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HESS Opinions: Applied hydrologic models in the era of machine learning—retain, revamp, reconcile, or replace?

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Abstract. Despite advancements in the performance of machine learning (ML) based hydrologic models, some institutions are hesitant to pursue ML as a replacement for existing conceptual or process-based hydrologic models in many applications. In several of these circumstances, traditional hydrologic models continue to be favored due to their familiarity, reliability, interpretability, established performance benchmarks under varied settings, availability of detailed training modules and a trained workforce, as well as close integration with data, processing, and decision-making pipelines. Recognizing these advantages, this perspective argues for two pragmatic and institutionally compatible paths forward for integration of ML within applied models: (1) reconciling ML as a complementary option in applied hydrologic modeling workflows; and (2) revamping or upskilling hydrologic modeling workflows using ML. To support this perspective, we highlight key opportunities where ML can be used as a tool to enhance results across various stages of the model implementation and operational workflow including data pre-processing, parameter calibration, parameter transferability, data assimilation, solver enhancement, accelerating scenario simulations and post-processing. Each of these two integration strategies can be implemented into current applied model frameworks, thereby combining the strengths of both physical modeling and ML. These strategies can help overcome current bottlenecks and address institutional needs of continuity and compatibility, while also offering the potential to improve model performance with ML.

1 Introduction: Applied hydrologic modeling at the crossroads in the era of ML

Applied hydrological models represent numerous process-based, conceptual, or mathematical models used by government agencies, utilities, consultancies, or other entities to support water resources management, regulation, forecasting, risk assessment, and emergency responses. Hydrologic models are used to predict and map water stores and fluxes to facilitate real-time decision-making, climate and land use/land cover change risk assessments, and other planning studies. These models are used for a wide variety of decisions, such as in flood and drought predictions (Samaniego et al., 2019), ecosystem service management and investment decisions (Guswa et al., 2014), hydroelectric management, water utility management, and

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infrastructure planning (Keller et al., 2023). Currently these models are predominantly conceptual or process-based (i.e., non-ML) and include models such as HEC-HMS, HEC-RAS, SWAT, SAC-SMA, PRMS, WRF-Hydro, MIKE SHE, MIKE HYDRO, MIKE 11, HBV, VIC, SUMMA, and many more. More details of some of these models and their example functional applications are listed in Table 1.

Model Name	**Abbreviation**	**Relevant Users**	**Functions**
Hydrologic Engineering Center- Hydrologic Modeling System	HEC-HMS	U.S. Army Corps of Engineers	Rain–runoff simulation (Sahu et al., 2023; González-Cao et al., 2019)˒ flood forecasting (Sahu et al., 2023; González-Cao et al., 2019; Laassilia et al., 2022), reservoir modeling (Hu et al., 2006), soil erosion and sediment routing
Hydrologic Engineering Center- River Analysis System	HEC-RAS	U.S. Army Corps of Engineers	Flood impact assessment (Garcia et al., 2020), 1D-2D flood modeling (Garcia et al., 2020; Dasallas et al., 2019; Hicks and Peacock, 2005), flood routing(Hicks and Peacock, 2005),˒ sediment transport, water quality modeling
Soil & Water Assessment Tool	SWAT	USDA	Evaluate climate and land use changes (Sahu et al., 2023; Janjić and Tadić, 2023; Zhao et al., 2024), sediment transport (Gassman et al., 2014), non-point source pollution control (Janjić and Tadić, 2023; Zhao et al., 2024; Gassman et al., 2014), and runoff modelling (Janjić and Tadić, 2023)
Sacramento Soil Moisture Accounting	SAC-SMA	NOAA River Forecast Centers	Runoff modelling (Buda et al., 2022; Wang et al., 2023), snowmelt estimation (Agnihotri and Coulibaly, 2020)
Precipitation Runoff Modeling System	PRMS	USGS	Runoff modelling (Teng et al., 2017), streamflow simulation (Teng et al., 2017; Roland, 2023), land cover change

