# AI-Assisted Voice Enabled Computing Framework for Hydrological Analysis

Carlos Erazo Ramirez[1,2,*], Ibrahim Demir[3,4]

[1] IIHR – Hydroscience & Engineering, University of Iowa
[2] Civil and Environmental Engineering, University of Iowa
[3] River-Coastal Science and Engineering, Tulane University
[4] ByWater Institute, Tulane University
[*] Corresponding Author, cerazoramirez@uiowa.edu

**Abstract**

This work presents a web-based, voice-enabled, no-code platform for AI-assisted hydrological analysis. The system allows users to interact through natural language—via both text and speech—to retrieve data, utilize hydrological functions, and visualize spatial and analytical outputs. Core components include a conversational AI assistant utilizing Large Language Models, a modular analysis engine based on HydroSuite, and direct integration with hydrological data from federal agencies using HydroShare and other data and web services. Structured intent parsing, persistent session state, and dynamic map-layer control support multi-turn interactions and reproducible workflows. A case study over the Mississippi River Delta demonstrates how the platform enables guided exploration, layered data integration, and low-latency execution with minimal technical overhead. The platform lowers barriers for research, education, and decision-making in hydrology by combining AI reasoning with a transparent, accessible user interface. By enabling natural language interaction, data integration, and reproducible, multi-turn task processing, this system lays the foundation for automated hydrological research and operational workflows.

**Keywords**

AI Platform; Hydroinformatics; Web-based Modelling; Workflow Automation; No-Code Voice-Enabled

## 1. Introduction

The emergence of large-scale web-based systems has significantly transformed the landscape of data analysis and real-time communication (Goodchild 2007; Ramirez et al., 2024). These systems, characterized by their capacity to process large amounts of information and enable instant interaction, play an essential role in diverse sectors, including education, healthcare, and environmental management. For instance, platforms like HydroShare facilitate the sharing of hydrologic data and models, thus advancing scientific research by improving data accessibility and enable collaborative efforts among researchers (Morsy et al., 2017).

The integration of artificial intelligence (AI) and machine learning (ML) with open-source web libraries is crucial for enhancing data accessibility, especially with the emergence of natural language processing through transformer architectures (Vaswani et al., 2017). These technologies have the power to automate data processing, optimize analysis workflows, and democratize data-driven decision-making for users with limited technical backgrounds (Cava et al., 2020). Moreover, hydrology—being a critical discipline within environmental science—requires specialized tools and methodologies to effectively understand water systems and their dynamics.

Current tools often involve complex programming and data manipulation, creating barriers for non-experts. Different researchers have indicated that integrating AI frameworks with traditional modeling techniques can enhance our understanding of hydrological processes and support the analysis of spatial and temporal water data (Beven, 2012; Dumpis et al., 2022; Sadler et al., 2015). However, existing systems frequently lack the integration needed for effective collaboration and real-time analytics (Teng et al., 2016). This gap in capabilities showcases the motivation for developing more intuitive, interactive platforms that cater to diverse users, increasing participation in hydrological research.

Despite the advances in hydrological data systems, there remains a significant technical barrier for users who possess limited programming or scientific computing knowledge. This issue is pronounced in hydrology, where analyses often require intricate skill sets that are not accessible to all potential researchers or policymakers. Existing platforms tend to be overly complex, thereby hindering the ability to conduct appropriate hydrological evaluations without extensive training (Dolder et al., 2021; Sivapalan 2006; Shen 2018). Additionally, there is a notable absence of interactive, and voice-enabled platforms tailored for hydrological research. Current systems are not yet fully leveraging modern technological advancements that can enhance usability and engagement. While the integration of voice-enabled interactions has been proposed to improve user experience in various fields, specific studies in hydrology are still emerging and warrant further exploration (Kumar et al., 2024; Bellamy et al., 2019; Gichamo et al., 2010). The opportunity lies in creating user-centered platforms that employ AI-driven solutions to bridge this divide by making data interpretation and analysis more intuitive and accessible, allowing an environment where researchers and practitioners can collaborate regardless of their technical background.

## 1.1. Background and Literature Review

### 1.1.1. Web-based Systems in Environmental Research

Web-based systems have become crucial in hydrology and environmental research by providing access to tools for data collection, analysis, and dissemination (Erazo et al., 2022; 2023; Pathak et al. 2020). These systems offer significant promises for research but introduce some limitations that must be considered for effective implementation, in particular for rainfall monitoring, hydrological modeling, flood-risk assessment, and water monitoring (Agliamzanov et al., 2020; Perez et al., 2024).

Many web-based solutions are introduced for hydrological and environmental research. HydroSHEDS provides global digital data layers for hydro-ecological applications (Lehner, 2008; Lehner et al., 2025). The Watershed Modeling System (WMS) (Singh & Frevert, 2010) provides optimization of river network representation data models in web systems (Demir & Szczepanek, 2017). HydroCloud is a web application for exploring stream gage data from multiple sources (McGuire et al., 2014). Additionally, the GEOGLOWS Toolbox offers hydrological modeling tools and data visualization applications (Emmerton et al., 2020; Hales et al., 2025). Platforms like HydroShare facilitate the provision of hydrologic data and models, allowing researchers to share and access environmental datasets effectively (Morsy et al., 2017; Peters-Lidard et al., 2017) for effective flood risk assessment and mitigation studies (Yildirim et al., 2022; Alabbad et al., 2023). Information platforms that allow the use of both hydrology datasets and machine learning capabilities are also prominent in the merge of purely web-based community spaces for shareable information (Sit et al., 2021).

The evolution of these systems is critically supported by relevant technologies such as Leaflet.js and GeoJSON, which enhance geospatial visualizations and interactivity within web applications (Cava et al., 2020). Leaflet.js is a lightweight JavaScript library for mobile-friendly interactive maps, playing an important role in presenting complex environmental data in an accessible format (Dumpis et al., 2022). Meanwhile, GeoJSON provides a standardized format for encoding geographical data structures, enhancing the interoperability of environmental datasets researched through web-based platforms (Sadler et al., 2015). Moreover, various Application Programming Interfaces (APIs), such as those from the U.S. Geological Survey (USGS) and the National Weather Service (NWS), are increasingly being utilized to build and extend the capabilities of these platforms.

For instance, the USGS's National Water Information System API allows for real-time water data retrieval, which researchers can then visualize through web applications integrated with Leaflet.js (Teng et al., 2016). These APIs facilitate the dynamic integration of comprehensive datasets, thus allowing environmental researchers to conduct robust analysis without the need for extensive technical expertise (Dolder et al., 2021). Consequently, the integration of these technologies into web systems enables a collaborative environment where researchers can interact with data in real-time and improve their analytical capabilities while democratizing access to vital environmental information.

### 1.1.2. AI and Machine Learning in Hydrology

The integration of AI and machine learning within hydrology has obtained attention in recent years, emphasizing the potential of data-driven approaches in environmental modeling, prediction, and analysis (Mosavi et al., 2018; Demiray at al., 2021). Multiple studies have demonstrated how machine learning techniques, such as random forests and neural networks, can enhance forecasting accuracy of hydrological events, thus researchers make informed decisions based on predictive analytics (Kumar et al., 2024; Krajewski et al., 2021). The literature highlights several successful case studies where data driven approaches and cloud computing are implemented to predict river discharge, flooding events, and rainfall-runoff processes (Seo et al., 2019; Bellamy et al., 2019; Xiang et al., 2021).

Many educational platforms use AI techniques to adapt and personalize learning experiences based on user interactions, demonstrating how AI can enhance educational tools, particularly in hydrology (Sajja et al., 2023; 2025). Additionally, emerging applications like the integration of AI in monitoring systems for water quality have showcased how machine learning can refine data interpretation and enhance decision-making capacities (Harris et al., 2022). However, there still lies a gap in user-friendly interfaces that can merge these advanced methodologies and cater to a broader audience without requiring extensive programming skills.

### 1.1.3. Voice-Enabled Interfaces and No-Code Platforms

Voice-enabled applications are gaining traction in various domains, facilitating interactive communication with technology through natural language processing capabilities (Sermet & Demir, 2021). These applications can ease interaction dynamics, allowing users to engage with complex systems intuitively (Anggraini & Faisal, 2024; Fang et al., 2023). For instance, incorporating voice assistants into research environments can streamline workflows by enabling hands-free operations, thus providing a more intuitive user experience. Furthermore, no-code platforms enable non-technical users to develop and deploy web applications without needing to write code. This trend is particularly relevant in environmental research, where user-driven applications can promote collaborative research activities (Sundberg & Holmström, 2023; Sarikaya et al., 2018).

### 1.1.4. Challenges in Hydrological Research and Education

Despite advances in hydrological research tools and platforms, several persistent challenges limit accessibility and usability for non-experts. One major issue is the pressing need for real-time data access, requiring systems that can aggregate, process, and visualize vast datasets in an interactive manner (Caprarelli et al., 2023; Ceola et al., 2015; Essawy et al., 2018). The lack of user-friendly tools contributes to a significant knowledge gap, wherein experts leverage advanced software while non-experts struggle to navigate overly technical interfaces (Baydaroğlu et al., 2022).

