remote sensing

Review

Monitoring Water Diversity and Water Quality with Remote Sensing and Traits

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Abstract: Changes and disturbances to water diversity and quality are complex and multi-scale in space and time. Although in situ methods provide detailed point information on the condition of water bodies, they are of limited use for making area-based monitoring over time, as aquatic ecosystems are extremely dynamic. Remote sensing (RS) provides methods and data for the cost-effective, comprehensive, continuous and standardised monitoring of characteristics and changes in characteristics of water diversity and water quality from local and regional scales to the scale of entire continents. In order to apply and better understand RS techniques and their derived spectral indicators in monitoring water diversity and quality, this study defines five characteristics of water diversity and quality that can be monitored using RS. These are the diversity of water traits, the diversity of water genesis, the structural diversity of water, the taxonomic diversity of water and the functional diversity of water. It is essential to record the diversity of water traits to derive the other four characteristics of water diversity from RS. Furthermore, traits are the only and most important interface between in situ and RS monitoring approaches. The monitoring of these five characteristics of water diversity and water quality using RS technologies is presented in detail and discussed using numerous examples. Finally, current and future developments are presented to advance monitoring using RS and the trait approach in modelling, prediction and assessment as a basis for successful monitoring and management strategies.

Keywords: water diversity; water quality; traits; earth observation; remote sensing; water trait diversity; water genesis diversity; water structural diversity; water taxonomic diversity; water functional diversity

1. Introduction

The sea, inland waters and rivers are crucial to the life and survival of all individuals and fulfil central functions in our aquatic and wider ecosystems [1]. They provide habitats and critical niches for a wide range of species and are essential components of water, carbon and nutrient cycles [2]. However, land use intensity (LUI), climate change, urbanisation and tourism are leading to major changes and even the complete destruction of the ecological functions and resilience of water bodies due to multiple interacting stress factors [3,4]. Local to global changes in the world's freshwater ecosystems are already apparent due to physical, chemical and biological changes [5], such as the biotic homogenisation of algae in watersheds (i.e., the decreasing differences in taxonomic and functional characteristics of algal communities) [6], the influence of microplastics [7,8], the effect in antibiotics [9], the increase in browning [10] or the increase in eutrophication and excess nitrogen in water bodies [11]. Many studies assume that the productivity of aquatic ecosystems will increase as a result of global warming [12–15] due to increased nutrient inputs and the intensification of internal nutrients. However, changes in stratification due to warming can also lead to (longer) interruptions to internal nutrient cycling. It is also evident that species respond very differently to, for example, heat stress in water bodies [16]. This requires a well-founded differentiation of species and knowledge of phylogeny, the entire aquatic ecosystem and its influencing factors in order to better understand the responses of organisms and ecosystems to environmental change.

Numerous national and international guidelines have been developed, such as the Water Framework Directive in Europe (https://environment.ec.europa.eu/topics/water/water-framework-directive_en, accessed on 26 June 2024), the US Clean Water Act (https://www.epa.gov/sites/default/files/2017-08/documents/federal-water-pollution-control-act-508full.pdf, accessed on 26 June 2024), the National Water Management Strategy of Australia and New Zealand (https://www.waterquality.gov.au/sites/default/files/documents/nwqms-charter.pdf, accessed on 26 June 2024), the Canada Water Act (https://laws-lois.justice.gc.ca/eng/acts/c-11/, accessed on 26 June 2024), and the International Initiative on Water Quality (IIWQ) of UNESCO's International Hydrological Programme (IHP) (https://www.unesco.org/en/ihp, accessed on 26 June 2024), which aim to maintain and sustainably improve the ecological status of water bodies. Improving water quality is one of the world's greatest societal challenges and is, therefore, a key issue in the UN 2030 Agenda for Sustainable Development Goal 6: "Ensure availability and sustainable management of water and sanitation for all". Strategies and actions to achieve this goal require the coherent measurement, analysis and visualisation of water quality from regional to global scales. The GlobeWQ project (https://www.globewq.info/, accessed on 26 June 2024) is embedded in the World Water Quality Alliance, led by the UN Environment Programme, with the challenging task of producing a World Water Quality Assessment of current and future freshwater quality. A common goal of these guidelines is to improve water quality by identifying pollutants and implementing sustainable management strategies that can be achieved through continuous monitoring of all water bodies [17–19]. Current monitoring programmes use labour-intensive, costly and time-consuming in situ methods such as distributed sampling, analysis, point measurements or other comparable methods. Although these provide detailed information on the physical, chemical and biological status of water bodies, their local and selective monitoring and low temporal resolution can lead to inaccurate assessments and, consequently, a false categorisation of water quality [20,21]. The temporal and spatial variability of phenomena and ongoing processes and changes, as well as disturbances caused by, for example, short-lived cyanobacteria or phytoplankton blooms in water bodies, cannot be sufficiently monitored by infrequent in situ point sampling measurements [22,23].

To gain an ecosystem-level understanding of water bodies and the role of lakes "as sentinels, integrators and regulators of climate change" [24], there is an urgent global need for long-term monitoring approaches that can capture standardised and transferable spatio-temporal monitoring of water status, quality and change [21]. Ecologists have repeatedly proposed the use of remote sensing (RS) for monitoring water diversity and water quality and coupling it with locally conducted in situ measurements to take advantage of both area-scale RS information and local measurements [25]. Complementary approaches such as the synergistic use of innovative RS technologies, in situ sensors and measurements, databases and modelling approaches are required to provide an assessment of the ecosystem integrity of water status and its health [25,26].

RS techniques are already being used to successfully monitor, model and assess terrestrial ecosystem properties such as vegetation diversity [27,28], geodiversity [29–31], geomorpho-diversity [32] and hydrology [33] to assess the quality and support the sustainable management of marine and coastal protected areas [34]. For some time now, various water characteristics and water quality indicators have been used, such as turbidity, chlorophyll-a, harmful algal bloom indicators and total absorption (IIWQ World Water Quality Information and Capacity Building Portal, https://www.eomap.com/world-water-quality/about-iiwq-portal/, accessed on 26 June 2024), which have been merged as global datasets based on different RS time series from RS missions such as Landsat and Copernicus or hyperspectral RS satellites (e.g., EnMAP and PRISMA) (https://climate.esa.int/en/projects/lakes/, accessed on 26 June 2024). Recent technological developments and satellite missions such as the DLR Earth Sensing Imaging Spectrometer (DESIS, [35], the hyperspectral Environmental Mapping and Analysis Programme (EnMap, [36]) and the first space-based GEDI Ecosystem LiDAR [37]) or ICESat-2 [38] are now available and largely free of charge. They help us to gain a deeper understanding of the processes and to specifically monitor water heat, water properties, processes and interactions. NASA's future Surface Biology and Geology (SBG) missions (https://sbg.jpl.nasa.gov/, accessed on 26 June 2024) with the Hyperspectral Infrared Imager (HyspIRI) will be particularly important for RS-based monitoring of water quality, as the sensor combination of hyperspectral and the Thermal Infrared RS (TIR) will simultaneously record and continuously monitor various water quality characteristics as well as additional vegetation and geodiversity characteristics on local to global scales [39].

The basic reason why RS can capture changes in water quality characteristics is that the spectral reflectance and absorption of pixels in an optical RS image is the result of complex interactions between light (the atmosphere); the water surface; the genesis; and optical, biochemical–biophysical, morphological, physiological, phenotypical, structural, taxonomic and functional characteristics of water and its constituents, such as phytoplankton [40] and water quality [41], vegetation [42], geodiversity [30,32] and their interactions [43]. The basis of the trait approach is the Spectral Variation Hypothesis (SVH) approach [44]. The Spectral Variation Hypothesis states that the pixel-to-pixel variability of the spectral response in an RS image is determined by several factors, such as environmental diversity, the diversity of biochemical and structural characteristics, e.g., leaf and canopy properties, as well as functional vegetation properties and their responses through interactions with the topography, soil and geodiversity as an expression of the integrability of the spectral signal and its changes [44]. RS can capture traits and trait variations. Therefore, traits are crucial indicators and proxies of terrestrial and aquatic status, opportunities, disturbances and resource limitations. They are also a crucial link between in situ and RS monitoring approaches [45]. Therefore, RS and the traits approach are appropriate for assessing changes to water diversity and water quality.

The traits approach for water has already been mentioned by numerous studies in the past, but they mainly refer to in situ measurements [41,46–51]. The traits approach is crucial for a better understanding of why organisms live where they do and how they respond to environmental change [52]. To date, trait approaches with RS have only been in the context of terrestrial vegetation diversity [45,53,54], forest heath [55–57], geodiversity (soil characteristics [31], geomorphology, [32], urban intensity [58] or social-ecological systems [59].

Therefore, the aims of this paper are as follows: (i) to apply the RS-based traits approach to aquatic and marine systems for the first time. For this purpose, five characteristics of aquatic diversity have been defined, namely: the diversity of water traits, the diversity of water genesis, the structural diversity of water, the taxonomic diversity of water and the functional diversity of water; (ii) to illustrate how RS technologies can monitor these five traits of water diversity; (iii) to summarise the characteristics of water diversity; and (iv) to discuss the future opportunity of an integrative approach and application of traits and RS to integrate a more focused RS and trait approach into water quality assessment and sustainable management.

2. Definition and Standards of Water Quality and Water Characteristics

The assessment of water quality is based on a set of definitions and standards established by various organisations. Monitoring of water quality and water characteristics is often conducted by in situ measurements, but the specific tests and measurements used will depend on the water's intended use for rivers, lakes, groundwater or drinking water. Here are some of the key parameters and definitions that are commonly used:

Physical characteristics: These relate to parameters such as light (Photosynthetically Available Radiation—PAR), temperature (thermal stratification), conductivity, transparency, colour, turbidity (clarity) and total suspended solids. The presence of suspended materials such as clay, silt, fine organic material, plankton and other inorganic materials in water is referred to as turbidity, which is a measure of water clarity. For example, the oxygen saturation in water depends on the temperature, and a higher level of turbidity can indicate pollution (Environmental Protection Agency (EPA), https://www.epa.ie/pubs/advice/water/quality/Water_Quality.pdf, accessed on 26 June 2024).

Chemical characteristics: These include parameters such as pH; hardness; alkalinity salinity; nutrients; dissolved organic carbon; anions such as chloride and sulphate; and cations such as calcium, natrium, magnesium, iron and manganese and the concentration of dissolved oxygen. Nutrients such as nitrogen, phosphorus and silicon are measured to estimate the eutrophication level [60]. The presence and concentration of chemicals that can be harmful to humans or ecosystems are also included, such as heavy metals or persistent organic pollutants (US Geological Survey, https://www.usgs.gov/, accessed on 26 June 2024).

Biological characteristics: These refer to the microbial quality of water, such as the presence and quantities of bacteria, viruses, microalgae, fungi and other microorganisms. Certain types of bacteria (e.g., *Escherichia coli*) are used as indicators of water pollution, especially from faecal sources (World Health Organization, https://www.who.int/publications/i/item/9789241549950, accessed on 26 June 2024).

Ecological characteristics/bioindicators: Certain species of animals (insect larvae, snails, mussels, amphibians and fish) and/or plants (cyanobacteria, microalgae, submerged macrophytes and reeds) serve as bioindicators of the state of an ecosystem. The presence or absence of species and changes in their populations can provide important information on the condition and changes to the water body and its environmental conditions and anthropogenic influences [60].

Standards and Guidelines

The recording of water quality and water properties is based on various standards and guidelines that are defined by several international organisations and frameworks. These organisations and guidelines significantly shape the way in which water properties and water quality are recorded and assessed worldwide. They provide frameworks to protect and promote both environmental impacts and human health. Here are some of the most important organisations and their associated guidelines:

3. Definition of Water Diversity Using Remote Sensing

The recording of water quality and thus water constituents is one of the most frequently requested RS applications. Due to the immense scale of the area to be monitored worldwide, the integration of RS technologies into a water monitoring system was not put into practice until the early 1980s [61]. However, RS approaches represent a target-oriented approach to monitor the properties and changes to water quality based on the following criteria:

RS can capture the traits and trait variations of water characteristics and water quality as well as those of plants, vegetation, geodiversity, geomorphology and land use intensity. Consequently, RS-based water quality monitoring can monitor not only water quality traits but also the terrestrial compartments of geodiversity and vegetation diversity and take into account the process interactions and drivers of water quality. The spectral reflectance and absorption of pixels are the result of interactions between light (the atmosphere), phylogenetic/genesis, biophysical, biochemical, physical, morphological, physiological, phenotypic, structural, taxonomic and functional traits of the captured characteristics of water, vegetation and geodiversity, as well as their interactions between vegetation diversity and geodiversity [42,43].

The traits approach forms the basis for the in situ monitoring [41] and RS monitoring of water quality and is therefore a crucial link between the two monitoring approaches [45]. Therefore, in the context of monitoring water diversity and water quality using RS, a new definition of monitoring water diversity and quality is required.

Water diversity can be described by its five characteristics, namely: the diversity of water traits, the diversity of water genesis, the structural diversity of water, the taxonomic diversity of water and the functional diversity of water (modified after Lausch et al. [62]). These five characteristics of water diversity exist on all spatial and temporal scales and can be defined as follows (modified after Lausch et al. [32]):

(I) The diversity of water traits, which represents the diversity of the biochemical-, physical, optical, morphological-, structural-, textural- and functional characteristics of water traits that affect, interact with or are influenced by their genesis-, taxonomic-, structural- and functional diversity;
(II) The diversity of water genesis, which refers to the diversity of the length of evolutionary pathways associated with a particular set of water traits, taxa, structures and functions of water diversity. Therefore, groups of water traits, water taxa, water structures and water functions that maximise the accumulation of functional diversity of water diversity are identified;
(II) The structural diversity of water, namely, the diversity of the composition and configuration of water characteristics;
(IV) The taxonomic diversity of water, representing the diversity of water components that differ from a taxonomic perspective;
(V) The functional diversity of water, which is the diversity of water functions and processes, as well as their intra- and interspecific interactions.

A clear separation and assignment of the five characteristics of water diversity monitored by RS is not always possible but nevertheless helps to monitor, assign and assess the various indicators derived with RS, as well as to understand the links between in situ and RS approaches [62].

4. Approaches for Monitoring Water Diversity and Water Quality

There are two methods for monitoring water characteristics and water diversity, as well as its properties, health and changes. These are in situ/field observations and the RS approach (see Figure 1).