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			impacts (Roland, 2023), groundwater and surface–water interactions (Markstrom et al., 2015), hydrologic parameter estimation (Archfield et al., 2015)
MIKE-SHE	MIKE-SHE	Select municipal water treatment plants	Spatiotemporal water resource management (Sahu et al., 2023), Managing groundwater/pipe interfaces , land use changes (Sahu et al., 2023), streamflow simulation (Golmohammadi et al., 2014; Dai et al., 2010), climate change impacts on water resources (Papadimos et al., 2022), irrigation modeling (Papadimos et al., 2022; Singh et al., 1999), solute transport (Daneshmand et al., 2019), water table depth estimation (Dai et al., 2010)
MIKE-HYDRO	MIKE-HYDRO	Select reservoirs & dams	Dam and reservoir operations , water demand and supply (Agrawal et al., 2024), hydrodynamic river modelling (Jahandideh-Tehrani et al., 2020)
Hydrologiska Byrans Vattenavdelning	HBV	Norwegian & Finnish hydrological services, select hydropower facilities	Streamflow simulation (Seibert and Bergström, 2022; Àvila et al., 2022; Driessen et al., 2010), mountainous region catchment management (Seibert and Bergström, 2022), snow processes (Àvila et al., 2022; Osuch et al., 2019), climate change impacts on water resources (Driessen et al., 2010), water storage estimation (Osuch et al., 2019)

Table 1: A few applied hydrologic models and their functions

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Applied hydrologic models have been developed and evaluated over decades and have a long history of use, interpretability, and regulatory acceptance. However, concerns exist about the inherent limitations of these models, such as their transferability (Nearing et al., 2020), computational requirements (Zhang et al., 2021; Clark et al., 2017), parameterization (Meert et al., 2018; Ghaith and Li, 2020; Pappenberger et al., 2005; Uhlenbrook et al., 1999), and process representation (Grimm and Chu, 2019; Uhlenbrook et al., 1999; Halwatura and Najim, 2013). Recent research advances in machine learning (ML) have demonstrated not only remarkable skill in simulating hydrologic variables (Ghimire et al., 2021; Malekzadeh et al., 2019; Kratzert et al., 2019), but have also highlighted their strong potential to alleviate the limitations of current applied hydrologic models, such as slow or computationally demanding calibration and poor transferability (Tsai et al., 2021; Song et al., 2022; Feigl et al., 2022). Given their advantages, ML models are increasingly finding applications in operations. For example, the USDA NRCS currently operates a process-based model, but is phasing it out for a ML ensemble water supply model in the western United States (US) (Fleming et al., 2021; Fleming and Goodbody, 2019). Google operates a global ML flood forecasting model with a 7-day lead time . Other entities have begun developing new models, such as the US Bureau of Reclamation and the private entity Upstream Tech piloting ML inflow forecasts (Bearup et al., 2024). Many other agencies and private companies are also exploring ways to incorporate ML research into hydrology workflows.

For those in the applied hydrologic modeling and operations community who have not integrated or replaced their traditional model with ML, a critical decision lies ahead: how and to what extent should ML-based data-driven models be integrated with applied models? Should ML completely replace applied models, be used selectively to revamp specific modeling workflow steps (e.g., parameter estimation), be reconciled as a complementary option, or retain the status quo models and procedures and risk falling behind?

The goal of this perspective is to highlight the key challenges that currently hinder the integration of ML within some current applied models, despite their researched promise of improved predictive accuracy. We advocate for an integrative path forward, where ML is used as a tool to augment legacy models instead of replacing. We detail (in Section 2) multiple reasons for the continued persistence of applied models. Next, we discuss different ways to enhance applied models, by using ML within specific process steps or alongside current model workflows (Sections 3.1 and 3.2). Then we highlight an example framework for evaluating applied model needs and for planning and implementing ML within the model workflows (Section 4). Finally, we discuss the implications of such model update strategies and conclude that reconciling or revamping operational workflows offers a path forward to more resilient applied hydrology (Section 5).

