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Key Points:

- The concept of "water security" (WS) is hard to operationalize due to its intrinsic complexity.
- Data gathering is not an end in itself but to strengthen the relationship between the data-information-stakeholders nexus.
- We propose a framework to help practitioners to design effective and systemic Data Gathering Strategies for Water Security.

Abstract

At the international level, the term "water security" (WS) has gained increasing attention in recent decades. At the operational level, WS is assessed using tools that define the concept using a variety of dimensions and sub-dimensions, with qualitative and quantitative indicators and parameters. The breadth of tools and concepts is an obstacle to the operationalization of the concept of water security (WS). Clearly we need a range of diverse data to evaluate water security (WS). However, there are several barriers to designing an optimal Data Gathering Strategy (DGS). Such a strategy must strike a balance between a wide range of competing and overlapping data requirements and characteristics including: resources, information, and impact. The conceptual aim of the framework can be summarised as shifting the focus of the DGS from a "data to information approach" to a "data to action approach". The specific aims of this paper are to: identify the key issues that should be addressed in designing a Data Gathering Strategy for Water Security (DGSxWS); communicate the key issues with a clear conceptual framework; and suggest approaches and activities that could help water practitioners in dealing with the issues identified.

Plain Language Summary

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1 Introduction

1.1 Water Security: a complex concept

In recent decades, the term "Water Security" (WS) has become commonplace at the international level. The World Economic Forum (WEF) recently described WS as "the gossamer that links together the web of food, energy, climate, and human challenges that the world faces over the next two decades" (WEF, 2019). The breadth of water security, its interconnectedness, and interdependencies, creates a complex system that militates against a simple one-size-fits- all definition (GWP, 2014). Consequently, and perhaps necessarily, the term WS has generated different framings, definitions, tools, indicators, and requirements.

Though several definitions of WS exist (e.g. Gain et al., 2016; Garrick and Hall, 2014; GWP, 2014; Lautze and Manthrithilake, 2012; Staddon and James, 2014; Tarlock and Wouters, 2009), they generally revolve around four main themes: water availability to human and ecosystems, human vulnerability to hazard, human needs and sustainability (Cook and Bakker, 2012), and thematic attributes e.g. quantity, quality, ecosystems, risk, policy, resilience, global change etc. (Gerlak et al., 2018).

The different elements contributing to WS definitions mean WS can be seen as a standalone system or in relation to others (food, economic, political security etc.). As a result, definitions create a complex web (see Figure 1). Some themes are shared with others (for example, sufficient availability of water quantity and quality), while still others are only included in some definitions (such as affordability or energy needs). According to Figure 1, the different framings given to the WS concepts in literature can be seen at L2 in relation to L3. Whereas L4 identifies the aim that WS wants to achieve in terms of activities, population, and environment. Some definitions refer to the external context or to a particular condition (L5).

Different frameworks are used to approach the WS concept: scarcity, risk, security, and development (Hoekstra et al., 2018; Mason and Calow, 2012). One consequence of this diversity is that the WS concept is also connected to different types of (in)securities: food, energy, infrastructure, geo-political (Cook and Bakker, 2012) . This diversity can be seen as a strength, by offering a broad spectrum of possibilities, but also as a weakness by creating an excess of information that decreases the usability of the concept.

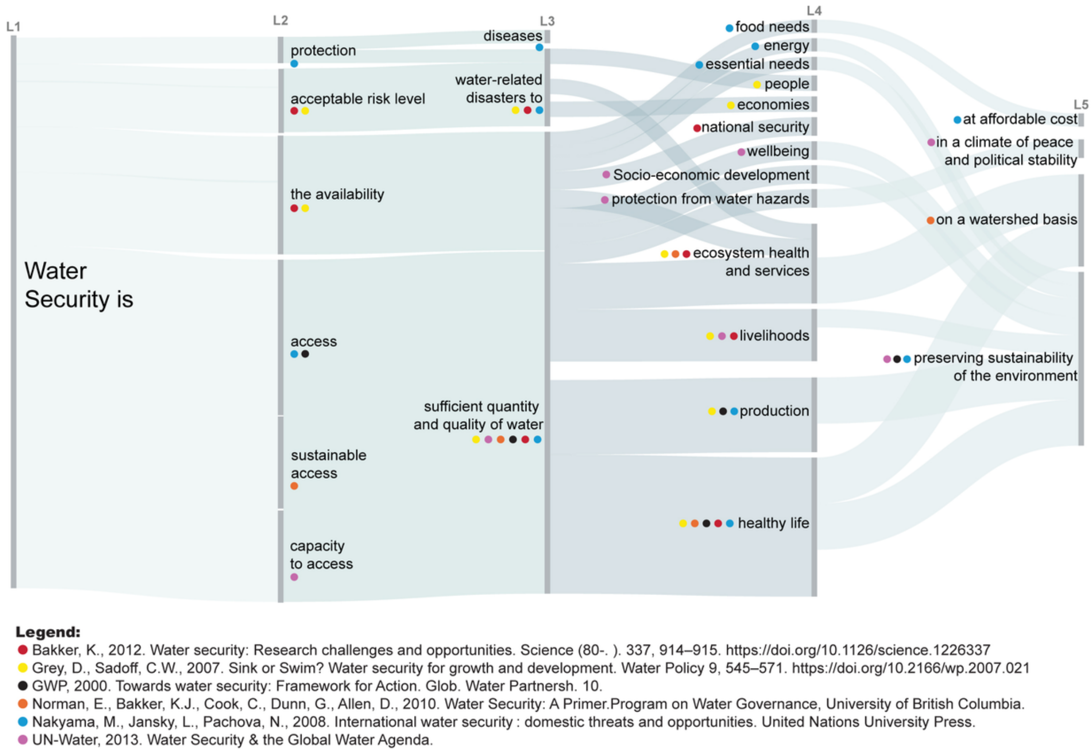

Figure 1. Visualisation of six of the most used definitions of WS according to interrelations and main aims/activities. The figure shows the framing given to WS (L2-L3) in order to support and satisfy a particular area of human society (L4) with a given condition (L5).

1.2 From conceptualization to operationalization

At an operational level, WS is assessed using tools that define the concept using dimensions and sub-dimensions (Gerlak et al., 2018; Plummer et al., 2012; Brown and Matlock, 2011) that rely on qualitative and quantitative indicators - and hence data (Lehtonen, 2015). Tools have been created for specific aspects of WS such as scarcity (e.g Brown and Matlock, 2011), freshwater (e.g. Norman et al., 2013), urban environments (e.g. Hoekstra et al., 2018), specific geographies such as small islands (e.g. Holding and Allen, 2016), different geographical scales, and different water domains (e.g. Octavianti and Staddon, 2021).

