remote sensing

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Review

Remote Sensing of Surface Water Dynamics in the Context of Global Change—A Review

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Abstract: Inland surface water is often the most accessible freshwater source. As opposed to groundwater, surface water is replenished in a comparatively quick cycle, which makes this vital resource—if not overexploited—sustainable. From a global perspective, freshwater is plentiful. Still, depending on the region, surface water availability is severely limited. Additionally, climate change and human interventions act as large-scale drivers and cause dramatic changes in established surface water dynamics. Actions have to be taken to secure sustainable water availability and usage. This requires informed decision making based on reliable environmental data. Monitoring inland surface water dynamics is therefore more important than ever. Remote sensing is able to delineate surface water in a number of ways by using optical as well as active and passive microwave sensors. In this review, we look at the proceedings within this discipline by reviewing 233 scientific works. We provide an extensive overview of used sensors, the spatial and temporal resolution of studies, their thematic foci, and their spatial distribution. We observe that a wide array of available sensors and datasets, along with increasing computing capacities, have shaped the field over the last years. Multiple global analysis-ready products are available for investigating surface water area dynamics, but so far none offer high spatial and temporal resolution.

Keywords: remote sensing; surface water; dynamics; global change; earth observation; hydrology; biosphere; anthroposphere; review

Citation: Sogno, P.; Klein, I.; Kuenzer, C. Remote Sensing of Surface Water Dynamics in the Context of Global Change—A Review. *Remote Sens.* **2022**, *14*, 2475. https://doi.org/10.3390/rs14102475

Academic Editor: José Darrozes

Received: 23 April 2022
Accepted: 19 May 2022
Published: 21 May 2022

1. Introduction

1.1. Surface Water in a Societal and Environmental Context

On Earth, most water is bound in the oceans, in ice caps, or is stored as groundwater or ground ice. Only a small percentage (ca. 0.01%) of Earth's water resources is fluid inland water. This group covers all water bodies, water courses, and flooded lands. The residence time in these storages is very short, on average 9–18 days. Due to of its fast renewal rate, surface water is an important part of the hydrological cycle [1]. Across the globe, inland surface water is unequally distributed. Its availability depends on fluxes from other storages in the hydrological cycle. Precipitation makes up the largest share of incoming water (>99%). Additionally, meltwater from glaciers and permafrost areas, and inflow from groundwater, are significant contributors to inland surface water. Conversely, existing fluxes like evapotranspiration (ET), surface water runoff, and groundwater infiltration steadily drain surface water storage. Hydrological fluxes themselves are subject to natural large-scale oscillations (e.g., El Niño Southern Oscillation–ENSO, Indian Ocean Dipole–IOD, or Atlantic Multi-decadal Oscillation–AMO) and seasonal variations, leading to inter- and intra-annual dynamics of surface water. With ongoing climate change, these fluxes—most notably precipitation—change or become more variable, leading to changes in surface water dynamics [2,3]. This affects surface water availability, increasing the likelihood and severity of droughts and floods [3]. Apart from climate change, human interference changes surface water dynamics through, for example, dam construction [4], water diversion [5], or surface sealing [6]. An overview of the components of surface water hydrology and the factors that impact surface water dynamics are given in Figure 1.

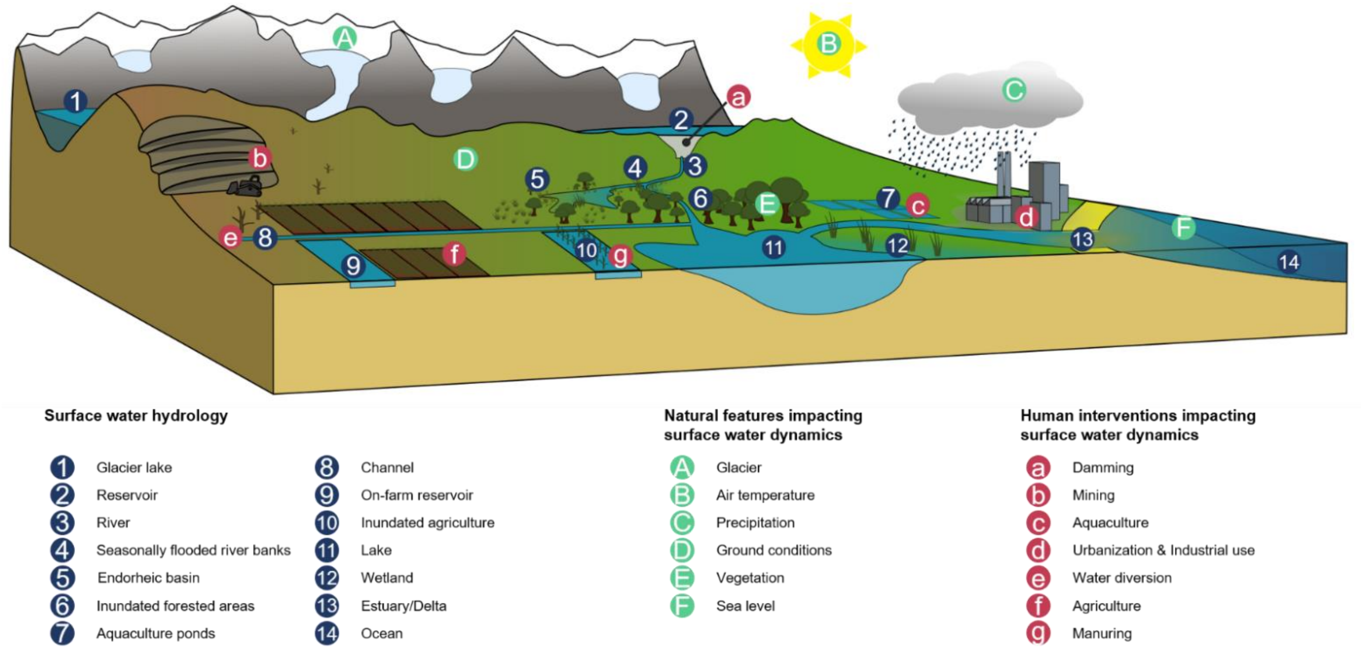

Figure 1. Model overview of surface water hydrology including natural and anthropological influences that affect surface water dynamics.

For the living environment, inland surface water is one of the most important resources. The availability of surface water—particularly freshwater—is a key factor for many ecosystems, as well as human society [7]. According to [8], surface water covers 50% of drinking water needs, 80% of irrigation water demand, and 60% of industrial water usage, albeit with substantial variation from country to country. The changes in inland surface water dynamics and, consequently, in water availability, affect both the natural environment and the anthroposphere.

Especially in semi-arid and arid regions, surface water availability decreases due to increasing ET and decreasing precipitation rates on the one hand, and the overexploitation of available water resources on the other hand [9]. In the case of Lake Urmia in Iran, for example, human water use has reportedly led to a decrease of up to 45% of lake inflow and between 39% and 43% of lake water loss over the timeframe of 2003–2013 [10]. Ref. [11] even reports a net permanent loss of surface water in the Middle East and Central Asia of >70%. Constant overuse of available water resources leads to ecosystem degradation, which manifests itself as changes in local flora, decreasing animal populations, and deterioration of soil quality through aridization and salinization [12,13]. The consequences for the local human population are reduced agricultural yields [14], problematic sanitation situations [15], and drinking water shortages [16]. There are also indirect effects of reduced water availability. Once degraded, even year-long conservation efforts only yield a minimal effect towards re-establishing the full capacity of ecosystem services [17]. Since they are often an integral part of local subsistence and economy, the degradation of natural environments decreases human livelihood [18] and security [19]. The effect of such destabilization is felt not only in the region that is directly affected, but also in areas connected to the original crisis through trade or migration flows [20,21].

In contrast to water scarcity, extreme precipitation events [22], ice-jams [23], increased inflow from upstream riparian areas [24], or sudden water discharge from reservoirs [25] can lead to intense flooding. Flood waves are a natural occurrence in river systems. They are important for local ecosystems, providing nutrient rich sediment and seasonal inundation. In a natural environment, once a flood wave exceeds the bankfull height, the retention areas and floodplains are inundated [26]. However, human intervention drastically inhibits the water storage capability of such areas. Most notably, many natural wetlands have been replaced with agricultural area and urbanized areas (e.g., [27,28]). On a global scale, wetlands have declined by 35% [29]. Due to the increase in impervious surface area, urban areas are more at risk of being flooded [30]. In highly populated areas, such events often cause high casualties [31] and an increased risk for disease [32] among the local population, as well as the destruction of infrastructure [33].

To prevent humanitarian and environmental crises due to water scarcity or sudden floods, sustainable management processes have to be in place. The Sustainable Development Goals (SDGs) [34] and other management agendas work towards better water availability and security. The topic of changing surface water dynamics ties into multiple goals at once. Twelve of seventeen formulated SDGs are reportedly concerned with or highly dependent on a secure water situation [35].

Focusing on SDG 6 (clean water), which is often mentioned as a key motivation for surface water dynamics monitoring (e.g., [36]), we see that, in the last years, there have been global efforts dedicated to reaching it. However, while positive effects like a global increase of water-use efficiency by 10% could be documented, no global indicator associated with this goal has been fully accomplished yet. On the contrary, some indicators, like SDG 6.2.1a (proportion of population using safely managed sanitation services), show negative development [15]. This indicates that plans for sustainable future management are still needed [37]. For the development, implementation, and impact monitoring of such initiatives, reliable and timely information on available water resources is vital [38]—even more so in the face of a changing climate, dynamic population growth, and industrial development in many countries [39,40].

1.2. Remote Sensing Perspective

Earth Observation (EO) provides datasets to monitor long-term dynamics as well as abrupt changes. Remote sensing (RS) in particular is able to provide data without disturbing the investigated area and offers a possibility to monitor otherwise inaccessible regions.

While already foreseen as an important tool for water resource monitoring and management at the beginning of this millennium [41], over the last years, the potential of EO for surface water dynamics research has increased considerably. Vast open archives like those of Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), or the Sentinel fleet enable research on all geographical scales from local to global at high temporal and spatial resolution. Data records of optical sensors like the Landsat mission, for example, reach far back into the last century (1972), which allows for the analysis of surface water dynamics on climatically relevant temporal scales [42], and with high spatial resolution as well. Other sensors, like MODIS, have since considerably increased the potential to monitor short-term changes in surface water by providing very high temporal resolution data (2 observations per day) [43]. However, up until the start of the Sentinel fleet, widely accessible data has always seen a duality of either high spatial or high temporal resolution. Increasingly, a trend can be seen towards sensor constellations that can overcome this limitation. As an example, records from high resolution sensors, like the Multispectral Instrument (MSI) onboard Sentinel-2, are available at temporal resolutions of 2–5 days. This trend towards more high resolution constellations can also be seen for commercial satellites (e.g., the PlanetScope constellation [44]).

Due to their sensitivity to cloud cover and the confinement to daytime observations, optical sensors are not always an ideal choice for the analysis of surface water dynamics.

Active and passive microwave sensors are valuable complementary assets as they can observe surface water through cloud and even vegetation cover (depending on the used wavelength) [45]. Traditionally, active microwave sensors, like Synthetic Aperture Radar (SAR) systems, have lower temporal resolution than optical systems [46]. This has changed over the last years with constellation missions like Sentinel-1 [4] or the Radarsat Constellation Mission [47].

Now more than ever, the potential of RS is vast due to open archives for long-standing satellite fleets, increasingly powerful computers, and the onset of cloud computing [48]. This enables the analysis of dense time series analysis, long-term change detection monitoring, and the observation of short-term inundation dynamics on multiple geographical scales.

1.3. Objective of this Review

In this review, we present how the RS-based investigation of inland surface water dynamics has developed over the last several decades. We concentrate on publications that show a multi-temporal development of inland surface water areas, thereby excluding approaches that solely focus on groundwater or water level, as well as those concerned with oceans and coasts. An overview of groundwater-related EO is given in [49]. Further, Ref. [50] provides a valuable overview of recent developments in the inclusion of Gravity Recovery and Climate Experiment (GRACE) data on terrestrial water storage in hydrological models. Satellite-based altimetry is reviewed in a comprehensive work on RS for deriving water extent and level by [51]. An overview of the Global Navigation Satellite System Reflectometry (GNSS-R) technique and its potential for wetland monitoring is given by [52]. Ref. [53] discusses the impact of humans and climate change on estuarine–coastal ecosystems.

There have been a number of contributions on topics related to that presented within this paper: Ref. [7], for example, provides an overview of optical sensor approaches for surface water detection and monitoring. Concentrating on SAR approaches, Ref. [54] details the strengths of SAR-based approaches and discusses the potential for future improvement. Ref. [55] offers insight on a large number of globally and freely available datasets related to hydrological dynamics and water management. Additionally, we identified reviews that describe and discuss recent proceedings in EO for specific hydrological applications (e.g., aquaculture [56] or model calibration and data assimilation [57]) or in selected geographical regions (e.g., India [58], the Tibetan Plateau (TP) [59,60]). Further, a human geography perspective on improving water security in large river basins is provided by [61].

Complementing existing works, the objective of this study is to provide an up-to-date view on the topic of RS of inland surface water area dynamics from a global perspective. To this end, we analyze the used timeframes, sensors, datasets, applications, and methods of 233 publications to answer the following research questions:

- How did the research field develop over time?
- Where are the hotspots of surface water dynamics research?
- What spatial and temporal scales are employed?
- What sensors are being used?
- What methods are utilized for delineating surface water?
- What are the strengths and limitations of available dynamic global surface water products?
- What are the predominant research foci?

In the following sections, we present our review method (Section 2) and our results with respect to the presented research questions (Section 3). The findings are discussed in Section 4, followed by a conclusion and outlook on the future (Section 5).

2. Materials and Methods

For our analysis we used the Web of Science platform (last accessed on 28 March 2022). It allows searches on the basis of search strings and additional filter criteria such as scientific discipline or publication year. Figure 2a presents the workflow we used, resulting in n = 233 reviewed publications. Our focus was on studies concerned with inland surface water, temporal dynamics, and EO, and is visualized as an overlap of the circles that represent our focus topics in Figure 2b. We used conditional statements to ensure the inclusion of each focus topic. To allow some leeway, we worked with a number of synonymous search terms per focus topic:

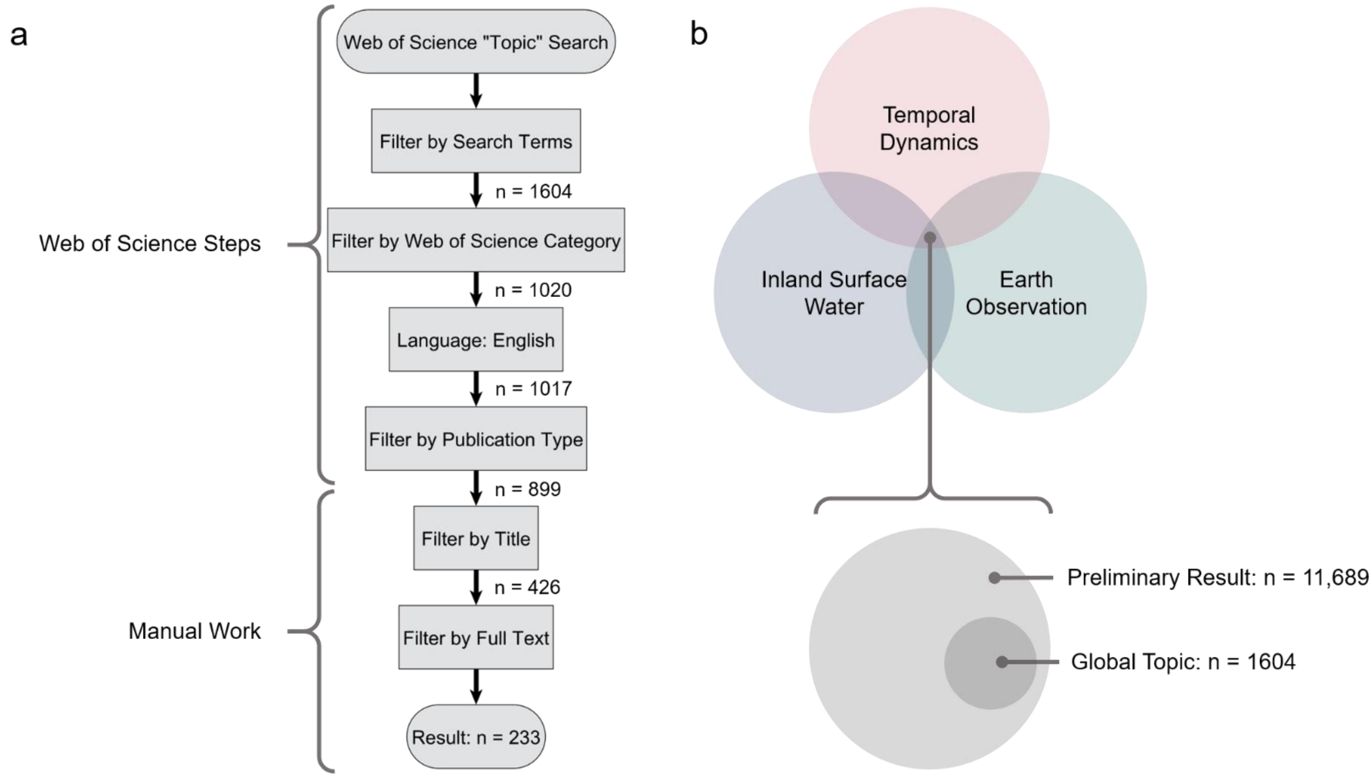

Figure 2. (**a**) Flowchart of filtering process to arrive at n = 233 publications. (**b**) Outline of the initial Web of Science "topic" search using search strings.

In the case of inland surface water, we included the terms "water" and "hydrology", if used in conjunction with the word "inland". Additionally, the mentioning of specific types of inland surface water, like "lake", "river", "reservoir", or any word starting with "flood" was also accepted. Studies that include temporal dynamics were selected via the terms "dynamic" and "time series". Also allowed was a conjunctional use of "change", "variability", and words starting with "seasonal" together with "multi temporal". Literature concerned with EO was selected if it included any of the terms "remote sensing", "satellite remote", "rs", "earth observation", "eo", or "mapping".

Based on these search terms, our initial search returned over 11,000 results. We therefore limited the scope to publications with a focus on the global perspective by including the term "global" in the search string. This yielded a more manageable n = 1604 results (Figure 2b). Going forward, we used the following search string to filter for publications that match our scope:

TS = ((((water OR hydrology) AND inland) OR lake OR river OR reservoir OR flood*) AND (dynamic OR time series OR ((change OR variability OR seasonal*) AND multi temporal)) AND (remote sensing OR satellite remote OR rs OR eo OR earth observation OR mapping) AND global)

Here, TS stands for "topic". Publications are considered on topic if given search terms appear in its title, abstract, or keywords. OR and AND are Boolean operators that we used together with brackets to formulate conditional statements. We filtered the returned n = 1604 publications by "Web of Science Category" to focus on publications from scientific disciplines that are within our scope. This process consists of two steps. In a first step, we refined our search so that the included publications fit at least one of the following categories: "Ecology", "Environmental Sciences", "Geography Physical", "Geosciences Multidisciplinary", "Imaging Science Photographic Technology", "Remote Sensing", or "Water Resources". In a second step, we excluded any "Web of Science Category" entries that were still included but did not fit our scope: "Archaeology", "Art", "Astronomy Astrophysics", "Biochemistry Molecular Biology", "Biophysics", "Chemistry Analytical", "Energy Fuels", "Engineering Aerospace", "Engineering Chemical", "Engineering Electrical Electronic", "Engineering Geological", "Engineering Ocean", "Engineering Petroleum", "Evolutionary Biology", "Genetics Heredity", "Geochemistry Geophysics", "Limnology", "Mechanics", "Microbiology", "Mining Mineral Processing", "Oceanography", "Paleontology", "Physics Fluids Plasmas", "Physiology", "Soil Science", "Spectroscopy", "Toxicology", or "Zoology". This reduced the number of publications to n = 1020.

We limited our scope to English papers, which excluded three publications. Further, we refined our search by limiting accepted document types to articles and review papers, thereby ensuring that publications considered have been under scrutiny through peer review. This returned n = 899 publications. After this filtering using the Web of Science platform, we proceeded by manually filtering the remaining publications by title (n = 426) and full text (n = 233), picking out results that do not match our thematic focus but include all search terms and other filter criteria thus far. In this last filtering step, only studies with a focus on inland surface water area or surface water storage remained. We filtered out studies that had no focus on inland surface water. With respect to coastal areas, we included river mouths, deltas, and estuaries, but excluded lagoons and other coastal water bodies with no freshwater access.

To only cover studies that monitor surface water dynamics, we considered time series as well as multi-temporal change detections with a minimum of three observations, but excluded uni- and bi-temporal studies. Further, publications on surface water modelling, like runoff simulations, were excluded if they did not include surface water dynamics from RS data. We did not set a temporal frame for the publication year of the included publications, the first publication that fit our search criteria was from 1994. However, the majority of included works have been published within the last ten years. Included in the final pool of publications are 16 review papers, which we considered in the investigations presented in the following section as applicable. For some of the following analyses, the publications considered were assigned to groups representing their thematic focus. Studies without a thematic focus were excluded in these cases. A full list of reviewed works is given in Table S1.

3. Results

In the following sub-sections, we present the results of our review. First, we show how research interest in the subject of surface water dynamics has changed over time and how it is distributed across the globe. We present used sensors and sensor types, as well as methods and used datasets for surface water dynamics analyses. Lastly, we analyze the thematic foci with respect to the geographic location and relevant findings.

3.1. Development of Research Interest over Time

The number of publications on the topic of surface water dynamics has significantly increased over the years (Figure 3). While a pioneer study from 1994 on inter-annual lake dynamics has been identified [62], only few peer-reviewed contributions to the topic have been published before 2006. In Figure 3, this is visible as data gaps for the years 1995–1999 and 2002–2005. Starting with 2014, an almost continuous increase in publication numbers per year can be seen. So far, the all-time peak of publication numbers is 2020. In 2021, there were fewer studies. The number of publications for 2022 only includes articles published within the first quarter, and is therefore much lower than for previous years. Overall, the development of publication numbers is in good accordance with previous works reviewing similar topics (e.g., [7]) and reviews on other EO applications (e.g., [30,63,64]). The general trend visible is attributable to the increased availability of satellite data, both through opening existing archives [65,66] and the start of new sensor fleets.

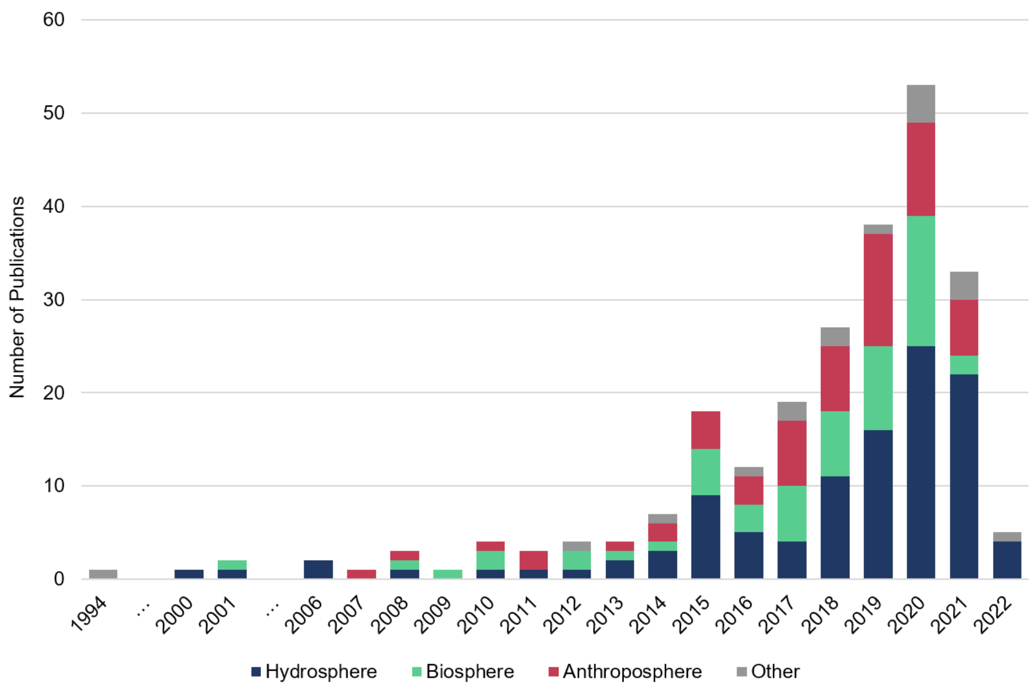

Figure 3. Increasing number of publications with indication of thematic focus (situation in March 2022). No publications fit our scope for the years 1995–1999 and 2002–2005, resulting in data gaps.

