaction between climate change and eutrophication exacerbates harmful algal blooms, affecting both harmful and nonharmful algal physiology. Recent studies suggest that global warming, together with factors such as population growth, food demand, and increased pollution, leads to a complex and multifactorial scenario that enhances the occurrence of HABs in various regions of the world. These changes manifest in subtle and often unexpected ways, complicating the prediction and management of HABs. The breakthrough in predicting HAB dynamics in the face of climate change lies in integrating omics data and numerical models. Professor Gwenn MM Hennon's studies highlight the promise of genomic, transcriptomic, proteomic, and metabolomic datasets for improving predictive models, whereas Professor David Ralston's work highlights the need to develop process-based models for more robust long-term projections. Additionally, Vera L. Trainer's research underscores the importance of time series and historical records as tools for identifying extreme events and forecasting the future frequency, intensity, and extent of HABs, providing a "general repeat" useful for anticipating extreme weather conditions.

The evolution of satellite monitoring techniques has significantly transformed the detection and management of Harmful Algal Blooms (HABs). Advances in remote sensing, such as the integration of ocean color imagery, Neural Networks and Linear Discriminant Analysis, have improved the accuracy and efficiency of identifying these events. These developments have not only increased the understanding of oceanographic phenomena but have also provided practical tools for the management and mitigation of environmental and economic impacts caused by harmful algal blooms. Recent research emphasizes the importance of addressing gaps in atmospheric correction methods and integrating multiple data sources to improve the accuracy of detecting and tracking these events, highlighting the potential of cloud computing platforms and the incorporation of new satellite sensors, such as GOCI-II, to optimize ocean monitoring.

The integration of environmental factors and remote sensing technologies has significantly improved the monitoring and prediction of Harmful Algal Blooms (HABs) in lakes. Studies have shown that increased nutrients are a critical factor in algal blooms, as observed in Hulun and Buir lakes, while multisource remote sensing has allowed the identification of bloom peaks in Lake Chaohu. Research at Lake Erie has provided open data to develop predictive models, and the use of convolutional neural networks at Lake Taihu has improved the prediction of CyanoHAB areas. In addition, the succession of CyanoHABs has been shown to be regulated by concurrent microorganisms, as observed in Lake Harsha. Innovative tools such as CyanoTRACKER, which integrates community reports, remote sensing data, and digital image analysis, have improved the detection and monitoring of CyanoHABs. Studies have also highlighted the risks that HABs pose to drinking water supplies, showing how they affect the bacterial diversity in biologically active filters during severe blooms.

These advances underscore the importance of multidisciplinary research and the development of technological infrastructure for the effective management of harmful algal blooms, providing improved strategies to mitigate environmental and health impacts in diverse aquatic ecosystems.

This study provides a delimited scientometric view of the literature related to the prediction of harmful algal blooms using mathematical models supported by optical detection methods. The integration of Scopus and Web of Science data provides a comprehensive view of interdisciplinary collaboration, technological evolution, and regional research trends. The findings revealed an upward trajectory in publications, with an increasing emphasis on machine learning, chlorophyll-a detection, and the use of satellite data. This knowledge can guide the development of hybrid predictive tools and foster greater integration between modelling, remote sensing, and ecological forecasting.

The findings should be interpreted within the scope defined by the search strategy, database coverage, and citation structure of the selected corpus. These methodological conditions should be considered when extrapolating the results to the broader HAB literature. Future studies may expand this line of inquiry by incorporating additional science-mapping techniques and broader corpus designs.

ACKNOWLEDGEMENT

None.

