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Citizen Science Applications for Water Quality Monitoring. A Review

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***Abstract*—In recent years citizen science emerged as a promising technology in environmental science and hydrology with the potential to overcome the lack of in-situ measurements and create efficient ecosystems. This paper provides an up-to-date systematic literature review of applications of citizen science technology in water quality monitoring and estimation. A bridge between citizen science and remote sensing will be established to provide a sound framework for comprehensively discussing the various approaches and applications. A scrutinizing of various water quality parameters and associated measurement & estimation methods is provided, delving into various remote sensing systems (microwave and optical systems) and imaging techniques (hyperspectral and hyperspectral methods). A special interest is focused on reviewing existing relevant crowd-sourcing mobile apps such as EyeOnWater, HydroColor, EnviObserver, Sechhi App, Hydro Crowd, and SIMILE-Lake monitoring, detailing their working mechanisms, algorithms, data acquisition processes, used sensors, and measured water quality parameters. Finally, the paper summarizes key knowledge gaps, challenges and promising directions in this research field.**

***Index Terms*—remote sensing, water quality parameters, citizen science, microwave, optical, hyperspectral, multispectral, artificial intelligence, mobile applications**

I. Introduction

Water is a fundamental resource for all life on Earth. It is essential for human health, agricultural productivity, and ecosystem sustainability. However, with the constant increase in urbanization, mass-tourism, mega-industry, large-scale agricultural activities, and climate change effects, water quality degradation has become a pressing global concern. Pollutants such as heavy metals, nutrients, pesticides, and pathogens are continuously introduced into water bodies, posing significant threats to both human and environmental health.

Traditional methods for measuring water quality parameters have relied on labor-intensive and often time-consuming processes, such as manual sampling and laboratory analysis. While these methods provide valuable data, they are limited in their spatial and temporal coverage, making it challenging to monitor large-scale or remote water bodies effectively. Moreover, traditional approaches may not capture real-time changes in water quality or provide sufficient spatial resolution for comprehensive monitoring. In response to these limitations, there is a growing need to implement remote sensing and citizen-science-based technologies for measuring water quality parameters.

Remote sensing technologies, including satellite, airborne, and unmanned aerial vehicle (UAV) [36], [120] platforms, offer the ability to collect spatially explicit and temporally continuous data over large areas [2], [3], [5], [7], [10], [14], [17], [18], [22], [23], [25], [26], [28], [39], [46], [52], [59], [60], [64], [66], [69], [79], [80], [86]–[89], [96], [97], [99]–[103], [105], [106], [108], [109], [113], [115], [116]. These technologies enable the monitoring of various water quality parameters with improved spatial resolution and coverage. Moreover, the availability of open-access remote sensing data, such as those from the Landsat [2]–[4], [7], [10], [23], [24], [28], [29], [39], [51]–[53], [59], [64], [69], [86]–[88], [90], [92], [95], [97], [99], [100], [102], [104], [108], [114], [116] and Sentinel [7], [14], [26], [34], [41], [47], [48], [60], [61], [68], [81], [87], [103], [106], [108], [113] missions, has facilitated widespread applications in water quality monitoring and management.

During the course of reviewing various research literature related to remote sensing techniques for measuring water quality parameters, different remote sensing sensors were considered, including Landsat 1-9, Sentinel-2A/2B, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Moderate Resolution Imaging Spectroradiometer (MODIS), Medium-Resolution Imaging Spectrometer (MERIS), and RapidEye. The extensive utilization of these sensors has enabled the accurate quantification of various water quality parameters. These parameters include and not limited to chlorophyll-a concentration [14], [60], [61], [69], [84], [103], [106], [108], [119], turbidity [34], [41], [104], total suspended solids (TSS) [68], total suspended matter (TSM) [10], [53], [81], [113], total phosphate (TP) [47], [51], [80], [109], [110], [114], [120], total nitrogen (TN) [51], [110], [114], ammonia nitrogen ($NH_3 - H$) [36], [88],nitrate nitrogen ($NO_3 - N$) [3], [18], [23], [29], [36], [97], [105], chemical oxygen demand (COD) concentration [22], [47], [59], [102], [109], [116], [120], biochemical oxy-

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gen demand (BOD) concentration [5], [39], [52], [101], algal bloom [96], [115], colored dissolved organic matter (CDOM) [24], [26], [66], [79], [80], [113], total organic carbon (TOC) [28], [116], dissolved organic carbon (DOC) [17], [25], [89], secchi disk transparency (SDT) [48], [92], [95], suspended particulate matter (SPM) [119], suspended solids concentration (SSC) [86], [100], secchi disk depth (SDD) [7], [87], [101], pH [7], [46], [87], [88], total dissolved solids (TDS) [2], [4], [10], [28], [53], [64], [81], [99], [117], and electrical conductivity (EC) [4], [39], [46], [119].

Also in recent years, the integration of citizen science into water quality monitoring efforts has gained significant traction. Citizen science involves the participation of non-professional volunteers in scientific research, data collection, and analysis. This approach not only enhances spatial and temporal data coverage but also fosters public engagement and environmental stewardship. Citizen scientists, equipped with simple monitoring tools and mobile applications, contribute valuable data on water quality from diverse geographical locations, including remote and under-served areas.

Citizen science-based mobile applications play a pivotal role in democratizing water quality monitoring by empowering individuals to become active participants in environmental conservation. These applications offer user-friendly interfaces, real-time data visualization, and educational resources, enabling users to easily collect, upload, and share water quality data. Furthermore, some applications incorporate machine learning algorithms and crowdsourced data validation mechanisms to ensure data accuracy and reliability.

Citizen science-based applications also pose several challenges. Firstly, ensuring data accuracy and reliability remains a significant hurdle, as citizen-contributed data may vary in quality due to differences in equipment, expertise, and sampling methods. Secondly, maintaining participant engagement and motivation over the long term or even the course of the study period is crucial for sustained data collection efforts. Lastly, addressing issues of data privacy, security, and ethical concerns surrounding the use of citizen-contributed data requires careful consideration and management.

The convergence of citizen science and remote sensing for water quality assessment is an emerging field that has only been incorporated into peer-reviewed literature within the past decade. Despite this recent inclusion, comprehensive review papers on this topic remain relatively sparse and widely underexplored. Previous reviews [12], [32], [72], [77], [107], [118] have focused on related aspects, such as crowdsourcing environmental data for flood modeling or utilizing remote sensing for water quality characterization. However, these reviews often lack a holistic examination of the collaborations between citizen science and remote sensing specifically for water quality monitoring issues. For instance, the review paper [72] explores the utilization of citizen-generated data to enhance flood modeling but it lacks a comprehensive discussion on water quality parameters and its relation to citizen science and remote sensing. Similarly, [118] delves into the Forel–Ule Index (FUI) for water color measurement using remote sensing but fails to address broader questions on how citizen science can augment traditional water quality monitoring methods. In contrast, while the paper [107] highlights the significance of data availability in wetland conservation, it does not specifically explore the intersection of citizen science and remote sensing for water quality monitoring. Likewise, authors in [77] elaborate on computational approaches for water quality index (WQI) assessment but overlook the role of citizen science and remote sensing in this domain. [12] discusses monitoring lake water quality with citizen-collected data but does not sufficiently elaborate on remote sensing applications or broader implications for water quality assessment. Review in [32] focuses on citizen science in phenology observations, showcasing models for broader data collection but lacks a focus on water quality parameters.

