Applications of GIS and remote sensing in public participation and stakeholder engagement for watershed management

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Abstract

The use of Geographic Information Systems (GIS) and remote sensing technologies for the development of water quality management programs and for post-implementation assessments has increased dramatically in the past decade. This increase in adoption has been made more accessible through the interfaces of many popular software tools used in the regulation and assessment of water quality. Customized applications of these tools will increase, as ease of access and affordability of directly monitored and remotely sensed datasets improve over time. Concurrently, there is a need for inclusive participatory engagement with stakeholders to achieve solutions to current watershed management challenges. This paper explores the potential of these GIS and remote sensing datasets, tools, models, and immersive engagement technologies from other domains, for improving public participation and stakeholder engagement throughout the watershed planning process. To do so, an initial review is presented about the use of GIS and remote sensing in watershed management and its role in impairment identification, model development, and planning and implementation. Then, ways in which GIS and remote sensing can be integrated with stakeholder engagement through (1) leveraging GIS and remote sensing datasets, and (2) stakeholder engagement approaches including outreach and education, modeler-led development, and stakeholder-led involvement and feedback, are discussed. Finally, future perspectives on the potential for transforming public participation and stakeholder engagement in the watershed management process through applications of GIS and remote sensing are presented.

Keywords

Geographic Information Systems; remote sensing; modelling; water quality; stakeholder engagement

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1. Introduction

The sustainable management of water resources is an important goal for communities around the world. In most cases this is attempted, and in some cases achieved, by appropriate regulation of discharges from watersheds and governance to ensure compliance with these regulations. Watershed management and regulation to protect water quality have been recognized as both a social and technical undertaking (Korfmacher, 2001). In the United States (US) where water quality protection is a major component of environmental regulation, there are multiple approaches to manage water quality. For example, (a) numeric and descriptive load allocations or assimilative limits of pollutants in impaired waterbodies known as Total Maximum Daily Loads (TMDLs; Box 1); (b) category 4b pollution control programs (Monschein & Reems, 2009; Box 2); and (c) watershed management plans (e.g., North Carolina Department of Environmental Quality (NCDEQ), 2021; New York State Department of Environmental Conservation (NYSDEC), 2021; Texas Commission on Environmental Quality (TCEQ), 2021), such as nine element (9E) plans (United States Environmental Protection Agency (USEPA), 2013; Box 3).

The TMDL program has achieved considerable success in regulating water quality pollution and assigning clean-up responsibility to those entities that contribute the greatest point source pollutant loads by explicitly tying loads to water quality standards. The category 4b program (so named for the regulation that allowed for this program), requires the identification and control of pollution loads within the watershed (NCDEQ, 2021). Watershed management plans are more participatory in design and allow the identification and mitigation of nonpoint source pollutant loads within the watershed, rather than focusing on water quality standards or objectives that have to be met within the impaired waterbodies (e.g., NCDEQ, 2021; NYSDEC, 2021; TCEQ, 2021). Watershed planning within a water quality management approach requires a thorough understanding of hydrologic processes, pollutant discharge and transport, and pollutant load allocations in time and space. Effective communication before and during the implementation of water quality restoration actions is critical for stakeholder buy-in and continued participation. Remote sensing datasets and Geographic Information System (GIS) tools can be used separately or jointly, to convey technical information in a way that can be more easily understood and appreciated (see Boxes 1, 2 and 3 for specific examples). Remote sensing data, viewed and analyzed through GIS software applications, can help to define the spatiotemporal water quality patterns within a watershed in a manner that the use of each technology alone might not provide. This has led to the embedding of remote sensed data acquisition, processing, and analysis capabilities in many GIS platforms. Users can often select the source of the data (satellite, aerial, or drone) and the specific tools with which the data is analyzed or viewed (e.g.,QGIS, ESRI ArcGIS, ENVI, Google Earth Engine, etc.).

Box 1: GIS and remote sensing for developing and implementing Total Maximum Daily Loads (TMDLs).

This Box demonstrates how GIS and remote sensing can be used to enhance the stakeholder engagement process in TMDL implementation as introduced in Section 1.

Background

The US Clean Water Act (CWA; Public Law 92-500; United States Code section 303(d)(1)(C)) requires listing of all waterbodies that fail to meet minimal water quality standards. Under this law, each jurisdictional entity (e.g., state or tribal regulatory agency) is required to develop a water quality management plan that identifies the major pollutants that impact receiving waters. Similarly, the total pollutant mass that can be safely assimilated by the environment (without causing an exceedance of water quality objectives) must be determined.

When the mechanism of achieving load reduction is through the quantification of load allocations and assimilation limits, this pollutant quantity is typically referred to as the TMDL. During TMDL development, the USEPA recommends that a comprehensive watershed strategy be undertaken, involving close stakeholder partnership with water quality management volunteer groups (e.g. citizen science collaboratives, contractors, local governments, and/or other state and federal agencies). Although few stakeholders are familiar with the scientific support and ecotoxicity research for the water quality standard or numeric objective for each pollutant, the fact that there is a compilation of accepted evidence often suffices.

TMDL Workflow

In developing a TMDL, the level of impairment of the water body is first evaluated. All contributing sources (point source (PS) and non-point source (NPS)) are then identified. Each source is allocated only a portion of the maximum allowable load, so that the net reduction in the load may meet the applicable water quality criteria. Natural background sources, seasonal variability, and Margin of Safety (MOS) (Nunoo et al., 2020) are all considered in the pollutant allocations.

Box 1 (continued)

TMDL Monitoring

Monitoring programs are generally designed to systematically collect data over key temporal and spatial scales to provide empirical evidence of the water quality impairment and its potential source, establish the current environmental status of the system, and quantify trends in local hydrometeorology, pollutant loading, anthropogenic factors and relevant water quality (American Society of Civil Engineers/Environmental and Water Resources Institute Total Maximum Daily Load Analysis and Modeling Task Committee (ASCE/EWRI TMDL-TC), 2022). Public access to information on data collection procedures and technologies helps to justify the activity and can lead to enhanced public support and aligned effort to improve the accuracy and precision of the acquired data.

As part of a TMDL effectiveness monitoring plan, additional parameters may be monitored simultaneously along with the primary water quality parameter(s) of concern to help explain trends in the data and compare before/after conditions. One of the common covariates for pollutants is streamflow. Precipitation and air temperature can also be useful supplemental factors to consider in statistical analysis to analyze changes in pollutant loading over time. In addition, land-use data can be included in subsequent analyses to explain data variability. Monitoring biological and habitat data can provide additional supporting information to the observed trends in certain water quality parameters (USEPA, 2017).

Role of GIS and remote sensing in modeling for TMDL development

Numerical models are typically used during the process of TMDL development to represent the linkage between pollutant sources and water quality targets. A typical TMDL modeling workflow can be specified as follows (ASCE/EWRI TMDL-TC 2022):

1) *Conducting preliminary assessment*: GIS and remote sensing tools can assist in data compilation for an initial assessment to establish the basis of an impairment, and to determine the need for a TMDL.
2) *Establishing the TMDL*: Depending on the available data, more sophisticated models may be constructed to evaluate event-based and temporal aspects of the impairment.
3) *Modeling the system*: Once the problem has been identified, a detailed TMDL model (such as a process-based model) can be constructed to evaluate the system response to both critical conditions and continuous long-term systemic changes. Geospatial information on the geography, land use, hydrology and loading, are vital in this step (Figure B1).
4) *Evaluating model results*: Once model results are available, GIS-based tools can be helpful to present this information to engaged stakeholders (Figure B1).
5) *Implementing the TMDL*: Once the timeline for TMDL implementation has been determined, GIS can be useful for engaging with stakeholders, reaching consensus on appropriate strategies for controlling pollutant loads, and developing market-based solutions for estimating and trading pollutant load allocations (Figure B1).

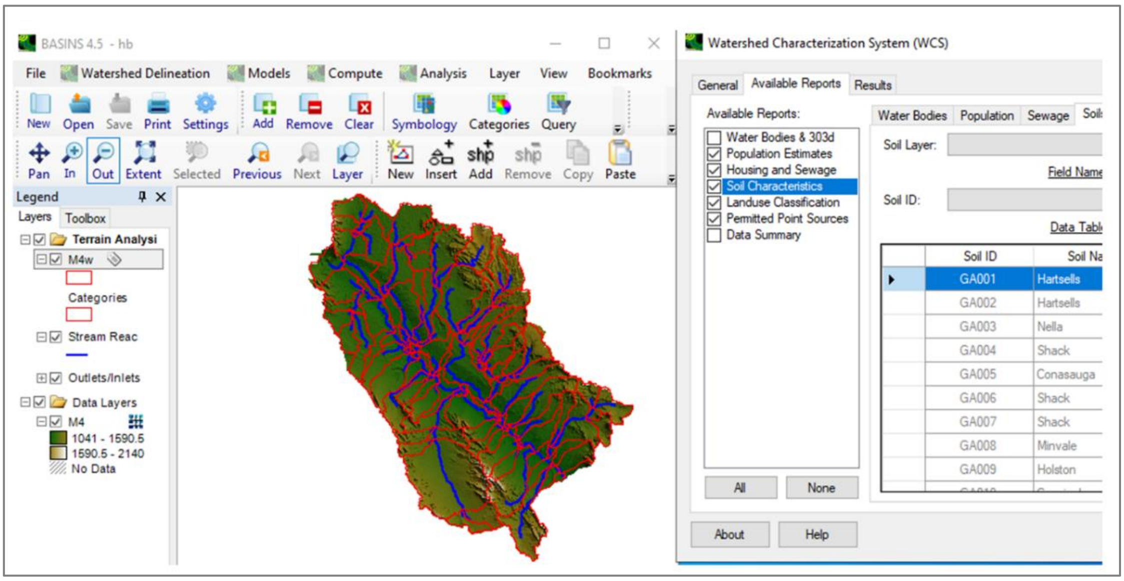

Figure B1: Example of the use of a GIS-based model user interface to enhance stakeholder access to model data and improve technical review of model simulation outputs. This application from the BASINS TMDL decision support system utilizes the open source MapWindows GIS platform to characterize the hydrograph and land use for the watershed, delineate pollutant point sources, and identify municipal sewerage in the study area.

