# HydroSuite-AI: Facilitating Hydrological Research with LLM-Driven Code Assistance

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**Abstract**
In the hydrology and environmental domains, researchers often encounter complex hydrological models, evolving frameworks and libraries, and complex documentation, which necessitate both domain knowledge and coding expertise. This paper introduces HydroSuite-AI, a large language model-enhanced web application designed to address these challenges by integrating three open-source libraries: HydroLang, HydroCompute, and HydroRTC. HydroSuite-AI assists researchers by generating code snippets, providing an execution environment, and answering factual questions related to these libraries, thereby facilitating seamless integration into existing hydrological workflows. Through natural language processing and generative AI techniques, HydroSuite-AI aims to streamline analysis processes and improve user productivity. The effectiveness of the application is assessed through case studies and user feedback, demonstrating its potential to support hydrological research and education by offering an accessible and comprehensive platform for data analysis, code generation, and knowledge dissemination.

**Software Availability**

| | |
|---|---|
| Software Name | HydroSuite AI |
| Developers | Vinay Pursnani, Carlos Erazo |
| Contact information | https://hydroinformatics.uiowa.edu |
| Cost | Free |
| Software required | Web Browser |
| Program language | Python, JavaScript |
| Software Availability | https://hydroinformatics.uiowa.edu/lab/hydrosuite/ai/ |

**Keywords**: web systems, AI agents, HydroSuite, large language model, conversational AI

## 1. Introduction

Hydrological research is becoming increasingly complex due to sophisticated models (Krajewski et al., 2021) required to address pressing environmental challenges, extensive data analysis, and specialized libraries (Sit et al., 2021a) with limited or no documentation. Researchers often face steep learning curves, needing both domain expertise and advanced coding skills to effectively utilize hydrological tools. This dual demand can lead to significant delays and obstacles in conducting vital research, as time is spent not on the scientific inquiry itself but on mastering the necessary computational frameworks.

In parallel, the field of artificial intelligence (AI) has witnessed remarkable advancements, particularly with the emergence of Large Language Models (LLMs; Sajja et al., 2024). These models have demonstrated capabilities in natural language processing (NLP; Sermet and Demir, 2021) and code generation, offering potential solutions to reduce the technical barriers faced by hydrologists. By leveraging AI, there's an opportunity to streamline workflows, automate complex tasks, and enhance accessibility to modeling tools without requiring extensive programming expertise (Samuel et al., 2024a).

Given these challenges with hydrological modeling and opportunities with LLM and generative AI, we present HydroSuite-AI, an innovative AI-powered assistant designed specifically for the hydrology and environmental science domains. HydroSuite-AI integrates three open-source libraries—HydroLang, HydroCompute, and HydroRTC—into a unified platform that simplifies hydrological modeling and data analysis. The assistant enables users to generate code snippets, execute computations, and retrieve factual information through natural language queries. By offering an intuitive interface and leveraging AI technologies, HydroSuite-AI aims to enhance research productivity, foster innovation, and lower the entry barriers for researchers and practitioners in the field.

## 2. Background

### 2.1. Potential of LLMs in Hydrology Sector

Within the span of the last two years, LLMs are proving to be more than just text generators; tasks like sentimental analysis, which once required data collection, labeling, and model training, can now be accomplished by anyone using simple prompts generated by these LLMs. One particular model that is a controversial leader is OpenAI's GPT series, has been pushing the capabilities of AI by streamlining complex workflows by combining the power of language patterns, probability of tokens, and sensible prediction, leading to the mining of valuable insights, from extensive datasets, a task that now can be performed providing simple prompts (Vogel et al., 2023; Gartlehner et al., 2024; Douglas et al., 2023).

In particular, the field of hydrology can benefit from the usage of AI, including LLMs (Pursnani et al., 2023), which can address various challenges within physical processes. Recent studies highlight the effectiveness of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, in achieving state-of-the-art hydrologic forecasts. These models leverage historical data to predict water flow and quality, thus enhancing the accuracy of hydrological predictions (Kadiyala et al., 2024; Kratzert et al., 2018). The application of LLMs in developing conversational agents can significantly improve communication and education regarding water quality issues, fostering greater public awareness and involvement in environmental science (Samuel et al., 2024b).

Examples of automation of complex workflows are analysis flood map images (Kadiyala et al., 2024; Li et al., 2023), time series for seasonal decompositions and early trend detection for decision-making in tasks such as watershed management (Mosavi et al., 2018; Kumar, et. al. 2023; Shahid et al., 2023) and perform nutrient analysis and prediction of critical masses (Herath et. al. 2023), among other tasks. Moreover, the advancements in AI-driven flood early warning systems (FEWS; Baydaroglu et al., 2023) further illustrate the transformative potential of these technologies. According to Perera et al. (2020), recent developments in AI, remote sensing, and information technologies have significantly enhanced the capabilities of FEWS, enabling more accurate and timely flood predictions (Sit et al., 2021b). This is particularly important in developing countries, where the sophistication of these systems lag in comparison to those in developed countries.

### 2.2. Related Work

LLMs are being heavily used in software development, which has begun a significant change in how coding and task executions are approached, with tools like GitHub Copilot and AWS CodeWhisperer leading this transformation (Yeo et al., 2024). LLMs, such as OpenAI's Codex and DeepMind's AlphaCode, have advanced in their capabilities of generating human-like code with assistive comments, thereby enhancing productivity in contrast to traditional software engineering processes (Wong et al., 2023). For instance, the introduction of Pythia, an end-to-end system that generates ranked lists of methods and API recommendations for software developers during coding, represents a substantial advancement in workflow deployment. Incorporated within the Intellicode extension for Visual Studio Code IDE, Pythia leverages state-of-the-art large-scale deep learning models trained on code contexts derived from abstract syntax trees.