This disparity not only affects the educational processes involved in hydrological analysis but also limits the involvement of potential contributors from diverse educational backgrounds in critical research. Moreover, existing software is often too complex for users without technical backgrounds, which limits broader collaboration in environmental research (Denef et al., 2013). Researchers have emphasized the need for intuitive, interactive platforms to make hydrological data and tools more accessible and reproducible (Lefaivre et al., 2019; Addor & Melsen, 2019; Wagner et al., 2022). Trends within the AI community make these efforts tangible, with studies on merging hydrology and AI inference for generalizable benchmarking datasets (Kizilkaya et al., 2025), showing the possibilities for addressing gaps previously out of reach.

### 1.2. Objectives and Contributions

This research highlights the development and evaluation of an AI-guided, voice-enabled, browser-native platform that allows users to conduct complex hydrological data exploration and analysis through natural language interaction. The system has been designed to lower the barriers traditionally associated with hydrological computing by allowing users to visualize, analyze, and progressively construct complex analytical workflows without requiring programming or deep expertise in software installations. We address this challenge in this study by: a) developing an intelligent conversational agent capable of guiding users through multi-step hydrological analyses via iterative dialogue; b) leveraging large language models, structured conversational scaffolding, and persistent session context to support progressive, context-aware interaction; c) connecting with data providers, as well as libraries that perform complex analysis; and d) visualizing hydrological features and datasets, perform timeseries and statistical analyses, and allow interactions with external models.

## 2. Methodology

The conceptual model underlying the platform is guided exploration where an AI assistant interprets user input, dynamically constrains the search space to relevant hydrological contexts, and orchestrates data retrieval and visualization accordingly. This pattern supports an evolving dialogue between user and system, wherein the AI agent maintains conversational state and progressively exposes new analytical pathways based on prior interactions. The architecture comprises four primary components: the AI Assistant and Command Processor, the Map Manager, the Data Manager and API Integrations, and the Hydrological Analysis Engine as shown in Figure 1. These components operate within a tightly integrated interaction loop, enabling users to iteratively construct complex analytical workflows through guided conversation.

### 2.1. AI Assistant and Command Processor

At the core of the platform lies the AI Assistant and Command Processor, managing the translation of natural language input into structured system actions. This component acts as the interface between the user and the underlying hydrological analysis engine, supporting multi-turn interaction, parameter resolution, and function routing. Each input—text or voice—is parsed by the assistant using a structured dialogue model grounded in large language models (LLMs), with additional domain-specific scaffolding that constrains interpretation to hydrology-relevant intents and entities. The models used are either locally trained small models—DialogGPT-small (Zhang et al., 2019) for conversational intents and Flan-T5-small (Pandya et al., 2023) for instruction setting—or GPT-3.5-turbo (Ye et al., 2023) through querying OpenAI. The model selection was based on the size of the model for training considering each has already been finetuned for its particular purpose. The implementation and use of each model will be explained in section 2.1.2.

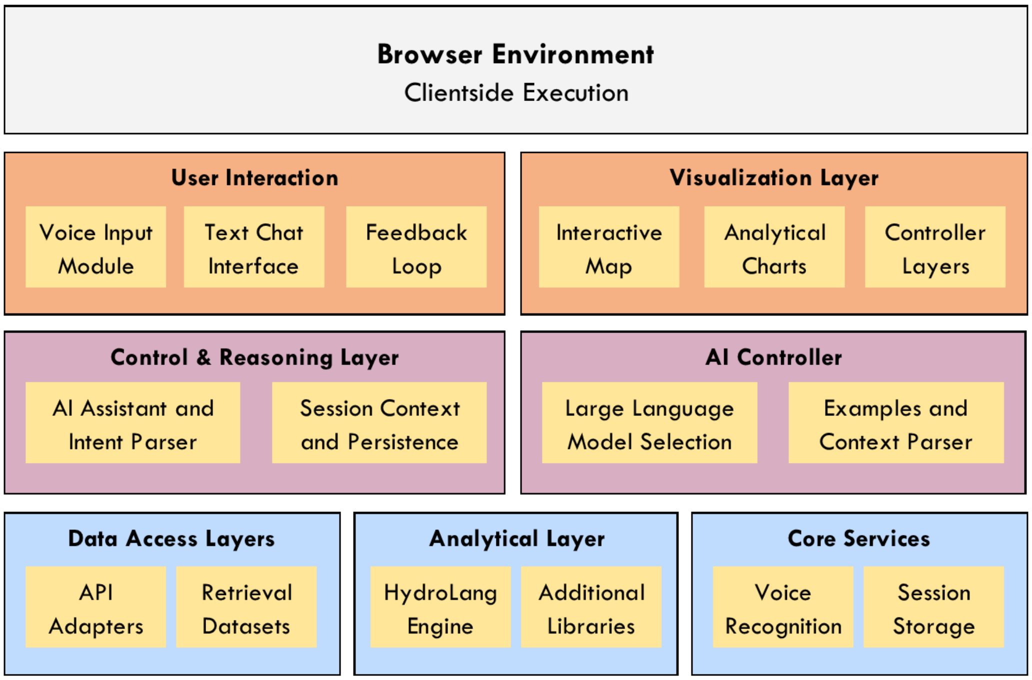


Figure 1. Architecture diagram of the platform. The user interaction is done through inputs from chat, voice, or direct map interaction which are afterwards given to the control layer that allows access to the hydrological analytical tools and core services within the browser.

### 2.1.1. Natural Language Processing and Command Routing

The system employs a structured natural language understanding (NLU) pipeline to enable robust and reproducible AI-guided interaction. This architecture ensures that user inputs—whether provided through voice or text—are consistently interpreted, structured, and mapped to actionable system commands within the hydrological analysis workflow. Following descriptions from Brown et al., 2020 and Rajani et al., 2019, input is started with user utterance. Voice input automatic speech recognition (ASR) layer performs initial transformation of acoustic signals $x(t)$ into a textual representation T (Eq. 1), with $x(t)$ representing the time-domain audio signal.

$$T = \mathrm{ASR}(x(t)) \quad \text{(Eq. 1)}$$

The ASR model is optimized to minimize the word error rate, and ensuring high transcription fidelity. This will be further discussed in later sections. The result text T undergoes a natural language preprocessing stage, combining rule-based tokenization, stop word filtering, and domain-specific entity recognition to normalize the input and highlight salient components from the command generation. This is represented by Eq. 2.

$$T' = f_{pre}(T) \qquad \text{(Eq. 2)}$$

The core natural language parsing is performed through the guided AI prompt engineering layer. The application utilizes a scaffolded prompt P, built from domain exemplars extracted from the hydrology engine layers $E = \{e_1, e_2, \dots, e_n\}$ and the current session context C, which jointly conditions the language model's response.

$$R = LLM(P(T', E, C, )) \qquad \text{(Eq. 3)}$$

The output R is structured such that it contains both a conversational response for the user-facing interaction, and a formal command representation $(I, \Theta)$, with I being the parsed intent and $\Theta$ the set of resolved parameters.

$$(I, \Theta) = g(R) \qquad \text{(Eq. 4)}$$

In this context, $g(\cdot)$ is the structured parsing of the LLM output, enforced through prompt constraints and output formatting patterns, commonly JSON-like command structures. The resulting intent-parameter pair $(I, \Theta)$ is then routed through the command processing, which implements deterministic mapping M from parsed intents to system actions.

$$A = M(I, \Theta) \qquad \text{(Eq. 5)}$$

With *A* representing the execution of a corresponding action across one or more system components. This architecture layer serves two critical purposes. First, it ensures interpretability and reproducibility where every AI-driven decision is mediated through a structured intent-command pipeline, with explicit parsing and routing of actions. Second, it supports progressive dialogue where the session context C evolves dynamically with each interaction turn, enabling multi-step workflows wherein subsequent user inputs are interpreted in relation to prior analytical state.

