Engineering AI-Assisted Client-Side Scientific Workflows: WebGPU Inference Architecture and Framework for Privacy-Preserving Hydrological Analysis

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Abstract

Deep learning has demonstrated strong potential for improving hydrological predictions, yet its practical adoption remains limited by software complexity, infrastructure requirements, data governance constraints, and fragmented analytical workflows. This study presents Hydro AI Lab, an AI-assisted client-side scientific workflow platform that enables end-to-end hydrological analysis, including data ingestion, model training, evaluation, and AI-assisted interpretation, entirely on the user's device without reliance on cloud infrastructure. The system is built on a four-layer architecture comprising a user interface layer, a framework-free deep learning engine, geospatial visualization layer, and a browser-native large language model (LLM) assistant powered by WebGPU. We introduced a WebGPU-based inference pipeline tailored for scientific workflows, incorporating tokenization, parallel prefill, autoregressive decoding with KV cache, 4-bit quantization, and a structured context injection mechanism that embeds analytical results directly into LLM interactions. Empirical benchmarks demonstrate real-time inference performance of 21 to 95 tokens per second across multiple model sizes on commodity hardware. Design decisions are informed by published usability evidence from related hydrological decision support systems. The results demonstrate that privacy-preserving, locally executable scientific AI workflow is feasible and practical, offering a scalable pathway toward more accessible, reproducible, and deployable machine learning workflows in hydrology and related environmental domains.

Keywords: Client-Side Artificial Intelligence, WebGPU, Hydrological Modelling, Privacy-Preserving Machine Learning, Scientific Workflow System

1. Introduction

Physics-based operational hydrological models generate predictions across thousands of USGS gauge locations but exhibit systematic biases arising from simplified parameterizations, limited calibration, and forcing uncertainty (Gauch et al., 2021; Nearing et al., 2021). Data-driven post-processing using deep learning has demonstrated strong potential for correcting these errors, with long short-term memory (LSTM) networks achieving benchmark performance in rainfall-runoff prediction (Kratzert et al., 2018, 2019; Lees et al., 2021). Convolutional neural networks (CNNs) and temporal convolutional networks (TCNs) further extend modeling capabilities through efficient feature extraction and flexible receptive fields (Bai et al., 2018), while transformer-based architectures continue to expand the methodological landscape (Wu et al., 2020). Despite these advances, translating high-performing models into operational hydrological workflows remains a persistent challenge.

Beyond predictive performance, effective adoption of machine learning in scientific domains depends on usability, reproducibility, and accessibility for domain experts who may not possess advanced software engineering expertise. Prior work in scientific workflow systems has shown that fragmented toolchains, heterogeneous software environments, and loosely connected analytical components reduce transparency and complicate reproducibility across users and platforms (List et al., 2017; Moreau et al., 2023). These challenges are compounded by the diversity of tools and dependencies required to execute modern machine learning pipelines, which often demand significant setup effort and system-level configuration (Hossain et al., 2023; 2024). In response, no-code and accessible machine learning platforms have emerged as a promising paradigm for lowering technical barriers, enabling domain specialists to develop and apply models through simplified interfaces without extensive programming requirements (Li & Wu, 2022; Naser, 2023; Sundberg & Holmström, 2023). Such approaches have been shown to accelerate adoption, improve usability, and facilitate collaboration between technical and domain-focused stakeholders (Raghavendran & Elragal, 2023; Giraldo & Laso, 2025).

Despite this progress, practical adoption of deep learning in hydrology remains constrained by a combination of scientific, technical, and organizational barriers. These include concerns regarding model interpretability, limited familiarity with machine learning methodologies among domain practitioners, and challenges in establishing trust in data-driven predictions (Shen, 2018; Nearing et al., 2021). In addition, three barriers are particularly consequential for operational deployment. First, modern deep learning frameworks such as PyTorch, TensorFlow, and JAX impose substantial technical prerequisites, including GPU drivers, CUDA toolkits, and version-specific dependencies, which limit accessibility and prevent deployment on restricted or managed computing environments (Shen, 2018). Second, cloud-based machine learning workflows introduce data transmission requirements that conflict with data governance policies and privacy constraints in many scientific and governmental contexts (Abdeen et al., 2021; Sajja et al., 2025c). Sensitive hydrological data, including operational forecasts and pre-publication datasets, often cannot be transmitted to external cloud services without extensive compliance procedures. Third, fragmented toolchains require users to move across multiple disconnected environments for preprocessing, training, evaluation, and interpretation, increasing complexity and reducing reproducibility (Addor et al., 2017; Kratzert et al., 2019). Collectively, these barriers restrict advanced machine learning workflows to well-resourced research settings and limit their broader operational adoption.

Recent advances in browser-native computing and lightweight AI deployment provide a pathway to address these limitations. Browser-based applications offer substantial advantages for scientific software deployment by eliminating installation requirements, simplifying updates, and enabling cross-platform access through standardized web technologies (Ramirez et al., 2022). At the same time, developments in model compression and efficient inference, including quantized large language models and lightweight architectures, have made it possible to execute advanced AI workloads on commodity hardware with reduced memory and computational demands (Lin et al., 2024; Liu et al., 2024). The emergence of WebGPU further extends these capabilities by enabling GPU-accelerated computation directly within the browser, allowing high-performance parallel processing without reliance on external infrastructure (Ramirez et al., 2024). Together, these advances make it feasible to design scientific AI systems that operate entirely on-device, combining accessibility, performance, and privacy.

Concurrent developments in hydroinformatics reinforce this opportunity. The community has established robust web-based cyberinfrastructure for hydrological data access (Tarboton et al., 2014), visualization, and decision support (Alabbad et al., 2024), including disaster information systems, geospatial data platforms, and collaborative hazard mitigation tools (Demiray et al., 2025; Sermet et al., 2020). Recent work has also explored conversational AI and domain-specific embeddings for environmental applications, demonstrating improved performance in question answering and decision support tasks (Sajja et al., 2025b). In parallel, browser-native inference frameworks such as web-llm have demonstrated that quantized large language models can achieve substantial fractions of native performance in browser environments, enabling real-time AI interaction without cloud dependencies (Ruan et al., 2024). However, existing systems have not integrated these advances into a unified, client-side scientific workflow that combines data ingestion, model training, evaluation, and AI-assisted interpretation.

This convergence creates the foundation for a new class of scientific platforms in which both model training and AI-assisted interpretation can be executed entirely on client-side. Such systems offer the potential to unify data ingestion, model development, evaluation, and context-aware interpretation within a single privacy-preserving analytical environment. However, despite recent advances in browser-native AI and hydrological cyberinfrastructure, the software architecture and inference design patterns required to realize this paradigm for scientific workflows remain under-described. This study addresses this gap by detailing the engineering of a client-side hydrological AI platform at the system architecture and inference pipeline levels.

This study presents Hydro AI Lab, a client-side scientific AI platform that addresses these challenges by enabling end-to-end hydrological analysis—including data ingestion, model training, evaluation, and AI-assisted interpretation—entirely within the user's browser, without reliance on cloud infrastructure. The system integrates a framework-free deep learning engine, interactive geospatial visualization, and a WebGPU-based large language model assistant into a unified, privacy-preserving analytical environment. By operating entirely on-device, the platform eliminates data transmission requirements while providing an accessible, no-code workflow for hydrological practitioners.

The contributions of this study are as follows: (1) a four-layer software architecture enabling complete client-side scientific AI with zero data transmission; (2) a WebGPU-based LLM inference pipeline designed for scientific workflow support, including KV cache management, quantization, and structured context injection; (3) system-level sequence diagrams and a six-stage operational workflow; (4) a framework-free deep learning execution engine implemented in pure NumPy; (5) empirical performance benchmarks of browser-based LLM inference across multiple model sizes and hardware configurations; and (6) a design rationale informed by published usability evidence from related hydrological decision support systems.

2. Related Work

This section reviews five areas of prior work that collectively motivate Hydro AI Lab: deep learning for hydrological post-processing, web-based decision support systems, scientific workflow accessibility, in-browser machine learning, and LLM inference architecture.

2.1. Deep Learning for Hydrological Post-Processing

Deep learning has become a major methodological paradigm for hydrological prediction and post-processing, particularly for correcting biases in physics-based operational forecasts. Long short-term memory (LSTM) networks established benchmark performance for rainfall-runoff and streamflow prediction, demonstrating that data-driven approaches can match or exceed process-based methods across diverse catchments and timescales (Kratzert et al., 2018, 2019; Gauch et al., 2021). Large-sample evaluations further showed that deep learning can outperform traditional hydrological models in both gauged and ungauged settings (Nearing et al., 2021; Lees et al., 2021). Beyond recurrent architectures, convolutional neural networks (CNNs) and temporal convolutional networks (TCNs) have been adopted for their parallelism, feature extraction capabilities, and flexible receptive fields in sequence modeling (Bai et al., 2018). Hybrid approaches that combine process-based and data-driven components have also demonstrated promise for improving predictive robustness and interpretability (Frame et al., 2022).

At the same time, the hydrological deep learning literature has diversified substantially in terms of architectures, tasks, and application domains. Sit et al. (2020) reviewed a wide range of deep learning families used across prediction, classification, and generation tasks in hydrology. More recent work has also explored transformer-based models, multimodal learning, and domain-specific representation learning for hydrological applications (Wu et al., 2020; Kadiyala et al., 2024). Collectively, this literature demonstrates that the field has made substantial progress in model design and predictive benchmarking. However, most prior work has focused primarily on algorithmic performance rather than on how trained models can be operationalized within accessible, privacy-preserving, and end-to-end analytical environments for non-programmer users.

