HydroModelSpec: Toward Standardized Machine Learning Model Exchange in Hydrology

Nikhil Singh[1], Ramteja Sajja[1], Yusuf Sermet[1], Ibrahim Demir[1,2]

[1] ByWater Institute, Tulane University, New Orleans, LA 70118, USA
[2] River-Coastal Science and Engineering, Tulane University, New Orleans, LA 70118, USA
* Corresponding author: Ramteja Sajja, rsajja@tulane.edu

Abstract

The rapid growth of deep learning models for hydrological forecasting (e.g., CNNs, LSTMs, Transformers) has created a fragmented ecosystem where trained models remain tied to their original frameworks, environments, and institutions. Despite substantial investments in model development, the hydrological community lacks a generalized structure for packaging models with their architecture, training provenance, I/O schema, performance benchmarks, and execution requirements into a portable, verifiable format that facilitates sharing and reproducibility. This study presents HydroModelSpec, a vendor-neutral, open-source, JSON Schema-based framework for encoding, validating, and exchanging hydrological machine learning models. Building on established practices in model documentation and metadata standards, the framework organizes model exchange through a layered architecture: a Core Schema for universal metadata, Domain Profiles for task-specific constraints (e.g., streamflow post-processing, water level forecasting, flood inundation, reservoir operations), Portable Document Types (including Model Cards, Execution Manifests, and Benchmark Reports) for contextualizing artifacts, and a Validator for enforcing structural and semantic conformance. The framework also incorporates a privacy attestation component, supporting trust-verified model sharing in regulated environments where training data cannot leave the originating device. By providing a standardized structure through which hydrological researchers and agencies can share trained models without sharing raw data, HydroModelSpec aims to lower the barriers to reproducibility, interoperability, and collaborative model development across the hydrological sciences.

Keywords: Model Exchange Framework, Machine Learning Interoperability, Hydrological Forecasting, Reproducible Model Sharing, JSON Schema

1. Introduction

The past decade has witnessed substantial growth in the diversity and capability of machine learning models applied to hydrological forecasting and water model post-processing. Long short-term memory (LSTM) networks have established benchmark performance for rainfall–runoff modelling across diverse catchments (Hochreiter & Schmidhuber, 1997; Kratzert et al., 2018; 2019), with large-sample evidence demonstrating that deep learning approaches can match or exceed traditional process-based methods for streamflow prediction (Nearing et al., 2021; Lees et al., 2021). Convolutional neural networks (CNNs) extract local temporal features with computational efficiency (Bai et al., 2018), while temporal convolutional networks (TCNs) provide causal dilated convolutions with configurable receptive fields (Sit et al., 2020). Transformer-based architecture has introduced attention mechanisms for time series forecasting (Wu et al., 2020), and hybrid encoder-decoder models combine feature extraction with temporal modelling for multi-step prediction (Frame et al., 2022). Shen (2018) provided an authoritative review establishing deep learning's relevance to water resources science, identifying both the transformative potential and the accessibility barriers that limit operational adoption.

Despite this architectural diversity, the hydrological machine learning ecosystem faces a persistent interoperability challenge: trained models often remain confined to the frameworks, environments, and institutions that produced them. A model trained in PyTorch cannot be directly loaded in TensorFlow without conversion. A model trained on one agency's infrastructure cannot be portably transferred to another without manual environment replication. A model's training provenance—what data it saw, how it was split, what metrics it was tested on, and how it should be executed—is rarely encoded in a standardized or machine-verifiable form. The result is a fragmented landscape in which substantial investments in model development yield artifacts that are difficult to reuse, compare, or share across institutional boundaries.

This fragmentation creates several interconnected challenges. First, it prevents efficient model reuse: a streamflow post-processor trained at one USGS gauge cannot be portably shared with a neighboring gauge operator without framework-specific export, ad hoc documentation, and environment replication. Second, it undermines reproducibility: without standardized metadata encoding for architecture, hyperparameters, training configuration, data splits, and evaluation protocol, independent verification of published results requires reverse-engineering from prose descriptions (Knoben et al., 2022; Addor et al., 2017; Hut & Hall, 2025), a challenge recognized as part of a broader reproducibility crisis in machine-learning-based science (Kapoor & Narayanan, 2023). Third, it complicates model sharing across agencies with different data governance requirements: organizations that cannot share raw data due to Federal Information Security Modernization Act (FISMA), Cybersecurity and Infrastructure Security Agency (CISA), or institutional data governance policies (Abdeen et al., 2021; Chen et al., 2023) could in principle share trained model weights, but no generalized mechanism exists to document, in a standardized form, the provenance and training context of such models. This challenge is particularly relevant given the growing demand for AI-assisted environmental monitoring (Kadiyala et al., 2024), conversational assistants for floodplain management (Pursnani et al., 2025), and domain-specific semantic retrieval systems (Sajja et al., 2025a), and the rapidly expanding landscape of conversational AI applications in environmental sciences (Sajja et al., 2025b), all of which benefit from trusted and well-documented model provenance.

Existing model serialization and documentation formats address important aspects of this problem but have not been specifically adapted for the hydrological domain. ONNX (Open Neural Network Exchange) standardizes computational graph representation but carries no training provenance, no domain-specific metadata, and no privacy attestation. SavedModel and TorchScript are framework-specific serialization formats that capture computation graphs with additional serving metadata but remain locked to their respective ecosystems. Hardware-optimized formats such as Core ML and TensorRT impose vendor lock-in. Model Cards (Mitchell et al., 2019) and Datasheets for Datasets (Gebru et al., 2021) established the practice of documenting model and dataset characteristics in structured, human-readable form, and subsequent work has explored interactive extensions to improve accessibility for non-expert users (Crisan et al., 2022). Platforms such as Hugging Face Hub operationalized model cards at scale, but these documents are not machine-verifiable against a formal specification. MLflow (Zaharia et al., 2018) Model Registry and Weights & Biases provide experiment tracking but use platform-specific schemas not designed for cross-agency exchange.