### 2.1.2. Model Training Schema and Execution Routing

The core of the LLM integration is the intent layer, which combines context awareness with domain-specific instruction sets and a prompt-engineered scaffolding framework that limits the model's reasoning to hydrology-relevant intents and entities. Local models are trained on HydroLang documentation plus compact single- and multi-step command sequences; these examples are converted to embeddings so the model can recognize the order of operations a user is likely to follow during a session. At runtime each prompt is routed to the analysis, data, or mapping domain, where the corresponding instruction template and parameter keys are applied. A persistent session context records the evolving analytical state, letting the system interpret each input in relation to prior steps and enabling users to refine spatial queries, add data layers, or run successive analyses in one conversational thread. Figure 2 pairs a runtime analysis-domain intent with the training example that defines its embedding. For calls sent to OpenAI, the same domain examples are supplied inline, so the cloud engine follows identical mapping logic without local fine-tuning.


```json
{
  "name":"find_upstream_features",
  "description":"Find upstream hydrological features like stations, dams, or monitoring points using NLDI navigation",
  "domain":"mapping",
  "keywords":[
    "upstream",
    "features",
    "stations",
    "dams",
    "monitoring",
    "nldi",
    "navigation"
  ],
  "parameters":{
    "type":"object",
    "properties":{
      "location":{
        "type":"string",
        "description":"Location name or coordinates"
      },
      "coordinates":{
        "type":"object",
        "properties":{
          "lat":{
            "type":"number"
```

```json
    {
      "user_input": "Calculate percentiles for water level data",
      "assistant_response": "I'll calculate statistical measures for the water level data. This will provide statistical insights into the dataset.",
      "intent": "statistical_analysis",
      "domain": "analysis",
      "function_name": "analysis_statistical_analysis",
      "parameters": {
        "domain": "analysis",
        "intent": "statistical_analysis",
        "parameter": "water level",
        "analysis_aware": true
      }
    },
    {
      "user_input": "What parameters does lagAndRoute need?",
      "assistant_response": "The lagAndRoute function accepts these parameters: params (Object)",
      "intent": "help_request",
      "function_name": "hydro_lagAndRoute",
      "parameters": {
        "module": "hydro",
        "function": "lagAndRoute",
        "parameter_details": [
          {
            "name": "params",
            "type": "Object",
            "description": "* @param {Object} data -
```


Figure 2. Example schema is utilized to provide context for domain specific routing. The left panel specifies example used for the map domain, while the right shows the example use case for training the local models.

Both local and cloud responses return a structured JSON object instead of free text. The object carries the canonical intent label, a dictionary of resolved parameters such as `stationID`, `variable`, and `dateRange`, the target functional module, and any optional execution flags or metadata. This uniform schema anchors all downstream processing, keeps analytical state consistent across turns, and lets the platform build complex hydrological workflows through natural-language interaction.

### 2.1.3. Session Memory and Workflow Continuity

The agent's decision-making process is governed by hierarchical command architecture. Parsed intents are mapped to structured commands through a decision layer that incorporates rule-based validation, parameter resolution, and dynamic generation of clarifying prompts when necessary. This ensures that each command dispatched to the visualization and analytical subsystems is well-formed and consistent with the current session context. Spatial interaction follows a progressive refinement pattern. Initial user queries typically establish a geographic context—

such as requesting the display of hydrological stations or basin boundaries—upon which further spatial overlays (e.g., flood extents, risk zones) can be layered.

The Map Manager synchronizes with the session context to maintain consistency across spatial updates and to support interactive exploration of the visualized data. Analytical interaction follows a similar progressive model. Users can request time series visualizations, statistical computations, or hydrological index analyses, with each request building upon previously retrieved datasets and established analytical context. Results are presented through integrated visualizations that align with the current spatial view, enabling integration of spatial and analytical insights, highlighted in Figure 3, with the intent and execution of context explained in Figure 4.

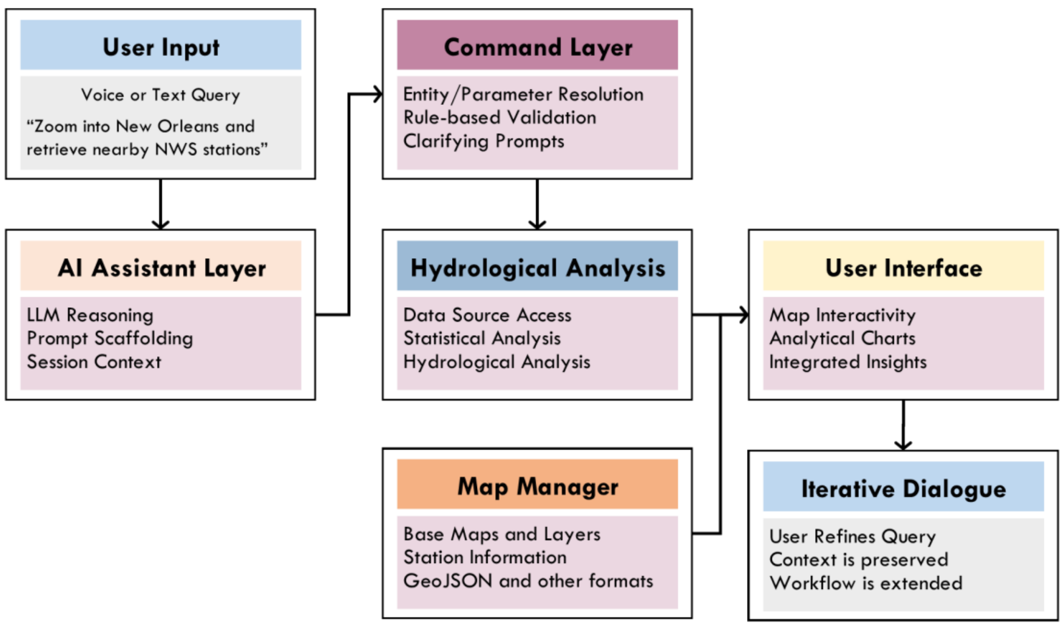



Figure 3. Input command interaction and flow of information across the application. The interaction between the user input (either text or voice) is handled by the LLM and parsed into instructions.

This interaction architecture is explicitly designed to support extensibility, with additional libraries mapped through a Message Processing Interface (MPI) system that enables exposing APIs into the application. The separation of natural language understanding, decision-making, data retrieval, and analytical processing into decoupled but coordinated layers ensures that the system can evolve to incorporate additional capabilities and domain knowledge without compromising interpretability or reproducibility. The use of algorithmic scaffolding and structured command processing ensures that AI-driven behavior remains grounded in transparent, verifiable logic, aligning with sound development practices.

Intent Parsing and Function Call Dispatch

```
procedure ProcessUserInput(userInput)
    response ← Await(LLM_Response(userInput, currentSessionContext))
    parsedIntent ← ParseStructuredIntent(response)
    if parsedIntent is invalid or incomplete then
        parsedIntent ← LocalPatternMatching(userInput)
    end if
    if parsedIntent is valid then
        targetFunction ← MapIntentToFunction(parsedIntent.target)
        parameters ← parsedIntent.parameters
        InvokeFunction(targetFunction, parameters)
    else
        HandleUnrecognizedIntent(userInput)
    end if
end procedure
```

(a)

InvokeFunction Procedure for Valid Parsed Intent

```
procedure InvokeFunction(targetFunction, parameters)
    if targetFunction is Map Function then
        MapManager.Execute(targetFunction, parameters)
    else if targetFunction is HydroLang Function then
        HydroLangEngine.Execute(targetFunction, parameters)
    else if targetFunction is Function in Other Library then
        ExternalLibrary.Execute(targetFunction, parameters)
    else
        HandleUnknownFunction(targetFunction)
    end if
end procedure
```

(b)

Figure 4. Input processing mapped into the LLM for parameter extraction and intent definition (a) and execution of the context based on the element required from the layered architecture (b).

## 2.2. Data Acquisition, Integration, and Analytical Processing

The platform generates modular architecture for data acquisition and analytical processing, including dynamic API interaction, ontology-informed query formulation, and browser-based execution of hydrological functions. The system is centered on two tightly coupled components: the Data Manager, responsible for external data retrieval and normalization, and the Hydrological Analysis Engine, which executes analytical routines on the processed inputs.

### 2.2.1. Modular Data Acquisition and API Integration

Data retrieval is initiated based on user commands, which are parsed and interpreted by the AI assistant into structured queries. These are routed through a generalized API access layer, which integrates multiple external sources including:

- USGS National Water Information System (NWIS): Historical and real-time streamflow and precipitation records via RDB, JSON, and WML2 formats. (USGS, 2023)
- USGS National Linked Data Index (NLDI): Hydrologically linked spatial features enabling upstream/downstream network navigation in GeoJSON. (Blodgett et al., 2020)
- National Weather Service (NWS): Hydrologic units, forecast zones, and precipitation grids in JSON, XML, and GRIB2 formats. (National Weather Service, 2024)
- National Water Model (NWM): forecast information on long term, short term and ensemble forecast (NOAA, 2023)
- International sources (e.g., EAUK, MeteoSTAT, World Bank) and user-defined datasets (GeoJSON layers, CSV time series) are also supported via HydroLang's generalized wrappers.

Retrieved data is standardized through a normalization pipeline with temporal alignment ensures consistent time series intervals using ISO 8601 timestamps, spatial projection maps feature a unified coordinate system (typically EPSG:4326), and metadata enrichment standardizes units, variable names, provenance to ensure interoperability across functions, and format translation that converts diverse encodings (e.g., XML, CSV, JSON) into a uniform internal representation.

### 2.2.2. Ontology-Guided Retrieval and Semantic Resolution

Domain-specific ontologies are used to map the user's intent to structured data queries. These define hierarchies and relationships among hydrological variables, spatial objects (e.g., watersheds, stream segments), temporal constructs, and analytical tasks. When users issue ambiguous or underspecified commands, the assistant applies ontology-guided reasoning to identify the appropriate API, parameters, and expected data structures. To aid this construct, a score-based system has been implemented through a filtering process that defines likelihoods based on the user intent. The confidence score utilizes keyword heuristics to provide a score based on the most likely semantic match. If an embedded word has a specific keyword within, it is considered a dominant domain, and a bonus is added as percentage.