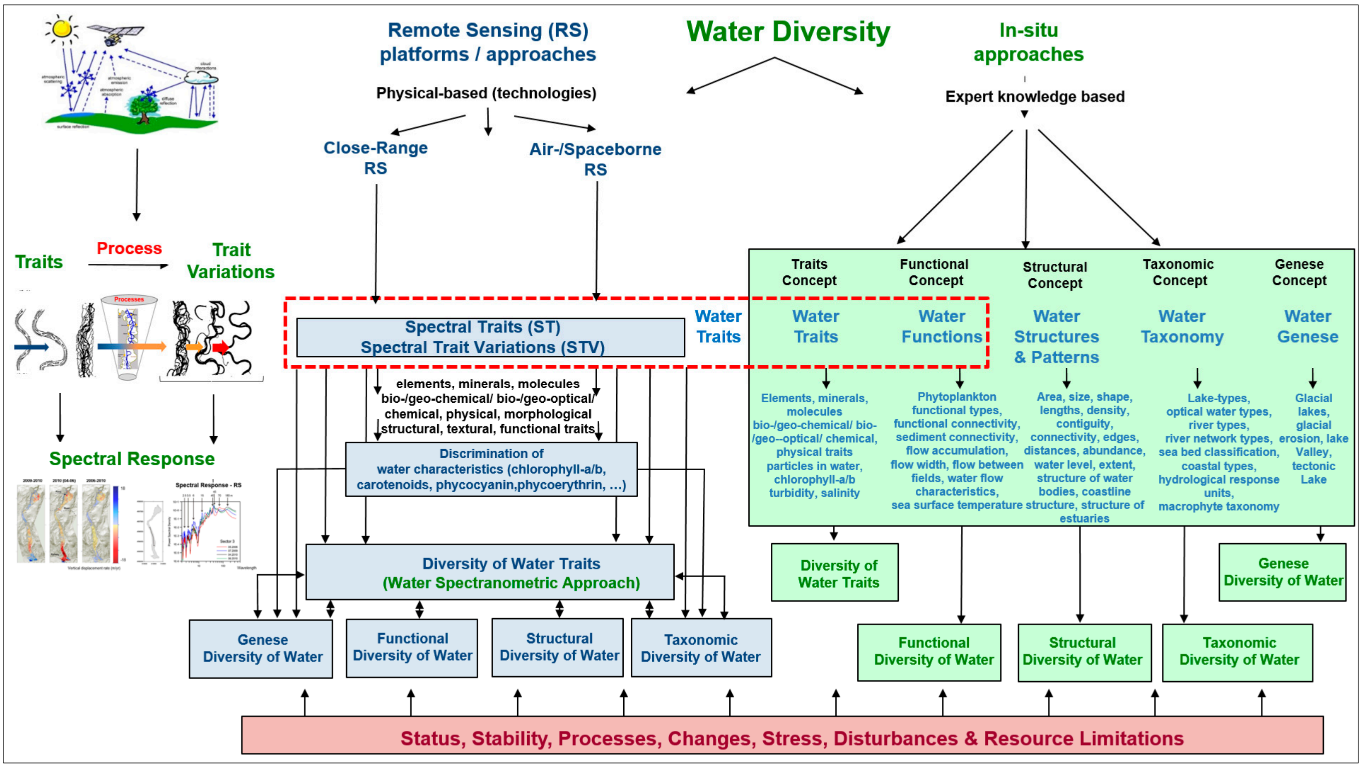

Figure 1. In situ and remote-sensing approaches and the five characteristics of water diversity (diversity of water traits, diversity of water genesis, structural diversity of water, taxonomic diversity of water and functional diversity of water). Diversity of water traits is the most important link between in situ and RS monitoring approaches (modified after Lausch et al. [32]).

4.1. In Situ Approaches

In situ monitoring refers to the direct expert recording, identification and monitoring of changes to water characteristics (traits), their diversity and health. Alexander von Humboldt was one of the first to adopt a holistic and standardised approach to in situ monitoring, in which the traits and processes of hydro-, geo- and biodiversity were observed, compared and evaluated, and their interactions and feedback mechanisms were recorded [63–65]. Organisations and guidelines (see Table 1) have a decisive influence on the way in which water properties and water quality are recorded and evaluated in a standardised manner worldwide (see Table A1, Appendix A).

In situ water quality monitoring is based on sampling and on-site observations. Increasingly, however, in situ measurements are also supported by reagent-free, low-maintenance, autonomous and continuous monitoring sensors and aquatic wireless sensor networks (WSN) ([66–68], such as the GLEON network (Global Lake Ecological Observatory Network) https://gleon.org/ accessed on 26 June 2024). Furthermore, low-cost automated GPS, electrical conductivity and temperature sensing devices and Android platforms for water quality monitoring are also used [69]. Recently, trait-based approaches have also been increasingly used for in situ monitoring to investigate and evaluate, e.g., short- and long-term phytoplankton dynamics and the establishment of phytoplankton communities in freshwater and marine research. There are some image-based efforts for more automated plankton analyses (see [70]). These are based on trait-based approaches, which are currently spreading rapidly [41,46,71].

Table 1. Standards and guidelines, recognised organisations and frameworks for monitoring water properties and water quality.

Organisation	Guidelines	Link
World Health Organisation (WHO):	○ The WHO sets guidelines for drinking water quality, which include standards for microbiological, chemical and radiological parameters. ○ These guidelines serve as the basis for national legislation and standards for drinking water quality worldwide.	https://www.who.int/publications/i/item/9789241549950, accessed on 26 June 2024
U.S. Environmental Protection Agency (EPA):	○ The EPA provides extensive regulations and standards for water quality in the U.S., including the Safe Drinking Water Act and the Clean Water Act. ○ These include limit values for impurities in drinking water and standards for surface water.	https://www.epa.ie/pubs/advice/water/quality/Water_Quality.pdf, accessed on 26 June 2024
European Union (EU):	○ The EU Water Framework Directive (WFD) is a key document that aims to bring all bodies of water (rivers, lakes, coastal waters and groundwater) to a "good status". ○ The EU also lays down specific guidelines for drinking water and bathing water.	https://environment.ec.europa.eu/topics/water/water-framework-directive_en, accessed on 26 June 2024
International Organisation for Standardisation (ISO):	○ ISO offers various standards for water quality, including methods for testing and analysing water. ○ Examples include ISO 14046 for the water footprint and various ISO standards for analysing specific contaminants.	https://www.iso.org/home.html, accessed on 26 June 2024
American Public Health Association (APHA):	○ APHA publishes the "Standard Methods for the Examination of Water and Wastewater", a comprehensive manual containing standardised laboratory procedures for the analysis of water quality.	https://www.apha.org/, accessed on 26 June 2024
European Union (EU) Water Framework Directive (WFD)	○ Citizens, nature and industry all need healthy rivers and lakes, groundwater and bathing waters. The Water Framework Directive (WFD) focuses on ensuring good qualitative and quantitative health, i.e., on reducing and removing pollution and on ensuring that there is enough water to support wildlife at the same time as human needs. ○ Finland is one of the few countries to have switched to RS-based national monitoring.	https://environment.ec.europa.eu/topics/water/water-framework-directive_en, accessed on 26 June 2024

Despite the increasing amount of in situ data and the development of water quality databases such as GEMStat (https://gemstat.org, accessed on 26 June 2024), as well as the increasing free availability of these data, the spatial and temporal continuous resolution of in situ data has so far been insufficient to provide comprehensive information and assessments of water quality from the local to the regional and the global scale [25]. Monitoring programmes or in situ buoys are often at one location in a lake, i.e., the point where the lake is deepest. This should then represent the whole lake, which is often not the case. Furthermore, these are often conducted in low-income countries and in regions known for their lack of policies for permanent in situ monitoring. The inclusion of areal RS data, as well as water quality modelling that provides relationships between water quality status and its influencing factors, such as agricultural practices and/or the discharge of untreated municipal wastewater, can close this gap [25].

In order to optimally incorporate airborne and spaceborne RS data for monitoring water quality, RS data must be validated by standardised in situ monitoring networks to monitor bio-geo-optical traits and the diversity of inland and coastal waters. For example, the GLObal Reflectance Community Dataset for Imaging and Optical Sensing of Aquatic Environments (GLORIA) provides an important dataset of 7572 local hyperspectral RS reflectance measurements, which were measured in 1 nm intervals in the wavelength range from 350 to 900 nm and distributed globally. In this dataset, in addition to spectral measurements, at least one measurement of water quality (chlorophyll-a, total suspended solids, dissolved solids absorption and Secchi depth) is also monitored and provided [72].

The optical complexity of coastal and inland waters with different trophic states is challenging for RS, especially for the retrieval of phytoplankton functional or pigment groups, and therefore requires additional in situ and laboratory measurements for validation [73]. The LakeLab, a large-scale experimental research facility in Lake Stechlin (NE Germany, Figure 2), provides such a unique opportunity for collaboration between aquatic ecologists and remote sensing experts for validation and calibration. The LakeLab is an experimental platform for studying the effects of climate change on aquatic organisms, their interactions and ecological processes in lake ecosystems [74,75]. It consists of a large central enclosure (30 metres in diameter) and 24 experimental units (enclosures), each 9 metres in diameter. All 24 enclosures of the LakeLab and 4 additional stations in Lake Stechlin are equipped with in situ sensors (YSI EXO, LiCor PAR) mounted on automatic profiling systems and provide continuous data from different water depths, including chlorophyll, phycocyanin, phycoerythrin, temperature, oxygen, conductivity, pH and light as PAR. Measurements such as HPLC-based chlorophyll-a and other pigments, image-based flow cytometry (FlowCam, MDPI, Amnis Image Stream) for plankton organisms, nutrients and carbon fractions are performed in the nearby laboratories of the Department of Plankton and Microbial Ecology of the IGB in Stechlin. Several international collaborations with measurement campaigns in the LakeLab have been carried out to characterise key optical properties of water and to understand the formation of the remote sensing signal, to compare and validate remote sensing data (multi- or hyperspectral cameras on satellites, aeroplanes, drones and handheld) with in situ and laboratory measurements in optically diverse and complex water bodies created in the LakeLab (Figure 2), supported by the AQUACOSM project.

4.2. Remote Sensing Approach

All RS technologies are contactless and detect traits and trait variations on and in the water at a distance of a few millimetres to thousands of kilometres. The sensors are used on different RS platforms such as aquatic wireless sensor networks (WSN), underwater cameras on submarines and robots, buoys, ships, drones, and airborne and spaceborne platforms, which use different RS technologies (RGB/photography, multispectral, hyperspectral, thermal, laser, radio/radar, acoustic, and LiDAR (Light Detection and Ranging) installed to monitor water diversity, water quality and traits of geodiversity such as bathymetry and depth of the basic composition of water bodies (see Figure 3). There is already extensive literature describing methodological and sensor technology for recording and monitoring water quality and water characteristics [1,76]; therefore, they are not the subject of this paper.

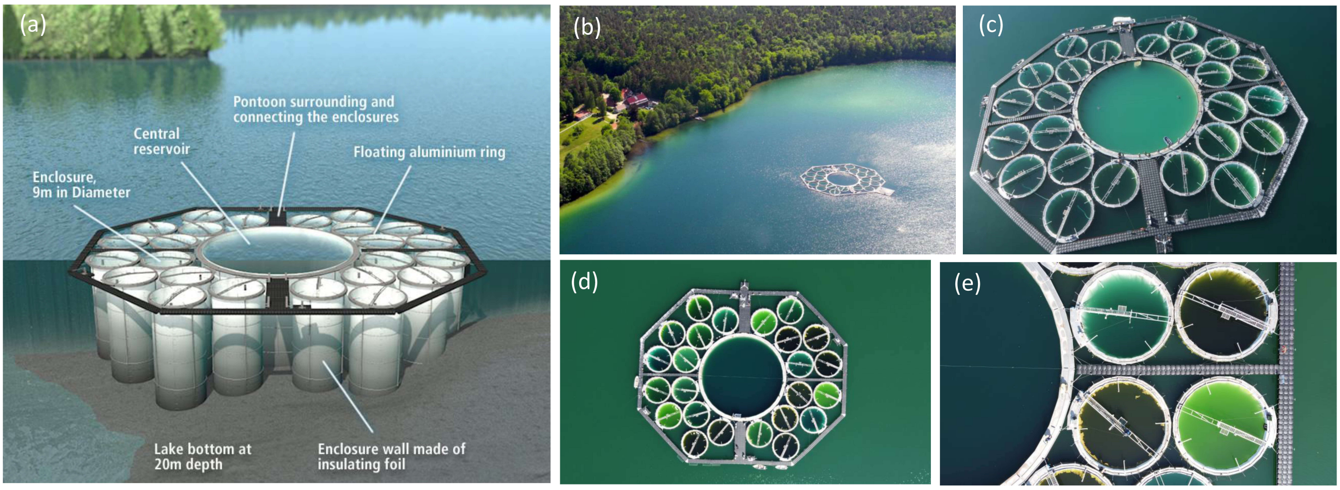

Figure 2. The IGB LakeLab in Stechlin Lake is a large-scale experimental research facility with 24 lake water basins (enclosures), each 9 metres in diameter and approximately 20 metres deep, isolated from the lake by a cylindrical watertight membrane extending from the surface to the natural bottom. The LakeLab can be used to simulate future environmental scenarios and study their effects on lake ecosystems. The LakeLab is well equipped with in-situ sensor profiling systems and is located in close proximity to the IGB laboratories of the Department of Plankton and Microbial Ecology, Stechlin, Germany. The IGB LakeLab also serves as a platform for validation and calibration of in-situ and laboratory measurements with remote sensing products. Graphic (**a**) shows the 24 enclosures around the central reservoir (Credit: IGB); Arial photo (**b**) shows the LakeLab in Lake Stechlin and the laboratories of the Department of Plankton and Microbial Ecology on the shore next to the Federal Weather Station (Credit: Dr. Peter Casper); Drone photo (**c**) illustrates the size of the LakeLab with people standing on the ring of the central reservoir (Credit: Dr Carmen Cillero, 3edata); Drone photos (**d**,**e**) illustrate replicated enclosures treated in four different ways (control, cDOM, nutrients, nutrients + cDOM) and the resulting colours after the additions and the response of the plankton community (credit: Prof. Andreas Jechow).

However, the monitoring of water bodies and their quality using RS poses a challenge compared to terrestrial RS for several reasons: (I) Light absorption and scattering in the water: water absorbs light, especially in deeper layers. This limits the penetration depth of the light and therefore the ability of the sensors to obtain information from deeper water layers. Water also scatters the light, which makes it more difficult to interpret the data recorded by the sensors. (II) Complex reflection patterns: The surface of water bodies can exhibit a variety of reflection patterns caused by waves, sediments, organic materials and other factors. These patterns can affect the accuracy of RS data. (III) Influence of the atmosphere: when passing through the atmosphere, RS signals are altered by water vapour, aerosols and other atmospheric components. All these factors make it difficult to obtain precise information about water quality. Globally consistent and harmonised water quality data from various different sensors can be ensured with physics-based approaches due to their relation to the absorption and scattering properties of water constituents. Other factors should also be considered, namely:

- The spatial and temporal resolution of RS data: many bodies of water change rapidly both spatially and temporally. Sensors with insufficient spatial or temporal resolution may therefore not be able to provide accurate or up-to-date data.
- The heterogeneity of water bodies: water bodies are often heterogeneous in their composition. Different areas of a water body can have different characteristics, which complicates the analysis and interpretation of RS data.
- The spectral signature of substances: various substances in water (such as chlorophyll, dissolved organic matter and sediments) have specific spectral signatures. The precise

identification and quantification of these substances require specialised sensors and complex analysis methods.

- Technical limitations: the available technology, in particular the spectral and spatial resolution of the sensors, as well as the limited availability of validation data sets, limits what can be recorded and analysed.
- Interdisciplinary challenges: the correct interpretation of RS data with regard to water quality often requires a deep understanding of different scientific disciplines, including limnology, oceanography and environmental sciences.

Due to these challenges, the monitoring of water bodies using RS is a complex endeavour that requires ongoing research and development in the fields of sensor technology, data analysis and environmental science. Therefore, as a first step, a new definition of the five characteristics for monitoring water diversity is needed to better understand the RS-based trait approach (see Chapter 3). RS can use proxies to directly or indirectly monitor the different indicators of the five characteristics of water diversity (see Figure 4).

However, to gain a basic understanding of the potential and limitations of RS techniques, the suitability for monitoring the five characteristics of water diversity is discussed in the following chapters.

