Advancing hydrological monitoring using image-based techniques: challenges and opportunities

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Abstract

Enhanced and effective hydrological monitoring plays a crucial role in understanding water-related processes in a rapidly changing world. This paper explores the challenges and opportunities associated with image-based hydrological monitoring techniques, and highlights the need for innovative approaches and technologies to overcome existing limitations. Image-based hydrological monitoring has shown to significantly enhance data collection, improve analysis and accuracy, and support effective and timely decision-making. The integration of remote and proximal sensing technologies, with the powers of big data analytics, and artificial intelligence are revolutionizing hydrological monitoring practices. By addressing these challenges and harnessing their potential, hydrological monitoring can evolve to meet the growing demands of water resources in order to face climate change and human needs. The present study reviews showcases and good practices of enhanced hydrological monitoring in different applications, reflecting the strengths and limitations of new approaches.

1 Introduction

Water resources management is facing critical challenges due to the combined effects of global warming, population growth, human pressures, and increased pollution. These factors collectively contribute to the global rise in hydrological extremes, including droughts and floods. Furthermore, they exacerbate the declining trend in water availability and degradation of water quality, which could ultimately result in chronic water scarcity affecting a substantial portion of the world's population. Already, around four billion people, approximately half of the global population, are affected by severe water scarcity (Mekonnen & Hoekstra, 2016), and future climate scenarios are expected to amplify this situation (Wheater & Gober, 2015; Lu et al., 2019; Tramblay et al., 2020; Boretti & Rosa, 2019), which poses an escalating risk to human health and rights, ecosystems, cultural heritage, and the global economy (e.g., Cammalleri et al., 2020). In addition, water quality is being degraded more rapidly and diversely than ever with an increasing number of pollutants such as plastics, nutrients, pesticides, and pharmaceuticals (Bhateria & Jain, 2016; Hannah et al., 2022). To address these challenges effectively, the field of water resources monitoring must evolve by considering the complex interconnections between the environment and human society (Montanari et al., 2013).

Although the commonly-used/existing hydrological monitoring systems have laid the foundation for our knowledge, these have been designed under different hydrological conditions compared to today's needs and challenges. These monitoring systems are laborious, expensive, and often provide discontinuous data in space and time (Sergeant & Nagorski, 2014). Whilst current low-frequency sampling methods fail to capture river water quality dynamics, in-situ high-frequency sampling is more likely to detect these dynamics (e.g. Outram et al, 2014; Rode et al. 2016). However, these approaches are prone to instrument degradation (e.g., bio-fouling, calibration issues) and human error, if no adequate instrumental maintenance and technical staff training are ensured. Thus, it is necessary to adopt new observational strategies, benefiting from the increasing technological development, to deepen our understanding and gain further insights on hydrological processes (Tauro et al., 2018a).

Advancements are expected to enhance the spatio-temporal resolution of observations in order to improve 'near real-time' water quality and quantity monitoring to move towards a more equitable, sustainable and efficient water management. In fact, water management practices face limitations regarding data availability, and timely delivery, particularly in rapidly changing environments.

Recent advancements in Earth Observation (EO) technologies, such as satellite data for geospatial digital soil mapping, environmental tracers (isotopes and biomarkers), new sensor technologies, and uncrewed aerial systems (UAS), present promising opportunities to significantly improve our understanding of natural sciences (Koparan et al., 2018; Wang & Yang, 2019; Eugenio et al., 2020; Fu et al., 2020; Koparan et al., 2020; Perks et al., 2020; Taramelli et al., 2020; Tmušić et al., 2020) and revolutionize hydrological monitoring and river processes descriptions (Demarchi et al., 2017, Manfreda et al., 2018; Carbonneau et al., 2020; Pearce et al., 2020; Piegay et al., 2020; Carbonneau & Bizzi, 2023; Strelnikova et al., 2023).

At the EU level, in recent years, all this has also been accompanied by strong investments aimed at managing and maintaining EO missions, EO-derived services and products, designing and launching new satellite missions or making operational new EO-based reliable tools (McCabe et al., 2017) and financing space research through EU funding programmes. This is the case of the European Copernicus Programme (https://www.copernicus.eu/), which provides EO data and information services for different domains, and of the EUMETSAT Satellite Application Facilities (SAFs), which includes a SAF devoted to provide datasets and products for operational hydrological applications (referred to as H SAF; https://hsaf.meteoam.it/). Similar investments are also ongoing at national levels. For instance, Italy is pursuing investments in its space economy through the Mirror Copernicus Programme, focusing on national downstream services tailored to end user requirements. Part of this program, known as the IRIDE Program, is now being put into action as part of the Italian National Recovery and Resilience Plan. This initiative aims to enhance hydrological monitoring by launching a hybrid satellite constellation and providing EO services, with a particular focus on water management (Mariani & Bussettini, 2021). At global scale also, a large effort was spent to accelerate EO uptake and impact by fully capitalising on the power of satellite EO in international development assistance operations such as the Global Development Assistance (GDA) program (https://gda.esa.int/). The GDA program is powered by the European Space Agency (ESA) and implemented in partnership with the World Bank and the Asian Development Bank through complementary thematic areas, including water resources (https://gda.esa.int/thematic-area/water-resources/).

Similar to how smartphones revolutionized communication, the field of remote sensing has undergone a significant transformation with the emergence of UAS technology. The miniaturization of advanced sensors and the relative affordability of UAS technology have fueled its development, leading to widespread adoption of these systems in academia, in operational institutional services, and in the commercial sector (Acharya et al., 2021; Eltner et al., 2022; Manfreda & Ben Dor, 2023). UAS have catalyzed a surge in research and studies centered around proximity sensors, encompassing both mobile and fixed installations.

This study is built upon the experiences of the authors who have been involved in European and national projects and have collaborated within the MOXXI Working Group of the International Association of Hydrological Sciences (IAHS – https://iahs.info/Initiatives/Working-Groups/MOXXI/). The objective is to highlight the potential, limitations, and challenges of new technologies in hydrological monitoring by exploiting the capabilities of remote sensing, camera systems mounted on board of UAS or in fixed locations, image processing, and Artificial Intelligence (AI) algorithms to comprehensively monitor fluvial systems. These methods and approaches may provide complementary and valuable information as well as processing capabilities to fully characterize hydraulic and hydrological processes and improve our understanding of river ecosystems and their quality.

2 Challenges in Hydrological Monitoring

Effective hydrological monitoring faces several challenges that need to be addressed in order to enhance our understanding of water resources and to ensure their sustainable management. This section will discuss three key challenges: data scarcity and limitations, spatial and temporal variability, and increasing demands for water resources.

2.1 Data Scarcity and Limitations

The primary challenge in hydrological monitoring is the scarcity and limitations of data. Traditional monitoring systems often suffer from inadequate spatial coverage, limited temporal resolution, and insufficient availability of data. This scarcity of data hinders the accurate assessment of water resources and their quality, making it difficult to develop robust management strategies.

One of the most pressing concerns in data collection is the fragmentation of agencies and institutions responsible for overseeing distinct monitoring networks aimed at various objectives while tracking the same variables. This results in a heterogeneous and non-uniform distribution of hydrological stations, which often lack connections to a shared database or are installed at locations not suitable for specific objectives (Kirchner, 2006). Despite the overall increase in the number of measurement sensors deployed over time, the availability of pertinent information has not shown significant improvement.

The development of monitoring networks over time have been significantly shaped by political decisions and mono-sectorial water management criteria. For instance, the Italian hydro-meteorological monitoring network, which transitioned from national to local control, has experienced relevant changes over time in the number and distribution of monitoring stations (Braca et al., 2021).

In addition, it is not uncommon to observe the redundancy of investments in multiple monitoring networks carried out by various agencies (see the example of Basilicata Region in Fig. 1), with different purposes (e.g., hydrological monitoring, agrometeorological monitoring, research). Even though these monitoring efforts have resulted in an increased number of monitoring stations, in-situ data fragmentation has increased over the course of time. These investments often fail to enhance the quality and quantity of information provided because none of them are synchronized or optimized with each other. Due to the lack of coordination and data harmonisation, it is hard to have a comprehensive picture of this issue at a larger scale (e.g., at a national level or European level).

As a consequence, the final total number of sensors that may be available over a certain area could comprise the combination of multiple networks established over the years, culminating in an exceedingly inefficient monitoring system. The heterogeneity of the monitoring networks also brings to light problems relating to the quality and officiality of the data.

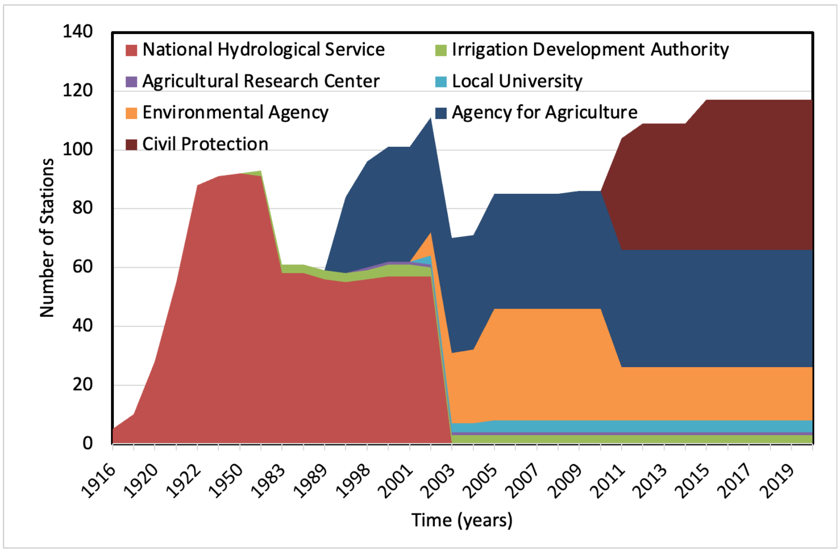

Figure 1: Total number of rain gauges installed over the Basilicata Region (Southern Italy) between 1910-2020. Initially, a national agency was in charge of the installation and maintenance of the monitoring network (SIMN), while several additional networks have been introduced in more recent years addressing different purposes managed by different agencies.

