

Review

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Review

A Systematic Review of the Application of GOCI to Water Quality Monitoring of Inland and Coastal Waters

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Abstract: In recent decades, as eutrophication in inland and coastal waters (ICWs) has increased due to anthropogenic activities and global warming, so has the need for timely monitoring. Compared with traditional sampling and laboratory analysis methods, satellite remote sensing technology can provide macro-scale, low-cost, and near real-time water quality monitoring services. The Geostationary Ocean Color Imager (GOCI), integrated onboard the Communication Ocean and Meteorological Satellite (COMS) from the Republic of Korea, was the first geostationary ocean color observation satellite and was operational from April 1, 2011 to March 31, 2021. Over ten years, GOCI has observed oceans, coastal waters, and inland waters within its 2,500 km×2,500 km target area centered on the Korean Peninsula. The most attractive feature of GOCI, compared with other commonly used watercolor sensors, was its high temporal resolution (1h, eight times daily from 0 UTC to 7 UTC), providing the opportunity to monitor the quality of ICWs, where optical properties can change rapidly throughout the day. This systematic review aims to comprehensively review GOCI features and applications in ICWs, analyzing progress in atmospheric correction algorithms and water quality monitoring. Analyzing 123 articles from the Web of Science and China National Knowledge Infrastructure (CNKI) through a bibliometric quantitative approach, we examined GOCI's strength and performance with different processing methods. These articles reveal that GOCI played an essential role in monitoring the ecological health of ICWs in its observation area in East Asia. GOCI has led the way to a new era of geostationary ocean satellites, providing new technical means for monitoring water quality in oceans, coastal zones, and inland lakes. We also discuss the challenges encountered by geostationary satellites in monitoring water quality and provide suggestions for improvements.

Keywords: GOCI; inland and coastal waters; atmospheric correction; algal blooms; water quality parameters

1. Introduction

Earth's surface water accounts for about 74% of the global area. Water is an important carrier and critical factor in studying the energy exchange of surface materials[1,2]. For research convenience in watercolor remote sensing, the Earth's water is usually divided into Case-I and Case-II waters based on the optical properties of water[3–5]. The optical properties of Case I waters (open oceans) are mainly determined by phytoplankton. Case II waters, including inland and coastal waters (denoted as ICWs; all abbreviations or symbols in this study are shown in Tables 1 and S1), are optical complexes determined by phytoplankton, detritus, and colored dissolved organic matter (CDOM)[6,7]. Most of the Earth's population lives near ICWs, making them the most economically and socially active regions on Earth. Large amounts of nutrients and pollutants discharged by humans enter some ICWs worldwide, destroying their ecological balance. Damaged waterbodies will, in turn, threaten human health and lead to economic losses[8–13]. Remote sensing can complement traditional methods by targeting optically active substance concentrations in monitoring

water quality. With the growing number of watercolor satellite sensors launched in recent decades, numerous algorithms have been proposed to retrieve water quality parameters from satellite images to monitor ICWs.

Table 1. Abbreviations and symbols used in this study.

Abbreviations or symbols		Abbreviations or symbols	
			Ocean Scanning
	Algal blooms		Multispectral Imager
	Alternative floating algae index		Optics EXPRESS
	Atmospheric correction		Particulate organic carbon
ABs	China National Knowledge		Phycocyanin
AFAI	Infrastructure	OSMI	Random forest
AC	Chlorophyll a	OE	Rayleigh-corrected
CNKI	Colored dissolved organic matter	POC	radiance
Chla	Cyanobacterial bloom intensity	PC	Red tide index
CDOM	Diffuse attenuation coefficient	RF	Remote sensing
CBI	Dissolved organic carbon	$L_{rc}(\lambda)$	Remote Sensing of
k_d	Floating algae cover	RI	Environment
DOC	Fluorescence line height	RS	Remote sensing
FAC	Generalized algal bloom index algorithm	RSE	reflectance
FLH	Generation Global Imager	$R_{rs}(\lambda)$	Science of the Total
GABI	Geostationary Littoral Imaging and	Sci Total	Environment
GLI	Monitoring Radiometer	Environ	Sea ice area
GLIMR	Harmful algal blooms	SIA	Sea ice thickness
HABs	IEEE TRANSACTIONS ON	SIT	Sea surface currents
IEEE T-	GEOSCIENCE AND REMOTE SENSING	SSCs	Sea surface salinity
GRS	Inland and coastal waters	SSS	Secchi disk depth
ICWs	International Journal of Applied Earth	SDD	Second Generation
JAG	Observation and Geoinformation	SGLI	Global Imager
Int J	International Journal of Remote Sensing	SWIR	Shortwave infrared
Remote	ISPRS Journal of Photogrammetry and	SZA	Solar zenith angle
Sens	Remote Sensing	SPM	Suspended particulate
ISPRS	Linear Combination Index	SCI	matter
LCI	Medium Resolution Imaging	GOCI	Synthetic chlorophyll
MERIS	Spectrometer Instrument	UV	index
MODIS	Moderate Resolution Imaging	VIIRS	The Geostationary
NASA	Spectroradiometer	WR	Ocean Color Imager
NIR	National Aeronautics and Space	YRE	Ultraviolet
NPP	Administration	YOC	Visible Infrared
NDVI	Near-infrared		Imaging Radiometer
NRTI	Net primary production		Water Research
	Normalized difference vegetation index		Yalu River estuary
	Normalized red tide index		Yellow and East China
			Sea Ocean Color

Remote sensing of watercolor from space began in 1978 with the successful launch of the Coastal Zone Color Scanner (CZCS) by the National Aeronautics and Space Administration (NASA)[14]. CZCS, an experimental radiometer intended to operate for only one year, had six bands ranging from visible to near-infrared (NIR). CZCS provided valuable experience for subsequent watercolor satellite development [15–17]. After ten years, several watercolor sensors were launched, including the Maritime Observation Satellite (MOS), Ocean Color and Temperature Scanner (OCTS), and

Polarization and Directionality of the Earth's Reflectances (POLDER) in 1996 and the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) in 1997. SeaWiFS was the first watercolor sensor that could provide continuous data on the bio-optical properties (i.e., those properties of organisms that can be visually recorded) of the oceans[18–20]. In 1999, the United States successfully launched the Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra satellite, the first advanced polar-orbiting environmental remote-sensing satellite with nine specific watercolor bands from 412 to 865 nm. MODIS also had three shortwave infrared (SWIR) bands (1240, 1640, and 2130 nm), which have very low reflectance due to the high absorption of pure water[21,22]. The SWIR-based atmospheric correction (AC) method is critical for obtaining reliable and high-accuracy remote sensing reflectance ($R_{rs}(\lambda)$) products of highly turbid ICWs. In 2002, the MODIS sensor on the Aqua satellite was launched and began to observe the Earth along with MODIS from Terra (Terra in the morning, Aqua in the afternoon), providing continuous watercolor observations. MODIS has been the most critical watercolor satellite of the past two decades [23–28]. The Visible Infrared Imaging Radiometer (VIIRS) extends and enhances the AVHRR and MODIS observation series with six watercolor wavelengths. The three VIIRS sensors (Suomi-NPP, NOAA-20, and NOAA-21) were launched in 2011, 2017, and 2022, respectively. Since VIIRS has spectral bands similar to MODIS, the water quality parameters that MODIS can extract or derive can also be directly monitored by VIIRS. VIIRS can provide watercolor products for highly turbid ICWs, improving the observations capabilities of MODIS, whose watercolor bands tend to saturate[29–34]. In December 2018, the United States launched SeaHawk-1, a CubeSat fitted with a low-cost, miniature ocean color sensor called HawkEye that enables fine spatial resolution observations of the ocean[35].

The Medium Resolution Imaging Spectrometer Instrument (MERIS) is a sensor deployed in March of 2002 onboard the polar-orbiting Envisat-1 environmental research satellite by the European Space Agency (ESA). The most significant advantage of MERIS is its various watercolor band selections (fifteen bands from 412 to 900 nm). For example, the 620 nm band of MERIS allows to estimate cyanobacteria biomass in ICWs by targeting characteristic pigments (phycocyanin (PC)) [36–38]. The Sentinel-3 OLCI instrument is based on ENVISAT MERIS's opto-mechanical and imaging design and was launched in 2016 (S3A) and 2018 (S3B). OLCI presents many improvements compared with MERIS, such as an increase in the number of spectral bands (from 15 to 21), mitigation of sun-glint contamination by tilting cameras in the westerly direction, and increased coverage of the global ocean (<4 days), land (<3 days with one satellite, ignoring the effect of clouds), compare to MERIS, which was approximately 15 days[39–42].

In addition to the United States and the European Union, other countries, such as Japan, China, India, and South Korea, have also released satellites with watercolor bands. Japan launched the ocean color satellite Advanced Earth Observation Satellite (ADEOS) in 1996. ADEOS had twelve bands in the wavelength range of 400–900 nm with a spatial resolution of 700 m[43–45]. Japan launched the ADEOS-II satellite with the Generation Global Imager (GLI) sensor, with thirty-three bands in the 375–12500 nm wavelength range in 2002. Among these thirty-three bands, six had a spatial resolution of 250 m. The Second Generation Global Imager (SGLI) satellite is an Earth observation satellite developed by the Japan Aerospace Exploration Agency (JAXA) and launched in 2017. SGLI can observe 19 bands of radiation from ultraviolet (UV) to thermal infrared region (380 nm–12 μ m). SGLI has two polarization channels (673.5 and 868.5 nm)[46–48]. Since 2002, China has launched a series of ocean watercolor satellites, including HY-1A (2002), HY-1B (2007), HY-1C (2018), HY-1D (2022), and HY-1E (2023). The watercolor bands of the early HY satellite series (e.g., HY-1A, HY-1B) are very close to the MODIS watercolor bands. Starting from HY-1C, the HY series satellites have specific watercolor bands (e.g., UV bands). The recently launched HY-1E has two sensors, Chinese Ocean Color and Temperature Scanner 2 (COCTS2) (with eighteen bands and a one-day revisit cycle) and Playful Magnetic Resonance Imaging Simulator (PMRIS) (with nineteen bands and a three-day revisit cycle) [49,50]. India has launched several watercolor satellites, including Oceansat-1 (1996), Oceansat-2 (2009), and Oceansat-3 (2022). The bands have increased from eight (Oceansat-1) to thirteen bands with a spatial resolution of 360 m (Oceansat-3) [51–53]. The Ocean Scanning Multispectral Imager (OSMI), mounted on the polar-orbiting satellite Korea Multi-Purpose Satellite-1 (KOMPSAT-1), was

launched by South Korea in 1999. OSMI was launched in 2010 and had six bands in the 400-900 nm wavelength range and a spatial resolution of 1km [54,55].

