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Perceived barriers and advances in integrating earth observations with water resources modeling

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ABSTRACT

Advances in computing, collection, and sharing of Earth Observations (EOs) have significantly improved the potential for integrating EO and water resources models. Inadequate observational data for the systems simulated have been a persistent limitation in developing robust water resources models. Although various EO datasets have been available for decades, they have been under-utilized for water resources modeling. This can be due to sensor and product limitations, including spatial, spectral, and temporal resolutions, and the reluctance of the water resources community to adopt the state-of-art quickly. Motivated by the dual agenda of engaging the water resources community on various aspects of integrating EOs with water resources modeling and understanding the likely factors that limit a deeper integration of EOs in water resources management, we investigated the communities' perception of water resources modeling and EO integration. This paper summarizes the findings of a web-based survey conducted at the annual ASCE-EWRI (American Society of Civil Engineers-Environmental Water Resources Institute) International Water Congress in 2022.

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The analysis of responses (n = 74) identified limited spatial resolution, atmospheric and cloud interference, and lack of in-situ validation data as the highest perceived barriers to integrating EOs with water resources modeling and management. Perceptions among different groups of participants and even within the groups were different. For example, the perceived barriers often differed between researchers and non-researchers (e.g., policymakers and practitioners). There were differences in perception among the remote-sensing and water resources researchers within the research community. Even among water resources communities, disparities existed between the perceptions of respondents who also identified as knowledgeable about remote sensing and those who didn't. These observations highlighted the need to intentionally develop a convergent group and domain to integrate the disciplines involved and capitalize on the advancements that have improved the EO for water resources management.

1. Introduction

Water resources management, which includes water quantity and quality for all types of water bodies and their tributary watersheds, remains a critical global challenge. The United Nations (UN) Sustainable Development Goal (SGD) 6 recognizes the importance of water as the core of sustainable development, which is critical for socio-economic development, energy and food production, healthy ecosystems, and human survival. Water resources management is also vital for adaptation to climate change (Michalak, 2016; Cui et al., 2023). The 2022 report on the UN SGD report notes that about three billion people depend on water with unknown quality due to a lack of monitoring. While monitoring challenges differ in different parts of the world, many challenges associated with insufficient or ineffective monitoring are universal. In addition to monitoring, effective water systems management requires numerical models that can help managers plan; however, access to in-situ observations to drive numerical models has been scant globally. The situation is particularly acute in developing and under-developed regions where the resources for observation and monitoring of water resources are particularly scant (Kirschke et al., 2020; Nowicki et al., 2020). Even within developed countries, there are significant regional and transboundary gaps along with data quality and availability issues that limit the water resources management potential (Josset et al., 2019; Kirschke et al., 2020; Talchabhadel et al., 2021; Jordan and Cassidy, 2022; Wyrwoll et al., 2022).

Water resources modeling is crucial in understanding how a watershed system behaves, its resilience and sustainability, where the stressors are, where and when to intervene, and the expected outcome of the interventions. The traditional paradigm has been to collect data about a watershed system from multiple sources, such as in-situ point monitoring of water quality and weather patterns, static land use maps, and information on geophysical parameters (e.g., soils), to develop a water system model that targets the parameters of interest. This method, at best, provides a static representation of the system, which does not evolve with change (e.g., changing land use or climate) and often is changed abruptly at a timescale in the order of five years to a decade when the models are updated to obtain drastically different predictions (e.g., Chesapeake bay model (Hood et al., 2021)). Though many models are based on governing physical equations (e.g., conservation of energy and momentum), many simplifications and empirical parameters are used. Often, these parameters are not directly observed but estimated as temporally static quantities with very limited spatial variations during the calibration process. Such calibration has several known adverse effects on the robustness of the resultant model (Acero Triana et al., 2019). These modeling schemes were devised in an era where satellite-based Earth Observations (EOs), which can be assimilated to update the estimated changes at fine temporal and spatial resolutions, were not readily available and have not changed since. Though shown to be useful for developing water resources models (Sun et al., 2016; Zhang et al., 2017), assimilating EO-based data products with model-estimated quantities to improve the model state variables and parameter estimation is uncommon outside the research domains. This creates a scenario where more in-situ data is needed to build and calibrate a robust model than what is available. For example, in the United States, the Clean Water Act (Copeland, 2012) mandates developing a plan (e.g., total maximum daily loads or watershed management plan) to mitigate water pollution by restoring the water quality in the water body to its designated use. These plans often require the development of numerical models to identify sources of pollutants and develop mitigation strategies. Lack of data is cited as one of the critical inhibitors in developing water system management models or failure of such models to represent the water systems involved robustly (TMDL A&M TC, 2017). Further, the in-situ observations are often collected at a scale different from the scale at which the model simulations are carried out or required, thus introducing a representation error (Beven, 2008).

EOs are often perceived to be a solution to the data limitation issues, albeit often without a clear conceptual model pathway for their integration into modeling. Research has shown how some regions of the United States are ideal for such an integration (Sridharan et al., 2022), which may be extended globally. Data from several modern satellite platforms are now available free of cost (e.g., Landsat and Sentinel), and new sensors (e.g., microwave, thermal, synthetic aperture radar) and data products (e.g., soil moisture, evapotranspiration, and chlorophyll-a concentrations) that are critical to water resources modeling are becoming available (Chen et al., 2022). There is much excitement around integrating remotely sensed data with water system models; however, such integration potential has yet to be realized in practice. It has been recognized that commonly used water resources models (e.g., SWAT, HSPF, HEC-RAS) must integrate better with remotely sensed data for robustness (TMDL A&M TC, 2017). But often, these models lack any mechanism to assimilate spatially discrete EOs (e.g., soil water, vegetation covers, algal bloom size, location, etc.) on a regular timescale. A preliminary study of reports submitted to the United States Environmental Protection Agency (USEPA) describing waterbody mitigation plans using the Total Maximum Daily Loads (TMDL) report selection tool (Quinn et al., 2019) did not identify reports of using EOs beyond using it for land use identification. Some reviews and discussions in the literature have documented the integration of remotely sensed data with water resources models describing the scale of integration and model data requirements satisfied by the EOs, e.g., Wang and Xie (2018); Quinn et al., (2022). However, in practice, integrating EOs with water system models is often limited to satellite data for static land-use maps. Most water system models do not have routines to integrate remotely sensed data, and the data are not efficiently and reliably available. Tools like Google Earth Engine (GEE), Open Data Cube (ODC), and Sentinel Hub offer platforms combining the data and computations necessary to process EOs. Still, they don't directly integrate with common water resources models. Additional challenges related to integrating EOs with water systems models include workforce training and the spatiotemporal resolutions available.

The ASCE-EWRI (American Society of Civil Engineering-Environment and Water Resources Institute) Remote Sensing Applications for TMDL Modeling Task Committee (RSTC) was established to understand and document these challenges. The RSTC conducted a workshop and a survey at the ASCE-EWRI annual water conference, Water Congress 2022, with a dual purpose: 1) to engage the water system professionals and 2) to understand the perceived barriers to a more holistic application of remotely sensed data in water quality modeling and advancements that may be needed for better integration. This paper presents the survey results and identifies some opportunities for better integrating remotely sensed data with water resources modeling.

1.1. Survey description

Members of the RSTC developed a survey instrument to solicit the perspectives of the water quality modeling community on their familiarity with and perceived barriers to using remote sensing data (see supplementary for the full instrument). The survey instrument has three broad sections:

1) "About you"—designed to understand the typologies of survey respondents based on their self-identified professional group associations.
2) "Barriers and Limitations"—a set of questions answered on a Likert-scale on the perceived barriers and limitations of remote sensing technologies and water resources modeling,
3) "Possible Solutions"—a final set of questions on the perceived efficacy of different solutions to improve the application of remote sensing for water resources management.

The intended audience of the survey included researchers, practitioners, and regulators/policymakers working in the water resources management domain. The online survey was administered through Qualtrics and sent initially to all participants of the 2022 EWRI Water Congress, an annual event hosted by the American Society of Civil Engineers (ASCE) that brings together different communities working on water management. However, there was no requirement for registration in the EWRI Water Congress to be able to take the survey. We received 109 responses; however, only 74 had data beyond the initial consent and self-identification. This latter set was retained for the subsequent analysis.

2. Remote sensing and water resources modeling community

Remote sensing and water resources modeling have developed as two separate scientific domains with a limited intersection. Nevertheless, even back in the 1970s, there were ideas on how remote sensing could assess water resources (Knipling, 1970; Anding and Kauth, 1970). In recent years, several water quality and watershed parameters have started to be reasonably estimated through remotely sensed EOs (Dube et al., 2015; Gholizadeh et al., 2016; Yang et al., 2022). Although remotely sensed data is used to derive water resource parameters, integration with water resources modeling workflow has been limited and ad hoc, performed on individual applications rather than on a widespread basis. Most water resources models were not developed in a manner that conforms to integration with remotely sensed data at the management scale. Similarly, remote sensing data products/sensors are typically developed to describe a landscape's physical and biological properties rather than to feed into water resources models. Although remote sensing communities have developed data products that can inform water resource parameters, such as soil moisture, integration with water resource models has yet to be widely or consistently realized. Most of the overlap in the literature has been incidental and often an afterthought. Remote sensing researchers have focused on methodological approaches to develop water quality and other estimates from remotely sensed observations. However, using these data to improve understanding of water system dynamics and modeling has been limited.