The shift towards the digital age has unlocked the potential to construct extensive databases amalgamating measurements gathered from various origins. This could potentially surmount the existing constraints of current independently operational systems. However, substantial efforts are required for the reconstruction and harmonization of all available hydrological information, along with the digitization of historical data previously recorded on strip charts. In this context, certain automated techniques for data reconstruction have been formulated, which may help to reconstruct time-series reported on strip charts (e.g., Deidda et al., 2007; Jaklic et al., 2016).

Despite the significant number of rain gauges distributed worldwide, which sum to a total number ranging between 150,000 and 250,000, the heterogeneity of rainfall fields challenges their ability to comprehensively capture precipitation patterns (Groisman & Legates, 1995; Kidd et al., 2017). These gauges, assuming each is independent and represents a 5 km radius area, cover only about 1% of Earth's surface (Becker et al., 2013). In contrast, river monitoring stations are, proportionately, fewer in number than rain gauges (e.g., in Italy, their number is approximately a third compared to approximately 3000 rain gauges available) and unevenly distributed across the globe. These stations are mainly concentrated in North America and Europe which represent about 50% of the global coverage, while Africa contains only 6% of the total (see, e.g., Herold and Mouton, 2011). In addition, water level stations only provide indirect measurements of discharge and require yearly surveys in order to reconstruct the corresponding updated flow rating curve. This activity is time consuming and expensive and for this reason has been interrupted in several sites in recent years. Therefore, the real number of river monitoring stations useful for water assessment is even lower with respect to the number mentioned above.

Water quality monitoring is probably one of the most complex activities which frequently implies field sampling standards, complex laboratory protocols and techniques as well as routine data analysis. According to the Waterbase European Environment Agency (EEA) databases on the status and quality of Europe's rivers, lakes, groundwater bodies and transitional, coastal and marine waters, on the quantity of Europe's water resources, and on the emissions to surface waters from point and diffuse sources of pollution (Waterbase - Water Quality ICM, 2022), there are about 1,550 monitoring locations, distributed over 24 European countries, having 3 or more years of data with an average of at least 4 samples per year. This database represents just a subset of the EU Water Quality Monitoring Network, but the limited temporal resolution of most of the Water Quality observations does not allow to capture variability of natural and anthropic processes especially with respect to pollution events (Alilou et al., 2019). At global scale, the Global Database of Freshwater Quality GEMStat (https://gemstat.org/) is one of the most comprehensive repositories of measured water quality data and gathered with voluntary submissions from different countries and organizations around the world. The GEMStat database contains over 15 million entries from about 130,000 stations gathered from more than 80 countries (https://gemstat.org/about/data-availability/). Even though The GEMStat database represents an important open-access and valuable reference for in-situ water quality at global scale, many gauging stations contain only a small fraction of available data. To overcome this limitation, GlobeWQ project (https://www.globewq.info/) is one of the leading initiatives worldwide that first proposes the relevance of integrating data from different sources including in-situ, EO and modelling results data to improve water quality information and assessment at global scale. In addition, the presence of macro- and micro-plastic in rivers is one of the most critical issues for ocean pollution, but there are no standardized protocols and sustainable systems for its monitoring. A recent study by Hurley et al. (2023) accounted for the total number of monitored sites for macroplastic around the world limited to approximately 57 rivers which is definitely irrelevant with respect to the dimension of the problem. Hence, it is vital to improve monitoring in space and time to better understand both the regional and global plastic fates.

2.2 Spatial and Temporal Variability

Another significant challenge is the spatial and temporal variability of hydrological processes and water resources. Their patterns exhibit substantial variations and are influenced by factors such as climate, land use, soil characteristics, morphology, human activities and interventions. Traditional monitoring systems, often based on pointwise measurements or sampling, struggle to adequately capture this variability. In fact, the spatial variability of hydrological parameters, such as discharge, turbidity and total suspended solids are influenced by rainfall regime, soil texture and also land use and deforestation within the basin; plastic transport are controlled by the agricultural activities or the presence of urban areas, soil water content is influenced by rainfall, vegetation patterns, morphology, and soil texture (e.g., Manfreda & Rodriguez-iturbe, 2006; Rodriguez-Iturbe et al., 2006; Metzger et al., 2017; Meijer et al., 2021).

Water resources regimes can differ significantly between and within river basins due to the heterogeneity of land cover, soil types, and human activities. This can lead to diverse hydrological responses across different regions. To account for this variability, monitoring networks must be designed to capture such heterogeneities.

This requires the optimal distribution and densification of monitoring stations, and the use and integration of remote sensing data to gather spatially explicit information. This is also a clear objective introduced by the Water Framework Directive 2000/60/EC (WFD), although not always fully implemented, due to tangible limitations (e.g., insufficient funding, lack of skilled human resources).

Temporal variability also poses an additional challenge for water availability and quality monitoring. Infrequent sampling or sparse data collection fail to adequately capture water dynamics that can vary dramatically over different timescales ranging from hourly fluctuations to seasonal variations, and long-term trends. Therefore, high-frequency monitoring, enabled by advanced sensor technologies and automated data collection systems, is crucial for accurately capturing these processes (e.g., Sergeant & Nagorski, 2014; Rode et al. 2016).

2.3 Increasing Demands for Water Resources

Population growth, urbanization, and industrial development exert pressure on water availability and quality. This pressure is emphasized by the current and likely future impacts of climate change on water resources. Balancing the competing demands for water resources while ensuring their sustainable use and allocation requires monitoring networks which are able to be expanded and upgraded to provide comprehensive coverage and real-time data. However, traditional monitoring approaches often struggle to keep pace with the increasing demands for data.

Furthermore, as water shortage and scarcity become more and more pressing, efficient water management strategies are needed to optimize water allocation and minimize waste. Integrated monitoring systems that combine hydrological data with socio-economic information can facilitate informed decision-making and support sustainable water resources management.

Addressing the challenges of data scarcity and limitations, spatial and temporal variability, and increasing demands for water resources requires a concerted effort from the scientific community, policy- and decision-makers, and water resources managers. Advances in technology, data collection methods, and analytical techniques offer promising opportunities to overcome these challenges and improve our understanding of water resources for a sustainable and integrated water management.

These challenges are clearly identified by IAHS Water Solutions Decade on “Science for Solutions: Hydrology Engaging Local People IN one Global world (HELPING)”. In this context, the theme 3 is promoting joint effort in order to integrate new technologies with existing ones (IAHS, 2023).

3 Advancing Hydrological Monitoring

Fast developing technologies such as remote sensing, uncrewed aerial systems (UAS), advanced sensor networks, and wireless data networks offer opportunities to improve data availability and accessibility, and to collect data more efficiently and comprehensively. These technologies can also provide relatively high-resolution data over large spatial extents and properly capture temporal variations of hydrological processes. Integration of these technologies with data-driven approaches, such as artificial intelligence (AI), can help to fill the gaps in data and enable more accurate and reliable hydrological monitoring.

This section will explore key areas such as: remote sensing and satellite-based technologies, sensor networks and citizen science.

3.1 Remote Sensing

Satellite-based technologies offer a wide-area coverage, capturing information on various hydrological parameters such as precipitation, evapotranspiration, soil moisture, and surface water dynamics (Chen & Wang, 2018). These data can be obtained at regular time intervals, allowing for the assessment of temporal changes and the characterization of spatial patterns.

Numerous observation systems are tailored for hydrological research. Within NASA's 19 Earth science missions, 9 are notably pertinent to hydrology, including AQUA,ICESat-2, GPM, GRACE, PMM, SLAP, SMAP, SWOT, and VIIRS (NASA, 2023). The European Space Agency (ESA) has 4 missions relevant to hydrology: CryoSat-2, EUMETSAT satellites, Copernicus Sentinel-1 and Sentinel-2, and SMOS (ESA, 2023). ESA intends to launch the EarthCARE mission to enhance understanding of clouds and aerosols' role in solar radiation reflection. China has made substantial progress in Earth hydrology-related observation with the Fengyun and Haiyang satellite series, which focuses on meteorological observations and oceanographic monitoring and plans to launch also the Water Cycle Observation Mission (WCOM) (Shi et al., 2016).

In addition, various national and international initiatives aim to advance the intersection of Earth observation and hydrological science. These include the International Precipitation Working Group (IPWG), NASA Energy and Water Cycle Study (NEWS), European Union WATer and Global CHange (WATCH), and the Global Energy and Water Exchanges (GEWEX, 2018) initiative.

The combined efforts of Earth observation missions and initiatives are propelling hydrology into the era of "Big Data", thus guaranteeing significant advancements in the field (Peters-Lidard et al., 2017). Big data techniques can handle vast amounts of data and extract meaningful insights and interpret complex hydrological datasets, leading to improved understanding and predictive capabilities.

UAS, alongside satellites, are also valuable tools for hydrological monitoring (Manfreda & Ben-Dor, 2023). These systems use advanced sensors to collect high-resolution data on a local scale, allowing for precise observations. UAS offer flexibility and can target specific areas of interest, enhancing our understanding of surface water dynamics, sediments, vegetation cover, topography, and bathymetry. UAS are versatile and agile, capable of capturing RGB and multi- or hyper-spectral data, thermal imagery, and LiDAR (Light Detection and Ranging) data for terrain mapping. They excel in covering large areas, reaching inaccessible regions and capturing data very flexibly, thereby improving the spatial and temporal resolution of hydrological observations.

