# Artificial Intelligence in Water Resource Management: The Past, Present and Opportunities thereof

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## INTRODUCTION

Understanding hydrologic systems at the scale of interconnected watersheds and associated river basins is critically important for developing and developed nations alike, when faced with extreme weather events, often affecting water security and quality, and ultimately affecting civilizations as a whole. Current state hydrological modeling has been largely deterministic and simplified to linear or linear like models, often being unable to respond to intra- and inter-basin variations in topography, weather patterns, land cover, soil drainage capacity, and other associated secondary factors. The need of the hour is for a quantum shift in the practice of hydrological modeling with the ability to handle data driven stochastic variables leveraging the availability of real-time data and capable of establishing explicit relationships between input variables and phenomena with little to no physical modeling.

The aim of this survey paper is to present a review of current artificial intelligence (AI) applications in the water resource management domain with an emphasis on surface hydrology. For the purpose of this paper, we will focus on what the US Defense Advanced Research Projects Agency (DARPA), one of the major public funders of AI research in the past decades, has recently labeled the second and third wave of AI. (DARPA, 2021) classifies the second and third wave of AI techniques as intelligent systems with the ability to learn and respond to a changing environment.

In the subsequent sections, the paper describes the review methodology adopted to identify relevant literature, outlines the DARPA second and third wave of AI application frameworks, describes two specific applications of AI frameworks in water resource management, followed by concluding remarks.

## SEARCH METHODOLOGY

The domain of water resource management spans across a vast expanse of topics and hence an objective screening method was paramount to filter pertinent research papers. Our study employed the ISI Web of Knowledge and Scopus research publication databases and applied a couple of selection statements to these databases to develop a curated list of research papers focused on AI applications in the water resource management domain.

To include both generic and technical papers published prior to 2021, relevant keywords like AI, Artificial Intelligence, ML, Machine Learning, Algorithm, Genetic, Genetic Computation, GAN, Markov Model, Evolutionary Computation, Computer Vision etc. along with the term "water" in the title and/or topic were employed. The query statement was as follows:

1. TITLE = (“AI” OR “Artificial Intelligen*” OR “ML” OR “Machine Learn*” OR ((“Evolutionary” OR “Genetic”) AND (“Algorith*” OR “Comput*”)) OR “GAN” OR “Generat* OR “Neural” OR “Network*” OR “Fuzzy” OR “Markov” OR “Hidden Markov” OR “Random Forest” OR “Tree bagger” OR “ELM”) AND TITLE/TOPIC: Water AND TIMESPAN: 1950–2020
2. TOPIC = (“AI” OR “Artificial Intelligen*” OR “ML” OR “Machine Learn*” OR ((“Evolutionary” OR “Genetic”) AND (“Algorith*” OR “Comput*”)) OR “GAN” OR “Generat* OR “Neural” OR “Network*” OR “Fuzzy” OR “Markov” OR “Hidden Markov” OR “Random Forest” OR “Tree bagger” OR “ELM”) AND TITLE/TOPIC: Water AND TIMESPAN: 1950–2020

The first search yielded 614 unique publications, whereas the second search yielded upwards of 5,700 publications. This could be attributed to the fact that the field tag “topic” on Scopus and Web of Knowledge spans across keywords, abstract and introduction. Refer Figure 1 for the screening process employed. This was further filtered to only consider the 50 most cited papers out of both search results.

