

A comprehensive review of deep learning applications in hydrology and water resources

Muhammed Sit, Bekir Z. Demiray, Zhongrun Xiang, Gregory J. Ewing, Yusuf Sermet and Ibrahim Demir 

ABSTRACT

The global volume of digital data is expected to reach 175 zettabytes by 2025. The volume, variety and velocity of water-related data are increasing due to large-scale sensor networks and increased attention to topics such as disaster response, water resources management, and climate change. Combined with the growing availability of computational resources and popularity of deep learning, these data are transformed into actionable and practical knowledge, revolutionizing the water industry. In this article, a systematic review of literature is conducted to identify existing research that incorporates deep learning methods in the water sector, with regard to monitoring, management, governance and communication of water resources. The study provides a comprehensive review of state-of-the-art deep learning approaches used in the water industry for generation, prediction, enhancement, and classification tasks, and serves as a guide for how to utilize available deep learning methods for future water resources challenges. Key issues and challenges in the application of these techniques in the water domain are discussed, including the ethics of these technologies for decision-making in water resources management and governance. Finally, we provide recommendations and future directions for the application of deep learning models in hydrology and water resources.

Key words | artificial intelligence, deep learning, hydroscience, machine learning, review, water

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HIGHLIGHTS

- A comprehensive review of deep learning applications in hydrology and water resources fields is conducted.
- Summaries of papers that employ deep learning for hydrologic modeling are presented, along with a concise deep learning synopsis.
- Key issues within the water-related deep learning application literature are reported.
- Future directions for research in the intersection of deep learning and hydroscience is presented.

LIST OF ACRONYMS

AE	Autoencoder	CNN, ConvNet	Convolutional Neural Network
AI	Artificial Intelligence	DBM	Deep Boltzman Machines
ANN	Artificial Neural Networks	DBN	Deep Belief Network
BMP	Best Management Practices	DEM	Digital Elevation Model
BP	BackPropagation	DNN	Deep Neural Network
ConvLSTM	Convolutional LSTM	DQN	Deep Q-Network

EC	Electrical Conductivity
EEMD	Empirical Mode Decomposition
ELM	Extreme Learning Machines
ENN	Elman Neural Network
FCN	Fully Convolutional Network
FFNN	Feed-Forward Neural Network
GAN	Generative Adversarial Networks
GIS	Geographic Information System
GPU	Graphics Processing Unit
GRACE	Gravity Recovery and Climate Experiment
GRU	Gated Recurrent Unit
IMF	Intrinsic Mode Function
LSTM	Long Short-Term Memory
LiDAR	Light Detection and Ranging
MAP	Mean Areal Precipitation
MAPLE	McGill Algorithm for Precipitation now-casting by Lagrangian Extrapolation
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NAR	Nonlinear Autoregressive
NARX	Nonlinear Autoregressive eXogenous
NDVI	Normalized Difference Vegetation Index
NOAH	National Oceanic and Atmospheric Administration
PDE	Partial Differential Equation
PLSR	Partial Least Square Regression
RBM	Restricted Boltzman Machine
RGB	Red Green Blue
RNN	Recurrent Neural Network
ReLU	Rectified Linear Unit
SAE	Stack AutoEncoder
SSIM	Structural Similarity
SST	Sea Surface Temperature
SVM	Support Vector Machines
SVR	Support Vector Regression
VAE	Variational AutoEncoders
VMD	Variational Mode Decomposition

INTRODUCTION

The global volume of digital data is expected to reach 175 zettabytes by 2025 (Reinsel *et al.* 2018). Large-scale sensor networks, as well as the increased awareness of climate change, water resources management and the monitoring

of water-related hazards, led to the substantial growth of the volume, variety, and velocity of water-related data (Weber *et al.* 2018; Sit *et al.* 2019a, 2019b). Modern data collection techniques, including satellite hydrology, Internet of Things for on-site measurements (Kruger *et al.* 2016), and crowdsourcing tools (Sermet *et al.* 2020b), has revolutionized the water science and industry as approached by the government, academia, and private sector (Krajewski *et al.* 2017). The effective utilization of vast water data holds the key for long-term sustainability and resilience, and presents opportunities to transform water governance for the upcoming decades (Grossman *et al.* 2015). In the hydrological domain, multivariate analysis relying on extensive and semantically connected data resources is required to generate actionable knowledge and produce realistic and beneficial solutions to water challenges facing communities (Carson *et al.* 2018; Jadidoleslam *et al.* 2019). However, the inaccessible, unstructured, nonstandardized, and incompatible nature of the data makes optimized data models (Demir & Szczepanek 2017) and smarter analytics approaches a necessity (Sermet & Demir 2018a).

Computerized methods to create an understanding of hydrological phenomena are based on various modeling strategies, which simplify a hydrological system to simulate its behavior (Antonetti & Zappa 2018). Physical models aim to achieve this goal by specifically designing complex simulations that are powered by mathematical and numeric specifications of conceptualized physical characteristics (Jaiswal *et al.* 2020). However, hydrological systems, as is the case with other natural systems, are inherently heterogeneous (Marçais & De Dreuzay 2017) as opposed to less complex human-made systems with defined rules. Therefore, physical models, although deterministic and reliable, do not always perform and scale well due to their intrinsic limitations (Islam 2011). As an alternative, statistical models have been employed to make use of the comprehensive set of available hydrological, environmental, and geophysical data (Evora & Coulibaly 2009). These approaches assume minimum awareness of the underlying mechanism and receive their strength by eliciting useful information and patterns from the available data through statistical analysis (McCuen 2016). However, they have displayed shortcomings in terms of accuracy and certainty, and also require excessive computational power (Ardabili *et al.* 2019; Agliamzanov *et al.* 2020).

Recent developments in artificial intelligence (AI) and graphics processor units (GPU) have paved the way for deep learning, a pioneering approach that is fueled by multi-layer artificial neural networks (ANN) (LeCun *et al.* 2015). Deep learning provides a black-box method to learn from

complex and high-dimensional data to infer robust and scalable insights while minimizing the degree to which manual labor is needed (Sengupta *et al.* 2020). One feature that separates deep learning from its superset machine learning is the use of multilayer models, which leads to a higher level representation of the underlying data sources (Saba *et al.* 2019). Furthermore, deep learning is capable of extracting substantial features without being explicitly instructed, and thus, is more immune to raw and noisy data (Sahiner *et al.* 2019). Successful implementations of deep learning permeate numerous domains and industries, including medical imaging (Haskins *et al.* 2020), healthcare (Esteve *et al.* 2019), finance (Heaton *et al.* 2017), geophysical sciences (Shen 2018), remote sensing (Ma *et al.* 2019), and hydrology. Due to its significant adoption rate and potential to be applicable to any domain that encompasses problems that can be expressed as control systems, numerous open-source and for-profit software tools, educational resources and generalized algorithms have been made available for use, opening up countless paths to advance hydrological studies.

This paper presents a systematic review of applications of deep learning within the scope of the hydrological domain. The literature has been thoroughly examined to identify the use cases of deep learning in the subfields of the water sector, including flooding, weather, land use and soil, water quality, surface water, water resources, and groundwater. Each study has been evaluated to extract information that is scientifically relevant to assess the study's contribution and reproducibility, including the hydrological tasks that were taken on to be approached by deep learning along with the utilized network architectures, datasets, software tools and frameworks, licenses, and deep learning practices and algorithms. The paper explores modern deep learning networks from the lens of the hydrological domain to investigate the shortcomings and challenges of the status quo and to highlight the opportunities and future directions to serve as a guide to researchers, professionals, and governmental organizations in the water sector.

The major contributions of this paper can be summarized as follows. Although there are various configurations of ANNs optimized for various data types and use cases, it is challenging to reduce a real-life hydrological task to a certain predefined approach given the depth and complexity of the tasks as well as the diversity of networks. The methodologies that need to be employed while developing deep learning-powered solutions in hydrology are not standardized in terms of data quality and preparation, execution, validation, and documentation. Furthermore, the strength,

usability, and reliability of a model lie on clearly set descriptions and procedures for deterministic reproducibility, given the variety of development frameworks, as well as the application areas. To the best of our knowledge, there has not been a thorough investigation of systematically approaching water challenges with deep learning. Thus, this paper serves as a meticulous guide for the stakeholders of the hydrology domain to advance the water industry with intelligent systems that are revolutionized by multifaceted data (Sermet *et al.* 2020a).

The remainder of this article is organized as follows. The Literature Review section provides the review methodology followed by a comprehensive literature review of deep learning applications in the water domain. Descriptions of deep learning concepts, tasks, and architectures are described to summarize the available methodology for use by the hydrological community. The Results section presents a detailed summary and analysis of reviewed papers grouped by their application area. The Key Issues and Challenges section highlights the key issues and challenges facing the stakeholders utilizing deep learning in the water domain with respect to technical limitations as well as ethical considerations. The Recommendations and Conclusions section outlines a vision entailing the adoption of prominent and deep learning-powered technologies to solve the water challenges of the future, and then concludes the paper with a concise summary of findings.

LITERATURE REVIEW

This section starts with a detailed description of the literature search methodology in the first subsection Review Methodology and then presents the information extracted from each reviewed manuscript. The subsection Deep Learning gives a brief overview of deep learning history, describes various neural network architectures, and elaborates on different machine learning task types. At the end of this section we share the summary of the literature as figures to provide an understanding of this review and a table of all the papers reviewed.

Review methodology

A systematic literature search on water domain was employed for this review. Web of Science, Scopus, Springer Link, Wiley Online Library, and The International Water Association Publishing Online were used as the databases and the keywords included 'deep neural network', 'deep

neural networks', 'deep learning', 'lstm', 'long short term memory', 'cnn', 'convolutional', 'gan', 'generative adversarial', 'rnn', 'recurrent neural', 'gru', and 'gated recurrent'. Hydrosience and water resources specific keywords were not included in the search queries because of the cardinality of domain-specific keywords. The cardinality is a result of many application fields within these domains and also many interchangeable and synonymous words used to refer the same terms within different scientific communities around the globe. Hydrology and water resources related papers are filtered at the journal level which provided a comprehensive coverage compared to keyword level filtering. After limiting the search with these keywords in the publication title, abstract, or keywords, an additional exclusion criterion was applied through each database's categorization system if applicable only to include the publications within the environmental fields. Also, searches were limited to only include journal publications. All articles published in 2018, 2019, and 2020 up until the end of March containing these keywords in their titles, keyword fields, or abstracts were included in the first list of articles gathered. This time interval is primarily chosen based on our initial literature search and availability of deep learning application papers to create a comprehensive review and curate insights within the water domain between 2018 and 2020. There were also other review articles partially covering the water domain and timeline (Shen 2018). After gathering the initial list totaling 1,515 publications, each of them was briefly reviewed to determine whether they were in alignment with the scope of this study. All publications that were not research papers were excluded, namely vision papers, editorials, and review papers. From the initial list of 1,515 publications, 315 remained after this filtering step. These publications were filtered further to keep publications that met certain technical criteria. This step eliminated all publications that did not involve some form of deep ANN in their pipeline of work.

After this step, 129 publications remained and were included in our comprehensive review. The comprehensive review process consisted of manually reviewing the papers one by one to extract specific publication features, including Architecture, Framework/Library/Programming Language, Dataset, Source Code Sharing, Reproducibility, Subfield: Deep Learning, Subfield: Environment, Summary. Each of the feature categories are described below:

- **Architecture** – The type of deep neural network (DNN) architecture(s) employed in the study. This could be simply ANN or more complex architectures like

Generative Adversarial Networks (GAN) or Variational Auto Encoders (VAE).

- **Framework/Library** – This column serves as a survey within the field to understand the programming language and numeric computation library choices of researchers.
- **Dataset** – Whether the dataset(s) used in the study were collected specifically for the study, acquired from an authority resource, or previously existing standalone.
- **Source Code Sharing** – A boolean field indicating if the code of the study is open-sourced and accessible by the public.
- **Reproducibility** – A boolean field indicating if the results of the study could be reproduced just by using the information provided in the manuscript.
- **Subfield: Deep Learning** – A classification of the machine learning task tackled in the paper. This field uses one of the following values: Regression, Classification, Sequence Prediction, Matrix Prediction, Unsupervised Learning, and Reinforcement Learning. Details of these are given in the next subsection where we describe deep learning practices.
- **Subfield: Environment** – A classification of the task carried out in an environmental field. This field uses one of the following values: Flood, Groundwater, Land Usage and Soil, Surface Water, Water Quality, Water Resources Management, Weather, and Others. Others include papers within the environmental field that do not exactly fit with the other subfields included here.
- **Summary** – The brief summary of the study.

The data for each publication reviewed herein are shared later in this section with figures and a table. Technical summaries of the papers reviewed are given in the Results section. Conclusions drawn from the acquired data are shared in the Key Issues and Challenges section.

Deep learning

Deep learning is a subfield of machine learning where a long-known algorithm, a neural network, an ANN, a DNN, or a Feed-Forward Neural Network (FFNN), referring to the same algorithm, is used to map features into an output or a set of outputs. Formed by an input layer, intermediate hidden layers, and an output layer, ANNs present an efficient way to learn linear and nonlinear relationships between input and output pairs (Figure 1). Neural networks, when formed by many stacked layers, can represent complex features in later layers by using simpler representations formed by earlier layers in the network

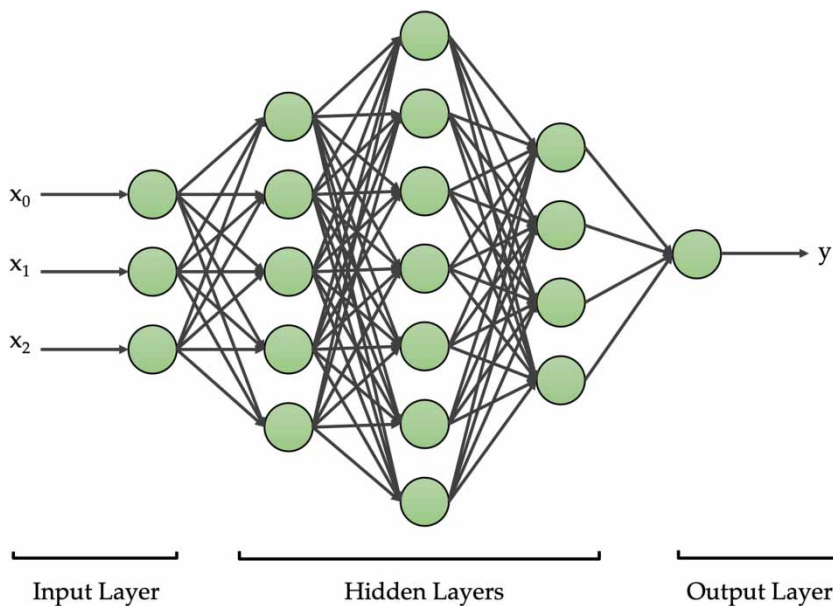


Figure 1 | A densely connected ANN architecture.