Concentrating on thematic foci, we see roughly proportional increases in publication numbers per year for all spheres from 2015 onwards. Hydrosphere-oriented publications mostly make up the largest share, followed by anthroposphere and biosphere-oriented works. "Other" works are publications with no discernable thematic focus, as is the case for some method papers and reviews included.

3.2. Discrepancy betweeen Areas of Interest and Authorships

Due to their impact on environment and society, inland surface water dynamics are a globally important topic. Figure 4 visualizes the hotspots of research as well as the first author countries for all research articles (n = 233). Areas of interest are shown in Figure 4a. Some studies have multiple areas of interest (AOIs). Multiple AOIs within one country are counted once and multiple AOIs across multiple countries are counted once per country. Additionally, the distribution of application foci for each continent is also presented with the respective number of publications. First author countries are shown in Figure 4b. Similar to Figure 4a, first authors could belong to multiple institutions. Authors belonging to multiple institutions within one country are counted once. Authors belonging to multiple institutions in multiple countries are counted once per country. The maps of Figure 4 are classified in seven Jenks Natural Breaks clusters to highlight high outliers but also include subtle differences between lower counters.

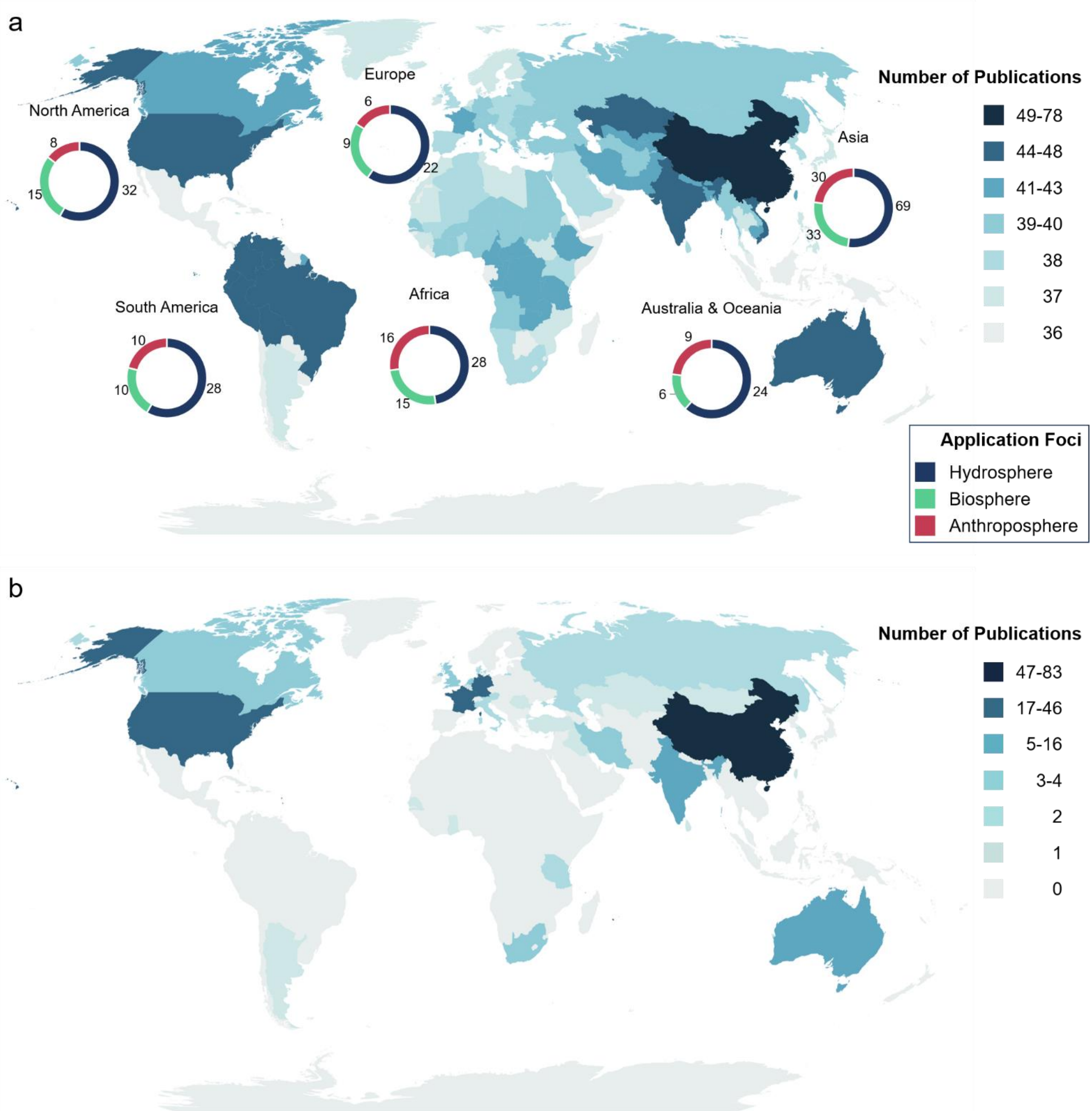

Figure 4. Global spatial distribution of (**a**) investigated areas and application focus distribution with number of publications per continent and (**b**) first authorships.

Visible in Figure 4a is a strong concentration of research on areas in China. Especially, the Chinese part of the TP is often in focus due to its high importance for freshwater availability in East and South Asia [24,60,67–71]. Several major Asian rivers are fed from the plateau, all of which are extremely important for downstream water availability.

Apart from TP, several other regions in China are often investigated. Many studies are, for example, concerned with the trends and dynamics of lakes along the Yangtze River, like Dongting or Poyang Lake [7,36,39,72–81]. Additional hotspots are visible in South America and Australia. In South America, most research activity is concentrated on the Amazon basin or its sub-basins. In Australia, most research is concentrated on the Murray–Darling Basin or its sub-basins. Furthermore, there is a high number of global approaches (e.g., [11,73,82–86]). Comparing Figure 4a,b, it becomes clear that the research hotspots in South America, Africa, and Central Asia are investigated by foreign research teams. Foreign research involvement is particularly visible in the Amazon and Congo River Basins (e.g., [87–89]).

Interestingly, the distribution of the application foci varies for different continents (Figure 4a). The share of hydrology-oriented publications is highest in Australia (62%) and lowest in Africa (48%). North America has the largest proportion of biology-oriented publications (28%), while Australia (15%) has the lowest. Lastly, anthroposphere-oriented studies have a high representation in Africa (27%). For other continents, the share is considerably smaller (16% in North America and 15% in Europe).

3.3. Spatial and Temporal Scales of the Studies

As shown before, the increased availability of satellite RS has a positive effect on the number of studies published per year on the topic of inland surface water dynamics. Figure 5 shows the development of investigated timeframes over the years. Figure 5a is a full representation of the start years, end years, and timeframe length for each investigated research article, Figure 5b presents the development of the investigated timeframe length over the years, while Figure 5c focuses on the distribution of the start years chosen. Studies concerned with intra-annual dynamics behave quite differently from those only focusing on inter-annual dynamics. For studies focusing on inter-annual dynamics, the length of considered timeframes did not change significantly over the years—apart from a gradual shift towards later "end" dates for considered timeframes with ongoing time (Figure 5a,b). However, studies that consider intra-annual dynamics exhibit a clear trend of increasingly long investigated timeframes (Figure 5b). Especially, studies published before 2010 all have relatively short temporal frames. In general, studies that only consider inter-annual dynamics have longer temporal frames than those concentrating on intra-annual dynamics (Figure 5a,b). Of the studies that only monitor inter-annual dynamics, many studies investigate long Landsat time series—the longest going back to the first available scenes from Landsat 1 [70,90–96]. Few studies consider even longer timeframes, all of those make use of "niche" satellite sensors that were not originally developed for EO but for espionage [27,97–100] or historic aerial imagery [101]. These approaches typically do not consider intra-annual dynamics, as the availability of historical RS data is limited. In newer publications, intra-annual dynamics are increasingly considered. Time series capable of capturing such dynamics can extend as far back as the 1970s when based on Landsat (1972-present) or the Advanced Very High Resolution Radiometer (AVHRR) (1978-present), but the bulk of studies considering intra-annual dynamics has "start" dates in the 1980s or around 2000. This coincides with the start of the operational phase of Landsat 5 and Terra MODIS, respectively (Figure 5c).

Approaches with "start" dates earlier than 2000 mostly rely on Landsat data. Many of them investigate surface water dynamics using the Global Surface Water (GSW) product developed by the European Commission's Joint Research Centre [11] or alternative products. Long time series that use data of higher temporal resolution start in the early 2000s and use MODIS data from Terra, Aqua, or often both. With the launch of the Sentinel fleet, more and more studies include Sentinel-1—especially—for shorter, but mostly weather independent, high-resolution time series of surface water [4,25,39,74,102–111]. Additionally, Sentinel-2 is often used for high spatial and temporal resolution time series, or as validation data [9,24,39,100,110,112–119].

The spatial and temporal resolution utilized in studies is visualized in Figure 6, under consideration of how many studies investigate intra-annual dynamics. At first glance, the dominance of approaches on a local to regional level becomes apparent. At these scales, most research is done at high (≤100 m) or medium (≤1000 m) spatial resolution. With respect to the temporal resolution, we see that studies with high (≤100 m) or very high (≤10 m) spatial resolution often do not take intra-annual dynamics into account. Forty-eight percent of these publications only focus on inter-annual dynamics. The largest group of these studies operates on a local to regional basis, mostly using Landsat data. While these data offer the temporal resolution for investigating intra-annual surface water dynamics, it is limited by long revisit times and additional influences that impact data availability for all optical sensors, like clouds or nighttime. When it comes to studies working on a geographical scale that spans an entire continent or even the entire globe, we see a shift in preference from high spatial resolution towards higher temporal resolution and the share of studies including intra-annual dynamics becomes larger (92% on a continental scale, 94% on a global scale).

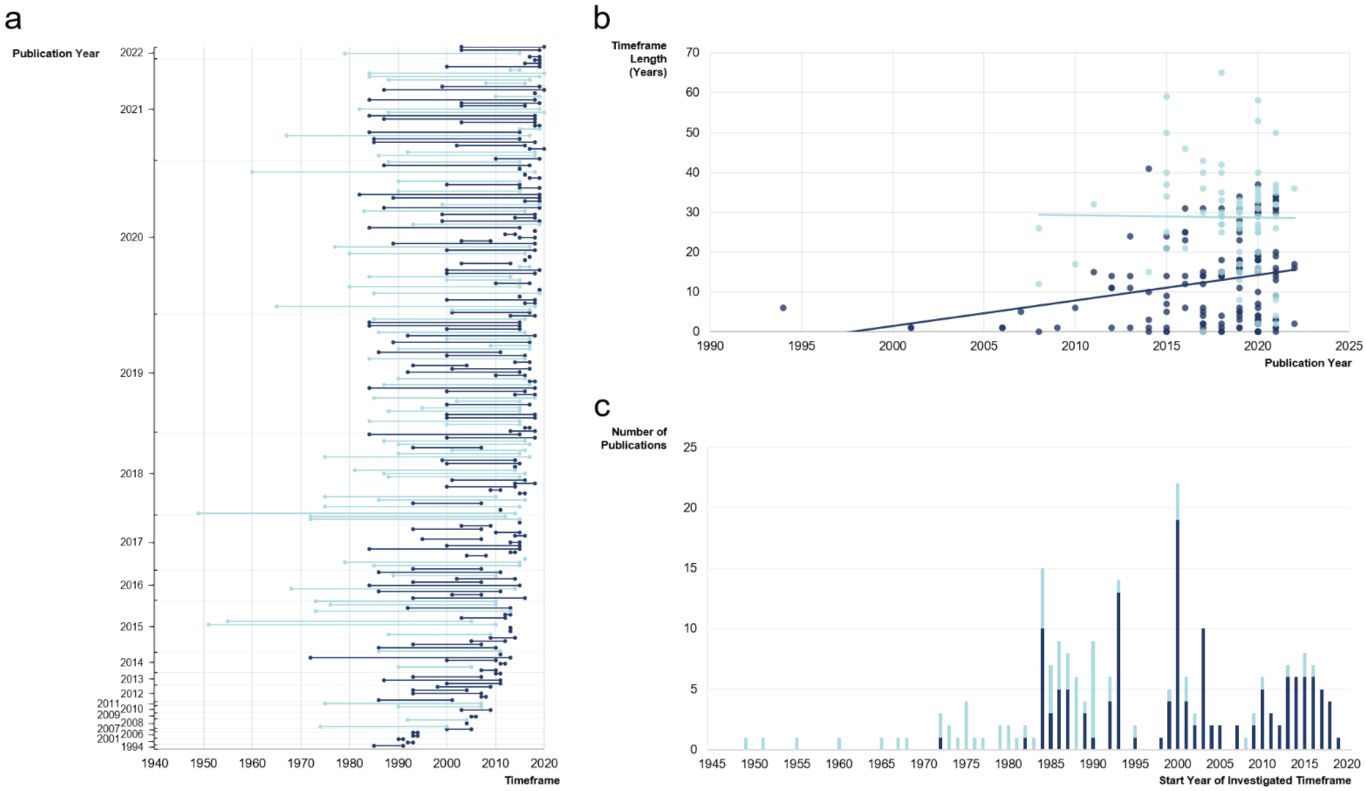

Figure 5. (**a**) Overview of investigated timeframes in reviewed publications. (**b**) Development of investigated timeframe lengths over the years. (**c**) Frequency and distribution of start years of investigated timeframes. Points signify studies, the general trend can be discerned from linearly fitted lines. Studies are color coded to show whether they did or did not consider intra-annual dynamics (dark and light blue, respectively).

What Figure 6 does not visualize is the intra-annual temporal resolution considered in these studies. The nominal temporal resolution of Landsat is 16 days, but due to data gaps, most Landsat-based approaches mostly work with monthly time series (e.g., [5,11,83,96,120,121]). MODIS-based approaches profit from a higher temporal resolution. This enables global and daily time series, as provided by Global WaterPack (GWP) [84,122], but at the cost of spatial resolution.

Generally, we see a duality between high spatial resolution and low temporal resolution studies versus low spatial resolution and high temporal resolution studies. However, there are approaches that seek to overcome this and produce high spatial and temporal resolution products based on data fusion. One approach in this regard is the blending of high spatial resolution time series with a high temporal resolution time series [39,81,122–124]. Another approach is downscaling based on empirical data (e.g., high resolution topographic data) [40,82,84,88,89,110,125–127]. Especially, the former is quite computationally intensive. Existing approaches—although providing convincing results on a local to regional level—are so far not suitable for global application. Apart from the data volume involved in the fusion process, this is mostly due to the available algorithms themselves. Especially, highly dynamic situations that demand high temporal and spatial resolution imagery cannot be represented accurately [128–130]. Empirical downscaling approaches have similar problems; here, static ancillary datasets used for the downscaling process introduce additional uncertainty [88]. Constellations of high-resolution sensors often are the preferred solution with global applicability (e.g., [44]), which explains their growing popularity with ongoing time of operation.

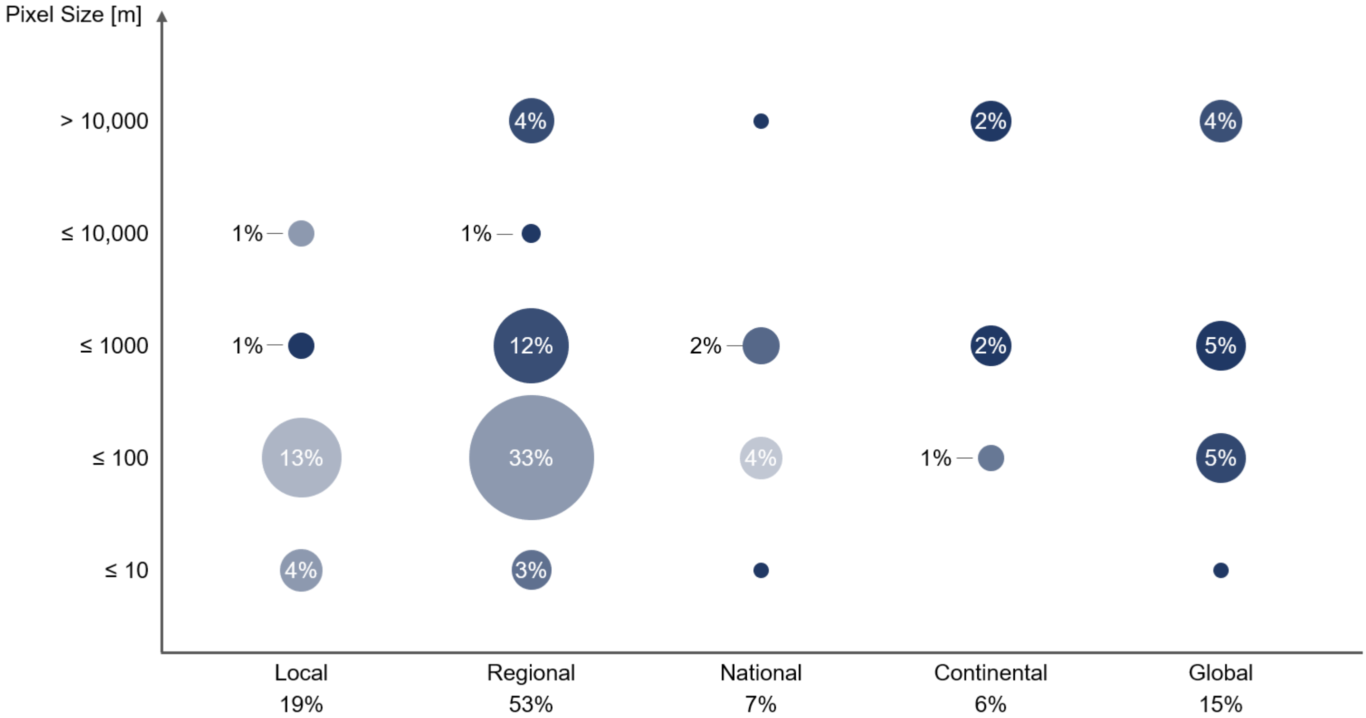

Figure 6. Visualization of spatial resolution versus study area size. Share of all included works is expressed in the area of scatter points and indicated as percentage values for each scatter point. Additionally, color shading from light to dark blue expresses the share of studies within a particular group that consider intra-annual dynamics. The darker the shading, the more studies of this group are considered intra-annual dynamics. For example: 100% of studies have a spatial resolution of ≤1000 m and global coverage analyze intra-annual dynamics, while only 30% of studies have a spatial resolution of ≤100 m and local coverage consider intra-annual dynamics.

3.4. Sensors and Sensor Types

The choice of sensor is mostly determined by the focus of a study (i.e., intra- vs. inter-annual dynamics), its area of interest, and the length of the considered timeframe. In general, four major categories of sensors are available for detecting surface water and monitoring dynamics: active and passive sensors working in the visible to infrared spectrum, or microwave spectrum, respectively. For visible and infrared wavelengths, active sensors use Light Detection and Ranging (LIDAR), while passive sensors work with the reflected light from the Earth's surface. Passive sensors operating in the visible to infrared spectrum are often called optical sensors. Microwave radiation is either actively emitted and the backscatter is analyzed (Radio Detection and Ranging–RADAR) or the natural microwave emission from Earth is analyzed (passive microwave). We show the utilized sensors and sensor types of investigated publications in Figure 7a,b, respectively. Here, we decided to concentrate on sensors used for water surface monitoring and omit all additional sensors that may be used in studies to, for example, include topography, water level, or rainfall. Several studies use multiple sensors and sensor types in combination, this is considered in this figure. As shown in Figure 7, an overwhelming amount of studies primarily used optical systems. Due to the high spatial resolution, the long continuity, and the availability of multiple analysis-ready products, the vast majority of studies work with Landsat data. Apart from that, a considerable number of studies rely on MODIS data due to its high temporal resolution. With any optical sensor, cloud contamination is a major problem. The lower the revisit frequency of the used sensor, the higher the impact on dynamics analyses. Given that, active microwave sensors—specifically SAR systems—are often seen as an alternative [110,131–134]. While, depending on the sensor wavelength, SAR-based imagery can also be affected by weather influences [4,46], in general, they offer higher data availability in regions that are often cloudy or affected by polar night. That being said, SAR sensors have a few sensor-specific drawbacks that limit their usability. Namely, SAR sensors are sensitive to surface roughness [46,102]. Especially in topographically heterogeneous areas, foreshortening, layover, and radar shadowing impact the return signal [135]. Additionally, misclassifications of land as water can happen, especially with threshold-based approaches when soil moisture content is high and incoming microwaves get scattered by wet ground in a similar way as water surfaces [109]. Water under canopy cover is partially detectable by SAR imagery, depending on the season and wavelength. While X- and C-band have limited accuracy [136], longer wavelengths like L-band SAR are able detect water surfaces under canopy, but come at the cost of reduced spatial resolution [137].

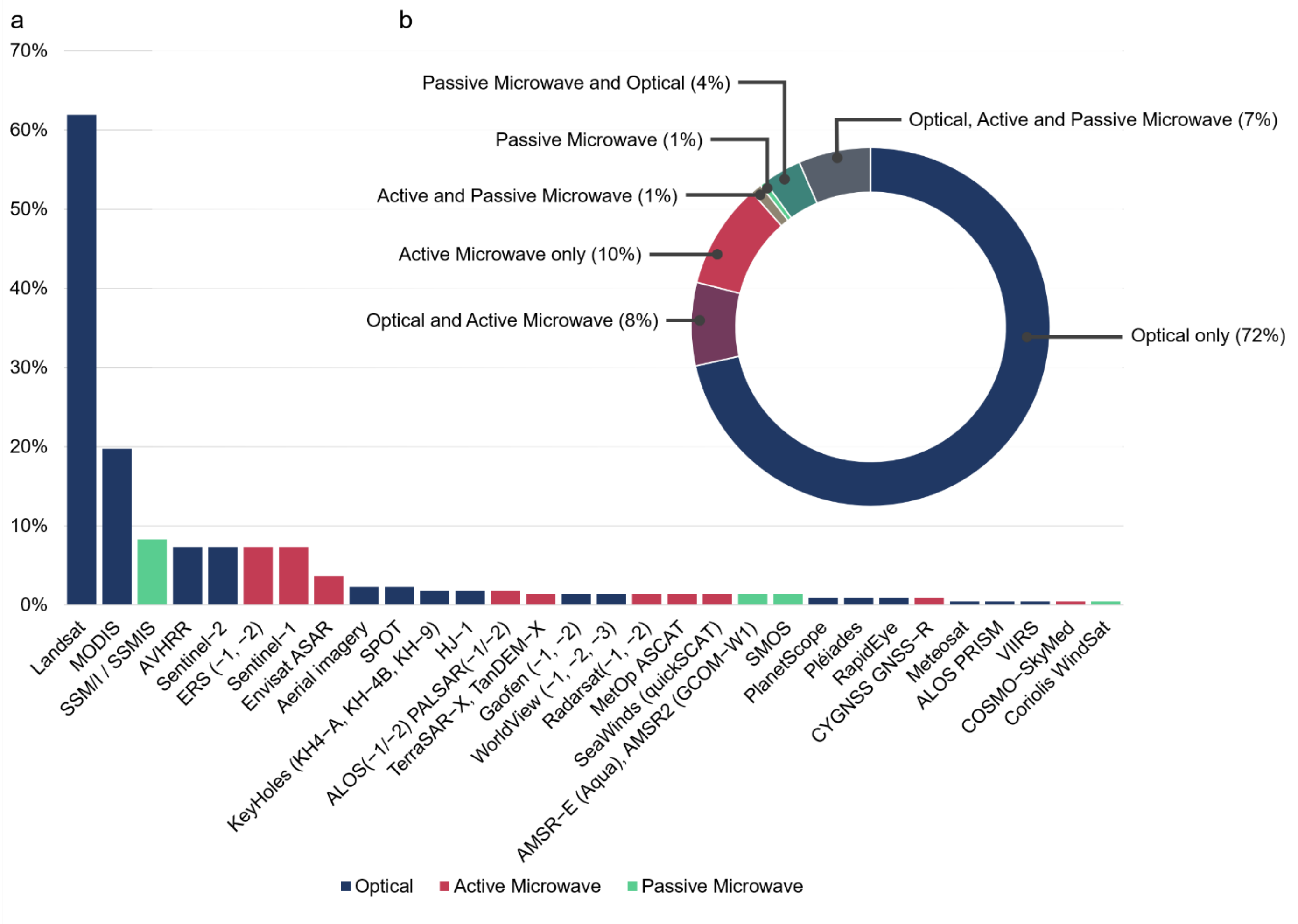

Figure 7. Used sensors (**a**) and sensor types (**b**) for surface water dynamics monitoring. Color coding indicates sensor type. Many studies use multiple sensors and sensor types.