While these approaches have advanced model exchange and documentation substantially, none define domain-specific profiles for hydrological tasks, standardize the metrics central to operational water forecasting, specifically NSE (Nash-Sutcliffe Efficiency), RMSE (Root Mean Square Error), KGE (Kling-Gupta Efficiency), and PBIAS (Percent Bias), or provide a unified structure for encoding hydrological model provenance alongside execution requirements. In geosciences more broadly, the Basic Model Interface (BMI 2.0; Ewing et al., 2024) established a standard coupling interface for numerical models (Hutton et al., 2020), and the MLCommons Croissant format introduced a layered metadata vocabulary for ML-ready datasets (Akhtar et al., 2024), while the FAIR principles have been extended to ML pipelines to promote findability, accessibility, interoperability, and reusability of trained models (Samuel et al., 2020). These efforts provide important foundations that HydroModelSpec builds upon and complement the specific needs of hydrological ML model exchange.

Within the hydroinformatics community, parallel efforts have built mature cyberinfrastructure for hydrological data exchange and decision support. HydroShare provides an extensible repository for hydrological datasets and model resources (Tarboton et al., 2014). The web technologies allowed researchers to establish generalized cyberinfrastructure for real-time flood data management (Yeşilköy et al., 2024; Ewing and Demir, 2021) and information-centric ontologies have formalized semantic interoperability across water management systems (Baydaroğlu et al., 2023). Web-based serious gaming platforms have engaged stakeholders in multi-hazard decision support (Alabbad et al., 2024; Kadiyala et al., 2025), and browser-native 3D visualization libraries have extended cyberinfrastructure capabilities toward real-time watershed visualization and digital twin integration (Sajja et al., 2025c). The benchmark dataset standardized hydrological and rainfall studies for large-sample studies (Addor et al., 2017; Sit et al., 2021), and CWARHM advanced reproducibility by decoupling preprocessing from model-specific configuration (Knoben et al., 2022). Most recently, GIFIS (Mudiyanselage et al., 2025) introduced JSON Schema contracts with validator enforcement for hydrological data exchange. These advances have substantially strengthened data interoperability, but none directly address the complementary problem of packaging trained ML models with their full provenance, domain-specific evaluation metrics, and execution requirements into a standardized format for portable exchange across institutions.

This study presents HydroModelSpec, a vendor-neutral, JSON Schema-based framework designed to provide a generalized structure for this model exchange problem. HydroModelSpec defines how a trained machine learning model can be packaged—together with its architecture specification, training provenance, input/output schema, performance benchmarks, execution requirements, and provenance documentation—into a single, portable, machine-verifiable artifact that any compliant platform can load, validate, and interpret. Rather than a single flat schema, HydroModelSpec is organized as a layered specification ecosystem that separates universal metadata, task-specific constraints, exchange documents, and validation logic. The framework is designed to be complementary to data exchange standards where data exchange standards address the movement and formatting of hydrological observations, HydroModelSpec addresses the packaging and sharing of the trained models that consume such data. Together with established hydroinformatics cyberinfrastructure, the framework contributes toward a more complete exchange ecosystem for reproducible and interoperable operational hydrology. The framework is designed to integrate with existing hydrological ML platforms, and its practical applicability is illustrated through example artifacts consistent with workflows on platforms such as Hydro AI Lab (Singh et al., 2026).

The primary contribution of this study is the framework itself: a layered, vendor-neutral set of JSON Schemas, document types, and validation rules that provide a generalized structure for portable hydrological ML model exchange. Specifically, the study contributes (1) a Core Schema defining universal model metadata; (2) a set of Domain Profiles constraining the framework for streamflow post-processing, water level forecasting, flood inundation, and reservoir operations; (3) Portable Document Types (Model Cards, Execution Manifests, Privacy Attestations, and Benchmark Reports) that contextualize artifacts for exchange; (4) a provenance and privacy attestation component supporting trust-verified model sharing; and (5) a Validator framework enforcing both structural and semantic conformance.

2. Methodology

2.1. Scope and Purpose

HydroModelSpec provides a generalized, vendor-neutral structure for packaging, validating, and exchanging trained machine learning model artifacts in operational hydrology. Its scope centers on the model itself—architecture, weights, training provenance, evaluation, execution requirements, and provenance documentation—and the relationships between models and the data, tasks, and platforms that produce and consume them. The framework deliberately refrains from prescribing training frameworks, weight storage formats, deployment infrastructure, or serving protocols. Instead, it ensures that any compliant producer can publish a model artifact once and any compliant consumer, whether a browser-based platform, a cloud-based inference service, or an air-gapped agency workstation, can interpret, validate, and execute the same artifact deterministically. The overarching purpose is to make reproducibility, portability, and standardized provenance intrinsic properties of the model artifact itself.

2.2. Design Philosophy

The design of HydroModelSpec emerged from analysis of operational ML workflows in hydrology, from established model exchange practices in the broader ML ecosystem (including MLflow, ONNX, Hugging Face Model Cards, and MLCommons Croissant), and from domain-specific standards in geosciences (BMI 2.0). The following five principles shaped the framework.