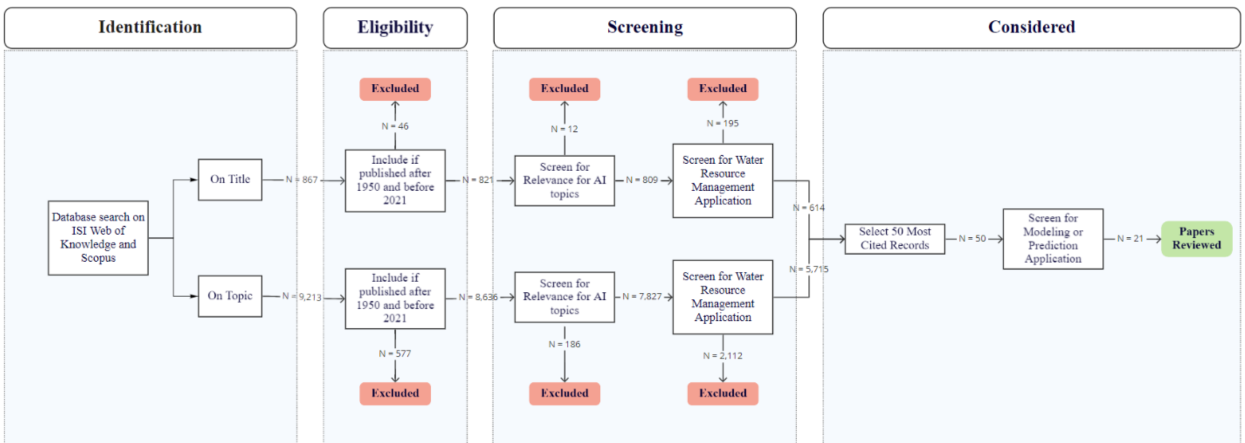


*Figure 1.* Flowchart depicting the screening process employed for literature review (based on *(Moher, Liberati, & Tetzlaff, 2009)* & *(Doorn, 2021)*)

The abstracts of these 50 most cited papers were reviewed for relevance with an emphasis on elaboration of specific applications of artificial intelligence in the water resource management domain. Any papers not explicitly complying with these parameters were excluded. The focus of the current survey paper was further narrowed down to the specific applications of artificial intelligence in modeling and prediction (or forecasting) of water management techniques, as these constituted the bulk of the applications. Other notable application categories that could be observed were focused on optimization, risk management, decision frameworks and quality management of water resources. It was observed that it was extremely difficult to draw the fine line between most of the above categories like modeling v/s prediction, modeling v/s optimization, risk management v/s decision frameworks etc as they seemed interdependent and highly contingent on the specific application and the subsequent role of various stakeholders. Eventually the search was narrowed down to 21 papers which are discussed in subsequent sections.

The inherent risk with relying on citations or just focusing on highly cited papers as a selection criterion is that this study might inevitably exclude relatively new novel approaches employing by emerging researchers. The current study acknowledges the bias and strives to expand the search using a more holistic framework soon.

## AI FRAMEWORKS IN WATER RESOURCE MANAGEMENT

The application of Artificial Intelligence in water resource management is highly concentrated in the realm of Hydrological modeling (Dawson & Wilby, 2001). (N & Deka, 2014) reiterated that Hydrological models are the foundation for a range of multi-disciplinary water resources planning and management activities, with the most critical applications focused on the characterization, modeling and forecasting of Surface Water Hydrology and Ground Water Hydrology. (Allaby, 1999) and (Anees, et al., 2016) describe hydrological modeling as the characterization of real hydrologic features and systems using small-scale physical models, mathematical analogues, and computer simulations.

Hydrological processes are complex, highly non-linear, and mostly dynamic, often characterized by variability of across temporal and spatial scales. (Belvederesi, Dominic, Hassan, Gupta, & Achari, 2020) and (Dawson & Wilby, 2001) observe that traditionally, hydrological processes have been modeled as deterministic process-driven closed systems by employing linear or linear transformed statistical models like autoregressive (AR), and derivates like autoregressive moving average (ARMA), autoregressive moving integrated average (ARIMA), autoregressive moving average with exogenous terms (ARMAX) etc. Such models often need a large collection of explanatory variables to define the complex physical processes, which most often are neither well identified nor well quantified, severely affecting their broad applicability.

However, with climate change being at the fore, the advent of ubiquitous remote sensing technology (and associated data) and the need to understand large-scale inter and intra-system processes better, a framework that can model data-driven heterogenous and distributed systems with wide applicability is needed. In the past three decades, a growing cohort of researchers have been leveraging artificial intelligence (AI) techniques for modeling non-linear hydrologic systems with a high degree of success and accuracy. They have spearheaded the use of artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS), feed forward neural networks (FFNNs), wavelet-neural network models (WA-ANN), wavelet-based adaptive neuro-fuzzy inference system (WANFIS) and support vector machines (SVMs), predominantly for hydrological process modeling. The same are briefly discussed with an overview of their applications in the following sections.