High altitude pseudo satellites (HAPS) that typically fly at 15,000-30,000 m above ground level for several months at a time are also currently in development and testing. They have the potential to fill the gap between satellites and UAS for earth observation and hydrological monitoring given their endurance (2-3 months) and spatial resolution (10-30 cm) (Fladeland, 2019).

3.2 Internet of Things (IoT) and Sensor Networks

The Internet of Things (IoT) represents a novel technological paradigm conceptualized as a worldwide network of machines and devices with the ability to engage in mutual interactions (Lee & Lee, 2015). It allows the integration of sensors interconnected through a variety of access networks, facilitated by cutting-edge technologies like embedded sensing and actuation, radio frequency identification (RFID), wireless networks, and semantic and real-time web services. The IoT's low-power wide area network (LPWAN) capabilities enable the utilization of battery-powered sensors. Among these, Long Range Wide Area Network (LoRaWAN) stands out as it employs open-source technology and operates on unlicensed frequency bands, offering significantly greater range compared to WiFi or Bluetooth connections. LoRaWAN is particularly advantageous for applications in remote regions where cellular networks experience limited coverage. Given the extensive multitude of devices connected, the number of local measurements may enormously increase offering the possibility to further explore complex dynamics of hydrological forcings (Perumal et al., 2015; McCabe et al., 2017; Balsamo et al., 2018; Tauro et al., 2018a; Tosi et al., 2020; Livoroi et al., 2021).

Sensor networks, combined with the Internet of Things (IoT), offer tremendous potential for enhancing hydrological monitoring (Zanella et al., 2023). This combination facilitates adaptive monitoring strategies by dynamically adjusting the spatial distribution and density of sensors based on evolving hydrological conditions. This flexibility allows for targeted data collection in response to specific events or areas of interest, i.e. having event-based triggers for sensor readings, thereby optimizing the allocation of monitoring resources (Marino et al., 2023).

3.3 Citizen Science and crowd-sourced data

Citizen science initiatives and crowd-sourced data collection platforms offer an innovative approach to hydrological monitoring (e.g., Nardi et al., 2022). Engaging the public in data collection and classification does not only increase data coverage but also promotes public awareness and participation in water resources management.

Recently, several initiatives have stimulated the participation of volunteers in data collection through methods such as mobile applications, community-based monitoring programs, or distributed sensor networks, as is the case, for example, with the CrowdWater project (Strobl et al., 2019). Participants have the opportunity to measure water levels, discharge, report on water quality observations, and share hydrological data collected from their personal monitoring stations. This collaborative endeavor significantly boosts data availability and offers valuable insights into the specific hydrological conditions within local areas, while also providing an avenue for active participation of key stakeholders in the community in order to foster technology localization and sustainability. The use of crowd-sourced data also holds the potential to complement conventional monitoring networks by capturing nuanced spatial and temporal variations on a finer scale (e.g. Etter et al., 2020; Strobl et al., 2020; Mapiam et al 2022). By integrating these data with professional monitoring data, remote sensing observations, or model simulations, the accuracy and resolution of hydrological analyses can be notably enhanced.

For instance, a number of private sensor networks has been growing significantly in the last few years offering a large amount of measurements that may be easily filtered and validated offering a dense network of observations (de Vos et al., 2019). Popular online platforms such as Netatmo (https://weathermap.netatmo.com) and Weather Underground (https://www.wunderground.com/) collect and visualize measurements from public, and even personal weather stations (PWSs) every ~5 to 10 min with a total number of sensors that exceeds one order of magnitude the number of stations of the national hydrological services (Graf et al., 2021; Coney et al., 2022).

The potential of a private network of rainfall stations connected to a web service has been clearly assessed in a recent work by Graf et al. (2021). Given the large number of measurements available, these opportunistic networks can lead, after filtering and sensor calibration (Krüger et al., 2023), to rainfall maps of higher accuracy and increased spatial variability, especially on smaller spatial and temporal scales.

In today's landscape, critical information can be gathered through the efforts of motivated groups of citizens. To maintain high data quality standards, initiatives in citizen science consistently incorporate training and implement measures for quality control. This enables participants to contribute effectively, following simple and reliable procedures.

The processing of big data is another challenge, in which citizen science plays an advantageous role. Zooniverse (https://www.zooniverse.org/), one of the largest people-powered research platforms, allows users to create big data projects and also assist researchers with their projects, such as the plastic litter project which aims to identify coastal litter (e.g., van Lieshout et al., 2020; Andriolo et al., 2023).

The successful use of citizen science's potential for hydrological monitoring relies on a crucial collaboration between scientists, water managers, and the general public. This engagement with the public also proves to be an effective approach for fostering a deeper understanding on water level measurements, discharge estimates, water conservation and shoreline changes (Harley et al., 2019; Seibert et al., 2019; Wang et al., 2022).

Furthermore, citizen science initiatives and crowd-sourced data collection platforms can contribute to data integration efforts. Engaging the public in data collection and monitoring processes can increase data coverage and improve community involvement in water management decisions, for instance, crowd-sourced data provided additional insights on flood risk management in Argentina, France and New Zealand (Le Coz et al., 2016).

4 The potential of image-based techniques for river monitoring

The proliferation of modern optical sensors, present in satellites, on UAS, and in smartphones as well as attached to low-cost single board computers or micro-controllers, has sparked a compelling interest in utilizing imagery to greatly broaden the scope of possible hydrological observations (e.g., Manfreda et al., 2018; Strelnikova et al., 2023).

For example, digital cameras have been successfully used in areas such as surveillance, facial recognition, object detection and tracking, inventory monitoring, and management. Additionally, some existing algorithms developed for general purposes have found intriguing applications in environmental monitoring, including the creation of 3D models (James et al., 2019), assessment of highway vehicle flux (Hsu et al., 2003), monitoring air pollution (Zhang et al., 2016), measuring rainfall intensity (Allamano et al., 2015; Kavian et al., 2018; Jiang et al., 2019), and mapping river velocity fields (Johnson & Cowen, 2017; Lewis & Rhoads, 2018), among others.

Numerous researchers are currently delving into the realm of river monitoring using image processing techniques. This includes a range of possibilities like traditional image processing methods from computer vision, but also new techniques utilizing AI. 3D reconstruction through Structure-from-Motion Multi-View Stereo (SfM-MVS) or photogrammetry is one application of these methods.

It is more and more frequent that ordinary stations are associated with nearby installed optical cameras. These cameras can capture a range of complementary information (e.g. water level, velocity, and water quality parameters) useful to interpret natural phenomena and may also be exploited to measure features with the support of new software and tools. In the following figure, we provide examples of images taken on different rivers during extreme events.

Figure 2. Three examples of cross-sections: A) Alcantara river during a recent drought observed in the summer of 2021; B) Sarno river with macroplastics and organic matter transport; C) Flood in northern Turkey with wood transport.

The following sections provide an in-depth exploration of various aspects that can be investigated through the use of image-based techniques, ranging from 3D reconstruction for analyzing river morphology to monitoring river water quality.

4.1 River morphology

SfM and MVS algorithms have produced a revolution in the field of high-resolution topographic reconstruction (Westoby et al. 2012). These methods may help estimating the elevation of the water surface (Niedzielski et al., 2016) and relative change in the river morphology throughout time (Carrivick et al., 2019; Carbonneau et al., 2020) allowing for frequent cross-section updates, which becomes especially important before and immediately after flood events (Bertalan et al., 2023). These surveys can be repeated several times over the year to define the cross-section geometry. To improve the change detection accuracies, multi-temporal image matching techniques can be used (Feurer et al., 2018) and when combined with error propagation methods, such as M3C2-PM (James et al., 2017), enable the identification also of small-scale events (Blanch et al., 2021). The river bed below the water surface can be reconstructed, using active or passive mapping approaches, and considering radiometric and geometric principles (Mandlburger, 2022). Geometric tools consider refraction impacts (Maas, 2015; Dietrich, 2017) and radiometric tools utilize the attenuation of light when travelling into deeper water (Flener et al., 2013; Legleiter et al., 2021; Mandlburger et al., 2021). Thus, images can be used to describe the observed river cross-section above and below the water surface (Eltner et al., 2021a), including the change of grain size distributions of the exposed river sediment bars (Lang et al., 2021; Marchetti et al., 2022) or growth of submerged vegetation which controls hydraulic roughness and conveyance in many lowland rivers or the change in geomorphic unit assemblages, which compose the physical habitat.

4.2 Image Velocimetry

Image sequences can be used to trace flow velocities and paths tracking and measuring the displacement of visible structures on the water surface. Generally, natural patterns on free surfaces, such as wave crests, vortexes, bubbles, foams or natural floating material (debris, vegetation) provide seeding for image processing. These conditions are especially prevalent during floods due to the presence of surface ripples caused by near-surface turbulence and pressure fluctuations.

In recent years, several image velocimetry methods have been developed, which include the classical correlation-based algorithms such as Large Scale Particle Tracking Velocimetry (LSPTV - Brevis et al., 2011; Tauro et al., 2017; Eltner et al., 2021a) and Large Scale Particle Image Velocimetry (LSPIV - Fujita et al., 1998; Muste et al., 2008; Sabrina et al., 2021). Other approaches measure patterns of image intensity in 1D, i.e., Space-Time Image Velocimetry (STIV - Fujita et al., 2007) or use the well-known computer vision technique of optical flow, e.g. implemented in the tools Optical Tracking Velocimetry (OTV - Tauro et al., 2018b) and Kanade–Lucas Tomasi Image Velocimetry (KLT-IV - Perks 2020).