Interoperability as a semantic problem. The specification prioritizes unambiguous encoding of architecture type, layer configurations, input/output schemas, metric definitions, and provenance fields, the semantics that routinely fracture model portability in practice. Rather than focusing exclusively on byte-level serialization, the specification treats interoperability as a question of shared meaning across institutions.

Extensibility through profiles. A disciplined profile system (Core, Domain-Specific, Experimental) allows innovation without destabilizing stable contracts. New hydrological tasks or architectural families can be supported through profile additions rather than core schema modifications, preserving backward compatibility for existing artifacts.

Verifiability through validation. Every schema is paired with validator rules and machine-readable diagnostics, making conformance testable and reproducible across platforms. This design is informed by formal analyses of JSON Schema validation, which have established the computational complexity characteristics of modern schema dialects and identified optimization pathways for practical validator implementations (Attouche et al., 2024). Structural validation alone is insufficient: the framework also enforces semantic constraints (for example, NSE values bound above by 1.0, and consistency between privacy attestation flags) through a rule engine.

Privacy as a first-class property. HydroModelSpec includes provenance and privacy attestation as a structured component of the model artifact rather than an external annotation. The Privacy Attestation document type provides machine-readable declarations about training data handling, supporting documented model exchange in environments where data governance requirements constrain how models can be shared.

Complementarity with GIFIS. HydroModelSpec is designed to be complementary to data exchange frameworks such as GIFIS (Mudiyanselage et al., 2025): where GIFIS addresses the structure and exchange of hydrological data, HydroModelSpec addresses the packaging and exchange of models trained on that data. Cross-references between the two frameworks can support traceability from data source through trained model to operational prediction.

2.3. Architecture Overview

HydroModelSpec is not a single flat JSON file but a hierarchical schema ecosystem in which universal metadata, task-specific constraints, exchange documents, and validation logic are intentionally separated. This layered design, consistent with patterns used in BMI 2.0, OGC Core/Extensions, and MLCommons Croissant, enables the framework to evolve along independent axes: the Core Schema can remain stable while new Domain Profiles are added; new Portable Document Types can be introduced without affecting the validation logic; and validator rules can be extended without modifying any schema. Figure 1 illustrates the four layers of architecture and their relationships. The framework treats the weight file as an external asset referenced by URI and verified by SHA-256 hash rather than embedded inline, enabling lightweight artifact exchange while preserving integrity verification.

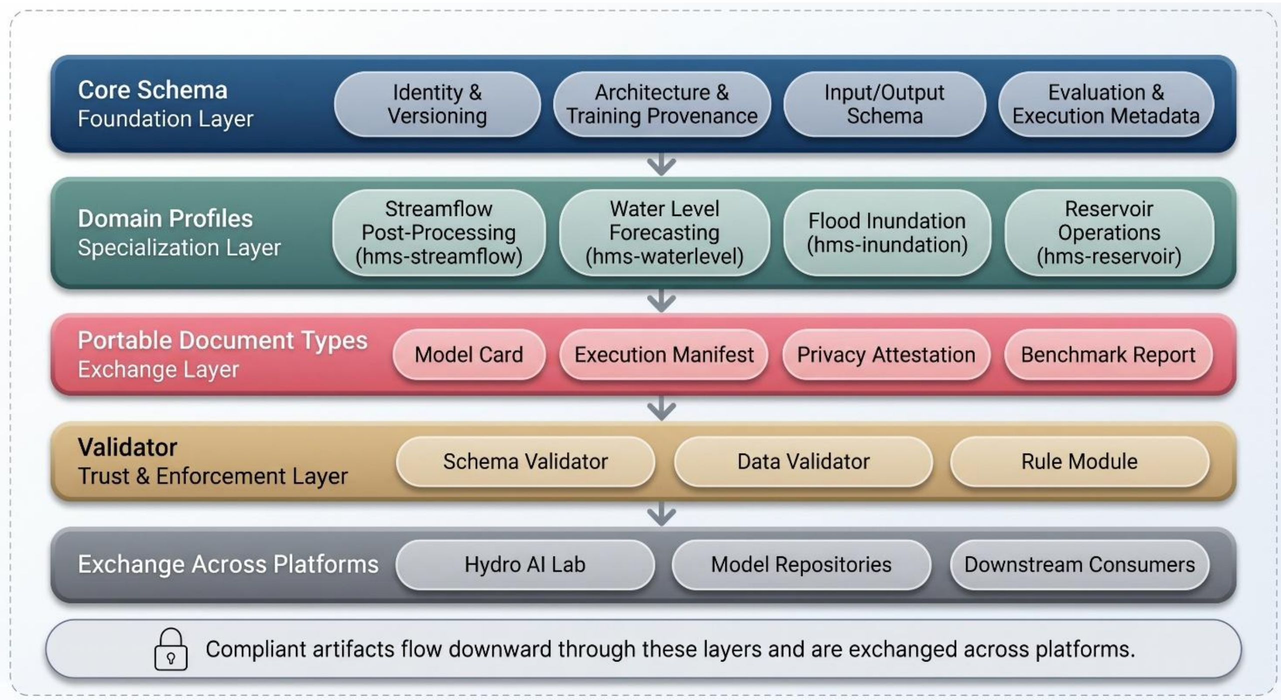

Figure 1. HydroModelSpec layered architecture: Core Schema, Domain Profiles, Portable Documents, Validator, and downstream platforms

2.3.1. Core Schema (Foundation Layer)

Every compliant artifact begins with the Core Schema, which defines the minimum universal contract that any HydroModelSpec-compliant model artifact must satisfy. The Core Schema specifies how every model regardless of architecture, training framework, target task, or deployment environment, must declare its identity, architecture, training provenance, input/output schema, evaluation results, execution requirements, and (optionally) privacy attestation. These fields constitute the minimal but sufficient structure for any ML model to be validated, exchanged, and executed deterministically across platforms. The Core Schema is intentionally domain-agnostic at this layer: although the framework targets operational hydrology, the foundation layer is designed to be reusable across other scientific domains that adopt the same layered design pattern.

