Environmental Modelling and Software 153 (2022) 105396

Contents lists available at ScienceDirect

Environmental Modelling and Software

journal homepage: www.elsevier.com/locate/envsoft

# An overview of visualization and visual analytics applications in water resources management

Haowen Xu *, Andy Berres, Yan Liu, Melissa R. Allen-Dumas, Jibonananda Sanyal

*Oak Ridge National Laboratory, 1 Bethel Valley Road, Oak Ridge, USA*

ARTICLE INFO

*Keywords:*
Big Data
Hydroinformatics
Visual Analytics
Visualization
Human-Computer Interaction

ABSTRACT

Recent advances in information, communication, and environmental monitoring technologies have increased the availability, spatiotemporal resolution, and quality of water-related data, thereby leading to the emergence of many innovative big data applications. Among these applications, visualization and visual analytics, also known as the visual computing techniques, empower the synergy of computational methods (e.g., machine learning and statistical models) with human reasoning to improve the understanding and solution toward complex science and engineering problems. These approaches are frequently integrated with geographic information systems and cyberinfrastructure to provide new opportunities and methods for enhancing water resources management. In this paper, we present a comprehensive review of recent hydroinformatics applications that employ visual computing techniques to (1) support complex data-driven research problems, and (2) support the communication and decision-makings in the water resources management sector. Then, we conduct a technical review of the state-of-the-art web-based visualization technologies and libraries to share our experiences on developing shareable, adaptive, and interactive visualizations and visual interfaces for water resources management applications. We close with a vision that applies the emerging visual computing technologies and paradigms to develop the next generation of hydroinformatics applications.

## 1. Introduction

To date, the water sciences discipline, like many other scientific domains, has been driven into the Big Data era with the advancement of next-generation information and communication technologies. Researchers are confronted with rapidly growing amounts and variety of water-related data, which arise in many areas of water resources research and management and challenge the capabilities of current data analytics (Guo et al., 2015; Adamala, 2017). Despite many computational methods (e.g., statistics, numerical simulation, machine learning [ML]) are developed to address the avalanche of Big Data through intelligent and automated data analytics, their implicit nature (Honegger, 2018) has limited their ability to conduct exploratory analyses for information and pattern extraction or to support complex decision-making for which human intelligence, collaboration, and justification are indispensable.

For decades, the visual computing discipline has played an important role in exploring, analyzing, and presenting scientific data (Kehrer, 2011; Earnshaw et al., 2019). It enables direct human interactions with computational methods to provide an effective integration of human reasoning into computational intelligence. Within the visualization community, the research is separated into information visualization, scientific visualization, and visual analytics (Andrienko et al., 2011).

Information visualization presents abstract data in visual formats (e.g., charts, graphs, lists, maps) to facilitate human cognition for insight and pattern extractions (Burley and Ashburn, 2010). Scientific visualization, on the other hand, focuses on rendering raw, scientific data as (often 3D) graphics to enable a better depiction and interpretation of real-world scientific phenomena and processes. Visual analytics emerges as an applied research discipline from computer graphics, design, and cognitive science to enable more advanced analytical reasoning capability on large information workloads by combining the strength of computational resources and human intelligence through sophisticated visual interfaces and dashboards (Thomas and Cook, 2006). These visual interfaces and dashboards often have more sophisticated analytical workflows that involve advanced user interaction techniques, data transformation, and coordinated views to enable users to explore different facets and perspectives of complex data simultaneously and

* Corresponding author.
*E-mail address:* xuh4@ornl.gov (H. Xu).

https://doi.org/10.1016/j.envsoft.2022.105396
Received 20 October 2021; Received in revised form 28 February 2022; Accepted 3 April 2022
Available online 28 April 2022

logically.

### 1.1. Visual computing for scientific research

In recent decades, visual computing techniques have been applied in many disciplines (Few and Edge, 2007; Koylu, 2019), including social sciences (Wu et al., 2016), climate science (Nocke et al., 2015; Wong et al., 2014), urban science (Zheng et al., 2016), transportation planning and mobility management (Andrienko et al., 2017; Berres et al., 2021), and biomedical informatics (Wu et al., 2019). To improve the knowledge building, hypothesis generation, and decision support of complex problems (Kohlhammer et al., 2011; Andrienko et al., 2007), visual computing techniques bring unique value to Big Data analysis in which information overload and data complexity hinder effective dissemination, communication, and perception of data and research output. As a particular example, the US Department of Homeland Security (DHS) has established the National Visualization and Analytics Center to promote the development and application of advanced visual analytics technologies to provide a strategic advantage in emergency response and counter-terrorism operations (Thomas and Cook, 2006; Councilet al., 2003; Wong, 2007). As a joint research effort of the National Science Foundation and DHS, the Foundations on Data Analysis and Visual Analytics (FODAVA) initiative was created to cultivate next-generation visual computing techniques for scientific research (Dill et al., 2012; Kielman et al., 2009).

Compared with other scientific disciplines, visual computing applications are relatively limited in the water-science sector. We compared the research trends of visualization and visual analytics in different domains using search results from Scopus (https://www.scopus.com). We only identified 127 water resources management–related documents from Scopus when searching article titles, keywords, and abstracts for "information visualization," "scientific visualization," "visual analytics," "visual analysis," "visual computing," or "visualization." Our search was conducted on 02-27-2022. For the time being, we discovered that visual computing applications in the water resources management sector are not as well-developed as they are for other science domains (e.g., social science, climate science, transportation planning), for which 1,000–4,000 visual computing–related research documents can be discovered using the same search terms. Review and vision articles in other science disciplines often systematically incorporate visualization and visual analytics techniques into their domain-specific approaches to create a well-defined interdisciplinary research area, whereas such articles do not exist for water resources management applications. We also conducted an exhaustive search for hydrologic and water resources research applications (defined as subject areas through the search terms) published in the top tier visualization venues (e.g., IEEE VIS and IEEE Transactions on Visualization and Computer Graphics) using Scopus and could not identify any articles related to water resources management. As many recent articles have presented fragmented visions to describe how certain types of data visualization and visual analytics techniques could practically benefit specific water-related research and management applications (Tague and Frew, 2021; Grainger et al., 2016), we believe that more advanced and system-based visual computing techniques can be applied to improve the water resources management repertoire from many different perspectives.

As the water-science discipline enters the Big Data age, more attention is given to the emerging computation techniques that enable AI through deep learning and hybrid models (Allen-Dumas et al., 2021; Adamala, 2017; Mar ç ais and de Dreuzy, 2017; Lange and Sippel, 2020). Past reviews that focus on the visualization of environmental data were limited to particular research applications. As an example, Grainger et al. (2016) provided a detailed review of environmental data visualization for non-scientific contexts. Nevertheless, the value of visual computing techniques as a critical investigative approach to support broad water resources research and management applications is often overlooked and rarely discussed in the literature. Review articles that focus on visualization and visual analytics applications in the water resources management sector are rare. This situation limits the public awareness of the visual computing approaches and their potential for playing more important roles in water resources research and management applications.

To fill this gap, we conduct a comprehensive review of recent visual computing applications in the water resource management domain. First, we focus on the methodological aspects of the visual computing techniques by reviewing a selection of successful research applications. During the review, we discuss the benefits and potential opportunities related to different visualization and visual analytics techniques for enhancing both the data-driven research and the communication and decision-making processes in various water resources management applications. Second, we discuss the contemporary visualization technologies used for implementing advanced visual computing techniques. We describe a strategy that integrates the emerging visual computing techniques into water resource management applications for amore holistic approach to smart-city management of water resources. We aim to share our experience and provide advice to lower the technical burden of development and allow non-computer science domain experts/researchers to develop useful visualization and visual analytics dashboards within shareable and accessible web applications.

### 1.2. Paper structure and organization

Our review is structured in the following way: Section 2 describes the motivation of this work. Section 3 focuses on the visual computing applications that support data-driven research in water resources management. Section 4 dives into the communication and decision support aspects of visual computing applications for supporting collaborative and integrated water resources management with an emphasis on the social dimension of water resources. Both sections are outlined based on detailed research and application areas summarized in Sections 2.3.1 and 2.3.2. Section 5 describes the technical advancement in web-based visualization technologies and their potential for benefiting hydroinformatics applications. Before going into detail on the visualization technologies, some basic notations for computer graphics rendering in a web environment are clarified. The remainder of the section summarizes popular web visualization libraries for creating charts, plots, web maps, and 3D geospatial environments. Many libraries provide intuitive and well-defined Application Programming Interfaces (APIs). We believe using these technologies can remarkably lower the technical burden of web development and allow both professional software developers and non-computer science domain experts to develop useful visualization and visual analytics dash boards to support their research and water resources management applications. Finally, Section 6 presents our vision to integrate the emerging visual computing technologies and paradigms to create next-generation hydroinformatics applications to support water resources management.

## 2. Motivation

In this section, we first review the current state of visual computing applications in the water resources management sector. Then, we discuss the unique strengths and benefits of visual computing for supporting research and decision-support applications through a dynamic human-computer feedback loop. Finally, we briefly discuss some application areas of visual computing techniques in the water resources research and management sectors. These areas are summarized through the review of selected studies.

### 2.1. Current state

Over a long period of time, data visualization tools have been developed for specific water management or hydroinformatics applications as marginal and supplementary components to support the production, presentation, and dissemination of analytical results from simulations and statistical models. A similar bottleneck also exists in many other science domains for which visualization tools are considered the end product or side product of scientific research. They are not deemed a pivotal research tool or major approach that can be adaptively and systematically applied to lead the scientific investigations themselves (Fox and Hendler, 2011). Developed in the early 1990s, the original concept of hydroinformatics stemmed from computational hydraulics (Abbott et al., 1991; Waldrop, 1979), in which research efforts are primarily driven by the numerical simulation of water flows and related processes (Abbott and Vojinovic, 2013). During that time period, data modeling and visualization techniques were complementary to the mainstream hydrologic and environmental modeling approaches. In the past two decades, however, the emergence of data-intensive science and increasing awareness of the social dimension of water management have expanded the scope of hydroinformatics and generated numerous opportunities for data-driven and collaborative water research applications (Vojinovic, 2012; Adamala, 2017; Abbott, 1996). Subsequently, these opportunities have triggered demands for effective analytical reasoning capabilities that require the involvement of multiple sectors (e.g., research institutes, management authorities, policy makers), including the public (Carson et al., 2018). To this end, these opportunities require a new hydroinformatics paradigm that can support the quantitative and qualitative analysis of big environmental data and address social needs and related concerns for water management (Manyika et al., 2011; Vojinovic and Abbott, 2017). The new paradigm could also benefit many emerging research efforts, such as social hydrology, which focuses on the exploration of the dynamic interactions and feedback between hydrologic and human processes (Sivapalan, 2015; Brelsford et al., 2020). These efforts often require public participation and the use of complex, multidomain urban-hydro datasets. With the emergence of the Open Government Initiative (Ginsberg, 2011) and Open Watre Data Initiative (Blodgett et al., 2016) and the formation of collaborative hydrologic research communities such as the Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI) and the National Water Center, a tremendous amount of hydrologic data and data-driven tools have become freely available and can be accessed through a variety of web platforms. Examples of these platforms include the USGS's National Water Information System and CUAHSI's HydroShare (Tarboton et al., 2014; Maidment, 2016). The new hydroinformatics paradigm has generated demands and opportunities for researchers to integrate more visual computing techniques into the water management sector. For now, most studies in the water-science sector only employ basic forms of visualization (e.g., graphs, charts, maps, data viewers) in their water management and hydroinformatics applications. They primarily use visualizations to facilitate the presentation and dissemination of hydrologic data, simulation results, and research output. Advanced visual computing and human-computer interaction techniques are often missing from these applications. These techniques include (1) visual analytical reasoning, (2) visual representations and interaction, and (3) data representation and transformation (Thomas and Cook, 2006).Given the current state of the water-science sector, we believe there are many opportunities to use visual computing techniques in a more systematic way and combine them with traditional investigative methods, such as environmental modeling and experimental methods. In Section 2.2, we detail a systematic use of visual computing techniques by developing a dynamic human-computer feedback loop (Endert et al., 2014).

### 2.2. Benefits of visual computing techniques

We believe the major benefit and strength of visualization and visual analytics in Big Data analytics is their capability to create cycles of feedback between humans and computers. We refer to these cycles as the feedback loops, which are important parts of a visual-analytical pipeline (Fig. 1). These loops have a significant advantage in facilitating human perception and reasoning during the analysis of massive and complex environmental datasets.

#### 2.2.1. Feedback between humans and computers

Within the feedback loop, visual computing techniques can address challenges that are difficult to solve using computational methods. These challenges are often related to the complexity of water-related data, which are becoming increasingly multifaceted (i.e., multivariate, spatiotemporal, multirun, multivalued/ensemble) (Kehrer, 2011). Furthermore, many environmental and hydrologic variables often exhibit a high degree of spatial and temporal variability (ASCE Task Committee on Application, 2000), and their underlying environmental processes often interconnect with other riverine processes (e.g., ecological, biological, stream morphological).

At a conceptual level, the feedback loop is designed to place domain experts into the analytical pipeline to supervise the data analysis by applying human experiences, justification, and domain knowledge (Keim et al., 2008). Within the first iteration of the loop, visual computing techniques are often combined with computational methods to present the abstract and processed data in an explicit way to help the domain expert understand the data and then extract useful data-driven insights (e.g., patterns, causal inferences, and anomaly detection). After the initial visual analysis, the domain expert (i.e., as the user of the visual computing application) can validate these insights using existing

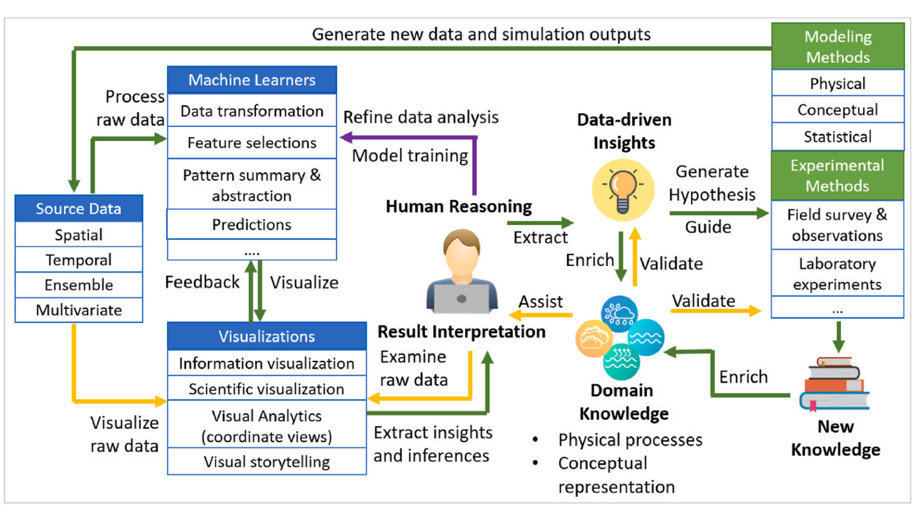


**Fig. 1.** Visual computing pipeline: analytical reasoning that combines computer intelligence with human involvement.

domain knowledge and principles, which often lead to a theory-guided interpretation for a better understanding of the insights. As the next step, the user can either use the derived insights to (1) enrich the existing body of knowledge, (2) tune the parameters of the computation and visualization methods for a better output, or (3) generate hypotheses to guide future research efforts using simulation models and experimental methods (Fox and Hendler, 2011). As the last step in the loop, the simulation models and experimental methods can generate more new data and simulation outputs. These outputs can be reintroduced into the feedback loop to start another iteration to further refine the data-driven analysis.

