HydroBlox: AI-Assisted Visual Programming Framework for Enhanced Scientific Reproducibility in Hydrology

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Abstract

Scientific workflow reproducibility for hydrological and environmental analyses remains a challenge due to the heterogeneity of data sources, analysis protocols, and evolving visualization needs. This study introduces HydroBlox, a client-side browser-based framework that supports the creation, execution, and export of hydrological workflows using a visual programming interface. The platform integrates modular web libraries to perform data retrieval, statistical analysis, and visualization directly in the browser. Two case studies are presented in the study includes analyzing precipitation-streamflow response relationships in the Iowa River Basin and computing the Standardized Precipitation Index using a WebAssembly-enhanced drought analysis workflow. Results demonstrate the system's capacity to facilitate reproducible, portable, and extensible hydrological analyses across spatial and temporal scales. The study discusses the architecture, implementation, and capabilities of the system and explores its implications for collaborative research, education, and low-code scientific computing in hydrology.

Software Availability

Name	HydroBlox
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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1. Introduction

Reproducibility of scientific process is a cornerstone of scholarly progress and yet it remains a persistent challenge in hydrological modeling studies (Gil et al., 2016; Stagge et al., 2019). The complexity of hydrological systems—spanning diverse spatial scales, forcing mechanisms, and land-atmosphere interactions—requires flexible, yet standardized workflows to ensure transparency and repeatability in research outcomes (Ewing et al., 2024). As hydrological science increasingly adopts computational methods, the ability to design, execute, and reproduce workflows has emerged as a key criterion for scientific credibility (Hutton et al., 2016; Hut et al., 2022).

Computational reproducibility in hydrology is often hindered by fragmented toolchains, proprietary software dependencies, and undocumented data processing steps. Ruiz-Pérez et al. (2016) and Essawy et al. (2018) highlight that the lack of open, shareable workflows impedes the replication of published results, limiting trust in analysis outcomes and model predictions. Calls for formalized workflows and open-source tooling have grown, emphasizing the need for platforms that support consistent execution, metadata preservation, and collaborative extension.

In parallel, advances in user-interface design and web technologies have created new opportunities for lowering the barrier to entry in environmental modeling. Visual programming languages (VPLs), such as those implemented in educational tools and embedded systems, enable users to construct logical workflows through block-based or diagrammatic interfaces without writing code (Kuhail et al., 2021). Within hydrology, such paradigms hold promise for empowering researchers, educators, and practitioners to build and share analyses without extensive software training (Finkenbiner & Semmendinger, 2021).

Despite the availability of platforms that promote reproducibility—such as HydroShare (Tarboton et al., 2014), HydroBench (Morges et al., 2022), and Jupyter-based environments—these systems often require local runtime environments, backend infrastructure, or scripting proficiency. There is currently a lack of browser-native, modular tools that enable fully visual workflow development, execution, and export within the client-side context. This limitation constrains accessibility, especially in educational or field-based settings.

This paper introduces HydroBlox, a web-based visual programming framework that addresses this gap. Built entirely on open web technologies, HydroBlox enables users to construct hydrological workflows using modular blocks (aka "Blox") representing data acquisition, analysis, and visualization tasks. The system integrates existing libraries supporting end-to-end reproducibility, client-side execution, and export for offline usage. We detail the system's architecture and demonstrate its application through two comprehensive case studies on streamflow response analysis and drought assessment using Standardized Precipitation Index (SPI). In doing so, we aim to contribute to the growing body of work advocating for open, modular, and reproducible computing while introducing a flexible interface that broadens participation in model-based environmental research.

2. Background and Related Work

2.1. Reproducibility and Open Workflows in Hydrology

Reproducibility remains a central challenge in computational hydrology. Despite widespread use of models and analytical pipelines, many studies lack publicly shareable workflows or clear documentation of data transformations (Demir & Szczepanek, 2017). Hutton et al. (2016) argue that without reproducible methodologies, computational hydrology risks undermining its scientific credibility. Tools like HydroShare (Essawy et al., 2018) and HydroBench (Moges et al., 2022) have made significant strides in enabling reproducibility through hosted environments and standardized benchmarking practices.

Cross-institutional hydrological research increasingly depends on interoperable systems and open data exchange standards. Frameworks such as OGC Web Services, HydroServer, and the CUAHSI WaterML (Almoradie et al., 2013) specification have enabled broader data sharing (Squividant et al., 2015). The need for accessible, integrable tools is particularly acute for responding to “wicked problems” in climate and water systems that require collaboration across scales and domains (Cushing et al., 2015). Despite the growing emphasis on reproducibility and data sharing, most hydrological workflows remain script-based or confined to legacy desktop applications. There is a need for tools that not only promote transparency but also make workflow construction more approachable and usable in educational and research settings (Merwade & Ruddell, 2012). Visual programming environments have emerged in other fields as a way to address this gap.

2.2. Cloud Services and Browser-Native Paradigms

The hydrological sciences have increasingly adopted cloud-native technologies to meet the demands of large-scale, distributed, and collaborative workflows. Cloud platforms provide scalable infrastructure for data storage, model execution, and multi-user access, making them central to recent advances in hydrology and water resource forecasting (Seo et al., 2019). Initiatives like the Cooperative Institute for Research to Operations in Hydrology (CIROH) have emphasized cloud-native design patterns, using containerization, microservices, and cloud object storage (e.g., Amazon S3) to support operational hydrology at national and regional scales (Burian et al., 2023).

These architectures facilitate integration of near real-time data, ensemble forecasting, and advanced Earth observation analytics. Cloud-hosted tools—such as NOAA's Big Data Program (Simonson et al., 2022), Google Earth Engine (Zhao et al., 2021), and NASA's AWS-based data access portals—have become essential to modern hydrological research and decision-making workflows. However, while cloud-native platforms offer flexibility and computational power, they often introduce significant overhead related to secure authentication, backend configuration, dependency management, and complexity of cloud-specific APIs. For educational use, field applications, or resource-limited environments, these requirements may present a barrier.

Web development ecosystem has matured to support browser-native scientific applications. Technologies such as WebAssembly, IndexedDB, Service Workers, and client-side JavaScript frameworks now allow for robust data analysis (Sit et al., 2021), visualization, and even model execution directly in the browser (Agliamzanov et al., 2020; Ewing et al., 2024). These browser-based systems operate entirely on the client side, requiring no server infrastructure or local installations, and can be distributed as static Progressive Web Applications (PWAs) that support offline use and session persistence (Shahid et al., 2023; Hume, 2017.

The convergence of cloud and browser-native capabilities presents a new paradigm for hydrological tools where cloud-hosted datasets and APIs can be accessed directly from lightweight, browser-executed workflows. This hybrid model reduces friction for tool adoption, improves reproducibility, and expands participation in hydrological computing by accommodating a wider range of users and technical environments.

2.3. Visual Programming in Science

Visual programming languages (VPLs) use graphical representations—such as blocks, nodes, or flowcharts—to define program logic and task sequences. These systems are widely used across science, engineering, and education to simplify complex processes and improve transparency in execution. A systematic review by Kuhail et al. (2021) classifies VPLs into block-based (e.g., Scratch, Blockly) and diagram-based (e.g., Simulink, Node-RED) paradigms, each enabling end users to construct executable workflows without direct scripting.

In educational settings, block-based languages have demonstrated strong benefits for introductory computing and STEM education. Tools like MIT Scratch, App Inventor, and Snap! support foundational learning in logic, algorithms, and event-driven programming, often improving student confidence and engagement (Stolpe & Hällström, 2023). Beyond education, visual programming has gained traction in automation, robotics, and embedded systems, where interfaces like Simulink (MATLAB) (Karris 2016), LabVIEW (National Instruments) (Kodosky, 2020), allow users to define signal processing, control logic, or real-time hardware operations.

In data science and machine learning, node-based platforms like Knime (Feltrin, 2015), Orange, and RapidMiner (Verma, et al., 2014) enable visual pipeline design for data preprocessing, model training, and evaluation. These systems allow analysts to link modular components—such as filters, classifiers, or visualizations—into reusable, interpretable workflows. Similar principles are applied in industrial automation (e.g., Node-RED) and geospatial processing (e.g., ArcGIS ModelBuilder, Google Earth Engine GUI), where task chains are visually represented to assist non-expert users.

The scientific community has also recognized the role of VPLs in improving workflow reproducibility. Workflow management systems such as Kepler, Taverna, and Apache NiFi offer visual environments for composing complex, multi-stage processes across disciplines including bioinformatics, climate modeling, and computational chemistry. These tools support documentation, version control, and dependency management through visual representations, facilitating collaboration and repeatable analyses (Gil et al., 2007; Deelman et al., 2009).

In hydrology and environmental science, the adoption of VPLs has been limited. Most existing tools rely on either point-and-click desktop interfaces or scripting through Python, R, or MATLAB. However, work by Finkenbiner and Semmendinger (2021) illustrates the potential of visual workflows in sensitivity analysis for hydrological models. While platforms like Tethys (Swain et al., 2016) and HydroShare (Horsburgh et al., 2016) support workflow reproducibility, they typically require backend infrastructure and are not designed for generalized visual programming. There remains a gap for client-side, modular VPLs tailored to hydrological research and education.