A systematic review on water vulnerability assessment tools (Plummer et al., 2012) reported a variety of indices (~50) that differed on geographical scale, on the number and type of dimensions and subdimensions considered (water resources, economics, institutions, social, physical environment), and on the number of indicators. Overall, 710 indicators were identified and grouped into five dimensions and 22 sub-dimensions. All these layers (conceptual framing, definition, dimensions, indicators, parameters) form a complex framework surrounding WS. To better understand the structure of a typical WS index, a tree diagram was used to break down WS dimensions into sub-dimensions, indicators, and - finally - parameters that could be measured. Figure 2 illustrates how the concept is defined across several dimensions. Dimensions are then divided into sub-dimensions that are assessed using one or multiple indicators. Indicators require single or multiple parameters to be defined. Finally, parameters may need one of several datasets to be compiled.

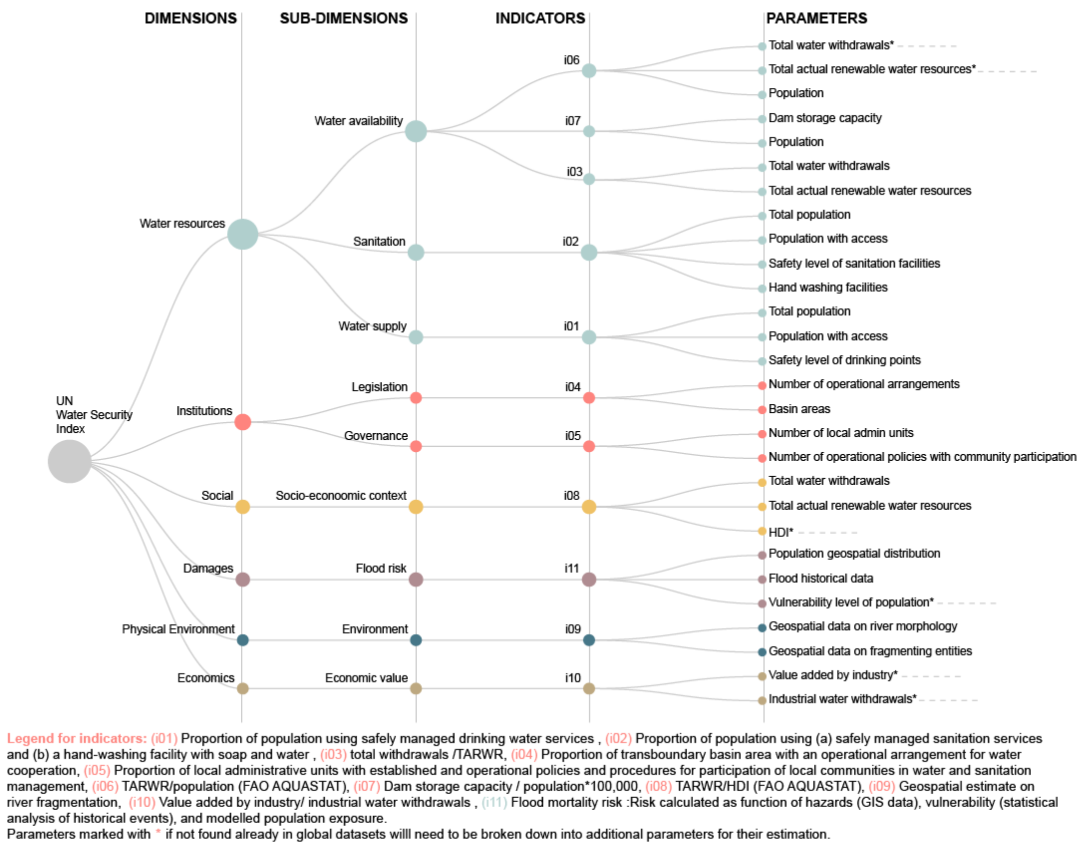

Figure 2: Typical structure of a WS index (in this case from Mason 2012) where the WS concept is defined across several dimensions.

This wide range of indicator possibilities is an obstacle for the operationalization of the concept of "water security" (WS). A large-scale survey of water practitioners in Canada on the use of WS assessment tools (Norman et al., 2011) found a number of different shortcomings, most alarmingly the lack of agreement on the definition of WS. They also found that monitoring and assessment is practised, but only a limited number of available indicators are used: 38% of the participants chose not to use the available tools due to difficulties and fragmentation (the main reason being tools were too specific to a region or a timeframe). In addition, the authors found other gaps such as the lack of centralised data and consistency, the low emphasis on governance in achieving WS (often not included in assessment tools), and the inadequate consideration given to the importance of non-state stakeholders in the governance of water systems.

1.3 The importance of data

Data is the foundation of WS assessment tools. The need for "high quality, accessible, timely and reliable disaggregated data" has been stressed and emphasised by the 2030 Sustainable Development Agenda (UN, 2018) and by the UN Deputy Secretary-General Eliasson who called data the "lifeblood of decision-making and the raw material for accountability" (UN-Water, 2016). The need for accessible data has been acknowledged on various occasions (UN-Water, 2010; UN-HLPW, 2017) but data gaps still exist (Schmidt-Traub et al., 2017; W.H.O./U.N.I.C.E.F., 2019; WHO, 2019; UN-Water, 2010), particularly in water insecure countries (Grey et al., 2013); naturally, this influences decision-making (York and Bamberger, 2020).

Different WS assessment tools have different data requirements. Octavianti and Staddon (2021) proposed a classification of data into two clusters. The first cluster, defined as experiential scale-based metrics, is associated with social sciences and was identified as aiming at, "Capturing water insecurity experiences, identifying vulnerable, water insecure groups and evaluating water interventions". The data requirements for this cluster are typically based on household and individual surveys. The second cluster, defined as resource-based metrics, adopts an engineering and natural-science approach, aimed at, "Improving water security, identifying mitigation targets, allocation of funding and raising awareness (benchmarking)". Data for this cluster are based more on secondary data from governmental agencies (see Interface A below).