The ability of these models to understand and generate code from natural language prompts allows for a more intuitive interaction between developers and coding tools, making programming more accessible, especially for those with limited experience. This shift in how many processes are conducted is seen across domains simply because of the speed and efficiency of these LLMs. Domains such as healthcare, where drafting patient response and replying to messages is now conducted by generative artificial intelligence (GAI), which is a superdomain of LLMs (Tai-Seale et al., 2024). In their study, Huespe et al. (2023) evaluated the efficacy of GPT-3.5 in generating the background section of a medical research article on acute kidney injury in sepsis, comparing it to contributions from researchers with H-indices of 22 and 13.

The authors found that GPT-3.5's contributions were highly rated, scoring similarly or better than the human-written sections. Surprisingly, the researchers participating in the study struggled to distinguish between AI-generated and human-generated texts, suggesting that GPT-3.5 can produce scientific writing indistinguishable from that of experienced researchers (Huespe et al., 2023). In finance, there have been positive impacts on businesses' financial decisions where GAI is involved (Akour et al., 2024). However, research indicates that while LLMs can produce high-quality outputs, there are instances where the generated result may contain errors or security vulnerabilities, particularly when the training data includes flawed or unsafe code (Pan, 2024; Improta, 2023).

To address these shortcomings, Retrieval Augmented Generation (RAG) is proving to be an effective approach. With RAG, data external to the LLM is used to augment prompts by adding relevant retrieved data in the context. This allows for integrating disparate data sources and the complete separation of data sources from the machine learning model entirely (Vogel, 2023). The self-attention mechanism, introduced in the Transformer architecture, allows LLMs to weigh the importance of different tokens within the context window. This capability enables models to understand relationships and dependencies between words, which is essential for tasks requiring deep comprehension of language (Vaswani et al., 2017).

Research indicates that a context window of up to 128K tokens–units of text understood by a model–significantly enhances the capabilities of LLMs, enabling them to perform tasks that were previously unattainable (Song et al., 2023). The use of these new technologies along with programming library documentation enables efficient code generation and enhances developer productivity. OpenAI's Codex and ChatGPT LLMs have been trained on extensive datasets that include both natural language and programming code, allowing them to understand and generate code based on user specifications and contextual information (Le, 2024; Zhong, 2024). This capability is particularly beneficial in scenarios where developers require assistance in writing code that adheres to specific libraries or frameworks, as LLMs can interpret and incorporate the nuances of library documentation into their generated code (Zhong, 2024; Liu, 2024).

Utilizing responses whether factual or code-like from AI is an active area of research due to the several nuances accrued to the responses. An example is Fang et al. (2024), which offers a comprehensive analysis of the phenomenon of "hallucinations" in LLMs used for code generation. The authors define hallucinations as instances where the generated code deviates from the user's intent, factual knowledge, or the code's context. The study's main contribution lies in the development of a taxonomy that categorizes hallucinations into five primary categories and 19 specific types, providing a structured framework for understanding the various ways LLMs can produce unexpected and potentially incorrect responses. The research also highlights the challenges LLMs face in recognizing and mitigating these hallucinations, even with advanced prompting techniques.

## 3. Methodology

Throughout this section, we are addressing the need for usage of LLMs technologies as previously outlined, including chatbots and interfaces for easier workflow integration, within the hydrology domain through the use of state-of-the-art libraries and applications for web development.

### 3.1. Scope and Purpose

HydroSuite-AI is designed to meet the operational needs of hydrologists and environmental researchers. HydroSuite-AI integrates well-known open-source software libraries, HydroLang, HydroCompute, and HydroRTC, into a unified question-answering platform, enhancing research productivity by generating context-informed code snippets, answering factual questions, and fitting into existing workflows. This paper explores the framework's architectural foundation, specific functionalities, and the tangible benefits it offers through case studies and user interactions. The development was guided by several key research questions:

RQ1. Can LLM-powered assistants generate code snippets that easily integrate with user workflows?

RQ2. Can AI assistants accurately answer factual questions regarding complex and evolving software library documentation?

RQ3. Can AI assistants provide contextually relevant and comprehensive responses to multifaceted and advanced hydrological queries?

RQ4. Does the implementation improve interoperability across various data formats, models, and tools prevalent in hydrology?

### 3.2. Overview of HydroSuite Libraries

HydroSuite is a state-of-the-art collection of web-based libraries designed for hydrology and environmental domains, leveraging open-source scalable architectures accessible directly through web browsers. The libraries within HydroSuite promote hydrologic data democratization and analysis by addressing key aspects including data management, scientific computing, communication, and community portals. The primary goal is to provide the ability to create end-to-end workflows through efficient data integration, whether by acquisition or dissemination, fostering collaboration, knowledge sharing, and innovation.

Key libraries and applications in HydroSuite include HydroLang, HydroCompute, and HydroRTC. HydroLang is a robust modular library offering a variety of tools for statistical and hydrologic analysis, modeling, and spatiotemporal analysis. It also includes visualization capabilities, such as maps, charts, and tables, and connects to global data sources (Erazo Ramirez et al., 2022). Expansions like HydroLang-ML (Erazo Ramirez et al., 2023) and HydroLang-BMI (Ewing et al., 2024) further enhance data democratization and cater to a broader user base.

HydroCompute is a high-performance computing library utilizing modern web technologies to support multithreading on the client side, optimizing resource use on the client devices. It includes web support for languages such as C, C++, WebGPU, AssemblyScript, JavaScript and leverages algorithmic optimizations to achieve efficient, low-level computing (Erazo Ramirez et al., 2024a). Lastly, HydroRTC is a library that facilitates large-scale data sharing and transfer between peers and servers through decentralized WebRTC and WebSocket technologies. It enables efficient transmission, streaming, and task allocation for complex data formats like NetCDF, GRIB, and HDF5, commonly used in the hydrologic domain (Erazo Ramirez et al., 2024b). All the libraries referenced in this manuscript come with comprehensive documentation, case studies, and publicly accessible self-guided training materials.

