Six decades (1965–2025) of phytoplankton absorption research: a bibliometric and systematic review with insights from the past decade

remote sensing

Systematic Review

Six Decades (1965–2025) of Phytoplankton Absorption Research: A Bibliometric and Systematic Review with Insights from the Past Decade

Mohammad Ashphaq [1,2] and Shovonlal Roy [2,*]

[1] Abu Dhabi Maritime, Abu Dhabi 54477, United Arab Emirates; ashphaq@gmail.com
[2] Department of Geography and Environmental Science, University of Reading, Reading RG6 6DW, UK
[*] Correspondence: shovonlal.roy@reading.ac.uk

Highlights

What are the main findings?

- A comprehensive bibliometric analysis reports the growth of research in the field and its evolution from thematic convergence to methodological divergence over six decades.
- The study identifies challenges in resolving optical degeneracy, vertical structure acquisition, and scaling methods for operational use of phytoplankton absorption from remote sensing.

What are the implications of the main findings?

- The increasing methodological diversity requires better integration and standardization to ensure consistent and reliable adoption of phytoplankton absorption-related research.
- Addressing the main challenges, such as optical complexity and scalability, will be essential for improving satellite-based retrievals of phytoplankton absorption for broader use in ocean monitoring and climate-related applications.

Abstract

Phytoplankton are primary producers in the aquatic ecosystems whose pigments, cell size, and physiological state affect how they absorb light and fix carbon. The phytoplankton absorption coefficient ($a_{ph}(\lambda)$) in the visible spectrum is a fundamental cellular optical property that determines phytoplankton–light interactions in the marine environment. This property links biological processes to ocean color remote sensing reflectance (*Rrs*), enabling an assessment of environmental and biogeochemical conditions in the ocean using ocean color satellites. This study presents a multi-stage systematic review of six decades (1965–2025) of $a_{ph}(\lambda)$ research, with a focused synthesis of developments in the past decade. A bibliometric analysis empirically examines the research growth of the field and its thematic convergence into methodological divergence across six decades. Cluster analysis was used to compile influential research topics as well as emerging trends, to determine the scope and design of the systematic review. A focused systematic review of studies in the past decade (2015–2025) has been carried out to identify conceptual and theoretical advances, major observational and algorithmic improvements, and ongoing challenges. The data analyses highlight the accuracy achieved by various studies, the complexity of applications of algorithms, and product-focused developments. The ongoing challenges identified include resolving optical degeneracy, vertical structure acquisition, and scaling methods for operational use. This review concludes the centrality of $a_{ph}(\lambda)$ as a key parameter to next-generation ocean color science, biogeochemical modeling, and climate-related ecosystem monitoring.

Academic Editor: Weimin Huang

Received: 27 April 2026
Revised: 6 June 2026
Accepted: 10 June 2026
Published: 22 June 2026

Keywords: phytoplankton absorption; ocean color remote sensing; machine learning; climate change; bibliometric analysis

1. Introduction

Phytoplankton are microscopic photoautotrophs that play a crucial role in regulating the global oceanic biogeochemical cycle and marine ecosystems dynamics. As the primary source of marine primary production, phytoplankton facilitate approximately 50% of global net carbon fixation [1], and are integral to the function as a biological carbon pump that exerts a critical regulatory control on atmospheric CO_2 and produces more than half of global O_2 [2]. They also help cycle key nutrients such as nitrogen, phosphorus, silica, and others [3]. The phytoplankton's composition, their biomass, and their physiological health are sensitive to environmental factors such as temperature and available sunlight. Thus, phytoplankton serves as a good indicator of ocean health, fishery productivity, and the ecosystem's response to changes due to climate and anthropogenic factors [4]. The apparent shifts in the community structure of diatoms, coccolithophores, cyanobacteria (e.g., Prochlorococcus), and dinoflagellates impact trophic transfer efficiency, carbon export, and seawater optical properties. These variations have significantly affected nutrient cycling and carbon dynamics in marine ecosystems in the past decade [5,6].

Accurate synoptic measurement of phytoplankton biomass, along with the classification of phytoplankton functional types (PFTs) or phytoplankton size classes (PSCs), is a major goal of contemporary marine remote sensing and biogeochemical oceanography. These observations and analyses are essential for understanding oceanic biological processes and carbon cycling [7,8]. The measurement of phytoplankton properties using ocean color radiometry tools relies on an associative relationship between the water-leaving radiance and the bulk inherent optical properties (IOPs) of the water column. Phytoplankton predominantly influence these IOPs by absorbing the light with their pigments [9,10]. The available advanced hyperspectral sensors and multi-variable algorithms use spectral IOP signatures for chlorophyll measurements, as well as allow for detailed analysis of pigment compositions and carbon-based biomass. This also supports improving more sophisticated marine carbon cycle models [11–13].

The empirical groundwork of ocean color remote sensing was established through numerical modeling of core radiative transfer equations [14] on bio-optical models, further extended to pigment packaging within phytoplankton cells [15] on the foundational Case I/Case II water classification paradigm [16], and atmospheric correction [17]. The subsequent shift to physics-based, semi-analytical ocean color inversion was enabled by pivotal algorithms like the globally optimized GSM model [18], the IOP-deriving quasi-analytical algorithm [19], supported by advances in aerosol modeling and global bio-optical datasets [20]. More recently, machine learning and deep learning are being explored to model complex, non-linear relationships between *Rrs* and IOPs, outperforming traditional methods in complex waters [21,22]. However, one of the major challenges in ocean color remote sensing remains the precise partitioning of the IOPs into their individual constituents. This is a key requirement for retrieving critical ocean biogeochemical parameters useful for studying climate impacts.

Despite six decades of rapidly expanding, cross-disciplinary research, a critical synthesis gap persists in the existing marine remote-sensing reviews [23–27], which have not explicitly traced the conceptual and methodological evolution of the studies involving $a_{ph}(\lambda)$ coefficients. This is particularly critical at this juncture, as $a_{ph}(\lambda)$ serves as a key bio-optical variable at the intersection of several intradisciplinary research areas related to marine ecology, biogeochemistry, and ocean color research. For example, among the several vital IOPs, $a_{ph}(\lambda)$ needs the highest spectral accuracy as its precise inversion is fundamental for deriving climate-critical variables like phytoplankton carbon biomass [28,29], functional types [30], and physiological diagnostics [31–33]. Also, the $a_{ph}(\lambda)$ serves as the critical bio-optical variable for taxonomic/functional group identification using accessory pigment features [34,35] and biogeochemical model integration to govern spectral light fields and primary production [36,37]. An integrated bibliometric and systematic assessment is timely and necessary to consolidate the foundational and applied research on phytoplankton absorption and identify pathways for its advancement.

Bibliometric analyses have been accepted as a crucial method for synthesizing the expansive and vast interdisciplinary literature. In marine remote sensing studies, they have elucidated the methodological evolution from empirical band ratio approaches to semi-analytical inversions as well as contemporary machine learning frameworks [38,39]. Thus, these methods can be applied to the $a_{ph}(\lambda)$ literature to systematically identify foundational studies, key transitions to the several sub-fields, and the collaborative dynamics driving ongoing research advances. Systematic reviews reflect an unbiased evidence synthesis of the existing literature [40], hence are critical for benchmarking algorithm performance in marine remote sensing research [41–43], evaluating phytoplankton functional type methods [44,45], quantify the estimation accuracy [46], validating physiological proxies [47], and mapping the key data gaps in the $a_{ph}(\lambda)$ research [48].

The objectives of this study are as follows: (1) to address the longstanding synthesis gap in $a_{ph}(\lambda)$ research by systematically evaluating spectral-resolution trade-offs among sensors and critically assessing the accuracy and ecological interpretability of machine learning versus physics-based retrievals, and (2) to synthesize the progress in integrating high-resolution in situ and satellite data to reconcile methodological gaps and challenges. To achieve these objectives, this study uses a dual methodological framework that combines bibliometrics to map the literature with a systematic review to critically evaluate evidence, providing a holistic benchmark for $a_{ph}(\lambda)$ research. The study will be able to guide future multispectral and hyperspectral algorithm selection and optimize the application of $a_{ph}(\lambda)$ in ocean ecology.

2. Six Decades (1965–2025) of Phytoplankton Absorption: Bibliometric Analysis

This study employs a bibliometric framework, beginning with clearly defined research objectives and implementing a triangulated data-sourcing strategy across well-known systematic databases, such as Scopus and Web of Science (WoS), as well as AI-based sources, such as Dimensions, CORE, Semantic Scholar and the widely used Google Scholar database, to comprehensively capture the interdisciplinary scope and citation impact on the literature of $a_{ph}(\lambda)$ research. The multi-source literature was merged and deduplicated using Python algorithms (by keys DOI, title similarity, author name, and journal), then subjected to descriptive statistics, network analyses, and convergent multi-dimensional impact profiling. This revealed publication trends, collaboration patterns, thematic evolution, and persistent research gaps, which provided a robust and evidence-based map of the $a_{ph}(\lambda)$ research landscape. The methodology is shown in the Figure 1 flowchart below. The entire data processing was carried out by scripting Python code using various Python libraries (including *pandas* and *NumPy* for data handling; *re*, *Counter*, and *itertools* for text preprocessing; *TF-IDF Vectorizer* and *KMeans* for keyword extraction and clustering; *SentenceTransformers* for semantic analysis; and *Matplotlib*, *Seaborn*, *Plotly*, and *WordCloud* for data visualization) for bibliometric analysis and data visualization for this study.

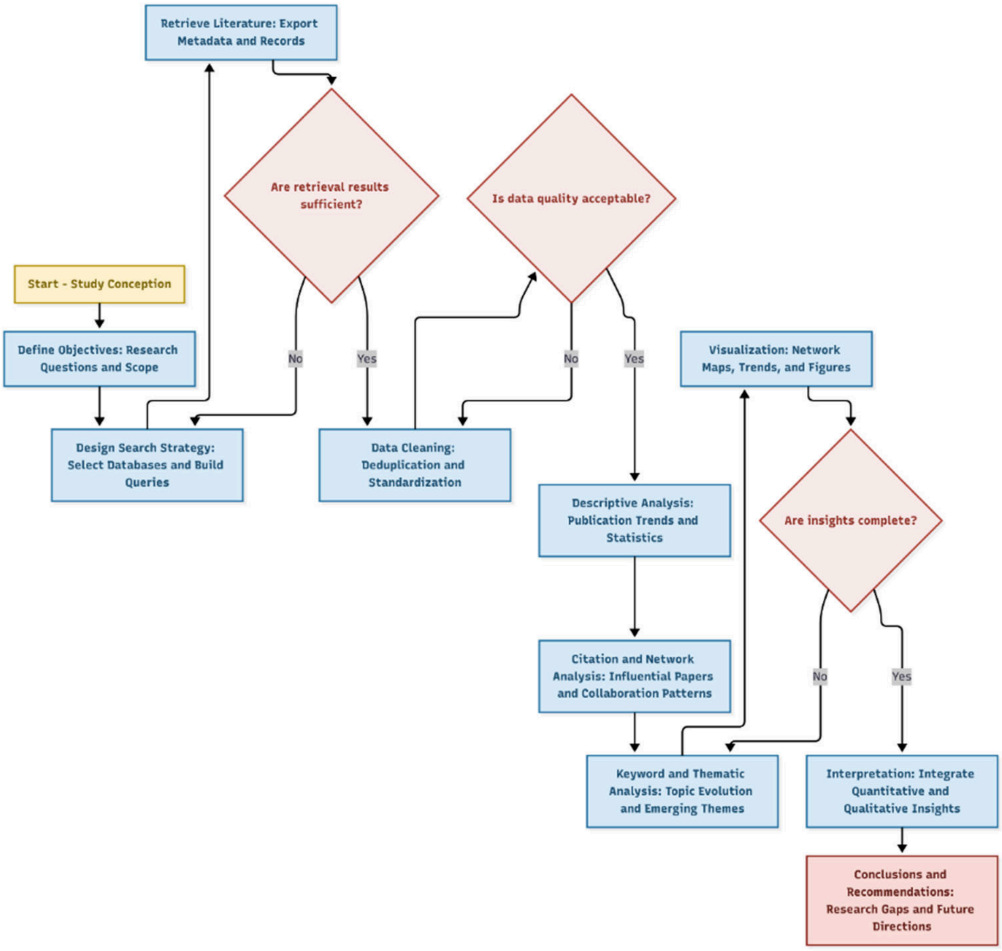


Figure 1. Flowchart of Bibliometric Analysis Methodology.

Table 1 below outlines the key statistical methods used in the study to process and analyze the bibliometric data, along with Python libraries, used in each technique. The tools used below enabled us to represent data structurally as well as support evidence-driven interpretation of trends, relationships, and thematic convergence of the dataset.

Table 1. Statistical methods and Python libraries used in this study.

Statistical Method	Descriptive Use in Study	Indices	Python Library
TF–IDF (with n-grams, df filtering)	Keyword extraction and weighting from abstracts	TF × IDF; IDF = log(N/df)	sklearn (TfidfVectorizer)
Text normalization (regex + mapping)	Standardizes scientific terms before analysis	Rule-based mapping	re, pandas
K-means clustering	Grouping abstracts into thematic clusters	To minimize within-cluster SS	sklearn.cluster.KMeans
Frequency analysis and citation metrics	Counts authors, years, citations; measures productivity and impact	Value counts; citations/article	pandas, numpy, collections. Counter, SentenceTransformers
Correlation analysis, linear regression, summary statistics	To analyze the relation between models, trends across variables, and the dataset description	Pearson r, R^2, RMSE, MAE, other aggregations	numpy.polyfit, sklearn, Matplotlib, Seaborn, Plotly, and WordCloud

2.1. Database Search by Keywords:

Although Scopus and Web of Science have traditionally dominated bibliometric studies, newer AI platforms such as Dimensions, CORE, Semantic Scholar, and Google Scholar offer broader coverage, open-access content, and diverse indexing, allowing for more complete assessments of the literature. We applied both Topic searches (scanning titles, abstracts, and keywords for breadth) and Title searches (for exact matches) using a hierarchical keyword search of "Remote Sensing", "Phytoplankton", and "Phytoplankton Absorption". Also, the keyword "Remote Sensing" was refined by "Ocean Color" and then "Phytoplankton Absorption". This approach identified 3774 articles after removing duplicates from 5312 articles across databases related to the objective of the study, including 397 exclusively focused on a_{ph} (λ) and 164 solely from ocean color retrieval. Figure 2 below depicts the search results for each keyword.

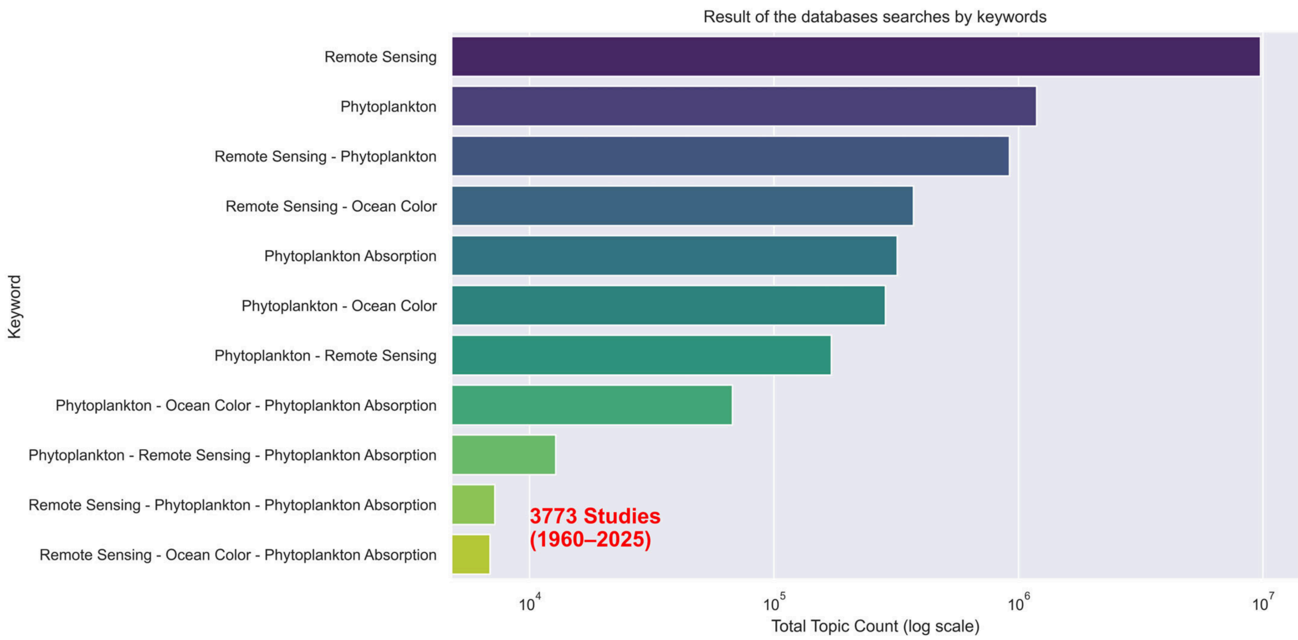


Figure 2. Result of the database searches by keywords.

As shown in Figure 3, *Topic* searches consistently yielded higher counts than *Title* searches, and database-specific variability, e.g., Semantic Scholar's high Title counts versus lower combined keyword retrieval in Google Scholar, illustrates how platform architecture and indexing practices critically influence the literature coverage. Broad keywords dominated overall retrieval, whereas combined and tertiary keywords captured specialized niches, revealing an exponential decay in the literature volume with increasing thematic specificity, such as "Remote Sensing" (up to 3.29 M *Topic* counts in Google Scholar) versus the precise niche "Remote Sensing–Ocean Color–Phytoplankton Absorption" (only two *Title* counts in Scopus/WoS). In comparison to the curated journal selections with keyword-based text mining tools, it becomes evident that text-derived keywords less consistently reflect the focus of the research. Instead, these curated keywords often provide contextual descriptors rather than core research objectives. Therefore, author-specific text-search tools underscore the necessity of alternate methodological approaches to achieve comprehensive literature coverage. It is also needed for integrating multiple data sources, minimizing omission prejudice, and ensuring a comprehensive and unbiased literature assessment.

The significant bibliometric contrast between high-context *Topic* mentions and low-frequency *Title* occurrences for focused terms like "Phytoplankton Absorption" empirically signifies the distinction between primary research focus and broad thematic discourse of the field. The most specific triadic *Title* niche, "Remote Sensing-Ocean Color-Phytoplankton Absorption", is almost absent as a primary focus of the research (with only two *Title* occurrences in the curated databases). This pattern suggests that the field has reached a high level of methodological maturity, but research specifically focused on the accurate retrieval remains narrowly concentrated. The analysis of *Topic* counts reveals a steep, non-linear decay in the literature volume with increasing thematic specificity. The different database search engine architecture critically biases absolute scale, with full-text engines (Google Scholar, Semantic Scholar) inflating counts up to three orders of magnitude compared to the curated indexes (Scopus, WoS). However, the hierarchical search results remain consistent across all source databases. The overall summary of bibliometric analysis is depicted in Figure 4.

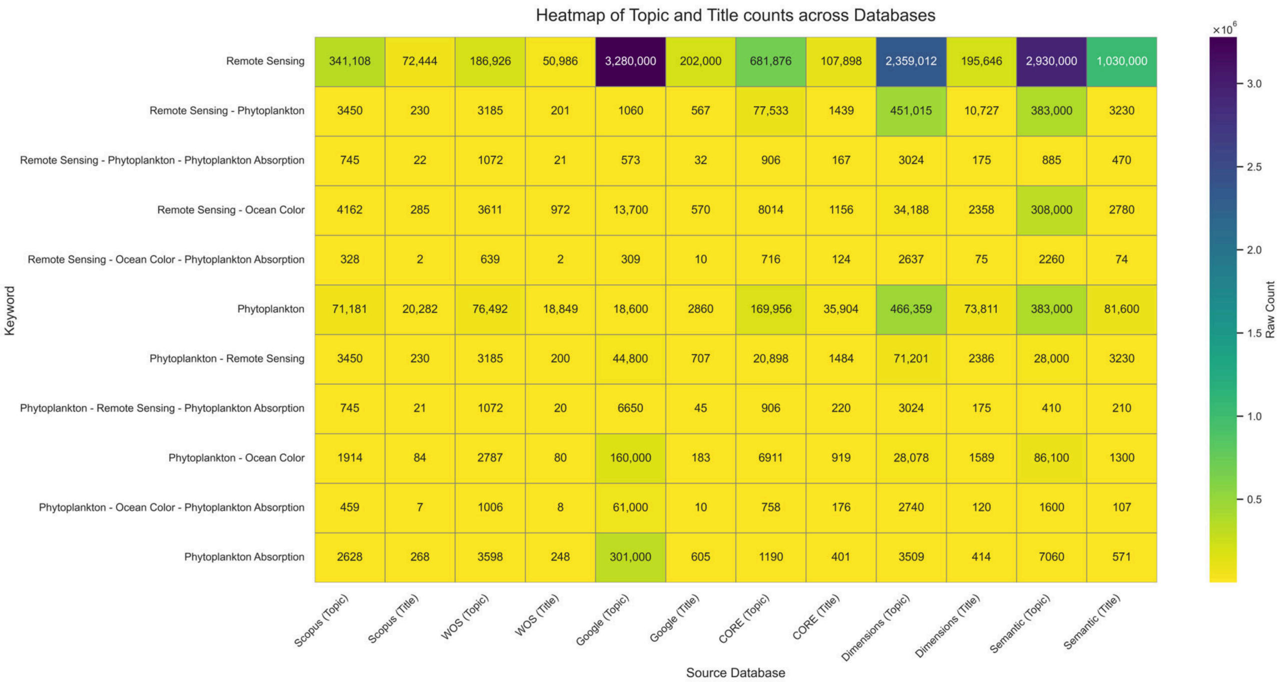


Figure 3. Search results for bibliometric analysis.

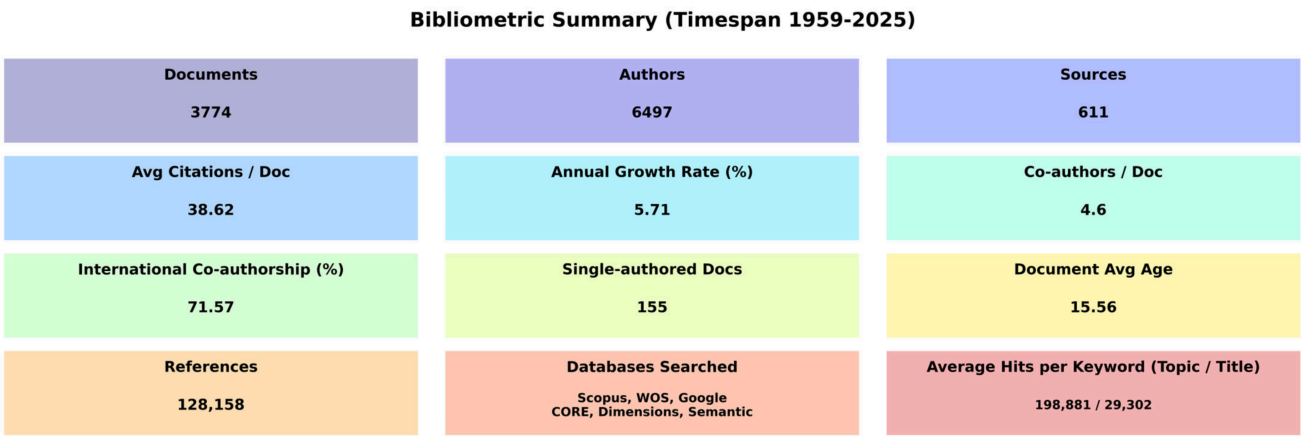


Figure 4. Summary of bibliometric analysis.