These methodologies have demonstrated their successful implementation in continuous monitoring systems (e.g., Peña-Haro et al., 2021) and they have been effectively applied in remote or hard-to-reach areas using footage captured from UAS (e.g., Perks et al., 2016; Tauro et al., 2016). More recently, the introduction of deep learning-based algorithms, as highlighted by Ansari et al. (2023), has significantly reduced the need for extensive parameter configuration. It is important to note that the accuracy of these methods in reconstructing surface velocities is influenced by various factors, including lighting conditions and other environmental variables. Nevertheless, the associated errors are typically quite small, often lower than 10% (Manfreda et al., 2019; Eltner et al., 2020).

Besides the usage of RGB imagery, thermal data is considered for the tracking tasks, which can become important in the case of low density or absence of floating features at the water surface (Lin et al., 2019) or in night-time conditions (Fujita, 2017). Thermal cameras can capture the inherent fluxes of river surface temperature and therefore trace the evolving vortices (Kinzel et al., 2019; Eltner et al., 2021c). Furthermore, these cameras have the potential to serve as valuable tools for monitoring the inflow of water with distinct thermal properties into the main river channel.

4.3 River discharge

The computation of river discharge primarily relies on integrating water velocity profiles with cross-sectional area. In this context, a crucial factor is the water level, which can be determined in various ways. One option is the imaging of a stage board for a straight-forward water level retrieval (Young et al., 2015; Leduc et al., 2018), or using synchronised cameras to 3D reconstruct the water surface (Ferreira et al., 2017). In ephemeral and intermittent streams, water level was monitored by applying automatic image thresholding to pictures of a reference thin pole installed in the stream (Noto et al., 2022; Tauro et al., 2022). Another approach is the masking of the water area in the image to identify the boundary between water and other elements and then transforming this waterline to water level data. The process involves two steps: image segmentation, which classifies pixels as water or non-water using image sequences or CNNs (Stumpf et al. 2016; Elias et al., 2019; Vandaele et al., 2021); and water level retrieval, where the waterline contour is converted into water level data, often through the intersection with a 3D model for accuracy (Eltner et al., 2021b).

Once water levels and velocities are determined, discharge can be determined with various approaches. One straightforward method involves deriving depth-averaged velocity with correction parameters, subsequently applying the velocity-area method (Hauet et al., 2008; Detert et al., 2017). Alternatively, the entropy model reconstructs flow velocity profiles (Bahmanpouri et al., 2022), utilizing known conditions like surface velocity to accurately estimate average water flow speed (Moramarco et al., 2013). A more recent approach uses river wave patterns to directly estimate discharge, without the need for cross-section measurements or velocity data, solely relying on physical principles (Dolcetti et al., 2022). The last methodology may be useful during high flood flows, but it still provides errors larger than 30%.

4.4 Water quality

Numerous water quality (WQ) parameters serve as key pollution indicators. Gholizadeh et al. (2016) identifies a list of most commonly measured qualitative parameters of water, which include: chlorophyll-a (CHL-a), Secchi Disk Depth (SDD), Temperature (T), Colored Dissolved Organic Matters (CDOM), Total Organic Carbon (TOC), Dissolved Organic Carbon (DOC), Total Suspended Matters (TSM), Turbidity (TUR), Sea Surface Salinity (SSS), Total Phosphorus (TP), Ortho-Phosphate (PO4), Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD), Electrical Conductivity (EC), and Ammonia Nitrogen (NH3-N). Some, like CHL and CDOM, have optical properties detectable with RGB cameras (Goddijn & White, 2006), while non-optical parameters like Total Phosphorus (TP) can be remotely sensed by leveraging their relationship with optically active parameters, such as CHL (Niu et al., 2021).

Furthermore, RGB cameras are effective in detecting floating materials, plumes, foam, or oil spills, with spatial image resolution matching object dimensions being the only limitation. Feature detection and labeling algorithms provide valuable insights into material density and distribution, aiding in prompt pollution event detection.

A recent review by Blanco Ramirez et al. (2023) underscores the potential of citizen science in diverse hydrological applications, especially pollution detection and water quality modelling. The review calls for guidelines and protocols to ensure data meets water quality standards and is comparable across projects.

Additionally, integrating discharge and flow velocity measurements enhances pollutant concentration and propagation velocity evaluation.

4.4.1 River turbidity

Turbidity detection is an important indicator of WQ and assumes great significance for environmental protection and aquatic ecosystems. It is used as a relative indicator for other physical properties such as suspended sediment concentration (SSC) and total suspended solids (TSS) and various compounds present in water such as chlorophyll, organic matter, microorganisms, algae, or chemicals, etc. Since turbidity is generally closely related to the above variables, it can often be used for quantitative estimation. Turbidity often varies with seasons and rainfall events that can cloud the water. The growth of algae and other organisms in the summer can also cause an increase in turbidity.

There are several applications of river turbidity monitoring from satellites which provide a clear overview about opportunities offered by different spectral indices (e. g., Lacaux et al., 2007; Wang and Shi, 2007; Fraser, 1998; Constantin et al., 2016). Among others, Garg et al. (2020) investigated the change in spectral reflectance of water across the visible to NIR range along the Ganga river. The temporal analysis indicates a reduction in reflectance across the visible to NIR range, likely due to decreased water turbidity. While the blue and green bands struggle to map turbidity variations because of bottom interference, the red and NIR bands prove more sensitive for turbidity estimation, particularly in optically deep water. Ehmann et al. (2019) also confirmed these findings, emphasizing the red band's sensitivity in depicting turbidity gradients within UAS imagery.

4.4.2 Macroplastics and litter

The global concern of plastic pollution in rivers is intensifying, fueled by the escalating issue of plastics entering waterways through direct disposal, wind dispersal, runoff, and sewage discharge. Macroplastics, which are large particles of plastic debris (>2.5 cm), account for about 70 to 80 % of total debris that mainly enters the oceans via rivers, posing serious threats to the environment and human health (Haseler et al, 2018; Kershaw et al., 2019; van Emmerik & Schwarz, 2020). This concerning issue is further compounded by an annual surge of 14 million tons of plastic leakage globally. Notably, the yearly discharge of mismanaged plastic waste (MPW) from land into the ocean was estimated to vary between 0.41 up to 12.7 million metric tons (Jambeck et al., 2015; Lebreton et al., 2017; Schmidt et al., 2017). The range of variability is relatively large given the high uncertainty and low availability of reliable observations (Roebroek et al., 2022; González-Fernández et al., 2023). It is also remarkable that the distribution of emissions is extremely uneven with few countries such as Philippines and India that contribute up to almost 50% of the pollution (Meijer et al., 2021). Recent work however suggests that the majority of plastic pollution never reaches the ocean, and accumulates in and around rivers for years to decades (van Emmerik et al., 2022). Currently, the plastic mobilization, transport and accumulation processes remain largely unresolved.

Flood events seem to play a key role, and globally lead to a 30-fold increase in plastic mobilization (Roebroek et al., 2021). Plastic transport can vary one to two orders of magnitude at daily, monthly and yearly timescales. However, current methods only allow for sporadic observations with limited temporal and spatial coverage (van Calcar & van Emmerik, 2019; González-Fernández et al., 2021).

Despite the low reflectance of plastic, RGB and multispectral imagery combined with machine learning tools (e.g., Gnann et. al., 2022) or in some cases with simpler tools, such as object detection (van Lieshout et al., 2020), Spectral Angle Mapper (Gonçalves and Andriolo, 2022), Naïve Bayesian classification (Biermann et al., 2020), image masking (Schreyers et al., 2021), and other RGB markers such as microorganisms (Corbari et al., 2020), are valuable tools for effective macroplastic monitoring. To overcome the large uncertainties in plastic transport, retention and emissions into the ocean, increased monitoring efforts are crucial.

5 Experimental activities and project of interest

The considerable enthusiasm for advancing hydrological monitoring becomes apparent through the myriad of global initiatives aimed at harnessing new tools and methodologies. In Table 1, we have diligently compiled the most promising recent endeavors. This compilation provides a captivating glimpse into the diverse projects that collaboratively expand our understanding of hydrological monitoring, leveraging the advantages of citizen science, image processing, and UAS.

Table 1. Initiatives oriented in promoting the use of new technologies in hydrological monitoring.

