UMIS: An Integrated Cyberinfrastructure System for Water Quality Resources in the Upper Mississippi River Basin

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Highlights

- A web-based cyberinfrastructure developed for water quality research and operations.
- Intuitive and interactive visualizations for community-oriented data analytics are provided.
- Big data access to nutrient and hydrological information is enabled.

Abstract

The Upper Mississippi Information System (UMIS) is a cyberinfrastructure framework designed to support large-scale real-time water quality data integration, analysis, and visualization for the Upper Mississippi River Basin (UMRB). UMIS is intended to directly address three of the Grand Challenges for Engineering including: 1) understanding access to clean drinking water, 2) management of the nitrogen cycle, and 3) engineering the tools of scientific discovery. The UMIS is designed to provide significant immediate and long-term impacts including a central platform for data access, integration, discovery, and adoption of cyberinfrastructure tools and services. The UMIS demonstrates that public data aggregators and central repositories can provide important services to anyone interested in water quality research or education. In addition, working across multiple scales (e.g., state, region, county, or watershed) allows researchers to understand broad and narrow effects of water quality strategies. Exploration of data across these scales encourages the development of problem-based research questions that can eventually provide feedback to public policies.

Keywords: water quality, web-based visualization, information system

1. Introduction

Mobilization and delivery of nutrients (nitrogen and phosphorous) from point sources and farmed fields to the UMRB stream network is a decades-long problem (e.g., Turner et al., 2008; David et al., 2010; Rabotyagov et al., 2014). In particular, seasonal Gulf of Mexico hypoxia caused by nutrient pollution delivered via the Mississippi and Atchafalaya rivers and their tributaries is a problem that seemingly defies solution (National Research Council, 2008). Consequences include eutrophication of local and regional water resources (Turner and Rabalais, 1994; Mueller and Helsel, 1996; Dodds and Welch, 2000) and drinking water impairment (Weyer et al., 2001; Jones et al., 2016). Pollutant loading resulting from agriculture and other sources and its runoff and streamflow transformation in the region have had national consequences (Yildirim and Demir, 2022). Reduction of the anoxic area (hypoxia) in the Gulf of Mexico has been a national priority for over 20 years.

The Mississippi River - Gulf of Mexico Watershed Nutrient Task Force was formed in 1997 to coordinate an effort to understand and mitigate Gulf hypoxia (EPA, 2017). The task force released an Action Plan in 2001 to serve as a strategy for hypoxic area reduction in the Gulf. Twelve states within the Mississippi River Basin continue to implement a revised plan, released in 2008. The task force's long-term goal, at that point, was to reduce the hypoxic area to 5,000 km^2 by 2015. Because the five-year average size of the hypoxic area has remained largely unchanged since 1994, the goal was extended to 2035. Stemming the loss of nitrate-nitrogen from row crop areas has been an especially difficult problem (Feyereisen et al., 2022).

The 2001 Action Plan estimated that nitrogen loads would need to be reduced by 30% to reach the hypoxic area objective; later research showed nitrogen reductions as high as 45% may be necessary (Scavia et al., 2003). Because NOx-N delivery to streams comes from a myriad of widely dispersed sources, including farm-field drainage pipes (tiles) and shallow groundwater (Baker et al., 1975; Burkart and James, 1999), regulations governing its release to the environment are nearly non-existent. As a result, reductions in NOx-N loads have relied on educating farmers, offering financial incentives, and encouraging voluntary actions in the region, as highlighted by Rabotyagov et al. (2014a). This approach has not demonstrated reduced NOx-N loading to the Mississippi River stream network (Sprague et al., 2011; Jones et al., 2018a; 2018b; 2018c). In fact, the 2017 hypoxic area is reported to be the largest ever (Rabalais and Turner, 2019).

In response to this lack of progress, several states in the UMRB have instituted nutrient loss reduction programs of their own (Anderson et al., 2016; Illinois Nutrient Loss Reduction Strategy, 2014; Iowa State University, 2013). By embracing strategies with specific targets, such as a 45% reduction, states have inherently integrated accountability into the process essential for utilizing public funds. It is crucial to quantify and monitor alterations in nutrient discharge to the watershed's stream network in order to quantify policy driven changes in a credible way (Schilling et al., 2017).

Strategic and scientifically credible monitoring is the best way to track progress toward water-quality objectives and support watershed management (D) and water infrastructure (Beck et al., 2010). The quantity of nitrate leaving Iowa is particularly well documented, as Iowa has a statewide network of about 75 real-time, continuous nitrate sensors co-located with river discharge measurements. Data from these sensors are transmitted to the Iowa Water Quality Information System (IWQIS), which is the established mechanism for tracking nitrate loads in Iowa (Jones et al., 2018). The IWQIS visualization platform provides immediate access to credible water-quality data to the public. Expansion of this platform to the entire UMRB will provide multiple benefits to scientists, policymakers, producers and land managers, municipal governments, agencies, and others seeking solutions to these difficult water-quality challenges. By defining and implementing data and semantics specifications as well as data service APIs (Application Program Interface), the expansion will be interoperable with other data systems used by partner organizations.

Web technologies and platforms have revolutionized the way information is collected, analyzed, and shared in various disciplines, including environmental science (Yesilkoy et al., 2023), watershed management (Demir and Beck, 2009), water quality and infrastructure challenges (Xu et al., 2019), and related fields. These technologies provide an efficient and accessible means of gathering data from multiple sources, such as remote sensing satellites (Li and Demir, 2023), weather stations, sensor networks and predictive models (Krajewski et al., 2017). With the help of web-based tools and platforms, researchers can collaborate and analyze vast amounts of complex data in real-time (Sit et al., 2021), leading to better decision-making and more effective management strategies (Li and Demir, 2022). Furthermore, web technologies enable the creation of online communities where scientists, policymakers, and the public can exchange information, knowledge, and experiences. This enhances transparency, encourages public participation, and facilitates the dissemination of valuable research findings, thereby promoting awareness and understanding of environmental issues.

We aimed at developing a cyberinfrastructure framework to support large-scale water-quality data integration, analyses, and visualization in the UMRB in real time using data-enabled information technologies. The system originated from a multi-institution project with researchers at the IIHR-Hydroscience and Engineering at the University of Iowa, Great Lakes to Gulf Virtual Observatory (GLTG) and National Center for Supercomputing Applications (NCSA) at the University of Illinois Urbana-Champaign, Iowa State University, and National Great Rivers Research and Education Center at the Lewis and Clark Community College.

Seamless integration of existing real-time and ad-hoc water quality data streams with continuous modeling in the context of relevant data resources is a major challenge in big data domain (Demir et al., 2022). Undertaking a project of this scale within the UMRB is only achievable by establishing a comprehensive big data ecosystem. This endeavor calls for a profound understanding of water quality data collection from a wide array of sources, including academic institutions, government agencies, and non-governmental organizations spanning multiple states. It also involves the seamless integration of data that may vary in quality, format, and duration into a unified, user-friendly system. Additionally, active collaboration with partners and stakeholders is essential to gain insights into the diverse ways in which the data can be optimally accessed and utilized. Finally, access to substantial computing resources is crucial to support the management and analysis of this extensive dataset.