### *Artificial Neural Network (ANN)*

ANNs are inspired by the structure and mechanism of biological neural networks, are defined as parallel computational models with superior generalization capabilities. ANNs have provided an appealing framework for co-relating input and output variables in complex systems, which earlier were neither well identified nor well quantified. The most widely employed ANN structure is the feed-forward multilayer perceptron (MLP), consisting of three layers: an input layer, one or more hidden layers, and an output layer (Figure 2). The network topology consists of a set of neurons connected by links and is normally organized in several layers. The number of neurons in the input and output layers is equal to the number of input and output variables, respectively. The network operates by assigning weights to values as they pass from one layer to the next and calculating outputs for each of the neurons in all other layers. The hidden layers help increase model adaptability. (Kalteh, 2013) recommends setting the number of neurons in the

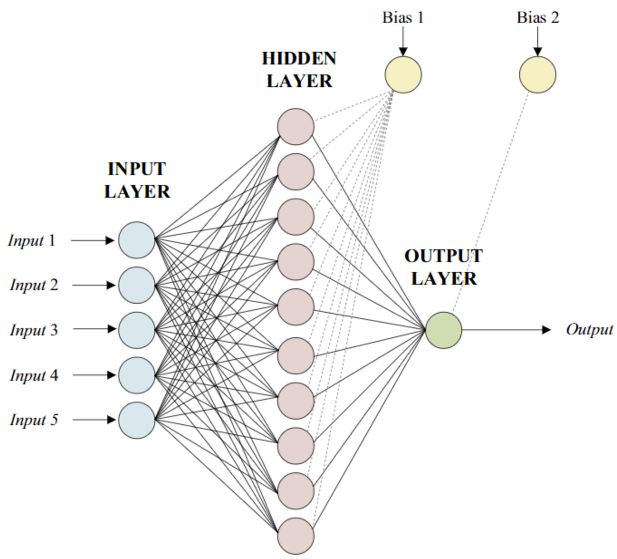


*Figure 2.* Typical Architecture of a feed forward Artificial Neural Network (ANN) (Adapted from *(Seo, Kim, Kisi, & Singh, 2015)*)

hidden layer(s) and the connection weights via a trial-and-error procedure to aid in best fitment between observed and predicted outputs. The feed-forward multilayer perceptron (MLP) is trained using the error backpropagation algorithm for most hydrological modeling applications, by iteratively changing the network's interconnecting weights such that the overall divergence between observed values and modeled network outputs is minimal.

### ***Adaptive Neuro-Fuzzy Inference System (ANFIS)***

ANFIS is the evolution of a MLP, specifically, it is a MLP that employs fuzzy reasoning to co-relate the input and output variables in complex systems (Figure 3). The fuzzy reasoning is supported by a Fuzzy Inference System (FIS) consisting of three components: a rule basis with mandatory IF-THEN rule sets, a database and an inference system capable of combining the fuzzy

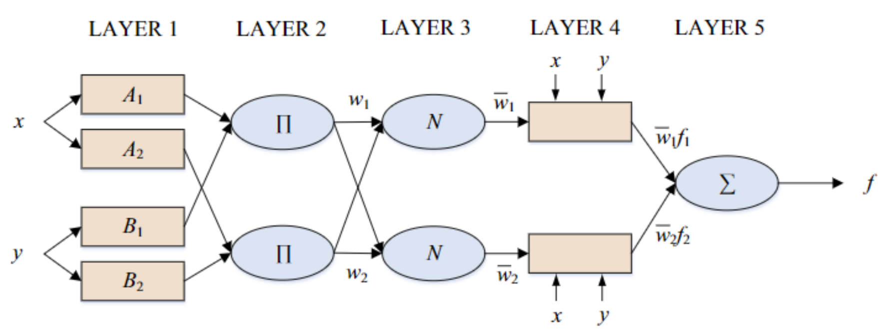


*Figure 3.* Typical Architecture of a feed forward Adaptive Neuro-Fuzzy Inference System (ANFIS) (Adapted from *(Seo, Kim, Kisi, & Singh, 2015)*)

rules. A FIS (Figure 4) is curated by first developing the membership functions of the input–output variables, followed by the construction of fuzzy rules and finally the determination of output characteristics, output membership function and system results. A hybrid learning algorithm often combining the backpropagation gradient descent method and least-square method, is employed to develop the membership functions and the fuzzy rules.