2.3.2. Domain Profiles (Specialization Layer)

The Core Schema alone is insufficient for hydrology, because different hydrological prediction tasks require different metrics, target variables, metadata, and validation rules. Domain Profiles constitute the specialization layer of HydroModelSpec: they inherit from the Core Schema and then constrain required metrics, constrain input/output expectations, and add task-specific fields. A profile may, for example, mandate that streamflow models report Nash–Sutcliffe Efficiency, RMSE, KGE, and PBIAS against a raw NWM baseline; require gauge identifiers and drainage area metadata; and constrain the input schema to NWM streamflow sequences. The current specification defines four profiles: Streamflow Post-Processing (hms-streamflow@1.0), Water Level Forecasting (hms-waterlevel@1.0), Flood Inundation (hms-inundation@1.0), and Reservoir Operations (hms-reservoir@1.0). Additional profiles can be added without modifying the Core Schema.

2.3.3. Portable Document Types (Exchange Layer)

HydroModelSpec artifacts are accompanied by Portable Document Types that make them interpretable, executable, comparable, and trustworthy across platforms. These documents constitute the exchange and usability layer of the specification. The Model Card extends the structured documentation pattern of Mitchell et al. (2019), widely adopted through platforms such as Hugging Face Hub, with machine-verifiable fields and domain-specific sections for hydrological context. The Execution Manifest declares runtime dependencies, hardware requirements, and input/output processing steps, enabling any compliant platform to load and run the model without consulting external documentation. The Privacy Attestation provides standalone declarations of the model's training provenance, including hash-based references designed to support verification without access to the original training data. The Benchmark Report packages standardized metric comparisons against a defined baseline (typically the raw NWM) using the domain profile's required metric suite, including evaluation period, gauge identifiers, and reproducibility information sufficient for independent verification.

2.3.4. Validator (Trust and Enforcement Layer)

As recognized in formal analyses of JSON Schema validation (Attouche et al., 2024), structural validity alone does not guarantee semantic correctness. A model artifact may be syntactically valid yet contain an NSE value greater than 1.0, an inconsistent privacy flag, a malformed weight hash, or a profile mismatch between declared task and required fields. HydroModelSpec therefore includes both schema-based structural validation and rule-based logical validation. The Validator is implemented as a modular Python application comprising three components: (1) a Schema Validator that ensures correctness of model artifact schemas against the HydroModelSpec meta-schema; (2) a Data Validator that evaluates artifact JSON instances against the appropriate Core and profile schemas; and (3) a Rule Module that enforces semantic constraints, including metric range validation, privacy attestation consistency (trainedLocally=true requires dataTransmitted=false), hash format verification, and cross-reference integrity between training configuration and evaluation protocol. Examples of conformance failures the Rule Module is designed to surface include missing required fields, invalid metric ranges, inconsistent privacy flags, malformed hashes, and profile mismatches. The Validator operates as both a CLI tool and a programmable module for CI/CD integration; each validation result includes a rule code, severity level (error, warning, info), human-readable message, and JSON path to the offending field.

2.3.5. Cross-Layer Relationships and Exchange Flow

The four layers of HydroModelSpec interact in a coordinated exchange flow. A compliant artifact is produced through their joint operation and consumed through the same layers in reverse. The artifact creation flow can be summarized in four steps. First, the Core Schema defines the base structure that the artifact must satisfy. Second, a Domain Profile is selected based on the model's target task, applying task-specific constraints and required metrics. Third, Portable Documents are attached to provide execution context, trust attestations, and reporting. Fourth, the Validator checks conformance across all of the above, surfacing structural or semantic violations before the artifact is published. The model artifact itself references concrete computational and provenance assets, including weight files, dataset and weight hashes, dataset references (which may point to GIFIS entities for end-to-end traceability), benchmark outputs, and runtime dependencies. Through this layered exchange flow, the same artifact can move across heterogeneous platforms, browser-based no-code environments, server-side training pipelines, model registries, and downstream consumers, while preserving its semantic integrity and provenance guarantees.

3. Results

3.1. HydroModelSpec Specification

This section presents the concrete specification of HydroModelSpec as a set of JSON Schema parameter tables. Tables 1 through 6 enumerate the fields defined by the Core Schema and its supporting objects (Architecture, Training, Evaluation, Execution, and Privacy Attestation). The tables document each field's JSON path, data type, requirement status, and intended semantics, and serve as the authoritative reference for producers and consumers of HydroModelSpec-compliant artifacts.

Table 1. Core Schema: top-level parameters for all HydroModelSpec-compliant model artifacts.

JSON Path	Type	Req.	Description
id	string	Yes	Globally unique model identifier (UUID with hms-prefix).
specVersion	string	Yes	Spec version (e.g., hms-core@1.0). Semantic versioning.
name	string	Yes	Human-readable model name.
description	string	No	Free-text model description and intended use.
createdAt	date-time	Yes	ISO-8601 UTC creation timestamp.
updatedAt	date-time	Yes	ISO-8601 UTC last modification timestamp.
architecture	object	Yes	Model architecture specification (see Table 2).
training	object	Yes	Training configuration and provenance (see Table 3).
inputSchema	object	Yes	Input tensor specification (shape, dtype, features).
outputSchema	object	Yes	Output tensor specification (shape, dtype, targets).
evaluation	object	Yes	Performance metrics and benchmark results (see Table 4).
execution	object	No	Runtime requirements and compatibility (see Table 5).