1.4 WS as a system of systems

A systems strategy for Data Gathering Strategy for WS (DGSxWS) is essential if that data is to serve its purpose and to connect stakeholders (through the data) to actions that improve WS (Checkland and Poulter, 2006), and thus give a purpose to the data. Data not only informs a WS system, but it also defines it, arguably as the first step in a systems approach by being a means of "finding out about the problematical situation and the characteristics of the intervention to improve it" (Checkland and Poulter, 2006). The data gathered to represent WS in a given basin are therefore representative of WS problems. Existing systemic indicators attempt to measure a 'level' of WS (as demonstrated in Dickson et al., (2016)), but do not provide the space for system lens to evaluate how the interconnections between elements of data gathering could be improved or better connected with stakeholders. These connections are needed if WS questions are to be linked to WS solutions and have a positive impact for those involved in the system.

Data gathering is not an end in itself. Data, and thus the DGSxWS, should form the basis for decisions that improve WS. DGSxWS should strengthen the linkage between data-information-stakeholders-positive impact. To achieve such a goal, several barriers need to be addressed including: insufficient data, unsuitable solutions to localised problems, limited community involvement, and trade-offs between available resources, information, and impact. An integrated systems approach to data gathering is crucial to overcoming and addressing some of these barriers. A whole systems approach to the gathering and role of data in informing water security can enable an understanding of the 'whole contextual water security picture'. Therefore, enabling the practitioner to better expose gaps and linkages between data and impact by observing an incomplete picture.

By a systems perspective, we mean the understanding that the emergent behaviour of water security is created by the aggregations and interactions within a system of systems - data associated with WS, which thus inherits the same trait. The systems are bound by the flow of water, and a systems perspective is required to understand the intersection of various data sub-systems (Hipel et al., 2013).

Using this system lens, we must observe two main qualities for WS data. First, the nestedness between elements and groups of elements. This is demonstrated by the levels of dimensions, sub-dimensions, indicators, and parameters in existing data gathering frameworks (see Figure 2). However, the system lens understands this 'breaking down' process as a formation of nestedness within the WS system, based more on the dynamics of emergent behaviours than the components of definitions. This aids the understanding of the role of data in the WS system.

Second, the connections and interactions with other elements. It is important to recognise the links between our data and how the data components of WS phenomenon do not sit alone in disciplinary silos. This can take the form of successful data sharing, but also encourages interdisciplinarity when assessing the data associated with WS components (Figure 3).

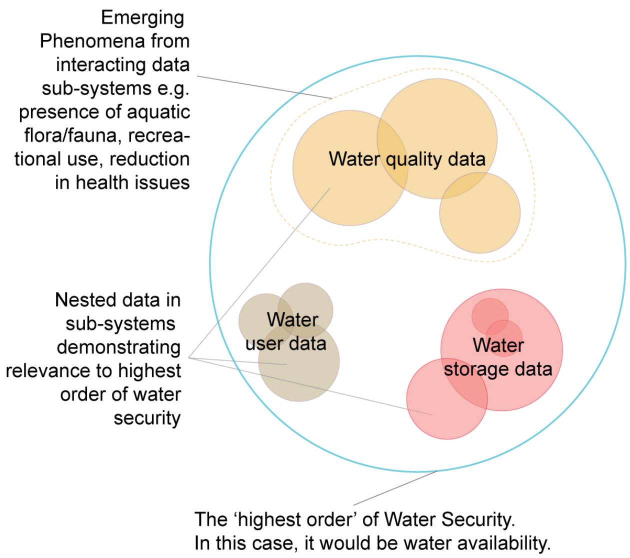

Figure 3: Conceptual diagram showing WS as an integrative system (light blue circle) that includes several subsystems (yellow, red and brown clusters).

An example of this is the socio-ecological framework for data analysis, supported by the understanding that environmental problems are at their root - almost invariably social problems (World Bank, 2002). These considerations suggest that water systems should be understood through human-nature linkages incorporating ecological, economic, cultural, and physical systems (Bogardi et al., 2012).

Socio-ecological systems are characterised by a systemic vision of the ecological and the social components, its structure, and functioning and emergent properties across spatial and temporal scales. This view supports a global architecture based on systems thinking (Grey et al., 2013) that not only considers information internal to the water system, but also external factors(Briscoe, 2009; Octavianti and Staddon, 2021). Hipel et al., (2013) observe that systems methodologies and techniques are important for addressing complex water problems that involve nature, technology, and society. However, we must look beyond this for WS, and include other interconnected subsystems with natural, social, and economic elements.

1.4 Aims

We present a framework to guide practitioners through the intrinsic complexity of gathering data for WS by fulfilling the following aims:

- Identify the key issues that a Data Gathering Strategy for Water Security (DGSxWS) must address.

- Document the key challenges and opportunities for each issue.
- Help researchers and practitioners in WS to itemise and categorise those challenges and opportunities for better planning and monitoring.
- Suggest activities, approaches, and references that can support the operationalization of the framework.

2 Proposed Interfaces of the DGSxWS

To avoid the "data rich but information poor syndrome" (Ward et al., 1986), data needs to be strongly linked to information requirements by a coherent purpose, collection method, and good communication. For information to be considered 'useful', it needs to have three necessary characteristics: credibility, legitimacy, and salience (Cash et al., 2005). Where:

- Credibility is the creation of authoritative, believable, and trusted information;
- Legitimacy is as how "fair" an information producing process is and whether it considers appropriate values, concerns, and perspectives of different actors;
- Salience is how relevant is to decision making bodies or the public.

To attain these characteristics, five relevant areas were identified and conceptualised as "interfaces". The first three (interfaces A,B,C) support the creation of credible data. Interface A relates to the existing "data-scape" because a DGSxWS must engage with existing knowledge gaps, using, and building upon, existing data. Interface B relates to the observed environment and seeks to describe the physical environment with data that has sufficient quality, robustness and certainty. Interface C relates to project resources and the need to optimise those resources while gathering, editing, and communicating data.

Salience is created by identifying which information is relevant. This is achieved by integrating the DGSxWS with the socio-economic context (Interface D) and existing stakeholders (Interface E). Legitimacy of information is conferred through the relationship between data, data practitioners/managers, and the communities present in the study area. This is explored in the interface with stakeholders (interface E), which aims to bring essential socio-cultural knowledge into the DGS.

The following sections give a concise overview of the five interfaces by underlining key concepts that need to be addressed and presenting essential references for an initial understanding of the most relevant issues. More specific suggestions on activities that could be conducted throughout the data gathering process are provided in Table 1.