Some approaches also use passive microwave sensors to identify water surfaces based on brightness temperature data. This approach is mostly based on passive L-band microwave data. While operating on low spatial resolution, this approach is mostly insensitive to cloud and rain [87,88,108,125,138–140]. However, L-band-based approaches tend to overestimate surface water. Therefore, so far, they have been mostly applied locally and under inclusion of a-priori data to reduce misclassifications [141,142]. LIDAR systems as well as hyperspectral optical sensors are not used for water surface delineation in any of the studies reviewed. Even though a number of studies successfully include LIDAR datasets as auxiliary topographic datasets and for altimetry [4,90,98,137,143–146] most studies analyzing water storage use auxiliary altimetry datasets. There are approaches that investigate the storage–area relationship based on optical and topographic or bathymetric data [147–150]. Yet, in these cases, changes in lake level can only be recognized if they are several times bigger than the pixel size (min. 6 pixel shift) of the used water surface dataset. The accuracy of the reconstructed lake level therefore strongly depends on the precision of water–land border retrieval, which demands very high-resolution data [149].

3.5. Methods for Surface Water Delineation

An overview of used methods for analyzing surface water dynamics is given in Figure 8. Many studies introduce custom classifications that often work similarly but are optimized for a specific sensor, area of interest, or thematic focus. The largest share of publications uses unsupervised classification techniques to classify surface water area (56%), especially threshold-based classifications, which are often utilized (29%). Such techniques are easy to implement and comparatively inexpensive in terms of computation [151]. In the visible and infrared spectrum, the spectral characteristics of water are, in most cases, strongly different from dry land. While water can have similar spectral characteristics to land in the visible spectrum, it absorbs infrared radiation much more strongly than dry land. Using this, thresholds can be applied on single infrared bands (e.g., [152,153]) or multiple channels. The latter is often done using ratio-based indices that include infrared bands (e.g., [9,69,78,80,117,154–156]). In SAR data, water is discernable due to its low backscatter intensity. Smooth water surfaces lead to a largely specular reflection. Incoming microwaves from side-looking radars are therefore reflected away from the sensor. Dry land has higher backscatter intensities because the microwaves are reflected more randomly. This leads to a largely bi-modal distribution of pixel values, and thus allows threshold-based approaches (e.g., [74,157,158]). Thresholds can be defined as fixed values or dynamically. Temporally and spatially dynamic thresholds have the ability to compensate for variations in the return signal and are therefore often implemented in large-scale studies that include intra-annual dynamics (e.g., [84,159,160]). However, they are also more sensitive towards cloud cover and other image contaminations [83]. Ultimately, the choice of thresholding technique therefore often depends on the performance in a specific use case. Surface water is not always distinguishable from its surroundings using a simple threshold. Therefore, some studies use more complex classification approaches, like decision trees (10%), specialized water classification algorithms (6%), or unsupervised clustering algorithms (5%).

Supervised classifications (17%) are used especially in studies where multiple land cover classes are considered (e.g., [90,161,162]). Here, labeled data points have to be prepared to train classification algorithms. While this offers advantages in comparison to unsupervised classifications, it also requires manual work. On a global scale, the production of training data is a very work-intensive task. Therefore, over 85% of studies that use supervised classification techniques work on a local to regional scale.

In many publications, surface water dynamics analyses are based on readily available data, like dynamic surface water area products (17%). A full overview of dynamic global surface water datasets is provided in Table 1. Particularly, Landsat-based products (GSW

5%, Water Observations from Space (WOfS) 1%, and Surface Water Extent Dynamics (SWD) 1%) are used in many studies [36,37,72,73,79,85–89,120,125,144,163–172].

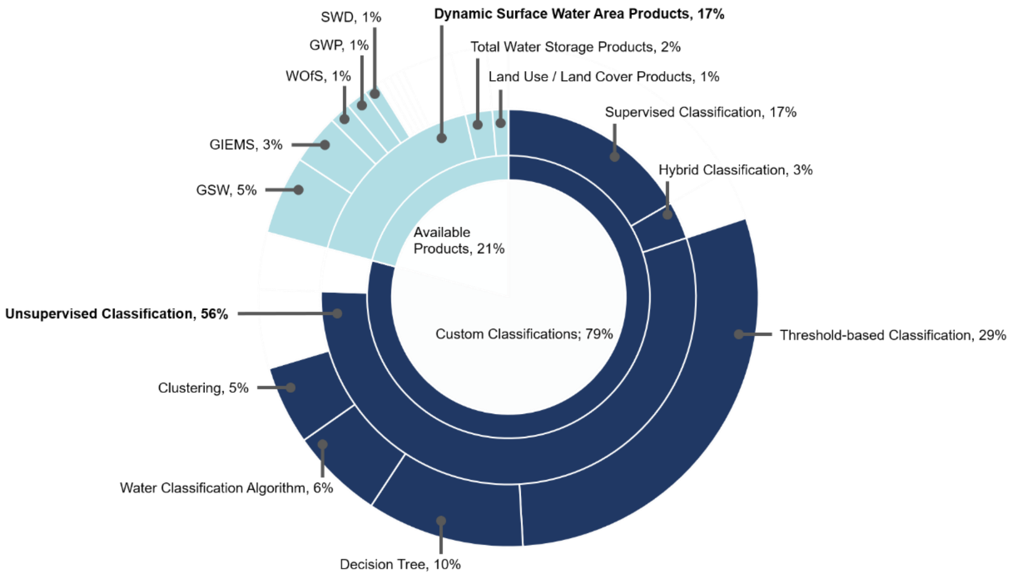

Figure 8. Detailed summary of methods used for the analysis of surface water dynamics. Custom classification approaches and approaches based on available products are shown in dark blue and light blue, respectively. The percentage value represents the share of all included works. All works are sorted as specifically as possible. Methods belonging to multiple subgroups or with too little detail to sort them correctly are not categorized further.

The dynamic GSW product and the static occurrence dataset GSWO are used more often than other available global surface water dynamics products. Within GSW, water occurrences are classified based on an expert system for the timeframe of 1984–2020 [11]. In addition to the 5% of studies that use GSW for surface water time series, 12% of studies incorporate it into their water classifications as an auxiliary dataset or use it for validation. However, the GSW dataset has several drawbacks that limit their accuracy and usability [173]. This has been found to especially be the case for frequently cloud-covered regions, polar regions, and the Sahel [139,166,167]. Other Landsat-based products try to advance on this. On a continental scale, the WOfS and SWD dataset are available for Australia ([174,175] and [42], respectively). WOfS has a ~25 m spatial resolution and is based on Landsat observations starting in 1987. The WOfS approach is based on a decision tree [176]. The temporal resolution of the product is ~16 days [175]. SWD is another Landsat-based water body time series product. It follows a slightly different approach, using a random forest classifier and spans the timeframe of 1986–2011 at a temporal resolution of ~3 months [42,177]. There are also global Landsat-based products and approaches that try to advance on GSW. Using cloud removal algorithms, Ref. [120] developed the Global Reservoir Surface Area Dataset (GRSAD) on the basis of GSW. This approach makes use of image enhancement based on water occurrence frequency to reduce cloud contamination and missing data effects to increase the availability and reliability of the monthly product [120]. Another dataset is the Global Land Analysis & Discovery Surface Water product (GLAD Surface Water), which provides monthly and global surface water data based on Landsat for 1999-2020. It uses multiple hierarchical decision trees for training a global classification model [173]. Apart from these products, there are approaches applied on a global scale that include Sentinel-2 observations in their time series [116], or fuse Landsat and MODIS data to obtain synthetic imagery with a higher temporal resolution [81].

Due to the low temporal resolution of Landsat, rapid events like sudden reservoir discharge [25], and events that are very time sensitive, like starts and ends of reservoir flooding [122], are difficult to observe using GSW. For this reason, a number of other global surface water datasets are available. Although MODIS offers a shorter timeframe and coarser spatial resolution than Landsat, MODIS-based surface water dynamics products like the GWP are a viable alternative due to their higher temporal resolution [165,178,179].

Table 1. Overview of available dynamic global inland surface water datasets.

Name	Spatial Resolution	Temporal Resolution	Timeframe	Sensor Type	Availability	Sources
GIEMS (Global Inundation Extent from Multi-Satellites)	Native: ~25,000 m GIEMS-D15: ~500 m GIEMS-D3: ~90 m	Monthly	1993–2007	Active Microwave Passive Microwave Optical	Upon request	[82,180–183]
GIEMS-2 (Global Inundation Extent from Multi-Satellites 2)	~25,000 m	Monthly	1992–2015	Active Microwave Passive Microwave Optical	Upon request	[139]
GLAD Surface Water (Global Land Analysis & Discovery Surface Water)	30 m	Monthly	1999–2020	Optical	Project Website [1]	[173]
GRSAD (Global Reservoir Surface Area Dataset)	30 m	Monthly	1984–2015	Optical	Project Website [2]	[120]
GSW (Global Surface Water)	30 m	Monthly	1984–2020	Optical	Project Website [3] GEE	[11]
GSWED (Global Surface Water Extent Dataset)	250 m	8 Days	2000–2020	Optical	Project Website [4]	[73]
GWP (Global WaterPack)	250 m	Daily	2003–2020	Optical	EOCGeoSer vice [5] Upon request	[75,84]
SWAMPS (Surface Water Microwave Product Series)	~25,000 m	Daily	1992–2020	Active Microwave Passive Microwave Optical	Project Website [6]	[140,184]
Daily Global Surface Water Change Database	500 m	Daily	2001–2016	Optical	Project Website [7]	[178]

[1] https://glad.umd.edu/dataset/global-surface-water-dynamics; [2] https://dataverse.tdl.org/dataset.xhtml?persistentId=doi:10.18738/T8/DF80WG; [3] https://global-surface-water.appspot.com/download; [4] http://www.dx.doi.org/10.11922/sciencedb.00085; [5] https://geoservice.dlr.de/web/maps/eoc:gwp; [6] https://asf.alaska.edu/data-sets/derived-data-sets/wetlands-measures/wetlands-measures-product-downloads/; [7] http://data.ess.tsinghua.edu.cn/modis_500_2001_2016_waterbody.html (all Websites last visited on 14 April 2022).

For the selected large-scale research areas, multi-satellite products offer distinct advantages. Global Inundation Extent from Multi-Satellites (GIEMS) and its follow-up, GIEMS-2, are based on active and passive microwave data as well as optical data, which increases their robustness against cloud and vegetation cover [126,139]. Downscaling approaches can be applied, as is the case with the GIEMS dataset. However, the downscaling procedure introduces, as briefly discussed earlier, new error sources. While downscaled GIEMS has proven useful for large-scale study areas like the Amazon basin [40,185,186] or the Ganges-Brahmaputra River Basin [16], variations in performance depending on the study region have been reported [126].

Other studies (e.g., [187]) include the Surface Water Microwave Product Series (SWAMPS), which offers global coverage and has low sensitivity to cloud cover due to its active–passive microwave approach. Yet, at a spatial resolution of ~25 km, the applicability of such a dataset is limited for smaller study areas.

3.6. Review of Thematic Foci in Research Hotspots

We sorted reviewed works into three spheres based on their main thematic focus: "hydrosphere", "biosphere", and "anthroposphere". We categorized n = 221 publications into these spheres and further divided them into groups and subgroups (Figure 9). Most publications cover more than one of the presented focus topics. It has to be kept in mind that some application topics are interrelated and most analyses are not confined to one specific topic. For example, studies analyzing ecosystem services (=anthroposphere) of a specific lake (=hydrosphere) are also concerned with ecological impact (=biosphere). We decided to group studies by their main thematic focus as we see differences in study layout and spatial distribution (Figure 10) depending on said focus.

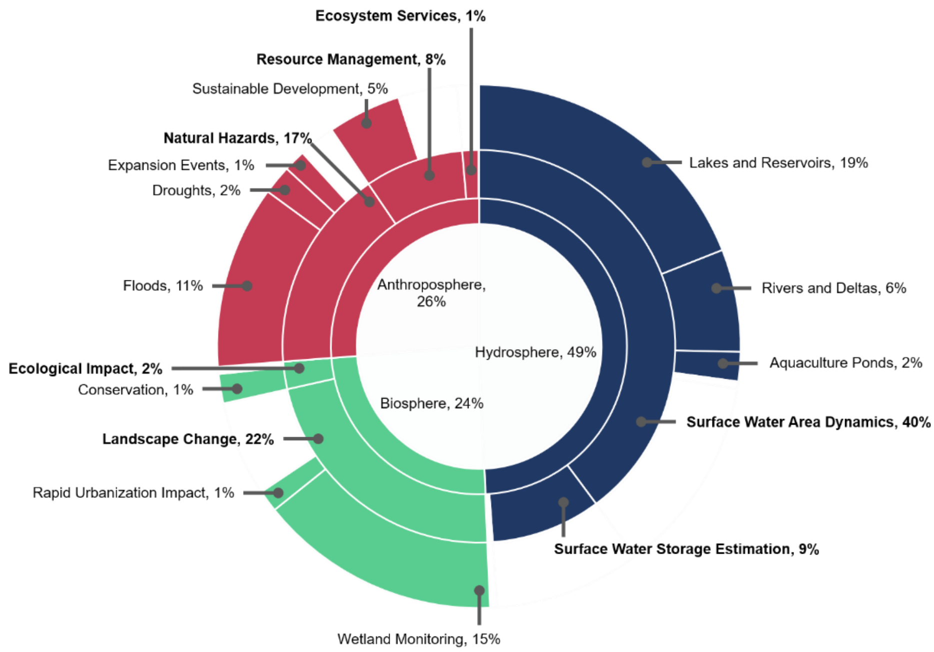

Figure 9. Detailed summary of investigated applications of n = 221 publications. Application fields are color-coded: Hydrosphere – blue, Biosphere – green, Anthroposphere – red. Most works are concerned with several of the given application topics. However, only the main focus is considered for this figure. Due to a rounding error, the numbers do not add up exactly. The closeness of spheres mimics the relatedness of focus topics. Those works that are not specified into further subgroups have a focus too broad to narrow it down further. As an example: 49% of included works have their primary focus on hydrosphere. A subset of 40% of all included works concentrates on surface water area dynamics. Narrowing it down further, a subset of 19% of included publications concentrates on lakes and reservoirs.

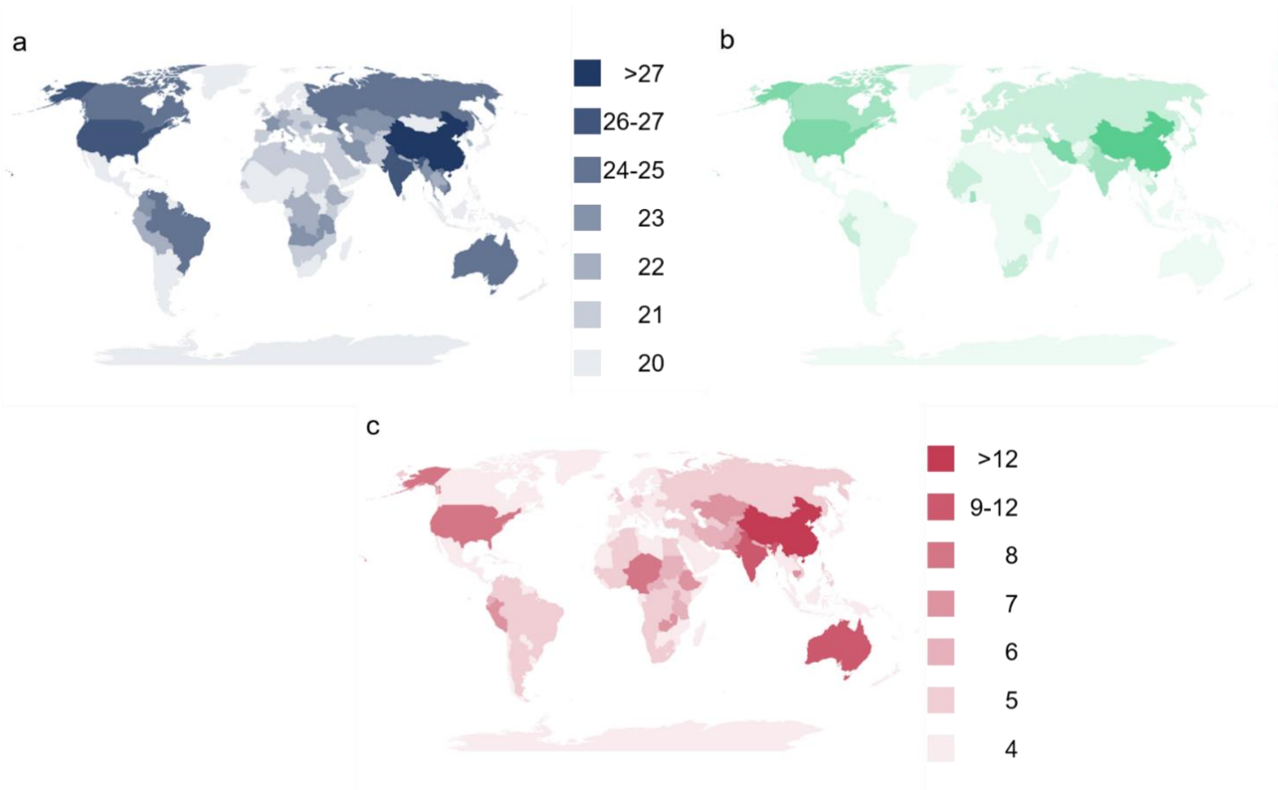

Figure 10. Number of studies mostly concerned with a thematic focus on hydrosphere (**a**), biosphere (**b**), and anthroposphere (**c**).

Nearly half of the studies (49%) mainly focus on the analysis of surface water hydrology. Within this sphere, studies generally operate on a large geographical scale, often spanning continents or the entire globe [11,73,75,82,83,85,86,122,125,126,131,139,140, 143,164,173,178,180]. While many global hydrological works investigate water surface dynamics of all inland water bodies, lakes, and reservoirs or large rivers, like the Amazon or Congo, which are sometimes exclusively in focus. Accordingly, the most dominant group belonging to this sphere is that of surface water area dynamics (40%). A further 9% of studies investigate surface water storage. Within the group of surface water area dynamics, we identified three subgroups. Twenty-seven percent of publications could be categorized further, according to the specific water body types they focus on. The largest subgroup, nearly one-fifth of the included works (19%), is concerned with dynamics analyses for lakes and reservoirs. Rivers and deltas are the primary focus of 6% of the studies. Aquaculture was analyzed in 2% of the studies.

Twenty-four percent of the studies focus on the biosphere. Biosphere-oriented publications mostly quantify the ecological impact of changing surface water dynamics and long-term trends. Few studies with this thematic focus work on a large geographical scale—examples are [40,80,187]. Often, drivers like human influence or climate change are associated with ecological deterioration. The main focus lies mainly on the analysis of landscape change (22%). Particularly, wetland monitoring (15%) is often a study focus (e.g., [13,71,74,110,137,144,163,170,187–191]). A smaller share of publications focuses on the impact of rapid urbanization (1%) [6,27,192]. Another 2% focus on the ecological impact of surface water dynamics.

In total, 26% of studies put their main focus on the anthroposphere. However, few of those operate on a global scale—[37,175,193] are examples. Especially, the analysis of natural hazards (17%) often is a thematic focus. A further 8% of studies had resource management as their thematic focus. This is the case for [25,36,37,69,90,92,104,167,171,194–196]. For such analyses, the study area is often a specific basin, lake, or reservoir. Ecosystem services are investigated in 1% of studies (e.g., [175,193]). Subdividing the natural hazards group—in particular, floods (11%)—are often the main thematic focus (e.g., [4,153,197,198]). Fewer studies mainly focus on droughts (2%) or rapid expansion events of glacier lakes (1%) (e.g., [86,199] and [70,200,201], respectively). A substantial share of studies concerned with resource management focus on sustainable development (5%). This includes EO-based efforts for SDG reporting, as demonstrated by [37].

On a global scale, 65% of studies primarily focus on the hydrosphere. Especially, surface water area dynamics are often investigated. For this, optical sensors are used predominantly, mostly Landsat 5, 7, and 8, or Landsat-based analysis-ready products like GSW, GLAD Surface Water, or GRSAD [11,83,85,120,173,202,203]. In contrast, high temporal resolution analyses rely on MODIS data or MODIS-based analysis-ready products like GWP [73,75,84,122,127,131,178]. Some approaches work on dynamic global surface water storage estimations that are based on area–storage relationships using Landsat-based analysis-ready data. In the case of Ref. [204], GSW observations and topographic information from the ETOPO1 Global Relief Model are used to estimate water height and volume. Using GSW and GRSAD for lake area, and including lake water level based on ICESat and ICESat-2 data, [205] creates a monthly time series of global lake volume for 2003–2020.

Another 26% of global studies are concerned with the biosphere, particularly the monitoring of wetlands. Early studies, like [159] use ENVISAT ASAR data for wetland delineation. However, as wetlands feature a high vegetation coverage, multi-sensor approaches are utilized more strongly. Mainly the GIEMS dataset is used [82,126,132,181,206], however, individual studies work with the alternative SWAMPS dataset [140,187]. As indicated before, the main limitation of these datasets is their very low native spatial resolution (~25 km). There are approaches for downscaling GIEMS to a higher resolution [82]—here, the limitations discussed earlier apply. Still, even in their native resolution, multi-sensor approaches are of sufficient resolution to evaluate global models, as Ref. [207] shows.

The rest of the global studies have a thematic focus on the anthroposphere. Landscape change is investigated by Ref. [180]. They use a multi-sensor approach that is based on the original GIEMS methodology [181] and adaptations made by Ref. [208]. Covering the timeframe of 1993–2007, a decline of inundated area by 6% globally is reported, mostly in tropical and subtropical South America and South Asia. It is suggested that this dynamic is due to high population pressure in these regions [180]. Focusing on global flood risk, Ref. [125] uses Soil Moisture Active Passive (SMAP) brightness temperature estimates from passive L-band observations with Advanced Microwave Scanning Radiometer 2 (AMSR-2) passive K-band retrievals and a static MOD44W MODIS surface water mask to assess global inundation dynamics. Global drought monitoring on the basis of reservoir dynamics is done by Ref. [86] using the GRSAD dataset.

As indicated earlier, most studies work on a regional or local scale. This is also visible in Figure 10. The global perspective is still considered in those works. As summarized in Table 2, the findings regarding surface water dynamics are strongly dependent on the investigated region, but associations with large-scale drivers are similar across most regions. In the following, we give a more detailed overview of the individual regions and application foci.

Table 2. Overview of researched areas, main findings, identified drivers, and challenges.

