AI-Driven Hydroinformatics for Physical Hydraulic Modeling and Climate Change Impact Assessment

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Abstract
This study provides an original investigation into artificial intelligence (AI)-driven hydroinformatics for physical hydraulic modeling in real-time and conventional hydrologic operations and climate change impact assessments. The blurred line between process-based models and machine learning (ML) models is exemplified by advanced hydraulic simulations for barotrauma. Advancements by combining, assimilating, and leveraging data obtained from process-based, approximate physical, and ML relationships are presented. Advancements are showcased for uncertainty quantification in nonstationary systems; hydraulic simulations of Twin Falls Dam on the South Fork of the Snake River; and engineering-economic trade-offs for potential dam modifications or upgrades.
For the latter, the CIRDSS Model Center running a VEFlow model paired AI-assisted engineering and economic models with Itakura-Saito simultaneous-cumulative scaling at Karst analysis of world dams to present a case study of Twin Falls Dam modifications on rockfall using parametrically censored biased thermistor data, computationally intensive One Phase Equilibrium (OPE), and Binary Particle Swarm Optimization (BPSO) screening, along with detailed hydraulic simulations. Before proposing modifications, however, OPE and BPSO were validated using detailed, high-fidelity barotrauma computational fluid dynamics (CFD) simulations. By drawing upon process-based and data-driven system knowledge, advances in AI-driven hydraulic modeling for impact assessments can provide significant improvements over hydraulic-only simulations.
Keywords: Artificial Intelligence, Hydroinformatics, Physical Hydraulic Modeling, Real-Time Hydrologic Operations, Climate Change Impact, Process-Based Models, Machine Learning,

1. Introduction

Climate change affects the discharge regime of rivers by modifying the rainfall patterns, which have an impact on hydraulics and the physical behavior of the river channel. Consequently, hydraulic modeling based on river cross-sectional data suitable for evaluating the impact of climate change is a major challenge. It is imperative to consider various AI techniques, as AI-based hydroinformatics can produce the necessary information from insufficient data. Accordingly, the focus of this research is to propose using a non-training, data-driven fluid mechanics model for overcoming these modeling challenges with turbulent thermal advection related to the climate change impact on a river's thermal environment. This multi-physics-based approach, in which a fluid mechanics model is incorporated within a computational fluid dynamics software, is expected to reveal the surface heat flux, which can be validated in terms of the field-measured value from the transported thermal energy.
S-1.1 reflects a brief overview of AI-ability-based hydroinformatics, “data-based” river hydraulic modeling, and the tug of war among AI enthusiasts and river engineers. On the one hand, hydroinformatics experts anticipate that AI-driven hydrological data analysis is leaner with different hydraulic applications (i.e., data-based physical hydraulic modeling), whereas, on the other side, field-experienced river engineers and modelers have high priority for physically based hydraulic modeling. In an evolving environmental and river engineering context, all engineers one day would favor both artificial data-generated physical hydraulic models and AI-driven physical hydraulic modeling. Currently, many AI techniques have still been adapted in isolation from the physical flow simulation-based hydraulic model. In the

absence of large-scale physical hydraulic simulation-based data, there remains one unresolved issue: "how physically based hydraulic river models may offer satisfactory performance in learning the given hydrology data set."

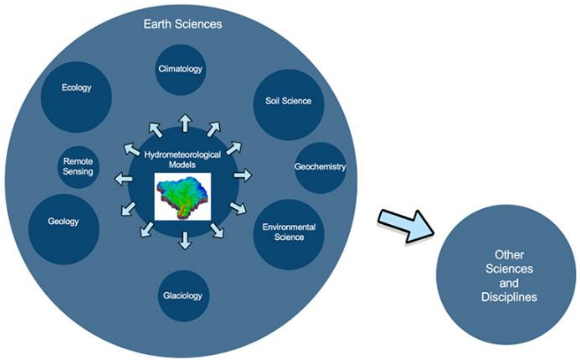

Fig 1 : Hydrologic Modeling as a Service

1.1. Background and Significance

Hydroinformatics is a progressively evolving field that converges hydrology with computer power in an interdisciplinary framework. In line with the evolution of hydroinformatics worldwide, the traditional physical modeling paradigm has experienced a computational surge in hydraulic modeling, including the process of parameter and model structure optimization. However, the propensity for terms of exchangeability and systematic heteroscedasticity in the residuals of the physical models shadows the predictive accuracy of the best input/output or current/force physical model. Consequently, the integration of expert-based systems with AI-based systems has been widely recommended to overcome the limitations of physical modeling and enhance predictive accuracy for decision support systems. Especially after the discovery and impact of climate change, effluent discharges, and extremes like tsunamis, storm surges, and greenhouse gas emissions have conveyed global sustainability problems. During the past few decades, AI-driven hydraulic modeling has developed promising capabilities for enhanced predictive accuracy. The prediction, management, and control of natural hydrological extremes such as rainfall, floods, and droughts are of critical importance in hydraulic management. The magnitude and/or frequency of these spatial complexes of hydrological catastrophes can change due to global warming and other factors like deforestation and urbanization. However, estimating one extreme flow or flood magnitude in a river basin is directly associated with a highly dimensional physical concept, as it needs to assess the entire lake or reservoir over the system in any form to estimate the sound relationship between inflow and outflow or storage and discharge with a confidence level of 95%, where the computational complexity suffocates the standard computing environment.