The Geostationary Ocean Color Imager (GOCI) was the world's first geostationary watercolor satellite. It was positioned in a geostationary orbit at approximately 128.2 degrees east longitude, providing continuous monitoring of the oceanic and ICW conditions over the East Asian region. Subsequently, South Korea launched GOCI-II in 2020. GOCI-II has many improvements over GOCI, with more watercolor bands and higher spatial resolution [56–58].

Compared with MODIS, VIIRS, or other commonly used watercolor sensors, the most attractive characteristic of GOCI was its high temporal resolution (1h, eight times daily from 0 UTC to 7 UTC), which is important for the accurate monitoring of water quality status, which can change on an hourly or even sub-hourly basis in ICWs [19,59–63]. GOCI was the first sensor with the ability to continuously monitor water quality variations in the ICWs with an hourly temporal resolution. GOCI provided images to monitor the water quality of oceans and ICWs in its target area (about 2,500 km×2,500 km centered on the Korean Peninsula) for nearly ten years, from the first image in 2011 to 2021, when it stopped observations.

Until now, systematic reviews of the research progress and challenges of GOCI applications in ICWs have seldom been documented[64–69]. Many countries have launched or plan to launch geostationary watercolor satellites such as GOCI-II and the Geostationary Littoral Imaging and Monitoring Radiometer (GLIMR)[62]. The insights garnered by reviewing GOCI's functionality have helped design sensors and construct water quality algorithms. This study aims to comprehensively review GOCI, providing information on the configuration parameters of the GOCI sensor, an overview of GOCI, an AC algorithm, ABs monitoring, estimation of water quality parameters (chlorophyll a (Chla), suspended particulate matter (SPM), water clarity and other parameters such as CDOM, particulate organic carbon (POC), dissolved organic carbon (DOC), net primary production (NPP), sea surface salinity (SSS), sea surface currents (SSCs), sea ice, sea fog, lake ice, diffuse attenuation coefficient (k_d), etc.). We also discuss advantages and disadvantages as well as future trends. A diagram of the paper's structure is shown in Figure 1. Before delving into the review, we compare its spatial and temporal resolutions with those of MODIS, Landsat, Sentinel, and other watercolor satellites, highlighting the high observation frequency of GOCI in Table 2.

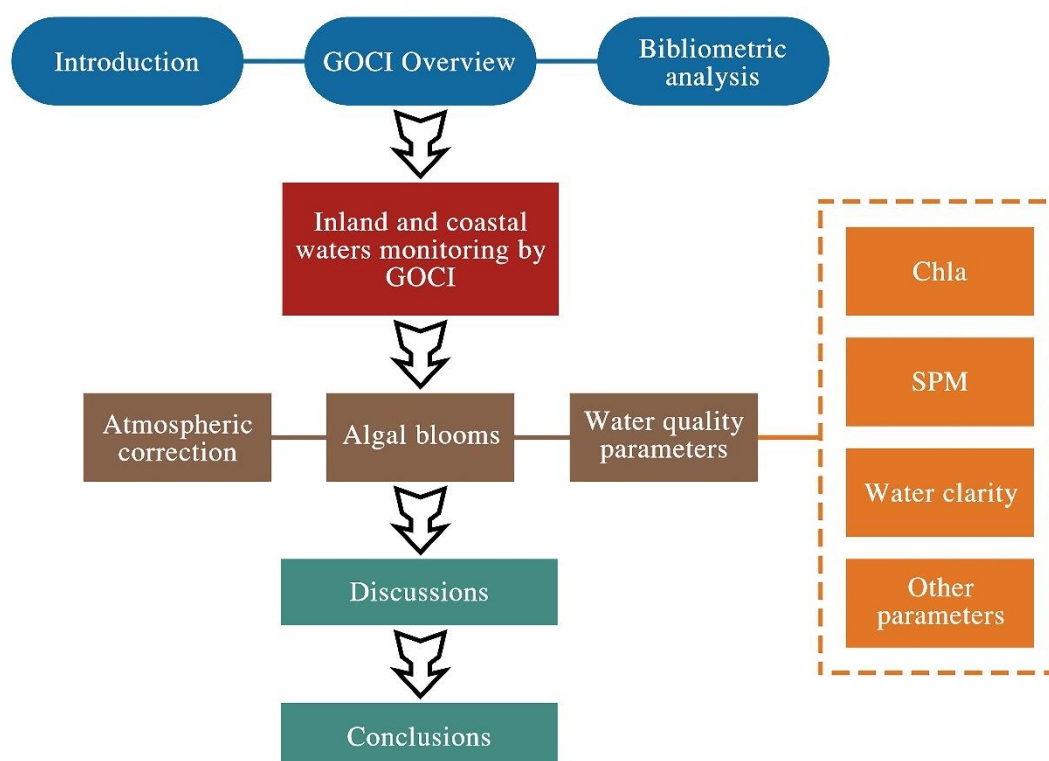


Figure 1. Structure of this paper.

Table 2. Comparison of spatial and temporal resolutions of typical watercolor remote sensing satellites and their launch dates.

Number	Data	Spatial Resolution (m)	Temporal Resolution	Launched Time
1	CZCS	1000	One day	1978
2	SeaWiFS	1100,4500	One day	1997
3	MODIS_TERRA	250,500,1000	One day	1999
4	MODIS_AQUA	250,500,1000	One day	2002
5	VIIRS Suomi NPP	375,750	One day	2011
6	VIIRS NOAA-20	375,750	One day	2017
7	VIIRS NOAA-21	375,750	Three days	2021
8	MERIS	300,1200	<Two days	2002
9	Sentinel-3A OLCI	300	<Two days	2016
10	Sentinel-3B OLCI	300	Ten days	2018
11	ADEOS	700	Four days	1996
12	ADEOS-II	250,1000	One day	2002
13	SGLI	250	Three days/Seven	2017
14	HY-1A	250	days	2002
15	HY-1B	250	One day/Seven	2007
16	HY-1C	250	days	2018
17	HY-1D	250	One day/Three days	2022
18	HY-1E	100	One day/Three days	2023
19	Oceansat-1	360	One day/Three days	1996
20	Oceansat-2	360	Two days	2009
21	Oceansat-3	360	Two days	2022
22	OSMI	1000	One day/Three days	1999
23	GOCI	500	Three days	2010
			One hour	
24	GOCI-II	250	One hour	2020

2. GOCI Overview

The Communication Ocean and Meteorological Satellite (COMS), launched in 2010, is South Korea's first geostationary orbit meteorological satellite and was designed for meteorological services and ocean monitoring research. It was equipped with a new generation of GOCI sensors, which acquired data in eight bands (including six visible light bands and two NIR bands), as shown in Table 3. Its main advantage was to provide satellite observation of the target area eight times daily, from 0 UTC to 7 UTC. Real-time monitoring was centered on South Korea (36°N 130°E) and also encompassed North Korea, Japan, Russia, and China, including the Bohai Sea, the Yellow Sea as well as the East China Sea (Figure 2). The total coverage area was about 2500 km×2500 km [70].

Table 3. GOCI bands and configuration parameter information.

Bands	Center Wavelength/nm	Band Width/nm	Spectrum Type	Signal-to-Noise Ratio
B1	412	20	VIS	1077
B2	443	20	VIS	1199
B3	490	20	VIS	1316
B4	555	20	VIS	1223
B5	660	20	VIS	1192
B6	680	10	VIS	1093

B7	745	20	NIR	1107
B8	865	40	NIR	1009

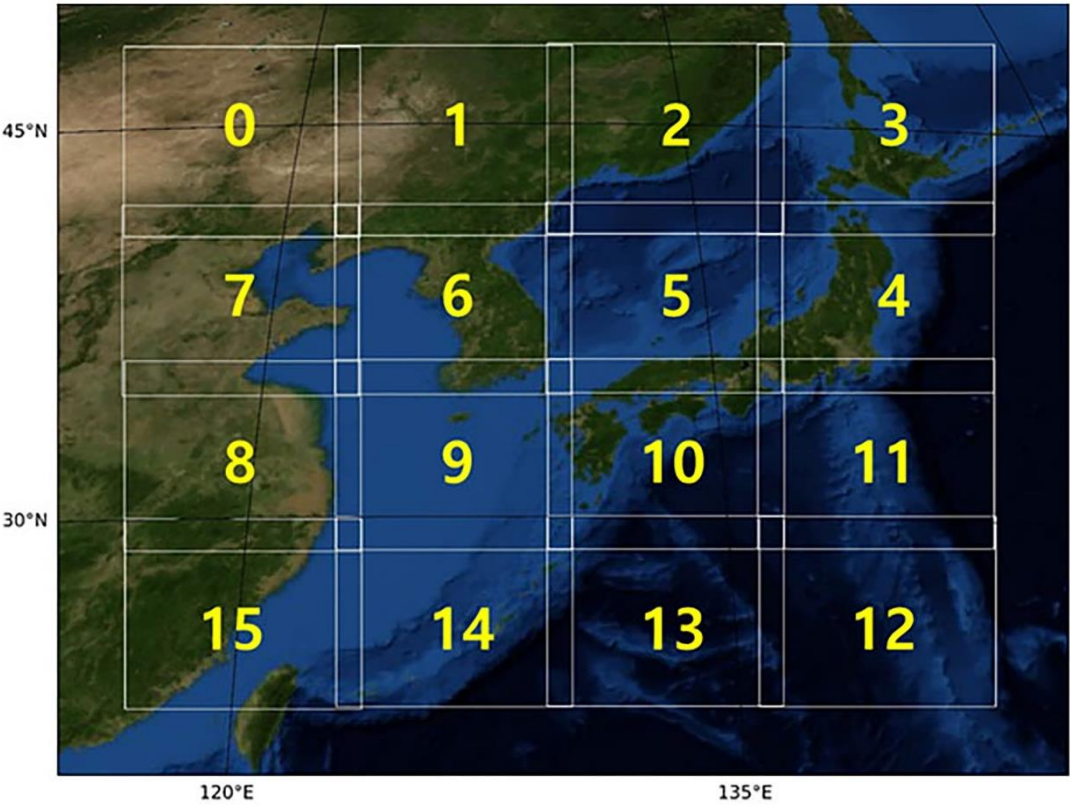


Figure 2. The Regional Observation Area of GOCI (<https://kosc.kiost.ac.kr/index.nm?menuCd=43&lang=en>).