2.2. Publication Trend Analysis (1959–2025)

The bibliometric trajectory of a_{ph} (λ) research exhibits discrete paradigm shifts in three major phases described in the following. First, a foundational phase (1959–1990) with minimal annual output (<10) corresponding to theoretical optics and pre-satellite bio-optical parameterization, e.g., noted works of [14,49,50]. Second, an exponential growth phase (1991–2012), where publications surged to ~196 annually, driven by the operationalization of ocean color sensors (e.g., SeaWiFS, MODIS) and the maturation of semi-analytical inversion algorithms (e.g., noted works of [18,19]). Third, a sustained high-output phase (2013–2025), characterized by ~195 outputs annually, which indicates field maturation and methodological diversification into several major themes (e.g., hyperspectral retrievals, physiological diagnostics, and machine learning approaches). The publication trend has been depicted below in Figure 5.

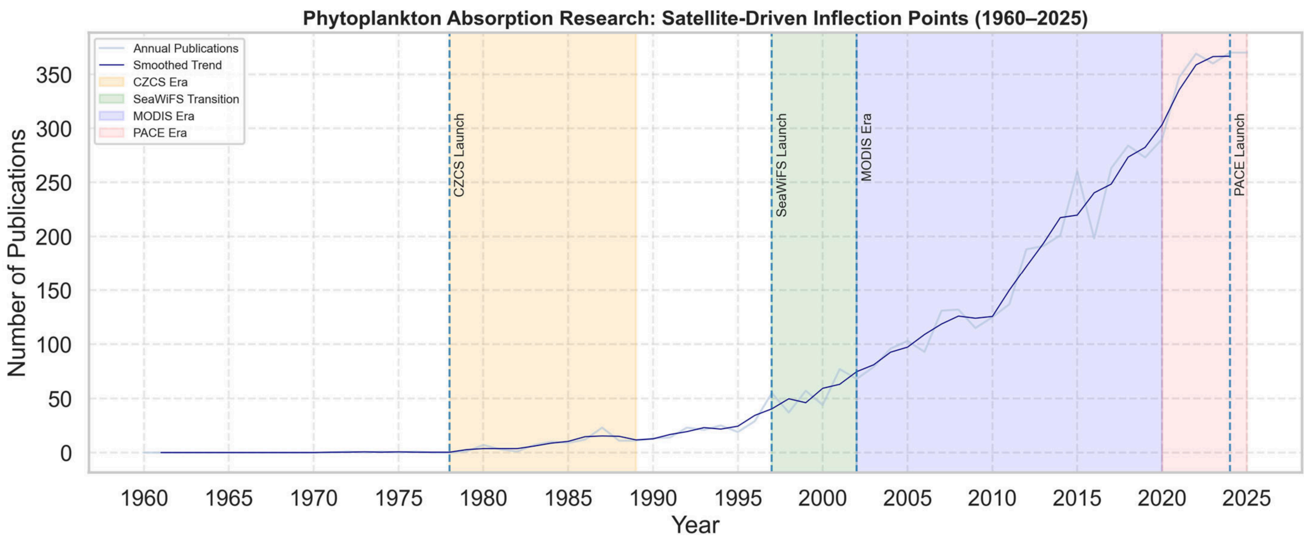


Figure 5. Publication trend analysis.

The plot shown in Figure 6 below depicts the cumulative distribution of publications across 20 journals, illustrating Bradford's Law [51] in scientific publishing. Journals are ordered on the x-axis (as represented by publication title) by their increasing cumulative contribution, and the y-axis shows the cumulative percentage of publications. The curve reveals a characteristic Bradfordian pattern, with a core group of *publication titles* accounting for a disproportionately higher share of publications and a long tail of less prolific journal sources. This distribution confirms the predicted "*stratification*" by Bradford's Law, signifying its relevance in the marine science, remote sensing, and environmental science literature.

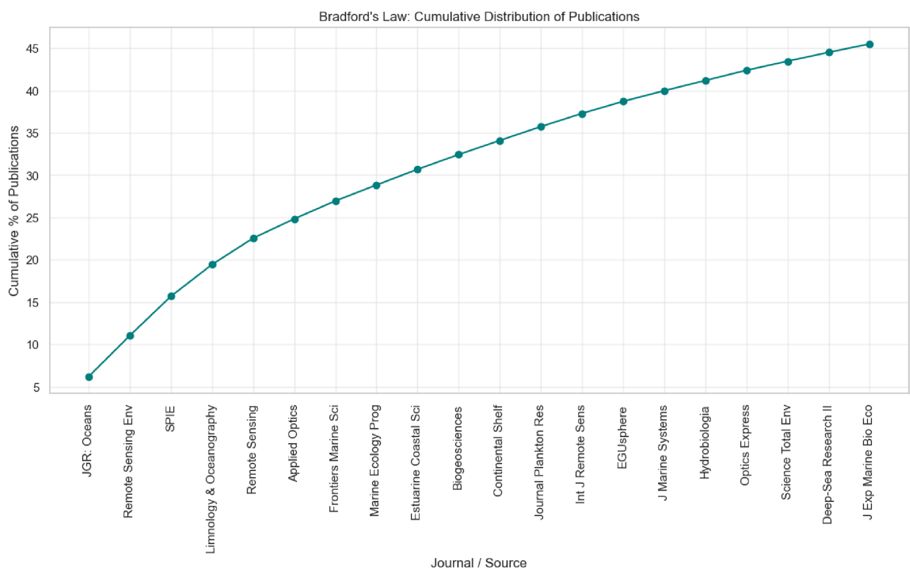
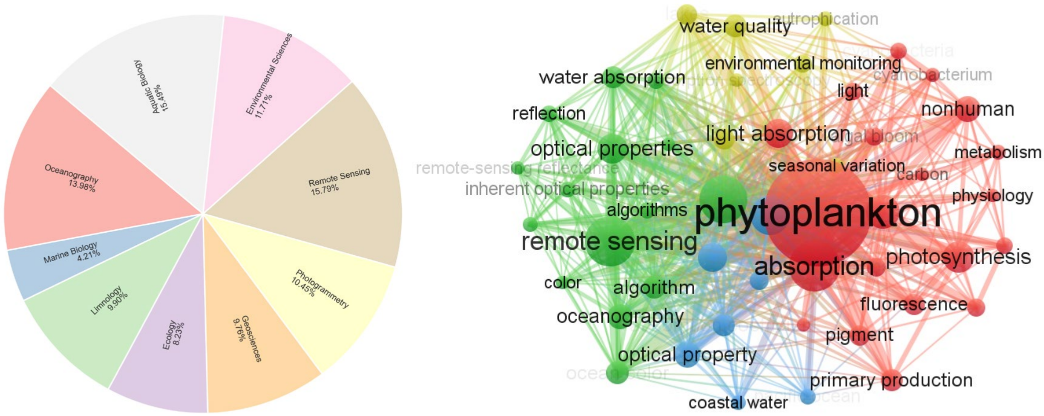


Figure 6. Bradford's curve in the distribution of publications.

2.3. Research Areas and Keywords Analysis

The research areas have been depicted below in Figure 7a; they show the oceanographic research, comprising 34.3% of the total studies, followed by aquatic biology research, 26% of the total studies, and environmental sciences, 21.7% the total studies. The other studies include research domains like remote sensing, photogrammetry, geosciences, ecology, optics, and limnology, each contributing to the marine ecosystem research. The keyword analysis included a dataset comprising 13,301 curated keywords by setting thresholds of 20 and 140 occurrences based on the interquartile range. The 402 keywords meet the 20-occurrence criterion, and only 35 meet the stricter 140-occurrence threshold, emphasizing the most relevant terms as shown below in Figure 7b.



(**a**) (**b**)

Figure 7. (**a**) Research areas and (**b**) keyword network analysis.

Based on the TF-IDF score (term frequency–inverse document frequency, which refers to a numerical measure that indicates the importance of a word to a document relative to a collection of documents, computed using key terms extracted from the abstracts of the papers), a word cloud is shown in Figure 8 above, indicating a focus on phytoplankton blooms, absorption, chlorophyll-a, and remote sensing terms as central themes. Prominent terms that emphasize quantifying physiological responses and estimating productivity under varying environmental conditions are significantly depicted in the word cloud.

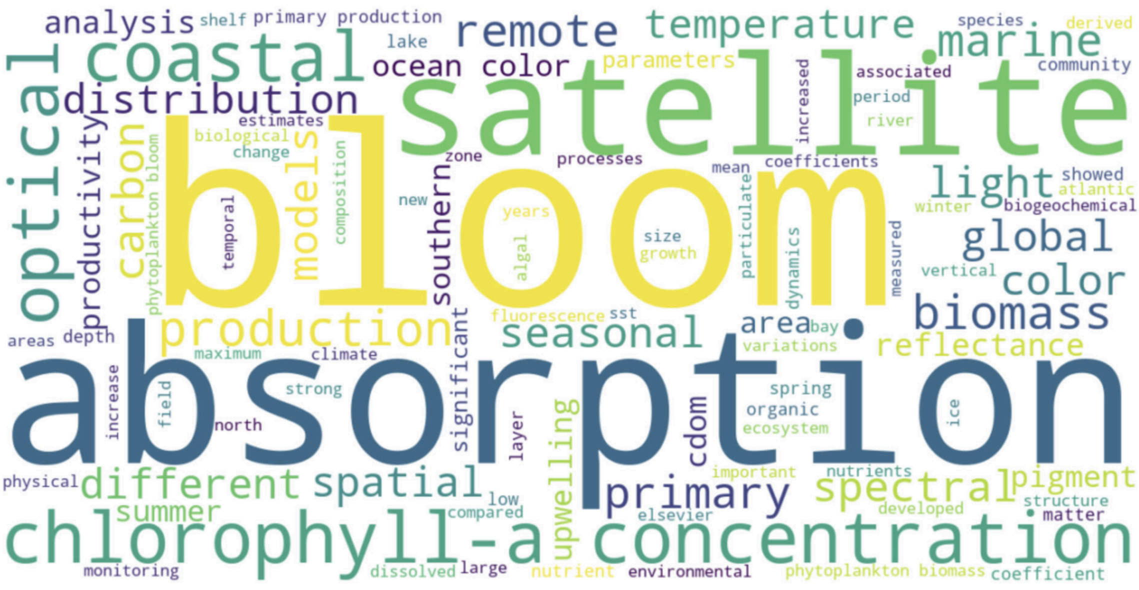


Figure 8. High-value keyword word cloud.

2.4. Journals and Authors

The plot shown in Figure 9 highlights the top 15 *publication titles* by record count on the x-axis of the plot. These publications, including *Journal of Geophysical Research Oceans*, *Remote Sensing of Environment*, *Proceedings of SPIE*, and *Limnology and Oceanography*, collectively represent a significant portion of the literature in these domains. Figure 10a shows the top 15 authors in terms of the number of their papers published, where S. Sathyendranath leads with approximately 155 coauthored articles, followed by Y. Zhang (~110) and R.J.W. Brewin (~95), making them the top three productive authors in this field. The data exhibit a wide range of productivity and influence, with citations per article varying from about 9 to 195. M. J. Behrenfeld [28,31,32] records the highest citations per article (~195), followed by M. Kahru with ~79 citations per article and S. Sathyendranath [15,24,29,30,50] having ~64 citations per article, signifying the strong influence on the publications related to a_{ph} (λ). The results displayed here are specific to a_{ph} (λ) publications, wherein the overall contribution of these researchers is much higher in the marine science domain.

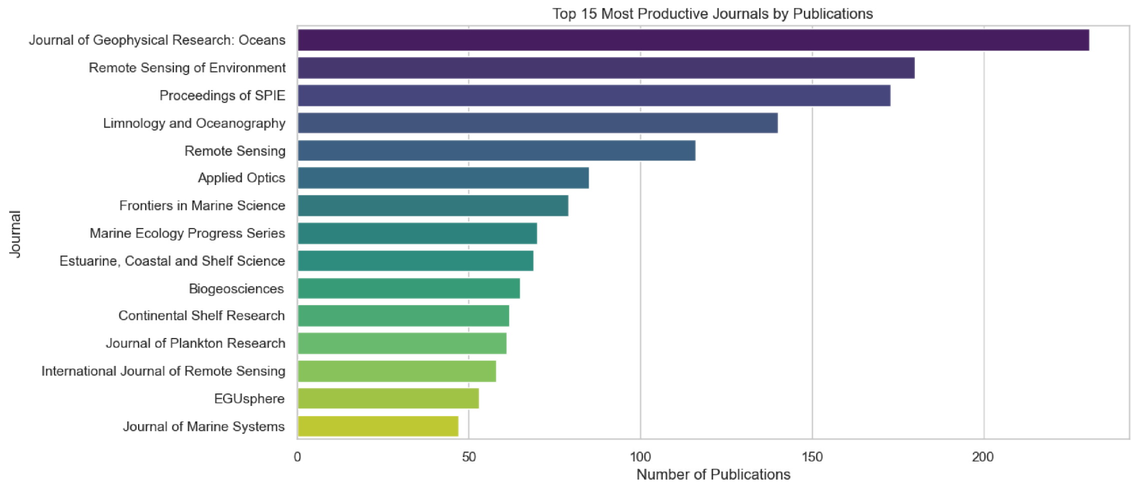
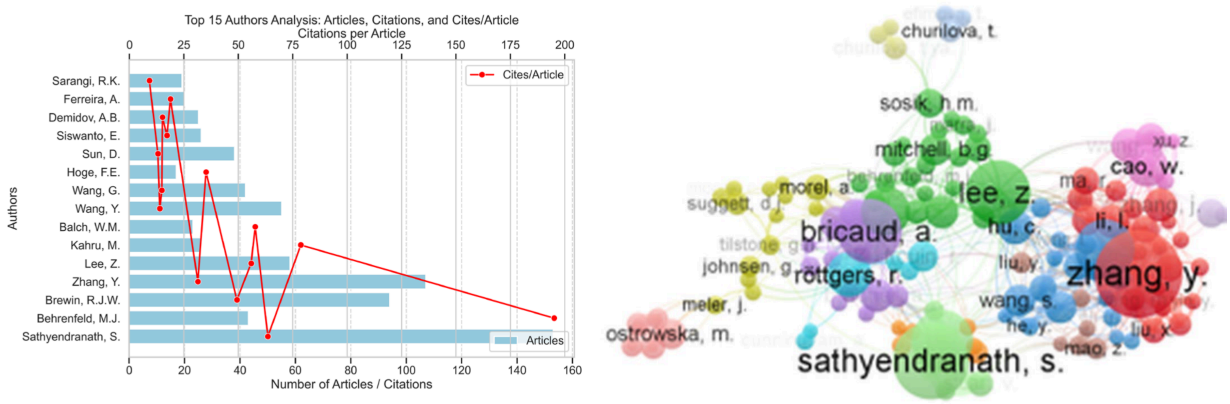


Figure 9. Journals as per publication numbers.



(**a**) (**b**)

Figure 10. (**a**) Top authors and (**b**) author network.

Figure 10b is a network plot depicting multiple network properties through bubble size (representing author prominence), edge thickness (representing the strength or frequency of collaboration), and color clustering (representing authors with dense internal collaboration and shared research focus). These properties together reflect underlying structural characteristics of the co-authorship network. The network is centered around prominent nodes represented by S. Sathyendranath, Y. Zhang, A. Bricaud, and Z. Lee with their respective groups. For example, a global hub centered around S. Sathyendranath links multiple clusters, facilitating intradisciplinary collaboration. In contrast, a cluster-centric hub like Y. Zhang's dominates the network with strong intra-group ties. Also, a pattern of localized hubs (e.g., A. Bricaud) within a tightly coupled subgroup and strategic intermediary position (e.g., Z. Lee) is exhibited, indicating high centrality that enables inter-cluster connectivity. The clusters exhibit that the green cluster, including S. Sathyendranath, acts as a bridge connecting the other clusters. The red cluster of Y. Zhang is more cohesive but relatively isolated compared to the purple cluster, which includes authors such as A. Bricaud and R. Rottgers. The yellow cluster represents legacy contributions, and the blue cluster (e.g., S. Wang and others) facilitates inter-cluster links to the orange cluster of emerging authors.

2.5. Affiliations and Country

The analysis of the top 15 affiliations contributing to research output highlights a strong presence of leading oceanographic and remote sensing institutions globally. Plymouth Marine Laboratory (UK) leads with 340 publications, followed by Sorbonne Université (France, 175 papers), CSIRO (Australia, 155 papers), NASA Goddard Space Flight Center (USA, 144 papers), and Scripps Institution of Oceanography (USA, 138 papers). Chinese institutions, including the University of Chinese Academy of Sciences (138 papers) and the Second Institute of Oceanography (120 papers), also feature significant contributions. Other notable contributing institutes include the Shirshov Institute of Oceanology (Russia, 104 papers), NOAA (USA, 99 papers), Alfred-Wegener-Institute (Germany, 96 papers), and the National Oceanography Centre Southampton (UK, 80 papers). At the country level, the United States dominates the research domain, followed by China, the United Kingdom, France, and Canada respectively reflecting their prominent role in advancing oceanographic and phytoplankton remote sensing studies. The Figure 11 below depicts the global distribution of the studies.

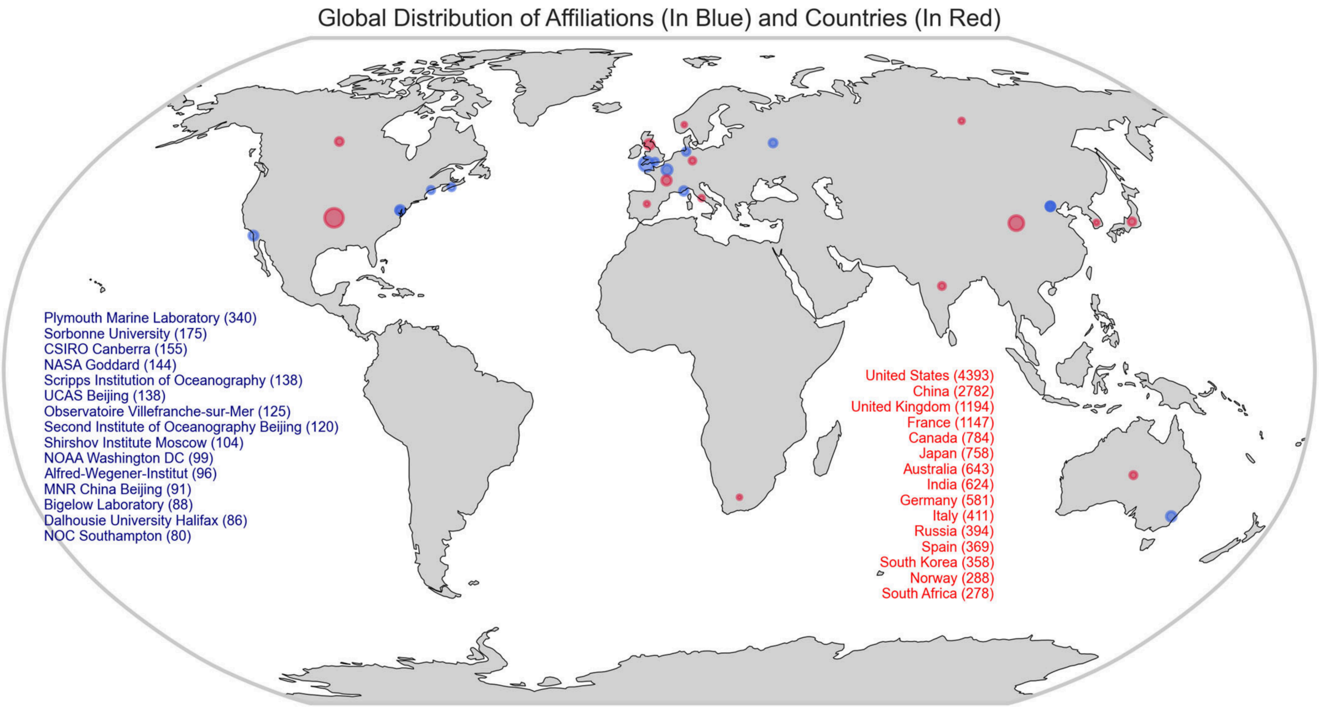


Figure 11. Map of affiliations of prominent research in the field.

2.6. Research Clusters Based on Abstract Clustering

The t-SNE (t-distributed stochastic neighbor embedding) map visualizes the similarity structure of bibliometric entities in a two-dimensional space. The spatial proximity reflects thematic relatedness, and distinct groupings represent major research clusters. The division of studies into four quadrants highlights differences in research focus and maturity across themes. A clear vertical structuring is evident in the t-SNE map at Figure 12, with the upper quadrants dominated by conceptual and methodological themes, while the lower quadrants emphasize physical, optical, and biogeochemical applications. The figure depicts a continuous research domain rather than discrete clusters, which gradually transitions from computational methods to optical physics, biogeochemistry, and ecological dynamics. The spread of points across quadrants signifies that only a few papers are confined to a single theme, and most studies are cross-disciplinary and are a combination of methods, observations, and ecological insights.

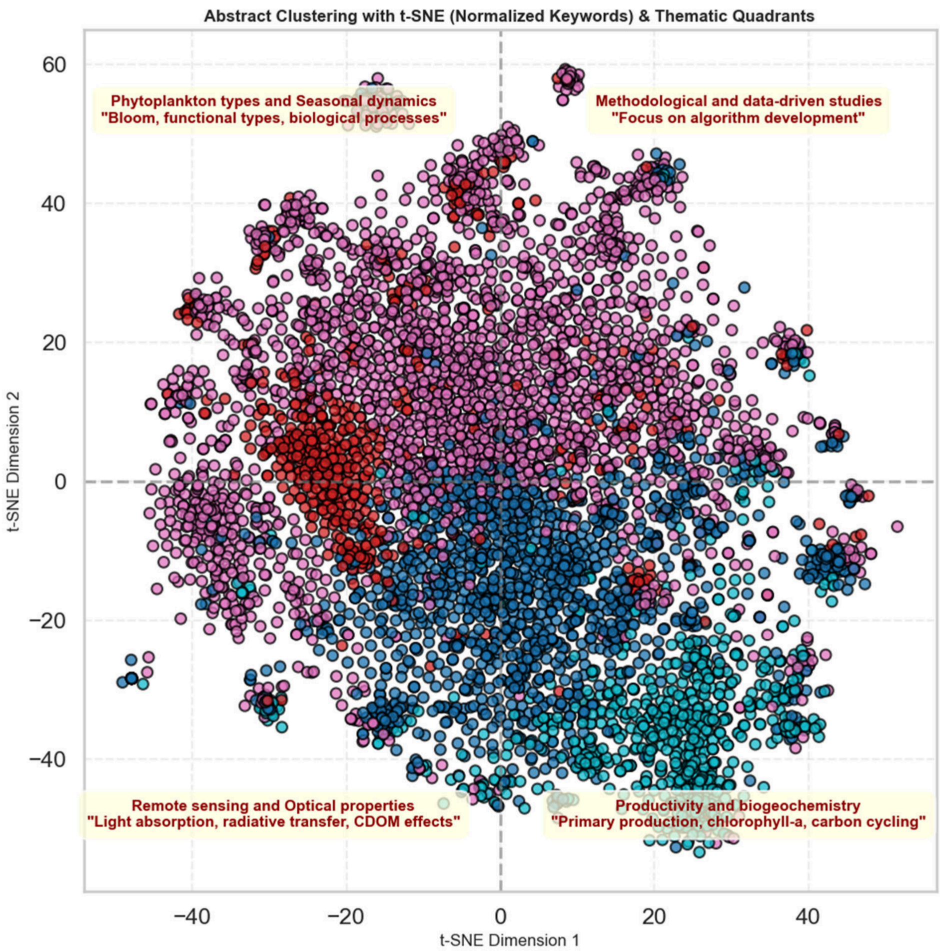


Figure 12. t-SNE Map of abstract clustering.