This study is organized as follows: (1) Section 2 discusses the methods used to create the cyberinfrastructure framework for the information system, (2) Section 3 presents the functionality of UMIS with an emphasis on the backend data services and user interface capabilities, and (3) Section 4 presents the overall results and conclusions of the project.

2. Methods

The UMIS framework can help address important issues around water quality by providing unfettered access to data that can be difficult to obtain and use. Although data incorporated into UMIS are publicly available, it requires accessing and processing multiple federal and state level data repositories (i.e., United States Geological Survey – USGS; Environmental Protection Agency - EPA), parameter codes, and data handling methods, to access and integrate environmental observations into easily accessible formats. These datasets can provide insights into the movement of nutrients, especially nitrogen and phosphorus, through stream networks.

UMIS programmatically acquires, aggregates and adds analytical capabilities to water quality data from existing repositories including USGS NWIS, EPA STORET, and Iowa Water Quality Information System (IQWIS, 2023). Additional ingestion sources can be added to include data from other federal, state, regional, and local organizations or individuals or research groups collecting their own data. Currently, all data are ingested automatically at defined intervals, however, one-off data collections can also be added and exposed in UMIS.

Figure 1. Upper Mississippi River Basin boundary

To address the water quality issues discussed earlier, UMIS offers several valuable features. These include the ability to access extensive and complex datasets spanning various spatial and temporal scales. UMIS also provides versatile visualization tools that can be applied to diverse datasets, including those from different locations or time periods, and supports visual correlations with the Soil and Water Assessment Tool (SWAT) ecohydrological model (Arnold et al., 1998; 2012a; 2012b; Bieger et al., 2017), and radar-rainfall maps known as Multi-Radar Multi-Sensor (MRMS) model (Zhang et al., 2016) and other models. Furthermore, UMIS serves as a unified platform for retrieving time series data from USGS, EPA, and IWQIS platforms, eliminating the need for manual downloading and processing of data from multiple sources. It simplifies the process of comprehending nutrient flow throughout the Upper Mississippi River Basin (see Figure 1) and offers a model for creating generalized value-added information systems using open-source tools and applications.

The UMIS framework can serve as a central platform for water quality data access, integration, and knowledge discovery and provide a focal point for water quality research, education and collaboration efforts.

2.1. Cyberinfrastructure Development

As part of the UMIS framework, a comprehensive web-based cyberinfrastructure is designed with emphasis on efficient high-dimensional spatiotemporal water quality-related data consumption and effective resource utilization.

2.1.1. System Architecture

UMIS is built from a series of open-source applications that provide all functionality for the information system (Figure 2). The core functionality of UMIS relies on several key software components. These include the PostgreSQL database with PostGIS spatial extensions for data management, the Nginx web server for web hosting, CentOS as the operating system, uWSGI for the API, and Python for scripting. The web interface is constructed using React, JavaScript, and HTML.

Backend: PostgreSQL is a powerful free and open-source database that has gained popularity over the last 25 years. PostgreSQL is an object relational database that supports many of the SQL standards while supporting a framework that can be extended by developers and normal users. For example, PostGIS is an extension that provides support for creating, storing and modifying spatial data, geometric and geographic analytical methods, data transformation and data export. PostgreSQL provides the central storage location for most of the data in UMIS. Nginx is a high-performance open-source web server, load balancer, proxy, and gateway. It is also non-blocking and capable of high concurrency. In UMIS, Nginx serves regular webpages and provides routing to the gateway API. The Web Services Gateway Interface (uWSGI) is the application server that works in conjunction with Nginx to provide functionality in UMIS. Any HTTP requests that include the API route are passed off from Nginx to uWSGI.

Frontend: We employed a component-based software architecture and encapsulated guidelines for maintainability and adaptability. A web application for intuitive client-side interaction, presentation, and data/service integration was developed and deployed. UMIS frontend is implemented on top of the React framework with Material-UI design library in accordance with best user interface and user experience (UI/UX) practices. Data visualization and analytics capabilities are served via a map-oriented interface (Google Maps API) for interactive raster, polygon, and point data with geospatial filtering as well as dynamic plotting for sensor data exploration.

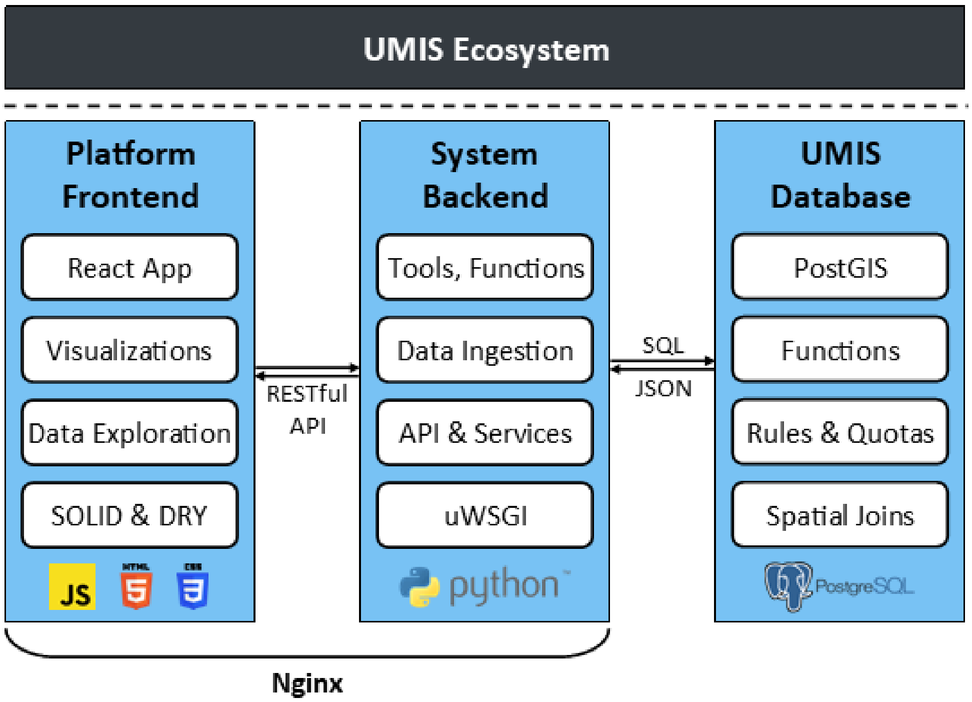


Figure 2. Architecture and components for front-end, back-end, and database layers

From an optimization and quality assurance standpoint, a generalized server communication mechanism was established with error handling for reliable data acquisition and service provision from a variety of sources. All external data and service requests are handled asynchronously to avoid throttling and promise-based chain operations are utilized to ensure client event queue and proper flow of actions. State-based and modular design of the platform allows partial rendering when triggered with user interaction or server-side update, and hence provides a responsive experience, and while minimizing the computational load both on the server as well as the client. The software is implemented abiding by the SOLID and DRY development practices to ensure long-term sustainability (Cabezas et al., 2020). Furthermore, polymorphic sensor provider classes and template-based data retrieval and service endpoints introduce flexibility to account for potential future changes in types, providers, and schemas of external data resources.