GOCI has fulfilled its mission for nearly a decade by playing a significant role in ICW monitoring. GOCI-II, which succeeded GOCI, was launched in February 2020 and has up to 13 bands (Table 4). Moreover, GOCI-II has a spatial resolution of up to 250 meters, generating ten views of imagery a day (23 UTC to 8 UTC) [71].

Table 4. Band parameters information for GOCI-II.

Band	Wavelength/nm	Bandwidth/nm	Primary Use
			CDOM
B1	380	20	CDOM, Chla
B2	412	20	Chla absorption maximum
B3	443	20	Chla, other pigments
B4	490	20	Chla, absorbing aerosol in ocean
B5	510	20	waters
B6	555	20	Turbidity, SPM
B7	620	20	Detect phytoplankton species
B8	660	20	Baseline of fluorescence signal, Chla,
B9	680	10	SPM
B10	709	10	Fluorescence signal
B11	745	20	Fluorescence base signal, AC, SPM
B12	865	40	AC, vegetation index
B13	PAN	483	AC, aerosol optical depth
			/

3. Bibliometric Analysis

Over the last decade, there has been a surge in research papers on ICWs based on GOCI satellites. Our bibliometric analysis, based on Web of Science queries with "GOCI" and "remote sensing" as keywords, retrieved a total of 164 papers, of which 123 meeting eligibility criteria. The number of publications showed a steady increase, starting from 4 papers published in 2010 to a peak of 13 in 2021 and 2022 (Figure 3 and Table 2). The study area for this article is shown in Figure 4. GOCI has been increasingly used in remote sensing monitoring research of ICWs due to its advantages and development potential. Articles have been published in more than 40 journals, of which 36 in Remote Sensing (RS), followed by 16 in Remote Sensing of the Environment (RSE), 7 in Ocean Science Journal(Ocean Sci J), 6 in Optics EXPRESS (OE), and 4 in the Science of the Total Environment (Sci Total Environ), International Journal of Remote Sensing (Int J Remote Sens), as well as in Environmental Science and Pollution Research (Environ Sci Pollut Res), 3 in Sensors, ISPRS Journal of Photogrammetry and Remote Sensing (ISPRS) and IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING (IEEE T-GRS) (Figure 5).

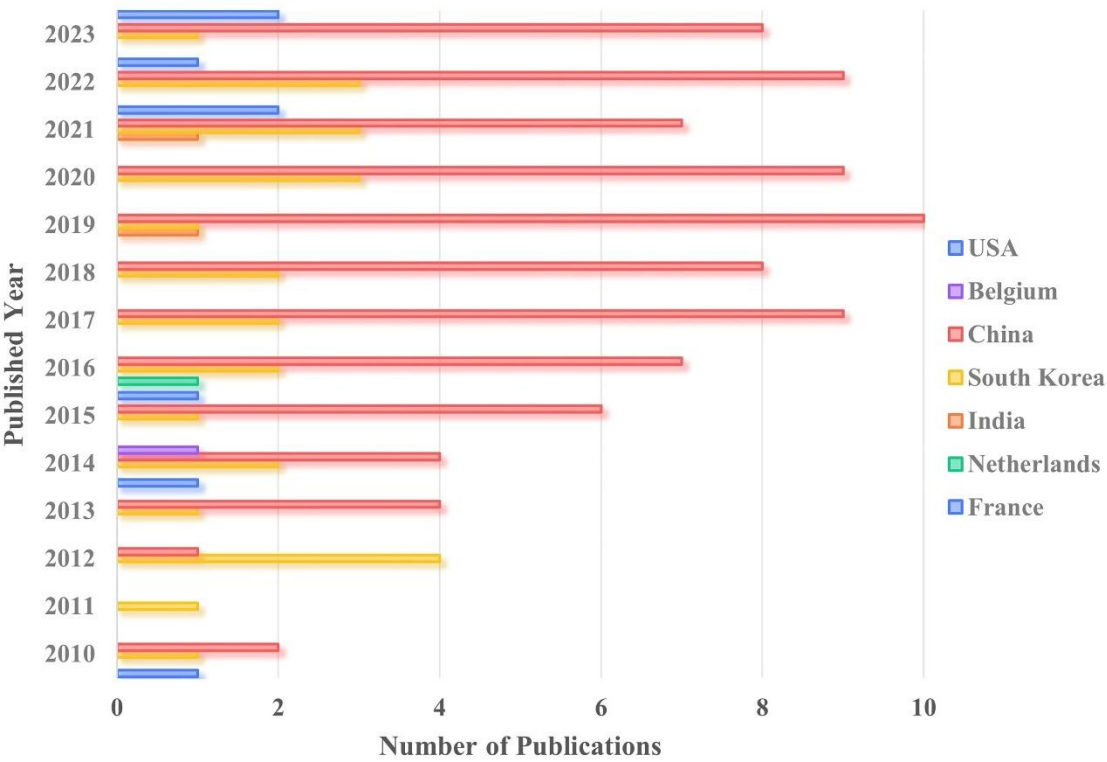


Figure 3. Number and countries of papers published by GOCI between 2010 and 2023.

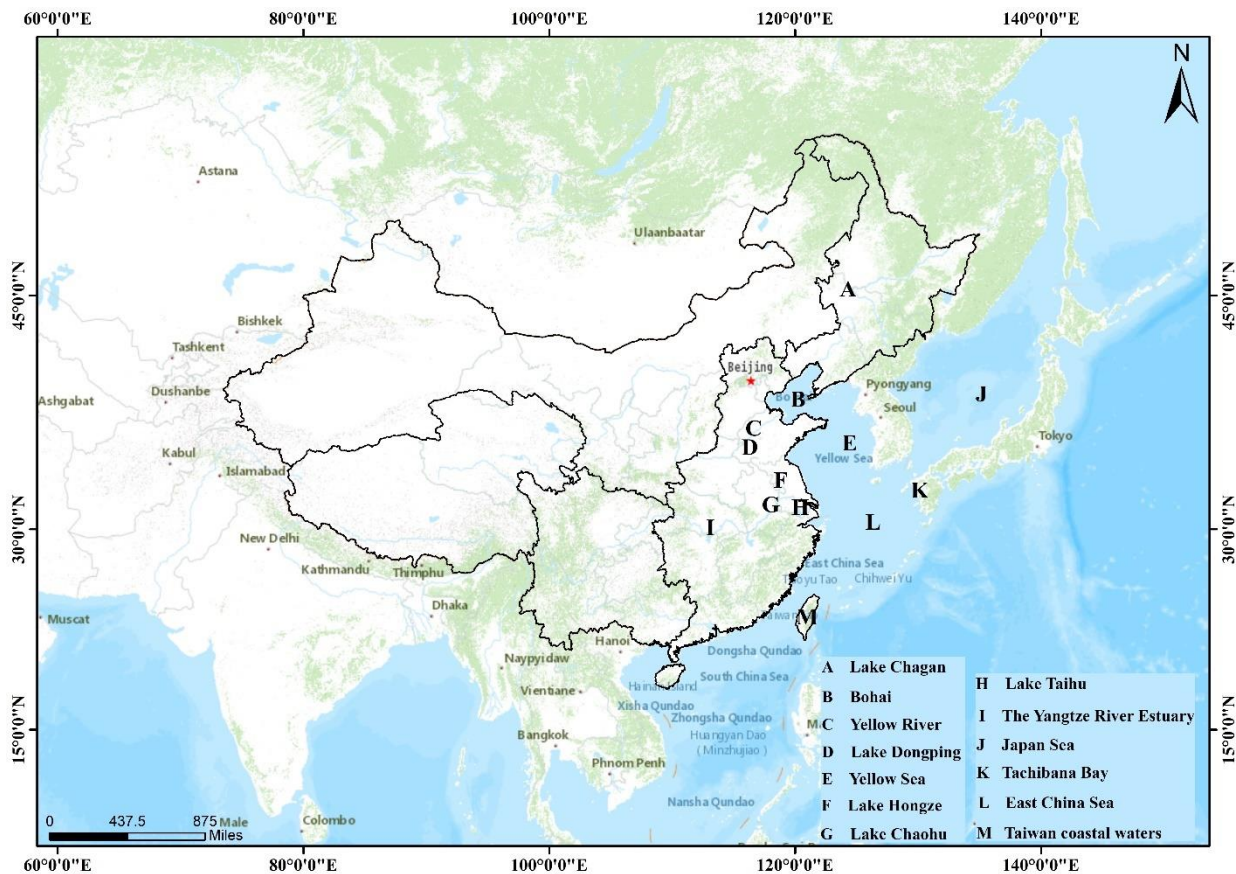


Figure 4. Map of the study area.

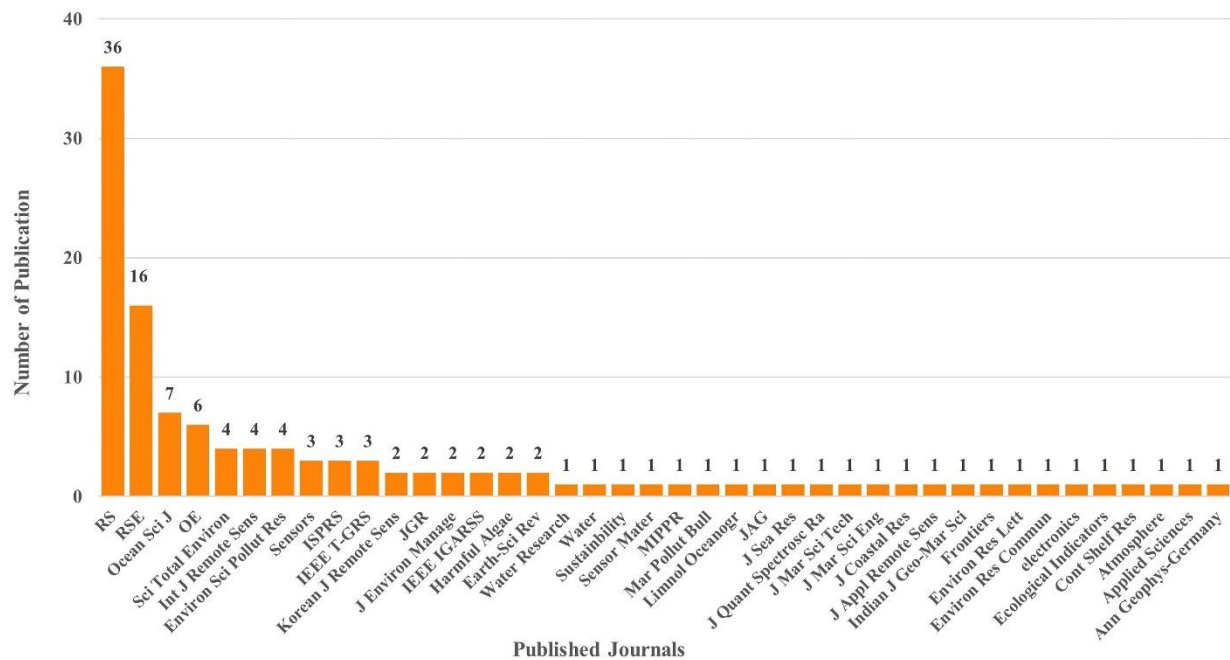


Figure 5. Journals and number of publications.