Consequently, these gaps underscore the pressing need for a comprehensive review that addresses key research questions associated with an up-to-date literature on applications of citizen science technology in water quality estimation / monitoring. This review aims to examine the impact of remote sensing and citizen science in water quality monitoring, exploring opportunities for estimation of water quality parameters, extending traditional monitoring capabilities, and assessing the effectiveness of hybridizing remote sensing methodologies and citizen science in analyzing water body quality.

Following are some of the research questions that this article attempts to answer through examining the intersection of remote sensing and citizen science within water quality monitoring.

1) What is the current the state-of-the-art in the application of citizen science technology for water quality estimation and monitoring?
2) How does citizen science based applications extend traditional monitoring capabilities in the context of water quality monitoring?
3) What are the opportunities presented by combining remote sensing and citizen science in water quality monitoring?

This paper presents a comprehensive compilation of research conducted through the years 2017 to 2024, focusing on the implementation of remote sensing techniques for estimating various water quality parameters. In this review article, we explore the opportunities

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offered by remote sensing and citizen science for water quality monitoring. The organization of the review article begins with an *Introduction* section outlining the importance and challenges associated with water quality monitoring. Next, the *Background and Motivation* section provides a conceptual understanding of the terms *Citizen Science*, *Remote Sensing*, discuss the relation between them, and their significance towards the assessment of water quality compared to the existing traditional methods. The *Methodology* section guides about the various stages of refining literature search resulting in exploring research articles that are closely related to the theme of the review paper. The *Results of Literature Review* section presents the detailed findings using the performed literature search related to the collaborative remote sensing and citizen science approaches for monitoring water quality and estimating various quality parameters. The *Citizen Science for Water Quality Analysis* section also presents the functionalities and different available citizen science based mobile applications utilized for collecting and analyzing data using various remote sensing and other techniques resulting in assessing the water quality of different water bodies in various regions.Finally, the *Discussion* section concludes with a summary of the discussed remote sensing and citizen science based methodologies in improving water quality management and also presents few recommendations for potential areas of research based on the specified research questions mentioned in the Introduction section.

II. Background and Motivation

A. Motivations grounds, Remote Sensing and Citizen Science

Water, the essence of life, is unequally distributed across the globe, with some regions facing acute scarcity while others having abundant reserves. This disparity underscores the critical importance of water resources and the need for vigilant monitoring to ensure equitable access and sustainable management. Water bodies, from rivers to lakes to oceans, serve as vital lifelines for ecosystems and human societies alike, supporting biodiversity, agriculture, industry, and recreation. However, they face myriad challenges aggravated by anthropogenic activities.

Human-induced pollution, originating from agricultural runoff, industrial discharge, and urban sewage, poses a significant threat to water quality. Nutrient enrichment, sedimentation, and chemical contamination degrade aquatic habitats and impair water usability. Moreover, the effects of climate change, such as altered precipitation patterns and rising temperatures, further strain water bodies, exacerbating issues of scarcity and pollution. Urbanization compounds these challenges, amplifying the demand for water while simultaneously increasing pollution through runoff and waste disposal.

Environmental concerns also loom large as the health of water bodies deteriorates, impacting aquatic ecosystems and human health alike. Eutrophication, harmful algal blooms, and the proliferation of pathogens pose direct threats to biodiversity and public safety. Additionally, poor water quality jeopardizes drinking water supplies, leading to widespread health risks and economic losses.

Traditional methods for measuring water quality typically involve in-situ measurements and periodic sampling [56], [91], [111]. In-situ measurements are conducted directly at the water body using handheld instruments or fixed sensors. These methods provide real-time data but are limited in their spatial coverage and may not capture dynamic changes adequately due to the fixed nature of sensor placement. Additionally, sampling involves collecting water samples at specific locations and times for laboratory analysis. These methods, while effective, often require trained personnel, specialized equipment, and can be costly and time-consuming.

Remote sensing techniques emerged as a response to these challenges, playing a crucial role in the modern water quality monitoring approaches by enabling the collection of essential data without the need for direct physical contact with the water bodies being studied. These techniques leverage various platforms, including satellites orbiting the Earth, unmanned aerial vehicles (drones), and specialized airborne sensors with each platform offering distinct advantages in terms of spatial coverage, temporal resolution, and accessibility.

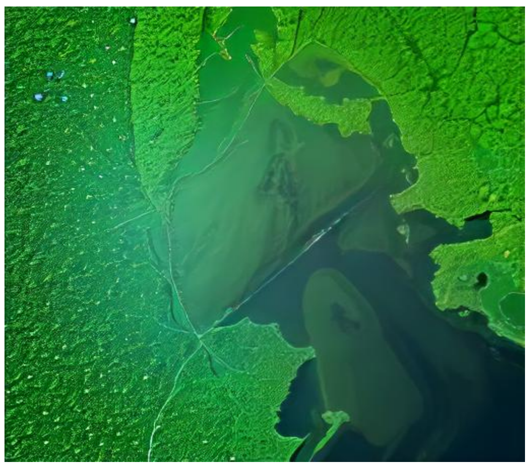

Fig. 1. An image highlighting spatial and temporal coverage of water area using advanced remote sensing technology for water quality assessment.

In recent years, there has also been a growing interest

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in utilizing the power of citizen science for water quality monitoring. In this context, citizen science aims to engage and empower communities in monitoring and understanding their local environment. Especially, citizen science involves engaging the public in scientific research and monitoring activities, enabling individuals to contribute to data collection and analysis. In the field of water quality monitoring, citizen science initiatives empower volunteers—ranging from random citizens to domain experts to participate actively in gathering water quality data. This inclusive approach enhances spatial and temporal coverage, allowing for a broader understanding of the dynamics of water quality across diverse landscapes.

Fig. 2. An illustration depicting the utilization of citizen science towards contributing environmental data for measuring water quality parameters.

The integration of remote sensing technologies with citizen science initiatives represents a collaborative approach that holds great promise for advancing water quality monitoring efforts [9], [15], [33], [63], [70]. For instance, citizen scientists can provide ground-truth data that can validate and enhance the interpretation of remote sensing observations. Remote sensing technologies, such as satellite imagery and drone-based sensors, excel in capturing large-scale spatial information on water quality indicators over expansive areas [10], [14], [53], [69], [81], [84], [90], [96], [99], [103], [106], [108], [117], [119]. However, the accuracy and specificity of these observations can be further refined and validated with localized data collected by citizen scientists on the ground. Therefore, by integrating citizen-collected data with remote sensing outputs, researchers can achieve a more comprehensive understanding of water quality dynamics. This combined approach not only improves data accuracy and coverage but also fosters a sense of community engagement and ownership in environmental monitoring efforts where citizen involvement empowers local communities to actively contribute to scientific endeavors, promoting environmental awareness and practises in analyzing water quality.

B. *Water Quality Components and Assessment*

Water quality can be defined as the assessment of a water sample's attributes against specific criteria. Assessing water quality involves various tests, including assessments of color, smell, temperature, acidity, presence of bacteria, biodiversity, and more. These approaches typically involves obtaining measurements of various water quality parameters which can be broadly categorized into physical, chemical, biological, and radioactive measurements [43] as highlighted in table I.

Physical parameters such as temperature, turbidity, and depth are fundamental for assessing water quality. Temperature readings, obtained using thermometers, reveal thermal fluctuations affecting aquatic ecosystems. Turbidity, a measure of water clarity, is determined with turbidimeters that gauge light scattering caused by suspended particles. Similarly, the evaluation of water quality heavily relies also on chemical parameters. pH, representing acidity or alkalinity, is gauged using pH meters or indicators. Dissolved oxygen levels, crucial for aquatic life, are monitored with oxygen meters. Nutrient concentrations (e.g., nitrogen, phosphorus) are assessed using spectrophotometry or colorimetry. Detection of contaminants such as heavy metals, pesticides, and organic compounds involves sophisticated techniques like chromatography (e.g., GC-MS) [6], [112] or atomic absorption spectroscopy [1], [42], [78], [85].