ABBREVIATIONS

HABs: Harmful Algal Blooms; **ML:** Machine Learning; **WoS:** Web of Science; **ToS:** Tree of Science; **DOI:** Digital Object Identifier; **API:** Application Programming Interface; **MODIS:** Moderate Resolution Imaging Spectroradiometer; **VIIRS:** Visible Infrared Imaging Radiometer Suite; **MERIS:** Medium Resolution Imaging Spectrometer; **GOCI-II:** Geostationary Ocean Color Imager-II; **CNN:** Convolutional Neural Network; **LSTM:** Long Short-Term Memory; **GRNN:** General Regression Neural Network; **LDA:** Linear Discriminant Analysis; **NN:** Neural Network; **NDCI:** Normalized Difference Chlorophyll Index; **CDOM:** Colored Dissolved Organic Matter; **TN:** Total Nitrogen; **TP:** Total Phosphorus; **CyanoHABs:** Cyanobacterial Harmful Algal Blooms; **BAFs:** Biologically Active Filters.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest

FUNDING

Financial support was provided by Minciencias under the program "Plataforma de analítica de datos como soporte a la gestión de la demanda operacional en la industria manufacturera de la red de aliados de RevloG" code 825223, Universidad Nacional de Colombia.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used Paperpal to support the translation of the document into English. After using this tool, the author(s) reviewed and edited the content as needed and took(s) full responsibility for the content of the published article.

AUTHOR CONTRIBUTIONS STATEMENT

Nini Valentina Naranjo-Castaño: Writing-original draft, Investigation, Formal analysis. **María Valentina Suarez León:** Conceptualization, Writing - original draft. **Natalia Alzate-Acevedo:** Conceptualization, Writing - original draft. **José Antonio Valencia Aricapa:** Conceptualization, Writing - original draft. **Juan Carlos Riaño Rojas:** Writing - original draft, Investigation, Resources. **Elisabeth Restrepo-Parra:** Methodology, Resources, Funding acquisition.

SUMMARY

- Scientometric analysis shows 24 years of HAB modelling and detection trends.
- Merged Scopus-WoS datasets expose global output and collaboration patterns.
- ToS analysis shows shift from statistics to AI models after 2018.
- Satellite data like chlorophyll-a are key in climate-driven HAB forecasts.

REFERENCES

Aguirre, K. A., and Paredes Cuervo, D. (2023). Water Safety and Water Governance: A Scientometric Review. Sustainability, 15(9), 7164. https://doi.org/10.3390/su15097164

Ahn, Y.-H., Shanmugam, P., Ryu, J.-H., and Jeong, J.-C. (2006). Satellite detection of harmful algal bloom occurrences in Korean waters. Harmful Algae, 5(2), 213-231. https://doi.org/10.1016/j.hal.2005.07.007

Anderson, D. M., Glibert, P. M., and Burkholder, J. M. (2002). Harmful algal blooms and eutrophication: Nutrient sources, composition, and consequences. Estuaries, 25(4), 704-726. https://doi.org/10.1007/BF02804901

Ariza-Colpas, P. P., Piñeres-Melo, M. A., Morales-Ortega, R. C., Rodriguez-Bonilla, A.-F., Butt-Aziz, S., Naz, S., del Carmen Contreras-Chinchilla, L., Romero-Mestre, M., and Ascanio, R. A. V. (2023). Augmented Reality and Tourism: A Bibliometric Analysis of New Technological Bets in the Post-COVID Era. Sustainability, 15(21), 15358. https://doi.org/10.3390/su152115358

Ariza-Colpas, P. P., Piñeres-Melo, M. A., Morales-Ortega, R.-C., Rodríguez-Bonilla, A. F., Butt-Aziz, S., Naz, S., Contreras-Chinchilla, L. del C., Romero-Mestre, M., and Vacca Ascanio, R. A. (2024). Sustainability in Hybrid Technologies for Heritage Preservation: A Scientometric Study. Sustainability, 16(5), 1991. https://doi.org/10.3390/su16051991

Azizan, A. (2024). Exploring the Role of Social Media in Mental Health Research: A Bibliometric and Content Analysis. Journal of Scientometric Research, 13(1), 01-08. https://doi.org/10.5530/jscires.13.1.1

Bearon, R. N., Grünbaum, D., and Cattolico, R. A. (2004). Relating cell-level swimming behaviors to vertical population distributions in Heterosigma akashiwo (Raphidophyceae), a harmful alga. Limnology and Oceanography, 49(2), 607-613. https://doi.org/10.4319/lo.2004.49.2.0607