Afterwards, the domain router attaches a score from 0 to 1 comparing each intent based on the resolved score and type—if it is a compounded action, this is handled through as a concatenated action and a regular expression is used to attach the score. For instance, for "show tributaries of this station," the router gives the data domain a baseline score of 0.60 ("tributaries" is on its high-priority list), adds 0.30 for a strong keyword match, and a context bonus of 0.10 because the session already contains a selected gauge, bringing the total to 1.00; the query is therefore mapped to an NLDI upstream-tributary request that uses the station's reach ID. For "display flood zones," the mapping domain starts at 0.70 ("display … zones" is a strong phrase), receives another 0.30 for the flood-zone keyword, and gains 0.15 because the map has focus, again reaching 1.00; the request is routed to a FEMA NFHL GeoJSON call bounded by the current map extent.

### 2.2.3. AI-Orchestrated Data Handling

The assistant coordinates data acquisition and preprocessing in real time. Upon receiving a command, it evaluates prior session context, identifies the relevant spatial or temporal scope, and dynamically formulates a structured JSON query which includes parsed intent, required and optional parameters (e.g., station ID, HUC code, date range), and target data source or adapter module. If critical inputs are missing or ambiguous, the assistant issues clarifying prompts or selects defaults based on historical session data. For multi-source workflows—e.g., correlation of rainfall and discharge—the assistant initiates parallel queries and merges the resulting datasets into a common analytical space.

### 2.2.4. Analytical Engine

Data provided to the Hydrological Analysis Engine are processed through well-defined instructions mapping the underlying libraries—primarily HydroLang—which includes time series transformation and aggregation, hydrological index computation, statistical analysis, and spatial overlays for flood extent comparison, watershed delineation, or station clustering. Each function is parameterized via the assistant-generated command structure and can be triggered, modified, or repeated through conversational input. Analytical results are rendered either as visual layers on the map or interactive plots aligned with session state.

## 2.3. User Interface Design and System Interaction

The platform is implemented as a fully browser-based application, requiring no software installation beyond a modern web browser with speech recognition capabilities. All components—user interaction, AI-guided reasoning, spatial visualization, data retrieval, and analytical processing—are executed client-side. This design ensures broad accessibility, platform independence, and low latency, making the system usable across diverse operating systems and hardware configurations.

Upon initialization, users are prompted to enter select the model usage: local models pretrained with the relevant queries, an OpenAI remote query, or a hybrid system that defaults into the local system, and to optionally activate HydroLang for advanced analytical capabilities. If HydroLang is not enabled, the system still supports exploratory spatial queries and basic analytical tasks through the AI assistant. The application is delivered as a single-page web app (SPA), loading all core modules dynamically to support an interactive environment. Figure 5 shows the entry point of the application.

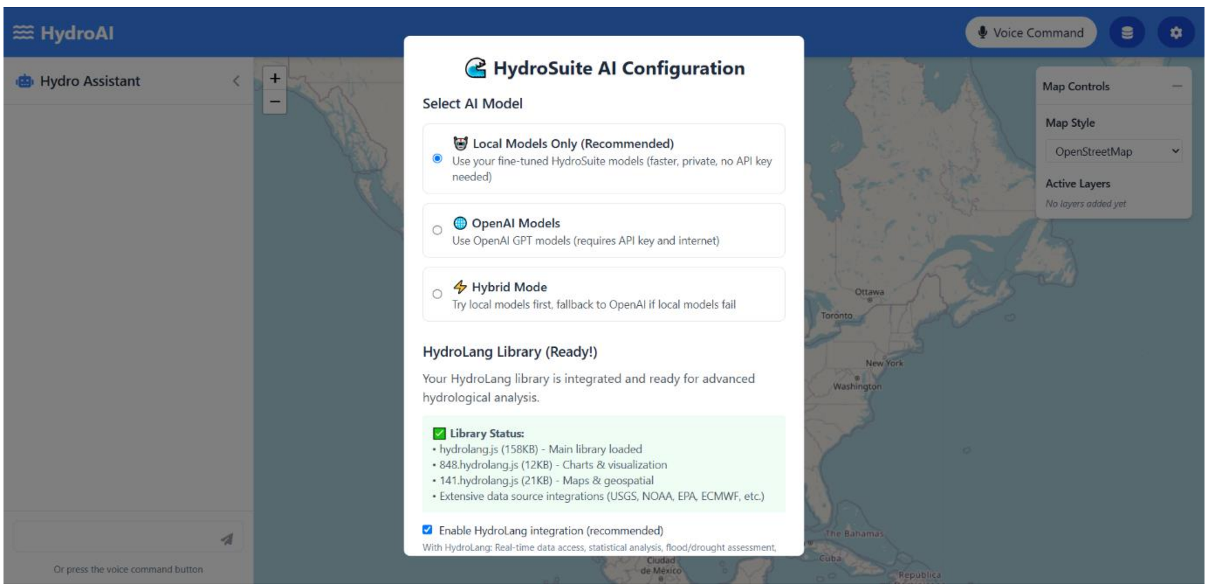



Figure 5. Entry screen of the application with API key and library details. The user can select how to utilize local models deployed through a local server or enable OpenAI services. Alternatively, the user can also select hybrid mode, with the OpenAI as fallback in case there are issues with the local models or vice versa.

Once initialized, the interface presents an integrated workspace. The primary elements of the interface consist of (Figure 6):

<u>Interactive Map Panel:</u> At the core of spatial visualization is the Map Manager, which manages a dynamic, interactive map interface. It renders base layers (e.g., terrain, satellite), hydrological features (e.g., streamflow stations, precipitation networks), and various geospatial overlays such as flood extents, hydrological boundaries, risk zones, and satellite imagery. It supports progressive layering of information, with visual elements updated in response to AI-

guided commands. The map not only serves as a visualization canvas but also anchors the spatial context for subsequent analytical requests, maintaining synchronization with the evolving session state.

Conversational Interaction Panel: Enables users to submit both text and voice inputs. Voice recognition is handled by a dedicated recognition service, which converts spoken queries into text prior to natural language processing. The panel also displays system responses, clarifications, and guidance, maintaining an interactive dialogue that informs and shapes the user's exploration of the system's capabilities. The conversational panel maintains a running dialogue history, providing transparency and continuity across interaction turns.

Visualization Panels: Presents analytical outputs, including time series plots, computed indices, and comparative statistics. Visualizations are generated dynamically in response to commands and complement the map display. The system supports interactive visualization features, enabling users to adjust time windows, compare variables, and inspect individual data points within graphical outputs.

Suggested Commands: in the initial interaction include spatial queries such as "show streamflow stations," overlay requests such as "add flood extent," and analytical operations such as "plot streamflow and precipitation."

The system follows a modular component design, with clearly separated modules for interaction, reasoning, data access, visualization, and analysis. This modularity supports future extensibility where new data sources can be integrated via the data access layer without impacting on the user interface, and additional analytical methods can be incorporated into the analysis engine while maintaining compatibility with existing interaction patterns. Datasets can be explored using layers added to the map, or timeseries that are provided as data layers that can be interacted with from the screen. Figure 7 shows the data layer pane with information on the resources available in the application.


Figure 6. Map interface upon initialization with relevant description for user interaction.

Beyond core user interaction, the system implements architectural mechanisms to support reproducibility:

- Deterministic Command Routing: Parsed user intents are mapped to well-defined system actions through a controlled routing layer, ensuring traceability of analytical workflows.
- Persistent Session Context: Maintains spatial and analytical state across multi-turn interactions, allowing users to iteratively refine analyses with reproducible outcomes.
- Structured Data Normalization: Retrieved data is consistently processed and aligned, supporting reproducible visual and analytical outputs across different sessions.
- Interaction Logging: Structured logging of user inputs, parsed intents, and executed actions enables reconstruction of analytical workflows and supports transparency.

All information from the platform can be accessed through reports, data exports, and reproducible command outputs. Additionally, the users can select different modalities of interaction with the assistant by changing default parameters in the settings, enabling voice feedback from the prompts given by the AI, model temperature and responsiveness, as well as changing themes. Figure 8 illustrates examples of these interfaces.