Biological parameters, being the third category, including microbial activity and biodiversity, are assessed through direct observation and sampling techniques [21], [49]. Microbial activity is often inferred through tests targeting bacterial or algal presence and metabolic rates, providing insights into water ecosystem health. Biodiversity assessments involve sampling organisms ranging from macroinvertebrates to fish populations, offering a comprehensive view of aquatic ecological conditions.

Lastly, radioactive parameters are also crucial in water quality analysis and monitoring, especially for assessing potential contamination from radioactive isotopes. Monitoring radioactive parameters entails measuring specific isotopes like tritium, radium, or cesium using sensitive detectors such as gamma spectrometers or liquid scintillation counters [31], [71]. These measurements are essential for understanding the presence and distribution of radioactive contaminants in water bodies.

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Table I presents an overview of the physical, chemical, biological, and radioactive categories of water quality parameters highlighting key metrics and their relevance in water quality monitoring efforts.

TABLE I
DIFFERENT CATEGORIES OF WATER QUALITY PARAMETERS

Physical	Chemical	Biological	Radioactive
Temperature	pH	Algae	Alpha Emitter
Color	DO, BOD	Bacteria	Beta Emitter
Turbidity	Chloride	Virus	
Taste	COD		
Solids	Acidity, Alkalinity		
Electrical Conductivity			

Despite their accuracy, traditional methods for measuring various categories of water quality parameters as mentioned above not only constitute substantial costs but are also prone to errors and inconsistencies due to human factors. The dependence on skilled personnel introduces a logistical challenge, particularly in remote or inaccessible areas where deploying experts may be challenging or costly. Furthermore, the spatial and temporal constraints associated with in-situ measurements hinder holistic assessments of water quality across expansive aquatic environments. These limitations impede our ability to obtain a detailed understanding of water quality dynamics, particularly the fluctuations influenced by seasonal changes or anthropogenic activities.

Amidst these challenges, the role of remote sensing and citizen science in water quality monitoring emerges as a beacon of hope. By harnessing technological innovations and community engagement, these approaches offer scalable and cost-effective solutions to gather real-time data and foster environmental stewardship. The next subsection explores the role of remote sensing in water quality analysis, focusing on optical and microwave systems and their unique capabilities. It discusses spectral imaging, comparing airborne and spaceborne sensors, and differentiating between optically and non-optically active water parameters. Methods for deriving water quality from spectral data are outlined, including empirical, semi-empirical, analytical, and AI-driven approaches. A table summarizes studies using remote sensing for water quality estimation.

C. Remote Sensing for Water Quality

Remote sensing systems play a pivotal role in the monitoring and assessment of water quality, offering a comprehensive understanding of aquatic ecosystems. These systems leverage various technologies and sensors to gather data remotely, enabling efficient and widespread monitoring over large geographic areas. There are two primary categories of remote sensing systems employed in water quality monitoring: optical remote sensing systems and microwave remote sensing systems. Each system offers unique capabilities and advantages, contributing to the advancement of research and applications in this field.

Optical remote sensing uses sensors to measure reflected or emitted electromagnetic radiation from Earth's surface. It captures data based on sunlight interactions, allowing for the retrieval of vegetation indices, land cover, and surface temperature. Satellites like Landsat, Sentinel-2, MODIS, and MERIS are key tools in global water quality monitoring. Microwave remote sensing excels in water quality monitoring, especially in challenging environments like cloudy or turbid waters. These systems operate in the microwave spectrum, penetrating water to reveal subsurface properties. They measure parameters such as temperature, salinity, and surface roughness, serving as indicators of water quality. Microwave sensors, including Synthetic Aperture Radar (SAR), can detect oil spills and algal blooms with high resolution and in any weather. Integrating microwave data with optical and in situ measurements improves the accuracy of water quality assessments, providing a holistic view of aquatic ecosystems and their responses to environmental changes.

1) Spectral Images: Spectral imaging, with its ability to capture detailed spectral characteristics alongside spatial information, holds significant advantages in the domain of water quality monitoring benefiting greatly from advanced imaging technologies. Spectral imaging captures and analyzes the spectral characteristics of various objects and scenes across different wavelengths of the electromagnetic spectrum. Unlike traditional imaging, which captures only spatial information, spectral imaging also records spectral information for each pixel in the image.

Based on difference in the spectral resolution, the spectral images can be further categorized into Multispectral images and Hyperspectral images. Multispectral images capture data across 3 to 10 spectral bands from the visible and near-infrared range of the electromangetic spectrum. The wavelength span of multispectral images typically covers wavelengths from 0.4 to 10 µm. On the other hand, Hyperspectral images capture data at hundreds of narrow contiguous spectral bands across a broad spectral range. This high spectral resolution allows hyperspectral sensors to capture fine spectral details and detect subtle spectral signatures. The wavelength span of hyperspectral images covers the same range as multispectral images.

2) Airborne and Spaceborne Sensors: Airborne and Spaceborne sensors represent two distinct yet complementary approaches to remote sensing, each offering unique advantages in observing and understanding the

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Earth's surface and atmosphere. Airborne sensors are typically mounted on aircraft or drones, allowing for versatile and targeted data collection at relatively low altitudes. They measure the reflectance and absorption propertie of various surfaces from incoming solar radiation operating in visible, near-infrared, mid-infrared, and thermal spectral bands enabling the acquisition of high-resolution imagery and detailed measurements of environmental parameters. Examples of airborne sensors include optical cameras, multispectral cameras, LiDAR (Light Detection and Ranging), and thermal infrared sensors.

Spaceborne sensors are deployed on satellites orbiting the Earth, offering a broader coverage area and continuous monitoring capabilities on a global scale. These sensors capture data across a wide range of wavelengths and resolutions, facilitating large-scale environmental monitoring and analysis. Examples of spaceborne sensors include Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Visible Infrared Imaging Radiometer Suite (VIIRS), Landsat, and Sentinel satellites.

3) Remote Sensing Applications in Water Quality Monitoring: Within the remote sensing applications, the process of determining the water quality parameters from remotely sensed spectral data involves several techniques, each tailored to the specific parameters of interest and the characteristics of the water body being studied.

1. **Empirical Methods**: Empirical methods [53], [69], [96], [108] rely on statistical relationships between spectral signatures and water quality parameters. These relationships are derived through in situ measurements and laboratory analysis of water samples collected concurrently with satellite or airborne imagery. Once established, these algorithms can be used to estimate water quality parameters from remotely sensed data. The empirical approaches are simple as easy to implement for retrieving water quality.
2. **Semi-Empirical Methods**: Semi-Empirical methods [117], [119] combine physical models with empirical relationships to improve the accuracy of water quality parameter estimation. These methods utilize theoretical principles such as radiative transfer theory to model the interaction of electromagnetic radiation with water bodies. Then, empirical relationships are incorporated to calibrate the model using in situ measurements. This calibration helps to refine the model's predictions and enhance its accuracy. Semi-empirical methods are particularly useful when dealing with complex environmental conditions and diverse water types.
3. **Analytical Methods**: These methods [2], [66], [117] involve the development of mathematical models based on physical principles governing the interaction between light and water. These models consider various factors such as absorption, scattering, and reflection of light by water constituents. Examples include the radiative transfer equation and the bio-optical model. Analytical models are often used to simulate the spectral reflectance of water bodies under different conditions. By comparing simulated reflectance with observed spectral data, water quality parameters can be inferred. Analytical methods provide a deeper understanding of the underlying physical processes but may require significant computational resources.
4. **Artificial Intelligence (AI) Methods**: AI based methods [10], [81], [99], [103], [117] such as machine learning and deep learning, have gained popularity for extracting water quality parameters from remotely sensed data due to their ability to handle complex relationships and patterns. These methods involve training algorithms on large datasets of spectral data and corresponding water quality measurements. Neural networks, support vector machines, random forests, and convolutional neural networks are commonly used AI techniques. These algorithms learn the intricate relationships between spectral features and water quality parameters, enabling accurate predictions even in heterogeneous environments. AI methods offer flexibility and scalability, making them suitable for a wide range of applications and data types.