(Goodfellow *et al.* 2016). Each layer within an ANN comprises at least one neuron. ANN is a network of these neurons connected to each other with some weights and these neurons run specific functions, namely activation functions, mapping its input to an output. Stacked on top of each other, the series of functions runs over the input of the network and translates the input to the output in the output layer. Typically, each neuron within a layer runs the same activation function and the type of the layer is determined by this activation function. Network type is determined by the combination of layers used and how neurons are connected to each other within and between layers. The quintessential form of an ANN is the Multilayer Perceptron (MLP). An MLP contains at least a single hidden layer while each neuron within the network is connected to every neuron within the next layer. This architecture forms a fully connected neural network.

An activation function in a typical MLP multiplies the input by a weight and outputs it to the next neuron in line. In modern neural networks the common (Goodfellow *et al.* 2016) and recommended (Nair & Hinton 2010) activation function is the Rectified Linear Unit (ReLU) function, which introduces nonlinearity to the network. A hidden layer that applies ReLU to the input could be referred to as an ReLU layer or an activation layer using ReLU. ANNs are generally trained using the BackPropagation (BP) algorithm (Rumelhart *et al.* 1986) to fit the network to the set of input-output pairs using a loss

function. A loss function or a cost function is used to determine how successful the mapping is done by a model. An easy and go-to loss function is Mean Squared Error (MSE), which computes the difference between an output of the ANN and the ground truth for each input-output sample, squares the difference to avoid negative values and computes the mean error of all the samples. BP trains an ANN using the loss function by computing the gradient of the loss function with respect to the weights between neurons and updates the weights to better fit the data samples in order to minimize the loss function.

ANNs are not a new concept, considering primitive versions were around in the 1940s (Goodfellow *et al.* 2016). Instead, ANNs attracted attention of researchers from various scientific disciplines when it became clear that they were extremely powerful in capturing representations in the data and with advances in GPUs, which enable extremely fast matrix operations (Goodfellow *et al.* 2016). In this way, a neural network architecture that previously was infeasible to utilize due to time complexity as the number of hidden layers increased, could be used in training on complex datasets learning representations.

For each of the reviewed papers we identify the machine learning subfield, which corresponds to task types. Task types are defined by the output form of a network. We consider the following as distinct task types: Regression, Classification, Sequence Prediction, Matrix Prediction,

Unsupervised Learning, and Reinforcement Learning. These task types are briefly discussed below:

- **Regression** – A machine learning task that predicts a continuous value. Forecasting the next measurement from a series of measurements would be an example of a regression task.
- **Classification** – When the aim of a model is to predict whether the set of inputs can be categorized into some classes, the task is a classification task. The number of classes are not limited. Predicting whether the next day will be a dry or wet one is a classification task.
- **Sequence Prediction** – Regression of a sequence of numeric values or a vector. Forecasting the next 24 h of measurements for a stream sensor is a sequence prediction task.
- **Matrix Prediction** – Regression of a matrix of numeric values. Forecasting the next precipitation measurements for a rectangular region would be a matrix prediction task. Each of the values in the predicted matrix would be the precipitation value of a subregion within the actual region.
- **Unsupervised Learning** – A learning task applying competitive learning instead of error correction learning like previous task types. Decreasing dimension of a high-dimensional hydrological input data to lower dimension visualizable data would be an example.
- **Reinforcement Learning** – A learning task where the output is unspecified. In a reinforcement learning task, the algorithm tries to find the optimal solution for any given input using a reward–penalty policy and a try–error mechanism. An example of a reinforcement learning task is an AI model that learns when to release water from a dam.

ARCHITECTURES

This section summarizes cornerstone neural network architectures used by papers reviewed in this study. Also, some ANN concepts are briefly discussed. For further understanding of these architectures, we refer readers to the cited works.

Convolutional neural networks (CNN)

A CNN (LeCun 1989) or a ConvNet comprises at least one convolutional layer, which methodologically expects a 3D tensor as the input (Figure 2). A convolutional layer applies multiple cascaded convolution kernels to extract intricate knowledge from the input. For example, a CNN for a red, green, blue (RGB) image tensor with a shape of image width $\times$ image height $\times$ 3 would have a convolutional layer that applies three different convolution operations with three separate kernels to each of the color channel matrices. Using a convolution kernel matrix, a convolutional layer that processes an image as such can extract 2D positional information from images, such as understanding objects that are close to each other.

To make a neural network with a convolutional layer cognize nonlinear correlations between the input and output along with linear correlations, one needs to introduce nonlinearity to the network via an activation layer. Typically, that is done using the ReLU as the activation function following the convolution layer. Another common layer used within a CNN is a pooling layer. A pooling layer is used to reduce the size of the input while keeping the positional knowledge intact. A frequently used pooling method within CNN literature is Max Pooling (Zhou & Chellappa 1988). This sample-based discretization moves the most

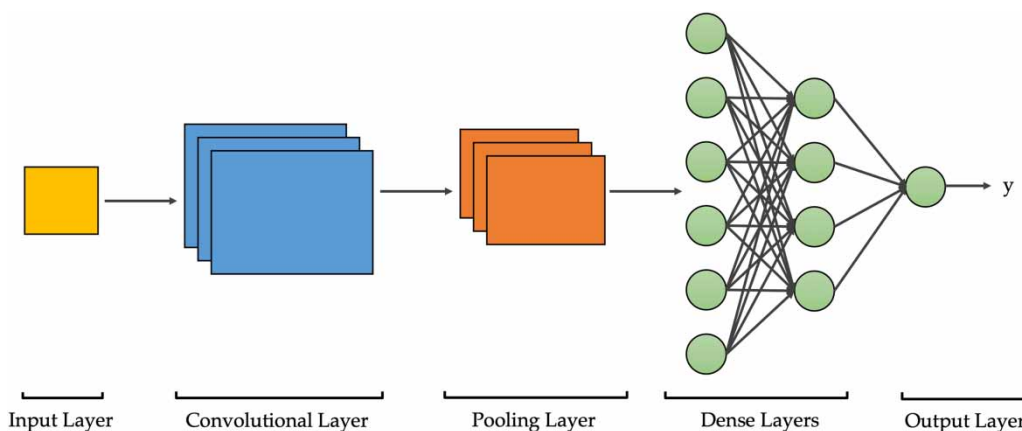


Figure 2 | A basic CNN structure for image classification.

important learned features to subsequent layers while reducing the size. Consequently, CNNs make good architectures for deep learning tasks with images or image-like objects as inputs. This ability of CNNs makes way for various breakthroughs in the fields of object detection, super-resolution, image classification, and computer vision.

Generative adversarial networks (GAN)

GANs (Goodfellow *et al.* 2014) consist of two seemingly separate CNNs working in unison and competing in a min-max game (Figure 3). One of these CNN, the generator, aims to generate fake examples out of a dataset while the other, discriminator, aims to reveal whether its input is fake or not. Since they try to beat each other, it causes them to improve over time in both generating fake outputs and discriminating fake from real.

GANs are initially used as generative models, as in randomly generating new samples from a dataset to appear as if they are from the originating dataset when visualized (Gautam *et al.* 2020). They achieve this goal by mapping

random noise to real samples from the given dataset, and then they generate new instances from new random noise tensors. Despite their success at generation, GANs are also capable of learning translation tasks such as super-resolution (Demiray *et al.* 2020) or image-to-image translation (Isola *et al.* 2017).

Recurrent neural networks (RNN)

RNNs (Pollack 1990) are a type of ANN that includes a recurrent layer. The difference of a recurrent layer from a regular fully connected hidden layer is that neurons within a recurrent layer could also be connected to each other (Figure 4). In other words, the output of a neuron is conveyed both to the neuron(s) within the next layer and to the next neuron within the same layer. Using this mechanism, RNNs can carry information learned within a neuron to the next neuron in the same layer.

This procedure becomes convenient when the data to be fed to the network is in sequential nature, such as a time-series data or a text. When training a model over a

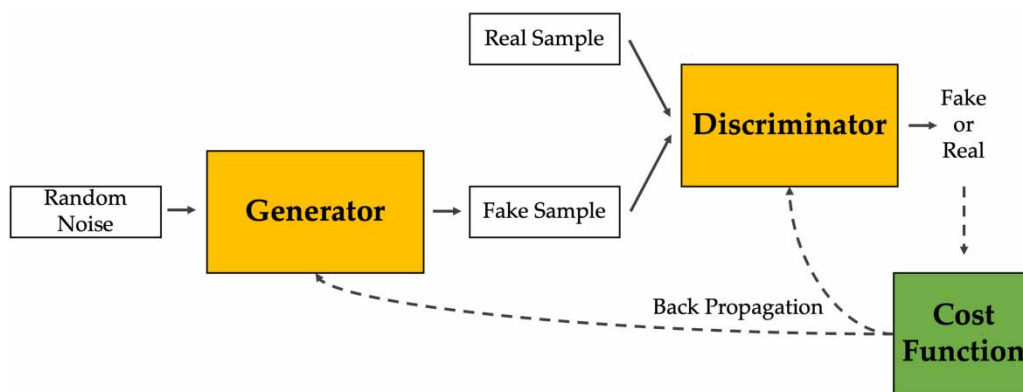


Figure 3 | Overview of GAN.

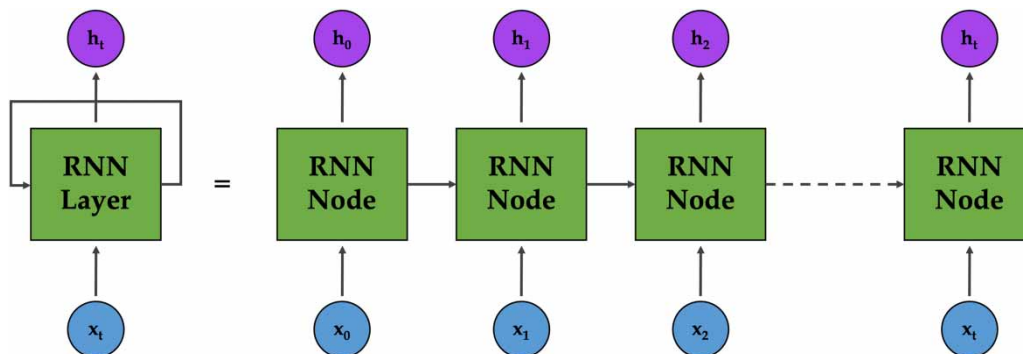


Figure 4 | Connections of a recurrent layer.

data sample like a text to extract the meaning, most of the time the beginning of the text could change the meaning that is to be extracted from the end of the text. RNNs aim to keep the information gained from earlier parts of a data sample in the memory and move it to the later parts of the same data sample to ensure better knowledge discovery (Goodfellow *et al.* 2016). A simple RNN implementation lacks the practicality in long sequences, such as long paragraphs, as it is common to encounter the vanishing gradient problem while training (Bengio *et al.* 1993). With the vanishing gradient problem, the gradients of the loss function become extremely high in some cases during training and consequently make the training process and the trained network deficient (Goodfellow *et al.* 2016). More complex RNN implementations like Long Short-Term Memory (LSTM) (Hochreiter & Schmidhuber 1997) networks or Gated Recurrent Unit (GRU) networks (Cho *et al.* 2014) solve this problem, but have greater computational complexity. Various RNN structures can be used for tasks that somewhat rely on sequential understanding of datasets such as language modeling (Sundermeyer *et al.* 2012), text classification (Yin *et al.* 2017; Sit *et al.* 2019a), and time-series forecasting (Sit & Demir 2019; Xiang & Demir 2020).

Long short-term memory (LSTM) networks

LSTM (Hochreiter & Schmidhuber 1997) Networks are developed for longer short-term memory life over the input, paving the way for more efficient but more resource-intensive training over datasets consisting of sequential

samples. Instead of an activation function producing one output and carrying the output to immediate neurons both in the next layer and the same layer, LSTM neurons produce two different values yielded by a series of activations and operations. Although both outputs are kept within the LSTM layer to keep track of things learned over the past part of the sequence, one of the outputs is transferred to the next layer (Figure 5).

Gated recurrent unit (GRU) networks

Although LSTM networks, most of the time, solved the vanishing gradients problem and helped many breakthroughs within the fields of Natural Language Processing and time-series prediction, their time complexity emerges as a downside. GRU (Cho *et al.* 2014) networks reduce the complexity while keeping the efficacy intact. Similar to a simple RNN neuron, a GRU neuron produces only one output after a series of computations and uses the same output to convey important features learned to both the next layer and the next neuron within the same layer.

