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

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

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

© IWA Publishing 2020
Water Science & Technology | 82.12 | 2020
doi: 10.2166/wst.2020.369
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. 2020a), 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 2011) 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 Dreuzy 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 multilayer 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 (Esteva 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’. Hydroscience 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.
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 it’s 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. ANN 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
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
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...
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-
ected 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
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).

Figure 7 | Visualization of an AE network.

Figure 8 | RBM and DBN examples.
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 data set 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
| 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. (2018c)   | 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 |
| Authors          | Models                  | Frameworks                      | Data Acquisition | Data Availability | Target Use          |
|------------------|-------------------------|---------------------------------|------------------|-------------------|---------------------|
| Sun et al. (2019) | CNN                     | Keras, TensorFlow               | Acquired         | No                | Sequence Prediction | Groundwater         |
| Jeong & Park (2019)| NARX, LSTM, GRU         | TensorFlow                      | Acquired         | No                | Sequence Prediction | Groundwater         |
| Zhou et al. (2020)| CNN                     | PyTorch                         | Acquired         | No                | Regression          | Groundwater         |
| Jeong et al. (2020)| LSTM                   | Tensorflow                      | Acquired         | No                | Sequence Prediction | Groundwater         |
| Zhang et al. (2018a)| CNN                    | Keras, Tensorflow               | Collected        | No                | Segmentation        | Land Use and Soil   |
| Zhang et al. (2018g)| LSTM                  | Tensorflow                      | Acquired         | No                | Regression          | Land Use and Soil   |
| Cao et al. (2018)  | CNN, ELM                |                                 | Existing         | No                | Segmentation        | Land Use and Soil   |
| Zeng et al. (2018) | ANN                     |                                 | Acquired         | No                | Regression          | Land Use and Soil   |
| Reddy & Prasad (2018)| LSTM                |                                 | Acquired         | No                | Yes                | Sequence Prediction | Land Use and Soil   |
| Fu et al. (2018)   | CNN                     |                                 | Acquired         | No                | No                 | Classification     | Land Use and Soil   |
| Jiang (2018)       | AE                      |                                 | Acquired         | No                | No                 | Classification     | Land Use and Soil   |
| Shen et al. (2019) | ANN                     | R/H2O                           | Acquired         | No                | No                 | Regression          | Land Use and Soil   |
| Jin et al. (2019)  | CNN                     | Tensorflow                      | Acquired         | No                | No                 | Segmentation        | Land Use and Soil   |
| Persello et al. (2019)| CNN                  |                                 | Acquired         | No                | No                 | Segmentation        | Land Use and Soil   |
| Kroupi et al. (2019)| CNN                   | Tensorflow                      | Existing         | No                | No                 | Classification     | Land Use and Soil   |
| Sun et al. (2019b) | CNN                     | PyTorch                         | Acquired         | No                | Classification     | Land Use and Soil   |
| Meng et al. (2019) | CNN                     |                                 | Acquired         | No                | No                 | Classification     | Land Use and Soil   |
| Kopp et al. (2019) | CNN                     |                                 | Collected        | No                | No                 | Segmentation        | Land Use and Soil   |
| Jiang et al. (2019) | CNN                    |                                 | Acquired         | No                | No                 | Classification     | Land Use and Soil   |
| Bhosle & Musande (2019)| CNN                | Tensorflow                      | Existing         | No                | No                 | Classification     | Land Use and Soil   |
| Zhang et al. (2019a)| ANN, CNN              |                                 | Existing         | No                | No                 | Classification     | Land Use and Soil   |
| Wang et al. (2020a)| DBN                    |                                 | Acquired         | No                | No                 | Matrix Prediction, Regression | Land Use and Soil   |
| Nam & Wang (2020)  | AE                      | R/H2O                           | Acquired         | No                | No                 | Classification     | Land Use and Soil   |
| O’Neil et al. (2020)| CNN                  | Tensorflow                      | Acquired         | Yes               | Yes                | Classification     | Land Use and Soil   |
| Yang et al. (2020) | CNN                     | Keras                           | Acquired         | No                | Yes                | Segmentation        | Land Use and Soil   |
| Abdi et al. (2018) | CNN                     |                                 | Existing         | No                | Yes                | Classification     | Others              |
| Li et al. (2018)   | CNN, AE                 | PyTorch                         | Acquired         | No                | Yes                | Segmentation        | Others              |
| Rohmat et al. (2019)| ANN                   | MATLAB                          | Acquired         | No                | No                 | Regression          | Others              |
| Amirkolaei & Arefi (2019)| CNN           | MATLAB                          | Existing         | No                | Yes                | Matrix Prediction  | Others              |
| Wang et al. (2019a)| CNN                    | Keras                           | Existing         | No                | No                 | Classification     | Others              |
| Kylili et al. (2019)| CNN                   |                                 | Collected        | No                | No                 | Classification     | Others              |
| Kang (2019)        | CNN                     | Keras, Tensorflow               | Acquired         | No                | No                 | Classification     | Others              |
| Haklidir & Haklidir (2019)| ANN            |                                 | Acquired         | No                | Yes                | Regression          | Others              |
| Kim et al. (2020)  | GAN, AE                 |                                 | Acquired         | No                | No                 | Unsupervised Learning | Others              |
| Zhang et al. (2018f)| LSTM                  | Theano                          | Acquired         | No                | No                 | Regression          | Surface Water       |
| Liu et al. (2019c) | ANN                     | Keras, Tensorflow               | Acquired         | No                | Yes                | Sequence Prediction | Surface Water       |