2.1 Interface with the existing data-scape

WS data has social, economic, and environmental components which, together, characterise the physical environment (Figure 4). Data varies in spatial scale from global to national level down to regional, municipal, urban, or basin level. The last two scales are the most popular in water research (Octavianti and Staddon, 2021). Primary data is collected "first hand" and is contrasted with secondary data, which is reused from existing resources, previous studies, or both (Hox and Boeije, 2005; NERC, 2021). This division between primary and secondary data applies to any type of socio-economic and environmental analysis, as well as qualitative and quantitative datasets.

Examples of secondary data might include water volumes stored in reservoirs, daily water treatment capacity, the percentage of households with access to tap water supply, number of serious flooding events per year, economic loss due to water pollution and so on. Such secondary data has been used to develop WS indices at the urban scale (Jensen and Wu, 2018). Data inaccessibility is a common problem, with secondary data retrieved from governmental and institutional agencies. Data inaccessibility hinders the assessment of data quality and water risk trends from historical data-series (Hering et al., 2010; Jensen and Wu, 2018). Conversely, when primary data is collected and preserved following the FAIR guiding principles (FAIR: Findable, Accessible Interoperable, Reusable (Wilkinson et al., 2016)) then it becomes easier to capture the variability and uncertainty of the data. The Water Quality Portal (Read et al., 2017) is a good example of the FAIR guiding principles. This resource includes millions of open-to-the-public water-related data, retrieved from multiple resources, that indicate the water quality life-cycle of lakes in the United States (US). Even with existing regulations for storing/sharing data in an open manner, there is still the need for seamless exchange of data and data harmonisation with existing datasets. Due to the absence of such regulated procedures, WS data development has lost its importance, hence data cannot easily be reused and interpreted.

Scientists collect data for research, for industry (including the water industry), and in collaboration with stakeholders at great expense of both time and resources. However, the studies are preserved and retrievable in journals and project reports where the data is seldom published and open for others to use. Unless the data is collected and published by government agencies, most of it is lost. There is however some good practice: in geosciences, for example, there are well-established websites for storing and sharing data such as OneGeology (One-Geology, 2021), the US Geoscience Information Network (US-GIN, 2021), and the Ocean Observatories Initiative (NSF, 2021). Nevertheless, there is the need for open data websites in WS (and more generally). Open data has an important role to play in WS and sustainable development. An alternative to this problem is the use of blockchain based methods, together with the FAIR guiding principles (Pincheira et al., 2020; Zhang et al., 2019; Farnaghi and Mansourian, 2020; Ren et al., 2019).

Primary data can be divided into two categories, in-situ (i.e. sensed in place (Teillet et al., 2002)) and remotely sensed data (i.e. observed from a great distance (Teillet et al., 2002)) depending on how it was collected. In-situ point sampling is the traditional method for monitoring water quality, river flows, discharge, water depth and so on. Point sampling typically requires either manual observations using portable devices (Acharya et al., 2020) from shoreline or boat, or automatic observations from permanently installed stations (Glasgow et al., 2004) at discrete locations with high temporal frequency (Soares and do Carmo Calijuri, 2021). In-situ data collection can be labour-intensive, relatively costly (e.g. maintenance costs due to damaged permanent stations (Soares and do Carmo Calijuri, 2021)) and can provide limited spatial resolution. There is also a risk to human health when operating in polluted environments (Lally et al., 2019). By contrast, remote sensing Earth Observations (EO) can provide high spatio-temporal resolution for national, regional, and basin level using freely-available satellite optical and radar imagery (e.g. Chawla et al., 2020) and even for local lake spatial level using unmanned aerial systems (UAS) (e.g. Lally et al., 2019). However, in-situ observations are typically required to calibrate, model, and validate remote sensing EO data.

Who physically collects observations is important. Conventionally, a professional acquires the data and such professionals are assumed to be reliable trustworthy analysts. With the advance of citizen science over the last decade, amateurs and non-experts from local communities have contributed in the various steps of the data cycle. Their contributions can range from collection to analysis, to interpretation (Bonney 2014). Previous studies have demonstrated the advantages of citizen science in: capturing data during episodic flooding events (Starkey 2017), gathering water-related data over data-poor regions especially in the Global South (Walker 2020), and collecting information related to previous years, where historical data might be missing.

Due to the multidimensional aspect of the proposed DGSxWS framework, an optimal data-scape could include the integration of in-situ/remotely sensed and citizen/expert - generated data and capture the synergies between these different sources. A recent comprehensive review (Sagan et al., 2020) demonstrated the potential of combining water quality sampling observations with freely-available satellite imagery alongside advanced deep learning approaches to predict water pollution events. The evolution of cloud computing services alongside open-source methodologies (e.g. Google Earth Engine (GEE) (Gorelick et al., 2017), Open Data Cube (Dhu et al., 2017)) with open data and "analysis ready data" (Dwyer et al., 2018) is very important. These advances have facilitated the cost efficient use of neural networks and EO data to analyse historical time series and to predict future scenarios (Hoeser et al., 2020). For instance, (Krause et al., 2021) investigated the use of Open Data Cube for Australia to estimate the water quantity of open water bodies using archival Landsat products since 1987. Similarly, Malthus et al, (2019) estimated algae bloom status by calculating chlorophyll and total suspended matter concentrations exploiting "analysis ready data" from Landsat over water bodies across the entire Australia. Both sets of findings have been integrated into the Digital Earth Australia's (DEA, 2018) platform to support stakeholders and decision making. In addition (Tiwari et al., 2020) demonstrated the potential of the GEE cloud computing platform for mapping flood extent in Kerala, India by exploiting radar satellite imagery accessed close to the time of the flooding event.

GEE and Open Data Cube platforms can handle Big Data volumes and offer multiple low level python scripts (e.g. CEOS, 2021) for retrieving, processing, analysing, and visualising multi-modal and multi-temporal satellite image series, tailored to several applications related to SDG 6 (Rizvi et al., 2020; Mubea et al., 2020), land cover changes (Liu et al., 2021), water quality (Malthus et al., 2019), water quantity (Krause et al., 2021), flooding (Tiwari et al., 2020) and many others.