2.1.2. Data Resources

There are three basic types of data used in the UMIS framework. Most spatial data in UMIS use the Geographic Coordinate System 1984 (GCS84, EPSG:4326). However, some imagery is overlayed in the map interface to fit within bounding coordinates. In these cases, latitude and longitude measurements provide the bounding box that Google Maps uses to compute the placement of images as overlays on the map. Table 1 shows the types of data available in UMIS and how they are used in the system.

Vector Data: The first type of data used in UMIS is vector spatial data. Vector data are composed of geometries based on points, lines, or polygons. zero-dimensional data are represented as points, one-dimensional data are lines and two-dimensional data are polygons. These data are generalizations of real-world phenomena and can be characterized in a variety of ways. For example, although cities are three-dimensional phenomena, they can be represented as points or polygons on the map. These are often based on the view scale, but the important aspect is that maps are generalizations of phenomena. Vector data are stored in spatial tables in PostgreSQL or generated on the fly. Since these are spatially explicit, they show in the correct locations on the maps.

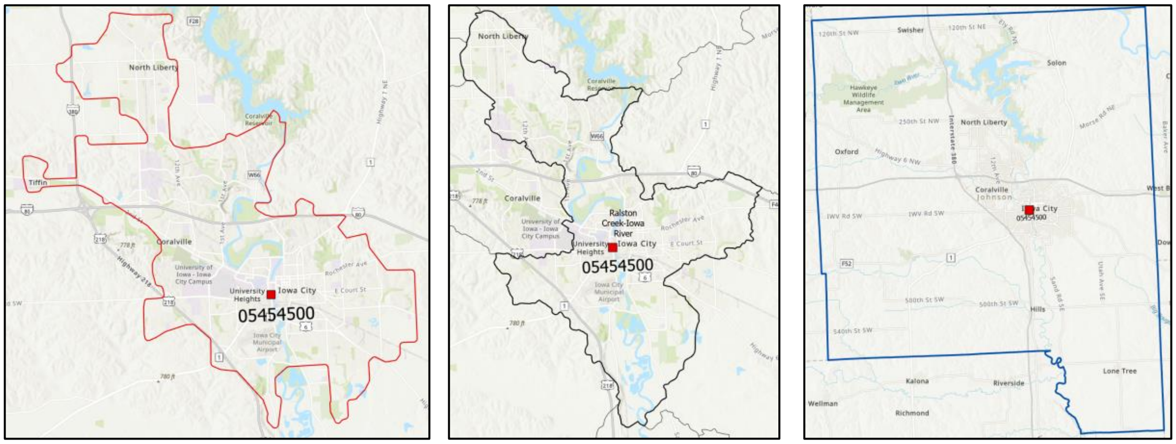
Aspatial Data: UMIS also collects and stores aspatial data. These kinds of data are not spatially explicit but can be linked to spatially explicit data based on a common id. For example, water quality information may not contain information about locations of stream gages, but these data can be joined to gage locations based on a gage id. Most of the data collected and stored in UMIS is considered aspatial data but all these data can be joined back to vector spatial data for representation. Examples of these kinds of data include times series observations about nutrients, streamflow, or temperature. UMIS uses aspatial data for map symbolization, graphs and charts, and animations.

Table 1. Data types and their usage in the UMIS framework

Data type	Usage in the framework
Vector spatial data	Spatial selection
	Relational joins with aspatial data
Aspatial data	Time series data storage and retrieval
	Informal metadata
	Relational joins with spatial data
	Temporally based aggregation statistics
Raster Data	Map overlays

Raster Data: The final class of data is raster data formats. Raster datasets are cell-based representations of continuous phenomena such as precipitation, temperature, or soil moisture. They are space-filling in that there generally is a value for all locations within the enumeration area. Cells, in this sense, represent a tessellation of the area within the bounding coordinates of the layer. Generally, all cells are the same size and orientation within the raster. In UMIS, raster data is only used for visual data exploration using map overlays.

Sites: In UMIS, the most common spatial feature is "site". A site is a physical location where sensors are installed, and environmental conditions are recorded. Sites are represented as 0-dimensional features with a coordinate pair describing their location and metadata storing aspatial attributes of the site. Ingestion of sites into database is through scheduled scripts (i.e., cronjobs) connecting to APIs on external servers. Every month, UMIS sites are checked against all available sites within the UMRB for each contributing agency. Sites that are not present in the site table in the database are automatically added.



(a) (b) (c)

Figure 3. The spatial join process (a) Site 05454500 gains attributes of urban area (red polygon) in which it is located, (b) then site is spatially joined with HUC geometries, (c) and spatial join with county geometries.

Metadata are aspatial attributes of sites including site id, elevation, agency, dates of activity, and descriptions of the site. Other site attributes are derived through spatial joins between sites and areal geometries including states, counties, urban areas, and hydrological unit codes (HUC) used by the USGS. These joins are geometric intersections between sites and other areal geometries. During the join process, attributes from the intersecting geometries are added to each site so queries to sites are based on attributes instead of geometries. The computational requirements for queries based on attributes are significantly lower than queries using spatial relationships. A series of spatial joins between sites and the other bounding geometries are used to transfer aspatial attributes from polygons to points (i.e., sites).

In Figure 3, USGS site 05454500 is spatially joined with urban areas (3a), HUC12 geometries (3b) and counties (3c). The site then contains all the attributes of the bounding geometries that the site falls within. This process is completed for encompassing features including states, counties, urban areas, and HUC geometries from HUC2-HUC12. Overall, sites are spatially joined with the following geometries: 1) state, 2) county, 3) urban areas, 4) HUC2, HUC4, HUC6, HUC8, HUC10 and HUC12.

New Sites: Eventually, there will be a disparity between sites available in a data repository (i.e., NWIS, STORET and IWQIS) as new sites are added. To avoid this problem, UMIS compares existing sites within its database to those available in the other data repositories. New sites will be added automatically to UMIS and available after updating (Figure 4).