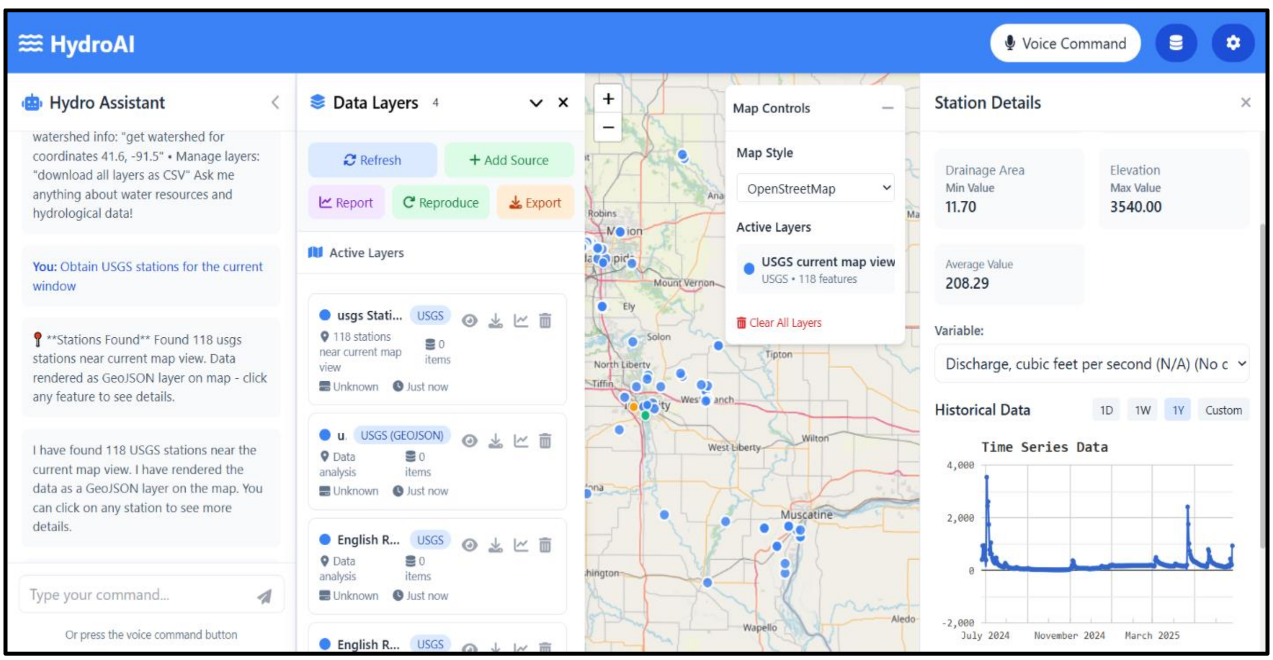



Figure 7. Display of available datasets through the data layers pane, as well as information per station. Panels for flowlines, stations, waterbodies, and radar imagery have been added and available to the AI agent for analysis.

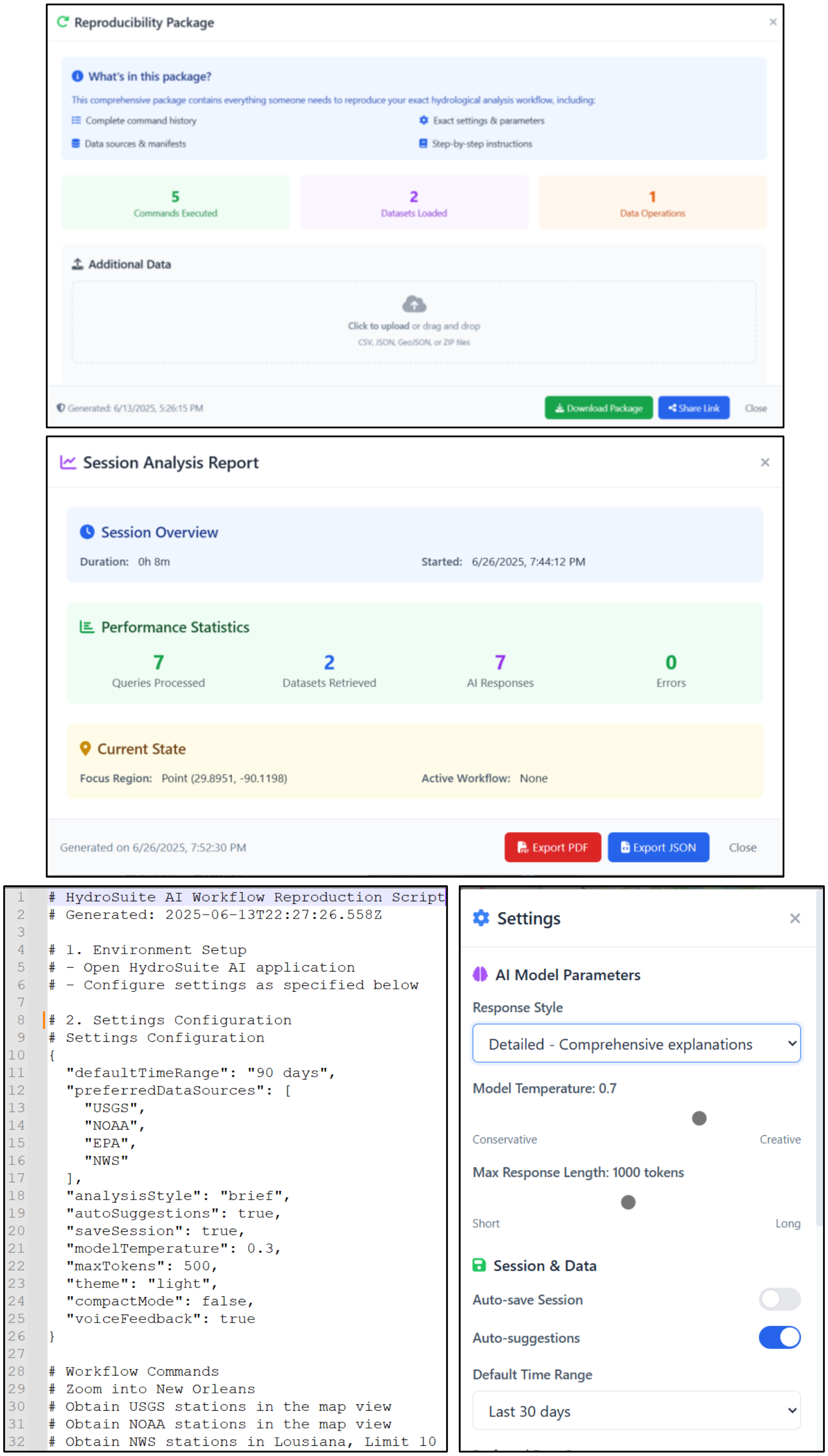



Figure 8. Interfaces aiming for reproducibility, and outputs example. Data can be retrieved as a single zip file, text commands showcasing errors, and actual prompts from the agent.

## 3. Results

A case study has been carried out to demonstrate the system's capability to support exploratory hydrological analysis through a natural language interface. The focus region—the Mississippi River delta around New Orleans, Louisiana—was selected due to its dense hydrological network, active forecasting infrastructure, and relevance to flood risk assessment. The development environment is an Intel Core i7 with 2.6GHz and 32GB of RAM, along with an NVIDIA GForce 1060 and 6GB of memory.

The testing environment was Google Chrome due to the voice recognition feature, however direct texting through the chatbox works in other browsers. The study emphasizes AI-guided query resolution, multi-source data integration, spatial visualization, and session continuity. To ensure controlled and reproducible output, temperature was set to 0.1, yielding deterministic model responses and maximum token limit was capped at 350, providing adequate space for functional encoding while reducing API costs and minimizing verbosity. A dark mode map style was used to improve visual clarity across overlapping data layers. A sample user session is outlined in Table 1.

Table 1. Sample user session for the case study.

<table>
<tr><td colspan="2">The session began with a spatial context initialization:</td></tr>
<tr><td>Prompt: "Zoom into the New Orleans area"</td><td>This command invoked map re-centering and updated session coordinates.</td></tr>
<tr><td colspan="2">Follow-up input focused on hydrological network features:</td></tr>
<tr><td>Prompt: "Obtain flowlines for the map window"</td><td>The assistant parsed the command, extracted bounding box coordinates, and dispatched an NLDI API request to fetch flowlines. The result was a dynamic overlay of NHDPlus river reaches (Figure 9), which included metadata such as COMIDs and network topology.</td></tr>
<tr><td colspan="2">With flowlines in place, the user clicked on a specific reach on the map. This triggered a query cascade. The COMID from the clicked feature was extracted and used to initiate an upstream basin search.</td></tr>
<tr><td>Prompt: "Get watershed basin for coordinates 29.858930, -89.973221"</td><td>The system queried the upstream navigation endpoint of NLDI and returned a polygon geometry (Figure 10).</td></tr>
<tr><td colspan="2">Next, to request regional observational data:</td></tr>
<tr><td>Prompt: "Obtain USGS and NOAA stations for New Orleans"</td><td>This triggered two adapter-based calls to NWIS and NOAA's monitoring services through waterOneFlow dataservice. Resulting stations were rendered with interactive popups (Figure 11), and metadata was exposed for time series linkage.</td></tr>
</table>

| | |
|---|---|
| **Prompt:** *"For station 07374525, obtain the discharge for the past week, and for flowline COMID 22798749 show the short-term prediction."* | Upon clicking on a station in the map, the exposed panel information is available to the agent, and querying information regarding variables attached to the station can be used to continue with the analysis (Figures 12 and 13). |
| Each station contains a connection to a separate service depending on the location to fetch real time data for 1 day, 1 week, 1 year, or custom date range, connected to a separate API service, depending on the monitoring station. | |

Information regarding each flowline's common identifier (COMID) was used to query the National Weather Prediction Service leveraging the National Water Model to obtain short-range deterministic forecasts, medium-range ensemble predictions, and long-range simulations. Upon selecting a station, the different available variables for the stations are made available for exploration. The time range definition is also user defined, showcasing the region-specific information for further decision making. Figure 13 shows the downstream river network station USGS07374525 that provides discharge information used to compare side by side with the upcoming short- and long-term forecasts from the National Water Model.