Project	Period	Aim of the Initiative/Project	Partners	Web-page
Harmonious COST Action (CA16219)	2016-2022	Establish harmonized monitoring practices for UAS-based observations.	26 countries involved and about 200 scientists	www.costharmonious.eu/
CrowdWater	2016-2020 2020-2024	Citizens data collection as a supplement to existing measurements.	University of Zurich, Switzerland	https://crowdwater.ch/
Habitat Mapping	2017-2021	Create innovative services for habitat mapping, including the hydromorphological characterizations of rivers (IRIS), through integration of Copernicus Sentinel images, UAS acquisitions and in situ and modelled data	ISPRA and Italian Space Agency (ASI), Italy	https://www.isprambiente.gov.it/en/projects/emergency-and-environmental-surveillance/asi-ispra-sentinel-collaborative-gs-thematic-platform-for-habitat-mapping-2017-2021?set_language=en
Plastic Spotter	2019-present	Engage citizens to spot, quantify and share data on plastics floating in the canals of Leiden using CrowdWater App.	University of Leiden, Netherlands Citizen Science Lab Wageningen University and Research wozfonds	https://eu-citizen.science/project/125

Plastic Origins		Map plastic pollution in European rivers and share data to the public.	Surfrider Foundation Europe, Private and Public organizations in France	www.plasticorigins.eu/
Plastic Pirates – Go Europe!	2016-2024	Uniform plastic collection in riverbanks and areas near bodies of water using a guideline, and data upload.	DLR Projektträger, 12 EU countries	www.plastic-pirates.eu/
Pescadors de Plàstic	2022-2023	Promotion of the scientific method instruction applied to plastic pollution in rivers.	BETA Technological Center, University of Vic-Central University of Catalonia, 4 private and public institutions and organizations in Spain	https://mon.uvic.cat/pescadors-de-plastic/
EU H2020 MONOCLE	2018-2022	Collection of water quality and color utilizing citizen science.	Plymouth Marine Laboratory Limited, 12 private and public institutions and organizations in EU	https://www.monocle-h2020.eu/
IRIDE Program, under Italian PNRR	2023-2026	Implementation of an end-to-end system made up of a set of sub-constellations of LEO satellites, the operational infrastructure on the ground, and the services intended for the Italian Public Administration, including tools for hydrology and water resource management.	Industrial teams, under ESA contracts, on behalf of the Italian government	https://www.esa.int/Space_in_Member_States/Italy/IRIDE_La_squadra_e_al_completo

Within this context, we are carrying out several experimental initiatives within international projects that are useful to underline the potential of alternative techniques with practical examples. Among others, we will mention: 1) ASI-ISPRA Habitat Mapping project; 2) the PRIMA-funded project named "OurMED: Sustainable water storage and distribution in the Mediterranean" and the 3) "RiverWatch: a citizen-science approach to river pollution monitoring" funded by Italian Ministry of University and Research PRIN. The first project aims to use remote sensing techniques for mapping terrestrial, aquatic and transitional habitats, including characterizing fluvial hydromorphology. The second project aims to explore new water saving strategies over several demo sites distributed in different countries in the Mediterranean. Within each demo site monitoring camera systems will be adopted to measure the water flow and turbidity. The third project will be focused on the Sarno River which is the most polluted river in Europe (Lofrano et al., 2015; Baldantoni et al., 2018). These examples trace the pace for a new trajectory in hydrological monitoring.

We are confident that both projects offer a unique opportunity to test new water monitoring ideas and tools. The Bode River is one of the most promising sites within the PRIMA project. It has been equipped with trap cameras that work in tandem with real-time water quality sensors. It has also been used for specific experiments on detecting water turbidity using various tracers.

The second case study presents a formidable challenge: developing pioneering monitoring systems for Europe's most polluted river, situated within a complex and socioeconomically disadvantaged setting. RiverWatch aims to engineer a cutting-edge monitoring solution harnessing state-of-the-art unsupervised computer vision. This comprehensive approach entails crafting a customized mobile application and employing image-based algorithms to analyze videos and images captured by citizens and fixed cameras.

More details about both case studies are given in the following with the aim to identify the expected impacts associated to the ongoing activities.

5.1 Hydromorphological characterization through satellite and UAS data

In the framework of the ASI-ISPRA Habitat Mapping project (Table 1), it was set up the "Italian Research and development Initiative for Spaceborne river monitoring" (IRIS) to develop a prototype of tools and algorithms able to map river forms and processes along hundreds of kilometers of river lengths. The combined use of Copernicus Sentinel-1 and Sentinel-2 data and UAS acquisitions (for ground truth) in a satellite-based classification algorithm has proven effective to identify and discriminate along the river corridor between spatial units with similar textural and spectral characteristics that constitute the key river geomorphic macro-units: "water", "vegetation" and "exposed sediment" (Fig. 3, Carbonneau et al., 2020; Mariani & Bussettini, 2021). These key geomorphic macro-units represent the external envelope of river geomorphic units of the same type (Belletti et al., 2017), whose temporal evolution is necessary to identify river channel dynamics, river form processes and future trajectories.

Such a prototype was developed and tested in IRIS by considering five Italian rivers characterized by different channel patterns, morphological types and flow regimes, namely the Po and Sesia Rivers (in NW Italy), the Tagliamento River (in NE Italy), the Paglia River (in Central Italy) and the Bonamico Torrent (in Southern Italy). The operational implementation of these algorithms and tools is underway within the IRIDE Program (Table 1).

In the meantime, they are currently being adopted in a 3-year study by ISPRA and ARPA Piemonte, the Regional Environmental Protection Agency of Piedmont, to assess river forms, processes and morphological quality of five rivers in Northwestern Italy, namely Dorea Baltea, Po, Scrivia, Sesia, and Tanaro Rivers. The potential of this tool is to have continuous river monitoring and support the local authorities in the assessment of rivers morphological status, needed for the WFD implementation.

From the classification of the three components (water, vegetation and sediments) in time (e.g., monthly, yearly) and space (river reach), ad hoc tools have been developed to derive a series of aggregated indicators (e.g., matrix of spatio-temporal distribution of the ratio between "units submerged" and "units submerged + units emerged") that express the interaction between the constituent components of the river, providing an analysis of seasonality and changes over time. Such analysis gives insights on the river dynamics and planimetric variations, useful for understanding past, current and potential future river processes. This type of analysis is conducted on specific river stretches characterised by similar morphological types, following the IDRAIM (Rinaldi et al., 2016, 2017) methodological approach for stream hydromorphological assessment, analysis, and monitoring.

In addition, exploiting a time series analysis of derived satellite data, the frequency of each macro-unit can be useful to assess the impact of natural events such as droughts and/or floods. Figure 3, boxes A and B, shows an example of a semi-quantitative assessment over a portion of the Po River of the impact of the extreme and persistent drought that took place in Northwestern Italy, from the end of 2021 to April 2023, reporting a zoom on the average frequency of the "water" component. The comparison between the period January-July 2022 vs January-July over the period 2016-2021 highlights a decrease in the number of pixels along the river corridor belonging to the "water" unit in 2022, highlighting the difference to the historical average. The same analysis was also conducted on the "vegetation" and "sediment" units (not shown) specific analysis can be carried on in a single date and through the whole river length, on each river component. For example, the map of "exposed sediments" can be used as a mask to perform correlation analyses between satellite data and sediment characteristics (e.g., sediment size and shape, sediment provenance, lithology). A first application of this kind can be found in Marchetti et al. (2022), which used Copernicus Sentinel-2 multispectral data to discriminate sediment size classes along 300 km of the Po River, in Italy. Main outcome of this work shows the potential of satellite data to derive gravel vs sand-dominated river bars, paving the way for future investigations in this direction, also by testing other satellite data (radar, hyperspectral).

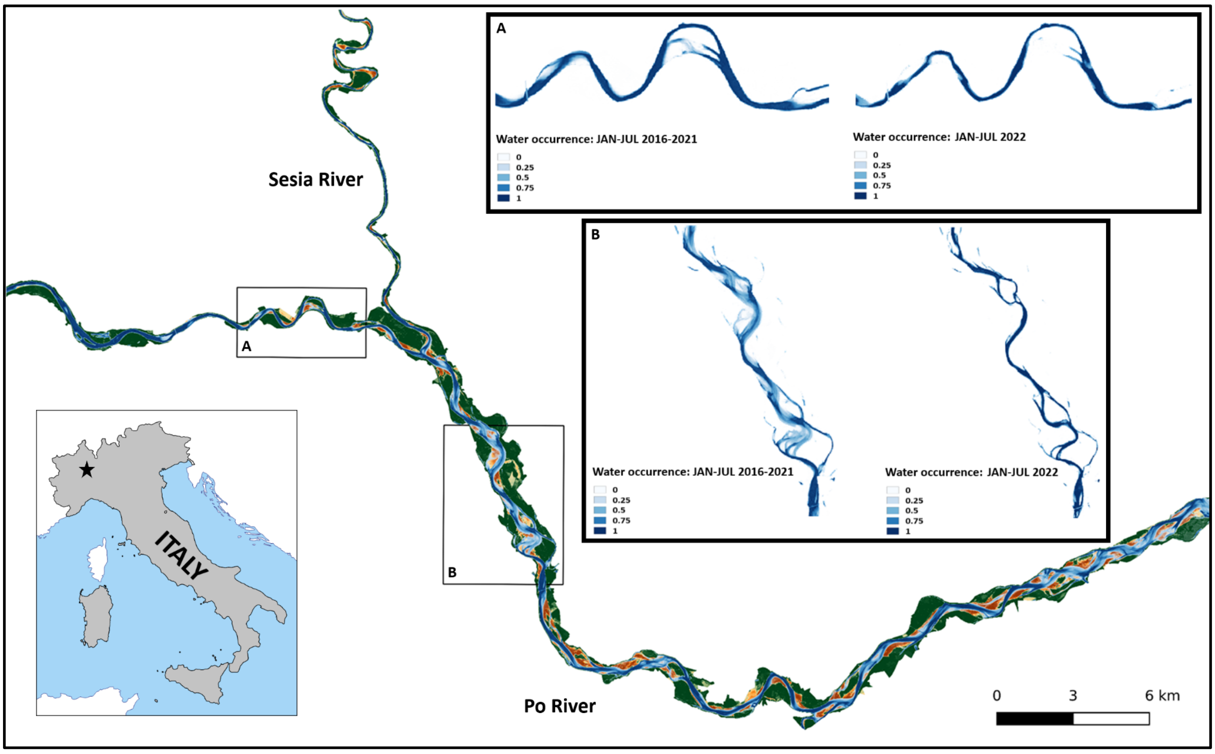

Figure 3. Example of satellite-based classification for the Po River (approximately from Morano sul Po and Castelnuovo di Scrivia, NW Italy) and the Sesia River over the period January-July 2016-2021 using Copernicus Sentinel-2 data. The location of the two river lengths analysed is indicated by a "star" in the bottom-left map. Frequencies of "water" units are reported in shades of blue, riverbed and riparian "vegetation" units are reported in shades of green and "sediment" units are reported in shades of brown. On boxes A and B, the impact of drought on "water" unit presence over the Po River is analyzed: in each box, the left-hand panel reports the "water" frequency over the period January-July 2016-2021, wheres the right-hand panel reports the "water" frequency over the period January-July 2022.