1.2. Research Objectives

The general objective of this topic is to underline the role of AI in hydroinformatics, discuss the potential advantages of using these models in comparison to classical models driven by numerical integration of the governing equations, and assess the main available models. Regarding the full paper, the aims of the research can be summarized as follows:

- To underline the current effective application of AI-informed models for water resources management distinguished by both a short computational time and a high degree of reliability in terms of predictive performance;
- To investigate the application of different AI algorithms, such as various artificial neural networks, hybrid models, AI-Kalman filter models, AI support vector machine models, and so on, able to address the following main water-hydrological challenges: prediction of monthly or annual streamflow, rainfall and runoff erosivity relationship derivation, missing data imputation, bathymetry derivation, estimation of sediment discharges, real-time flood forecasting, simulation of actual evapotranspiration, and metropolitan water demands;
- To analyze the possibilities offered by AI to significantly improve physics-based distributed hydraulic models to simulate complex flood routing phenomena, on an equal footing or better than the current numerical integration of the Saint Venant wave equations with more efficient non-meshing computational approaches;
- To assess the capabilities of AI methodologies to predict the impact of climate change on the availability of water resources worldwide. Where possible, case studies showcasing various AI applications were chosen to present, in an encompassing manner, the abilities and modus operandi of the selected AI examples listed in topics b-d. Moreover, to encourage more research and practicability related to the topic, studies (b-d) should focus only on hydrological modeling for water resources management.

The objectives of this paper aim to assess the numerous physical quantities derived from a numerical, engineering, and hydrodynamic approach that AI can predict accurately for water resources and hydraulic engineering. Nowadays, for instance, AI methods can predict very quickly and with a high degree of reliability, on an equal footing with other physical hydraulic software, the monthly streamflow, the rainfall and runoff erosivity relationships, missing rainfall or river discharge, riverbed computation, and the missing riverbed roughness coefficients. Hence, case studies were chosen to fully assess the potential of physical hydraulic engineering derived from AI applications.

Equation 1 : Hydraulic Model Prediction

$$\hat{y}_t = f(X_t; \theta)$$

$\hat{y}_t$: Predicted hydraulic behavior (e.g., flow rate, water levels).

X_t: Input features (e.g., precipitation, land use, topography).

f: Neural network function.

θ: Model parameters.

1.3. Scope and Delimitations

The original text concerning the research and current technical progress affected by AI is mainly based on machine learning and neural networks, and it is hoped that this situation can be included due to the data scale objectives.

Definition: Hydroinformatics is expected to result in the efficient development of mathematical models that can handle large quantities of data. Meanwhile, the definition on the other side points out that every point in a hydroinformatic model should be explicitly identified as a single, explicit stage or element. Nevertheless, numerous credible models and AI techniques are available to fulfill these specific requirements for a variety of use cases within the hydroinformatics community. This measured scope and standpoint: In this study, all explicitly cited floodplain and channel hydraulic modeling approaches have been confirmed as mentioned explicitly in the Introduction section for the hydroinformatic domain for worldwide use as specified in the section. It is important to mention that this category of hydraulic modeling does not apply to visually-based models, models with sub-grid scale or similar, that equal a value less than 50 m. Neither are all of the existing hydraulic models and modeling methods discussed in this study. The latter could be a broad and global review of all hydroinformatic complications, such as real-time flood forecasting models and decision support systems.

Geographical and temporal range: A general aim and intent are to streamline the workload by dealing with datasets in a limited geographical area and possibly decrease the error rate when studying climate change impact assessment for modeling studies affected by a restricted range of physical phenomena. This study mainly focuses on flow in river subordinate reaches, so dam-break hydraulic impact and bore phenomena are not discussed, as these events occur in long straight-reach channels.

More generally, the scope of this study is limited to: a revision of the state-of-the-art AI techniques for manipulating listed datasets; a detailed list of suitable data sources for initializing a hydraulic model by AI; a summary description of the hydraulic models if used; the description of some of the main technical limitations. Lastly, a few other related, but more controversial, issues are avoided, such as the value of AI models or perfectibility in flood forecasting, the main subject of another research study that is not discussed. Full consideration of all these elements should be useful to AI users when choosing the technique and datasets to use as inputs or targets or as independent assessments of damage. By knowing the data and models, the input future datasets can be demand-driven or offer-driven by the AI. In other words, a low-error AI may choose to manipulate or, in some circumstances, change or vary the future input scenario that a hydraulic model will evaluate for a given value of discharge. The demarcation of the study is helpful for all categories of professionals and decision-makers of all levels.

2. Hydroinformatics and Physical Hydraulic Modeling

Hydroinformatics is an interdisciplinary domain using information technology, computer modeling, and computational hardware to understand the hydrological cycle. Its significant section is dedicated to physical hydraulic modeling that involves the application of artificial intelligence.

Detailed data collection, creation of knowledge, and model output analyses have been identified as fundamental to understanding hydrology and providing some of the necessary information to make accurate predictions. In physical hydraulic modeling, data collection and management activities were significantly enhanced with the introduction of new technologies. Many traditional approaches to engineering have been heavily reliant on physical modeling. Physical models simulate flow conditions in an open environment by manipulating mobile water together with scale adjustments. It is a lacking approach for constructing a model/prototype and interpreting its results on a unique basic concept. Such scientific needs and conceptual definitions are far too approximated from the reality outside the physical environment lab. Data analysis is another driver in hydroinformatics and provides model implementation verification. Developed approaches for areas with large data ranges require the movement of models based on heuristics.