### 3.3. HydroSuite AI Architecture

HydroSuite-AI is a comprehensive AI-powered assistant that provides intelligent assistance for handling factual queries and executing code, trained using the HydroSuite libraries (Figure 1). The system is represented by four main modules as shown in the figure: External Libraries, HydroSuite UI, Data Sources, and HydroSuite Core. When a user submits a request, the Streamlit UI captures the query and hands it off to the Flask-managed backend. Flask determines if the query is seeking factual information or requires code execution. Regardless of the type, the query is transformed into vector embeddings and compared against the indexed documentation in the vector store, identifying the 20 most relevant results to provide context.

Leveraging OpenAI's API, a response is crafted based on these search results and the provided context. For factual queries, a clear textual response is generated. For code execution queries, relevant code snippets are assembled, converted into executable files, and processed within the Sandbox API to produce results. Finally, the results are presented to the user. Factual results are displayed as text or formatted content, while execution results are shown alongside interactive sandboxes for further exploration and refinement. The features within HydroSuite-AI are the following:

***Factual Question**:* Users can ask hydrology-related questions, and the AI provides accurate, easy-to-understand responses using its extensive knowledge base.

***Code Execution**:* Users can request code snippets for hydrological tasks. HydroSuite-AI generates the required code, executes it, and presents the results. It also supports sandbox environments for interactive exploration.

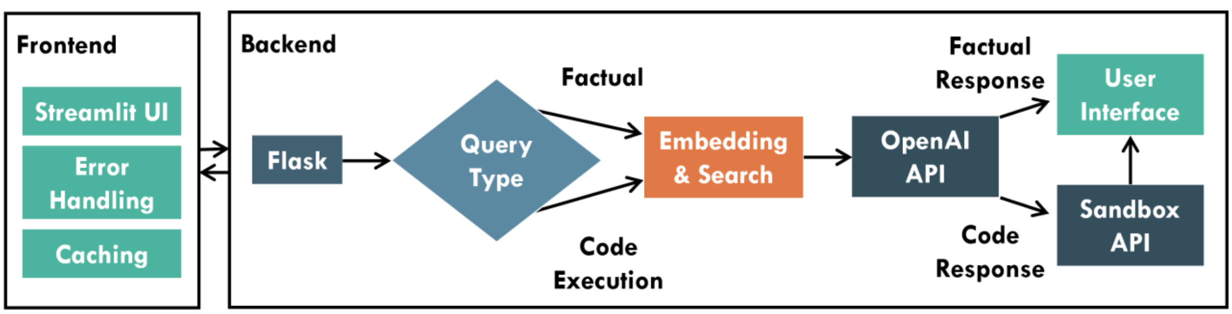


Figure 1: HydroSuite-AI system architecture and components

***Large Language Model:*** GPT-4o, is a powerful language model introduced by OpenAI, with the ability to handle multiple languages and process various types of data like text, images, and audio. It features a 128k token context window, enabling it to understand and generate extensive and complex responses, proving particularly beneficial for applications that require handling large amounts of data. Its knowledge base is reliant on the data it was trained on, which has a specific cutoff date. This means it might not have information about recent developments in certain areas, particularly specialized libraries and rapidly evolving documentation. So, while it's a strong tool for many tasks, it's important to be aware of its knowledge boundaries and use it judiciously, especially when dealing with information that might be very recent or highly specialized.

***OpenAI's Assistant API and Vector Store:*** The Assistant API and Vector Store provide significant advantages, particularly when equipped with advanced capabilities such as those found in AI Assistant Version 2. A large context window, like the one in GPT-4o, enhances these features. Query embedding involves the assistant understanding the meaning and intent behind a user's query, translating it into a format the model can process. This is achieved using an embedding model at 256 dimensions with default settings of chunk size of 800 tokens, chunk overlap of 400 tokens, and a maximum number of chunks added to context as 20.

For vector store search, vector embeddings are created from the documentation of the libraries within HydroSuite (Figure 2). When a query is made, the system leverages advanced vector search to return the most relevant results. In context retrieval, the assistant extracts the most pertinent information from the large context window populated with relevant vector store document chunks, ensuring that the model's response is directly relevant to the current conversation or task. Finally, instruction understanding allows the assistant to comprehend and execute a set of instructions (Table 1), enabling it to complete complex, multi-step tasks using the provided context.

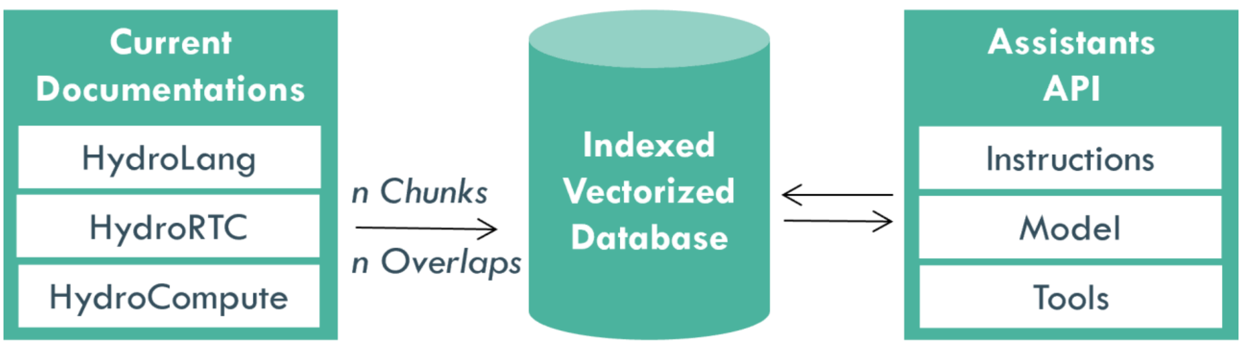


Figure 2: API setup with vectorized knowledge base, database and assistant APIs

***Streamlit User Interface:*** The user interface built using Streamlit allows users to interact with HydroSuite-AI easily. Users can input their queries, whether they pertain to factual questions or code execution, and interact with results directly through the UI. Streamlit's dynamic capabilities ensure that the interface can handle multiple tasks concurrently.