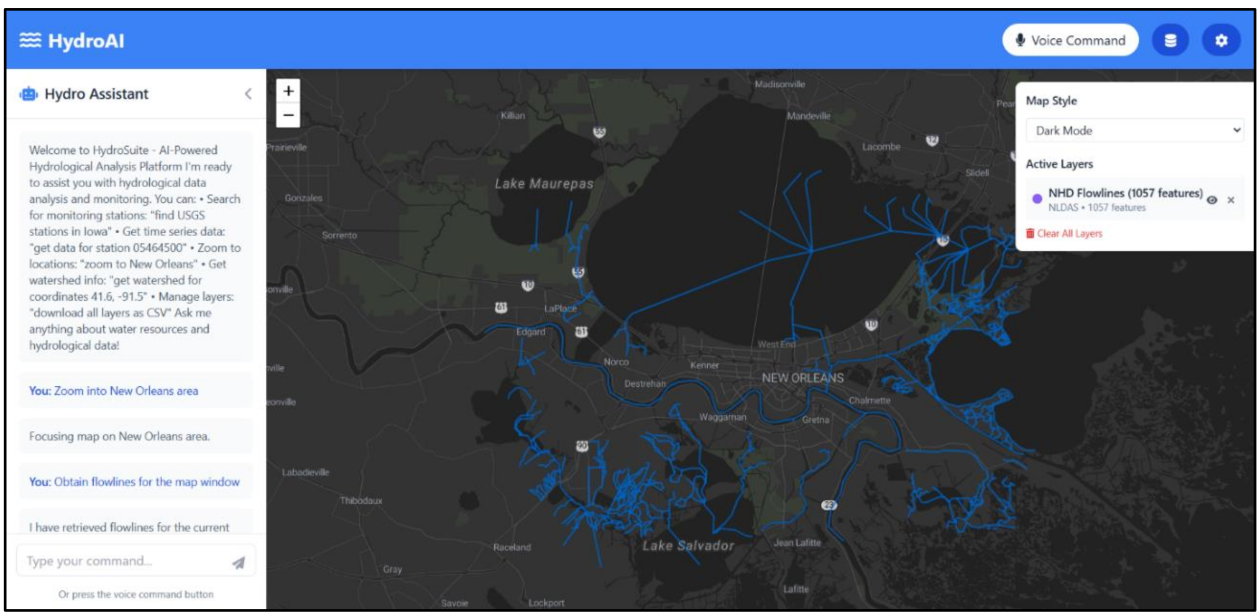


Figure 9. NLDI-derived river flowlines rendered across the map interface, highlighting sections of the Mississippi River network.

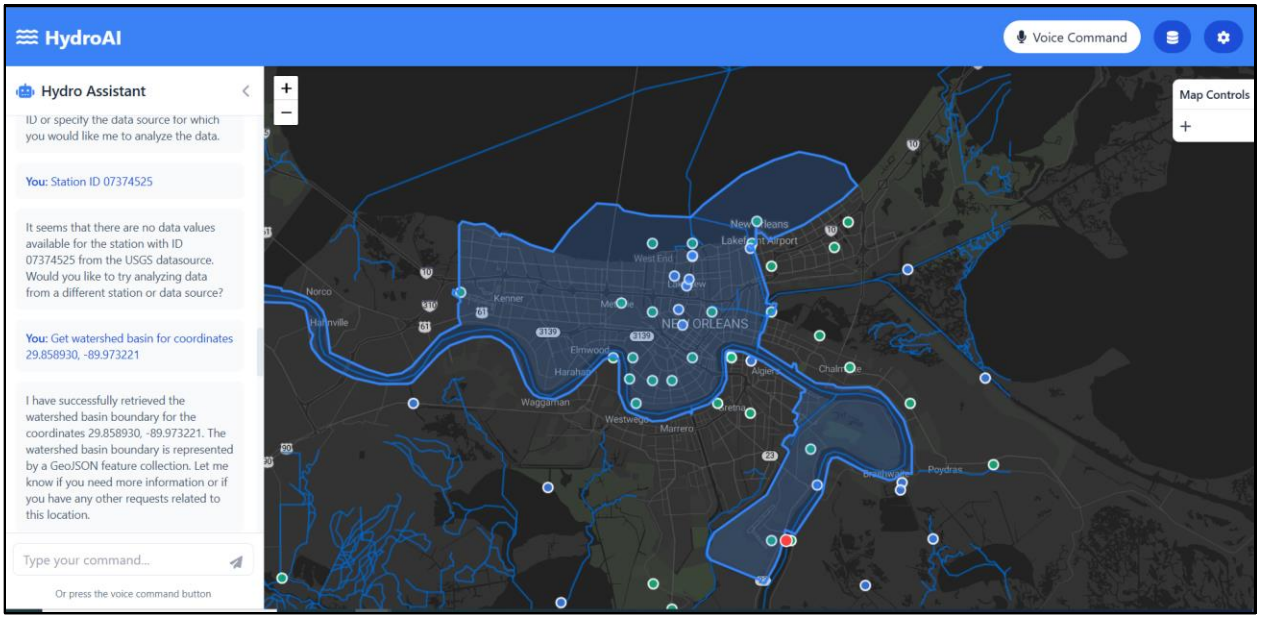



Figure 10. Basin catchment boundary retrieved via NLDI for the selected coordinate. The polygon is overlaid on the river network to show spatial context.

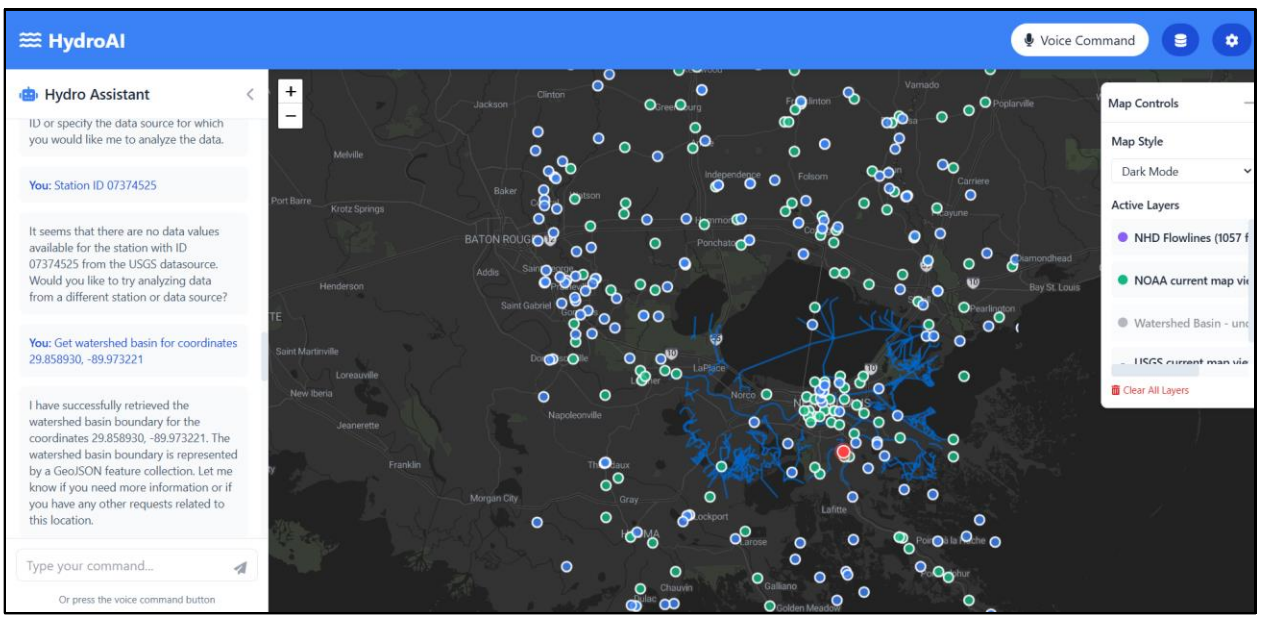



Figure 11. Multiple observation networks (USGS, NOAA) displayed concurrently. Each icon corresponds to a monitoring station; clicking reveals metadata and available variables.

## 2.4. Evaluation and Observations

Evaluation of the platform during targeted usage scenarios confirmed its capacity to support iterative, AI-guided hydrological workflows across spatial and analytical domains. The system maintained consistent session context, enabling multi-turn interactions that were built upon prior user inputs without re-specifying parameters. Spatial features (e.g., map clicks and bounding boxes) were automatically used to infer missing inputs to speed up command execution. All session data—including prompts, parsed intents, and executed functions—were stored as structured logs.