JSON Path	Type	Req.	Description
privacy	object	No	Privacy attestation (see Table 6).
weights	object	Yes	Weight artifact location, format, hash, and size.
metadata	object	Yes	Provider, license, contact, provenance lineage.
links	array	No	Related resources (datasets, papers, APIs).
keywords	array<string>	No	Discovery tags (uniqueItems: true).

Table 2. Architecture object: model structure specification.

JSON Path	Type	Req.	Description
architecture.type	string (enum)	Yes	Architecture family: CNN, LSTM, GRU, TCN, Transformer, CNN-LSTM, XGBoost, RandomForest, Ensemble, Custom.
architecture.variant	string	No	Specific variant (e.g., BiLSTM, DilatedTCN, ViT).
architecture.layers	array <object>	No	Ordered layer definitions: type, units/filters, activation, dropout.
architecture.hiddenSize	integer	No	Hidden dimension for recurrent/attention architectures.
architecture.numLayers	integer	No	Depth (number of stacked layers).
architecture.kernelSize	integer	No	Convolution kernel size for CNN/TCN architectures.
architecture.dilationFactor	integer	No	Dilation factor for TCN architectures.
architecture.attentionHeads	integer	No	Number of attention heads for Transformer architectures.
architecture.totalParams	integer	No	Total trainable parameter count.
architecture.framework	string	No	Training framework (PyTorch, TensorFlow, NumPy, JAX).

Table 3. Training object: configuration and provenance.

JSON Path	Type	Req.	Description
training.optimizer	string	Yes	Optimizer name (Adam, SGD, AdamW, RMSprop).
training.learningRate	number	Yes	Initial learning rate.

JSON Path	Type	Req.	Description
training.epochs	integer	Yes	Number of training epochs completed.
training.batchSize	integer	No	Training batch size.
training.lossFunction	string	Yes	Loss function (MSE, MAE, Huber, NLL).
training.gradientClipping	number	No	Max gradient norm threshold.
training.sequenceLength	integer	No	Input sequence length (lookback window).
training.dataSplit	object	Yes	Split ratios and method: {train, val, test, method: chronological|random}.
training.datasetHash	string	No	SHA-256 hash of training dataset for reproducibility.
training.datasetRef	string (uri)	No	URI reference to source dataset (GIFIS entity or HydroShare).
training.startedAt	date-time	No	Training start timestamp (ISO-8601 UTC).
training.completedAt	date-time	No	Training completion timestamp.
training.hardware	string	No	Training hardware description.
training.executionEnv	string (enum)	No	Where training ran: local_cpu, local_gpu, cloud_gpu, webgpu_browser.

Table 4. Evaluation object: performance metrics and benchmark protocol.

JSON Path	Type	Req.	Description
evaluation.metrics	object	Yes	Key-value metric results. Required keys per domain profile.
evaluation.metrics.nse	number	*	Nash–Sutcliffe Efficiency. Required for streamflow profiles.
evaluation.metrics.rmse	number	*	Root Mean Square Error in target units.
evaluation.metrics.kge	number	*	Kling–Gupta Efficiency.
evaluation.metrics.pbias	number	*	Percent Bias.
evaluation.baseline	object	No	Baseline model metrics for comparison (e.g., raw NWM).
evaluation.splitUsed	string (enum)	Yes	Which split metrics were computed on: test, val, full.
evaluation.temporalRange	object	No	Start/end dates of evaluation period.

JSON Path	Type	Req.	Description
evaluation.gaugeId	string	No	USGS gauge ID or station identifier.

Table 5. Execution object: runtime requirements and compatibility.

JSON Path	Type	Req.	Description
execution.runtime	string (enum)	Yes	Target runtime: numpy, pytorch, tensorflow, onnx, webgpu, tensorflowjs.
execution.minMemoryMB	integer	No	Minimum memory requirement for inference (MB).
execution.quantization	string (enum)	No	Quantization level: none, fp16, int8, int4.
execution.webgpuCompat	boolean	No	Whether the model is WebGPU-executable in-browser.
execution.onnxOpset	integer	No	ONNX opset version if runtime is onnx.
execution.inferenceLatencyMs	number	No	Measured inference latency on reference hardware.

Table 6. Privacy provenance for model exchange.

JSON Path	Type	Req.	Description
privacy.trainedLocally	boolean	Yes	Asserts training executed entirely on-device.
privacy.dataTransmitted	boolean	Yes	Asserts no training data left the device (must be false).
privacy.attestationMethod	string (enum)	Yes	How attestation was generated: self_declared, platform_verified, tee_attested.
privacy.platformId	string	No	ID of the training platform (e.g., hydrolabai-v1.0).
privacy.datasetHash	string	No	SHA-256 hash of training data (proves what data was used without revealing it).
privacy.weightsHash	string	No	SHA-256 hash of exported weight artifact.
privacy.attestedAt	date-time	Yes	Timestamp of attestation generation.
privacy.compliance	array <string>	No	Regulatory frameworks satisfied: FISMA, CISA, GDPR, CCPA.