Box 2: GIS and remote sensing in 4b pollution control programs.

This Box demonstrates how GIS and remote sensing can be used to enhance the stakeholder engagement process in a 4b pollution control program.

Background

In limited settings, the mechanism of achieving load reductions may be through watershed management by implementing 4b pollution control programs (Monschein & Reems, 2009; NCDEQ, 2021). This occurs when load reductions within the watershed are likely to result in attainment of water quality standards without having to resort to an explicit TMDL, such as in the case of pathogens and emerging contaminants, or when load reductions of other pollutants or implementation of management actions result in collateral pollution abatement. In such cases, the relationship between loads and impairments, as well as stakeholder action is unintuitive. Convincing stakeholders that such programs are in their best interest may be challenging, in which case using GIS tools can be helpful.

Workflow for 4b Programs

For these programs, the jurisdictional agencies must show through their monitoring and modeling programs that without the explicit implementation of a TMDL, load reduction may be achieved (e.g., Adkins & Monschein, 2009; Bresler et al. 2009; Flynn et al. 2009; Stevens et al. 2009). GIS-based tools are useful for conveying such important information for the 4b program (Figure B2).

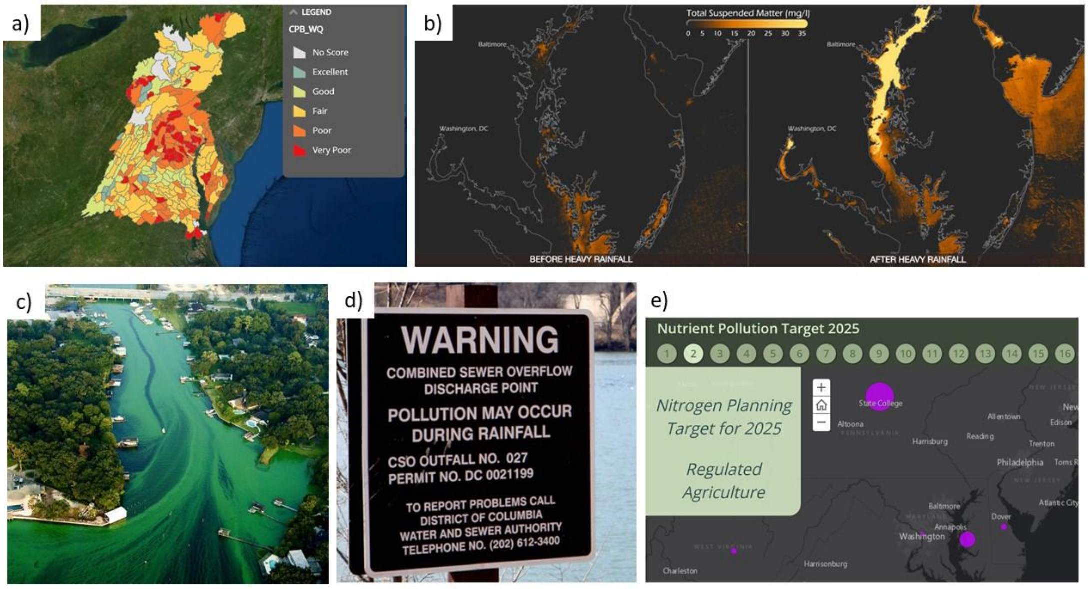

Figure B2: GIS layers, remotely sensed innovative use of GIS, and remote sensing imagery in a web dashboard can be used to contextualize and convey watershed information for nitrate pollution management: a) spatial distribution of water quality in Chesapeake Bay's subwatersheds, b) amount of suspended matter in Chesapeake Bay, before and after a heavy rainfall event (Source: NOAA, 2022), c) aerial true color imagery (Source: USEPA, 2022), d) example of a warning advisory, and e) example of a planning dashboard based on data, GIS and models.

Monitoring for 4b programs

The monitoring requirements for a 4b program are similar to those needed for a TMDL program and co-exist with TMDLs that have been completed or involve pollutants that will be mitigated by other pollution control methods (Adkins & Monschein, 2009; Bresler et al., 2009; Flynn et al., 2009; Stevens et al., 2009). These monitoring requirements also apply when physical processes such as critical conditions occur that cause non-attainment of water quality standards or objectives that cannot be readily mitigated.

Role of GIS and remote sensing in 4b programs

The biggest challenge for 4b programs is to convince stakeholders that such a program will actually result in the attainment of water quality objectives without explicitly managing the pollutant of concern. This requires a clear enumeration of point and nonpoint source loads, and a spatially explicit representation of the loads and watershed-wide practices to first educate stakeholders about the impairment. For example, atrazine impairment in the Little Arkansas River sub-basin has been handled effectively with stakeholder engagement and implementation of voluntary Best Management Practices (BMPs) under a 4b program, rather than by implementing TMDLs, because the stakeholders did not want their participatory actions to cool off under a regulatory imposition (Flynn et al., 2009).

In the authors' opinion, using GIS to enumerate loads and existing BMPs, and linking these to water quality datasets through visual portals would help in stakeholder education and outreach to local farming communities. Using high-resolution (<10m^2 per pixel) remote sensing datasets to monitor the health of agricultural fields and inform the application of herbicides would make the 4b program more effective.

Box 3: GIS and remote sensing in 9-element (9E) plans.

This Box demonstrates how GIS and remote sensing can be used to enhance the stakeholder engagement process in a 9E watershed management plan.

Background

Watershed management plans are participatory in design and allow the identification and mitigation of nonpoint source pollutant loads within the watershed rather than focusing on water quality standards or objectives that have to be met within the impaired waterbodies (e.g., NCDEQ, 2021; NYSDEC, 2021; TCEQ, 2021). In cases where impaired waters occur or a watershed spans multiple counties, state and regional jurisdictions, transboundary compacts such as the Chesapeake Bay Program (USEPA, 2010) are required to meet quality objectives. In the case of international boundaries, cooperation between nations must be facilitated under the auspices of treaty-bound collaborative programs such as the US-Canada Binational Toxics Strategy (USEPA, 2016a), or the US-Mexico Border 2025 program (USEPA, 2021a). Such transboundary problems will require ground-up stakeholder engagement to be successful (Medema et al., 2016).

Workflow for 9E programs

Watershed planning allows for a holistic addressing of nonpoint source pollution within the watershed, by engaging with stakeholders early and throughout the implementation process. These plans typically comprise six steps (USEPA, 2013):

1) building partnerships by identifying key stakeholders and understanding the impairment issues;
2) characterizing the watershed by collecting available data including identifying the sources of pollution;
3) finalizing goals and identifying solutions by describing management actions that will be needed to achieve load reductions in critical areas within the watershed;
4) designing an implementation program by first estimating resource needs and identifying funding sources, subsequently developing a stakeholder engagement plan and a project schedule, and finally quantifying interim goals and milestones and identifying indicators to measure progress;
5) implementing the watershed plan including monitoring and stakeholder engagement; and
6) measuring progress and adaptively managing the watershed.

Monitoring for 9E programs

Since the focus of this program is on watershed-wide nonpoint sources of pollution, GIS and remote sensing data resources can be effective in identifying and quantifying loading from these sources (as we discuss in Section 2.2 below). Monitoring is aimed at quantifying nonpoint sources of pollution, as well as comparing the impacts of the 9E plan on key indicators of progress. While these typically include water quality measurements, this type of monitoring program may also involve tracking demographic, and socio-economic indicators over time (such as land use changes), water consumption and recycling, loading processes and patterns, and ecosystem-level changes.

Role of GIS and remote sensing in modeling for and in implementing 9E programs

By combining spatially disaggregated socio-economic and land use/land cover datasets (e.g., georeferenced physical surveys of the environment) with geolocated stakeholder engagements (e.g., surveys and interviews), it may be possible to deduce data limitations and identify potential management actions to address these deficiencies. We support this statement with the following high-level example: stakeholders are more likely to behave with some type of bounded rationality (e.g., not recognizing the utility of voluntary load reductions, inconsistent behavior over time, responding to changing conditions with inertia, etc.) rather than as unbounded rational entities (Venkatachalam, 2008). Thus, understanding their behavioral response to existing conditions and proposed policies in different locations within a watershed or larger region would allow planners to understand how rational and irrational players work within a system, and how different typologies of stakeholders interact within the system and react to policies (Barnes et al., 2011). These georeferenced engagements will also allow planners to better understand the geospatial patterns in the motivations and aspirations of stakeholders, plan appropriate data collection strategies, and propose spatially explicit management plans.

By engaging with stakeholder entities such as beneficial users, water rights holders and polluters to seek structural and non-structural solutions to water quality impairments, there is considerable scope for a spatially explicit engagement approach. While developing a monitoring program for 9E planning activities, planners may find ways to seamlessly integrate *in-situ* monitoring, citizen science and remote sensing data products, to obtain a watershed-wide window into the pollution problem. Within a 9E plan, building and maintaining partnerships within the watershed is a necessary first step. Therefore, monitored key water quality, socio-economic, demographic and ecosystem indicators, and their comparison with performance milestones must be presented to stakeholders through easily accessible visual interfaces.