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., and Lefebvre, E. (2008). Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 2008(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Boegehold, A. G., Burtner, A. M., Camilleri, A. C., Carter, G., Denuyl, P., Fanslow, D., Fyffe Semenyuk, D., Godwin, C. M., Gossiaux, D., Johengen, T. H., Kelchner, H., Kitchens, C., Mason, L. A., McCabe, K., Palladino, D., Stuart, D., Vanderploeg, H., and Errera, R. (2023). Routine monitoring of western Lake Erie to track water quality changes associated with cyanobacterial harmful algal blooms. Earth System Science Data, 15(8), 3853-3868. https://doi.org/10.5194/essd-15-3853-2023

Botero, C. M., Milanes, C. B., and Robledo, S. (2023). 50 years of the Coastal Zone Management Act: The bibliometric influence of the first coastal management law on the world. Marine Policy, 150, 105548. https://doi.org/10.1016/j.marpol.2023.105548

Bu, X., Liu, K., Liu, J., and Ding, Y. (2023). A Harmful Algal Bloom Detection Model Combining Moderate Resolution Imaging Spectroradiometer Multi-Factor and Meteorological Heterogeneous Data. Sustainability, 15(21), 15386. https://doi.org/10.3390/su152115386

Caballero, I., Fernández, R., Escalante, O. M., Mamán, L., and Navarro, G. (2020). New capabilities of Sentinel-2A/B satellites combined with *in situ* data for monitoring small harmful algal blooms in complex coastal waters. Scientific Reports, 10(1), 8743. https://doi.org/10.1038/s41598-020-65600-1

Cao, H., Han, L., and Li, L. (2022). A deep learning method for cyanobacterial harmful algae blooms prediction in Taihu Lake, China. Harmful Algae, 113, 102189. https://doi.org/10.1016/j.hal.2022.102189

Carvalho, G. A., Minnett, P. J., Banzon, V. F., Baringer, W., and Heil, C. A. (2011). Long-term evaluation of three satellite ocean color algorithms for identifying harmful algal blooms (Karenia brevis) along the west coast of Florida: A matchup assessment. Remote Sensing of Environment, 115(1), 1-18. https://doi.org/10.1016/j.rse.2010.07.007

Chaffin, J. D., Bratton, J. F., Verhamme, E. M., Bair, H. B., Beecher, A. A., Binding, C. E., Birbeck, J. A., Bridgeman, T. B., Chang, X., Crossman, J., Currie, W. J. S., Davis, T. W., Dick, G. J., Drouillard, K. G., Errera, R. M., Frenken, T., MacIsaac, H. J., McClure, A., McKay, R. M., … Zhou, X. (2021). The Lake Erie HABs Grab: A binational collaboration to characterize the western basin cyanobacterial harmful algal blooms at an unprecedented high-resolution spatial scale. Harmful Algae, 108. https://doi.org/10.1016/j.hal.2021.102080

Chang, H., Wu, H., Zhang, L., Wu, W., Zhang, C., Zhong, N., Zhong, D., Xu, Y., He, X., Yang, J., Zhang, Y., Zhang, T., Liao, Q., and Ho, S.-H. (2022). Gradient electro-processing strategy for efficient conversion of harmful algal blooms to biohythane with mechanisms insight. Water Research, 222. https://doi.org/10.1016/j.watres.2022.118929

Chen, J., Wang, J., Wang, Q., Lv, J., Liu, X., Chen, J., and Li, N. (2021). Common fate of sister lakes in Hulunbuir Grassland: Long-term harmful algal bloom crisis from multi-source remote sensing insights. Journal of Hydrology, 594, 125970. https://doi.org/10.1016/j.jhydrol.2021.125970

Craig, S. E., Lohrenz, S. E., Lee, Z., Mahoney, K. L., Kirkpatrick, G. J., Schofield, O. M., and Steward, R. G. (2006). Use of hyperspectral remote sensing reflectance for detection and assessment of the harmful alga, Karenia brevis. Applied Optics, 45(21), 5414-5425. https://doi.org/10.1364/AO.45.005414