***Sandbox Environment:*** The Sandbox API executes the user-requested code securely within an isolated environment. This approach mitigates risks associated with running arbitrary code, providing a secure and reliable execution space while allowing users to validate and interact with code results directly.

***Flask Backend:*** HydroSuite-AI's backend is built using Flask, enabling efficient handling of user requests and interaction with the OpenAI API. The frontend utilizes Streamlit for a dynamic and user-friendly interface, allowing users to select task types, input queries, and view detailed responses and execution results.

Table 1: Instruction set given to assistant APIs

You are an expert at using Hydrolang/HydroCompute/HydroRTC
Analyze the user's message. Their message typically consists of:
**User Message:** The specific details of their question or code-related task.
The response should always be based on the information in your context window.
our typical response will depend on the identified task type:
**Factual Question:** Provide a direct answer to their question.
**Code Execution:** Return a JSON response that intelligently includes:

- **"code_file_name":** A relevant and descriptive name for the code file.
- **"code_file_content":** The appropriate code to address the user's query.
  the code should be generated for the HydroLang/HydroRTC/HydroCompute library.

**For Example:**
**Example 1:**
**Task Type:** Code Execution and User Message: How do I retrieve and visualize daily water data from USGS using the HydroLang library in a web application?
Your response should only contain:

```
[
    {
        "file_name": "main.js",
        "file_content": "#Code for Visual Data Retrieval"
    },
]
```

This is just an example but if a user asks a complex query you are going to decide how many files need to be generated and what code they have in the file. Feel free to ask users some more questions if the codebase requires you to populate some variables that you do not have in the user message already.

### 3.4. Case Study

To test the system's capabilities, we conducted a qualitative evaluation of various prompts and, based on the responses, assigned a rating from 1 to 5, with 1 indicating an unhelpful response and 5 indicating a correct answer to the question. Additionally, we utilized the hallucination taxonomy described by Liu et al. 2024, directly identifying which descriptions accurately addressed the question. The categorical error groups are as follows: [1] "Intent Conflicting"; [2] "Context Deviation," which includes subcategories such as [2][1] "Inconsistency", [2][2] "Repetition", and [2][3] "Dead Code," where the system's response diverges from the user's query context or includes non-functional code; and [3] "Knowledge Conflicting," which includes [3][1] "API Knowledge" and [3][2] "Identifier Knowledge," where the response conflicts with known facts or library documentation, or misapplies API functionalities or identifiers. We also categorized the questions based on their complexity. For instance, a question might ask to connect multiple data providers to create an application, or it could be a simpler question about a specific library module. The complexity was classified as: A - Low complexity, B - Medium complexity, and C - High complexity.

Answers in category A were straightforward regarding where the system was retrieving information. For example, basic questions like "What is a library and how is it used?" should be addressed by information already available in the library's documentation, which the system can easily access. Categories B and C, however, involved more complex coding tasks. For instance, asking how to translate code from one programming language to another and adapt it for real data usage requires navigating multiple pathways that could lead to the same solution. However, the system might not necessarily follow the approach outlined in the library's documentation. Therefore, assessing the tool became a matter of evaluating whether the solution provided enough information drawn from the material used during the system's development or whether it relied on external sources from the general training data.

## 4. Results and Discussions

### 4.1. Features and Functionality

The core features and functionality of the proposed system is outlined as follows. It is designed to support hydrological research through the integration of key libraries such as HydroLang, HydroRTC, and HydroCompute. The interface is structured to facilitate user engagement by providing clear navigation options and functionalities tailored to specific hydrological tasks. As shown in Figure 3, users can easily access different modules, each designed to address distinct aspects of hydrological analysis and data processing.

