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Deep learning and machine learning in hydrological processes climate change and earth systems a systematic review

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Abstract. Artificial intelligence methods and application have recently shown great contribution in modeling and prediction of the hydrological processes, climate change, and earth systems. Among them, deep learning and machine learning methods mainly have reported being essential for achieving higher accuracy, robustness, efficiency, computation cost, and overall model performance. This paper presents the state of the art of machine learning and deep learning methods and applications in this realm and the current state, and future trends are discussed. The survey of the advances in machine learning and deep learning are presented through a novel classification of methods. The paper concludes that deep learning is still in the first stages of development, and the research is still progressing. On the other hand, machine learning methods are already established in the fields, and novel methods with higher performance are emerging through ensemble techniques and hybridization.

Keywords: Machine learning, deep learning, big data, hydrology, climate change, global warming, hydrological model, earth systems

Nomenclatures

Artificial neural network	ANN	Random forest	RF
Extreme learning machine	ELM	Deep feedforward neural network	DFNN
Machine learning	ML	Recurrent neural network	RNN
Support vector machine	SVM	Partial least squares	PLS
Wavelet neural networks	WNN	Discriminant analysis	DA
Deep learning	DL	Principal component analysis	PCA
Autoregressive integrated moving average	ARIMA	Linear discriminant analysis	LDA
Feed-forward neural networks	FFNN	Support vector regression	SVR
Multi layered perceptron	MLP	Least-squares	LS
Decision tree	DT	Sparse Bayesian	SB
Response surface methodology	RSM	Standard precipitation evapotranspiration index	SPEI
Back propagation neural network	BPNN	Genetic programming	GP
Gradient boosting decision tree	GBDT	Multi linear regression	MLR

Adaptive neuro fuzzy inference system	ANFIS	Moderate Resolution Imaging Spectroradiometer	MODIS
Central processing unit	CPU	Reduced order model	ROM
Fire-fly algorithm	FA	wise step fire-fly algorithm	WSSFA
Deep neural network	DNN	Deep belief networks	DBN

1 Introduction

Studying the hydrological processes, climate change and earth systems are of utmost importance to expand knowledge and insight into the universe [1]. Thus, advancing the accurate models of the earth's various phenomena and systems have been the center of attention [2]. Physical models have a long tradition in simulation, understanding, and prediction of the hydrological processes, climate change, and earth systems [3-7]. Physical models are used worldwide as the trustworthy systems to study the environmental phenomena, climate behavior, atmospheric and hydrological systems, and further study of the natural hazards, extreme events, and ecosystems [8-11]. Statistical models, including the time series analysis form another major popular group of modeling techniques widely used by scientists for studying the earth systems and deliver insight on climate change and hydrological related events [12-18].

Various drawbacks are associated with physical and statistical models [19-21]. Among them, the accuracy, weakness in uncertainty analysis, high computation cost, and the need for a comprehensive amount of data, have been highlighted in the literature [22, 23]. Machine learning and deep learning methods have seen to tackle these shortcomings very well through their efficient computation and intelligence [24-29]. Only during the past few years, these methods have become

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very popular among the research communities [30-46]. Figure.1 represents the rapid progress of machine learning and deep learning in hydrological processes, climate change, and earth systems research and their subfields. The progressing domination of these intelligent methods is apparent. Thus, studying the novel methods and identifying the trend in using and advancement of these methods would be essential.

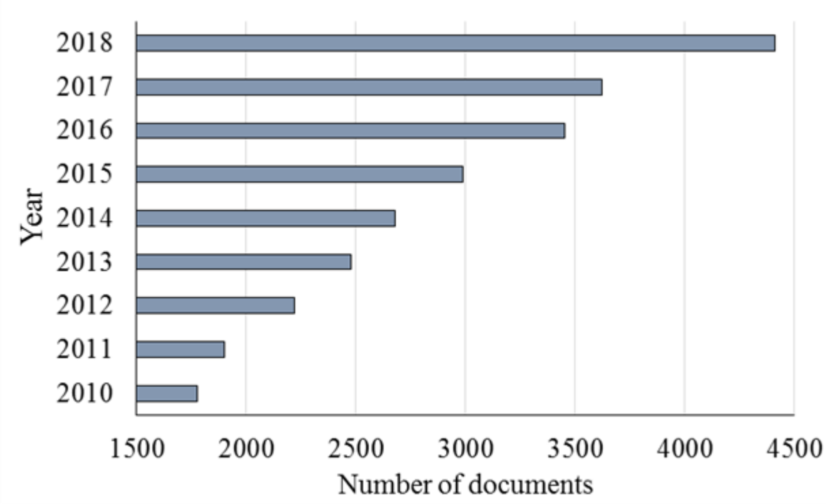

Fig. 1. The rapid growth of using machine learning and deep learning for modeling and prediction of the hydrological processes, climate change and earth systems (source: web of science)