Davidson, K., Whyte, C., Aleynik, D., Dale, A., Gontarek, S., Kurekin, A. A., McNeill, S., Miller, P. I., Porter, M., Saxon, R., and Swan, S. (2021). HABreports: Online Early Warning of Harmful Algal and Biotoxin Risk for the Scottish Shellfish and Finfish Aquaculture Industries. Frontiers in Marine Science, 8. https://doi.org/10.3389/fmars.2021.631732

Derviş, H. (2020). Bibliometric Analysis using Bibliometrix an R Package. Journal of Scientometric Research, 8(3), 156-160. https://doi.org/10.5530/jscires.8.3.32

Duque, P., Cárdenas, M., and Robledo, S. (2023). Marketing social: evolución y tendencias. Entramado, 20(1). https://doi.org/10.18041/1900-3803/entramado.1.10378

El-Habashi, A., Duran, C. M., Lovko, V., Tomlinson, M. C., Stumpf, R. P., and Ahmed, S. (2017). Satellite retrievals of Karenia brevis harmful algal blooms in the West Florida shelf using neural networks and impacts of temporal variabilities. Journal of Applied Remote Sensing, 11(3), 032408. https://doi.org/10.1117/1.JRS.11.032408

El-habashi, A., Ioannou, I., Tomlinson, M., Stumpf, R., and Ahmed, S. (2016). Satellite Retrievals of Karenia brevis Harmful Algal Blooms in the West Florida Shelf Using Neural Networks and Comparisons with Other Techniques. Remote Sensing, 8(5), 377. https://doi.org/10.3390/rs8050377

Fernandes-Salvador, J. A., Davidson, K., Sourisseau, M., Revilla, M., Schmidt, W., Clarke, D., Miller, P. I., Arce, P., Fernández, R., Maman, L., Silva, A., Whyte, C., Mateo, M., Neira, P., Mateus, M., Ruiz-Villarreal, M., Ferrer, L., and Silke, J. (2021). Current Status of Forecasting Toxic Harmful Algae for the North-East Atlantic Shellfish Aquaculture Industry. Frontiers in Marine Science, 8. https://doi.org/10.3389/fmars.2021.666583

Ghanea, M., Moradi, M., and Kabiri, K. (2016). A novel method for characterizing harmful algal blooms in the Persian Gulf using MODIS measurements. Advances in Space Research, 58(7), 1348-1361. https://doi.org/10.1016/j.asr.2016.06.005

Glibert, P. M. (2020). Harmful algae at the complex nexus of eutrophication and climate change. Harmful Algae, 91, 101583. https://doi.org/10.1016/j.hal.2019.03.001

Grisales, A. M., Robledo, S., and Zuluaga, M. (2023). Topic Modeling: Perspectives From a Literature Review. IEEE Access, 11, 4066-4078. https://doi.org/10.1109/ACCESS.2022.3232939

Guan, W., Bao, M., Lou, X., Zhou, Z., and Yin, K. (2022). Monitoring, modeling and projection of harmful algal blooms in China. Harmful Algae, 111. https://doi.org/10.1016/j.hal.2021.102164

Gupta, A., Hantush, M. M., and Govindaraju, R. S. (2023). Sub-monthly time scale forecasting of harmful algal blooms intensity in Lake Erie using remote sensing and machine learning. Science of The Total Environment, 900, 165781. https://doi.org/10.1016/j.scitotenv.2023.165781

Hennon, G. M. M., and Dyhrman, S. T. (2020). Progress and promise of omics for predicting the impacts of climate change on harmful algal blooms. Harmful Algae, 91. https://doi.org/10.1016/j.hal.2019.03.005

Hu, C., Barnes, B., Qi, L., and Corcoran, A. (2015). A Harmful Algal Bloom of Karenia brevis in the Northeastern Gulf of Mexico as Revealed by MODIS and VIIRS: A Comparison. Sensors, 15(2), 2873-2887. https://doi.org/10.3390/s150202873