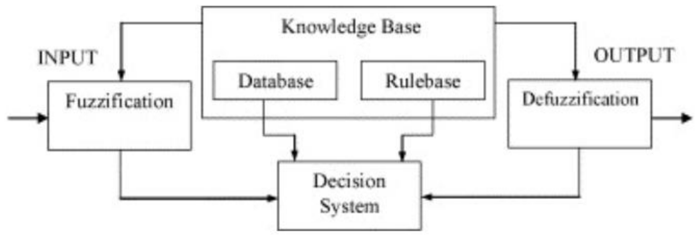


*Figure 4.* Typical Architecture of a Fuzzy Inference System (FIS) (Adapted from *(Firat & Güngör, 2007)*

(Chang & Chang, 2006), (He, Wen, Liu, & Du, 2014) and (Seo, Kim, Kisi, & Singh, 2015) have demonstrated that ANFIS can consistently provide high accuracy and reliable models for a host of applications in the hydrological systems domain. ANFIS is superior at learning, constructing, expensing, and classifying. It facilitates the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base, especially being able to attune the complicated conversion of human intelligence to fuzzy systems.

***Support Vector Machine (SVM)***

SVMs were proposed in the early 1990s by (Cortes & Vapnik, 1995) as machine learning systems that utilize a hypothesis space composed of linear functions in a multi-dimensional feature space and trained with optimization algorithms that implement a learning bias derived from statistical learning theory. The basic SVM architecture maps the original data sets from the input space to a multi- dimensional, or in the extreme case, infinite-dimensional feature space so that classification problem becomes simpler in the feature space (Figure 5).

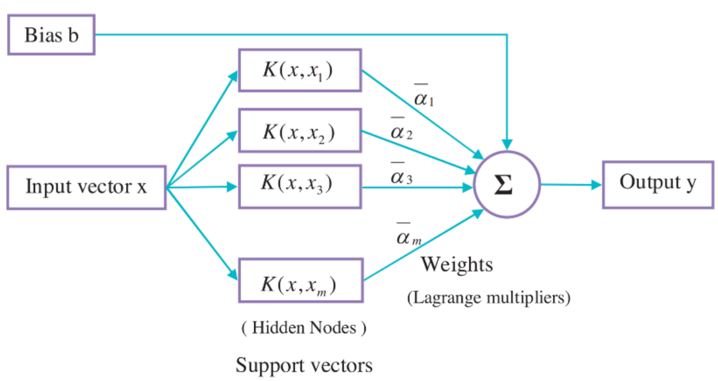


*Figure 5.* Typical Architecture of a Support Vector Machine (SVM) (Adapted from *(Chen & Yu, 2007)*

The strength of SVMs lies in its simplicity and the ability to decipher the unknown relationship present between a set of input variables and the output of a complex system. Scholars with sufficient statistical knowledge can readily understand the construct, yet it is powerful that the predictive accuracy of this approach overwhelms many other methods, such as nearest neighbors, neural networks and decision tree. Given its strong statistical framework, SVMs have proved to be much more robust in areas of research with noise mixed data, typical of large-scale hydrological systems. SVMs possess strong adaptability, global optimization, and good generalization performance, with (Yu, Liong, & Babovic, 2004) having observed that SVMs have been successful when applied in classification problems, regression, and forecasting.

(Han, Chan, & Zhu, 2007) and (Mukherjee & Vapnik, 1999) have demonstrated that with pertinent actual training vectors embedded in the models as support vectors, the SVM has the potential to trace back historical events so that future predictions can be improved with the lessons learnt from the past. (Samui, 2011) and (N & Deka, 2014) affirm the flexibility of SVM input vectors having facilitated the incorporation of other secondary and/or influential factors in a hydrological system like temperature, relative humidity, windspeed, forest cover etc into the forecasting model.

## AI APPLICATIONS IN WATER RESOURCE MANAGEMENT

In the past few decades, ANNs and ANFIS methods have been extensively used in a wide range of engineering applications including hydrology, such as for rainfall–runoff simulation (Nourani et al., 2009, Talei et al., 2010, Wu and Chau, 2011), groundwater modeling (Kuo et al., 2004, Daliakopoulos et al., 2005, Sahoo et al., 2005, Ghose et al., 2010, Taormina et al., 2012), river flow forecasting (El-Shafie et al., 2006, Shu and Ouarda, 2008) and water quality modeling (Singh et al., 2009, Yan et al., 2010).