(continued)
| Paper                    | Network type | Framework           | Dataset   | Open-source | Reproducible | Deep learning task               | Water field |
|-------------------------|--------------|---------------------|-----------|-------------|--------------|-----------------------------------|-------------|
| Xiao et al. (2019a)     | CNN, LSTM    | Keras, TensorFlow   | Acquired  | No          | No           | Matrix Prediction                 | Surface Water|
| Read et al. (2019)      | LSTM         | –                   | Acquired  | No          | No           | Regression                        | Surface Water|
| Liu et al. (2019b)      | CNN          | Caffe               | Existing  | No          | No           | Segmentation                      | Surface Water|
| Xiao et al. (2019b)     | CNN          | PyTorch             | Existing  | No          | No           | Classification                    | Surface Water|
| Mei et al. (2019)       | CNN          | PyTorch             | Existing  | No          | No           | Regression                        | Surface Water|
| Ling et al. (2019)      | CNN          | MATLAB              | Acquired  | No          | No           | Segmentation                      | Surface Water|
| Song et al. (2019)      | CNN          | Caffe               | Existing  | No          | No           | Classification                    | Surface Water|
| Hrnjica & Bonacci (2019)| LSTM         | –                   | Acquired  | No          | No           | Sequence Prediction               | Surface Water|
| Qi et al. (2019)        | LSTM         | –                   | Acquired  | No          | No           | Sequence Prediction               | Surface Water|
| Zhu et al. (2020a)      | LSTM         | ANNdotNET, CNTK     | Acquired  | No          | No           | Sequence Prediction               | Surface Water|
| Lee & Lee (2018)        | RNN, LSTM    | –                   | Acquired  | No          | No           | Regression                        | Water Quality|
| Hamshaw et al. (2018)   | RBM          | MATLAB              | Acquired  | Yes         | Yes          | Classification                    | Water Quality|
| Liu et al. (2019a)      | LSTM         | Keras, TensorFlow   | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Yurtsever & Yurtsever (2019)| CNN       | Caffe               | Collected | No          | No           | Classification                    | Water Quality|
| Li et al. (2019)        | LSTM, GRU, ENN| –                   | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Shin et al. (2019)      | LSTM         | –                   | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Banerjee et al. (2019)  | ANN          | R/H2O               | Collected | No          | No           | Regression                        | Water Quality|
| Wang et al. (2019c)     | LSTM         | –                   | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Yim et al. (2020)       | ANN          | MATLAB              | Collected | No          | No           | Regression                        | Water Quality|
| Zou et al. (2020)       | LSTM         | Keras               | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Liang et al. (2020)     | LSTM         | Keras               | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Barzegar et al. (2020)  | CNN, LSTM    | –                   | Collected | No          | No           | Sequence Prediction               | Water Quality|
| Yu et al. (2020)        | LSTM         | –                   | Acquired  | No          | No           | Sequence Prediction               | Water Quality|
| Zhang et al. (2018a)    | LSTM         | Keras, TensorFlow   | Acquired  | No          | No           | Sequence Prediction               | Water Resources Management|
| Zhang et al. (2018b)    | LSTM, GRU    | Keras, TensorFlow   | Acquired  | No          | No           | Sequence Prediction               | Water Resources Management|
| Zhang et al. (2018c)    | LSTM, NARX, ENN| Keras, TensorFlow  | Collected | Yes         | Yes          | Regression                       | Water Resources Management|
| Harrou et al. (2018)    | DBN          | –                   | Collected | No          | No           | Sequence Prediction               | Water Resources Management|
| Shi & Xu (2018)         | AE           | –                   | Collected | No          | No           | Regression                        | Water Resources Management|
| Zhou et al. (2019)      | ANN, CNN     | PyTorch             | Existing  | Yes         | Yes          | Classification                    | Water Resources Management|
| Fang et al. (2019)      | CNN          | –                   | Acquired  | No          | No           | Classification                    | Water Resources Management|
| Sun et al. (2020)       | ANN          | –                   | Acquired  | No          | No           | Regression                        | Water Resources Management|
| Karimi et al. (2019)    | ANN, LSTM    | MATLAB              | Collected | No          | No           | Sequence Prediction               | Water Resources Management|
| Xu et al. (2020)        | LSTM         | –                   | Acquired  | No          | No           | Regression                        | Water Resources Management|
| Nam et al. (2020)       | DQN          | –                   | Acquired  | No          | No           | Reinforcement Learning            | Water Resources Management|
| Mamandipoor et al. (2020)| LSTM       | Keras, TensorFlow   | Acquired  | No          | No           | Classification                    | Water Resources Management|
| Authors (Year)        | Method | Acquired | Segmentation | Classification | Regression | Prediction Type | Weather Type |
|-----------------------|--------|----------|--------------|----------------|------------|-----------------|--------------|
| Tang et al. (2018)    | ANN    | Acquired | No            | No             | No         | No              | Weather      |
| Klampanos et al. (2018) | AE, CNN | Acquired | No            | No             | No         | Yes             | Unsupervised Learning |
| Scher & Messori (2018) | CNN    | Keras, TensorFlow | Acquired | No             | No         | Yes             | Matrix Prediction |
| Ukkonen & Mäkelä (2019) | ANN    | Keras    | Acquired | Yes            | No         | Yes             | Classification |
| He et al. (2019a)     | LSTM   | –        | Acquired | No             | No         | Yes             | Classification |
| Jeppesen et al. (2019) | CNN    | Keras, TensorFlow | Existing | Yes            | Yes        | Yes             | Segmentation |
| Chen et al. (2019)    | GAN    | PyTorch  | Acquired | No             | No         | No              | Matrix Prediction |
| Wieland et al. (2019) | CNN    | Keras, TensorFlow | Existing | No             | Yes        | No              | Segmentation |
| Weyn et al. (2019)    | CNN, LSTM | Keras, TensorFlow | Acquired | No             | No         | No              | Matrix Prediction |
| Wei & Cheng (2020)    | ANN    | Weka     | Acquired | No             | No         | No              | Sequence Prediction |
| Zhang et al. (2019b)  | CNN    | –        | Acquired | No             | Yes        | Yes             | Classification |
| Kim et al. (2019)     | ANN    | –        | Acquired | No             | No         | No              | Regression |
| Pan et al. (2019)     | CNN    | –        | Acquired | No             | Yes        | Yes             | Matrix Prediction |
| Tran & Song (2019)    | LSTM, GRU, CNN | TensorFlow | Existing | No             | Yes        | Yes             | Matrix Prediction |
| Poornima & Pushpalatha (2019) | LSTM, ELM | Keras, TensorFlow | Acquired | No             | Yes        | Yes             | Sequence Prediction |
| Chai et al. (2019)    | CNN    | –        | Acquired | No             | Yes        | Yes             | Segmentation |
| Wu et al. (2020)      | LSTM, CNN | –        | Acquired | No             | No         | No              | Regression |
| Zhang et al. (2020)   | LSTM   | –        | Acquired | No             | No         | No              | Sequence Prediction |
| Su et al. (2020)      | LSTM, CNN | –        | Acquired | No             | No         | No              | Sequence Prediction |
| Chen et al. (2020)    | CNN, LSTM | PyTorch | Existing | No             | Yes        | Yes             | Matrix Prediction |
| Weber et al. (2020)   | CNN    | TensorFlow | Acquired | Yes            | Yes        | Yes             | Matrix Prediction |
| Yan et al. (2020)     | CNN    | TensorFlow | Acquired | No             | Yes        | Yes             | Sequence Prediction |
| Wang et al. (2020c)   | RNN    | –        | Acquired | No             | No         | No              | Matrix Prediction |
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 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 pretreatments, 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.
Gaussian process to deal with the probabilistic daily streamflow forecasting. These studies show that the pretreatment of input may help to improve the deep learning model accuracy.

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 macrodispersivity 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 CO$_2$ 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 classify 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 an 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 NH3–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. (2009). 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. Kyllili 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
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).

REFERENCES

Abdi, G., Samadzadegan, F. & Reinartz, P. 2018 Deep learning decision fusion for the classification of urban remote sensing data. Journal of Applied Remote Sensing 12 (1), 016038.

Aglamzanov, R., Sit, M. & Demir, I. 2020 Hydrology@ home: a distributed volunteer computing framework for hydrological research and applications. Journal of Hydroinformatics 22 (2), 235–248.

Amirkolae, H. A. & Arefi, H. 2019 Convolutional neural network architecture for digital surface model estimation from single remote sensing image. Journal of Applied Remote Sensing 13 (1), 016522.

Angwin, J., Larson, J., Mattu, S. & Kirchner, L. 2016 Machine Bias. ProPublica, May, 23, p. 2016.

Antonetti, M. & Zappa, M. 2018 How can expert knowledge increase the realism of conceptual hydrological models? A case study based on the concept of dominant runoff process in the Swiss Pre-Alps. Hydrology & Earth System Sciences 22 (8), 4425–4447.