Hu, C., Mullerkarger, F., Taylor, C., Carder, K., Kelble, C., Johns, E., and Heil, C. (2005). Red tide detection and tracing using MODIS fluorescence data: A regional example in SW Florida coastal waters. Remote Sensing of Environment, 97(3), 311-321. https://doi.org/10.1016/j.rse.2005.05.013

Huang, J., Zhang, Y., Arhonditsis, G. B., Gao, J., Chen, Q., and Peng, J. (2020). The magnitude and drivers of harmful algal blooms in China's lakes and reservoirs: A national-scale characterization. Water Research, 181. https://doi.org/10.1016/j.watres.2020.115902

Hurtado-Marín, V. A., Agudelo-Giraldo, J. D., Robledo, S., and Restrepo-Parra, E. (2021). Analysis of dynamic networks based on the Ising model for the case of study of co-authorship of scientific articles. Scientific Reports, 11(1), 5721. https://doi.org/10.1038/s41598-021-85041-8

Jang, J., Baek, S.-S., Kang, D., Park, Y., Ligaray, M., Baek, S. H., Choi, J. Y., Park, B. S., Lee, M.-I., and Cho, K. H. (2024). Insights and machine learning predictions of harmful algal bloom in the East China Sea and Yellow Sea. Journal of Cleaner Production, 459, 142515. https://doi.org/10.1016/j.jclepro.2024.142515

Jeon, Y., Li, L., Bhatia, M., Ryu, H., Santo Domingo, J. W., Brown, J., Goetz, J., and Seo, Y. (2023). Impact of harmful algal bloom severity on bacterial communities in a full-scale biological filtration system for drinking water treatment. Science of The Total Environment, 927, 171301. https://doi.org/10.1016/j.scitotenv.2024.171301

Jing, Y., Feng, C., Chen, T., Zhu, Y., Li, C., Tao, B., and Song, Q. (2024). Use of GOCI-II images for detection of harmful algal blooms in the East China Sea. Geoscience Letters, 11(1), 2. https://doi.org/10.1186/s40562-023-00317-3

Khan, R. M., Salehi, B., Mahdianpari, M., Mohammadimanesh, F., Mountrakis, G., and Quackenbush, L. J. (2021). A Meta-Analysis on Harmful Algal Bloom (HAB) Detection and Monitoring: A Remote Sensing Perspective. Remote Sensing, 13(21), 4347. https://doi.org/10.3390/rs13214347

Kim, J., Seo, D., and Jones, J. R. (2022). Harmful algal bloom dynamics in a tidal river influenced by hydraulic control structures. Ecological Modelling, 467. https://doi.org/10.1016/j.ecolmodel.2022.109931

Kurekin, A. A., Miller, P. I., and Van der Woerd, H. J. (2014). Satellite discrimination of Karenia mikimotoi and Phaeocystis harmful algal blooms in European coastal waters: Merged classification of ocean colour data. Harmful Algae, 31, 163-176. https://doi.org/10.1016/j.hal.2013.11.003

Letelier, R., and Abbott, M. (1996). An analysis of chlorophyll fluorescence algorithms for the moderate resolution imaging spectrometer (MODIS). Remote Sensing of Environment, 58(2), 215-223. https://doi.org/10.1016/S0034-4257(96)00073-9

Lin, J., Miller, P. I., Jönsson, B. F., and Bedington, M. (2021). Early Warning of Harmful Algal Bloom Risk Using Satellite Ocean Color and Lagrangian Particle Trajectories. Frontiers in Marine Science, 8. https://doi.org/10.3389/fmars.2021.736262

Ma, J., Jin, S., Li, J., He, Y., and Shang, W. (2021). Spatio-Temporal Variations and Driving Forces of Harmful Algal Blooms in Chaohu Lake: A Multi-Source Remote Sensing Approach. Remote Sensing, 13(3), 427. https://doi.org/10.3390/rs13030427

Mardones, J. I., Paredes-Mella, J., Flores-Leñero, A., Yarimizu, K., Godoy, M., Artal, O., Corredor-Acosta, A., Marcus, L., Cascales, E., Pablo Espinoza, J., Norambuena, L., Garreaud, R. D., González, H. E., and Iriarte, J. L. (2023). Extreme harmful algal blooms, climate change, and potential risk of eutrophication in Patagonian fjords: Insights from an exceptional Heterosigma akashiwo fish-killing event. Progress in Oceanography, 210. https://doi.org/10.1016/j.pocean.2022.102921