Continent	Hotspots	Main Findings	Drivers	Challenges	Sources
Africa	Sahel Congo River Basin East African Rift	• Ecosystem degradation • Changing seasonal and inter-annual variations in Lake Chad due to climate change • ENSO and IOD strongly impact inter-annual surface water dynamics • In (semi-)arid regions: Land use and land cover change with substantial decrease of surface water body extent • Extreme intra- and inter-annual fluctuations in surface water body extent (Tanzania)	• Human intervention • Climate change • Large scale oscillations (AMM, AMO, ENSO, IOD)	• Data gaps • Clouds and atmospheric influence • Mixed pixels (spatial resolution constraints) • Limited cooperation and data sharing • Water surface roughness (esp. for C-band SAR) • Limited temporal resolution • Satellite-based altimetry only for large enough water surfaces possible • Vegetation cover obstructs water surfaces • Spectral or backscatter similarity of water surfaces and other land cover • Attributability of observed changes to suspected drivers • Data volume (especially for large scale studies) • Impact of topography • Validation difficult to realize (especially for large scale studies)	[9,14,37,62,87,92,102,104,105,114,127,137,151–154,161,166,167,194,197,209–218]
Asia	Siberian Tundra Central Asia China High Mountain Asia South & Southeast Asia	• In alpine and arctic regions: Increase of available surface water due to increased precipitation and melting processes • In arid regions: Mostly decreasing trend of available surface water • Gradual and abrupt changes due to human interventions impacting established surface water dynamics • In humid low-lying regions: Changes in inundation dynamics	• Human intervention • Climate change • Large scale oscillations (ENSO, IOD)		[4–6,10,12,13,16,17,24,25,27,31,33,36,39,43,46,60,67–72,74,77–80,91,94,95,97,98,100,103,104,106–109,111–113,115–118,121,123,127,133,141,142,145,147,150,155,156,158,162,169,172,188,189,192,193,196,198,200,201,216,219–251]
Australia	Southeast Australia (Murray-Darling-Basin)	• Human activities impact existing intra- and inter-annual surface water dynamics • Established surface water dynamics stabilize important local ecosystems	• Human intervention • Climate change • ENSO	• Sensor ageing • Limited correlation of surface water extent and altimetry	[42,90,124,165,174,175,177,252,253]

Europe	Mediterranean Alpine regions Western Europe	• In Alps and Carpathians: Increase of glacier lake growth • Well researched areas used for proof-of-concept studies and performance testing	• Human intervention • Climate change (especially temperature increase)	• Limitations from static water masks • Global applicability of regional approaches • Inaccuracies of used DEMs • In SAR approaches: Surface wetness reduces classification accuracy • Spectral variations of different water bodies	[99,121,127,141, 149,163,168,236, 254–256]
North America	Arctic tundra Boreal regions Continental USA	• In Arctic: Inter-annual changes identified that correspond with surface water body size (growth of large lakes, retreat of smaller lakes) • In Arctic: Big impact of global warming and associated precipitation increase; incline in extreme thermokarst lake drainage • In Everglades: Dense vegetation cover and high cloud cover challenge conventional surface water detection approaches	• Human intervention • Climate change (especially temperature and precipitation change)		[5,23,43,44,47,93 ,96,101,110,127,1 44,148,157,169–171,199,236,252, 257–262]
South America	Amazon River Basin Pampas	• ENSO is a driving factor of monitored inter-annual surface water dynamics • In Amazon basin: Intra- and inter-annual surface water availability fluctuations are directly linked to precipitation • Dense vegetation cover and high cloud cover challenge conventional surface water detection approaches	• Human intervention • ENSO • Climate change (temperature and precipitation change)		[22,37,40,88,104, 127,135,138,141, 185,186,263–267]

3.6.1. Africa

Concentrating on the Sahel, especially the anthroposphere, is a central focus point in many publications (Figure 10c). Multiple studies document inter-annual changes and long-term dynamics in surface water due to changing land use [194,209,210]. Studies analyze changes in land cover and land use based on multi-temporal Landsat imagery. The water body extent changes due to reservoir constructions due to, for example, mining [210] or hydropower generation [194]. Such interventions directly affect the socio-economic situation of the local population, as well as the local biodiversity. For Lake Chad, Ref. [9] shows that extreme climatic shifts in the 1970s and 1980s led to an extreme decline in lake surface area (90%). Water surface dynamics are analyzed for 2015–2019 and are based on Sentinel-2 and Landsat 8 data. Additionally, the study makes use of altimetry time series based on TOPEX/POSEIDON and JASON-1 and -2 for 1993–2015 and a precipitation time series based on TRMM data for 1998–2013. Apart from RS data, surface water storage estimates from the Hydrological Modelling and Analysis Platform (HyMap) are included in the study. Due to the accelerated population growth in the region and the subsequent increased food and freshwater demand, water withdrawals additionally contributed to the rapid shrinking of the lake. On top of that, major shifts in land cover towards agricultural expansion and deforestation took place. This has led to the complete drying of the North pool of the lake. These findings highlight the global climate influence on the region by showing the significant relationships between climate models and drought patterns in the region. This is observed specifically for the AMO, the Atlantic Meridional Mode (AMM), and ENSO that all have significant correlations with the changes in lake area extent.

Especially in arid regions, accurate monitoring of surface water is important since small and highly dynamic surface water bodies are important for local livelihood. Thus, focusing on wetlands along the Senegal River, Ref. [114] tests multiple approaches for wetland mapping using optical sensors. They employ data from Landsat, Sentinel-2, and MODIS. Their findings suggest that flood dynamics are not accurately represented by Landsat before 2013 due to its low temporal resolution. The inclusion of MODIS data is therefore advised for the long-term monitoring of highly dynamic surface water. Further, Ref. [166] tests the performance of GSW for surface water detection in the Nigerien Sahel. Their results indicate the underestimations of small, turbid water bodies that are vital for local livelihood. Therefore, they suggest the use of methods optimized for the local environment in combination with very high-resolution data. Indeed, focusing on ephemeral water bodies in the Ferlo region in West Africa, Ref. [211] saw promising results in a direct comparison of very high spatial and temporal resolution PlanetScope data and Landsat 8 data. They suggest a complementary use of very high spatial resolution data and an established lower resolution time series.

Another research hotspot in Africa is the Congo River Basin (CRB). The Cuvette Central, a shallow depression along the equator, is often an area of focus [87,137,212,213]. This region is important for local surface water hydrology and the valuable ecosystems of the African inner tropics [213]. However, there are still considerable uncertainties regarding the intra- and inter-annual dynamics of inundated areas in this region. Therefore, the main focus for this area is quantifying the dynamics of the surface water area (e.g., [87]) or storage (e.g., [213]). Due to the high cloud cover and dense vegetation, all studies focusing on this region rely on water delineation methods that use microwave backscatter. Ref. [212] analyzed the behavior of CRB surface water dynamics using GIEMS, Ref. [87] using SWAMPS, and Ref. [137] using a multi-sensor approach that heavily relies on L-band SAR. Their findings show considerable inter-annual dynamics in surface water due to the larger hydro-climatic system. The main drivers of the CRB hydro-climatic system are the large-scale phenomena ENSO and IOD (Table 2).

In the East African Rift Region, the focus often lies on the anthroposphere (Figure 10c). Studies find that, similar to the situation in the Sahel, major socio-economic and environmental effects are connected to the identified water area decreases [14,92,105,214]. In a case study on Lake Manyara in northern Tanzania, Ref. [92] monitored the extreme inter-annual dynamics using a MODIS-based Modified Normalized Difference Water Index (MNDWI) time series. Throughout the studied time period (2000–2011), the lake lost over 90% of its surface water area on two occasions (97% in 2005 and 94% in 2011). The authors suggest that the monitored dynamics are due to regional and global climate fluctuations. Similarly, in a study focusing on the Awash River Basin in Ethiopia, Ref. [105] found that the regional droughts have an acute impact on the area's water resources. They made use of an active–passive approach, incorporating optical Landsat 7 and 8 data as well as Sentinel-1 (A,B) data to produce monthly 10 m water body maps. Ref. [215] investigates the impact of Gibe III in Ethiopia. They modeled the impact the dam will have on the Omo River and Lake Turkana once it is fully constructed. They use multi-temporal Landsat observations together with water level observations based on TOPEX/POSEIDON, JASON-1, and ENVISAT altimetry, as well as supporting climate and hydrological datasets. They conclude that during the filling period, the lake level would drop by 1–2 m. After the filling period, lake fluctuations will be within natural variability.

3.6.2. Asia

Several studies focus on surface water dynamics in the Siberian tundra due to the impact of the region on the global CH_4 budget [46,94]. Testing the suitability of C-band SAR data for this task, Ref. [46] monitored the permanently and seasonally inundated areas in the West Siberian Lowland from 2007–2008 based on ENVISAT ASAR data. On a longer temporal scale (1973–2013), the effect of rising temperatures due to climate change become obvious [94]. Also focusing on western Siberia, Ref. [94] utilizes Landsat data for a temporally extensive analysis. They monitor a rapid increase in the number of small thermokarst lakes formed due to degrading permafrost. At the same time, larger lakes disappeared, leading to a net loss of surface water area in the investigated region. The increased erosion rates of islands in anabranching rivers like the Lena are reported by Ref. [97]. They utilize data from multiple optical sensors, namely CORONA and HEXAGON KeyHole reconnaissance satellites; Landsat 5, 7, and 8; SPOT 5 and 6; and Pleiades, for a sparse (13 observations) time series covering 50 years. By including data from gauge stations as well as air and water temperature into their analysis, Ref. [97] shows that permafrost degradation increases along with discharge and temperature. Further, more frequent summer floods due to higher precipitation are recorded. Feedback loops may additionally increase permafrost degradation and morphodynamic change.

Central Asia is a research hotspot for studies concerned with any of the identified spheres (Figure 10). These studies mostly use Landsat data [189,193,219]. Temporal resolution ranges from sparse multi-temporal observations [219] to sub-monthly time series [189]. Within the region, smaller water bodies have been changing drastically between 2000 and 2015, as analyzed by Ref. [193]. Both the maximum and minimum water surface area decreased in a roughly linear fashion. With perennial water cover decreased by 15% from ~101,438 km^2 in 2000 to ~85,702 km^2 in 2015. Human activity and climate change influenced surface water dynamics considerably, thereby resulting in the retreat of several Central Asian lakes between 1975 and 2007 (e.g., Aral Sea −75%, Bosten Lake −9%, Ebinur Lake −8%) [219]. Focusing on Hanun Wetland in the border region of Iran and Afghanistan, Ref. [189] analyzed the intra-annual dynamics between March and August 2014 based on roughly biweekly land cover classifications. Their findings showed that, after an initial inundation period in the spring, the wetland dried up almost completely until August due to increased water consumption and blocking of upstream discharge. Case studies throughout Central Asia show that the overuse of available surface water resources results in desertification, salinization, degradation of vegetation, and biodiversity loss [189,193,220].

The main hotspot in any observed sphere is China (Figure 10). On a national level, the focus often lies on the study of lake and reservoir area dynamics [77,79]. On this geographical scale, MODIS-based approaches are in the majority [77,79]. Ref. [79] uses MOD09Q1 data with a modified Otsu thresholding method to produce a nation-wide 8-daily surface water product. Their Inland Surface Water Dataset in China (ISWDC) covers a timeframe from 2000 to 2016 and shows good consistency when compared to GSW. On a high spatial resolution, Ref. [39] fuses optical Sentinel-2 and Landsat 8 imagery with Sentinel-1 imagery for the years 2017–2020. They produce a 10 m monthly time series product. Focusing on drivers of long-term surface water dynamics in China, Ref. [200] investigates the decadal changes based on Landsat and Gaofen-2 data, as well as auxiliary climate and socioeconomic data. In the following, we present studies that investigate specific areas in and around China, we grouped these studies according to their geographic location:

In Mongolia and the arid Chinese North, ecosystem degradation and desertification is observed in the long-term trend analyses of optical sensors, primarily Landsat [91,113]. From a hydrological perspective, Ref. [230] investigates the inter-annual dynamics of Hulun Lake in Inner Mongolia. They use an annual time series of Landsat data and altimetry data from Jason-1 and -2 to observe the water area and height for 2002–2015.

In the densely populated and highly urbanized eastern Chinese lowland, numerous studies describe changes in surface water dynamics over the last decades. Over 50% of studies concentrating on this region focus on the hydrosphere perspective. Especially, surface water area dynamics are often investigated (49%). These studies overwhelmingly utilize time series from optical data, particularly Landsat or MODIS. Indiscriminate of the water body, Ref. [116,243] observe surface water dynamics in the middle Yangtze reaches. Ref. [116] uses Sentinel-2 along with Landsat 8 data for improved temporal resolution. Studies that focus on lakes or reservoirs include [12,69,81,228,231,242,248]. A smaller number of studies focuses on rivers and deltas throughout China [13,43,115,172,192] or monitor changes in aquaculture area [103,106,244]. It has to be noted that specifically the monitoring of aquaculture ponds is more often based on Sentinel-1 C-band SAR data than optical data [103,106]. Twenty-nine percent of studies concentrating on the East of China focus on a biosphere-related topic. Most studies concentrate on landscape change in general [123,196] or wetland monitoring in particular [74,155,188,222,224,232] and base their results on multi-temporal Landsat observations or Landsat-based time series. The exceptions are the SAR-based approach by Ref. [74], and the approach by Ref. [155] which fuses Landsat and MODIS data to fill data gaps in the analyzed time series. The remaining studies in this region focus on the anthroposphere. The single largest topic within this group is flood monitoring [31,108,238]. In contrast to other application fields, flood monitoring demands high temporal resolution data. Therefore, early studies work with sensors like AVHRR [238], while more recent studies propose multi-sensor approaches incorporating Sentinel-1 SAR data and passive microwave data from SMMR, SSM/I-SSMIS, and AMSR-E for high spatial and temporal resolution [108].

Due to its importance for surface water supply of multiple large Asian rivers, several studies focus on High Mountain Asia. Particularly, the Himalayas and the TP are popular research sites. Within this region, many studies concentrate on changes in the hydrosphere. Particularly, long-term changes of glacier lakes and other high-altitude lakes are investigated using yearly to decadal observations of Landsat data [60,68,100,225,234, 246,251]. For most lakes in the Himalayan and TP regions, increases in water area and storage are documented [70,72,77,80,98,100,220]. Apart from the mid- to long-term consequences of retreating glaciers and increasing temperatures [60], rapidly increasing glacier lakes and thawing permafrost increase the risk of lake outburst floods [24,229]. Particularly, expansion events of glacial lakes [70,201] are associated with these natural hazards. These studies concentrate on long-term changes and, therefore, mostly employ long-term multi-temporal Landsat data with yearly [24,70] or fewer observations [201,229,237].

Fifty-seven percent of studies in the regions of South and Southeast Asia focus on the hydrosphere. Especially, surface water area dynamics of rivers and deltas [43,111,221] or lakes and reservoirs [117,249] are often the main focus. Focusing on the Pearl River Delta and the Irrawaddy River Delta, Ref. [221] quantifies the changes in delta channel networks. They utilize all available Landsat 5, 7, 8 data for 1986–2018 to produce four multi-year composites to eliminate problems like cloud cover and hydrological extremes. Using object-based classification, they segment areas of water occurrence and then delineate the center- and banklines of the channel for each time step. Ref. [43] uses 250 m resolution MODIS data to investigate the intra-annual dynamics of multiple important delta regions, including the Mekong River Delta, Irrawaddy River Delta, and the Ganges-Brahmaputra Delta. Further, Ref. [111] models river discharge based on Sentinel-1 time series data for a test region in the middle Mekong. By calculating river width at multiple segments for each time step, they estimate the discharge using a width–discharge relationship. Twenty-four percent of studies concentrating on the region focus on the anthroposphere [33,37,198, 216,241]. As one major natural hazard in the area, floods are monitored by multiple studies [33,198,216]. As it is mostly insensitive to atmospheric influences, data from SAR sensors is preferred for this application. Ref. [216] investigates the short-term dynamics of floods based on multi-temporal Sentinel-1 SAR with a roughly weekly temporal resolution. Focusing on a region in Kerala, India, Ref. [33] assesses the flood dynamics for an event that occurred in 2018. They utilize Sentinel-1 data both from ascending and descending orbits to maximize the temporal resolution. The increasing variability of precipitation due to climate change leads to more pronounced intra- and inter-annual water body dynamics in the area [240]. Hydrologically complex regimes like the Tonle Sap Lake are increasingly impacted by the accumulating effects of changing flood pulses from the Mekong, thereby intensifying agricultural use, water diversion and damming, and increased water demand [4]. In an early study on multi-sensor approaches, Ref. [235] analyzes the wetland dynamics for the Indian subcontinent on a monthly basis for a two-year period (1993–1994). Ref. [198] investigates the dynamics of annual floods based on a MODIS 8-day composite image time series for 2000–2005. Producing a framework for analyzing land surface dynamics and corresponding drivers for the Indo-Gangetic River Basin, Ref. [250] incorporates GWP data with other MODIS-based analysis-ready time series and climatological and hydrological data.

3.6.3. Australia

The majority of studies concentrating on Australia (56%) have a focus on the anthroposphere, particularly the assessment of drought- and flood-related surface water dynamics [42,165,174,177,252]. The rest focus on surface water area dynamics in general [124,253], or specifically concentrate on certain water bodies like lakes and reservoirs [175] or estuaries [90]. The studies mainly utilize optical sensor data from Landsat, the exception being Ref. [165], who work with daily and 8-daily MODIS time series. Closing the gap between high spatial and high temporal resolution, Ref. [124] blends MODIS and Landsat imagery for multiple areas of interest in the Murray–Darling Basin to investigate the La Niña floods of 2010-2011 at a spatial resolution of 30 m and a temporal resolution of 8 days.

3.6.4. Europe

European studies are notably underrepresented as a study site (Figure 10). Mainly, studies with a focus on the hydrosphere are present [99,149,168,255,256]. Further, individual studies concentrating on flood dynamics [121,254] and wetland monitoring [236] have been identified. There is a considerable spread in size and spatial distribution of studies. Ref. [168] produces a 15-year time series (2000–2015) from 8-daily MODIS data for the entire Mediterranean region. With a focus on alpine glacier lakes, Ref. [255] investigates the inter-annual dynamics based on the GSW and GLAD Surface Water datasets for the time period between 2000–2019. Analyzing the impact of climate change on glacial lakes in the Romanian Carpathians, Ref. [99] studies the time period from 1968–2014. They find that north-facing lakes are slowly decreasing, while south-facing glacier lakes are growing. The authors utilize a number of optical sensors in their study, namely CORONA KH-4B, SPOT-5, WorldView-1, Pleiades, and aerial imagery. On a smaller geographical scale, Ref. [256] compares the time series based on Sentine-1 and Sentinel-2. They test multiple moving window sizes for an accurate representation of reservoir dynamics for French reservoirs with sizes as small as 20 ha. Working on a local scale, Ref. [149] tests an approach that uses very high-resolution RapidEye optical data to reconstruct lake level changes.

3.6.5. North America

In the tundra and boreal region of North America, many studies monitor lake area dynamics [93,169] and wetlands [157] over long timeframes. These studies use optical (Landsat) [93,169] or SAR (ERS-1/-2) data [157]. A method is proposed that, using GSW monthly data, generates a lookup table of lake shorelines. This is further used to estimate the lake area and volume on the basis of altimetry data alone using statistical regression [169]. Results from the North American tundra show strong inter-annual dynamics [23,257]. The outcomes vary to some degree depending on the study region. The findings for North-central Canada for 1985–2015 indicate that smaller water bodies shrank or disappeared entirely, while larger water bodies have grown [257]. For Lake Athabasca, however, decreasing trends are documented [169]. This is partially supported by the findings of Ref. [93]. They observe a decline in lake area for their study area in Yukon over the period of 1950–2009, but simultaneously record an increasing number of lakes. The reason being extreme drainage events from thermokarst lakes due to new or enlarged outlet channels that result from permafrost degradation [93]. In the Mackenzie Delta, flood events due to ice break-up events are recorded [23].

In the rest of North America, 47% of studies focus primarily on the hydrosphere. Particularly, surface water storage (e.g., [5,262]) and surface water area dynamics (e.g., [96,258]) are investigated. Twenty-four percent of studies concentrate on the anthroposphere. Flood dynamics are monitored on the basis of SAR data [259], while drying rivers are investigated based on the GSW product [199]. Further, biosphere-oriented studies predominantly analyze the wetland dynamics of the Florida Everglades [170,260]. In a MODIS-based approach, intra-annual inundation dynamics are monitored for 2004 [260]. With optical, and even most SAR sensors, the monitoring of wetlands is hindered by vegetation. Therefore, a novel approach is introduced that uses Cyclone Global Navigation Satellite System (CYGNSS) data [170]. It is found that CYGNSS is less sensitive to vegetation but more sensitive to water saturated soils and concludes that the use of CYGNSS can complement existing methods for wetland monitoring.

3.6.6. South America

Most studies located in South America concentrate on the Amazon River Basin. Sixty-seven percent of studies focus on the hydrosphere, particularly surface water area dynamics [88,104,149,264,267] and surface water storage dynamics [138,185,186]. Due to the high cloud cover and dense vegetation in the research area, most studies work with multi-sensor approaches. The GIEMS dataset or its downscaled version, GIEMS-D15, is used by [40,138,185,186]. An alternative approach based on Soil Moisture and Ocean Salinity (SMOS) passive microwave satellite data has been developed in recent years. It offers higher temporal resolution (3 days) but is limited in its spatial resolution (25 km) [88,267]. The findings from the Guayas watershed [263], the Orinoco River [138], and the Amazon basin [22] are in agreement that the intra- and inter-annual water dynamics are correlated by variations in precipitation. These, in turn, are often linked to ENSO [22,138,263]. In the case of floods and droughts in the Amazon basin, driver associations are not as clear-cut: Ref. [88] attributes dry years, in part (1997–1998), to El Niño occurrences and, in part (2005, 2010), to high sea surface temperatures in the Tropical

North Atlantic, thereby coming to a different conclusion than Ref. [22]. Floods are associated partly with La Niña occurrences (1999, 1012) (as [22] also conclude) and partly with high sea surface temperatures in the Tropical South Atlantic (2012, 2014) [88,89]. In contrast, the impact of human land use on flood risk is shown by Ref. [268]. Multi-temporal Landsat-based water surface estimations, 16-daily MODIS NDVI, as well as long-term hydrological modeling based on the HYDRUS 1D model, are used to investigate the sub-humid plains of the Pampas. Ref. [268] concludes that flood frequency and severity is linked to the expansion of grain production systems.

4. Discussion

4.1. Revisiting the Duality of Spatial vs. Temporal Resolution

From the presented results, a duality of spatial vs. temporal resolution is apparent. Generally, most studies use data from optical sensors—primarily Landsat and MODIS. Especially for long time series with high spatial resolution, there is virtually no alternative to using Landsat data. This limits temporal resolution to, at best, 16 days. Analyzing highly dynamic surface water is therefore not possible based on Landsat alone. Conversely, high temporal resolution data that extends into the pre-Sentinel era is of limited spatial resolution. The choice of high spatial or high temporal resolution primarily depends on the application focus. The assessments of rapid urbanization's impact on surface water bodies, for example, often rely on high spatial resolution data, but very low temporal resolution. The investigation of flood pulses in large-scale basins, on the other hand, is more reliant on high temporal resolution then on high spatial resolution. We see overcoming this duality as one of the most important enablers for future RS-based surface water dynamics analyses. Data fusion approaches and downscaling procedures show promising results, but introduce additional sources of error [88] and are limited in their ability to represent trends and variations [128–130]. The increased availability of satellite constellations like the Sentinel fleet ensures increased data availability with high spatial and temporal resolution data. However, since the timeframes of most studies are more than a decade, newer sensors do not yet see the same number of use cases as, for example, Landsat or MODIS.

4.2. Analysis-Ready Datasets

From the results presented and visualized in Figure 9, we conclude that the available surface water products are being adopted well by the research community. There are a number of reasons for this. Particularly, the transferability of approaches, comparability of results, and ease of use may be important. Especially, the GSW product sees a high number of use cases. Still, it's applicability is limited by it's low temporal resolution and reduced reliability for specific regions due to extensive cloud cover and/or polar night [167,173]. A larger share of reviewed publications therefore produces their own products to fulfill the needs of their analyses or to advance on existing, globally available products (e.g., [165,269,270]).

4.3. Drivers of Surface Water Change

Even though RS data, analysis-ready products, and computation infrastructure are widely available, there is no obvious trend towards global analysis approaches—as visualized in Figure 6. Instead, the study focus is what mainly determines the scale of the study area. Hydrology-oriented analyses are often performed on a global or continental scale. In contrast, biosphere- and anthroposphere-oriented studies are mostly performed on a regional or even local basis. Such studies have high relevance as they are able to connect observations with influencing factors and may provide more detailed insights regarding the underlying drivers of change. As drivers interfere with each other, such complex cause–effect relationships are mostly investigated and quantified on a local to regional level. However, as shown in Table 2, even though the effects of specific drivers differ from region to region, we can still deduct three main causes of surface water dynamics change:

- Human impact, specifically the construction of reservoirs, intensification of agriculture, rapid urbanization, and ineffective water management, has a great impact on global surface water. As is visible in Figure 10, humans are most often identified as drivers in densely populated areas with mostly high population increases. This interpretation is backed by other studies that show human impact on free flowing rivers [271] and surface water bodies in general [180,272].
- Climate change is often attributed with the highest or second highest impact on surface water dynamics. In contrast to human interventions, climate change impacts are reported for highly populated as well as nearly untouched regions of the world. Especially in cold and arctic regions, as well as those with acute water scarcity, these impacts are significant. In water scarce regions, the impacts of climate change (mainly temperature increase and more variable precipitation) often worsen the already tense situation. In cold and arctic regions, rising temperatures and precipitation changes have multiple effects: higher precipitation generally leads to increasing water body sizes. Water bodies fed by meltwater additionally increase in size due to higher temperature. Water bodies that are not fed by meltwater shrink if precipitation rates remain similar or decrease. This can be explained by simultaneously increasing temperatures and ET rates. Areas underlain by permafrost, due to rising temperatures, lead to a thawing process that can destabilize lake edges and rapidly drain lakes.
- Especially in tropical and subtropical regions, large scale oscillations affect the inter-annual dynamics of surface water. The impact of such climate modes spans multiple continents and can lead to adverse water situations in multiple and distant regions at the same time; even more so when they occur in combination with temperature increases and higher precipitation variations and human-induced changes in water dynamics.

