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Utility of satellite imagery in estimating coastal marine water attributes

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ABSTRACT

Coastal water resources are essential for sustaining biodiversity and community well-being, yet rapid population growth and climate change increasingly threaten their sustainability. Satellite remote sensing has emerged as a powerful tool for monitoring coastal water quality due to its extensive spatial coverage, cost effectiveness, and rapid data acquisition. The scientific community has seen considerable advances in recent years through these technologies. In view of these developments, this study presents a scoping review of 465 peer-reviewed journal articles published between 2019 and 2024, sourced from Scopus. The analysis identifies commonly used satellite platforms for assessing five critical water quality parameters chlorophyll-a (Chl-a), temperature, colored dissolved organic matter (CDOM), pH, and phosphate across predefined climatic zones and water types. We further examine prevalent algorithmic approaches and validation metrics. Findings indicate that most studies rely on data from Aqua, Sentinel, and Landsat satellites. Results also reveal that Chl-a and temperature are the most widely measured parameters, particularly in temperate and subtropical marine waters, whereas Arctic regions and freshwater systems remain understudied. Recent trends show a growing reliance on empirical and machine learning based algorithms, with root mean square error (RMSE) and coefficient of determination (R^2) as the most common validation metrics. These results highlight the need for standardized validation protocols and expanded research efforts in underrepresented regions and parameters to enhance global water quality monitoring.

1. Introduction

Coastal marine ecosystems are vital to global biodiversity and human livelihoods, providing essential services such as fisheries, recreation, and carbon sequestration (Eger et al., 2023; Johnson et al., 2023). Despite their ecological and economic importance, these ecosystems are increasingly under threat from anthropogenic activities, including coastal development, nutrient runoff, and pollution, as well as the overarching impacts of climate change (Halpern et al., 2008). Recent study in Indian Sundarbans, for instance, shows progressive declines in water clarity and mangrove health due to rising sea level and intensified human pressure (Mondal et al., 2021). Effective monitoring of coastal water quality is therefore essential to mitigate these threats and ensure sustainable management. However, the inherent variability of coastal systems, coupled with the logistical and financial challenges of traditional *in situ* monitoring, has driven the search for innovative tools that offer broader spatial and temporal coverage (Lakshmi et al., 2023).

The widespread adoption of satellite remote sensing began with the very first Landsat mission in 1972, launched by NASA and the U.S. Geological Survey, and has since delivered an unbroken archive of multispectral and thermal imagery (Avtar et al., 2020; Cohen and Goward, 2004). Exploiting this extensive archive, Bishop-Taylor et al. (2021) processed more than three decades of Landsat imagery to produce Digital Earth Australia Coastlines, a continent-wide product that maps the mean sea-level shoreline, while Luijendijk et al. (2018) extended the approach worldwide, tracking erosion and accretion along sandy coasts. Advancing from these achievements, ocean color sensors such as the Coastal Zone Color Scanner (CZCS), Sea-viewing Wide Field-of-View Sensor (SeaWiFS) provided the first global-scale observations of water-leaving radiance and chlorophyll concentrations (Hooker et al., 2000; Hovis, 1978). Subsequent sensors including the Moderate Resolution Imaging Spectroradiometer (MODIS), and Medium Resolution Imaging Spectrometer (MERIS) expanded spatial coverage and temporal frequency (Hu et al., 2012; Kratzer et al., 2008). While these sensors have been instrumental for global ocean monitoring, their moderate spatial resolution limited detailed observation of complex inland and nearshore waters (Garaba et al., 2018; Teodoro, 2016). Recent advances in satellite sensors, such as Sentinel-2 Multispectral Instrument (MSI) and Sentinel-3 Ocean and Land Color Instrument (OLCI), have markedly improved spatial and spectral resolution,

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allowing for the detection of fine-scale variability in coastal areas (Katlane et al., 2024). Demonstrating these capabilities in practice, Mondal et al. (2024a) validated the use of Sentinel-3 for retrieving Chl-a and total suspended matter in the Indian Sundarbans, showing strong agreement between satellite derived and *in situ* measurements in these dynamic estuarine systems. As a result, such sensors have significantly enhanced our ability to monitor critical coastal phenomena including harmful algal blooms, sediment plumes, and nutrient-rich runoff events which are essential for effective ecosystem management (Xu et al., 2021).

Considering this progress, satellite imagery has emerged as a critical resource for monitoring coastal water quality, providing large-scale, high-resolution observations that overcome the limitations of labour-intensive field sampling (Adjovu et al., 2023; IOCCG, 2018). By consistently capturing spatial and temporal patterns across broad areas, satellite imagery provides valuable insights into dynamic coastal processes shaped by tides, weather, and seasonal cycles, insights that would be challenging to track through traditional methods alone (Devi et al., 2015) (Fig. 1). Today, key water quality parameters, such as Chl-a, and turbidity, among others, are now routinely assessed using multispectral and hyperspectral satellites data (Bar et al., 2023; Mondal et al., 2024a; Wang and Shi, 2007). Moreover, a growing body of research underscores the expanding role of satellite observations in tracking climate driven coastal changes. For example, recent studies have detected algal blooms in the East China Sea with Second Generation Global Imager (SGLI) data Feng et al. (2023) and have monitored bloom dynamics in Japan and the Persian Gulf using MODIS (Siswanto et al., 2013). It has also facilitated research on sea level rise in the Netherlands (Aschenneller et al., 2024) and have revealed how sediment discharge and climate factors shape long-term coastal morphology in the Yellow River Delta (Zhu et al., 2021).

Yet, the application of satellite imagery in coastal water quality monitoring is not without challenges. Atmospheric correction, sensor calibration, and the optical complexity of coastal waters complicate the retrieval of accurate data (IOCCG, 2000; Mobley et al., 2016). Additionally, the presence of clouds and other atmospheric disturbances can limit the availability of useable imagery, particularly in tropical and subtropical regions where coastal waters are most vulnerable (Zhang et al., 2015). To help bridge these gaps, unmanned aerial vehicles (UAVs) have emerged as a powerful complement, offering enhanced spatial and temporal resolution for local-scale monitoring at a substantially lower cost (Ridolfi and Manciola, 2018). Compared to high resolution satellites such as QuickBird, RapidEye, WorldView, and IKONOS, UAVs are more flexible and efficient for acquiring real-time data (Nhamo et al., 2020; Ruwaimana et al., 2018). Efforts to overcome these challenges have also spurred the adoption of data fusion and machine learning techniques (Hedley et al., 2018). Such advances, along with cross-sensor fusion studies, highlight the growing potential of machine learning models to develop robust coastal water quality algorithms (Lioumbas et al., 2023; Mondal et al., 2024b).

Over the past decade, several influential syntheses have mapped the progress of remote sensing-based water quality monitoring, yet they converge on a narrow set of optically active indices. Early work catalogued as many as eleven parameters but centered on Chl-a, turbidity and suspended solids (Gholizadeh et al., 2016). Successive reviews on water security (Chawla et al., 2020), ocean applications (Mohseni et al., 2022), drone platforms (Pillay et al., 2024), African reservoirs (Bangira et al., 2024), inland-lake trends Ngamile et al. (2025) and the water quantity-quality nexus (Ellis et al., 2024) all reinforce this optical focus, while the most recent machine learning survey for lakes again evaluates only specific key parameters such as Chl-a, turbidity and colored dissolved organic matter (CDOM) (Deng et al., 2024). None of these reviews analyse satellite-based retrievals of seawater pH or phosphate, parameters that are pivotal to coastal acidification and eutrophication dynamics. Another important gap lies in the geographical framing of existing reviews. For instance, Mohseni et al. (2022) primarily focuses on open-ocean environments without distinguishing between different climatic zones. Similarly, Pillay et al. (2024) and Bangira et al. (2024) concentrate their analyses on inland UAV case studies and African reservoirs, respectively, which indicates that key regions like temperate and polar coastal zones remain largely unexplored. Finally, the evaluation of validation metrics across studies is another critical blind spot. While metrics such as RMSE, MAE, and R^2 are often reported, no existing review systematically quantifies their use or assesses consistency across platforms. Reviews by Yang et al. (2022) and Deng et al. (2024) mention these metrics but do not analyse trends.

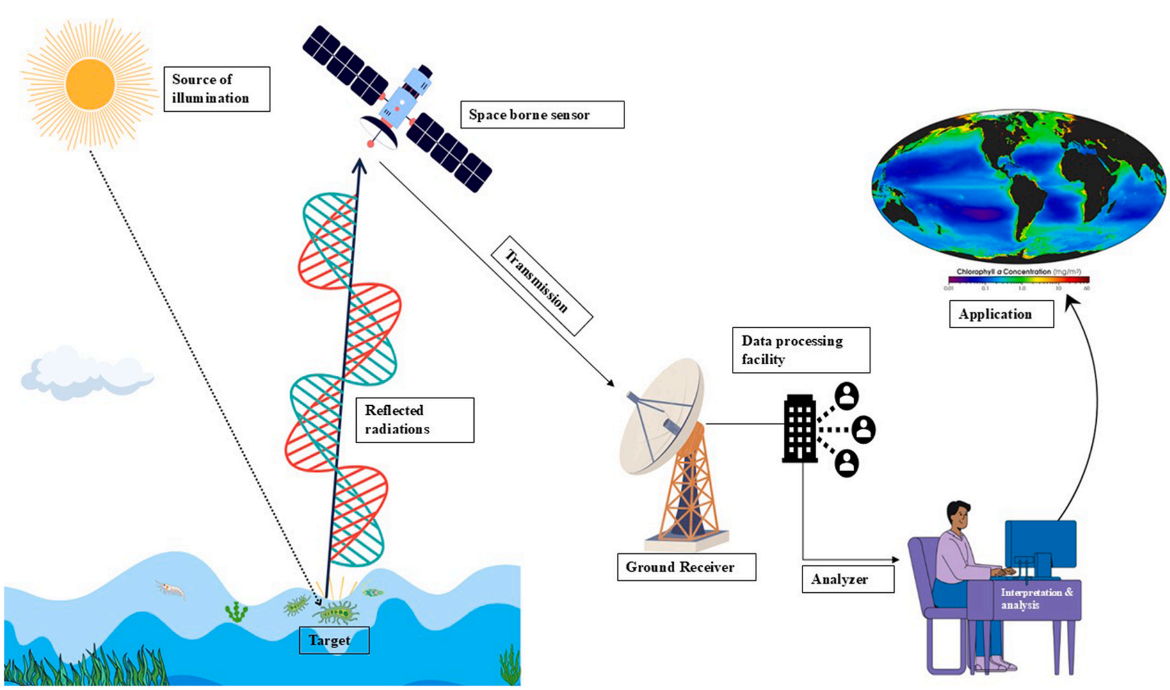

Fig. 1. Schematic of the satellite remote sensing process.