2.4. Intelligent Interfaces and AI Integration in Environmental Research

Recent advances in artificial intelligence (AI) and natural language processing (NLP) have enabled new types of interactive interfaces for scientific computing (Pursnani et al., 2025). In particular, large language models (LLMs) are now being explored to support code generation (Pursnani et al., 2024), workflow assistance, and automated interpretation of results for hydrological research, education and operations (Sajja et al., 2025), as well as benchmark datasets for the usage of LLMs in hydrology (Kizilkaya et al., 2025). These developments aim to reduce technical barriers and improve accessibility, especially for researchers who may not be familiar with traditional programming environments (Mishra et al., 2023; Luan et al., 2022; Haristiani, 2019).

In environmental and geoscience domains, AI-driven interfaces remain limited but are gaining attention. For example, tools such as EarthAI and Google Earth Engine Explorer have begun integrating machine learning support for automated classification and search. In broader data science contexts, platforms like Jupyter AI and OpenAI Codex have demonstrated the ability to assist in writing code, querying datasets, and explaining statistical outputs through natural language interaction (Perkel, 2023).

While hydrology-specific applications are still in early stages, rule-based decision support systems (e.g., within HydroShare or OpenDA (Ridler et al., 2014)) have provided foundational steps toward AI-guided workflows. These tools typically support task selection, parameter tuning, or metadata management based on user-defined rules (Essawy et al., 2018). The integration of LLMs promises to expand these capabilities by enabling dynamic assistance during workflow construction, parameter selection, and interpretation of hydrological indicators.

Combining visual programming with AI-guided assistance represents a promising path forward (Feng & Yan, 2024). Intelligent interfaces can help users—particularly those in training or applied fields—understand the role of each processing step, suggest next actions, or auto-complete workflow components based on contextual goals. These capabilities align with the broader trend of augmenting scientific tools with AI to support reproducibility, lower entry barriers, and accelerate exploratory analysis (Toshniwal et al., 2023; Wagner et al., 2022).

2.5. Proposed Framework

The objective of this work is to develop a browser-based framework that enables the construction, execution, and sharing of hydrological workflows through a visual programming interface. It has been designed to address limitations previously described for existing hydrological tools by leveraging client-side technologies and flexible architecture.

The specific goals of the framework are as follows: a) provide a visual workflow environment where hydrological functions can be composed using modular blocks with defined inputs, outputs, and parameters; b) enable full execution of workflows on the client side, requiring no server infrastructure, installation, or backend services; c) support extensibility through a modular design that allows integration of new functions and libraries; d) facilitate data sharing and reproducibility by enabling workflows to be exported, imported, and executed as standalone, portable packages; and e) serve as both a research and educational tool for teaching hydrological concepts, visual workflow design, and web-based application development. These objectives guide the design of the platform as a lightweight, extensible environment for hydrological computing, particularly in contexts where infrastructure, technical skill, or reproducibility remain barriers.

3. Methods and Implementation

HydroBlox is designed as a client-side web application built in JavaScript, with modular support for extensibility. It runs without the need for a backend server and uses open web standards (HTML/CSS, Bootstrap) as well as deliver a responsive and portable interface. Scientific computation and visualization are enabled through HydroSuite, a set of libraries that include HydroLang, HydroRTC (Ramirez et al., 2024) and HydroCompute. These libraries provide the core logic for data handling, transformation, and output rendering within each workflow. The system's architecture is structured into five primary modular components with hundreds of functions, summarized in Table 1 and interaction shown in Figure 1.

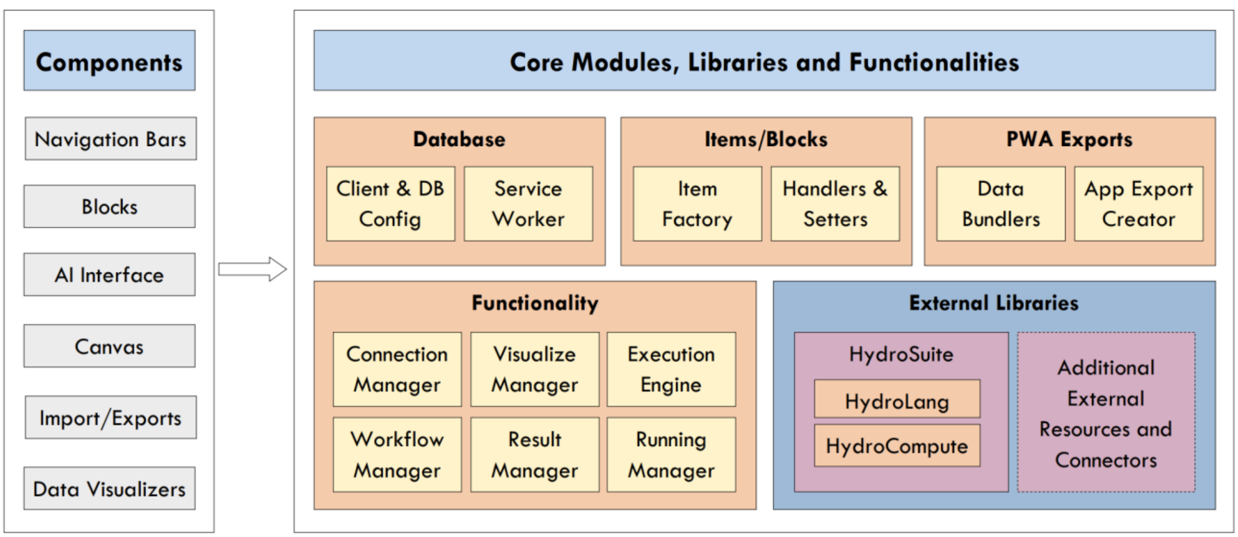

Figure 1. Architecture diagram of the platform. It has been created with an extensive methodology that allows new libraries to be readily added through an MPI or declarative function paradigm.

3.1. Introduction of HydroSuite

HydroSuite is a collection of web-based hydroinformatics tools, portals, benchmark datasets, and community portals that aim to improve web-based development of hydrology and environmental workflows, both browser based and server side. It provides a large collection of libraries that allow connection to a varied set of data sources, analytical engines for analysis and visualization, tools for exporting data and providing information through portals, and creates a synergic environment with the available tools from the user, exposed to their client-side technology. We have implemented several HydroSuite libraries within HydroBlox framework as described below.

Table 1. Responsibilities of each implemented manager on the platform.

Module	**Responsibility**
components/	UI templates (sidebar, navbar, modals, result panel)
functionality/items/	Creation and configuration of draggable logic blocks
functionality/managers/	Management of state transitions, task execution, and results rendering
functionality/database/	Internal result and state cache management for reproducibility
External integrations	HydroSuite libraries (HydroLang, HydroCompute, and many others) for logic execution and rendering

HydroLang is a web-based, open-source library designed to facilitate hydrological and environmental data processing, analysis, and visualization (Erazo et al., 2022). It offers a collection of functions implemented in JavaScript, enabling users to interact with various datasets and APIs without the need for extensive software installations. The library supports multiple functionalities, including statistical computations, hydrologic functions, and interactive visualizations, making it a flexible resource for researchers, practitioners, and educators. The library's architecture is modular, encouraging extensibility and ease of use through its predefined functions and adaptable workflow. HydroLang provides access to multiple data sources, including publicly available hydrological databases and APIs, enabling users to retrieve, manipulate, and visualize datasets efficiently. Its lightweight nature and web-based execution make it particularly suitable for real-time applications (Erazo et al., 2023)

HydroCompute is an open-source, client-side computational library designed to support high-performance data processing and analysis in hydrology and environmental sciences (Erazo et al., 2024). The library leverages modern web technologies, including Web Workers, WebGPU, WebAssembly, and WebRTC, to enable parallel and sequential execution of scientific computations directly within web browsers. Its modular architecture allows users to run complex simulations efficiently and to integrate existing codebases into JavaScript, C, or AssemblyScript. HydroCompute manages computational workflows through graphs, providing structured handling of functional dependencies across processing steps. The framework supports applications such as hydrological modeling, time series analysis, and real-time data visualization while maintaining interoperability with other tools and data sources commonly used in the environmental sciences.

3.2. General Overview of HydroBlox

Each workflow in HydroBlox is defined through a visual graph of interconnected blocks. These represent discrete functional units—such as data retrieval, transformation, analysis, or visualization—and are instantiated with metadata that includes a unique identifier, block type, configuration parameters, and connection points.

Each workflow is encoded internally as a Directed Acyclic Graph (DAG). Nodes correspond to blocks while directed edges define dependencies based on user-defined connections between input and output ports. The DAG structure is maintained via an adjacency list representation and updated dynamically as users modify the canvas. This is further explained in the next section. Cycles are explicitly prevented during connection validation, and disconnected (or "orphan") nodes are treated as standalone subgraphs that can be executed independently if they satisfy data conditioning. Execution follows a multi-phase lifecycle orchestrated by dedicated manager modules:

- *Connection Manager:* maintains updates on the edges of the blocks.
- *State Manager:* keeps control of the different elements on each of the workflow development stages.
- *Executor:* sets up the execution through traversing the DAG in topological order using a depth-first search, dispatching valid workflows to the HydroSuite.
- *Running Manager:* sets visual queues for active tasks and coordinates UI updates.
- *Results Manager:* handles result rendering, file exports, and visualization.
- *AI Helper:* handles user input and AI interaction.