4.4. Future Developments

It is apparent that there is a high motivation to globally monitor the impacts that large-scale drivers have on surface water dynamics. Especially, regions that already have a high population density and dynamic growth need strategies for effective surface water management in the face of climate change and the increasing likelihood of water stress. The information basis of such strategies can be provided by satellite RS [39].

Still, there are limitations to RS-based analyses that need to be kept in mind:

- As discussed above, all sensor types utilized in RS all have their respective shortcomings. Optical sensors, for example, are highly sensitive towards cloud coverage. SAR sensors have limitations depending on the wavelength they operate in. Shorter wavelength sensors like those operating in the X- and C-band are influenced by soil moisture and atmospheric influences, while sensors operating in longer wavelengths like L-band SAR are limited by their coarse spatial resolution.
- Depending on the classification scheme, the quality of results can vary substantially. Accurate measurements of RS-based analyses are especially complicated for large-scale applications such as global mapping initiatives. On this level, ground truth comparisons become unfeasible and accuracy has to be measured via proxies like visual image interpretation or comparison with high resolution sensors. All of these approaches carry over the uncertainties of the used proxies.
- Lastly, the duality of high spatial vs. high temporal resolution sensors can be seen as the largest hurdle that limits the applicability of RS-based approaches.

With increasingly long time series from high spatial and temporal resolution satellite constellations like the Sentinel fleet, we postulate that the spatial vs. temporal resolution duality will end. For many areas and applications, SAR and optical data enable high spatial and temporal resolution global surface water time series with increasingly long temporal frames. Regarding very long-term analyses, Landsat remains the most important tool available as it offers the longest continuous time series of any environmental satellite program. We see high potential in the use of multi-sensor approaches for challenging environments like tropical rain forests or inundated forests. Here, optical sensors and C-band SAR are limited in their applicability. Approaches that utilize longer wavelengths either as SAR or passive microwave data are reportedly capable of identifying inundated areas under canopy cover. Techniques like L-band reflectometry based on GNSS are a valuable tool in this regard. Further, with the launch of the Surface Water and Ocean Topography (SWOT) mission, which is planned for late 2022, a valuable tool for the analysis of surface water dynamics will become available. We prognose that, in the future, a synergistic use of the resources available will be able to overcome the main limitations that hold back RS-based approaches for surface water dynamics analyses.

5. Conclusions

We provide an extensive review of remote sensing of inland surface water dynamics. The literature included offered multi-temporal observations of surface water area with a global perspective. For a total of n=233 studies, we investigated the spatial distribution of research hotspots, temporal resolution and investigated timeframe, used sensors and sensor types, methods for surface water delineation, and thematic foci. Following, we briefly summarize our main findings regarding the defined research questions from Section 1.3.:

- We identified an overall increase in research activity over time. From 2006 onwards, multiple peer-reviewed contributions are identified each year. From 2014 onwards, a steep increase in research activity was identified.
- Research hotspots are foremost located in Asia. China alone was covered by ~33% of the publications on surface water dynamics. Further, areas in Central, South, and Southeast Asia are investigated in 19%, 20%, and 19%, respectively. Further, a high concentration of studies was found for the Amazon River Basin (20%), the Congo River Basin (18%), Australia (19%), and North America (20%). Most first authorships come from China (36%), the USA (20%), France, and Germany (each 12%). This shows a discrepancy in the spatial distributions of research areas and first author countries. A significant number of studies investigates surface water dynamics globally (15%).
- On the temporal scale, we differentiated between studies considering inter-annual dynamics versus those including intra-annual dynamics. We found that earlier studies including intra-annual dynamics use shorter timeframes than more recent works. Generally, studies focusing on inter-annual dynamics observe longer timeframes than those analyzing intra-annual dynamics. There is a duality between high spatial resolution and high temporal resolution approaches. While many studies working on a local or regional scale employ high spatial resolution and low temporal resolution data, studies on a large geographical scale mostly work with low spatial resolution but high temporal resolution data.
- Most studies include optical data (91%). Often, studies rely solely on optical data (72%). Landsat data is utilized in 62% of studies and MODIS data is used in 20% of studies. Further, microwave data is used in a significant number of studies. In terms of active microwave data, especially synthetic aperture radar (SAR), sensors are used in many studies (18%). Ten percent of studies include passive microwave data.
- Most studies use a custom approach to identify the surface water area (79%). In many cases, this approach is based on a threshold-based classification of water (29%). Supervised classifications are used in 17% of studies. Twenty-one percent of studies rely on analysis-ready datasets to describe surface water area. In 5% of studies, surface water is monitored using the Global Surface Water (GSW) used by Ref. [11].

Additionally, the Global Inundation Extent from Multi-Satellites (GIEMS) by Ref. [181] or newer iterations of the same product are used in 3% of studies.

- Global surface water products have the potential to provide comparable surface water observations. Landsat-based products offer the longest timeframes (e.g., Global Surface Water (GSW): 1984-present). However, due to the low temporal resolution of Landsat, its use for the analysis of highly dynamic surface water bodies is limited. Particularly for GSW, low accuracies for specific regions (e.g., the Sahel [166,167]) are reported. High temporal resolution products are exclusively based on MODIS data. To our knowledge, the Global WaterPack (GWP) by Ref. [84] provides the highest temporal resolution of any available global product at 250 m spatial resolution. Additionally, all products based on optical sensors are limited by weather-related data gaps and cannot accurately depict water under canopy. Multi-sensor products like Global Inundation Extent from Multi-Satellites (GIEMS) have an advantage here, but are limited in spatial and temporal resolution (~25 km, monthly). The mentioned duality of spatial vs. temporal resolution is therefore also visible in global surface water products. We postulate this duality will end due to the increasingly long time series of high spatial and high temporal resolution satellite constellations.
- We categorized studies based on their thematic focus. Three spheres were identified: ~49% of studies have a thematic focus on the hydrosphere, ~24% on the biosphere, and ~26% on the anthroposphere. We divided studies into further subgroups. Within the respective identified spheres, the largest groups would be publications with a focus on surface water area dynamics (40%), natural hazards (17%), or landscape change (22%). The respective foci are distinctly spatially distributed. There are more global studies with a hydrosphere focus than studies with a biosphere or anthroposphere focus. Hydrosphere research hotspots are the Arctic and cold regions, the Amazon River Basin, the Congo River Basin, China, and Australia. Biosphere research hotspots are concentrated in North America, Iran, and China. Anthroposphere research hotspots are situated in the USA, the Sahel, the East African Rift, Central Asia, South Asia, China, and Australia.

Our review complements the existing body of research on surface water dynamics with a comprehensive overview of the field. We presented important developments in used methodologies and applications of surface water dynamics studies. We highlighted the strengths and limitations of current approaches and offer our prognoses for possible future developments.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/rs14102475/s1, Table S1: Overview of Reviewed Publications.

Author Contributions: Conceptualization, P.S. and C.K.; Writing—Original draft preparation, P.S.; Writing—Review and editing, P.S., I.K. and C.K.; visualization, P.S.; supervision, C.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been supported by the DFG (Deutsche Forschungsgemeinschaft) within the framework of the Research Unit GlobalCDA (Global Calibration and Data Assimilation) (grant no. FOR 2630).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Oki, T.; Entekhabi, D.; Harrold, T.I. The global water cycle. In *Geophysical Monograph Series*; Sparks, R.S.J., Hawkesworth, C.J., Eds.; American Geophysical Union: Washington, DC, USA, 2004; Volume 150, pp. 225–237, ISBN 978-0-87590-415-3.
2. Koutsoyiannis, D. Revisiting the global hydrological cycle: Is it intensifying? *Hydrol. Earth Syst. Sci.* **2020**, *24*, 3899–3932. https://doi.org/10.5194/hess-24-3899-2020.

3. Pachauri, R.K.; Mayer, L.; Intergovernmental Panel on Climate Change (Eds.) *Climate Change 2014: Synthesis Report*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2015; ISBN 978-92-9169-143-2.
4. Chang, C.-H.; Lee, H.; Kim, D.; Hwang, E.; Hossain, F.; Chishtie, F.; Jayasinghe, S.; Basnayake, S. Hindcast and forecast of daily inundation extents using satellite SAR and altimetry data with rotated empirical orthogonal function analysis: Case study in Tonle sap lake floodplain. *Remote Sens. Environ.* **2020**, *241*, 111732. https://doi.org/10.1016/j.rse.2020.111732.
5. Singh, A.; Seitz, F.; Eicker, A.; Guntner, A. Water budget analysis within the surrounding of prominent lakes and reservoirs from multi-sensor earth observation data and hydrological models: Case studies of the aral sea and lake mead. *Remote Sens.* **2016**, *8*, 21. https://doi.org/10.3390/rs8110953.
6. Chen, Z.; Jiang, W.; Wang, W.; Deng, Y.; He, B.; Jia, K. The impact of precipitation deficit and urbanization on variations in water storage in the Beijing-Tianjin-Hebei urban agglomeration. *Remote Sens.* **2018**, *10*, 4. https://doi.org/10.3390/rs10010004.
7. Huang, C.; Chen, Y.; Zhang, S.; Wu, J. Detecting, extracting, and monitoring surface water from space using optical sensors: A review. *Rev. Geophys.* **2018**, *56*, 333–360. https://doi.org/10.1029/2018RG000598.
8. UNESCO International Initiative on Water Quality (IIWQ). Available online: https://en.unesco.org/waterquality-iiwq/wq-challenge (accessed on 18 November 2021).
9. Ndehedehe, C.E.; Ferreira, V.G.; Onojeghuo, A.O.; Agutu, N.O.; Emengini, E.; Getirana, A. Influence of global climate on freshwater changes in Africa's largest endorheic basin using multi-scaled indicators. *Sci. Total Environ.* **2020**, *737*, 139643. https://doi.org/10.1016/j.scitotenv.2020.139643.
10. Hosseini-Moghari, S.-M.; Araghinejad, S.; Tourian, M.J.; Ebrahimi, K.; Doell, P. Quantifying the impacts of human water use and climate variations on recent drying of lake urmia basin: The value of different sets of spaceborne and in situ data for calibrating a global hydrological model. *Hydrol. Earth Syst. Sci.* **2020**, *24*, 1939–1956. https://doi.org/10.5194/hess-24-1939-2020.
11. Pekel, J.-F.; Cottam, A.; Gorelick, N.; Belward, A.S. High-resolution mapping of global surface water and its long-term changes. *Nature* **2016**, *540*, 418–422. https://doi.org/10.1038/nature20584.
12. Du, B.; Wang, Z.; Mao, D.; Li, H.; Xiang, H. Tracking lake and reservoir changes in the Nenjiang watershed, Northeast China: Patterns, trends, and drivers. *Water* **2020**, *12*, 1108. https://doi.org/10.3390/w12041108.
13. Jia, M.; Wang, Z.; Liu, D.; Ren, C.; Tang, X.; Dong, Z. Monitoring loss and recovery of salt marshes in the Liao River Delta, China. *J. Coast. Res.* **2015**, *31*, 371–377. https://doi.org/10.2112/JCOASTRES-D-13-00056.1.
14. Bekele, B.; Wu, W.; Legesse, A.; Temesgen, H.; Yirsaw, E. Socio-Environmental Impacts of Land Use/Land Cover Change in Ethiopian Central Rift Valley Lakes Region, East Africa. *Appl. Ecol. Environ. Res.* **2018**, *16*, 6607–6632. https://doi.org/10.15666/aeer/1605_66076632.
15. UN-Water *Summary Progress Update 2021: SDG 6—Water and Sanitation for All*; United Nations: Geneva, Switzerland, 2021.
16. Salameh, E.; Frappart, F.; Papa, F.; Guentner, A.; Venugopal, V.; Getirana, A.; Prigent, C.; Aires, F.; Labat, D.; Laignel, B. Fifteen Years (1993–2007) of Surface Freshwater Storage Variability in the Ganges-Brahmaputra River Basin Using Multi-Satellite Observations. *Water* **2017**, *9*, 245. https://doi.org/10.3390/w9040245.
17. Meng, L.; Dong, J. LUCC and Ecosystem Service Value Assessment for Wetlands: A Case Study in Nansi Lake, China. *Water* **2019**, *11*, 1597. https://doi.org/10.3390/w11081597.
18. Dolan, F.; Lamontagne, J.; Link, R.; Hejazi, M.; Reed, P.; Edmonds, J. Evaluating the Economic Impact of Water Scarcity in a Changing World. *Nat. Commun.* **2021**, *12*, 1915. https://doi.org/10.1038/s41467-021-22194-0.
19. Rudincová, K. Desiccation of Lake Chad as a Cause of Security Instability in the Sahel Region. *GeoScape* **2017**, *11*, 112–120. https://doi.org/10.1515/geosc-2017-0009.
20. Kharraz, J.E.; El-Sadek, A.; Ghaffour, N.; Mino, E. Water Scarcity and Drought in WANA Countries. *Procedia Eng.* **2012**, *33*, 14–29. https://doi.org/10.1016/j.proeng.2012.01.1172.
21. Kamta, F.N.; Schilling, J.; Scheffran, J. Insecurity, resource scarcity, and migration to camps of internally displaced persons in Northeast Nigeria. *Sustainability* **2020**, *12*, 6830. https://doi.org/10.3390/su12176830.
22. Nie, N.; Zhang, W.; Guo, H.; Ishwaran, N. 2010–2012 Drought and Flood Events in the Amazon Basin Inferred by GRACE Satellite Observations. *J. Appl. Remote Sens.* **2015**, *9*, 096023. https://doi.org/10.1117/1.JRS.9.096023.
23. Normandin, C.; Frappart, F.; Lubac, B.; Belanger, S.; Marieu, V.; Blarel, F.; Robinet, A.; Guiastrennec-Faugas, L. Quantification of surface water volume changes in the Mackenzie Delta using satellite multi-mission data. *Hydrol. Earth Syst. Sci.* **2018**, *22*, 1543–1561. https://doi.org/10.5194/hess-22-1543-2018.
24. Li, D.; Shangguan, D.; Wang, X.; Ding, Y.; Su, P.; Liu, R.; Wang, M. Expansion and Hazard Risk Assessment of Glacial Lake Jialong Co in the Central Himalayas by Using an Unmanned Surface Vessel and Remote Sensing. *Sci. Total Environ.* **2021**, *784*, 147249. https://doi.org/10.1016/j.scitotenv.2021.147249.
25. Kim, D.; Lee, H.; Jung, H.C.; Hwang, E.; Hossain, F.; Bonnema, M.; Kang, H.; Getirana, A. Monitoring river basin development and variation in water resources in transboundary Imjin River in North and South Korea using remote sensing. *Remote Sens.* **2020**, *12*, 195. https://doi.org/10.3390/rs12010195.
26. Bates, P.D.; Neal, J.C.; Alsdorf, D.; Schumann, G.J.-P. Observing global surface water flood dynamics. *Surv. Geophys.* **2014**, *35*, 839–852. https://doi.org/10.1007/s10712-013-9269-4.
27. Brinkmann, K.; Hoffmann, E.; Buerkert, A. Spatial and temporal dynamics of urban wetlands in an Indian Megacity over the Past 50 Years. *Remote Sens.* **2020**, *12*, 662. https://doi.org/10.3390/rs12040662.

28. Gxokwe, S.; Dube, T.; Mazvimavi, D. Multispectral remote sensing of wetlands in semi-arid and arid areas: A review on applications, challenges and possible future research directions. *Remote Sens.* **2020**, *12*, 17. https://doi.org/10.3390/rs12244190.
29. Kingsford, R.T.; Bino, G.; Finlayson, C.M.; Falster, D.; Fitzsimons, J.A.; Gawlik, D.E.; Murray, N.J.; Grillas, P.; Gardner, R.C.; Regan, T.J.; et al. Ramsar wetlands of international importance-improving conservation outcomes. *Front. Environ. Sci.* **2021**, *9*, 643367. https://doi.org/10.3389/fenvs.2021.643367.
30. Uereyen, S.; Kuenzer, C. A review of earth observation-based analyses for major river basins. *Remote Sens.* **2019**, *11*, 2951. https://doi.org/10.3390/rs11242951.
31. Wang, Z.H.; Yao, W.Y.; Wang, M.; Xiao, P.Q.; Yang, J.S.; Zhang, P.; Tang, Q.H.; Kong, X.B.; Wu, J. The influence of river channel occupation on urban inundation and sedimentation induced by floodwater in mountainous areas: A case study in the Loess Plateau, China. *Sustainability* **2019**, *11*, 19. https://doi.org/10.3390/su11030761.
32. Cann, K.F.; Thomas, D.R.; Salmon, R.L.; Wyn-Jones, A.P.; Kay, D. Extreme water-related weather events and waterborne disease. *Epidemiol. Infect.* **2013**, *141*, 671–686. https://doi.org/10.1017/S0950268812001653.
33. Vanama, V.S.K.; Rao, Y.S.; Bhatt, C.M. Change detection based flood mapping using multi-temporal earth observation satellite images: 2018 Flood event of Kerala, India. *Eur. J. Remote Sens.* **2021**, *54*, 42–58. https://doi.org/10.1080/22797254.2020.1867901.
34. United Nations Sustainable Development Goals. Available online: https://www.un.org/sustainabledevelopment/ (accessed on 12 May 2022).
35. Wood, S.L.R.; Jones, S.K.; Johnson, J.A.; Brauman, K.A.; Chaplin-Kramer, R.; Fremier, A.; Girvetz, E.; Gordon, L.J.; Kappel, C.V.; Mandle, L.; et al. Distilling the role of ecosystem services in the sustainable development goals. *Ecosyst. Serv.* **2018**, *29*, 70–82. https://doi.org/10.1016/j.ecoser.2017.10.010.
36. Wang, C.; Jiang, W.; Deng, Y.; Ling, Z.; Deng, Y. Long time series water extent analysis for SDG 6.6.1 based on the GEE platform: A case study of Dongting Lake. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2021**, *15*, 1. https://doi.org/10.1109/jstars.2021.3088127.
37. Hakimdavar, R.; Hubbard, A.; Policelli, F.; Pickens, A.; Hansen, M.; Fatoyinbo, T.; Lagomasino, D.; Pahlevan, N.; Unninayar, S.; Kavvada, A.; et al. Monitoring water-related ecosystems with earth observation data in support of Sustainable Development Goal (SDG) 6 reporting. *Remote Sens.* **2020**, *12*, 1634. https://doi.org/10.3390/rs12101634.
38. Bueso-Bello, J.-L.; Martone, M.; González, C.; Sica, F.; Valdo, P.; Posovszky, P.; Pulella, A.; Rizzoli, P. The global water body layer from TanDEM-X interferometric SAR data. *Remote Sens.* **2021**, *13*, 5069. https://doi.org/10.3390/rs13245069.
39. Druce, D.; Tong, X.; Lei, X.; Guo, T.; Kittel, C.M.M.; Grogan, K.; Tottrup, C. An optical and SAR based fusion approach for mapping surface water dynamics over Mainland China. *Remote Sens.* **2021**, *13*, 1663. https://doi.org/10.3390/rs13091663.
40. Reis, V.; Hermoso, V.; Hamilton, S.K.; Bunn, S.E.; Fluet-Chouinard, E.; Venables, B.; Linke, S. Characterizing seasonal dynamics of amazonian wetlands for conservation and decision making. *Aquat. Conserv. Mar. Freshw. Ecosyst.* **2019**, *29*, 1073–1082. https://doi.org/10.1002/aqc.3051.
41. Schultz, G.A. Potential of modern data types for future water resources management. *Water Int.* **2000**, *25*, 96–109. https://doi.org/10.1080/02508060008686801.
42. Tulbure, M.G.; Broich, M. Spatiotemporal patterns and effects of climate and land use on surface water extent dynamics in a dryland region with three decades of Landsat satellite data. *Sci. Total Environ.* **2019**, *658*, 1574–1585. https://doi.org/10.1016/j.scitotenv.2018.11.390.
43. Kuenzer, C.; Klein, I.; Ullmann, T.; Georgiou, E.F.; Baumhauer, R.; Dech, S. Remote Sensing of River Delta Inundation: Exploiting the Potential of Coarse Spatial Resolution, Temporally-Dense MODIS Time Series. *Remote Sens.* **2015**, *7*, 8516–8542. https://doi.org/10.3390/rs70708516.
44. Cooley, S.W.; Smith, L.C.; Stepan, L.; Mascaro, J. Tracking Dynamic Northern Surface Water Changes with High-Frequency Planet CubeSat Imagery. *Remote Sens.* **2017**, *9*, 1306. https://doi.org/10.3390/rs9121306.
45. Kasischke, E.S.; Melack, J.M.; Craig Dobson, M. The Use of Imaging Radars for Ecological Applications—A Review. *Remote Sens. Environ.* **1997**, *59*, 141–156. https://doi.org/10.1016/S0034-4257(96)00148-4.
46. Bartsch, A.; Trofaier, A.M.; Hayman, G.; Sabel, D.; Schlaffer, S.; Clark, D.B.; Blyth, E. Detection of Open Water Dynamics with ENVISAT ASAR in Support of Land Surface Modelling at High Latitudes. *Biogeosciences* **2012**, *9*, 703–714. https://doi.org/10.5194/bg-9-703-2012.
47. Millard, K.; Brown, N.; Stiff, D.; Pietroniro, A. Automated Surface Water Detection from Space: A Canada-Wide, Open-Source, Automated, near-Real Time Solution. *Can. Water Resour. J.* **2020**, *45*, 304–323. https://doi.org/10.1080/07011784.2020.1816499.
48. Amani, M.; Ghorbanian, A.; Ahmadi, S.A.; Kakooei, M.; Moghimi, A.; Mirmazloumi, S.M.; Moghaddam, S.H.A.; Mahdavi, S.; Ghahremanloo, M.; Parsian, S.; et al. Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 5326–5350. https://doi.org/10.1109/JSTARS.2020.3021052.
49. Becker, M.W. Potential for Satellite Remote Sensing of Ground Water. *Ground Water* **2006**, *44*, 306–318. https://doi.org/10.1111/j.1745-6584.2005.00123.x.
50. Soltani, S.S.; Ataie-Ashtiani, B.; Simmons, C.T. Review of Assimilating GRACE Terrestrial Water Storage Data into Hydrological Models: Advances, Challenges and Opportunities. *Earth Sci. Rev.* **2021**, *213*, 103487. https://doi.org/10.1016/j.earscirev.2020.103487.

