A Systematic Review of Deep Learning Applications in Streamflow Data Augmentation and Forecasting

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Abstract
The volume and variety of Earth data have increased as a result of growing attention to climate change and, subsequently, the availability of large-scale sensor networks and remote sensing instruments. This data has been an important resource for data-driven studies to generate practical knowledge and services, support environmental modeling and forecasting needs, and transform climate and earth science research thanks to the increased availability of computational resources and the popularity of novel computational techniques like deep learning. Timely and accurate simulation and modeling of extreme events are critical for planning and mitigation in hydrology and water resources. There is a strong need for short-term and long-term forecasts of streamflow, benefiting from recent developments in data availability and novel deep learning methods. In this study, we review the literature for studies that employ deep learning in tackling tasks that are either to improve the quality of the streamflow data or to forecast streamflow. The study aims to serve as a starting point by covering the latest developments of deep learning approaches in those topics as well as highlighting problems, limitations, and open questions with insights for future directions.

1. Introduction

Large-scale sensors, radar, and satellite networks continuously generate raw digital Earth data. This data has been transformed into relatively understandable data points for decision making, modeling, disaster preparedness, monitoring, and response (Alabbad and Demir, 2022). Long-term sustainability and resilience hinge on the effective use of massive earth data, which presents chances to revolutionize climate change governance in the coming decades (Grossman et al., 2015). It is important to use multivariate analysis in the hydrological field to make actionable models and find practical solutions to climate change monitoring (Jadidoleslam et al., 2019).

Using computational resources for hydrological modeling has been around for decades (Ramirez et al., 2022). Computers have been used to run physical models that enable people to understand natural phenomena by simulating hydrological events and changes in hydrological systems. However, hydrological systems are non-linear and complex, like many physical systems, to comprehensively understand and then conceptualize fully using mathematical and numeric representations. For this very reason, advanced statistical methods are heavily used in the field. Starting with traditional machine learning models to increasingly complex deep learning approaches, statistical models have been a go-to tool for modeling both linear and non-linear systems. Even though they are generally far too complex for the human brain to infer any reasoning from, so to say, black box systems achieve many tasks that were hard to engineer in many disciplines, from image recognition, analysis (Li and Demir, 2022) and synthesis (Gautam et al., 2020), to speech to text systems and translation. Borrowing the methodology from various other fields of application research, researchers in earth and climate sciences have also been employing deep learning methods to simulate hydrological phenomena and augmented datasets (Demiray et al., 2021).

In order to capitalize on the opportunity created by the abundance of data, the number of publications in the literature that use the big data resources has increased in tandem with the volume of Earth data. These datasets have been an important resource for data-driven studies to generate practical knowledge and services in earth science, support environmental modeling and forecasting needs, and transform climate and earth science research. This is due to the increased availability of computational resources and the popularity of novel computational techniques like deep learning. Timely and accurate simulation and modeling of extreme events are critical for planning and mitigation in hydrology and water resources (Alabbad et al., 2022). There is a strong need for short-term and long-term forecasts of streamflow for decision making (Ewing and Demir, 2021) and operational needs (Xiang and Demir, 2022a) benefiting from recent developments in data availability and novel deep learning methods. Accurate streamflow forecasts are critical for flood mapping (Hu and Demir, 2021; Li et al., 2022), damage assessment (Alabbad et al., 2021), mitigation and decision support needs (Teague et al., 2021). In this study, we review the literature that covers manuscripts that employ deep learning in tackling tasks that focus on improving the quality of the streamflow data or forecasting streamflow.

Streamflow forecasting is a crucial component of many issues in hydrology and water management, such as watershed management, agricultural planning (Yildirim and Demir, 2022), flood prediction (Krajewski et al, 2021), and many other mitigation needs (Ahmed et al., 2021; Yaseen et al., 2018; Yildirim and Demir, 2021). However, accurate and reliable forecasting is challenging due to the complexity of hydrological systems, including nonlinearity and dynamic behavior as well as randomness in the datasets (Honorato et al., 2018; Yaseen et al., 2017). Over the years, many physical and data-driven methods have been proposed with different characteristics, including using various data types, specializing in certain locations, or generalization levels (Salas et al., 2000; Yaseen et al., 2015). With the recent development in deep learning and increasing availability of various data types, the number of approaches based on data-driven methods has dramatically increased, and many of the proposed methods use deep artificial neural networks (Sit et al., 2020).

Despite the attention in the field, there are limited numbers of studies that focus on the state of current developments in streamflow forecasting in terms of the usage of deep learning while explaining problems or contradictions as well as possible solutions to overcome limitations. However, each of them has some limitations in terms of focus, time interval, scope, etc. At the dawn of deep learning, Yaseen et al. (2015) gave the epitome of machine learning usage in streamflow forecasting. Shen (2018) covered the physical sciences, geosciences, and hydroscience literature for deep learning applications. Ardabili et al. (2019) presented a brief overview of machine learning and deep learning applications in hydrological processes, climate change, and earth systems. Sit et al. (2020) focused on deep learning studies in hydroscience and water resources. Ibrahim et al. (2022) focused mostly on the use of ANNs for streamflow forecasting, along with some studies that utilized CNNs but lacked studies that built their methodology on LSTMs. Also, to the best of our knowledge, there are no reviews in the literature that cover the augmentation of streamflow datasets or interpolation of streamflow in space and time using deep learning. As a result, this study aims to serve as a starting point by covering the latest developments of deep learning approaches for forecasting streamflow or improving streamflow datasets, as well as highlighting problems, limitations, and open questions with insightful opinions for future directions.

The rest of this paper is structured as follows: In section 2, the literature survey methodology employed in this study will be described. Then, in section 3, all the papers that were classified as related to the scope will be summarized briefly. In section 4, summary statistics will be shared, findings will be presented, and some open questions in the field will be articulated.

Table 1. Deep learning keywords that were used in combination with domain specific keywords

Keywords				
adversarial	ae	ai	albert	alexnet
ann	anns	antnet	attention	autoencoder
autoencoders	backprop	backpropagation	bart	bert
bigru	bigrus	bilstm	bilstms	birnn
birnns	camembert	cbam	cnn	cnns
convgru	convgrus	convlstm	convlstms	convnet
convnets	convolution	convolutional	convrnn	convrnns
cyclegan	dbn	dcgan	deep	delugenet
densenet	distilbert	distilgpt2	distilroberta	dqn
echo state	efficientnet	effnet	electra	elman
fcn	fractalnet	gan	gans	gated
generative	googlenet	gpt	gpt2	gpt3
gru	grus	inception	intelligence	lenet
long short term	long short time	lstm	lstms	machine
megatron	mobilenet	multi layer	neural	pggan
polynet	progan	pyramidalnet	recurrent	residual network
residual networks	resnet	resnext	resunet	rnn
rnns	roberta	rubert	sae	segnet
seq2seq	sequence to	spatial network	spatial networks	spatiotemporal network
spatiotemporal networks	stylegan	stylegan2	temporal network	temporal networks
transformer	transformers	unet	vae	vec2vec
vgg	vggnet	wav2vec2	xception	xlnet

2. Methodology

In this study, Google Scholar was employed as it indexes all manuscripts from various resources, whether they be peer-reviewed or not. Manuscripts from big publishers such as Elsevier, Springer, and Wiley, as well as pre-print sources like arXiv and EarthArXiv, are listed on Google Scholar. Google Scholar has advanced search functionality where users can specify keywords and where they occur, as well as manuscript year. Thus, we decided to use keywords on Google Scholar in combination to find related articles. Two lists of keywords were curated for manuscript searches; one list is for deep learning related keywords, and the other one is for streamflow keywords. A full list of keywords can be seen in Tables 1 and 2. For each search, a keyword from each of the lists was combined for manuscripts from 2014–2021 that have both keywords in their titles. This time period was chosen for three reasons: (1) previous machine learning reviews for streamflow failed to find much deep learning research prior to 2014; (2) many cardinal deep learning architectures were introduced beginning in 2014; and (3) the most cited deep learning application studies for streamflow were published after 2014.

Table 2. Domain specific keywords related to streamflow studies that were used in combination with deep learning keywords

Keywords				
discharge	flood	ground water	hydrologic	hydrological
hydrology	inundation	land use	land use	peak flow
peak flow	river	runoff	soil moisture	stream
streamflow	surface water			

In order to automate the data extraction from Google Scholar, a Python package, scholarly, was utilized. When a search is done in scholarly, the package returns an iterator that includes all the information publicly available for each manuscript on Google Scholar that fits into the search criteria. For each manuscript, the following fields were saved: title, authors, year, venue, URL, abstract. Among the manuscripts that were acquired, a total of 8,679 unique manuscripts were left after the removal of duplicates by title and URL.

8,679 manuscripts were labeled as related or unrelated by their titles only; whenever an article had an ambiguous title that did not have an apparent focus, it was included in this initial list. At the second elimination step, each article was skimmed to extract the methodology used as well as the end goal of the study. This step was necessary to remove manuscripts that used artificial neural networks (ANNs) but couldn’t be classified as "deep learning". We define "deep learning" as the use of specific mainstream ANN architectures, namely, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) Networks (Hochreiter and Schmidhuber, 1997), Recurrent Neural Networks (RNNs), Gated Recurrent Unit (GRU) Networks (Cho et al., 2014), Autoencoders (AE), Deep Belief Networks (DBNs) (Hinton, 2009), Elman Neural Networks (ENNs) (Elman, 1993), Echo State Networks (ESNs) (Jaeger, 2007), and Generative Adversarial Networks (GANs) (Goodfellow et al., 2014). While the use of a fully connected ANN could fulfill the deep learning criteria, we made a choice to only include manuscripts when they also defined their methodology as deep learning while using more than one hidden layer in their architecture. This approach made it possible to reduce the number of manuscripts significantly to a total of 230. A list of studies reviewed in this study, along with their classification and the deep neural network architectures that were used in them, can be seen in Table A3 in Appendix.

3. Literature

In this section, we will go through individual manuscripts, starting with previous deep learning review studies that cover the scope of this study at least partially.

3.1. Review Papers

As with any field that attracts vast attention from researchers, deep learning application studies for streamflow and precipitation augmentation and extrapolation have found space in various comprehensive review studies before. Although they cover slightly fewer manuscripts than this study, they do a great job of summarizing the literature and abstracting the concept of deep learning in the earth sciences. This section summarizes other review papers in the same domain.

Yaseen et al. (2015) gave the epitome of machine learning usage in streamflow forecasting at deep learning's dawn. While their study did not include a strict set of rules regarding the "depth" of the learning, they discussed a new strategy for simulating the streamflow, a novel way for preprocessing time series frequency based on Fast Orthogonal Search (FOS) approaches, and Swarm Intelligence (SI) as an optimization approach as potential study topics. Shen (2018), on the other hand, covered the physical sciences, geosciences, and hydroscience literature for deep learning applications. The study first introduced a few key architectures, then summarized manuscripts. In contrast, Ardabili et al. (2019) presented a brief overview of machine learning and deep learning applications in hydrological processes, climate change, and earth systems. Similar to Shen (2018), Sit et al. (2020) first summarized the state-of-the-art deep learning architectures as well as example deep learning tasks to give the reader an understanding, and then they outlined each article that falls into their systematic review criteria for deep learning studies in hydroscience and water resources. In more recent review studies, Ibrahim et al. (2022) focused mostly on the use of ANNs for streamflow forecasting, along with some studies that utilized CNNs but lacked studies that built their methodology on LSTMs.