The introduction of predictive patterns attracted attention to stochastic modeling approaches based on the concept of physical laws quantified from the associated system. This modeling tendency, which may respond to the system character when it is categorized as a random entity, is referred to as stochastic modeling. From the perspective of hydroinformatics, the second half of the last century defined the beginning of a period when traditional modeling trends could no longer cope with the complexity of the phenomena they were simulating. As opposed to the limited power of mathematical models, hydroinformatics has experienced a paradigm shift. This is the challenge that the alternative approach brought by hydroinformatics, enhancing the power of solving real-life problems, now seeks to address. A delicate combination and modification of all previously cited technologies, techniques, and methods have led to the identification of physically based equations of engineering.

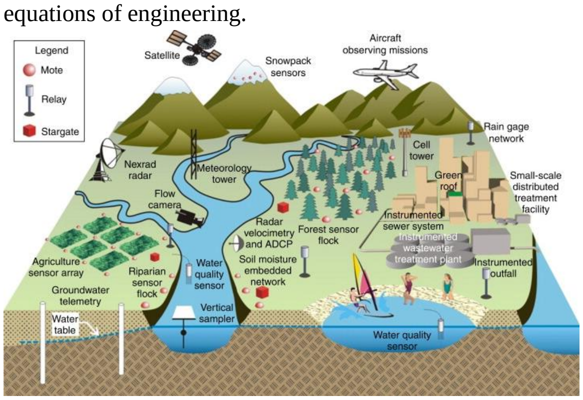

Fig 2 : Hydroinformatics - an overview

2.1. Definition and Conceptual Framework

Hydroinformatics has been mentioned for several decades; however, its terminology can sound quite broad and vague. This is because it is a multidisciplinary field for which it is difficult to reach a unique definition. Isolated, hydroinformatics comprehends the design and development of systems and software tools that can simulate, predict, optimize, and propose solutions to hydrological problems. However, following this narrow idea, hydroinformatics covers a huge scientific and technological area, which includes the use of hydraulic, hydrological, and hydrometeorological science. Concerning computational algorithms, it embraces not only numerical models but also data mining methodologies, artificial intelligence, control systems, and advanced computation applications, such as multi-agent systems, to design, manage, simulate, optimize, and deploy any kind of numerical or experimental hydrological information.

The conceptual framework for hydroinformatics is underlined, which links the aforementioned hydrological sciences and computational methodologies. Hydroinformatics is the science of collecting, organizing, and storing data electronically, having the final aim of simulating the hydrological behavior to face extreme events. Therefore, hydroinformatics is closely related to other disciplines that need to be open to new approaches because the climate change issue could require the transference of a vast amount of knowledge and technology to society about water resources. In particular, the evolution of data acquisition, processing, and transmission techniques has brought about substantial shifts in the way engineers and researchers have come to regard the fundamental components of hydroinformatics modeling; data, information, knowledge, and technology are, indeed, closely linked together. Data collection and storage form the basis of information, which must then be stored, managed, and processed to become useful. This process can be driven either by hypotheses and theories or by the availability of data. Any hydro informatics model thus guides the assimilative or deductive steps from data to knowledge, giving the ability to assess the facts and to understand and learn from them. This allows experts to generate scenarios, according to the fact that knowledge is the result of the feedback between deduction and induction. Since knowledge has an advantage over facts, and it is therefore used to forecast reality, once the internal rules of structures have been understood, it is also necessary to use the modeling rules of hydroinformatics simulations.

2.2. Traditional Approaches vs. AI-Driven Approaches

Some of the traditional modeling of water flow models has to rely on established formulas or equations from hydrology, physics, river, and hydraulic engineering. These formulas are sometimes empirically developed based on expert or domain knowledge in understanding the flow and behavior of the hydrological and hydraulic systems. One of the main limitations is that most of the traditional models require time and place data input and information about the physical conveyance of the channel, whereas any abstractness due to model simplifications can lead to the models becoming less adaptable to real-world phenomena and linked to the domain under investigation. In contrast, AI-driven technologies have developed based on advanced artificial intelligence algorithms and vast datasets that are proven to have a high capability of effectively predicting unknown values. In comparison, the AI-based models are a modern preponderant tool that can integrate and handle multiple variables, and different types of data, and perform relevant fast, pragmatic, and efficient advancements in the processing of data-driven and some mathematical-based data processing, including complex hydro mass release that is expected to be more adaptable than traditional models. The advantages of these AI-driven methods include complicated models because deep learning tracks them, integration of the evolution of a lot of appropriate and high-level data, incorporation of physical hydraulic and hydrological laws and procedures with little or no expert judgment, and more advantages than traditional data handling. The solution provides a means of classifying data and solving problems in real time. In contrast, traditional methods rely on expert knowledge with the need for frequent updates, complex mathematical equations or arithmetic operations, and require more complex and longer times to search for a solution in large datasets than AI, along with a lot of user-input data and time needed for hydrological and hydraulic data.

3. AI Techniques in Hydroinformatics

Hydroinformatics—the science and technologies applied to understand, model, and manage water systems—is benefiting from the advancement and widespread adoption of artificial intelligence (AI) and data analytics techniques. Machine learning (ML) techniques can learn from historical data using an optimization algorithm that fits a regression model from input and output datasets and can be continuously improved by learning from new examples. In hydrologic and hydraulic modeling, ML techniques make it possible to analyze large datasets and can be a cost-effective solution to enhance predictions. Data-driven models that utilize algorithms to fit the data may be used in integrated river, urban, and coastal systems to facilitate more transparent and accurate decision-making. Even though AI techniques offer significant improvement, the physical understanding of the underlying processes is equally important, and the impact of climate change can be included in these data-driven models using projected data instead of historical data.