In addition to the aforementioned parameters, water quality assessments also address the presence of contaminants, notably volatile organic compounds (VOCs), which pose significant risks to public health and environmental integrity. These compounds, prevalent due to industrial activities, include aromatic hydrocarbons (AHs) and chlorinated hydrocarbons (CHCs). Some common VOCs found in water sources include tetrachloroethylene and trichloroethylene, particularly in groundwater reservoirs, as well as polynuclear aromatic hydrocarbons (PAHs). Monitoring and mitigating the impact of such contaminants are essential components of comprehensive water quality management strategies, aimed at ensuring the sustainability and safety of water resources for present and future generations.

Numerous research endeavors have employed diverse remote sensing sensors and methodologies to extract water quality parameters, yielding a spectrum of precision levels. Summaries of selected investigations leveraging remote sensing data for retrieval of various water quality parameters are consolidated and presented in Tables II.

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TABLE II
AN OVERVIEW OF MEASUREMENTS FOR WATER QUALITY PARAMETERS IN COMBINATION WITH VARIOUS MODEL IMPLEMENTATIONS FOR REMOTE SENSING APPLICATIONS

Water Quality Parameters	Data / Sensor	Algorithm / Model	Study Region	References
Chl-a/SPM/Turbidity/EC/TDS	RapidEye	Semi-Empirical	Borabey Dam, Turkey	[119]
TDS/TSM/EC/pH/DO/BOD/Turbidity	Landsat 8 OLI	Empirical	Tuby River, Philippines	[53]
TDS/COD/BOD/NH_3-N	ASD Spectrometer	Semi-Empirical/AI/Analytical	Sewage Treatment Plant, China	[117]
TDS/DO/Temperature	Landsat 8 OLI	Artificial Intelligence	Latian Dam, Iran	[99]
Chl-a/TSS	Landsat 8	Empirical	West Flood Canal, Indonesia	[108]
Chl-a/TSS	Sentinel 2 MSI	Empirical/AI	Unisinos University / Broa Dam, Brazil	[103]
Chl-a/TSS	Landsat 8 OLI	Empirical	Different Dams, South Africa	[69]
TDS/pH/TSM/Turbidity	Landsat 8 OLI	Empirical/AI	Deepor Beel Lake, India	[10]
TDS/TSM	Sentinel-2 MSI	Empirical/AI	Chah-Nimeh Reservoirs, Iran	[81]
Algal Bloom	GLIMR	Empirical	West & East Coasts, USA	[96]
Chl-a/TDS/TOC	Landsat 8 OLI/TIRS	Empirical	Sanalona Reservoir, Mexico	[90]
Chl-a	Sentinel-2 MSI	Empirical/AI	Lake Balik, Turkey	[14]
Chl-a	Sentinel-2 MSI	Semi-Empirical	Reservoirs, North Texas, USA	[106]
Chl-a	GOCI sensor, COMS	Empirical/AI	Bohai–Yellow Sea, China	[84]
Chl-a/TSS	Sentinel-2 MSI	Empirical/AI	Unisinos University / Broa Dam, Brazil	[60]
Chl-a	Sentinel 2 Level 1C	Empirical	Bhadra Reservoir, India	[61]
Chl-a/TSS/SD	Sentinel 2A / 2B	Empirical/AI	Auburn Bay Wet Pond, Canada	[68]
Chl-a/TDS/TOC	Landsat 8 OLI	Empirical	J. A. Alzate Dam, Mexico	[28]
Chl-a/TDS/Turbidity	Landsat 8 OLI	Empirical/AI	Lake Tana, Ethiopia	[64]
EC/TDS	Landsat 8 OLI	Empirical	Syrdarya River, Uzbekistan	[4]
TDS	Landsat 8 OLI	Empirical/Analytical	Shatt al-Arab River, Iraq	[2]
CDOM/Chl-a/TSM	Sentinel-3 OLCI	Empirical/AI	Baltic Sea	[113]
CDOM	Land Cover Atlas	Empirical/Analytical	Yangtze River, China	[66]
CDOM/Chl-a	Sentinel-2A	Empirical/AI	Lake Huron, USA	[26]
CDOM/TN/TP/NH_3-N	Imaging Spectrometer, China	Empirical/AI	Guanhe River, China,	[80]
CDOM/TSM/Chl-a	PRISMA Imaging Spectrometer	Analytical	Lake Trasimeno, Italy	[79]
CDOM	Landsat 8 OLI	Empirical/Analytical	Lake Huron, USA	[24]
COD/TOC/BOD	Landsat-5 TM	Empirical	Shenzhen, China	[116]
COD/Turbidity/TSS/BOD/DO	Landsat 8 OLI	Artificial Intelligence	Saint John River, Canada	[102]
COD/TN/TP	Proximal Hyperspectral Imager	Empirical/AI	Lake Taihu, China	[109]
COD	SeaWiFS	Empirical/Analytical	Pearl River, China	[22]
COD/BOD/DO	Landsat TM	Empirical/AI	River Beas, India	[59]
COD/TP/TN	Sentinel-2 MSI	Empirical/AI	Urban Lake, China	[47]
COD/TP/TN/BOD/Chl-a,	Unmanned Aerial Vehicle	Empirical/AI	Maozhou River, China	[120]
pH/Chl-a/DO/TSS/SDD/TDS	Sentinal-2A/Landsat 2A/Gokturk-2	Empirical/AI	Gala Lake, Turkey	[7]
pH/Chl-a/SDD/Turbidity	Sentinel-2 MSI/Landsat-8 OLI	Empirical	Tres Marias Reservoir, Brazil	[87]
pH/DO/COD/NH_3-H	Landsat-8 OLI	Empirical/AI	Taihu Lake, China	[88]
pH/PO4/EC/TSS/Turbidity	Landsat 8 OLI/TIRS	Empirical	Playa Colorada Bay, Mexico	[46]
TN/pH/BOD/DO/SS/TP	Landsat-5 TM	Empirical/Semi-Empirical	Chugoku, Japan	[51]
TN/SD/Chl-a/TP/TSS	Landsat TM	Empirical/AI	Lower Peninsula, USA	[114]
TN/TP/COD	Proximal Hyperspectral Imager	Empirical/AI	Taihu, Liangxi, and Fuchunjiang, China	[110]
Turbidity	Sentinel-2 MSI	Empirical	Baysh Dam, Saudi Arabia	[34]
Turbidity	Sentinel-2A/2B MSI	Semi-Empirical	Ganga River, India	[41]
Turbidity	Landsat 8 TIRS	Empirical/Analytical	Maine Coast, USA	[104]
SSC	Landsat 7 ETM+	Empirical	Indus River, Pakistan	[100]
SSC/Turbidity	Landsat 8 OLI/7 ETM+/4–5 TM	Empirical	Mississippi/Missouri Rivers, USA	[86]
BOD/pH/DO/TDS/TSS/Turbidity/EC	Landsat 8 OLI	Empirical	Tubay River, Philippines	[52]
BOD/TSS/SDD/Chl-a/TP/TN	ATI Multispectral Sensor	Empirical	Ponds, USA	[101]
BOD	LIDAR DTM/DSM	Empirical/Analytical	Thames River Basin, UK	[5]
BOD/pH/EC/DO/NO_3-N/SRP	Landsat 8 OLI/TIRS	Empirical/AI	Four Rivers, Bangladesh	[39]
SDT/Chl-a/TN/TP	Sentinel-2A	Empirical	Burullus Lake, Egypt	[48]
Chl-a/TP/SDT	Landsat 8 OLI	Empirical/Analytical	Maninjau Lake,Indonesia	[92]
Chl-a/TP/SDT	Landsat 8 OLI	Empirical	Riam Kanan Reservoir, Indonesia	[95]
Chl-a/PC/TSS/TN/TP/NO_3-N/pH	ATP2000P Spectrometer	Empirical/AI	Haihe River, China	[18]
NO_3-N	Landsat 8 MSI	Empirical/Analytical	Plesne Lake, Czech Republic	[97]
DO/NH_4-N/NO_3-N/N-phenol	Landsat TM5/ETM7/OLI8	Empirical	Erlong Lake, China.	[3]
TSS/OP/TP/NH_4-N/NO_3-N/DO/BOD	OW Network/3 Satellite	Empirical/Analytical	Occoquan Watershed,USA	[105]
NO_3-N/NH_4-N/COD/DO/pH	Landsat 5/7 ETM+/8 OLI	Empirical/Analytical	Mitidja Basin, Algeria	[23]
BOD/NO_3-N/TSS/DO/NH_3-N	Landsat 4/5/7/8 OLI-TIRS	Empirical/Analytical	Muar River, Malaysia	[29]
NH_3-H/N2O	Unmanned Aerial Vehicle	Empirical	University of Illinois, USA	[36]