To the best of our knowledge, there are no reviews in the literature that cover the augmentation of streamflow datasets using deep learning. While the reviews and surveys above give a glimpse of mostly forecasting studies, they don't specifically cover interpolation of streamflow in space and time.

3.2. Streamflow Forecasting

Most of the studies reviewed in this study focused on streamflow forecasting. It is hard to compare the findings of these studies as they typically used separate datasets and, when they didn't, they chose to only compare their approach with other traditional machine learning and/or deep learning methods. For structuring purposes, we will categorize and review them based on their temporal resolution, including first hour (0-1hr), hourly, first day (2-23hr), monthly, and annually. It should be noted that, unless otherwise specified, a model proposed by a study is the best performing model in their comparisons.

0–1 Hour – Gude et al. (2020) developed an LSTM model that used gauge height data for the Meramec River in Valley Park, Missouri with 15-minutes of temporal resolution. Their model was more accurate than the physical models currently in use, which work in 6-hour increments. Similarly, Kim and Kim (2021) compared SVM (Support Vector Machines or Support Vector Regression), gradient boosting, and LSTMs for water stage in the Seolmacheon catchment in Korea for 10-minute increments and showed that LSTMs performed best among tested methods, marking the highest temporal resolution streamflow model that has been reviewed. Luppichini et al. (2022) developed an encoder-decoder LSTM model to forecast 24 hours of hydrometric height with 15 minutes of temporal resolution at 35 hydrometric stations using additional data from 48 rain gauges for the Arno River in Tuscany, Italy. Developing an LSTM model for the same temporal resolution Li et al. (2021b) proposed a model that focused on Brays Bayou in Houston, Texas. Their model took a time-series sequence and output the next measurement. Using the data for the same watershed, Li et al. (2021c) proposed another LSTM model for sequence-to-sequence forecasting, or in other words, for multiple step forecasts. They used 10-year precipitation from 153 rainfall gauges.

Hourly – Liu et al. (2017) integrated stacked autoencoders (SAE) with ANNs to build a model that takes advantage of values from upstream streamflow gauges. They built a model to forecast 6 hours of data using 4 hours of previous stream data and 4–7 hours of rainfall. They compared their model to SVMs, ANNs, and Extreme Learning Machines (ELMs). Similarly, Hitokoto et al. (2017) utilized SAE and ANNs to forecast the next measurement for one catchment of the Ooyodo River, one of the first-grade rivers in Japan. Wang et al. (2022) utilized deep ANNs for various basins in China. Taking it a step forward, Hikokoto and Sakuraba (2017) presented a similar neural network architecture to forecast 6 hours of streamflow for first-grade rivers in Japan; the Tokoro River and the Abashiri River. Instead of the streamflow at a certain point, their architecture outputs the change from the last measurement. In addition to streamflow data, Liu et al. (2018b) presented a context-aware attention LSTM (CA-LSTM) network for the Changhua River using data from 7 rainfall stations and 1 evaporation station. Liu et al. (2018a) extended their previous study by proposing a context and temporal-aware attention LSTM (CT-LSTM) network for flood forecasting. Using the same dataset for the Changhua River, their neural network took 24 hours of input and forecasted 6 hours of streamflow. They compared CT-LSTM to a CA-LSTM (proposed by Liu et al. 2018a), a TA-LSTM (temporal-aware LSTM), an LSTM, and a Fully Convolutional Network (FCN). Hu et al. (2018) developed two models, one ANN and the other LSTM Network, for the Fen River basin in China. They created 98 rainfall-runoff events using the raw data and used 86 of them as training data. As for the networks, they presented six different values, one for each lead time, for six hours of forecasts. In another recurrency-focused study, in their master's thesis, Rohli (2018) built an RNN to forecast streamflow. They divided the United States inland waterway system into 24 subnetworks and focused on the Atchafalaya, Lower Ohio, and Lower Mississippi subnetworks.

Utilizing another type of RNNs, Wan et al. (2019) presented their methodology based on Elman Neural Networks (ENNs) for the Xianghongdian reservoir of the Huai River in East China to forecast 3 hours of streamflow and compared the results to those of a Multi-layer Perceptron (MLP). In another study, Xu et al. (2019) built a sequence-to-sequence LSTM network for both hourly and daily streamflow in the Dadu River, China. Similar to Liu et al. (2017), Sit and Demir (2019) utilized streamflow sequences from upstream stream gauges as well as rainfall data to forecast hourly streamflow up to 24 hours for 45 stream gauges in Iowa using a GRU network. Encouraged by the literature so far on LSTMs, Ayzel (2019) explored deep learning's capabilities in rainfall-runoff modeling for the Rimbaud River basin in Collobrières, France and compared the performance to a process-based hydrological model. Investigating LSTMs in the Tunxi watershed in China, Yan et al. (2019), forecasted 6 hours of streamflow and compared LSTMs' performance to SVM's. For both hourly and daily streamflow forecasts, Ni et al. (2019) went for a deeper neural network that is LSTM-based. In contrast with studies mentioned so far, Chen et al. (2019) presented a convolutional approach where they model rainfall-runoff for the Xixian River Basin in Henan Province, China.

Xiang et al. (2020) explored how deep learning could be used in streamflow forecasting by employing an encoder-decoder sequence-to-sequence LSTM network for two watersheds in Iowa. They incorporated upstream information as well for better forecasts. Based on that, Xiang and Demir (2020) extended the model to cover 125 USGS sensors in Iowa. Wei (2020) took a different direction in terms of the data used. They incorporated radar reflectivity images as opposed to using time-series rainfall information in their LSTM and ANN models for forecasting streamflow up to 6 hours during typhoons. Unlike previous research, Kimura et al. (2019) explored transfer learning for flood forecasting to overcome data limitations using CNNs. As case studies for the Klang River basin, Malaysia, Faruq et al. (2020a) utilized LSTMs and Faruq et al. (2020b) compared them to a Radial Basis Function Neural Network (RBFNN). Kao et al. (2020) presented an encoder-decoder LSTM network for Shihmen reservoir in Taiwan for forecasts up to 6 hours. They claimed theirs is the first ever study that employs encoder-decoder sequence-to-sequence LSTMs in flood forecasting, but our review shows that they missed the study by Xiang et al. (2020) which was published before their study. In another case study for Henan, China, Song et al. (2020) utilized LSTMs for up to 10 hours of forecasts. In an attempt to build an IoT device that is able to forecast floods, Samikwa et al. (2020) developed an LSTM network that works on a low-power device to forecast streamflow for up to 10 hours in Melbourne, Australia.

Ding et al. (2020) employed LSTMs with spatial and temporal attention for basins in China and compared the network to CNNs, Graph Convolutional Networks (GCNs), LSTMs, spatial attention LSTMs, and temporal attention LSTMs. In a step beyond using LSTMs, Miau et al. (2020) proposed using Convolutional GRU networks and compared them to ANNs, CNNs, and LSTMs. They also proposed a similar neural network for anomaly detection in streamflow time-series. In a thesis to explore deep learning for streamflow in Germany, Fiedler (2020) presented an LSTM network that used nine different meteorological parameters. They then compared the model to a physically based Large Area Runoff Simulation Model (LARSIM). In other studies that employed LSTMs for watersheds in China, while Hu et al. (2020) and Gao et al. (2020) compared their findings to those of other machine learning models, Liu et al. (2020b) compared their model to the Xinanjiang model (XAJ), which is a hydrologic model in active use. While employing Temporal Convolutional Networks (TCNs), Lin et al. (2020) inferred that both in TCNs and encoder-decoder TCNs, forecast horizon has a significant effect on forecast accuracy. Kim and Han (2020) followed a different approach. They surveyed rainfall data and mapped rainfall into total accumulative overflow calculated from Storm Water Management Model (SWMM) simulations in Korea.

While Hadji (2021) employed CNNs for forecasts up to 6 hours, 12 hours, and 24 hours using streamflow data, Wang et al. (2021a) similarly utilized CNNs for the Tunxi watershed in Anhui Province, China by feeding 2D streamflow and rainfall matrices into the network. Also, Xu et al. (2021c) utilized CNNs to simulate runoff in the ZheXi reservoir in Hunan Province, China. In another convolution-based study, Xu et al. (2021b), used TCNs to simulate hourly rainfall-runoff and showed that TCNs perform better than LSTMs and the Excess Infiltration and Excess Storage Model (EIESM) for Jingle and Kuye watersheds in China. Coupling CNNs with LSTMs for Japan, Ishida et al. (2021a) developed a model for the Ishikari River watershed. They used a meteorological dataset that consists of precipitation, air temperature, evapotranspiration, and long- and short-wave radiation. Furthermore, Ishida et al. (2021b) proposed two effective methods to decrease the computation time in LSTM models where streamflow forecasting is the aim. Similarly, Nakatani et al. (2021) combined RNNs with CNNs to model streamflow using rainfall distribution data (XRAIN) for the Katsura River basin, Kyoto, Japan. Moreover, Chen et al. (2021a) developed Integrated Flood Analysis System (IFAS) model to simulate runoff in the Tokachi River, Japan. They trained an LSTM model to forecast hourly rainfall and then a flood prediction model by inputting the rainfall data forecasted by the LSTM model. As a case study for the Andun basin of China, Lin et al. (2021) combined First-order Difference (DIFF), ANNs, and LSTMs and compared the proposed model to the various combinations of these three approaches.

As literature so far suggests, LSTM models for hourly streamflow forecasting are in abundance. However, there are still many studies that deserve mention. In one of those studies, Xiang et al. (2021) proposed a sequence-to-sequence encoder-decoder LSTM network that works for 125 USGS sensors in Iowa. They input 72 hours of data, including evapotranspiration and precipitation, to predict 120 hours of discharge. They also proposed a generalized model that was trained on some of the sensors in their dataset and tested on the remainder of the sensors. In a similar fashion, Han et al. (2021) employed a sequence-to-sequence LSTM network for hourly forecasts up to 6 hours for the Russian River basin, California. They showed that their model outperforms SVMs and straightforward LSTM models. In a master's thesis, Zocholl (2021) proposed two models: a multi-shot sequence-to-sequence and an encoder-decoder architecture based on LSTMs that take 96 hours of input and output 24 hours of streamflow for the Regen catchment in the Upper Palatinate in Bavaria, Germany. Utilizing satellite precipitation products, Tang et al. (2021) trained an LSTM network for a poorly gauged mountainous catchment in southwestern China. Relatedly, Shuofeng et al. (2021) presented an LSTM network for the precipitation-only hourly water level forecasting problem for up to 6 hours in Japan. While Li (2021) discussed the problem of streamflow forecasting without streamflow data, considering rainfall as well, in their thesis, Yan et al. (2021b) presented an attention-powered LSTM network for 12 hours of prediction for the Tunxi watershed, China using all related weather data. In another study, Le et al. (2021a) used GRU networks for four hydrological stations on the Geum River, South Korea. Finally, Chen et al. (2021b) converted rainfall data into a graph to extract the spatial characteristics of rainfall using remote sensing images. Their methodology employed LSTMs for flood forecasting using graph data and streamflow.