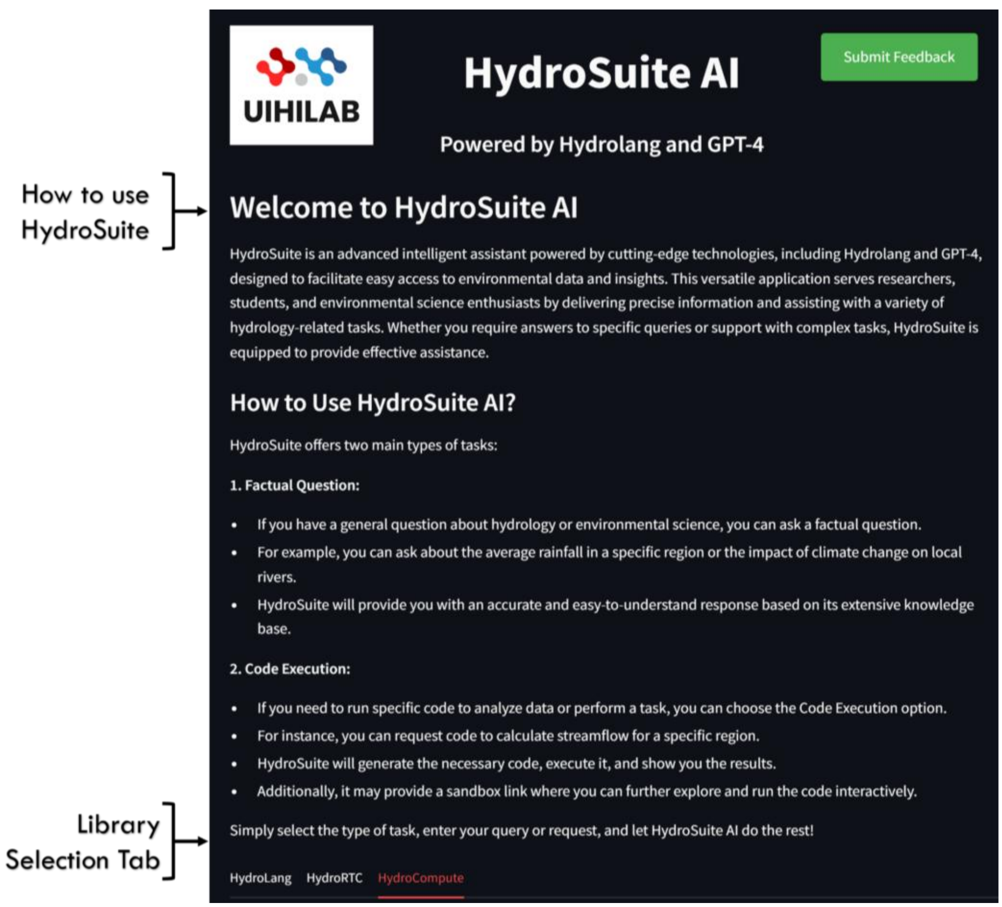


Figure 3: Landing page of the HydroSuite AI-Assistant with instructions

The "Factual Question" task type allows users to explore detailed information related to hydrology and environmental science. This functionality is supported by the system's ability to process complex queries and retrieve accurate information from its extensive knowledge base. As illustrated in Figure 4, when a user inquiries about "HydroCompute," the system delivers a comprehensive explanation highlighting its features and applications. This capability underscores HydroSuite-AI's effectiveness in providing contextually relevant and precise responses, drawing from its indexed documentation and resources.

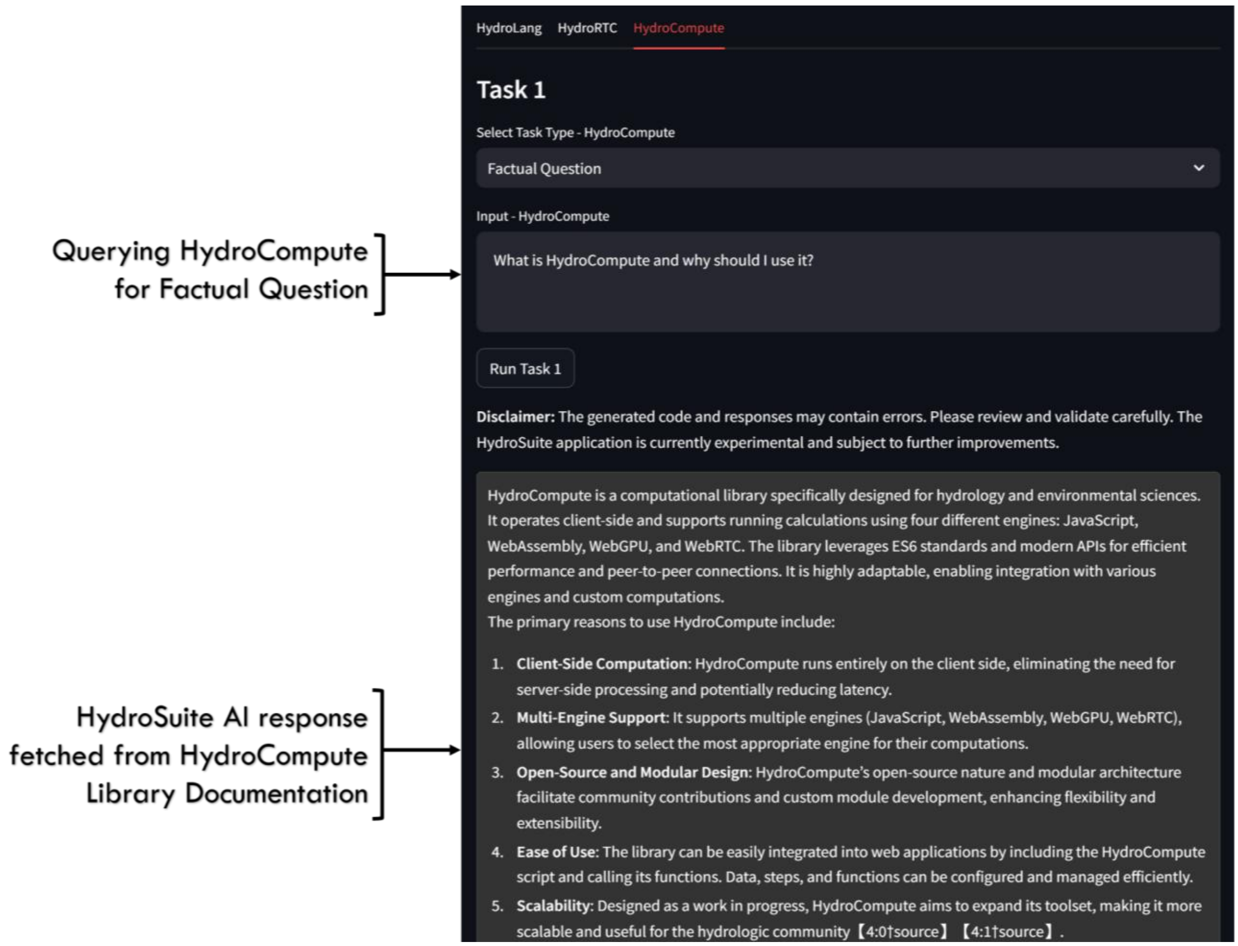

Figure 4: Task execution interface for a selected library, HydroCompute with instructions

The "Code Execution" option enables users to request specific code solutions tailored to their hydrological data processing needs. For example, a user might request code to "fetch and plot USGS Daily values with site ID 10010000 for year 2022." As depicted in Figure 5, HydroSuite-AI generates the necessary code and offers an interactive environment for execution. This process illustrates the system's proficiency in not only generating code snippets but also facilitating their practical application through an integrated sandbox tool, which supports various programming languages and libraries.