This review addresses these gaps by analysing recent studies published between 2019 and 2024, while focusing on five key water quality parameters: chlorophyll-a (Chl-a), temperature, CDOM, pH, and phosphate. In doing so, it evaluates emerging trends in satellite usage, algorithmic approaches, and validation practices. More specifically, this review contributes to the literature by drawing attention to underrepresented indicators such as pH and phosphate, categorizing studies based on climatic regions and water types, and systematically auditing the application of validation metrics to reveal common practices and inconsistencies. These insights are intended to support future research and improve the design and interpretation of satellite-based remote sensing applications in coastal water quality monitoring. Essentially, the following research questions guided this review: (1) How often do recent satellite-based studies assess the key water-quality parameters such as Chl-a, temperature, CDOM, pH, and phosphate? (2) Which satellite platforms are most frequently employed to monitor water quality? (3) In what ways do monitoring practices vary across climatic zones and water types? (4) What algorithmic approaches are applied frequently? And (5) Which validation metrics are reported, and how consistently are they used?

To ensure this review captures the latest advancements, we confine our synthesis to 2019–2024 because this five-year window captures the first operational wave of advanced sensors and analytics that now underpin coastal water quality monitoring. The launch of Sentinel-3A/B, equipped with the Ocean and Land Color Instrument (OLCI) entered routine with 21-band global service in 2019, delivering the 300 m ocean-color data on which most modern algorithms are built (Strømme, 2019; Staehr et al., 2023). Moreover, Landsat-9 doubled the 30 m eight-day revisit for near-shore scenes via its OLI-2 sensor (U.S. Geological Survey, 2021). Perhaps the most significant leap has come from the operational hyperspectral satellite missions such as PRISMA and EnMAP which have enhanced the retrieval of Chl-a and subtler variables such as CDOM with <10 nm spectra (Chabrillat et al., 2024; Cogliati et al., 2021; Fabbretto et al., 2023). Similarly, this period culminates with NASA's PACE mission, the first global, 2.5 nm ocean-color observatory (Werdell et al., 2024). Small satellite constellations such as PlanetScope and HawkEye now provide daily imagery for mapping (Bresnahan et al., 2024; Mullen et al., 2023; Perin et al., 2021), which illuminates the high revisit capabilities enabled by CubeSats (Cooley et al., 2017; Rahali et al., 2025). Complementing these polar orbiting systems, Geostationary Ocean Color Imager (GOCI) delivers truly continuous hourly data to map total suspended matter over Korean coastal waters (Choi et al., 2014). Concurrently, nationwide Google Earth Engine (GEE) pipelines and deep learning models for Sentinel-2 and PRISMA data also emerged (Amieva et al., 2023; Johansen et al., 2024; Zheng et al., 2023). Earlier literature has not evaluated this combination of advanced satellite platforms, algorithmic approaches, and validation practices; therefore, focusing on the 2019–2024 period ensures that our synthesis reflects the current state of tools and methods relied upon by practitioners and by international initiatives such as the United Nations Decade of Ocean Science for Sustainable Development for timely, water quality information (Guan et al., 2023). By synthesizing recent studies focused on five key water quality parameters, this study bridges the gap between emerging technological capabilities and their application in real-world coastal monitoring. The synthesis reveals which satellite platforms and algorithmic methods are most widely used, identifies geographical and parameter-based research gaps, and highlights persistent inconsistencies in validation metrics, thereby contributing to more transparent and rigorous scientific practices. From a policy perspective, the findings align with key regulatory frameworks such as the United Nations Sustainable Development Goal 14 (SDG 14) and the European Union Water Framework Directive (EU WFD), both of which increasingly emphasize the use of satellite-based data for coastal and marine water quality assessment.

Practical applications of this work are apparent in the operations of agencies like the Copernicus Marine Environment Monitoring Service (CMEMS) and Europe's Clean Sea Net (CSN), which employ Sentinel-2 and SAR imagery to monitor oil pollution and harmful algal blooms. Similarly, in the United States, the National Oceanic and Atmospheric Administration (NOAA), through programs like the National Estuarine Research Reserve System (NERRS), uses high-resolution Landsat and Sentinel data to monitor chlorophyll concentrations and turbidity levels in estuarine systems. These practical applications underscore the review's value in informing and extending current monitoring efforts. Technologically, advances such as Sentinel-3 and Landsat-9 provide more frequent and higher-resolution data, supporting early warning systems for coastal hazards like eutrophication and sediment discharge. By synthesizing recent trends, this review provides a timely, practical reference for environmental managers, researchers, and policymakers seeking to integrate satellite technologies into effective coastal water quality monitoring frameworks.

2. Methodology

This study follows a systematic scoping review approach to map and synthesize the recent developments in satellite-based remote sensing of coastal water quality. The aim was to identify trends, gaps, and commonly used techniques in the literature published between 2019 and 2024.

2.1. Literature search and filtering

On November 8, 2024, a comprehensive literature search was conducted in the Scopus database to identify relevant studies focused on remote sensing applications in coastal waters. The initial search employed the keywords: "remote sensing" and "coastal waters", specifically targeting occurrences of these terms within article title, abstract, and keywords fields, resulting in a preliminary set of 8709 documents (Fig. 2).

To refine the scope, several additional keyword filters were applied, including "remote sensing," "satellite imagery," "oceanography," "water quality," and "coastal waters." The search was further narrowed by limiting the publication date range to 2019–2024 and focusing on articles within the subject areas of Environmental Science, and Agriculture and Biological Sciences. Further constraints restricted the results to journal articles in English that were open access, yielding 498 documents.

2.2. Inclusion and exclusion criteria

Finally, to enhance the quality of sources, the selection was refined to include only articles published in Q1 and Q2 journals. This final filtration step resulted in a focused set of 465 articles representing high-impact studies relevant to the field of remote sensing in coastal water research (See supplementary file).

2.3. Search outcome analysis

To identify the thematic structure of the dataset concerning the role of satellite remote sensing applications in coastal waters, a keyword co-occurrence analysis was performed. For this purpose, VOSviewer (Version 1.6.20) was utilized to generate the keyword network visualization. The final dataset, consisting of 465 articles from the Scopus database, was exported with essential details such as authors names, titles, abstracts, author keywords, and indexed keywords, and subsequently saved as a CSV file on the local machine for further analysis.

The visualization procedure started by importing the saved CSV file into VOSviewer with the Scopus data option provided by the application. An initial reading was performed to identify and address variances in terminology, including synonyms and abbreviations. A thesaurus file was established to standardize these variances for uniformity. The data were subsequently reimported into VOSviewer with the thesaurus file

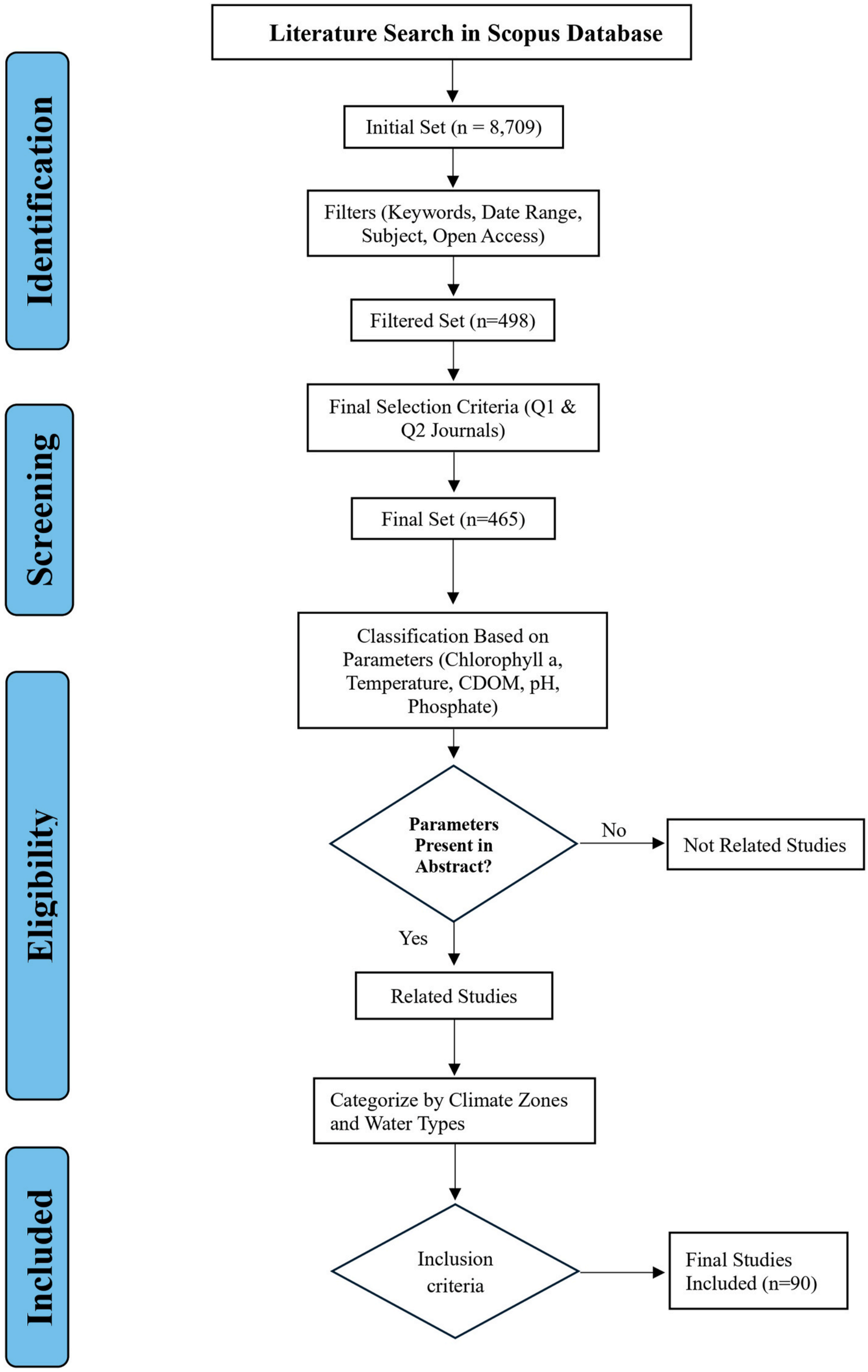

Fig. 2. Process of literature search and evaluation for inclusion.

implemented, facilitating accurate visualization and analysis. Consequently, "all keywords" option was selected to achieve a comprehensive overview of the research area. The dataset was analysed using two occurrence thresholds, set at 20 and 10, to capture varying levels of keyword significance.