3.3. Block Construction in Canvas

Functional logic is encoded in modular components blocks. Each block represents a discrete operation (e.g., data loading, filtering, statistical computation, visualization) and is rendered as a draggable unit on a grid-based canvas. Users define workflows by dragging these from a component palette onto the canvas and connecting them via input/output ports. Each block is created using a centralized factory class, which generates the object instance based on a predefined schema which defines the following:

- Unique id assigned at instantiation
- Type (e.g., 'data', 'analysis', 'visualization', 'logic')
- Configuration object, containing parameters and defaults
- Position object for canvas rendering (x, y, zoom level)
- A status field (idle, pending, running, completed)
- A set of allowed input/output connections

The visual rendering of a block is done using absolute positioning relative to the canvas, with snapping behavior to ensure alignment. These are rescaled based on zoom levels as well as the connection dependencies set by the user. Each block contains:

- A header displaying its type and title
- A configuration panel, rendered on double-click, allowing users to input function arguments, select datasets, or define thresholds
- Connection ports for inputs and outputs, which are used to form data dependencies with other blocks

Configuration data is stored in memory and synced to local IndexedDB for persistent sessions. Block states are automatically saved when workflows are modified. Connections between items are visualized as directed links between output and input ports. These connections are registered in the Workflow Manager, which ensures graph consistency and updates the internal DAG. Connections are validated in real time to prevent cycles or invalid data types.

An *Item Setter* module coordinates the configuration UI for each block, dynamically populating input fields based on the function definition of the underlying block. When opened, each setter displays:

- Accepted argument types and default values
- Tooltips or inline descriptions for each input
- Live previews for compatible datasets (e.g., previewing CSV headers)

Control-flow structures are supported through special blocks, such as:

- <u>If/Else:</u> evaluates boolean conditions to activate different branches
- <u>While:</u> allows iterative processing (evaluated with internal limits)
- <u>Code:</u> user-defined JavaScript functions with exposed inputs and outputs

Each block is represented as a structured JSON object that defines its type, configuration parameters, position, and connection metadata. A centralized factory class handles instantiation by assigning unique identifiers, default values from a function registry, and positional attributes for rendering. This approach ensures uniform initialization and enables dynamic registration of new functions or libraries at runtime. Parameter validation occurs both during configuration—where tooltips and input checks guide the user—and at execution, where missing inputs or invalid states are flagged by the system and excluded from task submission. Block status is tracked centrally and rendered visually to guide user interaction and debugging.

Blocks are created by instantiating libraries located within the external libraries folder. For the initial development phase, we focused on the HydroSuite collection. A wrapper module is used to facilitate integration by instantiating these libraries, extracting the user-facing functions they expose, and using those functions to generate corresponding blocks. To support the addition of new external libraries, a message-passing interface and a basic model interface have been developed—assuming the external library offers an accessible API that lists its available functions.

Each block is categorized based on its functionality into one of three areas including data sources, analysis, and visualization. In the initial version of the platform, integration efforts have primarily focused on the data sources already integrated into HydroLang, which currently include around 24 different national and international data sources. Each data source typically supports approximately 10 endpoints and offers hundreds of configurable options for data retrieval in various formats. Additionally, a generic "New Data Source" block has been implemented, enabling the structured integration of additional data sources or the uploading of custom datasets. Figure 2 shows the declaration of items, setting parameters, and the interface that shows more information about the block.

The analysis category encompasses the *hydro, stats*, and *machine learning* modules for hydrological analysis. It also includes a WebAssembly block, which will be discussed in more detail later. Each function within these modules is made accessible through a dropdown menu. Users can customize parameters for each function based on the documentation provided by the corresponding library.

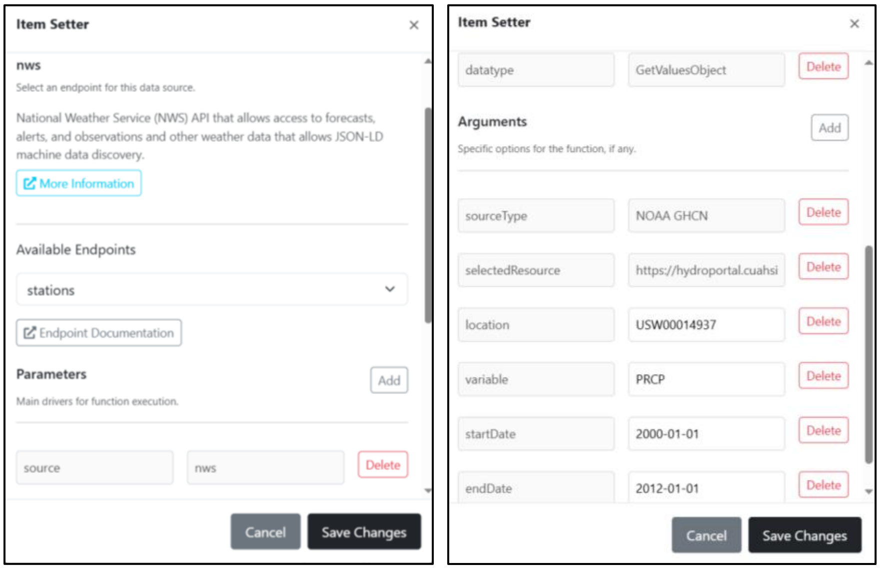

Figure 2. Example of a workflow being created. Users can edit workflow settings using a menu for options that supports the execution based on the function definition is shown.

3.4. Workflow Modeling and Execution

Once visual blocks are positioned and configured on the canvas, the system internally constructs a Directed Acyclic Graph (DAG) to represent the workflow logic. In this structure, each node corresponds to a visual block, and directed edges represent explicit data or computational dependencies between nodes, as established through user-defined connections, shown in Figure 3. This dependency graph is essential not only for visual coherence but also for managing execution order, concurrency, and data lineage. Workflow execution is initiated via the interface's Run command. Upon activation, the system transitions from Edit Mode into Running Mode, managed by a centralized State Manager. This component resets all node statuses to pending, disables editing capabilities, and coordinates state propagation across the interface.

Execution planning leverages the DAG structure: independent subgraphs are identified using connected component analysis and traversed via Depth-First Search (DFS) to determine execution ordering and resolve dependencies. These algorithmic mechanisms ensure that only data-consistent branches are processed in parallel. Each executable node delegates its computation to the HydroSuite runtime, which dynamically loads task-specific functionality to HydroCompute. These functions may internally invoke HydroLang utilities or WebAssembly-compiled routines, depending on the required precision or performance. Where DAG dependencies allow, independent branches are dispatched concurrently, enabling efficient parallelism. The Running Manager monitors active threads, updates UI status indicators in real time, and ensures consistent synchronization across asynchronous tasks. An example of items declared and running is shown in Figure 4, while Figure 5 shows the visual outputs from the run.

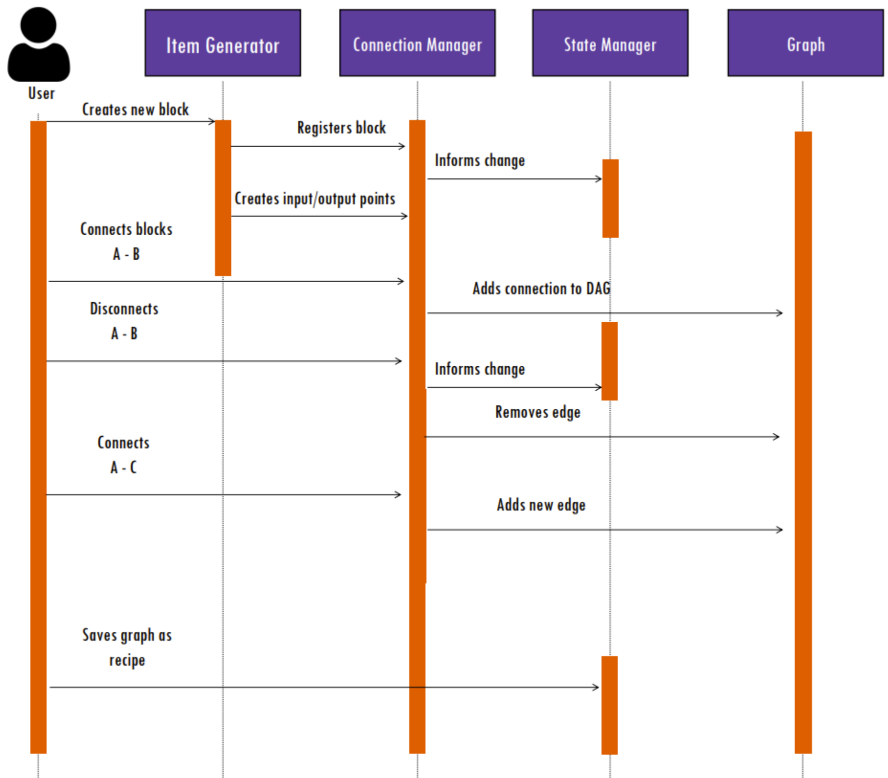

Figure 3. Sequence diagram on the execution and declaration of items.