Deep learning is a class of ML techniques that design algorithms to model or act like neural networks. These models can learn to make predictions from data by understanding how hidden layers can detect and understand complex, abstract, and high-level data features of massive datasets. In hydrology, these techniques are suitable for learning complex and nonlinear data patterns in time series that describe hydrologic, sediment, and water quality systems. Recent evidence of successful applications of deep learning architectures for hydraulic and hydrologic studies is available in various contexts and locations. Many reviewed works found that deep learning, particularly neural networks, could better estimate the different hydraulic parameters, are not significantly sensitive to input variations, and provide more accurate predictions. Nevertheless, the number of high-quality case studies in AI technologies is currently very limited in hydraulic practice. There are inevitable limitations and caveats in the use of AI technologies that must be taken into consideration in the process of hydraulic predictions. Therefore, we seek to address some of these open challenges by incorporating a correct hydraulic modeling strategy that is capable of automatic training from a wide range of samples. In addition, it is important to explore how we utilize AI-driven data-related simulations for investigating more complicated hydraulic issues, such as climate change impact assessment, which is the primary focus of this paper.

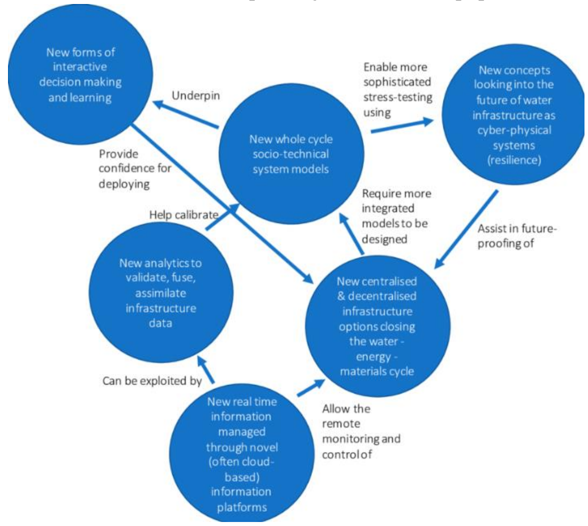

Fig 3 : Hydroinformatics research and practice

3.1. Machine Learning Algorithms

Machine learning (ML) is driving innovation across hydroinformatics applications. It forms the core of AI-driven support systems targeted at physical hydraulic modeling and climate change impact assessment. Various ML algorithms such as regression, classification, and clustering have been utilized for hydroinformatics applications. ML algorithms with high predictive accuracy are often selected. Classical algorithms and approaches have their advantages and limitations. The application of various ML algorithms has strengthened the predictive model used for hydrological data-driven modeling, such as decision trees for discharge prediction, random forests for evaporation or grassland evapotranspiration, SVM for discharge, and ANN for rainfall/runoff prediction in river basins. ML algorithms have different capabilities and often retrain or adapt to new information to improve model predictions. Supervised ML algorithms make predictions based on the analysis of labeled training data. Unsupervised ML algorithms, on the other hand, improve their learning over time based on unlabeled historical training data. Reinforcement algorithms make decisions based on feedback and consider the effect of the feedback, resulting in further adjustments to the predictions.

In any hydroinformatics modeling application, a trained ML algorithm may reveal cluster/class patterns that previous classical techniques may not. For example, a clustering algorithm can identify hidden patterns within input data that Euclidean distance may ignore. With consistent and high-quality observation site data, the accuracy of such class prediction may also be high. Another example can be reinforced learning with real-time sensor data for improved urban flooding response prediction. As these algorithms train overtime on a variety of storm designs, the model can also provide different what-if scenarios for future storms. Additionally, based on the categorical outcome, it could also assist industry professionals in designing and/or choosing the right type and size of infrastructure at the appropriate location before implementation.

3.2. Deep Learning and Neural Networks

The other popular subset of artificial intelligence used in hydroinformatics is achieved through deep learning, mostly by using a type of neural network inspired by the human brain. Deep learning and artificial neural networks have been rapidly gaining research attention in hydrology and hydraulics. With the capability of learning complex data patterns in vast amounts of raw data, both deep learning and neural networks have provided a substantial contribution towards a wide range of applications in hydroinformatics. Over the past years, AI-hydro informatics researchers have been exploring increasingly sophisticated neural network architectures to better handle real-world complex hydro-environmental data. The high performance of artificial neural networks is due to the ability to handle non-linear relationships, data characterization, and less reliance on data distribution. The building of the artificial neural network model ranges from simple to complex structures, up to the so-called deep learning method, particularly for research addressing hydrology, environmental engineering, and hydraulics. The emergence of deep neural networks and deep learning at large has provided opportunities for addressing challenges in applications such as the prediction of suspended solids and heavy metals. While such problems have been traditionally addressed using machine learning algorithms, the main advantage of deep learning is the ability to automatically extract features from the input data, thereby discovering higher-level abstractions. Therefore, several existing studies have started to utilize deep neural networks and deep learning for modeling various physical hydraulic systems, particularly floods and droughts. The majority of these studies are intended for flood prediction and drought forecasting, but other applications such as water quality predictions, typhoon surge activity, surface water level forecasting, and sediment transport modeling are also presented. The objective of the studies reviewed is not only to predict the hydraulic physical processes but also to cover the hydro-technical and hydro-environmental issues at various spatial and temporal scales. In the case of flood prediction, most of the reviewed studies focused on using rainfall data as a predictor for flood forecasts. These findings indicate the extent to which deep learning can be used effectively as an AI-hydro informatics tool for conducting physical hydraulic modeling and assessing the likely effects of climate change and other relevant issues.