Factors such as the type and size of the water body, concentration of contaminant of interest, type of water quality parameters (optically active vs. inactive parameters), and spatiotemporal resolution needed to calibrate water resources models restrict water quality monitoring applications using satellite based EOs. Nevertheless, to effectively utilize remotely sensed data for water quality modeling, various groups of stakeholders, including domain researchers (both water system and remote sensing), regulators (who develop incentives to improve water quality and enforce laws), software and computer scientists, and practitioners (who used models and develop management plans) should work together to tackle both the scientific and adoption challenges. In the survey, we strive to discover the motivations and characteristics of the early adopters of this technology, what could motivate other potential adopters to follow this initial cohort, and the constraints and obstacles to more widespread acceptance and innovation. We also seek to identify unifying visions of the type of integration between models and remote sensing data products that might stimulate further progress.

The survey's first question helped capture the self-reported groups of the participants (Fig. 1). It may be noted from Fig. 1 that several respondents self-identified in multiple groups, e.g., researchers, water system researchers, remote sensing researchers, and data science researchers. Such knowledge in multiple domains is crucial to understanding the nuances, capacity, and limitations of the technologies involved.

The respondents include a self-identified mix of researchers (60) (including remote sensing, water resources, and data science domains), practitioners (14), and regulators/policymakers (2) (see supplementary for grouping criteria); note that data science group is not shown in the plots, but they are included with the researchers. Two sub-groups within the researcher group – water system (19)

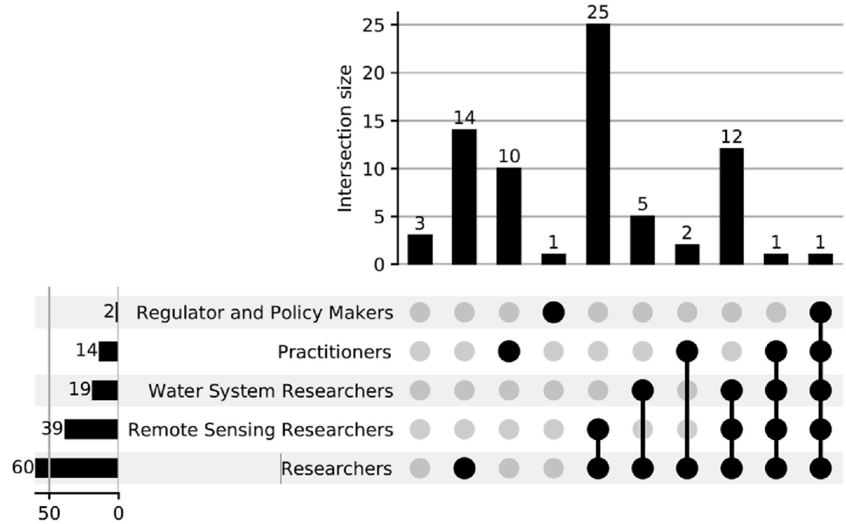

Fig. 1. Overview of the self-identified categories of respondents to the survey. Intersections between several groups are also shown.

and remote sensing (39) – were considered to understand differences in opinion among the responses. The mix is not entirely unexpected, as the primary mechanism for survey promotion was based on a water congress that includes water systems, researchers, and practitioners. A relatively large number of remote sensing experts participated in the survey, which was expected, given the community's interest in actionable and applied research (Wellmann et al., 2020; El Serafy et al., 2021). However, there was a lack of representation from regulators and practitioners that needs to be addressed in future surveys. This survey and its subsequent iterations likely not only gauge the opinions/beliefs of the respondents but may also have the potential to be educational tools. The respondents could learn about a new technology or application and consider its applicability in their domain. All participants were requested to rate their participation/understanding of some common remote sensing and water resources modeling technologies (see Supplementary Fig. S1) on a scale from 1 to 5, with one meaning little or no experience and five an expert. Most remote sensing technologies scored a high median of more than 3.5, while others scored an average of three (3). However, it seems there was a lack of understanding of data fusion technologies, with a median of about two. This is not entirely surprising as data fusion is a relatively new and active research topic.

3. Barriers and advancements

The second and third sections of the survey discussed the perception of barriers and limitations among the participants that inhibit the use of remote sensing technologies and data products more widely in water resources modeling. With the assumption that the perceived barriers can be both from the water system domain (e.g., the lack of water resources models to take advantage of the remotely sensed data) and from the remote sensing domain (e.g., lack of appropriate spatial or temporal resolution), the sections were divided into four questions.

Question 1"Thinking about the adoption of satellite-based remotely sensed data, please rate the prevalence of the following issues (see supplementary for the list of issues). Please rate on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier]. Put N/A if you are unfamiliar with an option."

Question 2"Thinking about water resources and quality management, please rate the prevalence of the following issues in adopting remote sensing technology (see supplementary for the list of issues). Please rate on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier]. Put N/A if you are unfamiliar with an option."

Question 3: "How would you rate the programmatic support for the following agencies (see supplementary for the list of agencies) ? Please rate on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier]. Put N/A if you are unfamiliar with an option."

Question 4: "Rate the ability of the following advancements to ease some of the barriers in incorporating remote sensing with water quality modeling (see supplementary for the list of advancements). Please rate on a scale of 1 [not likely a significant advancement] to 5 [extremely useful]. Put N/A if you are unfamiliar with an option."

Data collected for these questions is presented in Fig. 2, illustrating the general perception and the difference among groups. Note that boxplots in Fig. 2 include data from survey participants who self-identified with a particular group; one participant may be in multiple groups, and the same record may be used multiple times. It is clear from Fig. 2 that there are some divergences of opinion among groups, but overall spatial resolution and atmospheric and cloud-related issues are the key perceived barriers to the widespread adoption of remotely sensed data. The limited number of modeling parameters that can be parameterized using remote sensing, the cost of obtaining high-quality imagery, lack of in-situ data for validating remote sensing products, and inadequate training on water quality modeling are generally perceived as the key barriers to using water quality models that can ingest remotely sensed data. Programmatic support to space and water resources regulatory agencies is not perceived as a significant barrier by any group. Of the

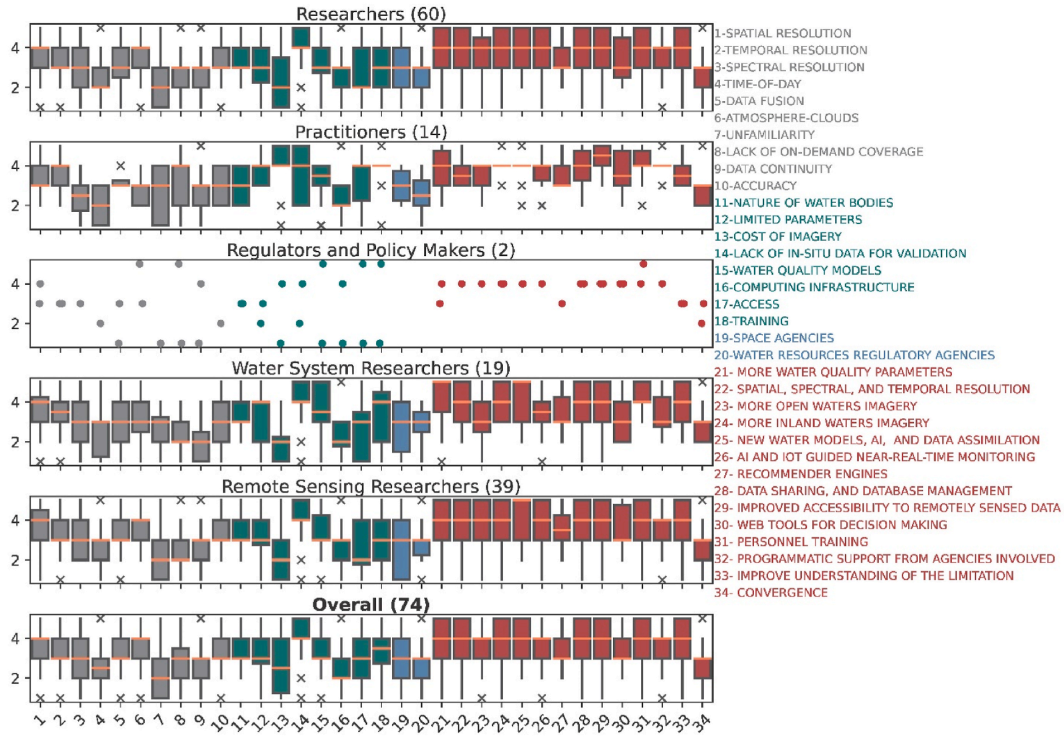

Fig. 2. Results from the survey were partitioned based on the self-identified association with different communities. Box plots display the lower quartile (Q1) and the upper quartile (Q3) values of the responses. Orange horizontal lines represent the median of the responses. The responses were recorded on a 1–5 scale, and the number in the bracket is the number of respondents in each group. Questions 1–10 are on likely perceived barriers for remotely sensed data products usage, 11–18 are related to water resources modeling issues, 19 and 20 are on programmatic support, and 21–34 are on possible solutions to improve the state of practice. Only two respondents identified as "Regulators and Policy Makers"; therefore, their responses are shown as dots. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

solutions tested for the enhancing widespread use of remote sensing in water quality modeling, the role of recommender engines, web-based decision support tools and convergence between sectors were generally not perceived to be particularly useful.