Literature includes a number of review papers on machine learning and deep learning methods [30-46]. There exists a number of papers where the applications domains of the ML methods have been evaluated [47-62]. How-

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ever, there is a gap in investigating the algorithmic advancements and application domains considering the hydrological processes, climate change, and earth systems. Consequently, the contribution of this paper is set to present the state of the art of machine learning and deep learning methods used for modeling the above-mentioned systems and identify the application areas.

2 Machine learning methods

In this section, the machine learning methods have been classified into the following popular subsections, i.e., tree-based, support vector-based, neural network-based, and hybrids and ensembles. Further, there are investigated according to their popularity and applications domains. The summary of the methods are provided in the tables bellow and methods are reviewed according to their efficiency and accuracy

Table 1. Top studies developed by ML methods in hydrology

References	Contribution	Method	Research domain
[63]	To estimate the hydrologic disturbance index for streams by the use of Random forest	RF	-Machine learning -Watershed management
[64]	To develop different machine learning methods for the estimation of daily reference evapotranspiration	SVM, ELM, RF, M5Tree, and GBDT	-Machine learning -Reference evapotranspiration

[65]	To develop ML methods for the prediction of the wheat production yield in the presence of satellite and climate data	RF, ANN, and SVM	-Machine learning -Hydrological data
[66]	To develop ML methods for the estimation of the atmospheric daily pollen concentration	RF and ANN	-Machine learning -Daily pollen concentration
[67]	To develop ML methods for the prediction of water flow forecasting as a hydrological parameter	MLP, SVR, RBF, and ANFIS	-Machine learning -Hydrologic parameter
[68]	To develop an innovative ML method for the prediction of daily solar radiation (monthly average values)	ELM-MODIS	-Machine learning -Daily solar radiation

Fox and Magoulick [63] developed a study to estimate the hydrologic disturbance index for streams by the use of Random forest in the presence of fish community and hydrologic data and landscape metrics for gaged streams as the training dataset. RF has been introduced as one of the effective methods for this task. RF also has been proposed in a study by Fan et al. [64], who developed SVM and ELM methods in comparison with different tree-based ensemble methods for the estimation of daily reference evapotranspiration in the presence of meteorological data. Tree-based ensemble methods included RF, M5tree, gradient boosting decision tree, and extreme gradient boosting. Evaluations have been performed using determination coefficient, root means a square error and means absolute error. Based on comparisons, RF could provide a higher accuracy compared with that of other methods.

In another study, Cai et al. [65] developed different ML methods for the prediction of wheat production yield by integrating hydrological data, including satellite and climate data. This study also could successfully present a comparison of the performance of methods using the determination coefficient. Methods included the least absolute shrinkage and selection operator, RF, ANN, and SVM. In all datasets, the highest determination coefficient value was owned by SVM followed by RF. Zewdie et al. [66] developed ML methods including RF and ANN for the prediction of atmospheric daily pollen concentration for the comparison with next-generation weather radar. Comparisons have been performed using correlation coefficient values. Based on results, RF and ANN could provide similar performance in the prediction of target values with a high correlation coefficient value.

Kovačević et al. [67] developed a study for the prediction of water flow using MLP, SVR, RBF, and ANFIS methodologies. Evaluation of results and comparison of the performance of methods have been performed using the employment of root mean square error, mean absolute error, and determination coefficient. The best method was ANFIS, followed by SVR with a linear kernel. Ghimire et al. [68] developed a novel ML method entitled the integrated ELM-MODIS. The proposed method has been compared with basic ELM, GP, ANN-GA, ANN-PSO, GA-SVR, and online sequential ELM methods in terms of determination coefficient, root mean square error and mean absolute error. Based on the results, the proposed method could significantly increase the estimation performance followed by hybrid GA-SVR and hybrid ANN-GA methods. The overall detailed results in terms of accuracy, reliability, and sustainability have been presented in table 2 for further considerations and applications.