Equation 2 : Generative Model for Climate Impact Assessment

$$p(\hat{y}_t|X_t) = g(X_t;\theta) + \epsilon$$

$\hat{y}_t$: Predicted climate impact (e.g., flooding risk, water quality changes).

X_t: Environmental and climate data.

g: Generative model function.

ϵ: Model error term.

4. Case Studies and Applications

Several case studies show the practical applications of AI in hydroinformatics. In particular, some existing AI applications can work as flood prediction systems, capable of providing timely alerts for possible overtopping and thus strategic management of the protection and defense of sites of any infrastructure and people potentially concerned. A DNN produces the rating curve of the data stream and, with the Monte Carlo Sample–Average method, the upper limits of the prediction intervals. Results will show that errors on prediction intervals become significantly wider if computed on outputs of Physically Based Rating Curve Generators. One case study focuses on the management of a dike located near the North Sea coastline. Results of a flood early warning system are described and discussed, illustrating how satellite altimetry data and specially tuned DNNs can provide necessary forecasts for dike management.

A second line of research considers AI as data assimilation models; for instance, the data assimilated system delivers more accurate predictions for both low and high return periods; however, it must be carefully calibrated and continuously adjusted to avoid divergence effects often reported not as a data-driven model but as a purely physical model. In general, data-driven AI models for flow forecasts tend to outperform reference models based on physical equations, especially if flow data is crucial for discharge forecasts. Moreover, this study shows improvements from a traditional data-driven forecasting approach based on the use of an attention-based DNN that adjusts the training phase data to the available input information at prediction time. This new predictive approach ensures more accurate forecasting of the inflows at medium to long temporal scales, but it is also more robust for short-term lead times when compared to traditional data-driven models. Further applications of AI in physical hydroinformatics regard water quality monitoring. Many approaches use DNNs for real-time data analysis and decision-making for both point and coastal waters. Such systems clearly show the ability to analyze more data with no human effort or human error and to be capable of quickly analyzing behaviors that may need attention.

4.1. Flood Prediction and Early Warning Systems

Substantial flooding, with impacts on communities, infrastructure, and the environment, is part of daily news worldwide. Early intervention in flooding transcends negatively impacting public health, the environment, and engineering infrastructure. The traditional qualitative description of physical phenomena using differential or stochastic equations has delved into the art of deriving production rules. AI has paved the way for a paradigm change in hydrological modeling using an incomplete description of the underlying processes. Unfortunately, there are still some barriers to the full use of AI in environmental physical processes to supplement or replace classic hydraulic mathematical regimes. One of the uses of AI in flood modeling is NCIA. This chapter focuses on a variety of applications for AI in flood science and hydraulic informatics for ECS.

Flood prediction is a highly active research field using a variety of approaches to AI. Various models have been proposed, and flood risks can be even better mitigated through data analysis as a strategic early warning system. Predictive modeling in hydroinformatics can be grounded on basic prediction methodologies based on AI techniques such as online learning. It is possible to develop a simple small network of ANNs or other computational methodologies to model early warning systems by using limited meteorological data with little support and less long-term data for a forecast. It has been proposed to use layered hydroinformatics, utilizing atmospheric data to model hydrological phenomena. Until the availability of modern data transmission and meteorological data sets, research in this area could only be performed on authenticated scenarios. Currently, a few proven solutions assist those overcoming the limitations experienced in the CNS. Providing precision forecasts and a few false alarms at a reasonable cost is a reality. Early warning systems have not been presented properly due to conclusions and discussions in the technical literature. Overall, this description tries to assess the viability of using AI to create a variety of potential applications. The early warning system based on AI supports management decisions in the face of enhanced flood disaster resilience. Moreover, it is necessary to revise the nature of information systems in early warning systems to accommodate meaningful, timely support as a global modus operandi. Moreover, in end-to-end systems from data acquisition to forecast, NS only has to be calibrated and provide technical advice in the context of requesting relevant CSS, which yields superior performance. This text discusses the methods for shifting from local, reactive controls to proactive, integrated, and improved decision-making.

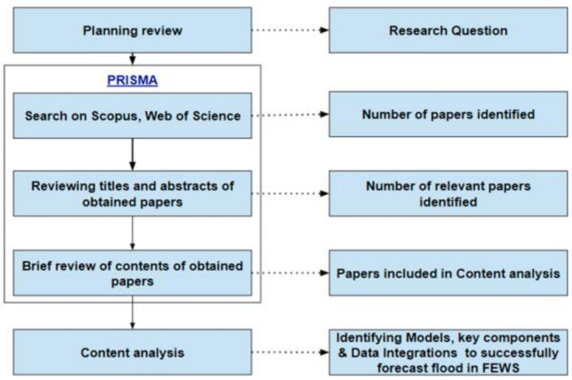

Fig 4 : Evolution of Flood Prediction and Forecasting Models for Flood Early Warning Systems