#### 2.2.2. Design techniques and strategy

A feedback loop typically consists of two major components: (1) computational methods and (2) objective-driven visual computing methods for achieving a specific data analysis goal or exploring certain facets of the data. These components are normally formulated based on one or multiple visual computing design techniques. Computational methods are introduced into the loop to facilitate the data representations and transformations. These methods are primarily applied to transform and simplify complex environmental datasets into abstract forms to highlight important features and patterns. The visual computing methods are created to facilitate the visual information-seeking process (Shneiderman, 1994), and they often employ one or many visual computing design techniques. Among these techniques are analytical reasoning, visual representations and interaction, data representations and transformations, and presentation and dissemination of results (Thomas and Cook, 2006; Ribarsky et al., 2009). Overall, combining these techniques into a visual interface can enable users to explore and understand different facets of a complex dataset and connect information and patterns identified at different data facets into a logical data story that complies with the existing domain knowledge and enables users to derive new insights for knowledge generation. A common design strategy for creating visual interfaces follows the visual information-seeking mantra (Shneiderman, 2003). The mantra defines seven common types of data (1D, 2D, 3D, temporal, multidimensional, tree, and network data) and seven visual-analytical tasks (zoom, filter, details-on-demand, relate, history, and extract). These visual-analytical tasks are often implemented in a visual interface as user-interaction techniques. To optimize the visual information–seeking process during a visual analysis, the mantra specifies a sequence of visual-analytical tasks: overview first, then zoom and filter, and then details-on-demand (Shneiderman, 2003). Based on this mantra, the designer should first identify the data type and data facets that must be analyzed to meet the objective of the visual analysis. Then, the designer should select a suite of visual representations (e.g., maps, graphs, charts, visual encoding) that can effectively visualize the identified data facets. Each of these visual representations is tasked with visualizing specific data facets (e.g., temporal, spatial, multivariate, multiscale). After the selection of graphs and charts, the designer must associate individual visual analytical tasks with each chart or graph. As an example, a map is designed to provide an overview of the spatial facets of a dataset. Therefore, it is associated with the overview task. Afterward, multiple charts and graphs should be linked to create coordinated views based on the task sequence specified by the mantra. Different tasks associated with graphs and charts are then translated into different user-interaction techniques. The user can directly interact with the data in a chart/facet (e.g., zoom and filter) through different keyboard and mouse events (e.g., mouse click and hover) and observe the variation and patterns in other data facets through the automatically updated coordinated views. Because the coordinated views can visually connect variations and patterns across different data facets, the user can use these views to observe interconnections and correlations between multiple variables, ensembles, and spatial and temporal scales. The process should eventually help the user derive new qualitative insights (e.g., empirical relationships). In addition, computational methods (e.g., statistical and ML models) are connected to the visual computing techniques, and they can be used to conceptualize and quantify the derived qualitative insights using mathematical representations and statistical metrics.

### 2.3. Applications in water resources management

Here we discuss application areas in the research sector, which is driven by scientific investigation and exploratory analysis of hydrologic data, as well as the water resources management sector, which is focused on water resources planning, management practices, and decision optimization. During the discussion of each sector, we summarize areas that can benefit from visualization and visual analytics based on the review of successful applications.

#### 2.3.1. Research sector

For supporting research activities in water resources management, visual computing techniques can support data-driven studies to facilitate the analysis and human understanding of massive, dynamic, ambiguous, multifaceted, and conflicting data. The human-computer feedback loop can bring unique capabilities to the data analytics and environmental modeling efforts by allowing the modeler to interact with hydrologic/ environmental simulations and data models and their outputs through visual interfaces and automated pipelines. Based on our literature review, we summarized a list of benefits enabled by visual computing techniques:

- improved discovery, management, and quality control of massive water-related data (Fuhrmann, 2000; Ames et al., 2012; Leonard et al., 2017; Horsburgh and Reeder, 2014; Jadidoleslam et al., 2020);
- improved interpretation and optimization of simulation models (Kratzert et al., 2019; Tian et al., 2016; Su et al., 2016; Zhang et al., 2017; Deval et al., 2022); and
- enhanced qualitative analysis and exploration (e.g., extraction of patterns and empirical relationships) of complex hydrologic and environmental data (Mazher, 2020; Xu et al., 2019; Walker et al., 2020; Accorsi et al., 2014; Marbouti et al., 2018; Smith et al., 2016; Sanyal et al., 2017; Clark, 2022).

Visual computing techniques can be applied to a number of water-related research areas to facilitate Big Data–driven studies. These areas include but are not limited to hydrologic response, water quality, soil-water interaction, water hazard mitigation, and the water-food-energy nexus. A detailed discussion and use-case analysis of how visualization and visual analytics can benefit these research areas are presented in Section 3.

#### 2.3.2. Planning and management sector

Unlike the research sectors, water resources planning and management applications often focus on complex decision-support processes with an emphasis on the social dimension of water resources. One of the critical needs is to bring the public sector into water resources planning and management processes (Paniconi et al., 1999) through effective communication because many watershed management activities require the understanding, consent, and support from local communities (e.g., water managers, landowners, residents, other local stakeholders). Examples of these activities include the installation or retrofitting of hydraulic structure and urban water infrastructure (e.g., weir, sensors, retention ponds, groundwater wells), the modification of land-use and land-cover (e.g., the Conservation Reserve Program) for increasing a communities' resilience to water-related hazards, and the relocation of structures and infrastructure for reducing potential flood damage (Carson et al., 2018). To this end, public engagement and participation are essential for enabling a holistic and integrated water resource management approach that addresses the needs of various social groups and communities in a watershed. To support this social dimension of the water resources management, many studies integrate visual computing techniques into the emerging web-based technologies to provide easy-to-understand visual representations. These practices serve as effective means for conveying and disseminating research output, visions, and complex concepts of environmental and watershed processes to the general public. In the spirit of the expression, "a picture is worth a thousand words," many of these visual techniques are friendly, explicit, and intuitive for nontechnical participants (e.g., stakeholders, policy makers, students) involved in water resources management. These visual techniques are then integrated into web applications that can be accessed through the internet using various devices, thereby providing efficient and low-cost agents to promote water science education to nontechnical audiences with the goal of raising public awareness of many water resource–related issues (Gober et al., 2003). More recent studies have integrated visual computing techniques into serious games, which are games developed for serious applications rather than entertainment, to encourage public participation and engagement in water management. Some of these techniques entail visually appealing representations and intriguing user interaction workflows. This practice can bring a fun factor to users during a water resources planning and education task. As a result, visual computing techniques, when devised properly, can be applied to lower the technical barrier of water management. They can effectively incentivize the public sector to participate and engage in the collaborative planning and decision-making processes. In addition, visual analytics techniques are frequently used as effective tools for optimizing multiobjective and multicriteria decisions to support the management of water resources in both rural and urban areas (Matrosov et al., 2015; Reed and Kollat, 2013). These application areas include the following:

- promoting water education and raising public awareness of various water-related issues (Demir et al., 2018; Haynes et al., 2018; Sermet and Demir, 2020),
- facilitating collaborative water management and public engagement (Xu et al., 2020; Sermet et al., 2020; Sermet and Demir, 2022), and
- optimizing multiobjective and multicriteria decision problems for water management (Aydin et al., 2015; Matrosov et al., 2015; Reed and Kollat, 2013).

## 3. Visualization for data-driven research

This section begins with the review of data visualizations to introduce popular graphs, charts, and visual encoding and representations that are often used for analyzing hydrologic and environmental data. The remainder of this section then reviews the application of visualization and visual analytics in various application areas (as summarized in Section 2.3.1) that benefit data-driven research for water resources management.

### *3.1. Visualization of hydrologic data*

Historically, visual analyses of hydrologic data were superseded by computational methods during the time period when most research was led by physical, conceptual, and statistical models (Ladsonet al, 2018). Many visualizations were integrated into domain-based methodologies and played critical roles in supporting hydrologic analyses. Examples of these visualizations include Thiessen polygons, unit hydrographs, and graphical routing methods (Adamala et al., 2019; Ladsonet al, 2018). The situation began to change when more data-driven analyses were introduced into water resources management. Water-related data are complex and entail multiple data dimensions and facets. Many hydrologic modeling efforts require mapping and displaying spatial data (e.g., topography and hydrologic units). With the recent evolution in information and sensor technologies that enable better data acquisition, access, and organization (Maidment, 2008a), more effort has been expended on the visualization of hydrologic and environmental data to support more advanced data management and analytics tasks. For example, many hydroinformatics systems use visualization to facilitate data discovery and quality control. Many recent research applications often share the spirit of "bringing water-observational data together" through Big Data cyberinfrastructure and hydroinformatics systems (Maidment, 2008a, 2008b; Josset et al., 2019). Examples of these applications include CUAHSI's Hydrologic Information System (HIS), USGS's National Water Information System, and the National Climatic Data Center's Climate Data Online.

#### *3.1.1. Simple charts, graphs, and maps*

Previous hydrologic visualization research mainly focused on the effective visual presentation of different types of hydrologic and environmental observations of multidimensional data (e.g., spatial, temporal, multivariate, and ensemble) (Tarboton et al., 2008). Similar to traffic flow data connected to road networks, water-related observation data are closely associated with individual hydrologic units (e.g., stream, river corridor, catchment) that topologically connect through a hierarchical network structure in a watershed system. In this regard, many hydrologic observations also have a topological dimension. To visualize a single dimension of hydrologic data (e.g., the temporal or spatial dimension), basic charts, graphs, and visual representations are adequate. Ladson et al. (Ladsonet al, 2018) summarized a list of basic visual representations that are frequently employed to visualize time series hydrologic data that present stage-discharge relationship, flood frequency and duration curves, and unit hydrographs. These representations consist of different variations of the line graph, bar chart, heatmap, and circular plot and can be used to present changes in a single variable or to compare multiple time series data.

#### *3.1.2. Advanced visual encoding and representation*

Visualizing multiple facets of the hydrologic data at the same time is a more challenging task that often requires more advanced visual encoding and representation. Many studies link multiple charts into coordinated views, each of which focuses on a single component or scale of the data. United States Geological Survey (United States Geological Survey, 2020a) encoded bar charts for visualizing time series data that reflect the number of water gauges in each US state into a matrix that presents state locations topologically in 2D space (Fig. 2a). The link graphs and charts can be used to view the temporal and spatial variability of the complex data to display the overall trends and can also depict detailed variations and patterns within a specific dimension. Linked visualizations often require well-defined user interaction techniques to synchronize the display of different charts and graphs based on different user actions (e.g., selection of a subset of data or filter data based on specific attributes or regions). Burch and Weiskopf (2011) devised an innovative TimeEdgeTrees representation to visualize time-varying water levels in multiple German rivers. The representation visually encodes individual time series data into color-gradient lines and rearranges them into a hierarchical structure that reflects river connectivity (upstream, downstream, and confluences) in a watershed. The representation uses a hierarchical node-link diagram as its basic layout to present the connectivity between individual streams. Each stream and its measuring site are denoted as a node, and any time-varying variables associated with the river can be visually encoded into that node (Fig. 2b). Users can interact with the visual representation by filtering and zooming to a specific node or branch of the node-link diagram. The TimeEdgeTrees can efficiently represent the temporal variation and topology of the water level data such that users can observe the dynamics of the time-varying data in the context of flow continuity. For example, the visual representation can provide insights on how water level or temperature changes could affect the same variable in neighboring rivers. Its node-link diagram can also be applied to visualize variables that reflect the wave propagation from upstream to downstream in a watershed. United States Geological Survey (United States Geological Survey, 2020b) adopted a stream graph representation to visually compare the flood duration measured at 65 stream flow sites over the

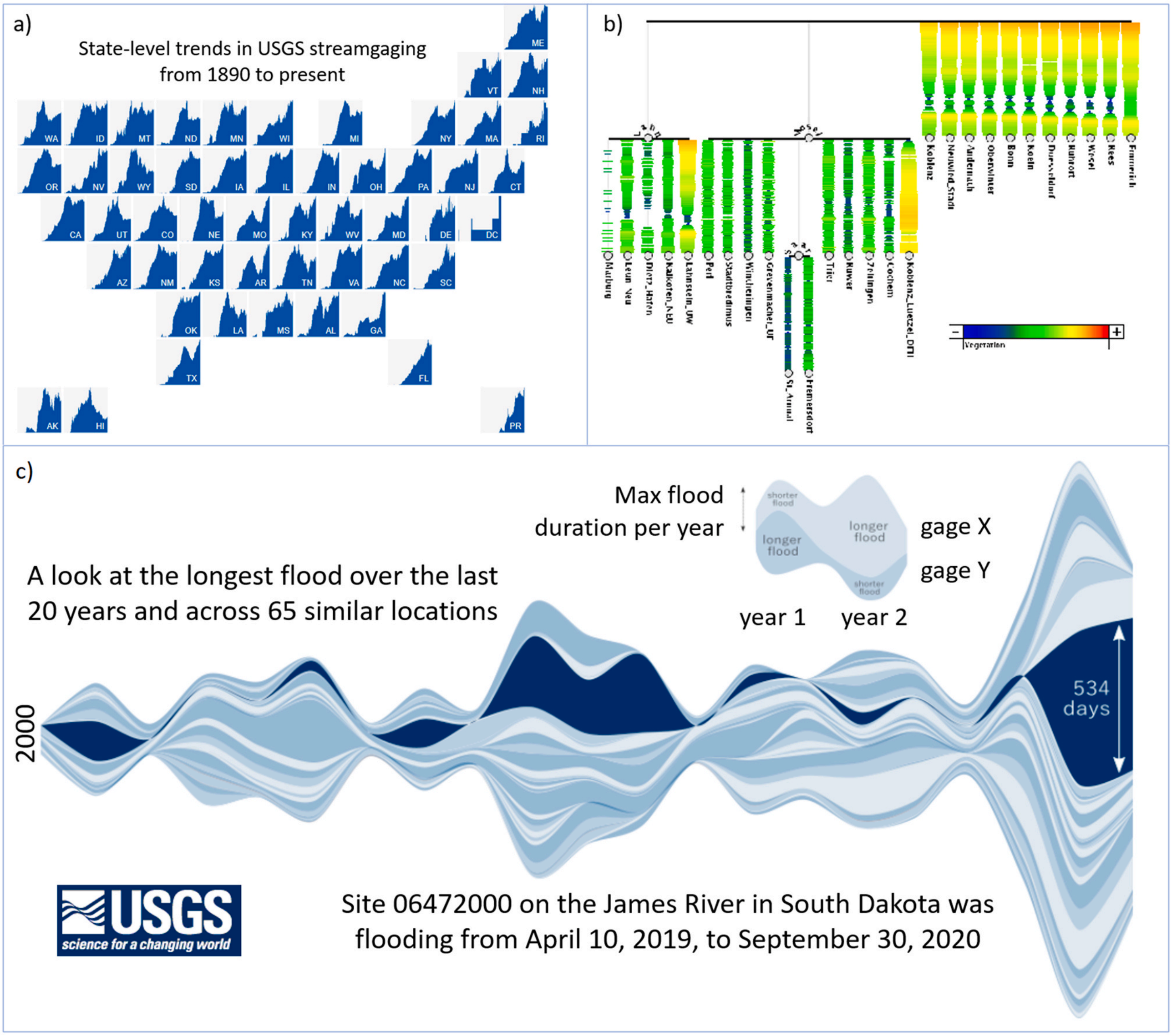


**Fig. 2.** Visual representations of hydrologic data with multiple facets: (a) visualizing the number of water gauges in different states across the United States for a long time period (United States Geological Survey, 2020a; Gunn et al., 2014); (b) TimeEdgeTrees for exploring the wave dynamics (e.g., amplitudes, temporal shifts) across different measuring points along the river Rhine (Burch and Weiskopf, 2011); and (c) Stream graph visual representation comparing flood duration at 64 stream gauges over the past 20 years (United States Geological Survey, 2020b).