III. METHODOLOGY

580 For this review article, a rigorous methodology was employed to identify relevant literature focusing on remote sensing and citizen science approaches for monitoring water quality. The aim was to comprehensively survey peer-reviewed papers pertaining to

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citizen science and remote sensing initiatives and their applications in monitoring water quality.

To access a wide range of scholarly works, two prominent academic databases, namely Web of Science and Scopus, were utilized. These databases offer extensive repositories of peer-reviewed literature across multiple disciplines, making them valuable resources for conducting comprehensive literature reviews. Moreover, each database provides distinct search functionalities and subject areas, enabling tailored searches to optimize the retrieval of relevant papers.

To ensure the inclusion of pertinent literature, the initial phase of literature search involved exploring various combinations of keywords as displayed in Fig. 3. These keywords were carefully selected to capture the breadth of the topic, ensuring a comprehensive exploration of the subject matter. Fig. 3 also presents the number of articles for each relevant combination of keywords.

The search results in both databases were further refined using filters such as *"Year,"*, *"Subject Area,"* and *"Article Source Type"*. In the Scopus database, the search was limited to specific subject areas: environmental sciences, social sciences, engineering, agricultural and biological sciences, computer science, and earth and planetary sciences. Within the Web of Science database, the selected subject areas included environmental sciences, ecology, water resources, engineering, science and technology other topics, remote sensing, computer science, public environmental and occupational health, agriculture, and geography. The *"Article Source Type"* filter contains attributes such as Article, Conference Paper, and Review for both databases.

The primary focus of this review article revolves around the integrated strategies and methodologies positioned at the intersection of citizen science and remote sensing for water quality monitoring as highlighted in the introduction and background section. Therefore, from the initial selected 1,489 number of research articles as presented in Fig. 4, we only chose those articles that are the result of searching keywords closely related to all three concepts namely citizen science, remote sensing, and water quality. This drastically reduces the achieved number of articles to 163. Table III presents the detailed division of the number of articles selected against each combination of keywords at this stage.

As the last step of the screening process, we remove possible duplicates and also manually remove any repeated or irrelevant articles that are not related to the review topic before reaching a comprehensive final aggregate of 47 articles within both databases as a result of keywords search that specifically addressed only the combined utilization of remote sensing techniques along with citizen science in the context of water quality assessment.

Fig. 4 offers a detailed summary of the literature searches and screening outcomes related to articles included in the systematic review. It outlines the pivotal stages of the screening process and illustrates the respective counts of articles incorporated at the implementation of each search filter; thereby, enhancing clarity regarding the selection methodology employed in this systematic review.

IV. Results of Literature Review

In the domain of water quality monitoring, combining remote sensing technologies with citizen science approaches has emerged as a promising strategy to improve data acquisition, analysis, and decision-making processes. This section presents the findings as a result of thorough screening process from the finalized 47 selected research papers, detailed in figure 4 of the *Methodology* section, highlighting recent advances in utilizing remote sensing techniques and citizen science methodologies for water quality assessment. Based on the findings from the literature search, this section is divided into three main categories presenting the frequently used methodologies concerning citizen science, remote sensing and the different estimated water quality parameters utilizing the mentioned approaches.

A. Frequent Citizen Science Approaches used for Water Quality Monitoring

In addressing the limitations of traditional water monitoring methods, it becomes evident that various citizen science-based approaches have been effectively employed to gather data for analyzing water quality across diverse water bodies.

From the selected studies, a range of citizen science based methodologies are implemented, including crowd-sourced data collection through smartphone applications [9], [15], [20], [40], [55], [63], [70], [73], [75], participatory sampling campaigns (PSP) [13], [37] based on conducting water quality sampling through utilization of airborne sensors including drones or placing sensors as part of other equipments used by professionals, and lastly community-based environmental monitoring (CBEM) programs [33], [38], [44] involving the scientific data collection involving the participation of youth, elders, researchers, and experts.

Figure 5 illustrates the distribution and frequency of these approaches across different studies, highlighting the versatility and comprehensiveness of citizen science initiatives in water quality monitoring.

B. Remote Sensing Methodologies

The literature surveyed deeply investigates into frequently used remote sensing methodologies to assess changes in water quality monitoring over time. Among the array of studies examined, diverse remote sensing

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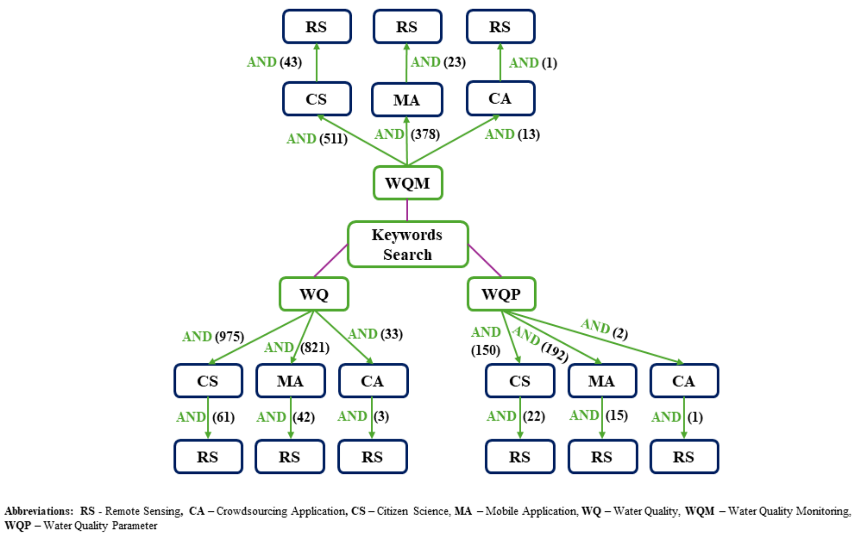

Fig. 3. The figure illustrates the combination of diverse set of keywords utilized within the search query system, encompassing keywords related to citizen science, remote sensing, and water quality monitoring.