For distributed hydrologic and water quality models, real-world socio-environmental datasets can be introduced to develop so-called "serious games" (Medema et al., 2016). Serious games are a set of powerful participatory engagement technologies that allow facilitators to create an atmosphere of trust between stakeholders and system managers, that can help to document the outcomes of collaborative or confrontational approaches to watershed management (Medema et al., 2016). GIS and remote sensing data can be combined with advanced visualization to develop games reflecting the real world more realistically. When combined with proposed policy trajectories, the outcomes of these games may provide planners insights into how management actions will impact watershed-wide outcomes. These games will also allow stakeholders to experience first-hand, how their own actions could dictate outcomes, and will thus help to make the 9E planning experience feel truly participatory with grassroots stakeholder involvement.

For TMDL development and performance assessment in the US, the use of GIS and remote sensing technologies has increased dramatically in the past decade. Many popular software tools used for developing TMDLs have adopted GIS and remote sensing in their interfaces. There is growing consensus within the scientific community that broader participation of multidisciplinary experts from different domains is needed to develop solutions to the most challenging water quality problems (e.g., Eakin et al., 2017; Ganjali & Guney, 2017; Sayles & Baggio, 2017; Flood et al., 2018; Jean et al., 2018; Bathke et al., 2019; Medema et al., 2019; Dhiman et al., 2020; Alamanos et al., 2021). The GIS and remote sensing-based visualization and analysis approaches apply not only to TMDLs but also to broader watershed planning and water quality management programs. In the past decade, there have been significant advances made in the ease of access and affordability of remotely sensed datasets collected by satellites and/or airborne sensors (e.g., through Google Earth Engine, USGS earth explorer, NASA earth observatory (NASA, 2022), etc.). These datasets are being routinely incorporated into water quality and watershed model user interfaces, which have the potential to revolutionize participation in water quality management planning and provide a means of tracking implementation performance and outcomes. Further, new technological advancements in citizen science, virtual and augmented reality, and effective engagement with stakeholders are pushing the boundaries on what can be achieved by tapping into the potential of the populace.

The objective of this paper is to explore how GIS and remote sensing – from data sources to methods – can be combined with cutting edge stakeholder engagement practices to deliver net societal benefits including ecosystem, economic and human health benefits for watershed management. We argue that the application of GIS and remote sensing has the potential to enhance watershed management by synergistically improving both the technical development and stakeholder engagement aspects of water quality management (Figure 1). For example, by providing geospatial data sources covering various domains within immersive interfaces, engagement with a wide variety of stakeholders is possible. This widespread engagement can potentially influence policy makers and key players, enhance citizen science efforts, strengthen socio-political-industry ties, and foster community buy-in and community ownership of shared water resources for a sustainable, equitable and resilient future. The data and interfaces can also potentially help drive more representative water system models and derive optimal solutions. In Figure 1, impairments and their sources, and socio-economic conditions within watersheds can be identified by a combination of remote sensing, *in-situ* monitoring, and stakeholder engagement to create a database of geospatial information that can be used to develop online data dashboards and inputs for numerical models using geospatial software. Such software can be used to evaluate alternate management scenarios and design management practices that can then be monitored post-implementation using remote sensing. This monitoring data can also be fed to the data dashboard, which can be subsequently used for immersive engagement for equitable and inclusive watershed management.

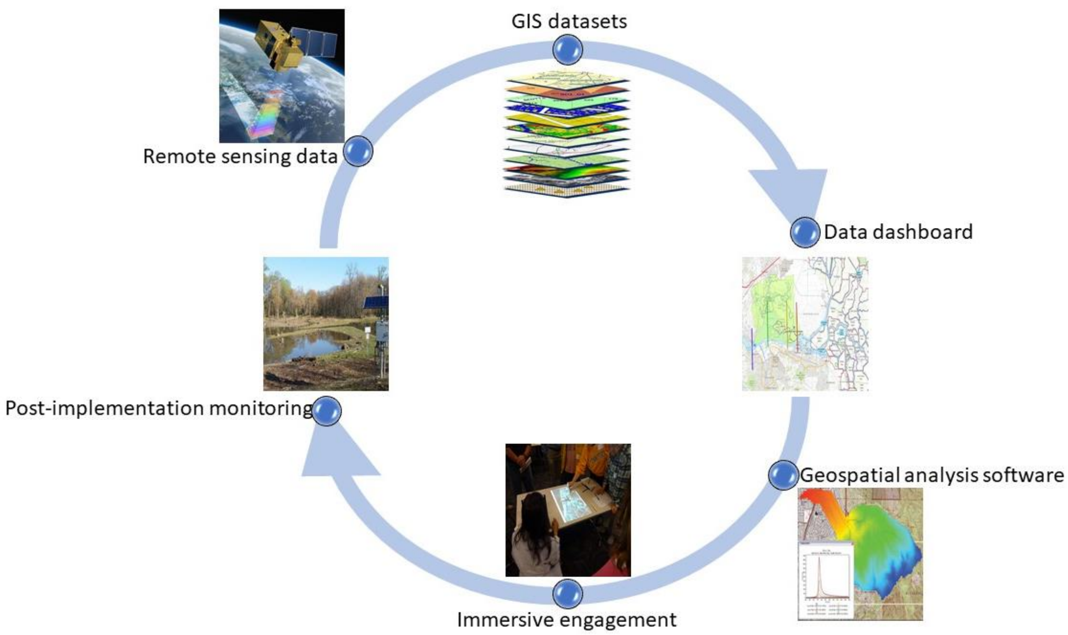

Figure 1: GIS and remote sensing technologies will result in better technical developments and enhanced stakeholder engagements that will improve the overall watershed management process.

The paper is arranged as follows: Section 2 discusses the use of GIS-based datasets, tools, and remote sensing technologies in watershed management. In Section 3, the discussion centers on various stakeholder engagement technologies, and ways to adopt participatory and immersive approaches developed in other fields to water management. Section 4 provides a roadmap for how GIS and remote sensing data and tools can be combined with emerging stakeholder engagement practices to transform the management of watersheds. Finally, our principal arguments are summarized in Section 5.

2. Use of GIS and remote sensing in watershed management

A large variety of GIS software tools exist for communicating spatial data passively (e.g., maps, figures, data, etc.) and actively (e.g., web maps, tools, etc.). The most popular tools are those that organize and display spatial data products in maps (De Freitas et al., 2013) and communicate the results of modeling in both space and time to illustrate the impact of potential watershed management decisions (Stewart et al., 2008). These tools have more recently been combined with web-based Graphical User Interfaces (GUIs) to convey information to a broad audience. Invoking GIS functionality through GUIs is useful in both legitimizing the stakeholder engagement process, as well as enhancing participation in watershed management programs. We believe that with emerging water quality issues, the use of GIS and remote sensing data sources should also be more integrated into watershed and water quality models for greater fidelity of these models.

For many impaired waterbodies in the US, TMDLs have been developed for a variety of pollutants. Some of these pollutants include sediments, pathogens, nutrients, metals, dissolved oxygen, temperature, pH, mercury, pesticides, and organics (USEPA, 2017). Use of active and passive remote sensing (see Box 4), to assess or determine the degree of environmental impairment caused by a pollutant, is limited to substances or conditions that directly or indirectly influence or change the optical (reflected) and/or thermal characteristics of the water surface. For example, changes in *chlorophyll-a* and turbidity result in strong optically active changes that may be observed by multispectral imagers. In contrast, total phosphorus and nitrogen do not result in significant change in optical activity and rely on correlation with other optically active constituents (Gholizadeh et al., 2016). In such cases, regression models have been developed between the surrogate indicators and variables based on *in-situ* measurements concurrent to satellite overpass (Gholizadeh et al., 2016). In addition, the thermal band of satellite data can be used to directly estimate the surface temperature of waterbodies. As the optical properties of the water column can change spatially and temporally, multi-temporal satellite data and multi-point *in-situ* measurements are required for these applications (e.g., Choi et al., 2014). Robust methods for water quality measurement using active and passive remote sensing for inland waters, remains an open challenge in the widespread adoption of GIS and remote sensing tools for watershed management.

2.1 Towards curated, open and commercial data

In the context of watershed management, it is important that searchable and easily retrievable digital geographical records of land holdings, loadings, watershed monitoring, and implementation measures be maintained. Remote sensing data can provide information required to describe the variability of loading from urban and suburban land areas (Box 4). This information can be applied to develop a library of loading rates and mean concentrations of pollutants in the waterbody during extreme hydrological events such as floods or droughts (Hantush, 2005). Within a watershed, remote sensing data can be used for land use and land cover (LULC) classification. For instance, Landsat, Sentinel-2, and Spot imagery are commonly used to classify land use types (Owojori & Xie, 2005; Johnson & Iizuka, 2016; Mohajane et al., 2018; Naikoo et al., 2020). Because land use is a significant driver of water body impairments and can be clearly communicated to stakeholders through maps, it has potential for guiding conversations with planners during both pre- and post-watershed management action implementation. For example, LULC change scenarios based upon stakeholder workshops have been used to evaluate the impact of load reduction plans on water body impairments (Ahmadisharaf et al., 2020).

In recent years, national-level GIS tools have become available for understanding the impact of watershed management decisions on water quality outcomes. The Catchment Land Use and Environmental Sustainability model (Semadeni-Davies et al., 2016; Semadeni-Davies et al., 2020) is a GIS based modeling system that can define the impact of land use changes on water quality. This modeling system's GIS interface makes communication of model inputs and outputs easily understood through data visualization in maps (Elliot et al., 2016). Agricultural water districts and other local agencies are increasingly making use of the web to provide their customers and other watershed stakeholders with access to their data. This is not only for good public relations, but can also facilitate coordinated watershed activity. Organizing and displaying data through maps can allow greater transparency in communicating risk assessments or displaying model results (Harris et al., 2017), such as communicating sediment sources through maps within a participatory model of watershed sediment transport (Cho et al., 2019).