past 20 years (Fig. 2c). The main goal of this visualization was to highlight a single stream gauge on the James River near Stratford, SD, which was flooding continuously for 534 days, while also comparing the flood duration at that site with that of other similar sites. The efficient stacking of area plots allows a single graph to cover multiple dimensions simultaneously and avoid visual clutter caused by the intersection and overlying of multiple points and line features.

With more variety of hydrologic data available in better spatial and temporal resolutions, the visualization of hydrologic data evolved from the utilization of simple and single graphs into the development of more advanced visual representations that can cover multiple facets of the water data. These visual computing techniques have played important roles in supporting various hydrologic analyses and modeling efforts. Despite the usefulness of encoding more aspects of data visually into a single chart, these visual representations are sophisticated and challenging for nondomain experts to interpret and understand compared with simple graphs and charts. In many more advanced visual computing applications in which visual analytics become critical components to lead data-driven research, advanced data transformation and visual analytical reasoning techniques are required to supplement the visual encoding and representations. We detail this aspect in Section 3.2 with an emphasis on the design of a visual analytics workflow.

### 3.2. Data discovery, management, and quality control

At the beginning of the 21st century, Fuhrmann (2000) pioneered the design and application of visual computing techniques for discovering and managing hydrologic data through the development of a low-cost multimedia hydrologic visualization system (HydroVIS). This system enables the visualization of digital hydrologic data and the documentation of hydrologic models for the Weser River catchment. HydroVIS's visualization components consist of electronic maps, temporal and nontemporal cartographic animations, the display of geologic profiles, interactive diagrams, and hypertext (e.g., photographs and tables). Many of these components, such as electronic maps and cartographic animations, could be considered prototypes of later web mapping and cyber geographic information system (GIS) technologies that arrived in the Web 2.0 age. HydroVIS was developed before the Open Data

Initiative (Luna-Reyes and Najafabadi, 2019) and served as a pilot study for exploring new media to promote visualizations of hydrologic data. Fuhrmann (2000) highlighted the future market and research needs for visualizing hydrologic data as well as the challenges posed by data-sharing restrictions at the government level. The advent of the Open Data Initiative and web-based technology brought the visualization of hydrologic data into the age of cyberinfrastructure. During this period, Ames et al. (2012) developed a web services–based and open-source software tool called HydroDesktop. This revolutionary software tool allows users to search across and access hydrologic data services published through CUAHSI HIS (Fig. 3a). Users can discover, download, manage, and visualize hydrologic data retrieved from the CUAHSI HIS data services using the HydroDesktop interface. The novelty of HydroDesktop includes its data search and discovery ability through web services and its software extensibility by which it can incorporate custom data analysis and visualization plug-ins. The HydroDesktop visualization features are designed to support the discovery of hydrologic time series data. These features include map-based geovisualizations of monitoring locations and other spatial data and a visual interface with different plots to support the downloading, organization, visualization, editing, and maintenance of hydrologic time series data

Building on top of the HydroDesktop software system, Horsburgh and Reeder (2014) addressed the interoperability aspect of the visualization and analysis of hydrologic data using web-based hydroinformatics applications by developing a software plug-in, named HydroR, to link the CUAHSI HIS with the R statistical computing environment (Fig. 3b). This link enables a straightforward hydrologic data management and analysis pipeline that allows hydrologists to discover and access a wide variety of hydrologic data provided from web-based systems and repositories. Through the plug-in, users can directly import these data into widely used native hydrologic visualization and analysis environments.

Demir et al. (2018) further expanded the cyberinfrastructure approach for promoting the discovery and sharing of real-time hydrologic data by developing an end-to-end, web-based platform called the Iowa Flood Information System (IFIS). The platform can effectively address multiple aspects of the decision-making process for flood-risk management and mitigation for the state of Iowa (Fig. 3c). The platform was initially developed to enable centralized data access to and visualization of real-time and historical water data (e.g., water levels, gauge heights, hourly and seasonal flood forecasts, rainfall conditions) collected from a wide range of sources, including Next-Generation Radar (NEXRAD) stations, Iowa Flood Center stream sensors, and USGS and National Weather Service stream gauges for over 1,000 communities in Iowa (Demir and Krajewski, 2013). Developed based on integrated, modular, and adaptive system design, IFIS later evolved into a generalized flood cyberinfrastructure able to incorporate a variety of flood-related data, cloud-based computing resources, data analytics tools, and advanced hydrologic models for supporting flood-risk management and disaster preparedness and response efforts in Iowa (Demir et al., 2014, 2018). From a visualization perspective, the platform employed a number of advanced web-based mapping and visual computing technologies to enable interactive visualization interfaces that allow users to explore and discover large volumes of diverse data retrieved from NEXRAD radars and over 500 sensors that describe real-time stream conditions, soil conditions, and precipitation (50 GB of data every day). The IFIS visual interface employs a variety of charts and plots to enable the platform users to visually inspect and verify the availability of different hydrologic time series data and compare measurements between multiple sensors in a watershed. These data visualizations (1) play an important role by allowing users to explore, filter, and discover flood-related datasets collected from distributed sources and (2) provide a centralized interface to support data query and downloads. The geovisualization capability of IFIS allows the platform to display various GIS layers and flood maps for selected communities in Iowa. These flood maps cover over 4,500 scenarios. The IFIS platform also provides evolutionary scientific visualizations and communication tools for promoting the social-water dimension of flood management, which will be detailed in Section 4. Demir et al. (2018) developed the idea of an adaptive and modular web framework using superior software engineering and data structure design. They built a generic and flexible pipeline for integrating a wide variety of hydrologic data, models, and data analytics with an HTML-based GUI and interactive web-based visualization libraries. The data visualizations provided by IFIS are aimed at helping both technical users (e.g., watershed managers, researchers) and nontechnical users (e.g., stakeholders, students). As the platform becomes a more comprehensive decision-support system for flood mitigation and watershed management, more advanced user interaction designs are adopted to arrange, coordinate, and reuse various visualization interfaces embedded in IFIS to ensure effective user interactions and clear design of userflows for various

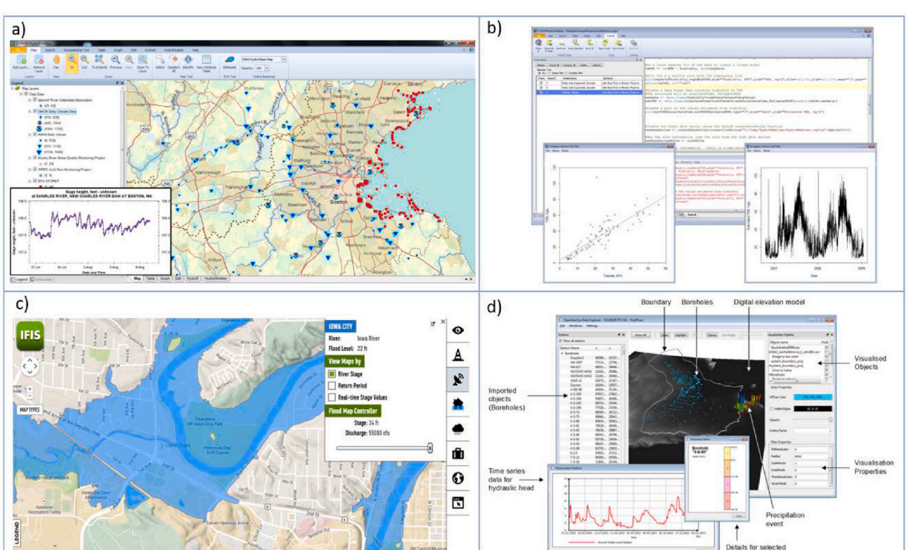


**Fig. 3.** Examples of hydrologic data visualization applications for data discovery and management: (a) CUAHSI hydro-desktop (Ames et al., 2012), (b) HydroR plugin (Horsburgh and Reeder, 2014), (c) IFIS web visualization of flood maps (Demir et al., 2018), and (d) visual exploration and management of hydrologic data (Rink et al., 2012).

data-discovery and decision-support tasks.

Rink et al. (2012) presented an integrated approach for visual data management for the analysis and simulation of hydrologic processes through a real-world use case. Their approach combines visual data management and numerical simulation to enable the discovery and selection of large datasets based on keywords and regions defined by users (Fig. 3d). The framework is built on a visual data management framework called the OpenGeoSys data explorer, which can import data from standardized file formats and databases and allow users to explore geoscientific data in a 3D space. By displaying data-related attributes on a digital terrain model, the framework can serve as an easy-to-use tool for many data management purposes, including surveying the availability of data, modeling results in a specific region, enabling integrated access to heterogeneous data collected from various sources, searching for a defined subset using keywords, and validating data through the detection of inaccuracies within a single dataset or inconsistencies across multiple datasets. The data validation process is supported by the integration of different data structures and data viewers, which allow the visualization of 2D data, such as time series from dataloggers or stratigraphic profiles of boreholes. Rink et al. (2012) also shared a vision to integrate tools for automatic parameter estimation into the framework to allow visual comparisons of measured data and simulated results in the future.

Along with visual computing applications for data discovery and management, advanced visual analytics workflows are developed to improve the quality control of large hydrologic and environmental datasets. Large-scale hydrography datasets, such as the National Hydrographic Dataset (NHD), often present limitations in stream and watershed connectivity, such as disconnected and intermittent streams and subbasins (Buttenfield et al., 2011). Manually validating and correcting the connectivity and flow direction issues in millions of streams in the NHD is a time-consuming and labor-intensive effort that presents a big challenge to hydrologic modelers. To address this challenge, Leonard et al. (2017) presented the development and application of a visual analytics approach for the data cleaning and integration of the continental United States (CONUS) heterogeneous national hydrography data products using multiscale graph models. The effort aims to support nation-scale hydrologic modeling. At the coarsest scale, the approach first constructs a smaller graph using level-12 Hydrologic Unit Code (HUC 12) watersheds as nodes to automatically validate the HUC 12 watershed connectivity. The concept of HUC is explained in Water Resources of the United States (Seaber et al., 1987).

This automation can significantly reduce the data cleaning efforts that do not necessarily require human judgment. When data issues require an expert judgement or high-resolution datasets, the graph model highlights these data issues and constructs a graph at a finer scale to assist human experts with reasoning and justification. In the finer graph, streams within a HUC 12 node are represented as edges. This setting allows expert users to inspect and correct data issues related to edge directions at a finer scale. A visual interface is then created to allow expert users to analyze and interface with the graph model. In summary, Leonard et al. (2017) applied a visual computing approach to automate the analysis and cleaning of a CONUS hydrography dataset, which consisted of about 851 million edges and 683 million nodes. The effort also successfully demonstrated the effectiveness of its visual analytics workflow's capability of combining the computational power with human reasoning to resolve large-scale data quality issues.

### 3.3. *Interpretation and optimization of model data*

Visualization also plays an important role in supporting hydrologic and environmental modeling efforts. Visual techniques have been widely applied to improve the presentation of hydrologic simulation output for the dissemination of model-driven insights to researchers and decision makers (Jones et al., 2014; Koutsoyiannis et al., 2003). Visualization and visual analytics foster a better understanding of complex and partially unknown environmental processes (Tian et al., 2016; Namwamba, 1998) and improve the evaluation and optimization of hydrologic models (Jadidoleslam et al., 2020; Rajib et al., 2016). In past decades, many applications were developed to visualize hydrologic modeling results using a variety of time series plots and geovisualizations powered by GIS and web-based mapping technologies. Sections 3.3.1 and 3.3.2 selectively review sophisticated visual analysis applications that utilize simulation data and ML to present unique visual analytics workflows that help the audience explore new insights in the simulation outputs. These efforts are designed to help audience develop an in-depth understanding of the modeling process (both physical and data-driven) for better optimization strategies.

#### 3.3.1. *Simulation model data*

A few studies have focused on developing visualization frameworks to examine and explore complex environmental and hydrologic processes that are simulated using domain models for new insights and hypotheses. These studies provide practical examples to demonstrate how visual computing techniques can be applied to support and improve modeling efforts in water and environmental research. Zhang et al. (2017) focused on the development and design of computer-based flow visualizations to help researchers explore and elucidate the dynamic flow process and the fluid movement laws. The overall objective of these flow visualizations is to foster a better understanding of the complicated hydrologic cycle, thereby improving watershed modeling and water resources management at the regional level.

Zhang et al. (2017) also evaluated various flow visualization methods (e.g., scalar field visualization, vector field visualization, and visual water effects) through a virtual watershed platform. The platform can generate flow data using spatially distributed hydrodynamic models and visualize these data in a virtual 3D environment. The platform allows end users to explore various hydrodynamic attributes of the flow and their interactions with other attributes, such as terrain, landforms, and inhabitants. Case studies were conducted to demonstrate the platform's ability to visualize hydrodynamic features in river flows and ocean currents.