To evaluate the presence of five specific parameters: chlorophyll-a (Chl-a), temperature, colored dissolved organic matter (CDOM), pH, and phosphate in the abstracts of articles extracted from the Scopus database, we carefully reviewed the abstracts of each study and classified each article according to its content in excel sheet. For articles where one or more of these parameters were mentioned in the abstract, we marked a "1″ in the respective column corresponding to each identified parameter. These articles were classified as "Related" in the "Relevance" column if the parameters were central to the analysis, particularly within the context of remote sensing for water quality monitoring. This classification system provided a clear and consistent way to identify studies aligned with the review's objectives, ensuring a focus on the parameters of interest.

Conversely, when none of these parameters were recorded and all parameter columns were marked as "0," articles were classified as "Not Related." While many of these studies do focus on aquatic or coastal environments, their primary themes diverged from the specific parameters at the core of this review. Instead, these studies addressed broader topics, such as vegetation and habitat monitoring, coastal and land management, hydrodynamic and environmental variables, and soil or nutrient management etc. They often explored ecosystem dynamics, including seagrass health, shoreline erosion, or atmospheric influences, concentrating on ecological and terrestrial processes rather than specific water quality indicators. Although such studies provided valuable environmental insights, their lack of focus on the targeted parameters led to their exclusion.

It is worth noting that some excluded studies did mention one or more key parameters, such as Chl-a and temperature, but only in a secondary capacity rather than as central research focus. To ensure clarity and consistency, all "Not Related" studies were assigned a value of zero for all five parameters, regardless of their presence or absence in the study abstracts. This approach made it possible to organize the articles in a clear and structured way, distinguishing each one based on whether it included the key parameters and how relevant it was to the study. It maintained clarity throughout the selection process and emphasized the relevance of each article for inclusion and analysis in the review, resulting in a systematic and focused evaluation.

To further categorize these studies, we organized them based on climatic zones and water types. The climate zones included Arctic, Antarctic, subtropical, tropical, and temperate, representing broad environmental settings. The classification was conducted in a broader context, sometimes based on the overall climate of the region or country where the study was conducted, rather than the specific microclimatic conditions of the study area. For instance, if a study was carried out in a country or region predominantly categorized as temperate, it was classified under the temperate zone, even if the specific study site within that region had slightly different climatic conditions at a local level. This approach provided a practical framework for fitting studies into one of the five overarching categories. Similarly, water types were systematically grouped into three broad categories: freshwater (encompassing lakes, ponds, rivers, streams, swamps, and marshes), estuaries (covering river mouths and estuarine zones), and marine (including coastal areas, seas, bays, and lagoons).

Moreover, studies mentioning both marine and freshwater types were identified as marine and freshwater; similarly, studies focused on both estuary and marine were identified as marine and estuary in the water column type. Additionally, studies consulting global waters or not specifying a specific water type were eliminated. The same classification was applied to climate zones as well. This organization provided a comprehensive understanding of how each study applied remote sensing across different climates and water bodies, helping to reveal patterns in parameter behaviour across various environmental contexts.

To identify the primary sources of remote sensing technology utilized, we conducted detailed analysis of the articles, focusing on their abstracts and methodology sections. This examination aimed to determine the most commonly used remote sensing platforms, whether satellites, unmanned aerial vehicles (UAVs) or other remote sensing-based techniques. Once the platforms were identified, further emphasis was placed on assessing the specific satellites employed across different studies. The standardized approach to naming and describing these satellite platforms is detailed in **(**Appendix A**)**.

The primary objective of this step in the review process was to examine and evaluate the statistical analysis methods used for the assessment of accuracy of algorithms in studies utilizing satellite platforms. To achieve this, we began by filtering studies that referenced chlorophyll-a (Chl-a) in their abstracts, as indicated by a "1" in the corresponding column of the dataset. This approach ensured that only studies where Chl-a was included as a parameter of interest were considered, though it is important to note that this does not necessarily confirm that Chl-a was the primary focus of each study.

To maintain consistency in the types of studies reviewed, we applied an additional filter to include only those studies that utilized exactly one satellite platform. This ensured that the analysis focused on studies using a single satellite, thereby minimizing potential variability due to the use of multiple satellite platforms. As a result, studies that relied on more than one satellite were excluded from further review.

After applying these filters, a total of 21 studies remained, which met the criteria of being related to chlorophyll-a (as per their abstract), using satellite platforms, and employing only one satellite for their analysis. Upon further review of these 21 studies, it was observed that five additional articles did not contain sufficient information related to the Chl-a algorithm or the statistical methods employed. These articles were, therefore, removed from the dataset.

As a result, 16 studies remained that provided the necessary details about the algorithms used for Chl-a retrieval and the corresponding statistical validation metrics. To facilitate a comprehensive understanding of the algorithms utilized across the reviewed studies, we classified the algorithms into broad categories based on their underlying methodologies and functional approaches. The need for this categorization arose from several key challenges encountered during the review process as a wide variety of algorithms, ranging from simple empirical band ratios to complex machine learning models, were used. Additionally, in many studies, more than one algorithm is applied, or modifications to existing models are made to adapt them to local conditions. Categories identified in this scoping review are as follows:

(1) Empirical−In this category we include algorithms like band ratios (e.g., Red/Blue, Green/Red) and spectral indices (e.g., NDCI). These types of algorithms are grounded in statistically derived relationships, often involving band ratios or spectral indices. Examples from the studies include the Normalized Difference Chlorophyll Index (NDCI), OC3M 3-band index, and blue-green ratio (Kramer et al., 2023; Kwong et al., 2022; Maciel et al., 2023). These algorithms are simple, computationally efficient, and effective for region-specific applications where conditions are relatively consistent.
(2) Semi-empirical-In this category, algorithms that combine theoretical frameworks (often derived from physical or optical models) with empirical data. For instance, algorithms such as Tassan, GROC4 and GOCI-standard (Abbas et al., 2019; Yoon et al., 2019) were included in the category. These algorithms are more robust than pure empirical models and offer better generalization across different regions.
(3) Semi-analytical-Algorithms categorized in this group, include those that blend theoretical models with empirical data but tend to have a stronger basis in bio-optical theory. They incorporate a combination of measured spectral data and statistical analysis to derive parameters. The Modified Quasi-Analytical Algorithm (MQAA) is an example of a semi-analytical algorithm (Lu et al., 2022).
(4) Machine learning-In this category, we classify algorithms that utilize data-driven approaches by learning patterns from large datasets. Examples from studies include Support Vector Machines (SVM), Artificial Neural Networks (ANN), Gradient Boosting Regression (GBR) and Random Forest (RF) (Quang et al., 2023; Staehr et al., 2023; Woo Kim et al., 2022).

3. Results

Water quality parameters, such as chlorophyll-a (Chl-a) and temperature, dominate research efforts, while others like pH and phosphate remain underrepresented, especially in specific geographic contexts. Climate zone and water type analysis highlights a significant focus on temperate and subtropical marine environments, contrasted by limited studies on Arctic regions and freshwater ecosystems. The study also evaluates the use of satellite remote sensing platforms, showcasing a strong dependence on satellite data, with Aqua and Sentinel emerging as the most frequently utilized platforms. In terms of validation metrics applied across the studies, the root mean square error (RMSE) and the coefficient of determination (R^2) were identified as the most frequent ones.

3.1. Remote sensing, satellite imagery and water quality interlink research publication themes

The examination of the keyword co-occurrence network revealed an interesting thematic perspective, with prominent networks emphasizing the use of remote sensing in water quality assessment, coastal environments, and satellite-based methods. Key terms like "remote sensing," "satellite imagery," and "water quality" establish interlinked clusters, highlighting their vitality in defining the structure of themes across research areas (Fig. 3). Both networks, with two-fold difference in their thresholds, notably show the red cluster, with "remote sensing" as a primary anchor, links broad themes such as "climate change," "ecosystems," and "land use." The cluster serves as a conduit between conventional environmental monitoring and evolved satellite data applications. The strong interconnections among the red, green, and blue clusters in both networks indicate the constant interaction among recognized environmental themes and the technical innovations influencing the future of remote sensing studies.

All in all, the threshold 20 network offers a concentrated and ordered viewpoint, with 49 keywords grouped into four separate clusters, interconnected via 1012 links and an overall link strength of 7973. This network emphasizes known research themes, providing a succinct overview of the prevailing domains within the discipline. The green cluster in this network highlights the progress in satellite technology, using important terms like "satellite imagery," "spatial analysis," and "Sentinel," which represent the fundamental function of satellite platforms in observing coastal regions. Meanwhile, the blue cluster focuses on the marine environment, covering terms such as "chlorophyll-a," "phytoplankton," and "oceanography," which highlights the essential function of satellite imagery in evaluating water quality metrics, nutrient dynamics, and ecological health.

Conversely, the threshold 10 network considerably broadens the subject depth, encompassing 85 keyword density, 2376 links, and a combined link strength of 11,274. The green group within this network exemplifies the use of modern computational methodologies, using key phrases like "random forest," "artificial neural networks," and "optical remote sensing." The above terms reflect the growing reliance on machine learning for the analysis and interpretation of satellite data. Furthermore, the blue cluster inside this network, which extends to new terms, illustrates a renewed focus on examining diverse aquatic variables.

3.2. Chlorophyll-a as a water quality parameter dominates the aquatic research interest

The largest portion, comprising more than half of the 90 related studies examined chlorophyll-a (Chl-a) (Fig. 4). This larger-than-average representation underscores its significance in water research, making it the most extensively studied parameter.

In comparison, temperature accounts for just over a quarter (26 %) of the studies, making it the second most emphasized parameter. Although smaller than chlorophyll-a portion, this section indicates a strong focus on understanding the thermal dynamics of water bodies. colored dissolved organic matter (CDOM) represents a considerably smaller section, appearing approximately one-third as often as temperature, indicating a moderate level of attention in the reviewed studies. However, pH and phosphate constitute the smallest sections of the chart, collectively contributing less than one-tenth of the total research focus. These minimal proportions emphasize their underrepresentation in the reviewed research despite their relevance to water quality assessments.

Overall, the chart highlights a clear emphasis on Chl-a and temperature, which dominates the research landscape. In comparison, the smaller segments attributed to pH and phosphate reveal gaps in the current investigations, indicating areas that warrant further exploration to provide a more comprehensive understanding of aquatic environments.

One of the most striking observations is the frequency with which Chl-a and temperature appear together, particularly in subtropical and temperate marine environments. Their co-occurrence implies that studies in these regions tend to view temperature as a critical contextual factor in assessing phytoplankton or algal activity, with both parameters contributing significantly to understanding of productivity and ecosystem health (Fig. 5).