2.2. Web-Based Hydrological Decision Support

In parallel with advances in predictive modeling, the hydroinformatics community has developed a mature ecosystem of web-based decision support systems for hydrological data access, visualization, and stakeholder engagement. Early efforts such as HydroShare established community-oriented infrastructure for sharing hydrological data, models, and workflows in collaborative research environments (Tarboton et al., 2014). Web-based information systems demonstrated how real-time hydrological data, forecasting products, and geospatial interfaces could be integrated into a generalized flood cyberinfrastructure for public and operational use (Yesilkoy et al., 2024). Additional work formalized information-centric approaches for flood knowledge representation and semantic interoperability, supporting more structured communication across environmental information systems (Baydaroglu et al., 2023).

Subsequent systems expanded these capabilities into interactive and participatory decision support. Serious gaming and collaborative web platforms have been used to support hazard mitigation, watershed planning, and multi-stakeholder environmental decision-making (Emiroglu et al., 2025). Published evaluations of these systems reported strong usability, realism, and decision confidence outcomes in hydrological planning contexts (Kadiyala et al., 2025). More recently, conversational AI and multimodal large language models have been evaluated for environmental monitoring, hydrological interpretation, and operational support (Pursnani et al., 2025). Domain-specific embedding models have also demonstrated improved semantic retrieval performance for hydrology-focused question answering tasks (Sajja et al., 2025a). Collectively, these systems demonstrate the maturity of web-based hydrological cyberinfrastructure for visualization, communication, and decision support, but they fall short of integrating locally executable machine learning training and browser-native AI interpretation as first-class components of the analytical workflow itself.

2.3. Scientific Workflow Accessibility and Reproducibility

Scientific adoption of machine learning depends not only on model performance but also on the usability, reproducibility, and deployability of the surrounding software environment. Prior work in scientific workflow systems has shown that fragmented toolchains, heterogeneous dependencies, and loosely connected analytical components complicate reproducibility and increase operational overhead across users and platforms (List et al., 2017; Moreau et al., 2023). These challenges are particularly pronounced in workflows that depend on multiple frameworks, runtime environments, or system-level configurations (Hossain et al., 2023; 2024). In many scientific settings, such fragmentation reduces transparency, hinders reuse, and makes it difficult to preserve provenance across evolving analytical workflows (Semmelrock et al., 2025).

In response, no-code and accessible machine learning systems have gained attention as a means of lowering technical barriers for domain experts without extensive programming backgrounds. Across scientific and engineering domains, such platforms have been shown to accelerate prototyping, improve collaboration between technical and non-technical users, and broaden access to advanced analytics (Li & Wu, 2022; Naser, 2023; Sundberg & Holmström, 2023). These systems are particularly relevant in settings where users need to configure, train, and interpret models without managing dependency-heavy machine learning stacks or infrastructure-specific deployment constraints (Raghavendran & Elragal, 2023; Giraldo & Laso, 2025). However, this line of work has not yet been meaningfully integrated into browser-native hydrological workflows that combine model training, evaluation, geospatial analysis, and AI-assisted interpretation within a single local environment.

2.4. In-Browser Machine Learning and WebGPU

Web browsers have increasingly emerged as a viable runtime environment for machine learning inference, motivated by their cross-platform accessibility, zero-install deployment model, and broad hardware reach. TensorFlow.js enabled browser-based neural network execution through WebGL, establishing an early foundation for machine learning directly within web applications (Smilkov et al., 2019). More recent browser-native runtimes such as ONNX Runtime Web have expanded support for framework-agnostic model execution in web environments. The standardization and adoption of WebGPU have further advanced this space by enabling GPU-class parallel computation directly in the browser through compute shaders and low-level memory control (WebGPU W3C, 2023).

Recent work has also demonstrated that browser-native execution is now feasible for large language models. The web-llm project showed that 4-bit quantized LLMs can achieve substantial fractions of native performance in-browser, with interactive decoding speeds on consumer hardware (Ruan et al., 2024). These advances significantly expand the scope of browser-native AI from lightweight inference tasks toward more capable, interactive, and locally executable language systems. However, existing browser-native machine learning work has focused primarily on demonstrating feasibility and runtime performance rather than on how these capabilities can be embedded into end-to-end scientific workflows where analytical outputs must be programmatically injected, interpreted, and communicated in a domain-specific context.

2.5. LLM Inference Architecture

The recent practicality of local large language model deployment has been enabled by a series of architectural and systems-level optimizations for transformer inference. Transformer generation typically consists of two phases: a prefill stage, in which the full input sequence is processed in parallel, and an autoregressive decode stage, in which tokens are generated sequentially (Vaswani et al., 2017). The KV cache reduces redundant computation by storing previously computed key and value tensors, allowing each newly generated token to attend to prior context without recomputing the entire sequence (Pope et al., 2023). This optimization is central to achieving interactive inference speeds for long-context or streaming applications.

Additional efficiency gains have come from model compression and attention optimization. Weight quantization methods such as GPTQ and AWQ reduce model memory requirements substantially while preserving usable inference quality, enabling deployment of multi-billion-parameter models on consumer hardware (Frantar et al., 2022; Lin et al., 2024). Memory-efficient attention techniques such as PagedAttention and FlashAttention further improve throughput and scalability by reducing memory fragmentation and optimizing attention computation on modern hardware (Dao et al., 2022; Kwon et al., 2023). However, these techniques were developed primarily for server-side and CUDA-native environments. Their application in browser-native scientific systems remains underexplored, particularly in settings where model loading, shader compilation, memory allocation, and domain-aware context injection must be coordinated within an interactive client-side analytical workflow.

Taken together, the preceding review reveals a clear convergence of capabilities that has not yet been realized within a single system. Deep learning has established strong benchmarks for hydrological prediction, web-based cyberinfrastructure has matured for visualization and decision support, no-code paradigms have lowered accessibility barriers for domain experts, and browser-native runtimes have demonstrated that both model training and LLM inference can execute on commodity hardware. However, no existing system integrates these advances into a unified, client-side scientific workflow that combines data ingestion, model training, evaluation, and AI-assisted interpretation within a single privacy-preserving environment. Bridging this gap requires not only assembling individual components but designing coherent software architecture and inference pipeline that coordinates local computation, structured context assembly, and interactive language-based explanation without external dependencies.

The following section describes the methodology and system design of Hydro AI Lab, which addresses this gap through a four-layer architecture that enables complete client-side scientific AI for hydrological analysis.

3. Methodology

3.1. Guided Analytical Workflow

The platform implements a six-stage analytical workflow (Figure 1) that guides users from data ingestion to AI-assisted interpretation within a structured, browser-accessible environment. The workflow is organized into three user-facing stages (data upload, location setup, and model configuration), followed by local computational execution for model training, evaluation, visualization, and AI-based interpretation. This staged design provides a clear separation between user interaction and computational processing while maintaining a unified end-to-end analytical experience.

Each stage is designed to be self-contained and sequential, with interface-level validation preventing incomplete or invalid progression through the workflow. This structure reduces configuration errors and lowers the technical barrier for users who may not have prior experience with machine learning pipelines or scientific programming environments. By exposing only the decisions relevant to each step while abstracting underlying implementation complexity, the workflow supports accessibility without sacrificing analytical flexibility.

The workflow design is informed by behavior-driven and user-centered principles commonly adopted in scientific decision support systems, where each stage corresponds to a discrete and testable user action. Importantly, the separation between interface operations and local computational stages also reinforces the platform's privacy-preserving design: all analytical tasks, including model training and AI inference, are executed locally on the user's device without external data transmission. As a result, privacy is enforced at the architectural level rather than relying solely on software policy or deployment assumptions.

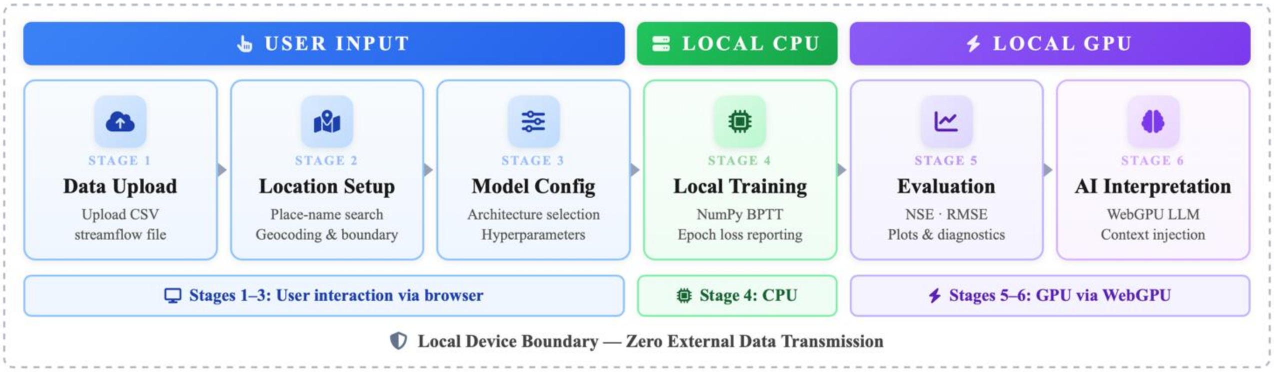


Figure 1. Six-stage operational workflow of Hydro AI Lab showing user input, local CPU execution, and local GPU execution within a zero-transmission device boundary

3.2. System Architecture

The system is designed as a four-layer architecture (Figure 2) to support modular, fully local execution of scientific workflows. The layers include: (i) a user interface (UI) layer; (ii) an analysis pipeline; (iii) a geospatial processing layer; and (iv) an AI assistant layer. Each layer is functionally decoupled while communicating through well-defined interfaces, enabling clear separation of concerns and maintainability across the system.