Tian et al. (2016) combined 3D exploratory visualizations with environmental modeling pipelines to facilitate the interpretation and validation of simulation output from physically based, fully integrated surface water–groundwater (SW-GW) models. Their visualization tool was devised and implemented to incorporate SW-GW modeling results, promote data and model sharing among the water resources research communities, and provide a virtual globe-based 3D environment for visually exploring and validating modeling results.

Su et al. (2016) introduced a data-oriented, multidimensional, and dynamic visualization software to explore massive marine hydrologic and environmental datasets and modeling results. The software tool can visualize marine-water environmental factors in a 3D interaction and volume rendering environment. Examples of these factors include an oceanographic planar graph, contour line rendering, isosurface rendering, factor field volume rendering, and dynamic simulation of the current field. The visualization system was developed using the CUDA (Sanders and Kandrot, 2010) parallel computing library to parallelize and increase the speed of volume rendering for marine-water environmental data in a NetCDF (Network Common Data Form) format. The tool's high performance enables users to generate interactive visualizations based on different user-defined scene and simulation properties.

The combined efforts of visualization and simulation models can help domain scientists and nontechnical water management communities to interpret simulation results from hydrodynamic models, with an overall objective of improving the understanding of the complex hydrologic cycle. These efforts also increase the practicability of hydrologic models for supporting decisions in real-world water resources management operations.

#### 3.3.2. Machine learning (ML) model data

As more traditional ML and deep learning models are increasingly used to model hydrologic processes and predict environmental variables, it is critical for both data scientists and hydrologists to understand the data models' implicit and hidden training processes to validate and optimize model configurations. One remarkable example is the application of long short-term memory (LSTM) networks for rainfall-runoff forecasting. LSTMs are particularly well suited for modeling the rainfall-runoff process because their memory cells can represent dynamic reservoirs and storage. Thus, this ML technique plays an important role in the state-space modeling approach for analyzing the hydrologic system (Kratzert et al., 2019). Inspired by the visualization tool (Strobelt et al., 2017) developed for recurrent neural networks with a focus on understanding changes in hidden state representations over time, Kratzert et al. (2019) demonstrate a visual analysis tool that can help domain experts interpret and analyze trained LSTM models for predicting discharge in two different catchments: one with snow influence and one without. They conducted a qualitative analysis of the correspondence between the hydrologic system and the learned behavior of the LSTM. In the first step of the analysis, multiple line charts were employed to visualize the time steps of snow influence on the network output over the day of year (DOY) unit and compare the discharge output with other variables, such as the median precipitation, discharge, and minimum temperature. The visual comparison revealed that the time steps of influence pattern matched the hydrologic understanding of the yearly pattern. In the second step, the study employed a scatter plot to show the average correlations between memory cells and hydrologic states for a basin.

Without effective visual analysis tools, deep learning networks such as LSTMs are difficult to interpret and understand, which limits their potential for environmental research. This is because many domain scientists value the physical representation of environmental processes and are not apt to trust deep learning models that involve black-box representations (Strobelt et al., 2017). In this regard, effective visual analytics methods allow a deeper understanding and validation of these learning models and can serve as a bridge to connect the ML approach with traditional environmental modeling approaches. These visual computing methods could bring judgment and intervention from domain experts into deep learning models to validate and optimize the construction of their networks for more reliable and explainable predictions of hydrologic variables. The combined approach of visual analytics and deep learning could expand the vision of the theory-guided data science approach that aims to fully leverage the power of ML and data-driven methods in water science disciplines by deeply coupling them with domain models based on scientific processes and theories (Karpatne et al., 2017).

### 3.4. Exploratory visual analytics

Many recent studies employ visualizations and visual analytics techniques as an independent investigative approach to conduct exploratory analysis of complex environmental datasets for data-driven insights. Apart from traditional environmental modeling approaches, these analyses can generate new data-driven insights that reveal spatiotemporal patterns of a single hydrologic variable as well as empirical relations and causal inferences between multiple environmental and hydrologic variables. These efforts often lead to knowledge discovery, hypothesis formation, and improved understanding of the environmental phenomenon that entails partially unknown and interlinked physical processes, which are challenging to solve using existing environmental models.

#### 3.4.1. Visual analytical reasoning

This subsection introduces the basic visual analytical reasoning components and methods for conducting exploratory visual analysis. The nature of exploratory visual analytics is to combine automated data analysis techniques with interactive visualizations for effective understanding, reasoning, and information seeking on the basis of very large and complex datasets (Keim et al., 2008). Therefore, the two major techniques involved in the design of exploratory visual interfaces are (1) data representation and transformation and (2) visual representation and user interaction.

Many visual analytics applications focus on the use of advanced data representation and transformation techniques powered by statistical and ML models to reduce dimensions of complex datasets and remove noise in the data. They allow the visual analytics interface to highlight, summarize, and abstract key patterns and relationships in the raw dataset in a form that can be logically perceived by target audiences.

After a heavy lift in data processing, analytical reasoning plays an important role in the design of a visual interface and its user interactions. There are many well-defined techniques for designing a visual interface for user interaction (e.g., selection of plots, chats, visual representation, coordination between different views). These techniques were developed based on the visual-analytical reasoning principles (Ribarsky et al., 2009) to ensure a visual analytics application can achieve its objective functions (e.g., easy-to-use, efficient data analysis, logical user workflows).

This subsection presents some example techniques to provide more context for visual-analytical reasoning methods. One of the most commonly used methods is the level of detail technique (Heok and Daman, 2004), which is a computer graphics technique for reducing visualization complexity based on the rendering object's importance, viewpoint-relative speed, or position (Heok and Daman, 2004). The technique is often applied in visual analytics to highlight important patterns based on (1) a user's interaction and selection of data facets and scale and (2) the importance of specific features in a massive dataset (Uchida and Itoh, 2009). The method can significantly improve the efficiency of a visualization by reducing potential visual clutter and noise caused by rendering unnecessary data. Other methods that can increase the effectiveness and evaluate the usability of a visual analytics technique include heuristic evaluation, cognitive walkthrough, and the human cognitive model (Nielsen w: Nielsen and Mack, 1994; Ribarsky et al., 2009). Ribarsky et al. (2009) provided a detailed summary and explanation of the analytical reasoning theory and its related techniques.

#### 3.4.2. Data transformation and representation

Many studies focus on exploratory data analysis in a specific water-research domain, such as water quality, surface runoff, erosion and sediment transport, and the Energy-Water Nexus (EWN). Many of these studies incorporated more sophisticated data transformation and abstraction techniques to support visual representation and user-interaction techniques for pattern extraction from complex data and simulation results. Common data transformation and representation techniques include statistical and mathematical models, metrics, and data mining techniques powered by ML models (e.g., classification and clustering methods).

Accorsi et al. (2014) developed HydroQual to facilitate visual analysis of river water quality affected by intertwined natural processes and human activities. This tool was developed to address the limitation faced by GIS and statistical methods that fail to produce reliable results owing to data scarcity in some regions. HydroQual combines spatiotemporal data mining and visualization techniques to help domain experts analyze and evaluate water-quality data and their relationships with other environmental and urban factors. During the visual interface design process, Accorsi et al. (2014) proposed a novel metric to assess sequential dissimilarity in data through clustering and an optimized algorithm to extract temporal patterns. In addition to the novel data transformation techniques, a new algorithm for visualizing clusters and their associated optimization processes was devised and integrated into the visual interface. In a case study, HydroQual was applied to successfully highlight the relationship between values of a biological index and physicochemical parameters describing river water quality.

Mazher (2020) presented a visual analytics workflow for analyzing high-dimensional spatiotemporal hydrologic gridded datasets using ML models created based on dimensionality reduction techniques (DRTs). The study first evaluated the performance of various ML-based DRTs in terms of their accuracy in data transformation, dimensional reduction, and visual presentation of transformed data. These DRTs include principal component analysis, generative topographic mapping, t-distributed stochastic neighbor embedding, and uniform manifold approximation and projection. The accuracy of these techniques was evaluated using a co-ranking framework as a quality metric. Afterward, Mazher (2020) selected the best-performing DRT and implemented it into a generic analytical workflow. The framework can project high-dimensional spatiotemporal data on a 2D plane using a DRT and then represent the 2D projection spatially using a 2D perceptually uniform background color map. This workflow was applied to analyze the output of an Australian Water Resource Assessment model for Tasmania, Australia. The integration between ML-powered data transformation/analysis techniques and the 2D visual representation of processed data could significantly improve the human reasoning and perception of complex patterns in high-dimensional multivariate environmental datasets.

Xu et al. (2019) devised a web-based visual analytics workflow that can integrate various ML-based data transformation techniques with a variety of spatial and multivariate visualizations to explore the complex environmental processes related to soil erosion and sediment transport near culverts. The workflow offers systematic procedures to (1) classify the culvert sedimentation degree using a time series of aerial images, (2) identify key process drivers from a variety of environmental and culvert structural characteristics through ML-powered feature selection algorithms and interactive visual interfaces, (3) support human interactions to perceive empirical relationships between drivers and the culvert sedimentation degree through multiple multivariate visualization techniques and a self-organizing map (SOM), and (4) forecast culvert sedimentation potential across Iowa using tree-based ML algorithms. Through a case study, Xu et al. (2019) applied the visual analytics workflow to analyze a large integrated environmental dataset that entails culvert operation conditions from the Iowa Department of Transportation's Structure Inventory and Inspection Management System, watershed characteristics from the EPA's stream catchment dataset, and stream corridor characterization using Iowa's land use and land cover dataset and the NHD Plus. The analysis generated new insights that revealed a strong correlation and quantitative relationships between the degree of sediment deposition at culverts in Iowa and the state's geological landform regions. This insight was converted to a hypothesis and used to guide further investigations using the physically based Water Erosion Prediction Project model's simulation outputs (Xu, 2019).

Clark (2022) developed a visual analytics-aided deep learning approach to improve the understanding of the sustainability of current groundwater extractions in the Namoi region of Australia. The approach combined unsupervised SOM with supervised long short-term memory (LSTM) models to effectively abstract patterns from a diverse set of groundwater monitoring time series to facilitate the exploratory analysis of complex hydrogeological dynamics in the Namoi region. The combined models enabled the predictions of water levels based on climate and anthropogenic conditions. At the same time, the SOM can also visualize the shared pattern information from across the Namoi system to reduce the complexity of analyzing multiple time series. The resulting visual analysis shares information between sparse time series that could not be modeled with the LSTM individually.

Sanyal et al. (2017) started with a broad strategy of investigating the complex dynamics of the EWN and its interactions with climate variability from a more holistic perspective. The strategy takes a variety of socioeconomic and environmental factors, such as energy production and urban climate, into consideration during the management of urban water resources. Along with this vision, a web-based geospatial visualization platform was developed to integrate various data analysis toolboxes with advanced data fusion and data visualization capabilities to create a knowledge discovery framework to analyze the EWN. The unique contribution of the study includes the creation of an adaptive, modular, and flexible architecture to generate dynamic visual analytics workflows through the integration of different software modules (Berres et al., 2018). These modules include data analysis and transformation packages for statistical visual analysis, clustering, principal component analysis, dynamic time warping, and various geovisualization and uncertainty visualization libraries.

#### 3.4.3. User interaction

Walker et al. (2020) focused on integrating advanced user interaction techniques into interactive visualizations by presenting a web-based data visualization framework. The framework debuted as the Interactive Catchment Explorer (ICE) and was developed to help natural resource managers and researchers (1) visually explore complex and multivariate environmental datasets and modeling results, (2) identify spatial patterns related to ecological conditions, and (3) prioritize locations for restoration or further investigation. The framework employs a client-side architecture and is deployed as an integral part of the Spatial Hydro-Ecological Decision System. A geovisual interface was created within the ICE to display catchments across the northeast region of the United States. Catchment characteristics can also be visualized through color-coded symbology displayed on a web map embedded within the visual interface. Through a series of user interaction techniques, users can select and examine the statistical summary of multiple catchment characteristics (represented as hydrography, hydrologic, ecological, and environmental variables) through an array of interactive histograms placed alongside each other. The map of color-coded catchments is displayed simultaneously. This stereo arrangement of the plots and web map can help users observe correlations between different catchment characteristics by providing a coordinated view with various user interaction options. This arrangement also allows users to filter and focus on subsets of data by defining thresholds through the interactive histograms. At the same time, the color-coded display of catchment characteristics is updated based on the user's interaction to present patterns and variability for a selected environmental variable.

Similarly, Marbouti et al. (2018) presented WaterVis, a geovisual analytics application designed to support the monitoring and management of hydrologic and environmental resources. The tool was designed to identify environmental factors that contribute to changes in river water levels as well as enable the predictive analysis of the river stage. Similar to ICE, the design and development efforts of WaterVis also focused on advanced user interaction techniques. In this regard, both tools can serve as effective and generalized visual analytical frameworks that allow domain experts to explore potential correlations between different environmental variables, which can help identify contributing factors associated with a specific environmental process.

## 4. Visualization for communication and decision support

Hydroinformatics and water resources management applications normally entail three major dimensions: the natural dimension, the social dimension, and the business dimension (Chen and Han, 2016). Among these dimensions, the social dimension is defined as the interaction between the water/environment and humans/society (Chen and Han, 2016; Abbott, 1996). It promotes the engagement and participation of the general public in various water management and planning processes to address social concerns and needs related to water management ethics and culture. This dimension also considers challenges associated with transboundary water issues and conflicting water management goals from different water management authorities (Priscoli, 2004).

Recent approaches for integrated water management often entail practices designed to address the social dimension of the water resources. These practices promote water education to raise public awareness of water management issues, facilitate collaborative planning and public engagement in water management, and encourage voluntary social sensing of water-related data (Floress et al., 2015; Seelen et al., 2019; Reges et al., 2016). They often rely on community-driven efforts that involve the participation of multiple water management–related participants (e.g., watershed managers, stakeholders decision-makers, and policy makers) to solve various water-related problems related to the security, supply, conservation, and sanitation of water resources in both agricultural watersheds and urban areas (Vojinovic and Abbott, 2017; Moglia and Sharma, 2009).

Among these practices, the communication between multiple water resources management sectors and participants is of great importance. To facilitate effective communication, visual computing techniques combined with the recent web-based technologies can produce effective media to bring various participants into a collaborative problem-solving environment to support the planning and decision-making processes (Koontz and Newig, 2014; Palmer et al., 2013). Visual computing techniques bring unique advantages to promote the social dimension of integrated water management. Many visualizations are intuitive and easy-to-understand, which allows nontechnical water management participants (e.g., stakeholders) to understand complex scientific concepts. Furthermore, visual analytics applications can also provide solutions to optimize complex decision problems in integrated water resources management applications while bringing human input (e.g., experiences of watershed managers) into the process (Biswas et al., 2012; Prato and Herath, 2007; Lai et al., 2008).