In contrast, CDOM, pH, and phosphate exhibit a more sporadic and isolated presence across climate zones and water types, particularly in studies where chlorophyll-a and temperature are less emphasized. This divergence points to a distinct thematic difference in how these parameters are applied. For example, phosphate appears prominently in certain marine studies, albeit infrequently paired with other parameters. Its relatively independent appearance rarely co-occurring with all five parameters highlights a compartmentalized approach in which nutrient-focused studies are somewhat separated from the broader water quality framework seen in more integrative studies.

CDOM and pH are more commonly studied in specific contexts, particularly showing dominance in freshwater and marine environments. Their infrequent inclusion in broader studies suggests they are typically used for specialized ecological inquiries rather than comprehensive ecosystem assessments. For example, CDOM is often examined in estuarine and marine environments for its effects on light penetration and biological processes but is rarely integrated into holistic ecological evaluations. Unlike Chl-a and temperature, their inclusion lacks a consistent upward trend in multi-parameter research, indicating a fragmented approach.

Interestingly, the distribution of studies across climate zones also reveals an underlying emphasis on certain ecological settings over others. Marine environments in subtropical and temperate zones receive the most attention, with multiple parameters studied together, reflecting the complex and productive nature of these waters. At the opposite end of the spectrum, Arctic and tropical environments show minimal parameter overlapping and overall sparse representation. This inconsistency suggests a potential research gap; while productive marine zones are studied with a comprehensive approach to understand complex interactions, less biologically diverse or less accessible regions, such as Arctic, receive a fragmented approach, often focusing on single parameters rather than a suite.

In essence, the heatmaps reveal that Chl-a and temperature are frequently studied together, especially in subtropical and temperate marine environments, while CDOM, pH, and phosphate appear less consistently and often independently. This pattern underscores the need for a more balanced approach, both geographically and in terms of parameter inclusion, to gain a complete understanding of global water quality trends and their ecological implications.

3.3. Interest in estimating chlorophyll-a levels is uniform of climate zone biased

Overall, the chart reveals a clear trend of strong focus on chlorophyll-a (Chl-a) studies in marine environments, particularly within temperate and subtropical climate zones (Fig. 6). These zones record the highest numbers of studies, reflecting a clear interest in understanding marine Chl-a presence in moderate climates. In contrast, Arctic and tropical display relatively fewer studies, with a broader spread across different water types.

As observed, temperate and subtropical zones show a dominant focus on Chl-a presence in marine environments, with 30 and 29 studies, respectively. In terms of specific water types, most studies in both zones focus on marine waters, recording 22 studies in the subtropical zone and 21 in the temperate zone. Estuary studies are also present but to a much lesser extent. Also, freshwater studies are minimal in both regions, with

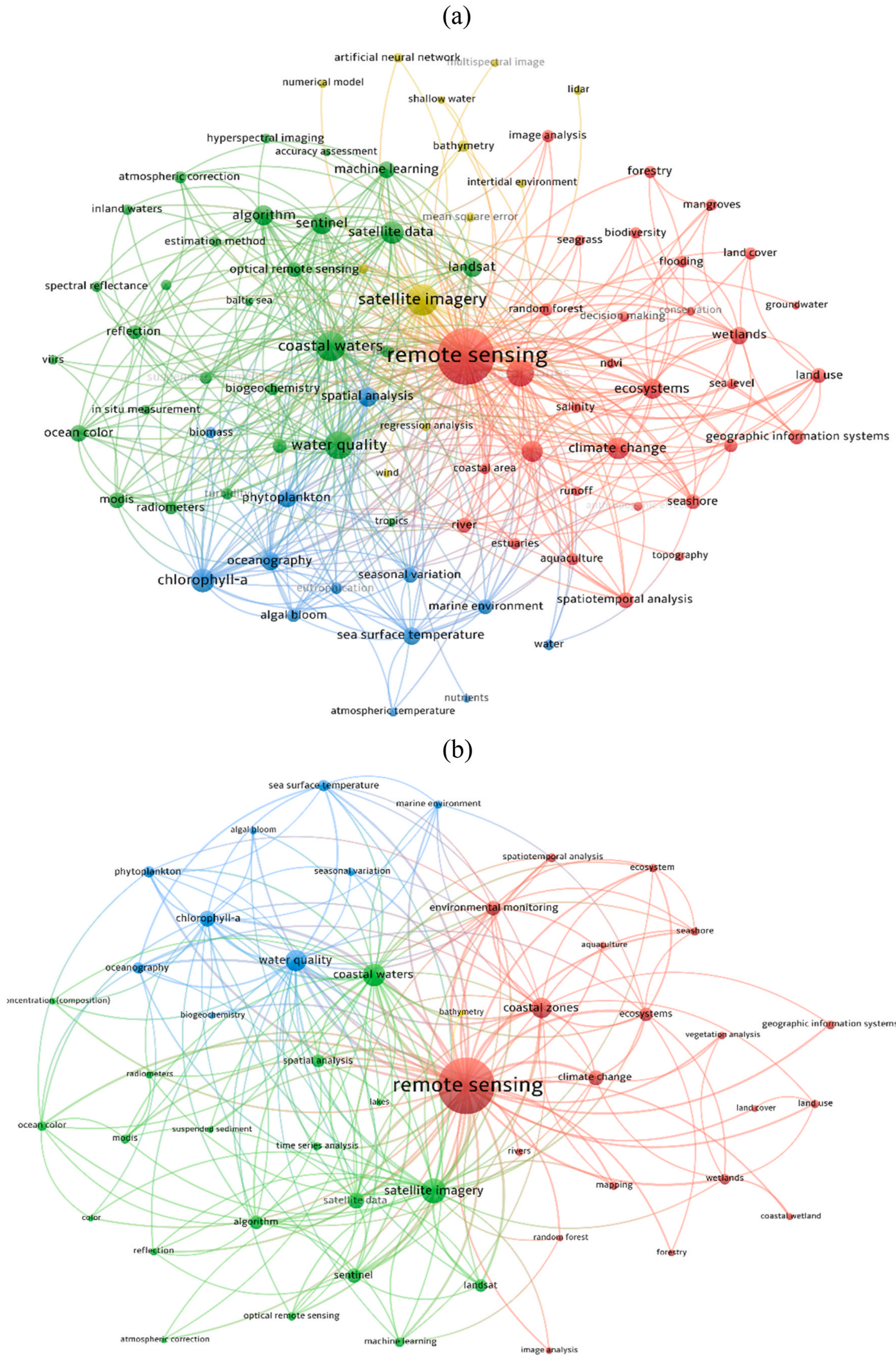

Fig. 3. Network visualization of keyword co-occurrence in remote sensing research on coastal waters, highlighting distinct thematic clusters at two co-occurrence thresholds: (a) 10 and (b) 20.

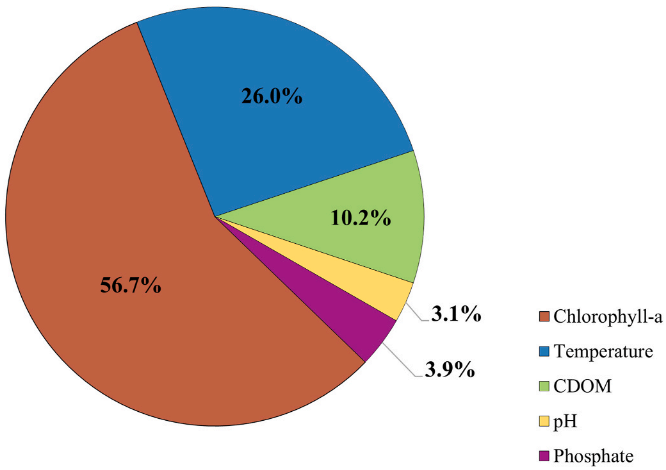

Fig. 4. Distribution of water quality parameters across the analysed studies.

only 1 study in the subtropical zone and 3 in the temperate zone, highlighting a clear preference for marine environments in these moderate climates.

In contrast, other climate zones, such as the Arctic and tropical, reveal different trends with relatively lower study counts and a more diverse distribution across water types. The Arctic zone, for instance, shows only 2 studies, both of which are focused solely on marine environments. The tropical zone has a slightly broader scope, with a total of 11 studies divided across various water types.

A chi-square test of independence was performed to examine the relationship between climate zones and studies focusing on Chl-a. The relationship between these variables was not significant, X^2 (2, N = 85) = 1.12, p = 0.57. This suggests that the distribution of studies focusing on Chl-a does not significantly differ across the three climate zones (subtropical, temperate, tropical).

3.4. Satellite platforms for coastal monitoring

A large portion of the total frequency is dominated by Aqua satellite, which accounts for 21 occurrences, representing most of the usage in the studies. This is followed by Sentinel-2 and Sentinel-3, which together account for more than a quarter (approximately 27 %) of the total frequency, underscoring their significant role in research (Fig. 7).

On the other hand, satellites such as GCOM-C, GK-2B, NOAA-20, and WorldView-2 demonstrate minimal usage with one instance each, while SNPP with 2 and Envisat with 4 indicate moderate usage and highlight their continued relevance in specific research contexts. Similarly, airborne platforms like UAVs exhibit a frequency of 4, underscoring their emerging but still limited role compared to traditional satellite platforms.

The data shows that legacy satellites like Landsat-7 and Terra, with 5 and 6 appearances respectively, remain moderately utilized and continue to contribute to long-term environmental monitoring. However, it is evident that they are significantly outpaced by newer platforms with advanced sensors on-board like Sentinel-2 and Sentinel-3, which offer higher resolution, larger swath width, and more frequent revisit times. In this context, Landsat-8, with 5 instances, remains relevant due to its advanced imaging capabilities. Yet, like the other Landsat satellites appeared in the analysis, it is overshadowed by the more modern Sentinel series. This shift suggests a gradual transition within the research community towards utilizing newer satellites equipped with higher-resolution sensors.

In summary, there is a diverse landscape of satellite utilization across studies. It illustrates the dominance of widely accessible and versatile platforms like Aqua and Sentinel satellites, the steady presence of legacy systems like Landsat, and the emerging role of UAVs (Table 1).

A detailed examination of the dataset reveals that only eleven studies utilized the Aqua satellite exclusively. Among these, the majority amounting to eight studies were conducted in marine waters, two studies focused on estuary environments, while just one was conducted in freshwater. This trend demonstrates Aqua's primary application in marine research, where its capabilities are most impactful. Its relatively limited presence in estuarine and freshwater studies suggests that the Aqua satellite and its onboard instruments may be less suited to the small-scale monitoring often required in freshwater systems or that other satellites are more commonly chosen for these tasks.

The distribution of Aqua satellite usage in studies that combines its data with other platforms, and alone data offered a broader picture of its application. By examining its usage across climate zones and water types (Fig. 8), subtropical zone emerges as the most dominant, with the highest frequency of studies, particularly in marine environments. Temperate zone follows, with a moderate number of studies, primarily in marine and estuary systems. In contrast, Tropical zone shows a notably lower frequency of Aqua utilization, with sparse representation across all water types. The Arctic zone, while the least represented, also shows a focus on marine environments. This combined analysis highlights that Aqua satellite data is most heavily utilized in Subtropical marine systems, while its use in other zones and water types is less frequent, reflecting its specialization in monitoring large-scale and dynamic aquatic environments.