2.2 Role in impairment identification

Remote sensing can be a valuable tool in impairment identification, as we discuss here. Remote sensing techniques provide spatial and temporal variation of water quality parameters and make it more effective and efficient to monitor waterbodies and estimate water quality issues. Satellite imagery have been successfully applied to monitor inland and coastal waters for more than 50 years (Anding & Kauth, 1970; Seyhan et al., 1986; Ferrari et al., 1996; Handcock et al., 2006; Schaeffer et al., 2012). They have been used to monitor stakeholder driven indicators such as Fowler’s Sneaker Depth index, and index analogous to Secchi disk depth, which is a citizen scientist metric used to assess water clarity in the Chesapeake Bay (Crooke et al., 2017). Commercially available data like Planetscope and Worldview provide spatial details on less than a meter resolution on a daily to even sub-daily scale. Hyperspectral imagers can be used to track water bodies and resolve many other types of impairments (e.g., Olmanson et al., 2013; Kudela et al., 2015).

Regulation such as the US Clean Water Act (CWA) require various agencies to identify designated uses of their waters and develop science-based water quality criteria, to ensure the protection of the designated uses. The vastness and remoteness of most waterbodies make it hard to monitor them effectively with conventional *in-situ* methods. Unlike the European Union Water Framework Directive, the CWA is silent on how to choose sampling sites, monitoring frequency, pollutants to sample, analysis process and method, and data sharing (Habermann & Ward, 2001). The lack of guidance on monitoring creates an obvious problem where impairments go undetected until a critical situation is reached with obvious markers. Even with the guidance, the scale and scope of monitoring required may overwhelm the monitoring system. Further there may be uncertainty around the background reference of the pollutants of concern to establish a criterion in the first place. For example, algal blooms happen in coastal waters naturally without any loading from the watersheds (Vargo, 2009), but to trigger a remediation action, the impact of nutrient loading has to be established. Schaeffer et al. (2012) have demonstrated a method based on remotely sensed data to develop a reference criterion and monitoring criteria for algal bloom in Florida’s coastal waters that could trigger remedial actions. It is important to note that in order to detect and track pollutants in marine environments, prior understanding of marine dynamics including ocean current direction and magnitude, direction and speed of surface winds is important. In addition to optical data, satellite remote sensing provides information about marine dynamics. For instance, information on sea surface winds can be derived from altimeters, which collect wave height data and synthetic aperture radar (SAR) that measures the sea surface roughness pattern (Kudryavtsev et al., 2012).

2.3. Role in model development

The availability of GIS and remotely sensed data has improved model development, facilitated data collection, and provided techniques for combining spatial heterogeneous information. Spatially distributed, parametric watershed and water quality models require topographic, hydrological, soil, land use and meteorological forcing information as input data. These data, obtained either by traditional gauging or remote sensing, are available online in the US from federal agencies such as National Oceanic and Atmospheric Administration (NOAA), National Aeronautics and Space Administration (NASA), the United States Geological Survey (USGS), and the United States Department of Agriculture (USDA), or posted on local agency web portals. By collecting data over large and remote areas, remote sensing technology has provided inputs for distributed models (see Box 4). These technologies have augmented data gathering and the ability to monitor water quality conditions in large watersheds. They additionally provide LULC information which helps with estimation of directly connected impervious areas and can be used for the development of detailed information on soil characteristics that can impact infiltration and runoff calculations in hydrologic models. Remote sensing data can also provide high resolution spatial precipitation data that significantly benefit development of hydrologic models (Kirschbaum et al., 2017; Maggioni & Massari, 2018).

GIS and remote sensing tools can be used to process data model inputs (e.g., parameters, forcings), and also synthesize spatial data from model outputs for water quality management applications (Kang, 2002; Kang & Park, 2003). Some GIS-based integrated model interfaces can help with preprocessing of input data, mapping, and visualization of modeling results (Table 1). For watershed and water quality modeling applications, GIS and remote sensing data sources are invaluable throughout the modeling pipelines. Initial spatial overlays can help to select and organize data for input to water quality models. Examples of initial preprocessing of water quality models using GIS are presented by Shafique et al. (2003), Ramirez et al. (2005), Viers et al. (2005) and Ramirez-Avila et al. (2017). To initialize and run these models, detailed information on local conditions, such as nutrient loading from farms and municipal waste discharges are often needed from local stakeholders or from direct field surveys (ASCE, 2022; Benham et al., 2006).

Table 1: Non-exhaustive list of watershed and water quality modeling suites with GIS capabilities

Model	Acronym	Capability	Reference
Agricultural Nonpoint Source Pollution	AGNPS	Interface	Young et al. (1994)
Annualized agricultural Nonpoint Source Pollution Model	AnnAGNPS	Interface	Bingner et al. (2003)
Generalized Watershed Loading Functions	GWLF	Interface	Haith et al. (1992)
Loading Simulation Program in C++	LSPC	Interface	USEPA (2016b)
Storm Water Management Model	PCSWMM	Interface	Smith & Banting (2005)
Soil and Water Assessment Tool	ArcSWAT	Interface	Arnold et al. (2012)
Agricultural Policy/Environmental eXtender Model	ArcAPEX	Interface	Gassman et al. (2009); Teet et al. (2021)
Better Assessment Science Integrating Point and Nonpoint Sources	BASINS	Model integration	USEPA (2019)
Watershed Analysis Risk Management Framework	WARMF	Model integration and decision support	Herr & Chen (2012)
Stream Network Watershed Scale Model	CCHE1D	Model integration	Wu & Vieria (2002)
Interactive Windows Interface to HSPF	WinHSPF	Model integration	Duda et al. (2001)
GIS-based Phosphorus Loading Model	GISPLM	Model integration	Walker (1997)

Subsequently, GIS can play an important role in developing and implementing remediation plans or pollutant reduction strategies, such as siting structural Best Management Practices (BMPs) and targeting non-structural BMPs in high-impact areas. The types of data that are required for developing and running watershed and water quality models are listed in Table 2, and links to these data can be found in the literature (Benham et al., 2006; Borah & Bera, 2003, 2004; Borah et al., 2006; Quinn et al., 2019). Data required to generate novel scenarios under which the impacts of management actions need to be investigated may, in rare circumstances, be obtained by synthesizing data from multiple sources, including other watershed simulation models. This can be a time-saver for some hydrometeorological data inputs to models since significant processing is often needed to transform raw data into formatted model input.

Occasionally, TMDLs are developed for watersheds within ungauged streams and where little ancillary data is available (ASCE/EWRI TMDL-TC, 2022; Zhang & Quinn, 2019). In such cases, data from an adjacent or reference watershed or stream with similar conditions may be used to develop the model (Wallace et al., 2018). The geographic and hydrologic properties of the target watershed typically need to be scaled and adjusted to emulate the characteristics of the reference watershed (Doherty & Hunt, 2010; Wallace et al., 2018). This is where GIS tools can serve in an effective role, not only in providing the model with essential data to perform simulations, but in elucidating the assumptions made in such an analysis more transparently to stakeholders. As reported by Wallace et al. (2018), geoprocessing algorithms can be applied to scale reference watershed land use patterns to the target watershed areal coverage, while retaining proportions of land use cover within the reference watershed. These assumptions can be carried over in proportion to the sediment and nutrient loads generated from the target watershed. By overlaying scaled maps of the two watersheds, the inherent proportionality assumption can be conveyed to stakeholders visually.

A reduction in the cost of imagery and processing software, and the increasing access to simple GUIs for popular image processing tools (e.g. ERDAS, ENVI and ArcGIS Image Analyst), has led to more frequent use of satellite images in watershed-scale modeling studies and TMDLs (ASCE/EWRI TMDL-TC, 2022) (Box 4). This contrasts with the limited operations from the past, in which remote sensing analysis and model development were independent tasks.

Table 2: Hydrological, meteorological and geographical data requirements for watershed and water quality model development amenable to representation in GISs (Quinn et al., 2022).

Type	Data category	Discrete	Continuous	Sources
Geographical	Topography		*	Terrestrial and aerial surveys
	Bathymetry		*	Terrestrial and aerial surveys
	Land use and land cover	*		Surveys, satellite imagery
	Vegetation and soil type	*		Terrestrial surveys, satellite imagery
	Stream bottom and bank roughness	*		Surveys
	Best management practice location and type	*		Terrestrial surveys, satellite imagery
Pedological	Soil permeability and infiltration capacity	*		Surveys, experiments
Meteorological	Air temperature		*	Measurements, models
	Wind speed and direction		*	Measurements, models
	Humidity		*	Measurements, models
	Rainfall		*	Gauges, radar, satellite imagery, models
	Heat budget		*	Measurements, models
	Ice cover and melt		*	Measurements, satellite imagery, models
	Soil heat budget		*	Measurements, models
Hydrological	Groundwater table elevation		*	Gauges, radar, satellite, models
	Soil moisture		*	Surveys, models
	Streamflow		*	Surveys, satellite
	Baseflow		*	Gauges, models
	Water stage		*	Gauges, rating curves, models, satellite altimetry
	Water quality		*	Surveys, measurements, models, satellite imagery
Water resources	Hydraulic structures and diversions	*		Surveys
	Water operations	*		Surveys
	Reservoir elevation and storage	*		Surveys

Note: * signifies whether the data is discrete or continuous.