Recently, SVMs are also gaining traction in hydrology, such as for surface hydrology characterization (Moradkhani et al., 2004, Yu et al., 2006, Lin et al., 2006, Wu et al., 2008, Lin et al., 2009, Chen et al., 2010, Yoon et al., 2011), groundwater modeling (Belayneh and Adamowski, 2013, Wei et al., 2007, Liu et al., 2011) and hybrid-dynamic modeling techniques (Remesan et al., 2009, Sudheer et al., 2013, Ozgur and Mesut, 2012).

This paper would like to discuss two trailblazing papers focused on the application of ANN, ANFIS, WANN and WANFIS frameworks for surface hydrology applications.

### *Daily Water Level Forecasting in reservoirs*

Most reservoir catchment areas are characterized by variability of precipitation across temporal and spatial scales, which affects the ability to accurately forecast reservoir inflow(s). Reservoir inflow forecasting is critical to the operations of a reservoir directly affecting the ability to ensure water security, flood mitigation, energy security, agricultural production etc.

Traditionally, such reservoir inflow forecasting has been conducted using linear or linear classified statistical models by employing time series analysis. Such statistical models included types like transfer function (TF), broken line (BL), fractional Gaussian noise (FGN), autoregressive (AR), and derivates like autoregressive moving average (ARMA), autoregressive moving integrated average (ARIMA), autoregressive moving average with exogenous terms (ARMAX) etc. While these were fairly accurate in the past and provided conservative forecasts, helping err on the side of caution, the underlying inflow pattern has and is anticipated to change in the future, owing to climate change and anthropogenic factors in the catchment basins.

This presses the need for a forecasting model capable of handling a highly nonlinear and dynamic inflow patterns. In the past decade, a group of researchers led by (Jain, Das, & Srivastava, 1999), (Bae, Jeong, & Kim, 2010), (Okkan, 2012) , (Kim, Shiri, & Kisi, 2013) and (Seo, Sungwon, & Singh, 2013) have been leveraging artificial intelligence (AI) techniques for modeling non-linear hydrologic systems with a high degree of success and accuracy. They have spearheaded the use of artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) in conjunction with wavelet transforms for efficient data processing, which adapt well to non-linear relationships and varying frequency components paving the way for a hybrid model construct with a high degree of accuracy and enhanced performance of forecasting models.

This study would like to highlight the research done by (Seo, Kim, Kisi, & Singh, 2015) which focuses on developing two hybrid models for forecasting daily water and reservoir inflow levels and comparing the accuracy of these model constructs. Building on (Okkan, 2012)'s work and their previous work, they apply wavelet decomposition theory (WDT or DWT), employing a host of mother wavelets like Coiflets, Daubechies and Symmlets, to ANN and ANFIS models and compare them against the forecasting performance of classical ANN and ANFIS models, for the Andong dam watershed in South Korea across a temporal scale spanning from 2002 through 2013. Figure 6 depicts the flowchart summarizing the research methodology employed.

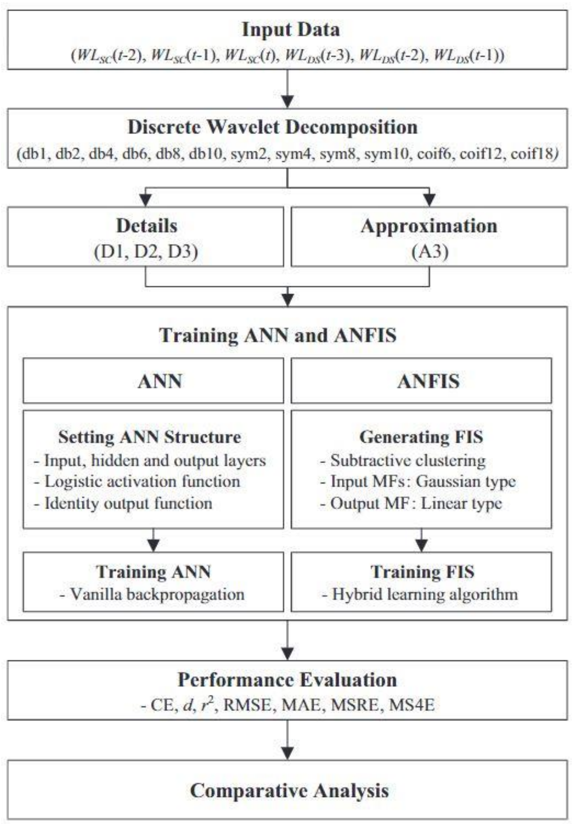


*Figure 6.* Flowchart depicting the forecasting model for daily water level using WANN and WANFIS (Adapted from *(Seo, Kim, Kisi, & Singh, 2015)*)