In summary, the Aqua satellite proves to be a versatile tool, excelling as both a primary and supporting resource, especially in larger aquatic environments. The heatmap provides a comprehensive view of studies involving the Aqua satellite, offering insights into its usage across various climate zones and water types in our review. It is vital to note that the visual representation does not solely represent studies where Aqua was the only satellite used (Fig. 8). Rather, it also includes studies where Aqua was used in conjunction with other satellites, highlighting its versatility as both a primary and complementary tool in multi-platform research frameworks.

3.5. Statistical approaches in water quality assessment

After the elimination review process, we examined 16 publications. A variety of algorithms were used for the retrieval of chlorophyll-a (Chl-a). We observed that there is no single, standardized approach across the studies in terms of algorithm selection. Each study tends to develop or adapt region-specific algorithms, and several utilize more than one algorithm in their studies, which are often designed to account for unique environmental conditions in the study area. This reflects the diversity of ecosystems and the unique challenges posed by different geographical areas. Alongside the development or deployment of algorithms, various statistical methods were used for model accuracy assessment and validation. The review of statistical validation metrics used in these studies reveals a significant diversity in approaches, reflecting the complexity of the field and the varied goals of different research efforts.

Commonly used validation metrics such as root mean square error (RMSE), coefficient of determination (R^2), and Pearson's correlation coefficient (r) were widely used to assess model accuracy, fit, and error, indicating a general preference for standard approaches in evaluating the performance of retrieval algorithms (Table 2). However, the presence of other metrics, such as mean absolute error (MAE), bias, and Spearman's correlation coefficient (r_s), among others, which are used less frequently, suggests a broader range of accuracy assessment strategies depending on the specific nature of the data, the algorithms, and the underlying research questions. This diversity in statistical methods points to a lack of uniformity in validation practices across studies, which may hinder direct comparisons between different satellite platforms and retrieval models. While this variability can be seen as a strength in terms of adapting methods to specific study requirements, it also underscores the need for more standardized guidelines in satellite-based research. Such standardization would enhance reliability,

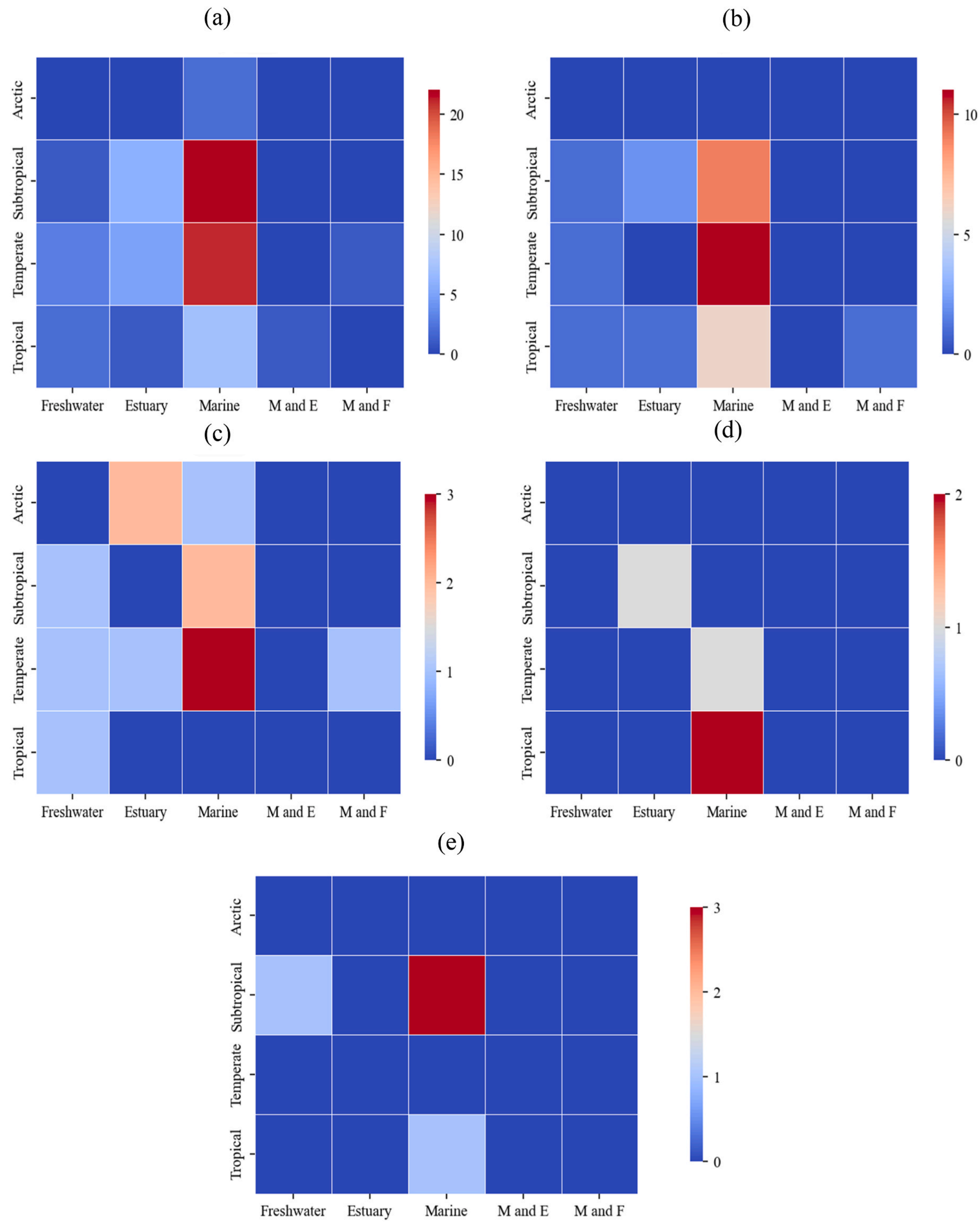

Fig. 5. Analysed water quality parameters across various climatic zones and water types: (a) chlorophyll-a, (b) temperature, (c) CDOM, (d) pH, and (e) phosphate. M and E = Marine and Estuary environments; M and F = Marine and Freshwater systems.

reproducibility, and comparability of findings, ultimately advancing the consistency of satellite remote sensing as a tool for environmental monitoring.

The root mean square error (RMSE) was the most frequently used validation metric, appearing in 10 out of the studies analysed. This suggests that researchers tend to rely on RMSE for evaluating the accuracy of models, likely due to its ability to quantify the difference between observed and predicted values. The coefficient of determination (R^2) was the second most used metric appearing in 7 studies. This metric is often used to assess the goodness of fit of a model, indicating how well the predictions align with the observed values. Interestingly, R^2 and RMSE were used together in 6 studies, highlighting a complementary approach to model evaluation. This combined use suggests researchers aim for a more comprehensive assessment of retrieval models, balancing accuracy with the strength of the model's fit. Using both metrics together helps capture both prediction errors and model performance, offering a more robust validation than relying on a single metric alone. Additionally, other statistical metrics such as Pearson's correlation

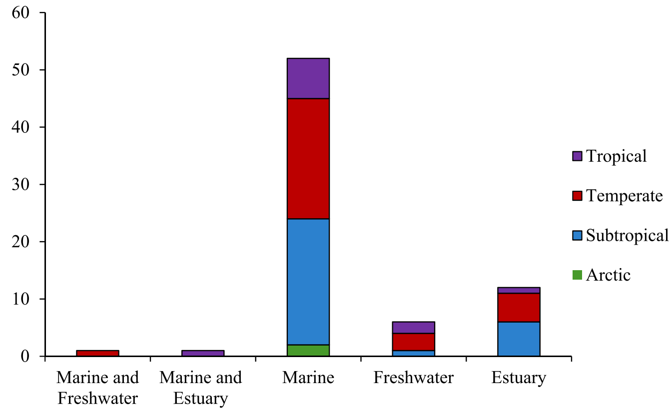

Fig. 6. Distribution of chlorophyll-a across climatic regions and water types.

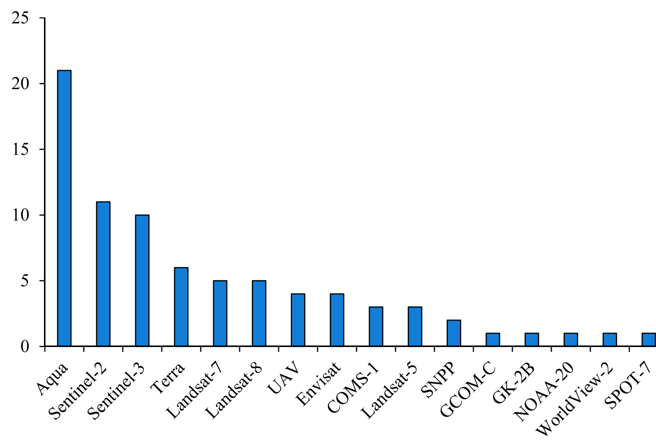

Fig. 7. Usage frequency of remote sensing platforms in analysed studies.

coefficient (r), MAE and bias were also used, but less repeatedly than RMSE and R^2.

Based on the analysis to determine the validation metrics used across studies focusing on Chl-a and utilizing a single satellite, it was found that Sentinel-2, Sentinel-3, and Aqua satellites were used mostly in studies employing R^2 and RMSE as validation metrics. To assess whether the choice of validation metric (R^2 or RMSE) varies across these satellites, a chi-square test of independence was conducted. The results yielded a chi-square statistic of X^2 (2, N = 12) = 0.25, p = 0.88. Since the p-value is much higher than the conventional significance level of 0.05, we fail to reject the null hypothesis. This indicates that there is no significant association between the satellite type and the choice of validation metric. In other words, the selection of either R^2 or RMSE as a validation metric is independent of the satellite used.

3.6. *Earlier publication employed empirical-based algorithms, but the trend shifts toward machine learning in recent years*

Empirical-based algorithms dominate the field, appearing in nine studies, which translates to a substantial 56.3 % of the total 16 selected publications, signifying their reliability and widespread applicability (Fig. 9). In stark contrast, semi-analytical methods make a solitary appearance, underscoring their niche application in this research landscape. Machine learning gained notable traction, appearing in nearly half of the studies reflecting a growing reliance on advanced data-driven computational approaches in recent research. It is worth noticing that semi-empirical methods, though less prevalent, are featured in four studies, indicating their relevance in bridging theoretical frameworks with practical applications.