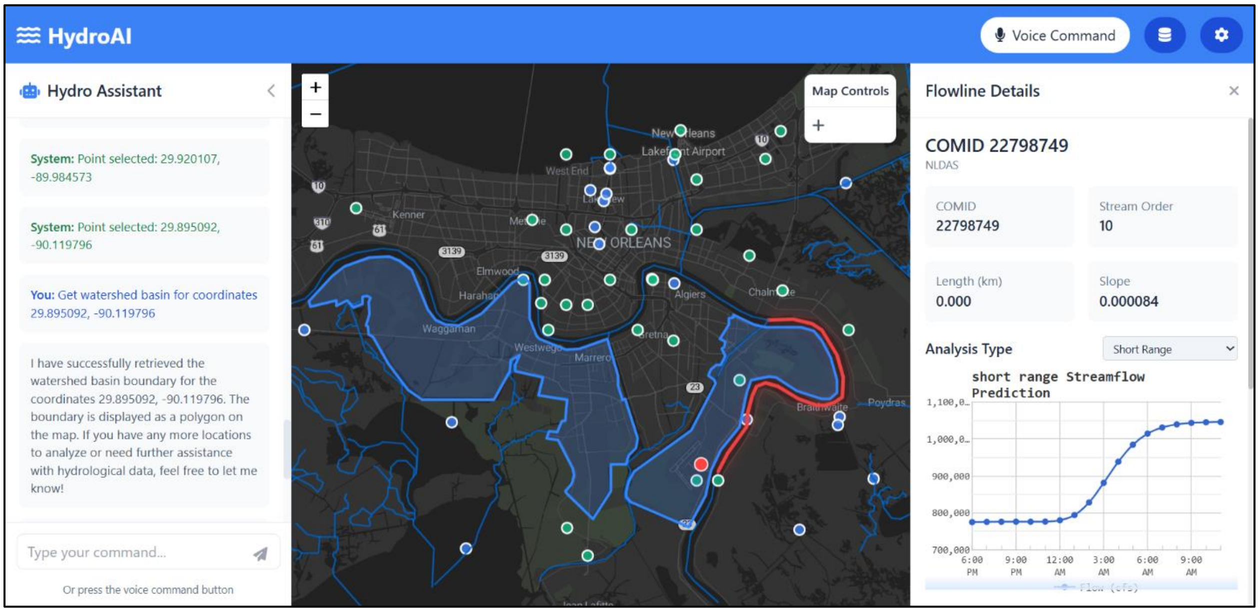
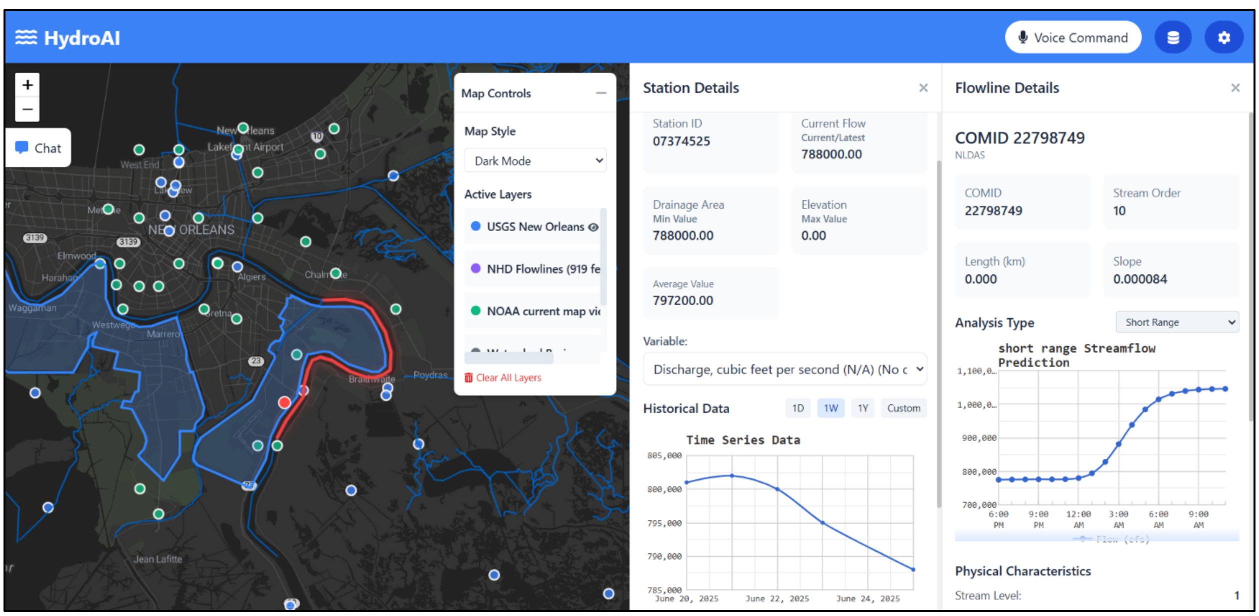



Figure 12. Forecast panel showing short-term streamflow predictions from the National Water Model API. Data is linked to the selected reach and aligned temporally with observational datasets.




1.1.1. Figure 13. Side by side comparison between observed streamflow for the last 7 days and the short-range prediction from the NWS prediction at Mississippi River station at Belle Chasse.

The assistant consistently translated natural language inputs into structured commands and coordinated their execution across modules such as the Map Manager and HydroLang analytical engine. Tasks such as retrieving hydrological stations, querying forecasts, rendering flood extents, or computing streamflow indices were performed reliably under well-formed queries. The structured command pipeline and modular architecture facilitated traceable mapping from user intent to system behavior across sessions.

However, limitations were also observed. Commands with ambiguous phrasing, compound structure, or omitted parameters occasionally failed due to incomplete or inaccurate intent parsing. These failures were most common when user instructions diverged from the predefined or AI-inferred function dictionary. For instance, a request such as "Load surrounding hydrology layers" did not match any valid function signature, resulting in an invalid operation. In such cases, while the system issued structured error prompts or null visual feedback, recovery behavior was inconsistent, particularly in guiding users toward reformulated instructions. It was also noted the lack of understanding from the local models when prompting general questions about the resources, provided the intent is for the conversation to be driven regarding the underlying hydrological library training datasets, with the OpenAI responses aiding in creating a more natural conversation.

To characterize system reliability, six core evaluation metrics are proposed, with their results highlighted in Table 2:

- <u>Command Interpretation Rate:</u> percentage of correct execution and outputs.
- <u>Intent Parsing Accuracy:</u> Number of failures attributed to semantic mismatch or paraphrased duplicates.
- <u>Parameter Resolution Completeness:</u> Inference on spatial and temporal parameters from context.
- <u>Interaction Consistency:</u> Maintenance of interaction control based on user interaction (i.e. map interface, panel interfaces).
- <u>Response Latency:</u> Response time on AI parsing, AI fetching (OpenAI and local models querying), and interactivity in map and visualization required by the user.
- <u>Error Recovery Capability:</u> Structured error messages were provided, though follow-up corrections were not always sufficient to ensure successful reformulation.

Latency was measured using Chrome Developer Tools, tracking AI parsing, API retrieval, and rendering time for each query. Considering the application has as main priority the transitional states between layers in an interactive map, the largest contentful pain, cumulative layout shifts, and interaction to next paint content were obtained from the application's testing environment, along with time lags from interaction once a query has been submitted to a particularly resources—in this case querying for datasets—with the results for each being satisfactory disregarding the user testing and interaction. These times fall within acceptable bounds for real-time exploration, especially with moderate data volumes as shown in Figure 14.