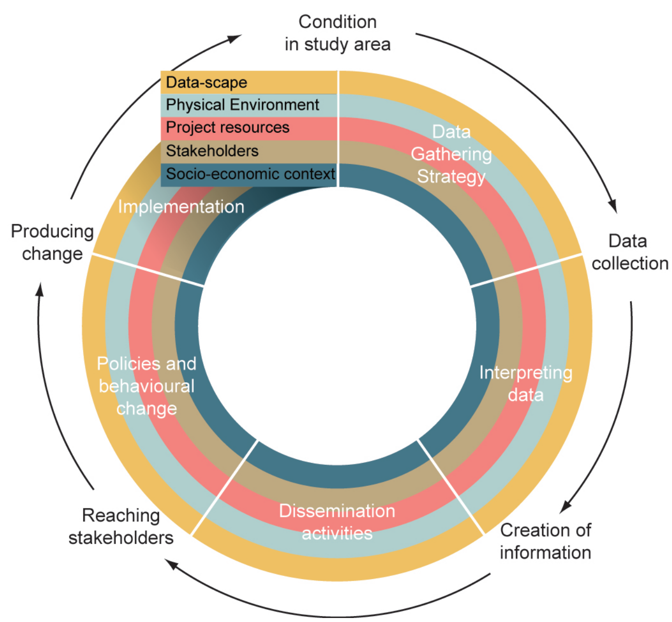

Figure 4: the figure shows how activities in the different interfaces could be carried out in order to strengthen the linkage between physical environment > data collection > production of information > stakeholder awareness > positive change > updated physical environment. These activities form a continuous cycle of transformation that may be repeated several times.

2.2 Interface with the existing data-scape

The quality of data gathering is a key aspect of data credibility. We recommend adopting a risk approach to WS (Grey et al., 2013; Garrick and Hall, 2014; Hall and Borgomeo, 2013). Such an approach is grounded in the idea that water users are usually more concerned with their needs not being satisfied and this concern can easily be framed as the risk of noncompliance with regard to a given threshold. Water-security risks can then be broadly categorised into four groups: risk of shortage, of excess, of inadequate quality, and undermining the resilience of the system (GWP, 2014). This approach also promotes dialogue across disciplines and institutions (World Bank, 2014; W.E.F., 2019) since risk concepts (hazard, vulnerability, exposure, mitigation, management, prevention) are commonly used by experts and communities and will favour stakeholder engagement. In addition, adopting a risk-based approach allows the conversion of different water security related phenomena into concepts such as probability of risk and odds ratio. This enables the comparison of such phenomena to different mitigation scenarios and or international guidelines as in the case of WHO ones.

When the purpose is to conduct water risk assessments, it is important to agree on clear definitions of hazards, consequences, and uncertainties. Since risk assessments are used to inform decision makers about measures for risk, a basic question about the quality of such assessments is the degree to which these are able to adequately characterise the risk. The two main challenges to a valid risk assessment are uncertainty and ambiguity (Aven, 2019).

2.2.1 Minimising uncertainty Uncertainty has different and distinct components, such as statistical variation, measurement errors, ignorance and indeterminacy (van Asselt, 2000). Such components have one thing in common: they reduce confidence in the estimated cause and effect chain(s) of risks (Renn et al., 2020). If complexity cannot be resolved by scientific methods and the available data, uncertainty increases (Renn et al., 2020). But even simple relationships may be associated with high uncertainty if either the knowledge base is missing or the effects are indeterminate due to the stochastic (randomly structured) nature of the functional relationships (Renn et al., 2020). One example is extreme weather events such as heavy rain and storms. As they are extreme and rare and a result of dynamic physical processes, their magnitude and consequences are uncertain. Looking at the past, i.e. relying on historical weather data, can lead to erroneous risk assessment. In cases like these, a focus on scenarios and resilience is advisable and decision makers should decide on what level of resilience they are able to adopt (Renn et al., 2011).

It is essential for data collection to be clearly linked to an objective, otherwise data may not necessarily translate into information. Rose and Smith (1992) observed that data is often gathered without a clear statement on how it is to be evaluated. The lack of attention to this aspect creates a situation where errors in the sampling strategy tend to dominate other types of errors related to analytical measurements (Zhang and Zhang, 2012) and ultimately produce different results (Abbatangelo et al., 2019; Olsen et al., 2012; Wang et al., 2015). Additional causes of gross and systematic errors and uncertainty include: the inadequacy of observations, the density of the network, its dissemination, the quality assurance, and calibration (Wheater, 2000). It is more difficult to turn data into valuable information (Ward et al., 1986) if it is inaccurate, of poor quality, or non-comparable (Milliman and Farnsworth, 2011).

A well-designed sampling strategy can also help minimise uncertainty. Several decisions can affect the final results such as sample location (Alilou et al., 2019), parameters, number of samples (Merrington and Sprang, 2013), frequency (Anttila et al., 2012), and location of laboratories (Wright et al., 2014). There is excellent literature on this topic covering: network design, statistical tools, parameters, and frequency of sampling (Sanders et al., 1983; Strobl and Robillard, 2008; Ward et al., 1990; Zhang and Zhang, 2012), and the optimization for data poor contexts (Taylor et al., 2018). The dynamic characteristics of the WS system should also be considered. Most WS indices do not account for the temporal dimension. Ignoring time may lead to a misinterpretation of the data and a failure to consider system dynamics. Incorporating time would allow the description of WS not as a static snapshot but as a trajectory (Wagener et al., 2010; Srinivasan et al., 2012) with the possibility of identifying trends (Doeffinger et al., 2020; Srinivasan et al., 2012). Assessment tools should take full advantage of information technologies (IT) using dynamic datasets and real-time data.

2.2.2 Minimising ambiguity Ambiguity denotes the variability of (legitimate) interpretations based on identical observations or data assessments and questions their impact according to different values and perspectives (Renn et al., 2011). Ambiguities may be minor or negligible when characterising the physical dimension of water security due to stronger scientific background supporting the information used for hazard identification. However, important ambiguities can emerge in the process of establishing the impacts of such hazards and defining actions to manage the associated risks.

Expert judgements may be a useful tool for combating ambiguity caused by the limitations of poorly defined data (it may be scarce, uncertain, and insufficient) and the difficulties of using hard data to describe events in complex systems. To reduce ambiguity in such judgements, events must be precisely defined. Furthermore, more evidence may still be required to identify whether uncertainties from global risk assessments can be lowered by reducing the scale and focusing more on local risks.

2.3 Interface with the available project resources

Water security (WS), whether addressed in terms of water risk assessment, mitigation strategies, solutions development, or research settings, is typically undertaken in the context of projects. There is a strong correlation between data and projects. Data and knowledge management play an essential role in a projects' success (Ekambaram et al., 2018). Project management approaches and techniques are widely considered as good practices in data gathering (Corti et al., 2019). Consequently, the classical project constraints - time, cost, and quality (Dobson, 2004) - are extended to the data gathering process (Figure 5). Therefore, it is crucial to have a dynamic and data-centric interface managing the available project resources.