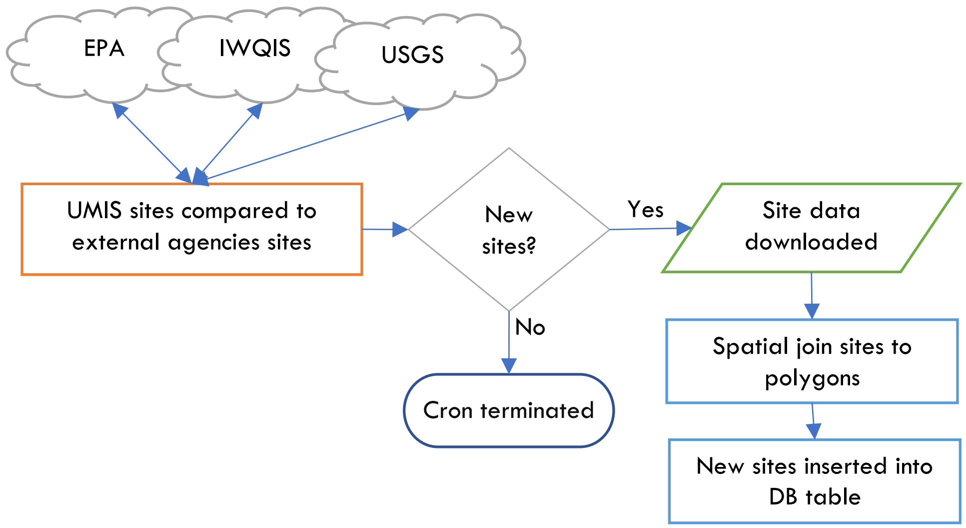


Figure 4. New site ingestion procedure in the framework

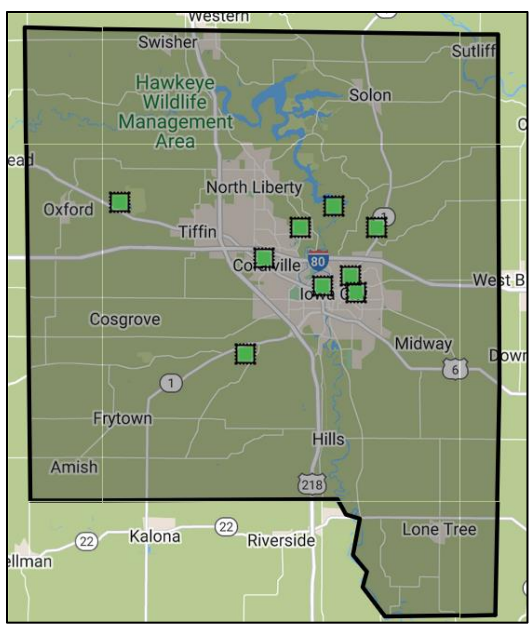


Figure 5. NWIS sites within Johnson County, Iowa

Bounding Geometries: In the front-end, sites are initially selected based on their spatial relationships with bounding geometries including state, county, urban area and HUC2-12 geometries. An example query might be – *select all sites located within Johnson County, Iowa*. Selections are made through queries through the API to the database and then rendered on the map interface. For example, once the bounding geometry is selected, a user may add sites to the map from NWIS, STORET or IWQIS database tables. Figure 5 shows NWIS sites located within Johnson County, Iowa.

Sensors: Sensors are devices that measure environmental parameters at a certain frequency. There are many types of sensors but all measure and record physical observations *in situ*. The type of phenomenon being measured is referred to as a parameter. In UMIS, we focus on the following parameters from different sources (Table 2). The data sources are discussed in detail later in this section.

Table 2. Parameters collected through remote repositories and web services

IWQIS	**NWIS DV/IV**	**STORET**
---	Air temperature C	Air temperature C
Discharge	Discharge	---
Dissolved Oxygen conc	Dissolved Oxygen conc	---
---	Dissolved Oxygen sat	---
Load	---	---
Nitrate	Nitrate	Nitrate
Ph	pH	pH
---	---	Phosphorus
Specific conductance	Specific conductance	Specific conductance
Turbidity	Turbidity	Turbidity
Yield	---	---
Water temperature C	Water temperature C	Water temperature C

2.1.3. Data Acquisition

Data ingestion is automated using Linux-based scheduled scripts (i.e., cronjobs). These are automated system processes that occur at set frequencies on the server. Most of our cronjobs fall into two basic categories including processes that connect to external resources such as application programming interfaces (APIs), and processes that run locally and provide server housekeeping services and local data handling.

The first type of cronjob can be viewed as a type of ingestion or collection service. These run at various times based on the type of data being collected. Some of these applications connect to external APIs using formal query parameters while others connect to open filesystems available through HTTP(S) queries. Currently, UMIS collects data using explicit API queries from the external sites including Iowa Water Quality Information System (IWQIS), National Water Information System (NWIS), EPA STOrage and RETrieval data waterhouse (STORET) and weather data from National Weather Service (NWS) provided by Iowa State University’s (ISU) Mesonet services.

IWQIS is an information system that offers real time nutrient levels and other water quality and quantity information (e.g., streamflow and soil moisture) for the State of Iowa (Weber et al., 2018). Currently, IWQIS monitors over 100 environmental sensors placed along Iowa rivers and watersheds. The platform is open to everyone so users can see real-time state-wide trends in water quality and stream conditions or drill down to specific sites to look at historical information.

National Water Information System (NWIS) data are provided by the USGS (2016) through a formal API that allows external access to real-time and historical stream data for the entire United States. Queries are shaped to explicitly retrieve desired data using a variety using spatial parameters including state or territory, hydrologic unit code or watershed, spatial bounding box, or county. Other aspatial query parameters include site name, date ranges, providing agency, status, altitude, and parameter types. A combination of spatial and aspatial attributes are provided as query parameters to tailor requests to exactly those sites of interest without the need to download all the data and exclude non-essential values. Data can also be returned in a variety of formats based on need. A single query to a well-designed API can return the desired data if the query is properly formatted. UMIS pulls daily values (DV) data and instantaneous values (IV) data from the NWIS API. Daily values are collected every day at 2am and rainfall data layers (Stage IV) are collected every hour using cronjobs. UMIS also collects site data from the NWIS platform to add new sites to the site table. In this way, UMIS stays current with the USGS gage locations. This is updated monthly, and new sites will automatically be available once updated.

STORET data are collected by federal, state, tribal, groups and individuals to monitor water quality conditions across the US. Over 900 partners have collected and shared their water quality data through the EPA Water Quality Portal (WQP). As there are a wide variety of agencies and individuals posting water quality data to the portal, data can be sparse with large gaps in collection dates. There are many collection sites and a very large number of parameters that are available in the WQP. Paring down parameters that may be of interest to UMIS users was difficult, so we tried to match parameters available from other systems that we query data.

Mesonet data are requested on-demand when a user selects data to view. The ISU Mesonet services provide access to important weather information such as precipitation, radar imagery, storm reports and weather condition data, and road conditions. We currently do not collect these data independently but add requested data as map overlays on the interface. Users can show these to visually help them understand the relationships between weather events and stream information. UMIS also ingests data from other sites which are basically exposed filesystems containing data including radar rainfall datasets and water quality model outputs.

MRMS is an automated system that integrates data from multiple radars, surface observation, weather detection systems, environmental models, and satellite feeds (Zhang et al., 2016). This system was developed by the Cooperative Institute for Severe and High-Impact Weather Research and Operations (CIWRO, formerly CIMMS) and the National Severe Storm Laboratory of NOAA. A wide variety of weather and other environmental data can be obtained from MRMS including precipitation rates, precipitation type, soil moisture, composite reflectivity, and surface temperature. Data are updated at given frequencies and images are overwritten every 24 hours.