Using “GOCI”, “remote sensing,” and “inland and coastal waters” as the subject terms in the “Web of Science” search, retrieved a total of 1546 eligible authors from the core collection. A Vosviewer statistical analysis of keywords using "author name" formed a keyword map (Figure 6). The authors with the highest number of occurrences were Kim, Jhoon, Ryu, and Joo-hyung, totaling

36 occurrences. The highest number of citations was 1090. Recognizing the significant contributions of Chinese scholars, we extended our search to China National Knowledge Infrastructure (CNKI), merging the search of Chinese and English papers to obtain a clearer picture of the application of GOCI. A total of 746 documents were retrieved through CNKI with GOCI as the keyword, of which 323 were classified and analyzed according to the "subject". Figure 7 shows that most research was on SPM with 40 publications, with Chla in second place with 36 papers, followed by estimation studies (31 articles).

In summary, it can be seen that awareness about GOCI satellites is increasing annually, and their application in various fields is becoming increasingly extensive. In the past decade, the application of GOCI in ICWs has become more and more comprehensive. We found that the highest number of studies on Chla concentration estimation by scholars was 23, followed by SPM concentration estimation (22) and ABs (17), while there were 13 and 10 studies on AC and water clarity, respectively.

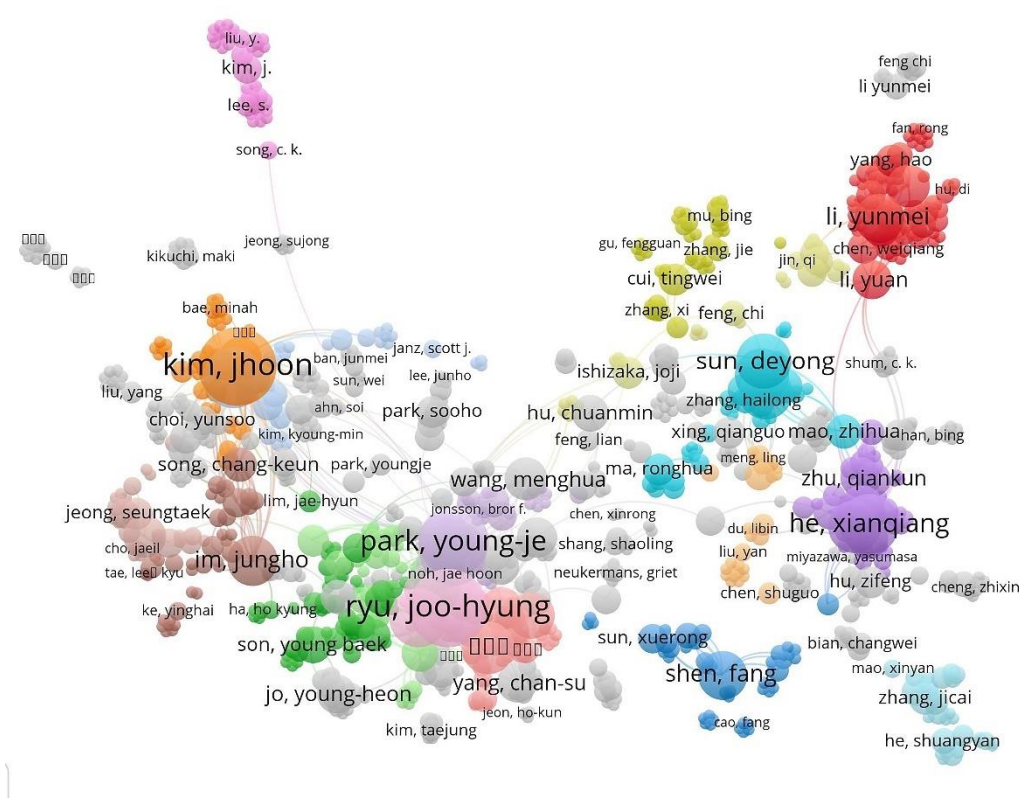


Figure 6. Keyword mapping from the Web of Science searched by author name.

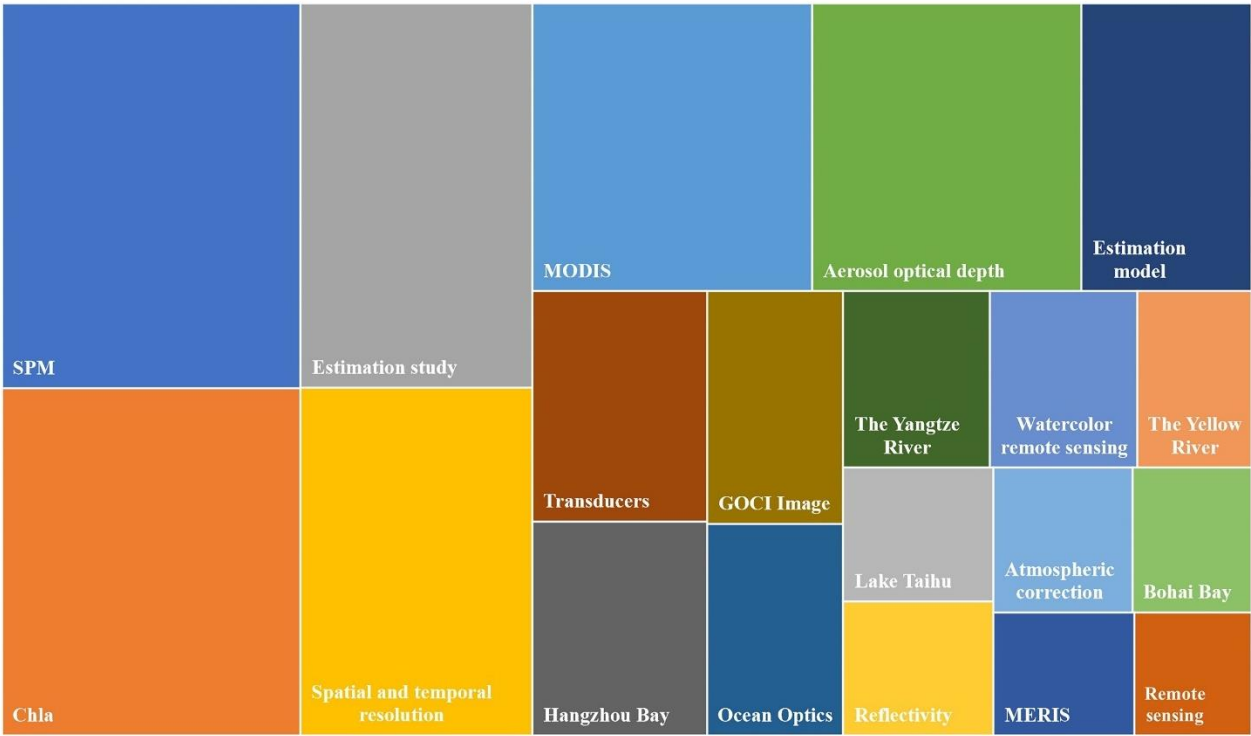


Figure 7. Overview of the application of GOCI retrieved by subject terms from CNKI.

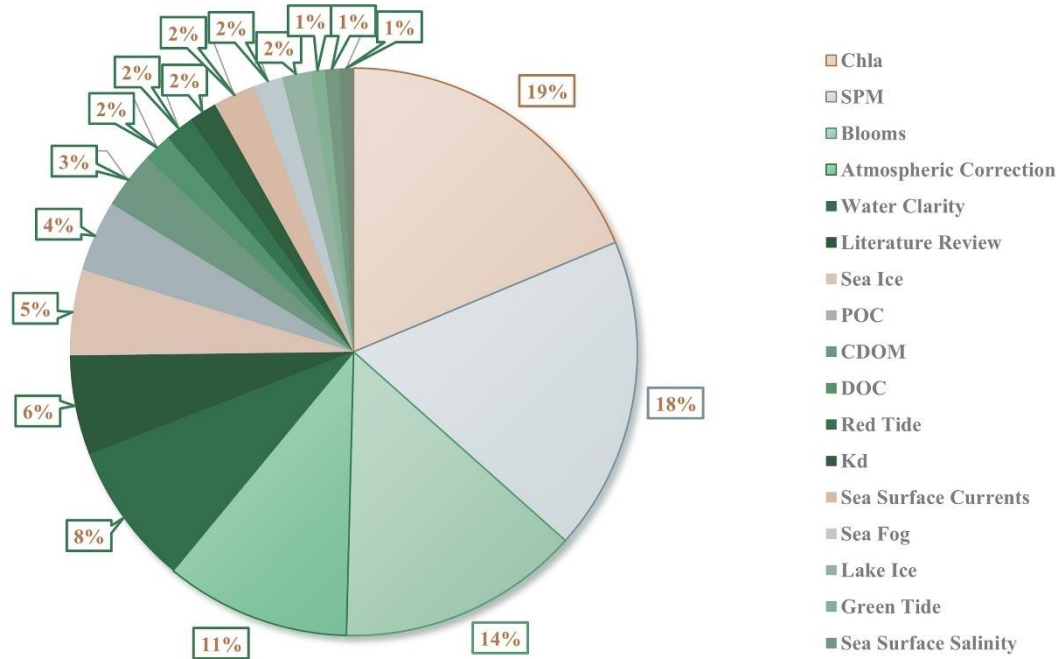


Figure 8. Application of GOCI in inland and coastal waters.