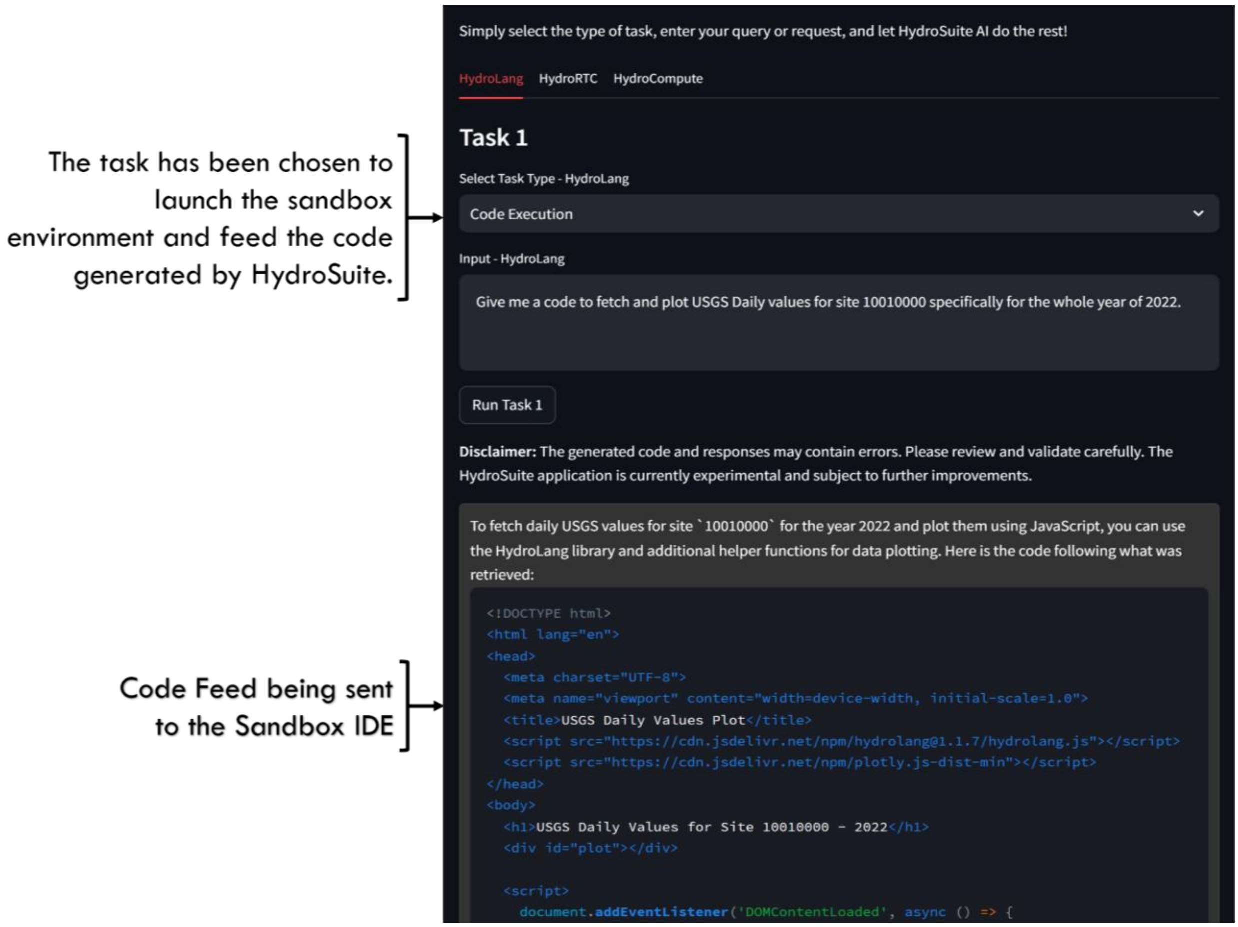


Figure 5: Code generation and interpretation interface for HydroLang with sample output

The sandbox environment allows users to execute the generated code. In Figure 6, the system displays a JavaScript code snippet aimed at performing basic data manipulation using HydroLang. Users can interactively run, edit, and explore the code within this secure, isolated environment. The interactive sandbox environment is an essential feature for testing and validating code snippets. Users can visualize immediate outputs, make modifications, and re-run the code, enhancing their understanding and facilitating better learning through hands-on practice. The interface incorporates dynamic UI elements, ensuring a smooth and responsive user experience. Comprehensive documentation and example-based learning are integrated within the platform, guiding users through their tasks. Moreover, users can provide feedback on the generated code snippets and responses, enabling continuous improvements to the AI's performance and the overall user experience. This iterative feedback loop is crucial for adapting the system to meet the evolving needs of its users.

## 4.2. Expert Assessment

For both HydroLang (Table 2) and HydroCompute (Table 3), four questions of varying complexity were tested for each. Throughout these evaluations, a clear pattern emerged, indicating that the system tended to hallucinate when more examples were needed in the training datasets. In terms of context, the main issue with code generation was the system's difficulty in following patterns, especially when several library implementations required clear decisions to make sense of their usage. However, the system was able to accurately retrieve and comprehend information from the trained materials for each library, utilizing the pre-context from the GPT training system to incorporate other important features not explicitly mentioned in the libraries. The prompts given by the HydroSuite-AI are found in the supplementary materials of this manuscript.

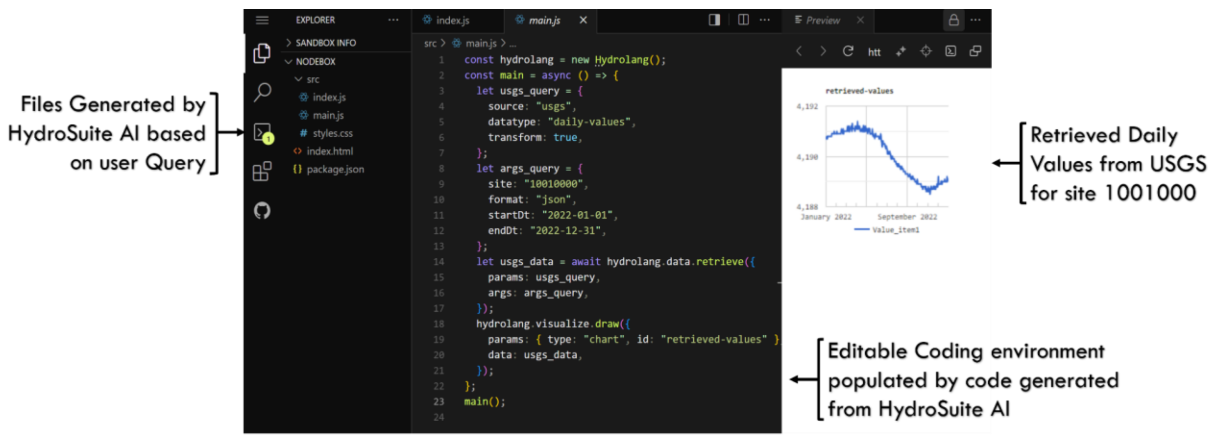


Figure 6: Code sandbox with editable coding environment and user query and results