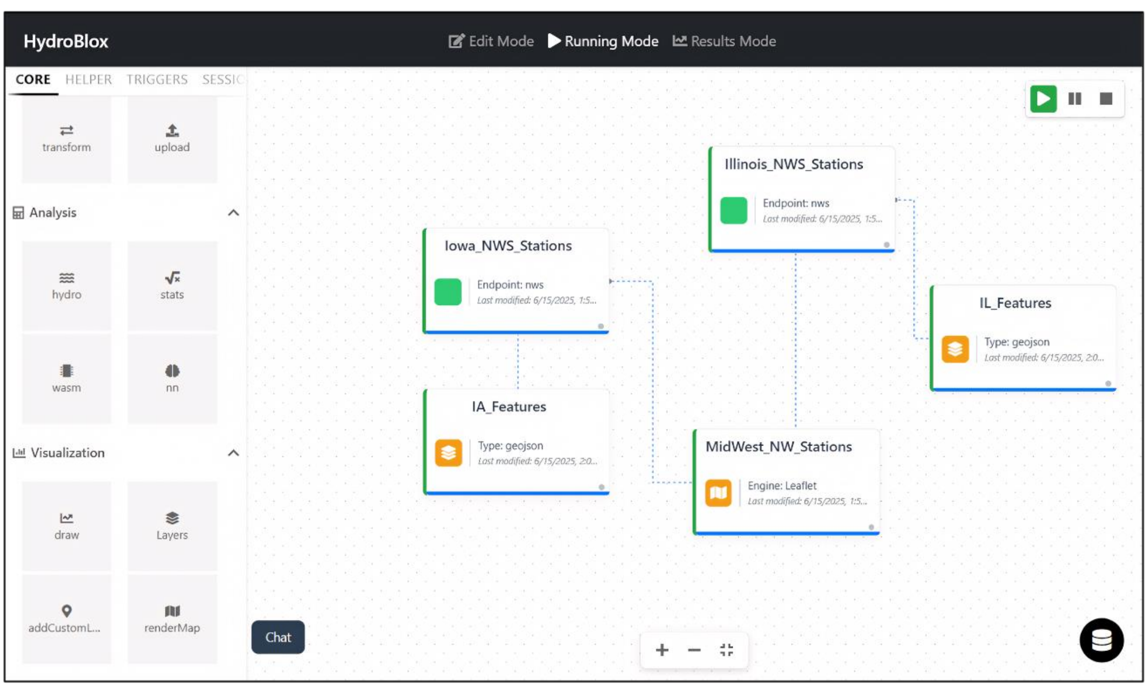

Figure 4. Example on the declaration of items and execution of workflows in running mode.

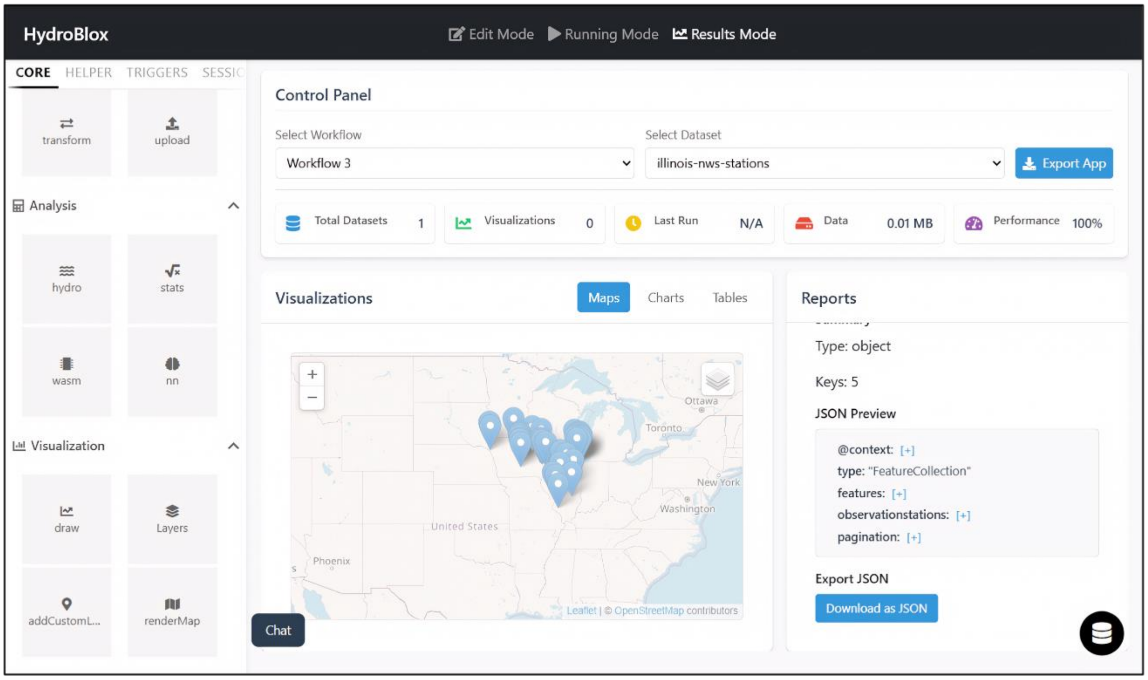

Figure 5. Result space showcasing a control panel, visualization of maps, tables, and charts; and a report space with option for downloading specified types of data.

Algorithm 1 WorkflowManager Core Functionality

```
function ManageWorkflows
    Load workflows from local storage and database
    Apply workflows to canvas if needed
    Listen for UI events (item rename, connection changes, zoom)
    Sync canvas items with workflows
    for all new canvas items do
        if connected to existing workflow then
            Add to workflow
        else
            Create new workflow
        end if
    end for
    for all deleted or renamed items do
        Update workflows and connections
    end for
    Save updated workflows to local storage and database
end function
```

Algorithm 1 Workflow Execution Algorithm

```
function ExecuteWorkflow
    Initialize processed set: 𝒫 ← ∅
    Load all workflows: 𝒲 ← set of all workflows
    for all workflow w ∈ 𝒲 do
        Extract items I ← w.items
        Separate visualization items V ← {i ∈ I | i.type = visualization}
        Filter executable items E ← I \ V
        for all item i ∈ E do
            if i has result in database and parameters unchanged then
                𝒫 ← 𝒫 ∪ {i}
            end if
        end for
        while exists i ∈ E \ 𝒫 such that all d ∈ i.deps are in 𝒫 do
            Prepare function configuration f_i
            Submit f_i to compute engine (JavaScript or WASM)
            Wait for result and transform if needed
            Save result to database
            𝒫 ← 𝒫 ∪ {i}
        end while
        if V ≠ ∅ then
            Emit visualization event for items in V
        end if
    end for
end function
```

Figure 6. Pseudocode execution for the workflow and executor managers where they both sync through the workflow manager, that is continuously checking if items have ran, finished, or were available in the database.

Execution status is visually encoded on the canvas where red indicates active tasks, green denotes successful completion, and gray marks skipped or failed nodes. This real-time feedback loop is not merely aesthetic; it provides users with an intuitive means of tracing data flow, identifying execution bottlenecks, and debugging dependency-related errors during iterative development. Once all tasks are completed, the platform enters Results Mode, where outputs from successfully executed blocks are rendered using HydroLang's visualization modules. Figure 6 shows the execution algorithms for the managers and executors. Output types vary based on the function executed and may include structured tables, statistical summaries, dynamic charts, geospatial visualizations, or even machine-readable JSON narratives. Each result is persistently associated with the producing block's unique identifier, facilitating provenance tracking and reproducibility.

3.5. Scientific Computation and Visualization

HydroBlox leverages the HydroLang library to perform analytical and visualization tasks within each workflow block. Upon execution, computational outputs from HydroLang or HydroCompute are rendered in-place inside the corresponding block container. Visualization types—such as tables, charts, maps, or narratives—are selected based on the function's output schema. Time series and statistical data are visualized using Google Charts, while geospatial overlays are rendered with Leaflet and Google Maps APIs. Common chart types include line plots, bar charts, and box plots. Spatial results—such as shapefile overlays, point-in-polygon queries, or map-based heatmaps—are projected onto embedded maps, with support for GeoJSON and raster tiles.

The rendering pipeline is declarative and modular. Each function includes a visualization profile that determines how results are displayed. Visuals are automatically inserted into the block's result panel, with responsive resizing, export options (CSV, PNG, JSON), and support for narrative summaries for text-heavy outputs. This approach allows for both quantitative and spatial insight without requiring post-processing. All visualizations are performed client-side, enabling reproducible, shareable visual outputs that are tightly coupled to the workflow structure. In order to allow for non-blocking UI, several service workers have been deployed to display summaries, fetch items from the database, download items, and create seamless stepwise interaction for the user. Moreover, where applicable, data partition and prefetching are encouraged—in particular when rendering large or displaying large JSON files—to allow users real-time interaction.