Overlapping methods due to the utilization of multiple algorithms in certain studies highlights the integrative and multidimensional nature of research in this field. It is apparent from the data that while traditional approaches like empirical algorithms maintain their prominence, the shift toward machine learning demonstrates the evolving dynamics of the field.

4. Discussion

This review systematically synthesized the recent research status and trend of applying satellite remote sensing in water quality monitoring and its evaluation across various climatic zones and water types (including the spatiotemporal patterns, practice of water quality indicators, satellite platforms, and accuracy assessments). From the spatiotemporal patterns, the assessment of water quality for marine water is observed to be accounting far more than that for inland water overall, indicating that researchers should pay more attention to inland water resources. Chlorophyll-a (Chl-a), along with temperature, emerged as the most commonly used water quality indicators. While in terms of data sources utilization for monitoring key water parameters via remote image sensing was found to be satellite imagery, and most prominently utilizing the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor data from Aqua and Terra satellites while the latest sensors with high spatial and temporal resolution on board Sentinel-2 and Sentinel-3 are also utilized more frequently than others. Moreover, within the context of algorithms, it is apparent that empirical-based algorithms are more frequently employed than other approaches, whilst root mean square error (RMSE) and coefficient of determination (R^2) are the prevalent validation metrics in the field.

4.1. *Water quality parameters assessed by satellites*

Various physical, chemical, and biological parameters are of utmost importance for assessing water quality, as they play a crucial role in the identification and characterization of the diverse sources of pollution (Khattab and Merkel, 2014). Within the scope of the current investigative study, Chl-a, a key biological parameter, has appeared as the most significant and prominent indicator for water quality assessment in a broad range of aquatic ecosystems, ranging from freshwater to marine environments and extending across a multitude of diverse climatic zones that impact these ecosystems.

Chlorophyll-a, a pigment primarily produced by plankton, has garnered significant interest among the researchers due to its vital role in water quality assessments (Vinh et al., 2019). As a marker of phytoplankton abundance, it functions as an essential tool for acquiring insights into the health and productivity status of aquatic ecosystems (Jiang et al., 2020; Quang et al., 2022). The widespread application of Chl-a concentration is attributed to its strong correlation with algal blooms and eutrophication, two significant concerns for both marine and inland waters. Furthermore, different models use it as an essential input to measure the oceanic response to climate change and anthropogenic activities (Lu et al., 2020b). Traditionally, its concentrations were measured using *in situ* methods such as spot sampling, ship-based surveys, and laboratory analysis. However, these methods often struggle to capture the heterogeneous distribution of Chl-a in water bodies due to spatial and temporal limitations (Tong et al., 2022). These constraints have been addressed with the high spread use of satellite remote sensing, which provides global high-frequency data with frequent and synoptic observations (Maslukah et al., 2021; Rabing et al., 2022). From satellite platforms, the availability of uninterrupted Chl-a data is precious for investigating long term and vast variations in phytoplankton biomass. Such data has shown promising results in the investigation of ocean primary productivity (Johnson and Bif, 2021; Xing et al., 2022), biochemistry (Mishra and Mishra, 2012) and the carbon cycle (Dutkiewicz et al., 2019).

Furthermore, it was noted that numerous studies have applied

Table 1
Overview of satellites and their sensors frequently used in the studies examined.

Specifications	Satellites				
	A	Terra	Sentinel-2	Sentinel-3	Landsat-8
Sensors	MODIS[a], AIRS[b], AMSR-E[c], AMSU-A[d], CERES[e], and HSB[f]	MODIS[a], MISR[g], ASTER[h], CERES[e], TES[i], and MOPITT[j]	MSI[k]	OLCI[l], SLSTR[m], SRAL[n], and MWR[o]	OLI[p] and TIRS[q]
Spatial resolution	MODIS[a]: 250m, 500m and 1000m (varies by bands)	MODIS[a]: 250m, 500m and 1000m (varies by bands)	MSI[k]: 10m, 20m, 60m (varies by bands)	OLCI[l]: 300m	OLI[p]: 30m, TIRS[q]: 100m
Temporal resolution (day)	MODIS[a]: 1–2 days	MODIS[a]: 1–2 days	5 days (with both sentinel-2a and sentinel-2b)	1–2 days (combined with sentinel-3a and sentinel-3b)	16 days
Spectral bands	MODIS[a]: 36 spectral bands	MODIS[a]: 36 spectral bands	MSI[k]: 13 spectral bands	OLCI[l]: 21 spectral bands	OLI[p]: 9 spectral bands, TIRS[q]: 2 spectral bands
Spectral range	0.4–14.4 μm (from visible to thermal infrared)	0.4–14.4 μm (from visible to thermal infrared)	0.443–2.280 μm (13 spectral bands)	0.4–1.2 μm (OLCI[l], 21 bands)	0.43–2.29 μm (OLI[p]), 10.6–12.51 μm (TIRS[q])
Area of spectrum sensed	Visible to thermal infrared, broad spectrum	Visible to thermal infrared, broad spectrum	Visible, near-infrared, shortwave infrared	Visible, near-infrared	Visible, near-infrared, shortwave infrared, thermal bands
Years of data availability/ mission time	Launched in 2002, the mission planned to last at least 15 years	Launched in 1999, the mission planned to last at least 15 years	Launched in 2015 (sentinel-2a) and 2017 (sentinel-2b), expected mission time 7+ years for each satellite	Launched in 2016 (sentinel-3a) and 2018 (sentinel-3b), mission expected to last at least 7 years	Launched in 2013, mission expected to last 5–10 years
Space agency	National Aeronautics and Space Administration (NASA)	National Aeronautics and Space Administration (NASA)	European space agency (ESA)	European space agency (ESA)	NASA and United States Geological Survey (USGS)

[a] Moderate Resolution Imaging Spectroradiometer.
[b] Atmospheric Infrared Sounder.
[c] Advanced Microwave Scanning Radiometer for EOS.
[d] Advanced Microwave Sounding Unit-A.
[e] Clouds and the Earth's Radiant Energy System.
[f] Humidity Sounder for Brazil.
[g] Multi-angle Imaging Spectroradiometer.
[h] Advanced Spaceborne Thermal Emission and Reflection Radiometer.
[i] Tropospheric Emission Spectrometer.
[j] Measurements of Pollution in the Troposphere.
[k] Multispectral Instrument.
[l] Ocean and Land Color Instrument.
[m] Sea and Land Surface Temperature Radiometer.
[n] Synthetic Aperture Radar Altimeter.
[o] Microwave Radiometer.
[p] Operational Land Imager.
[q] Thermal Infrared Sensor.

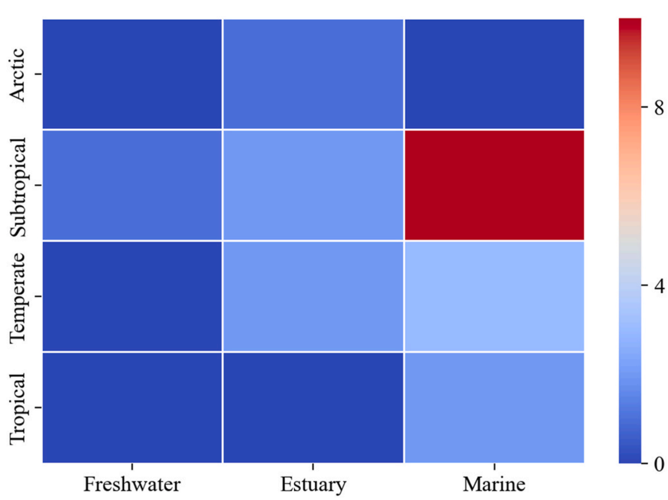

Fig. 8. Combined deployment of aqua satellite across climatic zones and aquatic environments.

optical remote sensing using satellite sensors such as Landsat, Sentinel-2, Sentinel-3, and MODIS to estimate Chl-a concentrations across various water bodies and regions (Erena et al., 2019; Lu et al., 2022; Staehr et al., 2023; Tong et al., 2022; Virdis et al., 2022; Xing et al., 2022). Recent work in the Hooghly estuary further supports this approach, where retrieval of Chl-a from Sentinel-3 using the regionally adapted C2RCC algorithm yielded reliable results (Bar et al., 2023). Given that Chl-a is a reliable indicator for detecting oceanic eutrophication (Gohin et al., 2019) and phytoplankton growth (Xing et al., 2022; Zhang et al., 2017), satellite-based monitoring of Chl-a at broad spatial scales is now increasingly integral to water quality assessment.

Temperature is another frequently studied water quality parameter, ranking just below Chl-a in our analysis. The heatmap (Fig. 5) demonstrates its high frequency of co-occurrence with Chl-a, particularly in subtropical and temperate marine habitats, highlighting its essential role in influencing biological production. As a fundamental abiotic factor, temperature profoundly impacts the physio-chemical characteristics of water, thereby influencing the development, metabolism, and dispersion of aquatic species (Konan et al., 2023; Querijero and Mercurio, 2016). It directly affects water quality by altering chemical reaction rates, dissolved oxygen levels, and the proliferation of aquatic organisms (Dallas, 2008; Fant et al., 2017). Additionally, temperature modulates the solubility and availability of various chemical constituents, influencing the distribution and transit of pollutants, including nutrients, throughout the water column. To remotely measure temperature, various sensors are used that can detect thermal radiation emitted from the surface of water within the 3–5 and 8–14 μm wavebands (Gholizadeh et al., 2016). The innovation of thermal infrared (TIR)

Table 2
Frequency of statistical approaches used to validate models.