4. Inland and Coastal Waters Monitoring by GOCI

This section reviews the capabilities of GOCI. We first provide an overview of AC algorithms. We compare the advantages and disadvantages of different methods and their applicability. Secondly, we highlight the research progress of scholars on AB monitoring. Finally, the estimation of water quality parameters is reviewed and divided into four aspects: Chla, SPM, water clarity, and other water quality parameters.

4.1. Atmospheric Correction over Inland and Coastal Waters

AC is the process of obtaining the reflectance from the top of the atmosphere as observed by satellites. This process is vital because the $R_{rs}(\lambda)$ is the primary input for most water-quality remote sensing algorithms [72–74]. The GOCI Data Processing System (GDPS) is the official data processing software for GOCI. The standard AC algorithm of GOCI evolved initially based on the algorithms of SeaWiFS and MODIS, then expanded and improved according to the characteristics of GOCI's own instrument design and research fields [70,75–78]. This model followed a regional empirical relationship between the $R_{rs}(660)$ and two NIR bands ($R_{rs}(745)$ and $R_{rs}(865)$) (denoted as SR660). Aerosol properties from neighboring non-turbid waters were also incorporated to finalize the AC process[75]. [79] improved the SR660 model by introducing two AC models. The first AC model used $R_{rs}(709)$ to replace the $R_{rs}(660)$, taking advantage of the lower contribution of the absorption signal of non-pure water constituents in $R_{rs}(709)$. SR709 has been shown to perform well in waters with only one sediment type. The second AC model used the 620 nm radiation (denoted as SRIOP) to estimate the $R_{rs}(\lambda)$ in the NIR bands. SRIOP showed good performance in waters with a variety of sediment types.

Another software, the SeaWiFS Data Analysis System (SeaDAS), provides an AC module to GOCI, including the Management Unit of the North Sea Mathematical Models (MUMM) algorithm, which is used to produce $R_{rs}(\lambda)$ products for the turbid Hangzhou Bay and Yellow River Estuary. MUMM assumes that the magnitude of $R_{rs}(\lambda)$ at 745 and 865 nm is dominated by the backscattering of particles. The ratio of $R_{rs}(745)$ and $R_{rs}(865)$ is assumed to be constant. As aerosol types do not usually vary over spatial scales of about 100 km, the ratio of aerosol reflectance in these two bands can also be regarded as a constant. However, this assumption of $R_{rs}(865)/R_{rs}(745)$ is deemed to be invalid for highly turbid waters. Therefore, [80], [81], and [17] used a 2nd order polynomial relationship to parametrize $R_{rs}(745)$ and $R_{rs}(865)$ for the AC of GOCI in highly turbid waters.

The Polymer software also offers a GOCI AC module. However, it is seldom used for GOCI, even though it has been shown to perform well in turbid coastal waters when applied to satellites like MODIS and OLCI. For extremely turbid waters, such as in parts of Changjiang Estuary, Huanghe Estuary, and Hangzhou Bay, where the SPM can be greater than 500 mg L⁻¹, researchers have proposed innovative AC algorithms for GOCI. [82] proposed an improved GOCI AC algorithm for the Changjiang (Yangtze) estuary and the adjacent coast. This approach, based on a spectral optimization algorithm (ESOA) with a coupled water-atmosphere model, employed the simple semi-empirical radiative transfer (SERT) model to parameterize $R_{rs}(\lambda)$ based on the SPM concentrations and the aerosol models proposed by [56]. SeaDAS was used to calculate the contributions in aerosols, and the genetic algorithm optimized the ESOA AC process. For highly turbid waters, the $R_{rs}(\lambda)$ in the UV band may be much less than $R_{rs}(\lambda)$ in the NIR band, enabling the UV band's use in estimating aerosol scattering. [83] applied the UV-AC algorithm to the GOCI by using the 412 nm band as the UV band to produce. The retrieved aerosol or apparent optical properties products of other satellite sensors can also be used to help GOCI obtain the $R_{rs}(\lambda)$ products.

Many researchers have also developed AC methods for GOCI under non-ideal observation conditions. [84] proposed a novel AC algorithm based on deep learning (denoted as DLACC) to improve the quality of $R_{rs}(\lambda)$ data contaminated by cloud edge effects, including stray light, cloud shadows, and cloud adjacent effects. The observation characteristics of GOCI images from morning to evening also determine that many images have a larger solar zenith angle (SZA) (>70°). It has been reported that a high SZA will increase the residual errors in satellite $R_{rs}(\lambda)$ products due to several factors (e.g., high atmospheric multiple scattering effects and underestimation of the Rayleigh scattering contribution). [85] proposed a new neural network (NN) AC algorithm for GOCI data with a high SZA that retrieves $R_{rs}(\lambda)$ directly from Rayleigh-corrected radiance ($L_{rc}(\lambda)$). This NN AC algorithm can retrieve $R_{rs}(\lambda)$ in the morning or evening when NIR and KOSC algorithms fail.

4.2. Algal Blooms

ICWs, due to their high population density, are prone to ABs when certain meteorological conditions arise [86–93]. The impact of ABs, such as the reduction in dissolved oxygen and the release

of toxins, presents major challenges to aquatic ecosystem management [9,94–96]. Monitoring ABs is essential for improving water quality and the inhabitants' quality of life and reducing unnecessary losses. A variety of strategies have been developed to monitor and understand algal blooms, integrating satellite data, modeling, and machine learning techniques for improved accuracy and efficiency[97].

As presented in Section 4.1, most existing AC algorithms do not apply to the pixels affected by harmful algal blooms (HABs) or red tides [79,98–101]. [102] developed PUK, a red tide quantification algorithm for GOCI that does not require an independent AC process, incorporating a radiative transfer simulation combined with a machine-learning technique. Other approaches for extracting the red tide area from the GOCI include the linear mixed model (LMM) and the normalized difference vegetation index (NDVI) threshold method[103]. Also, an improved Red Tide Index (RI) was established by [67] using normalized $L_{rc}(\lambda)$ data at 443, 490, and 555 nm to monitor red tide changes dynamically in East Lake. Additionally, [104] proposed a newly developed normalized red tide index (NRTI) (calculated with Equations (1)–(4)), utilizing a spectroradiometer to observe the spectral characteristics of red tides and seawater in real-time.

$$P555 = R_{rs}555 - (R_{rs}660 + \frac{660-555}{660-490}(R_{rs}490 - R_{rs}660)) \quad (1)$$

$$P680 = R_{rs}680 - (R_{rs}745 + \frac{745-680}{745-660}(R_{rs}660 - R_{rs}745)) \quad (2)$$

$$RTI = \frac{P555}{R_{rs}490} \times \frac{P680}{R_{rs}660} \quad (3)$$

$$NRTI = \frac{RTI}{R_{rs}555 - R_{rs}745} \quad (4)$$

Lagrangian particle tracking experiments allow us to understand the paths of floating green algae patches and explain the physical forcing factors that affect the distribution and advection of floating green algae. Using a combination of GOCI data and numerical simulations helped track and monitor extensive areas in the Yellow Sea and East China Sea[105]. Furthermore, [106] developed the Index of floating Green Algae for GOCI (IGAG) (Equation (5)) using multispectral band ratios of three wavelengths (555, 660, and 745 nm) in the Yellow Sea and East China Sea.

$$IGAG = \frac{R(555)+R(660)}{R(745)-R(660)} + \frac{R(745)}{R(660)} \quad (5)$$

A U-net model for the extraction of long-term spatial variations of ABs along the East China Sea was developed using GOCI and was trained on two different datasets –six-band channels (all visible bands) and RGB-band channels (443, 555, and 680 nm) [107]. [108] used a Multi-Layer Perceptron (MLP) machine learning algorithm to establish a novel automatic method to continuously monitor ABs in the Yellow Sea. The method consists of two MLP models, which consider both spectral and spatial features of R_{rc} maps. Accuracy assessment and performance comparison showed that the proposed method has the capability to provide highly accurate prediction maps of macroalgal blooms (F1-score approaching 90% or more) with more robustness than the traditional methods. A novel subpixel-level area estimation method for green algae blooms based on spectral unmixing can detect the existence of green algae and determine their proportion in each pixel. A fast endmember extraction method was proposed to calculate the endmember spectral matrix and the abundance map of green algae automatically, which outperformed existing techniques in experiments on GOCI data [109,110]. [111] used an algal index algorithm to quantify equivalent surface algae density (σ , 0–100%) at pixel and synoptic scales from each cloud-free image and offered an analysis of diurnal changing patterns of σ . [112] and [113] used the alternative floating algae index (AFAI) (Equations (6) and (7)):

$$AFAI = R_{rc}(\lambda_2) - R_{rc}(\lambda_2)' \quad (6)$$

$$R_{rc}(\lambda_2)' = R_{rc}(\lambda_2) + (R_{rc}(\lambda_3) - R_{rc}(\lambda_1)) \times \frac{\lambda_2 - \lambda_1}{\lambda_3 - \lambda_1} \quad (7)$$

where the subscripts refer to bands ($\lambda_1 = 660$ nm, $\lambda_2 = 745$ nm, and $\lambda_3 = 865$ nm). A classification method was then devised to classify the daily change patterns of ABs automatically into four types to monitor the daily dynamics in Lake Taihu. [114] used the cyanobacterial bloom intensity (CBI) index (Equation (8)), combined with meteorological factors, water stability, and nutrient factors, to monitor hourly changes in cyanobacterial blooms in Lake Taihu:

$$CBI = \sum_{i=1}^n (AFAI_i + 0.001) \quad (8)$$

[110] developed a new floating algae cover (FAC) model following a logistic curve and applied it to China's two large shallow eutrophic lakes, Lake Taihu and Lake Chaohu.

4.3. Water Quality Parameters

The estimation of water quality parameters involves the use of R_{rc} and the underwater irradiance ratio to estimate Chla concentration, SPM concentration, and yellow substances content by calculating the absorption coefficient of phytoplankton, the absorption coefficient of yellow substances, the absorption coefficient of non-pigmented SPM, and the backscattering coefficient ($b_{bp}(\lambda)$) of SPM [65,115,116]. Most commonly, empirical or semi-empirical and artificial intelligence models have been used [117–121]. This section mainly introduces Chla in Section 4.3.1, SPM in Section 4.3.2, water clarity in Section 4.3.3, and then briefly introduces other water quality parameters such as CDOM, POC, DOC, NPP, SSS, SSCs, sea ice, sea fog, lake ice, k_d , among others, in Section 4.3.4.