The UI layer (Streamlit with embedded HTML/JavaScript components) manages user interaction, workflow navigation, configuration dialogs, and visualization of outputs, including integration with the browser-based AI assistant. The analysis pipeline (Python with NumPy) performs core computational tasks, including data ingestion, validation, model training, and metric computation. The geospatial layer (PyDeck with Nominatim) provides location-based functionality, including geocoding, boundary retrieval, and spatial visualization. The AI assistant layer (WebGPU with web-llm) is responsible for model initialization, structured context assembly, and streaming inference for user queries.

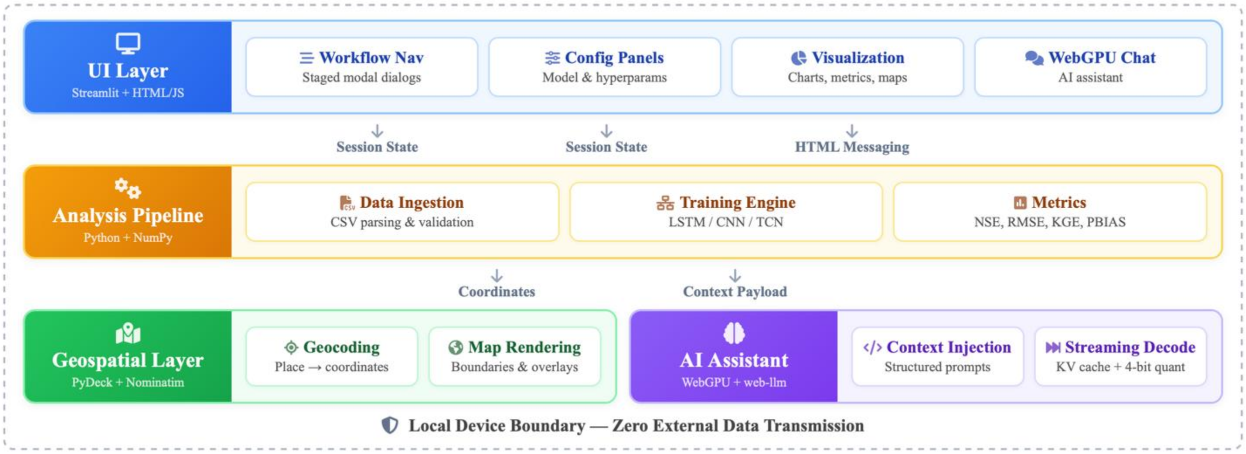
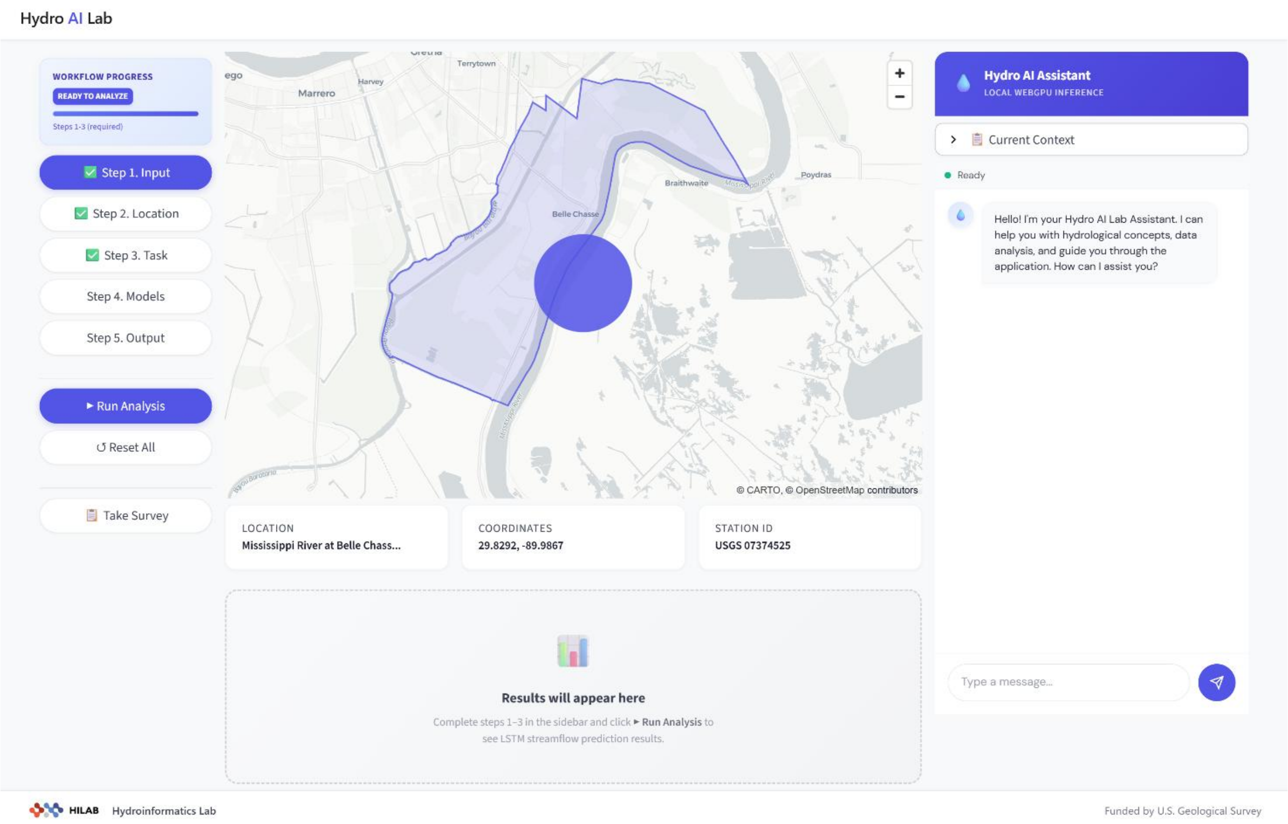


Figure 2. Four-layer system architecture of Hydro AI Lab showing UI, analysis pipeline, geospatial processing, and WebGPU-based AI assistant operating within a zero-transmission local device boundary

Communication between layers is implemented through Streamlit session state for Python-based components and HTML component messaging for interactions between Python and browser-executed JavaScript. This design enables seamless coordination between computational processes and user-facing interfaces while maintaining strict locality of execution. Importantly, no component of the system transmits hydrological data or analytical outputs to external services, ensuring that all computation occurs within the local device boundary.

3.3. Geospatial Visualization Layer

The geospatial visualization layer provides spatial context for hydrological analysis through interactive browser-based mapping and geocoding functionality (Figure 3). Implemented using PyDeck and Nominatim, this layer enables users to specify analysis locations through place-name search while dynamically retrieving associated coordinate metadata and administrative boundary geometries. This allows spatial selection to function as an integrated analytical input rather than a separate preprocessing step.



LOCATION
Mississippi River at Belle Chass...

COORDINATES
29.8292, -89.9867

STATION ID
USGS 07374525

Hello! I'm your Hydro AI Lab Assistant. I can help you with hydrological concepts, data analysis, and guide you through the application. How can I assist you?

Results will appear here

Complete steps 1–3 in the sidebar and click ► Run Analysis to see LSTM streamflow prediction results.

Figure 3. Hydro AI Lab geospatial interface showing Belle Chasse, Louisiana, with boundary visualization, coordinate metadata, and live AI assistant context

Once a location is selected, the system renders the corresponding spatial context using an interactive map interface, including boundary overlays, point-based location markers, and supporting geographic metadata. These outputs are used both for user-facing interpretation and as structured contextual inputs to downstream analytical and AI-assisted components. In this way, the geospatial layer serves not only as a visualization module, but also as a mechanism for linking hydrological analysis to place-specific environmental context within the overall workflow.

3.4. Design Principles

The interaction design of Hydro AI Lab is structured to support usability, workflow clarity, and seamless coordination between analytical computation and AI-assisted interpretation (Figure 4). The sequence diagram illustrates the end-to-end interaction flow across four primary system actors: the user, the UI layer, the analysis pipeline, and the AI assistant. Rather than treating model execution and AI interaction as separate processes, the system is designed so that analytical outputs can be directly incorporated into downstream interpretation within the same workflow.

Several design principles guided this interaction model. First, workflow configuration is staged through structured interface components that expose only the controls relevant to each step, reducing user error and lowering the complexity of model setup. Second, model training is accompanied by real-time progress updates, allowing users to observe computational progress and intermediate loss behavior during local execution. Third, analytical outputs are programmatically assembled into a structured context payload for the AI assistant, eliminating the need for users to manually transfer model results into a separate interpretive interface. Finally, AI responses are streamed incrementally during inference, supporting responsive interaction and improving continuity between computational output and natural language explanation.