In the latter figures (3 onwards, and in *Supplement*), the box plots are comprised of responses from participants who self-identified as belonging to one group, or an intersection of multiple groups, but each response was used only once. So, for instance, if a participant identified themselves as a water systems researcher, their responses were binned into that group. However, if a participant identified themselves as both a water systems researcher and a practitioner, then their responses were binned into the group comprised of the intersection of water systems researchers and practitioners. We will discuss each question and section in detail in the later sections of this paper. With a limited data set and the overall purpose of this work to simply provide guidance, not to test a hypothesis, no attempt was made to assess the statistical significance of these results.

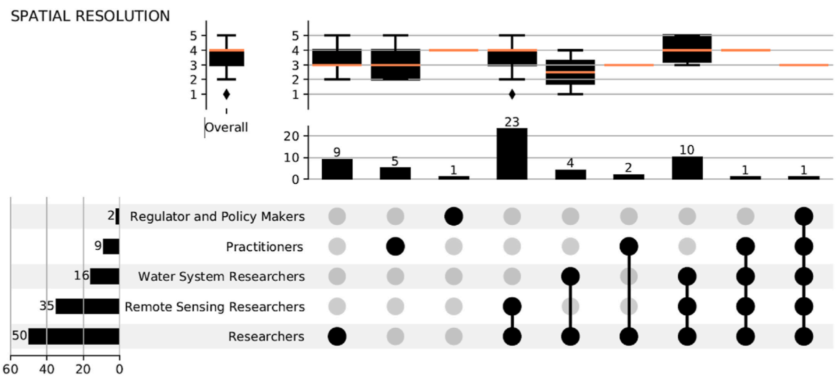

Fig. 3. Community perception on the spatial resolution of data products on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier].

3.1. Resolution of remotely sensed data

3.1.1. Spatial resolution of the data products

The spatial resolution of a satellite data product is the measure of the smallest object that can be resolved by the sensor. Spatial resolution is often represented by the linear dimension of the ground represented by each pixel. The resolution is often a function of the nature of the platform (e.g., altitude, orbit) and the sensor. Typically, it is desirable to have a finer spatial resolution (each pixel represents a small linear dimension of the ground); however, the signal-to-noise (SNR) ratio at finer resolution and computation limitations may make other coarser resolutions more attractive for larger water bodies or objects of interest. The finer spatial resolution satellites (e.g., Landsat, Sentinel-2, and Planetscope), which may be more suitable for smaller inland water bodies/reservoir studies, are often designed with an SNR for land and not water. As a dark target, water requires better SNR to resolve aquatic properties. Satellite-based sensors have gotten finer, particularly with the advent of commercial CubeSat/SmallSat infrastructure. Here we classify data products as – low resolution (>60 m/pixel), medium resolution (10–30 m/pixel), and high to very high resolution (<5 m/pixel). Most of the freely available data sources used by the water resources community are medium to low-resolution, with a relatively long history of data collection that spans decades. Sheffield et al. (2018) have discussed many such platforms and data products in their review. New datasets with a much finer resolution are also becoming available e.g., Maxar Worldview 3 (Cantrell et al., 2021) and Planet SkySat (Kim et al., 2022), that allow the assessment and classification of smaller objects of interest, particularly in urban areas, that can rival data collected from aerial operations. The high and very high-resolution datasets are still not available widely and often need to be procured, particularly for commercial use. NASA's Commercial Smallsat Data Acquisition (CSDA) Program and other similar programs from other space agencies are making commercial data available to some academics and other researchers (Harrison and Mascaro, 2021; McCarty et al., 2021). Data fusion from multiple sensors has been used to derive higher spatial and temporal resolution imagery. Fusion techniques enabling high and low spatial resolution data to derive high-resolution data products are also becoming increasingly popular, particularly for land use classification (Vali et al., 2020). These methods rely on establishing empirical relations between the fine (e.g., panchromatic band) and coarse-resolution (e.g., multispectral sensor) data products to derive a higher spatial resolution data product.

Spatial data are widely used in water resources modeling, and adequate spatial resolution is often critical to represent the water body, watershed, and other objects of interest. Water resources modeling explores the spatial and temporal relationships between water quality pollutants, watershed hydrology, river hydraulics, plant life, solute transport, and other river water pollutants. The spatial resolution of the data is significant in determining the spatial resolution of the model and various simulated quantities (Cotter et al., 2003; Baffaut et al., 2015; Fisher et al., 2018). There are several types of minimum input data required across water resources models, including Digital Elevation Models (DEM), land use and land cover assessment, soil data, and precipitation. And evapotranspiration. Data integrated into water resources models can also include remotely sensed data such as soil moisture (Abbaszadeh et al., 2020) reservoir storage (Dong et al., 2023) and evapotranspiration (Huang et al., 2020). Models are known to be sensitive to the spatial resolution of the data. A comparison of the effects of the resolutions of DEM, land use, and soils in a Soil and Water Assessment Tool (SWAT) model indicated that DEM was the most sensitive input variable that affected streamflow, sediment, and total maximum daily loads (TMDL) predictions (Cotter et al., 2003). DEM are used to capture the topographic features such as channel network, location of drainage divides, channel length and slope, and sub-catchment properties, and watershed boundaries. A comparison of the delineated drainage/watershed area showed that the drainage area decreased by 55% using a 10 m DEM compared to a 3.5 m DEM (Roostaee and Deng, 2020). A similar comparison of the effects of soil data in SWAT model predictions was performed that showed differences in streamflow and sediment (Geza and McCray, 2008). These observations demonstrate the importance of appropriate spatial resolution for water resources modeling.

The survey results show that spatial resolution was identified as a significant barrier with a median of about four (4) on a 1 to 5 scale (Figs. 2 and 3). Together with atmospheric effects and clouds, it was identified as the most significant barrier. Community members who identify as both water resources and remote sensing researchers or remote sensing researchers rank spatial resolution as a significant barrier (Fig. 4). However, water system researchers without a remote sensing research background and other researchers (not remote sensing or water systems) rated spatial resolution as lower at 2.5 and 3, respectively. The reasons for this disparity are unclear; perhaps it may be attributed to the different applications of remotely sensed data for different groups of researchers. For exam-

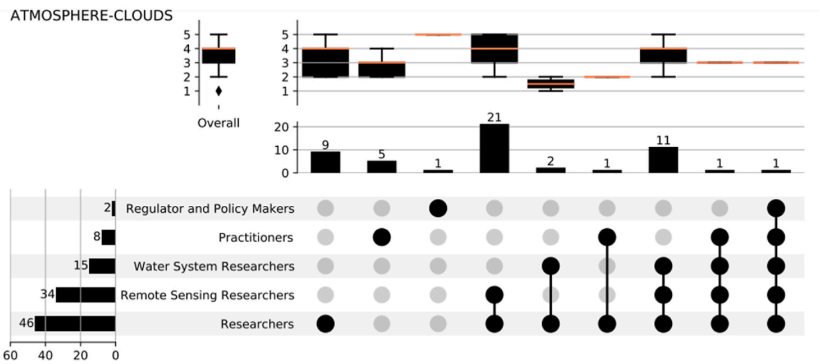

Fig. 4. Community perception of atmospheric and cloud interferences as a barrier on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier].

ple, for assessing non-point pollution mitigation measures (e.g., dry swales), even a resolution of ~5 m/px is coarse. However, such a resolution is adequate for identifying land-use types in a watershed. Also, many data products (e.g., DEM) are static and have been made available from aerial platforms at 1 m or even finer 30 cm resolution for many parts of the world.

3.1.2. Temporal resolution of data product

The temporal resolution of the EO data products refers to the time between data captures for the same area. For most satellite-derived data products, this is the time it will take for the satellite with the same equipment to pass over the same region. Most remote-sensing satellites are polar-orbiting satellites with a temporal resolution that generally varies from 1 day to 35 days (Toth and Jóźków, 2016). Some satellite platforms can act together as a constellation of satellites (e.g., PlanetScope) and improve temporal resolution. Recently satellites with limited propulsion are also becoming available that can enable sub-daily and video data capture (e.g., Skysat) as well as tasking for capturing images at specified periods of time. Passive and active imagers attached to propelled orbiting stations, such as ECOSTRESS(Fisher et al., 2020) and EMIT (Green et al., 2020) on the international space station, can also provide data at different time-of-day; the temporal resolution of data from such sensors may be hard to define which can present another issue for those requiring consistent overpass times for their applications.

Temporal resolution is essential to capture the watershed's biogeochemical dynamics such as the changes in streamflow, land-use change, and climate characteristics (Shuai et al., 2022). An evaluation of the Jason 2 satellite altimetry data products with observed gauge data showed that the uncertainties in the satellite altimetry measurements might be due to the temporal resolution of the satellite altimeter. It was suggested that 10 days per data point missed significant peak water levels with short duration (Darko et al., 2023). Similarly, the temporal variability of rainfall data impacts the watershed modeling results. A sub-daily precipitation data is expected to yield better results than daily data when calibrated to an observed gauge (Huang et al., 2019). There are also exceptions where a coarser dataset may perform better (Shuai et al., 2022).

