A scoping review of spatiotemporal ConvLSTM applications for predicting water balance components

Seyed Hossein Hosseini[*1], Harri Koivusalo[1], Jussi Nikander[1], Henrikki Tenkanen[1]

Abstract

Deep learning is renewing computational hydrology by offering advanced capabilities for modeling complex environmental processes characterized by spatiotemporal variability. Among these approaches, the Convolutional Long Short-Term Memory (ConvLSTM) network has gained considerable attention for its ability to learn spatial and temporal dependencies simultaneously, a feature particularly valuable for accurately predicting water balance components. Such predictions are essential for understanding hydrological processes, guiding water resource management, and informing climate adaptation strategies. In this work, we systematically combine scattered information about studies that have applied ConvLSTM to predict water balance–related variables, synthesize their methodologies and findings, and identify key research gaps to guide future developments. Our review shows that ConvLSTM possesses a flexible architecture and can be equipped with attention mechanisms, encoder–decoder structures, and deformable convolutions to improve its predictive accuracy for hydrometeorological variables. Beyond spatiotemporal prediction, reported applications include multisource satellite data fusion, bias correction, and spatial downscaling. Finally, we outline future research directions, including integrating physical constraints into ConvLSTM architecture, developing hydrologically meaningful explainable artificial intelligence methods, advancing spatiotemporal uncertainty quantification, and coupling ConvLSTM with available hydrological models.

Keywords: ConvLSTM; Spatiotemporal deep learning; Hydrological modeling; Water balance components; Hydrometeorological prediction

[*] Corresponding author
[1] Department of Built Environment, School of Engineering, Aalto University, Espoo, Finland.
Email: seyed.h.hosseini@aalto.fi – ORCID: 0000-0003-3391-7715
Email: harri.koivusalo@aalto.fi – ORCID: 0000-0002-3713-1579
Email: jussi.nikander@aalto.fi – ORCID: 0000-0002-1464-0549
Email: henrikki.tenkanen@aalto.fi – ORCID: 0000-0002-0918-4710

1. Introduction

Water balance is a foundational concept in hydrology, encompassing the quantitative assessment of water movement within a watershed or ecosystem and expressed in terms of water fluxes (e.g., mm/time or m^3/time) (Phukan, 2023). The transferred water can take the form of precipitation (input), evapotranspiration (loss to atmosphere), runoff (lateral flow), or recharge to groundwater. Changes in soil moisture and groundwater storage represent variations in terrestrial water storage, and can be expressed as a storage change rate ($\Delta S/\Delta t$) (Oliveira et al., 2014; S. Tian et al., 2017). Understanding these components together is crucial for quantifying the flux magnitudes and interactions, and dynamics between the water storages. Moreover, studying interactions between snow, groundwater, and surface water provides insight into how water moves through the hydrological cycle, responds to climatic and anthropogenic drivers, and sustains ecosystems and human needs (M. Li et al., 2020). Various factors lead to transitions in the water balance. For instance, changes in precipitation and temperature patterns due to climate change, along with human impacts, such as urbanization, deforestation, and water abstraction, can alter the spatial and temporal distribution of flow and storage of water within the system (Porporato et al., 2004; Schilling et al., 2008; Wang et al., 2009). Given these pressures, understanding and quantifying water balance components becomes essential, as the hydrological information is critical for managing surface and groundwater resources (Dastorani & Poormohammadi, 2012; Amen & Calvache, 2025), while also supporting risk assessment and mitigation against hydrological extremes (Sadhwani & Eldho, 2023; Nandi & Reddy, 2024), improving water conservation and irrigation efficiency, and resolving water-related conflicts (Dastorani & Poormohammadi, 2012; B. Wu et al., 2018; Mihaela et al., 2019; Amen & Calvache, 2025). Accurate and up-to-date hydrological information is crucial to sustainable water resources management, calling for the advancement of monitoring and modelling techniques.