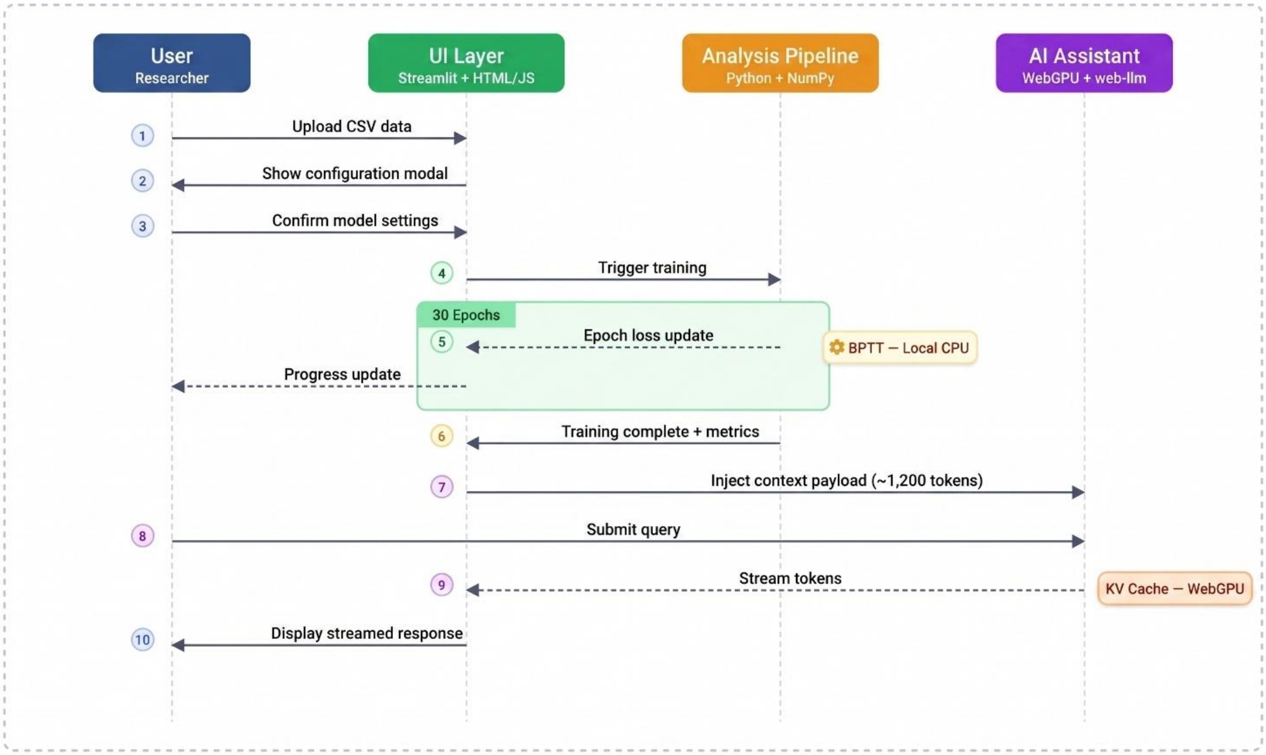


Figure 4. Sequence diagram of the Hydro AI Lab workflow showing local model training, context injection, and WebGPU-based AI response generation

An important architectural feature of this workflow is the asynchronous relationship between the analytical pipeline and the AI assistant. Context is injected only after model execution and metric computation are complete, ensuring that the assistant operates on finalized analytical outputs rather than transient intermediate states. This design improves interpretive consistency while preserving a clear boundary between computational execution and language-based explanation.

3.5. LSTM Post-Processing Methodology

A central design decision of Hydro AI Lab is the implementation of the complete model training and inference pipeline using a framework-free approach based on NumPy (Harris et al., 2020). Unlike conventional machine learning systems that rely on libraries such as PyTorch, TensorFlow, or JAX, this approach eliminates dependencies on compiled binaries, GPU drivers, and platform-specific toolchains. This design significantly improves portability and deployability, enabling execution in constrained environments such as institutional systems with restricted permissions or limited hardware support.

The analytical engine supports recurrent and convolutional architectures for hydrological post-processing tasks. For recurrent models, the implementation follows standard long short-term memory (LSTM) formulations (Hochreiter & Schmidhuber, 1997), where input sequences are processed through gated transformations at each timestep. The computational graph is explicitly unrolled across sequence length, and gradients are computed via backpropagation through time (BPTT), with gradient clipping applied to maintain numerical stability. Convolutional variants are implemented using one-dimensional sliding-window operations with configurable receptive fields, enabling alternative sequence modeling strategies within the same execution framework.

Parameter optimization is performed using the Adam algorithm (Kingma & Ba, 2014), with bias-corrected moment estimates for stable convergence. Model parameters are initialized using Xavier/Glorot scaling (Glorot & Bengio, 2010) to ensure balanced gradient propagation across layers. These choices reflect standard practices in deep learning while being implemented entirely within a lightweight, dependency-free computational environment.

The default training configuration is designed to provide a balance between computational efficiency and predictive performance for typical hydrological datasets. The baseline setup includes a single-layer LSTM with 32 hidden units, a sequence length of 168 timesteps (corresponding to a 7-day hourly lookback), and a chronological 70/15/15 train-validation-test split to preserve temporal structure and avoid data leakage (Gauch et al., 2021). Training is performed for 30 epochs using mean squared error loss and gradient clipping with a norm threshold of 1.0.

The framework-free implementation supports practical training speeds on commodity hardware. For a dataset of 4,321 hourly samples, training completes in approximately 35 seconds on Apple M1 hardware, 50 seconds on an Intel i7-10750H system, and 80 seconds on an Intel i5-8250U system. These results demonstrate that fully local model training for hydrological post-processing is feasible without specialized hardware or software dependencies, supporting the broader objective of accessible and privacy-preserving scientific machine learning workflows.

3.6. WebGPU In-Browser AI Assistant

The WebGPU-based AI assistant constitutes a central component of Hydro AI Lab, enabling fully local large language model inference for scientific interpretation tasks. The inference pipeline (Figure 5) is structured into six stages: context assembly, system prompt construction, tokenization, parallel prefill, autoregressive decoding, and streaming output.

The first two stages are specific to the scientific workflow setting, where analytical results, dataset metadata, and workflow state are programmatically assembled and embedded into the model input. The remaining stages follow standard transformer inference patterns, adapted for browser-native execution using GPU compute shaders. This decomposition separates domain-specific processing from model-generic operations, allowing the pipeline to be extended to other scientific domains with minimal modification.

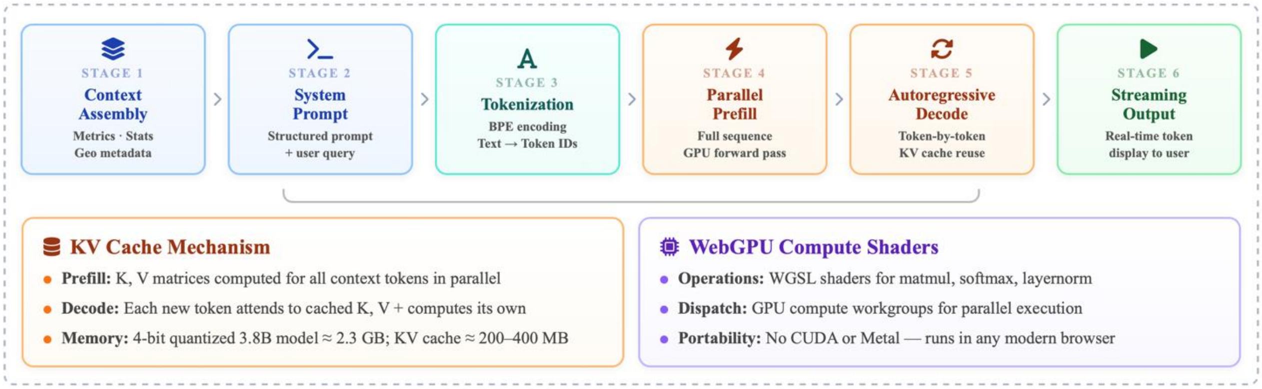


Figure 5. WebGPU LLM inference pipeline. Context Assembly through Streaming Output. Bottom panels detail the KV cache mechanism and WebGPU compute shader execution

Context Injection Mechanism. Prior to inference, the system constructs a structured context payload consisting of: (i) workflow configuration and parameters, (ii) geographic metadata, (iii) dataset statistics, and (iv) analytical outputs, including model performance metrics and training summaries. This information is embedded into the system prompt and combined with the user query. This approach enables the language model to operate as a context-aware scientific assistant without requiring fine-tuning, retrieval pipelines, or external APIs. By grounding responses in programmatically generated analytical context, the system reduces ambiguity and improves the relevance of generated interpretations.

Prefill and Decode Phases. Inference proceeds in two stages: a parallel prefill phase and an autoregressive decode phase (Figure 6). During prefill, all input tokens are processed simultaneously on the GPU, generating key and value tensors for each token. These are stored in the KV cache, which enables efficient reuse of previously computed attention states. During decoding, tokens are generated sequentially. Each new token attends to the cached key-value history without recomputing prior states, reducing computational complexity from quadratic to linear with respect to sequence length. This optimization is critical for achieving interactive performance in browser-based environments.