Table 2: HydroLang evaluation results with question text, score and error

| Question Text | Type & Complexity | Expert Score | Categorical Error | Description and Reasoning | Possible Corrections |
|---|---|---|---|---|---|
| What is HydroLang and how is it used? | Factual & A | 5 | None | Correctly prompts the input based on what's asked. | None required. |
| What are the different data sources available through HydroLang? | Factual & B | 3 | ***[3]***<br>***[3][1]*** | The response fails to capture several data sources available within the library. | Retrain the model with comprehensive data source examples. |
| How do I put a map in HydroLang and connect to a USGS station | Code & C | 3 | ***[3]***<br>***[3][2]*** | The bot generates map code correctly but struggles with connecting to external data sources linked to other modules. | Provide more examples on linking data sources and modules. |
| Write code for retrieving data using HydroLang retrieve function using the WaterOneFlow datasource and the GetSitesByBoxObject datatype for the USGS in the box east: -111.38, west: -112.46, north: 41.07, south: 40.19 for the USGS Unit Values | Code & C | 2 | ***[2]***<br>***[2][3]***<br>***[3]***<br>***[3][1]***<br>***[3][2]*** | Correctly uses functions for data retrieval but shows issues in parameter descriptions. | Train the system with new examples and updated library releases. |

Table 3: HydroCompute evaluation results with question text, score and error

| Question Text | Type & Complexity | Expert Score | Categorical Error | Description and Reasoning | Possible Corrections |
|---|---|---|---|---|---|
| What is HydroCompute and how do I use it? | Factual & A | 5 | None | Correctly prompts the input based on what's asked | None required. |
| How can I create a new set of functions in C so I can use them within HydroCompute? | Factual & C | 2 | ***[2] [2][1] [3] [3][1]*** | The first part of the question was correctly answered. However, the second part in porting code into the HydroCompute uses a separate way of integrating code. | Provide more detailed examples of code integration to avoid inconsistencies and improve API knowledge. |
| Given the existing examples for function running within the HydroCompute WASM module, how can I create a MonteCarlo-ARIMA model with real data using the library? | Code & C | 5 | None | Correctly assesses the process for generating code using the existing functions from the available library within HydroCompute. Generic solutions are given instead of direct examples. | Improvement with the use of more specific examples during training could enhance the answer. |
| Write code that shows how I can retrieve data using HydroLang from USGS at a streamflow station obtaining data from 100 years of daily hourly streamflow creating simple moving average from HydroCompute JS functions and display the results in a graph. | Code & C | 3 | ***[2] [2][1] [3] [3][1]*** | The code generated was correct in the call for HydroLang and partially correct for HydroCompute, particularly in using existing functionalities. Code would work but lacks extensibility. | More specific prompts and examples on particular uses for the modules would ensure the generation of semantically correct code. |

### 4.3. User Testing and Feedback

In July-August 2024, HydroSuite-AI along with the libraries that the application has been trained with was showcased and utilized at the WaterSoftHack 2024 (WaterSoftHack, 2024), a 3-year NSF project held online on a 2-week hackathon style aiming to provide practitioners–students, researchers, and educators–within the hydrology and environmental sciences with technological tools for data analytics, cyberinfrastructure, and machine learning capabilities. The event drew participants from hydrological departments and universities across the world managed by Clemson University, The University of Iowa, and CUAHSI. During the event, users were trained in the development of web technologies using the aforementioned libraries. The HydroSuite-AI was used as a helper to provide students with a resource that understands and can answer questions regarding the libraries.

Qualitative feedback from participants highlighted the ease with which they could access relevant documentation on the libraries, as well as the ability to create applications using features from the projects. Additionally, the AI bot proved useful in answering both factual questions and generating code. However, participants also noted the need for improved documentation on some of the libraries' features–though this cannot be attributed to the LLM-trained itself, which performed as expected. Overall, participants expressed positive feedback on the usability of the libraries, particularly in terms of developing web applications, integration features, and addressing challenges such as database connections, data source integrations, and visualization options.

In regard to challenges and limitations of the proposed framework, The AI assistant's dependency on the quality and scope of its training data poses limitations. Since HydroSuite-AI is trained primarily on the documentation of the focus libraries, its ability to assist with queries related to other tools, libraries, or the latest advancements not included in the training data is restricted. This narrow focus may limit the assistant's utility for users who require a more comprehensive toolset. Additionally, the current configuration of embedding dimensions (e.g., 256 dimensions for vector embeddings) may not be optimal for capturing the full complexity of hydrological data and queries. Increasing the embedding dimensions could improve search accuracy and result relevance but may also demand more computational power and storage, impacting scalability.

HydroSuite-AI's effectiveness is heavily reliant on the accuracy of the underlying documentation of the HydroSuite libraries. Maintaining synchronization between the libraries' developments and the assistant's training data is a continuous challenge that requires dedicated resources. Failure to keep the assistant updated can lead to outdated or incorrect responses, diminishing user trust and the tool's overall utility. Feedback from user evaluations highlighted the need for improved documentation and support materials to facilitate effective use.