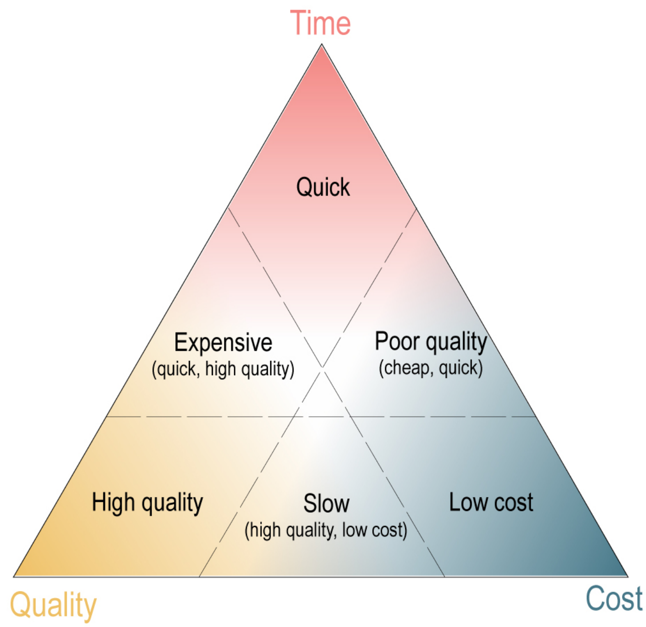

Figure 5. The trade-offs that are necessary in a project when dealing with the triple constraint of time, quality and cost. Since the three optimal goals (high quality, quickness and low cost) are not achievable all together, project managers need to decide what is the best balance between the constraints.

Like projects, data gathering requires different resources, such as: money, people, material, equipment, and technology (Sholarin and Awange, 2015). The type and size of resources required depends on the scope (contextual and geographical) and scale of data gathered. Naturally, resource limitation significantly affects the quantity and quality of data and thus may limit knowledge and understanding (Docherty et al., 2020). A lack of resources may also limit the uptake of tools (Norman et al., 2011). A survey of water managers in 57 countries found that financial resources, together with data transfer, were the main factors limiting data collection (Kirschke et al., 2020). This is to be expected due to the extended impacts of limited budgets on the other types of resources.

Since WS is essential for global sustainable development (Gain et al., 2016), international collaborations have long been established to overcome resource limitations. Despite significant achievements in the fields of capacity upscaling, sustainable infrastructure, and technological advances, we still cannot meet the required financial investments to achieve the availability and sustainable management of water and sanitation for all (in alignment with SDG6). These investments are estimated to cost $1.04 trillion globally every year until 2030 (Strong et al., 2020). For instance, the cost of producing SDGs monitoring data in 77 International Development Association (IDA)-eligible countries was estimated at 1 billion US Dollars (USD) per year over a 15-year period, including $134M-$173M for national survey programmes, $320M for censuses, and $114M for geospatial and hydrological monitoring data (Espey et al., 2015).

These numbers make it clear that a comprehensive and achievable data generation strategy must, inevitably, align with the resources available within the project. Effective project planning based on resources' optimal allocation is a key for the success of projects (including data gathering projects) (Roel and Herroelen, 2004).

The sophistication of water security data gathering and the associated management tools is increasing, an increase driven by our improved understanding of the subject matter. This sophistication emphasises the importance and the urgency of a comprehensive DGS for all the entities and individuals involved. Documents such as Knowledge Management (KM) plans at enterprise level (Pasher and Ronen, 2011) or Data Management Plans (DMP) in research projects (Burnette et al., 2016) have emerged recently as standard practice.

The leadership, structure, and management of a data gathering organisation are extremely important and should not be overlooked, irrespective of the regional settings (Global North or South). For example, a study on water quality monitoring in Sub-Saharan Africa (Peletz et al., 2018) identified leadership, knowledge, and staff retention as key drivers of success and arguably more important than equipment, procurement, infrastructure, and enforcement. Perhaps this is because caring leaders and knowledgeable staff can compensate for deficiencies in material. Conversely, excellent material cannot compensate for poor leadership and staff turnover.

2.4 Interface with stakeholders

Human processes can limit WS because of the divergent visions, perceptions, biases, and values of stakeholders and decision makers across multiple scales. Our understanding of the motivations that drive environmental degradation should include an ethical approach that connects the values, behaviours, and actions that affect WS.

Even though the need to link different types of knowledge and stakeholder motivations for WS and sustainability has been recognized, little actual progress has been made in this regard (Zhongming et al., 2021; Norman et al., 2013). Stakeholders are essential drivers of the WS system, due to the dynamics generated in the use, access, and management of water (Braden et al., 2009; Sullivan and Meigh, 2006; UN-Water, 2006; Gielczewski et al., 2011). Stakeholders should be understood through their different roles: as sources and receivers of new information and as drivers of change with their own agency (Timmerman, 2005; Timmerman et al., 2010; Kumpel et al., 2020). McNie (2017) identified the interface with stakeholders as a key area for improvements with knowledge gaps in: understanding better decision-making processes; creating linkages between scientists; boundary organisations and stakeholders; and understanding how funding organisations and research managers make decisions about research priorities.

Indices and approaches to WS often under emphasise social aspects - in particular governance (Cook and Bakker, 2012), an important factor in malfunctioning water systems (Srinivasan et al., 2017). Incorporating human capabilities, socio-cultural dynamics, and political institutions into water governance could lead to a better understanding of WS (Padowski et al., 2015; Wutich et al., 2017). Involving stakeholders in the co-creation of WS assessment tools (Jensen and Wu, 2018) could help increase the legitimacy and salience of data. Local knowledge should be incorporated into citizen science strategies: people are sources of information but they also generate a common understanding of water dynamics in the context of the socio-ecological processes involved. Co-creation will facilitate the communication of WS data in a harmonised and aggregated way that improves decision making based on real scenarios with actively involved and engaged stakeholders (Espey et al., 2015; Octavianti and Staddon, 2021; UN-TaskForce, 2010; Wheater, 2000).

Co-creation improves governance, as well as stakeholder cooperation and coordination around data availability - a weak aspect of many WS systems. One example of co-creation is through polycentric governance, where decision-making processes are more decentralised and diversified, by considering the relationships with stakeholders and the interactions among different scales of governance systems (Ostrom et al., 1961).