### 4.1. Water education for public awareness

Visual computing applications, especially scientific visualizations and visual storytelling workflows, can provide practical tools to support water education and training. Through intuitive and user-friendly visual communications, visual computing techniques can help students and local water management communities develop in-depth understandings of complex, interlinked, and multiscale environmental processes to support their development of essential knowledge, skills, and strategies for solving water management problems. Meanwhile, visual computing techniques are easy to understand and can be readily disseminated and shared through web applications and smartphone apps, which are an effective means to raise public awareness of contemporary water problems and survey the needs, concerns, and voluntary water resources data provided by the public.

Demir et al. (2018) and Xu et al. (2020) integrated a watershed search engine and catchment characterization tool in publicly accessible online watershed information systems to educate nontechnical users (e.g., urban residents, stakeholders) on the basic concepts of watershed systems, such as the hydrologic cycle and stream connectivity. These concepts could help many landowners understand where the water on their properties comes from and how different land-management practices could affect the quantity and quality of water flows in downstream areas.

Demir et al. (2018) also employed a series of advanced scientific visualizations as cyberlearning tools to enable the decision support and education to raise the public awareness for disaster preparedness and response. These tools include web-based interactive visualizations for displaying streamflow direction (Fig. 4b), a rainfall-runoff simulator (Fig. 4c), and a flood map flyover simulator (Fig. 4d).

Demir (2014) embedded a hydrologic simulation system within a web-based 3D interactive visualization environment that demonstrates different hydrologic processes and concepts for teaching purposes. The simulation system was developed using advanced web technologies and a graphics processing unit to render physical behaviors of water flow and object collisions on realistic terrains. It allows students to create or load predefined scenarios, control environmental parameters, and evaluate environmental mitigation alternatives using realistic terrain information and water simulation.

Both Sermet and Demir (2020) and Haynes et al. (2018) developed virtual and augmented reality applications that allow users to visualize 3D flood inundation scenes using holographic lenses (Fig. 4e) and smartphones (Fig. 4f). Rydvanskiy and Hedley (2020) explored how 3D geovisualization and emerging 3D mixed-reality interfaces could be used for understanding and managing flood risk. The study reviewed the existing cartographic tools and platforms developed in the risk

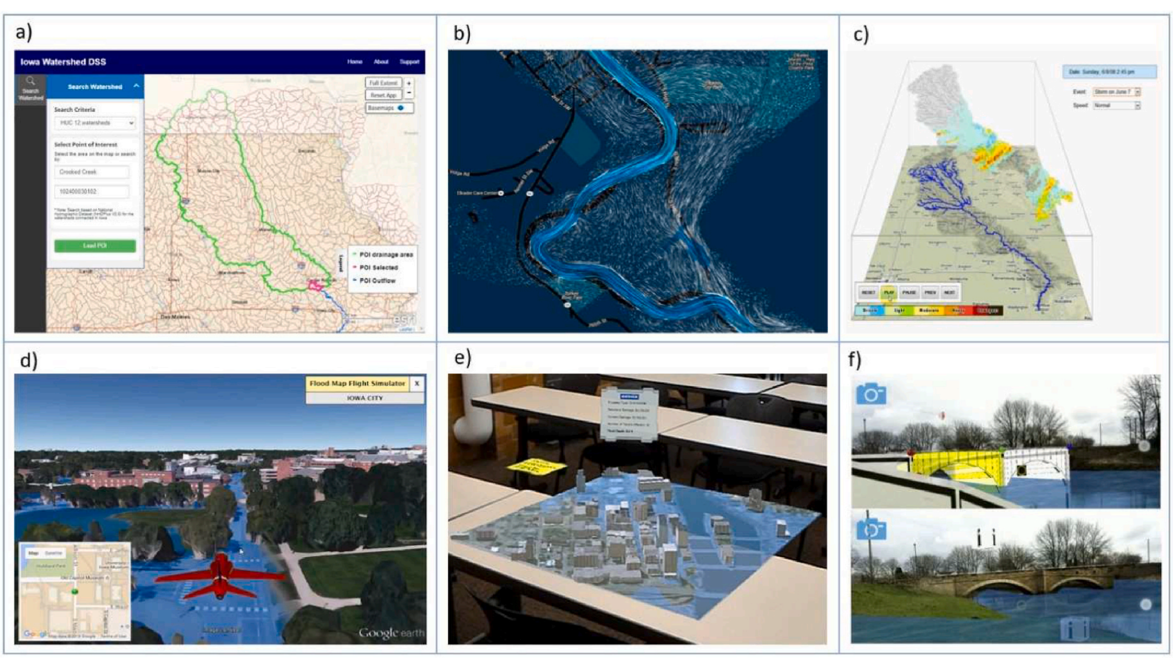


**Fig. 4.** Visualization applications for promoting water education: (a) watershed search engine from Iowa Watershed Decision Support System (Xu et al., 2020), (b) interactive stream flow direction visualization (Demir et al., 2018), (c) rainfall and flood forecast simulation for visualizing the hydrologic response (Hydroinformatics Lab at UIOWA, 2017), (d) flood map flight simulator (Demir et al., 2018), (e) holographic flood loss and damage application (Sermet and Demir, 2020), and (f) augmented reality for flood visualization (Haynes et al., 2018).

management sector and discussed their potential for improving the quality of representation and analysis and reducing the knowledge barriers that impede the understanding of flood risk for nontechnical audiences. Furthermore, the study discussed the emerging mixed-reality interfaces and their advantages over traditional desktop interfaces for user interaction with 3D content.

The recent advent of different Web Graphics Libraries (WebGLs), 3D web tiling services, and online game engines have significantly lowered the barrier to building immersive environments to promote water, urban, and forestry management. Section 5 presents a detailed summary and discussion of web technologies for creating online 3D immersive environments. Many of these visual computing applications could be designed to match the background and understanding of users that are in different age groups and have different educational backgrounds, thus supporting public education and college-level teaching and training tasks.

### 4.2. Collaborative water planning

Collaborative, holistic, and proactive water resources management practices are effective for solving transboundary, and interjurisdictional challenges (Carson et al., 2018; Cardwell et al., 2008). These practices have been favored by many watershed and nature-resources management communities in recent decades (Galvez and Rojas, 2019; Sajjadi et al., 2020). To address the technical challenges related to the communication and public engagement aspects of collaborative water management and planning tasks, Savic et al. (2016) proposed a serious gaming approach and presented a survey of published work on gaming applications with particular interest in water-systems planning and management. Many of the previous serious gaming applications were implemented using board game and desktop applications (Zagal et al., 2006). To further improve the game's ability to foster collaboration and communication between different participants in water management, many recent studies have integrated interactive, appealing, and realistic visualizations of watershed systems into web-based game engines to deliver online serious games. These games can provide engaging and accessible environments to facilitate public engagement in collaborative water planning processes (Carson et al., 2018).

Along with the advancement in web technologies, many aspects of modern serious games, such as realism, performance, progress monitoring, accessibility, and portability, have been significantly improved. At the same time, serious games are able to bring the fun factor to the problem-solving process of complex and technical water management problems. This practice creates an intriguing and intuitive means to attract public participation and promote water education. In the following, we review a few serious gaming applications that apply intuitive visual interfaces to emphasize the aspects of collaboration and public engagement in various water management operations (Fig. 5).

Xu et al. (2020) developed a web-based serious game to support multijurisdictional collaborative planning and decision-making for mitigation of multiple water hazards (i.e., floods, soil erosion, water quality deterioration). The serious game is available to the local watershed management communities as the Iowa Watershed Decision Support System (known as IoWaDSS), which provides an interactive multiuser geovisual interface that can engage different water management participants as players and allow them to select different adaptation options (i.e., management practices). The adaptation options are devised to reduce undesirable impacts of multiple water hazards in the Cedar Basin watershed. Examples of these adaptation options include relocation of structures, changing the land cover and land use, and installing additional hydraulic structures. The goal of the game is to find the best-performing combination of adaptation options. To this end, the application integrates multidomain environment models using a graph model to evaluate the adaptation options selected by different users. The gaming application produces scores for each individual player to evaluate their performance in the game. The player that receives the highest score becomes the winner. The web application employs various charts and geovisualizations to visualize the player's options, selections, different gaming scenario constraints, and game processes. A game referee interface is developed to allow players and judges (e.g., selected technical watershed management experts) to compare the performance and scores of different sessions.

Sermet et al. (2020) expanded the competitive gamification concept for water management into a generalized web-based framework. The framework can use public datasets to populate serious games and decision-support applications for mitigating various hydrologic hazards. The study focused on software design approaches and system architecture for building a modular, secure, and salable web-based geospatial

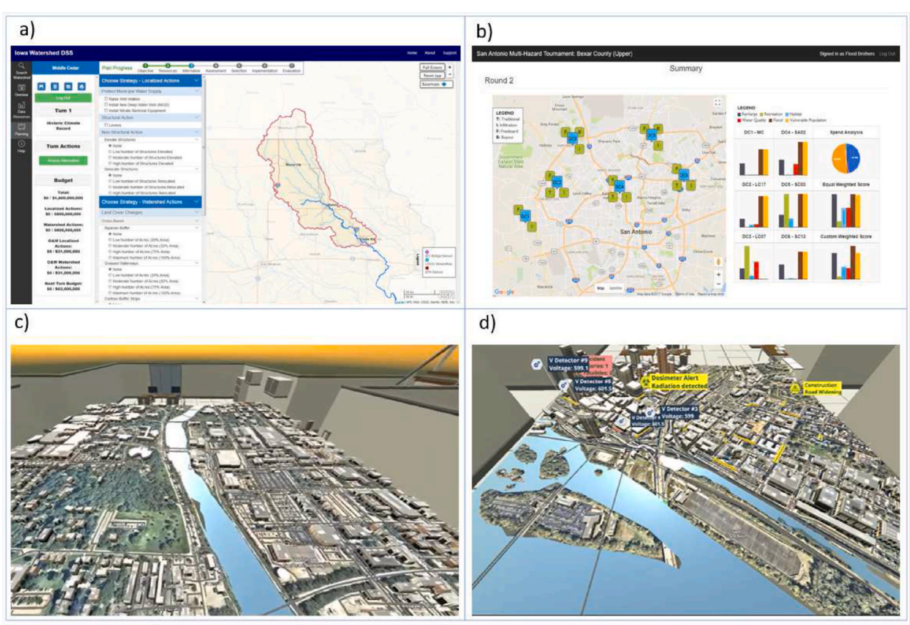


**Fig. 5.** Visualization-based serious games for collaborative water management. (a) The IoWaDSS gaming interface allows players to select adaptation options (Xu et al., 2020). (b) The decision support tool's visual interface summarizes player performance (Sermet et al., 2020).(c) Geospatial VR renders real-world 3D environments (Sermet and Demir, 2022), including (d) dynamic visualization of flood inundation (Sermet and Demir, 2022).

application as a web-based decision support tool for water hazards mitigation. The application aims to provide intuitive user interfaces and visualization for real-time and collaborative data analysis and damage assessment from multiple aspects (e.g., social, environmental, ecological).

To further improve the realism and immersion of the collaborative serious gaming approach, Sermet and Demir (2022) created an open-source collaborative virtual reality framework, introduced as Geospatial VR, which can render 3D real-world environments to host serious gaming applications intended to mitigate multiple natural hazards, including flooding and wildfire. The framework can automatically render realistic 3D simulation scenes of user-defined spatial extents. Within each simulated scene, users can view the digital terrain, elevation model, infrastructure, dynamic visualizations of hazards (e.g., flood inundation, fire spread), and different layers that characterize disaster damage and extent, sensor readings, occupancy, traffic, and weather. The framework also incorporates multiuser support for remote virtual collaboration. It enables immersive geospatial capabilities in information and decision support systems that are implemented using various open-source web technologies, such as the Unity game engine and the Node.js environment.

### 4.3. Decision support and optimization

Visual analytics enable decision-makers to visually compare multidimensional vectors that represent conflicting criteria in complex problems (Miettinen, 2014; Trindade et al., 2019). These techniques often employ intuitive visual representations that can be readily understood and interpreted by nontechnical decision-makers. These representations highlight similarities and differences between management alternatives that emphasize different needs. This subsection reviews applications that use visual analytics to enable interactive processes for decision-making (Miettinen, 2014; Miettinen et al., 2008).

Aydin et al. (2015) proposed a decision support system to assess the technical sustainability of water distribution systems (WDS) used to improve the effectiveness of the decision-making process. The method combines multiple maps with a modified network representation that consists of aggregated edges, circle views, and a grid layout to visualize the technical sustainability assessment results for various *new pump* and *reclaimed water* scenarios within a water distribution network at different time steps. The technical sustainability assessment evaluates the reliability, durability, flexibility, and adaptability of a WDS. Through coordinated views and visual abstractions, the visualization approach allows decision-makers to visually compare multiple facets (e.g., technical sustainability assessment, hydraulic efficiency, water quality) of different pump alternatives in the context of a water distribution network. Thus, the effort can assist decision-makers in improving raw data visibility and comparing multiple decision alternatives.

Matrosov et al. (2015) integrated a water system simulator with multiobjective search to generate a diverse set of Pareto-optimal water supply portfolios. Afterward, the study assessed the set by developing a state-of-the-art visual analytics approach. The approach integrates a variety of interactive plots to help planners identify more adequate water supply system designs to better understand their inherent trade-offs between the best scheme portfolios. The effort can help water-resources managers better understand projected water demands to improve planning in a real-world water resource system.

## 5. Advancements in visualization technologies

The technical capabilities of visual techniques have been further improved through next-generation web-based technologies, such as the emerging 5G network, web graphics libraries accelerated by general-purpose graphics processing units (GPGPUs), adaptive client-side web frameworks, and a number of online data analysis and visualization platforms. From a technical standpoint, these hardware and software improvements have significantly enhanced the following abilities for building powerful visual computing applications:

- Internet bandwidth to transfer massive amounts of data in a timely fashion,
- client-side computational power to render large amounts of data on computers or mobile devices, and
- organization and coordination of individual plots and charts to construct a visual analytics workflow with sophisticated user interactions.

Powered by these capabilities, online data analysis and visualization platforms, such as Tableau, PowerBI, Grafana, and Kibana, are gaining popularity in business analytics and academia. Combined with geospatial server applications, such as GeoServer and CartoDB, these platforms are increasingly introduced in college courses and scientific research sectors. The major advantage of these platforms is that they can integrate a suite of visualization techniques, user interface design, and data analysis tools into a generic web environment using modular and adaptive design. Through the web environment, nontechnical users (without computer science or web development backgrounds) could build data queries and visual dashboards without the need to write a substantial amount of code. These platforms bring big changes in software development in the hydroinformatics community, where web developers were previously required to write code from scratch using heterogeneous programming languages and software stacks.

These online visualization platforms are becoming popular in visual computing because they can lower the technical barriers for non-computer science students and domain experts for building advanced visual interfaces and dashboards. They also enable domain scientists to be directly involved in developing visual interfaces and dashboards, thereby promoting visual computing techniques as an integral part of the scientific process. Many of these platforms are also freely available and created under open-source licenses, which makes them accessible to scientific research communities.