3.2. Reference Implementation

To illustrate the framework's practical applicability, HydroModelSpec-compliant artifacts were generated consistently with workflows on the Hydro AI Lab platform (Singh et al., 2026). These example artifacts demonstrate that the framework can represent the full range of metadata produced by typical hydrological ML training workflows, including architecture specifications (CNN, LSTM, TCN, or hybrid), training provenance (dataset hash, chronological split ratios, optimizer configuration, and hardware description), all four standard hydrological metrics (Nash–Sutcliffe Efficiency, RMSE, KGE, PBIAS) with NWM baseline comparison, execution manifests declaring runtime compatibility, and provenance attestation fields. This exercise demonstrates that framework-compliant artifact generation can be straightforwardly integrated into existing hydrological ML workflows.

3.3. Validator Conformance Results

The Validator was tested against a suite of 50 model artifacts spanning all four domain profiles. The suite included 20 correctly-formed artifacts, 20 artifacts with intentional violations (missing required fields, out-of-range metrics, inconsistent privacy attestation, malformed hashes), and 10 edge cases (minimal valid artifacts and maximum-complexity artifacts). Table 7 summarizes the conformance test outcomes. The Validator achieved 100% detection of intentional violations with zero false positives on correctly formed artifacts; mean validation time was 12 ms per artifact on a commodity laptop. Because all 50 test artifacts were designed by the specification authors, these results confirm internal consistency of the validator against its own rule set but do not yet constitute independent conformance testing; external validation by independent implementers is planned for v1.1.

Table 7. Validator conformance results across the 50-artifact test suite.

Test Category	Count	Outcome	Detection Rate
Correctly-formed artifacts (all 4 profiles)	20	Passed validation, 0 false positives	100%
Missing required fields	5	Detected with rule-coded errors	100%
Out-of-range metric values (e.g., NSE > 1.0)	5	Detected by Rule Module	100%
Inconsistent privacy flags	5	Detected by Rule Module	100%
Malformed hashes	5	Detected by schema + rule check	100%
Edge cases (minimal / maximal artifacts)	10	Validated as expected	100%

3.4. Cross-Platform Exchange Demonstration

To validate portability, a HydroModelSpec-compliant model artifact (an LSTM for streamflow post-processing) was loaded and validated by three independent consumers: (1) a Python script using only the HydroModelSpec validator and standard JSON parsing; (2) a Node.js/TypeScript consumer simulating a web-based platform; and (3) a static analysis tool that extracted the Model Card and Benchmark Report for human review. All three consumers parsed and validated the artifact without modification, confirming the framework's vendor neutrality across runtime environments.

3.5. Practical Usage Scenario

To illustrate the end-to-end value chain that HydroModelSpec enables, consider the following scenario grounded in operational hydrology practice.

Step 1 - Train locally. A researcher at a USGS Water Science Center trains a streamflow post-processor for the Mississippi River at Belle Chasse, Louisiana using a local ML training environment. Training executes entirely on the researcher's laptop, and no data is uploaded to any external server. The model achieves NSE 0.858 on the held-out test set.

Step 2 - Generate artifact. Upon training completion, the researcher generates a HydroModelSpec-compliant JSON artifact containing: the LSTM architecture (32 hidden units, single layer), full training configuration (Adam optimizer, 168-hour lookback, 30 epochs, chronological 70/15/15 split), all four metrics with NWM baseline comparison, a NumPy execution manifest, weight file reference with SHA-256 hash, and a provenance attestation documenting that training data remained on the local device.

Step 3 - Share the model, not the data. The researcher uploads the artifact JSON and weight file to a shared repository (e.g., HydroShare, an institutional Git server, or an agency-internal model registry). Crucially, only the model artifact is shared—the underlying USGS gauge observations and NWM retrospective data remain on the researcher's device. The provenance attestation provides structured documentation of this data handling.

Step 4 - Validate and inspect. A colleague at a different USGS office or a state agency, or a university research group, downloads the artifact and runs the validator. A single command confirms the artifact is spec-compliant. The colleague can now programmatically inspect: what architecture was used, what data it was trained on (hash verification without seeing the data), how it performed on each metric versus the NWM baseline, what hardware and runtime it requires, and whether the training was privacy compliant.

Step 5 - Use or adapt. The colleague can (a) load the weight file directly for inference on new NWM data at the same gauge, using any NumPy-compatible environment; (b) use the model as a starting point for fine-tuning on their own local gauge observations, adapting the Belle Chasse model to their location's characteristics; or (c) compare the artifact's benchmark metrics against their own models using the standardized metric suite, enabling apples-to-apples comparison across institutions. All of this happens without the original researcher sharing a single row of gauge data.

This scenario demonstrates the core value proposition: knowledge can travel as models, not as data. The framework transforms model sharing from an ad hoc, trust-dependent process into a standardized exchange with embedded provenance, performance benchmarks, and documented data handling. This demonstration confirms that the artifact format is parsable and structurally portable across runtimes, but does not constitute a full interoperability test, which would require independent parties to produce and consume artifacts without author involvement. Such external conformance testing is a priority for the next framework version.

4. Discussion

4.1. Scientific and Technical Impact

HydroModelSpec addresses a gap that is widely recognized but has not been specifically addressed for operational hydrology: the need for a standardized, domain-aware structure for exchanging trained ML models. Existing model serialization formats (ONNX, SavedModel, TorchScript) solve the computational graph portability problem but carry none of the contextual metadata—training provenance, domain-specific metrics, baseline comparisons—that operational hydrology requires for meaningful model exchange. Model documentation practices (Model Cards, experiment tracking platforms such as MLflow and Weights & Biases, and metadata standards such as MLCommons Croissant) capture context but have not been adapted for the domain-specific requirements of hydrology. HydroModelSpec builds on these established approaches by unifying both perspectives for hydrological applications: the model artifact is simultaneously a portable computational reference and a provenance-rich, domain-specific, machine-verifiable document. The provenance attestation component, in particular, provides a structured mechanism for documenting training data handling—a capability that complements but does not replace existing ML supply-chain security tools (such as Sigstore Model Transparency and in-toto attestation frameworks). For federal agencies operating under FISMA, for research groups handling pre-publication data, and for international collaborations subject to data sovereignty regulations, this structured documentation supports more transparent model sharing across institutional boundaries.