51. Grimaldi, S.; Li, Y.; Pauwels, V.R.N.; Walker, J.P. Remote Sensing-Derived Water Extent and Level to Constrain Hydraulic Flood Forecasting Models: Opportunities and Challenges. *Surv. Geophys.* **2016**, *37*, 977–1034. https://doi.org/10.1007/s10712-016-9378-y.
52. Nghiem, S.V.; Zuffada, C.; Shah, R.; Chew, C.; Lowe, S.T.; Mannucci, A.J.; Cardellach, E.; Brakenridge, G.R.; Geller, G.; Rosenqvist, A. Wetland Monitoring with Global Navigation Satellite System Reflectometry. *Earth Space Sci.* **2017**, *4*, 16–39. https://doi.org/10.1002/2016EA000194.
53. Cloern, J.E.; Abreu, P.C.; Carstensen, J.; Chauvaud, L.; Elmgren, R.; Grall, J.; Greening, H.; Johansson, J.O.R.; Kahru, M.; Sherwood, E.T.; et al. Human Activities and Climate Variability Drive Fast-Paced Change across the World's Estuarine-Coastal Ecosystems. *Glob. Chang. Biol.* **2016**, *22*, 513–529. https://doi.org/10.1111/gcb.13059.
54. Shen, X.; Wang, D.; Mao, K.; Anagnostou, E.; Hong, Y. Inundation Extent Mapping by Synthetic Aperture Radar: A Review. *Remote Sens.* **2019**, *11*, 879. https://doi.org/10.3390/rs11070879.
55. Lindersson, S.; Brandimarte, L.; Mard, J.; Di Baldassarre, G. A Review of Freely Accessible Global Datasets for the Study of Floods, Droughts and Their Interactions with Human Societies. *Wiley Interdiscip. Rev. Water* **2020**, *7*, 20. https://doi.org/10.1002/wat2.1424.
56. Ottinger, M.; Clauss, K.; Kuenzer, C. Aquaculture: Relevance, Distribution, Impacts and Spatial Assessments—A Review. *Ocean Coast. Manag.* **2016**, *119*, 244–266. https://doi.org/10.1016/j.ocecoaman.2015.10.015.
57. van Dijk, A.I.J.M.; Renzullo, L.J. Water Resource Monitoring Systems and the Role of Satellite Observations. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 39–55. https://doi.org/10.5194/hess-15-39-2011.
58. Thakur, P.K.; Nikam, B.R.; Garg, V.; Aggarwal, S.P.; Chouksey, A.; Dhote, P.R.; Ghosh, S. Hydrological Parameters Estimation Using Remote Sensing and GIS for Indian Region: A Review. *Proc. Natl. Acad. Sci. India Sect. Phys. Sci.* **2017**, *87*, 641–659. https://doi.org/10.1007/s40010-017-0440-z.
59. Zhao, Z.; Zhang, Y.; Liu, L.; Liu, F.; Zhang, H. Recent Changes in Wetlands on the Tibetan Plateau: A Review. *J. Geogr. Sci.* **2015**, *25*, 879–896. https://doi.org/10.1007/s11442-015-1208-5.
60. Sun, J.; Zhou, T.; Liu, M.; Chen, Y.; Shang, H.; Zhu, L.; Shedayi, A.A.; Yu, H.; Cheng, G.; Liu, G.; et al. Linkages of the Dynamics of Glaciers and Lakes with the Climate Elements over the Tibetan Plateau. *Earth-Sci. Rev.* **2018**, *185*, 308–324. https://doi.org/10.1016/j.earscirev.2018.06.012.
61. Harshadeep, N.R.; Young, W. Disruptive Technologies for Improving Water Security in Large River Basins. *Water* **2020**, *12*, 16. https://doi.org/10.3390/w12102783.
62. Harris, A.R. Time-Series Remote-Sensing of a Climatically Sensitive Lake. *Remote Sens. Environ.* **1994**, *50*, 83–94. https://doi.org/10.1016/0034-4257(94)90036-1.
63. Hoeser, T.; Bachofer, F.; Kuenzer, C. Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review—Part II: Applications. *Remote Sens.* **2020**, *12*, 3053. https://doi.org/10.3390/rs12183053.
64. Reinermann, S.; Asam, S.; Kuenzer, C. Remote Sensing of Grassland Production and Management—A Review. *Remote Sens.* **2020**, *12*, 1949. https://doi.org/10.3390/rs12121949.
65. NASA Opening the Landsat Archive. Landsat Science Available online: https://landsat.gsfc.nasa.gov/article/opening-the-landsat-archive/ (accessed on 13 January 2022).
66. USGS *Opening the Landsat Archive*; Fact Sheet, Version 1.1, Revised 31 October 2008; US Geological Survey: Reston, VA, USA, 2008.
67. Chu, D.; Zhang, Y.; Bianba, C.; Liu, L. Land Use Dynamics in Lhasa Area, Tibetan Plateau. *J. Geogr. Sci.* **2010**, *20*, 899–912. https://doi.org/10.1007/s11442-010-0819-0.
68. Yan, L.; Zheng, M. Influence of Climate Change on Saline Lakes of the Tibet Plateau, 1973–2010. *Geomorphology* **2015**, *246*, 68–78. https://doi.org/10.1016/j.geomorph.2015.06.006.
69. Zhang, W.; Pan, H.; Song, C.; Ke, L.; Wang, J.; Ma, R.; Deng, X.; Liu, K.; Zhu, J.; Wu, Q. Identifying Emerging Reservoirs along Regulated Rivers Using Multi-Source Remote Sensing Observations. *Remote Sens.* **2019**, *11*, 25. https://doi.org/10.3390/rs11010025.
70. Zhao, Z.; Liu, F.; Zhang, Y.; Liu, L.; Qi, W. The Dynamic Response of Lakes in the Tuohepingco Basin of the Tibetan Plateau to Climate Change. *Environ. Earth Sci.* **2017**, *76*, 137. https://doi.org/10.1007/s12665-017-6446-7.
71. Zhao, Z.; Liu, L.; Wang, Z.; Zhang, Y.; Li, L.; Liu, F. Dynamic Changes of Plateau Wetlands in the Damqu River Basin, Yangtze River Source Region, China, 1988–2015. *Wetlands* **2020**, *40*, 1409–1424. https://doi.org/10.1007/s13157-020-01271-y.
72. Fang, Y.; Li, H.; Wan, W.; Zhu, S.; Wang, Z.; Hong, Y.; Wang, H. Assessment of Water Storage Change in China's Lakes and Reservoirs over the Last Three Decades. *Remote Sens.* **2019**, *11*, 1467. https://doi.org/10.3390/rs11121467.
73. Han, Q.; Niu, Z. Construction of the Long-Term Global Surface Water Extent Dataset Based on Water-NDVI Spatio-Temporal Parameter Set. *Remote Sens.* **2020**, *12*, 2675. https://doi.org/10.3390/rs12172675.
74. Huth, J.; Gessner, U.; Klein, I.; Yesou, H.; Lai, X.; Oppelt, N.; Kuenzer, C. Analyzing Water Dynamics Based on Sentinel-1 Time Series—A Study for Dongting Lake Wetlands in China. *Remote Sens.* **2020**, *12*, 1761. https://doi.org/10.3390/rs12111761.
75. Klein, I.; Dietz, A.; Gessner, U.; Dech, S.; Kuenzer, C. Results of the Global WaterPack: A Novel Product to Assess Inland Water Body Dynamics on a Daily Basis. *Remote Sens. Lett.* **2015**, *6*, 78–87. https://doi.org/10.1080/2150704X.2014.1002945.

76. Martinis, S.; Kuenzer, C.; Wendleder, A.; Huth, J.; Twele, A.; Roth, A.; Dech, S. Comparing Four Operational SAR-Based Water and Flood Detection Approaches. *Int. J. Remote Sens.* **2015**, *36*, 3519–3543. https://doi.org/10.1080/01431161.2015.1060647.
77. Sun, F.; Zhao, Y.; Gong, P.; Ma, R.; Dai, Y. Monitoring Dynamic Changes of Global Land Cover Types: Fluctuations of Major Lakes in China Every 8 Days during 2000–2010. *Chin. Sci. Bull.* **2014**, *59*, 171–189. https://doi.org/10.1007/s11434-013-0045-0.
78. Wang, C.; Jia, M.; Chen, N.; Wang, W. Long-Term Surface Water Dynamics Analysis Based on Landsat Imagery and the Google Earth Engine Platform: A Case Study in the Middle Yangtze River Basin. *Remote Sens.* **2018**, *10*, 1635. https://doi.org/10.3390/rs10101635.
79. Lu, S.; Ma, J.; Ma, X.; Tang, H.; Zhao, H.; Baig, M.H.A. Time Series of the Inland Surface Water Dataset in China (ISWDC) for 2000–2016 Derived from MODIS Archives. *Earth Syst. Sci. Data* **2019**, *11*, 1099–1108. https://doi.org/10.5194/essd-11-1099-2019.
80. Tan, C.; Guo, B.; Kuang, H.; Yang, H.; Ma, M. Lake Area Changes and Their Influence on Factors in Arid and Semi-Arid Regions along the Silk Road. *Remote Sens.* **2018**, *10*, 595. https://doi.org/10.3390/rs10040595.
81. Tan, Z.; Li, Y.; Xu, X.; Yao, J.; Zhang, Q. Mapping Inundation Dynamics in a Heterogeneous Floodplain: Insights from Integrating Observations and Modeling Approach. *J. Hydrol.* **2019**, *572*, 148–159. https://doi.org/10.1016/j.jhydrol.2019.02.039.
82. Aires, F.; Miolane, L.; Prigent, C.; Pham, B.; Fluet-Chouinard, E.; Lehner, B.; Papa, F. A Global Dynamic Long-Term Inundation Extent Dataset at High Spatial Resolution Derived through Downscaling of Satellite Observations. *J. Hydrometeorol.* **2017**, *18*, 1305–1325. https://doi.org/10.1175/jhm-d-16-0155.1.
83. Yao, F.; Wang, J.; Wang, C.; Cretaux, J.-F. Constructing Long-Term High-Frequency Time Series of Global Lake and Reservoir Areas Using Landsat Imagery. *Remote Sens. Environ.* **2019**, *232*, 111210. https://doi.org/10.1016/j.rse.2019.111210.
84. Klein, I.; Gessner, U.; Dietz, A.J.; Kuenzer, C. Global WaterPack—A 250 m Resolution Dataset Revealing the Daily Dynamics of Global Inland Water Bodies. *Remote Sens. Environ.* **2017**, *198*, 345–362. https://doi.org/10.1016/j.rse.2017.06.045.
85. Hou, J.; van Dijk, A.; Beck, H.; Renzullo, L.; Wada, Y. Remotely sensed reservoir water storage dynamics (1984–2015) and the influence of climate variability and management at global scale. *Hydrol. Earth Syst. Sci. Discuss.* **2021**, 1–23. https://doi.org/10.5194/hess-2021-350,
86. Zhao, G.; Gao, H. Towards Global Hydrological Drought Monitoring Using Remotely Sensed Reservoir Surface Area. *Geophys. Res. Lett.* **2019**, *46*, 13027–13035. https://doi.org/10.1029/2019GL085345.
87. Fatras, C.; Parrens, M.; Luque, S.P.; Al Bitar, A. Hydrological Dynamics of the Congo Basin From Water Surfaces Based on L-Band Microwave. *Water Resour. Res.* **2021**, *57*, e2020WR027259. https://doi.org/10.1029/2020WR027259.
88. Parrens, M.; Al Bitar, A.; Frappart, F.; Paiva, R.; Wongchuig, S.; Papa, F.; Yamasaki, D.; Kerr, Y. High Resolution Mapping of Inundation Area in the Amazon Basin from a Combination of L-Band Passive Microwave, Optical and Radar Datasets. *Int. J. Appl. Earth Obs. Geoinformation* **2019**, *81*, 58–71. https://doi.org/10.1016/j.jag.2019.04.011.
89. Parrens, M.; Kerr, Y.; Al Bitar, A. SWAF-HR: A High Spatial and Temporal Resolution Water Surface Extent Product Over the Amazon Basin. In Proceedings of the IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium, Valencia, Spain, 22–27 July 2018; pp. 8389–8392.
90. Al-Nasrawi, A.K.M.; Hamylton, S.M.; Jones, B.G. An Assessment of Anthropogenic and Climatic Stressors on Estuaries Using a Spatio-Temporal GIS-Modelling Approach for Sustainability: Towamba Estuary, Southeastern Australia. *Environ. Monit. Assess.* **2018**, *190*, 375. https://doi.org/10.1007/s10661-018-6720-5.
91. Batunacun; Nendel, C.; Hu, Y.; Lakes, T. Land-Use Change and Land Degradation on the Mongolian Plateau from 1975 to 2015—A Case Study from Xilingol, China. *Land Degrad. Dev.* **2018**, *29*, 1595–1606. https://doi.org/10.1002/ldr.2948.
92. Deus, D.; Gloaguen, R. Remote Sensing Analysis of Lake Dynamics in Semi-Arid Regions: Implication for Water Resource Management. Lake Manyara, East African Rift, Northern Tanzania. *Water* **2013**, *5*, 698–727. https://doi.org/10.3390/w5020698.
93. Lantz, T.C.; Turner, K.W. Changes in Lake Area in Response to Thermokarst Processes and Climate in Old Crow Flats, Yukon. *J. Geophys. Res. Biogeosci.* **2015**, *120*, 513–524. https://doi.org/10.1002/2014JG002744.
94. Polishchuk, Y.M.; Bryksina, N.A.; Polishchuk, V.Y. Remote Analysis of Changes in the Number of Small Thermokarst Lakes and Their Distribution with Respect to Their Sizes in the Cryolithozone of Western Siberia, 2015. *Izv. Atmos. Ocean. Phys.* **2015**, *51*, 999–1006. https://doi.org/10.1134/S0001433815090145.
95. Zhang, J.; Zhou, J.; Zhang, G.; Ji, Y.; Zeng, Y.; Fan, W.; Aikelamu, A. Climate- and Human-Driven Variations in Lake Area and Number in North Xinjiang, China. *Int. J. Remote Sens.* **2020**, *42*, 469–485. https://doi.org/10.1080/01431161.2020.1809740.
96. Adams, K.D.; Sada, D.W. Surface Water Hydrology and Geomorphic Characterization of a Playa Lake System: Implications for Monitoring the Effects of Climate Change. *J. Hydrol.* **2014**, *510*, 92–102. https://doi.org/10.1016/j.jhydrol.2013.12.018.
97. Gautier, E.; Depret, T.; Cavero, J.; Costard, F.; Virmoux, C.; Fedorov, A.; Konstantinov, P.; Jammet, M.; Brunstein, D. Fifty-Year Dynamics of the Lena River Islands (Russia): Spatio-Temporal Pattern of Large Periglacial Anabranching River and Influence of Climate Change. *Sci. Total Environ.* **2021**, *783*, 147020. https://doi.org/10.1016/j.scitotenv.2021.147020.
98. Hochschild, V.; Kropacek, J.; Biskop, S.; Braun, A.; Chen, F.; Fink, M.; Helmschrot, J.; Kang, S.; Krause, P.; Leiterer, R.; et al. Multi-Sensor Remote Sensing Based Modelling of the Water Balance of Endorheic Lakes on the Tibetan Plateau. In Proceedings of the Remote Sensing and Hydrology (Symposium Held), Jackson Hole, WY, USA, 27–30 September 2010; pp. 253–256.
99. Necsoiu, M.; Mindrescu, M.; Onaca, A.; Wigginton, S. Recent Morphodynamics of Alpine Lakes in Southern Carpathian Mountains Using High-Resolution Optical Imagery. *Quat. Int.* **2016**, *415*, 164–174. https://doi.org/10.1016/j.quaint.2015.12.032.

100. Shukla, A.; Garg, P.K.; Srivastava, S. Evolution of Glacial and High-Altitude Lakes in the Sikkim, Eastern Himalaya Over the Past Four Decades (1975–2017). *Front. Environ. Sci.* **2018**, *6*, 81. https://doi.org/10.3389/fenvs.2018.00081.
101. Liu, D.; Toman, E.; Fuller, Z.; Chen, G.; Londo, A.; Zhang, X.S.; Zhao, K.G. Integration of Historical Map and Aerial Imagery to Characterize Long-Term Land-Use Change and Landscape Dynamics: An Object-Based Analysis via Random Forests. *Ecol. Indic.* **2018**, *95*, 595–605. https://doi.org/10.1016/j.ecolind.2018.08.004.
102. Bertram, A.; Wendleder, A.; Schmitt, A.; Huber, M. Long-Term Monitoring of Water Dynamics in the Sahel Region Using the Multi-SAR-System. In Proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Prague, Czech Republic, 12–19 July 2016; pp. 313–320.
103. Ottinger, M.; Clauss, K.; Kuenzer, C. Large-Scale Assessment of Coastal Aquaculture Ponds with Sentinel-1 Time Series Data. *Remote Sens.* **2017**, *9*, 440. https://doi.org/10.3390/rs9050440.
104. Park, E.; Merino, E.; Lewis, Q.W.; Lindsey, E.O.; Yang, X. A Pathway to the Automated Global Assessment of Water Level in Reservoirs with Synthetic Aperture Radar (SAR). *Remote Sens.* **2020**, *12*, 1353. https://doi.org/10.3390/rs12081353.
105. Slinski, K.M.; Hogue, T.S.; McCray, J.E. Active-Passive Surface Water Classification: A New Method for High-Resolution Monitoring of Surface Water Dynamics. *Geophys. Res. Lett.* **2019**, *46*, 4694–4704. https://doi.org/10.1029/2019GL082562.
106. Stiller, D.; Ottinger, M.; Leinenkugel, P. Spatio-Temporal Patterns of Coastal Aquaculture Derived from Sentinel-1 Time Series Data and the Full Landsat Archive. *Remote Sens.* **2019**, *11*, 1707. https://doi.org/10.3390/rs11141707.
107. Tsai, Y.-L.S.; Klein, I.; Dietz, A.; Oppelt, N. Monitoring Large-Scale Inland Water Dynamics by Fusing Sentinel-1 SAR and Sentinel-3 Altimetry Data and by Analyzing Causal Effects of Snowmelt. *Remote Sens.* **2020**, *12*, 3896. https://doi.org/10.3390/rs12233896.
108. Zeng, Z.; Gan, Y.; Kettner, A.J.; Yang, Q.; Zeng, C.; Brakenridge, G.R.; Hong, Y. Towards High Resolution Flood Monitoring: An Integrated Methodology Using Passive Microwave Brightness Temperatures and Sentinel Synthetic Aperture Radar Imagery. *J. Hydrol.* **2020**, *582*, 124377. https://doi.org/10.1016/j.jhydrol.2019.124377.
109. Zhang, M.; Chen, F.; Liang, D.; Tian, B.; Yang, A. Use of Sentinel-1 GRD SAR Images to Delineate Flood Extent in Pakistan. *Sustainability* **2020**, *12*, 5784. https://doi.org/10.3390/su12145784.
110. Zou, Z.; DeVries, B.; Huang, C.; Lang, M.W.; Thielke, S.; McCarty, G.W.; Robertson, A.G.; Knopf, J.; Wells, A.F.; Macander, M.J.; et al. Characterizing Wetland Inundation and Vegetation Dynamics in the Arctic Coastal Plain Using Recent Satellite Data and Field Photos. *Remote Sens.* **2021**, *13*, 1492. https://doi.org/10.3390/rs13081492.
111. Mengen, D.; Ottinger, M.; Leinenkugel, P.; Ribbe, L. Modeling River Discharge Using Automated River Width Measurements Derived from Sentinel-1 Time Series. *Remote Sens.* **2020**, *12*, 3236. https://doi.org/10.3390/rs12193236.
112. Ali, S.A.; Sridhar, V. Deriving the Reservoir Conditions for Better Water Resource Management Using Satellite-Based Earth Observations in the Lower Mekong River Basin. *Remote Sens.* **2019**, *11*, 2872. https://doi.org/10.3390/rs11232872.
113. Liu, D.; Chen, W.; Menz, G.; Dubovyk, O. Development of Integrated Wetland Change Detection Approach: In Case of Erdos Larus Relictus National Nature Reserve, China. *Sci. Total Environ.* **2020**, *731*, 139166. https://doi.org/10.1016/j.scitotenv.2020.139166.
114. Ogilvie, A.; Poussin, J.-C.; Bader, J.-C.; Bayo, F.; Bodian, A.; Dacosta, H.; Dia, D.; Diop, L.; Martin, D.; Sambou, S. Combining Multi-Sensor Satellite Imagery to Improve Long-Term Monitoring of Temporary Surface Water Bodies in the Senegal River Floodplain. *Remote Sens.* **2020**, *12*, 3157. https://doi.org/10.3390/rs12193157.
115. Xu, W.; Shen, Q.; Wang, X.; Wang, Q.; Yao, Y.; Huang, W.; Wang, M.; Li, J.; Zhang, F.; Chen, X. Sensing Images for Assessing the Minimum Ecological Flux by Automatically Extracting River Surface Width. *Remote Sens.* **2020**, *12*, 2899. https://doi.org/10.3390/rs12182899.
116. Yang, X.; Chen, Y.; Wang, J. Combined Use of Sentinel-2 and Landsat 8 to Monitor Water Surface Area Dynamics Using Google Earth Engine. *Remote Sens. Lett.* **2020**, *11*, 687–696. https://doi.org/10.1080/2150704X.2020.1757780.
117. Kandekar, V.U.; Pande, C.B.; Rajesh, J.; Atre, A.A.; Gorantiwar, S.D.; Kadam, S.A.; Gavit, B. Surface Water Dynamics Analysis Based on Sentinel Imagery and Google Earth Engine Platform: A Case Study of Jayakwadi Dam. *Sustain. Water Resour. Manag.* **2021**, *7*, 44. https://doi.org/10.1007/s40899-021-00527-7.
118. Xia, H.; Zhao, J.; Qin, Y.; Yang, J.; Cui, Y.; Song, H.; Ma, L.; Jin, N.; Meng, Q. Changes in Water Surface Area during 1989–2017 in the Huai River Basin Using Landsat Data and Google Earth Engine. *Remote Sens.* **2019**, *11*, 1824. https://doi.org/10.3390/rs11151824.
119. Pahlevan, N.; Chittimalli, S.K.; Balasubramanian, S.V.; Vellucci, V. Sentinel-2/Landsat-8 Product Consistency and Implications for Monitoring Aquatic Systems. *Remote Sens. Environ.* **2019**, *220*, 19–29. https://doi.org/10.1016/j.rse.2018.10.027.
120. Zhao, G.; Gao, H. Automatic Correction of Contaminated Images for Assessment of Reservoir Surface Area Dynamics. *Geophys. Res. Lett.* **2018**, *45*, 6092–6099. https://doi.org/10.1029/2018GL078343.
121. Wieland, M.; Martinis, S. A Modular Processing Chain for Automated Flood Monitoring from Multi-Spectral Satellite Data. *Remote Sens.* **2019**, *11*, 23. https://doi.org/10.3390/rs11192330.
122. Klein, I.; Mayr, S.; Gessner, U.; Hirner, A.; Kuenzer, C. Water and Hydropower Reservoirs: High Temporal Resolution Time Series Derived from MODIS Data to Characterize Seasonality and Variability. *Remote Sens. Environ.* **2021**, *253*, 112207. https://doi.org/10.1016/j.rse.2020.112207.