SWAT is a watershed-/river basin-scale model that can be applied on a daily or sub-daily time step to simulate stream system hydrology and pollutant transport (Arnold et al., 2012a). A watershed is configured in SWAT by overlaying soil, land use, topographic, management, stream network and climate data within subwatersheds, which are further delineated with smaller homogeneous hydrologic response units (HRUs). The model has been used to analyze an extensive array of water resource problems worldwide for study areas ranging from less than 1 km^2 to multi-national transboundary river systems as documented in existing SWAT literature. This includes dozens of applications for the UMRB; over 40 of those studies were tabulated in a concise review by Chen et al. (2020).

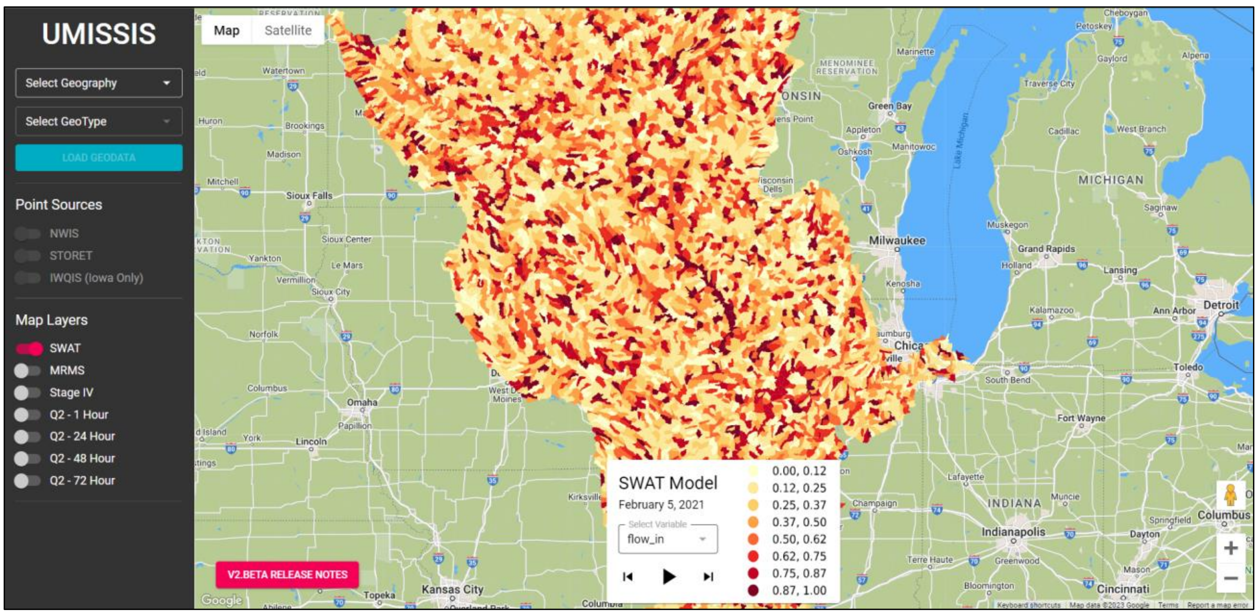


Figure 6. Raster visualization and spatiotemporal resource exploration for SWAT model.

Currently, Iowa State University researchers have the ability to generate “real-time output”, at daily, weekly or monthly time scales, for the UMRB using a previously developed SWAT model (Panagopoulos et al., 2015) and weather observations from the ISU Mesonet. Additional development is needed to facilitate automated processing of the tabular output from these SWAT runs to generate real-time images showing environmental variables at the HUC12 level within UMIS, such as shown in Figure 6. The UMIS system could also be used to support other SWAT applications generated for parts or all of the UMRB, including SWAT studies generated using the Hydrologic and Water Quality System (HAWQS) platform (e.g., Chen et al., 2020; Brighenti et al., 2022) or based on SWAT+ (Beiger et al., 2017) simulations executed within the National Agroecosystem Model (NAM; Arnold et al., 2020; White et al., 2020; Čerkasova et al., 2023).

Data Ingestion Process: Data ingestion is an event-driven set of Python processes that make HTTP requests to external APIs (i.e., USGS, EPA and IWQIS) to return new data from each web service. These events are triggered by scheduled cronjobs on the server-side at regular intervals. The code checks for the data already in the database before requesting for any new data and limits the request to new data available since the last ingestion. Any returned data is processed, checked for consistency or errors, and then inserted into the database.

Table 3. Types of weather data and description collected by UMIS.

Title	**Description**
MRMS_MultiSensor_QPE_01H_Pass2	Multi-sensor accumulation 1-hour (2-hour latency)
MRMS_PrecipRate	Radar-derived precipitation rate
MRMS_PrecipFlag	Surface Precipitation Type (Convective, Stratiform, Tropical, Hail, Snow)
MRMS_FLASH_SAC_MAXSOILSAT	FLASH QPE-SAC Soil Saturation

Derived Data: Other cronjobs build additional value-added datasets after ingestion of the raw data. These include hourly, weekly and monthly averages for the water quality observations. The UMIS system also automatically builds raster images from MRMS GRIB2 tables from National Centers for Environmental Prediction (NCEP, 2018). These are data from the National Severe Storm Laboratory (NSSL) branch of the National Oceanic and Atmospheric Administration (NOAA). The NSSL focuses on essential research into radar technology, forecast capabilities, and warning methods and events. They distribute data as sets of tables containing weather observations and predictions. These are publicly available and updated frequently so they provide a valuable resource for weather research. A list of the types of data available through the NSSL can be found on their website (NSSL, 2023). UMIS currently collects 5 types of weather data from this site (Table 3). The code that collects the GRIB2 data is extensible and can be easily modified to collect additional weather data. Figure 7 shows one type of MRMS data available in UMIS.

3. Results and Discussions

3.1. Data Web Service and APIs

The Application Programming Interface (API) provides the backend for the entire information system. In terms of functionality, the API provides and manages a broker relationship between the interactive part of the system and the database backend. It defines the syntax for queries, provides background security for interactions with the database, and manages data transformation and export. Figure 8 shows the API as information broker that manages the following: 1) access to raster imagery and the server filesystem, 2) access to vector data stored in the database using query parameters, and 3) access to aspatial information such as water quality observations.

In UMIS, requests are made to endpoints that define required parameter inputs from the requestor. Endpoints are basically URLs that the API listens to for requests. Endpoints provide isolation between user requests and the database, enforce rules regarding required information to make non-ambiguous queries, provide resilient and common access protocols, and tailor results to that requested by the user or system. The API sits in a middle position between users and data operating independently of external data aggregation and processing. Because of this, UMIS can continue to operate on existing data in the system even if there are issues with USGS servers, for example.