Statistical Methods	Frequency	References
Root Mean Squared Error (RMSE)	10	(Maciel et al., 2023; Quang et al., 2023; Kwong et al., 2022; Lu et al., 2022; Virdis et al., 2022; Woo Kim et al., 2022; Cherif et al., 2021; Gomaa et al., 2020; Abbas et al., 2019; Yoon et al., 2019)
Coefficient of Determination (R^2)	7	(Maciel et al., 2023; Quang et al., 2023; Tong et al., 2022; Lu et al., 2022; Woo Kim et al., 2022; Cherif et al., 2021; Gomaa et al., 2020)
Pearson Correlation Coefficient (r)	6	(Cherif et al., 2021; del Carmen Jiménez-Quiroz et al., 2021; Kratzer and Plowey, 2021; Kwong et al., 2022; Staehr et al., 2023; Yoon et al., 2019)
Bias	4	(Quang et al., 2023; Virdis et al., 2022; Woo Kim et al., 2022; Yoon et al., 2019)
Mean Absolute Error (MAE)	4	(Abbas et al., 2019; Kwong et al., 2022; Virdis et al., 2022; Woo Kim et al., 2022)
Slope	2	(Tong et al., 2022; Woo Kim et al., 2022)
Median Ratio (Med Ratio)	1	Tong et al. (2022)
Uncertainty	1	Le et al. (2019)
Mean ratio	1	Yoon et al. (2019)
Variance (S)	1	(del Carmen Jiménez-Quiroz et al., 2021)
Kruskal-Wallis Test (KW-H)	1	(del Carmen Jiménez-Quiroz et al., 2021)
Absolute Percentage Difference (APD%)	1	Kratzer and Plowey (2021)
Root Mean Squared Error Percentage (RMSE%)	1	Kratzer and Plowey (2021)
Mean Normalized Bias Percentage (MNB%)	1	Kratzer and Plowey (2021)
Nash-Sutcliffe Efficiency (NSE)	1	Virdis et al. (2022)
Mean Relative Deviation (MRD)	1	Tong et al. (2022)
Unbiased Root Mean Squared Deviation (URMSD)	1	Tong et al. (2022)
Standard Error (SE)	1	Virdis et al. (2022)
Spearman Rank Correlation Coefficient (Spearman r)	1	Virdis et al. (2022)
Absolute Relative Error (ARE)	1	Lu et al. (2022)
Symmetric Mean Absolute Percentage Error (SMAPE)	1	Kwong et al. (2022)
Overestimation Comparisons	1	Kramer et al. (2023)
Mean Squared Error (MSE)	1	Quang et al. (2023)
Mean Absolute Percentage Error (MAPE)	1	Abbas et al. (2019)

remote sensing has remarkably enhanced the spatial and temporal monitoring of water temperatures, especially in large water bodies (Handcock et al., 2006). Remote sensing technologies, such as Landsat imagery, have been widely used to monitor thermal pollution, especially near power plants (Chen et al., 2003). For instance, studies by (Ling et al., 2017; Nie et al., 2021; Yavari and Qaderi, 2020) utilized Landsat data to detect thermal anomalies around the Taiwan Nuclear Power Plant, Neka power plant, and dams on the Qingjiang River, respectively. These studies revealed significant temperature increases and expanding polluted areas over time. Additionally, MODIS sensor data was used by Fazelpoor (2016) to assess water surface temperatures in the Persian Gulf, demonstrating an inverse relationship between temperature and water depth. More advance satellite then the previously mentioned, such as Sentinel-2, have proven effective for measuring sea surface temperature and salinity in coastal regions (Medina-Lopez and Ureña-Fuentes, 2019). These cases underscore the essential role of remote sensing technologies in detecting and tracking thermal pollution and temperature variations across diverse aquatic environments.

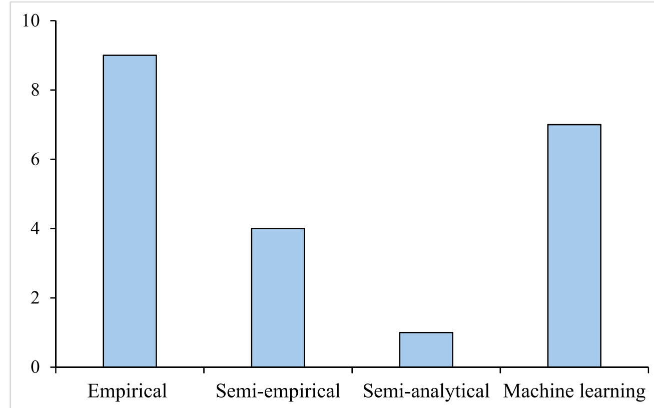

Fig. 9. Methods for retrieving chlorophyll-a concentrations through satellite-based remote sensing. Since multiple methods may be applied within a single study, the sum of total number of methods exceeds 16, the actual total number of reviewed studies.

Nevertheless, other parameters such as colored dissolved organic matter (CDOM), pH, and phosphate are infrequently assessed in the studies reviewed using remote sensing technology. This disparity indicates that present remote sensing techniques might be constrained in identifying these variables, maybe due to measurement complexities or inappropriate sensors. Rectifying this deficiency might result within enhanced water quality analyses, particularly in regions where these parameters serve as vital indications of contamination or ecological disruption.

4.2. Role of unmanned aerial vehicles (UAVs) in water quality monitoring

Recent improvements in remote sensing technology have signified a notable transition from standard satellite-based approaches to the more adaptable and efficient utilization of unmanned aerial vehicles (UAVs) for water quality monitoring. While satellites offer broad-scale insights, their limitations in spatial resolution, revisit frequency, and vulnerability to weather conditions render them ineffective for localized analyses (Pillay et al., 2024). In contrast, UAVs equipped with advanced multispectral and hyperspectral cameras provide high-resolution, cost-efficient, and flexible alternatives (Liu et al., 2024). For instance, a DJI P4 multispectral UAV operating at 50 m altitude can capture imagery with ~3.6 cm resolution over two orders of magnitude finer than Sentinel-2 MSI allowing for detailed mapping of fine-scale features (Ouma et al., 2024). Recent studies highlight UAVs ability to resolve sub-meter variability that is invisible to orbital sensors. For example (Román et al., 2022), used a five-band multispectral UAV to produce centimetre-scale Ortho mosaics at Maltese coastal sites, mapping Chl-a (0–3 mg m^{-3}) and TSS (10–20 mg m^{-3}) which was not possible through Sentinel-3 data. Similarly (Cheng et al., 2020), mapped Chl-a in coastal waters using UAVs for the very first time.

Far from operating in isolation, data from these platforms enhance satellite-based monitoring programs by providing high-resolution calibration and gap-filling. In Croatia's Kaštela Bay, merging UAV hyperspectral snapshots with Sentinel-2 imagery improved Chl-a, turbidity, and colored dissolved organic matter (CDOM) retrieval accuracy (Galešić Divić et al., 2023). Likewise, a study conducted in Galicia, Spain, combined UAV spectral data with Sentinel-2 and Landsat-8 satellite data to effectively monitor Chl-a concentrations. This multi-platform approach improved the detection of cyanobacterial blooms, particularly during periods of high cloud cover when satellite data alone were insufficient (Castro et al., 2020). This approach is mostly suitable for coastal waters management, where UAV based real time turbidity measurements have already achieved reliable predictions (Trinh et al., 2024). The integration of machine learning (ML) further improves UAVs based monitoring. By using ensemble approaches Xiao et al. (2022) managed to effectively measure the levels of nitrogen and phosphorus. In another study the use of ML models combined with data from UAV sensors provided reliable Chl-a forecasts (Liu et al., 2021). Nevertheless, challenges such as regulatory restrictions, limited battery life, and the necessity for specialized operational training remain, presenting opportunities for future advancements in UAVs based water quality monitoring (Acharya et al., 2021; Vélez-Nicolás et al., 2021).

4.3. Advances and limitations in algorithmic approaches

Water quality remote sensing has evolved significantly over time: during the 1980s and 1990s, empirical approaches emerged; in the late 1990s and early 2000s, semi-empirical and analytical methods gained prominence; and in the 21st century, advances in computer science have driven a shift toward automated, machine-learning (ML) techniques. Prior research categorizes these algorithms into four primary types empirical, semi-empirical, semi-analytical, and analytical while recognizing a fifth, machine-learning category today.

Empirical methods, which dominated in the 1980s and 1990s, rely on straightforward statistical correlations between *in situ* measurements and spectral reflectance (e.g., single- or multiband regressions) and are easy to implement but they are fundamentally site and sensor specific, requiring geographically and temporally matched field data for calibration and often failing to generalize beyond the conditions under which they were developed (Gao et al., 2015; Tesfaye, 2024; Yang et al., 2022;Kapalanga et al., 2021). While an additional category of empirical methods known as semi-empirical approaches, evolved in the late 1990s and early 2000s to address limitations of purely empirical methods by integrating statistical relationships with analytical insights (Adjovu et al., 2023; Keller, 2001). This integration improves spectral characterization and reduces noise, thereby enabling more generalizable retrieval of parameters such as Chl-a, Total Suspended Matter (TSM), colored dissolved organic matter (CDOM), Secchi disk depth, and turbidity with *in situ* data. Nevertheless, semi-empirical models still rely on extensive *in situ* datasets and offer only partial physical interpretability, which limits their applicability under diverse optical conditions (Hunter et al., 2010; Zhou et al., 2014). Similarly, semi-analytical methods incorporate statistical approaches to derive model variables, establishing a balance between empirical simplicity and analytical accuracy (He et al., 2015; Wang and Yang, 2019).

On the other hand, analytical models depend on bio-optical concepts and radiative-transfer theories to simulate light propagation in water bodies and the atmosphere, to invert off-water reflectance into constituent concentrations (Adjovu et al., 2023; Batina and Krtalić, 2023; Morel and Prieur, 1977). By utilizing extensive *in situ* measurements and well-established optical properties, these methods can theoretically retrieve multiple water-quality variables (Gholizadeh et al., 2016). However, their broad practical application is limited by the complexity of accurately measuring inherent optical properties, surface reflectance, and other water-quality factors, as well as by inconsistencies between satellite sensor and field spectroradiometers (Palmer et al., 2015; Yang et al., 2022).

By the 21st century advances in processing power and data availability have facilitated the estimation of water quality parameters at a variety of spatiotemporal scales. As a result, artificial intelligence-based machine learning (ML) techniques such as support vector machines (SVM), random forests (RF), decision trees (DT), and artificial neural networks (ANN) are increasingly applied to model complex, non-linear relationships between remote sensing data and water quality indicators (Hafeez et al., 2019; Pan et al., 2025; Tselemponis et al., 2023). However, their effective application requires careful assessment to prevent overfitting. For example, ANNs capture non-linear dynamics but require substantial training data, while SVMs perform well with smaller or high-dimensional datasets, albeit with higher computational demands (Singh et al., 2011; Yang et al., 2022). Empirical evidence further illustrates the adaptability of ML approaches: Tian et al. (2023) found that XGBoost, applied to Sentinel-2 imagery, outperformed other models in retrieving Chl-a and various water quality parameters. In a similar vein, Karmakar et al. (2024) used support vector machines with twenty years of MODIS data to estimate productivity indicators such as Chl-a and dissolved nitrate in the Sundarbans deltaic coast. In the same dynamic delta environment (Mondal et al., 2025), achieved notable success with a neural network C2RCC processor and Sentinel-3 imagery, retrieving Chl-a, TSM, and CDOM across 100 estuarine stations ($R^2 = 0.90–0.99$), confirming ML based models' reliability in optically complex waters. Moreover, ML utility extends to predictive applications as well. Deng et al. (2021) showed that artificial neural networks (ANNs) can provide rapid forecasts of algal blooms, while SVMs improve model selection accuracy, with both methods supporting the identification of key environmental drivers for effective coastal management. Overall, as machine learning algorithms continue to advance, they demonstrate considerable potential in assessing water quality using data from a variety of remote sensing sources (Bui et al., 2020; Yin et al., 2021).