Ardabili, S., Mosavi, A., Dehghani, M. & Várkonyi-Kóczy, A. R. 2019 Deep learning and machine learning in hydrological processes climate change and earth systems a systematic review. In International Conference on Global Research and Education. Springer, Cham, pp. 52–62.

Arora, V. K., Scinocca, J. F., Boer, G. J., Christian, J. R., Denman, K. L., Flato, G. M., Kharin, V. V., Lee, W. G. & Merryfield, W. J. 2011 Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases. Geophysical Research Letters 38 (5).

Badrinarayanan, V., Kendall, A. & Cipolla, R. 2017 Segnet: a deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence 39 (12), 2481–2495.

Bai, Y., Bezak, N., Sapař, K., Klun, M. & Zhang, J. 2019 Short-term streamflow forecasting using the feature-enhanced regression model. Water Resources Management 33 (14), 4783–4797.

Banerjee, A., Chakrabarty, M., Rakshit, N., Bhowmick, A. R. & Ray, S. 2019 Environmental factors as indicators of dissolved oxygen concentration and zooplankton abundance: deep learning versus traditional regression approach. Ecological Indicators 100, 99–117.

Barzegar, A., Aalami, M. T. & Adamowski, J. 2020 Short-term water quality variable prediction using a hybrid CNN–LSTM deep learning model. Stochastic Environmental Research and Risk Assessment 34, 415–435.

Bengio, Y., Frasconi, P. & Simard, P. 1995 The problem of learning long-term dependencies in recurrent networks. In: IEEE International Conference on Neural Networks. IEEE, pp. 1183–1188.

Bhola, P. K., Nair, B. B., Leandro, J., Rao, S. N. & Disse, M. 2019 Flood inundation forecasts using validation data generated with the assistance of computer vision. Journal of Hydroinformatics 21 (2), 240–256.

Bhosle, K. & Musande, V. 2019 Evaluation of deep learning CNN model for land use land cover classification and crop identification using hyperspectral remote sensing images.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.
Journal of the Indian Society of Remote Sensing 47 (11), 1949–1958.

Bui, D. T., Hoang, N. D., Martinez-Álvarez, F., Ngo, P. T. T., Hoa, P. V., Pham, T. D., Samui, P. & Costache, R. 2020 A novel deep learning neural network approach for predicting flash flood susceptibility: a case study at a high frequency tropical storm area. Science of The Total Environment 701, 134413.

Bui, Q. T., Nguyen, Q. H., Nguyen, X. L., Pham, V. D., Nguyen, H. D. & Pham, V. M. 2020b Verification of novel integrations of swarm intelligence algorithms into deep learning neural network for flood susceptibility mapping. Journal of Hydrology 581, 124379.

Cao, F., Yang, Z., Ren, J. & Ling, B. W. K. 2018 Convolutional neural network extreme learning machine for effective classification of hyperspectral images. Journal of Applied Remote Sensing 12 (3), 035005.

Carson, A., Windsor, M., Hill, H., Haigh, T., Wall, N., Smith, J., Olsen, R., Bashke, D., Demir, I. & Muste, M. 2018 Serious gaming for participatory planning of multi-hazard mitigation. International Journal of River Basin Management 16 (3), 379–391.

Chai, D., Newsam, S., Zhang, H. K., Qiu, Y. & Huang, J. 2019 Cloud and cloud shadow detection in Landsat imagery based on deep convolutional neural networks. Remote Sensing of Environment 225, 307–316.

Chen, H., Zhang, X., Liu, Y. & Zeng, Q. 2019 Generative adversarial networks capabilities for super-resolution reconstruction of weather radar echo images. Atmosphere 10 (9), 555.

Chen, L., Cao, Y., Ma, L. & Zhang, J. 2020 A deep learning-based methodology for precipitation nowcasting with radar. Earth and Space Science 7 (2), e2019EA000812.

Cho, K., Van Merriënboer, B., Bahdanau, D. & Bengio, Y. 2014 On the Properties of Neural Machine Translation: Encoder-Decoder Approaches. arXiv preprint arXiv:1409.1429.

Cybenko, G. 1989 Approximation by superpositions of a sigmoidal function. Mathematics of Control, Signals and Systems 2 (4), 303–314.

Damavandi, H. G., Shah, R., Stampoulis, D., Wei, Y., Boscovic, D. & Sabo, J. 2019 Accurate prediction of streamflow using long short-term memory network: a case study in the Brazos River Basin in Texas. International Journal of Environmental Science and Development 10 (10), 294–300.

Demir, I. & Szczepanek, R. 2017 Optimization of river network representation data models for web-based systems. Earth and Space Science 4 (6), 536–547.

Demir, I., Yildirim, E., Sermet, Y. & Sit, M. A. 2018 FLOODSS: Iowa flood information system as a generalized flood cyberinfrastructure. International Journal of River Basin Management 16 (3), 393–400.

Demiray, B. Z., Sit, M. & Demir, I. 2020 D-SRGAN: DEM Super-Resolution with Generative Adversarial Network. arXiv preprint arXiv:2004.04788.

Ebert-Uphoff, I., Thompson, D. R., Demir, I., Gel, Y. R., Karpatne, A., Guerereque, M., Kumar, V., Cabral-Can, E. & Smyth, P. 2017 A vision for the development of benchmarks to bridge geoscience and data science. In: 17th International Workshop on Climate Informatics. National Center for Atmospheric Research, Boulder, CO, USA.

Elman, J. L. 1990 Finding structure in time. Cognitive Science 14 (2), 179–211.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S. & Dean, J. 2019 A guide to deep learning in healthcare. Nature Medicine 25 (1), 24–29.

Evora, N. D. & Coulibaly, P. 2009 Recent advances in data-driven modeling of remote sensing applications in hydrology. Journal of Hydroinformatics 11 (3–4), 194–201.

Ewing, G. & Demir, I. 2020 An ethical decision-making framework with serious gaming: smart water case study on flooding. EarthArXiv: doi:10.31223/osf.io/y873 g.

Fang, Q., Zhang, J., Xie, C. & Yang, Y. 2019 Detection of multiple leakage points in water distribution networks based on convolutional neural networks. Water Supply 19 (8), 2231–2239.

Fu, T., Ma, L., Li, M. & Johnson, B. A. 2018 Using convolutional neural network to identify irregular segmentation objects from very high-resolution remote sensing imagery. Journal of Applied Remote Sensing 12 (2), 025010.

Gautam, A., Sit, M. & Demir, I. 2020 Realistic River Image Synthesis Using Deep Generative Adversarial Networks. arXiv preprint arXiv:2003.00826.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. & Bengio, Y. 2014 Generative adversarial nets. In: Advances in Neural Information Processing Systems. pp. 2672–2680.

Goodfellow, I., Bengio, Y. & Courville, A. 2016 Deep Learning. MIT Press, Cambridge, MA.

Grossman, D., Buckley, N. & Doyle, M. 2015 Data Intelligence for 21st Century Water Management: A Report From the 2015 Aspen-Nicholas Water Forum. Aspen-Nicholas Water Forum. Available from https://www.aspeninstitute.org/publications/data-intelligence-21st-century-water-management-report-2015-aspen-nicholas-water-forum/ (accessed 31 May 2020).