Graph Neural Networks (GNNs) have limited applications in the literature. Sit et al. (2021a) employed a Graph Convolutional GRU-based model to predict the next 36 hours of streamflow for a sensor location using the upstream river network in Iowa. Likewise, Xiang and Demir (2021) proposed the Graph Neural Rainfall-Runoff Model (GNRRM) and presented a fully distributed GNN (Xiang and Demir, 2022a) and found that, in comparison with baseline models, their model significantly improves model performance in an Iowa watershed. In another approach, Feng et al. (2021b) employed spatial and temporal aware Graph Convolution Network (ST-GCN). They combined Graph Convolutional Networks (GCNs) and LSTMs for flood prediction for the Tunxi and Changhua river datasets.

2–23 Hours – Studies that tackle streamflow forecasting for temporal resolutions that are more than an hour but less than daily are rather limited. As in correlation with reviewed papers so far, these studies mostly use some sort of RNNs, if not LSTMs. Ding et al. (2019) used 10 distinct environmental and meteorological characteristics to develop a spatial- and temporal-attention LSTM (STA-LSTM) model for the Lech river basin in Europe, covering May 2002 to January 2018 with 3-hour increments. Taking over the methodology from them, Wu et al. (2020) trained the STA-LSTM for the Lech and Changhua river basins with a temporal resolution of 3 hours and compared it to XAJ and other machine learning models. They showed that even though XAJ performs better, STA-LSTM outperforms other machine learning models and shows promise in flood forecasting. Similarly, for 3-hours of increments, for a relatively smaller watershed in Seoul, Korea, Nguyen and Bae (2020) trained LSTMs with LSTM-corrected precipitation products.

For 6-hours of increments, Le et al. (2019) trained a GRU network for the downstream of the An Tho irrigation culvert on the Luoc River, Vietnam to predict water level up to four time-steps. Zhou et al. (2020) utilized an unscented Kalman filter (UKF) to postprocess RNNs and ANNs for the Three Gorges Reservoir in China. Quite differently, using a different neural network structure, Gamma Memory Neural Networks, Agarwal et al. (2021) presented multiple input-multiple output (MIMO) and multiple input-single output (MISO) structures to forecast streamflow in the Tar River Basin, United States.

Daily – As daily streamflow forecasting using deep learning is in abundance in the literature, this subsection is the most lengthy part of this study. As mentioned before, our data acquisition did not yield many manuscripts that used the same data, but there is one benchmark dataset, Catchment Attributes and Meteorology for Large-sample Studies (CAMELS) (Newman et al., 2015), that is a daily streamflow analysis dataset, and it was employed by some of the daily streamflow forecasting studies. Thus, in order to provide a more manageable structure, we will review papers that utilize CAMELS separately.

Daily streamflow forecasting appears earlier than its hourly counterparts in the literature, going as far back as 2015. Manavalan and Bynagari (2015) trained an LSTM model on 516 basins in the United States. In parallel, Kim and Seo (2015) built an RNN-powered ensemble model with exploratory factor analysis (EFA) for three stations in the Nakdong River, Korea. Mhammedi et al. (2016) similarly trained various RNNs for two different stream flow datasets in Tasmania and compared RNNs to SVM. Conversely, Li et al. (2018) employed CNNs for the Luo River Basin, Guangdong Province, China. They show that their model outperformed the XAJ model for 1-day, 3-day, and 5-day forecasts. In an attempt to explore echo state networks in streamflow forecasting, Bahrami and Wigand (2018) compared their model to the adaptive neuro fuzzy inference system (ANFIS) and found that ANFIS performs better using climatic observation data. With a similar motivation, Tian et al. (2018) applied ENNs, ESNs, nonlinear autoregressive exogenous input neural network (NARX), and LSTMs to the Xiangjiang and Qujiang River basins in China. Their results showed that the LSTM and NARX performed better on their data.

Utilizing ESNs, Wigand and Bahrami (2018) presented a framework to forecast daily streamflow at ungauged locations.

In 2019, usage of LSTMs in daily streamflow forecasting gained momentum. Damavandi et al. (2019) for Brazos basin in Texas; Le et al. (2019c), for Da River basin in Vietnam; Le et al. (2019b) for Red River, Vietnam; Sudriani et al. (2019) for Leuwilisung and Tegaldatar in Indonesia; Aljahdali et al. (2019) for Black and Gila rivers in the US; Campos et al. (2019) for the Paraíba do Sul River, Brazil utilized LSTMs. Similarly, Liao et al. (2019) used historical precipitation, meteorological, and hydrological data for runoff modeling up to 2 days. They conclude that even though LSTMs outperformed the XAJ model, they were not good enough for their dataset. In another study, using predicted meteorological parameters, Li and Yang (2019) proposed an LSTM network with an attention mechanism for streamflow at Xingzi Station, China. Afzaal et al. (2019) presented a comparative study of the Baltic River and Long Creek watersheds in Prince Edward Island, Canada. They compared ANNs, LSTMs, and CNNs. Similarly, Feng et al. (2019) proposed an LSTM network with spatio-temporal attention and compared it to auto-regressive integrated moving average (ARIMA), ANNs, SVMs, DBNs, LSTMs, and context-aware LSTMs. Wang and Lou (2019) also proposed an LSTM network that is powered by wavelet de-noising and ARIMA. In their approach for the Chuhe River Basin, China, the prediction error of the ARIMA model is forecasted by the LSTM network and utilized to correct the ARIMA model's forecast result. In one of the rare studies that utilized DBNs, Li et al. (2019) forecasted daily streamflow at Zhangshu Hydrological Station, China. Furthermore, Djikstra (2019) trained a TCN for the Rhine River in Western Europe and compared it to an operational hydrological model. Combining Variational Mode Decomposition (VMD) with ANNs, He et al. (2019) modeled streamflow at Zhangjiashan Hydrological Station in the Jing River, China. Finally, Cherki (2019) utilized a deep ANN for daily streamflow at the Oued Isser watershed located in North Western Algeria.

Agena et al. (2020), for forecasts up to 8 days, compared streamflow predictions by a process-based Soil and Water Assessment Tool-Variable Source Area model (SWAT-VSA), an ANN, an ARIMA model, and a Bayesian ensemble model that combines the SWAT-VSA, ANN, and ARIMA. They presented that SWAT-VSA and ANN showed better performance for the sub-watershed of the Mahantango Creek, Pennsylvania. Qian et al. (2020) improved their loss function for their sparse autoencoder model with the inverse method of simulated annealing (ESA) for the runoff of the Kenswat Station in the Manas River Basin in northern Xinjiang, China. In DBN-based studies from 2020, Kinh et al. (2020) for the Srepok River in the Central Highlands of Vietnam, compared a SAE model to a DBN model that showed similar performance. Zhan et al. (2020) incorporated variational inference into the BNN model and proposed a variational Bayesian neural network (VBNN) model for ensemble daily mean flood forecasting. Various studies utilized many RNN structures. Prabuddhi and Seneviratne (2020) offered a recurrent neural network model for water level prediction in Deduru Oya, Sri Lanka, taking into account rainfall, temperature, evaporation, and historic water level. Likewise, Bi et al. (2020) proposed CAGANet, a neural network architecture consisting of a convolutional layer, an attention mechanism, and a GRU network. They compared their model to LSTMs and attention LSTMs for southwest China. On the other hand, Wang et al. (2020) used single-directional and bi-directional GRU networks for the Wei River basin in Shaanxi, China, for 1-day and 2-day forecasting.

The number of LSTM-based studies continued to increase in 2020. While Zhu et al. (2020) combined LSTMs with the gaussian process for the upper Yangtze River, China, for up to 5 days of forecasts, Zuo et al. (2020) coupled VMD with LSTMs for up to 7 days of forecasts in the Han and Jing Rivers, China. Similarly, Lama and Sánchez (2020) utilized VMD along with Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) with LSTMs for the Chira River, South America. Furthermore, Fan et al. (2020) trained an LSTM for the Poyang Lake Basin for 15 days of forecast horizon and compared their results to those of the Soil & Water Assessment Tool (SWAT) and an ANN. Using SWAT data in a different scope, Khandelwal et al. (2020) trained an LSTM to model SWAT with deep learning. To explore LSTMs in a tropical setting, Fu et al. (2020) trained a network for the Kelantan River, Malaysian Peninsula. Their tests showed that LSTMs outperformed ANNs for 100 and 300 days of forecasts. In an attempt to amplify streamflow forecasting with LSTMs, Feng et al. (2020a) explored data integration options to preprocess streamflow data before training any network with it and found that some methods increase the performance for basins with low discharge volumes. Modeling streamflow for a Himalayan basin that is typically affected by snowmelt, Thapa et al. (2020), used precipitation, temperature and snow products for 1 day ahead forecasts.

In other studies, Ayzel et al. (2020) for 200 basins in Northwest Russia; Chen et al. (2020) for the Mississippi River Basin, the US; Xu et al. (2020) for the Hun River and Upper Yangtze River basins in China; Lee et al. (2020) for Kratie station on the Mekong River, East Asia explored LSTMs. Compared to CNNs, Van et al. (2020) trained a 1D CNN for Chau Doc and Can Tho stations in Vietnam. They showed that CNNs performed slightly better than LSTMs for up to four days of forecasts. Due to the nature of time-series data, usage of 1D CNNs is not limited to Van et al. (2020). Similarly, while Hussain et al. (2020) applied CNNs to the Gilgit River, Pakistan for 1-day forecasts, Barino et al. (2020) trained a 1D CNN for the Madeira River, Amazon for multi-day streamflow prediction. Going beyond the data needs of studies so far, Song (2020) trained a CNN that needs rainfall, runoff, soil map, and land use data for daily average streamflow at Heuk River Bridge, South Korea. Finally, Huang et al. (2020) explored transfer learning for daily streamflow forecasts in the United Kingdom.

Integrating a Fuzzy C-means (FCM) clustering approach into a DBN, Chu et al. (2021b) trained a network for three stream gauge stations in the US. Similarly, Nguyen et al. (2021) modeled daily runoff for the Srepok and Dak Nong rivers from mountainous regions in Vietnam employing DBNs. They showed that DBNs outperformed LSTMs, BiLSTMs, and ANNs. In a rare attempt, Li et al. (2021d) tackled the daily streamflow forecasting problem by coupling GANs with a fuzzy inference system for the Huaihe River, China. In a comparative study, Zounemat-Kermani et al. (2021) explored ANNs and RNNs for daily streamflow in the Thames River, United Kingdom.