This activity has demonstrated that through the integration of Copernicus satellite data, multispectral (Sentinel-2) and radar (Sentinel-1), with data acquired by UAS, it is possible to generate a wide range of information to support the hydromorphological characterization of watercourses, although with some limitations. On the one hand, the EU Copernicus program is able to provide freely available satellite data over a long period, with reasonably frequent imagery acquisition, to the technical and scientific communities to derive statistical robust results for river monitoring. On the other hand, the spatial resolution of the Copernicus Sentinel-1 and Sentinel-2 missions, despite having improved in recent years, is still between 10 and 20 m. This places some limitations on the hydromorphological characteristics that can be derived from these satellite data: the methodology can currently be applied only to watercourses with an active river channel wider than 50 m, precluding, at the moment, its use in most mountain river basins, unless satellite information of higher spatial resolution is available (that, so far, would require high costs). However, in such a context, the possibility of using UAS acquisitions for a detailed hydromorphological characterization (e.g., pre and post a specific event), remains a great solution. The future availability for the Italian public administration of higher resolution imagery provided by the IRIDE satellite constellation (Table 1) will also improve the recognition of river forms and processes through these satellite-based algorithms.

5.2 Bode River study area

The Bode catchment is one of the meteorologically and hydrologically best-instrumented meso-scale catchments in Europe providing high resolution observation on water quantity and quality (Zacharias et al., 2011; Wollschläger et al., 2016). Within this catchment, the Meisdorf station has been chosen to assess the viability of camera systems for continuous water quality monitoring. Moreover, we have conducted targeted experiments involving controlled changes in water turbidity to enhance our understanding of these monitoring technologies.

Preliminary results of the long-term study are given in figure 4 which describe the turbidity measurements in terms of Nephelometric Turbidity Units (NTU) obtained by a submerged turbidimeter and the water level gauges. Within this figure, we have selected 7 significant images obtained by the trap camera which provides evidence of the relative changes of the water body colours at different levels of turbidity (Miglino et al., 2022).

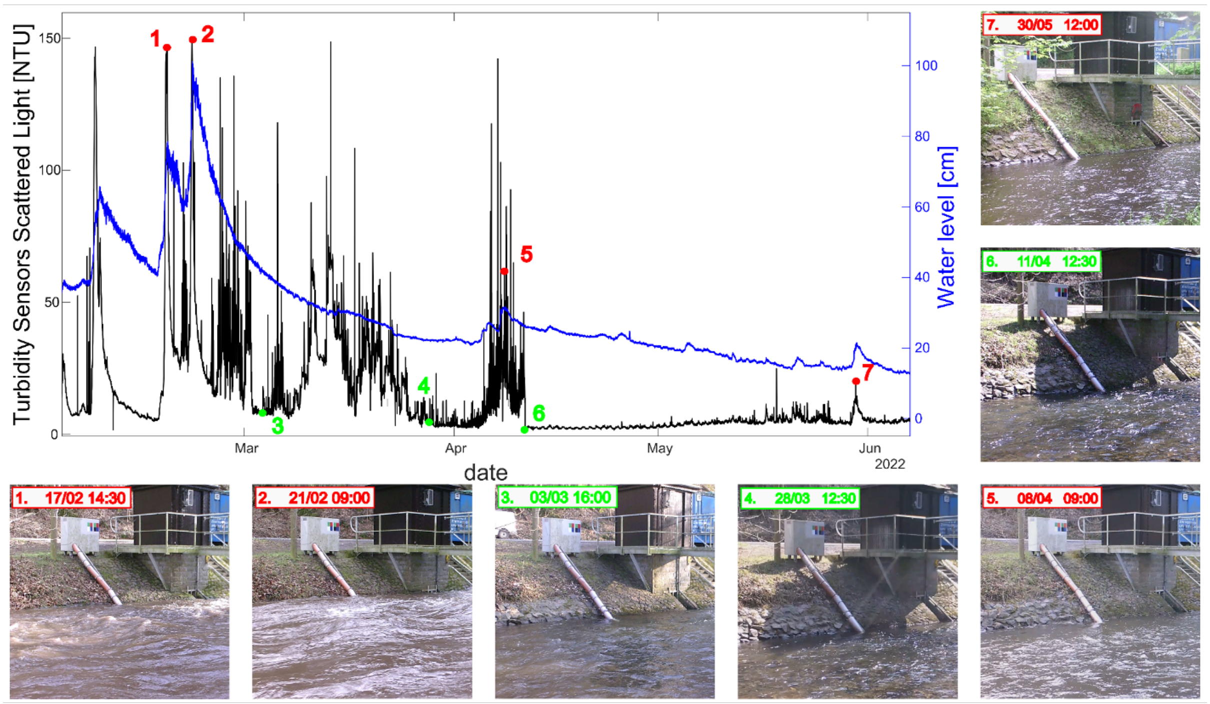

Figure 4. Turbidity and water level diagram from February 2022- June 2022 with associated camera shooting taken in different levels of turbidity.

In addition, supplementary tracer experiments were conducted adopting kaolin clay (a commonly used turbidity standard, which is readily available, safe, and cost-effective clay mineral) upstream of the monitored river cross-section. These artificial turbidity events were created to assess camera systems' capabilities. Figure 5 illustrates one of these simulated events. During these events, various sensors, including optical cameras, multispectral cameras, and a drone, were employed to capture different perspectives of the synthetic turbidity event. The data collected from these cameras were compared with the records from existing turbidity sensors at the Selke river cross-section.

Figure 5 provides an initial overview of the experiment results, emphasizing the phases of the experiment captured by RGB cameras. However, the UAS imagery offers a richer and more informative depiction of the water dynamic response, highlighting the advantages of zenithal camera positioning for comprehensive observations.

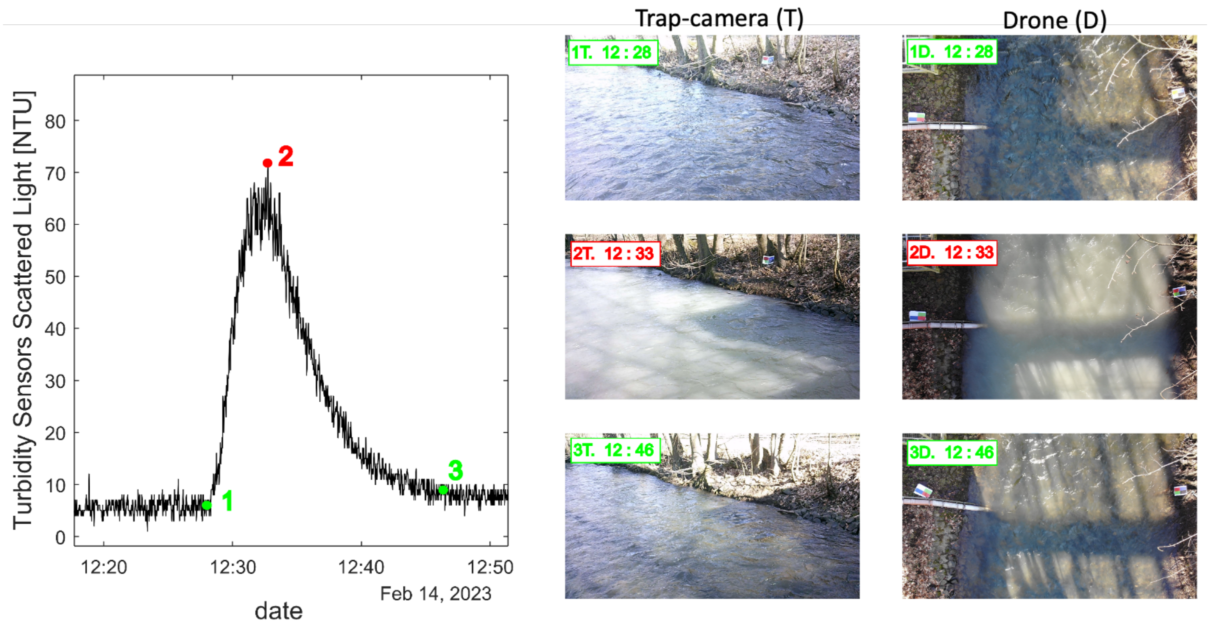

Figure 5. Turbidity diagram measured in February 2023 with associated camera shooting taken in different conditions from the trap-camera and UAS hovering.

This campaign has been extremely useful to develop and refine the methodology of the image processing procedure, also in the light of the field results, allowing us to test the camera monitoring system in many sites with different environmental and hydrological conditions, and to generalize the procedure as much as possible, considering the possibility to extend it to other water quality parameters that involve changes in optical properties. These experimental activities have shed light on both the potential and challenges associated with the utilization of camera systems. These systems offer a wealth of information but are also prone to considerable noise and difficulties. The initial findings unmistakably demonstrate that the system can provide insights into the trends and dynamics of river systems. However, there remain several practical issues that require resolution:

1) The significant variation in illumination conditions results in notable differences in spectral signatures within the days and seasons.