Minic, S. L., Milcic, M., Stanic-Vucinic, D., Radibratovic, M., Sotiroudis, T. G., Nikolic, M. R., and Velickovic, T. C. (2015). Phycocyanobilin, a bioactive tetrapyrrolic compound of blue-green alga Spirulina, binds with high affinity and competes with bilirubin for binding on human serum albumin. RSC Advances, 5(76), 61787-61798. https://doi.org/10.1039/c5ra05534b

Mishra, D. R., Kumar, A., Ramaswamy, L., Boddula, V. K., Das, M. C., Page, B. P., and Weber, S. J. (2020). CyanoTRACKER: A cloud-based integrated multi-platform architecture for global observation of cyanobacterial harmful algal blooms. Harmful Algae, 96, 101828. https://doi.org/10.1016/j.hal.2020.101828

Moron-Lopez, J., Rodriguez-Sanchez, M. C., Carreno, F., Vaquero, J., Pompa-Pernia, A. G., Mateos-Fernandez, M., and Pascual Aguilar, J. A. (2021). Implementation of Smart Buoys and Satellite-Based Systems for the Remote Monitoring of Harmful Algae Bloom in Inland Waters. IEEE Sensors Journal, 21(5), 6990-6997. https://doi.org/10.1109/JSEN.2020.3040139

Qian, J., Qian, L., Pu, N., Bi, Y., Wilhelms, A., and Norra, S. (2024). An Intelligent Early Warning System for Harmful Algal Blooms: Harnessing the Power of Big Data and Deep Learning. Environmental Science and Technology, 58(35), 15607-15618. https://doi.org/10.1021/acs.est.3c03906

Ralston, D. K., and Moore, S. K. (2020). Modeling harmful algal blooms in a changing climate. Harmful Algae, 91, 101729. https://doi.org/10.1016/j.hal.2019.101729

Rezazadegan, R., Sharifzadeh, M., and Magee, C. L. (2024). Quantifying the progress of artificial intelligence subdomains using the patent citation network. Scientometrics, 129(5), 2559-2581. https://doi.org/10.1007/s11192-024-04996-3

Robledo, S., Duque, P., and Aguirre, A. M. G. (2023). Word of Mouth Marketing: A Scientometric Analysis. Journal of Scientometric Research, 11(3), 436-446. https://doi.org/10.5530/jscires.11.3.47

Robledo, S., Vasquez, J. E., Duque3-Méndez, N. D., and Duque-Uribe, V. (2023). Networking as an entrepreneurial marketing tool: the link between effectuation and word of mouth. Journal of Research in Marketing and Entrepreneurship, 25(2), 270-285. https://doi.org/10.1108/JRME-08-2020-0112

Robledo, S., Zuluaga, M., Valencia-Hernandez, L.-A., Arbelaez-Echeverri, O. A.-E., Duque, P., and Alzate-Cardona, J.-D. (2022). Tree of Science with Scopus: A Shiny Application. Issues in Science and Technology Librarianship, (100). https://doi.org/10.29173/istl2698

Rodríguez-Benito, C. V., Navarro, G., and Caballero, I. (2020). Using Copernicus Sentinel-2 and Sentinel-3 data to monitor harmful algal blooms in Southern Chile during the COVID-19 lockdown. Marine Pollution Bulletin, 161, 111722. https://doi.org/10.1016/j.marpolbul.2020.111722

Ruiz-Rosero, J., Ramirez-Gonzalez, G., and Viveros-Delgado, J. (2019). Software survey: ScientoPy, a scientometric tool for topics trend analysis in scientific publications. Scientometrics, 121(2), 1165-1188. https://doi.org/10.1007/s11192-019-03213-w

Sellner, K. G., Doucette, G. J., and Kirkpatrick, G. J. (2003). Harmful algal blooms: causes, impacts and detection. Journal of Industrial Microbiology and Biotechnology, 30(7), 383-406. https://doi.org/10.1007/s10295-003-0074-9