Traditionally, data credibility has received most attention, but recent research shows that underestimating data legitimacy and salience can be detrimental, leading to the "information-rich but communication and action poor syndrome" (Behmel et al., 2016) due to a lack of effective communication between science and decision-making processes. If properly addressed, this interface could transform information into real impact. Stakeholders provide local and specific data that can strengthen data saliency and legitimacy (De Filippo et al., 2021): complementary tools such as the mapping and analysis of stakeholders (as referenced in Table 1) provide key information to make WS decisions more relevant.

2.5 Interface with the socio-economic context

Effective DGSxWS lies in understanding the context of water security in different environments/basins. This context must include the socio-economic dynamics occurring at different scales within basins. These dynamics impact WS availability through productive activities, water use and access, and socio-cultural processes. Each one of these dynamics, individually or grouped, define the framework in which data should be analysed for WS.

Different socio-economic processes across multiple scales in the basins are conveyed in the data analysis clusters with experiential scale-based metrics and resource-based metrics that guide WS strategies. However, the wide range of conceptualizations of WS is reflected in the great variation in the methods of assessment of WS, which also vary greatly (Gerlak et al., 2018). This variation in conception and assessment generates confusion that affects the course of decision making at individual, community, and government levels, as well as responses to development models, local conditions, market demands, and political frameworks.

Considering the socio-economic context of data collection will reinforce the saliency, legitimacy, and credibility of that data - characteristics that are necessary for the systemic approach, mentioned in the proposed interface of the DGSxWS. Socio-economic data collection should use both quantitative and qualitative research methods and consider different and complementary sources of data (stakeholder databases and primary data), type of systematisation requirements, and type of information analysis. For example, as the largest user of freshwater, the agricultural sector (land use, crop production, animal protein production, and supply chain) should be prioritised when developing a DGSxWS (Hotlos, 2008). Also, the increasing demand of water for domestic use may be directly tied to urbanisation and thus, the associated economic activities.

The socio-ecological framework with which data is analysed is supported by the understanding that environmental problems are, at their root, social problems (World Bank, 2002). These considerations suggest that water systems should be understood through the human-nature linkages incorporating ecological, economic, cultural, and physical systems at different levels (Bogardi et al., 2012). Socio-ecological systems are characterised by a systemic vision of the ecological and the social components, their structure, functioning, and emergent properties across spatial and temporal scales.

Studies around the world, including indices and approaches to WS, tend to focus on technical aspects (Xenarios et al., 2020), for example the cost of water quality monitoring for human consumptions (Delaire et al., 2017; Peletz et al., 2018; Crocker and Bartram, 2014; Peletz et al., 2016), indicators for sustainable consumption and production activities (Hoff et al., 2014), continuous access for water supply (Giné and Pérez-Foguet, 2010; Jepson, 2014; Sullivan et al., 2003), rural conditions for water security (Dickson et al., 2016), and urban metabolism (Ghosh et al., 2019). While these studies offer distinct and/or complementary perspectives, they do not consider or constitute system thinking.

One of the largest challenges in gathering socio-economic data for WS is ensuring that the complexities of the socio-ecosystem are captured. When approaching an analysis for socio-ecological systems, the use of reductionist frameworks oversimplifies the system, ignoring underlying causes or unforeseen effects. Water use is often analysed from the scale of individual users. In a socio-ecological system, while it is important to recognize the role and behaviours of individuals, it is the relationships and interactions between individuals that represents the patterns of the system as a whole (Maniates, 2014). Water use (i.e demand) is a key factor for socio-economic assessment. A systemic framework is needed to collect data that represents not just the surface level of water use, but the root drivers of water user behaviour (Spash and Dobernig, 2017)

In the field of ecological economics, a framework known as socio-economic metabolism has emerged as a way to analyse the human-nature relationship through their biophysical exchanges in socio-ecological systems (Fischer-Kowalski and Weisz, 1999). This method has potential for DGSxWS. Metabolism studies have historically focused on finite natural resources such as fossil fuels and minerals, however Fischer-Kowalski and Haberl (1998) argue that water should be included due to the negative impacts on WS that socio-economic activities have caused. Madrid-López (2015) found that water has been omitted from socio-economic metabolism not because of a lack of data, but due to the conceptual challenge of analysing a renewable resource that flows in a more cyclical manner. The utilisation of socio-ecological systems framework, which recognizes complexity and interactions within systems, could be helpful to incorporate metabolism studies into water security.

3 A Framework for Data Gathering Strategy in the Water Security Context

3.1 Challenges

There are several valuable frameworks and handbooks on data gathering for water security (WS) that have approached the issue from different perspectives (Bartram and Ballance, 1996; of Meteorology, 2017; Chapman, 1996; IISD, 2015; Timmerman et al., 2000; USEPA, 1997; Ward et al., 1990; WMO, 2013; UN-Environment, 2017). Due to the problem's complexity and technical improvements/variability across basins, there is no generally-accepted practical strategy that supports all phases of a Water Security Monitoring Plan planning and optimising in a holistic manner (Khalil et al., 2011; Strobl and Robillard, 2008).

We observed that existing tools give different emphases to the five interfaces identified. The interface between data and the physical environment is the one usually receiving most attention with information provided on sampling methods, approaches to sampling strategies, data quality best practices, statistical tools for analysis, and interpretation. This interface is key to creating credible (Lehtonen, 2015) and robust data. Further work can be done in incorporating the temporal dimension when assessing WS (Srinivasan et al., 2017), by considering the dynamic of the WS system (understanding how internal changes are happening), and understanding the external stressors of the system (economic and political situation). A dynamic assessment would also be able to better capture socio-political changes, which are usually more abrupt than physio-hydrological ones. Incorporating dynamics into the framework needs to be facilitated by a change in medium (and therefore in the content structure and usability) from printed to digital, since digital media is better for iterative processes, restriction, interlinkages, and dataset management (Behmel et al., 2016).

The relationship with project resources is usually addressed to produce an estimate of costs (Bartram and Ballance, 1996; WMO, 2013). In reality, resources are always finite and the tradeoff between cost-quality-time should be acknowledged and managed, with the intent of optimising results given available project resources. A more recent framework (UN-Environment, 2017) explicitly calls for a capacity assessment, underlining the importance of project-tailored solutions. Reporting data within existing requirements and legislation has been addressed extensively (Bartram and Ballance, 1996; WMO, 2013). Lastly, soft aspects (motivation & leadership, knowledge, and staff retention) are influential factors (Peletz et al., 2018) in the success of a monitoring project and should be considered of equal, if not greater, importance to financial and physical assets when evaluating project resources.