In the water balance of a catchment, the spatial and temporal variability of hydrological variables, whether on the land surface or in subsurface domains, is specific to each component. Precipitation serves as the primary input of water into the system. Depending on climatic conditions, it changes form between rain and snowfall, triggering the accumulation of water storage in snowpacks in cold regions. Precipitation has a complex spatial and temporal structure ranging across small to large scales, and precipitation information is still limited in remote areas and small local scales. Precipitation serves as a key source and influential factor for the spatiotemporal variability of runoff and changes in soil moisture, as well as ground and surface water resources (Gardiya Weligamage et al., 2023). The water stored in the rooting layers of soil, referred to as soil moisture, supports plant uptake and evaporation (Nolz, 2016; Z. Li et al., 2019). Soil water in unsaturated and saturated layers near the soil surface functions as a buffer, storing water during wet periods and gradually releasing it during dry periods, thereby sustaining vegetation and regulating evapotranspiration rates (Feltrin et al., 2011; Z. Li et al., 2019). Evapotranspiration—the combined loss of water from soil, water bodies, and plant transpiration—is one of the main components of the water balance (L. Zhang et al., 2021), and is largely influenced by vegetation cover, soil moisture, and climatic conditions (Lauenroth & Bradford, 2006). Surface water resources, which include rivers and lakes, play a central role in the storage and distribution of water (Amen & Calvache, 2025; Mohebzadeh & Fallah, 2019). More specifically, they represent the accumulated result of runoff, which aggregates to surface water bodies and has very high temporal variability with occasional extremes during floods and droughts (Sophocleous, 2002; Owuor et al., 2016). Groundwater, as the water stored in the saturated soil beneath the surface, provides long-term storage and links with precipitation through recharge from infiltration and percolation (Huntington & Niswonger, 2012). Given the complexity and high spatiotemporal variability of these interacting components, as well as inevitable trends in the hydroclimatic systems, information about the fluxes and states remains limited, which highlights the need for modeling approaches to fulfill the information gaps.

To represent the interconnected processes in hydroclimatic systems, researchers have implemented physically-based and data-driven models. The spatiotemporal study of water balance components across a watershed necessitates robust modeling approaches to accurately simulate their dynamics across space and time. Several physically-based hydrological models, such as Soil and Water Assessment Tool (SWAT) (Gemechu et al., 2021; Marcinkowski et al., 2023), WetSpass (Nannawo et al., 2021; Salem et al., 2023), ParFlow (O'Neill et al., 2021), PCRaster GLOBal Water Balance (PCR-GLOBWB) (López López et al., 2017), HYDRUS (Šimůnek & van Genuchten, 2008), and MODFLOW (Niswonger et al., 2011) have been used for this purpose. These models simulate hydrological processes and offer insights into the water cycle and its components at high resolution (Silvestro et al., 2013). Because they are grounded in physical principles, they picture a mechanistic representation of the processes within a catchment, such as changes in soil moisture, evapotranspiration, and groundwater flow (Baroni et al., 2019; Husic et al., 2022). While these models offer detailed process representation, their dependence on a large number of parameters for calibration increases the uncertainty of the simulation results and may compromise their reliability (Silvestro et al., 2013; dos Santos et al., 2018). Calibration of a complex model is challenging, as it requires measurements for most water balance components and is further complicated by parameter identifiability problems (Beven & Binley, 1992; Beven & Freer, 2001; Althoff & Rodrigues, 2021). The high spatial heterogeneity and the inherent variability of hydrological processes beyond the calibration ranges make it more difficult to define suitable process descriptions and parameter values (Herrera et al., 2022). These limitations have motivated the rise of data-driven approaches as a more straightforward approach. With the increasing availability of spatiotemporal datasets, particularly for precipitation and soil moisture, it is crucial to address potential data- and model-related challenges that influence the model's accuracy (Niemi, 2017). Issues such as sparse gauge coverage, spatial variability, scale mismatches, and biases in satellite-based products must be carefully handled during preprocessing and model implementation. In fact, hydrometeorological variables often exhibit non-stationary, non-linear, and spatiotemporal heterogeneity, all of which must be explicitly accounted for in modeling frameworks to ensure robust and physically meaningful modeling and predictions (Nourani et al., 2013; Cristiano et al., 2017; Ali et al., 2020).