4.3.1. Chla

The concentration of Chla, which is the most prevalent pigment in algae and relates to phytoplankton biomass [97,122–127]. Chla concentration is a key indicator of water quality and aquatic ecological health [128–130].

The GOCI official process software suggests using the empirical ocean Chla algorithm (OC3G) for GOCI using the 443, 490, and 555 bands (Equation (9)) [131]:

$$Chla = 10^{f_0 + f_1 * R + f_2 * R^2 + f_3 * R^3 + f_4 * R^4} \quad (9)$$

where R is calculated as:

$$R = \frac{\max(R_{rs}(443), R_{rs}(490))}{R_{rs}(555)} \quad (10)$$

and the values of f_0 , f_1 , f_2 , f_3 are 0.0831, -1.9941, 0.5629, 0.2944, and -0.5458, respectively.

Various studies have explored alternative models and algorithms for Chla estimation in ICWs. [94] explored the physical-biological interaction between anticyclonic mesoscale eddies and Chla secondary blooms after spring blooms in the East Sea and Japan Sea using the GOCI OC3G Chla products. [132] found diurnal changes in GOCI-derived Chla, with generally higher values in the afternoon than in the morning, and identified heterogeneities in the temporal and spatial domains. [133] applied the Linear Combination Index (LCI) algorithm to GOCI to map Chla distribution in Tachibana Bay, Japan, and found OC3G to have relatively large uncertainties in turbid ICWs. [134] developed MFNN, a neural algorithm that can classify the pixels of GOCI images into three Chla concentration categories (normal, abnormally high, and abnormally low) so that outliers can be identified and provide quality control of GOCI Chla products.

A spectral index method, such as the fluorescence line height (FLH) [135], helped construct a band conversion relationship from 681 to 685 nm to establish a phytoplankton retrieval model suitable for GOCI. [68] calibrated three empirical spectral index algorithms (OC4, OC5, and Yellow and East China Sea Ocean Color (YOC)) and constructed four machine learning algorithms (BP neural network (BPNN), random forest (RF), AdaBoost, and support vector regression (SVR)) using numerous in situ data collected in the Bohai Sea and Yellow Sea. The comparison illustrated that machine learning methods were more accurate than classic spectral index algorithms and that RF performed best. The waters in Hangzhou Bay were classified into moderately and extremely turbid

based on the ratio of $R_{rs}(745)/R_{rs}(490)$ [136]. Then, the OC3G and modified synthetic chlorophyll index (SCI) index were used for these two water types to map Chla distribution in this bay [136]. [97] modified the generalized algal bloom index algorithm (GABI) to map Chla in the turbid Changjiang Estuary. For this water region, the modified GABI algorithm showed better accuracy and stability than the two-band ratio, three-band, and four-band spectral algorithms.

Lake Taihu is a favorite research area for GOCI Chla model construction and application in inland waters. [137] proposed a weighted algorithm to estimate Chla concentrations based on spectral classification and weighted matching using normalized mutual information (NMI). [138] proposed a regional NIR red ratio algorithm ($R_{rs}(745)/R_{rs}(680)$) for Chla retrieval in Lake Taihu. Based on this model, the hourly Chla maps of Lake Taihu were produced from August 6 to August 9, 2013. In this paper, the GOCI-derived Chla products revealed clear evidence of hourly spatial and temporal variations of Chla in the eutrophic inland waters. The $R_{rs}(745)/R_{rs}(680)$ was also used by [115] to analyze the spatio-temporal dynamics of Chla and their response to river flow in the estuary of Lake Taihu. [139] proposed a three-band model using the GOCI 681, 745, and 865 nm bands. [140] proposed another three-band Chla model ($R_{rs}^{-1}(681) - R_{rs}^{-1}(709) * R_{rs}(753)$) for GOCI. Simulated and in situ data illustrated that the three-band model outperformed the two-band model under various SPM conditions. [141] proposed a bio-optical hyperspectral reconstruction (BBHR) algorithm to generate simulated hyperspectral $R_{rs}(\lambda)$ ranging in wavelengths from 400 to 800 nm from GOCI and five widely used watercolor sensors. Simulated hyperspectral $R_{rs}(\lambda)$ facilitate the construction of more accurate Chla estimation models for optically complex turbid inland waters. [142] compared the performance of different Chla algorithms for GOCI and GOCI-II in Lake Taihu, Lake Chaohu, and Lake Hongze with $L_{rc}(\lambda)$ as input. The results indicated that the RF algorithm outperformed the commonly used spectral index models.

4.3.2. SPM

SPM refers to the substances suspended in a water body and can be used to characterize its cleanliness [9,143–146]. The main sources of SPM are surface runoff, sediment resuspension, and organic debris composed of decaying organisms and excrements [147]. SPM directly affects the propagation of light in the water body, which in turn affects the aquatic ecological environment and ultimately determines the primary productivity of the lake [20,148–150].

The initial GOCI SPM standard product was based on the algorithm proposed by [151] and [152] as Equation (11):

$$SPM = 945.07 * (R_{rs}(555))^{1.137} \quad (11)$$

[153] applied the SPM model proposed by [154] to GOCI as Equation (12) for comparison with the first official SPM algorithm above:

$$SPM = A_{745} * \frac{\pi * R_{rs}(745)}{1 - \pi R_{rs}(745)/C_{745}} \quad (12)$$

where A_{745} equals to 1755 and C_{745} equals 0.198. This paper found that GOCI data can be used to qualitatively study SPM dynamics except in the extremely turbid waters, which are masked out of the GOCI official $R_{rs}(\lambda)$ products. The following standard GOCI SPM was retrieved by the YOC algorithm based on Siswanto's SPM retrieval model for the Yellow and East China Sea (as Equation (13)) [155–157]:

$$SPM = 10^{(0.649 + 25.623 * (R_{rs}(555) + R_{rs}(670)) - 0.646 * (\frac{R_{rs}(490)}{R_{rs}(555)}))} \quad (13)$$

He, Bai, Pan, Huang, Dong, Chen, Chen and Cui [83] developed a two-band ratio SPM algorithm ($R_{rs}(745)/(R_{rs}(490))$) for Hangzhou Bay and nearby coastal waters. The diurnal variations derived by GOCI showed a good relationship with the buoy data in the region. Yu [158] proposed an experiential SPM algorithm suitable for the Bohai Sea and Yellow Sea to evaluate the effects of typhoons on SPM by carrying out parameter optimization and genetic programming, as with Equation (14):

$$\lg(SPM) = 4.8581 + 0.8206 * \frac{R_{rs}(745)}{R_{rs}(490)} - 0.9998 * \frac{R_{rs}(555)}{R_{rs}(490)} - 3.6504 * \sqrt{\frac{R_{rs}(490)}{R_{rs}(555) + R_{rs}(660)}} \quad (14)$$

Also, using this model, [159] studied dynamic variations of SPM in China's macro-tidal Yalu River estuary. [160] and [161] developed a single-red band model ($R_{rs}(660)$) to retrieve SPM on the west coast of the Korean Peninsula and Bohai Sea. [149] developed an empirical SPM retrieval algorithm based on the spectral absorption index (SAI) in highly turbid Hangzhou Bay with Equations (15) and (16):

$$SAI = \frac{d * R_{rs}(490) + \left(1 - \frac{555-490}{745-490}\right) * R_{rs}(745)}{R_{rs}(555)} \quad (15)$$

$$SPM = 10^{2.01814 * SAI + 0.83774} \quad (16)$$

[119] developed a two-step SPM retrieval model using in situ simulated GOCI $R_{rs}(\lambda)$ and SPM data collected in Lake Taihu, Lake Chaohu, Lake Dianchi, and the Three Gorges Reservoir. Firstly, a clustering method was applied to classify the turbid inland waters into three types (Type 1, Type 2, and Type 3). Secondly, the best performing of the three SPM algorithms was gauged and determined by comparison of their results (Type 1: $R_{rs}(865)/R_{rs}(555)$, Type 2: $R_{rs}(745)/R_{rs}(555)$, and Type 3: $R_{rs}(745)/R_{rs}(555)$). Similarly, [138] proposed another classification-based SPM inversion algorithm in Lake Taihu. The waters were classified into two types based on the $R_{rs-depth}(680)$ index calculated with Equation (17):

$$R_{rs-depth}(680) = \left\{ R_{rs}(660) + [R_{rs}(745) - R_{rs}(660)] * \frac{745-680}{745-660} \right\} - R_{rs}(680) \quad (17)$$

For the waters with $R_{rs-depth}(680) \leq 0.005$, the two-band ratio (Equation (18)) was used, and for the waters with $R_{rs-depth}(680) > 0.005$, the three-band algorithm (Equation (19)) was used:

$$BR_{SPM} = 10^{2.2135 / (1 + \exp(-(\frac{R_{rs}(745)}{R_{rs}(555)} - 0.1223) / 0.1439))} \quad (18)$$

$$TBA_{SPM} = 10^{2.314 / (1 + \exp(-(\frac{R_{rs}(745) + R_{rs}(680)}{R_{rs}(555)} - 0.6263) / 0.431))} \quad (19)$$

[115] proposed a single NIR band algorithm ($R_{rs}(745)$) to retrieve SPM in the estuary of northwest Lake Taihu. [162] developed a semi-analytical SPM model for estimating SPM using the satellite-*in situ* matchup data collected in Lake Taihu and Hangzhou Bay. [163] calibrated the SPM model proposed by [83] to map SPM products using GOCI in Lake Taihu as Equation (20):

$$SPM = 10^{0.61 + 1.43 * R_{rs}(745) / R_{rs}(490)} \quad (20)$$

The GOCI-derived SPM products are consistent with a two-dimensional model that couples shallow water and SPM transport dynamics. The high-spatial-resolution GOCI SPM product combined with the hydrodynamic model has essential application value in high-time frequency suspended solids transport monitoring. [146] developed a quadratic polynomial model of one variable ($R_{rs}(745) + R_{rs}(865)$) to map SPM in Lake Taihu (Equation (21)):

$$SPM = 32517 * (R_{rs}(745) + R_{rs}(865))^2 + 1327.2 * (R_{rs}(745) + R_{rs}(865)) + 0.5 \quad (21)$$

From the hourly GOCI-derived SPM products, they found that the Tiaoxi River greatly influenced the spatial distributions of SPM in Lake Taihu by the plumes after heavy precipitation events. [148] developed a multivariate linear stepwise regression method for retrieval of the surface horizontal distribution of SPM using GOCI. Then, the estimation model of the vertical structure of

underwater SPM was constructed using layer-by-layer recursion. These efforts retrieved the horizontal and vertical distribution of SPM concentration from GOCI data over Lake Hongze.