The specification defines three attestation methods representing increasing levels of trust: self_declared relies on the producing platform's honesty and is appropriate for intra-institutional sharing where the platform is already trusted; platform_verified provides stronger assurance when the training environment is a known, auditable system; and tee_attested, when available, provides hardware-rooted guarantees independent of software trust. The term 'zero-trust' applies most precisely to the tee_attested pathway; the self_declared method is better understood as structured self-attestation that replaces informal claims with machine-readable, auditable declarations. It should be noted that these attestation levels describe a spectrum of trust rather than cryptographic guarantees, and production deployments may benefit from integration with established signing and attestation frameworks.

4.2. Comparison with Existing Model Exchange Formats

Table 8 provides a systematic comparison of HydroModelSpec with existing model serialization, documentation, and registry formats across eight capabilities critical for cross-institutional model exchange in operational hydrology. The comparison shows that existing formats address fragments of the exchange problem but, taken individually, do not provide the complete combination of capabilities required for privacy-preserving, domain-specific, machine-verifiable model sharing.

Table 8. Comparison of model exchange formats across eight capabilities. ✓ = supported, ✗ = not supported, ~ = partial.

Capability	ONNX	MLflow	HF Model Cards	W&B	HydroModelSpec
Computational graph portability	✓	~	✗	✗	~ (via weights ref)
Training provenance (optimizer, LR, epochs, splits)	✗	✓	~	✓	✓
Domain-specific metrics (NSE, KGE, PBIAS)	✗	~	~	~	✓
Privacy attestation (Privacy provenance)	✗	✗	✗	✗	✓
Execution manifest (runtime, memory, quantization)	~	~	✗	✗	✓
Machine-verifiable schema (JSON Schema validator)	✗	✗	✗	✗	✓
Domain profiles (task-specific constraints)	✗	✗	✗	✗	✓
Open standard (no vendor lock-in)	✓	~	✓	✗	✓

ONNX provides strong computational graph portability but carries no training provenance, no domain metrics, and no privacy attestation; it serializes the model's forward pass rather than its scientific context. MLflow tracks experiments comprehensively within an organization but uses platform-specific schemas not designed for cross-agency exchange and provides no privacy attestation. Hugging Face Model Cards document model characteristics in human-readable form but are not machine-verifiable, there is no validator that can programmatically confirm a Model Card's completeness or correctness. Weights & Biases offers rich experiment visualization but is a proprietary platform rather than an open standard. HydroModelSpec brings together training provenance, domain-specific metrics with validation constraints, structured provenance attestation, execution manifests, and machine-verifiable schema validation in a single, open, vendor-neutral artifact specifically designed for the hydrological community.

4.3. Complementarity with GIFIS

HydroModelSpec and GIFIS (Mudiyanselage et al., 2025) address complementary aspects of the hydrological exchange ecosystem. GIFIS addresses the data side: how observational data, model outputs, forecasts, and alerts are structured and exchanged. HydroModelSpec addresses the model side: how trained models are packaged, documented, and shared. The cross-reference mechanism, where a model artifact's training.datasetRef can point to a GIFIS entity ID, enables traceability from data source through trained model to operational prediction. Realizing this potential fully will require shared identifier conventions and joint conformance testing, which are priorities for future work.

4.4. Extensibility and Ecosystem Growth

HydroModelSpec is designed not as a static specification but as a foundation for ecosystem growth, consistent with the extensibility principles demonstrated by BMI 2.0 in geosciences and Croissant in the broader ML community. Several extension pathways are architecturally enabled. New domain profiles for any hydrological or environmental prediction task can be added by inheriting from the Core Schema and constraining the evaluation metrics, input/output schemas, and domain-specific metadata fields. Planned profiles include groundwater level prediction (with well ID, aquifer type, and drawdown metrics), coastal storm surge forecasting (with tide gauge datum, surge height, and wind field metadata), drought index prediction (with SPI/SPEI metrics and climate normal baselines), and sediment transport modelling. Because every HydroModelSpec artifact is a self-describing JSON document, it can be indexed by any document store, search engine, or metadata repository, supporting community model registries that allow users to discover models by gauge ID, architecture type, metric threshold, or privacy attestation level.

When multiple models targeting the same gauge and prediction task are published as spec-compliant artifacts, automated comparison pipelines can extract and rank them by metric suite, enabling systematic benchmarking without manual metadata extraction. Federated workflows in which multiple agencies independently train and share spec-compliant models for overlapping gauge networks become feasible: each model's privacy attestation confirms that no data was exchanged, while the model weights encode learned corrections that benefit the broader community. Finally, although the specification is hydrology-specific in its current profiles, the Core Schema's architecture, training, evaluation, execution, and privacy components are domain-agnostic; the same pattern can be instantiated for clinical, defense, or agricultural applications by defining new domain profiles with appropriate metric and attestation requirements. This aligns with broader calls to apply FAIR data principles to ML workflows, ensuring that not only datasets but also trained models and their provenance are findable, accessible, interoperable, and reusable across research communities (Samuel et al., 2020).