The rest of the studies from 2021 for daily streamflow modeling were mostly LSTM focused. In mostly basin-specific studies, Latif and Ahmed (2021) for the Kowmung River at Cedar Ford in Australia; Luu et al. (2021a, 2021b) for the Thu Bon-Vu Gia catchment, Vietnam; Yokoo et al. (2021, 2022) for the Ishikari River watershed in Japan; Li et al. (2021e) for the middle Yangtze River, China; Hashemi et al. (2021) for 740 gauges in France; Kwak et al. (2021) for the Hyeongsan River basin, South Korea; Zakhrouf et al. (2021) for two stations in Algeria; Rahimzad et al. (2021) for a station in Kentucky, US; Chen and Xu for the Dadu River Basin, China; Chen and Qiao (2021) for the Nanjing River, China; Kim and Kim (2021) for the Yeongsan River basin, South Korea; Wang et al. (2021b) for the Tunxi Basin, China utilized LSTMs.

In one of the ensemble model studies, Mirzaei et al. (2021) coupled LSTMs with Principal Component Analysis (PCA) for the Samarahan and Trusan river basins, Malaysia. Using PCA as well, Lian et al. (2021) utilized Bayesian optimization (BO) and LSTMs for the Yellow River, China. Similarly, Wang et al. (2021e) combined VMD, particle swarm optimization (PSO), and LSTMs for the Yellow River in China. In another PSO study, Feng et al. (2021c) built an ensemble of layer normalization, LSTMs, and PSO for the Jiulong River Basin in Fujian Province, China. Zhang et al. (2021) combined PCA with GRUs and LSTMs separately for the Muskegon River and the Pearl River, China, and showed that integrating meteorological data into the training increases the accuracy. Yuan et al. (2021) and Xiao and Wang (2021) employed EEMD with LSTMs. Ji et al. (2021) employed GRUs with Random Forest, Whale Optimization Algorithm (WOA) and Optimal Variational Mode Decomposition (OVMD) for daily streamflow of the Minjiang river basin in China.

Among comparative studies, Guo et al. (2021) trained LSTMs, GRUs, and SVMs for 25 reservoirs in China and concluded that even though LSTMs and GRUs performed similarly, GRUs trained faster. Similarly, Nath et al. (2021) compared LSTMs and GRUs for the Dikhow river basin in India and showed that both architectures shared the same outcome. Le et al. (2021b) trained ANNs, LSTMs, GRUs, and BiLSTMs for the Red River basin in Vietnam and found that more complex networks do not always mean better accuracy. Roy et al. (2021) compared an Extreme Learning Machine (ELM) to an ANN. In another ELM study, Yeditha et al. (2021) compared ELMs to LSTMs over two basins in India. For two different climatic regions, Adikari et al. (2021) compared CNNs, LSTMs, and Wavelet-ANFIS (WANFIS). They fed their models with 7 days of data to forecast the next day. In their comparative study for different temporal resolutions, Mao et al. (2021) concluded that while ANNs are better for monthly forecasts, LSTMs are better for daily forecasts. In a more comprehensive comparison of physically-based models and data-driven models, Kim et al. (2021) compared Sacramento Soil Moisture Accounting (SAC-SMA), XAJ, and Coupled Routing and Excess Storage (CREST) to ANNs and LSTMs. They concluded that data-driven models have great potential for generalized models. Similarly, Jia et al. (2020) employed a recurrent graph model and compared it to a physical model and LSTMs for the Delaware River Basin. In a study with a larger spatial length, Althoff et al. (2021) trained an LSTM network that uses meteorological features as well as static watershed features for 411 watersheds in Brazil. In an attempt to make understandable deep learning models for streamflow, Bhasme et al. (2021) proposed a framework inspired by hydrological models. The framework combines empirical questions with data-driven models such as LSTMs and SVMs. For an urban use case, Liu et al. (2021) trained an LSTM for rolling forecasts of water levels.

Bai et al. (2021b) proposed an LSTM with a cascade framework that used precipitation and evapotranspiration for the Ljubljanica River. Implementing an attention-based LSTM, Alizadeh et al. (2021) presented an approach that they compared to the National Weather Service's operational streamflow models. They also compared their approach to many machine learning models, namely, gradient boosting, LSTMs, and GRUs, for seven-day-ahead forecasts. Similarly, for the Hanjiang River basin of China, Liu et al. (2021) proposed a convolutional attention LSTM. They compared their approach to ConvLSTMs, LSTMs, and TA-LSTMs. In another ConvLSTM study, Wegayehu and Muluneh (2021) compared ANNs, LSTMs, ConvLSTMs, ConvGRUs, and GRUs for the Awash River Basin in Ethiopia and the Tiber River Basin in Italy. Likewise, Ghimire et al. (2021) employed ConvLSTM at the Brisbane River and Teewah Creek, Australia. Utilizing the spatial awareness of CNNs, Song (2022) used land cover maps and hydrologic soil group maps as well as rainfall and historic streamflow.

In a hydro plant focused study, de Faria et al. (2021) explored ANNs for a case study with 55 hydro plants in the Paraná Basin, Brazil. Their trained ANN takes 30 days of input and forecasts 14 days of streamflow. In addition to ANNs, Shu et al. (2021) utilized CNNs for Huanren Reservoir and Xiangjiaba Hydropower Station, China. In an LSTM-based study, Silva et al. (2021) created an ensemble model with three LSTM networks for the Madeira River in South America. Similarly, Lee and Kim (2021) proposed a sequence-to-sequence bidirectional LSTM network using meteorological datasets for daily forecasting of streams with dam influences.

CAMELS – Beside the original benchmark dataset, CAMELS, a Brazil version CAMELS-BR (Chagas et al., 2020) and the Great Britain version CAMELS-GB (Coxon et al., 2020) is used in the literature. Quiñones et al. (2021) trained LSTMs for 32 watersheds in Brazil using CAMELS-BR. Lees et al. (2021), on the other hand, employed entity-aware LSTMs (EA-LSTMs) to simulate discharge at 669 watersheds in Great Britain, using CAMELS-GB, comparing the model to a vanilla LSTM model.

Kratzert et al. (2018a) trained LSTMs for 241 watersheds in the CAMELS with snow influence. Similarly, Kratzert et al. (2018b), Lotsberg (2021), Yin et al. (2021a) and Feng et al. (2021a) utilized LSTMs for streamflow forecasting in ungauged locations. Then, in Kratzert et al. (2019b) they generalized LSTMs for 531 watersheds in the CAMELS. In Kratzert et al. (2019a) they showed how LSTMs interpretably performed in two specific watersheds in the CAMELS. In Nearing et al. (2020a), they proposed an LSTM network for 447 basins in the CAMELS and compared their approach to physical streamflow models. On the other hand, Boulmaiz et al. (2020) tested LSTMs over 20 watersheds in the Camels with diverse characteristics. In a structurally different approach, Duan et al. (2020) employed TCNs for long-term daily streamflow forecasts in California. Utilizing LSTMs again, Ouyang et al. (2021) looked for answers to three questions: (1) How effectively can LSTMs estimate long-term streamflow for basins in the CAMELS with only publicly available basin information? (2) How differently do basins with and without different-sized reservoirs behave in streamflow? (3) What types of reservoirs can and cannot be successfully modeled in a lumped fashion? Nearing et al. (2021) explored two options with LSTMs: autoregression and variational data assimilation. They concluded that autoregression outperforms variational data assimilation on the CAMELS data. In another study, Frame et al. (2021a) explored LSTMs for extreme streamflow events over 671 watersheds in the CAMELS.

Wang and Karimi (2021) focused on two watersheds in the CAMELS using the spatial distribution of rainfall data in a network that consists of an LSTM layer and 1D CNNs. They trained the network with different look-back window lengths. With another focus, Sadler et al. (2021) employed LSTMs for daily average temperature and streamflow from CAMELS. Xie et al. (2021) added synthetic samples to the training dataset for a physics-guided LSTM network for 531 watersheds in the CAMELS. Developing a sequence-to-sequence model with multiple state vectors for each timestep in the future, Yin et al. (2021b) trained LSTMs for 673 basins in the CAMELS. Gauch et al. (2021) presented two multi-timescale LSTM (MTS-LSTM) architectures that forecast various timeframes simultaneously within a single model. In their thesis, Fill (2021) supplied ranges where the discharge values are likely to be found as well as plain values to RNNs for streamflow forecasting over the CAMELS data. In comparison to LSTMs and GRUs, the influence of calibration data quantity on the accuracy of a conceptual hydrological model, GR4H, was investigated by Ayzel and Heistermann (2021). To understand precipitation products’ effects on forecasts, Kratzert et al. (2021) used multiple products to improve the accuracy of LSTMs. Finally, Sun et al. (2021) did a comparison study of different graph neural network architectures, like ChebNet, Graph Convolutional Network (GCN), and GraphWaveNet.

Monthly & Annual – Compared to hourly and daily, the literature on monthly streamflow forecasting is rather limited. In one of the earliest studies, Siqueira and Luna (2015), utilized ESNs to study the effects of the Sobradinho hydroelectric plant on streamflow. Ghose et al. (2018) modeled monthly streamflow for Rengali, Odisha, India by training an RNN with rainfall, temperature, humidity, and evapotranspiration data along with runoff. Ensembling LSTMs with the Ant Lion Optimizer (ALO), Yuan et al. (2018) trained a network for the Astor River basin, Pakistan. In an RNN study, Belotti et al. (2018) modeled monthly streamflow that is affected by Brazilian hydroelectric plants. In 2019, deep learning applications for monthly streamflow took advantage of RNNs. Samantaray et al. (2019) trained three methods for the Loisingha and Saintala watersheds: an ANN, an RNN, and an RBFNN. Their results suggested that different architectures could be a better fit for different watersheds. Similarly, Ghose (2019) compared ANNs and RNNs for the Dhankauda watershed of Sambalpur, Odisha, India and showed that RNNs outperformed ANNs for their data in monthly streamflow forecasts.

In 2020, Rice et al. (2020) trained a deep ANN with precipitation, evapotranspiration, and temperature for 2,731 watersheds in the conterminous United States. They compared their method to some machine learning algorithms such as SVMs, linear regression, and extreme gradient boosting. In a comparative study, Kanyama et al. (2020) trained LSTMs, GRUs, and ANNs for North West Namibia. Ensemble models were widely utilized as well. Sibtain et al. (2020) combined Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN), VMD, and LSTMs. They compared the performance of that ensemble to that of LSTM models with only ICEEMDAN and VMD separately, as well as vanilla versions of LSTMs and GRUs. Chu et al. (2020) built an ensemble based on DBNs with the Least Absolute Shrinkage and Selection Operator (LASSO) and FCM. Similarly, Yue et al. (2020) integrated DBNs with Partial Least-Squares Regression (PLSR) for the Yalong River in the Tibetan Plateau. Training an ensemble LSTM network with EMD, Liu et al. (2020a) forecasted long-term monthly streamflow for Hankou Hydrological Station on the Yangtze River, China. Likewise, Ni et al. (2020), trained two LSTM networks; one with wavelet transform and the second is a ConvLSTM. Along with streamflow for Cuntan and Hankou stations in the Yangtze River basin, their study also conducted a case study for rainfall at Jinan and Wenjiang stations in China. In other RNN studies, Long et al. (2020) for Zhutuo Hydrological Station, China; Rivero et al. (2020) for Cordoba, Argentina, utilized LSTMs. Similarly, Lv et al. (2020) employed LSTM Cyclic (LSTMC) for monthly streamflow in the Xixian basin, China.