Hagendorff, T. 2019 The Ethics of AI Ethics–An Evaluation of Guidelines. arXiv preprint arXiv:1903.03425.

Haklidir, F. S. T. & Haklidir, M. 2019 Prediction of reservoir temperatures using hydrogeochemical data, Western Anatolia geothermal systems (Turkey): a machine learning approach. Natural Resources Research 29, 2333–2346.

Hamshaw, S. D., Dewoolkar, M. M., Schroth, A. W., Wemple, B. C. & Rizzo, D. M. 2014 Monitoring of a wastewater treatment plant: a case study. EarthArXiv: doi:10.31223/osf.io/7c2k 1.

Haskins, G., Kruger, U. & Yan, P. 2020 Statistical monitoring of a wastewater treatment plant: a case study. Journal of Environmental Management 223, 807–814.

Haskins, G., Kruger, U. & Yan, P. 2020 Deep learning in medical image registration: a survey. Machine Vision and Applications 31 (1), 8.

He, K., Zhang, X., Ren, S. & Sun, J. 2015 Deep Residual Learning for Image Recognition. arXiv preprint arXiv:1512.03385.
He, B., Liu, X., Hu, S., Song, K. & Gao, T. 2019a Use of the C-band microwave link to distinguish between rainy and dry periods. Advances in Meteorology 2019, doi:10.1155/2019/3428786.

He, X., Luo, J., Zuo, G. & Xie, J. 2019b Daily runoff forecasting using a hybrid model based on variational mode decomposition and deep neural networks. Water Resources Management 33 (4), 1571–1590.

Heaton, J. B., Polson, N. G. & Witte, J. H. 2017 Deep learning for finance: deep portfolios. Applied Stochastic Models in Business and Industry 33 (1), 3–12.

Hinton, G. E. 2002 Training products of experts by minimizing contrastive divergence. Neural Computation 14 (8), 1771–1800.

Hinton, G. E. 2009 Deep belief networks. Scholarpedia 4 (5), 5947.

Hochreiter, S. & Schmidhuber, J. 1997 Long short-term memory. Neural Computation 9 (8), 1735–1780.

Hornik, K., Stinchcombe, M. & White, H. 1989 Multilayer feedforward networks are universal approximators. Neural Networks 2 (5), 359–366.

Hrnjica, B. & Bonacci, O. 2019 Lake level prediction using feed forward and recurrent neural networks. Water Resources Management 33 (7), 2471–2484.

Hu, R., Fang, F., Pan, C. C. & Navon, I. M. 2019 Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method. Journal of Hydrology 575, 911–920.

Huang, G. B., Zhu, Q. Y. & Siew, C. K. 2006 Extreme learning machine: theory and applications. Neurocomputing 70 (1–3), 489–501.

Islam, Z. 2011 A Review on Physically Based Hydrologic Modeling. University of Alberta, Edmonton, AB, Canada. doi:10.13140/2.1.4544.5924.

Isola, P., Zhu, J. Y., Zhou, T. & Efros, A. A. 2017 Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 1125–1134.

Jadidoleslam, N., Mantilla, R., Krajewski, W. F. & Cosh, M. H. 2019 Data-driven stochastic model for basin and sub-grid variability of SMAP satellite soil moisture. Journal of Hydrology 576, 85–97.

Jaiswal, R. K., Ali, S. & Bharti, B. 2020 Comparative evaluation of conceptual and physical rainfall–runoff models. Applied Water Science 10 (1), 1–14.

Jeong, J. & Park, E. 2009 Comparative applications of data-driven models representing water table fluctuations. Journal of Hydrology 572, 261–273.

Jeong, J., Park, E., Chen, H., Kim, K. Y., Han, W. S. & Suk, H. 2020 Estimation of groundwater level based on the robust training of recurrent neural networks using corrupted data. Journal of Hydrology 582, 124512.

Jeppeesen, J. H., Jacobsen, R. H., Inceoglu, F. & Toftegaard, T. S. 2019 A cloud detection algorithm for satellite imagery based on deep learning. Remote Sensing of Environment 229, 247–259.

Jiang, W. 2018 Object-based deep convolutional autoencoders for high-resolution remote sensing image classification. Journal of Applied Remote Sensing 12 (3), 035002.

Jiang, Z., Mallants, D., Peeters, L., Gao, L., Sorensen, C. & Mariethoz, G. 2019 High-resolution paleovalley classification from airborne electromagnetic imaging and deep neural network training using digital elevation model data. Hydrology and Earth System Sciences 23 (6), 2561–2580.

Jin, B., Ye, P., Zhang, X., Song, W. & Li, S. 2019 Object-oriented method combined with deep convolutional neural networks for land-use-type classification of remote sensing images. Journal of the Indian Society of Remote Sensing 47 (6), 951–965.

Jobin, A., Irca, M. & Vayena, E. 2019 Artificial Intelligence: The Global Landscape of Ethics Guidelines. arXiv preprint arXiv:1906.11668.

Kahir, S., Patidar, S. & Pender, G. 2020 Investigating capabilities of machine learning techniques in forecasting stream flow. In: Proceedings of the Institution of Civil Engineers-Water Management. Thomas Telford Ltd, Vol. 173, No. 2, pp. 69–86.

Kang, L. 2019 Wave monitoring based on improved convolution neural network. Journal of Coastal Research 94 (sp1), 186–190.

Kao, I. F., Zhou, Y., Chang, L. C. & Chang, F. J. 2020 Exploring a long short-term memory based encoder-decoder framework for multi-step-ahead flood forecasting. Journal of Hydrology 583, 124631.

Karimi, H. S., Natarajan, B., Ramsey, C. L., Henson, J., Tedder, J. L. & Kemper, E. 2019 Comparison of learning-based wastewater flow prediction methodologies for smart sewer management. Journal of Hydrology 577, 123977.

Kim, Y. J., Yura, E., Kim, T. W. & Yoon, J. S. 2019 Development of disaster prevention system based on deep neural network using deep learning with dropout. Journal of Coastal Research 91 (sp1), 186–190.

Kim, J., Kim, J., Kim, T., Huh, D. & Caires, S. 2020 Wave-tracking in the surf zone using coastal video imagery with deep neural networks. Atmosphere 11 (3), 304.

Klampanos, I. A., Davvetas, A., Andronopoulos, S., Pappas, C., Ikonomopoulos, A. & Karkaletsis, V. 2018 Autoencoder-driven weather clustering for source estimation during nuclear events. Environmental Modelling & Software 102, 84–93.

Kopp, M., Tuo, Y. & Disse, M. 2019 Fully automated snow depth measurements from time-lapse images applying a convolutional neural network. Science of The Total Environment 697, 134213.

Krajewski, W. F., Ceynar, D., Demir, I., Goska, R., Kruger, A., Langel, C., Mantilla, R., Niemeier, J., Quintero, F., Seo, B. C. & Small, S. J. 2017 Real-time flood forecasting and information system for the state of Iowa. Bulletin of the American Meteorological Society 98 (3), 539–554.