4.3.3. Water Clarity

Water clarity is a critical parameter for the optical properties of ICWs[146,164–167], vital for characterizing the turbidity and absorption/scattering of light by water bodies. It directly relates to the inherent optical properties of waterbodies, such as Chla, SPM, and phytoplankton biomass [168–173].

To estimate water clarity using GOCI data, [173] proposed a regional linear corrected Secchi disk depth (SDD) model based on the mechanical model developed by [174] (denoted as SDD_{Lee}). This model uses the GOCI $R_{rs}(\lambda)$ derived by the MUMM in Jiaozhou Bay, and its formulation is given in Equation (22):

$$SDD_{Lee} = \frac{1}{2.5 \text{Min}(K_d^{tr})} \ln\left(\frac{|0.14 - R_{rs}^{tr}|}{0.013}\right) \quad (22)$$

where $\text{Min}(K_d^{tr})$ is the minimum K_d in the visible bands (412, 443, 490, 555, 660, and 680 nm), while R_{rs}^{tr} is the $R_{rs}(\lambda)$ corresponding to the waveband with the minimum K_d value. The model considers factors like SZA, tides, and wind force to control diurnal variations. [175] validated the suitability of SDD_{Lee} using in situ $R_{rs}(\lambda)$ products and SDD in Jiaozhou Bay and Qingdao coastal areas. [176] compared the retrieved SDD by different atmospheric correction products and doubted the previous conclusions regarding the hourly variations of biochemical parameters using GOCI, finding them inconsistent. [169] found that the retrieved SDD by SDD_{Lee} was underestimated for their in situ data collected in the Bohai Sea and Yellow Sea due to the uncertainties in the estimation of $K_d(490)$ in SDD_{Lee} in turbid waters. They replaced the original $K_d(490)$ estimation method using a weighted $K_d(490)$ proposed by [177] combined by two $K_d(490)$ estimation methods (one for clear and one for turbid water) and a weighted coefficient. [178] used the GOCI-derived Chla and SPM products to calculate $a(\lambda)$ and $b_b(\lambda)$ and then input them into the semi-analytical model proposed by [179] and [180] (denoted as SDD_{He}) to retrieve SDD in the eastern China seas with Equation (23):

$$SDD_{He} = \frac{1}{4(a(\lambda) + b_b(\lambda))} \ln\left(\frac{\rho_p \alpha \beta (a(\lambda) + b_b(\lambda))}{c_e f b_b(\lambda)}\right) \quad (23)$$

Many studies have shown that SDD_{Lee} is biased in estimating SDD in inland waters[168,181]. [168] used a linear relationship to correct SDD_{Lee} (denoted as SDD_{Bai}) and applied this algorithm to GOCI in Lake Taihu with as Equation (24):

$$SDD_{Bai} = 2.68 * \frac{1}{2.5 \text{Min}(K_d^{tr})} \ln\left(\frac{|0.14 - R_{rs}^{tr}|}{0.013}\right) + 0.0046 \quad (24)$$

[182] proposed an improved Quasi-Analytical Algorithm (QAA)-estimated SDD algorithm (denoted as SDD_{Zeng}) for GOCI using in situ data collected in Lake Taihu, Lake Hongze, Lake Dongting, and Lake Erhai. SDD_{Zeng} firstly estimated $b_b(745)$ using QAA with an assumption of the pure water absorption ($a_w(745)$) is dominated at this band ($a(745) \approx a_w(745)$). $K_d(745)$ was estimated using Equation (25):

$$K_d(745) = (1 + 0.0124 * \theta_s) * a_w(745) + 3.16 * (1 - 0.52 * \exp(-10.8 * a_w(745))) * b_b(745) \quad (25)$$

where θ_s represents the SZA. [182] found that the $\text{Min}(K_d^{tr})$ is at 555 nm in Lake Taihu and Lake Hongze. Thus, a linear relationship was built to convert $K_d(745)$ to $K_d(555)$:

$$K_d(555) = 0.99 * K_d(745) - 1.96 \quad (26)$$

The retrieved $K_d(555)$ was used to retrieve SDD using Equation (22).

4.3.4. Other Parameters

In addition to the above main water quality parameters, scholars have also conducted research on CDOM, POC, DOC, NPP, SSS, SSCs, sea ice, sea fog, lake ice, k_d , and other parameters. CDOM is the main constituent of dissolved organic matter (DOM) and a key indicator of water quality conditions [183–185]. Based on QAA and QAA_CDOM, [186] developed a new algorithm named QAA_cj to estimate CDOM concentration. The algorithm can easily be applied to high turbidity coastal waters. A simple approach to estimate the CDOM concentration was also proposed based on the datasets derived from in situ measurements during four cruise surveys over the Bohai Sea and Yellow Sea. Eight band combination forms (using Xi as a delegate, where i denotes the numerical order of band combination forms), including single bands, band ratios, and other band combinations by $R_{rs}(\lambda)$ were trained to test the correlations with the CDOM concentrations [187]. POC is an essential form of water carbon, taking part in various biogeochemical processes and influencing both organic and inorganic carbon cycles [188–191]. A remote sensing algorithm that can monitor and accurately estimate the changes in POC fluxes in real-time at the Yangtze Estuary hydrological station was established using GOCI satellite data [192,193]. DOC refers to various dissolved organic molecules ubiquitous in aquatic systems. It is a dynamic reduced carbon pool with important ecological and geochemical functions in inland and coastal waters [194,195]. A regional, red-blue ratio algorithm was proposed to estimate Lake Taihu's surface DOC and analyze its spatiotemporal variation characteristics [196]. Accurate assessments of spatial and temporal changes of NPP in the euphotic zone are critical to understanding the role of the ocean in regulating Earth's climate and assessing future fisheries production, as well as predicting the impacts of ocean warming, hypoxia, and ocean acidification on marine ecosystems [197–199]. [199] used the Adsorption Based Productivity Model (Abpm) to monitor diurnal and daily surface and euphotic-column integrated NPP. Global changes of SSS can simulate and predict changes in exchanges between the atmosphere and the ocean surface, as well as the ocean surface and the deep sea. SSS is also involved in the intensification of the global water cycle. For the estimation of SSS, a multi-layer perceptron neural network (MPNN) was employed to train the nonlinear processes of GOCI-II spectral measurements as inputs and the SSS of Soil Moisture Active Passive (SMAP) as the target [102]. SSCs are one of the most important physical properties in ocean dynamics and are crucial for understanding ocean physical and biogeochemical processes [69,200,201]. A method based on maximum cross-correlation (MCC) was used to derive changes in SSCs in the highly turbid waters of Hangzhou Bay to capture better tidal phase variations [77]. Sea ice monitoring is vital for marine traffic, fisheries, ports, and weather forecasting. A simple method to monitor the sea ice area (SIA) and separate it from seawater was proposed, employing standard deviation filtering to enhance the spatial variability between sea ice and open water [202]. In addition, the accurate detection of sea ice thickness (SIT) is crucial for understanding climate change and preventing sea ice disasters. [203] proposed a SIT inversion method for Liaodong Bay based on Rayleigh scattering corrected reflectance, which has practical advantages in estimation accuracy and spatiotemporal resolution. This method can also be applied to the global ocean. Also, an object-based feature extraction method and an albedo-based thickness inversion model were used for estimating SIA and SIT, respectively, by [204] to reach a better effect. The emergence of sea fog leads to low visibility and seriously threatens the safety of maritime activities. Therefore, monitoring changes in sea fog is particularly important [205]. [206] proposed a method to identify sea fog based on the convolutional neural network transfer learning model (CNN-TL). [205] established a sea fog dataset (SFDD) and a dual-branch sea fog detection network (DB-SFNet). Lake ice is one of the essential climate variables of the cryosphere and is closely related to lake environments, ecological regulation, and the safety of human activities [207–209]. [210] used the enhanced spatial and temporal adaptive reflection fusion model (ESTARFM) to merge Landsat and GOCI images and extracted the length and angles of the linear structure to monitor the hourly changes in the surface morphology of Lake Chagan. k_d is an important optical property of water, which describes the penetration of incident solar radiation in the water column. k_d is a quasi-inherent optical property since it depends on the water constituents and the distribution of the ambient light field [211–214]. An improvement of the parameterization equations in the inverse scheme of the 2Seacolor model was used in the Yangtze Estuary to retrieve k_d [215].

5. Discussions

5.1. Integrating Geostationary Ocean Color Satellites, Unmanned Aerial Vehicles, and Ground Collaborative Observation

Due to cloud interference, it is difficult for GOCI to take advantage of its high temporal resolution characteristics, especially in cloudy and humid areas [216]. With the development of satellite remote sensing technology, unmanned aerial vehicles and ground observation technology are also growing rapidly, as shown in Figure 9. The development of unmanned aerial vehicles includes improved sensors and payloads, enhanced flight control systems, miniaturization, lightweight design, and higher battery life [217–219]. Ground observation technology progress includes improving sensors and algorithms, providing more accurate estimates of water quality parameters, and the ability to monitor continuously, long-term, in real-time, and automatically [220,221]. GOCI can be used to produce water-quality products in clear weather. In cloudy weather, unmanned aerial vehicle observation results and point ground observation results for an area of interest can be input into hydrodynamic models to generate a simulated numerical water quality dataset [222,223]. The integration of technology can achieve all-weather water quality monitoring of ICWs.