With a comparative focus, Hussain et al. (2021) trained various RNNs, LSTMs, CNNs, and ANNs to show that neural networks are good fits for monthly streamflow forecasts. Similarly, Ha et al. (2021) compared LSTMs, ConvLSTMs, Encoder-Decoder LSTMs, Encoder-Decoder GRUs, and Encoder-Decoder ConvLSTMs with the El Niño–Southern Oscillation (ENSO) approach for the Yangtze River, China. Ouma et al. (2021) compared wavelet ANNs and LSTMs in rainfall runoff modeling for the Nzoia River basin, Kenya. The rest of the manuscripts from

2021 were mainly for ensemble models. Sibtain et al. (2021) combined ICEEMDAN, VMD, and GRUs. Likewise, Yan et al. (2021a) trained models with ICEEMDAN and VMD but combined them with various LSTMs and CNNs for the Wei River Basin of China. Zhao et al. (2021a) also utilized ICEEMDAN and GRUs, combining them with the Improved Grey Wolf Optimizer (IGWO). They compared the ensemble approach with ELMs, SVMs, and vanilla GRUs. Utilizing IGWO, similarly, Zhao et al. (2021b) trained a GRU network for the Shangjingyou station in China. Güneş et al. (2021) combined Discrete Wavelet Transforms (DWT) and ANNs for the Çoruh river basin of Turkey. For 6 stream gages in the Murray Darling Basin, Australia, Ahmed et al. (2021) trained an LSTM network coupled with the Boruta Feature Selection algorithm (BRF). In an approach to modeling Tangnaihai and Zimenda hydrological stations in the Three-Rivers Headwaters Region in China, Chu et al. (2021a) trained a network that is powered by LASSO and DBNs. In a hydropower focused study, Wang et al. (2021c) explored GRUs with five data preprocessing approaches, namely, VMD, Wavelet Packet Decomposition (WPD), Complete Ensemble Empirical Mode Decomposition with adaptive noise (CEEMDAN), Extreme-point Symmetric Mode Decomposition (ESMD), and Singular Spectrum Analysis (SSA) for two hydropower stations in China. With a relatively simpler workflow, by training an ensemble of autoencoders and SVMs, Abbasi et al. (2021) improved streamflow forecasts for the Bookan Dam in Iran. Finally, Apaydin et al. (2021) employed SSA and Seasonal-Trend decomposition using LOESS (STL) for the Nallihan River, Turkey. Their approach coupled SSA and STL with ANNs, LSTMs, and CNNs to compare them to vanilla versions of those networks.

Studies of annual streamflow are rather limited. Zhang et al. (2018) coupled ENNs and EEMD for four main rivers in the Dongting Lake basin, China. They compared their approach to ANNs and ENNs. While Fang et al. (2021) built a vanilla LSTM model for CAMELS data, Wang et al. (2021d), similar to Zhang et al. (2018), utilized several decomposition options as well as residual connections in their LSTM model for 7 watersheds in China, comparing the model to ANNs, LSTMs, and ANFIS.

3.3. Forecast Improvement

We define streamflow forecast accuracy improvement as feeding deep learning models with the output of actual hydrological models. For 30 minutes of temporal resolution, Alperen et al. (2021) developed an ANN that was fed by the outputs of a hydrological model, RS Minerve. In a study for large watersheds in Japan, Hitokoto and Sakuraba (2020) fed the outputs of an hourly hydrologic model into a deep ANN and showed that the model accuracy could be improved by utilizing various statistical models. Similarly, for hourly forecasts, Li and Wu (2020) trained LSTMs with the output of the Excess Infiltration and Excess Storage (EIES) model and showed that an ensemble of EIES-LSTM worked better than LSTM-AutoRegressor and LSTM-ARIMAX (Autoregressive Integrated Moving Average with Explanatory Variable) ensembles. Cho and Kim (2021) coupled the Weather Research and Forecasting hydrological modeling system (WRF-Hydro) with LSTMs for hourly streamflow modeling. In a study that focused on a different temporal resolution of 3 hours, Cui et al. (2021) improved streamflow forecasts of the XAJ model with LSTMs.

The Model Parameter Estimation Experiment (MOPEX) is a dataset with physical model estimations that is widely used in the field of hydrology. Using MOPEX data for 10 basins, Muhammad et al. (2020) employed LSTMs and compared the results to LSTM-only and GRU-only modelling. In 278 basins, Bai et al. (2021a) developed an LSTM for daily streamflow and compared the approach to two hydrological models. In one of the infrequent studies, Mamani (2021) employed ESNs for monthly discharge data from the MOPEX data set. Similar to Bai et al. (2021a) in terms of temporal resolution, Yang et al. (2019) improved the accuracy of Global Hydrological Model (GHM)-based flood simulations with LSTMs. In CAMELS based daily streamflow corrections, Nearing et al. (2020b) and Frame et al. (2021b) improved the Sacramento Soil Moisture Accounting (SAC-SMA) Model with Snow-17 and the United States National Water Model (NWM) with LSTMs, respectively.

3.4. Other Studies

Aside from streamflow forecasting, there are not many studies that utilize hydrologic time-series in deep learning, including data imputation, segmentation, and generation. In one of the studies that did, Hamzah et al. (2021) trained an RNN to fill in missing values in streamflow data. Proposing a segmentation approach, Feng et al. (2020b) utilized LSTMs to detect effective sequences in hydrologic time-series data. Similarly, Kulanuwat et al. (2021) trained LSTMs for outlier detection and Li et al. (2021a) to model residual errors in hydrologic sequences. Finally, Ma et al. (2022) proposed a GAN to generate runoff sequences to augment datasets.

4. Results and Discussions

This review paper can be seen as a successor to another review that was done two years ago, focusing mainly on streamflow forecasting and datasets. In Sit et al. (2020), a more comprehensive set of fields through some big publishers' web catalogs was reviewed. The cardinality of the manuscripts reviewed then was not as great as the number of papers we have reviewed in this study. That was mainly due to the fact that the number of deep learning application papers is increasing drastically every year, and we can also speculate that it was because the literature is slightly larger than the scope of large publishers, especially when it comes to deep learning, since pre-print services (i.e., Arxiv, EarthArxiv) play a huge role in accessibility to deep learning research.

In this section, we provide an overall summary of the review, and the results inferred from this review study. We will start by sharing some summary statistics that would help the understanding of the field of deep learning applications in streamflow. In the Findings subsection, we will present our observations regarding the status of the literature: how it has changed beyond the statistics and how it could change. Then we will list some open questions.

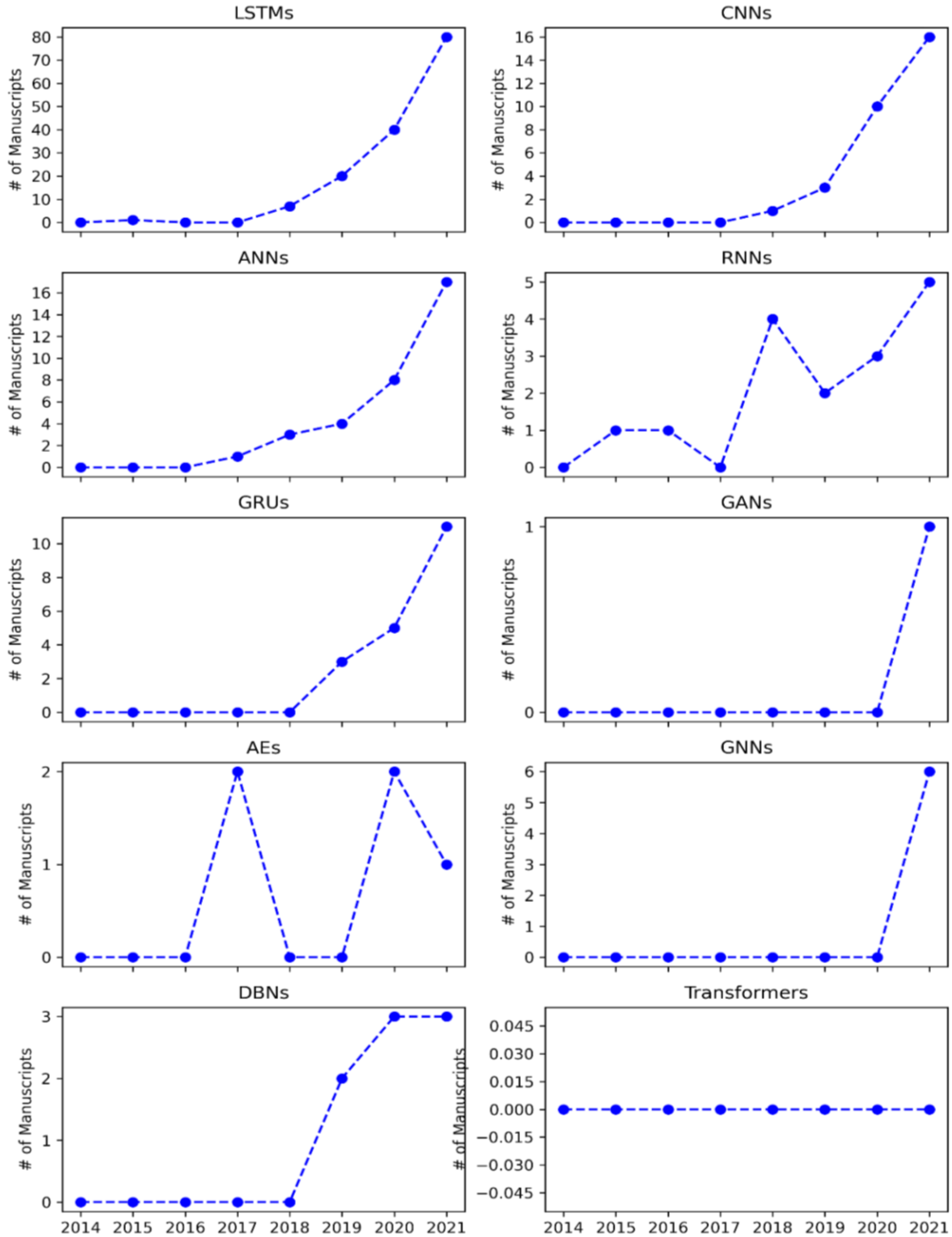

Figure 1. Distribution of architecture uses over the years.