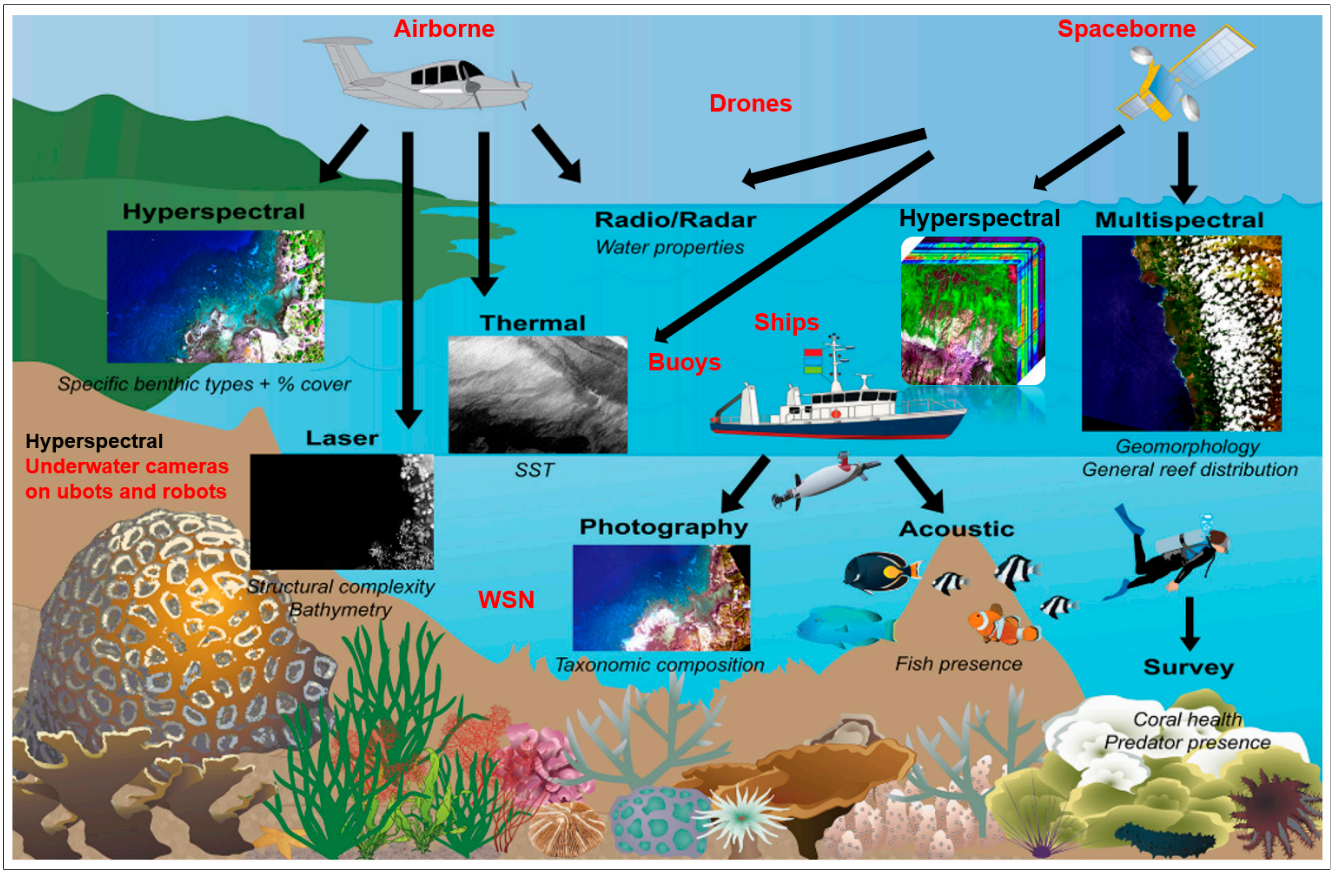

Figure 3. Different RS platforms; aquatic wireless sensor networks (WSN); underwater cameras on submarines and robots, buoys, ships, drones and airborne and spaceborne platforms; and RS technologies (RGB/photography, multispectral, hyperspectral, thermal, laser, radio/radar, acoustic and LiDAR) to capture water quality, water diversity and traits of geodiversity like aquatic geomorphology (bathymetry, depth, basic composition of waters) (from Foo and Asner [77]).

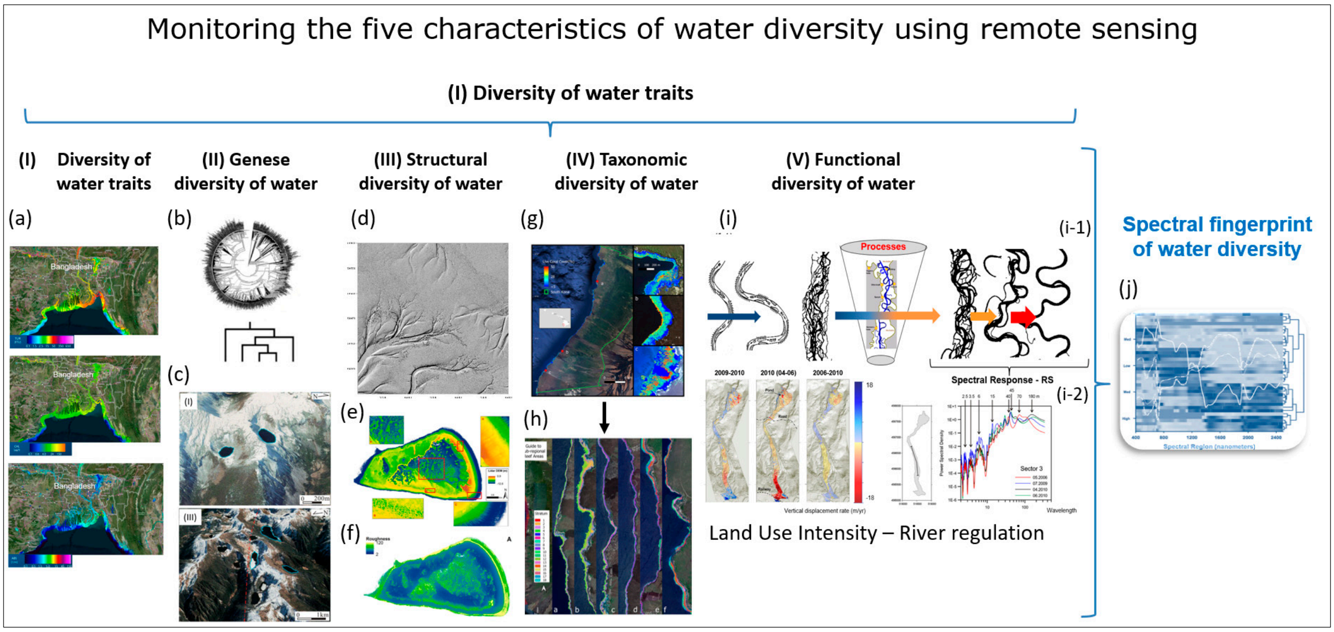

Figure 4. Remote sensing monitoring of the five characteristics of water diversity (see Chapter 3): (**I**) Diversity of water traits: spectral traits of water diversity monitored with remote-sensing approaches. (**a**) Monitoring of turbidity, chlorophyll content, ABS Indicator, Bangladesh, India, (https://aqua.eoapp.de, accessed on 26 June 2024). (**II**) Diversity of water genesis: (**b**) Geological genesis leads to the formation and shaping of different lakes. (**c**) Classification of glacial lakes based on Landsat TM/OLI and Aster DGM data (I) Glacial erosion lakes and (III) Tectonic lakes (from Weit et al. [78]). (**III**) Structural diversity of water: (**d**) Tideways in the Weser River, northeast of Wilhelmshaven, Germany monitored by airborne LiDAR (from Lausch et al. [62]). (**e**) The LiDAR-derived digital elevation model (DEM) (0.25 m cell-size) for One Tree Reef showing some key features (complex patch reef structure in the deep lagoon) that could not be quantified in the past using a coarse DEM and single beam echo-sounder surveys. (**f**) Indicator for the maximum roughness magnitude with LiDAR DEM. Figure (**e**,**f**) (from Harris et al. [79]). (**IV**) Water taxonomic diversity: (**g**) The location of the South Kona District is shown in the green lines on the left, with live coral cover mapped along the coast based on airborne hyperspectral data in 2019 and 2020. Example areas of live coral cover are shown at Honaunau Bay, Papa Bay and Okoe-Kapua Bay (from Asner et al. [80]). (**h**) The final 18-stratum map of coral reef conditions for the South Kona District coast was derived from the airborne hyperspectral data. The far-left panel indicates the location of each sub-regional zoom image (**a**–**h**) shown in the remaining panels. Each colour indicates the location of each ecological layer in the reef system (from Asner et al., [80]). (**V**) The functional diversity of water: (**i**) Different processes during the geological genesis lead to the formation of specific morphometric fluvial traits—the meanders. (**i-1**) The entire river system is characterised by these meanders. Processes/drivers such as land use intensity, river regulations or barrages lead to changes in structural and functional fluvial traits (fluvial trait variations) (**i-2**). These fluvial trait variations lead to spectral responses in the remote sensing signal. Example of monitoring temporal changes to fluvial traits—vertical displacement rate of the river system from 2006 to 2010 with remote sensing technologies (LiDAR). From Ventura et al. [81], reprinted with permission from Ventura et al. [81], 2021, Elsevier. license No. 5816961386058 (from Lausch et al. [32]). (**j**) Based on the five characteristics of water diversity, the spectral fingerprint, also known as the spectranometric approach, could be determined for water bodies.

4.2.1. Monitoring the Diversity of Water Traits Using Remote Sensing

"The diversity of water traits, which represents the diversity of the biochemical, physical, optical, morphological-, structural-, textural-, and functional characteristics of water traits, that affect, interact with, or are influenced by their genesis, taxonomic-, structural-, and water functional diversity" (see Chapter 3, modified after Lausch et al. [32]).

RS records the biochemical, physical, optical, morphological, structural, textural and functional characteristics (traits) of water, ranging from abiotic elements and molecular structures to individuals, populations and communities of aquatic plants to the entire aquatic ecosystem and its connectivity and interactions to components of geological and vegetation diversity. Furthermore, RS records water traits, as well as the trait variations altered by various processes or drivers. For example, river straightening due to the intensification of shipping leads to straightening and alteration of the meandering, which leads to changes in water structure, flow velocity and ecological self-purification. These trait variations can be recorded using RS.

In contrast to in situ approaches carried out by an expert, RS approaches (close-range, airborne and spaceborne RS) are not able to capture all characteristics and trait variations of and within the water column (see limitations, Chapter 4.2). We therefore speak of "spectral water traits" (properties that can be captured by RS) as opposed to "water traits" (total set of water properties) [55]. The reasons why far fewer water traits can be measured using RS are manifold and have already been addressed in Chapter 4.2. However, water traits are the crucial link between in situ and RS approaches for monitoring, assessing and modelling the status, changes, stress, health, disturbances and resource limitations and are crucial for understanding the processes and their diverse interactions with the water ecosystem.

Depending on the respective sensor characteristics (geometric, spectral, radiometric, temporal and angular resolution), RS sensors record the biochemical, physical, optical, morphological, physiological, genesis, structural, textural and functional characteristics (traits) of water. In addition to the sensor traits, the characteristics of the water traits and especially the composition and configuration (e.g., distribution, density, spatio-temporal variability, diversity, etc.) of water traits and their variations are of decisive importance for detectability from RS sensors. If the density is not high enough, it cannot be detected with any sensor if the density is below the detection limit. For example, the detection limit of Sentinel-2 for Chl is around 2 mg-m3 [82].

In the first step, RS records water traits and their variations (depending on RS characteristics and trait distribution). RS can discriminate phytoplankton, algae blooms, aquatic plant species, reef types and waterbody types if they differ from each other in terms of their traits or trait variations (multi-temporal) through process or temporal changes (seasonal changes). Likewise, water traits are the decisive basis for the RS-based quantification of the other four characteristics of water diversity: the genesis diversity, structural diversity, taxonomic diversity and functional diversity of water (see following chapters).

The spectral characteristics of water are recorded by RS either with single traits (chlorophyll-a, phycocyanin, phycoerythrin, salinity, nutrient level and pH value) or as a combination of different spectral traits and their variations (plant strategy types and biomass). For example, the latest generation of hyperspectral satellites (EnMAP, DESIS or multi-source satellite combinations) can be used to estimate the chlorophyll-a concentration in different plant species of water bodies, e.g., for the identification of algal blooms [83,84]. With the use of sensors such as MODIS, MERIS or OLCI (on Sentinel-3), the chlorophyll-a concentration in open marine waters can be estimated with an accuracy of about 10–20% [85]. The pigments phycocyanin and phycoerythrin, which are associated with cyanobacteria and cryptophytes, can be detected very well using RS, allowing an early warning of potentially harmful algal blooms using RS [86]. Furthermore, hyperspectral sensors can be used to estimate turbidity and total suspended solids (TSS) with high accuracy, as they can spectrally separate the effects of TSS from other components [87]. Hyperspectral technology can also be used to differentiate between phytoplankton pigments, phytoplankton functional types (PFTs), including phytoplankton size classes (PSC), phytoplankton taxonomic composition (PTC) and particle size distribution (PSD) [88]. The most recent mission was PACE (Plankton, Aerosol, Cloud, ocean Ecosystem), which was launched by NASA this year (https://pace.oceansciences.org/timeline.htm, accessed on 26 June 2024).

Spectral traits can either be captured by direct indicators (chlorophyll and turbidity) or indirect indicators, i.e., proxies (HAB and ABS indicators) (see Figure 5), which arise from interactions with traits of geodiversity, terrestrial vegetation diversity, LUI, urbanisation or climate change. It should be particularly emphasised that traits and trait variations are filters and proxies for changes and disturbance processes that are triggered by various drivers and stress indicators (e.g., contaminants in water bodies, river straightening, LUI, urbanisation). The sum of the water traits recorded by RS reflects the spectral footprint of the water and its changes or disturbances and is reflected by the water spectranometric approach. This is comparable to the spectrometric approach of terrestrial plants, where the diversity and functionality of plant traits can be quantified and assessed using hyperspectral sensors [89].

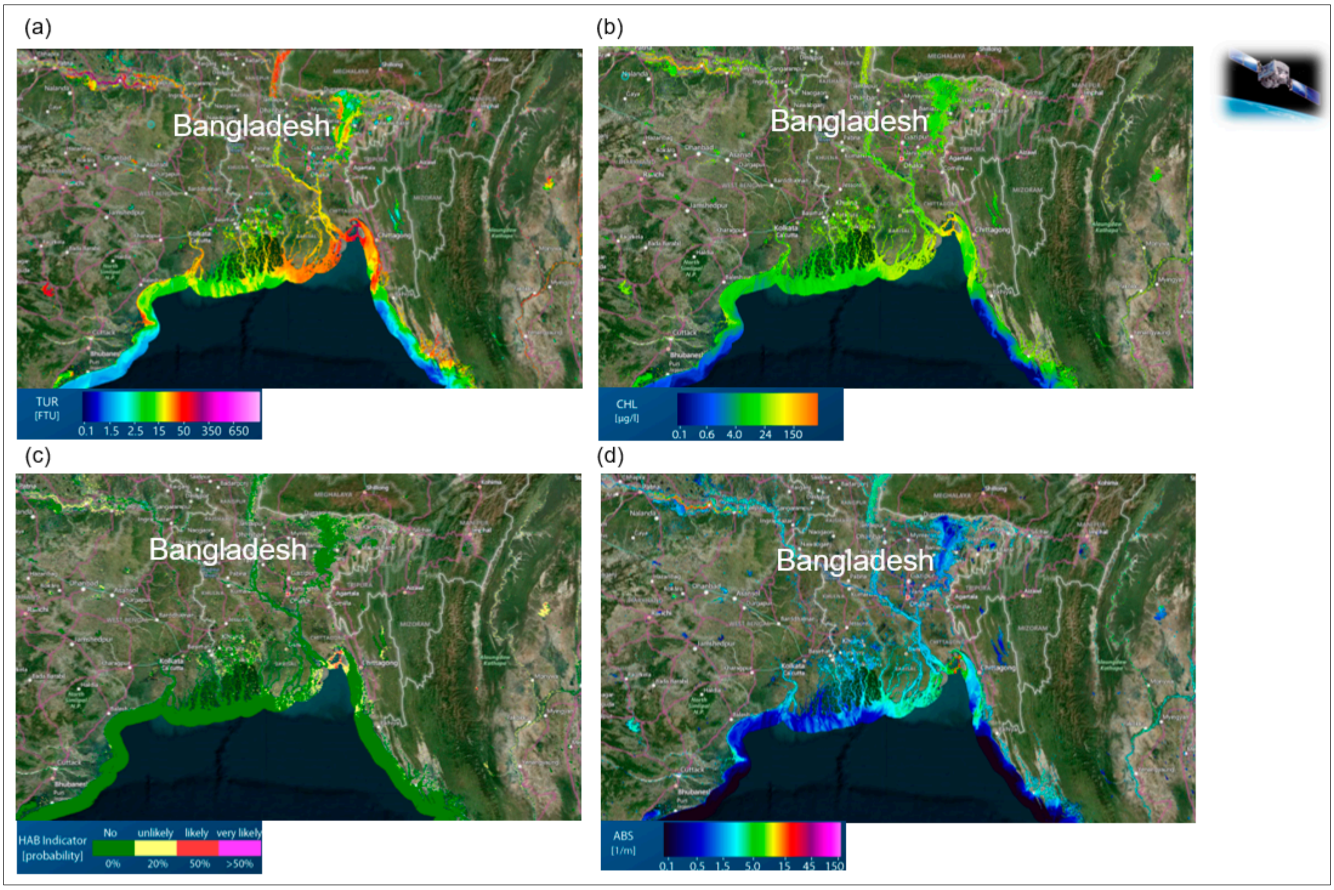

Figure 5. Spectral traits of water diversity monitored with remote sensing approaches, (**a**) Monitoring of turbidity (TUR), (**b**) Chlorophyll-a content (CHL), (**c**) Algal blooms indicator (HAB-Indicator), (**d**) and the Total absorption (ABS), Bangladesh, India, (online water analysis tool: https://aqua.eoapp.de, accessed on 26 June 2024).