The survey respondents did not identify temporal resolution as a significant barrier, with a median of 3 (see Supplementary Fig. S2). Researchers, however, with expertise in both remote sensing and water quality modeling, did rate temporal resolution as a significant hurdle with a median rating of 4, at par with spectral resolution. Temporal resolution can be effectively improved by adding more platforms, developing constellations, and cross-mission coordination, such as harmonized Landsat-Sentinel (Claverie et al., 2018). These can be especially effective in areas prone to cloud cover, where no coverage may be available for months. Homogenization can include higher frequency sub-daily datasets. However, the availability of sub-daily datasets is relatively new and expensive, limiting usage and demand. Nevertheless, recently developed techniques have shown some promising use of high temporal resolution imagery for applications such as coastal plume tracking (Johansen et al., 2022).

3.1.3. Spectral resolution of data products

Most satellite-based sensors collect multispectral EOs and use passive sensing systems, which detect and measure the natural radiation emitted or reflected by the Earth's surface, atmosphere, and objects on the Earth. In such passive systems, bands are used to designate regions on the electromagnetic spectrum where the measurement is being done by the onboard instruments. Multispectral satellites typically have 3 to 15 bands, but the number of bands can vary depending on the specific satellite and its sensor configuration. Bands are associated with bandwidth, which represents the region that is aggregated by the instrument. These band observations, sometimes from different platforms, are used to compute EO data products; for example, Landsat 8 Normalized Difference Vegetation Index (NDVI) is used to quantify vegetation greenness and is based on bands 5 (Near Infrared [NIR], 850–880 nm) and band 4 (Red, 640–670 nm) of the onboard Operational Land Imager (OLI) instrumentation. Based on the Sun's emission spectra, absorption in the atmosphere, reflection, emission from the earth, and other sensor-related factors, the amount of energy available at the satellite for detection varies widely within the electromagnetic spectra. Often, a tradeoff between band region, spatial resolution, bandwidth, and desirable signal-to-noise ratio controls an instrument's spectral bandwidth and spatial resolution.

In addition to multispectral, data from hyperspectral sensors, which have a large number of bands (>100) and narrow bandwidth (<10 nm), are also available at medium or low spatial resolutions (Transon et al., 2018). There is a perception that hyperspectral imaging, particularly at medium to high spatial resolution, can revolutionize earth imaging for several domains, including agriculture, water resources, geology, and disaster management. The spectral information from hyperspectral remote sensing has been demonstrated to be helpful in estimating many water quality parameters, including organic matter, chlorophyll, and total suspended matter concentrations (Brando and Dekker, 2003; Shafique et al., 2003; Boggs et al., 2003; Biology et al., 2014; Behmann et al., 2014; Rostom et al., 2017; Mbuh, 2019; Flores-Anderson et al., 2020; Zhang et al., 2020; Cao et al., 2021). Hyperspectral data collection presents some technical challenges related to data volumes and complexity (Paoletti et al., 2019) and is not reasonably available at the spatial/temporal resolutions needed for most water resources applications. High-resolution data collection with hyperspectral imagers needs very sensitive sensors, and the energy in each band is extremely low. Nevertheless, several planned missions tackle these challenges, such as Pixxel.space [https://www.pixxel.space/], and Planet Tanager [https://www.planet.com/products/hyperspectral/].

The community identified the spectral resolution as a moderate barrier with a median of 3 (See Supplementary Fig. S3). It may be noted that water system researchers and practitioners rated spectral resolution as a lower barrier than the general community. Also, there was significant divergence among the remote sensing researchers. We speculate that perception of the benefits and problems with hyperspectral imaging and readiness of the technology for application in satellite platforms may be one of the reasons for this divergence. There is a debate on the application and readiness of hyperspectral satellite platforms within the research community. However, this speculation was not tested in this survey and could be examined in future surveys and workshops.

3.1.4. Advancement in integration

The community rated the advancement in spatial, spectral, and temporal resolution high as a potential method to improve the integration of remotely sensed data in water resources modeling with a median score of 4 (Fig. S4). It is not surprising, as improving resolutions will likely enhance the capacity to detect smaller features and changes. We did not test the difference between spectral, temporal, and spatial resolution in the advancements section. Such differentiation may be possible in future survey iterations, especially if the response pool broadens and participants increase in numbers.

3.2. Time of satellite overpass

The time of day for overpass is important for EO parameters that vary diurnally (e.g., temperature, primary production, and evapotranspiration). Most satellites have relatively similar times of day when they pass over a location. The instantaneous observations are converted to daily averages for diurnally varying parameters using the empirical relations based on the solar radiation curve, location, and other characteristics (Xiao et al., 2021; Liang et al., 2022). Platforms such as the International Space Station (ISS), with about a 4-day revisit cycle at different times of the day, are particularly attractive for measuring parameters that vary diurnally. The various time-of-day observations may allow better diurnal variation analysis. For example, it is estimated that the phenomenon of stomatal closing in response to high heat may have a significant impact on the expected transpiration from large orchards and forests that are usually not very well understood or accounted for in climate models and sub-daily observations may be able to fill the gap (Winbourne et al., 2020; Xiao et al., 2021).

Time-of-day issues were not rated highly as a significant barrier, with a median score of 2.5 (See Supplementary Fig. S5). This may be expected, as many researchers and practitioners do not consider diurnal variations; only very specific applications will need such characterizations. This may also explain the outliers, who rate this as a persistent and significant barrier.

3.3. Data fusion

Data fusion refers to the process of integrating multiple data sources to produce more consistent, accurate, and useful information than that provided by one source. Data fusion is often also referred to as image fusion in remote sensing domains, defined as the integration of images derived from several remotely sensed instruments with different spectral, spatial, and temporal resolutions to generate a more informative composite image. Combining data from Landsat and MODIS sensors is one of the earliest examples of spatiotemporal fusion approaches. Algorithms such as spatial and temporal adaptive reflectance fusion model (STARFM) (Gao et al., 2006) and enhanced STARFM (ESTARFM) (Zhu et al., 2010) can compute fine spatial resolution reflectance on the prediction day with at least one coarse-fine image pair (coarse from MODIS and fine from Landsat) on temporally close days. Numerous other methods have been developed for image fusion and can be categorized into three levels: pixel-level fusion, feature-level fusion, and decision-level fusion (Chang et al., 2018). Pan-sharpened data products that are a fusion of multispectral (MS) and panchromatic (PAN) data, often from the same platform, aimed at generating data products with high spatial (equal to that of the PAN data) and spectral (similar to that of the MS image) resolution have become widely available (Vivone et al., 2021). Multi-sensor data fusion has also been broadly applied for object detection, classification, change detection, and target tracking (Dong et al., 2009). Multi-sensor data fusion provides information required to monitor water quality parameters on a near-real-time basis, which helps decision-makers take early actions before severe water quality issues occur. However, some of the challenges in generating fused multi-sensor satellite imagery include preprocessing images for accurate data co-registration, especially for image fusion at the pixel-level (Khaleghi et al., 2013), availability of concurrently observed data products, propagation of uncertainty and error, and the need for appropriate processing algorithms and infrastructure.

Data fusion was not rated as a significant barrier by the survey respondents, with a median score of three (Fig. S6). Researchers in remote sensing and water quality modeling domains rated it as a more significant (median 4) barrier. Though pan-sharpened data is becoming more available, multi-sensor data products are not widely available and are often used for research without much wider dissemination.

3.4. Atmospheric and cloud interferences

The radiation from the sun and reflectance from Earth's surface pass through the atmosphere before reaching the satellites' sensors. Part of this radiation is absorbed and scattered by the atmospheric content. Atmospheric interference refers to the effect of Earth’s atmosphere on electromagnetic radiation as it travels from a source to a sensor. This interference can cause a range of distortions and errors in data that must be corrected to obtain accurate and useful information. There are several types of atmospheric interference, including absorption, scattering, and refraction. Absorption refers to the phenomenon where atmospheric gases, such as water vapor and carbon dioxide, can absorb certain wavelengths of electromagnetic radiation. This can result in a loss of signal strength and make detecting certain features or objects more difficult. Scattering is a distortion of electromagnetic radiation by small particles in the atmosphere, such as dust, smoke, or water droplets. This scattering can cause the radiation to be redirected, making it more difficult to accurately measure the original source. Refraction is the changes to the electromagnetic waves caused by the changes in the atmosphere's density. Several techniques, such as atmospheric radiative transfer modeling, image correction algorithms, and filters, are used to correct these types of atmospheric interference (Moses et al., 2017). Cloud cover is another common atmospheric interference that can significantly impact remotely sensed data, especially in the context of satellite imagery. It can reduce visibility by obstructing the view of the Earth's surface, making it difficult to acquire clear images (Green et al., 1996; Prudente et al., 2020). This can result in missing or incomplete data, especially in areas with persistent cloud cover. Clouds can also affect the transmission of electromagnetic radiation through the atmosphere. This can result in signal attenuation, absorption, or scattering, leading to errors or inaccuracies in the remotely sensed data. Further, the shadow effects of cloud cover can affect the interpretation of remotely sensed data.

To mitigate the impact of cloud cover on remotely sensed data, various techniques can be employed, such as using multiple satellite sensors, utilizing data from different times of day, and employing algorithms that correct for atmospheric effects (Fraser et al., 2009; Lin et al., 2013; Eckardt et al., 2013; Li et al., 2019; Sarukkai et al., 2020; Liu et al., 2023). Additionally, some microwave based active EOs, such as radar, are less affected by cloud cover than optical sensors. They can penetrate clouds and provide data on the Earth's surface even under cloudy conditions (Prudente et al., 2020).