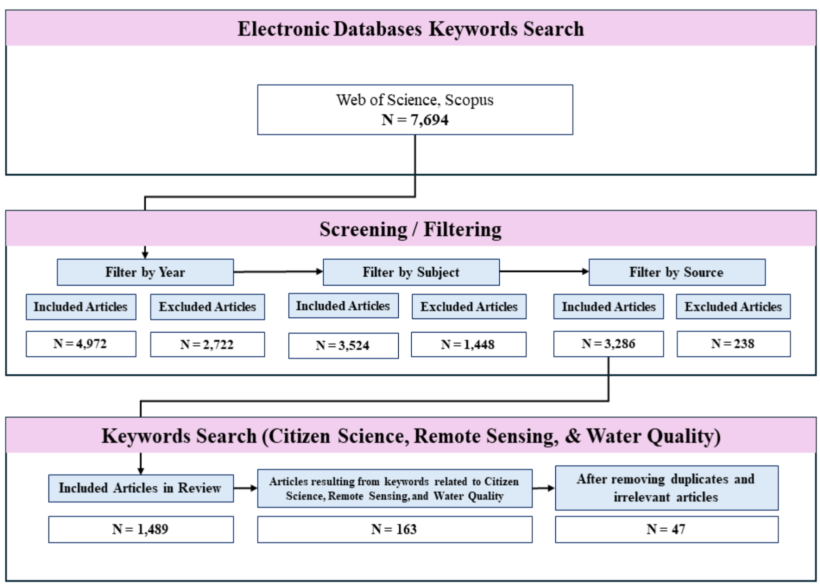

Fig. 4. The figure presents the sequence of steps performed and the results for screening of literature review at each stage.

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TABLE III
EXTRACTED NUMBER OF ARTICLES FOR EACH COMBINATION OF KEYWORDS RELATED TO CONCEPTS OF REMOTE SENSING, CITIZEN SCIENCE, AND WATER QUALITY MONITORING WITHIN THE TWO DATABASES.

List of Keywords	**Number of Papers**	
	Scopus	**Web of Science**
“Remote Sensing” AND “Citizen Science” AND “Water Quality”	16	27
“Remote Sensing” AND “Mobile Application” AND “Water Quality”	16	18
“Remote Sensing” AND “Crowdsourcing Application” AND “Water Quality”	2	1
“Remote Sensing” AND “Citizen Science” AND “Water Quality Parameter”	7	11
“Remote Sensing” AND “Citizen Science” AND “Water Quality Monitoring”	14	15
“Remote Sensing” AND “Mobile Application” AND “Water Quality Parameter”	7	7
“Remote Sensing” AND “Mobile Application” AND “Water Quality Monitoring”	9	11
“Remote Sensing” AND “Crowdsourcing Application” AND “Water Quality Parameter”	1	-
“Remote Sensing” AND “Crowdsourcing Application” AND “Water Quality Monitoring”	1	-

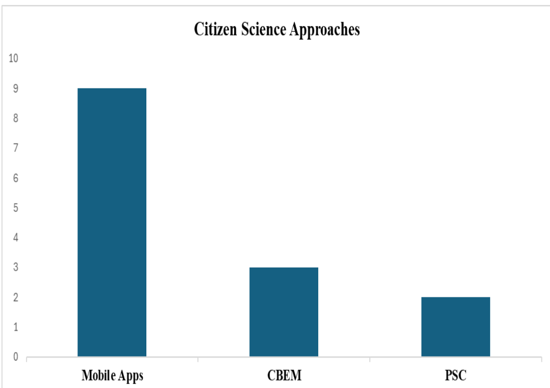

Fig. 5. The image depicts the distribution and variety of citizen science approaches across different research articles.

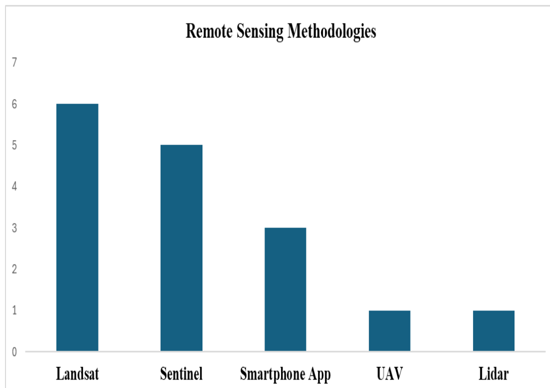

Fig. 6. The image presents the number (y-xis) and types (x-axis) of different remote sensing sensor technologies utilized in research articles.

approaches were employed to analyze shifts in landscape dynamics and ecological trends. An overview is depicted in Figure 6, which highlights the distribution and frequency of the remote sensing methods across multiple research works for analyzing water quality.

Predominantly, most of the studies involving remote sensing methodologies are concentrated on utilizing spatial and temporal data of Landsat Satellite [8], [11], [27], [67], [83], [121]. Other notable studies explored remote sensing techniques for monitoring water bodies include Sentinel Satellite [45], [57], [82], [83], [83], smartphone Camera Applications for Remote Sensing [15], [63], [70], Lidar [35], and Unmanned Aerial Vehicle (UAV) [65].

C. Common Estimated Water Quality Parameters

The reviewed literature included the estimation of various water quality parameters for analyzing water quality of water bodies. Within the finalized number of reviewed studies, various water quality parameters are estimated across different studies. A comprehensive summary is illustrated in figure 7 revealing the frequency and diversity of these parameters across multiple research studies.

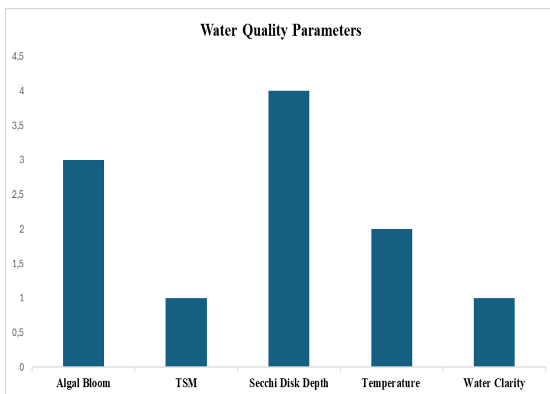

Fig. 7. The figure presenting the number of papers on the y-axis and the involved water quality parameter in the research studies on the x-axis.

Most of the studies focused on the estimation of

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Secchi Disk Depth [50], [67], [83], [93] parameter for assessing the water quality. There were also some studies which focused on other water quality parameters including algal blooms [8], [11], [57], [70], total suspended matter (TSM) [121], temperature [30], [74], [75], [82], [94], and water clarity [50], [67], [83].

V. Citizen Science for Water Quality Analysis

In recent years, the fusion of remote sensing technologies and citizen science has revolutionized water quality monitoring efforts. Leveraging the ubiquity of mobile devices and the power of crowdsourcing, citizen science-based mobile applications have emerged as invaluable tools in this domain. These applications not only empower individuals to contribute to scientific endeavors but also enable real-time data collection on a scale previously unimaginable. In this section, we delve into the diverse functionalities offered by various citizen science-based mobile applications dedicated to water quality analysis. From basic data collection to sophisticated analytical capabilities, these applications play a pivotal role in enhancing our understanding of water ecosystems and addressing environmental challenges.