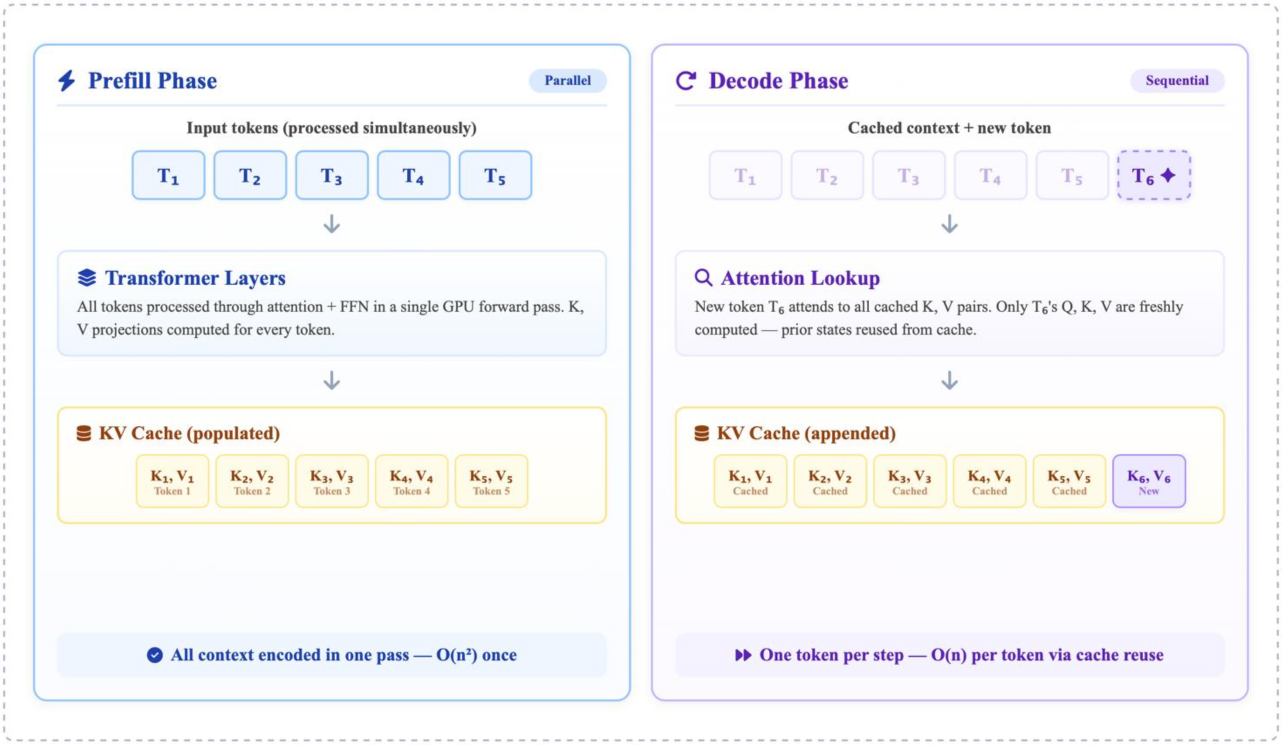


Figure 6. WebGPU inference workflow showing parallel prefill and autoregressive decode with KV cache reuse for efficient token generation

Quantization and Memory. To support deployment of LLMs on consumer hardware, models are quantized to 4-bit precision using methods such as GPTQ or AWQ. This reduces memory requirements substantially, enabling multi-billion-parameter models to execute within typical GPU memory limits (4-8 GB). The WebGPU runtime performs dequantization within compute shaders, allowing efficient browser-native execution without reliance on CUDA or external libraries.

4. Results

4.1. Experimental Evaluation: Belle Chasse Case Study

To evaluate the platform's end-to-end functionality, Hydro AI Lab was applied to a hydrological post-processing task using 4,321 hourly samples from USGS gauge 07374525 (Belle Chasse, Louisiana), where observed streamflow was compared against National Water Model (NWM) predictions. The case study was designed to assess whether the platform could support the full analytical workflow locally, including data ingestion, model configuration, training, evaluation, visualization, and AI-assisted interpretation, without reliance on external compute services.

Using the default LSTM configuration described in Section 3.5, the trained model achieved a Nash-Sutcliffe Efficiency (NSE) of 0.858 and a root mean square error (RMSE) of 740 cfs on the held-out test set. Training completed in approximately 35 seconds on Apple M1 hardware for the full dataset, confirming that practical hydrological post-processing can be executed on commodity consumer devices within an interactive time frame.

These results demonstrate that the platform is capable of supporting a complete scientific machine learning workflow entirely on-device. Importantly, the output is not limited to predictive performance alone; the platform also produces structured metadata, visual diagnostics, and contextual summaries that are subsequently available to the embedded AI assistant for interpretation. This enables the analytical workflow to proceed seamlessly from model execution to result explanation within the same software environment (the corresponding visual outputs are presented in Figure 8).

4.2. Browser-Native AI Inference Performance

To evaluate the practical performance of browser-native AI inference within Hydro AI Lab, we benchmarked three quantized language models across representative hardware configurations (Table 1). Three hardware configurations were tested: Apple M1 with 8 GB unified memory, Intel i7-12700H with NVIDIA RTX 3060 (6 GB), and Intel i5-1235U with Iris Xe integrated graphics. All benchmarks were conducted in Google Chrome (122+, WebGPU enabled) using the platform's standard context injection payload of approximately 1,200 tokens. Reported values correspond to median performance across 10 inference runs. Table 1 reports time to first token (TTFT, reflecting prefill latency), autoregressive decode speed, and peak GPU memory allocation for each configuration.

Table 1. WebGPU LLM inference benchmarks across model sizes and hardware configurations.

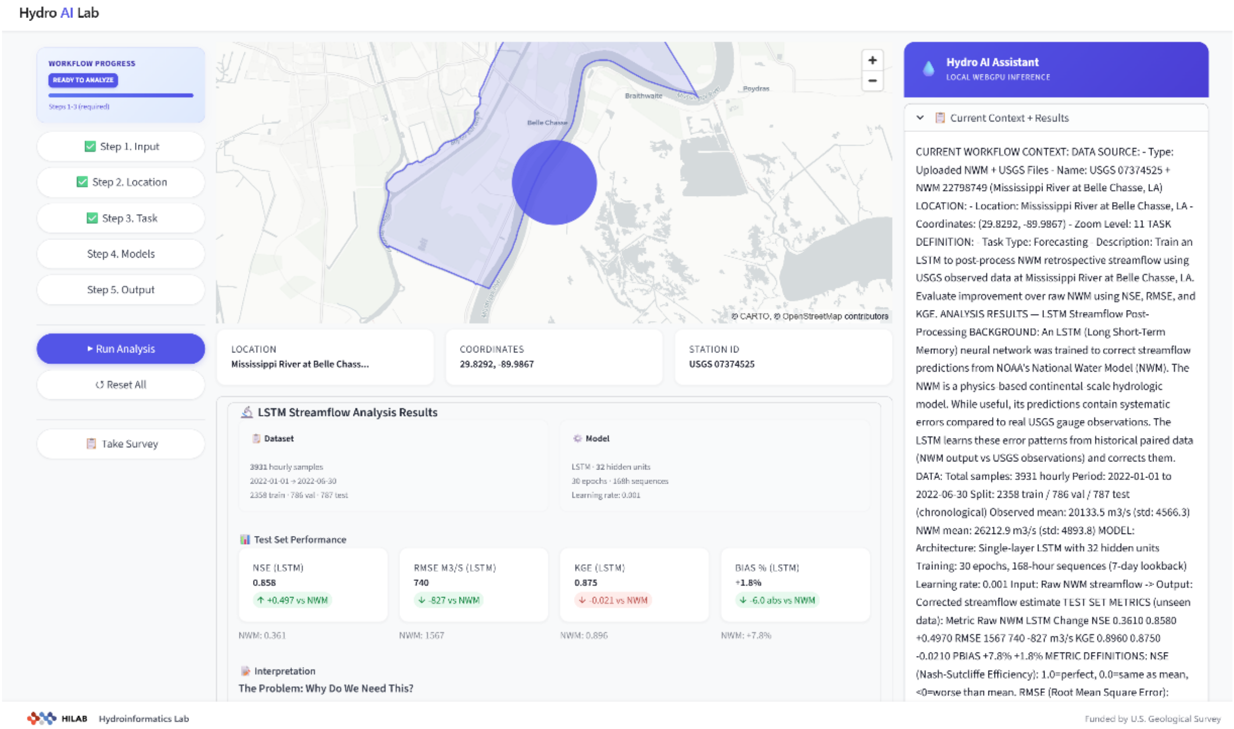
Model	**Params (4-bit)**	**GPU Mem**	**TTFT M1**	**Decode M1**	**TTFT i7+RTX**	**Decode i7+RTX**	**Decode i5 iGPU**
SmolLM2-360M	~220 MB	~350 MB	0.3 s	82 tok/s	0.2 s	95 tok/s	28 tok/s
SmolLM2-1.7B	~1.0 GB	~1.4 GB	0.8 s	38 tok/s	0.5 s	52 tok/s	12 tok/s
Phi-3.5-mini-3.8B	~2.3 GB	~2.8 GB	1.8 s	21 tok/s	1.1 s	34 tok/s	6 tok/s

The results show that Hydro AI Lab achieves interactive large language model inference directly within the browser, with decode speeds ranging from 21 to 95 tokens per second depending on model size and hardware. The smallest tested model (SmolLM2-360M) delivered near-instant interaction, while the largest supported model (Phi-3.5-mini-3.8B) remained deployable within consumer GPU memory limits. Time to first token ranged from 0.2 to 1.8 seconds, indicating that structured scientific context can be processed with acceptable latency for real-time analytical support.