Based on the normalized keywords, the largest thematic group is *methodological and data-driven studies* comprising 1518 papers (40.2%), which emphasizes algorithm development, computational approaches, and data analysis techniques. The *remote sensing and optical properties* cluster includes 915 papers (24.2%), which focus on absorption, radiative transfer, and CDOM dynamics. The *productivity and biogeochemistry* accounts for 742 papers (19.7%) that cover primary production, chlorophyll-a, and carbon cycling. The *phytoplankton types and seasonal dynamics* represent the smallest group with 599 papers (15.9%) that emphasize bloom dynamics, functional types, and ecological processes. Despite the quadrant-based thematic classification, the spatial distribution of points indicates the nonexistence of limiting boundaries between clusters. Instead, thematic overlap reflects the interdisciplinary nature of the field, where studies mostly integrate methodological tools, remote sensing data, and biogeochemical applications.

3. Review of Advances in Phytoplankton Absorption Research

In this section, we examined the past literature by employing thematic techniques to draw meaningful inferences. The *Systematic review* should involve assessing the literature using clear, accountable, and methodical procedures [40,52]. The best strategy to achieve this is through classifying the studies in some meaningful schema. Previously, several studies have adopted different methodological schemas, like classification-based (e.g., analytical, semi- or quasi-analytical, empirical, and semi-empirical [53]), research trends-based [54], machine learning-based [55], data fusion-based [56] and other similar discourse for review. We adopted the PRISMA methodology for systematic review as depicted below in Figure 13, and included a total of 397 research articles of the past decade in the review, focusing on details of the article with citations to date, data used, area of study, method, result, and conclusion of the study (Supplementary Table S1). After filtering 316 articles, 152 were used for the abstract clustering schema, and the selected studies were found to represent two overarching themes: The first describes the focus of the research detailing what each study investigated (Section 3.1), while the latter emphasizes the significance of a_{ph} (λ) research by explaining why these findings were important (Section 3.2).

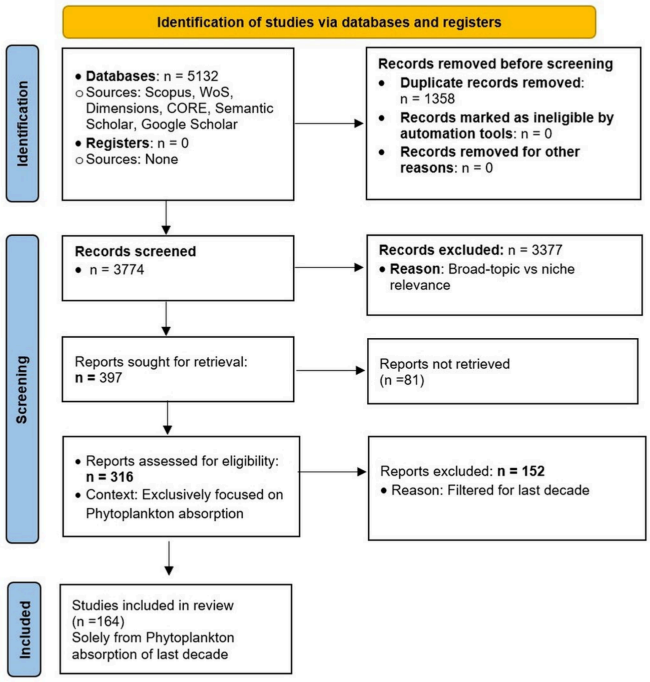


Figure 13. PRISMA flow diagram for systematic review of this study.

3.1. Focus of the Phytoplankton Absorption Research

The focus of the a_{ph} (λ) research, either theoretical or application-oriented, can be categorized primarily into four major sub-themes: 1. Theory of optical absorption mechanisms and bio-optical modeling, reflecting methodological and data-driven research; 2. phytoplankton functional types and the size classes classification of phytoplankton by traits or size, linking the community composition to ecosystem dynamics, aligning with the ecological focus; 3. environmental influences on a_{ph} (λ) that examines how factors like light, temperature, and nutrients affect absorption, integrating physiological and ecological responses across methodological and ecological themes; and 4. role in primary production and ecosystem functioning, which explores phytoplankton contributions to productivity and food webs, emphasizing process understanding and predictive modeling.

3.1.1. Phytoplankton Absorption Theory and Modeling

This strand of research primarily focused on understanding phytoplankton light absorption, analyzing absorption characteristics, and developing bio-optical computational models. Over the past six decades, theoretical frameworks considering bio-optical and physio-optical approaches that include analytical, quasi-/semi-analytical, and empirical/semi-empirical models have been employed through varied techniques from laboratory experiments to field expeditions. The data processing has advanced to analytical algorithms progressively evolved through interdisciplinary collaboration across the disciplines. The initial attempts for precise estimation were formulated based on the equation of chlorophyll-a absorption, light intensity, and temperature variations to accurately predict marine phytoplankton production [57]. The subsequent two decades saw major milestones arising from theoretical advances in IOP, particularly a_{ph} (λ) and radiative transfer processes, and their application in remote sensing to quantitatively estimate phytoplankton concentrations through spectral variations in ocean color observed in the upper water column [14,58–61]. Phytoplankton absorption varies with the size and strength of algal cells, challenging the applicability of Beer's law and thus affecting the estimation of productivity and biomass via remote sensing [14]. An iterative method to reveal dependence on chlorophyll-a content and water type, leading to an optical classification of water [58], was important to note. Significant research revolved around the disagreement regarding the specific absorption of algal particles and the significance of absorption peaks at 440 nm and 675 nm [62]. Further progress on a_{ph} (λ) was exploring the theory related to photo-adaptation [63], in vivo absorption [62,64,65], detrital absorption [66], and phytoplankton cross-section absorption [67,68] using absorption spectroscopy or fluorescence spectroscopy to study spectral variations [69] and phytoplankton growth [68,70].

Post 1990s, researchers focused on absorption spectra-based bio-optical models [49,71–73] and IOPs [74] to determine the major groups of phytoplankton pigments [71,75–77], the package effect [78], and theory building for evolving application areas like photosynthetic changes [79] and acclimation [80] using methods like chemical oxidation [81] and glass fiber filters [71]. Then, post-2000s, studies largely served the purpose of increasing the accuracy of estimation by numerical/bio-optical models [82,83], wavelet analysis [84] utilizing empirical models [85,86] such as Gaussian analysis [87], neural network clustering [88] where the focus still revolved around estimation and species identification [85,89,90] to advance harmful algal bloom (HAB) detection [84,91].

The last decade, since 2015, shows trends that continue to advance the knowledge around modeling and parameterization [92–95] for inland waters [96–98], spectral dataset creation [94,99–101], and functional types and ecosystem dynamics [29,30,102].

3.1.2. Dominance of Remote Sensing-Based Approach to Study Phytoplankton

Ocean color remote sensing theories were initially exploited in different application areas [60,61,103–105]. During this decade, a major contribution to a_{ph} (λ) may be attributed to Prieur and Sathyendranath [58], who not only laid out the semi-analytical model over a range of 400–700 nm (indicating absorption peaks at 443 and 676 nm), along with a comparison to previously existing models [14,106–108], but also provided basis for applications like the classification of water class. This decade, with the advent of satellite-based ocean color instruments like the coastal zone color scanner (CZCS) on board the Nimbus-7, was employing bio-optical models for methodological developments [109–113] and for regional modeling [114,115].

The ten-year gap (1985–1995) after CZCS has heavily impacted ocean color research, after which a new era of more modern ocean color satellites started. Figure 14 below shows the instruments, satellites, their operating dates, and radiometric, spectral, and spatial resolution information launched post-CZCS. The ocean color scientists rejuvenated the methodological progress on bio-optical modeling [116–120], improving predictive capabilities [83,121–124] and variability in the partitioning of optical properties [125–130].

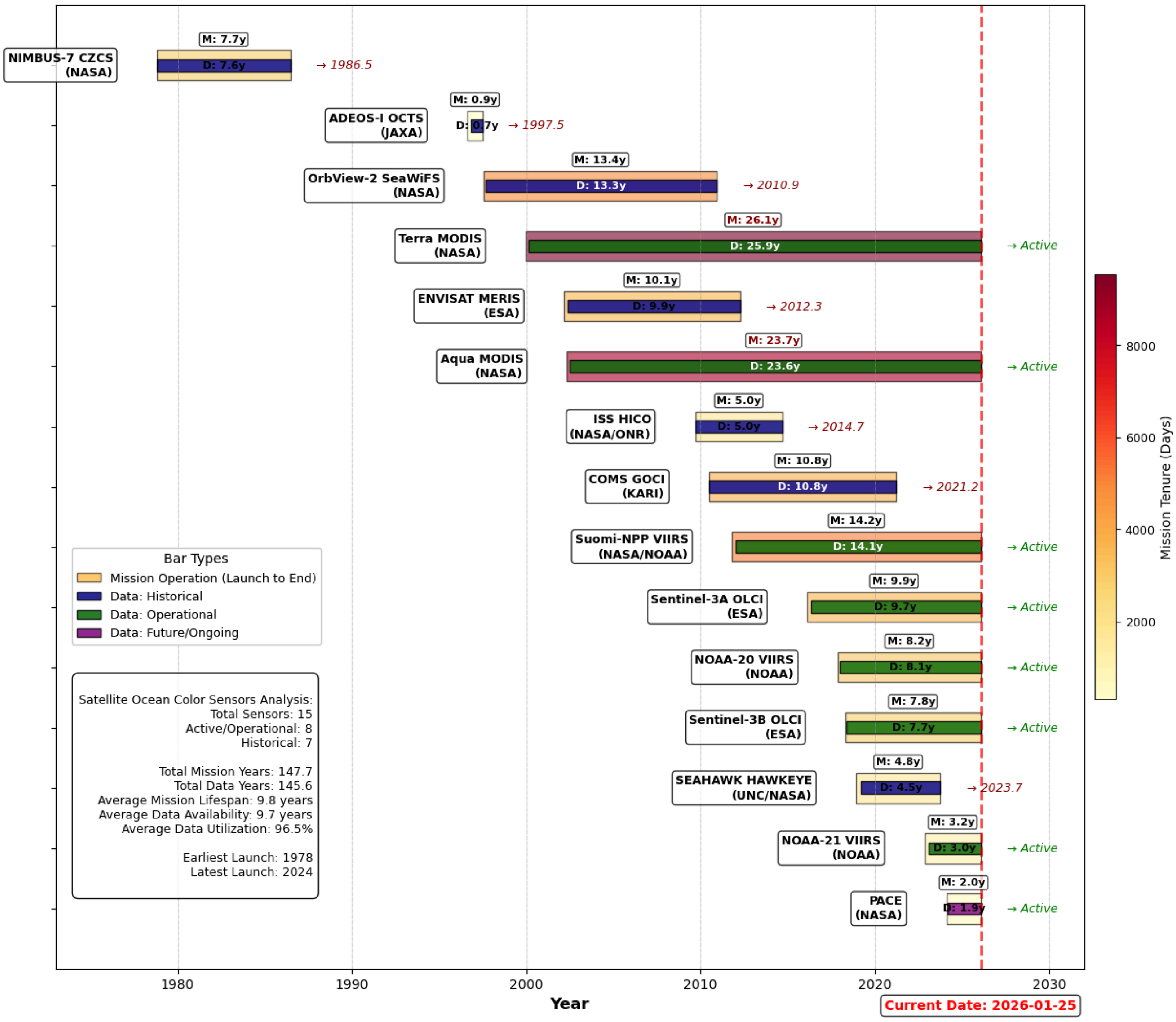


Figure 14. Ocean color satellites and data availability duration.

The studies post-2010 appreciated the time-series data of previous satellites to provide a critical analysis of the a_{ph} (λ) research. This resulted in expanding the scope of the methodological research into inverse-modeling [131,132], optical proxy models [133,134], physio-optical modeling [135–138], semi-analytical models [139], and quasi-analytical models [140]. In addition, several studies were focused on algorithm development for decomposition [141–144], parameterization [145–147], seasonal variability [148,149], and partitioning absorption [136,137]. Certain studies have also contributed to the evaluation of different models for predictive accuracy [22,150]. The theory for detecting HAB [91,151], assessing regional variability in cyanobacteria bloom [152,153], and spatiotemporal variability using longitudinal data [154,155] was also studied. More recently, the ensemble machine learning models have been used for optimized empirical modeling [22,156,157]. The notable studies using ocean color satellite data have been placed in Table S3 at annexure.

3.1.3. Phytoplankton Functional Types (PFT) or Phytoplankton Size Class (PSC)

These PFT studies primarily classified phytoplankton based on their traits, functional types, and size classes based on examining community composition influences on ecosystem dynamics, photosynthetic pigments (e.g., chlorophyll-a), ecological roles (e.g., primary producers, mixotrophs, HAB formers), and nutrient utilization [158]. PSC refers primarily to size-based classification, with picoplankton (0.2–2 μm), nanoplankton (2–20 μm), and microplankton (20–200 μm) encompassing various organisms from bacteria to small algae [159]. Understanding phytoplankton size classes is crucial for comprehending aquatic ecosystem dynamics, encompassing primary production, nutrient cycling, and food web interactions, analyzed through diverse sampling and measurement methodologies [30].

Initial PFT attempts were centered around using in situ data for relating to the derivative analysis of absorption spectra [160–163]; absorption spectra from chemometrics to PFT [164], which were further extended as absorption models to differentiate size classes [165–169], using the bio-optical model [170]; and their ecosystem dynamics [171–174]. The application of ocean color data has largely enriched this domain, where few studies utilized semi-empirical bio-optical models [29,165,175–180], inversion techniques [179,181,182], and upright empirical models using IOPs [183]. Regional variability [30,183–188] and seasonal/spatial variability [189–192] in PFT and PSC were also assessed by prominent studies. Recently, PFT and PSC studies have predominantly examined variations in phytoplankton size structure and their influence on absorption characteristics [165,193,194] at different scales using satellite data [29,154,195], examining the global distribution of the phytoplankton size spectrum [30,94], investigating the influence of the temperature [196], ecosystem complexity [102], salinity [171], and nutrient concentrations [172] on PFT and PSC.

3.1.4. Influence of Environmental Factors on Phytoplankton Absorption

This research category has investigated how environmental factors, such as temperature, light, or nutrient availability, affect a_{ph} (λ). Through experiments, field observations, and modeling, these studies integrated ecological and physiological responses to bridge methodological and ecological gaps in the research. The notable contribution indicates that a_{ph} (λ) is influenced by multifaceted environmental factors like nutrient availability [155,197–199], light intensity [90,200–202], temperature [196,203], and other water chemical parameters [183] which dictate growth rates and photosynthetic activity. Understanding these influences is pivotal for understanding the absorption of anthropogenic CO_2 [2,29] and environmental shifts [204].

A few other studies have focused on unique environmental conditions, like glacial meltwater influx in fjord ecosystems [145], red tide events [205–207], the Agulhas Current ecosystem [208], reservoirs across China [209], and other unique geographic areas as mentioned in Table S1 for accurately parameterizing absorption coefficients, improving model precision and predictive capability.

3.1.5. Primary Productivity and Ecosystem Functioning

This research focuses on the contribution of phytoplankton to primary production, exploring factors controlling productivity and how it impacts marine food webs. While more applied aspects of this research domain emphasize process understanding and predictive modeling of the oceanic productivity. Marine primary production by phytoplankton is a vital process that converts inorganic nutrients into organic matter, driving oceanic carbon cycling and supporting marine ecosystems, with implications for climate change [2,210]. Phytoplankton's light absorption is crucial for photosynthesis and directly related to their productivity and impact on the higher trophic order, as well as ecosystem dynamics [211,212]. Initial studies focused on assessing the importance of phytoplankton for primary production [213–216], followed by estimating uncertainties that impact primary production estimation [217], due to environmental factors [218,219] and regional modeling [115,201,220–222]. The contemporary researchers measure a_{ph} (λ) to primary productivity modeling [223–228] along with seasonal and regional variability in productivity [154]. The anthropogenic impacts on productivity [229]; environmental drivers [198,204], carbon sequestration and productivity [102,230], and the validation of productivity models [231–233] are a few concurrent research trends in the marine food web. Moreover, the promising extension of ocean color data and a novel bio-optical method can enable the initial estimation of carbohydrate, protein, lipid, and overall calorific values of phytoplankton on a global scale, also revealing regional variations [33,234].

3.1.6. Methodological Shift: From Variable Retrieval to Ecological Application

Over the past six decades, a_{ph} (λ) research has shown a methodological shift from radiative transfer model-based retrieval to application-driven ecological inference. The research trend highlights the early scholarly work predominantly focused on analytical and quasi-analytical inversion models, focusing on better modeling the variables with moderate accuracy, constrained by limited transferability. Subsequent improvements due to the integration of semi-analytical and statistical methods significantly improved estimation performance even in optically complex waters. Also, application areas have expanded beyond bulk absorption to pigments and size structure. The early 2015s indicate a pivotal shift toward machine learning-based research, which enabled the robust modeling of the nonlinear relationship between *Rrs* and bio-physical variables for the retrieval of functional types, size classes, and productivity. By the mid 2020s, advanced machine learning and ensemble models were employed largely to achieve consistently high accuracy and address explicit uncertainty and heterogeneity. These advances have positioned a_{ph} (λ) from a proxy variable to a fundamental geophysical and ecological indicator across the limnological systems.

Methodological trends have been examined over the past decade (as illustrated in Figure 15) using representative studies that report highly significant advances in performance. The representative phytoplankton retrieval algorithm studies were analyzed across five major methods of classification [53]. The *analytical* methods-based studies largely employed through absorption-based bio-optical models have provided moderate accuracy (R^2 ~ 0.77) and limited adaptability to optically complex waters [137,178,235]. The *quasi-analytical* methods show significantly improved performance (R^2 ~ 0.96) and offer a strong balance between theoretical robustness and empirical calibration [236–238]. The studies based on *semi-analytical* methods have shown to be an enhanced amalgam of integrating inversion, decomposition, and unmixing techniques and have achieved better accuracy (R^2 ~ 0.90) while ensuring multi-variable retrievals [239–241]. The *semi-empirical* studies were seen exploiting techniques like derivative analysis, wavelet transform, stepwise regression, and spectral feature engineering, to yield moderate improvements (R^2 ~ 0.85) and enhanced sensitivity to pigment variability [186,242,243]. Recent advances are dominated by *empirical* machine learning (ML) models, including ensemble methods, mixture density networks, and deep learning architectures, which are demonstrating the highest accuracies (R^2 > 0.95) and are enabling complex multiple products derivations [22,157,244–247]. Overall, the progress echoes a paradigm shift toward augmented usage of hybrid and AI-driven methodologies for more pragmatic solutions of a_{ph} (λ) applications.

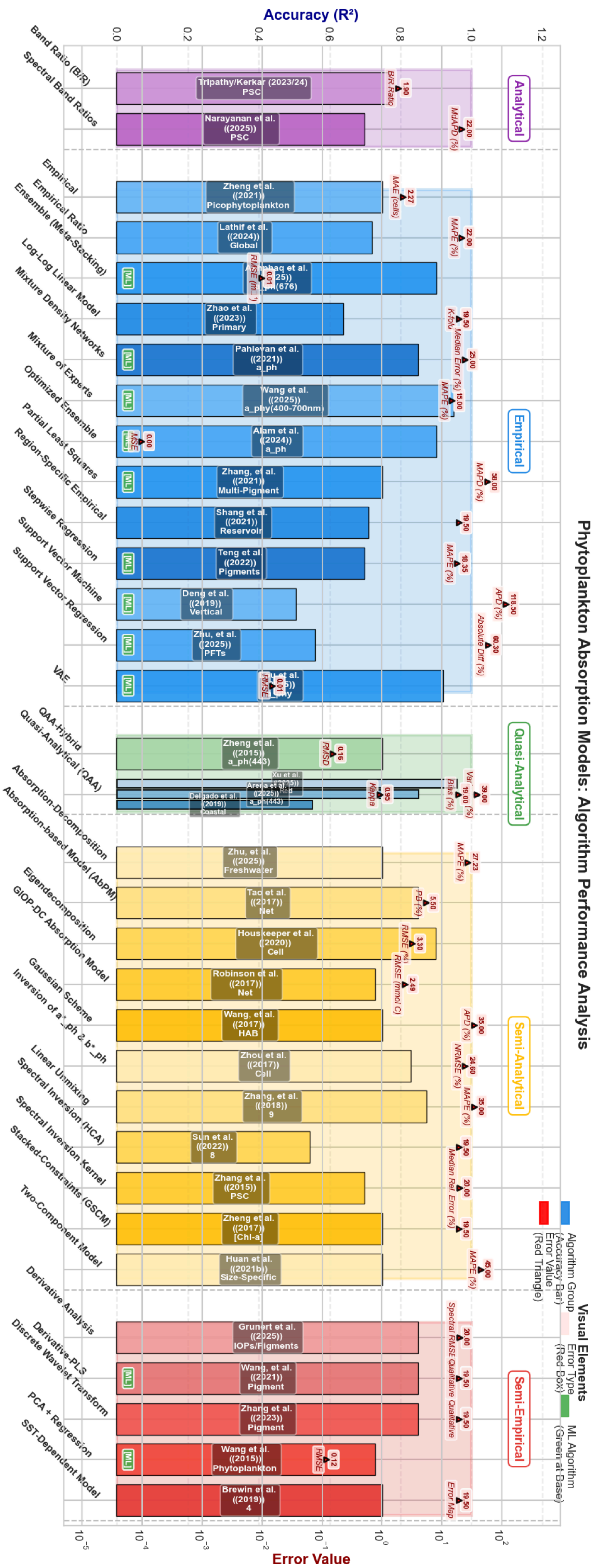


Figure 15. Methodological trends in the last decade.

3.2. Significance and Challenges of Phytoplankton Absorption Research (2015–2025)

This section highlights the significance of a_{ph} (λ) studies by contextualizing subsections around key research objectives and methodological advances. Given the vast body of literature, this review focuses on notable and representative studies from the last decade that showcase recent progress in estimation accuracy and ecological applications (refer to Table S2 for a concise tabulated summary of these studies).