The daily water level data (as obtained from government agencies) from two water gauges: Socheon and Dosan in the Andong dam watershed were used and prepared subsequently. The data from 2002-2010 was used for training the neural networks (by employing Vanilla or standard backpropagation) and the data from 2011-2013 was employed for model testing and analysis. (Seo, Kim, Kisi, & Singh, 2015) evaluated the performance of the forecasting models (hybrid and classical) using seven performance indices outlined by (Dawson & Wilby, 2001): the coefficient of efficiency (CE), the index of agreement (d), the coefficient of determination ($r^2$), the root mean squared error (RMSE), the mean absolute error (MAE), the mean squared relative error (MSRE), and the mean higher order error (MS4E). High model efficiency or co-relation between observed and predicted values are indicated by larger values of CE, d and $r^2$ and smaller values of RMSE, MAE, MSRE and MS4E.

(Seo, Kim, Kisi, & Singh, 2015) developed 196 models, 7 each of ANN and ANFIS type and 91 (13 times 7) WANN and WANFIS models by employing 13 mother wavelets. Upon evaluating the seven performance indices, it was observed that the hybrid WANN and WANFIS models performed better than and yielded better co-relation with observed data as compared to classical ANN and ANFIS models. Specifically, within the hybrid models, the WANFIS models were accurate than WANN models in forecasting daily water and reservoir inflow levels.

***River Flow Forecasting in water stressed regions***

River systems are one of the most complex physical systems often transcending through various watersheds and associated micro-weather patterns, converging tributaries, merging with other water bodies, and changing topography. Their flows subsequently are often characterized by variability of across temporal and spatial scales, making flow forecasting critical to the ability to ensure water security, flood mitigation, energy security, agricultural production etc.

(Remesan & Mathew, 2015) observe that traditional river flow models have been constructed in the past using deterministic physical models requiring swathes of calibration data and co-relation models. Such forecasting has been conducted using linear or linear classified statistical models by employing time series analysis like transfer function (TF), broken line (BL), fractional Gaussian noise (FGN), autoregressive (AR), and derivates like autoregressive moving average (ARMA), autoregressive moving integrated average (ARIMA), autoregressive moving average with exogenous terms (ARMAX) etc. While these were fairly accurate in the past and provided conservative forecasts, helping err on the side of caution, the underlying inflow pattern has and is anticipated to change in the future, owing to climate change and anthropogenic factors especially in the contributing and served watersheds.

This coupled with the ability to collect huge swathes of data using GIS and low-cost sensors, presses the need for a forecasting model capable of handling unprocessed data from a highly nonlinear and dynamic river system, especially when the underlying physical relationships might not have been established. In the past decade, a group of researchers led by (Atiya, El-Shoura, & Shaheen, 1999), (Jain, Das, & Srivastava, 1999), (Bae, Jeong, & Kim, 2010), (Okkan, 2012) , (Kim, Shiri, & Kisi, 2013), (Seo, Sungwon, & Singh, 2013), (Kalteh, 2013), (N & Deka, 2014) and (He, Wen, Liu, & Du, 2014) have been leveraging artificial intelligence (AI) techniques for modeling non-linear hydrologic systems with a high degree of success and accuracy. They have spearheaded the use of artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) in conjunction with wavelet transforms, and support vector machines (SVMs) for efficient data processing, which adapt well to non-linear relationships and varying frequency components paving the way for a hybrid model construct with a high degree of accuracy and enhanced performance of forecasting models.

This study would like to highlight the research conducted by (He, Wen, Liu, & Du, 2014) of the Heihe river system comparing the performance of three different data driven models in the water stressed semi-arid Qilian Mountain range in North-western China from 2001 to 2011. Complimenting the work by (Nayak, Sudheer, & Rangan, 2004), (Kalteh, 2013) and (N & Deka, 2014), the researchers employed artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS) and support vector machine (SVM) frameworks for forecasting river flow.