2 Challenges with complete replacement by ML: The rough road ahead

Despite recent research demonstrating the efficacy of ML for single hydrologic variable estimation (Ghimire et al., 2021; Malekzadeh et al., 2019; Kratzert et al., 2019) and a few instances of ML models being used in operations (Fleming et al., 2021; Fleming and Goodbody, 2019; Bearup et al., 2024), applied models continue to be used by several government agencies and private corporations. This persistence may reflect hesitance to trust ML's efficacy in applied settings, or, alternatively, concerns for the delay and challenges inherent in moving larger institutions to new directions. It could also reflect the lack of sufficiently mature domain-specific research, where gaps in ML research towards watershed analyses, planning and vulnerability studies, infrastructure design, or future climate change may discourage industry adoption. An unexplored avenue explaining the lack of adoption include a myriad of institutional factors, such as regulations, familiarity (Melsen, 2022; Addor and Melsen, 2018; Nearing et al., 2020), and interpretability (Xu and Liang, 2021) which reinforce the reliance on well-accepted hydrologic models.

In several applications, the use of particular models is codified by an agency. For example, US Federal Emergency Management Agency's (FEMA) National Flood Insurance Program (NFIP) requires hydrologic analyses to use models that "meet minimum requirements of 44 CFR 65.6." This regulation is under Title 44: Emergency Management and Assistance, Part 65, and deals with identifying and mapping Special Hazard Areas. It lays out the required technical specifications and documentation that must be met when requesting a Letter of Map Revision (LOMR) or submitting revised flood hazard data. FEMA even publishes a list of "accepted hydrologic models," which includes HEC-HMS and TR-20, for floodplain mapping and insurance studies. Similarly, the US Army Corps of Engineers (USACE) and state environmental agencies have detailed guidance for models used in planning studies , environmental impact analyses , and water-quality permits . These rules deter the use of a new model without re-certification. Even if ML methods could outperform legacy models, they are expected to face lengthy validation trials.

Workforce familiarity with process-based models over ML models is another important factor. Addor and Melsen (2018) explained the prevalence of process-based models throughout academia as a result of prior experience and exposure, which cyclically reinforces the use of these models; mentors teach early career scientists with what they are familiar. Familiarity with a modeling system allows newer users to learn from experienced users and institutional resources on how to parameterize, use, interpret, and troubleshoot these models, thus falling back on a wealth of institutional knowledge. For some agencies, the training of entry-level or junior staff is partially dependent on senior employees, such as in the USACE which expects senior mentors to, "support and mentor the junior modeler" (2023). This is a deterrence to immediate and large-scale replacement of applied models by ML, as senior staff with extensive experience in ML may not exist. Outside of user knowledge, there are institutional resources, such as the backlog of notes, references, and project documentation the USACE has on various HEC software (HEC-HMS, HEC-RAS, HED-PRM, HEC-RFA, and HEC-FIA), detailing the applicability, limitations, and usage of HEC models. If ML models replaced existing modeling and decision-system workflows, workforce retraining would be necessary, though such efforts would lack the plethora of available learning and troubleshooting resources that are available for well-established applied models (Keller et al., 2023). Accumulating the necessary resources for either onboarding new staff or training existing staff (and then retaining them) would require a substantial investment to proceed with an AI framework. The lack of resources and workforce familiarity with ML models impedes the wholesale replacement of applied models.

Finally, the replacement of applied hydrological models with ML is expected to face challenges associated with interpretability and predictability. Many current models are conceptual or process-based, allowing for a realistic connection with hydrologic processes. Agencies expect modelers to understand the model's internal structure and assumptions while completing

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computation quality checks (2023; 2024). ML models are often described as black box models. While advances have been made with interpretable machine learning (Xu et al., 2024; Jiang et al., 2022; Zhang et al., 2023), it is harder to extract meaningful insights regarding the reasons for extreme or unexpected responses, especially at the process level, from ML models (Xu and Liang, 2021). Trained modelers are required to interpret model results and justify their decisions (2023). Interpreting outputs could be challenging due to the lack of familiarity with the ML processes and the complex hidden layers involved with many ML hydrologic models.