Several practical observations follow from these benchmarks. First, SmolLM2-360M provides highly responsive interaction even on Apple M1 hardware, making it suitable for low-latency interpretive support. Second, Phi-3.5-mini-3.8B offers stronger response quality at the cost of higher latency and greater hardware dependence, with the best interactive performance observed on discrete GPUs. Third, the largest tested model remained within a 4 GB GPU memory budget when quantized, confirming that multi-billion-parameter browser-native inference is feasible on widely available consumer hardware. Collectively, these results demonstrate that WebGPU-based scientific AI assistance is not merely a proof of concept, but practically deployable within a browser-based analytical workflow.

4.3. Integrated Workflow Outputs and AI-Assisted Interpretation

Beyond standalone analytical and inference benchmarks, Hydro AI Lab was evaluated as an integrated workflow environment connecting model execution, geospatial context, and AI-assisted interpretation. Figure 7 shows the results dashboard generated following model execution, including dataset characteristics, model configuration, test metrics, and the structured analytical context payload passed to the embedded AI assistant. This interface allows the analytical state of the workflow to be made directly available for downstream interpretation without requiring manual transcription or external tools.



LOCATION: Mississippi River at Belle Chass...

COORDINATES: 29.8292, -89.9867

STATION ID: USGS 07374525

LSTM Streamflow Analysis Results

Dataset
3931 hourly samples
2022-01-01 → 2022-06-30
2358 train · 786 val · 787 test

Model
LSTM · 32 hidden units
30 epochs · 168h sequences
Learning rate: 0.001

Test Set Performance

NSE (LSTM)	RMSE M3/S (LSTM)	KGE (LSTM)	BIAS % (LSTM)
0.858	740	0.875	+1.8%
↑ +0.497 vs NWM	↓ -827 vs NWM	↓ -0.021 vs NWM	↓ -6.0 abs vs NWM
NWM: 0.361	NWM: 1567	NWM: 0.896	NWM: +7.8%

Interpretation

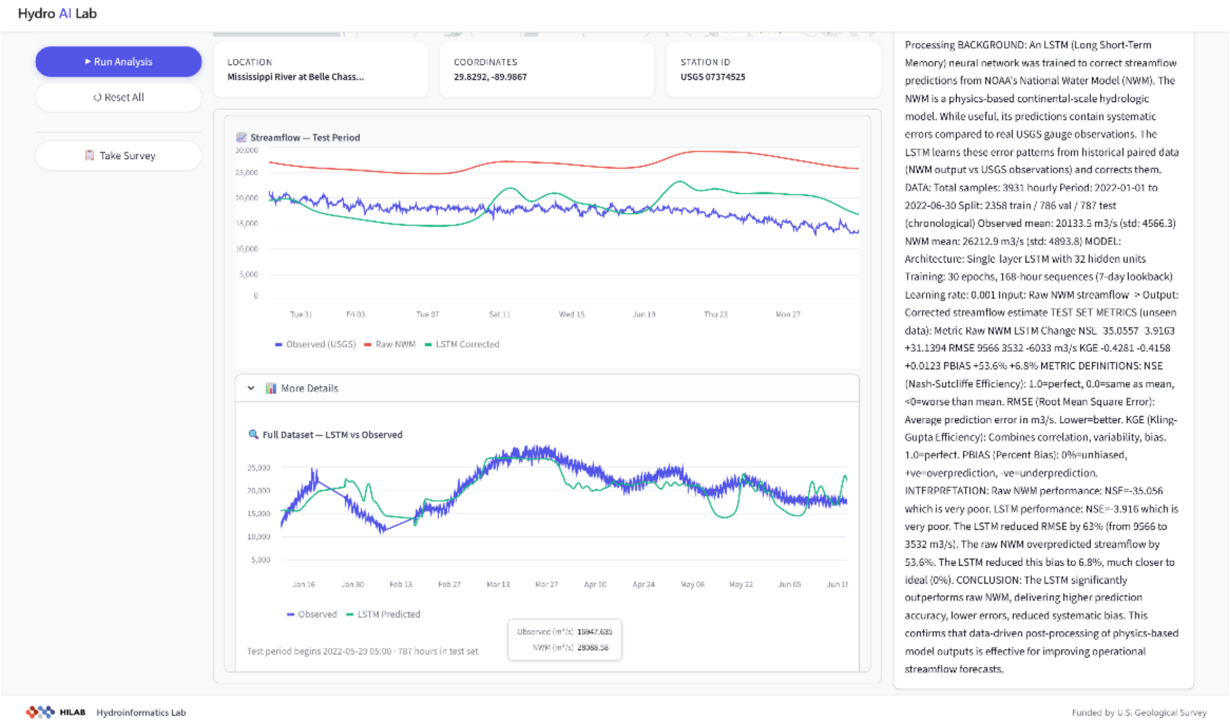
The Problem: Why Do We Need This?

CURRENT WORKFLOW CONTEXT: DATA SOURCE: - Type: Uploaded NWM + USGS Files - Name: USGS 07374525 + NWM 22798749 (Mississippi River at Belle Chasse, LA) LOCATION: - Location: Mississippi River at Belle Chasse, LA - Coordinates: (29.8292, -89.9867) - Zoom Level: 11 TASK DEFINITION: - Task Type: Forecasting - Description: Train an LSTM to post-process NWM retrospective streamflow using USGS observed data at Mississippi River at Belle Chasse, LA. Evaluate improvement over raw NWM using NSE, RMSE, and KGE. ANALYSIS RESULTS — LSTM Streamflow Post-Processing BACKGROUND: An LSTM (Long Short-Term Memory) neural network was trained to correct streamflow predictions from NOAA's National Water Model (NWM). The NWM is a physics-based continental-scale hydrologic model. While useful, its predictions contain systematic errors compared to real USGS gauge observations. The LSTM learns these error patterns from historical paired data (NWM output vs USGS observations) and corrects them. DATA: Total samples: 3931 hourly Period: 2022-01-01 to 2022-06-30 Split: 2358 train / 786 val / 787 test (chronological) Observed mean: 20133.5 m3/s (std: 4566.3) NWM mean: 26212.9 m3/s (std: 4893.8) MODEL: Architecture: Single-layer LSTM with 32 hidden units Training: 30 epochs, 168-hour sequences (7-day lookback) Learning rate: 0.001 Input: Raw NWM streamflow -> Output: Corrected streamflow estimate TEST SET METRICS (unseen data): Metric Raw NWM LSTM Change NSE 0.3610 0.8580 +0.4970 RMSE 1567 740 -827 m3/s KGE 0.8960 0.8750 -0.0210 PBIAS +7.8% +1.8% METRIC DEFINITIONS: NSE (Nash-Sutcliffe Efficiency): 1.0=perfect, 0.0=same as mean, <0=worse than mean. RMSE (Root Mean Square Error):

Figure 7. Results dashboard showing model outputs, performance metrics, and structured analytical context provided to the embedded AI assistant

Figure 8 further illustrates the system's integrated output environment, where users can inspect time series comparisons, predicted-versus-observed scatter plots, and training progress curves while simultaneously interacting with the browser-native AI assistant. Because the assistant is initialized with workflow-specific analytical context, it is able to respond to user queries about location, model behavior, and performance using the outputs of the completed analysis rather than relying on generic responses.

Taken together, these results demonstrate that Hydro AI Lab functions not only as a browser-based visualization or inference tool, but as a complete locally executable scientific AI environment. The platform supports model development, evaluation, geospatial contextualization, and interpretive consultation within a single privacy-preserving system boundary, enabling a more unified analytical workflow than conventional fragmented toolchains.



LOCATION: Mississippi River at Belle Chass...

COORDINATES: 29.8292, -89.9867

STATION ID: USGS 07374525

Test period begins 2022-05-29 05:00 · 787 hours in test set

Observed (m³/s) 18947.635
NWM (m³/s) 28088.58

Processing BACKGROUND: An LSTM (Long Short-Term Memory) neural network was trained to correct streamflow predictions from NOAA's National Water Model (NWM). The NWM is a physics-based continental-scale hydrologic model. While useful, its predictions contain systematic errors compared to real USGS gauge observations. The LSTM learns these error patterns from historical paired data (NWM output vs USGS observations) and corrects them. DATA: Total samples: 3931 hourly Period: 2022-01-01 to 2022-06-30 Split: 2358 train / 786 val / 787 test (chronological) Observed mean: 20133.5 m3/s (std: 4566.3) NWM mean: 26212.9 m3/s (std: 4893.8) MODEL: Architecture: Single-layer LSTM with 32 hidden units Training: 30 epochs, 168-hour sequences (7-day lookback) Learning rate: 0.001 Input: Raw NWM streamflow -> Output: Corrected streamflow estimate TEST SET METRICS (unseen data): Metric Raw NWM LSTM Change NSE -35.0557 -3.9163 +31.1394 RMSE 9566 3532 -6033 m3/s KGE -0.4281 -0.4158 +0.0123 PBIAS +53.6% +6.8% METRIC DEFINITIONS: NSE (Nash-Sutcliffe Efficiency): 1.0=perfect, 0.0=same as mean, <0=worse than mean. RMSE (Root Mean Square Error): Average prediction error in m3/s. Lower=better. KGE (Kling-Gupta Efficiency): Combines correlation, variability, bias. 1.0=perfect. PBIAS (Percent Bias): 0%=unbiased, +ve=overprediction, -ve=underprediction. INTERPRETATION: Raw NWM performance: NSE=-35.056 which is very poor. LSTM performance: NSE=-3.916 which is very poor. The LSTM reduced RMSE by 63% (from 9566 to 3532 m3/s). The raw NWM overpredicted streamflow by 53.6%. The LSTM reduced this bias to 6.8%, much closer to ideal (0%). CONCLUSION: The LSTM significantly outperforms raw NWM, delivering higher prediction accuracy, lower errors, reduced systematic bias. This confirms that data-driven post-processing of physics-based model outputs is effective for improving operational streamflow forecasts.