The survey results show that atmospheric and cloud interference was rated as a significant barrier, with a median of about four on a scale of 1–5 (Fig. 7). All researchers rated it as a significant barrier. This may be expected as cloud-cover-related limitations are widely known in the community, but methods such as multi-sensor fusion are not widely used. Further, homogenized multi-sensor data products that may be able to get around cloud-related issues are still under active research and have yet to be widely available.

3.5. Unfamiliarity with remotely sensed data

EO platforms and sensors are becoming available at a rapid pace (Zhang et al., 2022). The pace of advancement and specialization required makes it hard to assimilate and operationalize newer data. Likely, many new sensors (e.g., SWOT (Biancamaria et al., 2016)) are not known to the wider water resources modeling community. Further, using such data requires knowledge of sensors, data processing techniques, familiarity with new software, and geospatial analysis. Professionals not trained in remote sensing may not be familiar with the terminology, methods, or tools used to work with remotely sensed data. The perception of unfamiliarity with data being a barrier to water resources application was low overall (median 2). The only group that rated it higher (median 4) were the "practitioners" (See Supplementary Fig. S7). Practitioners who identified as researchers rated this not as a barrier (median 1). This observation reinforces the idea that the penetration of remote sensing methods may be low among non-research practitioners. One-stop searchable data archives, such as one integrated into GEE, can be highly beneficial for identifying useful data products.

3.6. On-demand coverage

On-demand satellite imaging refers to the ability to request and receive satellite images of a particular location on a flexible schedule, rather than having to rely on pre-scheduled or pre-planned imaging cycles. This capability has become increasingly important in recent years due to the growing demand for up-to-date and high-resolution imagery for a variety of applications. Typically, aerial platforms were considered ideal platforms for on-demand remote-sensing coverage. However, with satellite constellations, some on-demand coverage of a region is possible. For example, Planet through its Skysat constellation, can provide coverage 5–7 times a day coverage for a region of interest at 50 cm resolution. On-demand satellite imaging allows users to quickly obtain images of a particular area for various purposes, such as disaster response and recovery, agricultural monitoring, environmental management, and military and security operations. Some satellite imaging providers offer services that allow users to specify the location, resolution, and time frame for their requested images and receive the resulting images within a matter of hours or days. Such capacity is relatively new and expensive. Lack-of-on-demand coverage was not considered a major barrier (See Supplementary Fig. S8). However, like the "unfamiliarity with dataset" discussed above, there was a difference between researchers and others.

3.7. Continuity of remotely sensed data

Continuity of remotely sensed data refers to the ability to collect and analyze data over time, consistently and reliably, to monitor changes in the environment or track trends in a particular phenomenon. Maintaining the continuity of remotely sensed data is important because it allows the study of long-term changes in water resources and makes more accurate predictions about future trends. It also helps ensure that data collected from different sources or at different times can be compared and analyzed consistently and meaningfully. Factors such as sensor calibration and stability, data processing and analysis, data sharing, and continued funding for the effort will likely affect the continuity. Differences in sensors and orbital characteristics caused by changes in configuration and functionality or because satellites reach their lifespan affect the accuracy and continuity of measurements (Wimberly et al., 2021). Harmonized products can be developed to combine satellite data from different sources into consistent and reliable long-term datasets. However, the availability and accessibility of harmonized useable EO products depend on the requirements of the corresponding project. For example, harmonized datasets available for the Landsat program have been available for the last 50 years which are great for visual land use land cover changes, and such data (combining different Landsat platforms) has been used by the community widely for land cover land use change detection (Wulder et al., 2022). Data continuity will likely be a crucial consideration of remote sensing applications in water resources, especially if regulations (e.g., total maximum daily load assessment) integrate such data in assessments of water bodies. Data continuity, however, was not rated as an important impediment by the community, with a median of three (See Supplementary Fig. S9).

3.8. Accuracy and precision of remote sensing data product

Accuracy is a critical aspect of any remotely sensed data product and plays an important role in introducing bias into a water quality model. Precision, on the other hand, plays a role in propagating uncertainty through a water quality model. Inaccurate and imprecise data products can lead to erroneous model results, or the need for wider margins of safety, when designing water quality management alternatives. Often, accuracy is assessed in two broad categories: positional and thematic (Congalton and Green, 2019). Positional accuracy deals with how precisely the same location is represented in reference data and remotely sensed imagery. If good positional correspondence is not achieved, it will lead to thematic errors, e.g., misclassification. Often, positional accuracy is handled by the data provider and not addressed by the end user. Thematic accuracy assessment typically compares prediction or estimation with in-situ data, which itself may be erroneous. Assessing the accuracy of EO images is fundamental to most projects using such data, e.g., land-cover mapping projects (Strahler et al., 2006). For watersheds and water quality modeling projects, an accuracy assessment may help users evaluate the uncertainties associated with incorporating remote sensing datasets into the models or deciding between available datasets with different spectral or spatial resolutions (Comber et al., 2012). Adequate accuracy assessments of remote sensing data can be time-consuming and costly and depend on several factors, including the type of sensor used, atmospheric corrections, the spatial and spectral resolution of the data, the calibration and validation procedures employed, and the availability and accuracy of the ground truth data used for comparison. Also, the incommensurability between the spatial scales of remotely sensed and in-situ data is an issue. The precision of remote sensing products typically manifests itself through representation error between the scale of the remote sensing data and the scale of the model representation of processes. The representation error issue must be addressed by performing a match-up between in-situ measurements and the remotely sensed water quality products to use remote sensing data products reliably. Very few resources exist for performing this match-up in different parts of the world. In the United States, a first attempt at creating a comprehensive match-up dataset—AquaSAT--was undertaken by Ross et al. (2019) for inland waters. Often, for assessing spectral accuracy, data from cube-sat and small-sat is compared with reflectance data from other larger satellites, e.g., Planet SuperDove with Sentinel-2 (Tu et al., 2022), and geometric accuracy comparisons are performed by looking at similar location (Dobrinić et al., 2018; Aguilar et al., 2019).

Another important aspect when considering accuracy is the recognition that many derived and ready-to-use EO data products are indirect modeled estimates, not direct observations, and have associated uncertainty (Wu et al., 2019). They are often derived from machine learning models or empirical equations that may themselves have a high degree of uncertainty. This will add to the inherent uncertainty of the water resources models if not properly integrated and assumed to be accurate.

The respondents to the survey did not rate accuracy and precision as a major barrier (median 3). There was little difference among the different groups (See Supplementary Fig. S9), suggesting that the concept of accuracy and precision are recognized but perhaps considered not as important as other factors. This may also represent a disturbing lack of concern about the representation error. In the context of water resources modeling to manage critical conditions, this can result in catastrophic neglect of peak flows and concentrations. For some applications, anomalies (changes over space and time) or normalized band differences are more important (Sharma and Joshi, 2014; Xia et al., 2018) than the accuracy of data itself, which may help mitigate some data accuracy issues.

3.9. Types of water bodies

Different water bodies have different characteristics such as surface area, volume, depth profile, meteorological conditions (wind velocity, temperature, etc.), chemical composition (salt concentrations, turbidity, etc.), ecology, and biodiversity. These characteristics affect our ability to accurately estimate water quality parameters in situ or with EOs (Kruse, 2018). In-situ water quality sampling is based on understanding the optical, electrical, and chemical properties of the substance of interest and likely confounding compounds. Typically, only the surface properties are captured by EO platforms, thus limiting the ability to understand profiles and changes with depth. Nevertheless, EO can be a valuable tool for studying different water bodies, including oceans, lakes, rivers, and wetlands. Different types of water bodies have distinct characteristics and require specific remote sensing techniques to observe and analyze them accurately. In oceans, EOs have been used to study ocean temperature, ocean color, ocean currents, and sea level changes (Akbari et al., 2017). Satellite-based EOs can detect ocean surface temperature and track the movements of ocean currents. For lakes, EOs can help monitor the physical and chemical properties of lakes (Dörnhöfer and Oppelt, 2016). For example, multispectral satellite images can be used to detect changes in the amount of chlorophyll-a in the water, which can indicate the presence of harmful algal blooms (Gao, 2015; Li et al., 2020) and turbidity plumes (Caballero et al., 2018). Radar-based sensors can also be used to measure the lake's elevation and map its bathymetry (Chen et al., 2021). EO data can be used for rivers to monitor river flow and track changes in river morphology (Piégay et al., 2020). Synthetic Aperture Radar (SAR) is an effective technique for measuring water flow and mapping river channels (Ciecholewski, 2017) and oil slicks and spills (Jafarzadeh et al., 2021). LiDAR can be used to map the topography of riverbanks and detect changes in river morphology (Notebaert et al., 2009). For wetlands, EO can be used to monitor the extent and health of wetlands (Guo et al., 2017). Radar sensors can penetrate through vegetation to measure the surface height of wetlands and map their extent. Multispectral imagery can also be used to detect vegetation health and changes in wetland vegetation cover.