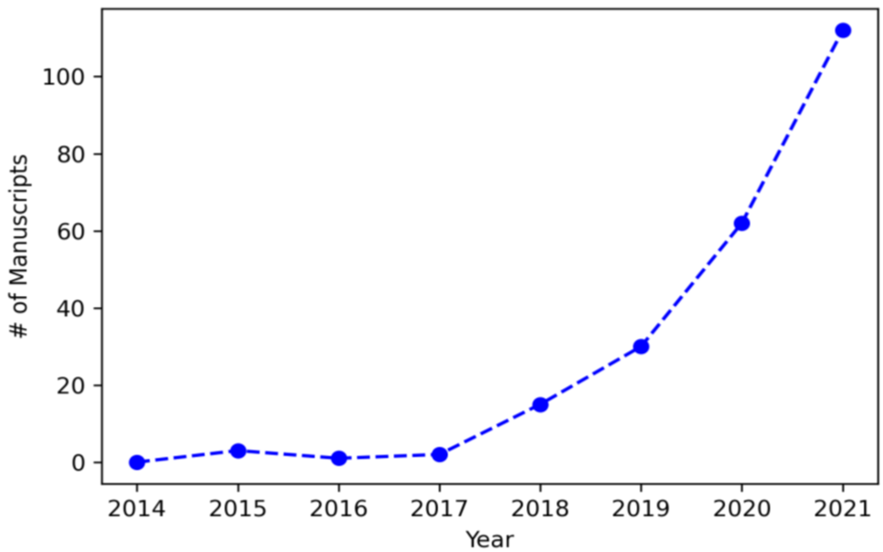

Figure 2. Number of manuscripts (by year) using deep learning for streamflow forecasting.

4.1. Summary Statistics

To understand patterns in the literature, we present here some findings using figures. Figure 1 shows how the use of the most commonly utilized architectures in deep learning is distributed over manuscripts and years. Similarly, in Figure 2, the number of manuscripts by year dealing with streamflow data augmentation and forecasting is presented. As shown in the figure, the cardinality of studies increased dramatically in 2017 and onwards.

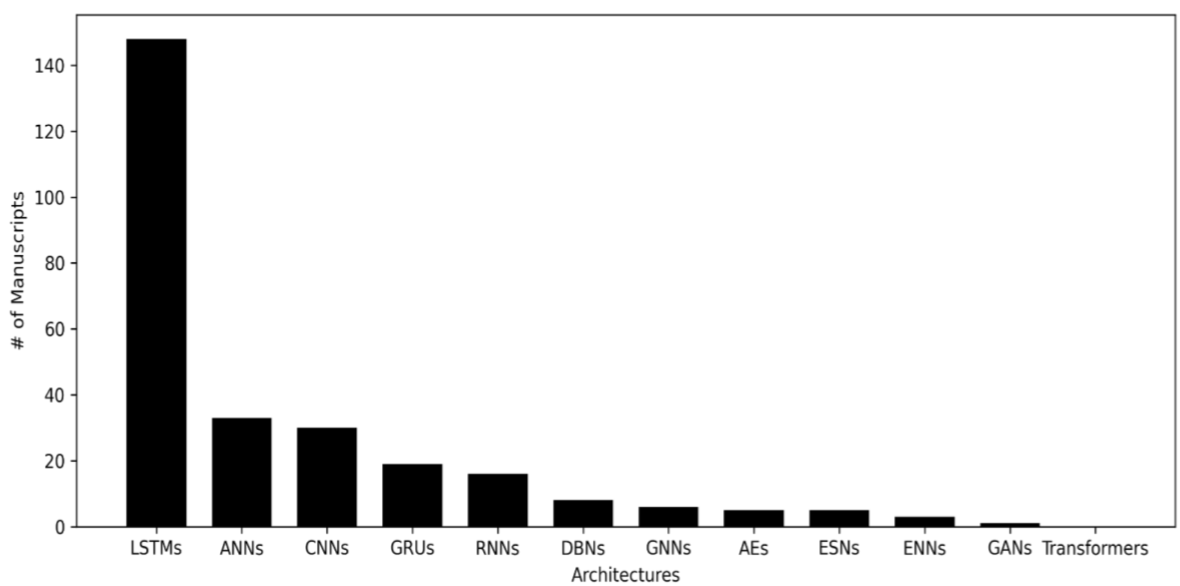

Figure 3. Number of studies by the deep learning architectures

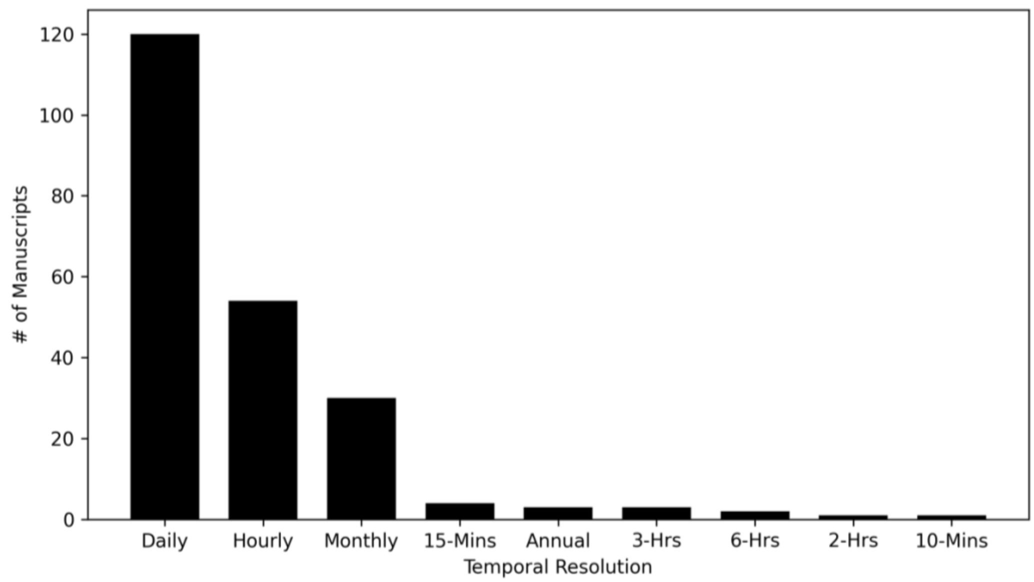

Figure 4. Number of streamflow forecasting studies by the temporal resolution

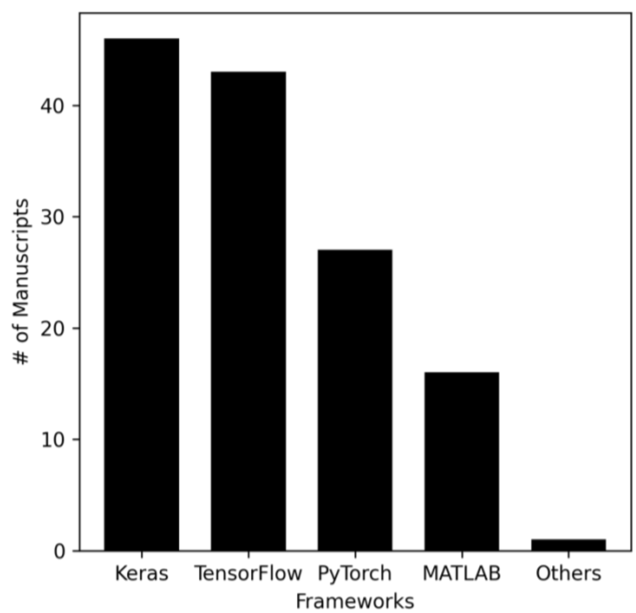

Figure 5. Frameworks or tools used for deep learning studies in the reviewed papers

In Figure 3, the number of appearances of all architectures in the review is shown. Figure 4 shows the cardinality of the forecasting studies by their temporal resolution to pinpoint the focus of the literature. One can infer that daily forecasting tasks were popular due to data availability and ease of forecasting daily values. Hourly predictions do not attract the same attention due to data limitations and it being a harder task to generate accurate forecasts for smaller time intervals. The usage of frameworks in the reviewed papers is summarized in Figure 5. According to the data, Keras is the most preferred framework, along with TensorFlow. Since Keras is working on top of TensorFlow, actual usage of Keras might be higher because some papers might mention only TensorFlow despite using Keras.

4.2. Research Findings

Here, we briefly mention some inferences from the review as well as advert some issues from the literature. Some of these were already noted in other reviews as well, such as Shen (2018) or Sit et al. (2020), so we will reiterate them as we deem them important, with some additions. Before diving into the details, here are a few remarks as a summary.

- Streamflow forecasting has been widely explored but without presenting a cumulative workflow that would allow researchers to build on top of each other's research.
- There are not many streamflow benchmark datasets to facilitate the previous point.
- Besides the approaches taken, definitions of key deep learning concepts are often misrepresented. Some machine learning algorithms are presented as "deep learning".
- Some papers clearly used "artificial intelligence" and "deep learning" terms just for the hype around them.

The most tackled problem throughout the literature we reviewed was streamflow forecasting. As a time-series forecasting task, streamflow forecasts were sometimes done for only one value, while the output was a sequence of values at other times. The task becomes a rather difficult one when sequences are forecasted from historic data, and thus such studies are relatively harder to come across in the literature. One other problem regarding streamflow forecasts is that there are many studies for different regions on earth, but they don't cumulatively build towards better models. What the literature does is to present quite similar models for different regions, but never to compare them to previously presented approaches, but instead to some other machine learning models. This tendency could be explained by how hydrologic modeling is conventionally done. Since geology, topography, soil, and climate drastically change from one location on earth to another, even when they are spatially close, hydrologic models for one location typically fail to perform well at other locations. That is typically due to the fact that models are optimized or calibrated for specific locations. The same attitude from domain scientists might be playing an important role in this correlation. Besides individual efforts, the methods presented are rarely reproducible. The only reproducible studies were the ones that shared the models and datasets used, or employed using publicly available curated datasets, such as CAMELS. But even in CAMELS studies, the literature abstained from comparing their results to the results of previous studies that employed the same datasets. It should be noted that CAMELS is not a dataset that was prepared with data-driven forecasting in mind, and this phenomenon might have taken its toll.

Beyond the papers we have reviewed, there are some issues in the deep learning literature that lower the quality of research and output. We believe the terminology is not well established among domain scientists. It is quite understandable that some terms are used interchangeably since the field of “deep learning” is relatively new. However, there are studies that discuss their model as deep learning, whereas what they employed is traditional machine learning methods like SVM from a software library that does not claim to be doing deep learning. Similarly, calling XGBoost a deep learning algorithm could easily be averted by a quick web search. When this was the case, we did not include those studies in the review even though they claimed to be doing deep learning research. Another issue in the literature is that deep learning applications research is becoming something that most researchers don’t develop anything on. Employing an algorithm that was used numerous times for the same task, even for the same data to publish another paper does not help anyone let alone scientific advancement. Yet, there are papers in remarkable numbers that treat deep and/or machine learning algorithms as only software packages that take inputs and give outputs rather than altering the algorithm or training process so that they show better promise in tackling the task at hand. The quality of some studies shows that some papers were published just to be on the hype train.