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Table 2. the comparison results of ML-based methods in hydrology

Method	Application	Accuracy	Reliability	Sustainability	Reference
RF	Estimation	++	++	++	[63]
RF	Estimation	+++	++	++	[64]
M5Tree	Estimation	++	+	+	[64]
ELM	Estimation	+	+	+	[64]
SVM	Estimation	+++	+++	++	[65]
RF	Estimation	++	++	+	[65]
NN	Estimation	++	+	+	[65]
RF	Estimation	++	++	+	[66]
ANN	Estimation	++	++	+	[66]
ANFIS	Estimation	+++	++	++	[67]

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SVR-Linear kernel	Estimation	++	++	++	[67]
RBF	Estimation	++	++	+	[67]
MLP	Estimation	++	+	+	[67]
ELM-MODIS	Estimation	+++	+++	+++	[68]
GA-SVR	Estimation	++	++	++	[68]
ANN-GA	Estimation	++	++	+	[68]

3 Deep learning methods

Deep learning techniques are considered as a significant part of ML methods based on ANN. DL techniques have been widely applied in analyzing, estimating, designing, filtering, processing, recognition, and detection tasks. The most popular DL methods are DNN, DBN, RNN, and CNN techniques.

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Table 3. Top studies developed by DL techniques in hydrology

References	**Contribution**	**Method**	**Research domain**
[69]	To develop a DL method for the prediction and estimation of flood	LSTM-ROM	-Deep learning -Flood prediction
[70]	To develop a DL technique for making a model for monitoring drought accurately.	DFNN	-Deep learning -Drought prediction
[71]	To develop DL technique for the analysis of atmospheric imaging of Cherenkov Telescopes	CNN	-CNN -Atmospheric imaging
[72]	To develop a DL technique for the estimation of tropical cyclones and their precursors	CNN	-Deep learning -Tropical cyclones
[73]	To develop an innovative DL method for the prediction of hydrological processes.	DL-FA	-Deep learning -Hydrological processes

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Hu et al. [69] developed a novel LSTM integrated by ROM method as an innovative DL method for the prediction of time-series flooding. This integrated method could successfully cop with the prediction of Spatio-temporal distribution of floods because it can use the advantage of both ROM and LSTM methods. The evaluation of results has been performed using root mean square error in the presence of different predicted periods. The validation data was included in the Okushiri tsunami test datasets. This method presented a high accuracy as well as reducing the cost of CPU. This can increase the sustainability of the proposed method significantly.

Shen et al. [70] developed DL technique architecture entitled deep feed-forward neural network for the prediction of SPEI as one of the main factors of drought in the presence of multi-source remote sensing data. The proposed method provided a good correlation with meteorological and agricultural droughts. Evaluating data included SPEI in Henan Province, China, which indicated a high-performance value.

Shilon et al. [71] developed a convolutional neural network method for the analysis of aerial imaging of Cherenkov Telescopes. This imaging system has a significant role in finding very high energy γ-ray emitters. The training phase was performed using datasets generated from Monte-Carlo simulated events and testing phase was performed on both measured and simulations data. CNN could successfully cope with the task with high accuracy. CNN also has been employed by Matsuoka et al. [72] who developed a CNN technique for the estimation of tropical cyclones. The training process was performed in the presence of longwave radiation outgoing during twenty-year simulation which has been calculated by employing a cloud-resolving global atmospheric simulation. The evaluation has been performed using the probability of detection factor.

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Xu et al. [73] integrated deep learning and fire-fly algorithm for training the SVR method with optimized parameters. Also, the performance of the developed methods has been compared with other methods in term of determination coefficient. Based on results, the highest correlation coefficient was owned by wise step fire-fly based SVR algorithm followed by DLFA based SVR algorithm in training step, but in testing step the accuracy of DLFA based SVR method has been significantly reduced. This reduction caused the lowest sustainability index for this method.

Table 4. the comparison results of DL based methods

Method	*Application*	*Accuracy*	*Reliabil-ity*	*Sustaina-bility*	*Reference*
LSTM-ROM	Estimation	+++	+++	+++	[69]
DFNN	Estimation	+++	+++	++	[70]
CNN	Detection	+++	+++	+++	[71]
CNN	Estimation	+++	+++	+++	[72]
WSSFA-SVR	Estimation	+++	+++	+++	[73]

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DLFA-SVR	Estimation	++	+	+	[73]
FA-SVR	Estimation	++	++	++	[73]

4 Conclusions

The survey of the advances in machine learning and deep learning are presented through a novel classification of methods. The paper concludes that deep learning is still in the first stages of development, and the research is still progressing. On the other hand, the machine learning methods are already established in the fields, and novel methods with higher performance are emerging through ensemble techniques and hybridization. Similar trends have also been reported in the other application domains [74-83].

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