3.6. WebAssembly Support in Subroutines

HydroBlox allows integration of external subroutines compiled to WebAssembly (WASM) for high-performance computing. This enables tasks written in low-level languages like C or C++ to be executed directly in the browser, offering near-native speed without requiring any server infrastructure. Users can integrate WebAssembly modules in two ways. The first method is by uploading a .c or .cpp source file, which triggers a background API request to compile the source into a WASM module and corresponding JavaScript interface. Once completed, the module is automatically loaded into the workspace and mapped to a functional block. Second method is by uploading a precompiled *wasm* module along with an optional JavaScript binding file, which defines the callable functions and expected input/output structures.

Each WASM-enabled block follows the same configuration and execution pattern as standard blocks. During execution, HydroCompute handles memory allocation, data transfer between JavaScript and the WASM memory space, and marshaling of inputs and outputs. The system supports both synchronous and asynchronous execution, and all computation is run in a dedicated Web Worker thread to avoid blocking the main user interface. This capability enables users to embed domain-specific numerical routines—such as drought indicators or optimization algorithms—without converting them to JavaScript. The modular design ensures that WASM blocks can interact with other blocks in the DAG, supporting seamless integration into broader workflows.

3.7. Reproducibility and Workflow Recipes

The platform enables complete export and import of workflows through a serialized structure known as a "recipe." A recipe includes all metadata required to reconstruct a workflow: block configurations, block positions, graph structure (connections), data connectivity, and metadata such as timestamps, authorship, and versioning, as seen in Figure 7. Recipes are encoded in JSON format and can be exported and shared as .blox files. The exports and loader modules manage the serialization and deserialization processes, respectively. Upon reloading a recipe, it is restored in full visual and logical structure, including precomputed results when available. Additionally, the platform supports drag-and-drop import of recipe files and offers session persistence using browser-based local storage. Figure 8 shows the menu dropdown that enables the interaction with the workflows.


```json
{
  "items": [
    {
      "uniqueId": "cleaned-data",
      "name": "cleaned-data",
      "itemName": "retrieve",
      "parameters": {
        "source": "database",
        "datatype": "reference",
        "referenceId": "cleaned-data"
      },
      "arguments": {
        "referenceId": "cleaned-data",
        "timestamp": "2025-06-03T14:56:51.171Z"
      },
      "data": [],
      "settings": {
        "name": "cleaned-data",
        "uniqueId": "cleaned-data",
        "type": "data",
        "itemName": "retrieve",
        "x": 533,
```

```json
  ],
  "name": "cleaned-data",
  "created": "2025-06-04T16:19:13.932Z",
  "id": "workflow-1",
  "connections": [
    {
      "sourceItemId": "spi-12",
      "targetItemId": "cleaned-data",
      "sourcePortType": "input",
      "targetPortType": "output",
      "sourcePortPosition": "left",
      "targetPortPosition": "right"
    },
    {
      "sourceItemId": "spi-1",
      "targetItemId": "cleaned-data",
      "sourcePortType": "input",
      "targetPortType": "output",
      "sourcePortPosition": "right",
      "targetPortPosition": "right"
    },
    {
```


Figure 7. Example of the reproducible JSON object defining an item, as well as the connections within.

3.8. AI-Assisted Workflow Generation

To support exploratory analysis and reduce the barrier to entry for non-programmers, HydroBlox integrates an optional AI assistant that can guide users in constructing workflows, defining functions, and selecting appropriate parameters. The assistant is built as a browser-embedded interface that interacts with large language models (LLMs) through user prompts contextualized by the current workflow state.

The AI assistant is capable of: a) summarizing active workflows and listing existing blocks and their types; b) generating new workflow suggestions based on user queries (e.g., "Add a block to compute average streamflow"); c) recommending function parameters or argument values, especially for users unfamiliar with specific hydrological terms or configuration options; and d) proposing next logical steps in a workflow, based on prior components and typical hydrological analyses.

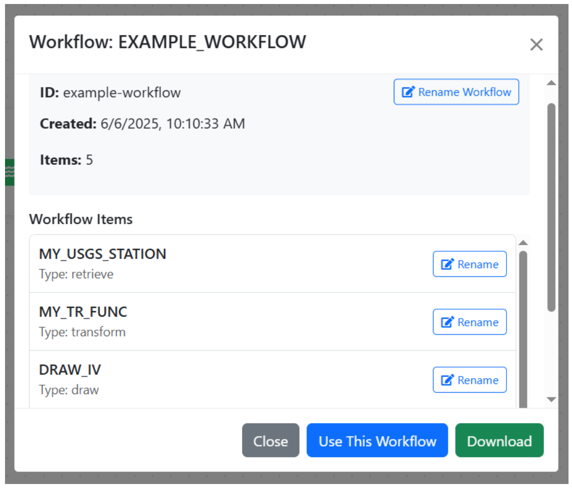

Figure 8. Example of a workflow quick access tooltip. Once workflows are generated, they are available for workflow operations including renaming items and the workflow. Users can also download the workflows, as well as upload new ones within the same context.

The assistant is implemented as a self-contained JavaScript module with a lightweight, interactive UI and streaming-based communication with external large language models (LLMs). It supports multiple model providers (e.g., GPT-4.1, Claude, DeepSeek) and can be configured by the user with API credentials. A contextual system prompt is generated at runtime, embedding a formalized description of the HydroBlox platform, including block types, runtime behavior, and data semantics. This prompt is dynamically coupled with a summary of the active workflow state to provide relevant context for each user query. Internally, the assistant maintains local session memory using the browser's storage system to support continuity in dialog. While the current implementation focuses on user assistance through prompt-response interaction, the architecture supports future extensions such as automatic workflow generation, tooltip-based contextual help, and onboarding tutorials.

To improve alignment between user intent and platform behavior, a platform-specific fine-tuning strategy is being developed. This includes prompt curation and the use of representative example workflows to provide the assistant with structured illustrations of common hydrological tasks and block configurations. These examples are embedded into the system prompt or injected dynamically depending on user input. The aim is to ground the assistant's responses in the operational semantics of the HydroSuite libraries, reducing ambiguity and improving the consistency of generated suggestions within the platform's context.

3.9. Progressive Web Application and Offline Mode

While HydroBlox runs as a standard browser-based web application, it includes a mechanism to export fully executable workflows as standalone Progressive Web Applications (PWAs). This export capability allows users to pack entire session workflows—including block configuration, execution logic, visual layout, and results—into a self-contained web bundle that can be shared, installed, and run offline on any device with a modern browser. When a workflow is exported as a PWA, the system generates an HTML scaffold embedding the visual workflow interface, logic for execution and rendering of results, required datasets and block configurations in JSON format, and a manifest file and service worker to enable offline support and installation.

This bundled export behaves like a portable application. Users can install the PWA on their device, open it in the browser, and interact with the saved workflow as if it were running within HydroBlox. All execution and visualization are handled client-side without external dependencies. This approach provides a reproducibility pathway that does not require cloud infrastructure or even internet connectivity after the export is created. Exported PWAs are particularly useful in educational and collaborative settings, where reproducible analyses can be shared with students or collaborators as ready-to-run packages. They also support long-term preservation of workflows by decoupling them from the HydroBlox runtime environment.

4. Results

The platform has been evaluated across multiple workflows and environments to assess interface responsiveness, execution stability, and scientific applicability. All workflows were executed entirely in the browser using local resources, without reliance on backend infrastructure or cloud-based services. Workflow performance is primarily influenced by the size of the input dataset and the complexity of the analytical tasks. For standard workflows involving large time series and event-based analyses, execution latency typically remains below 1 second per block. The use of multithreading enables non-blocking, parallel execution along independent branches.

Additionally, the integration of modules compiled to WebAssembly significantly reduces computation time for numerically intensive routines, achieving performance levels comparable to native or compiled desktop applications. These workflows have also been archived and used to inform the AI assistant, enhancing its contextual understanding for generating and executing user-defined tasks, thereby improving user interaction and support. We utilized Google Chrome's Lighthouse to test usability, best practices, and hindering issues within the platform shown in Figure 9.

The case studies demonstrate the platform's ability to support scientific analysis without requiring custom code. While code-based functionality is still supported, the core design emphasizes the interactivity of the block-based system. This allows users to adjust parameters and immediately observe resulting changes, facilitating iterative refinement of analytical logic. This capability is particularly useful in exploratory modeling and event-based filtering, where threshold testing and visual feedback are essential.

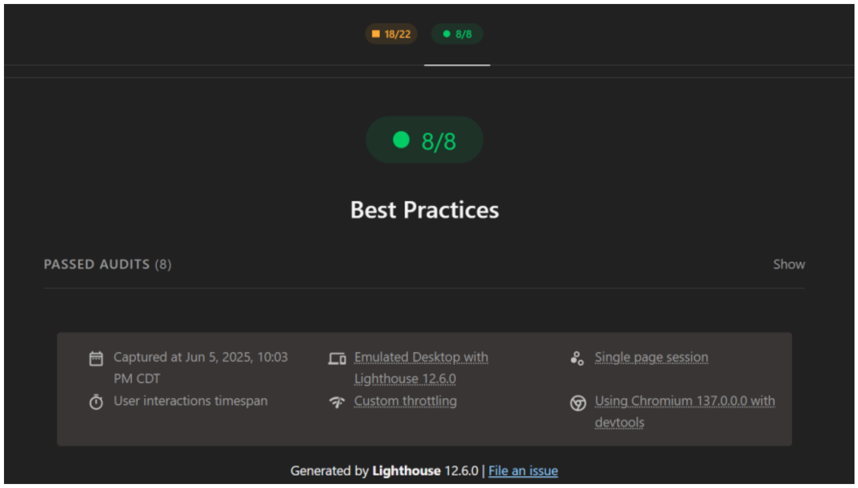

Figure 9. Results from utilizing Google Chrome's lighthouse features for web application.