In addition to physically-based models, deep learning (DL) models in this domain have gained attention (L. Li et al., 2023) due to their adaptability and flexibility in predicting hydrometeorological trends (Waqas & Humphries, 2024). DL, as a subfield of machine learning (ML), employs artificial neural networks (ANNs) with multiple layers to model complex patterns and relationships in time series. The main objective of DL is to automatically learn meaningful data representations and patterns through mathematical equations, which can be leveraged for a wide range of tasks, including classification and regression (X. Liu et al., 2015; Zhou, 2020). Although DL has been widely applied to point based predictions, there is growing emphasis on models capable of handling spatiotemporal data due to the distributed nature of many hydrological processes. Convolutional long short-term memory (ConvLSTM) is a type of neural network architecture that combines the strengths of convolutional neural networks (CNNs) and LSTM networks. In other words, ConvLSTM extends LSTM by replacing fully connected layers with convolutional operators, enabling simultaneous capture of spatial dependencies and temporal dynamics (Sainath et al., 2015). This architecture is particularly well-suited for hydrometeorological applications involving spatiotemporal data, as it enables the model to simultaneously capture temporal dependencies and spatial structures, an essential capability for accurately predicting water balance components and other dynamic environmental variables.

DL models have been widely applied in hydrology, prompting multiple review studies. Sit et al. (2020) performed a comprehensive review of state-of-the-art DL methods applied in the water industry for generation, prediction, enhancement, and classification tasks, offering guidance on how these approaches can be implemented to address future challenges in water resources. Moreover, Tripathy & Mishra (2024) reviewed the diverse applications of DL in hydrology and water resources, covering domains such as drought and flood forecasting, remote sensing, water quality assessment, subsurface flow inversion, groundwater level prediction, and hydro-climate variable downscaling. In another work, Ardabili et al. (2020) surveyed recent advances in ML and DL. They noted that while ML approaches are already well established in hydrology, with ensemble techniques and hybrid models continuing to improve performance, DL is still at a relatively early stage of development, with ongoing research needed to fully realize its potential. Additionally, Zhao et al. (2024) reviewed the capabilities of DL models and compared recent advancements in applying DL techniques for hydrological prediction. In addition to the mentioned reviews, other studies have been conducted on the application of DL models in this domain (Shen, 2018; T. Xu & Liang, 2021; Latif & Ahmed, 2023). DL has shown broad applicability in hydrology, offering novel capabilities for modeling complex environmental processes. While previous reviews have examined the use of DL models, highlighted their strengths, and discussed associated challenges, none have provided a focused synthesis of ConvLSTM applications, particularly in the context of spatiotemporal prediction of water balance components. The objective of this study is to address this gap by focusing on diverse applications of the ConvLSTM, emphasizing its ability to jointly model spatial and temporal dependencies. This makes it especially effective for grid-based hydrometeorological data, which underpins many spatiotemporally dense datasets. Rather than focusing on point-scale predictions, the aim is to synthesize studies that apply ConvLSTM to spatiotemporal prediction of water balance components, demonstrating its advantages over traditional DL models and distinct capabilities. By offering a structured assessment of current applications, this review sheds light on ConvLSTM’s potential to advance hydrological prediction and inform more robust water resource management strategies.

In this work, a systematic approach is adopted for the article selection process to identify the most relevant sources (Section 2). The study outlines an overview of the ConvLSTM model and its architecture (Section 3) and proceeds with a review of past research on hydrological variables related to the water balance, accompanied by a detailed table summarizing the information extracted from the reviewed studies (Section 4). Finally, current research gaps, challenges, and future directions are identified for implementing ConvLSTM in hydrology (Section 5), and the main findings are concluded (Section 6).