2) Changes in illumination direction, along with the resulting shadows from trees, alter the scene.

3) Flow conditions and ripples can potentially affect the spectral signature.

4) Changing the color of the suspended sediments can also affect the camera signal.

5) Wind conditions, human activity, or animal presence may unintentionally disrupt the positioning of the camera and even generate vibrations.

6) Lastly, the background of the cross-section can pose challenges, particularly in shallow rivers.

These are critical factors we take into consideration as we continue to refine the effectiveness of our camera systems. Consequently, the formulation of a fresh approach to water monitoring using a camera system is underway. However, further investigations are required to establish a sound workflow for generating high-quality measurements. This could involve fine-tuning the camera angle, implementing effective image filtering and calibration, ensuring camera stability, and providing comprehensive training for floating objects.

5.3 Plastic pollution and the Sarno River

The Sarno River is an extremely challenging one, a very critical site subject to political disputes over remediation measures for a long time. It is considered the most polluted river in Europe and one of the ten most polluted rivers in the world. The river drains a watershed area of 540 km^2 densely populated with heavy agricultural and industrial activities. The distribution of different activities in the basin is clustered, which leads to strong spatial variability and temporal fluctuations of environmental conditions (Montuori et al., 2013; Cicchella et al., 2014; Baldantoni et al., 2018).

Figure 6 shows four images of the Sarno River at Scafati in different conditions: ordinary condition, dense presence of macroplastic (Polystyrene foams) and organic material, presence of plastic elements, and presence of foam on the surface.

Figure 6. Examples of images taken on the Sarno River at Scafati where the presence of suspended material is clearly visible: A) ordinary condition; B) dense presence of macroplastic (Polystyrene foams) and organic material; C) presence of plastic elements; D) presence of foam on the surface.

UAS and camera images have been instrumental in capturing a comprehensive view of water quality dynamics, encompassing factors such as turbidity levels, plastic presence, and pollutant transport. Notably, images offer a distinct advantage in their ability to reveal the spatial distribution of pollution events. This capability enables us to precisely identify the sources of specific contaminants and accurately depict the intermingling processes between polluted and clean water. In this context, Figures 7 and 8 below provide a detailed representation of the mixing of contaminated water. Figure 7 illustrates the confluence of the Nocerino tributary into the Sarno River using thermal cameras, while Figure 8 depicts the outlet of the Sarno River using a turbidity index.
In Figure 7.A, we present an RGB aerial image showcasing the confluence of the Nocerino tributary and the Sarno River. This image distinctly highlights the significant chromatic differences between the two water bodies. These disparities are even more pronounced in the thermal image depicted in Figure 7.B, where it becomes evident that the pollution source exhibits a considerably higher temperature than the main river. This thermal contrast could likely be attributed to a substantial inflow of sewer water into the tributary.

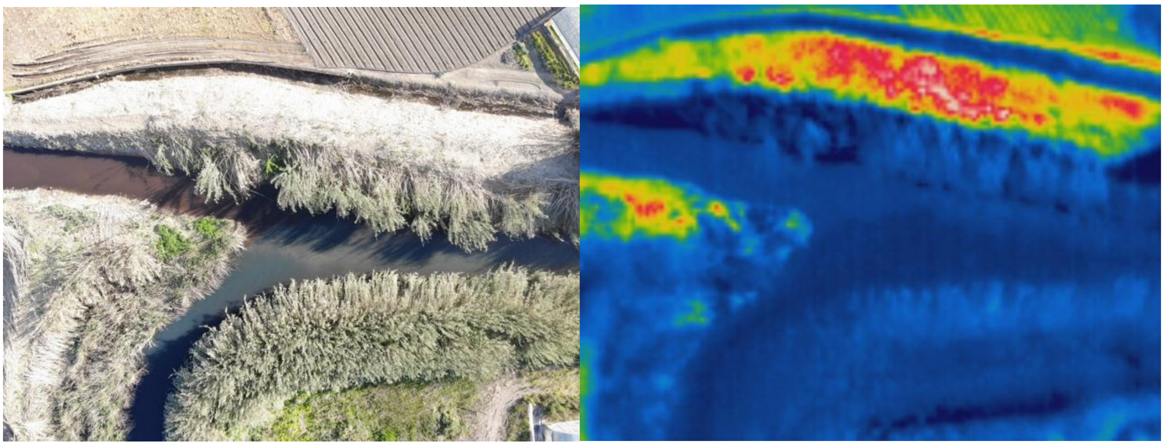

Figure 7. Example of UAS-based imagery obtained with a RGB and a thermal camera at the confluence of the Nocerino River in the Sarno river. Imagery shows a clear flow of pollutants coming from the left tributary.

Following this confluence, the river experiences a noticeable increase in turbidity, serving as a prominent indicator of the aquatic ecosystem's pollution. As the river nears its ultimate outlet at the Tyrrhenian Sea, a discernible blending of this heavily concentrated pollutant flow with seawater becomes evident. This mixing process is vividly illustrated in Figure 8.B, which portrays the turbidity index derived from RGB UAS imagery, providing a comprehensive depiction of this phenomenon.

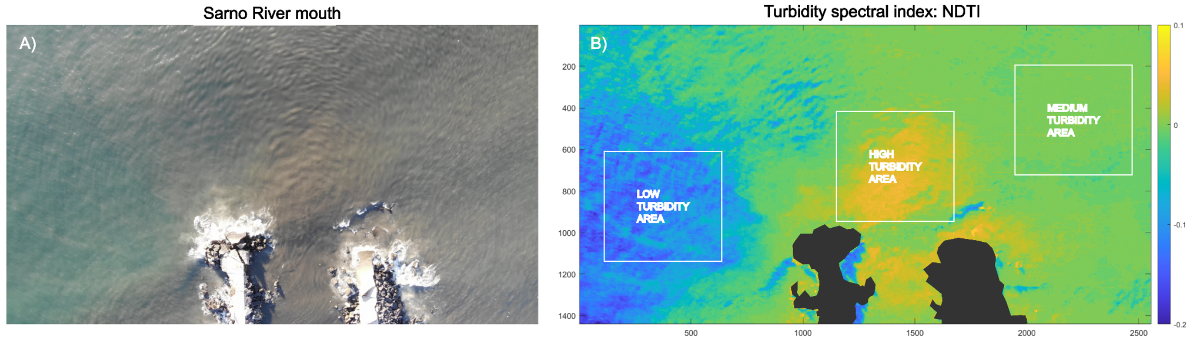

Figure 8. Outlet of the Sarno river: A) RGB UAS image, B) turbidity index NDTI=(R-G)/(R+G) obtained as the ratio between the red (R) and green (G) bands.

Besides the characteristics of the fluid, feature detection and classification algorithms can support the identification of floating objects on the water surface. In fact, van Lieshout et al. (2020) compared automatic procedure with manual counting and obtained promising results in several monitored sites in Jakarta (Indonesia). In particular, they developed a deep learning algorithm that allowed to estimate plastic density with a precision of 68.7% (see Figure 9).

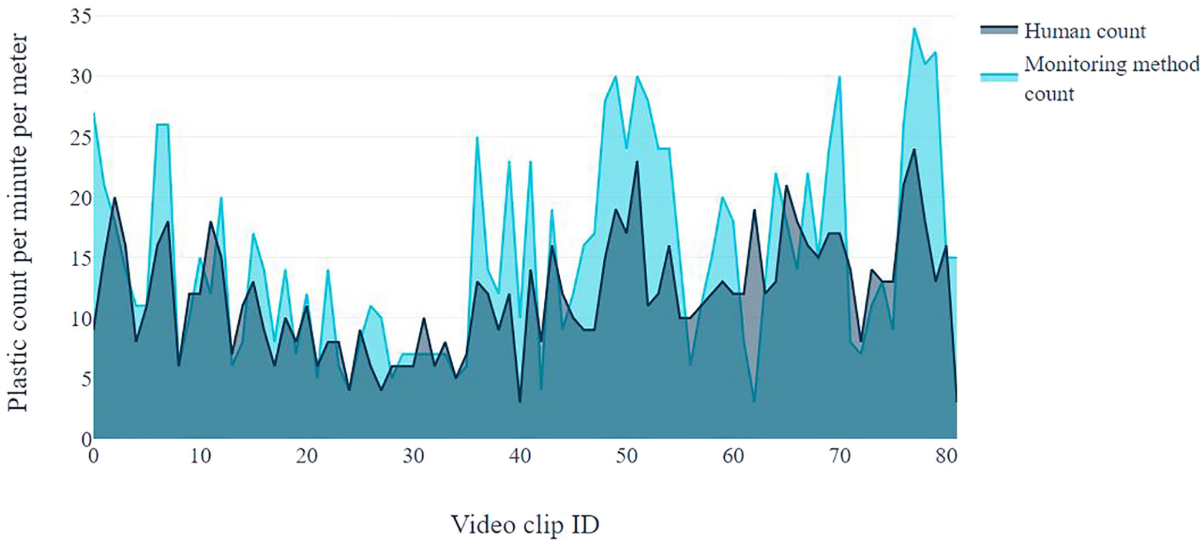

Figure 9. Performances of automatic feature detection for plastic detection applied on five different river locations across Jakarta, Indonesia (taken from van Lieshout et al., 2020).

In the literature, there are well established algorithms for feature detection and classification like the YOLO (You Only Look Once) generic algorithm originally developed by Redmon et al. (2016). It is one of the most promising tools for its low computational requirements. Its potential for plastic detection has been tested using the latest versions of the tool: YOLOv7 (Wang et al., 2023), and YOLOv8 (Jocher et al., 2023), but performances of both have been very poor. In particular, YOLOv7 was able to detect approximately 40% of the plastic bottles while YOLOv8 failed to detect anything (see Figure 10). This suggests that there is a pressing need to enhance its performance through environment-specific plastic training data with high variation in terms of color and geometry. The activities on the Sarno river will be used with the aim to incorporate new training data to optimize the use of a tool which is becoming extremely useful and versatile for many applications.