2.4. Role in planning and implementation

Applications of GIS and remote sensing have significant potential for supporting planning and implementation decisions (Zhang & Quinn, 2019). During pre-implementation modeling, water quality data from remote sensing at high-spatial resolutions can be used to parameterize and calibrate watershed models (Fisher et al., 2018). As highlighted, GIS-based systems have been developed to integrate a suite of watershed and water quality models and provide frameworks for decision support (Table 1). GIS workflows in these models can be used as a pre-processor and post-processor to TMDL modeling (ASCE/EWRI TMDL Analysis and Modeling Task Committee, 2017).

Remote sensing and GIS are becoming important tools in the development of management and load reduction plans aimed at improving the quality of impaired waterbodies (Giardino et al., 2010; Fink et al., 2020). By using remote sensing and GIS data for land use zoning and effective siting of BMPs, system managers could inhibit or slow down pollutant movement to a waterbody (Zaidi, 2012). Several GIS software interfaces with water resources models have been developed for such applications, such as ArcSWAT (Winchell et al., 2007) and InfoSWMM (Innovyze, 2017) (see Table 1 and Martin et al. 2005 for additional examples).

Remote sensing data is very valuable for extreme event risk management. To understand and quantify water quality and manage risks caused by extreme events, it is crucial to study the hydrologic cycle and its changes over time. The performance of hydrological modeling is a way to assess the accuracy of the representation of the hydrological cycle (Jiang & Wang, 2019). Global coverage of satellite-based images with their high spatial resolution and metronomic return periods can help to address the deficiency in *in-situ* data. For example *in-situ* data can be used to calibrate and verify geospatial statistical models of water color and associated water quality (Choi et al., 2014). Such models can serve as early warning for critical events such as harmful algal blooms, while the integration of near-real time remote sensing based statistical models with online data portals can serve as a communication channel for decision making (Dhiman et al., 2020).

On-line modeling systems, such as the USEPA Cyanobacteria Assessment Network (CyAN) smartphone app (USEPA, 2021b), can provide public access and interactive interfaces for community decision making. Data collected via the CyAN app can help local and state water quality managers make faster and better-informed management decisions related to cyanobacterial blooms. This app has a standardized approach for early identification of algal blooms using a set of satellites including Ocean Land Color Instrument (OLCI) on Sentinel-3, Sentinel-2, and Landsat for over 2,000 of lakes and reservoirs within the US. Thus, the maturity of the internet, coupled with easy access to freely available data sources and the proliferation of smart apps and programming interfaces, has allowed system managers and decision makers to have unprecedented access to remote sensing and GIS data for watershed decision support.

Box 4: Remote sensing sensor types, platforms, and datasets.

In this Box, the different types of remote sensing data that are applicable to watershed and water quality modeling and stakeholder engagement are discussed. It is important to note that the different types of sensors listed here collect data at various spatial scales, spectral resolutions and temporal return periods. However, with increasing maturity of technologies and the emergence of new ones, the number, and the spatial, temporal and spectral resolution of various sensors are increasing exponentially (Kuenzer et al., 2014). While they provide diverse windows into the natural world, the types and attributes of data they collect are not interchangeable.

Active sensors

These include technologies wherein electromagnetic signals are bounced off the planet's surface and their echoes are picked up by on-board scanners.

1) *RaDAR*: Radio Detection and Randing (RaDAR) technology is useful for measuring the thickness of precipitation clouds and the intensity of rainfall events by bouncing high-frequency (tens of gigahertz) radio waves off the surface of atmospheric obstructions. Missions such as NASA's Global Precipitation Measurement (GPM) core observatory include instruments such as the Dual Frequency Precipitation Radar for this purpose (World Bank, 2022).
2) *Microwave imaging*: By slightly lowering the frequency of radio waves that are used for scanning the cloud surface into the microwave bandwidths, the dynamic range of brightness of reflectances and rainfall intensities can be significantly increased (Bauer & Bennartz, 1998). An example of microwave precipitation detection is the microwave imager onboard the GPM core observatory. Active microwave sensing can also be used to measure the elevation of topography by measuring the distance between the sensor platform and the surface from which the signal is bounced. This application is known as microwave altimetry (JARS, 1996).
3) *LiDAR*: Light Detection and Ranging (LiDAR) is categorized as active remote sensing, which registers laser pulses that strike and detect an object, then determine the range (or distance) between the instrument and the object. The physical properties of an object are detected based on the interaction with the LiDAR radiation (Diaz et al., 2013). LiDAR has several applications in agricultural monitoring, forest planning and management, forest fire management, environmental assessment, flood and pollution modeling, watershed and stream delineation, ecological and land classification, land and river surveying, coastlines management and glacier volume changes. As such, it has utility for data acquisition in support of water quality modeling, especially in terms of extracting high-resolution Digital Elevation Models (DEMs). For example, high-resolution DEMs from LiDAR have been used to build decision support models for simulating field-scale implementation of conservation practices to achieve TMDLs and communicate management options to stakeholders (Srinivas et al., 2020). Access to this technology through modern smartphones

Box 4 (continued)

has potential for collaborative citizen science and could result in greater participatory planning activities with stakeholders more actively involved in model data acquisition activities. Particularly in urban settings, where every citizen with a LiDAR-equipped smartphone can capture highly detailed photogrammetry of small local areas, this technology could be used to augment models built using LiDAR topographies at the cityscape with nested, high-resolution detail as needed.

Passive sensors

These include technologies wherein airborne or spaceborne platform contain sensors which pick up radiated electromagnetic signals from the Earth surface and the atmosphere.

1) *Multispectral imagery*: Multispectral sensors typically capture the visible, near infrared, and shortwave infrared images in several broad wavelength bands (typically 3-10 bands) using passive remote sensing (i.e., by measuring the solar radiation reflected from objects on the earth and in earth's atmosphere). In recent years, the long-term multispectral imagery from platforms such as the Landsat, managed by the USGS/NASA, have been made available at no cost to users. Landsat based National Land Cover Database (NLCD) (Xian et al., 2011) has been commonly used for parameterizing hydrological models (Karpouzli & Malthus, 2003). Landsat is also increasingly used for remote sensing of water quality (Ross et al., 2019).
2) *Hyperspectral imagery*: Passive hyperspectral sensing acquires a narrow spectral bandwidth (2-10 nm), but a greater number of spectral bands (more than 100 contiguous bands) usually in the range from visible to shortwave infrared (VIS-SWIR) (400-2500nm). The higher spectral resolution of the hyperspectral imaging allows the user to better identify, characterize, quantify, and detect objects smaller than the spatial resolution (subpixels) (Wang et al., 2013). Hyperspectral imaging could be successfully used for acquiring data for TMDL modeling and evaluating management action outcomes for watersheds at different scales. Since hyperspectral data combines spatial and spectral information, the high cost of acquisition and the large size of the datasets are the key challenges for stakeholder utilization. These data processing challenges have meant this technology is still largely unused by the research community. The operating instruments used to acquire hyperspectral data are also costly and need specialized handling, particularly when mounted on airborne platforms. Several platforms, such as the NASA Airborne Visible Infrared Imaging Spectrometer (AVIRIS) are equipped with hyperspectral sensors, partially alleviating data acquisition problems. However, these platforms commonly have limited spatial swath and low resolution. If standardized workflows can be developed to deal with the large datasets from hyperspectral platforms, this would be a valuable addition for water quality modeling. Robust data quality control and assurance are key to the adoption of this technology for both pre- and post-planning applications. This is because, unlike in the case of multispectral imagery, hyperspectral image processing tools are still nascent, and many approaches of varying quality are possible.. Notwithstanding these challenges, the narrow spectral bands are especially useful for extracting water quality information, which has the potential to be conveyed through GIS layers to stakeholders as multiple overlays of various types of impairments.

Airborne data collection

Unmanned aerial systems (UAS) have driven down the cost of scene-based image acquisition. This includes the use of unmanned aerial vehicles for supporting urban stormwater management (McDonald, 2019), detecting algal blooms (Kislik et al,. 2018), and measuring relevant water quality parameters such as total suspended solids (Guimarães et al., 2019) and turbidity (Ehmann et al., 2019). The UAS are capable of providing necessary input data for watershed, hydraulic and channel evolution models, and data for calibrating these models and for enumerating localized sources of pollution within a watershed. However, the need for trained operators and stringent privacy laws currently limits the use of UAS as a source of water quality and pollutant loading data around the world (Sibanda et al., 2021).

Satellite-based data collection

Satellite-based remote sensing can provide alternatives to land-based observations of key watershed processes such as soil moisture content, surface water elevation, groundwater, precipitation and evapotranspiration rates, and land cover land use. Use of this information together with streamflow observations can improve the performance of hydrological models (e.g., Ines et al., 2006). In McCabe et al. (2017), a comprehensive review of hydrological variables and satellite missions indicates the potential of remotely sensed data for watershed management.

The water quality estimations at large scale from satellite remote sensing are relatively limited, largely due to a lack of training data. To close this knowledge gap, AquaSat has proved the largest matchup dataset (over 600,000 pairs) between ground-based total suspended sediment, dissolved organic carbon, chlorophyll a, and SDDSecchi disk depth measurements and spectral reflectance from Landsat 5, 7, and 8 (Ross et al., 2019). With the operational land surface temperature products from both Landsat (Cook et al., 2014) and the Moderate Resolution Imaging Spectroradiometer (MODIS) (Hulley & Hook, 2011), surface water temperature is much more available in time and space, as compared to other water quality variables. Furthermore, medium resolution sensors (e.g., MODIS, MERIS) are commonly used for monitoring chlorophyll-a over large inland water bodies (Sayers et al., 2015).