A. Mobile Applications for Measuring Water Quality

1) HydroColor: HydroColor [62] is a mobile application designed for measuring the remote sensing reflectance of water bodies. It employs the smartphone's digital camera as a three-band radiometer for calculating reflectance in the red, green, and blue broad wavelength bands of the collected input images. Eq 1 from Mobley [76] is used for determining the remote sensing reflectance of the water surfaces:

$$R_{rs} = \frac{L_t - \rho L_t}{\frac{\pi}{R_{ref}} L_c} \tag{1}$$

where L_t is the radiance leaving the water surface, L_s is the radiance of the sky, R_{ref} is the standard irradiance reflectance of a reflectance standard (18% gray card is used here), L_c is the measured radiance leaving the reflectance standard, and ρ is the sea surface reflectance factor.

To calculate the value of reflectance following eq 1, the user captures three images of the gray card, the sky, and the water surface. The application guides the user to orient the smartphone correctly using the internal compass and gyroscope ensuring accurate measurement by removing surface-reflected light entering the camera. The collected images are processed within the HydroColor application for the calculation of the remote sensing reflectance.

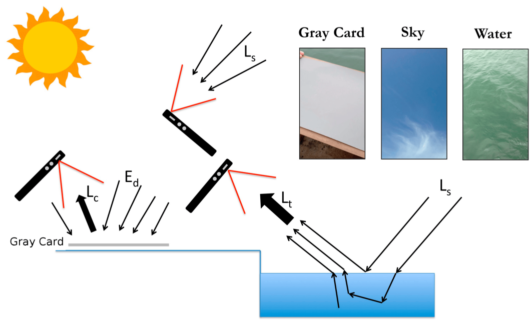

Fig. 8. The schema of data acquisition using HydroColor application (Picture Source: (Leeuw & Boss, 2018 [62]))

2) EnviObserver: The paper [58] presents a water quality monitoring approach called Secchi3000. The proposed architecture consists of a mobile application that allows the users to act as sensors by reporting the environmental observations using the mobile application. The performed analysis for measuring water quality makes use of the Secchi3000 device consisting of a container filled with water and two tags placed inside the device at different depths for measuring the water turbidity. After the device is filled with water, the user takes a picture through a hole while looking inside the container. The acquired picture along with additional information (GPS location, and measurement site ID) is sent to the server for automated water quality analysis. Here initially the application implements a tag recognition algorithm to extract the black, grey, and white areas within the two tags. Following tag recognition, the application employs a second algorithm dedicated to water quality analysis. This algorithm utilizes the RGB values extracted from the tags to assess the water quality.

3) SIMILE - Lake Monitoring: As part of the SIMILE (Informative System for the Integrated Monitoring of Insubric Lakes and their Ecosystems) Interreg Italy-Switzerland project, the water quality monitoring of the Maggiore, Como, and Lugano lakes is facilitated through the integration of techniques including in situ monitoring with buoys, remote sensing and the development of a citizen science mobile application. The mobile application [19] functions as a crucial tool for monitoring and preserving lake water quality, encompassing several key features. Initially, the users can precisely locate themselves on a map, ensuring their observations are accurately positioned. The primary function involves users submitting data, including mandatory picture observations, to assess lake areas. Additionally, users can provide supplementary details such as weather conditions and the presence of various elements like algae or oil stains, enhancing

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the observation's value. The application allows users to view both their own and others' entries on the map, fostering community engagement and awareness. The users also receive notifications about local initiatives and events, promoting involvement in lake conservation efforts. Emphasizing the project's objectives, the system operates as free and open-source software, aligning with the SIMILE project's commitment to promoting knowledge sharing.

4) EyeOnWater: EyeOnWater [16] revolutionizes water monitoring through a user-friendly smartphone application designed to estimate surface water color accurately. Leveraging the built-in capabilities of modern smartphones, including the camera, GPS receiver, accelerometer, and clock, the app seamlessly acquires essential data. When a user initializes the application, the user is navigated through specific instructions via an introductory video, ensuring optimal data collection. These instructions allow the user to correctly position the smartphone in relation to water surface and position of the sun when capturing an image. Once the user captures the image, they assign a color from the digital comparator scale of Forel-Ule (FU), conveniently provided within the application. Subsequently, users respond to two simple questions regarding rainfall and water bottom visibility. The captured image, along with the selected color index and user responses, is securely stored on the project server for further analysis (see Figure 4c). While additional tools such as a Secchi disk and paper/plastic based FU scale palette are optional, users may enhance data accuracy by providing Secchi depth and observed FU index values. Developed by a consortium including the Royal Netherlands Institute for Sea Research, Vrije University of Amsterdam, MARIS, and Veeder under the Citclops project (EU H2020), EyeOnWater is readily accessible on both the App Store and Google Play. Although not open-source, the application boasts intuitive usability, preventing image capture until quality controls, such as proper smartphone positioning, are met. A minor limitation lies in the application's post-processing, which exclusively provides FU values, neglecting parameters such as turbidity and total suspended solids. However, these parameters could be computed externally to augment the application's analytical capabilities.

5) Sechhi App: The Secchi Disk mobile application [98] serves as a comprehensive tool for citizen scientists and seafarers to measure ocean transparency and phytoplankton levels using a simple and cost-effective method. Users can access the application on iOS and Android devices as a native app or via a web browser on Windows operating systems. The application provides detailed instructions on making and using a Secchi Disk, including optimal measurement conditions such as time of day, sun position, and cloud cover. To

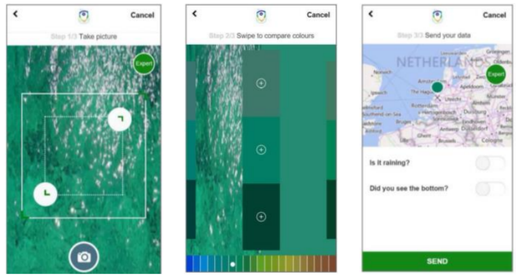

Fig. 9. Left to Right: (a) Capturing an image (b) Picking the color of water surface (c) Proving additional details for water quality monitoring (Source: ©Google Maps) (Image adapted from Stefan et al., 2019 [54]))

record a Secchi depth, users first use the application to obtain GPS coordinates, date, and time using the device's GPS receiver. They then lower the Secchi Disk into the sea and record the depth at which it disappears from sight. This data can be stored locally on the device and uploaded to an online database when connected to a network. Additionally, users can provide supplementary observations such as sea temperature, text notes, and photographs (if the device has a camera). The uploaded data is visualized on an interactive map publicly available on the Secchi Disk study website, allowing for easy access and analysis of collected data.

6) Hydro Crowd: The developed mobile application, created through close collaboration with hydrologists at the University of Oulu, aims to facilitate crowd-sourced data collection for various hydrological scenarios. HydroCrowd allows random users to contribute observations via a template questionnaire, textual descriptions, and image uploads. The crowdsourced data are stored in an online database, subsequently utilized to update corresponding hydrological models. Four distinct hydrological scenarios are addressed: Urban Flood, Vegetation Conditions, Lake Water Quality, and River Ice Properties. Implemented as an Android app using the Flutter framework, HydroCrowd features a user-friendly interface guiding users through sign-up, sign-in, and scenario selection processes. Each scenario prompts users to provide specific information relevant to the scenario, such as water depth and area coverage for Urban Floods, algae presence for Lake Water Quality, ice properties for River Ice, and vegetation details for Vegetation Conditions. The app validates submitted data before storing it in the online database. Additionally, HydroCrowd includes help functionalities to guide users through filling in information screens and understanding key hydrological terminologies, ensuring accurate and meaningful contributions from users. Overall, the application streamlines crowd-sourced data collection for diverse hydrological scenarios, enhancing

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the efficiency and effectiveness of water quality monitoring efforts.