Kratzert, F., Klotz, D., Brenner, C., Schulz, K. & Herrmegger, M. 2018 Rainfall–runoff modelling using long short-term memory (LSTM) networks. Hydrology and Earth System Sciences 22 (11), 6005–6022.

Kratzert, F., Klotz, D., Herrmegger, M., Sampson, A. K., Hochreiter, S. & Nearing, G. S. 2019a Toward improved predictions in ungauged basins: exploiting the power of machine learning. Water Resources Research 55, 11344–11354.
Kratzer, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S. & Nearing, G. 2019 Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. *Hydrology & Earth System Sciences* **23** (12), 5089–5110.

Krizhevsky, A., Sutskever, I. & Hinton, G. E. 2012 ImageNet classification with deep convolutional neural networks. In: *Advances in Neural Information Processing Systems*. pp. 1097–1105.

Kroupi, E., Kesa, M., Navarro-Sánchez, V. D., Saeed, S., Pelloquin, C., Alhaddad, B., Moreno, L., Soria-Frisch, A. & Ruffini, G. 2019 Deep convolutional neural networks for land-cover classification with Sentinel-2 images. *Journal of Applied Remote Sensing* **13** (2), 024525.

Kruger, A., Krajewski, W. F., Niemeier, J. J., Ceynar, D. L. & Goska, R. 2016 Bridge-mounted river stage sensors (BMRSS). *IEEE Access* 4, 8948–8966.

Kumar, D., Singh, A., Samui, P. & Jha, R. K. 2019 Forecasting monthly precipitation using sequential modelling. *Hydrological Sciences Journal* **64** (6), 690–700.

Kylli, K., Kyriakides, I., Artusi, A. & Hadjistassou, C. 2019 Identifying floating plastic marine debris using a deep learning approach. *Environmental Science and Pollution Research* **26** (17), 17091–17099.

Laloy, E., Hérault, R., Jacques, D. & Linde, N. 2019 Improved prediction of harmful algal blooms in four Major South Korea media. *Sustainability* **11** (7), 2058.

Lin, T., Horne, B. G., Tino, P. & Giles, C. L. 1996 Learning long-term dependencies in NARX recurrent neural networks. *IEEE Transactions on Neural Networks* **7** (6), 1329–1338.

Ling, F., Boyd, D., Ge, Y., Foody, G. M., Li, X., Wang, L., Zhang, Y., Shi, L., Shang, C., Li, X. & Du, Y. 2019 Measuring river wetted width from remotely sensed imagery at the subpixel scale with a deep convolutional neural network. *Water Resources Research* **55** (7), 5651–5669.

Liu, P., Wang, J., Sangaiah, A. K., Xie, Y. & Yin, X. 2019a Analysis and prediction of water quality using LSTM deep neural networks in IoT environment. *Sustainability* **11** (7), 2058.

Liu, Y., Piramanyagam, S., Monteiro, S. T. & Saber, E. 2019b Semantic segmentation of multisensor remote sensing imagery with deep ConvNets and higher-order conditional random fields. *Journal of Applied Remote Sensing* **13** (1), 016501.

Liu, Y., Qin, H., Zhang, Z., Yao, L., Wang, Y., Li, J., Liu, G. & Zhou, J. 2019c Deriving reservoir operation rule based on Bayesian deep learning method considering multiple uncertainties. *Journal of Hydrology* **579**, 124207.

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G. & Johnson, B. A. 2019 Deep learning in remote sensing applications: a meta-analysis and review. *ISPRS Journal of Photogrammetry and Remote Sensing* **152**, 166–177.

Mamandipoor, B., Majd, M., Sheikhalishahi, S., Modena, C. & Osmani, V. 2020 Monitoring and detecting faults in wastewater treatment plants using deep learning. *Environmental Monitoring and Assessment* **192** (2), 148.

Marçais, J. & de Dreuzy, J. R. 2017 Prospective interest of deep learning for hydrological inference. *Groundwater* **55** (5), 688–692.

McCuen, R. H. 2016 *Modeling Hydrologic Change: Statistical Methods*. CRC Press, Boca Raton, FL.

Mei, M. J., Maksym, T., Weissling, B. & Singh, H. 2019 Estimating early-winter Antarctic sea ice thickness from deformed ice morphology. *The Cryosphere* **11** (11), 2915–2934.

Meng, X., Zhang, S. & Zang, S. 2019 Lake wetland classification based on an SVM-CNN composite classifier and high-resolution images using wudalianchi as an example. *Journal of Coastal Research* **93** (sp1), 153–162.

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D. & Riedmiller, M. 2013 *Playing Atari with Deep Reinforcement Learning*. arXiv preprint arXiv:1312.5602.

Mo, S., Zabaras, N., Shi, X. & Wu, J. 2019a Deep autoregressive neural networks for high-dimensional inverse problems in groundwater contaminant source identification. *Water Resources Research* **55** (5), 3856–3881.

Mo, S., Zhu, Y., Zabaras, N., Shi, X. & Wu, J. 2019b Deep convolutional encoder-decoder networks for uncertainty quantification of dynamic multiphase flow in heterogeneous media. *Water Resources Research* **55** (1), 703–728.

Moyn de Vitry, M., Kramer, S., Wegner, J. D. & Leitão, J. P. 2019 Scalable flood level trend monitoring with surveillance cameras using a deep convolutional neural network. *Hydrology and Earth System Sciences* **23** (11), 4621–4634.

Nair, V. & Hinton, G. E. 2010 Rectified linear units improve restricted boltzmann machines. In: *Proceedings of the 27th
International Conference on Machine Learning (ICML-10), pp. 807–814.

Nam, K. & Wang, F. 2020 An extreme rainfall-induced landslide susceptibility assessment using autoencoder combined with random forest in Shimane Prefecture, Japan. Geoenvironmental Disasters 7 (1), 6.

Nam, K., Heo, S., Loy-Benitez, J., Ifaei, P., Lee, S., Kang, S. & Yoo, C. 2020 An autonomous operational trajectory searching system for an economic and environmental membrane bioreactor plant using deep reinforcement learning. Water Science and Technology 81, 1578–1587.

Nguyen, D. H. & Bae, D. H. 2020 Correcting mean areal precipitation forecasts to improve urban flooding predictions by using long short-term memory network. Journal of Hydrology 584, 124710.

Ni, L., Wang, D., Singh, V. P., Wu, J., Wang, Y., Tao, Y. & Zhang, J. 2019 Streamflow and rainfall forecasting by two long short-term memory-based models. Journal of Hydrology 583, 124296.

O’Neil, C. 2016 Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. Broadway Books, New York, NY.

O’Neill, G. L., Goodall, J. L., Behl, M. & Saby, L. 2020 Deep learning using physically-informed input data for wetland identification. Environmental Modelling & Software 126, 104665.

O’Reilly, T. 2015 Open data and algorithmic regulation. In: Beyond Transparency: Open Data and the Future of Civic Innovation (B. Goldstein & L. Dyson, eds). Code for America Press, San Francisco, CA, pp. 289–300.

Pan, B., Hsu, K., AghaKouchak, A. & Sorooshian, S. 2019 Improving precipitation estimation using convolutional neural network. Water Resources Research 55 (3), 2301–2321.