123. Ai, J.; Zhang, C.; Chen, L.; Li, D. Mapping Annual Land Use and Land Cover Changes in the Yangtze Estuary Region Using an Object-Based Classification Framework and Landsat Time Series Data. *Sustainability* **2020**, *12*, 659. https://doi.org/10.3390/su12020659.
124. Heimhuber, V.; Tulbure, M.G.; Broich, M. Addressing Spatio-Temporal Resolution Constraints in Landsat and MODIS-Based Mapping of Large-Scale Floodplain Inundation Dynamics. *Remote Sens. Environ.* **2018**, *211*, 307–320. https://doi.org/10.1016/j.rse.2018.04.016.
125. Du, J.; Kimball, J.S.; Galantowicz, J.; Kim, S.-B.; Chan, S.K.; Reichle, R.; Jones, L.A.; Watts, J.D. Assessing Global Surface Water Inundation Dynamics Using Combined Satellite Information from SMAP, AMSR2 and Landsat. *Remote Sens. Environ.* **2018**, *213*, 1–17. https://doi.org/10.1016/j.rse.2018.04.054.
126. Prigent, C.; Lettenmaier, D.P.; Aires, F.; Papa, F. Toward a High-Resolution Monitoring of Continental Surface Water Extent and Dynamics, at Global Scale: From GIEMS (Global Inundation Extent from Multi-Satellites) to SWOT (Surface Water Ocean Topography). *Surv. Geophys.* **2016**, *37*, 339–355. https://doi.org/10.1007/s10712-015-9339-x.
127. Ling, F.; Li, X.; Foody, G.M.; Boyd, D.; Ge, Y.; Li, X.; Du, Y. Monitoring Surface Water Area Variations of Reservoirs Using Daily MODIS Images by Exploring Sub-Pixel Information. *ISPRS J. Photogramm. Remote Sens.* **2020**, *168*, 141–152. https://doi.org/10.1016/j.isprsjprs.2020.08.008.
128. Zhu, X.; Chen, J.; Gao, F.; Chen, X.; Masek, J.G. An Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model for Complex Heterogeneous Regions. *Remote Sens. Environ.* **2010**, *114*, 2610–2623. https://doi.org/10.1016/j.rse.2010.05.032.
129. Jiang, J.; Zhang, Q.; Yao, X.; Tian, Y.; Zhu, Y.; Cao, W.; Cheng, T. HISTIF: A New Spatiotemporal Image Fusion Method for High-Resolution Monitoring of Crops at the Subfield Level. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 4607–4626. https://doi.org/10.1109/JSTARS.2020.3016135.
130. Gevaert, C.M.; García-Haro, F.J. A Comparison of STARFM and an Unmixing-Based Algorithm for Landsat and MODIS Data Fusion. *Remote Sens. Environ.* **2015**, *156*, 34–44. https://doi.org/10.1016/j.rse.2014.09.012.
131. Khandelwal, A.; Karpatne, A.; Marlier, M.E.; Kim, J.; Lettenmaier, D.P.; Kumar, V. An Approach for Global Monitoring of Surface Water Extent Variations in Reservoirs Using MODIS Data. *Remote Sens. Environ.* **2017**, *202*, 113–128. https://doi.org/10.1016/j.rse.2017.05.039.
132. Aires, F.; Prigent, C.; Fluet-Chouinard, E.; Yamazaki, D.; Papa, F.; Lehner, B. Comparison of Visible and Multi-Satellite Global Inundation Datasets at High-Spatial Resolution. *Remote Sens. Environ.* **2018**, *216*, 427–441. https://doi.org/10.1016/j.rse.2018.06.015.
133. Aires, F.; Venot, J.-P.; Massuel, S.; Gratiot, N.; Pham-Duc, B.; Prigent, C. Surface Water Evolution (2001–2017) at the Cambodia/Vietnam Border in the Upper Mekong Delta Using Satellite MODIS Observations. *Remote Sens.* **2020**, *12*, 800. https://doi.org/10.3390/rs12050800.
134. Sun, Y.; Huang, S.; Li, J.; Li, X.; Ma, J.; Wang, H.; Lei, T. Monitoring Seasonal Changes in the Water Surface Areas of Poyang Lake Using COSMO-Skymed Time Series Data in PR China. In Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016; pp. 7180–7183.
135. Heine, I.; Francke, T.; Rogass, C.; Medeiros, P.H.A.; Bronstert, A.; Foerster, S. Monitoring Seasonal Changes in the Water Surface Areas of Reservoirs Using TerraSAR-X Time Series Data in Semiarid Northeastern Brazil. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 3190–3199. https://doi.org/10.1109/JSTARS.2014.2323819.
136. Chen, Z.; Banks, S.; Behnamian, A.; White, L.; Montpetit, B.; Pasher, J.; Duffe, J. Characterizing the Great Lakes Coastal Wetlands with InSAR Observations from X-, C-, and L-Band Sensors. *Can. J. Remote Sens.* **2020**, *46*, 765–783. https://doi.org/10.1080/07038992.2020.1867974.
137. Betbeder, J.; Gond, V.; Frappart, F.; Baghdadi, N.N.; Briant, G.; Bartholome, E. Mapping of Central Africa Forested Wetlands Using Remote Sensing. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 531–542. https://doi.org/10.1109/JSTARS.2013.2269733.
138. Frappart, F.; Papa, F.; Malbeteau, Y.; Leon, J.G.; Ramillien, G.; Prigent, C.; Seoane, L.; Seyler, F.; Calmant, S. Surface Freshwater Storage Variations in the Orinoco Floodplains Using Multi-Satellite Observations. *Remote Sens.* **2015**, *7*, 89–110. https://doi.org/10.3390/rs70100089.
139. Prigent, C.; Jimenez, C.; Bousquet, P. Satellite-Derived Global Surface Water Extent and Dynamics Over the Last 25 Years (GIEMS-2). *J. Geophys. Res. Atmos.* **2020**, *125*, e2019JD030711. https://doi.org/10.1029/2019JD030711.
140. Schroeder, R.; McDonald, K.C.; Chapman, B.D.; Jensen, K.; Podest, E.; Tessler, Z.D.; Bohn, T.J.; Zimmermann, R. Development and Evaluation of a Multi-Year Fractional Surface Water Data Set Derived from Active/Passive Microwave Remote Sensing Data. *Remote Sens.* **2015**, *7*, 16688–16732. https://doi.org/10.3390/rs71215843.
141. Aires, F. Surface Water Maps De-Noising and Missing-Data Filling Using Determinist Spatial Filters Based on Several a Priori Information. *Remote Sens. Environ.* **2020**, *237*, 18. https://doi.org/10.1016/j.rse.2019.111481.
142. Takbiri, Z.; Ebtehaj, A.M.; Foufoula-Georgiou, E. A Multi-Sensor Data-Driven Methodology for All-Sky Passive Microwave Inundation Retrieval. *Hydrol. Earth Syst. Sci.* **2017**, *21*, 2685–2700. https://doi.org/10.5194/hess-21-2685-2017.
143. Ma, Y.; Xu, N.; Zhang, W.; Wang, X.H.; Sun, J.; Feng, X.; Sun, Y. Increasing Water Levels of Global Lakes Between 2003 and 2009. *IEEE Geosci. Remote Sens. Lett.* **2020**, *17*, 187–191. https://doi.org/10.1109/LGRS.2019.2920387.

144. Wu, Q.; Lane, C.R.; Li, X.; Zhao, K.; Zhou, Y.; Clinton, N.; De Vries, B.; Golden, H.E.; Lang, M.W. Integrating LiDAR Data and Multi-Temporal Aerial Imagery to Map Wetland Inundation Dynamics Using Google Earth Engine. *Remote Sens. Environ.* **2019**, *228*, 1–13. https://doi.org/10.1016/j.rse.2019.04.015.
145. Xu, Y.; Li, J.; Wang, J.; Chen, J.; Liu, Y.; Ni, S.; Zhang, Z.; Ke, C. Assessing Water Storage Changes of Lake Poyang from Multi-Mission Satellite Data and Hydrological Models. *J. Hydrol.* **2020**, *590*, 125229. https://doi.org/10.1016/j.jhydrol.2020.125229.
146. Chen, T.; Song, C.Q.; Luo, S.X.; Ke, L.H.; Liu, K.; Zhu, J.Y. Monitoring Global Reservoirs Using ICESat-2: Assessment on Spatial Coverage and Application Potential. *J. Hydrol.* **2022**, *604*, 12. https://doi.org/10.1016/j.jhydrol.2021.127257.
147. Lie, J.; Hu, J.; Deng, W.; Huang, S.; Jia, H.; Zhu, C.; Luo, H. Revealing Storage-Area Relationship of Open Water in Ungauged Subalpine Wetland—Napahai in Northwest Yunnan, China. *J. Mt. Sci.* **2013**, *10*, 553–563. https://doi.org/10.1007/s11629-013-2596-6.
148. Weekley, D.; Li, X. Tracking Lake Surface Elevations with Proportional Hypsometric Relationships, Landsat Imagery, and Multiple DEMs. *Water Resour. Res.* **2021**, *57*, e2020WR027666. https://doi.org/10.1029/2020WR027666.
149. Heine, I.; Stueve, P.; Kleinschmit, B.; Itzerott, S. Reconstruction of Lake Level Changes of Groundwater-Fed Lakes in Northeastern Germany Using RapidEye Time Series. *Water* **2015**, *7*, 4175–4199. https://doi.org/10.3390/w7084175.
150. Yapiyev, V.; Samarkhanov, K.; Tulegenova, N.; Jumassultanova, S.; Verhoef, A.; Saidaliyeva, Z.; Umirov, N.; Sagintayev, Z.; Namazbayeva, A. Estimation of Water Storage Changes in Small Endorheic Lakes in Northern Kazakhstan. *J. Arid Environ.* **2019**, *160*, 42–55. https://doi.org/10.1016/j.jaridenv.2018.09.008.
151. Bangira, T.; Alfieri, S.M.; Menenti, M.; van Niekerk, A. Comparing Thresholding with Machine Learning Classifiers for Mapping Complex Water. *Remote Sens.* **2019**, *11*, 21. https://doi.org/10.3390/rs11111351.
152. Leblanc, M.; Lemoalle, J.; Bader, J.C.; Tweed, S.; Mofor, L. Thermal Remote Sensing of Water under Flooded Vegetation: New Observations of Inundation Patterns for the "Small" Lake Chad. *J. Hydrol.* **2011**, *404*, 87–98. https://doi.org/10.1016/j.jhydrol.2011.04.023.
153. Fernandez, A.; Najafi, M.R.; Durand, M.; Mark, B.G.; Moritz, M.; Jung, H.C.; Neal, J.; Shastry, A.; Laborde, S.; Phang, S.C.; et al. Testing the Skill of Numerical Hydraulic Modeling to Simulate Spatiotemporal Flooding Patterns in the Logone Floodplain, Cameroon. *J. Hydrol.* **2016**, *539*, 265–280. https://doi.org/10.1016/j.jhydrol.2016.05.026.
154. Ogilvie, A.; Belaud, G.; Massuel, S.; Mulligan, M.; Le Goulven, P.; Calvez, R. Surface Water Monitoring in Small Water Bodies: Potential and Limits of Multi-Sensor Landsat Time Series. *Hydrol. Earth Syst. Sci.* **2018**, *22*, 4349–4380. https://doi.org/10.5194/hess-22-4349-2018.
155. Ye, X.C.; Meng, Y.K.; Xu, L.G.; Xu, C.Y. Net Primary Productivity Dynamics and Associated Hydrological Driving Factors in the Floodplain Wetland of China's Largest Freshwater Lake. *Sci. Total Environ.* **2019**, *659*, 302–313. https://doi.org/10.1016/j.scitotenv.2018.12.331.
156. Ning, F.S.; Lee, Y.C. Combining Spectral Water Indices and Mathematical Morphology to Evaluate Surface Water Extraction in Taiwan. *Water* **2021**, *13*, 17. https://doi.org/10.3390/w13192774.
157. Sass, G.Z.; Creed, I.F. Characterizing Hydrodynamics on Boreal Landscapes Using Archived Synthetic Aperture Radar Imagery. *Hydrol. Process.* **2008**, *22*, 1687–1699. https://doi.org/10.1002/hyp.6736.
158. O'Grady, D.; Leblanc, M.; Bass, A. The Use of Radar Satellite Data from Multiple Incidence Angles Improves Surface Water Mapping. *Remote Sens. Environ.* **2014**, *140*, 652–664. https://doi.org/10.1016/j.rse.2013.10.006.
159. Bartsch, A.; Wagner, W.; Scipal, K.; Pathe, C.; Sabel, D.; Wolski, P. Global Monitoring of Wetlands—The Value of ENVISAT ASAR Global Mode. *J. Environ. Manag.* **2009**, *90*, 2226–2233. https://doi.org/10.1016/j.jenvman.2007.06.023.
160. Westerhoff, R.S.; Kleuskens, M.P.H.; Winsemius, H.C.; Huizinga, H.J.; Brakenridge, G.R.; Bishop, C. Automated Global Water Mapping Based on Wide-Swath Orbital Synthetic-Aperture Radar. *Hydrol. Earth Syst. Sci.* **2013**, *17*, 651–663. https://doi.org/10.5194/hess-17-651-2013.
161. Hamandawana, H.; Atyosi, Y.; Bornman, T.G. Multi-Temporal Reconstruction of Long-Term Changes in Land Cover in and around the Swartkops River Estuary, Eastern Cape, South Africa. *Environ. Monit. Assess.* **2020**, *192*, 173. https://doi.org/10.1007/s10661-020-8136-2.
162. Kharazmi, R.; Tavili, A.; Rahdari, M.R.; Chaban, L.; Panidi, E.; Rodrigo-Comino, J. Monitoring and Assessment of Seasonal Land Cover Changes Using Remote Sensing: A 30-Year (1987–2016) Case Study of Hamoun Wetland, Iran. *Environ. Monit. Assess.* **2018**, *190*, 23. https://doi.org/10.1007/s10661-018-6726-z.
163. Chetan, M.-A.; Dornik, A.; Ardelean, F.; Georgievski, G.; Hagemann, S.; Romanovsky, V.E.; Onaca, A.; Drozdov, D.S. 35 Years of Vegetation and Lake Dynamics in the Pechora Catchment, Russian European Arctic. *Remote Sens.* **2020**, *12*, 1863. https://doi.org/10.3390/rs12111863.
164. Chen, T.; Song, C.; Ke, L.; Wang, J.; Liu, K.; Wu, Q. Estimating Seasonal Water Budgets in Global Lakes by Using Multi-Source Remote Sensing Measurements. *J. Hydrol.* **2021**, *593*, 125781. https://doi.org/10.1016/j.jhydrol.2020.125781.
165. Fuentes, I.; Padarian, J.; Van Ogtrop, F.; Vervoort, R.W. Spatiotemporal Evaluation of Inundated Areas Using MODIS Imagery at a Catchment Scale. *J. Hydrol.* **2019**, *573*, 952–963. https://doi.org/10.1016/j.jhydrol.2019.03.103.
166. Herndon, K.; Muench, R.; Cherrington, E.; Griffin, R. An Assessment of Surface Water Detection Methods for Water Resource Management in the Nigerien Sahel. *Sensors* **2020**, *20*, 431. https://doi.org/10.3390/s20020431.

167. Jones, S.K.; Fremier, A.K.; De Clerck, F.A.; Smedley, D.; Pieck, A.O.; Mulligan, M. Big Data and Multiple Methods for Mapping Small Reservoirs: Comparing Accuracies for Applications in Agricultural Landscapes. *Remote Sens.* **2017**, *9*, 1307. https://doi.org/10.3390/rs9121307.
168. Li, L.; Skidmore, A.; Vrieling, A.; Wang, T. A New Dense 18-Year Time Series of Surface Water Fraction Estimates from MODIS for the Mediterranean Region. *Hydrol. Earth Syst. Sci.* **2019**, *23*, 3037–3056. https://doi.org/10.5194/hess-23-3037-2019.
169. Luo, S.; Song, C.; Liu, K.; Ke, L.; Ma, R. An Effective Low-Cost Remote Sensing Approach to Reconstruct the Long-Term and Dense Time Series of Area and Storage Variations for Large Lakes. *Sensors* **2019**, *19*, 4247. https://doi.org/10.3390/s19194247.
170. Morris, M.; Chew, C.; Reager, J.T.; Shah, R.; Zuffada, C. A Novel Approach to Monitoring Wetland Dynamics Using CYGNSS: Everglades Case Study. *Remote Sens. Environ.* **2019**, *233*, 111417. https://doi.org/10.1016/j.rse.2019.111417.
171. Perin, V.; Tulbure, M.G.; Gaines, M.D.; Reba, M.L.; Yaeger, M.A. On-Farm Reservoir Monitoring Using Landsat Inundation Datasets. *Agric. Water Manag.* **2021**, *246*, 106694. https://doi.org/10.1016/j.agwat.2020.106694.
172. Yang, J.; Huang, X.; Tang, Q. Satellite-Derived River Width and Its Spatiotemporal Patterns in China during 199–2015. *Remote Sens. Environ.* **2020**, *247*, 111918. https://doi.org/10.1016/j.rse.2020.111918.
173. Pickens, A.H.; Hansen, M.C.; Hancher, M.; Stehman, S.; Tyukavina, A.; Potapov, P.; Marroquin, B.; Sherani, Z. Mapping and Sampling to Characterize Global Inland Water Dynamics from 1999 to 2018 with Full Landsat Time-Series. *Remote Sens. Environ.* **2020**, *243*, 111792. https://doi.org/10.1016/j.rse.2020.111792.
174. Huang, C.; Chen, Y.; Zhang, S.; Li, L.; Shui, J.; Liu, Q. Integrating Water Observation from Space Product and Time-Series Flow Data for Modeling Spatio-Temporal Flood Inundation Dynamics. *Remote Sens.* **2019**, *11*, 2535. https://doi.org/10.3390/rs11212535.
175. Krause, C.E.; Newey, V.; Alger, M.J.; Lymburner, L. Mapping and Monitoring the Multi-Decadal Dynamics of Australia's Open Waterbodies Using Landsat. *Remote Sens.* **2021**, *13*, 1437. https://doi.org/10.3390/rs13081437.
176. Mueller, N.; Lewis, A.; Roberts, D.; Ring, S.; Melrose, R.; Sixsmith, J.; Lymburner, L.; McIntyre, A.; Tan, P.; Curnow, S.; et al. Water Observations from Space: Mapping Surface Water from 25 Years of Landsat Imagery across Australia. *Remote Sens. Environ.* **2016**, *174*, 341–352. https://doi.org/10.1016/j.rse.2015.11.003.
177. Tulbure, M.G.; Broich, M.; Stehman, S.V.; Kommareddy, A. Surface Water Extent Dynamics from Three Decades of Seasonally Continuous Landsat Time Series at Subcontinental Scale in a Semi-Arid Region. *Remote Sens. Environ.* **2016**, *178*, 142–157. https://doi.org/10.1016/j.rse.2016.02.034.
178. Ji, L.; Gong, P.; Wang, J.; Shi, J.; Zhu, Z. Construction of the 500-m Resolution Daily Global Surface Water Change Database (2001–2016). *Water Resour. Res.* **2018**, *54*, 10270–10292. https://doi.org/10.1029/2018WR023060.
179. Soltani, K.; Azari, A.; Zeynoddin, M.; Amiri, A.; Ebtehaj, I.; Ouarda, T.B.M.J.; Gharabaghi, B.; Bonakdari, H. Lake Surface Area Forecasting Using Integrated Satellite-SARIMA-Long-Short-Term Memory Model. *Res. Sq.* **2021**, *preprint*, https://doi.org/10.21203/rs.3.rs-631247/v1.
180. Prigent, C.; Papa, F.; Aires, F.; Jimenez, C.; Rossow, W.B.; Matthews, E. Changes in Land Surface Water Dynamics since the 1990s and Relation to Population Pressure. *Geophys. Res. Lett.* **2012**, *39*, L08403. https://doi.org/10.1029/2012GL051276.
181. Prigent, C.; Matthews, E.; Aires, F.; Rossow, W.B. Remote Sensing of Global Wetland Dynamics with Multiple Satellite Data Sets. *Geophys. Res. Lett.* **2001**, *28*, 4631–4634. https://doi.org/10.1029/2001GL013263.
182. Prigent, C.; Papa, F.; Aires, F.; Rossow, W.B.; Matthews, E. Global Inundation Dynamics Inferred from Multiple Satellite Observations, 1993–2000. *J. Geophys. Res.* **2007**, *112*, D12107. https://doi.org/10.1029/2006JD007847.
183. Fluet-Chouinard, E.; Lehner, B.; Rebelo, L.-M.; Papa, F.; Hamilton, S.K. Development of a Global Inundation Map at High Spatial Resolution from Topographic Downscaling of Coarse-Scale Remote Sensing Data. *Remote Sens. Environ.* **2015**, *158*, 348–361. https://doi.org/10.1016/j.rse.2014.10.015.
184. Jensen, K.; Mcdonald, K. Surface Water Microwave Product Series Version 3: A Near-Real Time and 25-Year Historical Global Inundated Area Fraction Time Series From Active and Passive Microwave Remote Sensing. *IEEE Geosci. Remote Sens. Lett.* **2019**, *16*, 1402–1406. https://doi.org/10.1109/LGRS.2019.2898779.
185. Papa, F.; Frappart, F.; Guentner, A.; Prigent, C.; Aires, F.; Getirana, A.C.V.; Maurer, R. Surface Freshwater Storage and Variability in the Amazon Basin from Multi-Satellite Observations, 1993–2007. *J. Geophys. Res. Atmos.* **2013**, *118*, 11951–11965. https://doi.org/10.1002/2013JD020500.
186. Tourian, M.J.; Reager, J.T.; Sneeuw, N. The Total Drainable Water Storage of the Amazon River Basin: A First Estimate Using GRACE. *Water Resour. Res.* **2018**, *54*, 3290–3312. https://doi.org/10.1029/2017WR021674.
187. Ilyas, S.; Xu, X.; Jia, G.; Zhang, A. Interannual Variability of Global Wetlands in Response to El Nino Southern Oscillations (ENSO) and Land-Use. *Front. Earth Sci.* **2019**, *7*, 289. https://doi.org/10.3389/feart.2019.00289.
188. Liu, J.; Sheng, L.; Lu, X.; Liu, Y. A Dynamic Change Map of Marshes in the Small Sanjiang Plain, Heilongjiang, China, from 1955 to 2005. *Wetl. Ecol. Manag.* **2015**, *23*, 419–437. https://doi.org/10.1007/s11273-014-9392-0.
189. Maleki, S.; Soffianian, A.; Koupaei, S.S.; Saatchi, S.; Pourmanafi, S. Application of Remote Sensing in Monitoring Unsustainable Wetlands: Case Study Hamun Wetland. *J. Indian Soc. Remote Sens.* **2018**, *46*, 1871–1879. https://doi.org/10.1007/s12524-018-0842-7.
190. Wang, Z.; Jia, M.; Mao, D.; Ren, C. Remote Sensing of Spatial Distribution of Wetlands in Northeast China, 1990-2013. In Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016; pp. 3539–3542.