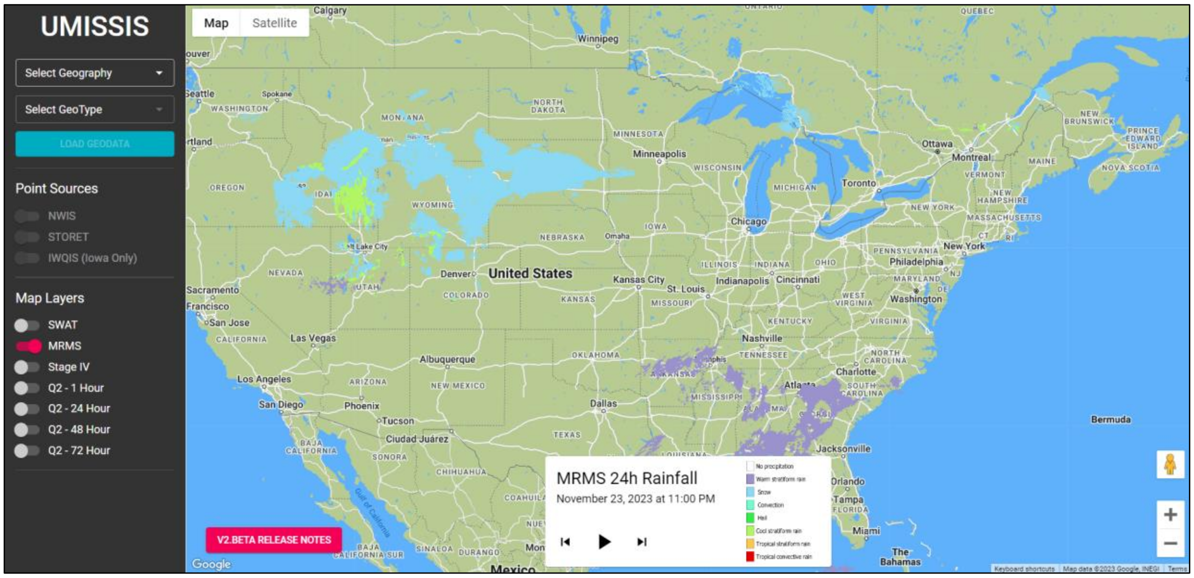


Figure 7. MRMS output for 24hr rainfall

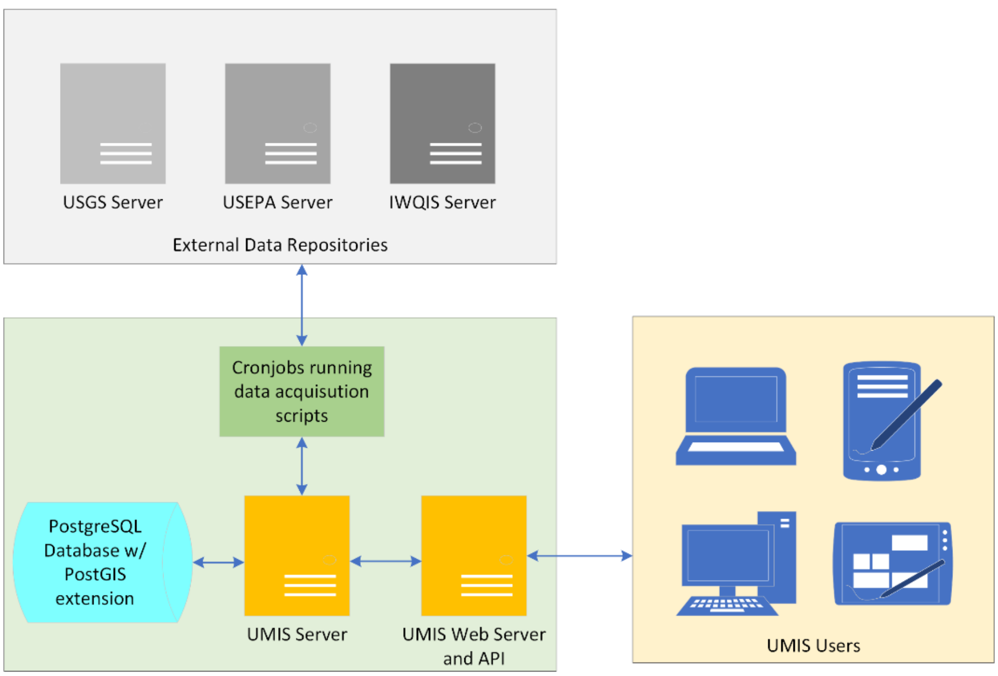


Figure 8. API architecture as an information broker

3.2. Platform Functionality

Data Discovery: The users can use the UMIS interface to intuitively discover available data within a selected geographic context. In order to set the workspace to a location, the user has the option to select the scope as one of the following: *State, County, City,* and *Watershed* (Figure 9). The system offers autocomplete functionality to search for administrative units as well as for HUCs. However, since searching for a specific watershed might be difficult given that the numerical codes may not be known, the autocomplete API performs a search in metadata for users to find appropriate catchment boundaries associated with communities and rivers of their preference. Once the context is set, the map reflects the boundary and enables the means to retrieve water quality sensor units for the supported providers (i.e., STORET, IWQIS, NWIS).

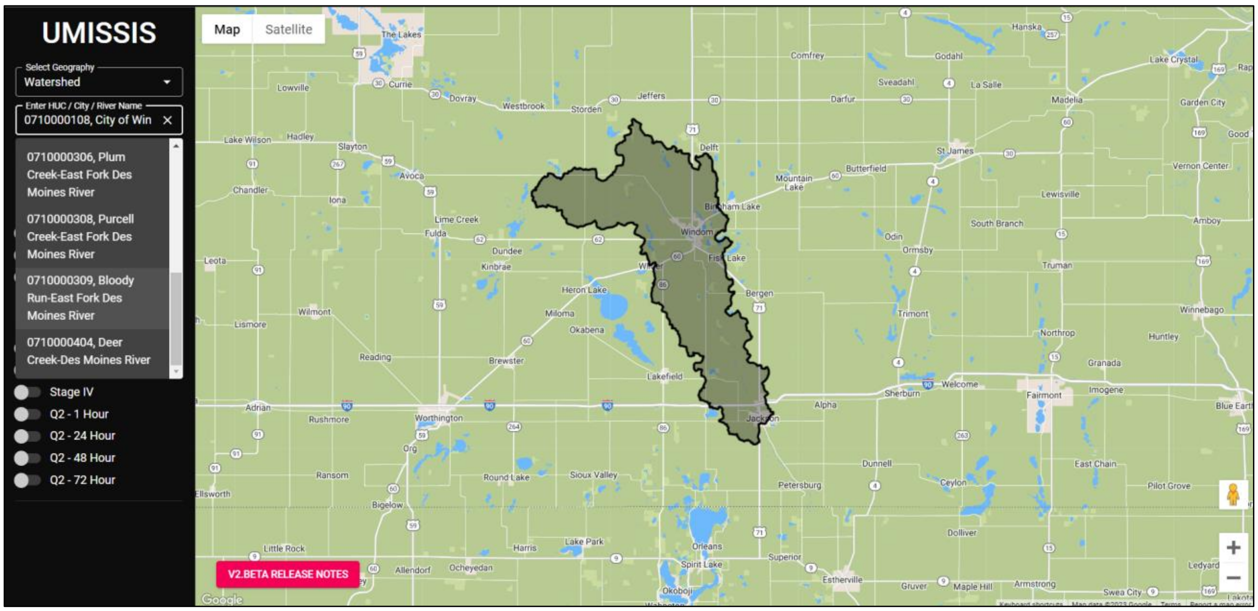


Figure 9. UMIS interface and autocomplete functionality to search for geo-context.