The daily river flow data (as obtained from government agencies) at the Pailugou station along the Heihe river system in the Qilian mountains in North-western China from 2001 to 2003 and 2009 to 2011 were used and prepared subsequently. The data from 2001-2003 was used for training the neural networks and the data from 2009-2011 was employed for model testing and analysis. Employing the recommendations by (Shanker, Hu, & Hung, 1996), (He, Wen, Liu, & Du, 2014) undertook data pre-processing and auto-correlation using transformation methods to ensure a normally distributed training data set. (He, Wen, Liu, & Du, 2014) evaluated the performance of the forecasting models (hybrid and classical) using four performance indices outlined by (Dawson & Wilby, 2001): the coefficient of correlation (R), the root mean squared error (RMSE), Nash–Sutcliffe efficiency coefficient (NS), and the mean absolute relative error (MARE). High model efficiency or co-relation between observed and predicted values are indicated by larger values of R and NS and smaller values of RMSE and MARE respectively.

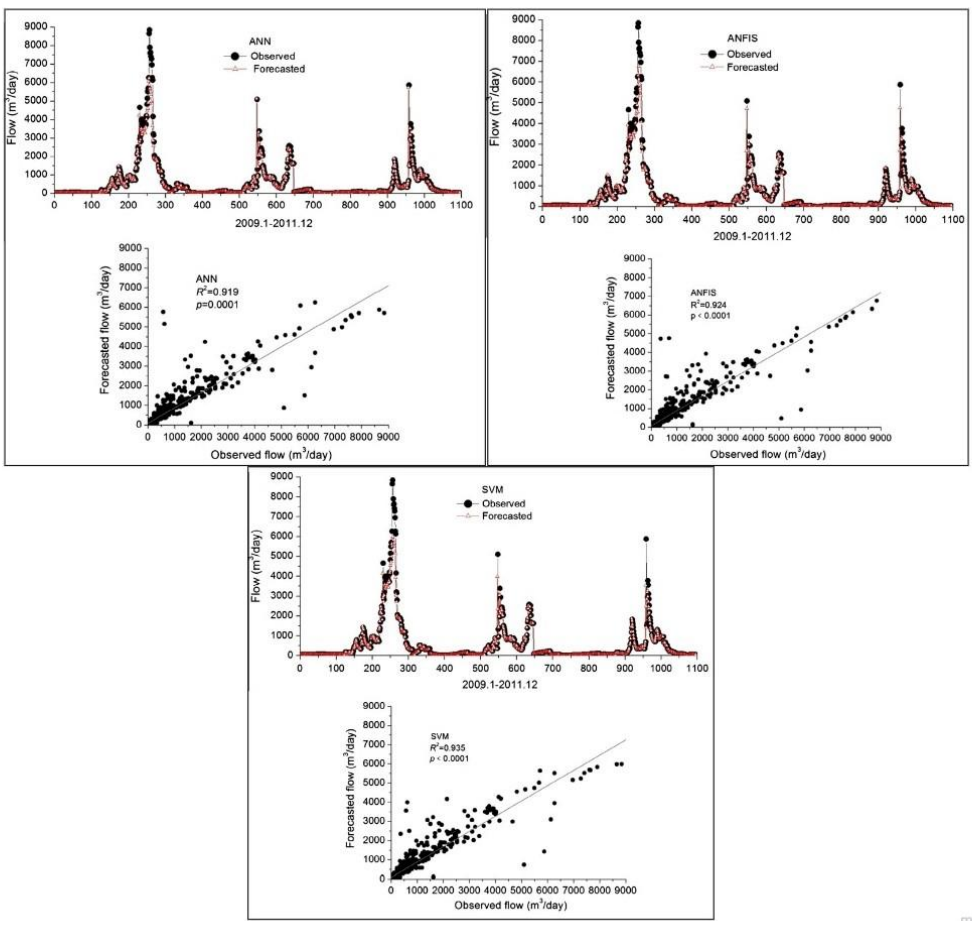


*Figure 7. Hydrograph and scatter plots of both the observed data and the predicted obtained by using the ANN, ANFIS and SVM model for the validation period (Adapted from (He, Wen, Liu, & Du, 2014)*

Figure 7 depicts the Hydrograph and scatter plots of both the observed data and the predicted obtained by using the ANN, ANFIS and SVM model for the validation period (2009-2011). The study infers that the SVM estimates were closer to and highly co-related with the corresponding observed flow values, followed by the ANFIS estimate with the ANN being the most divergent amongst the three frameworks.