In the literature, numerous well-established algorithms for feature detection and classification are available. One notable example is the YOLO (You Only Look Once) algorithm, initially developed by Redmon et al. (2016). This algorithm stands out for its exceptional computational efficiency, making it a highly promising tool. The effectiveness of YOLO in plastic detection has been explored through the application of YOLOv7 (Wang et al., 2023), which demonstrated good performance in identifying plastic objects, as illustrated in Figure 10. Nonetheless, there remains room for improvement in enhancing its performance, especially when it comes to adapting to the unique environmental characteristics of plastic objects. This can be achieved by incorporating environment-specific plastic training data that encompasses a wide range of colors and geometric variations. In this context, the activities along the Sarno river serve as an ideal source of new training data. Leveraging this data will contribute to optimizing the utilization of a tool that has rapidly evolved into an indispensable and versatile resource for a multitude of applications.

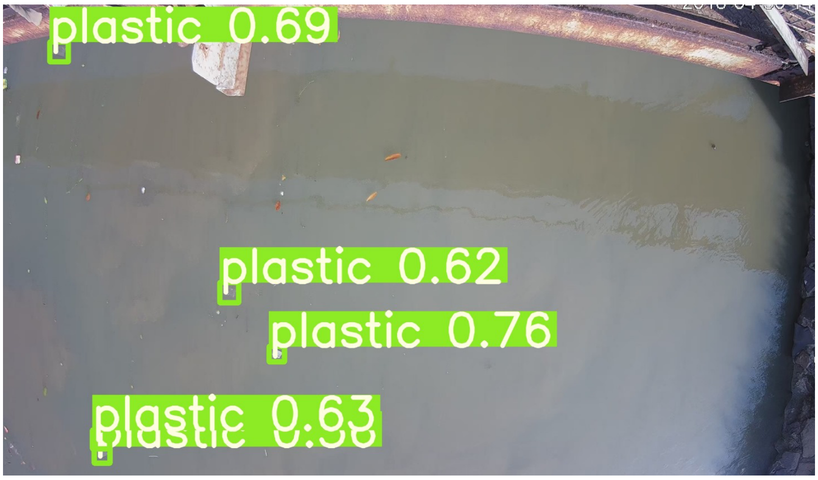

Figure 10. Sample floating plastic bottles images in the environment with floating macroplastic processed with YOLOv7 algorithm.

In order to improve the training of these algorithms, there is a need for a large amount of training data which could be provided by any volunteer. With this aim, we are promoting the construction of an imagery repository for YOLO training collecting images of rivers with the presence of different pollutants or floating materials. This activity will be carried out within the project RiverWatch and is already available at the following link: https://forms.gle/WHvGvqQc6p3zdEuN9 .

It is worthy to mention that a number of repositories of river images have been already implemented and these may represent a good starting point in future studies on plastic transport and identification of other pollutants. We have summarised some of the most recent repositories developed within different EU or national projects (see Table 2).

Table 2. Public repositories useful for image-based applications.

Locations	Project	Type of Data	Reference
13 case studies across Europe	Harmonious COST Action (CA16219)	Imagery collected for image velocimetry analysis (along with reference data)	https://doi.org/10.4121/uuid:014d56f7-06dd-49ad-a48c-2282ab10428e
Five station installed in Jakarta (Indonesia)	Funded by The Ocean Cleanup	Imagery and code for river plastic detection	https://zenodo.org/record/3817117
Saigon river (Vietnam)		Dataset of about 3,688 UAS images	https://data.4tu.nl/datasets/eca46016-b303-4227-9416-e70101dfd413
Saigon river (Vietnam)	River Plastic Monitoring Project (N. 18211)	Floating material annotations	https://data.4tu.nl/datasets/217004df-49d0-4ed7-9367-ed4f131679bd

6 Discussion

This paper has examined the challenges encountered in hydrological monitoring, encompassing issues such as data scarcity, spatial and temporal variability, and the growing demands for water resources monitoring, especially in the current context of a changing climate, which will increasingly lead to substantial environmental and socio-economic changes. This analysis has enabled us to clearly delineate these challenges and underscore the necessity for high-resolution observations in a more intricate environment, where various new pollutants are also observed within the water fluxes.

In this context, the international community is actively exploring the potential of innovative approaches and technologies, including satellite-based technologies, big data analytics, sensor networks, UAS, and citizen science. The integration of multiple data sources and the utilization of innovative approaches provide new prospects for addressing data scarcity, enhancing spatial and temporal resolution, and advancing our comprehension of complex hydrological processes.

The amalgamation of remote sensing-based monitoring methods with machine learning (ML) techniques holds substantial promise for innovating a more comprehensive river monitoring system (Maier & Keller, 2019; Arias-Rodriguez et al., 2020). The global community is currently experimenting with these techniques in various river basins and regions worldwide, elucidating both the challenges and advantages. The authors of this manuscript themselves have developed and/or participate in several initiatives aimed at utilizing fixed camera stations in conjunction with image processing techniques, offering a convenient and easily deployable solution for a wide array of applications. These experiences can pave the way for the development of a new generation of sensors using RGB, multispectral, hyperspectral, and thermal cameras, harnessing the potential of image processing to extract a wide range of hydraulic and water quality parameters.

The review of existing activities and research in this context allows for the identification of the following limitations and challenges associated with the use of innovative techniques, which are summarized as follows:

1. The primary challenge lies in creating a system that can effectively operate under a wide range of hydraulic, environmental, and climatic conditions. Various cross-sections within the same river can exhibit unique characteristics influenced by the specific features of their upstream river basin or the cross-section itself. Therefore, there is a need to test these ideas in different environments and share experiences and data with the research community.
2. Remote sensing stands out as one of the most promising tools for hydrological monitoring. However, its application remains constrained by the spatial resolution, preventing its usage in numerous river networks worldwide characterized by river widths smaller than the typical reference resolution of satellite data. In this context, the utilization of proximity sensors offers a promising avenue to overcome this limitation.
3. The use of image-based techniques is strongly influenced by local factors, such as illumination, the surrounding environment, shadows from trees, and the background of the cross-section. There is a need to develop standardized preprocessing techniques aimed at enhancing the quality and information content of each survey or measurement.
4. The spectral signature of individual pollutants, along with the combination of elements that may be present at the same time in a given cross-section, can introduce disturbances in the interpretation of the information contained in any type of imagery. This represents an additional significant issue to be addressed.
5. The potential volume of data collected by these sensors may result in an excess of information that is not always useful for specific purposes. Therefore, there is a need to synthesize the information and construct meaningful metrics capable of retaining useful data.
6. The new techniques based on the use of cameras or citizen participation may be susceptible to significant disturbances and procedural errors, which can degrade the quality of the collected information. Therefore, it is critical to establish standardized protocols and sustainable systems for the use of such methods.

There are still many issues that require further investigation to bring these methods to operational use. However, there are also numerous opportunities for advancing hydrological monitoring using these innovative techniques. Here, we highlight some of the key opportunities:

1) **Affordable Commercial Devices**: The use of image-based techniques could lead to the development of cost-effective commercial devices that can be integrated into sensor networks, even in remote regions around the world.

2) **Integration of Crowd-Sourced Data**: The integration of crowd-sourced data with image processing appears to be a natural progression for the evolution of new monitoring techniques.

3) **Citizen-Friendly Tools**: Creating user-friendly tools that could potentially be used on smartphones by the general public may expand the overall number of hydrological sensors. This could have significant environmental benefits by fostering a community engaged in river monitoring, raising awareness about the state of aquatic ecosystems, and working towards their protection.
4) **Multipurpose systems**: Leveraging these innovative tools can yield a wealth of information regarding watercourse dynamics that surpasses the capabilities of traditional methods. Such data can be invaluable in bolstering the management of river systems, offering a comprehensive depiction of the river's current condition.

Despite the various limitations and advantages at hand, a formidable challenge persists: the imperative to transition from qualitative observations to a quantitative paradigm. This pivotal transition looms as perhaps the most substantial obstacle on our path forward.

7 Conclusion

Advanced hydrological monitoring techniques and technologies enable the timely identification of hydrological and hydromorphological patterns, anomalies, and critical events like floods, droughts, pollution incidents, and debris flows. This facilitates proactive responses and the implementation of appropriate measures to mitigate risks and minimize extreme event impacts on water resources. In addition, integrating citizen involvement in monitoring may encourage responsible behavior. This information guides the development of adaptive water management strategies that account for uncertainties and future challenges.

In particular, the combined use of image processing and crowd source data has the potential to revolutionize river monitoring applications where traditional approaches, limited by technical and financial constraints, fail to provide the required level of detail to advance our understanding and description of underlying physical processes and mechanisms.

In this context, we envision the exciting potential for initiatives spearheaded by IAHS, like the MOXXI working group (https://iahs.info/Initiatives/Working-Groups/MOXXI/), to expedite the advancement of state-of-the-art solutions in hydrological monitoring. Such initiatives can serve as catalysts for extensive international collaboration. This partnership would not only encourage the sharing of crucial data but also pave the way for the establishment of significant collaborative ventures aimed at pioneering innovative solutions. Ultimately, this collective effort is poised to significantly enhance our comprehension of the intricate dynamics of the water cycle, supporting a real adaptive, integrated, inclusive and sustainable management of our waters.

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