Sensor View: The platform can retrieve sensors from external resources in real-time by relying on a standardized query mechanism to acquire the ones that are contained by the context geometry. Represented with multicolor markers (Figure 10), sensor units that carry water quality data can be observed on the map and investigated in terms of their location, provider agency or group, and other pertinent metadata depending on the data source (e.g., description, id, river).

Viewing Observations: UMIS Platform offers an intuitive structure to filter and visualize sensor observations over a timespan (Figure 11). As the nature and resolution of data varies among providers, an automatic approach has been taken to query the available parameters as well as the time range that data is available for the parameter and unit. This preprocessed and cached sensor-specific metadata ensures that the user can navigate through multivariate and nonuniform sets of information easily. Hence, as soon as the user activates the observation view, the list of available variables, their time ranges, as well as the resolution of data supported is auto filled, followed by the display of observations for one of the available parameters, selected randomly. An interactive, zoomable, and detailed chart view, accompanied with a smaller view to effectively navigate through multi-year data, is created.

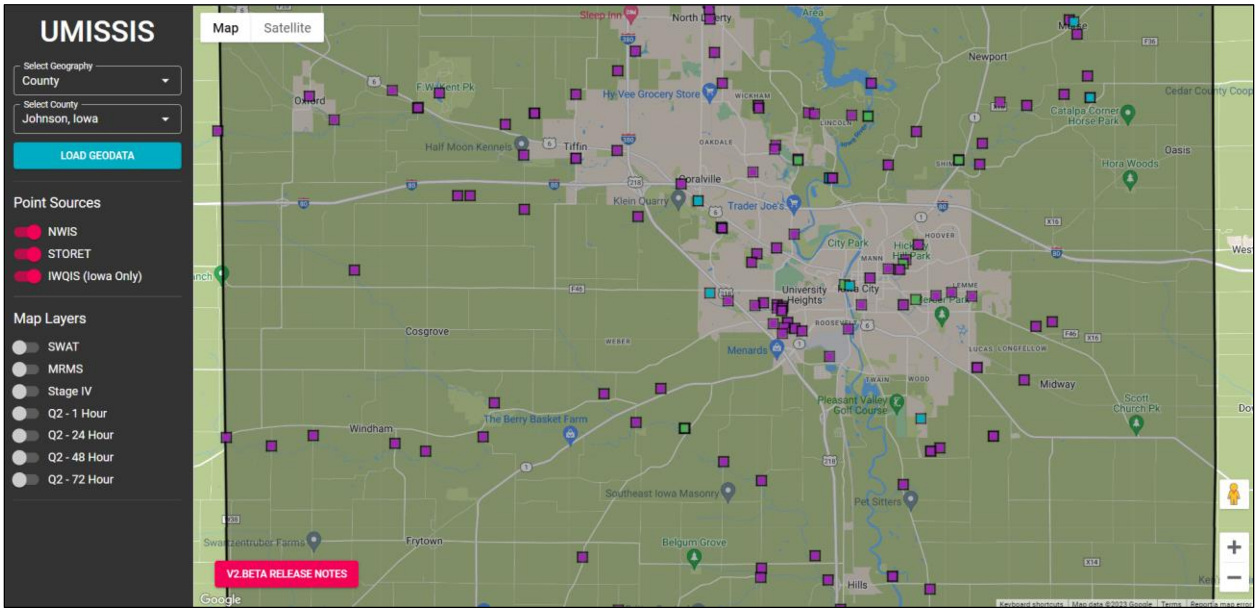


Figure 10. Available sensor locations within a geo-context by multiple providers.

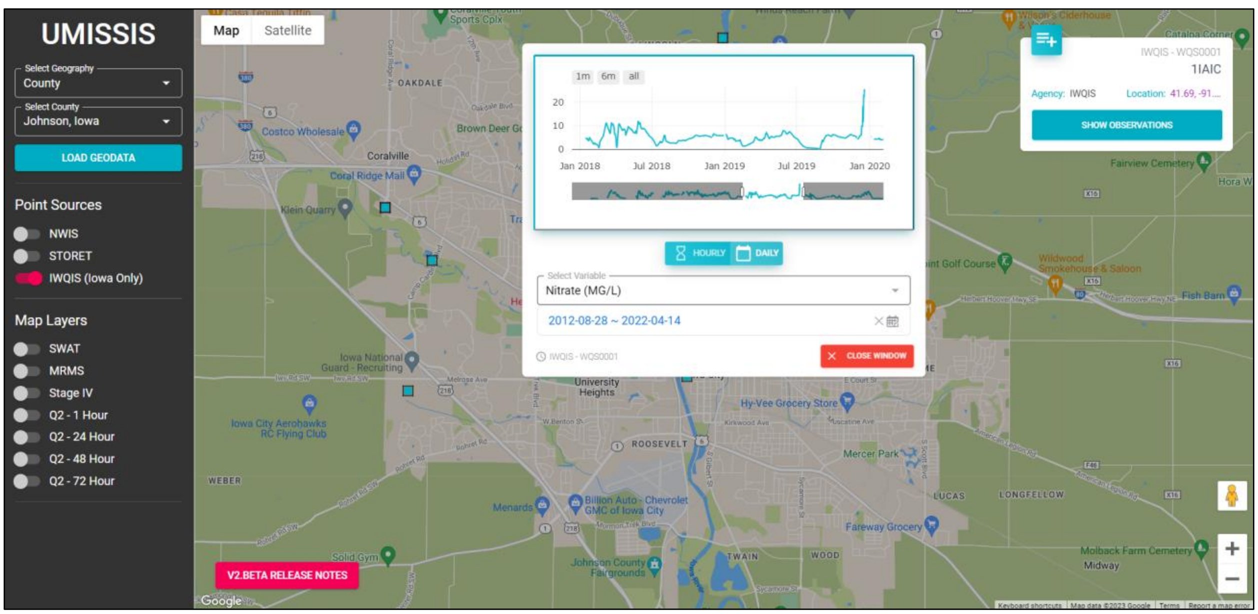


Figure 11. Sensor observations within an interactive chart environment.

Multi-Sensor Comparison: A major contribution of the platform is to enable an interactive visual analytics environment for historical and real-time water quality data (Figure 12). In that pursuit, the platform implements the mechanism to add sensors to the *compare view* list as they explore the system, sensors, and observations. A database table was created to keep record of desired sensors, which is then used to activate a panel to manipulate and display observations side-by-side. Such interaction permits the analysis of multiple parameters, timelines, data resolutions, and providers to discover patterns and uncover correlations. Furthermore, aggregated views (i.e. hourly, daily, weekly, monthly) are available where supported.