Nonlinear autoregressive (NAR) models

A NAR model is not necessarily a neural network model, but a model that is used for time-series prediction, taking into account both current and previous samples from a time-series to map input sequence to outputs. A NAR model needs a nonlinear function such as a polynomial function or a neural network to perform training. If a neural network is used, a NAR network would classify as

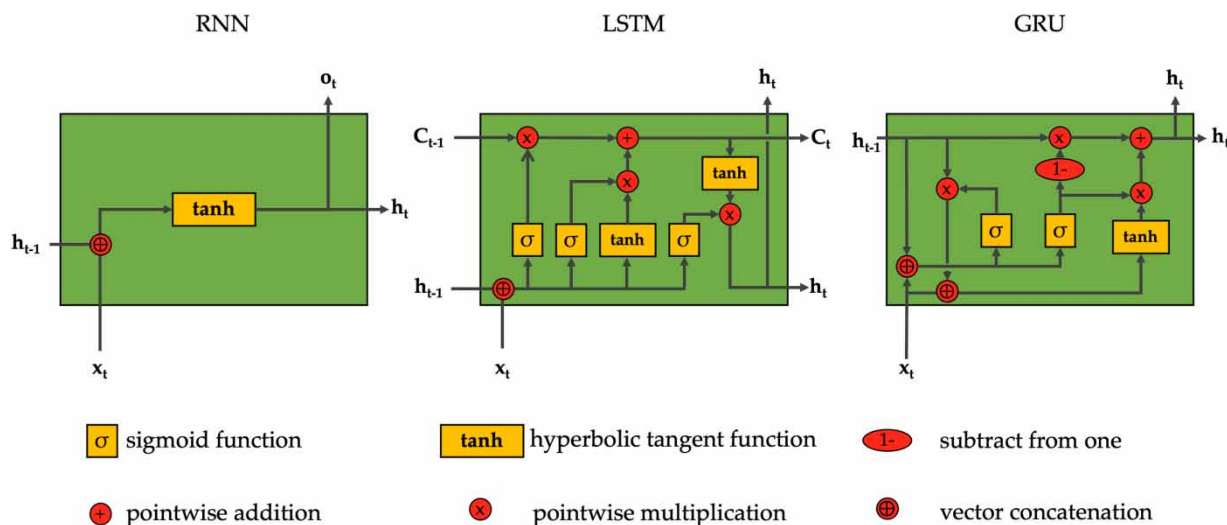


Figure 5 | Computation-wise comparison of RNN, LSTM, and GRU nodes.

an RNN based on the fact that it utilizes sequential complex-
ion of the given input. Papers reviewed within this study that
employ NAR thus implement a neural network as the func-
tion in their proposed models. There are many NAR
variations and one that deserves a mention, due to cardinal-
ity of papers reviewed in this study that employ it, is the
Nonlinear Autoregressive Exogenous Model (NARX) (Lin
et al. 1996). NARX is an RNN implementation that takes
advantage of exogenous inputs, hence the name.

Elman network (ENN)

An Elman Network (Elman 1990) is yet another RNN
implementation that has three layers, only one being a
hidden layer (Figure 6). The hidden layer of the ENN is con-
nected to a set of neurons called context units. In each
iteration after the first one over the network, the state of
the hidden layer is copied into the context units. Thus, the
state of the network for the previous sample in the data
stream is kept in the network each time to be used in the
next iterations. An ENN can train over sequential datasets
better than a regular ANN due to this mechanism acting
like a memory.

Autoencoders (AE)

Autoencoders (Rumelhart *et al.* 1985) are neural networks
that are used to reduce the dimensionality of datasets
(Figure 7). They are implemented in an unsupervised
fashion to generate only a representation of the dataset
within their hidden layer neurons, also called the latent
vector. Taking the same set of values for both input and
output of the network, an AE learns to reduce a dataset

into a representation state and additionally learns how to
reconstruct the data sample to its original form from the
learned representation.

Restricted boltzmann machines (RBM) and deep belief networks (DBN)

RBMs (Hinton 2002) present two-layer stochastic generative
models that are in the shape of bipartite graphs. RBMs form
the building block for DBN (Hinton 2009), but they can also
be used as standalone models. RBMs were initially used in
unsupervised tasks; they also enable the user to tackle classi-
fication and regression tasks by implementing them within
other networks. The paper reviewed in this study that
employs RBMs uses it in a setting where RBMs are followed
by a set of fully connected layers in order to perform a classi-
fication task. Formed by stacked RBMs, DBNs, similarly to
RBMs, could also be used to tackle many types of tasks by
training unsupervised beforehand. The bipartite connections
of RBMs are altered when they are stacked onto each other
to form a DBN (Figure 8). Only the top two layers of a DBN
have bipartite connections, while the rest of the layers have
one-way connections with each other. Although RBMs are
useful for many tasks, their use in research is decreasing
in the machine learning field as researchers adopt newer
architectures that could be utilized in the same fashion
such as AE, DBNs, and GANs.

Extreme learning machines (ELM)

ELMs (Huang *et al.* 2006) are three-layer neural networks in
which the weights connecting to the second layer from the
input layer are randomized, and the weights connecting to

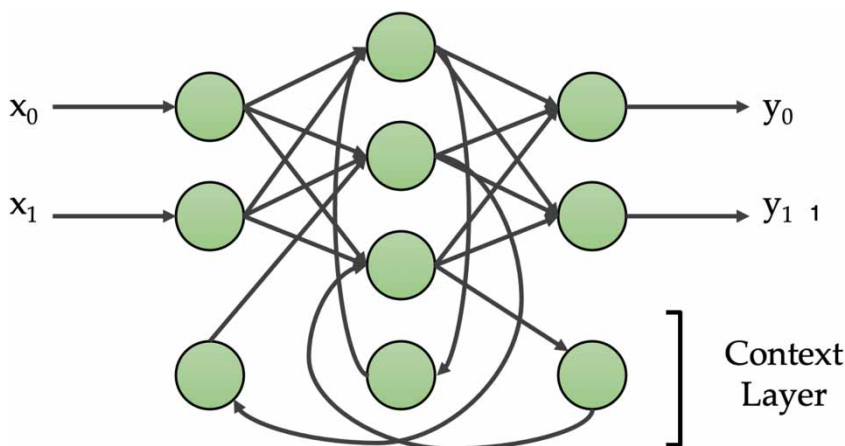


Figure 6 | An ENN architecture with two input and two output neurons.

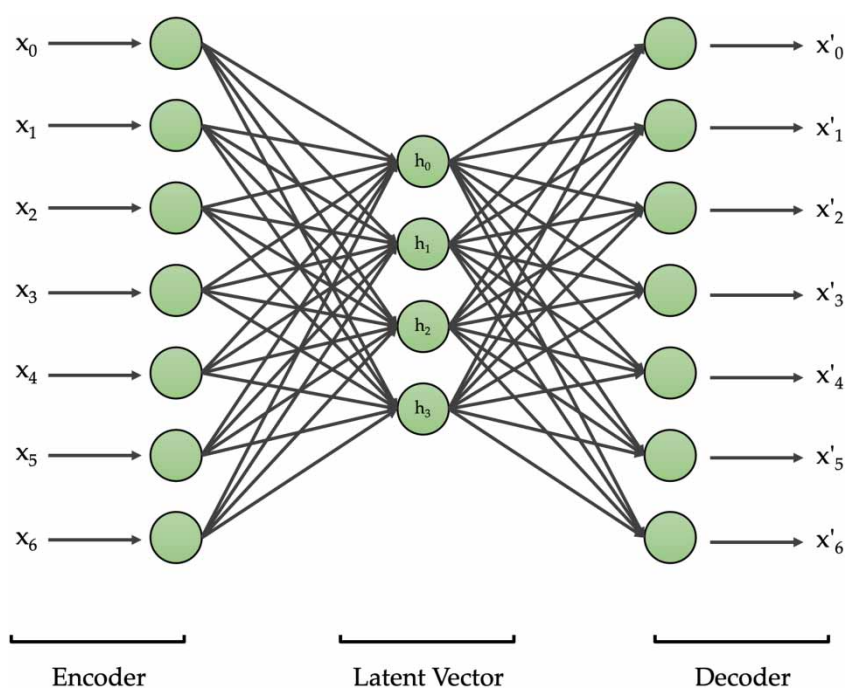


Figure 7 | Visualization of an AE network.

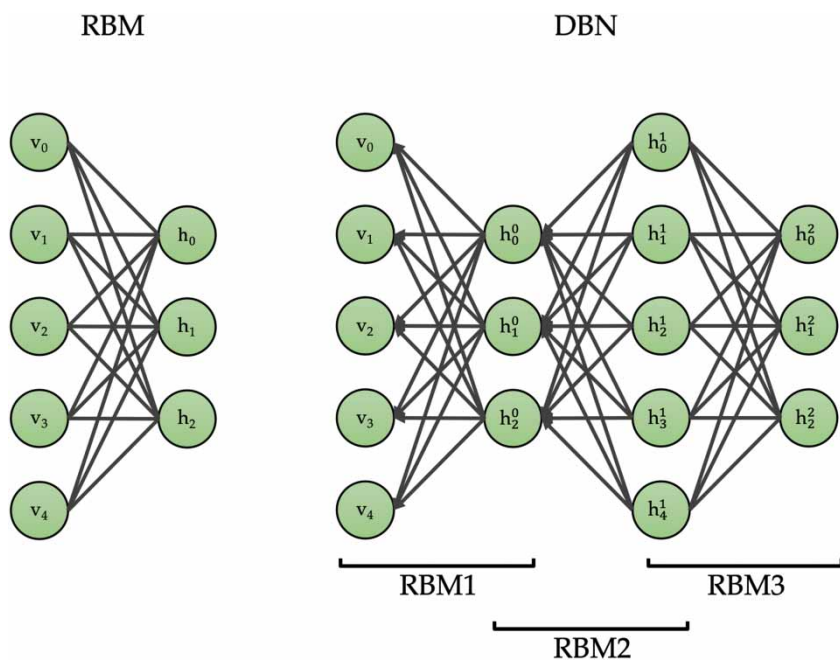


Figure 8 | RBM and DBN examples.

the third are trained. ELMs are designed to produce better generalization performance while training faster than BP-based ANNs consisting of one hidden layer on large datasets

thanks to its randomization mechanism. ELM networks have been criticized for being unoriginal (Wang & Wan 2008).

Deep Q networks (DQN)

DQN (Mnih *et al.* 2013) is a reinforcement learning algorithm in which there is a predetermined rewarding policy. The DQN works similarly to the Q-Learning algorithm, which works by providing a medium for the agent and the environment and tries to maximize the rewards the agent gets through its actions in the environment. A DQN differentiates from the conventional Q-Learning algorithm with how it generalizes. In other words, the agent in the Q-Learning algorithm cannot estimate the outcome from action–environment pairs it did not see before, while in DQN the agent is able to produce a reinforced action.

SUMMARY OF ARTICLES

This section presents visual summaries of the reviewed papers, as well as a summary table (Table 1) showing extracted information from each paper that received comprehensive review. As previously stated, information from a total of 129 papers are given; however, data points in shared figures do not always equal to this value depending on the data column, this is because some entries in the table may have multiple values in some data columns instead of one.

Among the reviewed papers, as in the deep learning literature, most used architectures are CNNs and LSTMs (Figure 9). We explain this aspect with their respective success in matrix prediction and sequence prediction, tasks that have high importance in hydrologic modeling. One confounding thing is that even though LSTM networks were widely employed, GRU networks, an architecture that yields similar performance, did not receive significant usage in the field. Additionally, we found it surprising that even though most of the studies reviewed here tackle tasks involving sequential data, Transformers were not employed by any of the studies we reviewed. It should be noted that a Transformer is a neural network architecture that is widely used in the field of natural language processing, which is another field that focuses on sequential data.

As the utilization of deep learning in the water field in a broad sense increases over time (Figure 10), annual usage of the DNN architectures increases. Figure 11 shows the change in usage up to March 2020 and also presents simple projections for the rest of the year built on top of the number of publications after March 2020. We expect to see growth in the usage of neural network architectures that have been widely used in other disciplines but not in the water field, such as DQNs and GANs.

The datasets used in publications reviewed are typically datasets acquired from authorities or governmental agencies (Figure 12). Even though in deep learning literature, the dataset acquisition is primarily done by using previously existing datasets, in the water field, on the contrary, this does not seem to be the case. Code accessibility of the papers is another aspect of the studies published in the water field that differentiates it from the deep learning field in general. Although open-sourced models are widely expected from deep learning researchers, open-sourcing the software built for a study is unusual for a publication in the water field, if not rare, as can be seen in Table 1. Cumulating from both the data acquisition type and code accessibility, reproducing the outcomes of a paper does not seem to be an easy task for the authorities and other researchers in the field.

Due to the fact that the field of hydrology relies on sequential data, most studies seem to work on sequence prediction and regression tasks (Figure 13). This phenomenon might also be linked with the fact that most of the studies reviewed were classified in the Flood subdomain (Figure 14). Figure 15 summarizes the usage of numerical computing frameworks. Although TensorFlow seems to be the first choice among water domain researchers, it should be noted that most of the usage comes from Keras, the second most-used framework, which typically works on top of TensorFlow by providing a higher level interface. Thus, our inference is that Keras is the most-used deep learning framework within the water field. In contrast, libraries like PyTorch, which is highly endorsed in deep learning literature, find a smaller place to themselves. The reason for this might be the ability of fast ANN prototyping and modeling that Keras provides to programmers without expecting many implementation-relevant details.

RESULTS

In this section we provide brief summaries of papers presented in the previous section (Table 1). Papers are grouped and interpreted by their use.

Streamflow and flood

Runoff prediction and flood forecasting are major tasks in rainfall-runoff modeling. Toward this end, many researchers have applied cutting-edge deep learning architectures to the runoff prediction and flood forecasting tasks. Since rainfall and runoff are both time-series data, the common networks for the streamflow prediction and flood forecast are RNN, LSTM, NAR, and ENN. Kratzert *et al.* (2018) applied an