From a system perspective, memory usage scales with both dataset size and the number of active blocks. The current implementation is optimized for moderate-scale datasets, such as daily records spanning 10–20 years or subnational shapefiles. For large-scale applications—such as gridded climate datasets or high-frequency sensor data—adding other libraries is primordial, along with the deployment in server-side integration.

The HydroBlox platform has shown value in developing and sharing reproducible workflows through multiple projects or institutions; teaching hydrological concepts through a well-structured, interactive computational interface; and rapid prototyping of analytical methods without needing direct scripting environments.

4.1. Case Studies and Applications

The following case studies illustrate how the system operates in practical scenarios, focusing on the application of user-defined workflows to address common hydrological questions. These examples emphasize the system's capacity for task composition, data integration, and visualization using publicly available datasets.

4.1.1. Case Study #1: Streamflow Response to Precipitation Events

This case study demonstrates the application of the HydroBlox framework to assess streamflow to precipitation responses in the Iowa River Basin using publicly accessible, daily-resolution hydrometeorological datasets. The aim is to identify and quantify lag times, runoff ratios, and hydrograph recession behavior for short term storm events while evaluating the influence of antecedent groundwater conditions. The analytical framework is based in methods for event-based hydrologic responses as found in Morin et al., 2001, Gaál et al., 2015 and DeFries & Eshleman, 2004.

Daily precipitation data is retrieved using HydroLang from the NOAA Global Historical Climatology Network – Daily (GHCND) dataset (Applequist et al., 2024). Five precipitation stations were selected within a ~20 km radius of the streamflow station that was for the analysis, in the Iowa City River network. Using the CUAHSI WaterML (Valentine et al., 2007) data sources for enabling spatial filtering in bounding box of 41.50–41.75°N, −91.70 to −91.40°W. The same resource was used to obtain precipitation values. The following stations were queried and data retrieved between January 2000 and January 2012:

- USW00014990 (Cedar Rapids MUNI AP)
- USW00014937 (Iowa City MUNI AP)
- USC00139067 (Williamsburg 1E)
- USC00138632 (Walford 2 SE)
- USC00138062 (Swisher #2)
- USC00134101 (Iowa City)

These stations were selected based on data completeness and geographic relevance. Daily precipitation totals were spatially averaged to produce a representative rainfall signal for the basin. Concurrently, daily mean streamflow data were obtained from the USGS National Water Information System station 05454500 – Iowa River at Iowa City (USGS, 2023).

Precipitation events were defined using a fixed threshold approach: any day with precipitation equal or greater than 10mm is a triggered candidate event, separated by at least two consecutive days of dryness. Associated streamflow responses were tracked over a five-day post-rainfall window. We computed the following response metrics using the block-based functionalities:

Lag time: time difference (in days) between the center of mass of the rainfall event and the streamflow peak. The formula (Eq. 1) used for these calculations is

$$\tau = t_{peak,Q} \frac{\sum t_i P_i}{\sum P_i} \qquad \text{Eq. 1}$$

Runoff ratio: the ratio of direct runoff volume (discharge above baseflow) to precipitation volume during the event (Eq. 2).

$$RR = \frac{\sum Q_{event} - Q_{baseflow}}{\sum P_i} \qquad \text{Eq. 2}$$

Recession duration: time interval following peak discharge until flow returns to near pre-event levels (Eq. 3).

$$Q_t = Q_0 e^{-kt} \qquad \text{Eq. 3}$$

These computations were performed using the hydro and stats modules in combination with rolling window smoothing, peak detection, and volume integration blocks. Baseflow separation was approximated using a threshold-based low-flow filter. All outputs were visualized using the visualizing components with the charting tools allowing rainfall blocks and streamflow to be plotted simultaneously with event annotations. The block definition of these items is shown in Figure 10, and results in Figure 11.

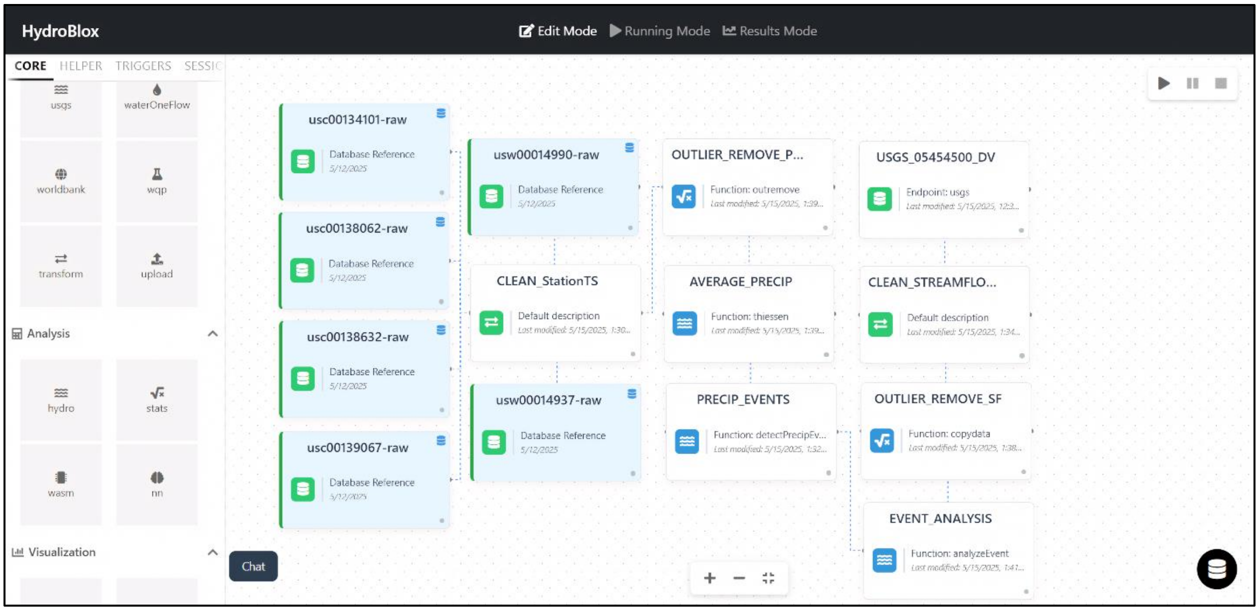

Figure 10. Block definition for the analysis workflow. The blocks with blue haze represent datasets that have already been computed and saved in the database.

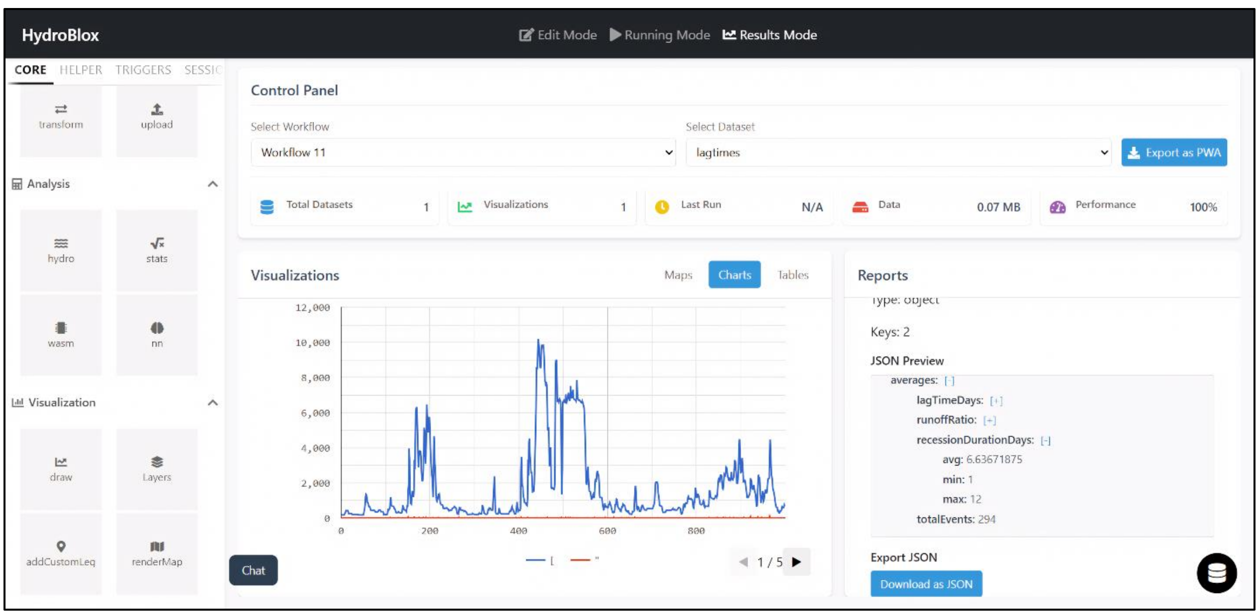

Figure 11. Result space for the case study which can be replicated through uploading the workflow .blox file in any device, or downloaded as app that can be rendered offline.