RS can detect the five spectral traits of water diversity: the diversity of water traits, the diversity of water genesis, the structural diversity of water, the taxonomic diversity of water and the functional diversity of water. Furthermore, the spectral traits of changes, stress factors and disturbances of water can be monitored using RS (see Table A1 (Appendix A)), which provides an exemplary overview.

4.2.2. Monitoring the Diversity of Water Genese Using Remote Sensing

"The diversity of water genese is the diversity of the length of evolutionary pathways associated with a particular set of water -traits, -taxa, -structures and -functions of water diversity. Therefore, groups of water traits, water taxa, water structures and water functions that maximise the accumulation of the functional diversity of water diversity are identified" (see Chapter 3, modified after Lausch et al. [32]).

The genesis, development and shaping of lake basins and watercourses resulted from various exogenous and endogenous geomorphological developments such as tectonic activity, volcanic activity or glacial erosion. The classification of lakes and watercourses is based on factors such as the genesis of the water body, the organic/inorganic ratio, the nutrient balance, the physiology, the depth, the size, the shape, the sediment types, the morphology of the lake basin and the oxygen content [90]. The presence of aquatic species and the physical and chemical processes taking place in a lake resulting from the influence of geological and terrestrial vegetation diversity and anthropogenic pressures such as LUI and climate change also play a decisive role.

Other factors such as mineral and rock composition, location or physical properties, such as thermal combinations and optical properties, chemical and trophic characteristics and species diversity, therefore lead to the formation of site-specific traits and a characteristic water diversity [91]. As tropical lakes behave differently due to high temperatures, a constant turnover and constant oxygen deficit, they must be monitored and modelled separately [90]. The monitoring of traits of/in and around water bodies is therefore at the forefront if the diversity of water genesis characteristics and water genesis quality is to be recorded with RS.

The following chapter discusses which of these traits can be analysed using RS in order to identify the diversity of water genesis characteristics and water genesis quality. Phylohydrology is a relatively new field that combines phylogenetics, i.e., the study of evolutionary relationships between species, with hydrology, i.e., the study of the characteristics and the distribution of water in the environment. Phylogeogeny, another new field, goes one step further and combines elements of phylogenetics, geology and hydrology.

Until now, RS could not be used directly to measure phylohydrological and phylogeogenic patterns, as its ability to detect individual traits of water or species or to determine their genesis was limited due to RS characteristics (spatial, spectral, temporal and directional resolution). With the increasing development and use of the latest RS technologies, such as hyperspectral RS (EnMAP) and multisensor RS sensors (HyspIRI), important gaps in this monitoring are increasingly being closed. However, RS has long provided important indirectly derived information on the diversity of water genesis. This ensues from monitoring environmental features and processes that are caused or influenced by phylogeogenic and phylohydrological patterns. It can therefore be said that RS can provide holistic monitoring (a combination of water diversity, geodiversity and terrestrial vegetation diversity) to better capture the diversity of water genesis and to better understand natural and anthropogenic causes of water quality and consequently provide better management strategies for its protection. The following exemplary phylogeogenic and phylohydrological traits recorded here have so far been recorded using RS technologies (see Table A1 (Appendix A)):

Structure and patterns of water bodies: RS can be used to record the structural traits of water bodies and their surroundings in great detail. Important indicators here are the area, size, length, shape, density or water level of the water body or river course or the contiguity and connectivity, whereby the water genesis played a decisive role in its formation.

Habitat characteristics: The most recent hyperspectral RS technologies can provide very detailed information on aquatic habitat traits such as the water temperature, depth, substrate type and trophic status [23,92]. These factors influence the processes occurring in water bodies as well as changes to and distributions of species, populations, communities and habitats, i.e., reef habitat structure [93].

Geology and mineralogy: In order to determine the mineralogical composition of the water bed surface, spatial high-resolution airborne hyperspectral RS techniques are used in particular. In the near future, the use of hyperspectral robots that can record the mineralogical composition of the water bed surface is also planned for water bodies and oceans.

Terrain modelling and hydrological modelling: RS has long been able to use airborne LiDAR, multispectral and hyperspectral RS to measure the topography of the water bed (bathymetry) and create digital elevation models (DEM) for still and flowing waters as well as shallow water in the oceans. These DEMs can be used in hydrological models to model water processes. They thus form a decisive basis for local to global modelling and its process understanding.

Hydrological processes: In addition to the aquatic DEM, RS can provide information on hydrological processes, e.g., changes in water level, flow direction and velocity or connectivity between water bodies. Connectivity provides crucial information on functionality and processes as well as the understanding of species migration and gene flow.

Water quality: Satellite images can be used to monitor water quality parameters such as the chlorophyll-a concentration, water surface temperature, turbidity, water colour, or salinity. For example, the water colour is a current driver of lake and river systems in boreal climate regions such as Scandinavia [75]. They are important indicators of processes of geogenic and/or anthropogenic influences and can be recorded worldwide at a high temporal frequency with remote sensing [76]. RS can therefore be used to map and monitor spatial and temporal changes in aquatic habitats.

The phylogenetic diversity of water promotes the resilience and stability of the entire aquatic ecosystem and is an important indicator of its functionality and response to environmental change [71]. Monitoring the phylogenetic diversity of water using RS is therefore crucial to understanding resilience and the reaction of drivers and changes to water on different scales. Most aquatic plant traits are manifestations of their phylogenetic and geogenic evolution [94]. Thus, the coupling of phenotypical-based taxonomy and the evolutionary history of phytoplankton led to a preliminary scientifically sound categorisation, as a large number of phytoplankton traits are linked to phylogeny [94,95].

In another example, Liu et al. [96] investigated and evaluated the taxonomic, phylogenetic and functional diversity of fish on the alpha and beta dimensions and their environmental drivers at a total of 84 river sites in 3 watersheds. The results showed that local (e.g., nutrients, dissolved oxygen, river width and transparency), regional (e.g., wetland), climatic (e.g., temperature) and spatial variables structured alpha and beta fish diversity. No significant differences in taxonomic and functional alpha diversity were found in the three watersheds, but significantly higher phylogenetic alpha diversity was found in the rivers of other watersheds. In terms of taxonomic and phylogenetic beta diversity, however, total beta diversity and the turnover component were higher in rivers of the same catchment, whereas total beta diversity was significantly lower in functional beta diversity. The analysis of variation partitioning showed that the pure contributions of local and spatial variables, i.e., characteristic genesis streams and catchments, were more important than those of climate and regional variables, suggesting that spatial effects and local environmental filtering are the main drivers of beta diversity of fish communities in these rivers. These studies also emphasise the importance of coupling in situ measurements to monitor local variables with RS-based monitoring to monitor regional variables (Landsat TM).

Figure 6 shows how geological genesis leads to the formation and development of different lakes—glacial erosion lakes, valley lakes and tectonic lakes—and it analyses the development and change characteristics of glacial lakes in the Niangmuco region on the eastern edge of the eastern Himalayas based on Landsat TM/OLI (2000–2021) and classifies the stability of lakes with an area of more than 0.02 km^2 using the fuzzy matrix method [78]. The results show that the development and change of glacial lakes in this area is primarily controlled by temperature and precipitation and that topography and fault activity have an important influence on the stability of glacial lakes.

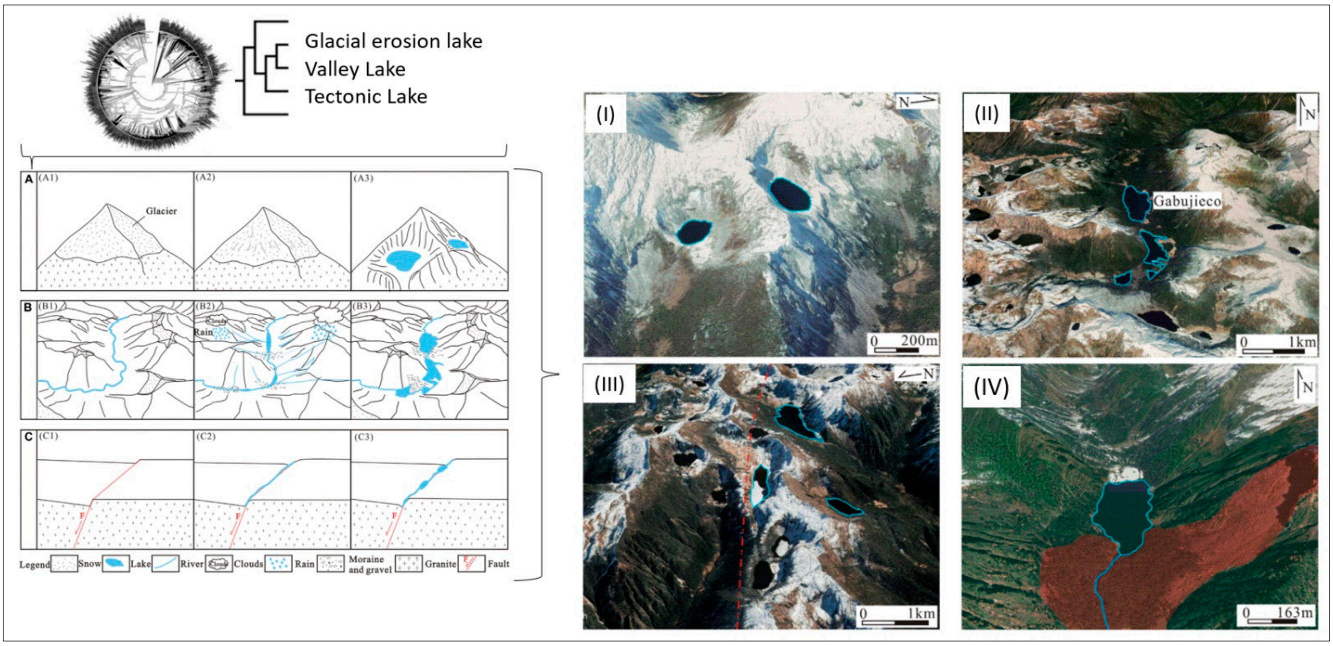

Figure 6. Geological genesis leads to the formation and shaping of different lakes. (**A**–**C**) Schematic diagram of the formation mechanism of (**A**) Glacial erosion lake, (**B**) Valley lake, and (**C**) Tectonic lake. Classification of glacial lakes based on Landsat TM/OLI and Aster DGM data. (**I**) Glacial erosion lakes, (**II**) Valley lakes (Gabujieco valley), (**III**) Tectonic lakes (fault marked by dotted red line), and (**IV**) Landslide dam lake (red area indicates landslide area) (from Weit et al. [78]).

4.2.3. Monitoring the Structural Diversity of Water Using Remote Sensing

"The structural diversity of water is the diversity of composition and configuration of water characteristics" (see Chapter 3, modified after Lausch et al. [32]).

Exogenous and endogenous processes, genesis, morphometry, morphology, mineral and rock composition, as well as processes of the earth's formation and evolution, are decisive for the emergence and formation of a characteristic water diversity with site-specific physical properties like thermal combinations and gradients, optical properties, chemical and trophic characteristics and species diversity [91]. Thus, evolutionary characterised structures and patterns of marine and freshwater systems lead to diversity and gradients and niches of species that increase the niche dimensionality of species [97] and consequently promote species richness and overall biodiversity [98]. Numerous marine and freshwater structures and patterns can be captured by different RS technologies, which are discussed in the following chapter (see Figure 1 and Table A1 in Appendix A).

With RS-based approaches, the recording and quantification of the structural diversity of water is more difficult compared to the recording of structural vegetation diversity [53] or geodiversity [32]. In many cases, indirect methods or proxies such as water temperature, salinity or environmental parameters such as light supply and turbulence are used to derive RS-based quantitative structural indicators. Indeed, RS techniques provide an efficient way to monitor indicators such as location, shape, area, size, depth, volume and the water level of various water bodies such as rivers, lakes and oceans. These measurements are useful for a range of applications, such as water resources management, flood forecasts and the monitoring of trophic levels in aquatic ecosystems. Different RS methods and technologies can be applied based on the specific structural and pattern characteristics of the water body and the information needed. Several types of satellites, such as Landsat, MODIS and Sentinel, carry multispectral and hyperspectral sensors that can be used to monitor water bodies. For instance, these can be used to identify changes in water area over time and to distinguish between water and land [99]. RADAR can provide information about the shape and size of water bodies. Synthetic Aperture Radar (SAR) data can detect water bodies, even in cloudy conditions or during the night. With the use of satellite radar altimetry, the spatial extent, distribution, area or surface water levels of water bodies and their changes can be recorded [100]. Since the 1990s, the water level fluctuations of around 6282 water bodies have been recorded in a permanent water database, and their changes have been monitored [100]. Furthermore, radar altimeters, such as those mounted on the satellites of the Sentinel-3 and Jason series, can measure changes in water level, changes in the extent of water bodies and river flow. In addition, LiDAR can be used to measure the depth of shallow water bodies by calculating the time it takes for the laser pulse to travel to the water surface and back [101]. A wide range of RS-based structural water traits is provided by the ESA Lakes Project (in the Copernicus Essential Climate Variables). These are, e.g., water extent, water level and surface water temperature (see https://climate.esa.int/en/projects/lakes/, accessed on 26 June 2024). Thermal Infrared RS (TIR) with, e.g., Landsat TM/ETM+/TIRS thermal infrared data, can be used to measure the temperature of spatially smaller water bodies. The surface temperature of water bodies can be related to their depth, as the water temperature tends to decrease with depth. Thus, the thermal properties of water bodies might be analysed to estimate their depth [102]. Sonar systems (sound navigation and ranging) are an RS technology that can be used to measure the water depth (only for rather shallow water, with ICESat up to approx. 12 m in turbid Baltic Sea water) and volume by sending sound pulses into the water and recording the time it takes for them to return [103]. Furthermore, optical RS technology such as Word View, Sentinel-2 MSI or Landsat 8/9 OLI can be used for quantifying the water level, especially in the case of lakes and reservoirs [104].