3.2.1. Beyond Chlorophyll-a: Retrieval of Phytoplankton Composition and Function

These studies represent a major shift beyond chlorophyll-a towards resolving phytoplankton composition and function from *Rrs*. Several studies focus on retrieving essential and photoprotective pigments using a_{ph} (λ) to better characterize physiological states [94,248,249]. Others target major taxonomic groups using a_{ph} (λ), enabling insight into functional assemblages rather than bulk biomasses [250–252]. Community-level frameworks further emphasize tracking assemblage shifts over time and space, which has proven more robust than species-level retrievals in dynamic systems [253,254]. Freshwater systems for detecting HAB remain critical for management and early warning for usability [252,255].

However, the functional and taxonomic retrievals are limited in optically complex waters and under low-light conditions. Figure 16 below shows the performance accuracy of different products using a_{ph} (λ) and depicts reported accuracy across major retrieval classes. The comparison shows that some products (e.g., HAB) can be retrieved more reliably, while more complex products (e.g., PSC, PFT, and primary production) are less accurate. The accuracy is impacted by the uncertainties attributable to model degeneracy (multiple possible model solutions) and the optical complexity (complexity of optical measurements), as discussed in the next section.

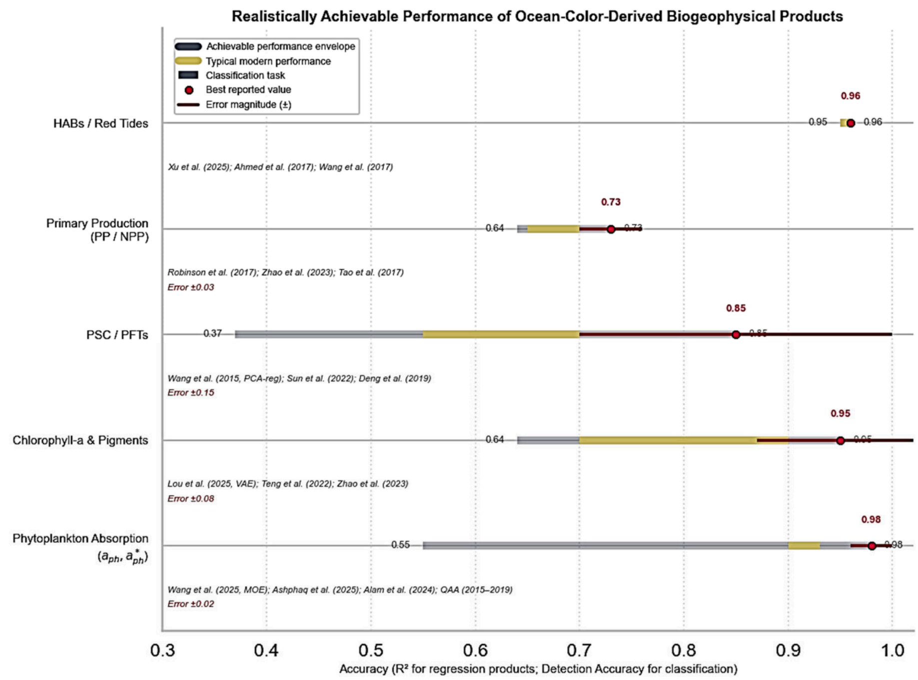


Figure 16. Ocean color-derived products and their accuracy as reported in the literature.

3.2.2. Resolving Optical Degeneracy in Phytoplankton Retrievals

A central challenge in bio-optical remote sensing is optical degeneracy, where *Rrs* correspond to discrete biological states. Several studies address this by isolating the effects of physiological light acclimation (referred to as the pigment packaging effect) due to biomass or species composition [256–258]. Other researchers separate the effects of cell size and pigment composition on a_{ph} (λ) to examine ecosystem structure and carbon cycling. [225,259,260]. Few recent methods acknowledge the many possible solutions of the inversion problem through probabilistic or mixture-model frameworks [22,261]. Alternatively, few spectral decomposition models extract meaningful products without imposing rigid pigment assumption bias in optically complex waters [242,262]. Thus, these transitions reflect a methodological shift from deterministic inversion methods to more probabilistic and multi-product frameworks.

Despite recent advances, a_{ph} (λ) retrieval remains constrained by heavy computational models and more detailed spectral signatures that are still missing in the absence of hyperspectral data. Therefore, future progress will depend on integrating probabilistic inversion models with hyperspectral remote sensing and targeted high-resolution in situ data. This will potentially help with the solution to optical degeneracy and improve robustness across optically complex waters.

3.2.3. Advancing Phytoplankton Absorption as a Fundamental Geophysical Variable

This area of research focuses on improving the accuracy, stability, and operational viability of a_{ph} (λ) as an independent geophysical variable. Some of these studies aim to produce reliable, low-bias products that work across different sensors and remain robust over longitudinal time scales [263,264]. Others exploit underutilized spectral regions (predominantly in the red and green bands) to reduce ambiguity in productivity, carbon, and HAB estimates [156,265,266]. For optically complex turbid waters, semi-analytical approaches have been extended to quasi-analytical solutions to advance the separation of a_{ph} (λ) from non-algal components [267–269]. Some studies also examined time-dependent changes in a_{ph} (λ) to limit spurious trends in the research and avoid seasonal misinterpretations [270,271]. These studies robustly transpose a_{ph} (λ) as a primary geophysical variable rather than a secondary proxy for chlorophyll concentration.

Advances in bio-optical modeling and machine learning have driven a_{ph} (λ) into a key geophysical variable for studying aquatic ecosystems. Despite improved performance even in optically complex waters, the transferability across regions remains limited due to bio-optical variability, sensor constraints, and insufficient calibration. Therefore, the operational reliability is restrictive at this stage. Future efforts should focus on globally harmonized a_{ph} (λ) products that integrate bio-optical and physio-optical models with machine learning frameworks.

3.2.4. Extending Ocean Color Observations into the Vertical Dimension

These studies focus on variable retrieval beyond the sea surface and attempt to capture the vertical column structure of marine ecosystems. Studies targeting vertical PFTs use absorption and size-class models to infer subsurface ecological structure [186,241]. The vertical dimension research includes deep chlorophyll maxima [272–275] and bio-optical models to better represent light attenuation and productivity at different depths across the water column [257,276], as well as studies on exclusive Arctic ecology focusing on ice cover, meltwater input, and low-sun-angle effects on vertical absorption profiles [226,277]. Together, these studies extend the traditional two-dimensional surface-based ocean color paradigm into a three-dimensional ecological framework across the water column to enable a profile of phytoplankton distributions and oceanic ecosystem dynamics.

With the exception of those efforts, current satellite retrievals are inherently focused on surface-based products. The vertical structure of the water column is constrained by light attenuation, optical nonlinearity, and limited depth-dependent calibration data. Progress toward three-dimensional ecosystem characterization will require integrated frameworks combining multi-angular satellite observations with autonomous in situ profiling (e.g., Argo floats) to better map vertical variability and reduce uncertainty in subsurface retrievals.

3.2.5. Making Optical Measurements Climatically Actionable

The relationships between phytoplankton spectral characteristics, carbon cycling, and ecosystem productivity have been exploited by measuring a_{ph} (λ) to be translated into primary productivity and the estimation of carbon stocks [278,279]. These climate models also advance primary production estimates, pigment class, and size effects more accurately than traditional chlorophyll proxies [233,280,281]. The analysis of size-dependent absorption correlates spectral information and carbon export processes, thereby providing a process-based understanding of carbon sequestration in marine systems [225,282]. Thus, a_{ph} (λ) is evident to be a climatically relevant variable.

Despite optical advances, the reliability of associating bio-optical indicators with carbon fluxes remains challenging in optically complex and turbid waters. The progress limited by the dominance of nonlinear ecosystem processes in turbid waters will need to be overcome by process-based models to robustly integrate a_{ph} (λ) with phytoplankton physiology, marine food web dynamics, and carbon sequestration. This may allow for a more robust conversion of ocean color data into biogeochemical and climate-relevant insights.

3.2.6. Operational Monitoring of HAB

Studies focusing on monitoring red tides aim to detect the HAB's spatial coverage and duration through analyzing variations in a_{ph} (λ) data and other bio-optical variables [283–286]. Research on HAB early-warning management and mitigation stresses time-series analysis to distinguish isolated episodic blooms from long-term regional phenomena [287–289] and enabling predictive insights [290]. This research advocates a_{ph} (λ) observation for a practical decision-support tool for monitoring and managing extreme ecological events.

Real-time HAB detection still remains constrained by satellite revisit time, seasonal cloud interference, and limited predictive model maturity. The progress of operational monitoring may be enhanced by synergistic integration of satellite data with autonomous in situ data platforms, and using advanced data-assimilative ML forecasting models to provide regular, spatially well-covered, and actionable bloom events.

3.2.7. Hyperspectral Transition

These studies primarily focus on preparing for upcoming hyperspectral satellite missions such as PACE (plankton, aerosol, cloud, and ocean ecosystem) that will be exploiting the full spectrum of ocean color *Rrs* rather than the limited band spectral variability. Researchers further advocate the use of hyperspectral data to discriminate phytoplankton communities and ecological states for more precise ecosystem monitoring [261,262,291,292]. The demand for processing large datasets from forthcoming missions needs to be scaled up using multivariate, heterogeneous data to retrieve more accurate estimates of a_{ph} (λ) through ensemble and neural network-based ML models [22,265].

The hyperspectral missions introduce massive, heterogeneous datasets that challenge current computational and calibration frameworks. The full potential of hyperspectral big data not only demands advanced ML models integrated with robust in situ validation to enable precisely scalable retrievals but also needs physics-informed grounding to better comprehend phytoplankton optical and ecological properties.

3.2.8. Summary of a_{ph} (λ) Research 2015–2025

Over the past decade, a_{ph} (λ) research has progressed from chlorophyll-centric surface retrievals to multivariate applied products inclusive of carbon-related optical derivatives. These advances enable a robust estimation of phytoplankton (including composition, PSC, PFT, and traits) through probabilistic and ML-based inversion. The a_{ph} (λ) research is transitioning from two-dimensional deterministic retrievals to three-dimensional water column pragmatic products. Integration of hyperspectral, multi-source, and high-resolution in situ data is enabling ecological mapping and linking the optical proxies to carbon fluxes. However, key challenges remain in the vertical water column structure retrieval, taxonomic resolution in complex waters, real-time monitoring of HABs, and scalable hyperspectral inversion models.

Figure 17 below depicts this progress as discussed in the above sections, positioning a_{ph} (λ) as a central geophysical variable in the ocean system. The associated studies are summarized in Supplementary Table S2.

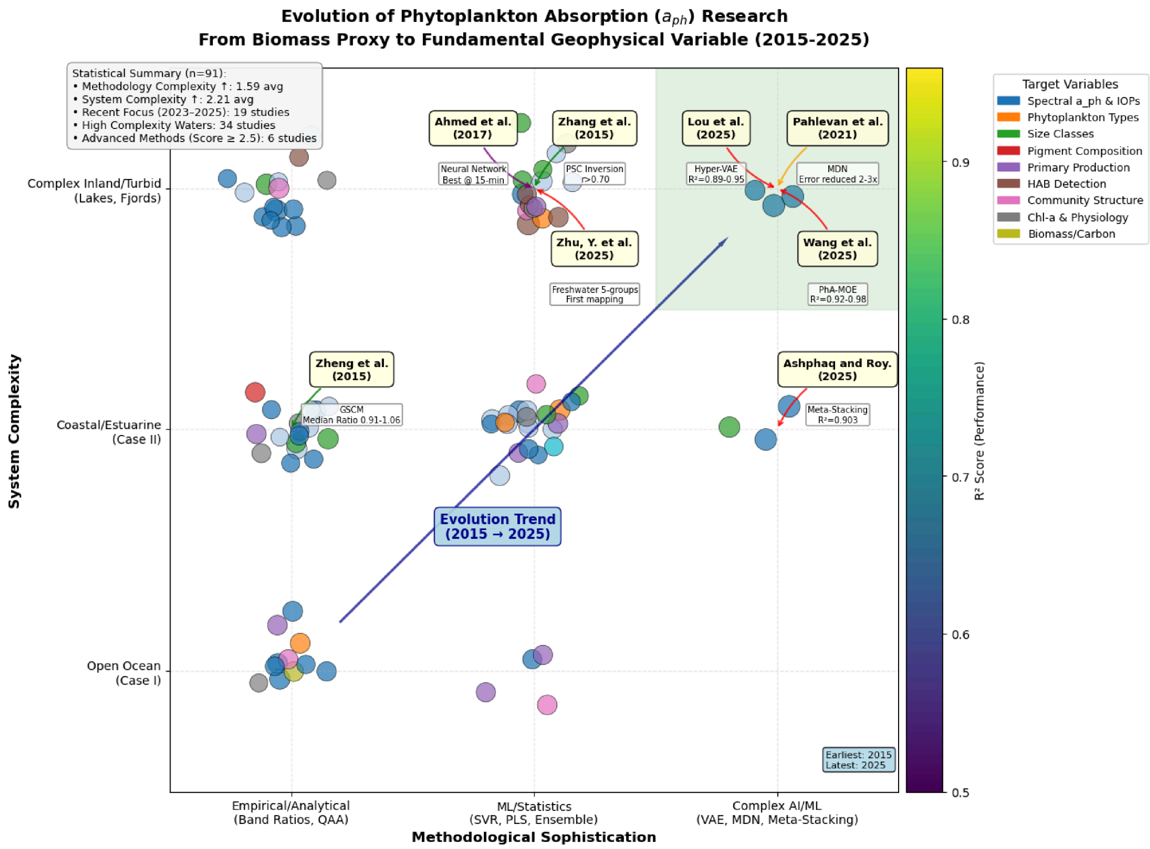


Figure 17. Methodological advances in a_{ph} (λ) products and variables over the last decade.

4. Challenges and Opportunities in Phytoplankton Absorption Research

This section outlines the trajectory of research, highlighting challenges and opportunities in the development of theory, methodology, and understanding of spatial-temporal variability. Despite notable progress discussed above, the key challenges persist, limiting the comprehensive knowledge of complex marine ecosystems. We have examined a few of the dominant contemporary impediments and emerging opportunities in the field of a_{ph} (λ) research as discussed in the section below.

4.1. Complexity of PFT and PSC

The research on a_{ph} (λ) faces persistent challenges in resolving the functional and structural diversity of marine phytoplankton. Despite methodological advances, research is constrained by ecological uncertainties, high-resolution and temporal data scarcity, and the sensitivity of retrievals to parameterization strategies across regional and global spatial scales [158,293]. Biological complexity, which includes cell size, pigment composition, and physiological state, interacts dynamically with environmental drivers impacting highly variable spectral signatures that complicate model development and validation [294,295].

An accurate characterization of PFTs and PSCs requires careful formulation and a gradual integration of complexity, complemented by empirical and semi-empirical approaches. Current gaps include the lack of standardized spectral libraries linking *Rrs* to specific PFTs and PSCs, limited understanding of species-specific absorption variability, and insufficient representation of dynamic environmental responses. Addressing these gaps presents an opportunity to advance a_{ph} (λ) retrievals from bulk proxies toward autonomous, operational-ready, and ecologically actionable products. Future directions include the systematic development of PFT/PSC spectral libraries, integration of multivariate datasets, and application of probabilistic AI frameworks to apprehend ambiguity and complex environmental interactions of the variables.

4.2. Complexity of Temporal and Spatial Variability

The research on a_{ph} (λ) exhibits apparent limitations posed by temporal and spatial variability (including seasonal cycles, nutrient fluxes, oceanic upwelling/downwelling, and mesoscale mixing) driven by dynamic physical and biogeochemical processes [158,291]. These processes modulate phytoplankton community composition, size structure, and pigment distributions, producing highly heterogeneous spectral signatures that challenge accurate satellite retrieval and predictive modeling [253,296–298].

Time-series observations from ocean color satellites (as listed in Supplementary Table S3) offer unprecedented potential for quantifying coarse resolution temporal and spatial variability [299–313]. The existing products (often aggregated monthly or weekly) frequently fail to resolve fine-scale temporal dynamics, limiting their ecological reliability. The gaps in data coverage, sensor revisit limitations, and inherent abstraction in derived *Rrs* products constrain the functional interpretation of a_{ph} (λ). The integration of high-frequency revisit satellite data with high-resolution autonomous in situ profile data may enhance temporal interpolation. The longitudinal studies targeting seasonal and mesoscale variability can enhance the temporal resolution and ecological relevance of a_{ph} (λ) products for robust mapping of dynamic phytoplankton processes across marine environments.

4.3. Complexity of Data, Measurements, and Methods:

Quantifying a_{ph} (λ) with precision remains constrained by both methodological and data-centric challenges. In situ data acquisition and processing are severely confounded by complex optical interactions of species-specific absorption spectra. The environmental heterogeneity needs robust instrumentation, standardized data protocols, and precise calibration prior to deployment in the field. The algorithm calibration or validation (or both) requires highly accurate ground-truth datasets and precise bio-optical or physio-optical models. The coverage gaps in the data and inconsistencies across acquisition platforms continue to impede reproducibility (see [291] for a comprehensive insight).

Hence, the data integration represents a critical frontier for synthesizing heterogeneous temporal, spatial, and spectral multivariate data. Existing resources, including satellite data archives, cruise datasets, and oceanographic models [21,314], offer unprecedented opportunities to improve predictive accuracy, resolve optical degeneracy, and reduce uncertainty of a_{ph} (λ) retrievals. Thus, computationally proficient data assimilation approaches to process multi-source high-resolution big data are the key for globally consistent mapping of a_{ph} (λ) and phytoplankton-based derivatives. Also, a_{ph} (λ) research signifies the diversity of measurement approaches (as well as units used). Optical methods directly measure a_{ph} (λ) coefficients (m^{-1}), whereas biogeochemical methods compute pigments (mg m^{-3}, μg L^{-1}), cell abundance (cells mL^{-1}), and particle size (μm). The remote-sensing methods derive

a_{ph} (λ) coefficients (m^{-1}) and the related products from *Rrs* data (sr^{-1}). Integrating longitudinal data (homogenous or heterogeneous across the scales, instruments, missions, etc.) provides opportunities to optimize methods for a_{ph} (λ) applications and monitoring.

4.4. Complexity Around Climate Change Impact Assessment

a_{ph} (λ) has gained ocean-climate coupling significance due to its influence as a vital variable impacting the biological carbon pump of the ocean [39,102,291], regulating atmospheric CO_2 uptake, oxygen production, and climate-relevant feedbacks [315]. Simultaneously, climate change is changing the ocean's temperature, nutrient layers, and marine chemistry, affecting the phytoplankton and their health, which affects how they absorb light. This coupled relationship introduces substantial uncertainty in attributing observed a_{ph} (λ) variability to climate forcing versus regional ecological dynamics.

The main constraint in integrating climate drivers with bio-optical and biogeochemical models to predict a_{ph} (λ) or vice versa differs at different levels and scales. The nonlinear responses to temperature, nutrient limitation, and ocean acidification complicate model parameterization and induce uncertainties in future projections. However, the emerging opportunities of growing prominence on (regional-to-global) climate impact assessments are enabling a more robust prediction of phytoplankton–carbon interactions. This can help improve constrained carbon sequestration estimates and ecosystem feedbacks by positioning a_{ph} (λ) as a critical parameter for progressing coupled ocean-climate prediction and mitigation strategies.

4.5. Complexity Around Absorption Peaks at 443 nm and 675 nm

The peaks of a_{ph} (λ) near 443 nm and 675 nm wavelengths are fundamental to ocean color remote sensing as they represent strong chlorophyll-a absorption in the blue and red regions of the visible spectrum [192,316]. The estimates of phytoplankton biomass and productivity are dependent upon these wavelengths *Rs*, but interpretation is constrained by pigment composition, cell structure, and species diversity variability. This may also lead to overlapping and non-unique spectral signals impacting accurate interpretation, especially in complex waters. The precise understanding of absorption variability at 443 nm and 675 nm is therefore critical for reliable ocean color products [157]. The current research aims to improve bio-optical models for different phytoplankton functional groups, their physiology, and environmental interaction, producing spectral characteristics. Advances in hyperspectral remote sensing (e.g., PACE) and ML-based probabilistic models are expected to improve estimation of a_{ph} (λ) derivatives by isolating confounding spectral signatures.

5. Conclusions

This review provides a comprehensive synthesis of six decades of a_{ph} (λ) research, with particular emphasis on the transformative advances achieved over the last decade (2015–2025). By analyzing foundational theory, bibliometric trends, and a systematic evaluation of recent methodological developments, we demonstrate that a_{ph} (λ) research has evolved from a supporting proxy for chlorophyll estimation into a vital geophysical variable. This progress further underpins its significance in modern ocean color science, ecosystem diagnostics, and biogeochemical modeling. Early analytical and quasi-analytical models have established the physical interpretability linked with IOPs, enabling robust retrievals of bulk absorption and chlorophyll-based variables even under relatively constrained optical conditions. However, these methods are proven to be less effective in complex coastal waters that have rich nutrients, as numerous phytoplankton assemblages coexist, and *Rrs* match-up spectral relationships are nonlinear. The last decade was characterized by a significant methodological transition toward hybrid, data-driven, and probabilistic frameworks, which include machine learning, deep learning, and ensemble approaches, consistently achieving high predictive estimates ($R^2 \approx 0.90$–0.96) across diverse aquatic environments.

The advances in spectrally derived a_{ph} (λ) retrievals have widened ocean color applications. Spectral signatures libraries of a_{ph} (λ) have progressed to pigment packaging, cell size, phytoplankton size classes, functional types, and HABs. Improved characterization of red-band peak-based absorption (~676 nm) could further strengthen estimates of phytoplankton carbon biomass and carbon-to-chlorophyll ratios. These advances indicate that a_{ph} (λ) is a critical quantity relating cellular phytoplankton physiology with ecosystem-scale carbon cycling, primary production, and climate processes.

Despite these advances, we found consistent challenges remain regarding optical degeneracy, which remains a fundamental limitation for corresponding *Rrs* to phytoplankton absorption. Retrieval of the vertical structure of a_{ph} (λ) in the water column remains challenging due to the surface-focused satellite products. This limitation reduces retrieval accuracy in distinguishing phytoplankton types, particularly in turbid waters. Monitoring HABs and extreme events remains limited by high-resolution satellite data, including its revisit times, cloud interference, and the integration of in situ data with real-time forecasting systems. However, the recent availability of hyperspectral satellite data enhances computational and validation challenges to overcome the scalability of physics-based models in consistency with in situ validation. The field is moving toward an integrated approach where a_{ph} (λ) is a dynamic indicator of the ecosystem. The key priorities for future researchers should remain as follows: combining hyperspectral satellite data with autonomous in situ observations to map ecosystems in three dimensions; using ML and physics-based models to better address uncertainty and optical degeneracy; and linking currently derived products to carbon fluxes and ecosystem processes for real-time monitoring and early-warning systems.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/rs18122059/s1, Table S1: Studies discussed in this review; Table S2: Studies included in systematic review 2015–2025; Table S3: Notable studies with ocean color satellite data.