Figure 8. Results interface showing model diagnostics, training curves, and AI-assisted interpretation of locally generated hydrological analysis outputs

5. Discussion

This work demonstrates that privacy-preserving, locally executable scientific AI workflow is not only technically feasible, but also practically deployable for real-world analytical workflows. Rather than treating browser-based AI as a lightweight visualization layer or a thin client for cloud services, Hydro AI Lab shows that the browser can function as a complete scientific execution environment supporting data ingestion, model training, evaluation, geospatial interaction, and AI-assisted interpretation within a unified local system. This represents an important shift in how scientific machine learning tools can be engineered and delivered, particularly for domains in which accessibility, reproducibility, and data governance are as important as predictive performance.

A central contribution of the platform is its architectural reframing of scientific AI around local-first execution. In most contemporary analytical systems, privacy and governance are handled as policy constraints layered on top of cloud-native software stacks. In contrast, Hydro AI Lab enforces privacy structurally: analytical data never leaves the user's machine because the platform is designed without any external inference dependency. This distinction is significant for scientific, governmental, and operational settings where even well-performing AI tools may be unusable if they require data transmission to external services. The platform contributes not only a software implementation, but also a deployable systems pattern for privacy-sensitive scientific computing.

Equally important is the system's treatment of AI assistance as workflow-native rather than externally appended. Many AI-enhanced analytical systems still rely on manual copying of outputs into generic chat interfaces, creating friction, context loss, and opportunities for error. Hydro AI Lab instead operationalizes a structured context injection mechanism that programmatically assembles model outputs, workflow state, dataset statistics, and geographic metadata directly into the inference context of the browser-native LLM. This enables the assistant to respond to the user's actual analysis state rather than to an isolated natural language prompt. The result is a more grounded and scientifically useful form of AI interaction that does not require model fine-tuning, external retrieval infrastructure, or API-based orchestration. From a software architecture perspective, this may be one of the most transferable contributions of the work.

The broader implication is that context-aware local LLMs can serve as interpretable interfaces for scientific workflows, particularly for users who may not be comfortable directly interpreting model diagnostics, metrics, or error patterns. In hydrology, this is valuable because the barrier to adoption is often not simply training a model, but understanding whether its outputs are trustworthy, how they compare to baseline forecasts, and what they imply for domain-specific decision making. By embedding interpretive assistance directly into the workflow, the platform helps bridge the gap between machine learning capability and operational usability. This framing positions Hydro AI Lab not merely as a hydrological application, but as an example of how scientific software can incorporate generative AI in a way that is computationally grounded, reproducible, and domain-aware.

Hydro AI Lab's interface and workflow design are also informed by prior evidence from hydrological decision support research. For example, Sermet et al. (2020) evaluated a web-based hydrological decision support system with 60 participants spanning agriculture, planning, emergency management, government, and academia, reporting high ratings for usefulness (4.55/5), pace appropriateness (4.26/5), and scenario realism (4.22/5), with 92% of participants indicating increased comfort with watershed planning decisions. These findings are relevant because they validate several of the same design principles adopted in Hydro AI Lab, including abstraction of technical complexity behind intuitive interfaces, real-time visual feedback, and geospatial interaction as a core analytical component. Hydro AI Lab extends these principles further by supporting user-supplied data, local model training, and AI-assisted interpretation within the same workflow, thereby moving beyond scenario-based decision support toward a more general-purpose scientific analysis environment.

At the same time, the present implementation has several limitations that define clear directions for future work. First, the analytical engine is intentionally framework-free and CPU-based, which improves portability and deployability but limits scalability for larger datasets, more complex architectures, and multi-site analyses. Second, the current implementation focuses on a single-gauge post-processing workflow, which provides a well-bounded demonstration environment but does not yet capture the broader complexity of regional or multi-source hydrological modeling. Third, while the WebGPU assistant achieves interactive performance on commodity hardware, response quality remains bounded by the capabilities of compact quantized models, particularly on lower-end integrated GPUs. Finally, the design validation in this study relies on comparative evidence from previously evaluated hydrological systems rather than direct user studies of Hydro AI Lab itself. Although this is appropriate for a novel framework study, direct usability and adoption studies will be essential to quantify the platform's effectiveness in practice.

Taken together, these findings suggest that the significance of Hydro AI Lab lies less in any single model or interface element and more in the software design pattern it establishes: a browser-native, zero-transmission, context-aware scientific AI workflow that is usable on ordinary hardware and adaptable to privacy-sensitive domains. While hydrology provides the motivating use case, the underlying architectural principles are readily extensible to other scientific and engineering settings in which users need to train models, interpret outputs, and interact with AI assistance without relying on cloud infrastructure. As lightweight models, browser runtimes, and local acceleration continue to improve, this class of systems is likely to become increasingly viable as a general paradigm for deployable scientific AI.

6. Conclusion and Future Work

This study presented Hydro AI Lab, a browser-accessible, client-side scientific AI framework designed to support end-to-end hydrological analysis without external computational infrastructure. By combining a four-layer software architecture, a framework-free analytical engine, interactive geospatial visualization, and a WebGPU-based large language model assistant, the platform demonstrates that modern scientific AI workflows can be executed entirely on the user's device while maintaining practical usability and interactive performance. In doing so, the work addresses a persistent gap between the growing methodological sophistication of machine learning in hydrology and the limited deployability of those methods in accessible, privacy-sensitive, and operationally constrained environments.

Beyond the hydrological use case, the primary contribution of this study is architectural. The proposed design shows how local model training, browser-native inference, structured analytical context injection, and AI-assisted interpretation can be integrated into a unified software workflow without cloud dependency, fine-tuning pipelines, or fragmented analytical tooling. The empirical benchmarks further demonstrate that this approach is not merely conceptual: quantized LLM inference at interactive speeds is achievable on commodity hardware, and meaningful scientific interpretation can be delivered within the same local environment as the analytical workflow itself. These findings support the broader claim that privacy-preserving, locally executable scientific AI is now a viable systems paradigm rather than a speculative future direction.

Future work will extend the framework in three main directions. First, the analytical engine will be expanded to support additional architectures, larger-scale datasets, and broader hydrological tasks beyond single-gauge post-processing. Second, formal user studies will evaluate usability, trust, interpretability, and decision support value across scientific and operational user groups. Third, the general architecture introduced here will be explored as a transferable pattern for other privacy-sensitive scientific domains in which AI must operate close to the data rather than through external cloud services. In this perspective, Hydro AI Lab should be understood not only as a hydrological framework, but as a proof-of-concept for a broader class of scientific systems in which accessible machine learning and local generative AI are engineered as part of the same deployable computational environment.

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Data Availability

The platform is hosted at https://hydroinformatics.tulane.edu/lab/hydroailab/ with source code at https://github.com/uihilab/HydroAILab. Released under the Apache-2.0 license.

Competing Interests

The authors declare that they have no competing interests.

Credit Author Statement

Nikhil Singh: Conceptualization, Software, Methodology, Visualization, and Writing - Original Draft. **Ramteja Sajja**: Methodology, Conceptualization, and Writing - Review & Editing. **Yusuf Sermet**: Conceptualization, Methodology, Writing - Review & Editing, Investigation, Validation, Supervision, Funding acquisition. **Ibrahim Demir**: Conceptualization, Methodology, Writing - Review & Editing, Project administration, Funding acquisition, and Resources.

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 took full responsibility for the content of the publication.

References

Abdeen, F. N., Fernando, T., Kulatunga, U., Hettige, S., & Ranasinghe, K. A. (2021). Challenges in multi-agency collaboration in disaster management: A Sri Lankan perspective. *International journal of disaster risk reduction*, *62*, 102399.

Addor, N., Newman, A. J., Mizukami, N., & Clark, M. P. (2017). The CAMELS data set: catchment attributes and meteorology for large-sample studies. Hydrology and Earth System Sciences, 21(10), 5293-5313.

Alabbad, Y., Mount, J., Campbell, A. M., & Demir, I. (2024). A web-based decision support framework for optimizing road network accessibility and emergency facility allocation during flooding. *Urban Informatics*, *3*(1), 10.

Bai, S., Kolter, J. Z., & Koltun, V. (2018). An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. *arXiv preprint arXiv:1803.01271*.

Dao, T., Fu, D., Ermon, S., Rudra, A., & Ré, C. (2022). Flashattention: Fast and memory-efficient exact attention with io-awareness. *Advances in neural information processing systems*, *35*, 16344-16359.