Table 1 | Reviewed papers with curated data points

Paper	Network type	Framework	Dataset	Open-source	Reproducible	Deep learning task	Water field
Yuan et al. (2018)	LSTM	MATLAB	Acquired	No	No	Sequence Prediction	Flood
Zhang et al. (2018e)	LSTM	–	Acquired	No	No	Sequence Prediction	Flood
Kratzert et al. (2018)	LSTM	Keras, TensorFlow	Existing	No	Yes	Sequence Prediction	Flood
He et al. (2019b)	ANN, DBN	–	Acquired	No	Yes	Sequence Prediction	Flood
Hu et al. (2019)	LSTM	–	Acquired	No	No	Regression	Flood
Wang et al. (2019b)	CNN	–	Acquired	No	No	Sequence Prediction	Flood
Yang et al. (2019a)	NAR, LSTM	Keras, TensorFlow	Acquired	No	No	Regression	Flood
Sankaranarayanan et al. (2019)	ANN	Keras	Acquired	No	No	Classification	Flood
Ni et al. (2019)	LSTM, CNN	–	Acquired	No	No	Sequence Prediction	Flood, Weather
Bai et al. (2019)	LSTM, AE	–	Acquired	No	No	Sequence Prediction	Flood
Yang et al. (2019b)	LSTM	–	Acquired	No	No	Regression	Flood
Bhola et al. (2019)	CNN	–	Collected	No	No	Segmentation	Flood
Damavandi et al. (2019)	LSTM	Keras, TensorFlow	Acquired	No	Yes	Sequence Prediction	Flood
Moy de Vitry et al. (2019)	CNN	TensorFlow	Collected	Yes	Yes	Matrix Prediction	Flood
Worland et al. (2019)	ANN	Keras, TensorFlow	Acquired	No	No	Regression	Flood
Kratzert et al. (2019a)	LSTM	PyTorch	Acquired	Yes	Yes	Sequence Prediction	Flood
Kumar et al. (2019)	RNN, LSTM	Keras	Acquired	No	Yes	Sequence Prediction	Flood
Wan et al. (2019)	ENN	–	Acquired	No	No	Sequence Prediction	Flood
Qin et al. (2019)	LSTM	TensorFlow	Acquired	No	No	Sequence Prediction	Flood
Kratzert et al. (2019b)	LSTM	PyTorch	Existing	Yes	Yes	Regression	Flood
Bui et al. (2020a)	ANN	MATLAB	Acquired	No	No	Classification	Flood
Nguyen & Bae (2020)	LSTM	TensorFlow	Acquired	No	No	Sequence Prediction	Flood
Bui et al. (2020b)	ANN	–	Acquired	No	No	Classification	Flood
Kabir et al. (2020)	DBN	TensorFlow	Acquired	No	No	Sequence Prediction	Flood
Kao et al. (2020)	LSTM	Keras	Acquired	No	No	Sequence Prediction	Flood
Xiang et al. (2020)	LSTM	Keras, TensorFlow	Acquired	No	No	Sequence Prediction	Flood
Zuo et al. (2020)	LSTM	Matlab, TensorFlow	Acquired	Yes	Yes	Sequence Prediction	Flood
Ren et al. (2020)	ANN, LSTM, GRU	–	Acquired	No	No	Sequence Prediction	Flood
Zhu et al. (2020b)	LSTM	Keras	Acquired	No	Yes	Sequence Prediction	Flood
Wang et al. (2020d)	CNN	Keras	Acquired	No	No	Classification	Flood
Laloy et al. (2018)	GAN	Lasagne, Theano	Existing	No	No	Matrix Prediction	Groundwater
Wang et al. (2020b)	ANN	–	Collected	Yes	No	Matrix Prediction	Groundwater
Santos et al. (2020)	CNN	Keras	Existing	Yes	Yes	Matrix Prediction	Groundwater
Mo et al. (2019a)	CNN	PyTorch	Collected	Yes	Yes	Matrix Prediction	Groundwater
Mo et al. (2019b)	CNN	PyTorch	Collected	Yes	Yes	Matrix Prediction	Groundwater

Sun <i>et al.</i> (2019a)	CNN	Keras, TensorFlow	Acquired	No	No	Sequence Prediction	Groundwater
Jeong & Park (2019)	NARX, LSTM, GRU	TensorFlow	Acquired	No	No	Sequence Prediction	Groundwater
Zhou <i>et al.</i> (2020)	CNN	PyTorch	Acquired	No	No	Regression	Groundwater
Jeong <i>et al.</i> (2020)	LSTM	TensorFlow	Acquired	No	No	Sequence Prediction	Groundwater
Zhang <i>et al.</i> (2018d)	CNN	Keras, TensorFlow	Collected	No	No	Segmentation	Land Use and Soil
Zhang <i>et al.</i> (2018 g)	LSTM	TensorFlow	Acquired	No	No	Regression	Land Use and Soil
Cao <i>et al.</i> (2018)	CNN, ELM	–	Existing	No	No	Segmentation	Land Use and Soil
Zeng <i>et al.</i> (2018)	ANN	–	Acquired	No	No	Regression	Land Use and Soil
Reddy & Prasad (2018)	LSTM	–	Acquired	No	Yes	Sequence Prediction	Land Use and Soil
Fu <i>et al.</i> (2018)	CNN	–	Acquired	No	No	Classification	Land Use and Soil
Jiang (2018)	AE	–	Acquired	No	No	Classification	Land Use and Soil
Shen <i>et al.</i> (2019)	ANN	R/H ₂ O	Acquired	No	No	Regression	Land Use and Soil
Jin <i>et al.</i> (2019)	CNN	TensorFlow	Acquired	No	No	Segmentation	Land Use and Soil
Persello <i>et al.</i> (2019)	CNN	–	Acquired	No	No	Segmentation	Land Use and Soil
Kroupi <i>et al.</i> (2019)	CNN	TensorFlow	Existing	No	No	Classification	Land Use and Soil
Sun <i>et al.</i> (2019b)	CNN	PyTorch	Acquired	No	No	Classification	Land Use and Soil
Meng <i>et al.</i> (2019)	CNN	–	Acquired	No	No	Classification	Land Use and Soil
Kopp <i>et al.</i> (2019)	CNN	–	Collected	No	No	Segmentation	Land Use and Soil
Jiang <i>et al.</i> (2019)	CNN	–	Acquired	No	Yes	Matrix Prediction	Land Use and Soil
Bhosle & Musande (2019)	CNN	TensorFlow	Existing	No	No	Classification	Land Use and Soil
Zhang <i>et al.</i> (2019a)	ANN, CNN	–	Existing	No	No	Matrix Prediction	Land Use and Soil
Wang <i>et al.</i> (2020a)	DBN	–	Acquired	No	No	Matrix Prediction, Regression	Land Use and Soil
Nam & Wang (2020)	AE	R/H ₂ O	Acquired	No	No	Classification	Land Use and Soil
O'Neil <i>et al.</i> (2020)	CNN	TensorFlow	Acquired	Yes	Yes	Classification	Land Use and Soil
Yang <i>et al.</i> (2020)	CNN	Keras	Acquired	No	Yes	Segmentation	Land Use and Soil
Abdi <i>et al.</i> (2018)	CNN	–	Existing	No	Yes	Classification	Others
Li <i>et al.</i> (2018)	CNN, AE	PyTorch	Acquired	No	Yes	Segmentation	Others
Rohmat <i>et al.</i> (2019)	ANN	MATLAB	Acquired	No	No	Regression	Others
Amirkolaee & Arefi (2019)	CNN	MATLAB	Existing	No	Yes	Matrix Prediction	Others
Wang <i>et al.</i> (2019a)	CNN	Keras	Existing	No	No	Classification	Others
Kylili <i>et al.</i> (2019)	CNN	–	Collected	No	No	Classification	Others
Kang (2019)	CNN	Keras, TensorFlow	Acquired	No	No	Classification	Others
Haklidiir & Haklidiir (2019)	ANN	–	Acquired	No	Yes	Regression	Others
Kim <i>et al.</i> (2020)	GAN, AE	–	Acquired	No	No	Unsupervised Learning	Others
Zhang <i>et al.</i> (2018f)	LSTM	Theano	Acquired	No	No	Regression	Surface Water
Liu <i>et al.</i> (2019c)	ANN	Keras, TensorFlow	Acquired	No	Yes	Sequence Prediction	Surface Water

(continued)

Table 1 | continued

Paper	Network type	Framework	Dataset	Open-source	Reproducible	Deep learning task	Water field
Xiao <i>et al.</i> (2019a)	CNN, LSTM	Keras, TensorFlow	Acquired	No	No	Matrix Prediction	Surface Water
Read <i>et al.</i> (2019)	LSTM	–	Acquired	No	No	Regression	Surface Water
Liu <i>et al.</i> (2019b)	CNN	Caffe	Existing	No	No	Segmentation	Surface Water
Xiao <i>et al.</i> (2019b)	CNN	PyTorch	Existing	No	No	Classification	Surface Water
Mei <i>et al.</i> (2019)	CNN	PyTorch	Existing	No	No	Regression	Surface Water
Ling <i>et al.</i> (2019)	CNN	MATLAB	Acquired	No	No	Segmentation	Surface Water
Song <i>et al.</i> (2019)	CNN	Caffe	Existing	No	No	Classification	Surface Water
Hrnjica & Bonacci (2019)	LSTM	–	Acquired	No	No	Sequence Prediction	Surface Water
Qi <i>et al.</i> (2019)	LSTM	–	Acquired	No	No	Sequence Prediction	Surface Water
Zhu <i>et al.</i> (2020a)	LSTM	ANNdotNET, CNTK	Acquired	No	No	Sequence Prediction	Surface Water
Lee & Lee (2018)	RNN, LSTM	–	Acquired	No	No	Regression	Water Quality
Hamshaw <i>et al.</i> (2018)	RBM	MATLAB	Acquired	Yes	Yes	Classification	Water Quality
Liu <i>et al.</i> (2019a)	LSTM	Keras, TensorFlow	Acquired	No	No	Sequence Prediction	Water Quality
Yurtsever & Yurtsever (2019)	CNN	Caffe	Collected	No	No	Classification	Water Quality
Li <i>et al.</i> (2019)	LSTM, GRU, ENN	–	Acquired	No	No	Sequence Prediction	Water Quality
Shin <i>et al.</i> (2019)	LSTM	–	Acquired	No	No	Sequence Prediction	Water Quality
Banerjee <i>et al.</i> (2019)	ANN	R/H ₂ O	Collected	No	No	Regression	Water Quality
Wang <i>et al.</i> (2019c)	LSTM	–	Acquired	No	No	Sequence Prediction	Water Quality
Yim <i>et al.</i> (2020)	ANN	MATLAB	Collected	No	No	Regression	Water Quality
Zou <i>et al.</i> (2020)	LSTM	Keras	Acquired	No	No	Sequence Prediction	Water Quality
Liang <i>et al.</i> (2020)	LSTM	Keras	Acquired	No	No	Sequence Prediction	Water Quality
Barzegar <i>et al.</i> (2020)	CNN, LSTM	–	Collected	No	No	Sequence Prediction	Water Quality
Yu <i>et al.</i> (2020)	LSTM	–	Acquired	No	No	Sequence Prediction	Water Quality
Zhang <i>et al.</i> (2018a)	LSTM	Keras, TensorFlow	Acquired	No	No	Sequence Prediction	Water Resources Management
Zhang <i>et al.</i> (2018b)	LSTM, GRU	Keras, TensorFlow	Acquired	No	No	Sequence Prediction	Water Resources Management
Zhang <i>et al.</i> (2018c)	LSTM, NARX, ENN	Keras, TensorFlow	Collected	Yes	Yes	Regression	Water Resources Management
Harrou <i>et al.</i> (2018)	DBN	–	Collected	No	No	Sequence Prediction	Water Resources Management
Shi & Xu (2018)	AE	–	Collected	No	No	Regression	Water Resources Management
Zhou <i>et al.</i> (2019)	ANN, CNN	PyTorch	Existing	Yes	Yes	Classification	Water Resources Management
Fang <i>et al.</i> (2019)	CNN	–	Acquired	No	No	Classification	Water Resources Management
Sun <i>et al.</i> (2020)	ANN	–	Acquired	No	No	Regression	Water Resources Management
Karimi <i>et al.</i> (2019)	ANN, LSTM	MATLAB	Collected	No	No	Sequence Prediction	Water Resources Management
Xu <i>et al.</i> (2020)	LSTM	–	Acquired	No	No	Regression	Water Resources Management
Nam <i>et al.</i> (2020)	DQN	–	Acquired	No	No	Reinforcement Learning	Water Resources Management
Mamandipoor <i>et al.</i> (2020)	LSTM	Keras, TensorFlow	Acquired	No	No	Classification	Water Resources Management

Tang <i>et al.</i> (2018)	ANN	–	Acquired	No	No	Regression	Weather
Klampanos <i>et al.</i> (2018)	AE, CNN	–	Acquired	No	No	Unsupervised Learning	Weather
Scher & Messori (2018)	CNN	Keras, TensorFlow	Acquired	No	No	Matrix Prediction	Weather
Ukkonen & Mäkelä (2019)	ANN	Keras	Acquired	No	Yes	Classification	Weather
He <i>et al.</i> (2019a)	LSTM	–	Acquired	No	No	Classification	Weather
Jeppesen <i>et al.</i> (2019)	CNN	Keras, TensorFlow	Existing	Yes	Yes	Segmentation	Weather
Chen <i>et al.</i> (2019)	GAN	PyTorch	Acquired	No	No	Matrix Prediction	Weather
Wieland <i>et al.</i> (2019)	CNN	Keras, TensorFlow	Existing	No	Yes	Segmentation	Weather
Weyn <i>et al.</i> (2019)	CNN, LSTM	Keras, TensorFlow	Acquired	No	No	Matrix Prediction	Weather
Wei & Cheng (2020)	ANN	Weka	Acquired	No	No	Sequence Prediction	Weather
Zhang <i>et al.</i> (2019b)	CNN	–	Acquired	No	Yes	Classification	Weather
Kim <i>et al.</i> (2019)	ANN	–	Acquired	No	No	Regression	Weather
Pan <i>et al.</i> (2019)	CNN	–	Acquired	No	Yes	Matrix Prediction	Weather
Tran & Song (2019)	LSTM, GRU, CNN	TensorFlow	Existing	No	Yes	Matrix Prediction	Weather
Poornima & Pushpalatha (2019)	LSTM, ELM	Keras, TensorFlow	Acquired	No	Yes	Sequence Prediction	Weather
Chai <i>et al.</i> (2019)	CNN	–	Acquired	No	Yes	Segmentation	Weather
Wu <i>et al.</i> (2020)	LSTM, CNN	–	Acquired	No	Yes	Matrix Prediction	Weather
Zhang <i>et al.</i> (2020)	LSTM	–	Acquired	No	No	Regression	Weather
Su <i>et al.</i> (2020)	LSTM, CNN	–	Acquired	No	No	Sequence Prediction	Weather
Chen <i>et al.</i> (2020)	CNN, LSTM	PyTorch	Existing	No	Yes	Matrix Prediction	Weather
Weber <i>et al.</i> (2020)	CNN	TensorFlow	Acquired	Yes	Yes	Matrix Prediction	Weather
Yan <i>et al.</i> (2020)	CNN	TensorFlow	Acquired	No	Yes	Sequence Prediction	Weather
Wang <i>et al.</i> (2020c)	RNN	–	Acquired	No	No	Matrix Prediction	Weather

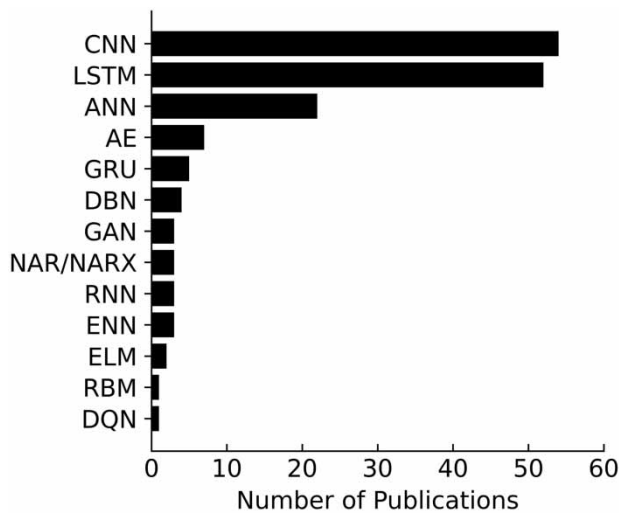


Figure 9 | Architectures described in the study and their usage in reviewed papers.