The nature and type of water bodies were not identified as a particularly important barrier, with a median of three. Researchers with both remote sensing and water system backgrounds rated it slightly higher than the median. When discussing advances needed, increasing in-land and open-water imagery was considered important for improving remote-sensing and water quality modeling integration (see Supplementary Fig. S10).

3.10. Detectable water quality parameters

Some of the water quality parameters monitored by EOs include chlorophyll-a, phycocyanin, phytoplankton, temperature, Secchi disk depth, colored dissolved organic matter, total organic carbon total suspended matters, turbidity, sea surface salinity, and chemical and biochemical oxygen demand (Chang et al., 2015; Gholizadeh et al., 2016; Wang and Yang, 2019). Recent reviews on using EOs for water quality monitoring, *e.g.,* Topp et al., (2020); Samarinas et al., (2023) provide insight into detectable parameters and mechanisms of the detection. For direct parameter detection, the parameter of interest must be related to an inherent optical property that satellite-based sensors can measure. This method often requires in-situ data, and the relationship developed cannot be generalized. Further, data processing for atmospheric correction, spatial, spectral, and temporal resolution affect the development of such relations between parameters of interest and the optical properties (Kutser, 2009; Gholizadeh et al., 2016). Spectral, radiometric, fluorescence, and thermal analysis have been used with satellite data to detect water quality parameters. Spectral analysis involves using remote sensing sensors to measure the reflectance or absorption of light by water at different wavelengths. By analyzing the reflectance spectra, it is possible to detect and quantify various water quality parameters, such as chlorophyll-a, total suspended solids, turbidity, and dissolved organic matter (Elhag et al., 2019; Sagan et al., 2020). Radiometric analysis involves using remote sensing sensors to measure the intensity of light reflected or emitted by the water surface. Light intensity is related to the concentration of water quality parameters, such as chlorophyll-a and TSS (Mouw et al., 2015). Fluorescence analysis involves using remote sensing sensors to measure the fluorescence emitted in the water (Slonecker et al., 2016). This technique can be used to detect and quantify dissolved organic matter, which can be an indicator of water quality. Thermal analysis involves the use of sensors to measure the temperature of the land and water surface. The temperature of the water surface can be related to the water quality parameters and can also be used to detect thermal pollution (Ling et al., 2017). Each technique has its site-specific advantages and limitations and can be used to detect specific water quality parameters.

The water quality parameters detected were not rated high as a barrier (median 3). The spread around the median is quite wide, with community members rating it from 1 to 5 (Fig. 5). The cause of this wide range of ratings within the same group is unclear. Nevertheless, advances in detecting more water quality parameters were rated as significant, with a median rating of 4 for improving integration between water quality modeling and remote sensing (see Supplementary Fig. S11). It is not surprising that a greater number of water quality parameters will improve integration, as many existing data gaps can be filled in current models with EOs. Hyperspectral and other multispectral multi-band missions offer the best possibility of detecting more water quality parameters.

3.11. Cost of satellite imagery

Satellite images are available both freely, provided by government organizations, and commercially. Economists have assessed the value of space-based EOs and have generally agreed that the value depends on the application, sector involved, and sensors/platforms, but that is largely unknown (Macauley, 2006; Tassa, 2020; Jabbour et al., 2020). Most natural and water system applications use freely available imagery and datasets provided by governments, space agencies, and other organizations. Recently, some commercial products that have typically higher temporal and spatial resolution (e.g., GeoEye, WorldView, and PlanetScope) are being used (Liew et al., 2011; Aguilar et al., 2019; Eugenio et al., 2020; Niroumand-Jadidi and Bovolo, 2021). Often the commercial and free data products are combined for higher resolution and longer-term assessment (Hively et al., 2019). Many commercial products are available free of cost for academic research through programs such as NASA CSDA and academic institutes' partnerships with data providers. For some applications, such as routine reservoir water quality monitoring, the cost of even commercial products is often an order of magnitude lower than the cost of a robust in-situ monitoring program. Furthermore, integration of remote sensing data into an existing in situ monitoring program can offer opportunities for efficiencies, such as using remote sensing data to optimize the timing and frequency of in-situ measurements. Aggregator services such as *Skywatch* (Jagula, 2022; Skywatch, 2023) bring many commercial EOs together, allowing users to collect the most relevant EOs from multiple platforms available.

The cost of satellite imagery was rated a relatively low barrier overall, with a median rating of 2, albeit a wide range from 1 to 5 (see Supplementary Fig. S12). There was a clear divide between practitioners and researchers. It is somewhat surprising that survey participants perceived spatial resolution as a significant barrier, but they perceived the cost of imagery as a low barrier, since many commercial satellite images are available at very fine spatial resolution. This may be because many researchers may be able to acquire satellite imagery for research purposes (even commercial) free of cost. Perhaps this also indicates that freely available satellite products typically occupy the mental space of the community, and integration of high-resolution data is low. The use of high-resolution data in water resources modeling is not commensurate with the availability of such data and needs to be incentivized.

3.12. Lack of in-situ data

Data derived through satellite images are a surrogate of the relevant physical parameters. Several algorithms are then used to convert satellite-derived data to physical parameters. Two important questions when performing such conversions are: (1) which of the spectral algorithms is better, and (2) how accurate is the best spectral algorithm? In-situ data are required to answer these questions. Ideally, in-situ data should be such that it captures the spatial variability of the relevant physical parameter within an image pixel. This, however, is rarely achieved because of a lack of resources (Ross et al., 2019). Thus, the average values over a pixel obtained by the satellite data are compared with the point values measured in situ. This may introduce significant uncertainty into the validation

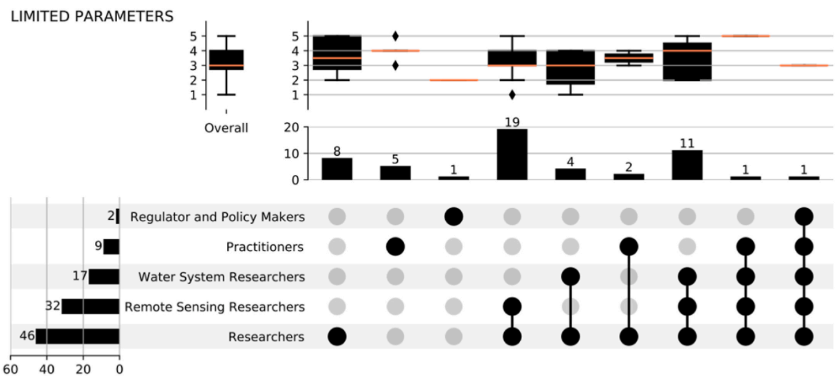

Fig. 5. Community perception on the parameter observed by remote sensing on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier].

processes depending upon the spatial variability of the physical parameters. For example, the International Soil Moisture Network (ISMN) maintains in-situ soil moisture data around the globe to be used for the validation of satellite-derived soil moisture data (Gruber et al., 2019). However, the ISMN data are very sparse, especially in low-income countries. Even within the United States, the availability of data in databases such as AquaSat (Ross et al., 2019)—the Water Quality database for inland water aligned with Landsat 5,7, and 8 varies widely. Further, the water quality parameters are typically highly variable in space. Given these limitations, validation of spectral algorithms with in-situ data appears to be one major challenge. Further, the exact parameter of interest may not be available due to differences in how the parameter is defined. It can be challenging to obtain in-situ data that precisely matches the variables derived from the EO (Malthus et al., 2012). A specific variable's definition or measurement methodology may differ between the in-situ data collection and remote sensing approaches. For example, how water quality parameters like turbidity or chlorophyll-a are measured in the field may not align perfectly with how they are estimated from satellite or airborne sensors (Dierssen, 2010).

Unsurprisingly, the survey respondents rated the lack of in-situ data for validation as a significant barrier (Fig. 6), with a median rating of 4 and several members rating it at 5. This highlights that successful EO for water resources application needs significant resources to be invested in validating and collecting in-situ data. AI and Internet of Things (IoT) guided near-real-time monitoring was also thought of as an advancement that can help bridge the gap of using remotely sensed data in water resources models. Another important discussion concerns the homogenization of water quality parameters that allow users to convert EO-based parameters to some in-situ measure with transfer functions. One strategy can include using portable or aerial spectroradiometers (hyperspectral imagers or point spectroradiometers) to collect targeted observations that can then be used to develop regional models that can extend to the EOs; see Schaepman (2007); Milton et al., (2009) for a review of processes. Coordinated datahubs, such as the EU Environment Agency Waterbase-Water Quality ICM [https://www.eea.europa.eu/en/datahub/datahubitem-view/fbf3717c-cd7b-4785-933a-d0cf510542e1], NASA SeaBASS [https://seabass.gsfc.nasa.gov], UN Environment Program GEMStat [https://gemstat.org/data-gemstat/], and National Ecological Observation Network (NEON) data [https://www.neonscience.org/data] can provide some in-situ observations too.