Demiray, B. Z., Sermet, Y., Yildirim, E., & Demir, I. (2025). FloodGame: An interactive 3D serious game on flood mitigation for disaster awareness and education. *Environmental Modelling & Software*, 188, 106418.

Emiroglu, E., Grant, C. A., Sermet, Y., & Demir, I. (2025). Floodcraft: Game-based interactive learning environment using Minecraft for flood mitigation for K-12 education. *International journal of disaster risk reduction*, 105799.

Frame, J. M., Kratzert, F., Klotz, D., Gauch, M., Shalev, G., Gilon, O., ... & Nearing, G. S. (2022). Deep learning rainfall–runoff predictions of extreme events. *Hydrology and Earth System Sciences*, *26*(13), 3377-3392.

Frantar, E., Ashkboos, S., Hoefler, T., & Alistarh, D. (2022). Gptq: Accurate post-training quantization for generative pre-trained transformers. *arXiv preprint arXiv:2210.17323*.

Gauch, M., Kratzert, F., Klotz, D., Nearing, G., Lin, J., & Hochreiter, S. (2021). Rainfall–runoff prediction at multiple timescales with a single Long Short-Term Memory network. *Hydrology and Earth System Sciences*, *25*(4), 2045-2062.

Giraldo, L., & Laso, S. (2025). Democratizing Machine Learning: A Practical Comparison of Low-Code and No-Code Platforms. *Machine Learning and Knowledge Extraction*, *7*(4), 141.

Glorot, X., & Bengio, Y. (2010, March). Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics* (pp. 249-256). JMLR Workshop and Conference Proceedings.

Harris, C. R., Millman, K. J., Van Der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., ... & Oliphant, T. E. (2020). Array programming with NumPy. *nature*, *585*(7825), 357-362.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.

Hossain, M. M., Roy, B., Roy, C., & Schneider, K. (2023, July). Extensibility challenges of scientific workflow management systems. In *International Conference on Human-Computer Interaction* (pp. 51-70). Cham: Springer Nature Switzerland.

Hossain, M. M., Roy, B., Roy, C., & Schneider, K. (2024, June). Reproducibility challenges of external computational experiments in scientific workflow management systems. In *International Conference on Human-Computer Interaction* (pp. 189-207). Cham: Springer Nature Switzerland.

Kadiyala, L. A., Mermer, O., Samuel, D. J., Sermet, Y., & Demir, I. (2024). The implementation of multimodal large language models for hydrological applications: A comparative study of GPT-4 vision, gemini, LLaVa, and multimodal-GPT. Hydrology, 11(9), 148.

Kadiyala, L., Sajja, R., Sermet, Y., Muste, M., & Demir, I. (2025). AI-driven decision-making for water resource planning and hazard mitigation using automated multi-agents. *Journal of Hydroinformatics.*

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2018). Rainfall–runoff modelling using long short-term memory (LSTM) networks. *Hydrology and Earth System Sciences*, *22*(11), 6005-6022.

Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. Hydrology and Earth System Sciences, 23(12), 5089-5110.

Kwon, W., Li, Z., Zhuang, S., Sheng, Y., Zheng, L., Yu, C. H., ... & Stoica, I. (2023, October). Efficient memory management for large language model serving with pagedattention. In *Proceedings of the 29th symposium on operating systems principles* (pp. 611-626).

Lees, T., Buechel, M., Anderson, B., Slater, L., Reece, S., Coxon, G., & Dadson, S. J. (2021). Benchmarking data-driven rainfall–runoff models in Great Britain: a comparison of long short-term memory (LSTM)-based models with four lumped conceptual models. *Hydrology and Earth System Sciences*, *25*(10), 5517-5534.

Li, L., & Wu, Z. (2022, June). How can no/low code platforms help end-users develop ml applications?-a systematic review. In *International Conference on Human-Computer Interaction* (pp. 338-356). Cham: Springer Nature Switzerland.

Lin, J., Tang, J., Tang, H., Yang, S., Chen, W. M., Wang, W. C., ... & Han, S. (2024). Awq: Activation-aware weight quantization for on-device llm compression and acceleration. *Proceedings of machine learning and systems*, *6*, 87-100.

List, M., Ebert, P., & Albrecht, F. (2017). Ten simple rules for developing usable software in computational biology. *PLoS computational biology*, *13*(1), e1005265.

Liu, H. I., Galindo, M., Xie, H., Wong, L. K., Shuai, H. H., Li, Y. H., & Cheng, W. H. (2024). Lightweight deep learning for resource-constrained environments: A survey. *ACM Computing Surveys*, *56*(10), 1-42.

Moreau, D., Wiebels, K., & Boettiger, C. (2023). Containers for computational reproducibility. *Nature Reviews Methods Primers*, *3*(1), 50.

Naser, M. Z. (2023). Machine learning for all! Benchmarking automated, explainable, and coding-free platforms on civil and environmental engineering problems. *Journal of Infrastructure Intelligence and Resilience*, *2*(1), 100028.

Nearing, G. S., Kratzert, F., Sampson, A. K., Pelissier, C. S., Klotz, D., Frame, J. M., ... & Gupta, H. V. (2021). What role does hydrological science play in the age of machine learning?. *Water Resources Research*, *57*(3), e2020WR028091.

Pope, R., Douglas, S., Chowdhery, A., Devlin, J., Bradbury, J., Heek, J., ... & Dean, J. (2023). Efficiently scaling transformer inference. *Proceedings of machine learning and systems*, *5*, 606-624.

Pursnani, V., Sermet, Y., & Demir, I. (2025). A conversational intelligent assistant for enhanced operational support in floodplain management with multimodal data. International Journal of Disaster Risk Reduction, 122, 105422.

Raghavendran, K. R., & Elragal, A. (2023, June). Low-code machine learning platforms: a fastlane to digitalization. In *Informatics* (Vol. 10, No. 2, p. 50). MDPI.

Ramirez, C. E., Sermet, Y., Molkenthin, F., & Demir, I. (2022). HydroLang: An open-source web-based programming framework for hydrological sciences. *Environmental Modelling & Software*, 157, 105525.

Ramirez, C. E., Sermet, Y., & Demir, I. (2024). HydroCompute: An open-source web-based computational library for hydrology and environmental sciences. *Environmental Modelling & Software*, 175, 106005.

Ruan, C. F., Qin, Y., Zhou, X., Lai, R., Jin, H., Dong, Y., ... & Chen, T. (2024). Webllm: A high-performance in-browser llm inference engine. *arXiv preprint arXiv:2412.15803*.

Sajja, R., Mermer, O., Sermet, Y., & Demir, I. (2025c). Hydro3DJS: A modular web-based library for real-time 3D visualization of watershed dynamics and digital twin integration. *Environmental Modelling & Software*, 106853.

Sajja, R., Sermet, Y., Demir, I. (2025a). Domain-specific embedding models for hydrology and environmental sciences: enhancing semantic retrieval and question answering. Water Science & Technology, 92(9), 1328. doi:10.2166/wst.2025.156.

Sajja, R., Xiong, S., Mermer, O., Sermet, Y., & Demir, I. (2025b). A Bibliometric Overview of Conversational AI in Hydrology and Environmental Sciences. *Information Geography*, 100030.

Semmelrock, H., Ross-Hellauer, T., Kopeinik, S., Theiler, D., Haberl, A., Thalmann, S., & Kowald, D. (2025). Reproducibility in machine-learning-based research: Overview, barriers, and drivers. *AI Magazine*, *46*(2), e70002.

Sermet, Y., Demir, I., & Muste, M. (2020). A serious gaming framework for decision support on hydrological hazards. *Science of The Total Environment*, *728*, 138895.

Shen, C. (2018). A transdisciplinary review of deep learning research and its relevance for water resources scientists. *Water Resources Research*, *54*(11), 8558-8593.

Sit, M., Demiray, B. Z., Xiang, Z., Ewing, G. J., Sermet, Y., & Demir, I. (2020). A comprehensive review of deep learning applications in hydrology and water resources. *Water Science and Technology*, *82*(12), 2635-2670.

Smilkov, D., Thorat, N., Assogba, Y., Nicholson, C., Kreeger, N., Yu, P., ... & Wattenberg, M. M. (2019). Tensorflow. js: Machine learning for the web and beyond. *Proceedings of machine learning and systems*, *1*, 309-321.

Sundberg, L., & Holmström, J. (2023). Democratizing artificial intelligence: How no-code AI can leverage machine learning operations. *Business Horizons*, *66*(6), 777-788.

Tarboton, D. G., Idaszak, R., Horsburgh, J. S., Heard, J., Ames, D., Goodall, J. L., ... & Maidment, D. (2014). HydroShare: advancing collaboration through hydrologic data and model sharing. 7th International Congress on Environmental Modelling and Software.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

WebGPU W3C (2023). WebGPU Specification. W3C GPU for the Web Community Group. https://www.w3.org/TR/webgpu/

Wu, N., Green, B., Ben, X., & O'Banion, S. (2020). Deep transformer models for time series forecasting: The influenza prevalence case. *arXiv preprint arXiv:2001.08317*.

Yeşilköy, S., Baydaroğlu, Ö., Singh, N., Sermet, Y., & Demir, I. (2024). A contemporary systematic review of cyberinfrastructure systems and applications for flood and drought data analytics and communication. *Environmental Research Communications*, 6(10), 102003.