### 5.1. Graphics in web-based visualization

Most graphics in web-based visual interfaces and dashboards are rendered on the client-side in a user's browser as HTML Document Object Model (DOM) elements. Popular web visualization libraries and frameworks rely on two major types of DOM elements to construct plots, charts, and visual representations: (1) Scalable Vector Graphics (SVG) and (2) HTML5 Canvas. Each type uses distinct graphics rendering mechanisms. SVG uses vector shapes to generate geometries, whereas the Canvas display geometries use a raster of pixels (Reddy et al., 2021). Depending on the type of DOM element, some visualization libraries are more suitable for fulfilling specific visualization and visual analytics needs (e.g., displaying Big Data, enabling advanced user interaction, scaling plots and graphics to different scales and screen resolutions) than other libraries.

Plots, charts, and geovisualizations (e.g., markers, symbols, glyphs) rendered through SVG-based libraries use vector graphics to represent different geometries (e.g., lines, boxes, dots, circles) and visualization components (e.g., plot axes, ticks, map labels). These vectors are defined as XML-format objects in an SVG viewer (defined as <svg>), which can be embedded in the HTML page that then renders the client-side views (any components that a user can visually see) of a web application. In this setting, vector graphics rendered in a chart or web map are scalable, which allows them to change size to fit any user-defined resolution or scale without losing quality. Because these vectors are defined as client-side objects, their styles and shapes can be modified dynamically through client-side JavaScript and Cascading Style Sheets. This allows SVG-based visualizations to be very responsive to user interactions (e.g., filtering data, changing line color, stroke width, dragging a point/marker across a chart or map). Users can click or hover on a graph, which can be applied to represent the stream network in a catchment, and highlight edges that represent a specific stream to access its geometric information and other properties. In another example, multiple SVG-based plots can be readily connected through the common DOM manipulation techniques because their graphics objects can be connected through the DOM element's ID. This setting allows the visual interface to highlight corresponding graphics in other charts or maps when the user hovers over or clicks on a specific element in a chart or on a web map. This feature allows developers to create coordinated views using multiple maps and charts to help users explore multiple facets of complex data simultaneously. In general, SVG-based libraries are suitable for developing visualizations and visual analytics interfaces that emphasize user interaction and view coordination. A major limitation of SVG-based visualizations is that they are unable to efficiently render large amounts of data (e.g., millions of points).

In contrast, HTML Canvas-based libraries represent geometries as pixels in an HTML Canvas element (defined as <canvas>), which is raster-based and rendered in a way that resembles images, such as JPEG and PNG. Compared with the SVG-based visualizations, static Canvas-based visualizations cannot be readily scaled to any resolution without reconstructing the raster. Because individual geometries (e.g., lines, circles) are defined as image pixels in a Canvas element, their styles cannot be dynamically modified, and their attributes cannot be accessed the same way a user can interact with a vector object. Changing the color, shape, or position of a geometry in a Canvas-based chart would normally require the client-side JavaScript to reconstruct the entire raster image in its Canvas element. However, Canvas-based visualization libraries have better performance when they are used to render a large number of graphics, such as drawing thousands of lines and circles in a chart or on a map, in which graphics are represented as pixels, not objects. Therefore, handling these graphics does not require significant memory on the client side. In recent years, much effort has been dedicated to integrating the WebGL into regular Canvas elements. The WebGL is a JavaScript API that enables the GPU-accelerated usage of physics and image processing and effects on the client side. WebGL-based libraries can render interactive 3D graphics or visualize a tremendous amount of data in a web environment (e.g., eighty-trillion point locations on an interactive web map) without noticeable delay or lag in visualization performance (Sumbera, 2019). Many popular 3D web applications, such as the Unity Real-Time Development Platform (Buyuksalih et al., 2017) and Cesium 3D Geospatial platform (Tsai et al., 2016), employ WebGL to create interactive 3D environments in web browsers (Kr ä mer and Gutbell, 2015) and can be used to develop web-based geospatial applications to benefit research in water resources management and other urban science sectors (e.g., digital twin cities) (Sermet and Demir, 2020; Kr ä mer and Gutbell, 2015; Laksono and Aditya, 2019).

### 5.2. Visualization libraries and tools

In this section, we review several popular web-based visualization libraries and frameworks and share our early experience of developing visualization-oriented applications and tools that can benefit the water science community's research efforts and management operations. Because many visualization-driven studies reviewed and discussed in previous sections are implemented using these libraries and frameworks, we would like to discuss their advantages and applicability to provide insights and share our experiences regarding selecting the most appropriate web visualization technologies for a task.

Table 1 summarizes popular web-based visualization libraries and their capabilities for developing visual computing applications for research purposes through a few qualitative metrics. We use GitHub stars as an evaluator of each library's popularity, which indicates the number of times the library gets endorsed by the web development community. Selecting a popular and trending visualization library for hydroinformatics and water management applications is important because plots and charts developed using popular libraries typically exhibit more consistent and frequent maintenance and versioning. The underlying technologies of these libraries are continuously supported and improved by the open-source software development community. We also list the number of prebuilt chart types in each library that can be readily used and integrated into a web application as an API with minimal coding efforts. Most of these libraries provide a number of standard charts, such as line, bar, area, and pie. Some libraries offer

**Table 1**
Summary of recent web-based visualization technology (updated in February 2022).

| Library Name | Description | GitHub Popularity | Visualization Elements | Prebuilt Charts | Geovis Ability |
|---|---|---|---|---|---|
| Vega | Declarative grammar for defining interactive web visualizations | 9.6K stars | SVG | 100+ | Static maps |
| D3.js | JavaScript library for producing dynamic, interactive data-driven visualizations | 100K stars | Canvas, SVG | 1,000+ | Integrable with map engines |
| C3.js | D3.js-based reusable chart library | 9.2K stars | Canvas, SVG | 15+ | N/A |
| Recharts | D3.js integration with the React framework | 17.7K stars | Canvas,SVG | 60+ | N/A |
| Raphael.js | JavaScript library for working with vector graphics on the web. | 11K stars | SVG | Very few | N/A |
| FusionCharts | Role-based visualization and dashboard library | 2K stars | Canvas, SVG, VML | 100+ | Static maps |
| ECharts & Highcharts | Interactive JavaScript charting and visualization library | 49.8K stars | Canvas, SVG, VML | 100+ | Static maps |
| React Vis | JavaScript visualization library for the React framework | 8.1K stars | SVG | 15+ | N/A |
| Chart.JS | Lightweight JavaScript library for data visualization | 56.1K stars | Canvas | 30+ | N/A |
| Rawgraphs | D3.js-based data visualization library for spreadsheets | 1.8K stars | Canvas,SVG | 30+ | N/A |
| Cubism.js | D3.js-based time series visualization plugin | 4.9K stars | Canvas | Time series only | N/A |
| Metrics graphics | D3.js-based time series visualization library | 7.4K stars | SVG | Time series only | N/A |
| Epoch charts | D3.js-based time series visualization library with real-time update capability | 5K stars | Canvas,SVG | 6+ | N/A |
| Dygraphs | Fast and flexible open-source JavaScript charting library | 3K stars | Canvas | 18+ | N/A |
| visgl/deck.gl | WebGL-powered framework for visual exploratory data analysis of large datasets | 54K stars | WebGL | 3D and 2D vis environment | Integrable with map engines |
| ThreeJS | WebGL-powered 3D animation and visualization library | 30.6K stars | WebGL | 3D vis environment | N/A |
| CesiumJS | 3D visualization library for geo-spatial data | 8.3K stars | WebGL | 3D vis environment | N/A |
| Harp.gl | WebGL-powered 3D web map rendering engine | 1.1K stars | WebGL | 3D maps | Integrable with map engines |
| Regl | Fast functional WebGL visualization framework | 4.5K stars | WebGL | 3D and 2D environment | N/A |

more sophisticated chart types, such as graphs, parallel coordinate plots, edge bundles, and radar plots. Many WebGL-based libraries do not provide prebuilt charts but can create 2D and 3D environments for visualizing terrain and buildings (Cesium, 2015; Mamoowala, 2020), 3D objects, and point clouds from Lidar measurements (Cesium, 2021). The geovisualization ability indicates if the library could be used to visualize GIS data. Some libraries can be used to design and develop innovative visual representations of complex spatial data and choropleth maps. To produce interactive web maps, they can export DOM elements to be readily integrated into popular web map engines, such as Leaflet, OpenLayers, Mapbox, and Google Maps.

## 6. Conclusion and vision

Here, we summarize our review of visual computing applications developed for water resources management (Section 6.1), and we present our vision (Section 6.2) for integrating the emerging state-of-art visual computing technologies and paradigms into next-generation hydroinformatics applications in pursuit of the smart-water-city approach.

### *6.1. Summary of past applications*

Recent improvements in environmental monitoring technologies have enabled efficient and economic acquisitions of tremendous amounts of water-related data, which has led to the emergence of innovative Big Data applications that can address past challenges and generate useful insights in water science disciplines. Among these applications, visual computing techniques empower the synergy of computational techniques (e.g., ML and statistical models) and human reasoning capabilities through visual interfaces to improve the understanding and solution of complex decision problems in many scientific domains. We reviewed past studies that employ various visual computing techniques as their core component to benefit research efforts in the water resources management sector. We also discussed visual computing methodologies in these studies from the perspectives of visual analytical reasoning, visual representation and user interaction, and data representation and transformation.

Many past studies integrated visual computing techniques into GIS, cyberinfrastructure, and domain models to benefit the big data analysis aspect of water resources management. These aspects broadly include (1) improvement of discovery, management, and quality control of large-scale hydrologic and environmental data and (2) interpretation and optimization of simulation and data models. More recent studies have adopted visualization and visual analytics as independent research investigation efforts to enable qualitative analysis and exploration (e.g., patterns, dependencies, interrelationships). With the recent increase in volume, variety, and quality of environmental and hydrologic data, we envision a future trend of leveraging visual computing techniques as a more significant scientific and investigative tool for solving complex research problems, which are defined by Big Data and are challenging to solve through traditional domain-specific approaches (e.g., statistical models, physical models). From a social-technical viewpoint, visual computing techniques could be applied to various watershed and urban water management efforts to promote (1) water education and public awareness of various water-related issues; (2) collaborative management, planning, and public engagement; and (3) optimization of complex multiobjective and multicriteria decision problems.

With the advent of web-based visualization and immersive reality, visual computing applications in water resource management are becoming more accessible and intuitive and serving as an effective medium to connect different participants (e.g., hydrologists, decision-makers, watershed managers, stakeholders) in a more collaborative and integrated water management approach. In the near future, we expect visual computing techniques to become the foundation for disseminating water education, raising public awareness of various water problems, and increasing public engagement.

We also discussed recent advancements in visualization technologies, their mechanisms for rendering graphics in web applications, and the advantages of different technologies for building visualization and visual analytics applications with different focuses. We summarized a list of popular web visualization libraries for developing charts, plots, web maps, and 3D geospatial environments. Many recent online platforms for data analysis and visualization are combined with geospatial server applications to integrate a stack of visualization, GUI design, and data analysis tools into a generic web environment using a modular and adaptive design. These online platforms enable nontechnical users (without a computer science or web development background) to build data queries and visual dashboards through GUIs without writing a substantial amount of code. Additionally, many modern web visualization libraries provide intuitive and well-defined APIs that can lower the technical barriers for non-computer science students and domain scientists to build advanced web apps and dashboards with web mapping, data visualization, and visual analytics capability.

### *6.2. Vision*

In recent decades, many emerging visual computing technologies and paradigms have garnered attention in the scientific software community (Bernholdt et al., 2021). We summarize several visions for emerging visualization and visual analytics approaches, which are proposed through the Advanced Scientific Computing Research (ASCR) Workshop on Visualization for Scientific Discovery, Decision-Making, and Communication (U.S. Department of Energy, 2022), and propose our vision for using these technologies to benefit next-generation hydroinformatics applications for water resources management.

At the technological level, several white papers from the workshop discussed the potential application and opportunities of the recently emerging Extended Reality (XR) technology for environmental science and earth science disciplines (U.S. Department of Energy, 2022). Based on our review of existing virtual reality (Luo et al., 2011) and augmented reality (Carmigniani et al., 2011) applications in the water resources sector, we believe the XR technology and its related metaverse concept could be integrated with hydroinformatics and smart-city applications. The integration can further overcome sociotechnical challenges and improve public education, engagement, voluntary data collection, and collaborative planning of water resources through immersive and realistic visualizations. As the metaverse concept captures the tech industry's imagination and investments, it has potential as a major contributor to the next-generation internet, through which future XR-based applications for water education and voluntary data collection could be seamlessly incorporated into our daily lives. Meanwhile, several ASCR white papers discussed a vision of developing intelligent visual analytics (Nazemi, 2018), a concept that further leverages the capability of AI to improve visualization algorithms and visual analytics design. These improvements include (1) increasing the computational capacity (e.g., volume rendering, particle tracing) for visualizing Big Data and (2) enhancing human perception and cognition abilities during complex and analytical tasks through AI-driven annotations and storytelling workflows (Nazemi, 2018). We believe intelligent visual analytics techniques can be integrated into future hydroinformatics applications to reduce human perception efforts in exploratory visual analysis, thereby making charts, graphs, and visual analytical workflows more intelligent and easier to understand. Many physical phenomena in environmental systems (e.g., hysteresis in river flow) can be captured by special graphical characteristics (e.g., a certain shape in the line charts) through the visualization of sensor observations. A computer vision application powered by deep learning models can automatically detect these characteristics and then guide the expert users to the subset of big environmental observation data that discloses the graphical characteristics through annotations and automated visual storytelling workflows.

At the paradigm level, many of the next-generation internet technologies (e.g., Internet of Things, 5G networks) are employed by a broad environmental and urban science community to develop smart-city platforms and digital twin cities. In this ongoing trend, visual computing techniques serve as a bridge to connect smart-city applications with the existing hydroinformatics applications and water management platforms. This connection aims to shed light on a more integrated smart-water-city approach that incorporates water resources management with the planning and optimization of other urban subsystems (e.g., building energy, transportation, urban microclimate). We believe next-generation water resources management applications will be able to address a broad scope of social demands and socioeconomic factors and have more opportunities to solve complex problems that combine urban dynamics with environmental processes. Examples of these applications include (1) incorporating the urban green water infrastructure design into the transportation system planning to lower the risk of roadway inundation and culvert overtopping during flood events and (2) considering the risks of water-related hazards (e.g., flood, excessive soil erosion, water-induced landslides) during urban planning to protect critical energy infrastructure (e.g., electrical grid, gas).