Hyperspectral RS data like PRISMA and DESIS or multispectral data like Sentinel-2/3, Landsat, MODIS and airborne LiDAR data can estimate the water depth and clarity (highly correlated with Secchi-depth, an indicator of the clarity or turbidity of the water by measuring the visibility depth of a white disc lowered into the water [105–107]. Monitoring water clarity helps to monitor changes in habitat quality and ecosystem health. Information on water depth is obtained by measuring the change in water colour with depth using hyperspectral RS (such as EnMAP, PRISMA or DESIS [108]) and multispectral RS (such as Landsat or Sentinel-2 [109]). Airborne LiDAR, but also increasingly multi- and hyperspectral RS technologies, have been used for bathymetric surveys of the morphology of seabeds, lake beds and riverbeds for some time now [108,110,111]. Furthermore, in clear and shallow waters, information on the substrate type (sandy, muddy and rocky) and its distribution at the bottom of a water body can also be recorded, which provides important information on potential habitats (Niroumand-Jadidi et al. [112,113]. Conclusions can also be drawn about the intensity of matter influx as a cause of intensification or river straightening in reservoirs or dams.

Monitoring hydrological connectivity is important for maintaining the stability and function of wetland ecosystems, streams, riparian zones, floodplains, alluvial aquifers, standing waters and oceans, which are connected by longitudinal, lateral and vertical fluxes of water, matter and energy. This is crucial for understanding, for example, the migration patterns of different species and gene flow, as well as the influence of human activities on this connectivity [114]. With the help of the RS time series, these networks can be recorded, and their changes and effects on biodiversity can be documented [115].

Furthermore, airborne LiDAR can be used to accurately measure the height of the water surface, which allows conclusions to be drawn about the flow characteristics of rivers. In some cases, these data can be used to estimate the discharge of a river, which is an important parameter for water quality modelling [116]. Information on the flow velocity in rivers is crucial for infrastructure planning, the modelling of pollutant and matter flows and habitat assessment. Moving Aircraft River Velocimetry Monitoring can be used to measure the flow velocity effectively and rapidly [117].

Furthermore, high spatial-resolution RS data will be used to determine the complexity, structure, shape and changes in the shoreline of a water body. More complex shorelines can increase habitat diversity and provide niches for different species [118]. However, the choice of sensor technology with appropriate properties (spectral, radiometric, geometric and temporal resolution) is crucial to capturing accurate geomorphological structures and shorelines. For example, hydrological model predictions are only as good as the quality of the RS-based input data [62]. By capturing detailed terrain structures of coastal regions with airborne LiDAR data, it was shown that more than three times as many people are at risk from climate change and sea level rise than previously calculated with less detailed SRTM-DEM-RS data [119].

By monitoring currents, eddies and ocean circulation patterns, RS helps to understand the movement and transport of water masses. RADAR (Radio Detection and Ranging) data can be used specifically to recognise surface features such as waves and currents that indicate deeper water properties. This information is imperative for studying marine habitats, identifying potential sources of pollution and predicting the spread of pollution or the effects of climate change as a result of changes to natural processes such as El Niño [120]. Furthermore, RS technologies are valuable for estimating water surface roughness and other parameters from a distance using data gathered from aircraft or satellites. Several types of RS techniques are applied for this task, such as optical imaging, thermal infrared and RADAR. Radar RS is commonly used for measuring water surface roughness, whereby radar waves are emitted towards the Earth's surface and then reflected back to the radar system. The degree of backscatter is influenced by the roughness of the water surface. Synthetic Aperture Radar (SAR) is particularly sensitive to surface roughness and has been used in a number of studies to estimate water surface roughness [121] as well as LiDAR [122]. Optical and Infrared RS can monitor the patterns of light reflected off a water body and can provide clues about its roughness. Similarly, rougher surfaces will distribute heat differently compared to smoother ones, leading to detectable differences in thermal infrared data. However, these techniques are generally less accurate than RADAR for this particular application [123,124].

RADAR, microwave radiometer, LiDAR and thermal infrared data provide valuable information on the complex interactions between fresh- and saltwater in coastal areas and estuaries. The sensors can distinguish between different water types and pH values and detect the mixing of freshwater and seawater, which is essential for the study of coastal ecosystems and the management of coastal resources [125,126]. For example, the salinity of the sea surface is indirectly determined using RS by recording the changes in sea surface radiation density caused by changes in salinity. This is conducted using L-band microwave radiometers from the SMOS (Soil Moisture and Ocean Salinity) and Aquarius satellites [127].

Satellites such as Landsat or AVHRR (Advanced Very High-Resolution Radiometer) can collect information on the temperature of the sea surface using TIR sensors. Different temperature regimes can favour different types of organisms, indicating a certain kind of diversity. Water bodies with different thermal properties cause different temperature patterns. Thermal fluctuations and changes provide important insights into phenomena such as the upwelling of nutrient-rich water or currents of colder water rising to the surface. The rise in sea temperature is one of the most important indicators of climate change [128,129]. The surface temperature of water bodies is an outcome variable of energy and mass fluxes in the contact zone between the atmosphere and the water body as a result of interacting environmental processes, whereby the temperature controls the physical, chemical and biological processes in the water [130]. Consequently, the detection of surface temperature using different RS technologies has become one of the key variables for understanding ecological phenomena and processes in marine, coastal and lake environments.

One of the key applications of satellite data is in the use of time series, which now enables almost 40 years of continuous monitoring (e.g., Landsat) of seasonal and annual changes to water extent, water temperature, flow processes and numerous water quality parameters, providing crucial knowledge about spatio-temporal patterns of water diversity and water quality [131].

The composition, dispersion, richness, diversity and homogeneity of phytoplankton [46,132] are good indicators to describe the structural and functional diversity of phytoplankton populations and communities [41,133]. There are numerous environmental factors that shape phytoplankton communities, but also lots of interactions, such as zooplankton gating. Thus, phylogenetic as well as geogenic factors shape and control the functional traits of phytoplankton structure and their seasonal dynamics in marine and freshwater ecosystems [134]. Traits are crucial for answering the questions of intraspecific and interspecific competition of phytoplankton and thus control not only the composition of the community but also the functioning and processes of ecosystems such as the primary production, the transfer of biomass and the entire nutrient cycle (Abonyi et al. [135]). For example, temperature influences photosynthesis, respiration, growth, resource availability and motility, as well as the dominance of various taxonomic groups of phytoplankton and all aquatic organisms [47]. As the main groups of phytoplankton have different optimum temperatures, the temperature plays a crucial role in the seasonal dynamics and distribution of phytoplankton in both marine and freshwater habitats. The temperature mainly affects heterotrophic organisms and thus plays an indirect role in the seasonal succession of phytoplankton (e.g., [136,137]). Freshwater cyanobacteria have a higher optimum temperature compared to other taxonomic groups, leading to dominance in late summer when water temperatures are higher [138]. Higher optimum temperatures of cyanobacteria are therefore also important indicators of global warming, leading to the spread of harmful toxic algal blooms. However, some other studies have also shown that blooms also like the cold [139].

Initial RS-based surveys of phytoplankton were based on estimates of phytoplankton biomass and its seasonal variation, which can be monitored by chlorophyll concentrations [140]. Recent methods, however, combine RS data with in situ high-performance liquid chromatography (HPLC) measurements of pigments and deep learning-based modelling to estimate the concentrations of different phytoplankton pigments on a global scale [120]. This novel approach enables a global estimate of the concentration of different pigments and thus the dynamics of the phytoplankton community on a large spatio-temporal scale. Vostokov et al. [141] investigated the seasonal and long-term variability of phytoplankton in the ocean based on SeaWiFS and MODIS-Aqua-Scanner RS time series (1998–2021) and in situ data, which allowed them to capture the seasonal variabilities, as well as the main periods for autumn and winter seasons of phytoplankton production [141]. The application of hyperspectral RS technologies (EnMAP, Prisma, DESIS) will greatly improve the monitoring of phytoplankton species composition and configuration as well as influencing factors such as the composition and type of photosynthetic pigments [142], as well as the phytoplankton species composition based on the spaceborne Hyperspectral Imager for the Coastal Ocean (HICO) imagery [143]. Cyanobacterial harmful algal blooms (cyanoHABs) are a progressive problem in freshwater bodies as the growth and decay of cyanoHABs lead to anoxic and hypoxic conditions, which can result in human health impacts, the death of fish and benthic invertebrates, imbalances in the existing food web and loss of biodiversity in the water body [144]. Therefore, monitoring and predicting the distribution and intensity of cyanoHAB in lakes using RS is an approach that has been successfully implemented for some time [145]. In addition to drone-based approaches [146] and airborne hyperspectral RS (AISA) [147], multispectral RS technologies such as Meris (Matthews et al.) [148], Landsat and Sentinel-2 [149], Sentinel-3A and -3B (OLCI) [145]. Matthews [145] was able to predict cyanobacteria and cyanobacterial harmful algal blooms (cyanoHABs) based on Sentinel-3A and -3B (OLCI) satellite data with an accuracy of 80% for one week in advance.

RS can capture the ecological complexity and diversity of aquatic habitats, such as variations in water depth, ecological gradients (thermal gradients and freshwater to saltwater transitions), shoreline complexity or the presence of aquatic and riparian vegetation. These gradients are often areas of high biodiversity [150]. RS is therefore ideal for monitoring aquatic habitats and providing RS-based indicators for habitat modelling. Asner et al. [151]

were able to quantify and assess the live coral cover density, spatial distribution, coral cover of living corals and the relative condition of reefs down to a water depth of 16 m on the main islands of Hawaii using airborne data visible-to-shortwave infrared (VSWIR) imaging spectrometer and a light detection and ranging (LiDAR) scanner. Li and Asner [152] used spectroscopy to determine the three-dimensional complexity of shallow benthos (also referred to as benthic roughness), which reflects the physical conditions of shallow coral reefs and is used to estimate fish biomass and coral cover on the reefs. Figure 7 shows the monitoring of tideways in the Weser River, northeast of Wilhelmshaven in Germany, based on Airborne Laser Scanning (ALS) [62].

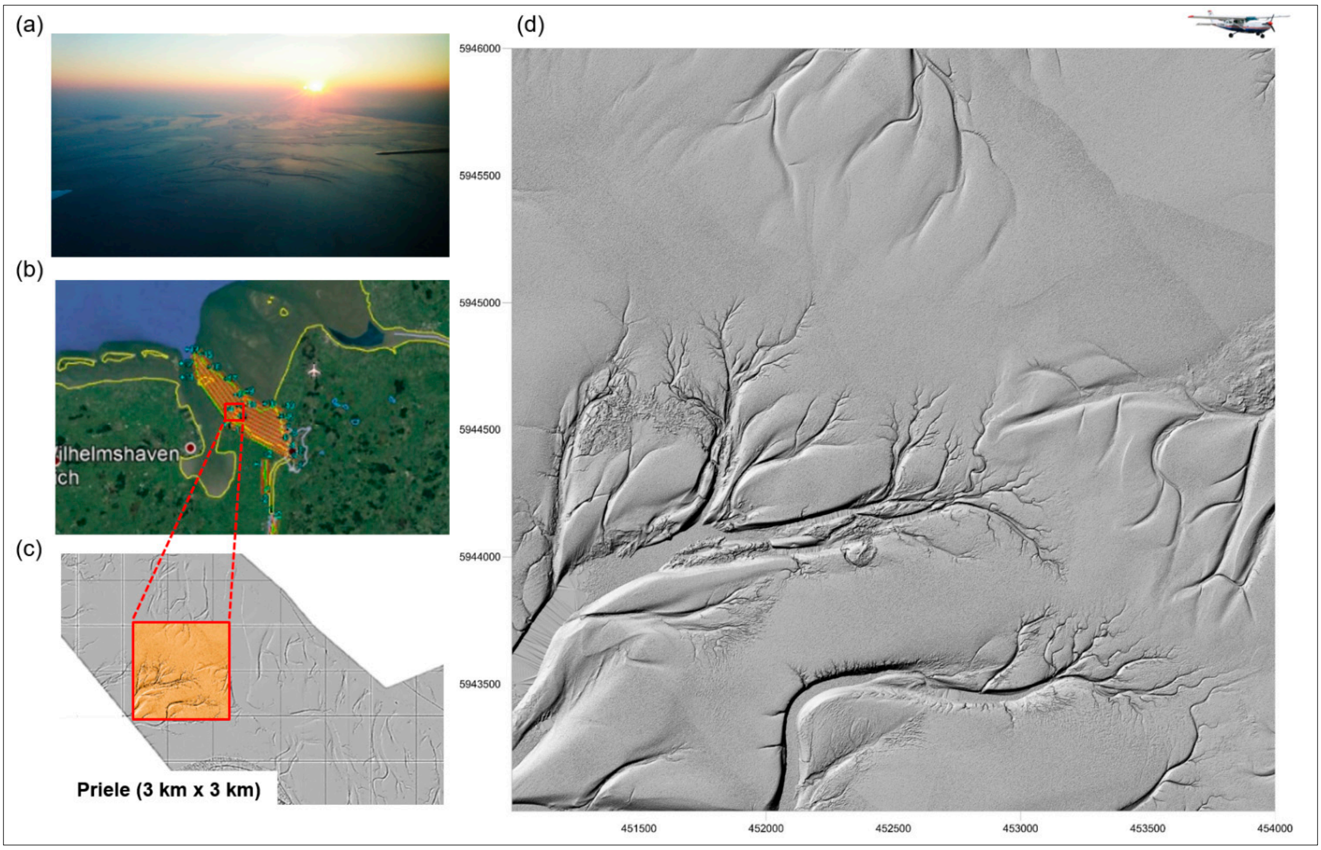

Figure 7. Tideways in the Weser River, northeast of Wilhelmshaven, Germany: (**a**) Photo of the tideways acquired from the aeroplane. (**b**) Location (Google Maps) of the monitored area (in orange). (**c**) Digital Elevation Model (DEM) monitored by Airborne Laser Scanning (ALS) with a blue rectangle (>5 LMW/m^2), highlighting the location of the (**d**) 3 × 3 km tideways, shown as shaded relief (elevation of the contours Z = 20) (from Lausch et al. [62]).

4.2.4. Monitoring the Taxonomic Diversity of Water with Remote Sensing

The "taxonomic diversity of water represents the diversity of water components that differ from a taxonomic perspective" (see Chapter 3, modified after Lausch et al. [32]).

Geogenic factors led to the formation of different types of lakes, such as tectonic and volcanic lakes, dam lakes and erosion lakes [62]. In addition, other factors such as genesis, morphometry, morphology and location; physical properties such as thermal combinations and optical properties; and chemical and trophic status led to the establishment of seas and lakes [91], which exhibit a characteristic aquatic trait diversity.

For example, Reynolds et al. [153] monitored phytoplankton taxa based on their characteristic environmental conditions such as seasons, lake morphology, trophic state of the lake or light availability, as phytoplankton communities are filters of environmental factors such as vertical water dynamics and depth, trophic state, predation and growth [47]. The taxonomic diversity and abundance of different taxonomic phytoplankton groups or coral communities and their changes are key parameters to describe the status, disturbance, stability, functionality and resilience of aquatic ecosystems [41,154,155].