LSTM model on daily runoff prediction for the first time, which included meteorological observations, and obtained results better than a well-established physical model – the Sacramento Soil Moisture Accounting Model SAC-SMA + Snow-17. In 2019, Kratzert *et al.* (2019a) further applied the LSTM model to 531 watersheds in the USA with k-fold cross-validation and showed that LSTM can be applied on ungauged watersheds with better results than physical models, such as calibrated SAC-SMA and the National Water Model. Other researchers applied RNN to the runoff forecast and compared their outputs to other machine learning models. Damavandi *et al.* (2019) proposed an LSTM model on a Texas watershed predicting the next day's daily streamflow using climate data and the current day's

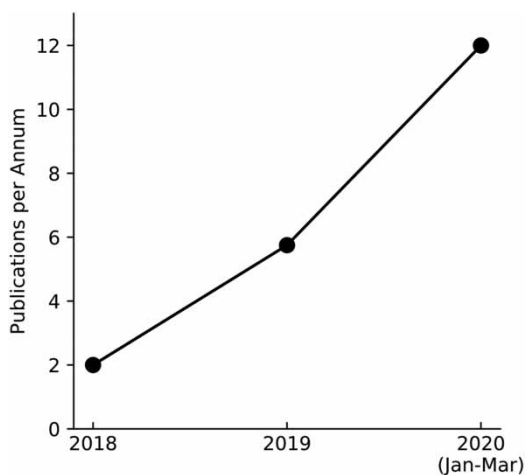


Figure 10 | Average number of papers published each month during 2018, 2019, and 2020 from January to March.

streamflow. Their results showed that LSTM performs better than the physical model CaMa-Flood. Zhang *et al.* (2018e) applied an LSTM model on monthly reservoir inflow and outflow predictions in hourly, daily, and monthly basis and achieved better results than Support Vector Machines (SVM) and BackPropagation Neural Networks. Kumar *et al.* (2019) applied RNN and LSTM models for the monthly rainfall prediction in India and showed that LSTM provided better results. Qin *et al.* (2019) applied the LSTM on the streamflow prediction and compared it with the Auto-regression model. Yang *et al.* (2019a) applied an LSTM model to the daily reservoir overflow prediction. NAR with external input and LSTM are used for three reservoirs with geographic information, daily precipitation, air temperature, wind speeds, relative humidity, and sunshine duration. Wan *et al.* (2019) also successfully applied ENN to a real-time 3-h ahead flood forecasting.

Since hyper-parameter optimization is a problem in deep learning, some studies focused on applying additional optimization algorithms on deep learning models. Yuan *et al.* (2018) proposed two models that use the Ant Lion Optimization (ALO) and Particle Swarm Optimization (PSO) to optimize the parameters and hidden layers of an LSTM model, which are named LSTM-ALO and LSTM-PSO. Their results show that the LSTM-PSO outperformed the LSTM and LSTM-ALO. Yang *et al.* (2019a) proposed a genetic algorithm-based NARX, which outperforms the NARX and LSTM. Ni *et al.* (2019) proposed two LSTM based models, which are wavelet-LSTM and CNN + LSTM for the rainfall and streamflow forecasting, and both models have better results than LSTM. Kabir *et al.* (2020) proposed a wavelet-ANN to make the hourly streamflow predictions. Results show that wavelet-ANN can make acceptable predictions for, at most, 6 h ahead, which outperforms ANN, DBN, and Support Vector Regression (SVR).

Some studies focused on the data pretreatment such as the decomposition of rainfall and runoff prior to deep learning models. He *et al.* (2019b) proposed a DNN model for daily runoff prediction where the inputs are the runoff series that were decomposed into multiple Intrinsic Mode Functions (IMF) with Variational Mode Decomposition (VMD). Hu *et al.* (2019) proposed an LSTM model for flood forecast with the preprocessing of Proper Orthogonal Decomposition and singular value decomposition. Zuo *et al.* (2020) proposed three LSTM models with different pre-treatments, which are VMD, Ensemble Empirical Mode Decomposition (EEMD), and Discrete Wavelet Transform for daily streamflow up to 7 days ahead. Zhu *et al.* (2020b) proposed a probabilistic LSTM model coupled with the

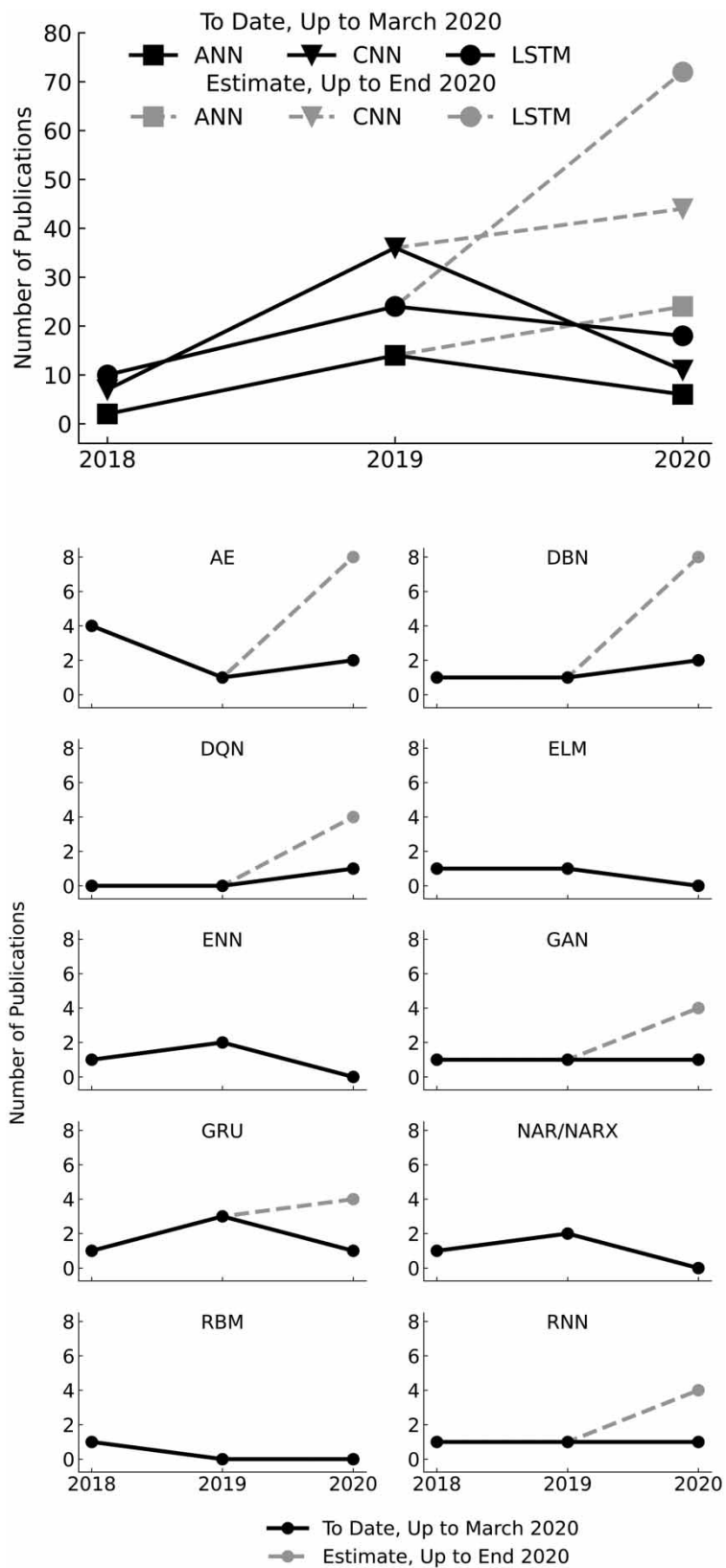


Figure 11 | Architectures described and their annual usage in reviewed papers.

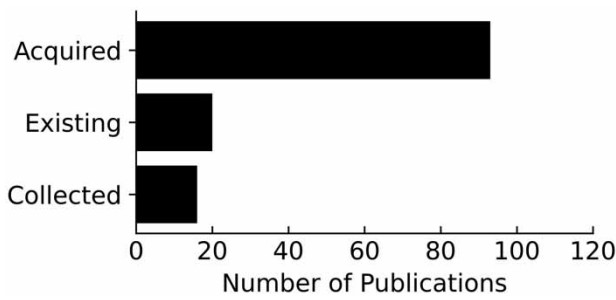


Figure 12 | Distribution of dataset acquisition types in reviewed papers.

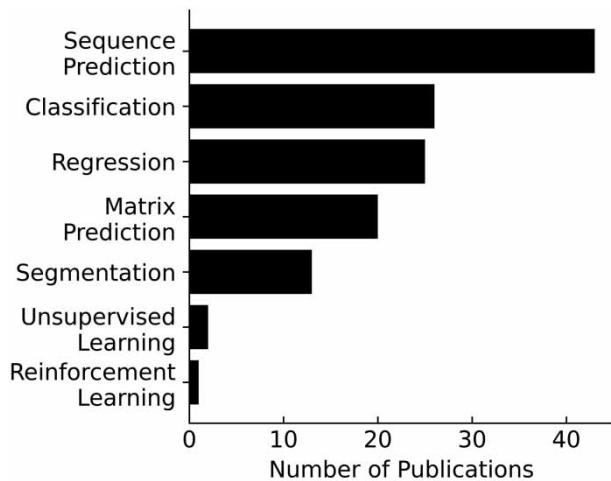


Figure 13 | Histogram of machine learning task types studied in reviewed papers.

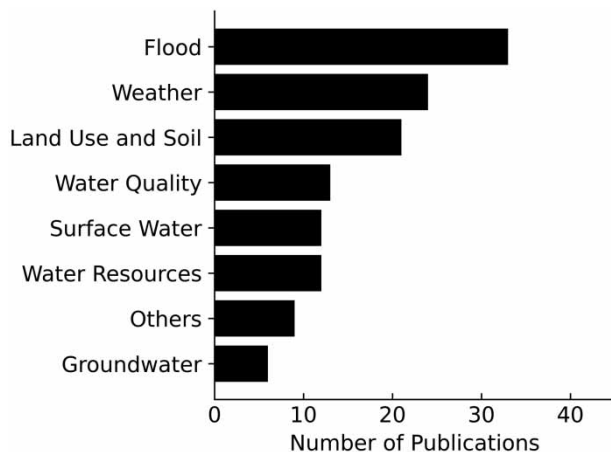


Figure 14 | Histogram of Water domain subfields studied in reviewed papers.

Gaussian process to deal with the probabilistic daily stream-flow forecasting. These studies show that the pretreatment of input may help to improve the deep learning model accuracy.

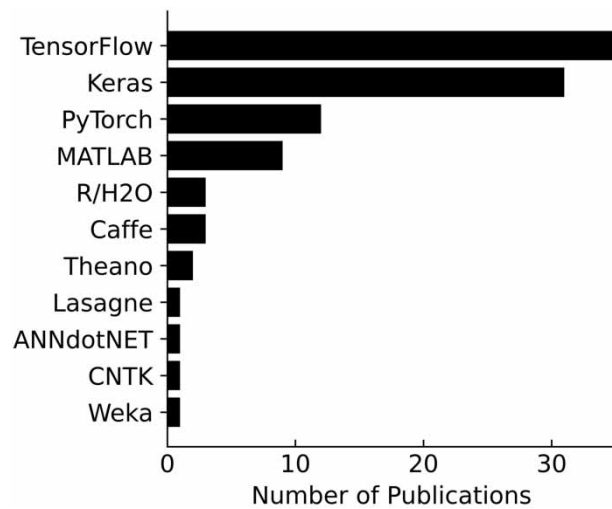


Figure 15 | Machine learning frameworks described in the study and their usage in reviewed papers.

Other studies focused on constructing more complex deep learning architectures such as autoencoder, encoder-decoder, and customized layer based on the LSTM. Bai *et al.* (2019) proposed an LSTM model with Stack Autoencoder (SAE) to predict daily discharge values based on one-week discharge values, and the results of SAE-LSTM outperform LSTM alone. For multiple time-step flood forecast tasks, an encoder-decoder LSTM is proposed for the runoff prediction by Kao *et al.* (2020) and Xiang *et al.* (2020). Kao *et al.* (2020) proposed an encoder-decoder LSTM model that can be used on multi-timestep output predictions for up to 6 h. Xiang *et al.* (2020) proposed an encoder-decoder LSTM model that can be used to predict for up to 24 h ahead. Both studies showed the encoder-decoder LSTM is better than LSTM. In particular, Kratzert *et al.* (2019b) proposed the Entity-Aware-LSTM network, which designed a specific layer for the rainfall-runoff modeling based on LSTM. This network allows for learning catchment similarities as a feature layer, and data from multiple watersheds can be used to provide runoff for a watershed. These studies applied some high-level designs to the LSTM network and can perform much better than normal LSTM on the long-term or multiple watersheds.

Several studies coupled physical models with deep learning networks. Yang *et al.* (2019b) proposed a model using LSTM to improve the performance of flood simulations of a physical model. The watershed-averaged daily precipitation, wind, temperature, and model-simulated discharge from the Global Hydrological Model GHMs + CaMa-Flood between 1971 and 2020 were used to model

the discharge. This indicates the deep learning models can be used to improve the streamflow forecast accuracy of physical models. [Nguyen & Bae \(2020\)](#) proposed an LSTM network using the Quantitative Precipitation Forecasts of the McGill Algorithm for Precipitation nowcasting by Lagrangian Extrapolation (MAPLE) system to reproduce 3-h Mean Areal Precipitation (MAP) forecasts. Corrected MAPs are used as input to a coupled 1D/2D urban inundation model to predict water levels and relevant inundation areas (1D conduit network model and 2D overland flow model). In this model, LSTM takes a forecast from MAPLE and then reproduced MAPs are used by the coupled 1D/2D urban inundation model. [Worland *et al.* \(2019\)](#) proposed a DNN model to predict the flow-duration curves using United States Geological Survey streamflow data by constructing 15 output values representing 15 quantiles of the curve. These indicate that deep learning models can be used as surrogate models of physical models or curves.