Box 4 (continued)

Data processing and access

Over the past decade, many competing technologies have emerged to transform aerial and satellite-based imagery into usable analysis-ready data products. The USGS Earth Explorer engine and NASA Earth Observatory provide searchable access to thousands of raw satellite reflectance images, and analysis ready data products. In the private sector, Google Earth Engine began as an ambitious data assimilation and analysis platform within the philanthropic arm of Google.org. The success of the platform and the easy access to software tools for geoprocessing of data has led to a plethora of innovative environmental applications. The OpenET platform based on Earth Engine and its customizable Application Programming Interface (API) launched in early 2022 (https://openetdata.org/api/) and will enable users to request evapotranspiration data via both scripted queries and the graphical user interface for integration with other applications for irrigation scheduling, farm management, water use reporting, and water management.

These data analysis and sharing tools have been standardized for multispectral imagery. There are now a large number of data web portals and user interfaces such as the USGS Earth Explorer, NASA Earth data, and Google Earth Engine. These platform-based applications provide near-real-time processing of global Landsat imagery. For example, long-term data records from these platforms have been used in deforestation and reforestation analysis (Hansen et al., 2013), land cover (Wickham et al., 2014), daily crop evapotranspiration estimates for irrigated agriculture (Beamer et al., 2013), mapping surface water (Pekel et al., 2016; Zhao & Gao, 2018), water quality (Olmanson et al., 2013), among other uses.

3. GIS and remote sensing in stakeholder engagement for watershed management

The advent of customizable dashboards on agency and stakeholder-maintained web portals in recent years has created an opportunity to tailor simulation model outputs and the results of associated analysis to the individual needs of the stakeholder (Di Luzio et al., 2004). Here, the stakeholder is defined broadly as anyone involved in the discharge of a pollutant or impacted by the discharge of a pollutant by other entities in the watershed. An agency can be a stakeholder as in the case in the San Joaquin River Basin in California where the US Bureau of Reclamation as the purveyor of water supply pumped from the Sacramento San Joaquin Delta has responsibility for a portion of the salt load imported to the Basin through this conveyance (CVRWQCB, 2004). In this case the State Water Resource Control Board apportioned responsibility for salinity management in the salinity and boron TMDL in direct relation to the average annual salt load imported relative to the salt load measured at the single compliance monitoring station in the San Joaquin River (CalEPA, 2002; CVRWQCB, 2004; Quinn et al., 2018; Quinn, 2020; Quinn & Oster, 2021). The stakeholder role is distinct from the regulator – the regulator typically sets water quality objectives (Hoffman, 2010) and enforcement with the power to set fines or other financial incentives to encourage compliance. The regulatory framework has bearing on the form of stakeholder engagement practices and the participatory goals that are realistic. Obviously the greater the police power exerted by regulator, the lower the requirement to achieve results by collaborative behavior and cooperation.

GIS-based analysis and the use of remote sensing to contextualize data visualization can be incorporated in these dashboards for stakeholder decision support (Figure 1). In combination with these web-based tools, the increase in participatory planning and immersive engagement approaches in recent years (see below) means that, in our opinion, the full potential for stakeholder engagement using GIS and remote sensing in watershed management is nascent and waiting to be unleashed. Being able to see one's own property or contribution to impairment on a GIS map or analysis can sometimes be sufficient for a stakeholder to feel "represented." This could be as simple as providing a scanned high-resolution map or terrain image as a backdrop to model-based analysis. By geographically collocating such information with stakeholders represented in a watershed management process, underrepresented stakeholders can be identified. In this way, GIS can be used to overcome threats posed by detractors of watershed management initiatives that are critical of the authenticity of stakeholder representation (Hall, 2016).

3.1. Leveraging GIS and remote sensing data and tools

Gainful stakeholder engagement can be achieved by incorporating geospatial information through immersive, visual mediums (Figure 2). In Figure 2, we expand on the overarching themes presented in Figure 1. Both *in-situ* data collection as well as remote sensing can be augmented by citizen-science programs such as the Fresh Water

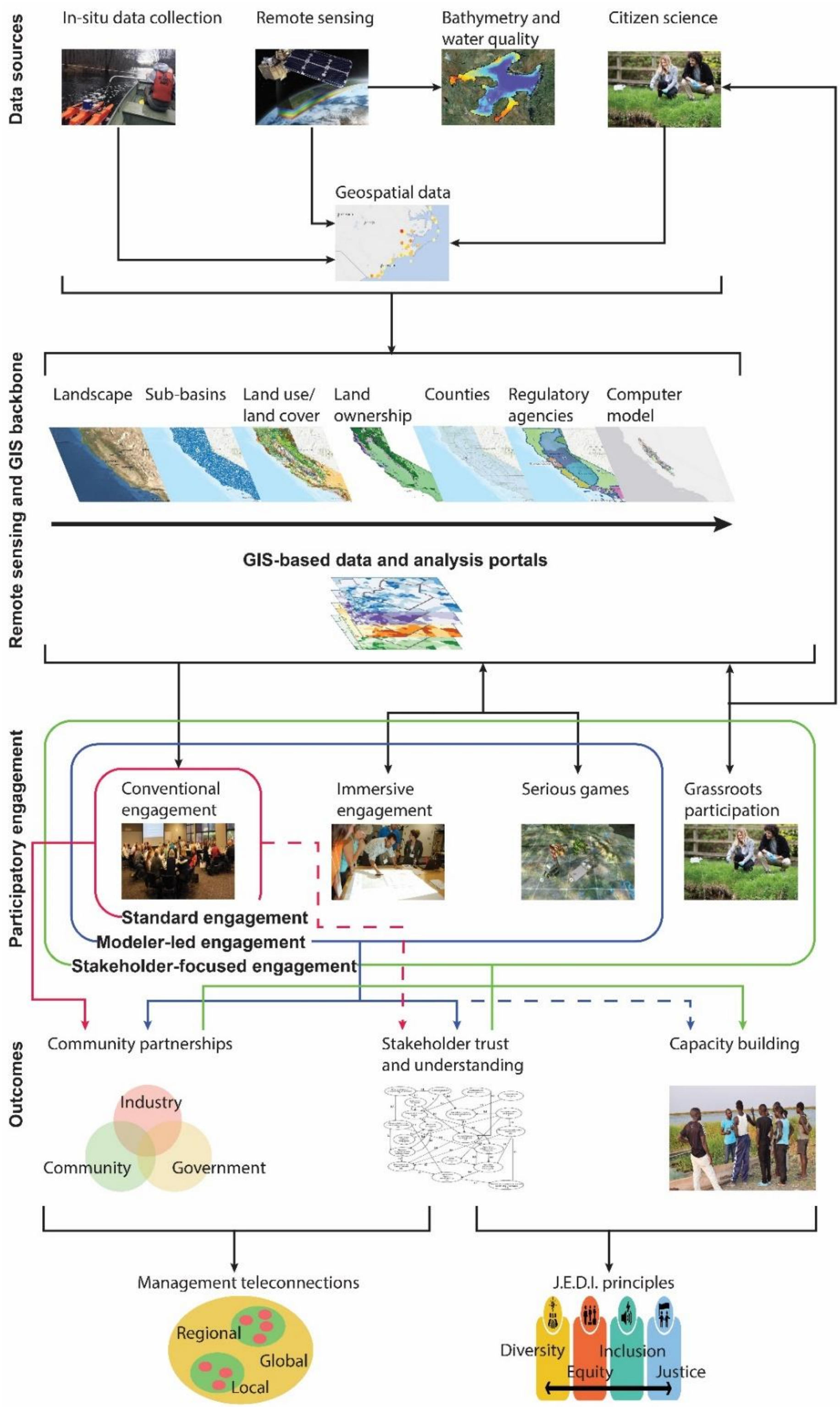

Figure 2: Data sources, GIS and remote sensing-based stakeholder engagement framework, technologies for participatory engagement and beneficial outcomes for water quality management.

Watch (Hadj-Hammou et al., 2017) for calibrating and validating computer models (Figure 2: first row). In contemporary settings, such models will involve multiple GIS layers containing physical, loading and land use information relevant to watersheds and water management (Figure 2: second row). The model results from watershed and receiving water quality models can be applied in conjunction with GIS-based socio-economic and geopolitical data to develop data portals and insightful local, regional and global analyses (Figure 2: third row). This can subsequently be used to engage with stakeholders at various levels (Figure 2: fourth row), for example using of immersive visual tools such as the WeTable (Yusuf et al., 2018), GWWebFlow, or serious games that include a spatial component (Mayer et al., 2001). These tools can also engage the public directly through citizen-science programs like the Fresh Water Watch (Hadj-Hammou et al. 2017), potentially leading to positive outcomes (Figure 2: fifth and sixth rows). In Figure 2, dashed lines indicate outcomes that may be difficult to achieve at one level of stakeholder engagement, while the same outcome may be a natural consequence of engagement at a different level. For example, through immersive serious game play and citizen-science programs, outcomes such as the understanding of complex interlinked water quality and management processes can result (Mayer et al., 2001), perhaps by the development of fuzzy cognitive maps in stakeholder groups. These outcomes can help to forge a sound industry-community-government nexus.

Additionally, through stakeholder trust, potentially built by deeply immersive engagements, regional and global teleconnection between individuals or local communities can be developed. Such connections across local neighborhoods, communities, not-for-profit and private entities, and various social groups lead to trust in the engagement process by inclusive representation of major stakeholder groups (Hall, 2016). The equitable representation of vested parties will result in consideration of justice, equity, diversity, and inclusivity (JEDI) principles in sustainable watershed management (Box 5) more readily than if underrepresented and underserved stakeholders were not involved. The State of California (USA) has made the inclusion of disadvantaged communities in resource planning decisions a high priority and has tailored the use of GIS and remote sensing technologies to provide easy access to information such as nitrate levels in rural domestic wells and hazardous algal bloom maps to those with internet access. An allied effort is underway in the State to increase web access targeted at those in underserved rural communities.