2. Review Methodology

In this study, a systematic literature search was conducted within the field of hydrology to identify relevant publications about the application of ConvLSTM models in the prediction of water balance–related components. Two widely recognized academic databases, namely Web of Science and Scopus, were employed using a carefully constructed search string. This search string consisted of two primary components: the first targeting variations of the term *ConvLSTM*, and the second encompassing a comprehensive set of keywords related to *water balance components*. The full search string used in this study was as follows: *("Conv-LSTM" OR "ConvLSTM" OR "Convolutional LSTM" OR "Convolutional long short-term memory") AND ("water balance" OR "hydrological budget" OR "water storage" OR "surface water dynamics" OR "evapotranspiration" OR "evaporation" OR "soil moisture" OR "groundwater" OR "runoff" OR "rainfall" OR "precipitation" OR "streamflow").*

Keywords were selected based on the authors' expert judgment and their relevance to the review topic to ensure the inclusion of core concepts relevant to this domain. No date restrictions were applied during the initial search. Here, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was applied to guide the selection process (Moher et al., 2009). The preliminary results yielded 432 publications, which were then screened to remove non-English, conference papers, and technically problematic entries, reducing the count to 395. Subsequently, a title and keyword-level screening was conducted to exclude studies that were not directly aligned with the objectives of this review, resulting in the exclusion of 124 publications. The remaining 271 publications underwent a more detailed screening based on their abstracts and main texts. This step identified 81 studies as highly relevant to the review's scope. Finally, duplicate records were removed, yielding a total of 37 publications for inclusion in the review. The selection process is presented in Figure 1.