Some studies focused on flood susceptibility and flood prediction capabilities. [Bui *et al.* \(2020b\)](#) applied a DNN network with 11 variables such as Digital Elevation Model (DEM), aspect, slope, etc. to predict the flood susceptibility, a value between 0 and 1, for an area. [Wang *et al.* \(2020d\)](#) proposed a CNN network with 13 flood-triggering factors in the study area to map the flood susceptibility for the study area. In this project, each pixel may have different flood susceptibility values. [Sankaranarayanan *et al.* \(2019\)](#) applied a DNN network to classify if flooding is possible in an area for the month given total precipitation and temperature. This study simplified the project into a binary prediction task of if there will be a flood event or not. The same simplification is done by [Bui *et al.* \(2020a\)](#), who applied a DNN network to classify if a region is flash flood prone or not using the elevation, slope, aspect, curvature, stream density, Normalized Difference Vegetation Index (NDVI), soil type, lithology, and rainfall data as input.

With CNNs, some innovative flood monitor and forecast projects are now possible. [Wang *et al.* \(2019b\)](#) applied a CNN model that predicted the real-time hourly water levels for warning systems during typhoons using satellite images. [Bhola *et al.* \(2019\)](#) proposed a model that estimates the water level from CCTV camera images using a CNN model. The model performed the edge detection to find the water body in the photo, and the water level is then calculated from physical measurements. [Moy de Vitry *et al.* \(2019\)](#) proposed a model that calculated the flooded area and the surface observed flooding index with CCTV cameras using CNN. U-net CNN is used to segment the stream shape

from a CCTV camera and another CNN model is used to calculate the flooded areas in pixels from the segmented photo.

Subsurface and groundwater

There are several different types of studies in subsurface and groundwater. Different deep learning models can be used in each of different types of studies. One type of groundwater study is the estimation of water table level or flow rate. With the groundwater monitoring wells data, this is a 1D regression task similar to the surface water predictions using recurrent models. [Jeong & Park \(2019\)](#) applied the NARX, LSTM, and GRU on the water table level estimations with observed data from monitoring wells. It found that the estimations from the NARX and LSTM models are superior to those of the other models in terms of prediction accuracy. [Jeong *et al.* \(2020\)](#) further applied LSTM with multiple loss functions, which shows that the proposed LSTM model with cost function of MSE with Whittaker smoother, least trimmed squares, and asymmetric weighting has the best performance on groundwater level prediction with data corrupted by outliers and noise. For groundwater flow prediction, [Wang *et al.* \(2020b\)](#) proposed a theory-guided DNN, which not only makes the predictions of groundwater flow, but also estimates the parameters of the Partial Differential Equation (PDE) as well as the initial condition and boundary condition of the PDE. By constructing the loss function, the theory-guided neural network can provide the prediction results with reasonable parameters of the physical model PDE.

More groundwater studies take a cross-section in time-series and focus on a 2D map. Examples include the groundwater water balance map ([Sun *et al.* 2019a](#)), hydraulic conductivity field map ([Zhou *et al.* 2020](#)), pressure, and CO₂ saturation field map ([Mo *et al.* 2019a](#)). CNN models can be used in these studies. [Sun *et al.* \(2019a\)](#) proposed a CNN model using the physical model National Oceanic and Atmospheric Administration (NOAH) simulation results as input to predict the groundwater water balance. Thus, the CNN model is used to correct the physical model results by learning the spatial and temporal patterns of residuals between Gravity Recovery and Climate Experiment (GRACE) observations and NOAH simulations. Results show that the CNN can significantly improve the physical model simulation accuracy. [Zhou *et al.* \(2020\)](#) proposed a CNN of eight layers to learn a map between stochastic conductivity field and longitudinal macro-dispersivity based on synthetic 2D conductivity fields. The estimations are in acceptable accuracy with moderate

heterogeneity. Mo *et al.* (2019a) proposed an Encoder-Decoder CNN to approximate the pressure and CO₂ saturation field map in different time-steps as a surrogate model. Furthermore, some studies in groundwater focus on 3D mapping. An example is the flow-rate estimation in a 3D rock. Santos *et al.* (2020) proposed a 3D CNN to predict the estimated state solution of the Navier–Stokes equation for laminar flow, which is the flow rate, with 3D rock images. This 3D CNN is a surrogate model of the Navier–Stokes equation, and takes less than a second.

In groundwater studies, one of the other deep learning applications is inversion, such as to identify the contaminate source in groundwater. Some complex traditional algorithms can be used to solve this problem. However, it will be not efficient when the data is in high dimensions. Mo *et al.* (2019b) developed a deep autoregressive neural network which was used as the surrogate model of this high-dimensional inverse problem and provides more accurate inversion results and predictive uncertainty estimations than physical models. Laloy *et al.* (2018) proposed another approach for the inversion by using GAN. With the GAN models, the inversion rapidly explores the posterior model distribution of the 2D steady state flow and recovers model realizations that fit the data close to the true model results.

Finally, Sun *et al.* (2020) investigated three learning-based models, namely DNN, Multiple Linear Regression, and SARIMAX, to find missing monthly data in total water from GRACE data (Tapley *et al.* 2004). Based on the results, the performance of DNN is slightly better than SARIMAX, and significantly better than MLP in most of the basins. The three learning-based models are reliable for the reconstruction of GRACE data in areas with humid and no/low human interventions. Dynamic multiphase flow in heterogeneous media is a problem in groundwater studies. These studies show that deep learning models can work as surrogate models by improving computational efficiency in groundwater dynamic predictions and inversions.

Land and soil

The segmentation and classification of land use and land cover are important for water and soil resources management. Many studies have applied the deep learning networks to create a more accurate land cover map from satellite or radar imagery. Abdi *et al.* (2018) applied SAE and CNN on land cover classification of urban remote sensing data. Tests on nine datasets show that SAE and CNN are better than machine learning models like logistic regression, Naive Bayes, K-Nearest Neighbors, and SVM. Cao *et al.*

(2018) applied ELM and CNNs to classify land cover categories on satellite imagery and the results show that the combined CNN–ELM method has the highest accuracy. Shen *et al.* (2019) applied a DNN network to predict the land drought index using the precipitation data, meteorological drought index data, and soil relative moisture data. Bhosle & Musande (2019) applied a CNN model on the land cover land-use classification on Indian Pines dataset. Some studies applied more complex coupled models, including encoder–decoder, AE, 3D networks, and coupled machine learning models to achieve a higher model accuracy. Zhang *et al.* (2019a) applied 3D-CNN and 3D-DenseNet models on the land cover land-use classification on Indian Pines and Pavia University datasets. All these studies showed a high accuracy of the land cover identification task. Nam & Wang (2020) applied the AE prior to the random forest, SVM, and other machine learning models to the landslide susceptibility prediction. Results show that random forest with an AE gives more accurate results than other machine learning methods. In the study of wetland-type identification by Meng *et al.* (2019), results show that the ensemble model SVM-CNN performs better than CNN and SVM. O’Neil *et al.* (2020) applied an Encoder-Decoder CNN model to classify the wetland types using Light Detection and Ranging (LiDAR) radar dataset and NDVI index data. This study used the LiDAR DEM and remote sensing images to generate physically informed input, including Slope, NDVI, DTW, and Topographic Wetness Index. In particular, Kroupi *et al.* (2019) applied a CNN-based model to land-cover classification that trained on the European satellite dataset, EuroSAT, and tested in a region outside Europe. It still provided promising results despite differences in tested and trained regions. These results indicate the CNN models have a high model accuracy as well as high robustness in the land-use land-type classification task.

In addition to applying known networks, some researchers developed objective-based CNN rather than traditional pixel-based CNN to better identify the land use and land types. Zhang *et al.* (2018d) proposed an object-based CNN to label very fine spatial resolution remotely sensed images to do object-wise segmentation rather than pixel-wise segmentation in urban areas. Fu *et al.* (2018) proposed a blocks-based object-based CNN for classification of land use and land-cover types and achieved end-to-end classification. This model works well on irregular segmentation objects, which is a common in-land use classification. Jiang (2018) proposed an object-based CNN with an AE for extracting high-level features automatically. Results show the AE-object-CNN is better than three manual design feature systems. Jin *et al.* (2019)

proposed an object-oriented CNN that used a typical rule set of feature objects to construct the object-oriented segmentation results before using a CNN to make the classification. These studies show object-based studies have a better performance than simple CNN.

Some studies focus on more specific tasks based on different study purposes such as the identification of agricultural fields, impervious surfaces, wetland types, water body types, and crop types. Persello *et al.* (2019) applied two CNN models, SegNet (Badrinarayanan *et al.* 2017) and VGG16 (Simonyan & Zisserman 2014), for the segmentation and classification of agricultural fields. Sun *et al.* (2019b) applied a CNN model to classify if the land is impervious surfaces, vegetation, or bare soil from satellite imagery or both the satellite and LiDAR data. Results show that the model with LiDAR data provides better results than the model with satellite imagery only. Meng *et al.* (2019) identified the wetland types in one lake using the Chinese remote sensing imagery GF-2. Bhosle & Musande (2019) applied a CNN model to identify crop types on EO-1 Hyperion sensor hyperspectral imagery. Yang *et al.* (2020) applied CNNs to identify the water body types from remote sensing images. Mask R-CNN is used to segment the water body, and the ResNets (He *et al.* 2015), including ResNet-50 and ResNet-101, are used to identify the water body types. Results show a high accuracy on regular-shaped water bodies.

Similar networks can be used to generate DEMs, which is another type of land use study. Jiang *et al.* (2019) applied a CNN model to predict the paleo-valley DEM using the original DEM data and electrical conductivity (EC). The EC data are collected from the field study, and the CNN models used in this study distinguish the valley and non-valley pixels, which can find the spatial connectivity of the paleo-valley. The CNN can efficiently constrain 3D paleo-valley geometry DEM.

Snow cover, a special study in land-cover studies, can be measured by deep learning models in different approaches. Kopp *et al.* (2019) proposed a model to predict the snow depth using OpenCV and Mask R-CNN on the surveillance camera photos. The Mask R-CNN is used to segment the detectable measuring rod, and then the OpenCV library can be used to identify the snow depth by measuring how much of the measuring rod is covered by snow. Wang *et al.* (2020a) applied a DBN and CNN to estimate snow depth from the geographical data. DBN takes multiple inputs, including latitude, longitude, elevation, forest cover fraction, time, passive microwave horizontal, and vertical polarization brightness temperatures of 19 and 37 GHz. Results show that the DBN outperforms CNN in this study.

Additional land and soil related studies include the land surface temperature, soil salinity, and vegetation dynamics over time, and these can be done with time-series related models such as LSTM. Zhang *et al.* (2018g) applied the ensemble composition-based LSTM models on the daily land surface temperature simulation. The original daily land surface temperature data series were decomposed into many IMFs and a single residue item. The Partial Autocorrelation Function is used to obtain the number of input data sample points for LSTM models. Zeng *et al.* (2018) applied Partial Least Square Regression (PLSR), SVM, and DNN for predicting soil salinity from images. Surprisingly, DNN performs worse than PLSR for this task. Reddy & Prasad (2018) applied a LSTM model to predict the vegetation dynamics using NDVI images from 2000 to 2016 in a 7-day gap. This study shows that the single feature NDVI can be used to provide accurate vegetation prediction over time.

Surface water

The prediction of water level is crucial for water resources management and protecting the natural environment. Many studies have applied deep learning methods, such as LSTM and ANN, to forecast the water level from one day to one year. Hrnjica & Bonacci (2019) investigated two different ANNs, namely LSTM and FFNN, to forecast the lake water level. Monthly measurements for the last 38 years of Vrana Lake, Croatia, is utilized for training the models to predict 6 or 12 months ahead of the lake water level. The set of sequences with different lengths created from the obtained data is used in the networks, instead of using classical lagged data. The results of LSTM and FFNN are compared with classical time forecasting methods and ANN. According to the results, the performance of LSTM is the best among the models in all scenarios, while FFNN provides better accuracy than the compared methods in both 6 and 12 months prediction. Zhu *et al.* (2020a) also investigates LSTM and FFNN in their work with data from a different region. However, the models in this paper are designed to predict one month ahead of the lake water level for 69 temperate lakes in Poland. Their results indicate that LSTM and FFNN perform similarly most of the time, unlike in the previous paper. The reasons for this situation can be the differences between the datasets, prediction intervals, or model designs.

In addition to lake water-level prediction, Liu *et al.* (2019c) developed a Bayesian neural network, which is based on ANN with posterior inference, to forecast the water level in a reservoir to derive operation rules. According

to the paper, the current reservoir status and future inflows are the primary factors that affect operational decisions. The influence of inflow uncertainties on reservoir operations is also more than model parameter uncertainty. Their findings show the impact of the input data alongside the promising results of the Bayesian neural network. Qi *et al.* (2019) forecasted daily reservoir inflow by ensembling the different results from the LSTM models with different decomposed inflow data as inputs for more accurate assumptions. Zhang *et al.* (2018f) proposed an LSTM model to predict water table depth in agricultural areas. The LSTM model takes monthly water diversion, evaporation, precipitation, temperature, and time as inputs for prediction of the water table depth. The results of the LSTM model are compared with the FFNN model, and the LSTM model performs better than the FFNN model. It also highlights that the dropout method increases the LSTM model's accuracy in this task.

Alongside the water level or flow, the prediction of water temperature has received much attention in the scholarship. Xiao *et al.* (2019a) proposed a convolutional long short-term memory (ConvLSTM) model to predict the sea surface temperature (SST). In the paper, 36 years of satellite-derived SST data are used. Based on the results, the ConvLSTM model produces more accurate results than the linear SVR model and two different LSTM models for short and mid-term temperature prediction. Read *et al.* (2019) aimed to predict lake water temperatures based on depth. A hybrid LSTM and theory-based feedbacks (model penalties) model was developed. According to the results, the hybrid model produces the best results among the tested methods in the paper. The results from the paper can be seen as an example of improving predictions by integrating scientific rules with deep learning methods.