3.13. Usage of remotely sensed data in water quality models

Water resources modeling has a rich history; the basic structure of most modern water resources models were developed in 1970-the 80s and have since been updated (Council, 2001; TMDL A&M TC, 2017; Camacho et al., 2019). They are also commonly used for regulatory requirements such as TMDL development. Though some models have a map-based interface, they were not designed to in-

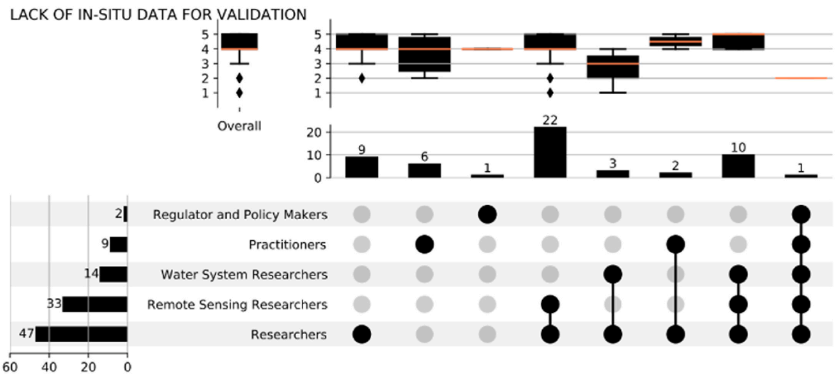

Fig. 6. Community perception on the in-situ data availability for the validation of remotely sensed products on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier].

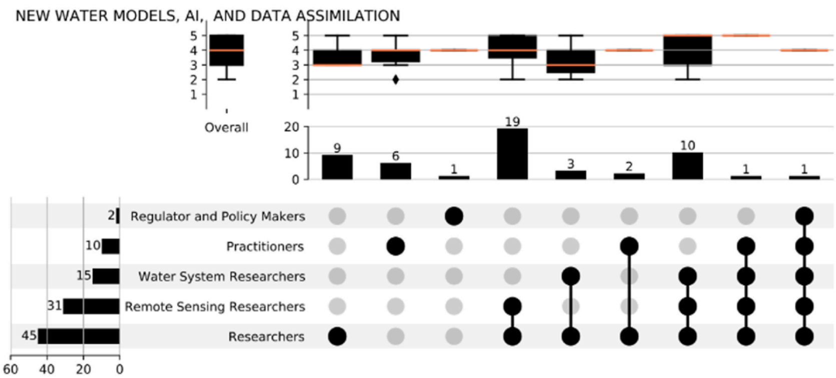

Fig. 7. Community perception on the role of AI, IoT, and near-real time monitoring on improving integration between remote sensing and water resources modeling on a scale on of 1 [not likely to be a significant advancement] to 5 [extremely useful].

terface with remotely sensed data. For example, though some data products can be used for calibration or validation of the model, the assimilation of remotely sensed data products when they become available at different time-step to perhaps estimate other complex and hard-to-know state variables, is not supported. Further, different water quality models incorporate different levels of spatial details in their process descriptions. The scale at which model simulations are available and the scale at which remote sensing data are available may not be aligned. Even if models could incorporate fine-scale remote sensing data, the model may not be capable of handling the increase in processing power needed to cater to the smaller spatial processing units. These problems make it difficult to incorporate remotely sensed data into modeling.

These problems were rated as a moderate barrier, with a median rating of 3 by the survey respondents (see Supplementary Fig. S13). Water system researchers, who are most likely to be familiar with the models, rated it even lower (median 2). These results perhaps indicate a difference in understanding about the capability of models and the relevance of remote sensing data to water resources models. When discussing the role of new water resources models, AI, and data assimilation in integrating water resources models with remote sensing data, it was rated of high importance with a median of four (Fig. 7). It was also noted that water system researchers with a remote sensing background rated it very high (median 5) but those without a remote sensing background rated it lower (median 3). This divergence is perhaps due to the lack of guidelines within the water system research community on how remotely sensed data may be used.

3.14. Computing infrastructure

Satellite data are spatiotemporal data that require large storage space, often in the order of terabytes, even for small projects. Also, the processing of satellite data requires significant computing power. Often, these facilities are available for non-commercial use through research supercomputing networks and others. For commercial uses and locations without ready access to adequate computing resources, especially in developed nations, this can be a problem. The advent of platforms such as GEE, Open Data Cube (ODC), and other cloud-based computing resources has made accessing computing and data together easier. GEE is a Google-supported endeavor free of cost for academic and not-for-profit research with an extensive library of co-located data and computational capacity (Gorelick et al., 2017). GEE has extensive documentation and community support. ODC is an open-source software project designed to manage and analyze large volumes of EO data. Its functionalities center around simplifying access to and exploitation of EO. Though ODC may not directly provide compute capacity, the libraries make it easier to process EOs and leverage cloud-optimized geospatial datasets in any cloud environment. It is also connected with GEE, which allows access to a larger library of datasets.

The survey respondents did not consider the computing infrastructure a significant barrier, with a median of two (see Supplementary Fig. S14). However, there was a clear divide between the water resources and remote sensing researchers. Remote sensing researchers, who are likely more acquainted with computing requirements for running models with remote sensing data, rate it slightly higher (median 3).

3.15. Access to remotely sensed data

To use EOs, one must first be able to find and access that data. There are many data distribution platforms in which collect and make EOs available. Most such platforms are controlled by the entity that collects and disseminates the data. These entities can be public (e.g., NASA, CNES, ESA, etc.) or private (e.g., Planet, SkyWatch, Maxar, etc.). There are several data aggregation platforms, such as Google Earth Engine (Gorelick et al., 2017), Planet Explorer [https://developers.planet.com/docs/apps/explorer/], Skywatch [https://skywatch.com/], Descartes Labs [https://descarteslabs.com/], Radiant Earth Foundation [https://radiant.earth/], EOS Data Analytics [https://eos.com/], Earthdata [https://www.earthdata.nasa.gov/] (Earth Data, 2023) and Terrascope [https://terrascope.be/]. These platforms include collecting remotely sensed data from sensors and data products and provide a range of tools for data analysis and visualization, including web-based viewers and application programming interfaces (API) for programmatic access to data.

Access to remotely sensed data was a moderate concern among the survey respondents, with a median of three (see Supplementary Fig. S15). Not surprisingly, remote sensing researchers had the lowest score (2), indicating that those who primarily conduct research with remotely sensed data can find and access data. However, among those who identified themselves as remote sensing and water system researchers, this increases to 3. The scores increased for those who identified as a practitioner (a score of 4) and a regulator (a score of 5).

When discussing advancement, improved accessibility, data sharing, and data management were rated high as tools that can be improved for improving water resources modeling and remote sensing integration. However, tools such as recommender engines (that can recommend data based on usage), and tools for decision-making were rated lower (median 3). This lower rating may be due to the lack of existing prevalence of such tools, where there is no unique method to query all remotely sensed data sets of relevance for water resources. This low weight likely indicates inertia in the status quo that is unlikely to change unless information systems, computer science, and data science research mature to a point where remote sensing products are available as ready-to-use products that can be readily ingested into water resources models. Increasing popularity and acceptance of standards, such as Cloud Optimized GeoTIFF (COG), may also help. Traditional EO dataset files aren't designed for efficient web access, often requiring the download of the entire file to access a small part of the image. COG addresses this by structuring the file to allow easy access to small portions of the file over the web.

3.16. Personnel training

It may be the case that those who are interested in and would benefit from using remotely sensed data for water quality modeling do not have training in it. Typical engineering programs, even at a graduate level, focus on fundamentals of hydrology, hydraulics, and modeling approaches, and may not have courses that explicitly focus on how to obtain, analyze, and assess remote sensing data. Even courses that teach Geographic Information Systems (GIS) and geospatial modeling may omit remote sensing data for estimating water quality or other important parameters for water systems modeling. Given that the domain is new compared to other more established topics and there is limited curriculum around the topic, it was not surprising that the overall personnel training was found to be high barrier with a median score of 3.5 (Fig. 8). This was lowest among remote sensing researchers (median 2) and highest for practitioners, water systems researchers, and regulators (median 4). Similar to access, personnel training may be a perceived barrier for those whose profession is not explicitly focused on remote sensing. Advances in personnel training were thought of as important (median 4) to better integrate remotely sensed data with water resources modeling.

3.17. Programmatic support

Programmatic support from involved agencies includes the availability of resources, training materials, or customer support for end users and incentivizing convergence. This was not perceived as a particularly high barrier (median 3). Although the barrier was not considered a significant issue, improving support was rated as a high-impact advancement (median 4). State and Federal rulemaking agencies can play a critical part in integrating the remote sensing and water resources modeling field by developing incentives, guidelines, and regulations that allow and encourage the use of remotely sensed data, also by testing and piloting programs that demonstrate the benefits and barriers of such operational integrations.