To summarize, replacing applied hydrologic models with ML poses several institutional challenges. These include codified regulations related to tools to be used, workforce familiarity and trust with existing tools, and strong institutional trust due to the interpretability of established hydrologic models. In lieu of replacing applied hydrologic models with ML, an alternative is to use ML to augment current applied models.

3 Augmenting applied models using ML: The road less taken

Given the many reasons to continue favoring well-established applied models, it is not a surprise that many public agencies and private organizations are approaching ML adoption cautiously and incrementally. Beyond sticking with existing models or jumping to wholesale replacement, two promising alternatives are parallel ML workflows and strategically implemented ML modules. Parallel ML workflows aim to adjust or recreate applied model outputs, while ML modules allow for selective integration within the existing model to improve computational cost, output accuracy, or decrease uncertainty. Both hybrid approaches offer a way to enhance model outputs while preserving usability, interpretability, and institutional trust. Compared to a full-scale replacement, these two strategies require phased effort and less disruption, while potentially expanding the capabilities and adaptability of applied hydrologic models.

3.1 The use of ML alongside applied model workflows

ML can be reconciled or incorporated within current applied model workflows as a complementary option. This approach could serve as a transitional step towards complete applied model replacement but may also remain independently viable based on its merits. The goals of the complementary option may include: (a) providing stakeholders and operational modelers with the flexibility to choose, combine, or present all models' outputs, based on known model limits and expert discretion; (b) saving computational expense through the use of surrogate models.

When the goal is to combine models' outputs, these two strategies may be employed: weighted ensembling of individual model outputs and creating probabilistic outputs via ensemble dressing. Weighted ensembles of ML and process-based model outputs may improve output accuracy, while providing physical insight into the mechanisms within the ML (Du and Pechlivanidis, 2025; Gichamo et al., 2024). ML can also be used to transform deterministic outputs into statistical distributions (i.e. ensemble dressing), improving risk based decision-making without modifying core models (Papacharalampous et al., 2019). Transforming deterministic data into probabilistic outputs can provide additional insights for practitioners and operators

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(Papacharalampous and Tyralis, 2022). While the reconciliation approach may increase the computational cost, it provides rightsholders with the flexibility to choose, combine, or present all models' outputs, based on known model limits and expert discretion. This approach could serve as a transitional step towards complete applied model replacement but would also be viable independently due to the improved applied hydrologic model outputs It should be noted, however, that ensemble-based approaches typically incur additional computational cost.

Implementing ML-based surrogate or emulator models can reduce model simulation and calibration times. For example, when compared to hydrodynamic models, surrogate models have a faster run-time (Dai et al., 2025). While the training time for emulators must be considered, prior study suggests only a small amount of runs outweighs the initial time investment (Dai et al., 2025). An improvement in model run speed would be a benefit for emergency situations requiring quick outputs. While emulator error must be considered, the benefit of emulators for rapid predictions cannot be understated. Surrogate modeling approaches have shown promise for small and large scale water depth prediction (Zahura et al., 2020; Yan et al., 2023; Fathi et al., 2025), rapid flood zone mapping (Zahura et al., 2020), and parameter or calibration optimization (Garzón et al., 2022; Xingpo et al., 2021).

3.2 ML within applied modeling workflows

ML can be integrated within applied hydrologic model workflows, revamping their core steps, oftentimes reducing errors. Sources of error within legacy models include those due to structural limitations in representation of processes and their numerical solution, input data uncertainties, and parameter uncertainties (Mcmillan et al., 2018; Renard et al., 2010; Gupta and Govindaraju, 2023). By improving data pre-processing streams, calibration and parameter selection, data assimilation mathematical techniques, and post-processing techniques using ML, many of the aforementioned uncertainties can be reduced. Below, we present a few examples highlighting ML methods that can be used within the applied model workflows to improve their efficacy.