In addition to the aforementioned subtopics in surface water, various tasks are also investigated by scholars such as segmentation, change detection, or super-resolution. Despite extensive usage of LSTM or ANN in previously aforementioned papers, CNN models are generally used in these tasks. Liu *et al.* (2019c) labeled objects in aerial images as water, tree, etc. with the help of a fully convolutional neural network (FCN) model and multinomial logistic regression. FCN takes the aerial image and returns a probability. At the same time, LiDAR data passes into multinomial logistic regression and returns another probability. These two probabilities are combined with higher-order conditional random field formulation to produce a final probability. Based on the final probability, objects are labeled with the corresponding group. Mei *et al.* (2019)

developed a CNN-based model to measure the sea-ice thickness in Antarctica from LiDAR data. The input is a windowed LiDAR scan (snow freeboard), and the mean ice thickness is the output of the model. In addition to the LiDAR scan, the paper investigated the effects of different inputs such as surface roughness and snow depth on the task. Ling *et al.* (2019) used the CNN model to generate a finer resolution of the image to measure the wetted river width. Then, the output of CNN is used to measure the width of the river. Song *et al.* (2019) aimed to detect the change in surface water in remote sensing images. An FCN model is proposed and used for the same regions at different times. The FCN model returns the surface water regions for each time. The outputs for the same regions are compared, and a change map created to show the difference. In addition to these publications, Xiao *et al.* (2019b) introduced a dataset for the classification of ice crystals. The dataset contains 7,282 images in ten different categories. The performance of numerous pre-trained models, such as AlexNet (Krizhevsky *et al.* 2012) and VGGNet(s) (Simonyan & Zisserman 2014), are also provided in the paper.

Water quality

Water quality monitoring and prediction are vital operations for many fields, such as water resources management and water treatment. Water quality and safety depend on numerous parameters with complex biological, chemical, and physical interactions. As such, deterministic water quality models are a realistic option in only the simplest and idealized scenarios. However, data-driven models are increasingly used in a variety of water quality applications. One such application area is predicting surface water quality. Li *et al.* (2019) proposed an ensemble approach that combines three RNN models with Dempster-Shafer (D-S) evidence theory (Shafer 1976) to predict the quality of water. The results of three RNN models, namely LSTM, GRU, and ENN, are combined by D-S evidence theory for the final output. The combined model predicts, at most, 50 h in advance, and the results show that the model accuracy reduces significantly over 25 h. Liu *et al.* (2019a) used an LSTM model to forecast drinking water quality for up to 6 months. Zou *et al.* (2020) developed an ensemble approach to predict water quality data, such as pH, dissolved oxygen (DO), Permanganate Index (CODMn), and $\text{NH}_3\text{-N}$. The approach is based on using three LSTM models with different size interval data feeding each of them. The final prediction is a combination of the results of three LSTM models. Banerjee *et al.* (2019) choose

the indicators, namely DO and zooplankton abundance, to reflect the water quality level of a reservoir.

An ANN model is proposed to model the selected indicators to represent the water quality level. Yu *et al.* (2020) combined the LSTM model with Wavelet Mean Fusion and Wavelet Domain Threshold Denoising to simulate the change of chlorophyll-a concentration in Dianchi Lake, China, and used 15 water quality parameters as inputs, such as pH and DO. Liang *et al.* (2020) also worked with the prediction of the chlorophyll-a concentration level. Fabricated data are created by the Environmental Fluid Dynamics Code to train an LSTM model. The LSTM model can forecast the chlorophyll-a concentration level for up to one month. Chlorophyll-a, water temperature, and total phosphorus are identified as critical inputs that affect the performance of the LSTM model. Barzegar *et al.* (2020) investigated multiple models to predict the level of DO and chlorophyll-a in Small Prespa Lake, Greece. Three different neural network models, namely CNN, LSTM, and CNN-LSTM, were developed to forecast the DO and chlorophyll-a concentrations and pH, oxidation-reduction potential, water temperature, and EC were used as inputs for the models. In addition to the ANN models, SVM and decision tree models are used for the performance comparison. According to results, the hybrid CNN-LSTM model provides the best accuracy to predict both DO and chlorophyll-a.

Yim *et al.* (2020) developed a stacked autoencoder-deep neural network (SAE-DNN) to predict phycocyanin concentrations in inland waters from in-situ hyperspectral data. The proposed architecture's ability for the prediction from airborne hyperspectral imagery is examined. Shin *et al.* (2019) introduced an LSTM model to forecast the occurrence of harmful algal blooms in the South Sea of Korea. SST and photosynthetically available radiation are extracted from satellite data to be used as inputs for the LSTM model to minimize damage. Lee & Lee (2018) aimed to predict the occurrence and number of harmful algal blooms with an LSTM model by providing weekly water quality and quantity data. The LSTM model's performance is compared with RNN and MLP models, and the LSTM provides better results among all the investigated methods based on the results. Hamshaw *et al.* (2018) used the RBM to classify the sediment-discharge curve in 14 categories from the 2D image of the suspended-sediment discharge plots from more than 600 storm events. Finally, an LSTM-based system was proposed to identify the characteristics of the water pollutants and trace its sources in the work of Wang *et al.* (2019c). In the system, a water quality cross-validation map is generated to identify

pollutants and, based on defined rules, track the pollutants to common industries.

Water resources management

Urban water systems are essential to modern cities. Efficient operation of water treatment plants, wastewater treatment plants, and conveyance networks require accurate modeling of these interconnected systems. Zhang *et al.* (2018b) investigated the multiple models to simulate and predict the water level of Combined Sewer Overflow structure. In the study, the collected data from Internet of Things is used separately with four different neural networks, namely MLP, ANN with Wavelet, LSTM, and GRU, to compare the networks with each other. According to the results, LSTM and GRU have good performances with respect to others, but GRU has a quicker learning curve, fewer parameters, and simpler architecture. Despite these advantages, the accuracy of GRU is slightly lower than the LSTM. Zhang *et al.* (2018a) predicted the next hour's wastewater flow to avoid sewer overflow using LSTM with the traditional hydraulic model on the sewer system. This 1-h prediction is tested in several scenarios, which are: 1-time step prediction at the 1-h sampling frequency, 2-time steps prediction at the 30-min sampling frequency, 4-time steps prediction at 15-min sampling frequency, and 6-time steps prediction at 10-min sampling frequency. The performance of the LSTM-based model is compared with SVR and FFNN, and the LSTM-based model has the best accuracy in all scenarios. Zhang *et al.* (2018c) also predicted the next hour's wastewater inflow for the wastewater treatment plant. The paper aims to identify which parts of the sewer system have more free space and take action based on the outcome. LSTM, NARX, and ENN are compared, and the LSTM model provides better results than other methods based on the results. Karimi *et al.* (2019) proposed an LSTM model to forecast flow in sanitary sewer systems. It claimed that accepting the groundwater as an additional input for the LSTM model increases the overall accuracy of the task.

In addition to the prediction of the wastewater level or flow, some studies aimed to detect conveyance network conditions. Xu *et al.* (2020) aimed to detect abnormal working conditions in the water supply network. In addition to the detection of abnormal conditions, pressure in the water supply network is predicted. An LSTM model is developed to achieve these goals. The performance of the LSTM model outperforms the traditional prediction models, such as SVM. Zhou *et al.* (2019) used an ANN model to identify burst locations in a water distribution network. The model

takes the pressure data as input and returns one or several possible pipes, which can be the location of the burst. Fang *et al.* (2019) focused on detecting multiple leakage points in a water distribution network with a CNN-based model. The model accepts the pressure measurements of the distributed water system as input and returns the possible locations of leakage points.

Various studies explored the strength of deep learning-powered modeling in water and wastewater treatment procedures. Shi & Xu (2018) developed a Stacked Denoising Autoencoders to predict a two-stage biofilm system's performance. Nam *et al.* (2020) proposed a DQN-based system to operate a membrane bioreactor more efficiently. It aims to maximize the system's energy efficiency while meeting stringent discharge qualities. GoogLeNet (Szegedy *et al.* 2015) architecture is used to identify and classify microbeads in urban wastewater into five categories based on microscopic images in the work of Yurtsever & Yurtsever (2019). Harrou *et al.* (2018) provided a case study using a DBM-SVM model to identify abnormal signals from the water features such as pH, conductivity, etc. in wastewater treatment plants. The results show that it is possible to detect the abnormal conditions in order to alert the system early based on the outcome of the DBM-SVM model. Mamandipoor *et al.* (2020) developed an LSTM model to monitor a wastewater treatment plant for detecting faults during the oxidation and nitrification processes.

Weather

Rainfall forecasting is one of the significant tasks in the domain of meteorology. Several techniques have been proposed to forecast rainfall with the help of statistics, machine learning, and deep learning. Zhang *et al.* (2020) introduced an ensemble approach to forecast rainfall. In the first step, eight major meteorological factors are selected via correlation analysis between control forecast meteorological factors and real-time rainfall. Then, samples are divided into four categories by K-means clustering. The LSTM-based model is fed by each cluster, and outputs are combined to reach the final prediction. Weber *et al.* (2020) developed a CNN-based surrogate model for one of the global climate model CanESM2 (Arora *et al.* 2011). The CNN model is fed by 97 years of monthly precipitation output from CanESM2, and the model preserves its performance even when the forecast length is expanded to 120 months. According to the paper, the accuracy of the model can be increased by deeper networks. Poornima & Pushpalatha (2019) investigated an LSTM model to forecast

the rainfall using 34 years of rainfall data. In the paper, the LSTM model results are compared with multiple methods, such as Holt-Winters and AutoRegressive Integrated Moving Average (ARIMA). Tang *et al.* (2018) introduced a DNN model to predict rain and snow rates at high altitudes. In the paper, passive microwave, infrared and environmental data are trained to the reference precipitation datasets, which are obtained by two space-borne radars for the estimations. The results of the DNN model are compared with many methods, such as the Goddard Profiling Algorithm. The experiment results show that the DNN model is capable of predicting snow and rain rate more accurately than other tested methods at high altitudes.

Some studies specifically focused on the improvement of quantitative precipitation estimation accuracy, alongside precipitation nowcasting. Since the prediction of precipitation generally is a time-series problem, the usage of LSTM architecture is common for this task. Wu *et al.* (2020) designed a fusion model, which is a combination of CNN and LSTM, to improve quantitative precipitation estimation accuracy. The proposed model uses satellite data, rain gauge data, and thermal infrared images. The CNN part of the model extracts the spatial characteristics of the satellite, rain gauge, and thermal infrared data, where the LSTM part of the model handles the time dependencies of the provided data. The performance of the CNN-LSTM model is better than the comparative models, such as CNN, LSTM, and MLP. Yan *et al.* (2020) used a CNN model to forecast short-term precipitation with the help of radar reflectance images for a local area in China. As a dataset, the radar reflection images and the corresponding precipitation values for 1 h are collected. The model takes the images as inputs and returns the forecast value for 1-h precipitation. The CNN model contains residual links between the layers, which increase the efficiency of the model. Chen *et al.* (2020) focused on precipitation nowcasting using a ConvLSTM model. The model accepts the radar echo data to forecast 30 or 60 min of precipitation value. According to results, using the customized multisigmoid loss function and group normalization provides better performance than ConvLSTM with classical loss functions, such as cross-entropy loss function, and conventional extrapolation methods.

Statistical downscaling methods often provide more accurate precipitation estimation than using raw precipitation values in the models.

Deep learning methods can be used as statistical downscaling methods to improve the accuracy of the tasks. Pan *et al.* (2019) proposed a CNN model as a statistical downscaling method for daily precipitation prediction. The method is

tested with 14 geogrid points in the USA, and statistical downscaling results from the CNN model outperform other tested methods, including linear regression, nearest neighbor, random forest, and DNN. Wang *et al.* (2020c) developed an RNN model to perform statistical downscaling on temperature and precipitation in order to improve the accuracy of hydrological models. The RNN model provides better accuracy than the compared methods, such as ANN, for extreme temperature and precipitation downscaling based on the evaluation of downscaled data on the Soil and Water Assessment Tool model.

In meteorology and remote sensing, cloud or cloud shadow detection has received attention in the recent literature. Because U-net (Ronneberger *et al.* 2015), a CNN model for biomedical image segmentation, and SegNet (Badrinarayanan *et al.* 2017), a convolutional encoder-decoder architecture for image segmentation, provide successful results in their domain, many researchers use those models as a base model for their works. Jeppesen *et al.* (2019) used U-net to detect clouds in satellite imagery. The model is trained and tested with Landsat 8 Biome and SPARCS datasets. Wieland *et al.* (2019) aimed to segment cloud, shadow, snow/ice, water, and land in multispectral satellite images. The U-net based model is proposed and trained with Landsat datasets to segment images into five categories. According to results, contrast and brightness augmentations of the training data improve the segmentation accuracy, alongside adding shortwave-infrared bands. Zhang *et al.* (2019b) applied the U-net based model on the RGB and infrared waveband images from the Landsat-8 dataset for cloud detection. LeGall-5/3 wavelet transform is used on the dataset to accelerate the model and make it feasible to implement on-board satellite. Chai *et al.* (2019) proposed a CNN model based on SegNet to detect clouds and cloud shadow in Landsat imagery.

Thunderstorms and typhoons are one of the extreme natural disasters that can cause massive damages. Some studies focused on the prediction of those hazardous natural events to take early actions to minimize the damage. Ukkonen & Mäkelä (2019) aimed to predict the occurrence of thunderstorms from parameters related to instability, inhibition, and moisture. A DNN model is trained with lightning data and a high-resolution global reanalysis. Various regions, such as Sri Lanka and Europe, are used as test areas for the model. Many valuable findings are provided related to the correlation between thunderstorm occurrence and parameters specific to regions. Kim *et al.* (2019) aimed to find similarities between a typhoon and a previous typhoon for helping to mitigate the effect of the typhoon. In the study,

a DNN model is used to encode the typhoon event by typhoon parameters, such as route, pressure, and moving speed. The model returns the typhoon events' similarities to the historical ones, which provide insights for officials to take early action. During the work, a database was created for 189 typhoons that occurred between 1950 and 2017. Wei & Cheng (2020) aimed to predict wind speed and wave height of a typhoon with the help of an RNN model, namely the Two-step Wind-Wave Prediction (TSWP). The TSWP model predicts wind speed first, followed by wind height for 1–6 h in the future. The results of the TSWP model outperform the comparative methods, such as MLP, DNN, and logistic regression.