Box 5: The Justice, Equity, Diversity and Inclusivity (JEDI) principles in stakeholder engagement

The JEDI principles as introduced in Section 3.1 are discussed in this Box.

In the US, TMDL outcomes and watershed protection plans require stakeholder participation and acceptance for success; ultimately selected stakeholders have the authority to reject or adopt these vehicles for environmental protection. Stakeholders are usually identified and invited using emails and announcements on local government agencies' websites and a self-selecting group of motivated participants from local government, academia, and the local environmental groups engage in the process of developing the watershed protection plans. While the inclusion of entities such as American Indian tribes, citizen groups, and community service organizations is encouraged by current watershed protection plan development guidelines (USEPA, 2020), a structured framework for the integration of JEDI (justice, equity, diversity, and inclusion) principles has not been established. The four components of JEDI applied to water or environmental systems may be thought of as:

1) *Justice*: The right to an equitable, safe, healthy, productive, and sustainable environment for all members of a community.
2) *Equity:* Impartiality and fairness in the procedures, processes, and allocation of resources.
3) *Diversity:* Including a broad demographic mix (including race, age, gender, ethnicity, cultural background, geography, etc.), within a group or organization, which reflects the makeup of the community.
4) *Inclusion:* Ability of diverse individuals to participate fully in all aspects, including decision-making processes.

Inclusion of the JEDI principles in the science and communication framing can provide an essential point of access for marginalized communities to engage with scientific communication, preventing critical gaps in stakeholder representation.

Furthermore, a more innovative participatory approach is needed to overcome critical communication barriers (e.g., language, environmental/scientific literacy), creating an opportunity for individuals to understand and engage with the planning process through immersive and experiential learning. GIS and remote sensing based platforms are particularly suitable for such learning, as geospatial data is naturally ingested and contextualized visually by humans. This is because human beings are able to anchor geospatial inputs to fixed anchor points and use specific parts of the brain to analyze this data for high-level operations (Epstein et al., 2017). Scientists may need to develop models and tools that specifically facilitate such interventions. For example, stakeholder selection strategies can be based on social media microtargeting to include underrepresented communities in the affected regions. Such engagement can be designed to include stakeholders in decision making through use of GIS-based decision support tools (Assaf & Saadeh, 2008) by documenting stakeholder needs in different subareas of the watershed (Soutter et al., 2008) and soliciting their participation at various levels.

Levels of engagement range from unidirectional participatory facilitation such as (1) outreach to collect data on impairment, local practices, and needs (Eakin et al., 2017; Ponce-Romero et al., 2017), and (2) education about water quality management plans and tools designed for personal and community contribution to the program (e.g., De Freitas et al., 2013; Sun et al., 2015; Daniels et al., 2018; Yusuf et al., 2018; Quinn & Oster, 2021), to fully bi-directional participation such as (3) modeler-led engagement (e.g., Swick, 2007; Estalaki et al., 2016; Criollo et al., 2019; Alamanos et al., 2021; Balestrini et al., 2021), and (4) stakeholder-led engagement (e.g., Petherick 2014; Hadj-Hammou et al. 2017; Vaneeckhaute et al. 2021). The methodologies associated with these approaches are described in Section 3.2. Such interaction and engagement provide managers with a deeper understanding of environmental issues most important to local communities. This, in turn, allows organizations responsible for the socio-political and regulatory infrastructure to be explicitly recognized (Sayles & Baggio, 2017), supports better watershed-level sustainable water use practices, and provides resilience to uncertainty (Eakin et al., 2017).

The fully bi-directional engagement approach can facilitate the development of fuzzy cognitive maps for stakeholders, illustrating how their actions affect water quality, and how management actions are often needed as a consequence of their own activities (Eakin et al., 2017). Such cognitive mapping can occur without explicit recognition of the decision space using GIS-based visualization combined with other participatory information gathering (Voinov et al., 2018). Rendering of socio-economic, political, preferential and water quality datasets upon remotely sensed imagery sometimes helps stakeholders recognize the complexity of water quality management program objectives and encourages managers to develop multi-criteria strategies cognizant of these multi-scale watershed-wide challenges (Wardropper et al., 2015; Eakin et al., 2017; Yusuf et al., 2018). By identifying key actors who are the principal polluters or major water users in a watershed and geolocating their actions, sustainable and targeted management solutions providing greater accountability may be achieved (Franks et al., 2014).

3.2. Stakeholder engagement approaches

While outreach and education have historically been the most commonly practiced engagements, the methods of engagement have modernized substantially owing to GIS based tools. GIS and remote sensing data sources have also allowed watershed managers to adopt more innovative and deeper forms of engagement that include (1) outreach and education, (2) modeler-led engagement, and (3) stakeholder-led involvement and feedback.

3.2.1. Outreach and education

Recently, modelers and nodal agencies such as the California Central Valley Region State Water Resources Control board (Quinn & Oster, 2021) and the National Marine Fisheries Service (Daniels et al., 2018) have developed online portals through which model-generated basin-scale water quality information can be viewed in innovative ways as well as downloaded for interested stakeholders to understand the system better. In the case of the River Assessment and Forecasting Tool for water temperature in the Sacramento River (Daniels et al., 2018), historic water temperature hindcasts and periodically updated forecasts in the Sacramento River can be viewed in multiple graphical formats such as on a spatio-temporal grid, as a snapshot in time across space, or as multiple timeseries. It can also be downloaded by water operations managers to better manage reservoir and water operations to aid in multipurpose water use in the system.

More recently, some nodal agencies have created powerful online visualization tools that allow model results to be superimposed on familiar backgrounds such as regional maps, which allows both practitioners and policy makers the ability to visualize model predictions in familiar settings (Aquaveo, 2017). With dedicated software development expertise, agencies such as the USGS have been able to extend this type of geospatial visualization to a variety of groundwater flow and water quality and quality flow models such as GWWebFlow (USGS, 2022; HAWQS, 2020)). Around the world, such Web-GIS approaches are facilitating engagement and high-level information sharing between government, nodal agencies and stakeholders providing a unique, essential link between modelers and watershed water quality managers (Dhiman et al., 2020). Web-based easy-to-use GIS tools that allow local landowners to see the impacts of their water use or loading actions can also help develop stakeholder trust and encourage voluntary contributions to load reduction (De Frietas et al., 2013).

In participatory watershed management programs, some environmental decision support systems are powered by stripped-down, reduced complexity models that are lean versions of mechanistic models that support web-based visual analytics. These tools retain much of the pedigree of the models from which they are derived and allow stakeholders to "play with" the model with some assurance of the model's capability to simulate system dynamics and some of its complexity (Sun et al., 2015). For these approaches, the key is to allow stakeholders control of the derived "model" through a series of knobs and levers – variable parameters and actions within set physically plausible ranges – that they can modify to experience the outcomes for themselves. This type of approach will allow stakeholders to construct and analyze what-if scenarios, and brainstorm potential management ideas.

Human Computer Interface technologies that are immersive, such as serious games or the WeTable (Yusuf et al., 2018), allow stakeholders to engage at a more direct level with remote sensing and geospatial data. However, for these techniques to be most effective, adequate training should be provided by the nodal agencies or facilitators engaged by them. These types of tools are better suited for face-to-face and large-scale community engagement, than personalized web-based engagement, and to a large extent, require active modeler-led involvement.

3.2.2. Modeler-led engagement

Several tools and approaches have been developed to facilitate modeler-led involvement, and these typically involve showing stakeholders geospatial data, analysis and inferences and engaging with them to develop solutions. For example, the FREEWAT suite of tools allows stakeholders to investigate the implication of water management policy on groundwater quality. This is supported by a backend data management and visualization system known as AkvaGIS which is based on QGIS (Criollo et al., 2019). Such integration with open-source tools fosters continuous development and refinement of software tools and facilitates a strong developer and user community. Another approach, known as Greenprinting (Swick, 2007), combines GIS tools and stakeholder input to create scenarios to help communities plan watershed conservation actions. By systematically analyzing public goals, quality of life, natural hazards risk and water quality benefits at a fine spatial scale, the Greenprinting approach allows communities to build spatial maps of priorities and implementation strategies. By visualizing these priorities and strategies on a map of the region, teleconnections between different localized regions, and the interactions of multi-level regulatory frameworks can be better understood. These types of approaches are stakeholder centric, even though the underlying models and approaches must be led primarily by the modelers.

Box 6: Contextualizing citizen science

Citizen science is a powerful stakeholder engagement approach that deserves to be fully contextualized in diverse governance settings. While this information may not pertain directly to the use of GIS and remote sensing in watershed management, it is essential to understand how powerful this approach can truly be; therefore, some background is presented in this Box.

Background

While the true potential of these types of approaches has not yet been realized in the US, in many Latin American and African countries, these approaches have proved essential to sustainable water and water quality management amid administrative milieus suffering systemic resource shortages and general lack of public trust (Capdevila et al., 2020; Quinlivan et al., 2020; Weingart & Meyer, 2021). In European nations, these approaches augment existing monitoring, modeling and implementation programs by nodal agencies, and allow communities to develop pride about their participation in protecting and fostering their watersheds (Datashift, 2015; Balestrini et al., 2021). Even within the US, several private grassroots, and not-for-profit organization led efforts such as river restoration campaigns and conservation groups are applying social and political pressure on local and regional governments and nodal agencies to manage the nation's waters more effectively (Sneddon et al., 2017).