Having noted all these, it also warrants mentioning that modeling the environment and earth is like modeling chaos, and in earth data, chaos kicks in relatively quickly compared to most computer vision tasks. So, a different set of rules applies to earth data when it comes to evaluating the approaches and their impact. For instance, as the literature review suggested, very complex network architectures that did wonders for other fields can show limited success in earth science modeling. In some cases of streamflow, complex DNN architectures performed poorly, even worse than basic machine learning algorithms.

4.3. Open Questions

In this subsection, we will note some open questions and/or application fields where deep learning and its extensions might become handy. Similar to the Research Findings, we will start by listing some important open questions.

- Taking advantage of the nature of the spatial connectivity in earth data, Graph Neural Networks could be utilized for better earth modeling.
- Earth data augmentation and completion have yet to be fully understood or explored in the literature. For example, the use of deep neural networks to downscale hydrologic time-series has not been studied.
- Attention mechanism, specifically transformers, have not been fully utilized in time-series forecasts for streamflow.
- Generalized streamflow models pose a critical challenge that needs addressing.

Taking advantage of the spatial connectivity of various data points, GNNs provide an alternative solution for many tasks that involve Earth data. Although there are some studies that employ GNNs either as their proposed approach or an approach that they used to compare their results, the utilization of GNNs is fairly sparse. Since 2D rainfall forecasts already use spatial correlations with the convolution operation, most of the time, the applicability of GNNs might be limited to that extent. However, since most earth data could be represented using graphs, over 1D rainfall data as well as streamflow data, researchers could make better use of GNNs by exploring their capabilities, if not improving already proposed approaches by GNNs. Consequently, the capabilities of GNNs should be explored in forecasting, especially for streamflow, as the river networks are great examples of graphs by their nature.

Even though there are some studies to augment streamflow data, the capabilities of ANNs are not fully explored for improving hydrological time-series data. Since we were only able to find and review one study that filled in the missing points in hydrologic time series, we believe better approaches could be developed for missing data imputation tasks. Similarly, temporal super resolution of hydrologic datasets could be explored by taking advantage of the skills of recurrent neural network architectures over sequential earth data.

Streamflow datasets that are preprocessed for data-driven modeling are not easily available at the moment. Especially for hourly data, researchers need to resort to collecting or acquiring their own datasets, which in turn, as mentioned earlier, limits the cumulative nature of science. Even though there are some recently published datasets (Godfried et al., 2020; Demir et al., 2022) more openly available datasets should be curated and presented to researchers.

Many studies have employed attention mechanisms, but the utilization of transformers themselves remains fairly low. Since transformers and attention have, in a way, revolutionized natural language processing, in which the sequential nature of data is just as important as time-series data, we strongly believe temporal attention and transformers should be explored in depth, specifically for streamflow.

As we have mentioned, the problem of generalized models remains unresolved for streamflow, and there is a good reason for that. However, since the amount of streamflow data increases at any given time from already operational stream gauges and accessibility increases as agencies deploy new sensors, data-driven modeling could be explored for truly generalized flood modeling that works for multiple diverse regions on Earth.

5. Conclusions

This paper presents a detailed overview of recent applications of deep neural networks in tackling tasks that either improve the quality of streamflow data or forecast streamflow. In the process, 8,679 distinct manuscripts dating between January 2014 and January 2022 were systematically acquired using Google Scholar and eliminated by their relevance to the review scope. A total of 230 manuscripts were then selected for a detailed review. The reviewed papers were grouped according to their types, like review or research papers, and their tasks, such as daily or hourly prediction, as well as certain features like dataset selection, to provide a more comprehensive overview.

We believe this study describes the state-of-the-art in the general sense and summarizes the strong suits and open aspects of the literature well in order to open up opportunities for both deep learning practitioners and domain scientists. The paper confirms that the usage of deep neural networks is gaining more and more attention in the field and provides good results in comparison to classical approaches. However, it should be noted that the comparisons between previously presented approaches are generally limited in the papers, and this situation makes the performance of the models questionable in some senses. As a solution, we believe that scholars should make their projects open source and accessible with relevant code and data on some platforms such as EarthAIHub (Sit and Demir, 2022) or Github. Also, it is crucial to create or share benchmark datasets similar to those in other areas, such as computer vision (Deng et al., 2009; Krizhevsky and Hinton, 2009), NLP (Wang et al., 2018; Rajpurkar et al., 2018), or other hydrological areas (Sit et al., 2021b; Newman et al., 2015).

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Appendix

Table A1. Reviewed papers with curated data points

Paper	Network	Framework	Dataset	Open-source	Reproducible
Abbasi et al., 2021	AE	-	Acquired	No	No
Adikari et al., 2021	CNN, LSTM	MATLAB	Acquired	No	No
Afzaal et al., 2019	LSTM, CNN, ANN	-	Acquired	No	No
Agarwal et al., 2021	ANN	-	Acquired	No	No

Ahmed et al., 2021	LSTM	TensorFlow, Keras	Acquired	No	No
Alizadeh et al., 2021	LSTM	TensorFlow	Acquired	No	No
Aljahdali et al., 2019	LSTM	MATLAB	Acquired	No	No
Alperen et al., 2021	ANN	-	Acquired	No	No
Althoff et al., 2021	LSTM	TensorFlow, Keras	Existing	Yes	Yes
Apaydin et al., 2021	CNN, LSTM, ANN	Keras	Acquired	Yes	Yes
Ayzel and Heistermann, 2021	LSTM, GRU	TensorFlow, Keras	Existing	Yes	Yes
Ayzel et al., 2020	LSTM	-	Acquired	No	No
Ayzel, 2019	LSTM	-	Acquired	No	No
Bahrami and Wigand, 2018	ESN	-	Acquired	No	No
Bai et al., 2021a	LSTM	MATLAB	Existing	Yes	Yes
Bai et al., 2021b	LSTM	-	Acquired	No	No
Barino et al., 2020	CNN	-	Collected	No	No
Belotti et al., 2018	RNN	-	Acquired	No	No
Bhasme et al., 2021	LSTM	-	Acquired	No	No
Bi et al., 2020	GRU	-	Acquired	No	No
Boulmaiz et al., 2020	LSTM	-	Existing	No	No
Campos et al., 2019	LSTM	-	Acquired	No	No
Chen and Qiao, 2021	LSTM	-	Acquired	No	No
Chen and Xu, 2021	LSTM	-	Acquired	No	No
Chen et al., 2019	CNN	-	Acquired	No	No
Chen et al., 2020	LSTM	PyTorch	Acquired	No	Yes
Chen et al., 2021b	GNN, LSTM	-	Acquired	No	No
Chen et al., 2021a	LSTM	-	Acquired	No	No
Cherki, 2019	ANN	MATLAB	Acquired	No	No
Cho and Kim, 2022	LSTM	Keras	Acquired	No	No
Chu et al., 2020	DBN	-	Acquired	No	No
Chu et al., 2021a	DBN	-	Acquired	No	No

Chu et al., 2021b	DBN	-	Acquired	No	No
Cui et al., 2021	LSTM	-	Acquired	No	No
Damavandi et al., 2019	LSTM	TensorFlow, Keras	Acquired	No	No
de Faria et al., 2021	ANN	TensorFlow	Acquired	No	No
Dijkstra, 2019	CNN	Keras	Acquired	No	No
Ding et al., 2019	LSTM	-	Acquired	No	No
Ding et al., 2020	LSTM	-	Acquired	No	No
Dong et al., 2020	LSTM	-	Acquired	No	No
Duan et al., 2020	CNN	-	Existing	No	No
Fan et al., 2020	LSTM	-	Acquired	No	No
Fang et al., 2021	LSTM	PyTorch	Acquired	Yes	Yes
Faruq et al., 2020a	LSTM	MATLAB	Acquired	No	No
Faruq et al., 2020b	LSTM	MATLAB	Acquired	No	No
Feng et al., 2019	LSTM, DBN	TensorFlow	Acquired	No	No
Feng et al., 2020a	LSTM	PyTorch	Acquired	Yes	Yes
Feng et al., 2020b	LSTM	TensorFlow, Keras	Acquired	No	No
Feng et al., 2021a	ANN	PyTorch	Acquired	Yes	Yes
Feng et al., 2021b	GNN	TensorFlow	Acquired	No	No
Feng et al., 2021c	LSTM	TensorFlow	Acquired	No	No
Fiedler, 2020	LSTM	TensorFlow	Acquired	No	No
Fill, 2021	RNN	PyTorch	Acquired	No	No
Frame et al., 2021a	LSTM	PyTorch	Acquired	Yes	Yes
Frame et al., 2021b	LSTM	PyTorch	Acquired	Yes	Yes
Fu et al.,2020	LSTM	TensorFlow	Acquired	No	No
Gao et al., 2020	LSTM, GRU	TensorFlow	Acquired	No	No
Gauch et al., 2021	LSTM	TensorFlow	Existing	Yes	Yes
Ghimire et al., 2021	CNN, LSTM	TensorFlow, Keras	Acquired	No	No
Ghose et al., 2018	RNN	-	Acquired	No	No
Ghose, 2019	RNN	-	Acquired	No	No

Gude et al., 2020	LSTM	Keras	Acquired	No	No
Güneş et al., 2021	ANN	MATLAB	Acquired	No	No
Guo et al., 2021	LSTM, GRU	-	Acquired	No	No
Ha et al., 2021	LSTM, CNN	-	Acquired	No	No
Hadji, 2021	CNN	Keras	Acquired	No	No
Hamzah et al., 2021	RNN	-	Acquired	No	No
Han et al., 2021	LSTM	-	Acquired	No	No
Hashemi et al., 2021	LSTM	Keras	Acquired	No	No
He et al., 2019	ANN	-	Acquired	No	No
Hitokoto and Sakuraba, 2018	ANN	-	Acquired	No	No
Hitokoto and Sakuraba, 2020	ANN	-	Acquired	No	No
Hitokoto et al., 2017	AE	-	Acquired	No	No
Hu et al., 2018	LSTM, ANN	Keras	Acquired	No	No
Hu et al., 2020	LSTM	Keras	Acquired	No	No
Huang et al., 2020	CNN	-	Acquired	No	No
Hussain et al., 2020	CNN	-	Acquired	No	No
Hussain et al., 2021	RNN, LSTM, CNN, ANN	Keras	Acquired	Yes	No
Ishida et al., 2021a	CNN, LSTM	PyTorch	Acquired	No	No
Ishida et al., 2021b	LSTM	PyTorch	Acquired	No	No
Ji et al., 2021	GRU	-	Acquired	No	No
Jia et al., 2020	GNN	-	Acquired	No	No
Kanyama et al., 2020	LSTM, GRU, ANN	-	Acquired	No	No
Kao et al., 2020	LSTM	Keras	Acquired	No	No
Khandelwal et al., 2020	LSTM	-	Collected	No	No
Kim and Han, 2020	ANN	-	Acquired	No	No
Kim and Kim, 2021a	LSTM	-	Acquired	No	No
Kim and Kim, 2021b	LSTM	-	Acquired	No	No
Kim and Seo, 2015	RNN	-	Acquired	No	No
Kim et al., 2021	LSTM	MATLAB	Acquired	No	No