Persello, C., Tolpekin, V. A., Bergado, J. R. & de By, R. A. 2019 Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping. Remote Sensing of Environment 231, 112535.

Pullack, J. B. 1990 Recursive distributed representations. Artificial Intelligence 46 (1–2), 77–105.

Poornima, S. & Pushpalatha, M. 2019 Prediction of rainfall using intensified LSTM based recurrent neural network with weighted linear units. Atmosphere 10 (11), 668.

Qi, Y., Zhou, Z., Yang, L., Quan, Y. & Miao, Q. 2019 A decomposition-ensemble learning model based on LSTM neural network for daily reservoir inflow forecasting. Water Resources Management 35 (12), 4123–4139.

Qin, J., Liang, J., Chen, T., Lei, X. & Kang, A. 2019 Simulating and predicting of hydrological time series based on tensorFlow deep learning. Polish Journal of Environmental Studies 28 (2), 796–802.

Rahwan, I. 2018 Society-in-the-loop: programming the algorithmic social contract. Ethics and Information Technology 20 (1), 5–14.

Read, J. S., Jia, X., Willard, J., Appling, A. P., Zwart, J. A., Oliver, S. K., Karpatne, A., Hansen, G. J., Hanson, P. C., Watkins, W. & Steinbach, M. 2019 Process-guided deep learning predictions of lake water temperature. Water Resources Research 55, 9173–9190.

Reddy, D. S. & Prasad, P. R. C. 2018 Prediction of vegetation dynamics using NDVI time series data and LSTM. Modeling Earth Systems and Environment 4 (1), 409–419.

Reinsel, D., Gantz, J. & Rydning, J. 2018 The Digitization of the World From Edge to Core. IDC White Paper.

Reisman, D., Schultz, J., Crawford, K. & Whittaker, M. 2018 Algorithmic Impact Assessments: A Practical Framework for Public Agency Accountability. AI Now Institute, pp. 1–22.

Ren, T., Liu, X., Niu, J., Lei, X. & Zhang, Z. 2020 Real-time water level prediction of cascaded channels based on multilayer perception and recurrent neural network. Journal of Hydrology 585, 124783.

Rohmat, F. I., Labadie, J. W. & Gates, T. K. 2019 Deep learning for compute-efficient modeling of BMP impacts on stream-aquifer exchange and water law compliance in an irrigated river basin. Environmental Modelling & Software 122, 104529.

Ronneberger, O., Fischer, P. & Brox, T. 2015 U-net: convolutional networks for biomedical image segmentation. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, pp. 234–241.

Rumelhart, D. E., Hinton, G. E. & Williams, R. J. 1985 Learning Internal Representations by Error Propagation (No. ICS-8506). University of California San Diego La Jolla Institute for Cognitive Science.

Rumelhart, D. E., Hinton, G. E. & Williams, R. J. 1986 Learning representations by back-propagating errors. Nature 323 (6088), 533–536.

Saha, L., Biswas, M., Kuppili, V., Godia, E. C., Suri, H. S., Edla, D. R., Omerzu, T., Laird, J. R., Khanna, N. N., Mavrogeni, S. & Protogerou, A. 2019 The present and future of deep learning in radiology. European Journal of Radiology 114, 14–24.

Sahiner, B., Pezeshki, A., Hadijiiski, L. M., Wang, X., Drukker, K., Cha, K. H., Summers, R. M. & Giger, M. L. 2019 Deep learning in medical imaging and radiation therapy. Medical Physics 46 (1), e1–e36.

Sankaranarayanan, S., Prabhakar, M., Satish, S., Jain, P., Ramprasad, A. & Krishnan, A. 2019 Flood prediction based on weather parameters using deep learning. Journal of Water and Climate Change.

Santos, J. E., Xu, D., Jo, H., Landry, C. J., Prodanović, M. & Pyrcz, M. J. 2020 PoreFlow-Net: A 3D convolutional neural network to predict fluid flow through porous media. Advances in Water Resources 158, 103539.

Scher, S. & Messori, G. 2018 Predicting weather forecast uncertainty with machine learning. Quarterly Journal of the Royal Meteorological Society 144 (717), 2830–2841.

Sengupta, S., Basak, S., Saikia, P., Paul, S., Tsalavoutis, V., Atiah, F., Ravi, V. & Peters, A. 2020 A review of deep learning with special emphasis on architectures, applications and recent trends. Knowledge-Based Systems 194, 105596.

Sermet, Y. & Demir, I. 2018 An intelligent system on knowledge generation and communication about flooding. Environmental Modelling & Software 108, 51–60.

Sermet, Y. & Demir, I. 2018b Flood action VR: a virtual reality framework for disaster awareness and emergency response.
training. In: Proceedings of the International Conference on Modeling, Simulation and Visualization Methods (MSV). pp. 65–68.

Sermet, Y. & Demir, I. 2020 Virtual and augmented reality applications for environmental science education and training. In: New Perspectives on Virtual and Augmented Reality: Finding New Ways to Teach in A Transformed Learning Environment. (L. Daniela, ed.). Routledge, London, UK, p. 261–275.

Sermet, Y., Demir, I. & Muste, M. 2020a A serious gaming framework for decision support on hydrological hazards. Science of The Total Environment 728, 138895.

Sermet, Y., Villanueva, P., Sit, M. A. & Demir, I. 2020b Crowdsourced approaches for stage measurements at ungaged locations using smartphones. Hydrological Sciences Journal 65 (5), 813–822.

Shafer, G. 1976 A Mathematical Theory of Evidence, Vol. 42. Princeton University Press, Princeton, NJ.

Shen, C. 2018 A transdisciplinary review of deep learning research and its relevance for water resources scientists. Water Resources Research 54 (11), 8558–8593.

Shen, R., Huang, A., Li, B. & Guo, J. 2019 Construction of a drought monitoring model using deep learning based on multi-source remote sensing data. International Journal of Applied Earth Observation and Geoinformation 79, 48–57.

Shi, S. & Xu, G. 2018 Novel performance prediction model of a biofilm system treating domestic wastewater based on stacked denoising auto-encoders deep learning network. Chemical Engineering Journal 347, 280–290.

Shin, J., Kim, S. M., Son, Y. B., Kim, K. & Ryu, J. H. 2019 Early prediction of Margalefidium polykrikoides bloom using a LSTM neural network model in the South Sea of Korea. Journal of Coastal Research 90 (sp1), 236–242.

Simonyan, K. & Zisserman, A. 2014 Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1486.

Sit, M. & Demir, I. 2019 Decentralized Flood Forecasting Using Deep Neural Networks. arXiv preprint arXiv:1902.02308.

Sit, M., Sermet, Y. & Demir, I. 2019a Optimized watershed delineation library for server-side and client-side web applications. Open Geospatial Data, Software and Standards 4 (1), 8.

Sit, M. A., Koylu, C. & Demir, I. 2019b Identifying disaster-related tweets and their semantic, spatial and temporal context using deep learning, natural language processing and spatial analysis: a case study of Hurricane Irma. International Journal of Digital Earth 12 (11), 1205–1229.

Song, A., Kim, Y. & Kim, Y. 2019 Change detection of surface water in remote sensing images based on fully convolutional network. Journal of Coastal Research 91 (sp1), 426–430.