Shen, L., Xu, H., and Guo, X. (2012). Satellite Remote Sensing of Harmful Algal Blooms (HABs) and a Potential Synthesized Framework. Sensors, 12(6), 7778-7803. https://doi.org/10.3390/s120607778

Shimasaki, Y., Mukai, K., Takai, Y., Qiu, X., and Oshima, Y. (2021). Recent progress in the study of peroxiredoxin in the harmful algal bloom species chattonella marina. Antioxidants, 10(2), 1-22. https://doi.org/10.3390/antiox10020162

Siswanto, E., Ishizaka, J., Tripathy, S. C., and Miyamura, K. (2013). Detection of harmful algal blooms of Karenia mikimotoi using MODIS measurements: A case study of Seto-Inland Sea, Japan. Remote Sensing of Environment, 129, 185-196. https://doi.org/10.1016/j.rse.2012.11.003

Smith, M. E., and Bernard, S. (2020). Satellite Ocean Color Based Harmful Algal Bloom Indicators for Aquaculture Decision Support in the Southern Benguela. Frontiers in Marine Science, 7. https://doi.org/10.3389/fmars.2020.00061

Stroski, K. M., Roelke, D. L., Kieley, C. M., Park, R., Campbell, K. L., Klobusnik, N. H., Walker, J. R., Cagle, S. E., Labonté, J. M., and Brooks, B. W. (2024). What, How, When, and Where: Spatiotemporal Water Quality Hazards of Cyanotoxins in Subtropical Eutrophic Reservoirs. Environmental Science and Technology, 58(3), 1473-1483. https://doi.org/10.1021/acs.est.3c06798

Stumpf, R. P., Wynne, T. T., Baker, D. B., and Fahnenstiel, G. L. (2012). Interannual Variability of Cyanobacterial Blooms in Lake Erie. PLoS ONE, 7(8), e42444. https://doi.org/10.1371/journal.pone.0042444

Summers, E. J., and Ryder, J. L. (2023). A critical review of operational strategies for the management of harmful algal blooms (HABs) in Inland reservoirs. Journal of Environmental Management, 330. https://doi.org/10.1016/j.jenvman.2022.117141

Sun, X., Wang, X., Han, Q., Yu, Q., Wanyan, R., and Li, H. (2024). Bibliometric analysis of papers on antibiotic resistance genes in aquatic environments on a global scale from 2012 to 2022: Evidence from universality, development and harmfulness. Science of The Total Environment, 909, 168597. https://doi.org/10.1016/j.scitotenv.2023.168597

Tester, P., and Stumpf, R. (1998). Phytoplankton blooms and remote sensing: What is the potential for early warning. Journal of Shellfish Research, 17, 1469-1471.

Tobin, E. D., Grünbaum, D., Patterson, J., and Cattolico, R. A. (2013). Behavioral and Physiological Changes during Benthic-Pelagic Transition in the Harmful Alga, Heterosigma akashiwo: Potential for Rapid Bloom Formation. PLoS ONE, 8(10). https://doi.org/10.1371/journal.pone.0076663

Tomlinson, M. C., Wynne, T. T., and Stumpf, R. P. (2009). An evaluation of remote sensing techniques for enhanced detection of the toxic dinoflagellate, Karenia brevis. Remote Sensing of Environment, 113(3), 598-609. https://doi.org/10.1016/j.rse.2008.11.003

Trainer, V. L., Moore, S. K., Hallegraeff, G., Kudela, R. M., Clement, A., Mardones, J. I., and Cochlan, W. P. (2020). Pelagic harmful algal blooms and climate change: Lessons from nature's experiments with extremes. Harmful Algae, 91, 101591. https://doi.org/10.1016/j.hal.2019.03.009

Urina-Triana, M. A., Piñeres-Melo, M. A., Mantilla-Morrón, M., Butt-Aziz, S., Galeano-Muñoz, L., Naz, S., and Ariza-Colpas, P. P. (2024). Machine Learning and AI Approaches for Analyzing Diabetic and Hypertensive Retinopathy in Ocular Images: A Literature Review. IEEE Access, 12, 54590-54607. https://doi.org/10.1109/ACCESS.2024.3378277