During the analysis period from 2001 through 2012, the key findings include:

- Average lag time: ~ 4 days, ranging from 0.7 to 5.
- Runoff ratios: spanning 0 to 13,905. with a mean of 1,707.
- Recession durations: averaged 6.62 days after peak flow.

These values are consistent with regional literature, where 1-4 days lags and relatively low runoff efficiencies have been observed in similar Midwestern basins (Schilling et al, 2008; Zhanf et al., 2014). Notably, rainfall events above ~25 mm produced rapid and intense streamflow responses, suggesting the non-linearity of responses influenced possibly by the antecedent moisture or soil saturation thresholds.

The results of the application are exported as an app, exporting all the results and analysis into a contained application where these can be observed, replicated, and shown. Moreover, the exported workflows are also provided into the application. The latter validates the platform's capacity to replicate standard hydrological analyses entirely within a browser-based workflow environment. The modular architecture allows for intuitive composition of analytical routines, while data and computation remained fully on the client side through a multithreading environment.

4.1.2. Case Study #2: Drought Monitoring Using SPI Computation

Droughts are complex and gradual phenomena with widespread environmental and socioeconomic impacts. Their detection and quantification rely on robust indicators that capture multi-scale precipitation anomalies. Among these, the Standardized Precipitation Index (SPI) is widely recognized for its simplicity, probabilistic interpretability, and flexibility across temporal scales (McKee et al., 1993; WMO, 2012). SPI is based solely on precipitation and can identify meteorological drought conditions over various durations (e.g. 1-month to 24-month time scales), making it suitable for agricultural, hydrological and climatological assessments.

This case study aims to demonstrate the creation and execution of long-term, computationally intensive hydrological analysis through the integration of external libraries compiled into WebAssembly. We also explore the multi-decadal drought dynamics for the Iowa River basin using publicly available NOAA precipitation data, highlighting the platform's relevance for regional drought monitoring and scientific reproducibility. Monthly precipitation data was retrieved from NOAA's Global Historical Climatology Network – daily dataset for the Iowa City station USC00136955. Daily records from 1980 to 2023 were aggregated into monthly totals using resampling and aggregation functionalities. Figures 12 and 13 showcase the definition of items and results.

An SPI algorithm implemented in C and compiled into WebAssembly module as a tooltip was implemented following the definition of SPI by McKee et al., 1993. The implementation includes:

- Rolling N-month precipitation sums (e.g., 12-month totals).
- Fitting a gamma distribution to the series using method of moments
- Computing the cumulative probability for each value.
- Transforming to a standard normal z-score, interpreted as the SPI.

The approach is as follows. The rolling sum is composed of the following series (Eq. 4):

$$S_i = \sum_{j=0}^{s-1} \max(p_{i+j}, 0), i = 1,2, \dots n - s + 1 \qquad \text{Eq. 4}$$

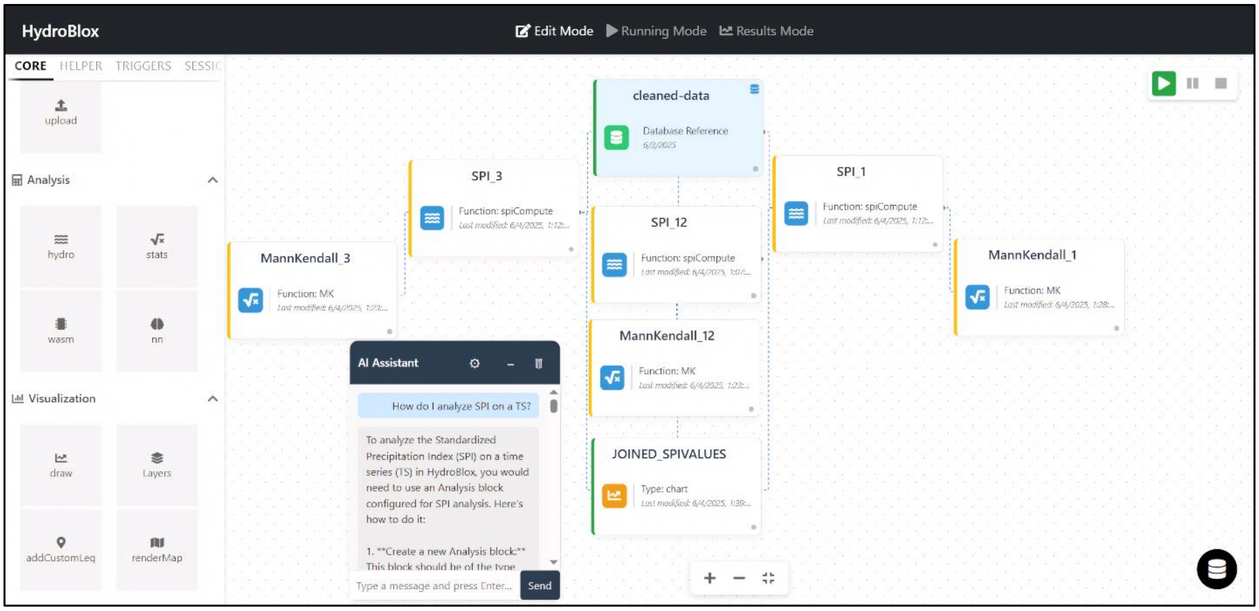

Figure 12. Block definition for case study 2, as well as interaction with the AI chat for the execution and declaration of blocks.

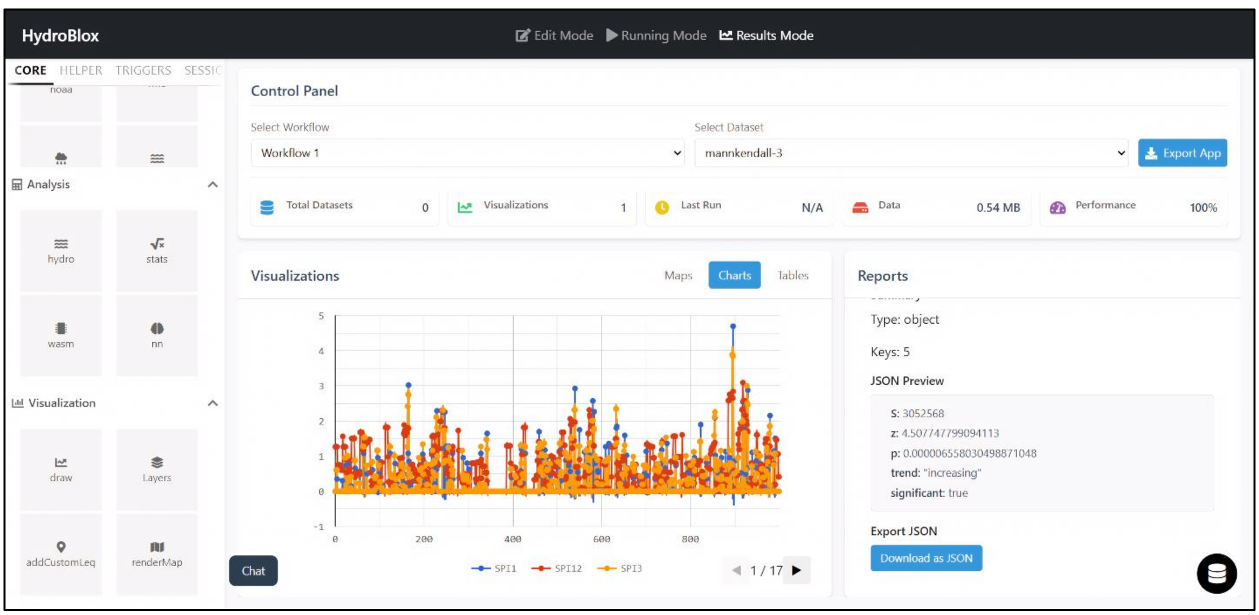

Figure 13. All SPI values in time series for 1980-2023 at Iowa City, IA, highlighting multi year drought intervals and trend direction.

The latter is then fitted into a two-parameter gamma distribution using the method of moments (Eq. 5 and Eq. 6).

$$\bar{x} = \frac{1}{N}\sum_{i=0}^{N} S_i\,; \quad \overline{\log x} = \frac{1}{N}\sum_{i=0}^{N} \log S_i \qquad \text{Eq. 5}$$

$$s = \log \bar{x} - \overline{\log x} \qquad \text{Eq. 6}$$

And the distribution parameters equal to (Eq. 7):

$$\alpha = \frac{1+\sqrt{1+\frac{4s}{3}}}{4s}, \beta = \frac{\bar{x}}{\alpha} \qquad \text{Eq. 7}$$

Each value S_i is then converted to a non-exceedance probability P_i using the cumulative distribution function of the fitted gamma distribution (Eq. 8).

$$P_i = \Gamma(S_i; \alpha, \beta) \qquad \text{Eq. 8}$$

The SPI is obtained by transforming the P_i to the standard normal distribution using the inverse normal CDF. We evaluated the SPI values based on three timescales, with severity classes as defined in the following table:

- 1-month (SP-1): for short-term moisture anomalies
- 3-month (SPI-3): for seasonal droughts
- 12-month (SPI-12): for long-term hydrological drought patterns

Table 2. Drought severity classes were assigned as following (WMO, 2012).