Su, A., Li, H., Cui, L. & Chen, Y. 2020 A convection nowcasting method based on machine learning. Advances in Meteorology 2020, 5124274. https://doi.org/10.1155/2020/5124274.

Sun, A. Y., Scanlon, B. R., Zhang, Z., Walling, D., Banja, S. N., Mukherjee, A. & Zhong, Z. 2019a Combining physically based modeling and deep learning for fusing GRACE satellite data: can we learn from mismatch? Water Resources Research 55 (2), 1179–1195.

Sun, Z., Zhao, X., Wu, M. & Wang, C. 2019b Extracting urban impervious surface from worldview-2 and airborne LiDAR data using 3D convolutional neural networks. Journal of the Indian Society of Remote Sensing 47 (3), 401–412.

Sun, Z., Long, D., Yang, W., Li, X. & Pan, Y. 2020 Reconstruction of GRACE data on changes in total water storage over the global land surface and 60 basins. Water Resources Research 56 (4), e2019WR026250.

Sundermeyer, M., Schlüter, R. & Ney, H. 2012 LSTM neural networks for language modeling. In: Thirteenth Annual Conference of the International Speech Communication Association. International Speech Communication Association, Portland, OR, USA.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. & Rabinovich, A. 2015 Going deeper with convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. The Computer Vision Foundation & IEEE, Boston, MA, USA, pp. 1–9.

Tang, G., Long, D., Behrangui, A., Wang, C. & Hong, Y. 2018 Exploring deep neural networks to retrieve rain and snow in high latitudes using multisensor and reanalysis data. Water Resources Research 54 (10), 8253–8278.

Tapley, B. D., Bettadpur, S., Watkins, M. & Reigber, C. 2004 The gravity recovery and climate experiment: mission overview and early results. Geophysical Research Letters 31 (9).

Tran, Q. K. & Song, S. K. 2019 Computer vision in precipitation nowcasting: applying image quality assessment metrics for training deep neural networks. Atmosphere 10 (5), 244.

Ukkonen, P. & Mäkelä, A. 2019 Evaluation of machine learning classifiers for predicting deep convection. Journal of Advances in Modeling Earth Systems 11 (6), 1784–1802.

Wan, X., Yang, Q., Jiang, P. & Zhong, P. A. 2019 A hybrid model for real-time probabilistic flood forecasting using elman neural network with heterogeneity of error distributions. Water Resources Management 33 (11), 4027–4050.

Wang, L. P. & Wan, C. R. 2008 Comments on ‘The extreme learning machine. IEEE Transactions on Neural Networks 19 (8), 1494–1495.

Wang, C., Tandeo, P., Mouche, A., Stopa, J. E., Gressani, V., Longepe, N., Vandemark, D., Foster, R. C. & Chapron, B. 2019a Classification of the global Sentinel-1 SAR vignettes for ocean surface process studies. Remote Sensing of Environment 234, 114457.

Wang, J. H., Lin, G. F., Chang, M. J., Huang, I. H. & Chen, Y. R. 2019b Real-time water-level forecasting using dilated causal convolutional neural networks. Water Resources Management 33 (11), 3759–3780.

Wang, P., Yao, J., Wang, G., Hao, F., Shrestha, S., Xue, B., Xie, G. & Peng, Y. 2019c Exploring the application of artificial intelligence technology for identification of water pollution characteristics and tracing the source of water quality pollutants. Science of The Total Environment 695, 133440.

Wang, J., Yuan, Q., Shen, H., Liu, T., Li, T., Yue, L., Shi, X. & Zhang, L. 2020a Estimating snow depth by combining
satellite data and ground-based observations over Alaska: a deep learning approach. *Journal of Hydrology* 585, 124828.

Wang, N., Zhang, D., Chang, H. & Li, H. 2020b Deep learning of subsurface flow via theory-guided neural network. *Journal of Hydrology* 584, 124700.

Wang, Q., Huang, J., Liu, R., Men, C., Guo, L., Miao, Y., Jiao, L., Wang, Y., Shoaib, M. & Xia, X. 2020c Sequence-based statistical downscaling and its application to hydrologic simulations based on machine learning and big data. *Journal of Hydrology* 586, 124875.

Wang, Y., Fang, Z., Hong, H. & Peng, L. 2020d Flood susceptibility mapping using convolutional neural network frameworks. *Journal of Hydrology* 582, 124482.

Weber, L. J., Muste, M., Bradley, A. A., Amado, A. A., Demir, I., Drake, C. W., Krajewski, W. F., Loeser, T. J., Politano, M. S., Shea, B. R. & Thomas, N. W. 2018 The Iowa watersheds project: Iowa’s prototype for engaging communities and professionals in watershed hazard mitigation. *International Journal of River Basin Management* 16 (3), 315–328.

Weber, T., Corotan, A., Hutchinson, B., Kravitz, B. & Link, R. 2020 Technical note: Deep learning for creating surrogate models of precipitation in Earth system models. *Atmospheric Chemistry and Physics* 20, 2303–2517. doi:10.5194/acp-20-2303-2020.

Wei, C. C. & Cheng, J. Y. 2020 Nearshore two-step typhoon wave-prediction using deep recurrent neural networks. *Journal of Hydroinformatics* 22 (2), 346–367.

Weyn, J. A., Durran, D. R. & Caruana, R. 2019 Can machines learn to predict weather? Using deep learning to predict gridded 500hPa geopotential height from historical weather data. *Journal of Advances in Modeling Earth Systems* 11 (8), 2680–2693.

Wieland, M., Li, Y. & Martinis, S. 2019 Multi-sensor cloud and cloud shadow segmentation with a convolutional neural network. *Remote Sensing of Environment* 230, 112103.

Worland, S. C., Steinschneider, S., Asquith, W., Knight, R. & Wieczorek, M. 2019 Prediction and inference of flow duration curves using multioutput neural networks. *Water Resources Research* 55 (8), 6850–6868.

Wu, H., Yang, Q., Liu, J. & Wang, G. 2020 A spatiotemporal deep fusion model for merging satellite and gauge precipitation in China. *Journal of Hydrology* 584, 124664.

Xiang, Z. & Demir, I. 2020 Distributed long-term hourly streamflow predictions using deep learning–a case study for state of Iowa. *Environmental Modeling & Software* 131, 104761.

Xiang, Z., Yan, J. & Demir, I. 2020 A rainfall-runoff model with LSTM-based sequence-to-sequence learning. *Water Resources Research* 56 (1).

Xiao, C., Chen, N., Hu, C., Wang, K., Xu, Z., Cai, Y., Xu, L., Chen, Z. & Gong, J. 2019a A spatiotemporal deep learning model for sea surface temperature field prediction using time-series satellite data. *Environmental Modelling & Software* 120, 104502.

Xiao, H., Zhang, F., He, Q., Liu, P., Yan, F., Miao, L. & Yang, Z. 2019b Classification of ice crystal habits observed from airborne Cloud Particle Imager by deep transfer learning. *Earth and Space Science* 6 (10), 1877–1886.