191. Ma, C.; Zhang, G.Y.; Zhang, X.C.; Zhao, Y.J.; Li, H.Y.; Yang, Z.; Chen, B. Application of Markov Model in Wetland Change Dynamics in Tianjin Coastal Area, China. In Proceedings of the 18th Biennial Isem Conference on Ecological Modelling for Global Change and Coupled Human and Natural System, Beijing, China, 20–23 September 2012.
192. Xu, N.; Jia, D.; Ding, L.; Wu, Y. Continuously Tracking the Annual Changes of the Hengsha and Changxing Islands at the Yangtze River Estuary from 1987 to 2016 Using Landsat Imagery. *Water* **2018**, *10*, 171. https://doi.org/10.3390/w10020171.
193. Che, X.; Feng, M.; Sexton, J.; Channan, S.; Sun, Q.; Ying, Q.; Liu, J.; Wang, Y. Landsat-Based Estimation of Seasonal Water Cover and Change in Arid and Semi-Arid Central Asia (2000–2015). *Remote Sens.* **2019**, *11*, 1323. https://doi.org/10.3390/rs11111323.
194. Asamoah, M.; Kabo-Bah, A.T.; Antwi-Ofosu, E. Spatial and SocioEconomic Impacts Analysis of BUI Hydropower Dam on Downstream Communities. In Proceedings of the Data-Driven Modeling for Sustainable Engineering, ICEASSM 2017, Accra, Ghana, 18–21 April 2017; pp. 303–322.
195. Gain, A.K.; Giupponi, C.; Wada, Y. Measuring Global Water Security towards Sustainable Development Goals. *Environ. Res. Lett.* **2016**, *11*, 124015. https://doi.org/10.1088/1748-9326/11/12/124015.
196. Sun, P.; Xu, Y.; Yu, Z.; Liu, Q.; Xie, B.; Liu, J. Scenario Simulation and Landscape Pattern Dynamic Changes of Land Use in the Poverty Belt around Beijing and Tianjin: A Case Study of Zhangjiakou City, Hebei Province. *J. Geogr. Sci.* **2016**, *26*, 272–296. https://doi.org/10.1007/s11442-016-1268-1.
197. De Groeve, T. Flood Monitoring and Mapping Using Passive Microwave Remote Sensing in Namibia. *Geomat. Nat. Hazards Risk* **2010**, *1*, 19–35. https://doi.org/10.1080/19475701003648085.
198. Sakamoto, T.; Van Nguyen, N.; Kotera, A.; Ohno, H.; Ishitsuka, N.; Yokozawa, M. Detecting Temporal Changes in the Extent of Annual Flooding within the Cambodia and the Vietnamese Mekong Delta from MODIS Time-Series Imagery. *Remote Sens. Environ.* **2007**, *109*, 295–313. https://doi.org/10.1016/j.rse.2007.01.011.
199. Gao, S.; Li, Z.; Chen, M.Y.; Allen, D.; Neeson, T.; Hong, Y. Monitoring Drought through the Lens of Landsat: Drying of Rivers during the California Droughts. *Remote Sens.* **2021**, *13*, 18. https://doi.org/10.3390/rs13173423.
200. Song, S.; Cao, Z.; Wu, Z.F.; Chuai, X.W. Spatial and Temporal Dynamics of Surface Water in China from the 1980s to 2015 Based on Remote Sensing Monitoring. *Chin. Geogr. Sci.* **2022**, *32*, 174–188. https://doi.org/10.1007/s11769-021-1252-2.
201. Zhang, M.M.; Chen, F.; Zhao, H.; Wang, J.X.; Wang, N. Recent Changes of Glacial Lakes in the High Mountain Asia and Its Potential Controlling Factors Analysis. *Remote Sens.* **2021**, *13*, 19. https://doi.org/10.3390/rs13183757.
202. Pickens, A.H.; Hansen, M.C.; Stehman, S.V.; Tyukavina, A.; Potapov, P.; Zalles, V.; Higgins, J. Global Seasonal Dynamics of Inland Open Water and Ice. *Remote Sens. Environ.* **2022**, *272*, 14. https://doi.org/10.1016/j.rse.2022.112963.
203. Gao, S.; Li, Z.; Chen, M.Y.; Lin, P.R.; Hong, Z.; Allen, D.; Neeson, T.; Hong, Y. Spatiotemporal Variability of Global River Extent and the Natural Driving Factors Revealed by Decades of Landsat Observations, GRACE Gravimetry Observations, and Land Surface Model Simulations. *Remote Sens. Environ.* **2021**, *267*, 15. https://doi.org/10.1016/j.rse.2021.112725.
204. Mu, M.F.; Tang, Q.H.; Han, S.J.; Liu, X.M.; Cui, H.J. Using GRanD Database and Surface Water Data to Constrain Area-Storage Curve of Reservoirs. *Water* **2020**, *12*, 13. https://doi.org/10.3390/w12051242.
205. Feng, Y.H.; Zhang, H.; Tao, S.L.; Ao, Z.R.; Song, C.Q.; Chave, J.; Le Toan, T.; Xue, B.L.; Zhu, J.L.; Pan, J.M.; et al. Decadal Lake Volume Changes (2003–2020) and Driving Forces at a Global Scale. *Remote Sens.* **2022**, *14*, 20. https://doi.org/10.3390/rs14041032.
206. Bousquet, E.; Mialon, A.; Rodriguez-Fernandez, N.; Prigent, C.; Wagner, F.H.; Kerr, Y.H. Influence of Surface Water Variations on VOD and Biomass Estimates from Passive Microwave Sensors. *Remote Sens. Environ.* **2021**, *257*, 13. https://doi.org/10.1016/j.rse.2021.112345.
207. Ringeval, B.; Decharme, B.; Piao, S.L.; Ciais, P.; Papa, F.; de Noblet-Ducoudre, N.; Prigent, C.; Friedlingstein, P.; Gouttevin, I.; Koven, C.; et al. Modelling Sub-Grid Wetland in the ORCHIDEE Global Land Surface Model: Evaluation against River Discharges and Remotely Sensed Data. *Geosci. Model Dev.* **2012**, *5*, 941–962. https://doi.org/10.5194/gmd-5-941-2012.
208. Papa, F.; Prigent, C.; Aires, F.; Jimenez, C.; Rossow, W.B.; Matthews, E. Interannual Variability of Surface Water Extent at the Global Scale, 1993–2004. *J. Geophys. Res.* **2010**, *115*, D12111. https://doi.org/10.1029/2009JD012674.
209. Aduah, M.S.; Warburton, M.L.; Jewitt, G. Analysis of Land Cover Changes in the Bonsa Catchment, Ankobra Basin, Ghana. *Appl. Ecol. Environ. Res.* **2015**, *13*, 935–955.
210. Akiwumi, F.A.; Butler, D.R. Mining and Environmental Change in Sierra Leone, West Africa: A Remote Sensing and Hydrogeomorphological Study. *Environ. Monit. Assess.* **2008**, *142*, 309–318. https://doi.org/10.1007/s10661-007-9930-9.
211. Mishra, V.; Limaye, A.S.; Muench, R.E.; Cherrington, E.A.; Markert, K.N. Evaluating the Performance of High-Resolution Satellite Imagery in Detecting Ephemeral Water Bodies over West Africa. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *93*, 102218. https://doi.org/10.1016/j.jag.2020.102218.
212. Becker, M.; Papa, F.; Frappart, F.; Alsdorf, D.; Calmant, S.; Santos da Silva, J.; Prigent, C.; Seyler, F. Satellite-Based Estimates of Surface Water Dynamics in the Congo River Basin. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *66*, 196–209. https://doi.org/10.1016/j.jag.2017.11.015.
213. Frappart, F.; Zeiger, P.; Betbeder, J.; Gond, V.; Bellot, R.; Baghdadi, N.; Blarel, F.; Darrozes, J.; Bourrel, L.; Seyler, F. Automatic Detection of Inland Water Bodies along Altimetry Tracks for Estimating Surface Water Storage Variations in the Congo Basin. *Remote Sens.* **2021**, *13*, 22. https://doi.org/10.3390/rs13193804.
214. Msofe, N.K.; Sheng, L.X.; Lyimo, J. Land Use Change Trends and Their Driving Forces in the Kilombero Valley Floodplain, Southeastern Tanzania. *Sustainability* **2019**, *11*, 25. https://doi.org/10.3390/su11020505.

215. Velpuri, N.M.; Senay, G.B. Assessing the Potential Hydrological Impact of the Gibe III Dam on Lake Turkana Water Level Using Multi-Source Satellite Data. *Hydrol. Earth Syst. Sci.* **2012**, *16*, 3561–3578. https://doi.org/10.5194/hess-16-3561-2012.
216. Debusscher, B.; Landuyt, L.; Van Coillie, F. A Visualization Tool for Flood Dynamics Monitoring Using a Graph-Based Approach. *Remote Sens.* **2020**, *12*, 11. https://doi.org/10.3390/rs12132118.
217. Hawker, L.; Neal, J.; Tellman, B.; Liang, J.Y.; Schumann, G.; Doyle, C.; Sullivan, J.A.; Savage, J.; Tshimanga, R. Comparing Earth Observation and Inundation Models to Map Flood Hazards. *Environ. Res. Lett.* **2020**, *15*, 13. https://doi.org/10.1088/1748-9326/abc216.
218. Kittel, C.M.M.; Jiang, L.; Tottrup, C.; Bauer-Gottwein, P. Sentinel-3 Radar Altimetry for River Monitoring—A Catchment-Scale Evaluation of Satellite Water Surface Elevation from Sentinel-3A and Sentinel-3B. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 333–357. https://doi.org/10.5194/hess-25-333-2021.
219. Bai, J.; Chen, X.; Li, J.; Yang, L.; Fang, H. Changes in the Area of Inland Lakes in Arid Regions of Central Asia during the Past 30 Years. *Environ. Monit. Assess.* **2011**, *178*, 247–256. https://doi.org/10.1007/s10661-010-1686-y.
220. Qiu, B.; Li, H.; Chen, C.; Tang, Z.; Zhang, K.; Berry, J. Tracking Spatial-Temporal Landscape Changes of Impervious Surface Areas, Bare Lands, and Inundation Areas in China during 2001–2017. *Land Degrad. Dev.* **2019**, *30*, 1802–1812. https://doi.org/10.1002/ldr.3352.
221. Chen, C.P.; Tian, B.; Schwarz, C.; Zhang, C.; Guo, L.C.; Xu, F.; Zhou, Y.X.; He, Q. Quantifying Delta Channel Network Changes with Landsat Time-Series Data. *J. Hydrol.* **2021**, *600*, 14. https://doi.org/10.1016/j.jhydrol.2021.126688.
222. Chen, L.; Zhang, G.; Xu, Y.J.; Chen, S.; Wu, Y.; Gao, Z.; Yu, H. Human Activities and Climate Variability Affecting Inland Water Surface Area in a High Latitude River Basin. *Water* **2020**, *12*, 382. https://doi.org/10.3390/w12020382.
223. Chen, X.; Liu, L.; Zhang, X.; Xie, S.; Lei, L. A Novel Water Change Tracking Algorithm for Dynamic Mapping of Inland Water Using Time-Series Remote Sensing Imagery. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 1661–1674. https://doi.org/10.1109/JSTARS.2020.2983729.
224. Dong, J.W.; Xiao, X.M.; Kou, W.L.; Qin, Y.W.; Zhang, G.L.; Li, L.; Jin, C.; Zhou, Y.T.; Wang, J.; Biradar, C.; et al. Tracking the Dynamics of Paddy Rice Planting Area in 1986–2010 through Time Series Landsat Images and Phenology-Based Algorithms. *Remote Sens. Environ.* **2015**, *160*, 99–113. https://doi.org/10.1016/j.rse.2015.01.004.
225. Dong, S.; Peng, F.; You, Q.; Guo, J.; Xue, X. Lake Dynamics and Its Relationship to Climate Change on the Tibetan Plateau over the Last Four Decades. *Reg. Environ. Chang.* **2018**, *18*, 477–487. https://doi.org/10.1007/s10113-017-1211-8.
226. Hong, H.; Peng, X.; Chen, Z.; Zhang, X.; Liu, Q.; Li, H. Spatiotemporal Patterns of Land Use/Cover Change along Coastal Areas of the Pearl River Estuary in China during 1990 to 2005. In Proceedings of the Piageng 2010: Photonics and Imaging for Agricultural Engineering, Qingdao, China, 4 February 2011; Volume 7752, pp. 1–9.
227. He, C.; Liu, Z.; Tian, J.; Ma, Q. Urban Expansion Dynamics and Natural Habitat Loss in China: A Multiscale Landscape Perspective. *Glob. Chang. Biol.* **2014**, *20*, 2886–2902. https://doi.org/10.1111/gcb.12553.
228. Huang, C.; Chen, Y.; Zhang, S.Q.; Li, L.Y.; Shi, K.F.; Liu, R. Spatial Downscaling of Suomi NPP-VIIRS Image for Lake Mapping. *Water* **2017**, *9*, 20. https://doi.org/10.3390/w9110834.
229. Jiang, S.; Nie, Y.; Liu, Q.; Wang, J.; Liu, L.; Hassan, J.; Liu, X.; Xu, X. Glacier Change, Supraglacial Debris Expansion and Glacial Lake Evolution in the Gyirong River Basin, Central Himalayas, between 1988 and 2015. *Remote Sens.* **2018**, *10*, 986. https://doi.org/10.3390/rs10070986.
230. Li, S.; Chen, J.; Xiang, J.; Pan, Y.; Huang, Z.; Wu, Y. Water Level Changes of Hulun Lake in Inner Mongolia Derived from Jason Satellite Data. *J. Vis. Commun. Image Represent.* **2019**, *58*, 565–575. https://doi.org/10.1016/j.jvcir.2018.12.031.
231. Li, Z.; Feng, Y.; Gurgel, H.; Xu, L.; Dessay, N.; Gong, P. Use of Spatial Autocorrelation and Time Series Landsat Images for Long-Term Monitoring of Surface Water Shrinkage and Expansion in Guanting Reservoir, China. *Remote Sens. Lett.* **2019**, *10*, 1192–1200. https://doi.org/10.1080/2150704X.2019.1671634.
232. Li, Z.; Liu, M.; Hu, Y.; Xue, Z.; Sui, J. The Spatiotemporal Changes of Marshland and the Driving Forces in the Sanjiang Plain, Northeast China from 1980 to 2016. *Ecol. Process.* **2020**, *9*, 24. https://doi.org/10.1186/s13717-020-00226-9.
233. Liu, H.; Zheng, L.; Jiang, L.; Liao, M. Forty-Year Water Body Changes in Poyang Lake and the Ecological Impacts Based on Landsat and HJ-1 A/B Observations. *J. Hydrol.* **2020**, *589*, 125161. https://doi.org/10.1016/j.jhydrol.2020.125161.
234. Liu, H.C.; He, G.J.; Peng, Y.; Wang, G.Z.; Yin, R.Y. Dynamic Monitoring of Surface Water in the Tibetan Plateau from 1980s to 2019 Based on Satellite Remote Sensing Images. *J. Mt. Sci.* **2021**, *18*, 2833–2841. https://doi.org/10.1007/s11629-020-6482-8.
235. Papa, F.; Prigent, C.; Durand, F.; Rossow, W.B. Wetland Dynamics Using a Suite of Satellite Observations: A Case Study of Application and Evaluation for the Indian Subcontinent. *Geophys. Res. Lett.* **2006**, *33*, 4. https://doi.org/10.1029/2006gl025767.
236. Papa, F.; Prigent, C.; Rossow, W.B.; Legresy, B.; Remy, F. Inundated Wetland Dynamics over Boreal Regions from Remote Sensing: The Use of Topex-Poseidon Dual-Frequency Radar Altimeter Observations. *Int. J. Remote Sens.* **2006**, *27*, 4847–4866. https://doi.org/10.1080/01431160600675887.
237. Shen, W.S.; Zou, C.X.; Liu, D.; Ouyang, Y.; Zhang, H.; Yang, C.Y.; Bai, S.Y.; Lin, N.F. Climate-Forced Ecological Changes over the Tibetan Plateau. *Cold Reg. Sci. Technol.* **2015**, *114*, 27–35. https://doi.org/10.1016/j.coldregions.2015.02.011.
238. Sheng, Y.; Gong, P.; Xiao, Q. Quantitative Dynamic Flood Monitoring with NOAA AVHRR. *Int. J. Remote Sens.* **2001**, *22*, 1709–1724. https://doi.org/10.1080/01431160118481.

239. Talukdar, S.; Eibek, K.U.; Akhter, S.; Ziaul, S.; Islam, A.R.M.T.; Mallick, J. Modeling Fragmentation Probability of Land-Use and Land-Cover Using the Bagging, Random Forest and Random Subspace in the Teesta River Basin, Bangladesh. *Ecol. Indic.* **2021**, *126*, 107612. https://doi.org/10.1016/j.ecolind.2021.107612.
240. Somasundaram, D.; Zhang, F.; Ediriweera, S.; Wang, S.; Li, J.; Zhang, B. Spatial and Temporal Changes in Surface Water Area of Sri Lanka over a 30-Year Period. *Remote Sens.* **2020**, *12*, 3701. https://doi.org/10.3390/rs12223701.
241. Talukdar, S.; Singha, P.; Shahfahad; Mahato, S.; Praveen, B.; Rahman, A. Dynamics of Ecosystem Services (ESs) in Response to Land Use Land Cover (LU/LC) Changes in the Lower Gangetic Plain of India. *Ecol. Indic.* **2020**, *112*, 106121. https://doi.org/10.1016/j.ecolind.2020.106121.
242. Wang, R.; Pan, L.; Niu, W.; Li, R.; Zhao, X.; Bian, X.; Yu, C.; Xia, H.; Chen, T. Monitoring the Spatiotemporal Dynamics of Surface Water Body of the Xiaolangdi Reservoir Using Landsat-5/7/8 Imagery and Google Earth Engine. *Open Geosci.* **2021**, *13*, 1290–1302. https://doi.org/10.1515/geo-2020-0305.
243. Wang, R.; Xia, H.; Qin, Y.; Niu, W.; Pan, L.; Li, R.; Zhao, X.; Bian, X.; Fu, P. Dynamic Monitoring of Surface Water Area during 1989–2019 in the Hetao Plain Using Landsat Data in Google Earth Engine. *Water* **2020**, *12*, 3010. https://doi.org/10.3390/w12113010.
244. Xu, M.Z.; Cui, B.L.; Lan, S.B.; Li, D.S.; Wang, Y.; Jiang, B.F. Exploring Dynamic Change of the Tidal Flat Aquaculture Area in the Shandong Peninsula (China) Using Multitemporal Landsat Imagery (1990–2015). *J. Coast. Res.* **2020**, *99*, 197–202. https://doi.org/10.2112/si99-028.1.
245. Yang, J.M.; Ma, L.G.; Li, C.Z.; Liu, Y.; Ding, J.L.; Yang, S.T. Temporal-Spatial Variations and Influencing Factors of Lakes in Inland Arid Areas from 2000 to 2017: A Case Study in Xinjiang. *Geomat. Nat. Hazards Risk* **2019**, *10*, 519–543. https://doi.org/10.1080/19475705.2018.1531942.
246. Zhao, Z.L.; Zhang, Y.; Hu, Z.Z.; Nie, X.H. Contrasting Evolution Patterns of Endorheic and Exorheic Lakes on the Central Tibetan Plateau and Climate Cause Analysis during 1988–2017. *Water* **2021**, *13*, 12. https://doi.org/10.3390/w13141962.
247. Zheng, L.L.; Xia, Z.L.; Xu, J.H.; Chen, Y.N.; Yang, H.Q.; Li, D.H. Exploring Annual Lake Dynamics in Xinjiang (China): Spatiotemporal Features and Driving Climate Factors from 2000 to 2019. *Clim. Chang.* **2021**, *166*, 20. https://doi.org/10.1007/s10584-021-03136-7.
248. Han, X.X.; Chen, W.; Ping, B.; Hu, Y. Implementation of an Improved Water Change Tracking (IWCT) Algorithm: Monitoring the Water Changes in Tianjin over 1984–2019 Using Landsat Time-Series Data. *Remote Sens.* **2021**, *13*, 17. https://doi.org/10.3390/rs13030493.
249. Liu, X.L.; Shi, Z.T.; Huang, G.C.; Bo, Y.C.; Chen, G.J. Time Series Remote Sensing Data-Based Identification of the Dominant Factor for Inland Lake Surface Area Change: Anthropogenic Activities or Natural Events? *Remote Sens.* **2020**, *12*, 20. https://doi.org/10.3390/rs12040612.
250. Uereyen, S.; Bachofer, F.; Kuenzer, C. A Framework for Multivariate Analysis of Land Surface Dynamics and Driving Variables-A Case Study for Indo-Gangetic River Basins. *Remote Sens.* **2022**, *14*, 24. https://doi.org/10.3390/rs14010197.
251. Wu, Y.H.; Zhang, X.; Zheng, H.X.; Li, J.S.; Wang, Z.Y. Investigating Changes in Lake Systems in the South-Central Tibetan Plateau with Multi-Source Remote Sensing. *J. Geogr. Sci.* **2017**, *27*, 337–347. https://doi.org/10.1007/s11442-017-1380-x.
252. Fuentes, I.; Padarian, J.; van Ogtrop, F.; Vervoort, R.W. Comparison of Surface Water Volume Estimation Methodologies That Couple Surface Reflectance Data and Digital Terrain Models. *Water* **2019**, *11*, 19. https://doi.org/10.3390/w11040780.
253. Heimhuber, V.; Tulbure, M.G.; Broich, M. Modeling 25 Years of Spatio-Temporal Surface Water and Inundation Dynamics on Large River Basin Scale Using Time Series of Earth Observation Data. *Hydrol. Earth Syst. Sci.* **2016**, *20*, 2227–2250. https://doi.org/10.5194/hess-20-2227-2016.
254. Giustarini, L.; Chini, M.; Hostache, R.; Pappenberger, F.; Matgen, P. Flood Hazard Mapping Combining Hydrodynamic Modeling and Multi Annual Remote Sensing Data. *Remote Sens.* **2015**, *7*, 14200–14226. https://doi.org/10.3390/rs71014200.
255. Ma, J.S.; Song, C.Q.; Wang, Y.J. Spatially and Temporally Resolved Monitoring of Glacial Lake Changes in Alps During the Recent Two Decades. *Front. Earth Sci.* **2021**, *9*, 11. https://doi.org/10.3389/feart.2021.723386.
256. Pena-Luque, S.; Ferrant, S.; Cordeiro, M.C.R.; Ledauphin, T.; Maxant, J.; Martinez, J.M. Sentinel-1&2 Multitemporal Water Surface Detection Accuracies, Evaluated at Regional and Reservoirs Level. *Remote Sens.* **2021**, *13*, 25. https://doi.org/10.3390/rs13163279.
257. Carroll, M.L.; Loboda, T.V. Multi-Decadal Surface Water Dynamics in North American Tundra. *Remote Sens.* **2017**, *9*, 497. https://doi.org/10.3390/rs9050497.
258. Labuzzetta, C.; Zhu, Z.; Chang, X.; Zhou, Y. A Submonthly Surface Water Classification Framework via Gap-Fill Imputation and Random Forest Classifiers of Landsat Imagery. *Remote Sens.* **2021**, *13*, 1742. https://doi.org/10.3390/rs13091742.
259. Lin, Y.N.; Yun, S.H.; Bhardwaj, A.; Hill, E.M. Urban Flood Detection with Sentinel-1 Multi-Temporal Synthetic Aperture Radar (SAR) Observations in a Bayesian Framework: A Case Study for Hurricane Matthew. *Remote Sens.* **2019**, *11*, 22. https://doi.org/10.3390/rs11151778.
260. Ordoyne, C.; Friedl, M.A. Using MODIS Data to Characterize Seasonal Inundation Patterns in the Florida Everglades. *Remote Sens. Environ.* **2008**, *112*, 4107–4119. https://doi.org/10.1016/j.rse.2007.08.027.
261. Roy, S.; Robeson, S.M.; Ortiz, A.C.; Edmonds, D.A. Spatial and Temporal Patterns of Land Loss in the Lower Mississippi River Delta from 1983 to 2016. *Remote Sens. Environ.* **2020**, *250*, 112046. https://doi.org/10.1016/j.rse.2020.112046.

262. Bhagwat, T.; Klein, I.; Huth, J.; Leinenkugel, P. Volumetric Analysis of Reservoirs in Drought-Prone Areas Using Remote Sensing Products. *Remote Sens.* **2019**, *11*, 20. https://doi.org/10.3390/rs11171974.
263. Frappart, F.; Bourrel, L.; Brodu, N.; Salazar, X.R.; Baup, F.; Darrozes, J.; Pombosa, R. Monitoring of the Spatio-Temporal Dynamics of the Floods in the Guayas Watershed (Ecuadorian Pacific Coast) Using Global Monitoring ENVISAT ASAR Images and Rainfall Data. *Water* **2017**, *9*, 12. https://doi.org/10.3390/w9010012.
264. Hou, J.; van Dijk, A.I.J.M.; Renzullo, L.J.; Vertessy, R.A. Using Modelled Discharge to Develop Satellite-Based River Gauging: A Case Study for the Amazon Basin. *Hydrol. Earth Syst. Sci.* **2018**, *22*, 6435–6448. https://doi.org/10.5194/hess-22-6435-2018.
265. Jensen, K.; McDonald, K.; Podest, E.; Rodriguez-Alvarez, N.; Horna, V.; Steiner, N. Assessing L-Band GNSS-Reflectometry and Imaging Radar for Detecting Sub-Canopy Inundation Dynamics in a Tropical Wetlands Complex. *Remote Sens.* **2018**, *10*, 29. https://doi.org/10.3390/rs10091431.
266. Luo, X.Y.; Li, H.Y.; Leung, L.R.; Tesfa, T.K.; Getirana, A.; Papa, F.; Hess, L.L. Modeling Surface Water Dynamics in the Amazon Basin Using MOSART-Inundation v1.0: Impacts of Geomorphological Parameters and River Flow Representation. *Geosci. Model Dev.* **2017**, *10*, 1233–1259. https://doi.org/10.5194/gmd-10-1233-2017.
267. Parrens, M.; Al Bitar, A.; Frappart, F.; Papa, F.; Calmant, S.; Crétaux, J.-F.; Wigneron, J.-P.; Kerr, Y. Mapping Dynamic Water Fraction under the Tropical Rain Forests of the Amazonian Basin from SMOS Brightness Temperatures. *Water* **2017**, *9*, 350. https://doi.org/10.3390/w9050350.
268. Nosetto, M.D.; Paez, R.A.; Ballesteros, S.I.; Jobbagy, E.G. Higher Water-Table Levels and Flooding Risk under Grain vs. Livestock Production Systems in the Subhumid Plains of the Pampas. *Agric. Ecosyst. Environ.* **2015**, *206*, 60–70. https://doi.org/10.1016/j.agee.2015.03.009.
269. Mayr, S.; Klein, I.; Rutzinger, M.; Kuenzer, C. Determining Temporal Uncertainty of a Global Inland Surface Water Time Series. *Remote Sens.* **2021**, *13*, 17. https://doi.org/10.3390/rs13173454.
270. Mayr, S.; Klein, I.; Rutzinger, M.; Kuenzer, C. Systematic Water Fraction Estimation for a Global and Daily Surface Water Time-Series. *Remote Sens.* **2021**, *13*, 21. https://doi.org/10.3390/rs13142675.
271. Grill, G.; Lehner, B.; Thieme, M.; Geenen, B.; Tickner, D.; Antonelli, F.; Babu, S.; Borrelli, P.; Cheng, L.; Crochetiere, H.; et al. Mapping the World's Free-Flowing Rivers. *Nature* **2019**, *569*, 215–221. https://doi.org/10.1038/s41586-019-1111-9.
272. Cooley, S.W.; Ryan, J.C.; Smith, L.C. Human Alteration of Global Surface Water Storage Variability. *Nature* **2021**, *591*, 78–81. https://doi.org/10.1038/s41586-021-03262-3.