ML can be used to address a myriad of quality issues inherent in forcings data, either due to equipment malfunctions at automatic weather stations, extreme weather events, or coarse sampling occurrences. Previous studies have addressed data quality concerns, like missing and erroneous data, by implementing ML based data filling (Chivers et al., 2020; Boujoudar et al., 2024; Park et al., 2023), anomaly detection (Vries et al., 2016), or bias reduction (Zhang and Ye, 2021). ML can also be used for a more effective and computationally efficient parameter calibration. Notably, most prevailing automatic calibration approaches have the challenge of computational cost (Herrera et al., 2021). Recent studies have shown that ML techniques relying on mapping catchment surface attributes to parameters can yield accurate initial parameter sets (Sun et al., 2022; Jin et al., 2024; Tsai et al., 2021). ML models can also be used to estimate transfer functions (TFs) as a substitute for providing parameters in ungauged regions (Feigl et al., 2022; Song et al., 2022). Additionally, ML can serve as a proxy for current data assimilation (DA) methods. One specific advantage ML may provide over traditional filtering methods is its ability to manage non-Gaussian problems, which is a leading concern for methods based on Kalman Filtering (Zhang et al., 2024; Jeung et al., 2023). ML has demonstrated proficiency in outperforming Kalman techniques (Zhang et al., 2024; Boucher et al., 2020).

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An essential part of some applied models is the computation of ordinary differential (ODEs) or partial differential equations (PDEs) (Kochkov et al., 2021; Kumar et al., 2009; Spiteri et al., 2024; Bisht and Riley, 2019). These are computationally intensive, in particular at fine resolutions or long-time scales (Wang et al., 2018; Kumar and Duffy, 2015). ML can help accelerate the calculation of these complex equations, either by improving numerical solving simulations or innovating traditional mathematical methods. Research shows ML being used to simulate Navier Stokes simulations with faster results (Obiols-Sales et al., 2020; Kochkov et al., 2021). Other studies have focused on expanding mathematical techniques, such as coarse grid estimation for a splitting algorithm (Efendiev et al., 2022) or approximating basis functions for the Generalized Multiscale Finite Element Method (Rudikov et al., 2025).

Beyond reducing uncertainties in the model workflow, ML post-processing techniques can be implemented on applied model outputs to develop further hydrologic insights. Methods include ML-based algorithms for bias reduction, model evaluation, downscaling of outputs, and hydrologic response understanding and support. ML bias correction post-processing modules can be implemented to adjust outputs, such as to ensure proper calibration (Liu et al., 2022) or incorporate unaccounted catchment attributes like water infrastructure (Neisary et al., 2025) into models. To understand the performance of a hydrologic model, an evaluation strategy utilizing ML may be used to identify if the model has reached its optimal state (Rozos et al., 2021). Applied models often run at relatively coarse resolutions (e.g., 1–4 km or larger), whereas users may want fine-scale information (e.g., localized flood depths, field-level streamflow). Computational intensity and fine scale data availability limits the ability of applied models to be run for finer resolutions. ML can downscale applied model outputs to finer resolutions with high accuracy (Schneider et al., 2022; Folberth et al., 2019), paving the way for fine scale data availability.

ML can also assist in understanding hydrologic responses and making decisions. Clustering ML algorithms have demonstrated the ability to connect catchment behavior to landscape characteristics, identifying hydrologic signatures which outperformed expert selections (Addor et al., 2018; Botterill and Mcmillan, 2023). ML techniques may also aid in decision making. For example, deep learning algorithms have been used to support real-time water mapping by utilizing remote sensor images (Sun et al., 2021) or emulating hydrodynamic models (Yan et al., 2023; Fathi et al., 2025). These maps can be used to issue flood warnings or guide emergency managers. Emergency communication frameworks can be supported with large language models (LLM). ML in decision support can assist in the comprehension of flood warnings; for lay-people, trained flood risk large language models (LLM) can answer flood-related questions and therefore reduce an individual's flood risk (Zhu et al., 2024). A similar LLM for applied hydrologic decision making could turn raw model output into actionable "features." Overall, these examples highlight the different ways ML can be integrated into applied modeling workflows to reduce prediction errors and more effectively communicate results to experts, emergency managers, and lay-people.