Specific characteristic aquatic traits can be captured by RS approaches, enabling the determination of taxonomic diversity, e.g., phytoplankton taxonomic groups, coral reef classification or aquatic vegetation taxa or river systems, river network types, coast types, catchment areas, hydrological response units (HRUs) and watersheds (see Figure A1 and Table A1 in Appendix A). Aquatic taxonomic diversity, such as phytoplankton taxonomic groups or coral classification, can be discriminated by RS if species, populations or communities differ in their aquatic traits (e.g., structure, chemical–mineral composition or photosynthetic pigments). Furthermore, the distribution, density, composition and configuration of the aquatic traits of different taxa play a decisive role in RS-based discrimination. For example, the Great Barrier Reef in Australia can be discriminated more easily using RS due to its high density of identical aquatic traits than, for example, reefs in the Red Sea, where traits occur at a lower density. The radiometric, spectral, geometric and temporal resolution of the RS technology also plays a decisive role in discrimination. Only RS sensor technology that can spectrally record these aquatic traits and thus discriminate between taxa will be successful. This is very complex and similar taxa still have different spectral distributions, but in the future, it could work with a high hyperspectral resolution and combinations of validated methods (including optically more complex inland waters).

Airborne LiDAR RS technologies have been successfully used for the taxonomic classification of coral reefs for some time now, providing valuable insights into reef structure, complexity and taxonomy [156,157]. Thus, detailed 3D-LiDAR maps capture complex features of the coral reef, such as the height, 3D complexity and spatial arrangement of corals, which is crucial for the discrimination of different coral species, as each species differs phylogenetically in terms of its unique morphological traits [158]. By integrating RS time series from the same reef, changes in the structure, composition and healthy status of coral reefs are recorded. This is important to understand how reefs respond to environmental changes and to take protective measures [159,160]. Multi-sensor RS approaches can be used to capture a range of aquatic features, e.g., to better distinguish between different reef components such as hard and soft corals and different coral genera or species [161]. In addition, coral reef habitats and their restoration will be monitored using high spatial resolution unmanned aerial systems [162] or satellite imagery from PlanetScope and Sentinel-2 [163].

In order to facilitate the global monitoring of coral reefs, the Millennium Coral Reef Mapping Project was established between 1999 and 2002 by the World Conservation Monitoring Centre of the United Nations Environment Programme in order to use satellite images (IKONOS 2, Landsat, SPOT, High-Resolution Visible (HRV) and the airborne hyperspectral Compact Airborne Spectrographic Imager (CASI)) to understand, classify and map coral reefs, their composition and changes [164]. In 2020, Arizona State University, together with Planet, the Coral Reef Alliance and the University of Queensland, released the world's first high-resolution coral reef monitoring data product (Allen Coral Atlas) [165]. The classification and description of phytoplankton biodiversity was an early area of research, as phenotype-based taxonomy and the phylogeny of phytoplankton are closely linked, and a large number of traits are linked to phylogeny. This ensures the development of different ecological strategies and the occupation of specific niches [94].

Phytoplankton taxonomic classes or groups can be discriminated by different proportions of bio-optical traits using RS, such as, e.g., the Chl-a concentration, accessory pigments (Chl-b, Chl-c, carotenoids and phycobillins) or pigment ratios (TChl-a/AP, TChl-a/TP, PPC/TC) [41]. Furthermore, accurate monitoring of the spatio-temporal distribution, taxonomy and variability of phytoplankton groups using RS approaches is crucial to gain a better understanding of marine ecosystem dynamics and biogeochemical cycles [166]. Li et al. [88] reported on the global satellite observation of the distribution of marine phytoplankton taxonomic groups over the past two decades (2002–2022), with six main taxa globally, namely, chlorophytes (~26%), diatoms (~24%), haptophytes (~15%), cryptophytes

(~10%), cyanobacteria (~8%) and dinoflagellates (~3%), which account for the majority of the variation (~86%) in the phytoplankton communities, compared to diatoms that dominate the spatial distribution. It was further shown that diatoms dominate in high latitudes, marginal seas and coastal upwelling areas, while haptophytes and chlorophytes dominate the open oceans [88]. Due to the increasing free availability of multispectral and hyperspectral RS data, the creation of spectral libraries for green macrophytes for coastal and aquatic biodiversity RS is steadily progressing [167,168]. Similarly, global RS data availability and the use of spaceborne hyperspectral RS (EnMAP and DESIS) facilitates the classification and monitoring of mangrove species as an important part of the global blue carbon pool [169,170].

One of the first applications of RS is the monitoring of the trophic state (eutrophication) of seas, lakes and rivers. Using the RS satellite sensors MODIS MERIS [171], Landsat-8 OLI, Sentinel-2 [172–175] or spaceborne hyperspectral PRISMA data [176]), the trophic state is determined based on different variables of water quality such as chlorophyll-a, total phosphorus and transparency/Secchi disc depth.

The world's rivers are undergoing accelerated change in the Anthropocene and are subject to the increasing influence of human intensification. Based on the geomorphological, structural and trophic state of these rivers, Piégay et al. [177] developed a classification system of rivers that discriminates between rivers whose structure and functions have been characterised by natural and anthropogenic processes.

Another application of taxonomic diversity is the discrimination of water catchment areas as well as river courses. For example, based on the Shuttle Radar Topography Mission (SRTM) DEM with a pixel resolution of 3 arc seconds (~90 m at the equator), Linke et al. [178] calculated, for the first time, globally available hydro-ecological sub-catchment and river section characteristics (HydroATLAS). This provided information on, e.g., runoff accumulation, runoff distances, river orders, catchment boundaries and river networks on a global scale and represents the first standardised classification of water catchment areas (BasinATLAS) and rivers (RiverATLAS) on a global scale [178].

Coastal geomorphology describes the dynamic interface between the ocean and the land surface. Since different coastal types filter water differently, the ecosystem services of the different coastal types can be classified using RS methods, allowing their functionality and resilience to be assessed. Hence, coastlines can be discriminated from each other using RS, as they can be classified into different types based on hydrological, lithological and morphological characteristics, such as small deltas, tidal systems, lagoons, fjords, large rivers, tidal estuaries and karst [179].

Coral reefs are subject to change due to coastal development, resource use and climate change. Using airborne hyperspectral RS data, Asner et al. [80] were able to demonstrate the extent and rate of reef change with robust and spatially explicit monitoring that can support RS-based management and conservation decisions. An airborne approach was developed to plan and optimise field surveys of reef fishes over an ecologically complex reef ecosystem along the islands of Hawaii. Reef habitat variability was best determined by a combination of variables derived from airborne hyperspectral RS data: the water depth, coral and macroalgal cover, fine-scale reef structure, reef curvature and latitude as a proxy for a regional climate–ecosystem gradient. Modelling was used to classify 18 different reef habitats from the combination of these different RS variables. This modelling also required 117 in situ monitoring sites to quantify fish diversity and biomass with minimal uncertainty [80] (see Figure 8).

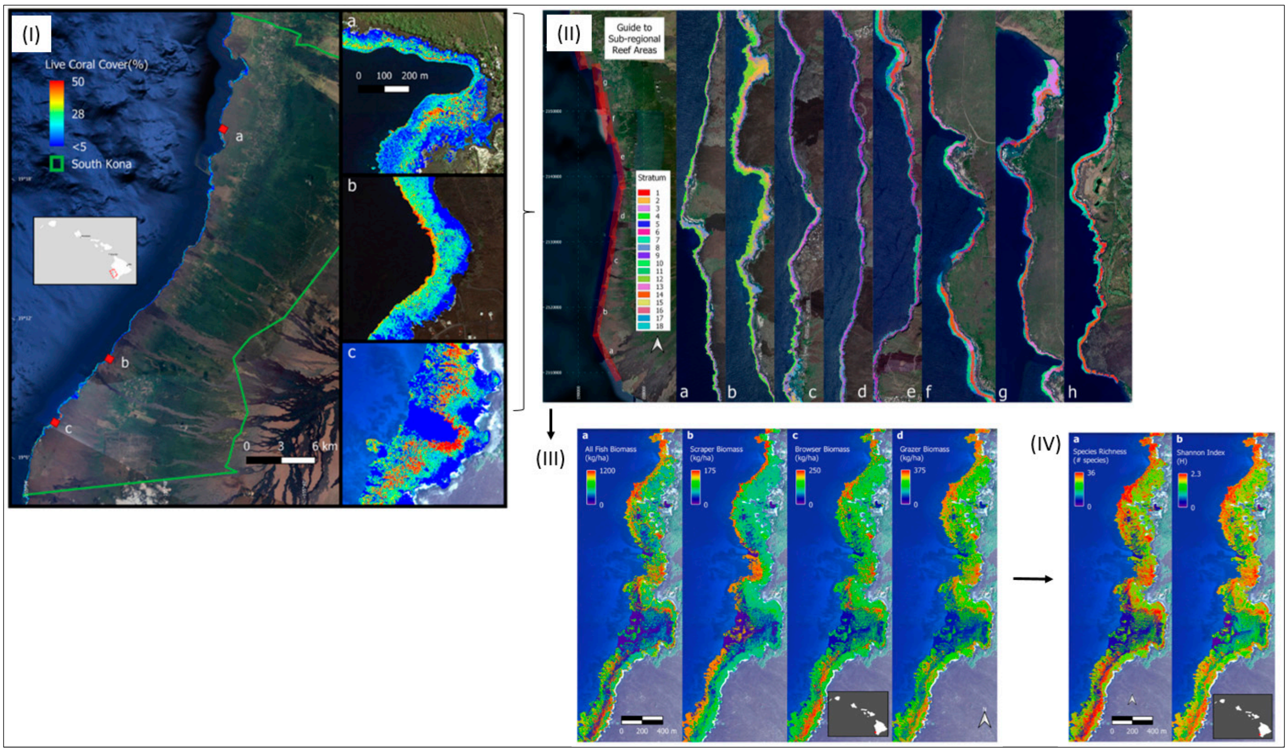

Figure 8. (**I**) The location of the South Kona District is demarcated by the green lines on the left, with live coral cover mapped along the coast based on airborne hyperspectral data in 2019 and 2020. Example areas of live coral cover are shown at (**a**) Honaunau Bay, (**b**) Papa Bay and (**c**) Okoe-Kapua Bay. (**II**) The final 18-stratum map of coral reef conditions for the South Kona District coast was derived from the airborne hyperspectral data. The far-left panel indicates the location of each sub-regional zoom image (**a**–**h**) shown in the remaining panels. Each colour indicates the location of each ecological layer in the reef system. (**III**) Ecological modelling was then applied to produce fish biomass maps of Honomalino Bay for (**a**) all fish and for fish classified as (**b**) scrapers, (**c**) browsers and (**d**) grazers. Differences in distribution patterns between the different trophic groups can be seen, especially across depth gradients. (**IV**) Finally, upscaled biodiversity maps of Honomalino Bay were generated using (**a**) species richness and (**b**) the Shannon diversity index (from Asner et al.) [80].

4.2.5. Monitoring the Functional Diversity of Water with Remote Sensing

The "functional diversity of water is the diversity of water functions and processes, as well as their intra- and interspecific interactions" (see Chapter 3, modified after Lausch et al. [32]).

Monitoring the status and changes of functional diversity in water bodies is crucial for assessing the status, changes and shifts of ecosystem functions such as productivity, nutrient cycling or trophic regulation. In monitoring aquatic functional diversity, the traits approach plays a crucial role with regard to in situ monitoring [41,46] and RS-based monitoring. The traits approach is a proxy and indicator that is crucial for quantifying and assessing the functionality, trade-offs and maintenance of ecosystem services in water bodies [41,154]. On the one hand, the concept of the functional diversity of water refers to the functional diversity of aquatic species such as marine bacteria, macroalgae [180], eutrophication, the composition of freshwater phytoplankton [155] and the changes to the macrosystem community of phytoplankton in lakes, which has an impact on diversity and numerous functions [71,154]. On the other hand, processes and interactions with components of geodiversity, terrestrial vegetation diversity and land use intensification, such as river straightening and urbanisation, influence the functionality and resilience of aquatic diversity. For example, geodiversity influences the functional diversity in freshwater macroinvertebrate systems [181]. In this chapter, the monitoring of functional diversity using RS can only be discussed as an example. Table A1 (Appendix A) provides an overview of RS-based monitoring of aquatic functional traits.

Plant Functional Types (PFTs) refers to the grouping of plants based on their common functional traits (growth rate, leaf shape, type of photosynthesis or response to stress factors), which is in contrast with the taxonomic classification. PFTs are used to better understand the impact of environmental changes such as climate change or land use intensity on vegetation by focussing on functional traits. The first naming of functional plant types defined the plant strategy types by Grimme [182], where plant characteristics have adapted to stressors and disturbance regimes through structural and functional properties and thus survival strategies over longer periods of time. The term PFTs was coined by Smith [183] and defines groups of plant species that show comparable responses to the environment and the functioning of ecosystems through similar functional characteristics. Reynolds [184] transferred this concept to a functional classification of phytoplankton by assigning 14 phytoplankton associations to specific environmental conditions such as lake size, nutrients, light and carbon availability. This approach was further developed by Reynolds et al. [153], whereby 31 associations of phytoplankton are currently described. The different phytoplankton species that make up a single PFT may have similar morphological characteristics and yet be adapted to similar environmental conditions by implementing different ecological strategies [46].

If aquatic ecosystem functions are to be recorded using RS, the aquatic traits that influence and regulate ecosystem functions must be defined. The traits and trait variations triggered by their processes (e.g., photosynthesis, photosynthetic pathways and carbon sequestration) must be recorded using RS. The RS-based detection of phytoplankton functions in aquatic environments is based on the spectral analysis of light reflected from the surface of a water body, as different PFTs have characteristic optical properties that are reflected in their light spectrum. Most techniques for the detection of phytoplankton with RS focus on the measurement of chlorophyll-a concentration [185,186]. Furthermore, different classes of algae contain different photosynthetic pigments that produce characteristic colour ratios in the reflected light. Optical RS sensors are able to classify different pigments and thus assign them to specific PFTs [120]. By using hyperspectral RS technology (PRISMA, DESIS and EnMAP), much finer discrimination of PFTs is possible compared to multispectral RS data, as spectral information of phytoplankton abundance, particle size distribution (PSD), bio-optical properties, chlorophyll-a and other pigments or spectral features (absorption, backscattering and/or reflectance) of the water in the VIS-NIR range are used [187]. The particle size distribution (PSD) of suspended particles in near-surface seawater is another crucial property that combines biogeochemical and ecosystem characteristics with optical properties and is reflected in the sea colour, which can be detected using RS. For example, small phytoplankton (picoplankton) are found in continuously stratified waters with lots of light at the surface and limited light in deep layers as well as limited nutrients, while large phytoplankton (microplankton) occur in turbulent systems with lots of light and nutrients near the surface [188]. Furthermore, phytoplankton size classes (PSCs) influence the physiological cell properties and, consequently, their biogeochemistry and biological carbon pump, which is crucial for the global carbon cycle and climate [189]. LiDAR technology can also be used to detect the structure of phytoplankton, which is used to distinguish PFTs based on structure and shape [190]. Some studies on RS-based PFT quantification use complex bio-optical models to identify specific phytoplankton species and classes. These models take into account various factors such as water quality, light absorption and scattering [191]. When in situ measurements are combined with RS, it can increase the accuracy of PFT classification, as in situ samples are used to calibrate and validate models [191,192], which is imperative. Furthermore, a tremendous advantage of RS is to use continuous waters using RS time series to capture seasonal and temporal patterns in phytoplankton dynamics, including the dominant occurrence of certain PFTs [186,193,194].