4.2. River Flow Forecasting

Canal and river flow forecasting has been of interest since early times due to its critical role in short-term water resources planning, operation of hydraulic structures, and estimation of potential flood events. Two types of forecasting are usually employed for these purposes, including short-term forecasting for up to a few days and medium- and long-term forecasting for both monthly and annual scales. River flow forecasting is about predicting either available flow at a point of interest or any ungauged site within a river basin based on the relationship of the historical observed data with various environmental variables that govern flows. Today, various methodologies, such as physical models, conceptual models, machine learning models, and data-driven models, exist for predicting river flows at different time scales. The basic operational principle of these models is to process input data from monitoring gauging stations by using mathematical relationships. River flows can be forecasted by establishing the representation of the relationship between input and output based on numerical simulations. The physical hydraulic models of river flows are usually written as a collection of partial differential equations consisting of continuity equations as well as equations representing the fundamental laws of fluid dynamics including bed friction, inertia, and conservation of mass and energy. The solution to the equations is obtained by numerical solving procedures using computer software. Though physical hydraulic models are widely accepted to be used for simulating flood inundation extents and depths, bed, and bank morphodynamic changes, and accordingly for the design of hydraulic infrastructures, they are now being used in flood forecasting and early warning systems. The disadvantage of using physical hydraulic models is their high computational demand. Consequently, various conceptual and artificial intelligence methodologies are utilized for real-time flood forecasting.

4.3. Water Quality Monitoring

Integration of AI-based data analytic approaches has shown promising outcomes in water quality monitoring applications, enhancing the assessment of various water quality parameters with the capability to analyze diverse and sometimes non-traditional data at a deeper level. A reactive approach based on data obtained from traditional methods cannot help to make a quick decision about the water health parameters. Machine learning techniques have become a useful tool to analyze real-time measurement data and relate it to the type of pollutants in the water and their concentration. Frequent pattern mining and anomaly detection are widely adopted to identify various types of patterns in the monitoring time-series data. An innovative method for real-time analysis of water quality monitoring was developed; the monitoring data were utilized to infer the water health based on the data-driven association rules algorithm. The methodology was implemented for the drinking water supply system, and real-time analysis showed that the water supply was healthy in the region and suitable for consumption. The interaction between data generated through the monitoring provides information to relate the water level time series to the bulk parameter values such as turbidity and chlorophyll-a, algae, and other major pollution levels to assess the river's health. Water quality monitoring data were used for the mapping index of surface water and identification of risk zones for the water pipelines. The study was conducted on existing spatial clustering mining methods in the development of the River State Index as a foundation for water quality monitoring and identification of potential drinking water sources. The source of the drinking water catchment area was introduced. The daily monitoring data were used to develop an RSI framework for the classification and intercomparison of precipitation downscaling variables for the simulation of discharge, water temperature, BOD, and total nitrogen within the hydrological model. The water monitoring status by spatiotemporal index was classified in a catchment, which supplies drinking water to the western part of the country. Long-term spatiotemporal BOD monitoring was analyzed and reported. Long-term daily monitoring data were used for the case study area to generate spatial and temporal cluster characterization from specific monitoring sites in the river and sub-basin segments for the study area. There is a close relationship between the temporal clusters and the different land use changes observed in the catchment, with the different clusters having an inverse relationship with the semi-urban and agricultural clusters. However, the lowest of the wastewater treatment plants had the highest BOD values. Deep learning methods have also been widely used for the discrimination of illumination correction in image processing and the replacement of low-cost routine tests instead of additional expensive laboratory tests.

5. Climate Change Impact Assessment

Increasing water availability, particularly in water-stressed regions around the world, is a key area of inquiry in water resources research. Owing to the complexities of future climate uncertainty, there are numerous challenges involved in assessing climate change impacts on local hydrology, such as water availability and flood frequency. There is a critical need to connect engineered systems to climate dynamics. Tools such as informational computation and artificial intelligence should be employed to expose the functioning of very complex systems. Population growth, high rates of immigration and urbanization, and increasing industry and energy demands will all result in the availability of fresh, reliable water. Climate change solutions must account for demand, quality, and current policies on the environmental side with predictability and system constraints effectively modeled. AI can correctly model non-stationary disturbance in time series in this context. To detect and track a developing trend (increase in flood risk, water level frequency, and so on, derivative impacts from climate solution implementation), the model must also be used as a predictive test. Therefore, for policy implementation moving toward a climate-resilient future, adaptive modeling is integrated with predictive analytics. Upon this base, we intend from this perspective paper to conceptualize hydroinformatics and demonstrate examples of how it is used in emerging research settings.

The majority of traditional climate change vulnerability assessments offer static views of changing hydro-climatic statistics of maximum possible floods or drought severity that the system should prepare for while expecting that other functional aspects of the hydrologic cycle remain constant in the future. However, physical triggers as well as operative regulation alterations, as occur in water reservoirs and power utilities, would render current static vulnerability assessments meaningless or only useful for the study of a specific isolated phenomenon. Traditional assessment tools are, in general, unsuitable for informing the investigator with tactically relevant policy or engineering decisions requiring flexibility for the changing scope. Consequently, in response to the issues outlined above, it was shown that a trained Echo State Network model could effectively simulate climate change's impact on river flow or surface water quality by coupling with a hydrodynamic or surface water quality model. It has been shown not only how to propagate climate change uncertainty into river flow/output uncertainty but also combined climate-Earth system models uncertainty for sediment and respectively the nutrient propagation in this catchment. A conventional hydro-climatology General Additive Model could underestimate the river flow simulation by the Echo State Network due to the difference in the model physics, precipitation or evaporation input error, and a simplified parameterization method in human activity inputs to the hydrodynamic model.