Currently, deep learning (DL) architectures, especially convolutional neural networks (CNNs) and recurrent models have further refined retrieval accuracy due to their capacity to analyse large datasets as well as by extracting high-order spatial and temporal features from multispectral and hyperspectral imagery (Alzubaidi et al., 2021; Liu et al., 2022; Moon et al., 2025). These approaches have demonstrated significant results across diverse fields (Sigopi et al., 2024). A range of studies highlights the advancements achieved through deep learning (DL) architectures in aquatic remote sensing. For instance, Yu et al. (2024), introduced a CNN with a dual attention mechanism using MODIS time-series data for Chl-a estimation in the Taiwan Strait, the result of the study shows an improvement of 0.55 in R^2 over traditional band-ratio model. In a comparable manner, Wu et al. (2022) further confirmed that spatiotemporal DL models can decrease nutrient and water quality estimation errors by over 40 % in coastal waters. In parallel, Lumban-Gaol et al. (2022) also found that CNNs trained on multi-temporal Sentinel-2 imagery can predict coastal depths more precisely than traditional empirical or analytic methods. In addition, Zhan et al. (2025) demonstrated that a singular value decomposition deep neural network (SVD-DNN) achieved the highest performance in Chl-a estimation using Landsat-8 data in Hong Kong coastal waters, surpassing established machine learning algorithms such as SVM and RF. Taken together, these studies underscore the considerable gains in retrieval accuracy and generalizability offered by contemporary DL techniques, particularly when applied to complex coastal environments.

In agreement with Wang and Yang (2019) and Bangira et al. (2024), our synthesis determines that empirical and machine learning approaches remain predominant, whereas semi-empirical, semi-analytical, and analytical methods are less commonly applied. To further advance the field, future research should pursue a more detailed evaluations of specific algorithms, with particular emphasis on the emerging potential of deep learning methods and Internet of Things (IoT) technologies in coastal applications. Such efforts will be crucial for enhancing the monitoring and management of these vital ecosystems.

4.4. Multisensor integration for coastal water monitoring

The monitoring of coastal waters has long relied on optical remote sensing technologies, particularly satellite-based platforms such as Sentinel and Landsat, which have demonstrated significant value in retrieving surface-level parameters including chlorophyll-a, turbidity, and colored dissolved organic matter at high spatial and temporal resolutions (Boss et al., 2018; El Serafy et al., 2021). While these sensors are widely adopted for their clarity and broad coverage, they face notable limitations. Chief among these is their vulnerability to atmospheric interference, such as cloud cover and haze, and their inability to penetrate beneath the water's surface, which restricts insight into the vertical structure of coastal ecosystems (Jiang et al., 2023; Werdell et al., 2018). In response to these shortcomings, the scientific community has increasingly turned to active remote sensing technologies to complement optical data and improve overall monitoring accuracy. LiDAR (Light Detection and Ranging) stands out as a particularly transformative tool in this regard. Both airborne and spaceborne LiDAR systems have been employed extensively in coastal environments to map subsurface features and biological structures with high resolution. For instance, LiDAR has proven highly effective in detecting and analyzing fish populations (Churnside et al., 2003), identifying vertical phytoplankton layers (Churnside and Donaghay, 2009), and tracking geomorphic changes along coastlines. Notably, ICESat-2 spaceborne LiDAR has enabled the retrieval of depth-resolved backscattering profiles, revealing spatial patterns in particulate organic carbon (POC) and phytoplankton carbon biomass in the coastal Antarctic Ocean (Lu et al., 2020a). These vertical observations are crucial for ecological studies, as they help monitor species distributions, nutrient dynamics, and overall ecosystem health information that is fundamental for biodiversity conservation and sustainable fisheries management (Chen et al., 2023; Davies and Asner, 2014). In parallel, Synthetic Aperture Radar (SAR) has proven to be highly effective in capturing data where optical sensors don't perform well. Unlike optical sensors, SAR can operate regardless of cloud cover or lighting conditions, providing continuous data acquisition both day and night. Its capacity to detect oil spills, phytoplankton scums, and subtle bathymetric changes in shallow waters has made it a vital tool in coastal observation (Bresciani et al., 2014; Lin et al., 2002). Moreover, SAR's strength under adverse weather conditions significantly enhances the temporal reliability of coastal datasets (Tsokas et al., 2022; Yasir et al., 2024).

These advancements have opened new doors for observing the marine environment with greater accuracy and depth. When combined, optical, LiDAR, and SAR technologies form a powerful toolkit that overcomes the limitations of each individual system. For example, Jiang et al. (2025) showed that integrating Sentinel-1 SAR with Sentinel-2 optical data effectively tracked both the rate and extent of coastline changes in the Black Sea highlighting the real-world value of multi-sensor fusion. However, this review does not explore in detail the evolving roles of LiDAR and SAR or their integration frameworks. We therefore recommend future studies to specifically evaluate the fusion of these technologies within coastal water monitoring. For readers interested in a broader perspective, we suggest Samadzadegan et al. (2024) for an extensive overview of multi-sensor data fusion techniques, and Chen et al. (2023) for insights into the capabilities of airborne oceanic LiDAR systems.

5. Conclusion

5.1. Major findings

Growing concern for coastal water quality and rapid advances in satellite technology have steered recent research toward space-borne water-quality monitoring. Our synthesis shows that the field still relies heavily on the long-serving Aqua and Terra MODIS missions, with the higher-resolution Sentinel platforms now gaining momentum. Across the studies, chlorophyll-a and sea-surface temperature remain the most frequently retrieved variables. In terms of algorithmic approaches, empirical methods continue to dominate, yet data-driven machine-learning techniques now appear in a significant proportion of the literature, reflecting a clear shift toward AI-assisted retrieval. The use of validation metrics is varied, with root mean square error (RMSE) and the coefficient of determination (R^2) routinely reported. Moreover, a thematic breakdown by climate zone and water type reveals a strong focus on marine settings within subtropical and temperate regions, and far fewer investigations in Arctic waters and freshwater bodies, while chemical indicators such as pH and phosphate remain comparatively understudied.

5.2. Limitations

This study has several limitations. As a systematic scoping review, it may overlook some emerging approaches due to its focused scope, which can limit generalizability beyond the specific topic addressed. The synthesis focused only on five key water quality parameters and included studies that used a single satellite platform in order to clearly identify current research trends. Additionally, it does not provide an in-depth comparative analysis of each algorithm used within individual studies and does not cover studies that apply deep learning models. Likewise, studies involving IoT networks and multi-sensor fusion were not included, as these integrated approaches involve different data structures, operational setups, and validation requirements that require a separate and more specific review.

5.3. Recommendations for future research

Looking ahead, there are several key areas where future research can grow and improve. One important step is expanding the geographic coverage of coastal water quality studies, particularly in underrepresented regions such as the Arctic and sub-polar zones. Equally, broadening the thematic scope to include chemical parameters like pH and phosphate, often overlooked despite their importance, would support a more complete understanding of coastal conditions. While satellite remote sensing has been the primary focus of this review, future studies should also explore the integration and application of emerging tools, including IoT-enabled sensor networks and multi-sensor data fusion techniques, for coastal water monitoring, as these approaches can offer more detailed and timely observations. Additionally, subsequent work should include comparative analyses of advanced algorithmic approaches, particularly deep learning, which remains underexplored in coastal environments. Addressing these areas will be key to building a more accurate, comprehensive, and responsive coastal water quality monitoring framework for the future.

CRediT authorship contribution statement

Abdul Majid: Writing – original draft, Visualization. **Natrah Ikhsan:** Supervision, Resources. **Zafri Hassan:** Writing – review & editing, Supervision, Conceptualization.

Statement

During the preparation of this work the authors used ChatGPT to improve clarity and readability of the writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.csr.2025.105509.

Appendix a

6.1. Sensor and platform reference standardization

In this work we recognized the importance of maintaining consistency and clarity when referring to satellite missions and their data. Satellite programs often involve multiple platforms and onboard instruments, which can lead to inconsistencies in terminology across studies. To address this, we standardized references to satellite platforms, focusing on the satellites themselves rather than the specific sensors or instruments they carry. This method ensured a uniform approach to organizing and interpreting data. For example, the Sentinel series, part of the European Space Agency's Copernicus program, is a cornerstone for environmental monitoring. Among the Sentinel series, Sentinel-2 and Sentinel-3 are frequently used in this era, each consisting of two satellites A and B that operate together to increase the frequency of observations. While Sentinel-2 specializes in high-resolution multispectral imagery for land and water studies, Sentinel-3 is dedicated to ocean and land monitoring, including sea surface temperature and ocean color. To simplify references, we grouped them under a single name for identification purposes: Sentinel-2A and Sentinel-2B as Sentinel-2, and similarly, Sentinel-3A and Sentinel-3B as Sentinel-3.

For NASA's Terra and Aqua satellites, we adopted a similar approach. Both satellites host the Moderate Resolution Imaging Spectroradiometer (MODIS), among other instruments, but rather than specifying the sensor (e.g., MODIS Aqua or MODIS Terra), we referred solely to the satellite platforms Terra and Aqua. In cases where studies only mentioned MODIS without specifying the satellite, we assumed that data from both Terra and Aqua were used. This choice was motivated by the inconsistent terminology in studies, where data was variously reported as MODIS, Aqua, MODIS Aqua, or MODIS Terra. By referring solely to the satellite platforms, we ensured clarity and simplified data attribution without detracting from the information's accuracy.

For the Landsat satellites, we categorized them by their generation, such as Landsat-8 or Landsat-7, without detailing onboard sensors like the Operational Land Imager (OLI), the Thermal Infrared Sensor (TIRS), or the Enhanced Thematic Mapper Plus (ETM+). Similarly, for geostationary satellites equipped with the Geostationary Ocean Color Imager (GOCI), we prioritized referencing the satellite platforms themselves. For example, COMS-1 and GK-2B, which host GOCI and GOCI-II respectively, were referred to by their satellite names to maintain clarity and consistency, shifting the focus from the instruments to the platforms hosting them.

A similar approach was applied to other satellite sensors identified in the study. Instead of referencing the onboard sensors or instruments mentioned in the articles, we standardized our terminology by using satellite names to ensure clarity and consistency across the analysis.

Despite these efforts to standardize, some studies utilized satellite derived data obtained from aggregated datasets platforms like the Copernicus Marine Environment Monitoring Service (CMEMS) and others. While these datasets are of paramount importance, such studies were categorized under the "datasets" category to make a clear distinction between studies leveraging pre-processed data and those directly analysing raw or minimally processed satellite data to identify satellites used across the studies. By focusing exclusively on studies that clearly referenced individual satellites or instruments our review prioritized analyses with clear methodologies and direct satellite attributions, improving the accuracy and comparability of findings across the body of work.

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