In the 19th–21st century, anthropogenic influences such as river straightening, urbanisation and land use change have increasingly led to irreversible changes and, consequently, the structural and functional disturbances of watercourses. By using aerial and satellite data, RS is able to monitor these change processes in the morphology, structures and functions of watercourses and their interactions and to assess their impacts on ecosystems and ecosystem functions. Rivers are the result of millions of years of morphogenesis. They are highly dynamic and adapt their course (meanders) according to the temporal changes in their discharge. Their meanders were formed by convergent and divergent flow movements that ran transversely to the general direction of the flow [32] (see Figure 9). The shape and structure of a river's meanders are a proxy of a stable, dynamic equilibrium between the river and the riverbed, leading to the development of a characteristic fluvial biodiversity, resulting in the stability of ecosystem functions such as a high self-purification potential. For example, numerous flood protection measures were implemented on the Upper Rhine in Germany in the 19th century. Areas at risk of flooding were reduced in size; measures were implemented to regulate low water levels, e.g., for year-round navigation, and power stations were built to make use of hydropower. These changes to the natural course of the Rhine in Germany led to strong influences and changes in the erosion and sediment behaviour (strong vertical erosion of up to 7 m) of the river, as well as an increase in flow velocity. The eroded material led to an increased formation of sand and gravel banks, whereby the barrages, in turn, acted as sediment traps, which consequently made further measures for low water regulation necessary [195]. These river regulation measures lead to irreversible changes in the geomorphology as well as the structural, functional and fluvial characteristics of rivers.

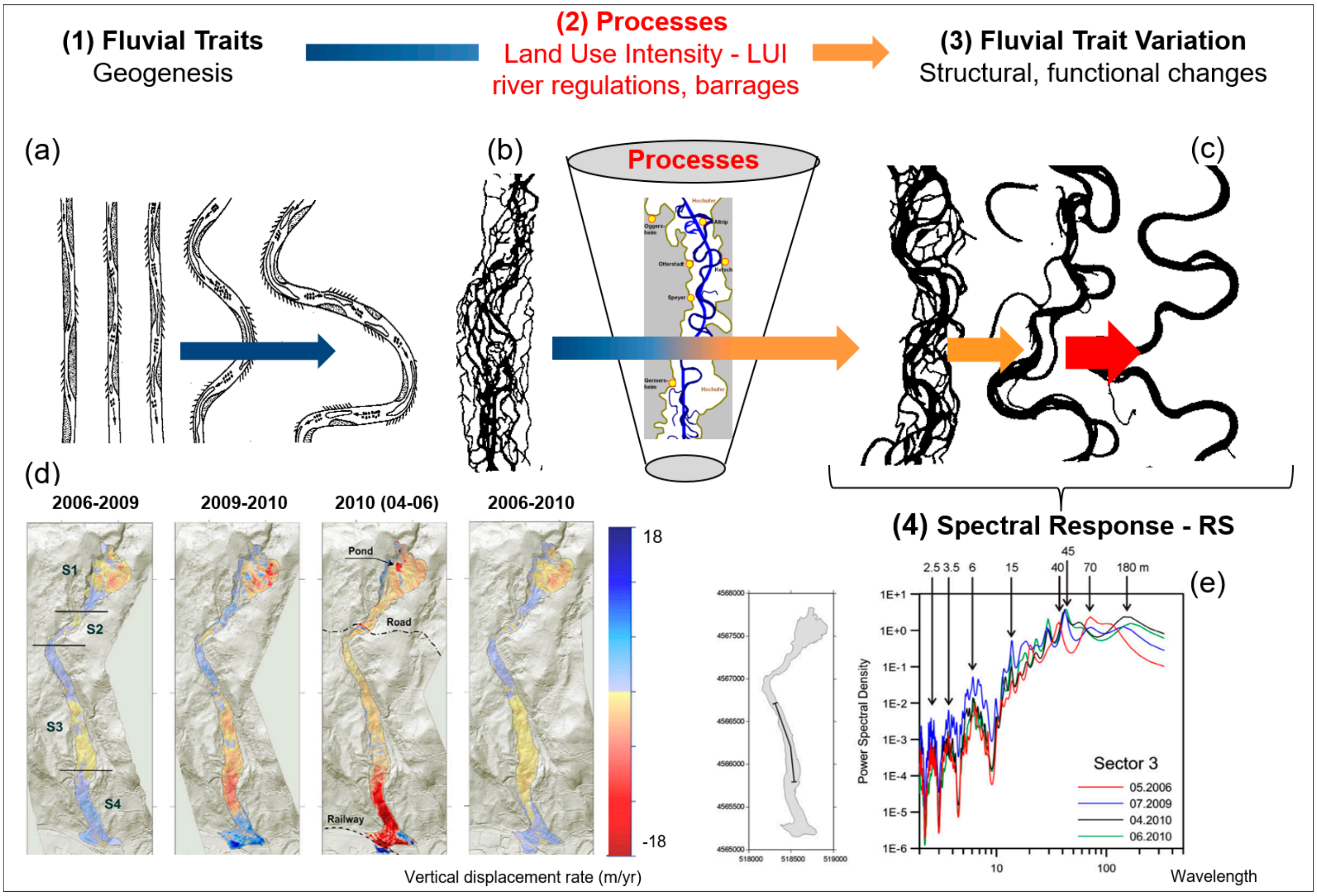

Figure 9. Monitoring status and changes to geomorphic characteristics with RS. (**a**) Different processes during geogenesis lead to the formation of specific morphometric fluvial traits—the meanders. (**b**) The entire river system is characterised by these meanders. (2) Processes/drivers such as land use intensity, river regulations and barrages lead to (**c**) changes in structural and functional fluvial traits

(fluvial trait variations–(3)) (**d**,**e**). These fluvial trait variations lead to spectral responses (4) in the remote sensing signal (**d**,**e**). An example of monitoring temporal changes to fluvial traits—vertical displacement rate of the river system from 2006 to 2010 with remote sensing technologies (LiDAR) (**d**,**e**). From Ventura et al. [81], reprinted with permission from Ventura et al. [81], 2021, Elsevier. License No. 5816961386058 (from Lausch et al. [32]).

RS approaches are able to continuously monitor these structural geomorphological changes of the meanders or sediment displacements over longer periods of time, as these changes to fluvial features lead to spectral responses in the RS signal (see Figure 9e). For example, the temporal changes of fluvial features—the vertical displacement rate of the river system from 2006 to 2010—were recorded using airborne LiDAR technologies (see Figure 9d). In addition to structural changes, the latest hyperspectral sensors, such as HySPEX, AISA, CHIME and EnMAP, can be used to make statements about changes to the functional diversity of water, changes to vegetation diversity (increasing eutrophication, chlorophyll content and turbidity) and the effects of river degradation on the neighbouring terrestrial ecosystem.

5. Conclusions and Further Research

The sea, inland waters and rivers play a central role in our aquatic and other ecosystems and provide the most important ecosystem services that enable and sustain life on Earth. The monitoring of water diversity and quality and their changes are complex, multidimensional and multi-scale in terms of space, time, processes and driving forces.

RS approaches have been successfully used for many years to implement monitoring on local to global scales. The traits approach was already introduced back in the 1980s for aquatic traits, but monitoring was based only on in situ measurements and observations. The aim of this paper was to apply the traits approach to monitoring water diversity and quality using RS approaches, as RS can monitor traits and trait variations for water diversity and quality. Traits form a crucial interface between in situ, airborne and spaceborne RS approaches and are filters or proxies for monitoring status, changes, disturbances and resource limitations on all scales. Therefore, RS approaches and the traits concept can be used to cover water diversity and quality, as well as changes and disturbances to them on all spatio-temporal scales, in a standardised way.

In order to understand how RS approaches monitor water diversity and water quality, five characteristics for the RS-based monitoring of water diversity and water quality were defined in this paper. These five characteristics are (i) the diversity of water traits, (ii) the diversity of water genesis, (iii) the structural diversity of water, (iv) the taxonomic diversity of water and (v) the functional diversity of water. The diversity of water traits is imperative to derive the other four characteristics with RS. The monitoring of the five characteristics of water diversity and water quality using RS technologies is presented in detail in this paper and discussed using numerous examples. Similar to the approach of Diaz (The Global Spectrum of Plant Forms and Functions) and Asner, the "Global Spectrum of Water Diversity and Water Quality" (Spectranometric Approach) can be created based on RS and the traits approach on the basis of traits, genesis, structures, taxonomy and the function of water diversity.

Monitoring water diversity and water quality and their interactions is complex. Therefore, future monitoring requires a holistic and interdisciplinary approach (a combination of water, geological and vegetation diversity) with analytical tools that combine in situ data, RS platforms and databases and integrate ecological modelling (see www.globewq.info). In addition, the traits approach allows the application of semantic data integration methods that enable the monitoring and modelling of ecosystem integrity (see the eReefs Research in Australia, https://research.csiro.au/ereefs/ accessed on 26 June 2024, Figure 10).

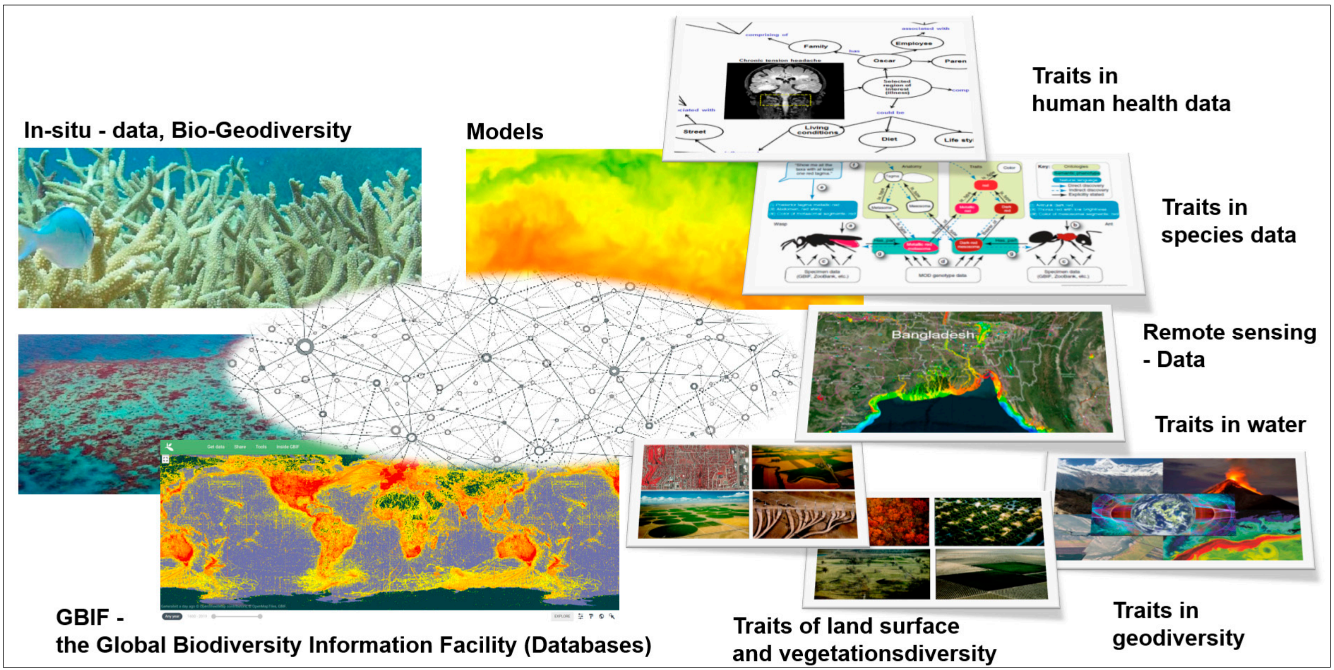

Figure 10. The trait approach allows the application of semantic data integration methods that enable monitoring and modelling of ecosystem integrity (see the eReefs Research in Australia, https://research.csiro.au/ereefs/ accessed on 26 June 2024).

In addition, the freely available tool (ESIS/Imalys—Ecosystem Integrity Remote Sensing/Modelling Tool and Service) has been developed based on traits and RS data [196]. The tool is under continuous development and can be downloaded from GitLab (https://doi.org/10.5281/zenodo.8116370, accessed on 26 June 2024). The tool can therefore be used to support research, application and planning to better classify and model RS data based on the traits approach in order to achieve a better understanding of ecosystems and integrative processes.

Author Contributions: A.L.: conceptualisation, methodology, writing—original draft preparation, writing—review and editing, visualisation, supervision; L.B.: investigation, resources; S.A.B.: investigation, resources, writing—original draft preparation, writing—review and editing, visualisation; E.B.: investigation, resources, writing—review and editing, visualisation; J.B.: investigation, resources; J.M.H.: investigation, resources, visualisation; T.H.: writing—review and editing, visualisation; M.H.: investigation, resources, writing—original draft preparation, writing—review and editing; A.J.: investigation, resources; K.K.: investigation, resources, writing—original draft preparation, writing—review and editing; N.O.: investigation, resources, writing—original draft preparation, writing—review and editing; M.P.: investigation, resources; F.S.: investigation, resources; P.S.: investigation, resources; F.v.T.: writing—review and editing, visualisation; M.V.: investigation, resources; C.G.: investigation, resources. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Author Thomas Heege and Fabian von Trentini were employed by the company EOMAP GmbH & Co KG. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

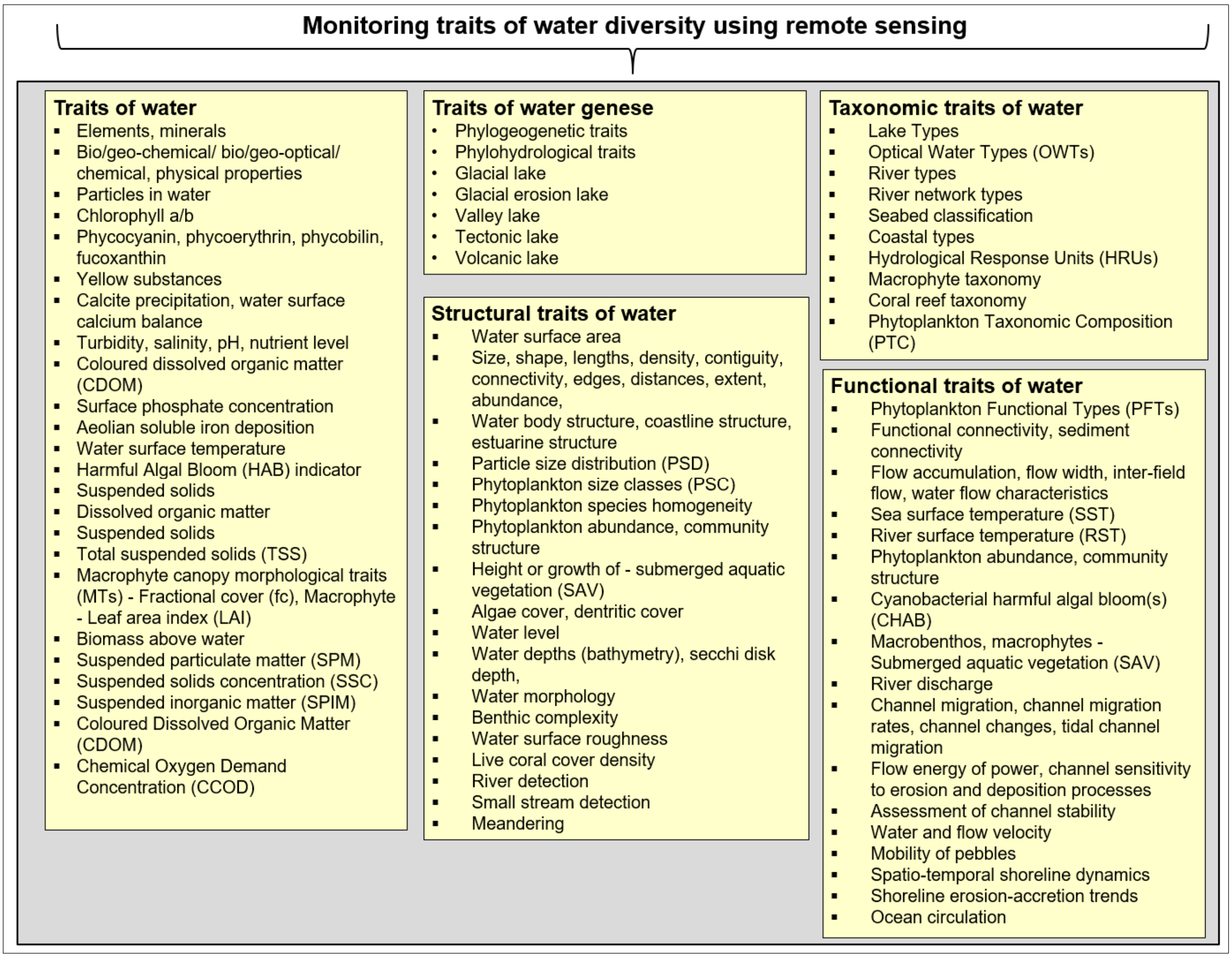

Figure A1. Monitoring traits of water diversity using remote sensing, the traits of water, the traits of water genesis, the structural traits of water, the taxonomic traits of water and the functional traits of water.