Though the results demonstrate that ANN, ANFIS and SVM can be applied successfully to establish accurate and reliable river flow forecasting in complex river systems, (He, Wen, Liu, & Du, 2014) also observed that prediction accuracy was high only for low values of flow with high flow values prediction (typical during floods and high precipitation events) being challenging for all three models. (Campolo, Andreussi, & Soldati, 1999) and (Ming, Liang, & Xia, 2020) attribute such a divergence in high flow longer duration simulation to the perturbation in the physical response time of the river system that is severely affected by the saturation of the river basin.

## CONCLUSION

This paper attempts to present a review and rudimentary categorization of different types of applications of AI in the water resource management domain, spanning across typical applications like modeling, prediction and forecasting, decision support frameworks, and optimization. The following specific observations were made based on the review of around 30 papers and associated conference proceedings and books :

- Of all the papers reviewed as part of the literature survey one factor, above all others, was deemed crucial to the implementation of ANN models - the availability of suitable, high-quality and in most cases pre-processed transformed data (Smith and Eli, 1995; Tokar and Johnson, 1999).
- A general lack of objectivity, consistency and reliability was observed in the way in which most hydrological models are assessed or compared.
- ANN construction in most studies involved many arbitrary decisions, with little guidance as to the best means of practice or choice of standard error measures.
- One would expect a model with many parameters to ‘fit’ data better than one with fewer degrees of freedom especially in the case of ANFIS and SVMs. However, more complex models did not necessarily lead to proportionate increases in accuracy and scholars might question whether the additional effort is justifiable?
- The importance of not relying on individual error measures to assess model performance was not emphasized enough. Different studies used varying combinations of standard error measures to justify model fitment. Perhaps a statistically sound practice could be combining both goodness of fit error measures (e.g., CE, d, and $r^2$) and absolute error measures (RMSE and MAE).
- Most studies did not provide details of how the neural networks and training models were developed, so it could be assumed that in many cases the scholars developed their own program using a high-level language. In other cases, ‘off-the-shelf’ packages might have been used. The lack of a peer-reviewed open-source package repository could lead to tool fatigue and no standard operating procedures.
- A major gripe with with fuzzy logic is the lack of systematic procedure for the design of a fuzzy controller or FIS. This often led to the the time requested for the training and determining parameters of a typical ANFIS predicting model to extremely prolonged.

- To analyze hydrological data statistically, the scholar must be adept at basic definitions and understand the purpose and limitations of SVMs. The application of SVMs often requires measurement of physical phenomena, requiring the modeler/scholar to evaluate the accuracy of the data collected and have a domain knowledge on how the data are accumulated and processed before they are used in modelling activities.
- The application of AI in hydrology has been characterized by poor physical modeling practice and the lack of consistency of approach. This situation has arisen because the choice of network type, training method(s) and data handling technique(s) has often been undertaken in unsystematic ways by scholars. A specialized role of "neurohydrologists" has been proposed by (Dawson & Wilby, 2001) to ensure repeatability and adaptability across use-cases.
- One of the main drawback of SVM is the fact that selection of the suitable kernel function and hyper parameters are heuristic and dependent on a trial and error process which is did not rely on the quality of human judgment for the optimal choice of the linearization function of non-linear input data, ultimately making this a time-consuming approach. Hence the training process becomes much slower when compared to that of linear models.
- The ability to incorporate human judgement in the kernel function selection in the feature space could help better rationalize processing times, but is extremely cumbersome as the behavior of the nonlinear SVR model cannot be easily understood and interpreted due to the inherent complexity involved in mapping nonlinear input space into a high dimensional feature space.
- Most of the reviewed literature on AI in the water resource management domain paid minimal to no attention to highlight the ethical aspects of AI applications and the biases the skewed datasets propagate. Most scholars were gung-ho about the benefits of a data driven approach and failed to highlight the pitfalls of such an approach.
- Probably the development and application of responsible AI techniques for the water domain should not be left to data scientists or neurohydrologists alone, but might require the involvement of other stakeholders like ethical AI scholars, complemented with expertise from the social sciences and humanities
- (Doorn, 2021) and (DARPA, 2021) literature, while elucidating on AI and ethics suggest that principles like transparency, justice and fairness, responsibility and accountability, privacy, and non-maleficence that should be considered when developing AI applications, at a minimum.

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