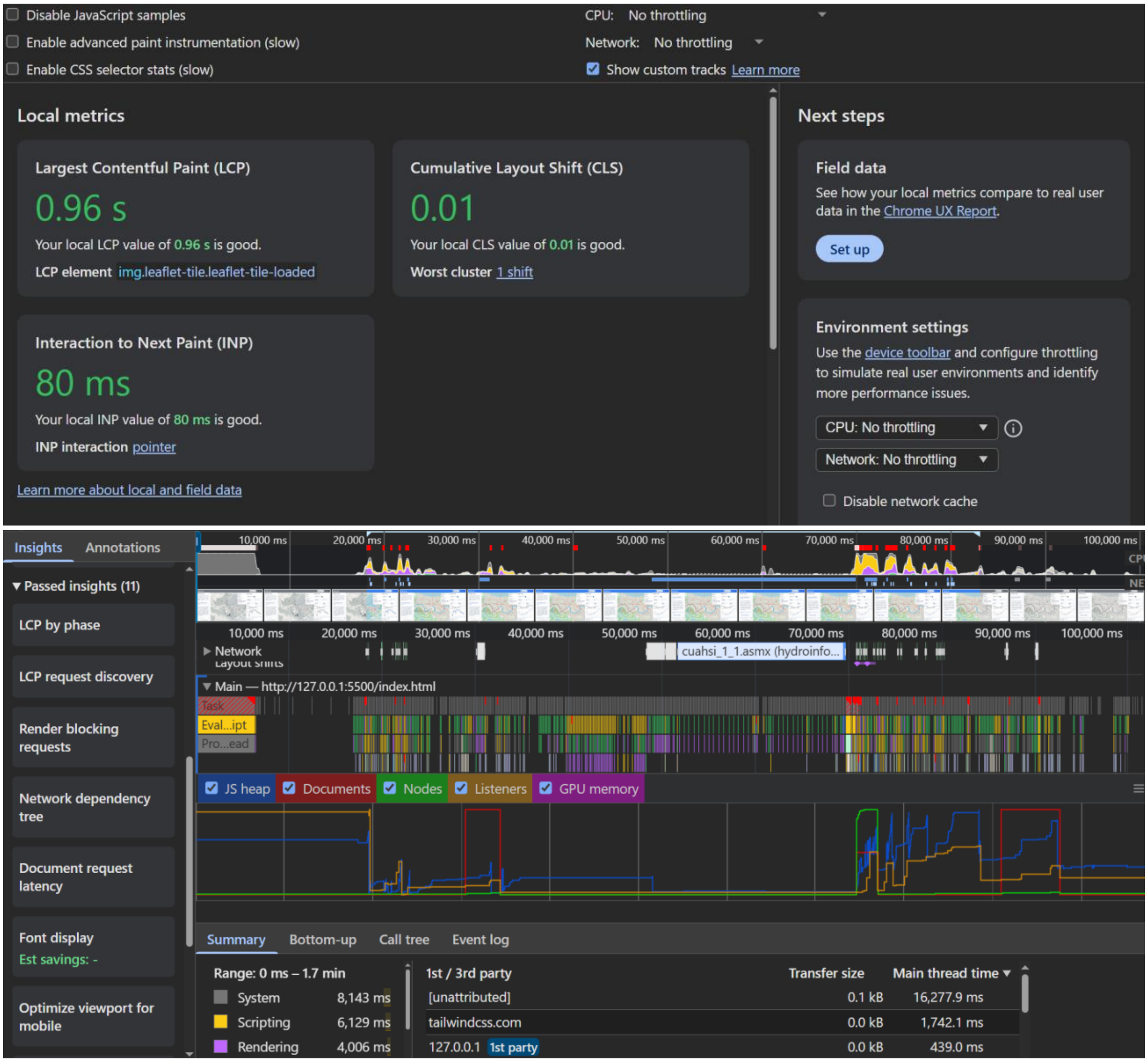



Figure 14. Evaluation metrics from Chrome developer tools showcasing the speed of the application upon data retrieval, rendering, and AI intent querying, with a snapshot of user interaction of 16 seconds. Bundling the application can optimize the sizing and speed of interaction further.

A qualitative comparison against equivalent manual workflows revealed substantial efficiency gains. For example, loading USGS stations, querying streamflow, and visualizing time series required 8–12 discrete steps via HydroLang scripts and UI components. The AI-guided interaction reduced this to 2–3 prompts with automatic execution. This represents a 3x–5x reduction in user effort, making the platform especially valuable for rapid prototyping and for users without programming expertise.

Table 2. Evaluation of the prompts provided to the system during the example session.

| Metric | Result |
|---|---|
| Command interpretation rate | 83% (with 17%) with correct execution and outputs. |
| Intent parsing | 5 of 30 failures due to semantic mismatch or paraphrased duplicates. Issues with domain resolution were observed |
| Parameter completeness | Spatial and temporal parameters correctly inferred from most queries. |
| Interaction consistency | States persistence throughout modalities. |
| Response latency (avg) | 2.5s AI parsing + 1.8–4.2s data fetch and responses 300-650 ms for AI response times and 800-1500 for visualization and data fetching updates. |
| Interaction consistency | Maintained spatial + analytical state. |
| Error recovery capability | Structured error messaging for out-of-coverage datasets or out of scope intents. |

These gains, however, depend on accurate function-to-intent mapping. In current implementation, unrecognized phrasing or missing verbs may prevent execution. To address this, future work will include training the underlying language model with annotated prompts and function mappings, as well as developing an internal prompt-function alignment schema. This effort will enhance both parsing accuracy and user experience, particularly in edge cases with unconventional phrasing or under-specified inputs.

## 4. Discussions

Modern browser technology, coupled with domain-aware language models and the HydroSuite family of libraries, can support the full cycle of hydrological analysis—from data discovery to map-based visualization. The exploratory session over the Mississippi River Delta confirms that the concept is feasible: the assistant interpreted plain-language requests, assembled the necessary API calls, ran HydroLang functions in the client, and updated the map and charts in a single, uninterrupted workflow. Users moved from a broad spatial query to layered analyses (flowlines, basin boundary, discharge retrieval, forecast overlay) without writing code or refreshing the page.

A central design decision is the strict separation between language understanding and numerical execution. By forcing every prompt be rewritten as a discrete intent label plus an explicit parameter set, the platform creates a machine-readable provenance record that can be replayed on any standard-compliant browser. This scheme preserves the transparency of script-based workflows while removing the need for users to edit code. In contrast to prompting only final outputs, the session log captures each intermediate response—API results, derived arrays, layer additions—so failed or contentious steps can be inspected in detail.

The conversational interface addresses a long-standing adoption barrier: many water-resources professionals understand the logic of hydrological calculations yet remain reluctant to install or maintain scripting environments. By routing prompts through three domain blocks—analysis, data, and mapping—the system narrows linguistic ambiguity while still accommodating terminology. The same routing logic is agnostic to subject matter; once a hydrologic module is registered, its functions become available through normal speech or text, whether the task involves streamflow, water quality, or remote-sensing composites. Local inference adds two practical advantages. First, sensitive prompts and proprietary datasets never leave the browser, meeting confidentiality requirements that preclude cloud processing. Second, the platform remains usable during network interruptions, provided the required data are cached.

### 2.5. Limitations and Future Work

Despite its demonstrated benefits and contributions, the platform has several areas where further development is needed. Dependency on explicit mappings between parsed intents and internal functions is crucial for evolving and improvement. As the diversity of queries increases, gaps in the function dictionary can result in unhandled inputs, particularly where synonyms, compound requests, or vague phrasing are used. To address this, future work will include the development of semi-automated tools to suggest new mappings based on interaction logs, including updating the already fine-tuned models with the latter examples.

A second major limitation is the reliance on third-party data sources whose availability, response time, and schema stability vary. These services are essential to many platform workflows but lie outside the control of the platform itself. Downtime, API changes, or inconsistencies in metadata can affect session reliability. Although basic error handling and normalization routines are in place, more sophisticated techniques are needed—such as version-aware schema validation and automated adapter updates—to ensure long-term robustness and reduce user-facing disruptions.

Performance remains an open area for improvement, especially for large-scale spatial queries and time series analyses. Running local models can be memory-intensive, the current 4 GB quantized models exceed the capacity of low-spec tablets. Although this is offloaded with the use of Open AI server sage, this comes with monetary cost. Planned distillation and optional GPU off-load are expected to reduce this footprint, but the trade-off is inherent to any on-device model. Moreover, as the platform runs entirely in the browser, memory and computational capacity for the application could be limited. Considering the broad potential of the application to grow as a tool for GIS dataset exploration and analysis, next steps will focus on offloading intensive tasks—such as raster reprojection, polygon clipping, or hydrological modeling—onto WebAssembly (WASM) modules. In particular, the integration of GDAL compiled to WASM is under active development, which will enable direct manipulation of raster and vector datasets (e.g., reprojecting, clipping, format conversion) within the browser environment.

## 5. Conclusions

This study describes a browser-native platform that unifies spatial exploration, hydrological computation, and conversational AI in a single workflow environment. The system shows that domain-aware intent parsing can drive full-fidelity hydrologic routines directly in the client, eliminating server-side code yet preserving the analytical breadth normally associated with desktop or cloud tools.

By translating every request into a deterministic JSON command, the platform couples ease of use with strict scientific reproducibility. Each parameter, data source, and intermediate result is captured in session context; replaying an analysis therefore reproduces bit-wise identical outputs across operating systems and network conditions. This provenance model satisfies FAIR principles without forcing users to manage scripts or notebooks.

The no-code interface lowers the entry barrier for practitioners who understand hydrology but not necessarily program. Prompts are mapped to fixed analysis, data, and mapping domains, allowing users to chain tasks—such as retrieving discharge records, computing a drought index, and rendering a flood map—through plain language while the platform resolves variables, units, and spatial references behind the scenes.

The architecture remains extensible, with new data adapters or analytical kernels dropping in by registering a target module and intent labels; no changes are required in the interaction layer. A lightweight fallback to an on-device language model preserves functionality during network outages and offers a privacy-first option: users can run the platform with local inference only, ensuring that prompts and datasets never leave the browser. This capability is crucial for organizations handling sensitive information and for field deployments where connectivity is limited. Local inference also reduces operating cost and keeps workflows reproducible because model weights, data, and command logs reside together.

Future work will broaden dataset coverage, optimize execution of larger complex datasets, and refine prompt guidance so that intent resolution remains accurate as the underlying libraries grows. These extensions aim to deliver a scalable, maintainable, and widely adoptable tool for hydrological research and decision support, advancing open, reproducible practice across environmental science.

**Software Availability**

| | |
|---|---|
| Name | HydroAI |
| Developers | Carlos Erazo Ramirez |
| Contact Information | https://hydroinformatics.uiowa.edu |
| Cost | Free |
| Software required | Web Browser |
| Program language | JavaScript, HTML, CSS |
| Platform Access | Access can be provided upon request |

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