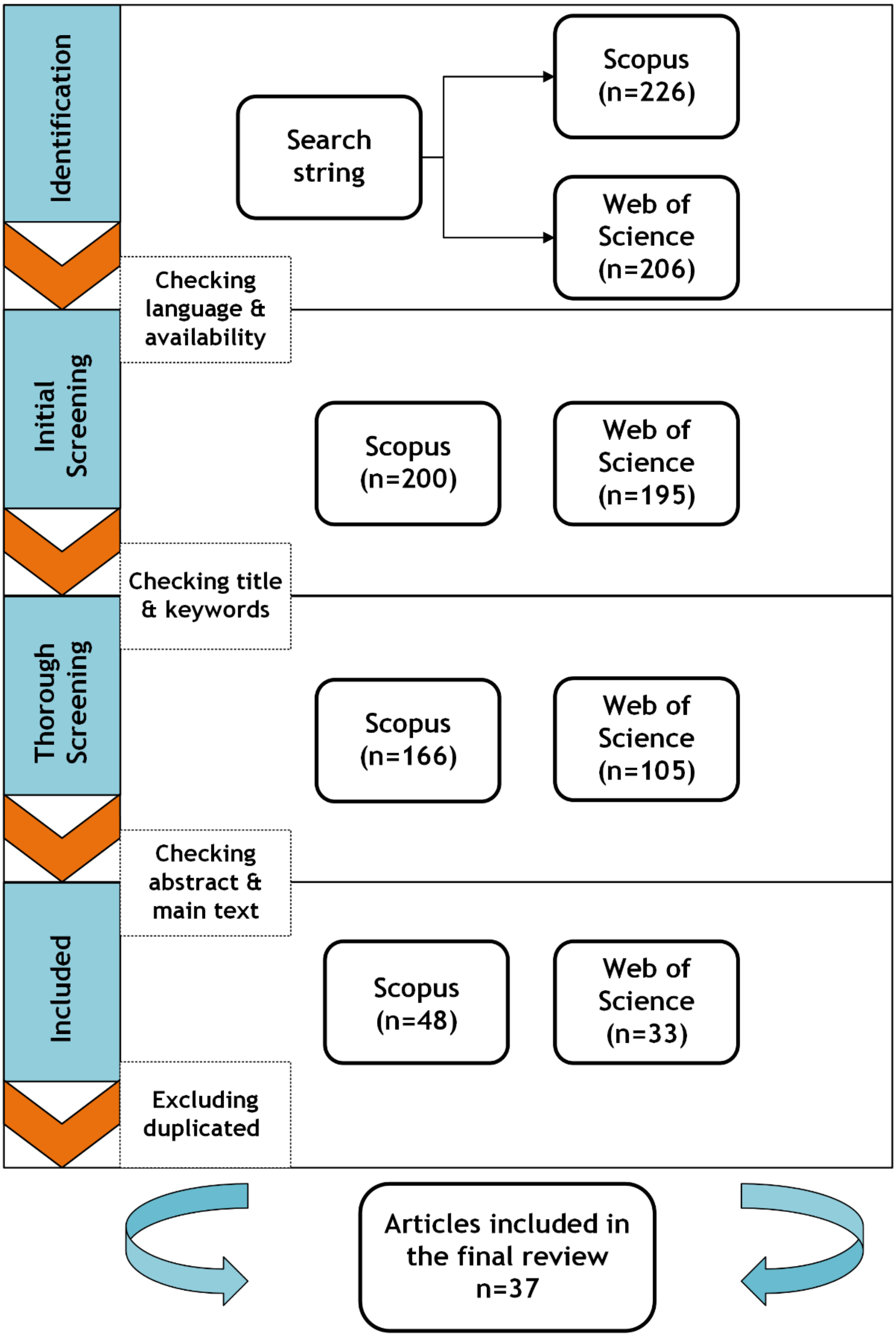

Figure 1. PRISMA flow diagram illustrating the selection process of studies included in the review based on Scopus and Web of Science databases.

To characterize each publication, a careful manual extraction of key information was conducted. This process enabled the identification of selected critical features, including: the geographical region and area of the case studies, types of data employed, temporal span of the modeling dataset, data sources and access platforms, model input and output variables, spatial and temporal resolution of the target variable, comparative models used, validation against physical models, software tools, and programming libraries utilized. In addition to these technical attributes, insights and findings from selected studies are systematically compiled, with the most informative ones presented in the following sections as a foundation for the scoping review. Following the information extraction process, five core hydrometeorological topics were identified where ConvLSTM has been applied: precipitation, soil moisture, evapotranspiration, surface water, and groundwater. These topics reflect the central thematic areas addressed across the reviewed literature and correspond to the direct outcomes of the hydrological assessments, which will be further discussed in the following sections. While the water balance can include other components, they were excluded from this analysis due to their similarity or dependence on the selected variables in order to maintain a clear focus on the primary drivers.

3. The ConvLSTM Model

In practice, ConvLSTM integrates the CNNs with LSTM networks to capture both the temporal correlations within the data sequences and the spatial patterns in the data. The following subsections provide an overview of LSTM, CNNs, and ConvLSTM architectures.

3.1 LSTM

LSTM, as a DL model, is capable of storing significant sequential information due to its unique design, and this type of recurrent neural network (RNN) overcomes the limitation of models in capturing long-sequence behaviors of data (Hochreiter & Schmidhuber, 1997). Unlike RNNs, which consist of a single *tanh* layer, LSTM has a more complex architecture with generally four layers designed to avoid issues like vanishing and exploding gradients (Olah, 2015). LSTM alleviates the gradient problem using a constant error carousel within each cell (Hochreiter & Schmidhuber, 1997; Waqas & Humphries, 2024). This model has specific memory units, which are called gates and cell states. The memory cell is responsible for controlling the passing of information and helps LSTM to retain long-term patterns, and the gates also have different roles. At the time step of *t*, the input gate (i_t) identifies which features should be stored in the next state, the forget gate (f_t) manages which previous information should be discarded, and the output gate (o_t) controls which information from the current state will be output. For each input, forget, and output gate, a *sigmoid* activation function ($\sigma(x)$) is used. In other words, in LSTM networks, the gating mechanism uses values between 0 and 1 with a *sigmoid* function to control information flow. A high gate value (close to 1) indicates that the gate is open and allows information to pass through strongly. On the other hand, a low gate value (close to 0) shows the gate is closed and has less influence on passing information.