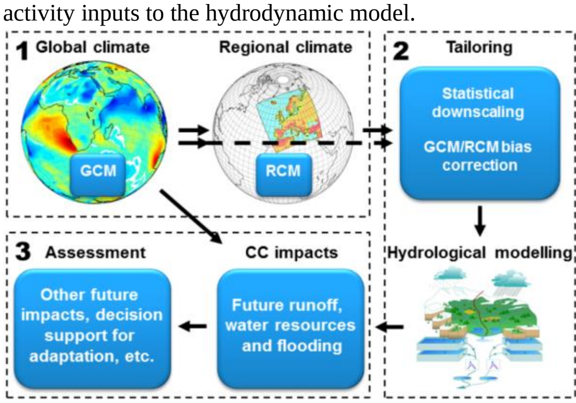

Fig 5 : Hydrological Climate Change Impact Assessment at Small and Large Scales

5.1. Challenges and Opportunities

Given the substantial difficulties in performing comprehensive and objective climate change assessments for hydroinformatics, it is important to address the uncertainties in climate models at the methodological level using adaptable approaches. There are several different factors inherent in hydrological systems that exhibit significant long-term variability, including temperature changes, various impacts from variations in precipitation statistics, changes in frequency distribution due to variations in within-season or between-season variability, changes in the ranges or boundaries of the season, and so forth. These are aspects not directly given by climate scenarios but are crucial for assessing local impacts, as the system can react differently to the same type of forcing. Furthermore, the effects can be non-monotonic and counterintuitive, making the process even more complex. While machine learning allows one to deploy more complex models of overfitting with the issue of limited memory errors, the philosophical background should move from focusing on building the most accurate model to a more data analysis-oriented approach, where it is important to understand aspects that lead to poor performance, such as data lability. As the scientific community calls for water, environmental, and climate scientists to develop a joint cross-disciplinary approach to impact assessments, it appears significant to question our capacity to deal with different and multidimensional data sources, our ability to couple data from different disciplines, and our capability of addressing discrepancies and associated uncertainties. Hydroinformatics should include AI-inspired uncommon physical measurements, large-scale monitoring provided by mobile applications or new sensors, and new methods for knowledge extraction and data mining from non-physical models, effectively focusing on a system approach in which the method is developed using a case-study-driven behavior. Case studies exist that highlight generalized drawbacks, opportunities, and new possibilities for climate change impact assessment with hydroinformatics.

5.2. Integration of AI in Climate Models

Level 5: Integration of AI in Climate Models

One critical method for enhancing traditional climate models has been to incorporate AI methods into existing formulations. Machine learning approaches are inherently based on data and patterns in the data and can provide unique and improved predictions if sufficient diverse datasets can be accessed. The key benefits of using AI and machine learning are scalability, computational efficiency, predictive ability, data-driven analysis beyond the process-based understanding, and adaptability according to the ever-changing environment. Climate modeling is highly reliant on historically collected data and vast distributed datasets. When real-time and continuously updating datasets are available, AI could be deployed to obtain a much more detailed picture. Additionally, because AI methods are designed to handle big data, even in the case of a lack of data, AI methods can be robust for filtering, filling in, and/or interpolating the missing data. While some sectors have already implemented climate models with real-time data, at a global level, they are yet to be used on a large scale. The main challenges facing these models are the inherent complexity of the data integration between AI representation and physical laws, the need for specialized hardware to run such simulations, and computational expenses.

For real-time assessment, accurate and fast-updated datasets of climate and non-climate variables are essential. Climate models may also be required to adapt to the new data. Given the complexity and computational requirements of existing climate prediction systems, when other types of non-climate datasets are added to produce such AI-based climate forecasts, a term that has been used to describe this integration of different data streams is "big data serious." The use in policy and decision-making of AI-only or AI-disaggregated data is still in its nascent stage. Many propose that real-time predictions will evolve, enabling a greater and new set of service opportunities. The economic advantages of developing climate-resilient communities downscaling to sectors, and even to regional infrastructure projects, are well established. Prediction benefits, packaged in the form of prediction services or such corporations, are projected to reach trillions of dollars. Statements released by global institutions are consistent in addressing the urgent need to convert climate data into actionable information and to deliver accurately targeted products and services. For the LDCs, a landmark climate initiative that is now being piloted provides new services and is addressing mitigation, helping define mission-critical environmental data enterprise requirements in a collective initiative under UN-funded work.

6. Future Directions and Research Gaps

Artificial intelligence is evolving into emerging technologies like reinforcement learning and transformers, which could provide improvements in non-convex and nonlinear systems related to business applications and water resources. These technologies could be integrated with high-performance computing for data assimilation and physical numerical simulations, to improve the accuracy of predictive modeling for physical systems. Within data analysis, sparse data representation and intrinsic data analysis could be further developed to identify physical drivers among large volumes of data and spatiotemporal scales. Meanwhile, interdisciplinary research should be encouraged for the development of software, tools, and relevant models that bridge the gap between hydrologists and data scientists in the extraction of new knowledge from data and optimal processing of experts' knowledge.
Research must go beyond the improvements over existing applications and delve more into the fundamental impacts of AI innovations. Fundamental research beyond application should develop an understanding of the impact of AI on water management practices, policy, and strategies. Automatic operations must incorporate the advantages of AI into financial, social, operational, managerial, governance, legal, and policy aspects. Policy implications need to be made based on interdisciplinary research that involves academia, industry, and policymakers. Potential problems could emerge due to recent AI studies that do not thoroughly interpret such implications or those aforementioned factors. As hydrologists and data scientists envision updating a software tool that informs data processing, they need an overview that explores the impacts, opportunities, and risks of automatic operation once AI is incorporated. Afterward, AI tools need to address specific protocols in tackling such implications and risks. Furthermore, the research must conduct the ability to deploy these actions. The methodological scheme and exploration of uncharted territories will, therefore, be considered sacrosanct.
The frontier in AI-driven hydroinformatics is rapidly advancing, and thus the future directions to come would answer the unexplored research gaps. There are several areas where innovative research is urgently needed to provide supporting systems to researchers and practitioners.