Bridging the gap between gathering, accessing, and sharing data is a strategically important step to global water security and achieving the associated SDGs (SDG6, but also SDGs 1, 2, 3, 4, 5, 7, 8, 9, 11, and 14). Technological innovation in the past decades has dramatically increased the amount of data that is gathered. Despite these advances, the creation of an open data culture is still in its infancy and will not only require a change of mindset, but also a revision of the whole process of data gathering, editing, storage, and access. As a starting point, following the FAIR guiding principles (Wilkinson et al., 2016) is essential, yet the problem of properly transferring such knowledge to all users' levels remains. While FAIR principles are known and accepted internationally in global scale datasets, those working at small scales (e.g., municipalities, basins) are not always aware of, or follow, such principles. This is an important problem because most of the data required for understanding and assessing WS is gathered at these smaller scales. Thus, there is a need to bridge the gap between data gathering, access, and sharing.

The linkage between stakeholders and information is often approached from a top-down perspective where the research community produces new information to be communicated to relevant stakeholders. The engagement of stakeholders as data producers has only emerged in recent years through the phenomenon of citizen-science (Conrad and Hilchey, 2010; Walker et al., 2020) and therefore is typically absent from older frameworks. Stakeholders should not be seen only as information receivers but as active players in the identification of information needs (Timmerman et al., 2000). Timmerman et al's study proposes different information categories (information for policy evaluation, for policy preparation, and for operational water management) but there is no mention of users and communities nor information-related to behavioural change, which is essential to achieving water security.

The socio-cultural context is often acknowledged but not incorporated into the data gathering framework. While this is not strictly part of a DGS, it benefits to be aware of social aspects since they may influence data quality salience and legitimacy (Peletz et al., 2018). Additionally, the involvement of stakeholders in the process is very beneficial in creating information that is understood and used. This requires a stronger collaboration between hard and social sciences and the co-creation of tools for implementation.

Operationalisation of a framework is, obviously, extremely important. The only data on the usage of WS assessment tools that was found (Norman et al., 2011) reported a gap between the abundance of analytic tools produced by academics and uptake by water professionals. A balance should be found between the necessary complexity needed to address WS and the tool usability. This also implies finding a compromise between the needs for generalisation and practicality. In this paper, the issue was addressed not by prescribing strict procedures but bringing attention to key relationships and qualities that a DGS should have.

The conceptual aim of this framework can be summarised as shifting the focus of DGS from a “data-to-information approach” to a “data-to-action approach”. This implies moving from an intra-disciplinary perspective (e.g. water quality, hydrology) to an interdisciplinary one that prioritises the relationship between produced information and stakeholders.

3.2 Suggested steps

To address and overcome the obstacles, we have identified a set of activities that a research team or project could undertake when addressing a DGSxWS. These activities are intended as an initial step to bring attention to specific issues pertinent to the five interfaces (Table 1). For each interface a set of goals was identified with a related activity and key references. This table is a suggestion, it is not to be understood as mandatory or limiting. In order to move from a “data-to-information approach” to a “data-to-action approach”, activities in Table 1 can be used as a starting point to evaluate and understand the current situation of a certain place in relation with the WS problem/concept.

Table 1: summary of key activities related to each interface

Goal
A. Data-scape (data collected is harmonised and comparable with existing one)
A.1 Determine data requirements
A.2 Harmonise data with existing ones to fill gaps and avoid duplication
A.3 Set data management plan
A.4 Collect and preserve data following the FAIR guiding principles
B. Physical Environment (data is able to capture variability with acceptable level of statistical
B.1 Basic characterization of study area
B.2 Define scope and aim of investigation to ensure that data will translate into valuable information
B.4 Collect secondary data
B.4 Primary data: sampling design and data collection

B.5 Ensure data quality control
B.6 analyse risks I

C. Project resources (data strategies optimise project resources)
C.1 Understand project constraints (time, cost and quality) and the feasibility of sampling strategy these con

C.2 Optimise the drafted sampling strategy in relation to available resources
C.3 Plan for data while you plan the project
C.4 Maintain agility and ensure a continuous cycle of feedback

C.5 Avoid the failure of either project or data strategy through maintaining the right balance of resource allo
C.6 Invest in training and capacity development
D. Stakeholder (Information produced by data reaches relevant stakeholders (policy makers, co
D.1 Understand role of stakeholders and their possible engagement
D.2 Understand from key stakeholder, their information needs related to the study topic
D.3 Analyse risks II

D.4 Plan how to reach stakeholder with new information produced
D.5 Involve key stakeholders in the dissemination and process
D.6 Incorporate local knowledge from informal pathways
D.7 Ethical considerations
D.8 Co-production of information on local scales
E. Socio-economic context (data strategy takes into consideration specific characteristics)
E.1 Identify elements that characterise the context

E.2 Assess external context identifying key factors that could promote water insecurity
E.3 analyse risks III

4 Conclusion

The main purpose of this paper was to understand how a Data Gathering Strategy for Water Security (DGSxWS) could be designed in a way that ensures the data gathered is credible, legitimate, and salient. Additional attention should be given to how data is stored and shared amongst stakeholders so that the generated information can form the foundation for action to improve WS.

A complex system of knowledge emerged from a review of the literature. WS can be approached using different frameworks, has several accepted definitions, and has a multitude of indices and indicators which in turn often need more than one parameter to be estimated. This complexity constitutes a barrier to the operationalization of data and DGS by practitioners and thus change on the ground.

In order to orientate practitioners and researchers within this complexity, a logical framework was proposed. Given the diversity of approaches, research scopes, and socio-cultural contexts found across basins, a single rigid approach is not appropriate. Therefore, a logical framework was proposed that would capture the key dimensions of an effective data collection strategy but have sufficient flexibility to be applied in different contexts.

The proposed tool directs the attention of practitioners to five key areas that should be addressed: the description of the observed environment, the available project resources, the relation with the existing data-scape, the relation with the socio-economic context, and the stakeholders. For each area, a set of activities that could help address key challenges was proposed.

The proposed framework does not give a definitive answer to the issue of data-gathering. This is appropriate as in reality a single defined method is not appropriate. We advocate a a new approach that addresses multiple spheres (physical environment, socio-economic), uses different data types (qualitative and quantitative data, primary and secondary), and stresses the importance of seeing the data gathering process as a step in the data-information-stakeholder-impact chain and thus real change on the ground.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Contribution

Conceptualization: GB, TC, CW.

Writing and editing: GB, YTSC, MVP, RM,NT XP, CMP, CW, TC and Victoria Anker.

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