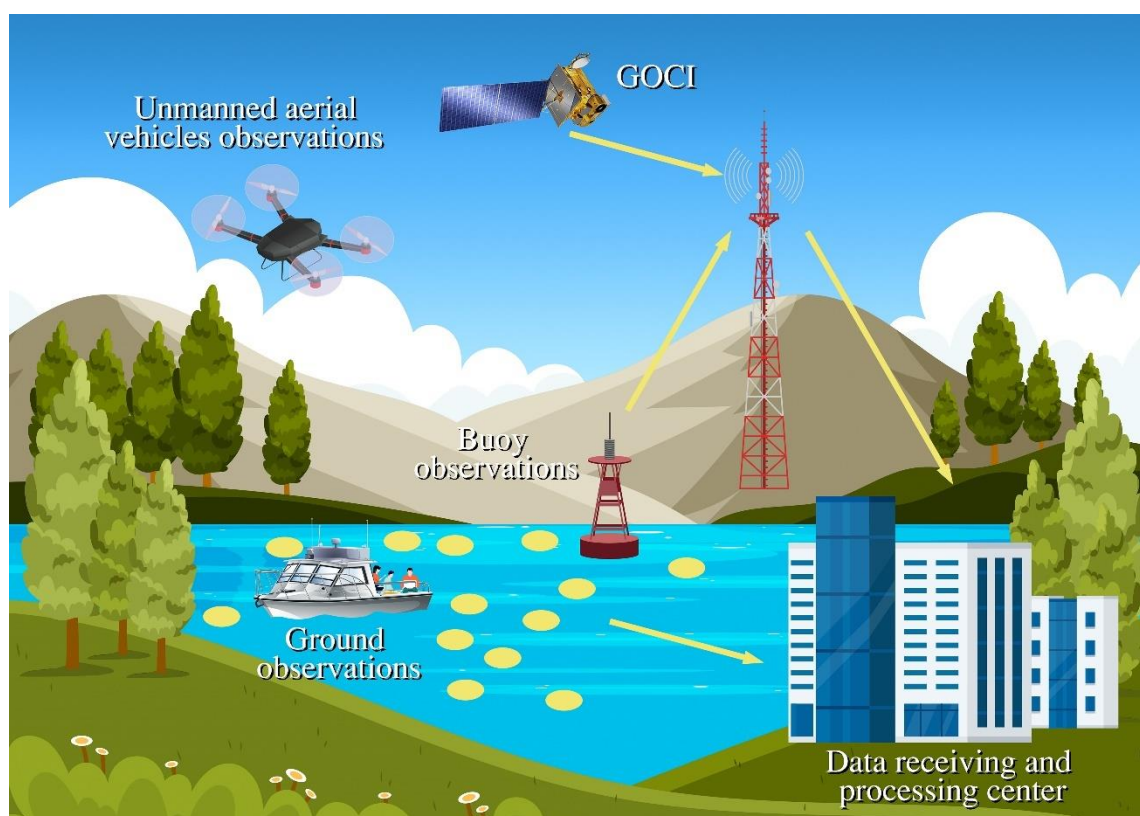


Figure 9. Schematic diagram of integrated ground-air-space.

5.2. Fusion of Geostationary Ocean Color Satellites with Other Satellite Products

Image fusion can combine the advantages of different temporal, spatial, and spectral resolution sensors to improve the monitoring of water quality in ICWs [176,224]. Geostationary meteorological satellites (GMST) tend to have higher temporal resolution than geostationary ocean color satellites (GOCS). For example, Himawari 8/9 acquires data every ten minutes. However, low signal-to-noise ratio and spatial resolution limit the application of GMST in water quality monitoring [225]. With the GOCS as a reference, the spatial resolution of the GMST can be improved, and the spectral information can be enhanced. The fused GMST may produce better water quality products in ICWs than the original images [226]. The schematic diagram of image fusion is shown in Figure 10.

Similarly, fusion can also improve GOCS products. The fusion of GOCS and medium- and high-resolution satellites can improve the spatial resolution of GOCS, providing more spatial details of ICW quality changes [227]. The fusion of GOCS and hyperspectral satellites will enhance the spectrum of GOCS, improving the accuracy of the water quality products of GOCS [228]. In addition to multiple daily observations, GOCS, like GOCI, can provide long-time series observation data. Developing technologies to integrate GOCS products with other long-term series satellite products (SeaWiFS, MODIS, and VIIRS) will contribute to long-term series of water quality assessments [229–232].

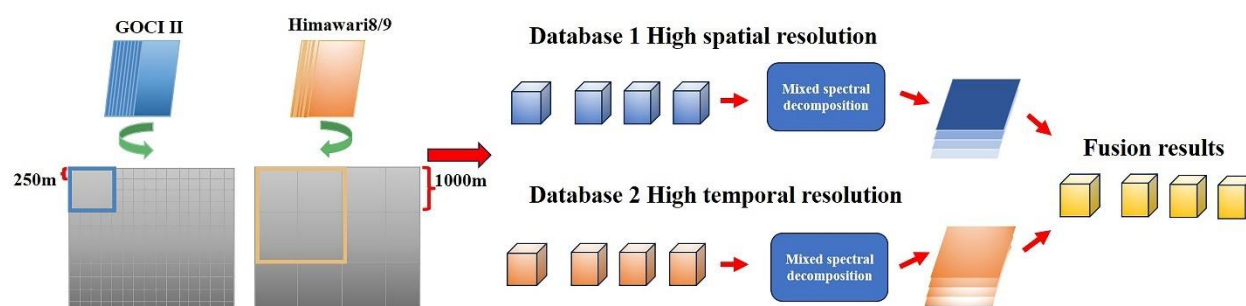


Figure 10. Schematic diagram of image fusion, taking GOCI-II and Himawari8/9 as an example.

5.3. Improving Spectral, Spatial, and Temporal Resolution of Geostationary Ocean Color Sensors

5.3.1. Improving Spectral Resolution

GOCI was equipped with eight bands (six for visible light and two for NIR). The next generation of GOCI (GOCI-II) increased the number of bands to thirteen (one for UV, eight for visible, three for near-infrared, and one for broad bandwidth). The new 380 nm ultraviolet band can be used to retrieve parameters related to the absorption of CDOM (e.g., DOC, carbon dioxide, or organic pollutants) [117,233]. It also allows for applying ultraviolet AC methods to GOCI to provide more reliable $R_{rs}(\lambda)$ products [66,234]. The 510 nm band can potentially improve the performance of OC3G or other blue-green Chla algorithms in relatively clear ICWs [235]. PC can characterize cyanobacterial biomass, which has a distinct absorption peak at about 620 nm [236,237]. Many inland lakes on the Korean Peninsula and East China have frequent occurrences of cyanobacterial blooms [238–241]. The newly added 620 nm band allows GOCI-II to monitor cyanobacteria blooms quantitatively. The last new band of GOCI-II is 709 nm. Many studies have illustrated this band's usefulness in Chla retrievals [242,243]. GOCI-II has the potential to provide more accurate Chla products in turbid ICWs.

The newly added five bands provide many advantages to GOCI-II compared with GOCI. The GLIMR is a geostationary sensor funded by the NASA Earth Venture Instrument program, which is anticipated to launch within this decade (around 2026-2027) [244]. GLIMR is planned to provide 340-1025 nm hyperspectral data of aquatic ecosystems. The hyperspectral characteristic of GLIMR may provide more reliable atmospherically corrected $R_{rs}(\lambda)$ products and more accurate water quality products (e.g., Chla, SPM, or SDD). By targeting absorption or backscatter characteristics at different wavelengths, GLIMR may provide more new water quality parameters (e.g., algae species, oil spills, microplastics, or greenhouse gases). GOCI, GOCI-II, and GLIMR (planned) have only visible and NIR bands. The complex optical properties of ICWs require that $R_{rs}(\lambda)$ products are combined with different AC algorithms based on the bands' wavelengths (e.g., UV, visible, NIR, and SWIR bands) [245]. The next-generation GOCS should have more band choices.

The observation characteristics of GOCS from morning to afternoon determine that the SZA of many images is relatively large (e.g., $>70^\circ$), especially in high latitudes regions, in the northern hemisphere winter seasons, or in the early morning or late afternoon observation time. The satellite images with a high SZA will increase the residual errors in satellite-derived $R_{rs}(\lambda)$ products due to many factors (e.g., higher atmospheric multiple scattering effects and underestimation of the Rayleigh contribution) [24,60,72]. A higher spectral signal-to-noise ratio is the prerequisite for

constructing effective AC methods under high SZA [60]. The next-generation GOCS should improve spectral resolution through better sensor design.

5.3.2. Improving Spatial Resolution

Most of the applications of GOCI in inland waters have been carried out in Lake Taihu, Lake Hongze, and Lake Chagan. The coarse spatial resolution of 500 m makes it hard to use GOCI to monitor water quality in small lakes. With an improved spatial resolution of 250 m, GOCI-II can monitor more inland waters than GOCI. Inland waters with small sizes are more easily affected by human activities and global warming than large lakes [246,247]. We very much hope to have higher spatial resolution GOCS to serve the water environment health monitoring of small and medium-sized lakes.

5.3.3. Improving Temporal Resolution

The most significant advantage of GOCS is its high temporal resolution. The observation times of GLIMR, GOCI, and GOCI-II are six (planned), eight, and ten per day. Many water quality changes, such as ABs vertical and horizontal movements [248,249], lacustrine greenhouse gas emission fluxes [250], and estuary sediment fluxes [251,252] tend to happen rapidly, at sub-hourly time scales. It is better to improve the temporal resolution of GOCS from hours to minutes when these conditions are met.

6. Conclusions

In this work, we reviewed the applications of GOCI for AC and water quality parameter retrieval in ICWs. First, we introduced the GOCI specifications and compared them with those of other satellites, highlighting the advantages of GOCI in high-temporal water quality monitoring. Then, AC and water quality (such as ABs, Chla, SPM, SDD, or others) algorithms for GOCI were systematically introduced. The results of the bibliometric analysis showed that many papers were published in the last thirteen years, starting in 2010.

A number of AC or water quality retrieval models for GOCI have been proposed over the years. These models form a GOCI algorithm library for monitoring water quality in various ICWs. Due to the complex optical properties of ICWs, it is difficult to identify one best performing model of AC or one specific water quality parameter (ABs, Chla, SPM, SDD, or others), as they differ across ICW waterbodies or even across the seasons in the same waterbody. GOCI provides valuable experience for effectively using GOCS to monitor the water qualities of ICWs. So far, there is still no official GOCI product for water quality monitoring in ICWs. Classifying the ICWs into different water types and retrieving the water quality by the most suitable model for each type may provide an official, reliable, and high-accuracy watercolor product for various ICWs.

We partly summarize and introduce future directions for GOCI and other next-generation GOCS to serve the water quality monitoring of ICWs better. Cloudy weather limits the use of high-temporal GOCS satellites. Integrating GOCS, unmanned aerial vehicles, and ground collaborative observation can achieve all-weather water quality monitoring of ICWs. GMST tends to have higher temporal resolution than GOCS and lower spatial and spectral resolutions. The fusion of GOCS with other GMSTs will improve the spatial and spectral ability of GMST. The fusion of GOCS with other high spatial or spectral sensors will enhance the image quality of GOCS itself to monitor ICWs. We suggest the next generation of GOCSs can improve their spatial, spectral, and temporal resolution to monitor the water quality of ICWs better.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

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