4.5. Limitations

The current framework has several limitations that define the development roadmap. First, all implementations to date—the example artifacts, the three cross-platform consumers, and the 50-artifact test suite—were produced by the framework authors. True interoperability requires independent implementation by parties not involved in the design; community conformance testing in which external developers produce and consume framework-compliant artifacts and report failures is essential for establishing the framework's practical value and is a priority for v1.1. Second, the framework does not yet address model versioning workflows (how artifacts evolve through fine-tuning iterations), ensemble composition (how multiple framework-compliant models are combined), or real-time serving protocols.

Third, the provenance attestation relies on platform-level honesty for the self_declared method and does not currently integrate with established ML supply-chain signing frameworks (such as in-toto ITE-6 or Sigstore); such integration would strengthen the attestation layer substantially. The stronger tee_attested method requires hardware trusted execution environments that are not yet widely available in browser contexts. Fourth, the 50-artifact validation suite, while comprehensive in its coverage of schema rules, consists of synthetic test cases designed by the framework authors validation against real-world model metadata from published studies would provide stronger evidence of the framework's expressiveness and would reveal gaps in field coverage. This concern is consistent with broader findings that scientific data documentation frequently falls short of ML transparency requirements even in peer-reviewed contexts (Giner-Miguelez et al., 2025). Fifth, the framework currently lacks a formal governance structure—including a profile registry, namespace policy, and deprecation procedure—that would be necessary to sustain community adoption. Finally, sustained community governance of profiles, validator rules, and conformance suites will be essential to prevent re-fragmentation as the framework evolves.

The framework does not currently address adversarial threats to shared weight files, such as backdoor attacks or model poisoning. The SHA-256 hash verifies that weights have not been modified after attestation but does not guarantee that the weights themselves are free from adversarial manipulation introduced during training. Additionally, free-text fields in Model Cards could present injection risks if consumed by automated agents. Future versions should incorporate integration with established model signing frameworks (e.g., Sigstore, SLSA) and consider content sanitization requirements for automated consumers.

4.6. Broader Implications

The framework's design principles—layered schemas, domain profiles, structured provenance, and semantic validation—extend in principle to any scientific domain where trained models require standardized documentation for exchange: clinical ML models trained on patient data, agricultural models trained on proprietary yield data, and environmental models across domains. Recent work has demonstrated the practical demand for such capabilities: federated learning frameworks for water quality management have shown that sharing model parameters rather than raw data can achieve strong predictive performance while maintaining full privacy protection (Wang et al., 2025). The provenance attestation component, the domain profile extensibility mechanism, and the validator framework are all domain-agnostic. HydroModelSpec demonstrates the layered design pattern; other communities can instantiate it with their own domain profiles and metric suites (for example, Nash–Sutcliffe and KGE for hydrology may be replaced with AUC and F1 for clinical AI). For the hydroinformatics and cyberinfrastructure community specifically, the specification supports a class of decision support workflows in which no-code edge AI platforms automatically generate spec-compliant artifacts that are then shared, validated, and consumed by other platforms without manual intervention contributing to a federated ecosystem of interoperable, privacy-preserving model exchange.

5. Conclusion and Future Work

This study has presented HydroModelSpec, an open-source, JSON Schema-based framework that provides a generalized structure for encoding, validating, and exchanging trained machine learning model artifacts in operational hydrology. Building on established practices in model documentation (Model Cards, MLflow, Croissant) and geoscientific model coupling (BMI 2.0), the framework combines a vendor-neutral Core Schema with domain-specific profiles for streamflow post-processing, water level forecasting, flood inundation prediction, and reservoir operations, complemented by Portable Document Types and a Validator that enforces both structural and semantic conformance. The provenance attestation component provides structured, machine-readable documentation of training data handling, supporting more transparent model sharing across agencies governed by FISMA, CISA, and related data governance regulations. Complementary to data exchange standards such as GIFIS, HydroModelSpec contributes toward a more complete exchange ecosystem for hydroinformatics cyberinfrastructure. The framework is designed to integrate with existing hydrological ML platforms, and example artifacts illustrate that framework-compliant artifact generation can be straightforwardly incorporated into existing training workflows.

Future work will expand the specification through community engagement: additional domain profiles (groundwater, coastal, drought, sediment transport), ensemble composition schemas, model versioning workflows, real-time serving manifests, expanded WebGPU and quantized model execution manifests, and multi-language validators (Python, TypeScript, C#). Independent conformance testing by external developers and validation against real-world published model metadata will be a primary focus for the next framework version. The framework is maintained openly and governed through public RFCs, with the goal of evolving as a living standard responsive to the operational hydrology community's needs.

Funding

This research was supported by the U.S. Department of the Interior (DOI) – U.S. Geological Survey (USGS) under Award No. G25AP00137. The statements, findings, conclusions, and recommendations are those of the author(s) and do not necessarily reflect the views of the U.S. Geological Survey.

Software Availability

Name	HydroModelSpec
Developers	Nikhil Singh, Ramteja Sajja, Yusuf Sermet, Ibrahim Demir
Contact	rsajja@tulane.edu
Software Required	Any JSON Schema validator; Python 3.8+
Program Language	JSON Schema, Python, JavaScript/TypeScript
Specification Repository	https://github.com/uihilab/HydroModelSpec

Data Availability

The HydroModelSpec schemas, validator, documentation, and reference materials are openly available at https://github.com/uihilab/HydroModelSpec.

Competing Interests

The authors declare that they have no competing interests.

Credit Author Statement

Nikhil Singh: Conceptualization, Software, Methodology, Visualization, Writing - Original Draft.
Ramteja Sajja: Methodology, Conceptualization, 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 in the writing process

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

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