Author Contributions: Conceptualization, M.A. and S.R.; methodology, M.A.; software, M.A.; validation, M.A. and S.R.; formal analysis, M.A.; data curation, M.A.; writing—original draft preparation, M.A.; writing—review and editing, M.A. and S.R.; visualization, M.A.; supervision, S.R.; project administration, S.R.; funding acquisition, S.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by a Research Endowment Trust Fund (RETF) grant from the University of Reading.

Institutional Review Board Statement: We declare that all authors have agreed to submit this manuscript to Remote Sensing Applications: Society and Environment. This work is not under consideration for publication elsewhere, and it will not be submitted elsewhere before a final decision is made. The written work is entirely original, and any work and/or text from others has been appropriately cited or quoted. Declaration of PRISMA, generative AI, and AI-assisted technologies in the writing process: This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. During the preparation of this work, the authors used AI-assisted technologies in order to get help with language corrections. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data Availability Statement: The data supporting this systematic review study are derived from previously published articles, which are duly cited and compiled in accordance with the PRISMA framework within the manuscript. No new datasets were generated. Additional information related to the data analysis is available from the authors upon reasonable request.

Conflicts of Interest: The authors declare that they do not have any competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Bricaud, A.; Bédhomme, A.; Morel, A. Optical properties of diverse phytoplanktonic species: Experimental results and theoretical interpretation. *J. Plankton Res.* **1988**, *10*, 851–873. [CrossRef]
2. Falkowski, P.G.; Wilson, C. Phytoplankton productivity in the North Pacific ocean since 1900 and implications for absorption of anthropogenic CO_2. *Nature* **1992**, *358*, 741–743. [CrossRef]
3. Wang, W.-T.; Cao, X.-H.; Yuan, Y.-Q.; Song, X.-X.; Yu, Z.-M. Variation and controlling factor of nutrient distribution in Changjiang River estuary and adjacent areas in 2012. *Oceanol. Limnol. Sin.* **2016**, *47*, 804–812. [CrossRef]
4. García-Muñoz, C.; Lopéz-Urrutia, Á.; Lubián, L.M.; García, C.M.; Hernández-León, S. A comparison of primary production models in an area of high mesoscale variability (South Shetland Islands, Antarctica). *J. Sea Res.* **2013**, *83*, 30–39. [CrossRef]
5. Kramer, S.J.; Maritorena, S.; Cetinić, I.; Jeremy Werdell, P.; Siegel, D.A. Phytoplankton communities quantified from hyperspectral ocean reflectance correspond to pigment-based communities. *Opt. Express* **2024**, *32*, 34482–34491. [CrossRef] [PubMed]
6. Silió-Calzada, A.; Bricaud, A.; Uitz, J.; Gentili, B. Estimation of new primary production in the Benguela upwelling area, using ENVISAT satellite data and a model dependent on the phytoplankton community size structure. *J. Geophys. Res. Ocean.* **2008**, *113*, 1–19. [CrossRef]
7. Ioccg, I. *Remote Sensing of Ocean Colour in Coastal, and Other Optically-Complex, Waters*; IOCCG: Plymouth, UK, 2017.
8. Ye, S.; Zhang, R.; Wang, H.; Tian, F.; Shi, Q. Tropical Cyclone-Induced Ecological Responses and Their Feedback on Physical Fields: A Case Study for Hurricane Fernanda (2017). *J. Geophys. Res. Ocean.* **2024**, *129*, e2024JC021150. [CrossRef]
9. Ciotti, Á.M.; Lewis, M.R.; Cullen, J.J. Assessment of the relationships between dominant cell size in natural phytoplankton communities and the spectral shape of the absorption coefficient. *Limnol. Oceanogr.* **2002**, *47*, 404–417. [CrossRef]
10. Mobley, C.D. *Light and Water Radiative Transfer in Natural Waters*; Academic Press: Cambridge, MA, USA, 1994.
11. Zäncker, B.; Bracher, A.; Röttgers, R.; Engel, A. Variations of the organic matter composition in the sea surface microlayer: A comparison between open ocean, coastal, and upwelling sites off the Peruvian coast. *Front. Microbiol.* **2017**, *8*, 2369. [CrossRef] [PubMed]
12. Erickson, Z.K.; Cetinić, I.; Zhang, X.; Boss, E.S.; Werdell, P.J.; Freeman, S.A.; Hu, L.; Lee, C.M.; Omand, M.M.; Perry, M.J. Alignment of optical backscatter measurements from the EXPORTS Northeast Pacific Field Deployment. *Elementa* **2022**, *10*, 00021. [CrossRef]
13. Machado, K.B.; de Andrade, A.T.; de Almeida, M.F.; Nabout, J.C. Systematic mapping of phytoplankton literature about global climate change: Revealing temporal trends in research. *Hydrobiologia* **2023**, *850*, 167–182. [CrossRef]
14. Morel, A.; Bricaud, A. Theoretical results concerning light absorption in a discrete medium, and application to specific absorption of phytoplankton. *Deep Sea Res. Part A Oceanogr. Res. Pap.* **1981**, *28*, 1375–1393. [CrossRef]
15. Prieur, L.; Sathyendranath, S. An optical classification of coastal and oceanic waters based on the specific spectral absorption curves of phytoplankton pigments, dissolved organic matter, and other particulate materials. *Limnol. Oceanogr.* **1981**, *26*, 671–689. [CrossRef]
16. Morel, A.; Prieur, L. Analysis of variations in ocean color. *Limnol. Oceanogr.* **1977**, *22*, 709–721. [CrossRef]
17. Yang, H.; Gordon, H.R. Remote sensing of ocean color: Assessment of water-leaving radiance bidirectional effects on atmospheric diffuse transmittance. *Appl. Opt.* **1997**, *36*, 7887–7897. [CrossRef] [PubMed]
18. Maritorena, S.; Payri, C.; Babin, M.; Claustre, H.; Bonnafous, L.; Morel, A.; Rodière, M. Photoacclimatization in the zooxanthellae of Pocillopora verrucosa and comparison with a pelagic algal community. *Oceanol. Acta* **2002**, *25*, 125–134. [CrossRef]
19. Lee, Z.; Carder, K.L.; Arnone, R.A. Deriving inherent optical properties from water color: A multiband quasi-analytical algorithm for optically deep waters. *Appl. Opt.* **2002**, *41*, 5755–5772. [CrossRef] [PubMed]
20. Bricaud, A.; Morel, A.; Babin, M.; Allali, K.; Claustre, H. Variations of light absorption by suspended particles with chlorophyll a concentration in oceanic (case 1) waters: Analysis and implications for bio-optical models. *J. Geophys. Res. Ocean.* **1998**, *103*, 31033–31044. [CrossRef]
21. Werdell, J.P.; Scott, J.; Vandermuelen, R. A brief introduction to ocean color remote sensing of water quality. In Proceedings of the NASA Water Quality Workshop, NASA Goddard Space Flight Center, Ocean Ecology Laboratory, Greenbelt, MD, USA, 27 September 2017.

22. Pahlevan, N.; Smith, B.; Binding, C.; Gurlin, D.; Li, L.; Bresciani, M.; Giardino, C. Hyperspectral retrievals of phytoplankton absorption and chlorophyll-a in inland and nearshore coastal waters. *Remote Sens. Environ.* **2021**, *253*, 112200. [CrossRef]
23. Mouw, C.B.; Hardman-Mountford, N.J.; Alvain, S.; Bracher, A.; Brewin, R.J.W.W.; Bricaud, A.; Ciotti, A.M.; Devred, E.; Fujiwara, A.; Hirata, T.; et al. A Consumer's Guide to Satellite Remote Sensing of Multiple Phytoplankton Groups in the Global Ocean. *Front. Mar. Sci.* **2017**, *4*, 41. [CrossRef]
24. Groom, S.B.; Sathyendranath, S.; Ban, Y.; Bernard, S.; Brewin, B.; Brotas, V.; Brockmann, C.; Chauhan, P.K.; Choi, J.; Chuprin, A.; et al. Satellite ocean colour: Current status and future perspective. *Front. Mar. Sci.* **2019**, *6*, 485. [CrossRef] [PubMed]
25. Malone, T.C.; Newton, A. The Globalization of Cultural Eutrophication in the Coastal Ocean: Causes and Consequences. *Front. Mar. Sci.* **2020**, *7*, 670. [CrossRef]
26. Li, Y.; Zhao, H.; Bi, S.; Lyu, H. Research progress of remote sensing monitoring of case II water environmental parameters based on water optical classification. *Natl. Remote Sens. Bull.* **2022**, *26*, 19–31. [CrossRef]
27. Serra-Pompei, C.; Hickman, A.E.; Britten, G.L.; Dutkiewicz, S. Assessing the Potential of Backscattering as a Proxy for Phytoplankton Carbon Biomass. *Glob. Biogeochem. Cycles* **2023**, *37*, e2022GB007556. [CrossRef]
28. Graff, J.R.; Milligan, A.J.; Behrenfeld, M.J. The measurement of phytoplankton biomass using flowcytometric sorting and elemental analysis of carbon. *Limnol. Oceanogr. Methods* **2012**, *10*, 910–920. [CrossRef]
29. Roy, S.; Sathyendranath, S.; Platt, T.C. Size-partitioned phytoplankton carbon and carbon-to-chlorophyll ratio from ocean colour by an absorption-based bio-optical algorithm. *Remote Sens. Environ.* **2017**, *194*, 177–189. [CrossRef]
30. Roy, S.; Sathyendranath, S.; Bouman, H.; Platt, T. The global distribution of phytoplankton size spectrum and size classes from their light-absorption spectra derived from satellite data. *Remote Sens. Environ.* **2013**, *139*, 185–197. [CrossRef]
31. Behrenfeld, M.J.; Hu, Y.; Hostetler, C.A.; Dall'Olmo, G.; Rodier, S.D.; Hair, J.W.; Trepte, C.R. Space-based lidar measurements of global ocean carbon stocks. *Geophys. Res. Lett.* **2013**, *40*, 4355–4360. [CrossRef]
32. Bisson, K.M.; Boss, E.S.; Werdell, P.J.; Ibrahim, A.I.; Behrenfeld, M.J. Particulate Backscattering in the Global Ocean: A Comparison of Independent Assessments. *Geophys. Res. Lett.* **2021**, *48*, e2020GL090909. [CrossRef] [PubMed]
33. Roy, S. Distributions of phytoplankton carbohydrate, protein and lipid in the world oceans from satellite ocean colour. *ISME J.* **2018**, *12*, 1457–1472. [CrossRef] [PubMed]
34. Suggett, D.J.; Moore, C.M.; Hickman, A.E.; Geider, R.J. Interpretation of fast repetition rate (FRR) fluorescence: Signatures of phytoplankton community structure versus physiological state. *Mar. Ecol. Prog. Ser.* **2009**, *376*, 1–19. [CrossRef]
35. Gittings, J.A.; Brewin, R.J.W.; Raitsos, D.E.; Kheireddine, M.; Ouhssain, M.; Jones, B.H.; Hoteit, I. Remotely sensing phytoplankton size structure in the Red Sea. *Remote Sens. Environ.* **2019**, *234*, 111387. [CrossRef]
36. Gregg, W.W.; Rousseaux, C.S.G.; Franz, B.A. Global trends in ocean phytoplankton: A new assessment using revised ocean colour data. *Remote Sens. Lett.* **2017**, *8*, 1102–1111. [CrossRef] [PubMed]
37. Bisson, K.M.; Cael, B.B. How Are Under Ice Phytoplankton Related to Sea Ice in the Southern Ocean? *Geophys. Res. Lett.* **2021**, *48*, e2021GL095051. [CrossRef]
38. Blondeau-Patissier, D.; Gower, J.F.R.; Dekker, A.G.; Phinn, S.R.; 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]
39. Adhiambo, R.; Mensah, P.K.; Acheampong, E. Widespread Geographical Disparities in Phytoplankton Ecology Research in the Face of Climate Change: A Review. *Water* **2023**, *15*, 4288. [CrossRef]
40. Gough, D.; Thomas, J.; Oliver, S. *An Introduction to Systematic Reviews*; SAGE Publications Ltd.: London, UK, 2017.
41. Tilstone, G.H.; Lange, P.K.; Misra, A.; Brewin, R.J.W.; Cain, T. Micro-phytoplankton photosynthesis, primary production and potential export production in the Atlantic Ocean. *Prog. Oceanogr.* **2017**, *158*, 109–129. [CrossRef]
42. Hyde, K.J.W.; O'Reilly, J.E.; Oviatt, C.A. Evaluation and application of satellite primary production models in Massachusetts Bay. *Cont. Shelf Res.* **2008**, *28*, 1340–1351. [CrossRef]
43. Werdell, P.J.; Bailey, S.W. An improved in-situ bio-optical data set for ocean color algorithm development and satellite data product validation. *Remote Sens. Environ.* **2005**, *98*, 122–140. [CrossRef]
44. Leles, S.G.; Valentin, J.L.; Figueiredo, G.M. Evaluation of the complexity and performance of marine planktonic trophic models. *An. Acad. Bras. Cienc.* **2016**, *88*, 1971–1991. [CrossRef] [PubMed]
45. Srichandan, S.; Baliarsingh, S.K.; Samanta, A.; Jena, A.K.; Lotliker, A.A.; Balakrishnan Nair, T.M.; Barik, K.K.; Acharyya, T. Satellite-Based Characterization of Phytoplankton Blooms in Coastal Waters of the Northwestern Bay of Bengal. *J. Indian Soc. Remote Sens.* **2022**, *50*, 2221–2228. [CrossRef]
46. Wang, G.; Zhang, Y.; Xu, W.; Zhou, W.; Wu, H.; Xu, Z.; Cao, W.; Guifen, W.; Yinxue, Z.; Wenlong, X.; et al. Estimation of Phytoplankton Pigment Concentration in the South China Sea from Hyperspectral Absorption Data. *Guangxue Xuebao/Acta Opt. Sin.* **2021**, *41*, 0601002. [CrossRef]
47. Yadav, S.; Yamashita, Y.; Yamashiki, Y.A. Multi-sensor approach for chlorophyll-a monitoring in the coastal waters of Japan: A case study of the Yura Estuary. *Ocean Dyn.* **2024**, *74*, 655–667. [CrossRef]

48. Painter, S.C. The biogeochemistry and oceanography of the East African Coastal Current. *Prog. Oceanogr.* **2020**, *186*, 102374. [CrossRef]
49. Bricaud, A.; Babin, M.; Morel, A.; Claustre, H. Variability in the Chlorophyll-Specific Absorption-Coefficients of Natural Phytoplankton—Analysis and parameterization. *J. Geophys. Res.* **1995**, *100*, 13321–13332. [CrossRef]
50. Bricaud, A.; Morel, A.; Prieur, L. Absorption by dissolved organic matter of the sea (yellow substance) in the UV and visible domains. *Limnol. Oceanogr.* **1981**, *26*, 43–53. [CrossRef]
51. Wiggins, B.J. Confronting the Dilemma of Mixed Methods. *J. Theor. Philos. Psychol.* **2011**, *31*, 44–60. [CrossRef]
52. Pranckutė, R. Web of Science (WoS) and Scopus: The titans of bibliographic information in today's academic world. *Publications* **2021**, *9*, 12. [CrossRef]
53. Ashphaq, M.; Srivastava, P.K.; Mitra, D. Review of Near-Shore Satellite Derived Bathymetry: Classification and Account of Five Decades of Coastal Bathymetry Research. *J. Ocean Eng. Sci.* **2021**, *6*, 3. [CrossRef]
54. Kim, I. Trace Element in the Indian Ocean: Current Research Trends and Future Needs. *Ocean Polar Res.* **2021**, *43*, 335–352. [CrossRef]
55. Zhang, Z.; Chen, P.; Zhang, S.; Huang, H.; Pan, Y.; Pan, D. A Review of Machine Learning Applications in Ocean Color Remote Sensing. *Remote Sens.* **2025**, *17*, 1776. [CrossRef]
56. Khan, R.M.; Salehi, B.; Mahdianpari, M.; Mohammadimanesh, F.; Mountrakis, G.; Quackenbush, L.J. A meta-analysis on harmful algal bloom (Hab) detection and monitoring: A remote sensing perspective. *Remote Sens.* **2021**, *13*, 4347. [CrossRef]
57. Eppley, R.W.; Sloan, P.R. Growth Rates of Marine Phytoplankton: Correlation with Light Absorption by Cell Chlorophyll a. *Physiol. Plant.* **1966**, *19*, 47–59. [CrossRef]
58. Gordon, H.R.; Clark, D.K. Remote sensing optical properties of a stratified ocean: An improved interpretation. *Appl. Opt.* **1980**, *19*, 3428–3430. [CrossRef] [PubMed]
59. Gordon, H.R. Simple Calculation of the Diffuse Reflectance of the Ocean. *Appl. Opt.* **1973**, *12*, 2803–2804. [CrossRef] [PubMed]
60. Gordon, H.R.; Morel, A.Y. *Remote Assessment of Ocean Color for Interpretation of Satellite Visible Imagery: A Review*; Springer: New York, NY, USA, 1983; 114p. [CrossRef]
61. Gordon, H.R.; Mccluney, W.R. Estimation of the Depth of Sunlight Penetration in the Sea for Remote Sensing. *Appl. Opt.* **1975**, *14*, 413–416. [CrossRef] [PubMed]
62. Maske, H.; Haardt, H. Quantitative in vivo absorption spectra of phytoplankton: Detrital absorption and comparison with fluorescence excitation spectra. *Limnol. Oceanogr.* **1987**, *32*, 620–633. [CrossRef]
63. Neori, A.; Holm-Hansen, O.; Mitchell, B.G.; Kiefer, D.A. Photoadaptation in marine phytoplankton: Changes in spectral absorption and excitation of chlorophyll a fluorescence. *Plant Physiol.* **1984**, *76*, 518–524. [CrossRef] [PubMed]
64. Soohoo, J.B.; Kiefer, D.A.; Collins, D.J.; Mcdermid, I.S. In vivo fluorescence excitation and absorption spectra of marine phytoplankton: I. Taxonomic characteristics and responses to photoadaptation. *J. Plankton Res.* **1986**, *8*, 197–214. [CrossRef]
65. Bidigare, R.R.; Morrow, J.H.; Kiefer, D.A. Derivative analysis of spectral absorption by phytoplankton pigments. In Proceedings of the SPIE Defense + Security, Los Angeles, CA, USA, 11–12 January 1988; Volume 925, pp. 101–108. [CrossRef]
66. Iturriaga, R.; Siegel, D.A. Microphotometric characterization of phytoplankton and detrital absorption properties in the Sargasso Sea. *Limnol. Oceanogr.* **1989**, *34*, 1706–1726. [CrossRef]
67. Perry, M.J.; Porter, S.M. Determination of the cross-section absorption coeffcient of individual phytoplankton cells by analytical flow cytometry. *Limnol. Oceanogr.* **1989**, *34*, 1727–1738. [CrossRef]
68. Kiefer, D.A.; Mitchell, B.G. A simple, steady state description of phytoplankton growth based on absorption cross section and quantum efficiency. *Limnol. Oceanogr.* **1983**, *28*, 770–776. [CrossRef]
69. Sathyendranath, S.; Lazzara, L.; Prieur, L. Variations in the spectral values of specific absorption of phytoplankton. *Limnol. Oceanogr.* **1987**, *32*, 403–415. [CrossRef]
70. Colijn, F. Light absorption in the waters of the Ems-Dollard estuary and its consequences for the growth of phytoplankton and microphytobenthos. *Neth. J. Sea Res.* **1982**, *15*, 196–216. [CrossRef]
71. Arbones, B.; Figueiras, F.G.; Zapata, M. Determination of phytoplankton absorption coefficient in natural seawater samples: Evidence of a unique equation to correct the pathlength amplification on glass-fiber filters. *Mar. Ecol. Prog. Ser.* **1996**, *137*, 293–304. [CrossRef]
72. Roesler, C.S.; Perry, M.J.; Ferry, M.J. In-Situ Phytoplankton Absorption, Fluorescence Emission, and Particulate Backscattering Spectra Determined from Reflectance. *J. Geophys. Res.* **1995**, *100*, 13279–13294. [CrossRef]
73. Hoepffner, N.; Sathyendranath, S. Bio-optical characteristics of coastal waters: Absorption spectra of phytoplankton and pigment distribution in the western North Atlantic. *Limnol. Oceanogr.* **1992**, *37*, 1660–1679. [CrossRef]
74. Zaneveld, J.R.V.; Kitchen, J.C. The variation in the inherent optical properties of phytoplankton near an absorption peak as determined by various models of cell structure. *J. Geophys. Res.* **1995**, *100*, 13309–13320. [CrossRef]
75. Hoepffner, N.; Sathyendranath, S. Determination of the major groups of phytoplankton pigments from the absorption spectra of total particulate matter. *J. Geophys. Res.* **1993**, *98*, 22789–22803. [CrossRef]