4 A roadmap for revamp or reconciliation

How to go about integrating ML within or alongside applied model workflows remains an unexamined topic. Here we detail a multi-step roadmap for such an integration. It is to be noted that relevance and implementation of individual steps in the

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roadmap may vary by application, the type of legacy model being used, current limitations in the system, the modification done with ML, and the complexity of the chosen adjustment. Within each step, we highlight key considerations for integration and discuss them with some illustrative examples.

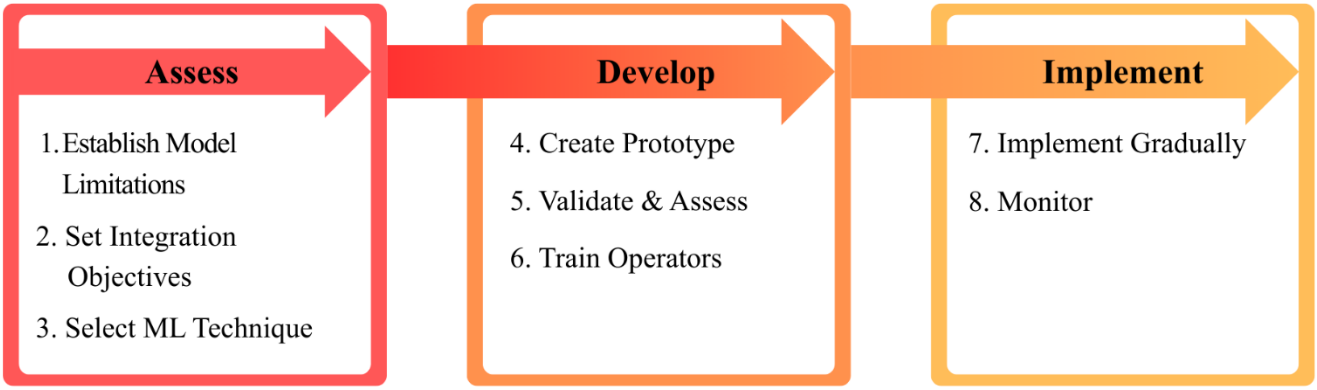

Figure 1: A framework for implementing ML into an applied hydrologic model

4.1 Step 1: Assessment of limitations in current applied model workflows

Applied models often have well-known limitations, recognized by organizations based on their past use. Additional insights can be gained from (meta-analysis of past) academic research. Limitations could be divided into specific sub-components which can be addressed individually. As an example, an agency may recognize their calibration process limiting SAC-SMA potential. The broad limitation can be further divided into sub-components, such as into the need to improve predictive accuracy and the need to transfer parameters to ungauged regions.

4.2 Step 2: Set ML integration objectives

After identifying the applied model limitations, integration objectives can be set. These may include selecting specific objectives and identifying resource needs and time constraints associated with each limitation. Extending the SAC-SMA calibration example, the agency may want to address both calibration accuracy and parameter transferability or focus on only one of these objectives based on operational priorities.

4.3 Step 3: Select an appropriate ML technique

Once limitations and desired integration objectives have been defined, ML techniques that best address the existing limitation(s) or integration objectives (Section 3) can be identified. For example, to address the desired SAC-SMA calibration objectives, the agency may select a modular ML technique based on suitability (Tang et al., 2025; Mudunuru et al., 2022).