## CRediT authorship contribution statement

**Haowen Xu:** review, writing, and original draft preparation. **Andy Berres:** data curation, writing, and revision. **Yan Liu:** revision and administration. **Melissa R. Allen-Dumas:** data curation, writing, and revision. **Jibonananda Sanyal:** revision and administration.

## Disclaimer

Oak Ridge National Laboratory is managed by UT-Battelle, LLC, for the US Department of Energy under contract DE-AC05-00OR22725. This manuscript has been authored by UT-Battelle, LLC, under Contract NumberDE-AC05-00OR22725 with the US Department of Energy DOE). The US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains, a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US government purposes. DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

## 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.

## References

Abbott, M., 1996. The sociotechnical dimension of hydroinformatics. Hydroinformatics 96, 3–18.
Abbott, M., Vojinovic, Z., 2013. Towards a hydroinformatics for China. J. Hydroinf. 15 (4), 1189–1202.
Abbott et al, M.B., 1991. Hydroinformatics: Information Technology and the Aquatic Environment. Avebury Technical, Aldershot, Hampshire, UK.
Accorsi, P., Lalande, N., Fabrègue, M., Braud, A., Poncelet, P., Sal-laberry, A., Bringay, S., Teisseire, M., Cernesson, F., Le Ber, F., 2014. Hydro-qual: Visual Analysis of River Water Quality," In2014 IEEE Conferenceon Visual Analytics Science and Technology (VAST). IEEE, pp. 123–132.
Adamala, S., 2017. An overview of big data applications in water resources engineering. Machine Learn. Res. 2 (1), 10–18.
Adamala, S., Singh, R., Raghuwanshi, N., Prasad, A., Chamoli, A., 2019. Hydrologic calculator: an educational interface for hydrological processes analysis. Agri. Eng. Int.: CIGR J. 21 (1), 1–17.
Allen-Dumas, M.R., Xu, H., Kurte, K.R., Rastogi, D., 2021. Toward urban water security: broadening the use of machine learning methods for mitigating urban water hazards. Front. Water 2.
Ames, D.P., Horsburgh, J.S., Cao, Y., Kadlec, J., Whiteaker, T., Valentine, D., 2012. HydroDesktop: Web Services-Based Software for Hydrologic Data Discovery, Download, Visualization, and Analysis, 37. Environmental Modelling & Software, pp. 146–156.
Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M.-J., MacEachren, A., Wrobel, S., 2007. Geovisual analytics for spatial decision support: setting the research agenda. Int. J. Geogr. Inf. Sci. 21 (8), 839–857.
Andrienko, G.L., Andrienko, N., Keim, D., MacEachren, A.M., Wrobel, S., 2011. Challenging problems of geospatial visual analytics. J. Vis. Lang. Comput. 22 (4), 251–256.
Andrienko, G., Andrienko, N., Chen, W., Maciejewski, R., Zhao, Y., 2017. Visual analytics of mobility and transportation: state of the art and further research directions. IEEE Trans. Intell. Transport. Syst. 18 (8), 2232–2249.
ASCE task committee on application of artificial neural network sin hydrology, "artificial neural networks in hydrology. I: preliminary concepts. J. Hydrol. Eng. 5 (2), 2000, 115–123.
Aydin, N.Y., Zeckzer, D., Hagen, H., Schmitt, T., 2015. A Decision Support System for the Technical Sustainability Assessment of Water Distribution Systems, 67. Environmental Modelling & Software, pp. 31–42.
Bernholdt, D.E., Cary, J., Heroux, M., McInnes, L.C., 2021. Position Papers for the ASCR Workshop on the Science of Scientific-Software Development and Use, 12 [Online] . Available: https://www.osti.gov/biblio/1843575.
Berres, A., Karthik, R., Sorokine, A., Nugent, P., Allen, M., McManamay, R., Chandola, V., Zaidi, S.M., Sanyal, J., Bhaduri, B., 2018. Ewn-kdf:A knowledge discovery framework to understand the energy water nexus. In: CaGIS Autocarto 2018/USGIS Symposium, pp. 1–10.
Berres, A.S., Xu, H., Tennille, S.A., Severino, J., Ravulaparthy, S., Sanyal, J., 2021. Explorative Visualization for Traffic Safety Using Adaptive Study Areas," Transportation Research Record, 0361198120981065.
Biswas, S., Vacik, H., Swanson, M.E., Haque, S.S., 2012. Evaluating integrated watershed management using multiple criteria analysis - a case study at Chittagong hill tracts in Bangladesh. Environ. Monit. Assess. 184 (5), 2741–2761.
Blodgett, D., Read, E., Lucido, J., Slawecki, T., Young, D., 2016. An analysis of water data systems to inform the open water data initiative. JAWRA J. Am. Water Res. Assoc. 52 (4), 845–858.
Brelsford, C., Dumas, M., Schlager, E., Dermody, B.J., Aiuvalasit, M., Allen-Dumas, M.R., Beecher, J., Bhatia, U., D'odorico, P., Garcia, M., et al., 2020. Developing a sustainability science approach for water systems. Ecol. Soc. 25 (2), 1–6.
Burch, M., Weiskopf, D., 2011. Visualizing dynamic quantitative data in hierarchies. In: Proceedings of International Conference on Information Visualization Theory and Applications, pp. 177–186.
Burley, D., Ashburn, V., 2010. Information visualization as a knowledge integration tool. J. Knowl. Manage. Pract. 11 (4), 1.
Buttenfield, B.P., Stanislawski, L.V., Brewer, C.A., 2011. Adapting generalization tools to physiographic diversity for the United States National Hydrography Dataset. Cartogr. Geogr. Inf. Sci. 38 (3), 289–301.
Buyuksalih, I., Bayburt, S., Buyuksalih, G., Baskaraca, A., Karim, H., Rahman, A.A., 2017. 3d modelling and visualization based on the unity game engine–advantages and challenges. ISPRS Ann. Photogram. Remote Sens. Spat. Inform. Sci. 4.
Cardwell, H., Langsdale, S., Stephenson, K., 2008. The Shared Vision Planning Primer: How to Incorporate Computer Aided Dispute Resolution in Water Resources Planning. Institute for Water Resources, Alexandria. IWR Report.
Carmigniani, J., Furht, B., Anisetti, M., Ceravolo, P., Damiani, E., Ivkovic, M., 2011. Augmented reality technologies, systems and applications. Multimed. Tool. Appl. 51 (1), 341–377.
Carson, A., Windsor, M., Hill, H., Haigh, T., Wall, N., Smith, J., Olsen, R., Bathke, D., Demir, I., Muste, M., 2018. Serious gaming for participatory planning of multi-hazard mitigation. Int. J. River Basin Manag. 16 (3), 379–391.
Cesium, 2015. Introducing 3d Tiles. https://cesium.com/blog/2015/08/10/introducing-3d-tiles/.
Cesium, 2021. Point Clouds Tiler. https://cesium.com/platform/cesium-ion/3d-tiling-pipeline/point-clouds/.
Chen, Y., Han, D., 12 2016. On big data and hydroinformatics. Procedia Eng. 154, 184–191.
Clark, S.R., 2022. Unravelling Groundwater Time Series Patterns: Visual Analytics-Aided Deep Learning in the Namoi Region of Australia. Environmental Modelling & Software, p. 105295.
Council, N.R., et al., 2003. Information Technology for Counterterrorism: Immediate Actions and Future Possibilities. National Academies Press.
Demir, I., 2014. Interactive web-based hydrological simulation systems as an education platform using augmented and immersive reality. In: Proceedings of the 2014 ASEE North Midwest Section Conference. Iowa City, IA., pp. 1–6. October 16-17, 2014.
Demir, I., Krajewski, W.F., 2013. Towards an Integrated Flood Information System: Centralized Data Access, Analysis, and Visualization, 50. Environmental Modelling & Software, pp. 77–84.
Demir, I., Small, S., Goska, R., Keahey, K., Armstrong, P., Riteau, P., Seo, B., Mantilla, R., 2014. Hydroinformatics on the cloud: data integration, modeling and information communication for flood risk management. In: Proceedings of the 11th International Conference on Hydroinformatics, pp. 1–3.
Demir, I., Yildirim, E., Sermet, Y., Sit, M.A., 2018. Floodss: Iowa flood information system as a generalized flood cyberinfrastructure. Int. J. River Basin Manag. 16 (3), 393–400.
Deval, C., Brooks, E.S., Dobre, M., Lew, R., Robichaud, P.R., Fowler, A., Boll, J., Easton, Z.M., Collick, A., Pi-vat, 2022. A web-based visualization tool for decision support using spatially complex water quality model outputs. J. Hydrol. 127529.
Dill, J., Earnshaw, R., Kasik, D., Vince, J., Wong, P.C., 2012. Expanding the Frontiers of Visual Analytics and Visualization. Springer.
Earnshaw, R.A., Dill, J., Kasik, D., 2019. Data Science and Visual Computing. Springer.