76. Aguirre-Gómez, R.; Boxall, S.R.; Weeks, A.R. Identification of algal pigments using high-order derivatives. In *Proceedings of the IGARSS '95: 1995 International Geoscience and Remote Sensing Symposium, Firenze, Italy, 10–14 July 1995*; IEEE: Piscataway, NJ, USA, 1995; Volume 3, pp. 1769–1771. [CrossRef]
77. Morel, A.; Maritorena, S. Bio-optical properties of oceanic waters: A reappraisal. *J. Geophys. Res.* **2001**, *106*, 7163–7180. [CrossRef]
78. Nelson, N.B.; Prezelin, B.B.; Bidigare, R.R. Phytoplankton light absorption and the package effect in California coastal waters. *Mar. Ecol. Prog. Ser.* **1993**, *94*, 217–227. [CrossRef]
79. Kyewalyanga, M.N.; Platt, T.; Sathyendranath, S. Estimation of the photosynthetic action spectrum: Implication for primary production models. *Mar. Ecol. Prog. Ser.* **1997**, *146*, 207–223. [CrossRef]
80. Woźniak, B.; Dera, J.; Ficek, D.; Majchrowski, R.; Kaczmarek, S.; Ostrowska, M.; Koblentz-Mishke, O.I. Modelling the influence of acclimation on the absorption properties of marine phytoplankton. *Oceanologia* **1999**, *41*, 187–210.
81. Ferrari, G.M.; Tassan, S. A method using chemical oxidation to remove light absorption by phytoplankton pigments. *J. Phycol.* **1999**, *35*, 1090–1098. [CrossRef]
82. Churilova, T.Y.; Berseneva, G.P. Absorption of light by phytoplankton, detritus, and dissolved organic substances in the coastal region of the Black Sea (July–August 2002). *Phys. Oceanogr.* **2004**, *14*, 221–233. [CrossRef]
83. Zhang, Y.L.; Liu, M.L.; Wang, X.; Zhu, G.W.; Chen, W.M. Bio-optical properties and estimation of the optically active substances in Lake Tianmuhu in summer. *Int. J. Remote Sens.* **2009**, *30*, 2837–2857. [CrossRef]
84. Ting-lu, Z.; Xiang-zhi, D.; Qing-na, X.; Guo-qiang, Q.; Zhang, T.-L.; Du, X.-Z.; Xu, Q.-N.; Qiu, G.-Q. Application of 1D Wavelet Analysis in Detecting Species of Harmful Algae Blooms with Absorption Spectra of Phytoplankton. *Spectrosc. Spectr. Anal.* **2009**, *29*, 2743–2747. [CrossRef]
85. Lokuhewage, A.U.M.; Naiki, Y.; Toyooka, S. Quantitative estimation of phytoplankton species in freshwater by two step linear regression analysis using spectral absorption method. *Opt. Rev.* **2005**, *12*, 420–426. [CrossRef]
86. Chazottes, A.; Bricaud, A.; Crépon, M.; Thiria, S. Statistical analysis of a database of absorption spectra of phytoplankton and pigment concentrations using self-organizing maps. *Appl. Opt.* **2006**, *45*, 8102–8115. [CrossRef] [PubMed]
87. Ficek, D.; Kaczmarek, S.; Stoń-Egiert, J.; Woźniak, B.; Majchrowski, R.; Dera, J. Spectra of light absorption by phytoplankton pigments in the baltic; conclusions to be drawn from a gaussian analysis of empirical data. *Oceanologia* **2004**, *46*, 533–555.
88. Chazottes, A.; Crépon, M.; Bricaud, A.; Ras, J.; Thiria, S. Statistical analysis of absorption spectra of phytoplankton and of pigment concentrations observed during three POMME cruises using a neural network clustering method. *Appl. Opt.* **2007**, *46*, 3790–3799. [CrossRef] [PubMed]
89. Le Floc'h, E.; Malara, G.; Sciandra, A. An automatic device for in vivo absorption spectra acquisition and chlorophyll estimation in phytoplankton cultures. *J. Appl. Phycol.* **2002**, *14*, 435–444. [CrossRef]
90. Suggett, D.J.; Macintyre, H.L.; Geider, R.J. Evaluation of biophysical and optical determinations of light absorption by photosystem II in phytoplankton. *Limnol. Oceanogr. Methods* **2004**, *2*, 316–332. [CrossRef]
91. Lei, H.; Pan, D.; Bai, Y.; Chen, X.; Zhou, Y.; Zhu, Q.; Hui, L.; Delu, P.; Yan, B.; Xiaoyan, C.; et al. HAB detection based on absorption and backscattering properties of phytoplankton. In *SPIE Environmental Remote Sensing, Prague, Czech Republic, 20–22 September 2011*; Bostater, C.R., Mertikas, S.P., Neyt, X., Velez Reyes, M., Eds.; SPIE: Bellingham, WA, USA, 2011; Volume 8175. [CrossRef]
92. Meler, J.; Wózniak, S.B.; Stón-Egiert, J.; WoÅ°niak, B. Parameterization of phytoplankton spectral absorption coefficients in the Baltic Sea: General, monthly and two-component variants of approximation formulas. *Ocean Sci.* **2018**, *14*, 1523–1545. [CrossRef]
93. Le Deunff, E.; Malagoli, P.; Decau, M.-L. Modelling Nitrogen Uptake in Plants and Phytoplankton: Advantages of Integrating Flexibility into the Spatial and Temporal Dynamics of Nitrate Absorption. *Agronomy* **2019**, *9*, 116. [CrossRef]
94. Soja-Woźniak, M.; Clementson, L.; Wojtasiewicz, B.B.B.; Baird, M.; Soja-Wozniak, M.; Clementson, L.; Wojtasiewicz, B.B.B.; Baird, M. Estimation of the Global Distribution of Phytoplankton Light Absorption From Pigment Concentrations. *J. Geophys. Res. Ocean.* **2022**, *127*, e2022JC018494. [CrossRef]
95. Roy, S.; Platt, T.; Sathyendranath, S. Modelling the time-evolution of phytoplankton size spectra from satellite remote sensing. *ICES J. Mar. Sci.* **2011**, *68*, 719–728. [CrossRef]
96. Huang, T.; Zhao, Y.; Xu, Z.; Zhou, L. A spectral model of phytoplankton absorption for inland lake. *J. Comput. Theor. Nanosci.* **2016**, *13*, 6555–6562. [CrossRef]
97. Perkins, M.; Effler, S.W.; Strait, C.M. Phytoplankton absorption and the chlorophyll a-specific absorption coefficient in dynamic Onondaga Lake. *Inl. Waters* **2014**, *4*, 133–146. [CrossRef]
98. Effler, A.J.P.; Peng, F.; Effler, S.W.; Strait, C.M.; Perkins, M.; Schulz, K.L. Light absorption by phytoplankton and minerogenic particles in Cayuga Lake, New York. *Inl. Waters* **2015**, *5*, 433–450. [CrossRef]
99. Clementson, L.A.; Wojtasiewicz, B. Dataset on the absorption characteristics of extracted phytoplankton pigments. *Data Brief* **2019**, *24*, 103875. [CrossRef] [PubMed]
100. Clementson, L.A.; Wojtasiewicz, B. Dataset on the in vivo absorption characteristics and pigment composition of various phytoplankton species. *Data Br.* **2019**, *25*, 104020. [CrossRef] [PubMed]

101. Li, N.; Sun, D.; Huan, Y.; Wang, S.; Zhang, H.; Qiu, Z.; He, Y.; Nan, L.; Deyong, S.; Yu, H.; et al. Determination and Application of Specific Absorption Spectra of Phytoplankton Species in Yellow Sea and Bohai Sea. *Guangxue Xuebao/Acta Opt. Sin.* **2020**, *40*, 0601004. [CrossRef]
102. Asselot, R.; Lunkeit, F.; Holden, P.B.; Hense, I. The Relative Importance of Phytoplankton Light Absorption and Ecosystem Complexity in an Earth System Model. *J. Adv. Model. Earth Syst.* **2021**, *13*, e2020MS002110. [CrossRef]
103. Polcyn, F.C.; Rollin, R.A. *Remote Sensing Techniques for the Location and Measurement of Shallow-Water Features*; University of Michigan Library: Ann Arbor, MI, USA, 1969; pp. 1–80. Available online: https://hdl.handle.net/2027.42/7114 (accessed on 9 June 2026).
104. Wezernak, C.T.; Lyzenga, D.R.; Polcyn, F.C. *Remote Sensing Studies in the New York Bight: Final Report*; Environmental Research Institute of Michigan: Ann Arbor, MI, USA, 1975; Available online: https://hdl.handle.net/2027.42/8263 (accessed on 9 June 2026).
105. Gordon, H.R. Radiative transfer: A technique for simulating the ocean in satellite remote sensing calculations. *Appl. Opt.* **1976**, *15*, 1974–1979. [CrossRef] [PubMed]
106. Yentsch, C.S. The influence of phytoplankton pigments on the colour of sea water. *Deep Sea Res.* **1960**, *7*, 1–9. [CrossRef]
107. Lorenzen, C.J. Extinction of light in the ocean by phytoplankton. *ICES J. Mar. Sci.* **1972**, *34*, 262–267. [CrossRef]
108. Bannister, T.T. Quantitative description of steady state nutrient-saturated algal growth, including adaptation. *Limnol. Oceanogr.* **1979**, *24*, 76–96. [CrossRef]
109. Giles-Guzma, A.D.; Alvarez-Borrego, S. Covariance of the absorption of phytoplankton, colored dissolved organic matter, and detritus in case i waters, as deduced from the coastal zone color scanner bio–optical algorithm. *Appl. Opt.* **1996**, *35*, 2109–2113. [CrossRef]
110. Stuart, V.; Sathyendranath, S.; Platt, T.; Maass, H.; Irwin, B.D. Pigments and species composition of natural phytoplankton populations: Effect on the absorption spectra. *J. Plankton Res.* **1998**, *20*, 187–217. [CrossRef]
111. Roelke, D.L.; Kennedy, C.D.; Weidemann, A.D. Use of discriminant and fourth-derivative analyses with high-resolution absorption spectra for phytoplankton research: Limitations at varied signal-to-noise ratio and spectral resolution. *Gulf Mex. Sci.* **1999**, *17*, 75–86. [CrossRef]
112. Hoge, F.E.; Wright, C.W.; Lyon, P.E.; Swift, R.N.; Yungel, J.K. Satellite retrieval of the absorption coefficient of phytoplankton phycoerythrin pigment: Theory and feasibility status. *Appl. Opt.* **1999**, *38*, 7431–7441. [CrossRef] [PubMed]
113. Mitchell, B.G.; Kahru, M.; Wieland, J.; Stramska, M. Determination of spectral absorption coefficients of particles, dissolved material and phytoplankton for discrete water samples. In *Ocean Optics Protocols for Satellite Ocean Color Sensor Validation, Revision 3, Volume 2*; Mueller, J.L., Fargion, G.S., Eds.; NASA Technical Memorandum 2002-210004; NASA: Greenbelt, MD, USA, 2002; pp. 231–257.
114. Cleveland, J.S.J.S. Regional Models for Phytoplankton Absorption as a Function of Chlorophyll-A Concentration. *J. Geophys. Res.* **1995**, *100*, 13333–13344. [CrossRef]
115. Lutz, V.A.; Sathyendranath, S.; Head, E.J.H.H.H. Absorption coefficient of phytoplankton: Regional variations in the North Atlantic. *Mar. Ecol. Prog. Ser.* **1996**, *135*, 197–213. [CrossRef]
116. Lee, Z.; Carder, K.L. Absorption spectrum of phytoplankton pigments derived from hyperspectral remote-sensing reflectance. *Remote Sens. Environ.* **2004**, *89*, 361–368. [CrossRef]
117. Sydor, M. Use of hyperspectral remote sensing reflectance in extracting the spectral volume absorption coefficient for phytoplankton in coastal water: Remote sensing relationships for the inherent optical properties of coastal water. *J. Coast. Res.* **2006**, *22*, 587–594. [CrossRef]
118. Woźniak, B.; Majchrowski, R.; Ostrowska, M.M.; Ficek, D.; Kunicka, J.; Dera, J.; Wozniak, B.; Majchrowski, R.; Ostrowska, M.M.; Ficek, D.; et al. Remote sensing of vertical phytoplankton pigment distributions in the Baltic: New mathematical expressions. Part 3: Non-photosynthetic pigment absorption factor. *Oceanologia* **2007**, *49*, 513–526.
119. Bracher, A.; Vountas, M.; Dinter, T.; Röttgers, R.; Peeken, I.; Bernitt, E.; Burrows, J.P. Phytoplankton distribution and light absorption from space using differential optical absorption spectroscopy. In Proceedings of the European Space Agency, (Special Publication) ESA SP, Montreux, Switzerland, 23–27 April 2007.
120. McClain, C.R. A Decade of Satellite Ocean Color Observations: A Review of Recent Achievements, Challenges, and Future Directions. *Annu. Rev. Mar. Sci.* **2009**, *1*, 19–42. [CrossRef]
121. Neumüller, M.; Cunningham, A.; Mckee, D. Assessment of a microscopic photobleaching technique for measuring the spectral absorption efficiency of individual phytoplankton cells. *J. Plankton Res.* **2002**, *24*, 741–746. [CrossRef]
122. Toepel, J.; Langner, U.; Wilhelm, C. Combination of flow cytometry and single cell absorption spectroscopy to study the phytoplankton structure and to calculate the chl a specific absorption coefficients at the taxon level. *J. Phycol.* **2005**, *41*, 1099–1109. [CrossRef]
123. Zhang, Q.-Q.; Wang, L.; Lei, S.-H.; Zhu, C.-J.; Wang, X.-L.; Qian-qian, Z.; Lei, W.; Shu-he, L.; Chen-jian, Z.; Xiu-lin, W. Characteristics of absorption spectra of phytoplankton. *Spectrosc. Spectr. Anal.* **2006**, *26*, 1676–1680.

124. Xu, J.; Gu, X.; Zhang, B.; Yu, T.; Li, F.; Li, J. Improved models for Chla estimation by considering the effect of phytoplankton specific absorption. In *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS)*; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2010; pp. 616–619. [CrossRef]
125. Frouin, R.; Deschamps, P.-Y.; Dubuisson, P. *Remote Sensing of Solar-Stimulated Phytoplankton Chlorophyll Fluorescence by Differential Absorption in the Oxygen B-Band*; SPIE: Bellingham, WA, USA, 2008; Volume 7150, p. 715005. [CrossRef]
126. Sun, D.; Li, Y.; Wang, Q.; Lv, H.; Le, C.; Huang, C.; Gong, S. Partitioning particulate scattering and absorption into contributions of phytoplankton and non-algal particles in winter in Lake Taihu (China). *Hydrobiologia* **2010**, *644*, 337–349. [CrossRef]
127. Wang, G.; Cao, W.; Yang, D.; Zhao, J. Partitioning particulate absorption coefficient into contributions of phytoplankton and nonalgal particles: A case study in the northern South China Sea. *Estuar. Coast. Shelf Sci.* **2008**, *78*, 513–520. [CrossRef]
128. Devred, E.; Sathyendranath, S.; Stuart, V.; Maass, H.; Ulloa, O.; Platt, T. A two-component model of phytoplankton absorption in the open ocean: Theory and applications. *J. Geophys. Res. Ocean.* **2006**, *111*, C03011. [CrossRef]
129. Woźniak, B.; Woźniak, S.B.; Tyszka, K.; Dera, J. Modelling the light absorption properties of particulate matter forming organic particles suspended in seawater. Part 1. Model description classification of organic particles, and example spectra of the light absorption coefficient and the imaginary part. *Oceanologia* **2005**, *47*, 129–164.
130. Fujiki, T.; Taguchi, S. Variability in chlorophyll a specific absorption coefficient in marine phytoplankton as a function of cell size and irradiance. *J. Plankton Res.* **2002**, *24*, 859–874. [CrossRef]
131. Moisan, J.R.; Moisan, T.A.H.; Linkswiler, M.A. An inverse modeling approach to estimating phytoplankton pigment concentrations from phytoplankton absorption spectra. *J. Geophys. Res. Ocean.* **2011**, *116*, C09018. [CrossRef]
132. Montes-Hugo, M.; Xie, H. An inversion model based on salinity and remote sensing reflectance for estimating the phytoplankton absorption coefficient in the Saint Lawrence Estuary. *J. Geophys. Res. Ocean.* **2015**, *120*, 6958–6970. [CrossRef]
133. Roesler, C.S.; Barnard, A.H. Optical proxy for phytoplankton biomass in the absence of photophysiology: Rethinking the absorption line height. *Methods Oceanogr.* **2013**, *7*, 79–94. [CrossRef]
134. Yang, C.; Yang, D. A non-linear model of phytoplankton absorption based on cluster analysis. *Zhongguo Jiguang/Chin. J. Lasers* **2015**, *42*, s114001. [CrossRef]
135. Zheng, G.; Stramski, D. A model based on stacked-constraints approach for partitioning the light absorption coefficient of seawater into phytoplankton and non-phytoplankton components. *J. Geophys. Res. Ocean.* **2013**, *118*, 2155–2174. [CrossRef]
136. Zheng, G.; Stramski, D. A model for partitioning the light absorption coefficient of suspended marine particles into phytoplankton and nonalgal components. *J. Geophys. Res. Ocean.* **2013**, *118*, 2977–2991. [CrossRef]
137. Zheng, G.; Stramski, D.; Digiacomo, P.M. A model for partitioning the light absorption coefficient of natural waters into phytoplankton, nonalgal particulate, and colored dissolved organic components: A case study for the Chesapeake Bay. *J. Geophys. Res. Ocean.* **2015**, *120*, 2601–2621. [CrossRef]
138. Ye, H.; Zhang, B.; Liao, X.; Li, T.; Shen, Q.; Zhang, F.; Zhu, J.; Li, J. Gaussian decomposition and component pigment spectral analysis of phytoplankton absorption spectra. *J. Oceanol. Limnol.* **2019**, *37*, 1542–1554. [CrossRef]
139. Wei, J.; Lee, Z.; Shang, S.; Yu, X. Semianalytical Derivation of Phytoplankton, CDOM, and Detritus Absorption Coefficients From the Landsat 8/OLI Reflectance in Coastal Waters. *J. Geophys. Res. Ocean.* **2019**, *124*, 3682–3699. [CrossRef]
140. Shang, S.; Dong, Q.; Lee, Z.; Li, Y.; Xie, Y.; Behrenfeld, M. MODIS observed phytoplankton dynamics in the Taiwan Strait: An absorption-based analysis. *Biogeosciences* **2011**, *8*, 841–850. [CrossRef]
141. Shaju, S.S.; Minu, P.; Srikanth, A.S.; Ashraf, P.M.; Vijayan, A.K.; Meenakumari, B. Decomposition study of in vivo phytoplankton absorption spectra aimed at identifying the pigments and the phytoplankton group in complex case 2 coastal waters of the Arabian Sea. *Oceanol. Hydrobiol. Stud.* **2015**, *44*, 282–293. [CrossRef]
142. Letelier, R.M.; White, A.E.; Bidigare, R.R.; Barone, B.; Church, M.J.; Karl, D.M. Light absorption by phytoplankton in the North Pacific Subtropical Gyre. *Limnol. Oceanogr.* **2017**, *62*, 1526–1540. [CrossRef]
143. Wei, J.; Lee, Z. Retrieval of phytoplankton and colored detrital matter absorption coefficients with remote sensing reflectance in an ultraviolet band. *Appl. Opt.* **2015**, *54*, 636–649. [CrossRef] [PubMed]
144. Li, J.; Ma, R.; Xue, K.; Loiselle, S.A. Drivers to spatial and temporal dynamics of column integrated phytoplankton biomass in the shallow lake of Chaohu, China. *Ecol. Indic.* **2020**, *109*, 105812. [CrossRef]
145. Mascarenhas, V.J.; Zielinski, O. Parameterization of spectral particulate and phytoplankton absorption coefficients in Sognefjord and Trondheimsfjord, two contrasting Norwegian Fjord Ecosystems. *Remote Sens.* **2018**, *10*, 977. [CrossRef]
146. Paavel, B.; Kangro, K.; Arst, H.; Reinart, A.; Kutser, T.; Nõges, T. Parameterization of chlorophyll-specific phytoplankton absorption coefficients for productive lake waters. *J. Limnol.* **2016**, *75*, 423–438. [CrossRef]
147. Churilova, T.; Suslin, V.; Sosik, H.M.; Efimova, T.; Moiseeva, N.; Moncheva, S.; Mukhanov, V.; Rylkova, O.; Krivenko, O. Phytoplankton light absorption in the deep chlorophyll maximum layer of the Black Sea. *Eur. J. Remote Sens.* **2019**, *52*, 123–136. [CrossRef]
148. Goela, P.C.; Icely, J.; Cristina, S.S.; Newton, A.; Moore, G.; Cordeiro, C.; Costa Goela, P.; Icely, J.; Cristina, S.S.; Newton, A.; et al. Specific absorption coefficient of phytoplankton off the Southwest coast of the Iberian Peninsula: A contribution to algorithm development for ocean colour remote sensing. *Cont. Shelf Res.* **2013**, *52*, 119–132. [CrossRef]

149. Wei, J.; Wang, M.; Mikelsons, K.; Jiang, L. Chlorophyll-Specific Absorption Coefficient of Phytoplankton in World Oceans: Seasonal and Regional Variability. *Remote Sens.* **2023**, *15*, 2423. [CrossRef]
150. Tiwari, S.P.; Shanmugam, P. An evaluation of models for the satellite-estimation of phytoplankton absorption coefficients in coastal/oceanic waters. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 364–371. [CrossRef]
151. Ahmed, S.; El-Habashi, A.; Lovko, V. Neural network retrievals of phytoplankton absorption and Karenia brevis harmful algal blooms in the West Florida Shelf. In *Ocean Sensing and Monitoring IX*; Hou, W., Arnone, R.A., Eds.; SPIE: Bellingham, WA, USA, 2017; Volume 10186, p. 101860L. [CrossRef]
152. Wang, G.; Lee, Z.; Mouw, C.B. Multi-spectral remote sensing of phytoplankton pigment absorption properties in cyanobacteria bloom waters: A regional example in the Western Basin of Lake Erie. *Remote Sens.* **2017**, *9*, 1309. [CrossRef]
153. Kalenak, D. Discriminating four temperate lakes using phytoplankton absorption spectra. *Lakes Reserv. Sci. Policy Manag. Sustain. Use* **2014**, *19*, 98–117. [CrossRef]
154. Bricaud, A.; Ciotti, A.M.; Gentili, B. Spatial-temporal variations in phytoplankton size and colored detrital matter absorption at global and regional scales, as derived from twelve years of SeaWiFS data (1998–2009). *Glob. Biogeochem. Cycles* **2012**, *26*, GB1010. [CrossRef]
155. Mitchell, C.; Cunningham, A.; McKee, D. Derivation of the specific optical properties of suspended mineral particles and their contribution to the attenuation of solar irradiance in offshore waters by ocean color remote sensing. *J. Geophys. Res. Ocean.* **2016**, *121*, 104–117. [CrossRef]
156. Alam, M.S.; Tiwari, S.P.; Rahman, S.M. Optimized Ensemble Machine Learning Models for Predicting Phytoplankton Absorption Coefficients. *IEEE Access* **2024**, *12*, 5760–5769. [CrossRef]
157. Ashphaq, M.; Roy, S. A machine learning algorithm to retrieve the red peak of phytoplankton absorption spectra from ocean-colour remote sensing. *Remote Sens. Appl. Soc. Environ.* **2025**, *39*, 101702. [CrossRef]
158. Anderson, T.R. Plankton functional type modelling: Running before we can walk? *J. Plankton Res.* **2005**, *27*, 1073–1081. [CrossRef]
159. Sieburth, J.M.N.; Smetacek, V.; Lenz, J. Pelagic ecosystem structure: Heterotrophic compartments of the plankton and their relationship to plankton size fractions. *Limnol. Oceanogr.* **1978**, *23*, 1256–1263. [CrossRef]
160. Johnsen, G.; Samset, O.; Granskog, L.; Sakshaug, E. In vivo absorption characteristics in 10 classes of bloom-forming phytoplankton—Taxonomic characteristics and responses to photoadaptation by means of discriminant and HPLC analysis. *Mar. Ecol. Prog. Ser.* **1994**, *105*, 149–158. [CrossRef]
161. Aguirre-Gómez, R.; Weeks, A.R.; Boxall, S.R. The identification of phytoplankton pigments from absorption spectra. *Int. J. Remote Sens.* **2001**, *22*, 315–338. [CrossRef]
162. Lutz, V.A.; Sathyendaranath, S.; Head, E.J.H.; Li, W.K.W. Changes in the in vivo absorption and fluorescence excitation spectra with growth irradiance in three species of phytoplankton. *J. Plankton Res.* **2001**, *23*, 555–569. [CrossRef]
163. Seppälä, J.; Ylöstalo, P.; Kuosa, H. Spectral absorption and fluorescence characteristics of phytoplankton in different size fractions across a salinity gradient in the Baltic Sea. *Int. J. Remote Sens.* **2005**, *26*, 387–414. [CrossRef]
164. Moberg, L.; Karlberg, B.; Sørensen, K.; Källqvist, T. Assessment of phytoplankton class abundance using absorption spectra and chemometrics. *Talanta* **2002**, *56*, 153–160. [CrossRef] [PubMed]
165. Varunan, T.; Shanmugam, P. A model for estimating size-fractioned phytoplankton absorption coefficients in coastal and oceanic waters from satellite data. *Remote Sens. Environ.* **2015**, *158*, 235–254. [CrossRef]
166. Brewin, R.J.W.; Devred, E.; Sathyendranath, S.; Lavender, S.J.; Hardman-Mountford, N.J. Model of phytoplankton absorption based on three size classes. *Appl. Opt.* **2011**, *50*, 4535–4549. [CrossRef] [PubMed]
167. Devred, E.; Sathyendranath, S.; Stuart, V.; Platt, T. A three component classification of phytoplankton absorption spectra: Application to ocean-color data. *Remote Sens. Environ.* **2011**, *115*, 2255–2266. [CrossRef]
168. Zhou, W.; Sun, Z.-H.; Cao, W.-X.; Wang, G.-F.; Wen, Z.; Zhao-hua, S.; Wen-xi, C.; Gui-fen, W. Variations in the optical absorption and attenuation properties of cultured phytoplankton and their relationships with cell size. *Guang Pu Xue Yu Guang Pu Fen Xi/Spectrosc. Spectr. Anal.* **2012**, *32*, 3347–3352. [CrossRef]
169. Zhou, W.; Wang, G.; Li, C.; Xu, Z.; Cao, W.; Shen, F. Retrieval of phytoplankton cell size from chlorophyll a specific absorption and scattering spectra of phytoplankton. *Appl. Opt.* **2017**, *56*, 8362–8371. [CrossRef] [PubMed]
170. Junfang, L.; Wenxi, C.; Wen, Z.; Shuibo, H.; Guifen, W.; Zhaohua, S.; Zhantang, X.; Qingjun, S.; Lin, J.; Cao, W.; et al. A bio-optical inversion model to retrieve absorption contributions and phytoplankton size structure from total minus water spectral absorption using genetic algorithm. *Chin. J. Oceanol. Limnol.* **2013**, *31*, 970–978. [CrossRef]
171. Pandi, S.R.; Kiran, R.; Sarma, N.S.; Srikanth, A.S.; Sarma, V.V.S.S.; Krishna, M.S.; Bandyopadhyay, D.; Prasad, V.R.; Acharyya, T.; Reddy, K.G. Contrasting phytoplankton community structure and associated light absorption characteristics of the western Bay of Bengal. *Ocean Dyn.* **2014**, *64*, 89–101. [CrossRef]
172. Mercado, J.M.; Sala, I.; Salles, S.; Cortés, D.; Ramírez, T.; Liger, E.; Yebra, L.; Bautista, B. Effects of community composition and size structure on light absorption and nutrient uptake of phytoplankton in contrasting areas of the Alboran Sea. *Mar. Ecol. Prog. Ser.* **2014**, *499*, 47–64. [CrossRef]