The current implementation has seen improvements in the search functionality for common workflows in hydrological research with HydroSuite. The use of an interactive platform provides added benefits for hands-on learning and offers a deeper understanding of the hydrological processes. However, there are limitations including the assistant API's default configurations and the lack of micromanagement for tasks such as fine-tuning. This could limit the search accuracy, and may need improvement in areas like embedding dimensions, currently set at 256. A higher-value increase could potentially offer better search output. Within the realm of possible improvements lie models like CodeGen, StarCoder, WizardCoder, CodeT5, and Incoder (Idrisov and Schlippe, 2024). Employing these models may significantly enhance the effectiveness and fine-tune the accuracy of the search in this context, which borrows heavily from the precision required in coding and programming languages.

To ensure the successful adoption of the system within the hydrological research and education communities, several key steps must be taken. The need for enhanced documentation with expanded examples and use cases is vital for users to understand the functionalities, proper usage, and potential of HydroSuite-AI, highlighting the need of keeping track of changes and improvements on the libraries used for training to ensure continuous adoption of new features. From the libraries' standpoint, this means the development of comprehensive user guides, providing annotated code examples, implementing an update mechanism for documentation, and sharing real-world case studies.

Allowing community contributions is crucial for improving the user experience and adoption rate. This involves establishing multiple support channels and encouraging the hydrological research community to contribute their own examples and use cases within the trained libraries. Educational initiatives including organizing workshops and webinars, partnering with academic institutions to integrate HydroSuite and the AI into hydrology-related curricula, and developing certification programs, will allow a growth in the usage of the libraries and expand based on the needs of the community.

### 4.4. Discussions of Research Questions

The study was guided by several key research questions, and the results obtained from the HydroSuite-AI evaluations provide insights into these questions. Regarding RQ1, the results from the code generation and execution tasks indicate that HydroSuite-AI can generate code snippets that integrate well with user workflows, especially for straightforward tasks. For instance, the system accurately generated JavaScript code for retrieving and plotting USGS daily values, which executed correctly within the provided sandbox environment (Figure 6). However, for more complex tasks, such as integrating multiple libraries or data sources, the system exhibited some limitations, including occasional hallucinations and incomplete parameter descriptions. This suggests that while the assistant is effective for simpler tasks, there is room for improvement in handling more complex integrations. Expert assessments also highlighted the need for more comprehensive training data and examples to enhance the system's performance in generating complex code snippets.

In regard to RQ2, HydroSuite-AI demonstrated a strong capability in answering factual questions accurately. For example, when asked "What is HydroLang and how is it used?", the system provided a detailed and accurate description based on its indexed documentation (Table 2). This indicates that the assistant can effectively utilize NLP and information retrieval techniques to provide accurate and contextually relevant responses. However, the accuracy of responses decreased slightly for more complex queries, highlighting the need for continuous updates and improvements in the underlying documentation and training data to ensure the system remains current with evolving library features.

In discussion of RQ3, the system's performance in addressing multifaceted and advanced hydrological queries was mixed. While it excelled in generating accurate responses for simpler queries, such as describing library functionalities and providing basic code snippets, it struggled with more complex requests. For instance, in the case of creating a MonteCarlo-ARIMA model with real data using HydroCompute, the system provided a generic solution rather than a direct example (Table 3). This suggests that while the assistant can offer valuable insights and starting points, it may require further refinement and additional training data to provide fully comprehensive responses to advanced queries.

Finally, HydroSuite-AI's integration of HydroLang, HydroCompute, and HydroRTC into a unified platform shows promise in improving interoperability across various data formats and tools in response to RQ4. The system's ability to generate code snippets that utilize these libraries demonstrates its potential to streamline workflows and facilitate the integration of different data sources and models. However, the expert assessments revealed that the system sometimes struggled with connecting external data sources and integrating multiple modules seamlessly. This indicates that while the implementation has made significant strides in improving interoperability, further enhancements are needed to fully realize its potential in handling diverse and complex hydrological data and tools.

## 5. Conclusion and Future Work

HydroSuite-AI represents a significant advancement in hydrological research by providing a specialized AI-powered platform tailored to the needs of hydrologists and environmental scientists. By integrating open-source libraries like HydroLang, HydroCompute, and HydroRTC, HydroSuite-AI offers a unified environment that simplifies complex hydrological workflows. This integration allows researchers to generate code snippets, execute computations, and retrieve factual information efficiently, thereby reducing the time and expertise required to harness advanced hydrological tools. The feedback from user evaluations and the deployment during events like WaterSoftHack 2024 showcase its practicality and effectiveness in real-world usage. HydroSuite-AI enhances productivity, fosters innovation, and can help transform both research and education in hydrology by making advanced computational tools more accessible to a broader audience.

To further enhance the system's capabilities and broaden its impact, future efforts will focus on expanding and updating the knowledge base to include additional hydrological libraries and the latest advancements in the field. Incorporating more sophisticated language models could improve code generation accuracy and expand the range of supported programming languages and frameworks. Improving the vector embedding dimensions and fine-tuning the assistant's configurations may also lead to better search outputs and handling of complex queries. Developing comprehensive documentation, including detailed tutorials and diverse use cases, will help users of varying technical backgrounds to navigate and maximize the platform's features. Encouraging community engagement through contributions, feedback, and collaborative projects can help create a supportive ecosystem. Exploring interoperability with other commonly used hydrological tools and integrating cloud-based computing resources could further extend HydroSuite-AI's utility and adoption across the research community.

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## 7. Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT to improve the flow of the text, correct any potential grammatical errors, and improve the writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## 8. CRediT author statement

**Vinay Pursnani**: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, and Visualization. **Carlos Erazo**: Methodology, Validation, Formal analysis, Writing - Original Draft **Yusuf Sermet**: Conceptualization, Methodology, Writing - Review & Editing, Investigation, Validation, and Visualization. **Ibrahim Demir**: Conceptualization, Methodology, Writing - Review & Editing, Project administration, Supervision, Funding acquisition, and Resources.

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