Valencia-Hernandez, D. S., Robledo, S., Pinilla, R., Duque-Méndez, N. D., and Olivar-Tost, G. (2020). SAP Algorithm for Citation Analysis: An improvement to Tree of Science. Ingeniería e Investigación, 40(1), 45-49. https://doi.org/10.15446/ing.investig.v40n1.77718

Vivares, J. A., Avella, L., and Sarache, W. (2022). Trends and challenges in operations strategy research: Findings from a systematic literature review. Cuadernos de Gestión, 22(2), 81-96. https://doi.org/10.5295/cdg.211543ja

Wang, K., Mou, X., Cao, H., Struewing, I., Allen, J., and Lu, J. (2021). Co-occurring microorganisms regulate the succession of cyanobacterial harmful algal blooms. Environmental Pollution, 288, 117682. https://doi.org/10.1016/j.envpol.2021.117682

Wells, M. L., Trainer, V. L., Smayda, T. J., Karlson, B. S. O., Trick, C. G., Kudela, R. M., Ishikawa, A., Bernard, S., Wulff, A., Anderson, D. M., and Cochlan, W. P. (2015). Harmful algal blooms and climate change: Learning from the past and present to forecast the future. Harmful Algae, 49, 68-93. https://doi.org/10.1016/j.hal.2015.07.009

Xu, G., Li, X., Liu, X., Han, J., Shao, K., Yang, H., Fan, F., Zhang, X., and Dou, J. (2024). Bibliometric insights into the evolution of uranium contamination reduction research topics: Focus on microbial reduction of uranium. Science of The Total Environment, 917, 170397. https://doi.org/10.1016/j.scitotenv.2024.170397

Yan, Z., Kamanmalek, S., Alamdari, N., and Nikoo, M. R. (2024). Comprehensive Insights into Harmful Algal Blooms: A Review of Chemical, Physical, Biological, and Climatological Influencers with Predictive Modeling Approaches. Journal of Environmental Engineering (United States), 150(4). https://doi.org/10.1061/JOEEDU.EEENG-7549

Yan, Z., Kamanmalek, S., and Alamdari, N. (2024). Predicting coastal harmful algal blooms using integrated data-driven analysis of environmental factors. Science of The Total Environment, 912, 169253. https://doi.org/10.1016/j.scitotenv.2023.169253

Yu, Y., Wang, S., Yu, P., Wang, D., Hu, B., Zheng, P., and Zhang, M. (2024). A bibliometric analysis of emerging contaminants (ECs) (2001–2021): Evolution of hotspots and research trends. Science of The Total Environment, 907, 168116. https://doi.org/10.1016/j.scitotenv.2023.168116

Yussof, F. N., Maan, N., Md Reba, M. N., and Khan, F. A. (2022). Mathematical Modelling of Harmful Algal Blooms on West Coast of Sabah. Mathematics, 10(16), 2836. https://doi.org/10.3390/math10162836

Zhou, Z.-X., Yu, R.-C., and Zhou, M.-J. (2022). Evolution of harmful algal blooms in the East China Sea under eutrophication and warming scenarios. Water Research, 221, 118807. https://doi.org/10.1016/j.watres.2022.118807

Zuluaga, M., Robledo, S., Arbelaez-Echeverri, O., Osorio-Zuluaga, G. A., and Duque-Méndez, N. (2022). Tree of Science - ToS: A Web-Based Tool for Scientific Literature Recommendation. Search Less, Research More! Issues in Science and Technology Librarianship, (100). https://doi.org/10.29173/istl2696

Cite this article: Rojas JCR, Castaño NVN, León MVS, Acevedo NA, Aricapa JAV, Parra ER. Scientometric Trends in Harmful Algal Bloom Prediction: Integrating Optical Remote Sensing and Mathematical Models (2000-2024). J Scientometric Res. 2026;15(1):294-309.