Xu, Z., Ying, Z., Li, Y., He, B. & Chen, Y. 2020 Pressure prediction and abnormal working conditions detection of water supply network based on LSTM. *Water Supply* 20, 963–974.

Yang, S., Yang, D., Chen, J. & Zhao, B. 2019a Real-time reservoir operation using recurrent neural networks and inflow forecast from a distributed hydrological model. *Journal of Hydrology* 579, 124229.

Yang, T., Sun, F., Gentine, P., Liu, W., Wang, H., Yin, J., Du, M. & Liu, C. 2019b Evaluation and machine learning improvement of global hydrological model-based flood simulations. *Environmental Research Letters* 14 (11), 114027.

Yan, Q., Ji, F., Miao, K., Wu, Q., Xia, Y. & Li, T. 2020 Convolutional residual-attention: a deep learning approach for precipitation nowcasting. *Advances in Meteorology* 2020, https://doi.org/10.1155/2020/6484812

Yang, F., Feng, T., Xu, G. & Chen, Y. 2020 Applied method for water-body segmentation based on mask R-CNN. *Journal of Applied Remote Sensing* 14 (1), 014502.

Yin, I., Shin, J., Lee, H., Park, S., Nam, G., Kang, T., Cho, K. H. & Cha, Y. 2020 Deep learning-based retrieval of cyanobacteria pigment in inland water for in-situ and airborne hyperspectral data. *Ecological Indicators* 110, 105879.

Yin, W., Kinn, K., Yu, M. & Schütze, H. 2017 Comparative Study of cnn and rnn for Natural Language Processing. arXiv preprint arXiv:1702.01923.

Yu, Z., Yang, K., Luo, Y. & Shang, C. 2020 Spatial-temporal process simulation and prediction of chlorophyll-a concentration in Dianchi Lake based on wavelet analysis and long-term memory network. *Journal of Hydrology* 582, 124488.

Yuan, X., Chen, C., Lei, X., Yuan, Y. & Adnan, R. M. 2018 Monthly runoff forecasting based on LSTM–ALO model. *Stochastic Environmental Research and Risk Assessment* 32 (8), 2199–2212.

Yurtsever, M. & Yurtsever, U. 2019 Use of a convolutional neural network for the classification of microbeads in urban wastewater. *Chemosphere* 216, 271–280. https://doi.org/10.1016/j.chemosphere.2018.10.084.

Zeng, W., Zhang, D., Fang, Y., Wu, J. & Huang, J. 2018 Comparison of partial least square regression, support vector machine, and deep-learning techniques for estimating soil salinity from hyperspectral data. *Journal of Applied Remote Sensing* 12 (2), 022204. https://doi.org/10.1117/1.JRS.12.022204.

Zhang, D., Holland, E. S., Lindholm, G. & Ratnaweera, H. 2018a Hydraulic modeling and deep learning based flow forecasting for optimizing inter catchment wastewater transfer. *Journal of Hydrology* 567, 792–802. https://doi.org/10.1016/j.jhydrol.2017.11.029.

Zhang, D., Lindholm, G. & Ratnaweera, H. 2018b Use long short-term memory to enhance internet of things for combined sewer overflow monitoring. *Journal of Hydrology* 556, 409–418. https://doi.org/10.1016/j.jhydrol.2017.11.018.

Zhang, D., Martinez, N., Lindholm, G. & Ratnaweera, H. 2018c Manage sewer in-line storage control using hydraulic model and recurrent neural network. *Water Resources Management* 32 (6), 2079–2098. https://doi.org/10.1007/s11269-018-1919-3.
Zhang, C., Sargent, I., Pan, X., Li, H., Gardiner, A., Hare, J. & Atkinson, P. M. 2018d An object-based convolutional neural network (OCNN) for urban land use classification. Remote Sensing of Environment 216, 57–70. https://doi.org/10.1016/j.rse.2018.06.034.

Zhang, D., Lin, J., Peng, Q., Wang, D., Yang, T., Sorooshian, S., Liu, X. & Zhuang, J. 2018e Modeling and simulating of reservoir operation using the artificial neural network, support vector regression, deep learning algorithm. Journal of Hydrology 565, 720–736. https://doi.org/10.1016/j.jhydrol.2018.08.050.

Zhang, J., Zhu, Y., Zhang, X., Ye, M. & Yang, J. 2018f Developing a long short-term memory (LSTM) based model for predicting water table depth in agricultural areas. Journal of Hydrology 561, 918–929. https://doi.org/10.1016/j.jhydrol.2018.04.065.

Zhang, X., Zhang, Q., Zhang, G., Nie, Z., Gui, Z. & Que, H. 2018g A novel hybrid data-driven model for daily land surface temperature forecasting using long short-term memory neural network based on ensemble empirical mode decomposition. International Journal of Environmental Research and Public Health 15 (5), 1052. https://doi.org/10.3390/ijerph15051032.

Zhang, C., Li, G., Du, S., Tan, W. & Gao, F. 2019a Three-dimensional densely connected convolutional network for hyperspectral remote sensing image classification. Journal of Applied Remote Sensing 13 (1), 016519. https://doi.org/10.1117/1.JRS.13.016519.

Zhang, Z., Iwasaki, A., Xu, G. & Song, J. 2019b Cloud detection on small satellites based on lightweight U-net and image compression. Journal of Applied Remote Sensing 13 (2), 026502. https://doi.org/10.1117/1.JRS.13.026502.

Zhang, C. J., Zeng, J., Wang, H. Y., Ma, L. M. & Chu, H. 2020 Correction model for rainfall forecasts using the LSTM with multiple meteorological factors. Meteorological Applications 27 (1), e1852. https://doi.org/10.1002/met.1852.

Zhou, Y. T. & Chellappa, R. 1988 Computation of optical flow using a neural network. In: IEEE International Conference on Neural Networks. Vol. 1998, IEEE, Anchorage, AK, USA, pp. 71–78.

Zhou, X., Tang, Z., Xu, W., Meng, F., Chu, X., Xin, K. & Fu, G. 2018 Deep learning identifies accurate burst locations in water distribution networks. Water Research 166, 115058.

Zhou, Z., Shi, L. & Zha, Y. 2020 Seeing macro-dispersivity from hydraulic conductivity field with convolutional neural network. Advances in Water Resources 138, 103545.

Zhu, S., Hrnjica, B., Ptak, M., Choiński, A. & Sivakumar, B. 2020a Forecasting of water level in multiple temperate lakes using machine learning models. Journal of Hydrology 585, 124819.

Zhu, S., Luo, X., Yuan, X. & Xu, Z. 2020b An improved long short-term memory network for streamflow forecasting in the upper Yangtze River. Stochastic Environmental Research and Risk Assessment 1–17.

Zou, Q., Xiong, Q., Li, Q., Yi, H., Yu, Y. & Wu, C. 2020 A water quality prediction method based on the multi-time scale bidirectional long short-term memory network. Environmental Science and Pollution Research 27, 1–12.

Zuo, G., Luo, J., Wang, N., Lian, Y. & He, X. 2020 Decomposition ensemble model based on variational mode decomposition and long short-term memory for streamflow forecasting. Journal of Hydrology 585, 124776.

First received 16 June 2020; accepted in revised form 22 July 2020. Available online 5 August 2020