Endert, A., Hossain, M.S., Ramakrishnan, N., North, C., Fiaux, P., Andrews, C., 2014. The human is the loop: new directions for visual analytics. J. Intell. Inf. Syst. 43 (3), 411–435.
Few, S., Edge, P., 2007. Data Visualization: Past, Present, and Future. IBM Cognos Innovation Center.
Floress, K., Akamani, K., Halvorsen, K.E., Kozich, A.T., Davenport, M., 2015. The role of social science in successfully implementing watershed management strategies. J. Contemp. Water Res. Educ. 154 (1), 85–105.
Fox, P., Hendler, J., 2011. Changing the equation on scientific data visualization. Science 331 (6018), 705–708. https://doi.org/10.1126/science.1197654.
Fuhrmann, S., 2000. Designing a visualization system for hydrological data. Comput. Geosci. 26 (1), 11–19.
Galvez, V., Rojas, R., 2019. Collaboration and integrated water resources management: a literature review. World Water Pol. 5 (2), 179–191.
Ginsberg, W.R., 2011. Obama Administration's Open Government Initiative: Issues for Congress. DIANE Publishing.
Gober, P.A., Redman, C.L., Bolin, R., Gammage Jr., G., Taylor, T., 2003. Decision center for a desert city: the science and policy of climate uncertainty. NSF Prop. NSF 3–552.
Grainger, S., Mao, F., Buytaert, W., 2016. Environmental Data Visualization for Non-scientific Contexts: Literature Review and Design Framework, 85. Environmental Modelling & Software, pp. 299–318.
Gunn, M.A., Matherne, A.M., Mason, R.E., 2014. The USGS at Embudo, New Mexico: 125 Years of Systematic Streamgaging in the United States. US Department of the Interior, US Geological Survey.
Guo, H., Li, Z., Lan-Wei, Z., 2015. Earth observation big data for climate change research. Adv. Clim. Change Res. 6 (2), 108–117.
Haynes, P., Hehl-Lange, S., Lange, E., 2018. Mobile Augmented Realityfor Flood Visualisation, 109. Environmental Modelling & Software, pp. 380–389.
Heok, T.K., Daman, D., 2004. A review on level of detail. In: Proceed Ings. International Conference on Computer Graphics, Imaging and Visualization. IEEE, pp. 70–75, 2004. CGIV 2004.
Honegger, M., 2018. Shedding Light on Black Box Machine Learning Algorithms: Development of an Axiomatic Framework to Assess the Quality of Methods that Explain Individual Predictions, 05054 arXiv preprintarXiv:1808.
Horsburgh, J.S., Reeder, S.L., 2014. Data Visualization and Analysis within a Hydrologic Information System: Integrating with the R Statis-Tical Computing Environment, 52. Environmental Modelling & Software, pp. 51–61.
Hydroinformatics Lab at UIOWA, "Rainfall and Flood Forecast Simulation, 2017 [Online] . Available. https://hydroinformatics.uiowa.edu/projects/projects_rainanim.php.
Jadidoleslam, N., Goska, R., Mantilla, R., Krajewski, W.F., 2020. Hydro-vise: a non-proprietary open-source software for hydrologic model and data visualization and evaluation. Environ. Model. Software 134, 104853.
Jones, N., Nelson, J., Swain, N., Christensen, S., Tarboton, D., 2014. andP. Dash, "Tethys: a software framework for web-based modeling and decision support applications. In: Proceedings of the 9th International Congress on. Environmental Modelling and Software, pp. 170–177.
Josset, L., Allaire, M., Hayek, C., Rising, J., Thomas, C., Lall, U., 2019. The us water data gap-a survey of state-level water data platforms toinform the development of a national water portal. Earth's Future 7 (4), 433–449.
Karpatne, A., Atluri, G., Faghmous, J.H., Steinbach, M., Baner-jee, A., Ganguly, A., Shekhar, S., Samatova, N., Kumar, V., 2017. Theory-guided data science: a new paradigm for scientific discovery from data. IEEE Trans. Knowl. Data Eng. 29 (10), 2318–2331.
Kehrer, J., 2011. Interactive Visual Analysis of Multi-Faceted Scientific Data. Ph.D. dissertation. The University of Bergen.
Keim, D., Andrienko, G., Fekete, J.-D., Görg, C., Kohlhammer, J., Melançon, G., 2008. Visual analytics: definition, process, and challenges. In: Information Visualization. Springer, pp. 154–175.
Kielman, J., Thomas, J., May, R., 2009. Foundations and frontiers in visual analytics. Inf. Visual. 8 (4), 239–246.
Kohlhammer, J., Keim, D., Pohl, M., Santucci, G., Andrienko, G., 2011. Solving problems with visual analytics. Procedia Comput. Sci. 7, 117–120.
Koontz, T.M., Newig, J., 2014. From planning to implementation: top-down and bottom-up approaches for collaborative watershed management. Pol. Stud. J. 42 (3), 416–442.
Koutsoyiannis, D., Karavokiros, G., Efstratiadis, A., Mamassis, N., Koukouvinos, A., Christofides, A., 2003. A decision support system for the management of the water resource system of Athens. Phys. Chem. Earth 28 (14–15), 599–609. Parts A/B/C.
Koylu, C., 2019. Modeling and visualizing semantic and spatio-temporal evolution of topics in interpersonal communication on twitter. Int. J. Geogr. Inf. Sci. 33 (4), 805–832.
Krämer, M., Gutbell, R., 2015. A case study on 3d geospatial applications in the web using state-of-the-art WebGL frameworks. In: Proceedings of the 20th International Conference on 3D Web Technology, Ser. Web3D '15. Association for Computing Machinery, New York, NY, USA, pp. 189–197. https://doi.org/10.1145/2775292.2775303 [Online] . Available:
Kratzert, F., Herrnegger, M., Klotz, D., Hochreiter, S., Klam-bauer, G., 2019. Neural hydrology–interpreting LSTMS in hydrology. In: Explainable Ai: Interpreting, Explaining and Visualizing Deep Learning. Springer, pp. 347–362.
Ladsonet al, A., 2018. Visualising Hydrologic Data," inHydrology and Water Resources Symposium (HWRS 2018): Water and Communities. Engineers Australia, p. 456.
Lai, E., Lundie, S., Ashbolt, N., 2008. Review of multi-criteria decision aid for integrated sustainability assessment of urban water systems. Urban Water J. 5 (4), 315–327.
Laksono, D., Aditya, T., 2019. Utilizing a game engine for interactive3d topographic data visualization. ISPRS Int. J. Geo-Inf. 8 (8) [Online] . Available: https://www.mdpi.com/2220-9964/8/8/361.
Lange, H., Sippel, S., 2020. Machine learning applications in hydrology. In: Forest-water Interactions. Springer, pp. 233–257.
Leonard, L., MacEachren, A.M., Madduri, K., 2017. Graph-based visual analysis for large-scale hydrological modeling. Inf. Visual. 16 (3), 205–216.
Luna-Reyes, L.F., Najafabadi, M.M., 2019. The us open data initiative: the road ahead. Inf. Polity 24 (2), 163–182.
Luo, X., Xu, Y., Zhou, F., 2011. Research on the integration of data warehouse, virtual reality and geographical information system in water resources management. In: Proceedings 2011 IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services. IEEE, pp. 497–500.
Maidment, D.R., 2008a. Bringing Water Data Together, pp. 95–96.
Maidment, D.R., 2008b. Bringing water data together. J. Water Resour. Plann. Manag. 134 (2), 95–96 [Online] . Available: https://ascelibrary.org/doi/abs/10.1061/.
Maidment, D.R., 2016. Open water data in space and time. JAWRA J. Am. Water Res. Assoc. 52 (4), 816–824 [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/1752-1688.12436.
Mamoowala, A., 2020. Mapbox Gl Js V2: 3d Maps + Camera Api + Sky Api Launch. https://www.mapbox.com/blog/mapbox-gl-js-v2-3d-maps-camera-api-sky-api-launch/.
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., Hung Byers, A., et al., 2011. Big Data: the Next Frontier for Innovation, Competition, and Productivity. McKinsey Global Institute.
Marçais, J., de Dreuzy, J.R., 2017. Prospective interest of deep learning for hydrological inference. Groundwater 55 (5), 688–692.
Marbouti, M., Bhaskar, R., Abad, Z.S.H., Anslow, C., Jackson, L., Maurer, andF., 2018. Watervis: geovisual analytics for exploring hydrological data. In: Highlighting the Importance of Big Data Management and Analysis for Various Applications. Springer, pp. 157–166.
Matrosov, E.S., Huskova, I., Kasprzyk, J.R., Harou, J.J., Lambert, C., Reed, P.M., 2015. Many-objective optimization and visual analytics reveal key trade-offs for London's water supply. J. Hydrol. 531, 1040–1053.
Mazher, A., 2020. Visualization framework for high-dimensional spatio-temporal hydrological gridded datasets using machine-learning techniques. Water 12 (2), 590.
Miettinen, K., 2014. Survey of methods to visualize alternatives in multiple-criteria decision making problems. Spectrum 36 (1), 3–37.
Miettinen, K., Ruiz, F., Wierzbicki, A.P., 2008. Introduction Multiobjective Optimization: Interactive Approaches. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 27–57. https://doi.org/10.1007/978-3-540-88908-3_2 [Online] .Available:
Moglia, M., Sharma, A., 04 2009. Incorporating the social dimension into the assessment of urban water services: with a particular focus on greenfield developments," CSIRO Land and Water Science Report series. Tech. Rep.
Namwamba, F.L., 1998. Simulation Modeling and Visualization of Hydrologic Response of an Agricultural Watershed. Ph.D. dissertation. Iowa State University. http://lib.dr. iastate. edu/.
Nazemi, K., 2018. Intelligent visual analytics–a human-adaptive approach for complex and analytical tasks. In: International Conference on Intelligent Human Systems Integration. Springer, pp. 180–190.
Nielsen, J., 1994. In: Nielsen, j., Mack, rl (Eds.), Heuristic evaluation, w, Usability Inspection Methods.
Nocke, T., Buschmann, S., Donges, J.F., Marwan, N., Schulz, H.-J., Tominski, C., 2015. Visual analytics of climate networks. Nonlinear Process Geophys. 22 (5), 545–570.
Palmer, R.N., Cardwell, H.E., Lorie, M.A., Werick, W., 2013. Disciplined planning, structured participation, and collaborative modeling-applying shared vision planning to water resources. JAWRA J. Am. Water Res. Assoc. 49 (3), 614–628.
Paniconi, C., Kleinfeldt, S., Deckmyn, J., Giacomelli, A., 1999. Integrating GIS and data visualization tools for distributed hydrologic modeling. Trans. GIS 3 (2), 97–118.
Prato, T., Herath, G., 2007. Multiple-criteria decision analysis for inte-grated catchment management. Ecol. Econ. 63 (2–3), 627–632.
Priscoli, J.D., 2004. What is public participation in water resources management and why is it important? Water Int. 29 (2), 221–227.
Rajib, M.A., Merwade, V., Kim, I.L., Zhao, L., Song, C., Zhe, S., 2016. Swatshare–a Web Platform for Collaborative Research and Education through Online Sharing, Simulation and Visualization of Swat Models, 75. Environmental Modelling & Software, pp. 498–512.
Reddy, P., Gharbi, M., Lukac, M., Mitra, N.J., 2021. Im2vec: synthesizing vector graphics without vector supervision. In: Proceedings of theIEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7342–7351.
Reed, P.M., Kollat, J.B., 2013. Visual analytics clarify the scalability and effectiveness of massively parallel many-objective optimization: a groundwater monitoring design example. Adv. Water Resour. 56, 1–13.
Reges, H.W., Doesken, N., Turner, J., Newman, N., Bergantino, A., Schwalbe, Z., 2016. Cocorahs: the evolution and accomplishments of a volunteer rain gauge network. Bull. Am. Meteorol. Soc. 97 (10), 1831–1846.
Ribarsky, W., Fisher, B., Pottenger, W.M., 2009. Sci. anal. reason., "Inform. Visual. 8 (4), 254–262.
Rink, K., Kalbacher, T., Kolditz, O., 2012. Visual data exploration for hydrological analysis. Environ. Earth Sci. 65 (5), 1395–1403.
Rydvanskiy, R., Hedley, N., 2020. 3d geovisualization interfaces as flood risk management platforms: capability, potential, and implications for practice. Cartographica: The Int. J. Geogr. Inform. Geovisual. 55 (4), 281–290.
Sajjadi, P., Bagher, M.M., Cui, Z., Myrick, J.G., Swim, J.K., White, T.S., Klippel, A., 2020. Design of a Serious Game to Inform the Public about the Critical Zone," In2020 IEEE 8th International Conference on Serious Games and Applications for Health (SeGAH). IEEE, pp. 1–8.
Sanders, J., Kandrot, E., 2010. CUDA by Example: an Introduction to General-Purpose GPU Programming. Addison-Wesley Professional.

Sanyal, J., Chandola, V., Sorokine, A., Allen, M., Berres, A., Pang, H., Karthik, R., Nugent, P., McManamay, R., Stewart, R., et al., 2017. Towards a web-enabled geovisualization and analytics platform for the energy and water nexus. In: AGU Fall Meeting Abstracts, 2017, IN24A–01.
Savic, D.A., Morley, M.S., Khoury, M., 2016. Serious gaming for water systems planning and management. Water 8 (10), 456.
Seaber, P.R., Kapinos, F.P., Knapp, G.L., 1987. Hydrologic Unit Maps. US Government Printing Office, Washington, DC, USA.
Seelen, L.M., Flaim, G., Jennings, E., Domis, L.N.D.S., 2019. Savingwater for the future: public awareness of water usage and waterquality. J. Environ. Manag. 242, 246–257.
Sermet, Y., Demir, I., 2020. Virtual and augmented reality applications for environmental science education and training. In: New Perspectives on Virtual and Augmented Reality: Finding New Ways to Teach in a Transformed Learning Environment. Routledge, pp. 261–275.
Sermet, Y., Demir, I., 2022. Geospatialvr: a web-based virtual reality framework for collaborative environmental simulations. Comput. Geosci. 159, 105010 [Online] . Available. https://www.sciencedirect.com/science/article/pii/S0098300421002934.
Sermet, Y., Demir, I., Muste, M., 2020. A serious gaming framework for decision support on hydrological hazards. Sci. Total Environ. 728, 138895.
Shneiderman, B., 1994. Dynamic queries for visual information seeking. IEEE software 11 (6), 70–77.
Shneiderman, B., 2003. The eyes have it: a task by data type taxonomy for information visualizations. In: The Craft of Information Visualization. Elsevier, pp. 364–371.
Sivapalan, M., 2015. Debates-perspectives on socio-hydrology: changing water systems and the "tyranny of small problems"–socio-hydrology. Water Resour. Res. 51 (6), 4795–4805.
Smith, J.P., Hunter, T.S., Clites, A.H., Stow, C.A., Slawecki, T., Muhr, G.C., Gronewold, A. D., 2016. An Expandable Web-Based Platform for Visually Analyzing Basin-Scale Hydro-Climate Time Series Data, 78. Environmental Modelling & Software, pp. 97–105.
Strobelt, H., Gehrmann, S., Pfister, H., Rush, A.M., 2017. Lstmvis: a tool for visual analysis of hidden state dynamics in recurrent neural networks. IEEE Trans. Visual. Comput. Graph. 24 (1), 667–676.
Su, T., Cao, Z., Lv, Z., Liu, C., Li, X., 2016. Multi-dimensional vi-sualization of large-scale marine hydrological environmental data. Adv. Eng. Software 95, 7–15.
Sumbera, 2019. Many points with leaflet WebGL. Available: http://bl.ocks.org/Sumbera/c6fed35c377a46ff74c3.
Tague, C., Frew, J., 2021. Visualization and ecohydrologic models: opening the box. Hydrol. Process. 35 (1), e13991.
Tarboton, D.G., Horsburgh, J.S., Maidment, D.R., 2008. CUAHSI Community Observations Data Model (Odm) Version 1.1 Design Specifications [Online] . Available: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.596.9676&rep=rep1&type=pdf.
Tarboton, D.G., Idaszak, R., Horsburgh, J.S., Heard, J., Ames, D., Goodall, J.L., Band, L., Merwade, V., Couch, A., Arrigo, J., et al., 2014. HydroShare: advancing collaboration through hydrologic data and model sharing. In: inProceedings of the 9th International Congress on Environmental Modelling and Software, pp. 23–29.
Thomas, J.J., Cook, K.A., 2006. A visual analytics agenda. IEEE Comp. Graph. Appl. 26 (1), 10–13.
Tian, Y., Zheng, Y., Zheng, C., 2016. Development of a visualization tool for integrated surface water–groundwater modeling. Comput. Geosci. 86, 1–14.
Trindade, B., Reed, P., Characklis, G., 2019. Deeply uncertain pathways: integrated multi-city regional water supply infrastructure investment and portfolio management. Adv. Water Resour. 134, 103442.
Tsai, F., Lai, J.S., Liu, Y.C., 2016. An alternative open source web-based 3d GIS: cesium engine environment. In: Asian Conference on Remote Sensing: Fostering Resilient Growth in Asia. Citeseer, pp. 1–4.
Uchida, Y., Itoh, T., 2009. A visualization and level-of-detail control technique for large scale time series data. In: in2009 13th International Conference Information Visualisation. IEEE, pp. 80–85.
United States Geological Survey, 2020a. Gages through the Ages [Online] . Available: https://labs.waterdata.usgs.gov/visualizations/gages-through-the-ages/index.html#/.
United States Geological Survey, 2020b. The 534-day Flood at Site 06472000on the James River, Sd [Online] . Available: https://www.usgs.gov/media/images/534-day-flood-site-06472000-james-river-sd.
U.S. Department of Energy, 2022. ASCR Workshop on Visualization for Scientific Discovery, Decision-Making, & Communication. Available: https://web.cvent.com/event/fc8f3c09-0e35-4189-82b4-17f2d3e4e73e/summary.
Vojinovic, Z., 03 2012. Flood Risk and Social Justice: from Quantitative to Qualitative Flood Risk Assessment and Mitigation. Water Intelligence Online.
Vojinovic, Z., Abbott, M.B., 2017. Twenty-five years of hydroinformatics. Water 9 (1) [Online]. Available: https://www.mdpi.com/2073-4441/9/1/59.
Waldrop, W.R., 1979. Computational Hydraulics: Elements of the Theory of Free Surface Flows. Mb Abbott. pitman publishing, London, p. 325. £ 22.50," 1979.
Walker, J.D., Letcher, B.H., Rodgers, K.D., Muhlfeld, C.C., D Angelo, V.S., 2020. An interactive data visualization framework for exploring geospatial environmental datasets and model predictions. Water 12 (10), 2928.
Wong, P.C., 2007. Visual analytics science and technology. Inf. Visual. 6 (6), 1–2. PNNL-SA-53463, 2007.
Wong, P.C., Shen, H.-W., Leung, R., Hagos, S., Lee, T.-Y., Tong, X., Lu, K., 2014. Visual Analytics of Large-Scale Climate Model Data," In2014 IEEE 4th Symposium on Large Data Analysis and Visualization(LDAV). IEEE, pp. 85–92.
Wu, Y., Cao, N., Gotz, D., Tan, Y.-P., Keim, D.A., 2016. A survey on visual analytics of social media data. IEEE Trans. Multimed. 18 (11), 2135–2148.
Wu, D.T., Chen, A.T., Manning, J.D., Levy-Fix, G., Backonja, U., Borland, D., Caban, J.J., Dowding, D.W., Hochheiser, H., Kagan, V., et al., 2019. Evaluating visual analytics for health informatics applications: a systematic review from the American medical informatics association visual analytics working group task force on evaluation. J. Am. Med. Inf. Assoc. 26 (4), 314–323.
Xu, H., 2019. Data-driven Framework for Forecasting Sedimentation at Culverts. Ph.D. dissertation, University of Iowa.
Xu, H., Demir, I., Koylu, C., Muste, M., 2019. A web-based geo-visualanalytics platform for identifying potential contributors to culvert sedimentation. Sci. Total Environ. 692, 806–817.
Xu, H., Windsor, M., Muste, M., Demir, I., 2020. A web-based decision support system for collaborative mitigation of multiple water-related hazards using serious gaming. J. Environ. Manag. 255, 109887.
Zagal, J.P., Rick, J., Hsi, I., 2006. Collaborative games: lessons learned from board games. Simulat. Gaming 37 (1), 24–40.
Zhang, S., Li, W., Lei, X., Ding, X., Zhang, T., 2017. Implementation methods and applications of flow visualization in a watershed sim-ulation platform. Adv. Eng. Software 112, 66–75.
Zheng, Y., Wu, W., Chen, Y., Qu, H., Ni, L.M., 2016. Visual analytics in urban computing: an overview. IEEE Transact. Big Data 2 (3), 276–296.