Table A1. Remote sensing-aided examples derived in monitoring the characteristics of water diversity (water trait diversity, geogenic water trait diversity, structural water diversity, taxonomic water diversity and functional water diversity) and shifts and disturbances.

Water Traits	Mission/Platform Sensor	References
Sea surface temperature (SST), river surface temperature (RST)	GOES-8 IMAGER [3], METEOSAT (MSG) SEVIRI [3], NOAA POES AVHRR [3], Aqua MODIS [3], Terra ASTER [3], Landsat 5 TM [3], Landsat 7 ETM+ [3], ERS-1/-2/ATSR1 [3], FLIR Tau [2]	[197–211]
Chlorophyll-a (CHL)—phytoplankton (large/small phytoplankton)	OrbView-2 SeaWiFS [3], Terra/Aqua MODIS [3], Envisat MERIS [3], Sentinel-3 OLCI [3], Sentinel-2 [3], Landsat 8 OLI/TIRS [3], APEX [2], LiDAR [1]	[23,186,212–231]

Table A1. *Cont.*

Water Traits	Mission/Platform Sensor	References
Phycocyanin (PC) and phycoerythrin—other photosynthetic and accessory pigments (cyanobacterial blooms indicated by phycocyanin (PC) and phycoerythrin)	Terra/Aqua MODIS [3], Sentinel-3 OLCI [3], Landsat 8 OLI/TIRS [3], NOAA GLERL [2], Sentinel-2 MSI [3]	[214,219–221,232,233]
Fluorescence—sun-induced fluorescence emission by phytoplankton/open-ocean phytoplankton chlorophyll fluorescence, (Fsat) distributions	Terra/Aqua MODIS [3]	[219,229,234]
Chemical oxygen demand concentration (CCOD) Water pollution	Sentinel [3] A/Ocean [3], Land Colour Instrument (OLCI) [3]	[235]
Algal blooms indicator (HAB)/Cyanobacterial Harmful Algal Bloom(s) (CHAB)	Landsat 8 [3], Sentinel-2A,2B [3], Sentinel-3A, 3B, 3C [3], WorldView-3 [3], PRISMA [3]	[236–239]
Phytoplankton populations, community structures (e.g., phaeocystis and diatoms, phaeocystis globosa spp)	OrbView-2 SeaWiFS [3]	[219,240]
Aquatic Phytoplankton Functional Types (A-PFTs)	OrbView-2 SeaWiFS [3], MERIS [3], APEX [2]	[188,219,241,242]
Macrobenthos, macrophytes—submerged aquatic vegetation (SAV)	QuickBird BGIS2000 [3], RapidEye REIS [3], Sentinel-2 [3], Landsat 8 OLI/TIRS [3], HJ-WVC [3], Daedalus MIVIS [2], Ocean Portable Hyperspectral Imager for Low-Light [2], Spectroscopy (Ocean PHILLS) [2], VarioCAM [1]	[82,228,243–250]
Lake-type classification	Landsat TM/ETM +/OLI [3], ASTER GDEM [3]	[78,251]
Optical water types (OWTs)	Sentinel-3 OLCI [3]	[214]
Channel landforms, hydrogeomorphic units including coarse woody debris, hydraulic (fluvial) landform classification, hydro-morphological units, riverscape units, river geomorphic units, in-stream mesohabitats, tidal channel characteristics	SAR [3], aerial images [2], LiDAR [2]	[252–255]
Coast taxonomy, coast types (small delta, tidal system, lagoon, fjord and fjärd, large river, tidal estuary, ria, karst, arheic)	Different RADAR sensors [3], different optical RS sensors [3]	[179]
Macrophyte taxonomy/macrophyte taxa/aquatic plant species	Canon Ixus 70 ® [1], Sentinel 2 [3] Airborne Hyperspectral [2]	[167,256]
Coral classification, coral reef habitat mapping, seagrass, aquatic vegetation community	Landsat 8 OLI/TIRS [3], RapidEye REIS [3], Ocean Portable Hyperspectral Imager for Low-Light [3], Spectroscopy (Ocean PHILLS) [2], Sentinel-2 [3], QuickBird [3], WorldView [3], NOAA [3] Worldview-2 [3], HyMAP [2], airborne (imaging spectrometer (hyperspectral) [2], Planet Dove satellite imagery [2], Airborne data visible-to-shortwave infrared [2], (VSWIR) imaging spectrometer and a light detection and ranging [2] LiDAR [2], CASI [2]	[113,151,219,249,257–263]
Coral mortality	Airborne data visible-to-shortwave infrared [2], (VSWIR) imaging spectrometer and a light detection and ranging [2], LiDAR [2]	[261]

Table A1. *Cont.*

Water Traits	Mission/Platform Sensor	References
Live coral cover density	Airborne data visible-to-shortwave infrared [2], VSWIR imaging spectrometer and a light detection and ranging [2], LiDAR [2]	[151]
Reef rugosity	LiDAR [2], VSWIR spectrometer Data [2]	[264]
Macrophyte canopy morphological traits (MTs)—fractional cover (fc)	APEX [2]	[242]
Macrophyte—Leaf Area Index (LAI)	Spot-5 HRG [3], Sentinel-2 MSI [3] Landsat 7 ETM+ [3], Landsat 8 OLI/TIRS [3], APEX [2]	[242,245]
Above-water biomass	Landsat 8 OLI/TIRS [3], Terra/Aqua MODIS [3], Landsat 8 OLI/TIRS [3], GaoFen-1 WFV [3], WorlsView-2 WV110 [3], APEX [2]	[242,265,266]
Macrophyte seasonal dynamics (phenology)/spatial distribution patterns/species-dependent variability, interannual changes of aquatic vegetation	Spot-5 HRG [3], Sentinel-2 MSI [3], Landsat 7 ETM+ [3], Landsat 8 OLI/TIRS [3], HJ-1A/B WVC [3], Landsat 5 TM [3]	[245,267]
Growth height of submerged aquatic vegetation (SAV)	Spot-6 NAOMI [3]	[268]
Suspended Particulate Matter (SPM), also referred to as the Total Suspended Matter (TSM)	Envisat MERIS [3], Terra/Aqua MODIS [3], Landsat 8 OLI/TIRS [3], Sentinel 3 OLCI [3], AHS [2]	[23,219,224,265,269–272]
Suspended Sediment Concentration (SSC)	Envisat MERIS [3]	[219,273]
Suspended inorganic particulate matter (SPIM)	Sentinel-2 MSI [3], Daedalus MIVIS [2]	[219,248,274]
Coloured Dissolved Organic Matter (CDOM)	OrbView-2 SeaWiFS [3], Envisat MERIS [3], Landsat 5 TM [3] < Landsat 7 ETM+ [3], Landsat 8 OLI/TIRS [3], Sentinel-2 MSI [3],Sentinel-3 OLCI [3], Daedalus MIVIS [2]	[23,212,217,219,222,224,248, 275,276]
Sediment and sediment dynamic, carbon and nutrient loads, particulate organic carbon (POC)	EO-1 Hyperion [3], Terra/Aqua MODIS [3], Landsat 5 TM [3], Landsat 7 ETM+ [3], Sentinel-2 MSI [3]	[82,269,277,278]
Calcite precipitation, calcium balance in the water surface layer	Landsat 8 OLI/TIRS [3], Sentinel-2 MSI [3]	[279,280]
SEA or ocean water acidification/salinity	SMOS MIRAS [3], PLMR [2], MODIS-OCGA [3]	[281–285]
Surface nitrate concentration	Terra/Aqua MODIS [3]	[229]
Surface phosphate concentration	Terra/Aqua MODIS [3]	[229]
Aeolian soluble iron deposition	Terra/Aqua MODIS [3]	[229]
Secchi disk depth, turbidity	OrbView-2 SeaWiFS [3], Terra/Aqua MODIS [3], Landsat 5 TM [3], Landsat 7 ETM+ [3], Landsat 8 OLI/TIRS [3], Sentinel-2 MSI [3], Sentinel-3 Ocean [3], Land Colour Instrument (OLCI) [3], Planet Dove satellites [3]	[221,222,270,271,286–291]
Wather depth, water transparency	Terra ASTER [3],Terra/Aqua MODIS [3], Landsat 8 OLI/TIRS [3], Sentinel-2 MSI [3], RapidEye REIS [2] RIEGL VQ-820-G [2], Ocean Portable Hyperspectral Imager for Low-Light Spectroscopy (Ocean PHILLS) [2], AISA-EAGLE [2]	[82,202,247,249,292–295]
Bathymetry, seabed mapping	Landsat 8 [3], Sentinel-2 [3], Multispectral [3], Hyperspectral Imagery [3], ICESat-2 [3], LiDAR [2]	[152,296–300]

Table A1. *Cont.*

Water Traits	Mission/Platform Sensor	References
River bathymetry	CASI 2/H, Daedalus 2/H, aerial images [2], LiDAR [2]	[255,301–304]
Water height, water level	ENVISAT [3], AMSR-E [3] TRMM [3] Daedalus 2/H, aerial images [2], LiDAR [2]	[255,304–308]
Water surface roughness	LiDAR [2], RADAR [3]	[122]
Water colour	Envisat MERIS [3], Sentinel-3 OLCI [3]	[23,309]
Submarine Groundwater Discharge (SGD)	Landsat 5 TM [3], Landsat 7 ETM+ [3] Landsat 8 OLI/TIRS [3], FLIR Systems [2], FLIR Tau [2]	[310–315]
Groundwater nutrient fluxes	Landsat 5 TM [3], Landsat 7 ETM+ [3]	[311]
Riverine discharge	Terra/Aqua MODIS [3]	[316]
Coastal fronts, plumes, oil slicks	OrbView-2 SeaWiFS [3], Terra/Aqua MODIS [3], Landsat 5 TM [3], Landsat 7 ETM+ [3]	[219,317]
Morphology, water level, water surface area, storage variations, extent, size, structure of water bodies, coastline changes	TerraSAR-X/TanDEM-X [3], SRTM [3], Landsat 5 TM [3], Landsat 7 ETM+ [3], Landsat 8 OLI [3], Sentinel-2 [3], WorldView-2 WV110 [3]	[219,318–326]
Shallow water inversion	Sentinel-2 [3]	[82]
Benthic complexity	Sentinel-2 [3]	[152]
Salinity	MODIS-OCGA [3]	[285]
River detection, small streams detection	SAR [3], Landsat-5 TM/-7 ETM+/-8 OLI [3], aerial images [2], aerial images [1], LiDAR [2]	[255,327–330]
Channel characteristics, floodplain morphology hydraulic channel morphology, geometries, topography, river width arc length, longitudinal transect (width, depth and longitudinal channel slope, below water line morphology), morphometric patterns of meanders (sinuosity, intrinsic wavelength, curvature and asymmetry), meander dynamics, channel geometry	SAR [3], ENVISAT [3], Terra/Aqua MODIS [3], Landsat-5 TM/-7 ETM+/-8 OLI [3], Sentinel-2 [3], aerial images [2], LiDAR [2]	[327,331–338]
Channel migration, channel migration rates, channel planform changes and tidal channel migration Channel changes, disturbances, temporal evolution of natural and artificial abandoned channels, canal position, systematic changes of the river banks and canal centre lines	SAR [3], SRTM [3], Landsat-5 TM [3], Landsat-7/8 ETM+ [3] OLI [3], aerial images [2]	[254,339–344]
Flow energy of stream power, channel sensitivity to erosion and deposition processes and channel stability assessment	Landsat-1 MSS/-5 [3] TM/-8 OLI [3], LiDAR [2]	[345,346]
River discharge estimation (river discharge, run-off characteristics)	ENVISAT [3], Jason-2/-3 [3], Sentinel-3A [3] OLCI/SLSTR [3], CryoSat-2 [3], AltiKa [3], ENVISAT [3], Advanced RADAR Altimeter (RA-2) [3], Terra/Aqua MODIS [3]	[308,347]
Water and flow velocity	ENVISAT [3], Terra/Aqua MODIS [3], Aerial images [2], LiDAR [2]	[255,333,348]

Table A1. *Cont.*

Water Traits	Mission/Platform Sensor	References
Fluvial sediment transport, sediment budget, channel bank erosion, exposed channel substrates and sediments, suspended soil concentration and bed material, percentage clay, silt and sand in inter-tidal sediments, suspended sediments, flood bank overbank sedimentation, sediment wave and sand mining	LiDAR [2], Radio frequency identification [1]	[337,349–351]
Stream bank retreat	Aerial images [2], LiDAR [2]	[352–357]
Grain characteristics, grain size, gravel size, shape, bed and bank sediment size	Daedalus [2], aerial images [2], aerial images [2], LiDAR [2]	[177,358–362]
Pebble mobility	Radio frequency identification technologies [1]	[363]
Coastal dynamical and bio-geo-chemical patterns	NOAA/MetOp AVHRR [3], ERS-1 [3], TOPEX [3], Nimbus-7 CZCS [3]	[364]
Coastal landforms and coastline and shoreline detection	SRTM [3], ALOS [3], NOAA [3], Landsat-7 ETM+ [3], Terra ASTER [3], IKONOS OSA [3], LiDAR [2]	[119,365,366]
Spatio-temporal shoreline dynamic, shoreline erosion–accretion trends, coast changes, cliff retreat and erosion hotspots	SRTM [3], SAR [3], Landsat-4 MSS/-5 TM [3], Landsat-8 OLI [3], SPOT 5 [3], Sentinel-2 [2], aerial images [2], LiDAR [2]	[367–374]
Different morphometric shoreline indicators: morphological reference lines, vegetation limits, instant tidal levels and wetting limits, tidal datum indicators, virtual reference lines, beach contours and storm lines	Different optical RS sensors [3], LiDAR [2]	[118,375,376]
Coastal dynamical and bio-geo-chemical patterns	NOAA/MetOp AVHRR [3], ERS-1 [3], TOPEX [3], Nimbus-7 CZCS [3]	[364]
Trophic state (eutrophication): Chlorophyll-a (CHL-a), total phosphorous and Secchi disk transparency	MODIS [3], MERIS [3], Landsat-8 OLI [3], Sentinel-2B [3], PRISMA [3]	[171–176,377,378]
Phytoplankton Functional Types (PFTs), Chlorophyll-a-Konzentration, different photosynthetic Pigments, Particle Size Distribution (PSD), Phytoplankton Size Classes (PSCs), Bio-Optical Characteristics (BOT)	NOAA [3], LiDAR [1], PRISMA [3], DESIS [3], EnMAP [3], MERIS [3]	[120,185,187–189]
Ocean Circulation	SAR Nadir Altimetry [3]	[379]

The sensor is used on the RS platform: UAV 1—unmanned aerial vehicles (UAV); airborne 2—airborne RS platform; spaceborne 3—spaceborne RS platform.

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