4.4 Step 4: Develop prototypes

Depending on the selected ML technique, prototype development strategies should be defined. Important constraints to consider include the level of user-interaction, whether the tool will be implemented at a single or across multiple sites, whether it will run simultaneously across locations, and whether multiple realizations are required. Additional considerations include benchmark thresholds in terms of accuracy and computational constraints, and data storage requirements. In the case of the SAC-SMA model, benchmark target accuracy thresholds may be defined using prior model runs or values reported in the literature (Addor et al., 2017). These criteria will adjust the variance of data used to train the decided ML technique, dataset size, deployment over single or multiple processors, the use of cloud computing, and the interface design.

4.5 Step 5: Conduct validation

To ensure that the prototype behaves as expected, it is important to compare the original applied model to different iterations of the modified model on validation and test datasets. Only after establishing that the ML modules add value to the original process can the prototypes be ready for deployment. Extending on the illustrative narrative of an agency using SAC-SMA, adapting SAC-SMA should compare the efficacy of the developed ML calibration to the current baseline model. The parameter transferability improvement may require additional metrics such as a score quantifying its ability to generalize to nearby catchments.

4.6 Step 6: Train staff and stakeholders

If possible, an expert on ML should be brought in to educate staff on the process which occurs behind the scenes. ML models are difficult to interpret, which may promote distrust. Training may educate users on the mechanics of the specific model, and the benefits, improvements, and potential challenges which will come with its utilization. At the same time, emphasis can be placed on the current applied model remaining in place. In the case of SAC-SMA, staff and stakeholders should be shown the validation results and have the process thoroughly explained. Emphasis should be placed on how the ML modules replicate or modulate the processes of the model schema they understand.

4.7 Step 7: Implement incrementally

Slow implementation of ML tools will support the development of trust with operators and staff in the model's capabilities. It will also allow for the gradual development of intuition for operators. In the beginning, the original and the modified frameworks could run in parallel (regardless of the revamp or reconciliation decision). Over time, this will create trust with the modules as stakeholders and staff see consistent out-performance or other advantages. When sufficient trust has been gained and performance demonstrated, the original model may be discontinued as needed.

4.8 Step 8: Monitor and update

Continually monitor staff capabilities and comfortability, as well as model performance. If a discrepancy or new limitation appears, the analysis cycle should restart to allow for continued optimization within the organization.

5 Conclusions

Machine learning models have been gaining prominence for making hydrologic variable predictions. Yet, the complete replacement of legacy models remains slow, and may not occur, due to the necessity of maintaining current institutional trust, established decision-making frameworks, and interpretability. This perspective argues that in many instances, instead of pursuing wholesale replacement, the strengths of both ML and applied physical models can be realized through the deliberate integration of ML alongside or within existing applied models. When used alongside applied models, ML can generate complementary predictions, support ensemble-based analyses, and enable rapid scenario exploration. When embedded within or alongside existing models, ML can enhance individual workflow components, including data pre-processing to fill time-series gaps and manage uncertainty in inputs, parameter calibration, increasing spatial and temporal transferability, data assimilation for state variable validity, solver enhancement for increased processing speed, and post-processing to reduce bias, evaluate models, downscale outputs, and understand hydrologic responses.

The perspective hopes to orient the hydrologic modeling community to focus not only on the continual development of increasingly sophisticated ML-based hydrologic models, but also towards the practical integration of ML within operational systems through modular revamping or complementary reconciliation. These integrative approaches are expected to balance the maintenance of institutional trust, decision-making frameworks, and interpretability while reducing model uncertainty, model computational resources, and improving model applicability. Overall, using the integration approaches presented here, modelers can harness the strengths of both paradigms, i.e., ML and applied process-based models, to improve decisions related to water quality, water access, urban growth and development, emergency planning, and disaster mitigation.

Author contributions

Initial conceptualization was carried out by DW and MK. DW conducted further investigation, project administration, and original draft writing. MK provided funding and supervision. All authors contributed to manuscript review and editing following the initial draft.

Competing interests

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