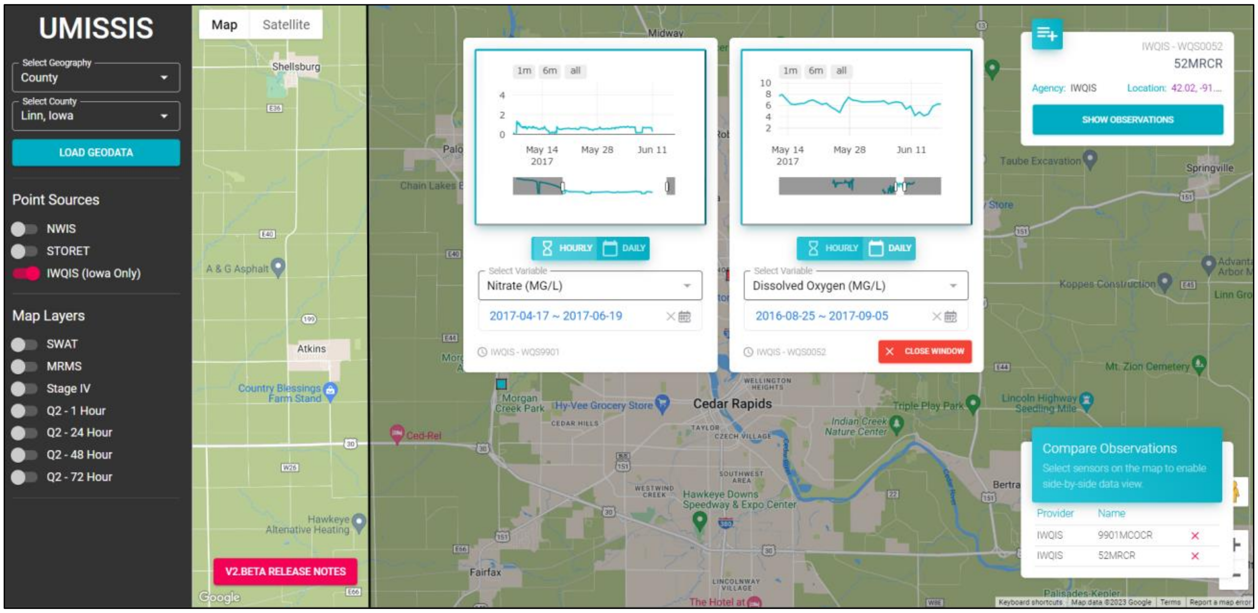


Figure 12. Multi-sensor and multivariate temporal analysis and visualization

Raster-Based Info-Layers: In addition to the point-level sensor data and vector geometries, the UMIS platform further provides raster-format information layers to assist in conveying the spatiotemporal relationships and correlations. The user can enable different layers simultaneously, including SWAT Model outputs for each pertinent variable, MRMS rainfall information, different precipitation temporal resolutions, and Stage IV overlays. For raster data with a temporal variability, such as SWAT and MRMS data, the platform offers a play and pause interface to move through acquired data at different dates and times as well as to automatically play to observe progression.

3.3. Big Data Challenges and Opportunities

Engagement with vast repositories of time series data, extensive spatial datasets, and imagery highlighted the necessity of technological proficiency. The handling of tables containing billions of rows of data was found to be a non-trivial task, necessitating the consideration of best practices for data manipulation. The significance of seemingly minor factors, such as query commit frequency in the database, was brought to the fore when processing extensive datasets. Code and methodologies often had to be adjusted to expedite essential operations. Furthermore, a comprehensive understanding of software idiosyncrasies was acquired, enabling the navigation of behaviors that were previously unencountered or insignificant in smaller-scale operations.

Given the role of UMIS as a data aggregator, it became distinctly evident that fault-tolerant ingestion methods were required. Interactions with external data repositories via APIs introduced challenges in data ingestion and subsequent management. Initially, the presumption was made that API calls would remain stable. However, following the experience of a series of cascading failures within UMIS subsystems, the necessity of fortifying the ingestion process against faults was recognized. In the event of a failure, a system was implemented to record the point of failure and reattempt the process at a later time.

While UMIS currently offers a wide range of features and capabilities, there is still substantial room for improvement and growth in future studies. The implementation of requested functionalities presents a substantial avenue for further development. Feedback from our user community is highly valued, as it will help guide the future enhancements of UMIS, making it an even more robust tool for water quality research and analysis.

Additionally, we welcome contributions from federal, state, regional, local, and individual sources to expand the scope of data ingestion within UMIS. Although we already collect data published in federal water quality portals, providing the option for other researchers to directly share their data with UMIS offers an alternative method of data acquisition. This collaborative approach will further enrich the data ecosystem of UMIS, ultimately benefiting the entire water quality research and education community. As we continue to evolve and refine UMIS, we look forward to the collaborative efforts and feedback of our diverse user base and contributors in shaping the system's future.

4. Conclusion

In conclusion, UMIS stands as a comprehensive and powerful one-stop information system, accessible at https://umissis.org, which aggregates and enhances water quality data from significant contributors. This system encompasses and exposes billions of records detailing nutrient data and streamflow characteristics, presented through an intuitive interface that accommodates users of various skill levels, facilitating the exploration of extensive data repository of UMIS. Users can readily select and compare observation data from numerous major data repositories, enhancing their research and analysis capabilities.

The potential benefits of UMIS extend far beyond its current capabilities, with significant implications for the realms of water quality management, research, education, and policymaking. First and foremost, UMIS serves as a vital tool for data-driven decision-making in water quality management. Its ability to aggregate and enhance data from diverse sources enables stakeholders to gain a comprehensive understanding of the UMRB's water quality, facilitating the identification of critical areas and trends. This, in turn, can inform targeted interventions and strategies to improve water quality and mitigate issues such as nutrient pollution and eutrophication. Furthermore, UMIS fosters collaborative research endeavors by providing a centralized platform for data access and integration, enabling scientists to tackle complex, cross-scale questions related to water quality. This, in turn, supports innovation and the development of sustainable solutions.

For educational purposes, UMIS offers a valuable resource for students, educators, and researchers. It provides a real-world, dynamic dataset for educational institutions, enabling the integration of practical, hands-on experiences into curricula. Students can explore and analyze water quality data, gaining insights into the environmental challenges faced by the region. Moreover, UMIS can serve as a catalyst for future water quality research by inspiring students and researchers to pursue innovative inquiries and projects.

From a policy perspective, UMIS contributes to evidence-based decision-making. Policymakers and regulators can utilize the platform to access reliable, up-to-date data, supporting the formulation of more effective and targeted policies to address water quality issues. As UMIS continues to grow and evolve, it has the potential to become a cornerstone in shaping public policies related to water quality, enabling data-backed regulations and interventions that safeguard the environment and public health.

In sum, UMIS holds the promise of playing a pivotal role in advancing water quality management, fostering groundbreaking research, enriching educational experiences, and informing sound policymaking, all contributing to the sustainable stewardship of water resources in the UMRB. The potential also exists to extend the UMIS system beyond the UMRB to the entire Mississippi-Atchafalaya River Basin (MARB), to support broader MARB-focused initiatives including implementation of natural (green) infrastructure practices (Gassman et al., 2022; Schilling et al., 2023a; 2023b).

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