Equation 3 : Optimization for Hydraulic System Performance

$$\min_{\theta} \mathcal{L}(\hat{y}_t, y_t) + \lambda\|\Delta\theta\|^2$$

$\mathcal{L}$: Loss function (e.g., root mean squared error).

y_t: Actual hydraulic or climate outcomes.

$\lambda\|\Delta\theta\|^2$: Regularization term.

6.1. Emerging Technologies and Innovations

The hydroinformatics field is changing at an unprecedented pace. Disruptive and cutting-edge developments in artificial intelligence, big data, and data analytics are revolutionizing the way we conduct research and operate, manage, and plan for the future in the domain of hydroinformatics. Model-driven data analytics are incorporated in many fields, and many machine learning or AI models can embrace the integrated water management system, sustainable urban water management, planning and design of urban water infrastructure, and agriculture, which adds value to society, the economy, the environment, and ecological aspects. Successful hydrological or hydraulic modeling usually requires a large amount of input data. Examples of relevant datasets include hydro-meteorological observations, rainfall patterns, land use and soil types, topographical data, water body bathymetries, and more.
With the appearance of the Internet of Things and corresponding big data approaches, an increasing amount of observational data is being processed, supporting more realistic and near-real-time calibration strategies of hydraulic models. Given the inherent capability of remote

sensing data to capture structural changes in land and hydraulic infrastructure systems, the task of detecting and responding to model structural changes and forecasting system behavior under these conditions is emerging as a relevant task in operational hydrological and hydraulic systems. To summarize, existing hydraulic models focus extensively and solely on structure and parameter model approaches, rather than on the use of AI and contemporary system optimization and control systems. Challenges such as compatibility and integration into existing policies, administrative procedures, and regulatory frameworks need to be adapted and assured in the forthcoming years. This will allow existing frameworks to embrace them and cope with the data processing workload involved in efficient real-time data analysis of future AI-enhanced hydroinformatics applications in operation, engineering, research, environmental monitoring, disaster management, and initial operational systems. AI in hydraulic model applications may contribute to fostering a reduction in the proportion of responses to activities in the fields of water resources management and disaster management. It will also resolve engineering management conflicts in design and operation or offer solutions to optimize water-use predicaments between environmental and anthropogenic needs in the upcoming years.

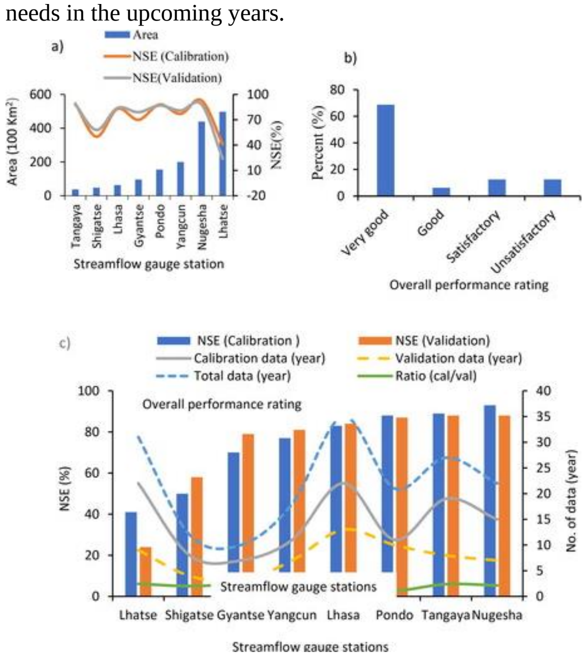

Fig 6 : Performance evaluation of various hydrological models with respect to hydrological

6.2. Policy Implications and Recommendations

Subsection 6.2. "Policy Implications and Recommendations"

This demonstrates the momentous implications that policy and decision-makers could face in the coming years to develop frameworks and guidelines for responsible usage of AI in hydroinformatics and the enhancement of its related infrastructure. There is a notable need to devise new regulatory standards and guidelines for the penetration of digital data. This addresses privacy and ethical concerns that are becoming increasingly important in hydroinformatics, particularly regarding water quality models that carry ramifications for public health. These standards would also curtail the potential misuse of water data. Furthermore, policymakers should endeavor to undertake changes in the context of their existing water management strategies.

The public should be educated about the potential for integrating AI-powered technologies into existing processes—the public's awareness is instrumental in determining whether or not these technologies can be effectively leveraged. Such an education program can be considered ethical, as it will inform people about their drinking water like a form of "nudging" to improve the quality of life and public health outcomes. However, policymakers must be cognizant of the idea that AI's potential applications can expand and change; in effect, making it necessary for water managers to possess a modicum of technological literacy before companies can market their products to implement AI in an industry-wide spectrum. Policymakers should adapt their decisions to build frameworks that proactively adapt to the pace of technology. Finally, this paper suggests that public infrastructure should consider implementing aid-driven technologies to replace physical equipment. This would be cost-effective for both the community and the companies that integrate their models.

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