SPI Value	**Classification**
>= 0.0	Normal/Wet
-0.99 to -1.49	Moderate Drought
-1.50 to -1.99	Severe Drought
<= -2.00	Extreme Drought

Trend detection was performed using Man-Kendall test and Sen's slope estimator via the statistics module, to highlight the insights into long-term changes in drought and intensity. The latter states that for a time series $x = [x_1, x_2, \dots x_n]$, the test evaluates all possible pairs (x_i, x_j) where $j > i$, and computes S value (Eq. 9 and Eq. 10).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \qquad \text{Eq. 9}$$

$$\operatorname{sgn}(x_j - x_i) = \begin{Bmatrix} +1 \text{ if } x_j - x_i > 0 \\ 0 \text{ if } (x_j - x_i) = 0 \\ -1 \text{ if } x_j - x_i < 0 \end{Bmatrix} \qquad \text{Eq. 10}$$

For the null hypothesis of no trend, S is given by Eq. 11:

$$\mathrm{Var(S)} = \frac{n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)}{18} \qquad \text{Eq. 11}$$

With t denoting the number of tied ranks of equal value. The standardized test statistic Z is then calculated as below (Eq. 12):

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var(S)}}} \text{ if } S > 0 \\ 0 \text{ if } S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var(S)}}} \text{ if } S < 0 \end{cases} \qquad \text{Eq. 12}$$

Assuming the null hypothesis, Z approximately follows a standard normal distribution with p-value computed from the cumulative distribution Φ of the standard normal distribution (Eq. 13).

$$p = 2(1 - \Phi(|Z|) \qquad \text{Eq. 13}$$

We set the following for the test:

- If $p < \alpha$, the trend is statistically significant.
- The sign of Z indicates the direction of the trend
  - Positive Z: increasing trend
  - Negative Z: decreasing trend
  - Zero Z: no trend

The SPI analysis yielded the following results. Drought episodes were identified during 1988–1989, marked by multiple months of severe drought (SPI-12 < -2.0); in 2012, a short but intense summer drought occurred (SPI-3 = -1.8); and from 2021 to 2023, a sustained SPI-12 below -1.0 indicated a moderate hydrological drought. The SPI-12 series exhibited a statistically significant negative trend ($p < 0.05$), suggesting increasing dryness over time. In contrast, SPI-1 and SPI-3 trends were more variable, reflecting short-term climate fluctuations rather than long-term shifts in drought patterns. Seasonally, summer SPI-3 values showed high variability and more frequent moderate droughts after 2000.

Using multi-scale SPI indices allows for the characterization of both short-term agricultural and long-term hydrological droughts. When paired with information from governmental institutions, this approach enhances drought monitoring. The trend analysis reveals growing signs of persistent dryness in the region, consistent with broader hydrological studies in the Midwestern U.S. (e.g., Fuchs et al., 2014; Svoboda et al., 2002).

However, limitations of the case study must be acknowledged. The analysis was conducted using data from a single station, representing point-scale conditions. As such, spatial heterogeneity was not captured. For regional-scale drought assessments and policy applications, multi-site aggregation or spatial interpolation techniques such as kriging, or the use of gridded datasets like

PRISM, would be necessary. This an application for improving on the case study to create a generalizable, global app for drought monitoring.

This case study was designed to demonstrate the system's ability to connect to diverse datasets and execute advanced analytics not limited to standard web programming. By integrating high-performance C code through WebAssembly, the platform supports robust in-browser computing without reliance on external servers or installations.

5. Discussions and Limitations

HydroBlox presents a novel and powerful approach for browser-based, visual workflow construction for hydrological data analysis and visualization. The platform enables users to assemble analytical pipelines using modular blocks, integrating web-based hydrological tools with no-code interaction. Built primarily upon the HydroSuite collection—including HydroLang and HydroCompute—it provides support for a wide range of hydrological computations and statistical evaluations directly in the browser, without the need for backend infrastructure.

The platform has demonstrated robust performance and scientific utility across multiple use cases, enabling rapid prototyping, reproducibility, and the development of sharable workflows. By leveraging WebAssembly for compute-intensive modules, HydroBlox achieves near-native performance for several operations, laying the groundwork for scalable and responsive web-based hydrological computing. Workflows are persistent, parameter-tunable, and enriched with real-time feedback, providing a unique environment for both exploratory analysis and structured modeling tasks.

5.1. Contributions and Broader Impact

This study contributes to ongoing efforts in hydrological and environmental modeling to formalize workflows as reusable, transparent computational structures. HydroBlox focuses on the design of a lightweight, client-side interface where workflows are not scripted but constructed visually, allowing users to specify task logic and data dependencies through an interactive canvas.

The platform is developed based on the HydroSuite ecosystem—a collection of modular, browser-native libraries including HydroLang, HydroCompute—which handle data retrieval, processing, and analysis. These libraries are designed for portability and are loosely coupled through standardized function registries and message-passing interfaces. This design enables additional tools, including third-party or custom-built functions, to be integrated into the system without modifying core components. The ability to add analytical capabilities dynamically is a key distinction from monolithic systems that tightly bind interface and computation.

By enabling workflows to be built and executed with minimal infrastructure, the system addresses cases where reproducibility, rapid prototyping, or educational accessibility are central. The ability to export workflows as self-contained applications, and the use of AI-assisted support for block construction and interaction, further positions the platform for experimentation with human-software interaction models in scientific computing. As the environmental sciences move toward greater workflow sharing and formalized analysis structures, HydroBlox provides one example of how a modular, browser-native interface can facilitate this transition while maintaining flexibility in design and extensibility in function.

5.2. Limitations

Despite the progress made, certain limitations and development priorities remain. Advanced spatial analysis tools—such as watershed delineation, raster processing, and terrain-based modeling—are not yet fully integrated into the visual interface, although they are available within the broader HydroSuite ecosystem. Similarly, while the platform supports evaluation metrics such as NSE, KGE, and RMSE, it does not currently include full calibration workflows or iterative optimization routines necessary for more comprehensive hydrological modeling. However, these can be developed from the blocks through recipes, that can be shared across the platform.

A central goal of the next development phase is to enhance the platform's extensibility and scalability. HydroBlox has been designed with a flexible architecture that allows integration of external libraries through modular block definitions. By adhering to community standards such as the Basic Model Interface (BMI) (Hutton et al., 2020), the Message Passing Interface (MPI) (Alvioli & Baum., 2016), and similar interoperability protocols, the platform can support coupling with externally defined hydrological and environmental models. This design allows for scalable growth; integrating new libraries and exposing hundreds of additional blocks is feasible through well-defined interfaces.

The integration of a dedicated AI assistant introduces a novel interface paradigm, where natural language understanding can enhance user onboarding, workflow construction, and exploratory analysis. Although still in early development, this feature is reinforced by a large language model that can leverage both embedded workflows and context-specific metadata. When fully realized, it will support intelligent recommendations, cross-resource integration, and improved user onboarding through guided interactions.

Formal user testing and evaluation efforts are forthcoming. While initial feedback from demonstration sessions and workshops has been positive—in particular, we have presented the work in CIROH Developers Conference in 2025—broader usability studies are needed to assess the platform's effectiveness across user groups including researchers, educators, and practitioners. These engagements will also inform design refinements and feature prioritization, ensuring HydroBlox remains aligned with community needs.

Rather than merely replacing scripting environments, HydroBlox redefines how users—regardless of programming background—interact with data, models, and visual tools in a seamless, browser-based environment. As development progresses, the platform's strength lies in its flexibility, both in its technical design, which allows for high-performance execution and block-level customization, and in its role as an interface between domain expertise and computational systems. This positions HydroBlox not just as a tool, but as a blueprint for scalable, interactive scientific computing in hydrology and beyond.

6. Conclusions

This work presents HydroBlox, a web-based platform for constructing, executing, and sharing hydrological workflows using a visual programming paradigm. Built entirely on client-side technologies, the system supports modular integration of data sources, analytical functions, and visualization components through a structured, block-based interface. It enables users to define and modify workflows interactively, with no requirement for server infrastructure or programming expertise.

Through its integration with the HydroSuite library ecosystem and support for WebAssembly execution, HydroBlox supports both general-purpose hydrological processing and advanced, domain-specific computation with potential hooks and integrations to legacy desktop applications and python libraries in hydrology. The inclusion of an AI-assisted interface further enhances the modeling experience by providing contextual suggestions and reducing the effort needed to assemble valid workflows.

The case studies demonstrate that the system is capable of supporting real-world hydrological analyses, including event-based streamflow response assessment and drought index calculation. Results can be visualized within the platform and exported as reproducible, portable applications for further use, instruction, or archiving. By focusing on browser-native deployment and structured, declarative workflow logic, HydroBlox provides a foundation for rethinking how environmental models and analyses are built, shared, and sustained in hydrological science.

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