Kimura et al., 2019	CNN	Keras	Acquired	No	No
Kinh et al., 2020	DBN, AE	Keras	Acquired	No	No
Kratzert et al., 2018a	LSTM	TensorFlow, Keras	Existing	Yes	Yes
Kratzert et al., 2018b	LSTM	-	Existing	No	No
Kratzert et al., 2019a	LSTM	-	Existing	No	No
Kratzert et al., 2019b	LSTM	PyTorch	Existing	Yes	Yes
Kratzert et al., 2021	LSTM	PyTorch	Existing	Yes	Yes
Kulanuwat et al., 2021	LSTM	-	Acquired	No	No
Kwak et al., 2021	LSTM	Keras	Acquired	No	No
Lama and Sánchez, 2020	LSTM	-	Acquired	No	No
Latif and Ahmed, 2021	LSTM	-	Acquired	No	No
Le et al., 2019a	GRU	TensorFlow	Acquired	No	No
Le et al., 2019b	LSTM	TensorFlow	Acquired	No	No
Le et al., 2019c	LSTM	TensorFlow	Acquired	No	No
Le et al., 2021a	GRU	-	Acquired	No	No
Le et al., 2021b	LSTM	TensorFlow, Keras	Acquired	No	No
Lee and Kim, 2021	LSTM	TensorFlow, Keras	Acquired	Yes	Yes
Lee et al., 2020	LSTM	TensorFlow	Acquired	No	No
Lees et al., 2021	LSTM	PyTorch	Existing	Yes	Yes
Li and Wu, 2020	LSTM	-	Acquired	No	No
Li and Yang, 2019	LSTM	-	Acquired	No	No
Li et al., 2018	CNN	-	Acquired	No	No
Li et al., 2019	DBN	-	Acquired	No	No
Li et al., 2021a	LSTM	PyTorch	Acquired	No	No
Li et al., 2021b	LSTM	PyTorch	Acquired	No	No
Li et al., 2021c	LSTM	PyTorch	Acquired	No	No
Li et al., 2021d	GAN	-	Acquired	No	No
Li et al., 2021e	LSTM	Keras	Acquired	No	No
Li, 2021	LSTM, RNN	PyTorch	Acquired	No	No

Lian et al., 2022	LSTM	-	Acquired	No	No
Liao et al., 2019	LSTM	-	Acquired	No	No
Lin et al., 2020	CNN	-	Acquired	No	No
Lin et al., 2021	LSTM, ANN	-	Acquired	No	No
Liu et al., 2017	AE, ANN	-	Acquired	No	No
Liu et al., 2018a	LSTM	-	Acquired	No	No
Liu et al., 2018b	LSTM	-	Acquired	No	No
Liu et al., 2020a	LSTM	-	Acquired	No	No
Liu et al., 2020b	LSTM	TensorFlow	Acquired	No	No
Liu et al., 2021a	LSTM	MATLAB	Acquired	No	No
Liu et al., 2021b	LSTM, CNN	-	Acquired	No	No
Lotsberg, 2021	LSTM	PyTorch	Existing	No	No
Luppichini et al., 2022	LSTM	TensorFlow	Acquired	No	No
Luu et al., 2021a	LSTM	Keras	Acquired	No	No
Luu et al., 2021b	LSTM, ANN	Keras	Acquired	No	No
Lv et al., 2020	LSTM	Keras	Acquired	No	No
Ma et al., 2022	GAN	TensorFlow	Acquired	No	No
Mamani, 2021	ESN	-	Existing	No	No
Manavalan and Bynagari, 2015	LSTM	-	Acquired	No	No
Mao et al., 2021	LSTM	-	Acquired	No	No
Mhammedi et al., 2016	RNN	Theano	Acquired	No	No
Miau and Hung, 2020	CNN, GRU	Keras	Acquired	No	No
Mirzaei et al., 2021	LSTM	-	Acquired	No	No
Muhammad et al., 2019	LSTM, GRU	-	Acquired	No	No
Nakatani et al., 2020	CNN, RNN	-	Acquired	No	No
Nath et al., 2021	GRU, LSTM	-	Acquired	No	No
Nearing et al., 2020a	LSTM	-	Existing	No	No
Nearing et al., 2020b	LSTM	PyTorch	Existing	No	No
Nearing et al., 2021	LSTM	PyTorch	Existing	Yes	Yes
Nguyen and Bae, 2020	LSTM	TensorFlow	Acquired	No	No
Nguyen et al., 2021	DBN	PyTorch	Acquired	No	No

Ni et al., 2019	LSTM	-	Acquired	No	No
Ni et al., 2020	LSTM	-	Acquired	No	No
Ouma et al., 2021	LSTM	MATLAB	Acquired	No	No
Ouyang et al., 2021	LSTM	PyTorch	Acquired	Yes	Yes
Prabuddhi and Seneviratne, 2020	RNN	-	Acquired	No	No
Qian et al., 2020	AE	MATLAB	Acquired	No	No
Quiñones et al., 2021	LSTM	-	Existing	No	No
Rahimzad et al., 2021	LSTM	TensorFlow	Acquired	No	No
Rice et al., 2020	ANN	TensorFlow, Keras	Acquired	No	No
Rivero et al., 2020	LSTM	-	Acquired	No	No
Rohli, 2018	RNN	TensorFlow, Keras	Acquired	No	No
Roy et al., 2021	ANN	-	Acquired	No	No
Sadler et al., 2021	LSTM	TensorFlow	Existing	No	No
Samantaray et al., 2019	ANN, RNN	-	Acquired	No	No
Samikwa et al., 2020	LSTM	TensorFlow	Acquired	No	No
Shu et al., 2021	CNN, ANN	MATLAB	Acquired	No	No
Shuofeng et al., 2021	LSTM	-	Acquired	No	No
Sibtain et al., 2020	LSTM	TensorFlow, Keras	Acquired	No	No
Sibtain et al., 2021	GRU	TensorFlow, Keras	Acquired	No	No
Silva et al., 2021	LSTM	TensorFlow, Keras	Acquired	No	No
Siqueira and Luna, 2015	ESN	-	Acquired	No	No
Sit and Demir, 2019	GRU	PyTorch	Acquired	No	No
Sit et al., 2021a	GNN	PyTorch	Acquired	No	No
Song et al., 2019	LSTM	Keras	Acquired	No	No
Song, 2020	CNN	TensorFlow, Keras	Acquired	No	No
Song, 2022	CNN	Keras	Acquired	No	No

Sudriani et al., 2019	LSTM	-	Acquired	No	No
Sun et al., 2021	GNN	PyTorch	Existing	No	Yes
Tang et al., 2021	LSTM	-	Acquired	No	No
Thapa et al., 2020	LSTM	TensorFlow, Keras	Acquired	No	No
Tian et al., 2018	LSTM, RNN, ENN, ESN	Keras	Acquired	No	No
Van et al., 2020	CNN, LSTM	-	Acquired	No	No
Wagena et al., 2020	ANN	-	Acquired	No	No
Wan et al., 2019	ENN	-	Acquired	No	No
Wang and Karimi, 2021	LSTM, CNN	-	Existing	No	No
Wang and Lou, 2019	LSTM	MATLAB	Acquired	No	No
Wang et al., 2020	GRU	-	Acquired	No	No
Wang et al., 2021a	CNN	-	Acquired	No	No
Wang et al., 2021b	LSTM	-	Acquired	No	No
Wang et al., 2021c	GRU	-	Acquired	No	No
Wang et al., 2021d	LSTM	-	Acquired	No	No
Wang et al., 2021e	LSTM	-	Acquired	No	No
Wang et al., 2022	ANN	-	Acquired	No	No
Wegayehu and Muluneh, 2021	LSTM, CNN, GRU	Keras	Acquired	No	No
Wei, 2020	LSTM, ANN	Keras	Acquired	No	No
Wigand and Bahrami, 2018	ESN	-	Acquired	No	No
Wu et al., 2020	LSTM	-	Acquired	No	No
Xiang and Demir, 2020	LSTM	TensorFlow, Keras	Acquired	No	No
Xiang and Demir, 2021	GNN	-	Acquired	No	No
Xiang et al., 2020	LSTM	Keras	Acquired	No	No
Xiang et al., 2021	LSTM, ANN	TensorFlow, Keras	Acquired	No	No
Xiao and Wang, 2021	LSTM	-	Acquired	No	No
Xie et al., 2021	LSTM	Python	Existing	No	No

Xu et al., 2019	LSTM	Keras	Acquired	No	No
Xu et al., 2020	LSTM	-	Acquired	No	No
Xu et al., 2021b	CNN	TensorFlow, Keras	Acquired	No	No
Xu et al., 2021c	CNN, ANN	-	Acquired	No	No
Yan et al., 2019	LSTM	TensorFlow	Acquired	No	No
Yan et al., 2021a	CNN, LSTM	-	Acquired	No	No
Yan et al., 2021b	LSTM	-	Acquired	No	No
Yang et al., 2019	LSTM	-	Acquired	No	No
Yeditha et al., 2021	LSTM, ANN	MATLAB	Acquired	No	No
Yin et al., 2021a	LSTM	-	Existing	No	No
Yin et al., 2021b	LSTM	PyTorch	Existing	No	No
Yokoo et al., 2021	LSTM, RNN, GRU	PyTorch	Acquired	No	No
Yokoo et al., 2022	LSTM	PyTorch	Acquired	No	No
Yuan et al., 2018	LSTM	MATLAB	Acquired	No	No
Yuan et al., 2021	LSTM	-	Acquired	No	No
Yue et al., 2020	DBN	-	Acquired	No	No
Zakhrouf et al., 2021	LSTM, ANN	-	Acquired	No	No
Zhan et al., 2020	ANN	-	Acquired	No	No
Zhang et al., 2018	ENN, ANN	-	Acquired	No	No
Zhang et al., 2021	LSTM	TensorFlow	Acquired	No	No
Zhao et al., 2021b	GRU	-	Acquired	No	No
Zhao et al., 2021c	GRU	-	Acquired	No	No
Zhou et al., 2020	RNN, ANN	MATLAB	Acquired	No	No
Zhu et al., 2020	LSTM	Keras	Acquired	No	No
Zocholl, 2021	LSTM	TensorFlow, Keras	Acquired	No	No
Zounemat-Kermani et al., 2021	RNN, ANN	-	Acquired	No	No
Zuo et al., 2020	LSTM	TensorFlow	Acquired	Yes	Yes