173. Organelli, E.; Nuccio, C.; Lazzara, L.; Uitz, J.; Bricaud, A.; Massi, L. On the discrimination of multiple phytoplankton groups from light absorption spectra of assemblages with mixed taxonomic composition and variable light conditions. *Appl. Opt.* **2017**, *56*, 3952–3968. [CrossRef] [PubMed]
174. Chakraborty, S.; Lohrenz, S.E.; Gundersen, K. Photophysiological and light absorption properties of phytoplankton communities in the river-dominated margin of the northern Gulf of Mexico. *J. Geophys. Res. Ocean.* **2017**, *122*, 4922–4938. [CrossRef]
175. Xue, K.; Ma, R.; Wang, D.; Shen, M. Optical Classification of the Remote Sensing Reflectance and Its Application in Deriving the Specific Phytoplankton Absorption in Optically Complex Lakes. *Remote Sens.* **2019**, *11*, 184. [CrossRef]
176. Organelli, E.; Bricaud, A.; Antoine, D.; Uitz, J. Multivariate approach for the retrieval of phytoplankton size structure from measured light absorption spectra in the Mediterranean Sea (BOUSSOLE site). *Appl. Opt.* **2013**, *52*, 2257–2273. [CrossRef] [PubMed]
177. Wang, G.G.; Cao, W.; Wang, G.G.; Zhou, W.; Guoqing, W.; Wenxi, C.; Guifen, W.; Wen, Z. Phytoplankton size class derived from phytoplankton absorption and chlorophyll-*a* concentrations in the northern South China Sea. *Chin. J. Oceanol. Limnol.* **2013**, *31*, 750–761. [CrossRef]
178. Wang, S.; Ishizaka, J.; Hirawake, T.; Watanabe, Y.; Zhu, Y.; Hayashi, M.; Yoo, S. Remote estimation of phytoplankton size fractions using the spectral shape of light absorption. *Opt. Express* **2015**, *23*, 10301–10318. [CrossRef] [PubMed]
179. Sun, X.; Shen, F.; Brewin, R.J.W.; Li, M.; Zhu, Q. Light absorption spectra of naturally mixed phytoplankton assemblages for retrieval of phytoplankton group composition in coastal oceans. *Limnol. Oceanogr.* **2022**, *67*, 946–961. [CrossRef]
180. Brewin, R.J.W.; Lavender, S.J.; Hardman-Mountford, N.J.; Hirata, T. A spectral response approach for detecting dominant phytoplankton size class from satellite remote sensing. *Acta Oceanol. Sin.* **2010**, *29*, 14–32. [CrossRef]
181. Zhang, X.; Huot, Y.; Bricaud, A.; Sosik, H.M. Inversion of spectral absorption coefficients to infer phytoplankton size classes, chlorophyll concentration, and detrital matter. *Appl. Opt.* **2015**, *54*, 5805–5816. [CrossRef] [PubMed]
182. Zhang, J.; He, H.; Fan, D.L.; Fu, B.; Wang, S.; Dong, S. Research of chlorophyll-a concentration inversion at different depths in Hong Kong offshore waters based on gaussian process regression. In *5th International Workshop on Environment and Geoscience*; Chen, Y., Ed.; Institute of Physics: London, UK, 2022; Volume 1087. [CrossRef]
183. Kun, S.; Yun-mei, L.; Yu, Y.; Yan-fei, W.; Xin, J.; Hong, Z.; Bin, Y.; Shi, K.; Li, Y.-M.; Yang, Y.; et al. Analysis of phytoplankton absorption coefficients and their effect factors in Taihu Lake. *Spectrosc. Spectr. Anal.* **2010**, *30*, 2223–2227. [CrossRef]
184. Organelli, E.; Nuccio, C.; Melillo, C.; Massi, L. Relationships between phytoplankton light absorption, pigment composition and size structure in offshore areas of the Mediterranean Sea. *Adv. Oceanogr. Limnol.* **2011**, *2*, 107–123. [CrossRef]
185. Kheireddine, M.; Ouhssain, M.; Organelli, E.; Bricaud, A.; Jones, B.H. Light Absorption by Suspended Particles in the Red Sea: Effect of Phytoplankton Community Size Structure and Pigment Composition. *J. Geophys. Res. Ocean.* **2018**, *123*, 902–921. [CrossRef]
186. Deng, L.; Zhou, W.; Cao, W.; Zheng, W.; Wang, G.; Xu, Z.; Li, C.; Yang, Y.; Hu, S.; Zhao, W. Retrieving phytoplankton size class from the absorption coefficient and Chlorophyll a concentration based on support vector machine. *Remote Sens.* **2019**, *11*, 1054. [CrossRef]
187. Huang, X.; Shi, K.; Zhang, Y.-L.; Zhu, G.-W.; Zhou, Y.-Q. Effect of Phytoplankton Community Composition and Size Structure on Light Absorption Properties. *Huanjing Kexue/Environ. Sci.* **2021**, *42*, 808–818. [CrossRef]
188. Watanabe, F.S.Y.; Alcântara, E.H.; Rodrigues, T.W.P.; Bernardo, N.M.R.; Rotta, L.H.S.; Imai, N.N. Phytoplankton community dynamic detection from the chlorophyll-specific absorption coefficient in productive inland waters. *Acta Limnol. Bras.* **2017**, *29*, s2179–s2975. [CrossRef]
189. Morrison, J.R.; Nelson, N.B. Seasonal cycle of phytoplankton UV absorption at the Bermuda Atlantic Time-series Study (BATS) site. *Limnol. Oceanogr.* **2004**, *49*, 215–224. [CrossRef]
190. Barocio-León, Ó.A.; Millán-Núñez, R.; Santamaría-del-Ángel, E.; González-Silvera, A.; Trees, C.C. Spatial variability of phytoplankton absorption coefficients and pigments off Baja California during November 2002. *J. Oceanogr.* **2006**, *62*, 873–885. [CrossRef]
191. Millán-Núñez, E.; Millán-Núñez, R. Specific absorption coefficient and phytoplankton community structure in the southern region of the California Current during January 2002. *J. Oceanogr.* **2010**, *66*, 719–730. [CrossRef]
192. Ferreira, A.; Garcia, V.M.T.; Garcia, C.A.E. Light absorption by phytoplankton, non-algal particles and dissolved organic matter at the Patagonia shelf-break in spring and summer. *Deep. Res. Part I Oceanogr. Res. Pap.* **2009**, *56*, 2162–2174. [CrossRef]
193. Babin, M.; Stramski, D.; Ferrari, G.M.; Claustre, H.; Bricaud, A.; Obolensky, G.; Hoepffner, N. Variations in the light absorption coefficients of phytoplankton, nonalgal particles, and dissolved organic matter in coastal waters around Europe. *J. Geophys. Res. Ocean.* **2003**, *108*, 3211. [CrossRef]
194. Ferreira, A.; Stramski, D.; Garcia, C.A.E.; Garcia, V.M.T.; Ciotti, Á.M.; Mendes, C.R.B. Variability in light absorption and scattering of phytoplankton in Patagonian waters: Role of community size structure and pigment composition. *J. Geophys. Res. Ocean.* **2013**, *118*, 698–714. [CrossRef]

195. Lorenzoni, L.; Toro-Farmer, G.; Varela, R.; Guzman, L.; Rojas, J.; Montes, E.; Muller-Karger, F. Characterization of phytoplankton variability in the Cariaco Basin using spectral absorption, taxonomic and pigment data. *Remote Sens. Environ.* **2015**, *167*, 259–268. [CrossRef]
196. Brewin, R.J.W.; Ciavatta, S.; Sathyendranath, S.; Skákala, J.; Bruggeman, J.; Ford, D.; Platt, T. The influence of temperature and community structure on light absorption by phytoplankton in the North Atlantic. *Sensors* **2019**, *19*, 4182. [CrossRef] [PubMed]
197. Sosik, H.M.; Mitchell, B.G. Light absorption by phytoplankton, photosynthetic pigments and detritus in the California Current System. *Deep. Res. Part I* **1995**, *42*, 1717–1748. [CrossRef]
198. Mercado, J.M.; Ramírez, T.; Cortés, D. Changes in nutrient concentration induced by hydrological variability and its effect on light absorption by phytoplankton in the Alborán Sea (Western Mediterranean Sea). *J. Mar. Syst.* **2008**, *71*, 31–45. [CrossRef]
199. Kiefer, D.A.; Cullen, J.J. Phytoplankton growth and light absorption as regulated by light, temperature, and nutrients. *Polar Res.* **1991**, *10*, 163–172. [CrossRef]
200. Churilova, T.; Suslin, V.; Krivenko, O.; Efimova, T.; Moiseeva, N.; Mukhanov, V.; Smirnova, L. Light absorption by phytoplankton in the upper mixed layer of the Black Sea: Seasonality and parametrization. *Front. Mar. Sci.* **2017**, *4*, 90. [CrossRef]
201. Stambler, N. Primary production, light absorption and quantum yields of phytoplankton from the Bellingshausen and Amundsen Seas (Antarctica). *Polar Biol.* **2003**, *26*, 438–451. [CrossRef]
202. Moiseeva, N.; Churilova, T.; Efimova, T.; Krivenko, O. Dependence of fluorescence intensity on chlorophyll a concentration and light absorption coefficients by phytoplankton in the Black Sea (October 2017). *Proc. SPIE* **2018**, *10833*, 108336M. [CrossRef]
203. Stæhr, P.A.; Markager, S.; Sand-Jensen, K. Pigment specific in vivo light absorption of phytoplankton from estuarine, coastal and oceanic waters. *Mar. Ecol. Prog. Ser.* **2004**, *275*, 115–128. [CrossRef]
204. Robinson, C.M.; Cherukuru, N.; Hardman-Mountford, N.J.; Everett, J.D.; McLaughlin, M.J.; Davies, K.P.; Van Dongen-Vogels, V.; Ralph, P.J.; Doblin, M.A. Phytoplankton absorption predicts patterns in primary productivity in Australian coastal shelf waters. *Estuar. Coast. Shelf Sci.* **2017**, *192*, 1–16. [CrossRef]
205. Xu, X.; Chen, J.; Shu, F. A new algorithm based on phytoplankton absorption coefficient for red tide monitoring in the East China Sea. *Proc. SPIE* **2018**, *10784*, 1078415. [CrossRef]
206. Barlow, R.; Lamont, T. Phytoplankton absorption and pigment adaptation of a red tide in the Benguela ecosystem. *Afr. J. Mar. Sci.* **2012**, *34*, 241–248. [CrossRef]
207. Sosa-Ávalos, R.; Millán-Núñez, E.; Quijano-Scheggia, S.I.; Lara-Lara, J.R.; Silva-Iñiguez, L. Variability of the absorption coefficient for phytoplankton influence of red tide in manzanillo and santiago bays, Mexico [Variabilidad del coeficiente de absorción por fitoplancton con influencia de marea roja en las bahías de Manzanillo y Santiago, México]. *Rev. Biol. Mar. Oceanogr.* **2015**, *50*, 427–438. [CrossRef]
208. Barlow, R.; Lamont, T.; Gibberd, M.-J.; Russo, C.; Airs, R.; Tutt, G.; Britz, K.; van den Berg, M. Phytoplankton adaptation and absorption properties in an Agulhas Current ecosystem. *Deep. Res. Part I Oceanogr. Res. Pap.* **2020**, *157*, 103209. [CrossRef]
209. Shang, Y.; Jacinthe, P.-A.; Li, L.; Wen, Z.; Liu, G.; Lyu, L.; Fang, C.; Zhang, B.; Hou, J.; Song, K. Variations in the light absorption coefficients of phytoplankton, non-algal particles and dissolved organic matter in reservoirs across China. *Environ. Res.* **2021**, *201*, 111579. [CrossRef] [PubMed]
210. Dubinsky, Z. The Functional and Optical-Absorption Cross-Sections of Phytoplankton Photosynthesis. In *Proceedings of the Primary Productivity and Biogeochemical Cycles in the Sea*; Falkowski, P.G., Woodhead, A.D., Eds.; Plenum Press Div Plenum Publishing Corp.: New York, NY, USA, 1992; Volume 43, pp. 31–45.
211. Roy, S.; Chattopadhyay, J. The stability of ecosystems: A brief overview of the paradox of enrichment. *J. Biosci.* **2007**, *32*, 421–428. [CrossRef] [PubMed]
212. Bemal, S.; Anil, A.C.; Shankar, D.; Remya, R.; Roy, R. Picophytoplankton variability: Influence of winter convective mixing and advection in the northeastern Arabian Sea. *J. Mar. Syst.* **2018**, *180*, 37–48. [CrossRef]
213. Koblentz-Mishke, O.J.; Wozniak, B.; Kaczmarek, S.; Konovalov, B. V The assimilation of light energy by marine phytoplankton. Part 1. The light absorption capacity of the Baltic and Black Sea phytoplankton (methods; relation to chlorophyll concentration). *Oceanologia* **1995**, *37*, 145–170.
214. van der Lingen, C.D. Nitrogen excretion and absorption efficiencies of sardine *Sardinops sagax* fed phytoplankton and zooplankton diets. *Mar. Ecol. Prog. Ser.* **1998**, *175*, 67–76. [CrossRef]
215. Navarro, J.M.; Thompson, R.J. Physiological energetics of the horse mussel Modiolus modiolus in a cold ocean environment. *Mar. Ecol. Prog. Ser.* **1996**, *138*, 135–148. [CrossRef]
216. Tanaka, Y.; Tsuda, R.; Mizutani, M.; Mitamura, O. Quantum yield of photosynthesis and spectral absorption of phytoplankton during the stratified periods at the northern basin of Lake Biwa. *Jpn. J. Limnol.* **1999**, *60*, 507–529. [CrossRef]
217. Babin, M.; Therriault, J.; Legendre, L.; Condal, A. Variations in the specific absorption coefficient for natural phytoplankton assemblages: Impact on estimates of primary production. *Limnol. Oceanogr.* **1993**, *38*, 154–177. [CrossRef]
218. Finkel, Z.V.; Irwin, A.J. Light absorption by phytoplankton and the filter amplification correction: Cell size and species effects. *J. Exp. Mar. Bio. Ecol.* **2001**, *259*, 51–61. [CrossRef] [PubMed]

219. Markager, S.; Vincent, W.F. Light absorption by phytoplankton: Development of a matching parameter for algal photosynthesis under different spectral regimes. *J. Plankton Res.* **2001**, *23*, 1373–1384. [CrossRef]
220. Duarte, C.M.; Agustí, S.; Kalff, J. Particulate light absorption and the prediction of phytoplankton biomass and planktonic metabolism in northeastern Spanish aquatic ecosystems. *Can. J. Fish. Aquat. Sci.* **2000**, *57*, 25–33. [CrossRef]
221. Barlow, R.G.; Aiken, J.; Holligan, P.M.; Cummings, D.G.; Maritorena, S.; Hooker, S. Phytoplankton pigment and absorption characteristics along meridional transects in the Atlantic Ocean. *Deep. Res. Part I Oceanogr. Res. Pap.* **2002**, *49*, 637–660. [CrossRef]
222. Aguirre-Hernández, E.; Gaxiola-Castro, G.; Nájera-Martínez, S.; Baumgartner, T.; Kahru, M.; Greg Mitchell, B. Phytoplankton absorption, photosynthetic parameters, and primary production off Baja California: Summer and autumn 1998. *Deep. Res. Part II Top. Stud. Oceanogr.* **2004**, *51*, 799–816. [CrossRef]
223. Barnes, M.K.; Tilstone, G.H.; Smyth, T.J.; Suggett, D.J.; Astoreca, R.; Lancelot, C.; Kromkamp, J.C. Absorption-based algorithm of primary production for total and size-fractionated phytoplankton in coastal waters. *Mar. Ecol. Prog. Ser.* **2014**, *504*, 73–89. [CrossRef]
224. Hirawake, T.; Takao, S.; Horimoto, N.; Ishimaru, T.; Yamaguchi, Y.; Fukuchi, M. A phytoplankton absorption-based primary productivity model for remote sensing in the Southern Ocean. *Polar Biol.* **2011**, *34*, 291–302. [CrossRef]
225. Kerkar, A.U.; Tripathy, S.C.; Sabu, P. Concurrent measurements of phytoplankton productivity and light absorption from a global carbon hotspot: Variability, features, and causes. *Glob. Planet. Change* **2023**, *228*, 104193. [CrossRef]
226. Futsuki, R.; Hirawake, T.; Fujiwara, A.; Waga, H.; Kikuchi, T.; Nishino, S.; Isada, T.; Suzuki, K.; Watanabe, Y.W. Performance of primary production algorithm using absorption coefficient of phytoplankton in the Pacific Arctic. *J. Oceanogr.* **2022**, *78*, 311–335. [CrossRef]
227. Ma, S.; Tao, Z.; Yang, X.; Yu, Y.; Zhou, X.; Ma, W.; Li, Z. Estimation of marine primary productivity from satellite-derived phytoplankton absorption data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 3084–3092. [CrossRef]
228. Zhao, H.; Cao, W.; Deng, L.; Liao, J.; Zeng, K.; Zheng, W.; Zhang, Y.; Xu, J.; Zhou, W. Estimation of primary production from the light absorption of phytoplankton and photosynthetically active radiation in the South China Sea. *Front. Mar. Sci.* **2023**, *10*, 1249802. [CrossRef]
229. Churilova, T.Y.; Suslin, V.V.; Sosik, H.M. Dependence of the photosynthetic quantum yield on phytoplankton light absorption: Equations for assessing primary production in the black sea. *Phys. Oceanogr.* **2021**, *28*, 67–77. [CrossRef]
230. Fox, J.; Kramer, S.J.; Graff, J.R.; Behrenfeld, M.J.; Boss, E.; Tilstone, G.; Halsey, K.H. An absorption-based approach to improved estimates of phytoplankton biomass and net primary production. *Limnol. Oceanogr. Lett.* **2022**, *7*, 419–426. [CrossRef]
231. Arst, H.; Nõges, P.; Nõges, T.; Kauer, T.; Arst, G.-E. Quantification of a Primary Production Model Using Two Versions of the Spectral Distribution of the Phytoplankton Absorption Coefficient. *Environ. Model. Assess.* **2012**, *17*, 431–440. [CrossRef]
232. McKee, D.; Röttgers, R.; Neukermans, G.; Calzado, V.S.; Trees, C.; Ampolo-Rella, M.; Neil, C.; Cunningham, A. Impact of measurement uncertainties on determination of chlorophyll-specific absorption coefficient for marine phytoplankton. *J. Geophys. Res. Ocean.* **2014**, *119*, 9013–9025. [CrossRef]
233. Tao, Z.; Wang, Y.; Ma, S.; Lv, T.; Zhou, X. A Phytoplankton Class-Specific Marine Primary Productivity Model Using MODIS Data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2017**, *10*, 5519–5528. [CrossRef]
234. Roy, S. Algorithmic procedure for retrieving calorific contents of marine phytoplankton from space. *MethodsX* **2021**, *8*, 101579. [CrossRef] [PubMed]
235. Tao, Z.; Ma, S.; Yang, X.; Wang, Y. Assessing the uncertainties of phytoplankton absorption-based model estimates of marine net primary productivity. *Acta Oceanol. Sin.* **2017**, *36*, 112–121. [CrossRef]
236. Delgado, A.L.; Guinder, V.A.; Dogliotti, A.I.; Zapperi, G.; Pratolongo, P.D. Validation of MODIS-Aqua bio-optical algorithms for phytoplankton absorption coefficient measurement in optically complex waters of El Rincón (Argentina). *Cont. Shelf Res.* **2019**, *173*, 73–86. [CrossRef]
237. Xu, X.; Huang, Y.; Chen, J.; Zeng, Z. A New Algorithm Based on the Phytoplankton Absorption Coefficient for Red Tide Monitoring in the East China Sea via a Geostationary Ocean Color Imager (GOCI). *Remote Sens.* **2025**, *17*, 750. [CrossRef]
238. Arena, M.; Pratolongo, P.D.; Loisel, H.; Tran, M.D.; Jorge, D.S.F.; Delgado, A.L. Full-Resolution Sentinel-3 Satellite Observations of Phytoplankton Phenology in Optically Complex Waters of the Northern Patagonian Shelf. *Estuaries Coasts* **2025**, *48*, 138. [CrossRef]
239. Brewin, R.J.W.; Morán, X.A.G.; Raitsos, D.E.; Gittings, J.A.; Calleja, M.L.; Viegas, M.; Ansari, M.I.; Al-Otaibi, N.; Huete-Stauffer, T.M.; Hoteit, I. Factors Regulating the Relationship Between Total and Size-Fractionated Chlorophyll-a in Coastal Waters of the Red Sea. *Front. Microbiol.* **2019**, *10*, 1964. [CrossRef] [PubMed]
240. Xu, J.; Zhao, Y.; Lyu, H.; Liu, H.; Dong, X.; Li, Y.; Cao, K.; Xu, J.; Li, Y.; Wang, H.; et al. A semianalytical algorithm for estimating particulate composition in inland waters based on Sentinel-3 OLCI images. *J. Hydrol.* **2022**, *608*, 127617. [CrossRef]
241. Zhu, P.; Ma, M.; Jin, Y.; Yin, X.; Zhu, Z.; Wang, S.; Shang, S. Nutrient enrichment modulates phytoplankton biodiversity-resource use efficiency relationships in temperate lakes and reservoirs of Northern China. *Hydrobiologia* **2025**, *853*, 1937–1950. [CrossRef]