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i), \tag{1}$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right), \tag{2}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o), \tag{3}$$

$$\sigma(x) = \frac{1}{1+e^{1-x}}, \tag{4}$$

$$c_t = i_t \odot g_t + f_t \odot c_{t-1}, \tag{5}$$

$$h_t = o_t \odot tanh(c_t), \tag{6}$$

$$g_t = tanh\left(W_{xg}x_t + W_{hg}h_{t-1} + b_g\right), \tag{7}$$

Where x_t is the input, W and *b* respecetively denotes weight and bias of each gate, c_t is the cell memory, h_t is the hidden state, g_t is the candidate value, $\odot$ denotes the element-wise multiplication and other variables have been defined earlier in the text.

3.2 CNN

CNNs are a specialized type of ANNs and use convolutional filters to extract meaningful features from spatially structured data. One important difference between CNN and ANN is their application in image, or raster files, by considering a specific architecture. Generally, a CNN consists of four parts: (1) the input layer, (2) the convolutional layers, (3) the pooling layer, and (4) the fully-connected layer. The input layer stores the pixel values of the image. The convolutional layers are an integral part of a CNN. By applying small convolutional kernels, CNNs detect features and generate activation maps that highlight key spatial patterns. Convolutional layers help reduce model complexity by adjusting three key hyperparameters:

depth, stride, and zero-padding. Depth controls the number of filters, affecting both model size and feature extraction. Stride determines how far filters move, influencing output size and overlap. Zero-padding adds borders to the input, allowing control over output dimensions. The pooling layer, which reduces the dimensionality of the data, in turn lowers the number of parameters and computational complexity. Max pooling, average pooling, and *L1/L2* normalization are among the common approaches for this purpose. Finally, the fully-connected layer, which links each neuron to all neurons in the previous and next layers, is similar to the structure used in traditional ANNs (O'Shea & Nash, 2015). A typical CNN can be mathematically formulated as follows (Shu et al., 2021):

$$o_l^j = f\left(\sum_{k=1}^{M_l-1} w_l^j x_l^k + b_l\right), \tag{8}$$

where j is the index of the convolution kernel in the convolution layer (l), o_l^j is the output, w_l^j is the weight, x_l^k is the ith channel of the x_l, M_l is the number of kernel, and b_l is the bias.

Compared to fully connected networks, CNNs are connected to only a small subset of neurons, which reduces the number of parameters and speeds up convergence. Additionally, convolutional layers share the same weights across different regions, further decreasing the number of parameters. The pooling layers retain the most important features by using local correlations in the image, since nearby pixels often contain similar information, which results in reducing data size while preserving essential content (Z. Li et al., 2022).

3.3 ConvLSTM

Taking advantage of LSTM and CNNs and combining them leads to developing ConvLSTM (Sainath et al., 2015; X. Shi et al., 2015). This model, typically, by receiving a 3D spatiotemporal tensor (channel, height, width), can predict desired variables spatiotemporally. ConvLSTM not only captures the trends in the time series and sequences (LSTM characteristics), but also finds spatial patterns within the spatial extent (convolutional characteristics). The ConvLSTM network enhances the traditional LSTM architecture by incorporating convolutional operations in place of fully connected layers for both input-to-state and state-to-state transitions, instead of the matrix multiplication in LSTM. The temporal information is still derived from the current input vectors and past cell states, meaning that the

ConvLSTM network not only leverages the strengths of CNNs for extracting spatial features, but also effectively captures temporal dynamics at the same time (Sun & Zhao, 2020).