In addition to the aforementioned studies, various works have been published for different meteorological tasks. Su *et al.* (2020) used the pyramid delaminating technique to generate the global optical flow field. A ConvLSTM model takes the RGB image and generated flow field in order to improve the forecast accuracy of echo position and intensity. The generation, dissipation, and merging of convective cells were also better identified comparison to other classical methods. Weyn *et al.* (2019) forecast weather at 500-hPa geopotential height using a CNN model. The paper uses historical gridded reanalysis data in the model without explicit knowledge about the physical process. The CNN model produces promising results for capturing the climatology and annual variability of 500-hPa heights and predicts realistic atmospheric states for 14 days. However, the CNN model still did not perform as well as an operational weather model. He *et al.* (2019a) proposed an LSTM model to classify periods as rainy or dry using microwave links. Scher & Messori (2018) aimed to predict the uncertainty of a forecast based on past forecasts and their occurrence rate with a CNN model. The CNN model takes the atmospheric fields at three different heights as inputs and returns the scalar value representing the predictability (or the uncertainty) of precipitation forecast. Klampanos *et al.* (2018) studied the relationship between nuclear events and weather. A model with AE and CNN is used for rapid source estimation during radiological releases. The model clusters weather events first and looks over their correlations with nuclear events. Chen *et al.* (2019) designed a GAN model based on Super-Resolution with Generative Adversarial Network (Ledig *et al.* 2017), which is a GAN architecture for single image super-resolution, to improve the resolution of radar echo images of weather radar systems in order to increase the accuracy of the tasks that accepts echo images as inputs. Tran & Song (2019) designed a Convolutional RNN

model for the radar echo extrapolation task. The model uses multiple (five) satellite images and predicts ten steps ahead at the pixel level. During the training process, Structural Similarity (SSIM) and multiscale SSIM are used to obtain better results.

Unclassified studies

Some literature included in this review did not fit within any of the defined categories in this review. Summaries of these papers are provided in this section. Many of these papers apply deep learning methods to ocean processes. In coastal hydraulics, Kang (2019) used an improved CNN on images to classify and monitor waves. Also in coastal hydraulics, Kim *et al.* (2020) used a number of DNN with coastal video imagery to develop a framework to track nearshore waves. Kylili *et al.* (2019) used a CNN to identify floating plastic debris in ocean images. Wang *et al.* (2019a) used a CNN architecture with a satellite radar product to classify ocean surface roughness into ten geophysical phenomena. Li *et al.* (2018) also used a CNN to classify hurricane damage from post-event aerial imagery.

The following three papers applied deep learning in a variety of disciplines. Haklidir & Haklidir (2019) used a DNN to predict the temperature of geothermal springs and wells using hydrogeochemical data, including chemical concentrations. Amirkolaee & Arefi (2019) implemented a very deep CNN structure to estimate a digital elevation model from single airborne or spaceborne images. Finally, Rohmat *et al.* (2019) developed and embedded a DNN into a GIS-based basin-scale decision support system to assess the impacts of best management practices (BMP). Based on geographic information and potential BMP, the DNN returns multiple outputs that describe net flow separation between groundwater recharge, groundwater return flow, and overland flow. This project demonstrates the potential of deep learning to integrate into decision-making on large-scale water resources projects.

KEY ISSUES AND CHALLENGES

Deep learning captures the nonlinear complex representations with datasets, making it a viable and efficient option in predictive model creation. In machine learning literature, capturing the representation is known as representation learning (Goodfellow *et al.* 2016). Representation learning relies on ANN's ability in acting as a universal approximator (Cybenko 1989; Hornik *et al.* 1989;

Leshno *et al.* 1993), meaning that ANNs with only one hidden layer, theoretically, could represent any function. The drawback regarding this ability is that the task in hand might need a hidden layer that is too large to be feasible to be trained and executed. Adding new hidden layers to neural networks comes into play in order to cover this negation. Consequently, one important principle of representation learning is that, with minimal data engineering, the datasets should be fed to the neural network and the neural network should decide which features within the dataset are important for the goal of representing that dataset. Although this should be the case, the literature in the water domain does not widely apply this principle. We attribute this to the fact that datasets are neither extensive enough in terms of the number of given data, nor have vast spatial and/or temporal coverage.

As opposed to fields like computer vision and natural language processing, the water field lacks high quality, collected, curated, labeled, and published datasets that are used for benchmarking and method development. We identify this lack of benchmarking datasets as a key challenge (Ebert-Uphoff *et al.* 2017) that slows the state-of-the-science deep learning applications in the water domain. Most studies reviewed herein acquire datasets from governmental agencies, depending on their needs. Although potentially convenient for a contained effort of a single work, each one-off dataset dampens the speed of improvement of the state-of-the-science in this field. If researchers had the opportunity to build on a widely accepted dataset in their fields, they would be able to improve the accuracy of their models by taking advantage of previous models created using the same dataset. This collaboration around common datasets and models would open opportunities in the field, such as paving the way for their real-time usage. However, as we do not have many benchmarking datasets, many research groups around the globe run similar networks on custom datasets that they acquired with limited scientific interaction.

One other problem with the data provided by authorities is that they are dispersed among different agencies and they occasionally have mismatches in temporal and/or spatial coverage. Although the data provided extends to many years before and covers decades, one might need to access various databases created by several different government agencies in order to build a dataset. The period of record also commonly differs across agencies and areas, which causes the data acquisition process to be time-consuming and sometimes inconclusive. Further complicating data acquisition, water data are suppressed due to their military significance in some strategic instances, which contributes

to limiting progress in the field. We support growing access to governmental and agency-collected water data and its use in deep learning.

We consider the fundamental understanding of deep learning within the literature as another problematic issue emerging from the reviews made in this study. A common mistake is what deep learning is and what deep learning is not. Most papers seem to interpret deep learning as a specific technique. However, deep learning is simply a broad term for various machine learning algorithms centered upon ANNs. Various studies reviewed here claim that they employ deep learning, yet they only take advantage of traditional ANN approaches. Most of the time this utilization does not surpass the extent of a study that employs conventional statistical modeling. This phenomenon raises questions about whether these studies attempt to exploit the keywords, using the term 'deep learning' to take advantage of the current scientific zeitgeist. We observe that these motives rarely result in work that forwards the deep learning literature. We particularly note the poor practice of ascribing work 'deep learning' while not employing representation learning principles.

This comprehensive review identified that literature at the intersection of deep learning and water do not cover the used methods in detail. Most of the studies appear reluctant to give model/architecture details that are vital to reproduce the proposed training pipeline. Combined with the aforementioned dataset problems, this causes consistent barriers to reproducibility of work. This overshadows the reported accuracy of studies and slows advancement in the deep learning-powered water field.

In contrast, some studies discuss unnecessary details over and over again in their manuscript. Discussing how the most efficient number of hidden layers or hyper-parameters are found by trial and error extensively without a hint of intuition, or discussing the optimal batch size beyond a few sentences do not appear because the authors use pertinent deep learning theory. Not sharing intuition regarding technical choices also prevents the papers reaching their goal. There are many papers utilizing LSTM networks, but few discuss the rationale behind their decision. One would at least expect a paper to describe why they choose LSTM networks over GRU networks in their setting. Although this needs a comparison of two similar RNN implementations, it should also be noted that networks like GANs and DQNs find a very limited place for themselves in the literature. Furthermore, researchers use networks like ELM, ENN, and NAR in various tasks without sharing their relative success to more complex architectures widely used in state-of-the-art deep learning models.

Ethics in deep learning applications

Ethics are broadly concerned with describing the appropriateness of an act; whether something is 'right' or 'wrong' to do. Meanwhile, deep learning is a tool that can be used to produce algorithms that automate prediction and decision-making. Thus, most ethical concerns of deep learning derive from the central question: what will the deep learning application do? The ethical considerations of deep learning in water are no exception. Take, for example, a deep learning application that predicts streamflow within an urban catchment. By appearances, the act of streamflow prediction alone lacks any ethical character. However, if the same tool is then used to make decisions in disaster mitigation (Demir *et al.* 2018) or public planning, many questions with ethical dimensions arise (Ewing & Demir 2020). What data were, and were not, used to develop the model? What biases exist in the dataset? How do these biases affect decision-making and human lives, and do the decisions reveal any discriminating behaviors? From this example, it is clear that the primary ethical considerations for the application of deep learning in water should be concerned with how entities – people, the environment, communities – will be affected by deep learning in decision-making workflows.

Although powerful, these deep learning tools simultaneously expand the reach and speed of decision-making, while also stripping away layers of context that would possibly be relevant to a humans' decision-making process. However, many of the ethical decisions in the water field remain unchanged and are primarily distributional: who receives water services, and their level of quality, and what level, and for whom, of risk is acceptable. These persistent ethical water dilemmas must be resolved within the new paradigm of deep learning in water.

As revealed by this literature review, few deep learning applications in the water literature include decision-making components. One paper, Rohmat *et al.* (2019), that was reviewed in this paper, explicitly states that their deep learning tool is integrated into a decision support system. This lack of attention to deep learning in service of decision-making in water academia presents an opportunity for a new line of research. It is also an opportunity to incorporate the work of other fields early, such as the well-documented ethical concerns stemming from deep learning decision and recommendation engines in social and civil applications (such as policing, criminal justice, and self-driving cars (Angwin *et al.* 2016; O'Neil 2016).) Furthermore, a proliferation of AI ethics frameworks have been developed and reviewed in Hagendorff (2019) and Jobin *et al.* (2019), as well as numerous

guidelines for applying and assessing algorithms in social and civil domains (O'Reilly 2013; Rahwan 2018; Reisman Schultz Crawford & Whittaker 2018). These guidelines stress a deep understanding of the task the algorithm is in service of, feedback on algorithm performance, and rigorous assessment procedures.

The discussions of ethics in the context of deep learning are part of a continued conversation of ethics generally. Questions of how to treat those in our communities, how to treat the environment, what is the 'right' priority, or priorities, are not questions exclusive to the AI/deep learning domain; rather, the new scale and speed provided by deep learning require the inspection of age-old ethical questions in a new light.

RECOMMENDATIONS AND CONCLUSIONS

This paper provides a comprehensive review of the recent application of DNN as novel solutions to tackle hydrological tasks and challenges. A total of 129 publications were systematically selected for rigorous review and analysis as grouped by their application area. Based on the statistical meta-analysis of journal publications dating between January 2018 and March 2020, it was empirically observed that the average number of deep learning applications per month in the water sector steadily increased in an exponential fashion. Furthermore, the rapidly increasing body of work from these publications show deep learning's potential in a diversity of water sector applications. Key issues and challenges that may constitute setbacks and hindrances of deep learning adoption in the water industry have been identified and reported, accompanied by recommendations to persevere in spite of the logistical, computational, expertise-related, and data-related challenges to its principled adoption. Based on the extent of this review and the broad spectrum of application areas, we anticipate the water sector will continue to incorporate deep learning at an accelerating rate and deep learning will play a key role in the future of water.

Deep learning-powered technologies opened up a plethora of application and research opportunities to revolutionize hydrological science and workflow. In a bird's eye view fashion, key areas of innovation for future research include:

1. Automated forecasting: As this review outlined, the majority of current deep learning applications in the hydrological domain focus on forecasting of numerous variables (e.g. water level, discharge) given the problem's suitability for machine learning. In the future, efforts can be coordinated between agencies and research organizations to collaboratively develop complementary models that will yield actionable and reliable information. These models can be maintained and powered by a stream of real-time data influx to constitute the future of decision-making systems and geographical information systems.
2. Published datasets: Lack of deep learning-ready datasets within the water field was stressed in the previous section. The main problem caused by this absence of many datasets is that the research community does not build upon previous work in terms of constructing better neural network architectures and moving the state of art to the next iteration. This inference is supported by the fact that among the 30 papers related to flooding reviewed in this study, there are only a few that use a previously curated, labeled dataset. The result is that many papers are published that achieve the same task with almost identical methods but different data. This absence implicitly causes redundancy in the field. We believe if more studies focus on creating benchmark datasets that are open to researchers, both cumulativeness of the science would be satisfied and deep learning-powered modeling in water resources research would go further in terms of generic applicability.
3. AI as a service: As the popularity and usefulness of AI tools increase, a new research area came to prominence in the computer science field. This area is focused on developing generalized and centralized web frameworks that can readily provide the means to develop custom AI solutions through Platform-as-a-Service systems. These systems hold great potential for the hydrological community because they allow developers to focus on designing and managing intelligent applications without the burden of infrastructure maintenance and adjustment of computing resources. They can provide intuitive graphical user interfaces to allow the development of hydrological deep learning applications by connecting predefined and custom models with provided datasets.
4. Edge computing: The main propeller in the creation of smart applications is the consistent and diverse data flux. However, as the frequency and type of data resources expand, a centralized approach to collect and analyze data simply may not be viable for multivariate tasks. Furthermore, the costs associated with the transfer of large data from distributed sensors are not trivial and may discourage stakeholders to increase sensor coverage and data reporting interval. As a solution, edge computing offers a new perspective to process the data on the sensor. There is extensive research on utilizing deep learning for the

Internet of Things through edge computing, which can allow the stakeholders of the water domain to innovate novel applications with existing or low-cost sensor networks. As a tangible example, a camera-equipped river monitoring sensor can employ deep learning to analyze pictures on the edge to detect any foreign objects (e.g. tree, human) in the river, and transmit only the useful information to a centralized system.

5. Intelligent assistants: The massive amount of environmental and hydrological data makes it challenging to efficiently and effectively extract required knowledge in a timely manner. Manual efforts are often needed to analyze comprehensive raw data for decision-making purposes. As a solution, intelligent assistants serve as voice-enabled knowledge engines that can interpret a natural language question, apply human-like reasoning, and extract the desired factual response out of curated data. These assistants can be integrated into various communication channels for easy access, including web systems, messaging applications (e.g. Skype, Messenger, SMS), personal assistants (e.g. Google Assistant, Apple Siri), home automation devices (e.g. Google Home, Amazon Alexa), augmented and virtual reality systems (e.g. HoloLens, Magic Leap, Oculus Quest), and automated workflow systems. The voice-enabled communication and immediate access to knowledge can facilitate hydrological research as well as natural disaster preparedness and response (Sermet & Demir 2018a).
6. Virtual and augmented reality: Incorporation of deep learning with virtual and augmented reality environments provides a prominent research area due to its immersive nature that allows effective analysis of complex environmental phenomena that is not feasible to be orchestrated in real-life. For example, deep learning can power realistic flood simulations while mimicking human behavior to train first-responders, aid decision-makers, and educate the public (Sermet & Demir 2018b). Another use may be guiding on-site personnel that may require expertise, such as sensor maintenance, structural renovation, and field experiments, through heads-up displays and deep learning-powered recognition and decision support applications (Sermet & Demir 2020).

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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