242. Teng, J.; Zhang, T.; Sun, K.; Gao, H. Retrieving Pigment Concentrations Based on Hyperspectral Measurements of the Phytoplankton Absorption Coefficient in Global Oceans. *Remote Sens.* **2022**, *14*, 3516. [CrossRef]
243. Zhang, T.; Tai, F.; Hu, L.; Chen, S. Method for extracting pigment characteristic spectra from the phytoplankton absorption spectrum. *Opt. Express* **2023**, *31*, 22233–22249. [CrossRef] [PubMed]
244. Peng, C.; Jamet, C.; Di Girolamo, P.; Dionisi, D.; Li, X.; Zhang, S.; Zhang, Z.; Chen, W.; He, Y.; Shi, K.; et al. Airborne blue lidar reveals the ocean's hidden biological engine in the South China Sea. *Commun. Earth Environ.* **2025**, *6*, 1051. [CrossRef]
245. Xu, H.; Yang, F.; Wang, Y.; Wang, L. Comparative study of the variability of the phytoplankton biomass in two upwelling zones of the western Arabian Sea from 2003 to 2020. *Mar. Pollut. Bull.* **2025**, *212*, 117522. [CrossRef] [PubMed]
246. Lou, J.; Liu, B.; Xiong, Y.; Zhang, X.; Yuan, X. Variational Autoencoder Framework for Hyperspectral Retrievals (Hyper-VAE) of Phytoplankton Absorption and Chlorophyll a in Coastal Waters for NASA's EMIT and PACE Missions. *IEEE Trans. Geosci. Remote Sens.* **2025**, *63*, 4206316. [CrossRef]
247. Wang, W.; Liu, B.; Gao, S.; Li, J.; Zhou, Y.; Zhang, S.; Ding, Z. PhA-MOE: Enhancing Hyperspectral Retrievals for Phytoplankton Absorption Using Mixture-of-Experts. *Remote Sens.* **2025**, *17*, 2103. [CrossRef]
248. Li, T.; Bai, Y.; He, X.; Tao, B.; Chen, X.; Gong, F.; Wang, T. Phytoplankton size classes changed oppositely over shelf and basin areas of the South China Sea during 2003–2018. *Prog. Oceanogr.* **2021**, *191*, 102496. [CrossRef]
249. Jia, T.; Zhang, Y.; Weng, C.; Dong, R. Improving remote sensing retrieval of global ocean transparency with optical water classification. *Ecol. Indic.* **2022**, *143*, 109359. [CrossRef]
250. Sun, D.; Huan, Y.; Wang, S.; Li, Z.; Zhang, H.; Qi, L.; Liu, J.; He, Y. Monthly average satellite-estimated dataset of phytoplankton size class in the Bohai Sea, Yellow Sea and East China Sea during a period of 2002—2022. *Natl. Remote Sens. Bull.* **2024**, *28*, 1425–1432. [CrossRef]
251. Ye, H.; Yang, C.; Dong, Y.; Tang, S.L.; Chen, C. A daily reconstructed chlorophyll-A dataset in the South China Sea from MODIS using OI-SwinUnet. *Earth Syst. Sci. Data* **2024**, *16*, 3125–3147. [CrossRef]
252. Zhu, X.; Li, T.; Cooper, L.W.; Yang, E.; Jung, J.; Cho, K.; Yao, Y.; Tang, Y. Bio-optical properties and radiant heating rates in the borderlands region of the Chukchi Sea: The roles of phytoplankton biomass and sea ice cover. *Deep. Res. Part I Oceanogr. Res. Pap.* **2025**, *218*, 104458. [CrossRef]
253. Catlett, D.; Siegel, D.A. Phytoplankton Pigment Communities Can be Modeled Using Unique Relationships With Spectral Absorption Signatures in a Dynamic Coastal Environment. *J. Geophys. Res. Ocean.* **2018**, *123*, 246–264. [CrossRef]
254. Devred, E.; Perry, T.; Massicotte, P. Seasonal and decadal variations in absorption properties of phytoplankton and non-algal particulate matter in three oceanic regimes of the Northwest Atlantic. *Front. Mar. Sci.* **2022**, *9*, 932184. [CrossRef]
255. Wang, X.; Bian, C.; Bi, R.; Jiang, W.; Zhang, H.; Zhang, X. Particle size distributions and organic-inorganic compositions of suspended particulate matters around the Bohai Strait. *J. Ocean Univ. China* **2017**, *16*, 25–34. [CrossRef]
256. Huan, Y.; Sun, D.; Wang, S.; Bilal, M.; Zhang, H.; Qiu, Z.; He, Y. Phytoplankton "Missing" Absorption in Marine Waters: A Novel Pigment Compensation Model for the Packaging Effect. *J. Geophys. Res. Ocean.* **2021**, *126*, e2020JC016458. [CrossRef]
257. Pérez, G.L.; Galí, M.; Royer, S.-J.; Gerea, M.; Ortega-Retuerta, E.; Gasol, J.M.; Marrasé, C.; Simó, R. Variability of phytoplankton light absorption in stratified waters of the NW Mediterranean Sea: The interplay between pigment composition and the packaging effect. *Deep. Res. Part I Oceanogr. Res. Pap.* **2021**, *169*, 103460. [CrossRef]
258. Padhi, P.; Panda, M.K.; Singh, Y.D.; Bharadwaj, K.K.; Malik, K.K.; Nayak, B. *Phytoplankton Mediated Nanoparticles for Cancer Therapy*; Springer: Singapore, 2021; ISBN 978-981162516-9, 978-981162515-2. [CrossRef]
259. Ferreira, A.; Garrido-Amador, P.; Brito, A.C. Disentangling environmental drivers of phytoplankton biomass off Western Iberia. *Front. Mar. Sci.* **2019**, *6*, 44. [CrossRef]
260. Asselot, R.; Holden, P.B.; Lunkeit, F.; Hense, I. A Missing Link in the Carbon Cycle: Phytoplankton Light Absorption under RCP Emission Scenarios. *Earth Syst. Dyn.* **2024**, *15*, 875–891. [CrossRef]
261. Xi, H.; Hieronymi, M.; Röttgers, R.; Krasemann, H.; Qiu, Z. Hyperspectral differentiation of phytoplankton taxonomic groups: A comparison between using remote sensing reflectance and absorption spectra. *Remote Sens.* **2015**, *7*, 14781–14805. [CrossRef]
262. Grunert, B.K.; Ciochetto, A.B.; Mouw, C.B. A hyperspectral approach for retrieving inherent optical properties, phytoplankton pigments, and associated uncertainties from non-water absorption. *Front. Mar. Sci.* **2025**, *12*, 1549312. [CrossRef]
263. Lathif, S.A.; Hariharasudhan, V.G.; Al Shehhi, M.R. An improved bio-optical model for remote sensing of phytoplankton absorption coefficient in global waters. In *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS)*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2024; pp. 5897–5901. [CrossRef]
264. Arena, M.; Funk, F.A.; Pratolongo, P.D.; Delgado, A.L. Phytoplankton absorption in coastal waters of the Patagonian continental shelf: In situ characterization and satellite-derived variability. *Int. J. Remote Sens.* **2025**, *47*, 1104–1128. [CrossRef]
265. El-habashi, A.; Ioannou, I.; Tomlinson, M.C.; Stumpf, R.P.; Ahmed, S. Satellite Retrievals of *Karenia brevis* Harmful Algal Blooms in the West Florida Shelf Using Neural Networks and Comparisons with Other Techniques. *Remote Sens.* **2016**, *8*, 377. [CrossRef]
266. Wang, T.; Zhang, S.; Chen, F.; Ma, Y.; Jiang, C.; Yu, J. Influence of sequential tropical cyclones on phytoplankton blooms in the northwestern South China Sea. *J. Oceanol. Limnol.* **2021**, *39*, 14–25. [CrossRef]

267. Zheng, G.; DiGiacomo, P.M. Progress in Oceanography Uncertainties and applications of satellite-derived coastal water quality products. *Prog. Oceanogr.* **2017**, *159*, 45–72. [CrossRef]
268. Xu, K.; Lavaud, J.; Perkins, R.; Austen, E.; Bonnanfant, M.; Campbell, D.A. Phytoplankton σPSII and excitation dissipation; Implications for estimates of primary productivity. *Front. Mar. Sci.* **2018**, *5*, 281. [CrossRef]
269. Arena, M.; Delgado, A.L.; Celleri, C.; Pratolongo, P.D. Preliminary assessment of spatial and short-term variability of bio-optical properties in a tidal dominated estuary (Bahía Blanca, Argentina). *Reg. Stud. Mar. Sci.* **2019**, *29*, 100639. [CrossRef]
270. Lee, D.; Son, S.; Joo, H.; Kim, K.; Kim, M.; Jang, H.; Yun, M.; Kang, C.K.; Lee, S.H. Estimation of the particulate organic carbon to chlorophyll-a ratio using modis-aqua in the East/Japan sea, South Korea. *Remote Sens.* **2020**, *12*, 840. [CrossRef]
271. Wei, Y.; Chen, X.; Liu, Y.; Wang, Y.; Qu, K.M.; Sun, J.; Cui, Z. Key determinants controlling the seasonal variation of coastal zooplankton communities: A case study along the Yellow Sea. *Mar. Pollut. Bull.* **2023**, *193*, 115175. [CrossRef] [PubMed]
272. Hickman, A.E.; Holligan, P.M.; Moore, C.M.; Sharples, J.; Krivtsov, V.; Palmer, M.R. Distribution and chromatic adaptation of phytoplankton within a shelf sea thermocline. *Limnol. Oceanogr.* **2009**, *54*, 525–536. [CrossRef]
273. Chen, X.; Schallenberg, C.; Phillips, H.E.; Chase, Z. Biogeochemical characteristics of eddies in the East Australian Current depend on eddy type, history and location. *J. Mar. Syst.* **2021**, *216*, 103512. [CrossRef]
274. Xing, X.; Claustre, H.; Wang, H.; Poteau, A.; D'Ortenzio, F. Seasonal dynamics in colored dissolved organic matter in the Mediterranean Sea: Patterns and drivers. *Deep. Res. Part I Oceanogr. Res. Pap.* **2014**, *83*, 93–101. [CrossRef]
275. Erickson, Z.K.; Thompson, A.F.; Cassar, N.; Sprintall, J.; Mazloff, M.R. An advective mechanism for deep chlorophyll maxima formation in southern Drake Passage. *Geophys. Res. Lett.* **2016**, *43*, 10–855. [CrossRef]
276. Skorokhod, E.Y.; Churilova, T.Y.; Efimova, T.V.; Moiseeva, N.A.; Suslin, V. V Bio-optical characteristics of the black sea coastal waters near sevastopol: Assessment of the modis and viirs products accuracy. *Phys. Oceanogr.* **2021**, *28*, 215–227. [CrossRef]
277. Narayanan, A.; Reynolds, R.A.; Stramski, D. Variations in Phytoplankton Assemblages in the Western Arctic Seas as Evidenced by Changes in Pigment Composition and Associated Spectra of Light Absorption. *J. Geophys. Res. Ocean.* **2025**, *130*, e2024JC021769. [CrossRef]
278. Fox, J.; Behrenfeld, M.J.; Haëntjens, N.; Chase, A.P.; Kramer, S.J.; Boss, E.S.; Karp-Boss, L.; Fisher, N.L.; Penta, W.B.; Westberry, T.K.; et al. Phytoplankton Growth and Productivity in the Western North Atlantic: Observations of Regional Variability From the NAAMES Field Campaigns. *Front. Mar. Sci.* **2020**, *7*, 24. [CrossRef]
279. Evers-King, H.; Martinez-Vicente, V.; Brewin, R.J.W.; Dall'Olmo, G.; Hickman, A.E.; Jackson, T.; Kostadinov, T.S.; Krasemann, H.; Loisel, H.; Röttgers, R.; et al. Validation and Intercomparison of Ocean Color Algorithms for Estimating Particulate Organic Carbon in the Oceans. *Front. Mar. Sci.* **2017**, *4*, 251. [CrossRef]
280. Fu, L.; Zhou, Y.; Liu, G.; Song, K.; Tao, H.; Zhao, F.; Li, S.; Shi, S.; Shang, Y. Retrieval of Chla Concentrations in Lake Xingkai Using OLCI Images. *Remote Sens.* **2023**, *15*, 3809. [CrossRef]
281. Tripathy, S.C.; Kerkar, A.U.; Sabu, P.; Padhi, S.K.; Pandi, S.R.; Sarkar, A.; Bhaskar, P.V.; Mohan, R. Short-term time-series observations of phytoplankton light-absorption and productivity in Prydz Bay, coastal Antarctica. *Front. Mar. Sci.* **2024**, *11*, 1420179. [CrossRef]
282. Siegel, D.A.; Cetinić, I.; Graff, J.R.; Lee, C.M.; Nelson, N.B.; Perry, M.J.; Ramos, I.S.; Steinberg, D.K.; Buesseler, K.O.; Hamme, R.C.; et al. An operational overview of the EXport processes in the ocean from RemoTe sensing (EXPORTS) northeast pacific field deployment. *Elementa* **2021**, *9*, 00107. [CrossRef]
283. Luang-On, J.; Ishizaka, J.; Buranapratheprat, A.; Phaksopa, J.; Goés, J.I.; Maúre, E.D.R.; Siswanto, E.; Zhu, Y.; Xu, Q.; Nakornsantiphap, P.; et al. MODIS-derived green Noctiluca blooms in the upper Gulf of Thailand: Algorithm development and seasonal variation mapping. *Front. Mar. Sci.* **2023**, *10*, 1031901. [CrossRef]
284. El-Habashi, A.; Duran, C.M.; Lovko, V.; Tomlinson, M.C.; Stumpf, R.P.; Ahmed, S. Satellite retrievals of Karenia brevis harmful algal blooms in the West Florida shelf using neural networks and impacts of temporal variabilities. *J. Appl. Remote Sens.* **2017**, *11*, 032408. [CrossRef]
285. Yao, Y.; Hu, C.; Cannizzaro, J.P.; Barnes, B.B.; English, D.C.; Xie, Y.; Hubbard, K.A.; Wang, M. Detection of Karenia brevis red tides on the West Florida Shelf using VIIRS observations: Accounting for spatial coherence with artificial intelligence. *Remote Sens. Environ.* **2023**, *298*, 113833. [CrossRef]
286. Rolim, S.B.A.; Veettil, B.K.; Viero, A.P.; Kessler, A.B.; Gonzatti, C. Remote sensing for mapping algal blooms in freshwater lakes: A review. *Environ. Sci. Pollut. Res.* **2023**, *30*, 19602–19616. [CrossRef] [PubMed]
287. Bosse, K.R.; Shuchman, R.A.; Sayers, M.J.; Lekki, J.D.; Tokars, R.P. Improved Detection of Great Lakes Water Quality Anomalies Using Remote Sensing. *Water* **2024**, *16*, 3602. [CrossRef]
288. Lefebvre, A.; Devreker, D. How to learn more about hydrological conditions and phytoplankton dynamics and diversity in the eastern English Channel and the Southern Bight of the North Sea: The Suivi Régional des Nutriments data set (1992–2021). *Earth Syst. Sci. Data* **2023**, *15*, 1077–1092. [CrossRef]
289. Hu, W.; Ma, J.; Qin, B.Q. Analysis on scientific knowledge graph of global algal bloom studies. *Chin. Sci. Bull.* **2023**, *68*, 3196–3210. [CrossRef]

290. Horvat, C.; Bisson, K.M.; Seabrook, S.; Cristi, A.; Matthes, L.C. Evidence of phytoplankton blooms under Antarctic sea ice. *Front. Mar. Sci.* **2022**, *9*, 942799. [CrossRef]
291. Cetinić, I.; Rousseaux, C.S.; Carroll, I.T.; Chase, A.P.; Kramer, S.J.; Werdell, P.J.; Siegel, D.A.; Dierssen, H.M.; Catlett, D.; Neeley, A.; et al. Phytoplankton composition from sPACE: Requirements, opportunities, and challenges. *Remote Sens. Environ.* **2024**, *302*, 113964. [CrossRef]
292. Balch, W.M.K.; Mitchell, C. Remote sensing algorithms for particulate inorganic carbon (PIC) and the global cycle of PIC. *Earth-Sci. Rev.* **2023**, *239*, 104363. [CrossRef]
293. Wang, C.; Liu, Y.; Li, X.; Lai, Z.; Tackx, M.; Lek, S. A bibliometric analysis of scientific trends in phytoplankton research. *Ann. Limnol.* **2015**, *51*, 249–259. [CrossRef]
294. van Oostende, M.; Hieronymi, M.; Krasemann, H.; Baschek, B. Global ocean colour trends in biogeochemical provinces. *Front. Mar. Sci.* **2023**, *10*, 1052166. [CrossRef]
295. de Moraes Rudorff, N.; Kampel, M. Orbital remote sensing of phytoplankton functional types: A new review. *Int. J. Remote Sens.* **2012**, *33*, 1967–1990. [CrossRef]
296. Li, Y.; Zhou, Q.; Zhang, Y.; Li, J.; Shi, K. Research Trends in the Remote Sensing of Phytoplankton Blooms: Results from Bibliometrics. *Remote Sens.* **2021**, *13*, 4414. [CrossRef]
297. Wilson, C. The rocky road from research to operations for satellite ocean-colour data in fishery management. *ICES J. Mar. Sci.* **2011**, *68*, 677–686. [CrossRef]
298. Xue, K.; Zhang, Y.; Ma, R.; Duan, H. Variability of light absorption properties in optically complex inland waters of Lake Chaohu, China. *J. Great Lakes Res.* **2017**, *43*, 17–31. [CrossRef]
299. Zhang, H.; Devred, E.; Fujiwara, A.; Qiu, Z.; Liu, X. Estimation of phytoplankton taxonomic groups in the Arctic Ocean using phytoplankton absorption properties: Implication for ocean-color remote sensing. *Opt. Express* **2018**, *26*, 32280. [CrossRef] [PubMed]
300. Huan, Y.; Sun, D.; Wang, S.; Zhang, H.; Qiu, Z.; Bilal, M.; He, Y. Remote sensing estimation of phytoplankton absorption associated with size classes in coastal waters. *Ecol. Indic.* **2021**, *121*, 107198. [CrossRef]
301. Zheng, G.; DiGiacomo, P.M. Remote sensing of chlorophyll-a in coastal waters based on the light absorption coefficient of phytoplankton. *Remote Sens. Environ.* **2017**, *201*, 331–341. [CrossRef]
302. Zheng, G.; DiGiacomo, P.M. Detecting phytoplankton diatom fraction based on the spectral shape of satellite-derived algal light absorption coefficient. *Limnol. Oceanogr.* **2018**, *63*, S85–S98. [CrossRef]
303. Williams, G.N.; Larouche, P.; Dogliotti, A.I.; Latorre, M.P. Light absorption by phytoplankton, non-algal particles, and dissolved organic matter in San Jorge gulf in summer. *Oceanography* **2018**, *31*, 40–49. [CrossRef]
304. Mitchell, C.; Cunningham, A. Remote sensing of spatio-temporal relationships between the partitioned absorption coefficients of phytoplankton cells and mineral particles and euphotic zone depths in a partially mixed shelf sea. *Remote Sens. Environ.* **2015**, *160*, 193–205. [CrossRef]
305. Barlow, R.G.; Aiken, J.; Sessions, H.E.; Lavender, S.; Mantel, J. Phytoplankton pigment, absorption and ocean colour characteristics in the southern Benguela ecosystem. *South Afr. J. Sci.* **2001**, *97*, 230–238.
306. Ciotti, A.M.; Bricaud, A. Retrievals of a size parameter for phytoplankton and spectral light absorption by colored detrital matter from water-leaving radiances at SeaWiFS channels in a continental shelf region off Brazil. *Limnol. Oceanogr. Methods* **2006**, *4*, 237–253. [CrossRef]
307. Hirata, T.; Aiken, J.; Hardman-mountford, N.; Smyth, T.J.; Barlow, R.G. An absorption model to determine phytoplankton size classes from satellite ocean colour. *Remote Sens. Environ.* **2008**, *112*, 3153–3159. [CrossRef]
308. Mao, Z.; Stuart, V.; Pan, D.; Chen, J.; Gong, F.; Huang, H.; Zhu, Q. Effects of phytoplankton species composition on absorption spectra and modeled hyperspectral reflectance. *Ecol. Inform.* **2010**, *5*, 359–366. [CrossRef]
309. Moisan, T.A.H.; Moisan, J.R.; Linkswiler, M.A.; Steinhardt, R.A. Algorithm development for predicting biodiversity based on phytoplankton absorption. *Cont. Shelf Res.* **2013**, *55*, 17–28. [CrossRef]
310. Ferreira, A.; Ciotti, Á.M.; Mendes, C.R.B.; Uitz, J.; Bricaud, A. Phytoplankton light absorption and the package effect in relation to photosynthetic and photoprotective pigments in the northern tip of Antarctic Peninsula. *J. Geophys. Res. Ocean.* **2017**, *122*, 7344–7363. [CrossRef]
311. Zhang, Y.; Feng, L.; Li, J.; Luo, L.; Yin, Y.; Liu, M.; Li, Y. Seasonal-spatial variation and remote sensing of phytoplankton absorption in Lake Taihu, a large eutrophic and shallow lake in China. *J. Plankton Res.* **2010**, *32*, 1023–1037. [CrossRef]
312. Wang, G.; Lee, Z.; Mishra, D.R.; Ma, R. Retrieving absorption coefficients of multiple phytoplankton pigments from hyperspectral remote sensing reflectance measured over cyanobacteria bloom waters. *Limnol. Oceanogr. Methods* **2016**, *14*, 432–447. [CrossRef]
313. Álvarez, E.; Losa, S.N.N.; Bracher, A.; Thoms, S.; Völker, C.; Alvarez, E.; Losa, S.N.N.; Bracher, A.; Thoms, S.; Voelker, C.; et al. Phytoplankton Light Absorption Impacted by Photoprotective Carotenoids in a Global Ocean Spectrally-Resolved Biogeochemistry Model. *J. Adv. Model. Earth Syst.* **2022**, *14*, e2022MS003126. [CrossRef]

314. Sathyendranath, S.; Brewin, R.J.W.; 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] [PubMed]
315. Asselot, R.; Lunkeit, F.; Holden, P.B.; Hense, I. Climate pathways behind phytoplankton-induced atmospheric warming. *Biogeosciences* **2022**, *19*, 223–239. [CrossRef]
316. Rodrigues, T.; Alcântara, E.; Rotta, L.; Bernardo, N.; Watanabe, F. An investigation into the relationship between light absorption budget and trophic status in inland waters. *Ecol. Indic.* **2020**, *115*, 106410. [CrossRef]