3.18. Convergence

Remote sensing, water resources, and, to some extent, computer science communities face similar challenges in developing better models or “digital twins” of their respective systems. The advantages of such systems are tremendous as they let us understand complicated systems better and how interventions can be better utilized. Though different domains have been working on the problem, their ontologies (what does the world look like), epistemologies (what can be known about the world), methodologies (how to understand the world), and axiology (what is the role of the research and researcher) vary, and concordance is necessary for convergence (Blair and Buytaert, 2016; Wesselink et al., 2017). Often, remotely sensed parameters for water quality are based on optical activity directly or indirectly associated with the parameter (e.g., color, turbidity). However, many of the water quality models don’t estimate or utilize these parameters. By leveraging our understanding of water systems dynamics, we can perhaps better estimate some non-optically active water quality parameters. The convergence required to integrate water resources modeling and remote sensing is likely not limited to researchers, but practitioners and regulators must be engaged. Forging a convergent research group can be challenging, as it involves bringing together individuals with different backgrounds, skills, and perspectives and aligning them towards a common research goal. Research in convergence in different domains has identified some barriers (Council, 2014; Seeber et al., 2017; National Academies of Sciences, 2019,; Ernakovich et al., 2021) such as *communication barriers*, e.g., if team members speak different languages, come from different disciplines that have different nomenclature or have different levels of expertise, this can lead to inefficiencies; *misaligned and conflicting priorities,* e.g., if a team member may have their own priorities, goals, and research interests, which can create conflicts within the group; *lack of trust and collaboration*, e.g., if members don't trust each other or don't feel comfortable collaborating, it can lead to a breakdown in teamwork and lack of progress; *inadequate leadership*, *resource constraints*, e.g., limited funding, time, and access to equipment can pose significant challenges for a research group; *lack of diversity and inclusion*, research groups that lack diversity in terms of gender, ethnicity, or socio-economic backgrounds may struggle to generate new ideas and perspectives. Further, if team members feel excluded or marginalized, it can lead to a lack of motivation and engagement; and *personal issues,* which are magnified as many researchers have to commit time together to work on a problem. However, it is imperative to make scientific progress that affects water resources modeling positively to strive for the long-term goal of convergence.

The community did not rate convergence as an especially high advance, with a median of three. This was a surprising result, as many of the other advances rated highly could be achieved through convergence. We suspect that convergence is still novel even in the research domain and not properly incentivized in academia.

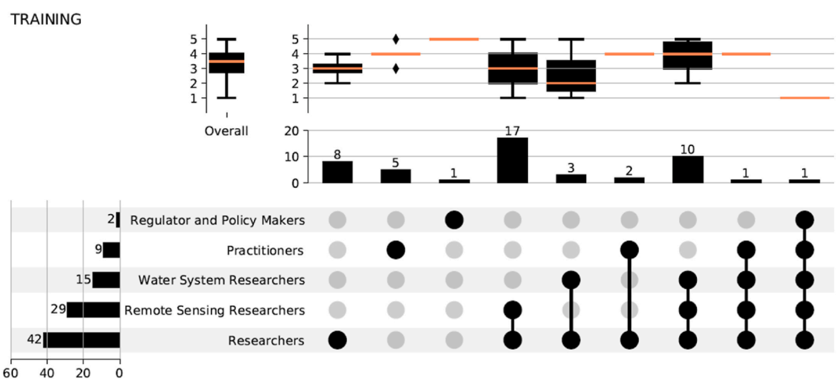

Fig. 8. Community perception on the lack of personnel training as a barrier to the integration of water resources modeling and remote sensing on a scale of 1 [not a significant barrier] to 5 [a persistent and significant barrier].

4. Outlook and conclusions

Spatial resolution, atmospheric interferences and clouds, and lack of in-situ data were perceived as the major barriers to integrating EOs with water resources modeling. Advancements in sensor technologies, smart processing, and fusion algorithms can help remedy many of these perceived barriers. There have been significant advancements in spatial resolution with commercial EO, especially at very high resolutions (< 5 m/pixel) scale. Even larger satellites are striving for higher resolutions. For instance, the next-generation Landsat is expected to have data at 10-m resolution. Further harmonizing and fusing the datasets will help mitigate some cloud cover issues. Several studies have combined data from different sensors, including SAR-optical, to address cloud cover limitations. Some of these harmonized data (e.g., Landsat Sentinel 2 Harmonized data (Claverie et al., 2018)) are available on a continental scale in data-sharing platforms like the GEE.

In-situ monitoring, however, remains a challenge. There have been four major issues with in-situ water resources data: 1) inadequate collections, (2) scale mismatch between in-situ and remote sensing data, 3) disaggregation and lack of sharing, and 4) the unclear provenance and reliability of available data from various sources. The water informatics community has been struggling with these problems for a long time and has developed sharing frameworks such as WaterML (Valentine et al., 2012). However, adoption has been slow and limited to more developed countries. More coordination and resources on a grander scale are necessary to make these data available globally. Projects such as AquaSat (Ross et al., 2019) and RiverSR (Gardner et al., 2021) will be crucial for future model developments. Another issue is that of uncertainties associated with the remotely sensed data. The measured remotely sensed entity is typically converted to a physical quantity using an interpretation model. Comparison of in-situ data with the interpretation model partly reduces the uncertainty, but not all. Acquiring and converting sensor observations to surface reflectance requires the development of empirical models that involve numerous assumptions about the target and the atmosphere. These models are established for large satellites but are prone to errors, particularly for smaller platforms (e.g., small/cube-sat) (Li et al., 2021; Florczak et al., 2022). The uncertainties associated with the interpretation models must be quantified to integrate the EO products with water resources modeling properly. Platforms such as GEE and ODC can enable deeper integration between water resources models and EOs. Both GEE and ODC allow on-demand retrieval and processing of relevant EO datasets. The fact that they can be programmed using Python opens many opportunities for quick linkages with water resources modules in platforms such as Landlab at timestep scale (Barnhart et al., 2020).

Another finding from this survey is that the stakeholders have different perspectives and rate the problems with EOs and advances needed differently. Investments in convergence and education will better align the expectations of different communities and future acceptance. Although there is mixed evidence of success (e.g., bioinformatics (Council, 2014)) and lack thereof (Ernakovich et al., 2021) in fostering convergence in other domains, we argue that it is imperative to try and forge this convergence. The data and modeling needs for water resources management are too large and integrating with EO can help mitigate these issues at a global scale.

The analysis represents an initial and novel effort to identify the gaps in the understanding and barriers to implementing EOs for water quality management. Although the number of respondents was limited to fewer than 100, and there were some clear imbalances in the constitution of the group, the insights gained from this survey will allow us to refine the remote sensing workshop and subsequent iterations of this survey. We intend to conduct this survey periodically, and over time, it will allow us to identify temporal and institutional trends across disciplines in adopting EOs for water resources management. We expect future survey structures to be updated to reflect what we have learned from this survey and accompanying discussions. However, sufficient similarity will be maintained to allow comparisons. The survey and the results also serve an important educational purpose by exposing readers to the research trends and likely areas of advancement. A lack of awareness about EO or the perceived requirement of specialized skill sets may be hindering their widespread implementations to some extent. Practitioners are often unaware of the myriad data products that are available. Subsequent iterations of our survey will explore these areas further and identify online platforms that bridge the knowledge gaps and accessibility of remote sensing products prevalent today.

The survey did not discuss crop yield, crop stress, or groundwater-related issues impacting the water system. Understanding crop yield and water stress is important for water resource modeling as it provides valuable insights into the availability and demand of water resources. Remote sensing methods have been used for large-scale groundwater recharge estimation, typically by measuring groundwater storage fluctuations. For example, the Gravity Recovery and Climate Experiment (GRACE) satellite measures water storage anomalies at very coarse resolutions (300 km), which can help set model boundary conditions for large-scale water resource models. These topics will be included in future iterations of the survey.

There is no doubt that EOs will impact water resource modeling. The promise of EOs being globally available and breaking traditional regimes of data "have" and "have-not" would rely on training the right personnel, sharing of in-situ data, and new algorithms, e.g., transfer learning (Xie et al., 2016; Naushad et al., 2021) that can use the limited data to calibrate the models necessary for EO and water resources integration. Besides providing direct measurements of the water quality of water bodies (e.g., for algal blooms), EOs can be used to prioritize what to monitor with limited in-situ modeling efforts. Within the United States, when and where to monitor has been opaque, with no clear guidance from the Environmental Protection Agency (EPA), which has been detrimental to understanding the true magnitude of waterbody degradation. Even in more monitoring-focused frameworks such as the European Water Framework Directive (WFD), less than 50% of the surface water bodies are deemed sufficiently monitored for ecological status and less than 30% for chemical status (Kristensen et al., 2018). This highlights the lack of resources needed for comprehensive in-situ monitoring and prioritizing monitoring locations based on criteria such as the likelihood and impact of water quality changes. EOs can be utilized globally, which will be useful in both developed and developing nations and, in turn, help with broader adoption.

Ethical statement

All ethical practices have been followed in relation to the development, writing, and publication of the article.

CRediT authorship contribution statement

Saurav Kumar: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Sanaz Imen:** Conceptualization, Methodology, Writing – review & editing. **Vamsi Krishna Sridharan:** Writing – review & editing. **Abhinav Gupta:** Writing – original draft, Writing – review & editing. **Walter McDonald:** Writing – original draft, Writing – review & editing. **John J. Ramirez-Avila:** Writing – original draft, Writing – review & editing. **Omar I. Abdul-Aziz:** Writing – original draft, Writing – review & editing. **Rocky Talchabhadel:** Writing – original draft, Writing – review & editing. **Huilin Gao:** Writing – review & editing. **Nigel W.T. Quinn:** Writing – review & editing. **W. Josh Weiss:** Writing – review & editing. **Thomas Poulose:** Writing – original draft, Writing – review & editing. **Santosh S. Palmate:** Writing – original draft, Writing – review & editing. **Christine M. Lee:** Writing – review & editing. **Latha Baskaran:** Writing – review & editing.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

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IRB Exemptions:

Data Collection: IRB 2022-0504M (Texas A&M, 4/20/2022).

Data Analysis: STUDY00016524 (Arizona State University, 9/14/2022).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2023.101119.

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