Applications in nations with and without robust water management frameworks

Two initiatives exemplify the bookends of these approaches – full-fledged public-driven management and augmentation of government efforts. In the former case, participatory budgeting is an approach being employed in many South American countries to allow communities to decide the budget allocation for water quality management programs. Citizen oversight councils are promulgated to ensure that there is public accountability for the use of funds. This approach has the twin benefits of greater community accountability and reduced corruption, as well as delinking financial spending cycles with election cycles. In countries such as Brazil, this approach has been shown to effectively end corrupt water pricing practices in small communities, as well as improve flood risk mitigation (Petherick et al., 2014). In England, the Fresh Water Watch, a citizen water quality monitoring program, complements data collection by the Environmental Agency, particularly in small, neighborhood lakes and ditches, and in periods outside the regular agency-led monitoring cycles (Hadj-Hammou et al., 2017).

3.2.3. Stakeholder-led involvement and feedback

An emerging alternative to modeler led involvement is full-fledged stakeholder-led involvement. In these approaches, the emphasis is on citizen participation and citizen science (see Box 6). There are opportunities for citizen science to integrate with remote sensing in a way that facilitates information gathering and stakeholder input (e.g., Bardar, 2022). For example, Secchi-depth measurements obtained through networks of citizen scientists have been applied to validate satellite products of water quality (Deutsch et al., 2021; George et al., 2021; Menon et al., 2021). In addition, water level measurements from citizen scientists have been integrated with lake surface area measurements from remote sensing to develop water storage estimates (Little et al., 2021) and remote sensing has been used to validate observed flood heights from citizen scientists (Graham & Butts, 2005). There are also ways for citizen scientists to derive their own water quality estimates without the need for special equipment through smart phone apps that can estimate water quality based upon analysis of pictures from smartphones (Malthus et al., 2020). Each of these examples demonstrates the utility of citizen science data to enhance remote sensing data by validating or deriving new information pertinent to a TMDL process.

4. Potential for transforming stakeholder engagement

As we have shown in Figure 2, conventional approaches to remote sensing data and GIS integration in stakeholder engagement for water quality management only have limited potential to result in multiple benefits to water quality management. These approaches have traditionally included some form of stakeholder outreach such as through public comment periods, or through web-based interactive tools, which result in the one-way transfer of information about the physical and environmental water quality processes and management actions (Estelaki et al., 2016). Alternately, participatory modeling has involved presenting stakeholders with alternate model scenarios (Estalaki et al., 2016), or has engaged them through web data portals (e.g., Daniels et al., 2018; Quinn & Oster, 2021; USGS, 2022), workshops or serious games (e.g., Mayer et al., 2001). The more immersive engagement experiences can also result in bi-directional information exchange and deeper cognitive development among stakeholders, as well as improve group cognition of complex processes and management actions. The primary needs of managing stakeholder engagement are better and more intuitive tools for big data management and more fully integrated engagement with stakeholders.

These types of approaches require the management of “big water data” and have resulted in proprietary systems such as the Source Apportionment GIS System (SAGIS) for load source cataloging (Ponce-Romero et al., 2017). Such systems should be able to combine and link diverse sources of spatially distributed data ranging from physical and ecological datasets to socio-economic metrics. For example, health risk has been linked with water pollution data by combining municipal health indicator datasets with regional water quality data to develop management priorities in three cities in China (Zhang et al., 2017). By compiling records with space and time stamps on targeted water quality interventions with regulatory promulgations such as land acquisition, incentives for load reduction and direct management actions, nodal agencies in Wisconsin’s Yahara watershed have been able to quantify the efficacy of management actions. The key idea behind these linkages is to create socio-spatial datasets that can be meaningfully combined with water quality and watershed-wide datasets (Yusuf et al., 2018). This type of combination of traditional and non-traditional sources of GIS data can help agencies identify data discrepancies and exploit opportunities to improve monitoring programs through better data resource management. These analytical links are constrained by stakeholder diversity, locality-specific environmental concerns, and legislative constraints. Local, state and federal policies designed to encourage start-ups and technology innovation in the water data sector can help realize the power of these diverse datasets. Some potential benefits include:

1) Sustainable management of watersheds that include private firms and polluters as keystone players in a voluntary management process, provided social and economic risks due to impairment can be translated to business costs (Franks et al., 2014). It may even be possible to encourage business strategists to create opportunities to minimize these costs. By providing local and regional governments with diverse datasets and the links between them, positive actions such as requiring commercial polluters to build diversity into their workforce, predictive risk-assessment of their loading practices and engagement with stakeholders can be realized. With a diverse, risk-savvy and engaged commercial structure, local polluters can be challenged to convert resource management costs into opportunities.

2) Two-way coupling between management actions and biophysical processes can influence and incrementally change the mental cognitive maps of key stakeholders. Such two-way couplings can foster local-to-regional networks of cooperation and collaboration across multiple counties, watersheds, and even in transboundary watersheds to achieve greater productivity and cooperation (Sayles & Baggio, 2017).

More fully integrated engagement with stakeholders is often difficult even in well-designed engagement scenarios, such as in the Hueco Bolson transboundary aquifer between the US and Mexico (Mayer et al., 2021). Alamanos et al. (2021) suggest various approaches to create more fruitful engagement such as: dividing stakeholders into groups based on their aspirations and responses to proposed management measures; adopting a sliding scale of educational and dissemination efforts required to bring different groups of stakeholders to the same level of problem understanding; finding connections on technical, social, cultural and economic levels with stakeholders to build trust; and finding financial resources and facilitation approaches to break barriers and foster lasting partnerships. Various approaches have been tried in the past across fields to make the stakeholder engagement process more fruitful and immersive and these can provide a basis for regional water quality management:

1) In-person and web-based public participation through the use of GIS layers in visually intuitive interfaces in coastal inundation management (Yusuf et al., 2018).
2) Stakeholder-led user-interface and decision support tool design using georeferenced data sources and demographic data supported by mathematical process-based models to optimize the collection and disposal or organic solid waste (Vaneeckhaute et al., 2021). In this approach, the interface and decision support system were created using stakeholder inputs to prioritize and focus on their needs and applications.
3) Top-down citizen generated data, which requires long-term policy commitment, infrastructure and stable sources of funding (Hadj-Hammou et al., 2017; Balestrini et al., 2021).
4) Bottom-up citizen generated data and stakeholder-led engagement, where data is collected by citizens which focuses on what matters most locally (Datashift, 2015; Balestrini et al., 2021), and where the stakeholders themselves organize and convene water quality management programs (Petherick et al., 2014). This, in the spirit of democratization of science, has the potential for improved scalability and sustainability, provided it is guided by a rigorous scientific process (Maccani et al., 2020). Maccani et al. (2020) identify several necessary conditions to make this approach work: new monitoring or participatory technology that is as off-the-shelf as possible, easy to understand and use; participatory tools that are compatible with prevailing cultural values, widespread visibility and coverage; and champions of the approach who are well regarded within the communities. For these types of approaches, researchers and practitioners facilitating the citizen science may themselves benefit by observing and learning local practices by stakeholders, i.e., the so-called “train-the-trainer” paradigm applies (Maccani et al., 2020).
5) Both top-down unidirectional and bottom-up bi-directional citizen-generated data and modeler- or stakeholder-led engagement approaches can benefit by identifying messaging narratives that resonate with the target communities, and by adaptively nudging such narratives in the direction of desired outcomes (Maccani et al., 2020). Obviously, this is easier to do in a top-down or modeler-led approach than in a bottom-up setting. The Bristol municipality identified local matters of concerns and investigated how citizen-generated data could help bridge infrastructure data gaps. Using this information, they developed strategies, analytical and model user interfaces and a number of public engagement activities designed to guide actions such as narrative design, data publishing and governance designed to enhance urban infrastructure projects. Known as the Bristol Approach, this form of top-down engagement puts stakeholders at the center of sustainable urban design and incorporates contemporary needs and aspirations of the citizens (Bristol City Council, 2019). A similar approach could be applied to improve watershed management programs in the US.
6) Exploiting the potential of game theory in spatially distributed water supply management. Ganjali and Guney (2017) identified keystone or important actors that were principal levers of change, and they allocated costs and utilities to various parties in water quality management. Using an approach gleaned from an extensive survey, Ganjali and Guney (2017) provide a roadmap for improving water quality management by combining game-theoretic insights from the outcomes of serious games with spatially distributed physical and socio-economic data.

5. Summary and Conclusions

The use of GIS and remote sensing in TMDL modeling and analysis has evolved rapidly in the past decade to the point that both are available to practitioners using state-of-the-art watershed and water quality modeling tools. These tools, such as BASINS (USEPA, 2019) and other integrated modeling approaches, can provide information about the watershed that facilitates visual identification of stakeholder locations, pollutant sources, hydrologic connectivity, and load allocations. In addition to scene imagery, LiDAR surveys are being used to develop digital elevation models of land surfaces. Popular watershed models such as SWAT (Neitsch et al., 2011) have extensive user communities which has led to continual updating of these models with new capabilities and easier use of remotely sensed data that can now be invoked from within the model user interface. Free access to planetary scale data and powerful spatial analysis and assessment tools such as Google Earth Engine, and the provision of free remotely sensed imagery by governments and the private sector under data sharing agreements, has led to significant innovation, with respect to data availability and use. The proliferation of low-cost drones and the simultaneous development of low cost and powerful image processing and quality control software has made these tools affordable for watershed management applications.

Recently, Internet-based technologies have become a practical medium for management of data, analysis techniques, and tools to support TMDLs (Hantush, 2005). These technologies are geared to eliminate data sharing limitations. The coupling of the internet, and tools of global access, including smartphone technology and low-cost data acquisition tools like phone-based LiDAR systems, will herald a new digital democratization of remote sensing and GIS data. Coupled with participatory engagement approaches tweaked for specific cultural and systemic milieus, GIS and sensing data and tools have potential to usher in the principles of JEDI-based stakeholder involvement in watershed management.

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