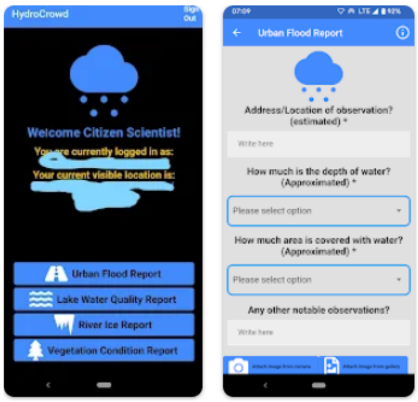

Fig. 10. From left to right: Fig (a) Home Page Fig (b) Urban Flood Report page. (Image Source: Retrieved from ©Google Play (www.play.google.com))

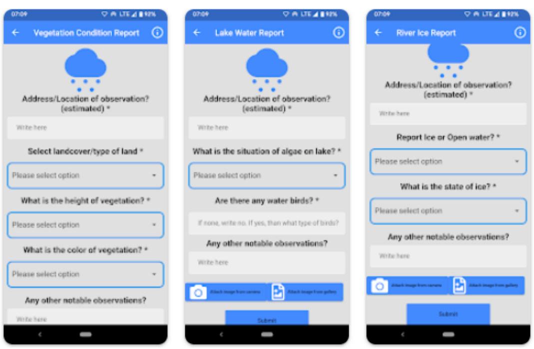

Fig. 11. From left to right: Three screens corresponding to different scenarios Fig (a) Lake Water Quality Fig (b) River Ice Properties Fig (c) Vegetation Conditions. (Source: Retrieved from ©Google Play

The table IV below provides a comprehensive overview of mobile applications utilized in citizen science projects for water quality monitoring. It details the names of these applications, the platforms they are available on, associated costs, as well as accessibility to source code and data. This summary provides valuable insights for researchers, practitioners, and stakeholders interested in leveraging citizen science for water quality analysis, facilitating informed decision-making regarding the selection and utilization of these tools in environmental monitoring endeavors.

VI. Discussion

In essence, conventional methods for monitoring water quality parameters through on-site measurements are not only expensive but also demand continuous laboratory and field efforts. Conversely, the utilization of remote sensing techniques alongside geospatial tools presents a cost-efficient avenue for comprehensively assessing water quality parameters across vast spatial extents with reliable temporal consistency. Both spaceborne and airborne remote sensing sensors demonstrate the potential to accurately estimate water quality parameters. The derivation of these parameters from remote sensing imagery entails a variety of methodologies, including Empirical, Analytical, Semi-Empirical, and Artificial Intelligence (AI) techniques.

Multispectral sensors have gathered widespread adoption in water quality monitoring, largely owing to the global availability of their imagery. Their utilization is particularly gaining traction in developing regions. However, the use of multispectral imagery, such as MERIS, in the examination of small inland lakes may present accuracy challenges due to its coarse resolution. Coarse-resolution images, wherein one pixel represents a sizable area, pose a potential source of error as distinct features within small regions may not be adequately captured. For instance, a study comparing the Chinese high-resolution GF-1 Wide Field Imager (WFI) data with MODIS for Suspended Particulate Matter (SPM) estimation revealed significant spatial distribution and concentration consistency between GF-1 and Landsat 8 OLI data. GF-1 effectively resolved over 75% of spatial variations, whereas MODIS, with its 250-meter resolution, only addressed 40%, underscoring the limitations of coarser-resolution imagery like MODIS.

The use of Unmanned Aerial Vehicle (UAV) airborne sensors is witnessing an upward trajectory due to their rapid advancement. Airborne spectrometers offer efficient and adaptable solutions to mitigate temporal, spectral, and spatial resolution limitations associated with certain satellite sensors.

Remote sensing based retrieval of water quality parameters hinges upon the optical properties of the water. Parameters such as total suspended solids (TSS), colored dissolved organic matter (CDOM), chlorophyll-a concentration, and turbidity can be directly inferred from remote sensing images due to their optical activity. Conversely, optically weak or inactive parameters like total dissolved solids (TDS), total nitrogen (TN), total phosphorus (TP), chemical oxygen demand (COD), and pH can be estimated through correlation with optically active parameters.

Based on the literature survey, the following table V recommendations are proposed for future endeavors in water quality assessment.

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TABLE IV
SUMMARY OF THE REVIEWED CITIZEN SCIENCE BASED MOBILE APPLICATIONS FOR MONITORING WATER QUALITY

Application	Cost	Platforms	GitHub / Project Site	Open Access to Data
HydroColor	Free	Android / iOS	github.com/Thomas-Leeuw/HydroColor	No Access
Sechhi App	Free	Android / iOS	playingwithdata.com/secchi-disk-project	User's own data can be downloaded
SIMILE App	Free	Android / iOS	github.com/interreg-simile/simile-app	No Access
Lake Observer	Free	Android / iOS	lakeobserver.org	Yes (lakeobserver.org)
EyeOnWater	Free	Android / iOS	eyeonwater.org	Yes (eyeonwater.org)
Hydro Crowd	Free	Android	No Access	No Access

TABLE V
RECOMMENDATIONS FOR INTEGRATING REMOTE SENSING AND CITIZEN SCIENCE IN WATER QUALITY MONITORING

Sr.No	Recommendations	Description
1.	Incorporating Citizen Science Approaches with Remote Sensing Data	Citizen scientists can contribute valuable ground-truth data, enhance spatial coverage, and validate remote sensing-derived water quality parameters. Establishing platforms for citizen engagement and collaboration can strengthen community involvement in environmental stewardship.
2.	Automated Data Processing Pipelines	Implement automated data processing pipelines to streamline the analysis of remote sensing imagery. This includes pre-processing steps such as atmospheric correction, image registration, and feature extraction. Utilizing cloud-based computing resources can expedite data processing tasks and facilitate timely dissemination of water quality information.
3.	Enhancement of Spatial-Temporal Monitoring	Expand the spatial and temporal resolution of monitoring efforts by integrating data from diverse remote sensing platforms. This includes satellite-based observations, UAVs, and ground-based sensors. By combining data from multiple sources, researchers can capture fine-scale variability in water quality parameters and monitor changes over time with greater accuracy.
4.	Incorporation of Advanced Data Fusion Techniques	Explore advanced data fusion techniques to integrate multi-source remote sensing data effectively. Fusion methods such as Bayesian inference, data assimilation, and multi-resolution analysis can synergistically combine information from disparate sensors, enhancing the reliability and robustness of water quality assessments.
5.	Development of Open-Source Analytical Tools	Foster the development of open-source analytical tools tailored for water quality monitoring applications. Providing access to user-friendly software packages and algorithms encourages collaboration, transparency, and reproducibility in research endeavors. Additionally, investing in capacity building programs can empower stakeholders to leverage remote sensing data for informed decision-making.
6.	Promotion of Interdisciplinary Research Collaborations	Encourage interdisciplinary collaborations between remote sensing scientists, water resource experts, policymakers, and stakeholders. By fostering cross-disciplinary dialogue and knowledge exchange, researchers can address complex water quality challenges from holistic perspectives and develop innovative solutions grounded in scientific rigor and practical relevance.

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