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + b_i), \quad (9)$$

$$f_t = \sigma\big(W_{xf} * X_t + W_{hf} * H_{t-1} + b_f\big), \quad (10)$$

$$g_t = tanh\big(W_{xg} * X_t + W_{hg} * H_{t-1} + b_g\big), \quad (11)$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + b_o), \quad (12)$$

$$C_t = i_t \odot g_t + f_t \odot C_{t-1}, \quad (13)$$

$$H_t = o_t \odot tanh(C_t), \quad (14)$$

Where X_t is the input, H_t is the hidden state, C_t is the cell memory, which are multi-dimensional tensors, * is the convolutional operation, and other variables have been defined earlier. 2D convolutional operation is defined as follow (Xu et al., 2022; Goodfellow et al., 2016):

$$S(i,j) = (K * I)(i,j) = I(i-m, j-n)K(m,n), \quad (15)$$

Where I is the 2D input, K is the kernel at position (m,n), and S denotes the feature map at position (i,j). In Figure 2, an overview of the ConvLSTM model for implementing gridded hydrometeorological prediction is presented.

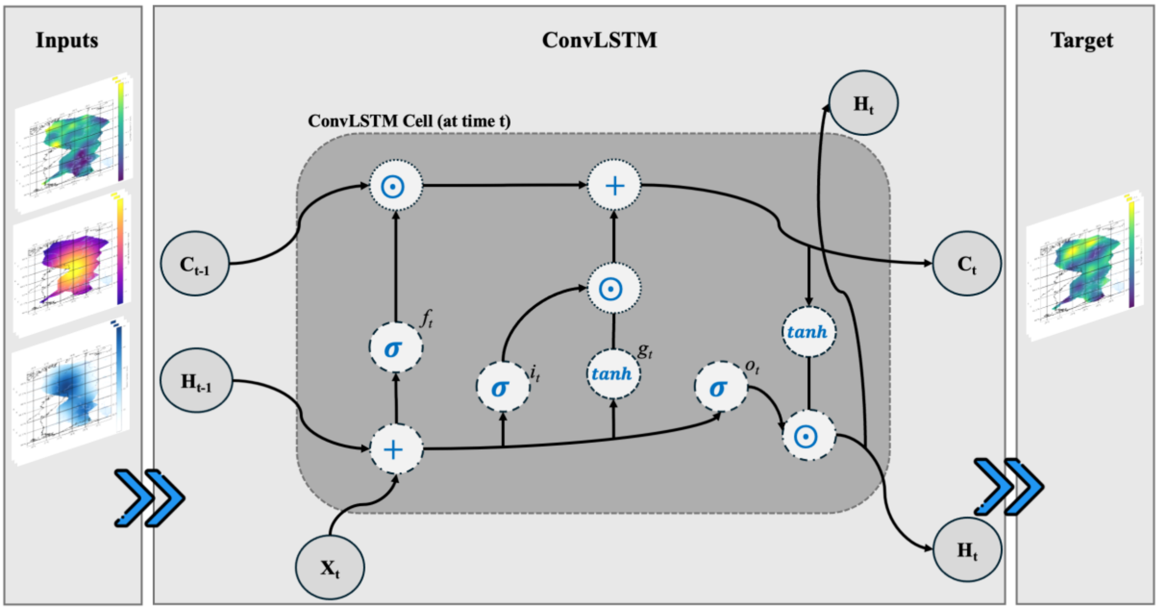

Figure 2. Architecture of the ConvLSTM model for spatiotemporal hydrometeorological prediction.

4. Review of Past Research

In this section, selected articles on five topics, including precipitation, soil moisture, evapotranspiration, surface water, and groundwater, are presented. Additionally, in Table 1, key information extracted from the selected articles for each variable across different regions is presented. The table highlights variations in data sources, model structures, and supporting tools used in these studies, and an overall description related to Table 1 is provided at the end of each variable's subsection. Table 2 presents the list of abbreviations for the variables used in the modeling described in Table 1.

Table 1. Past research on ConvLSTM in modeling water balance–related variables. Gb refers to ground-based data sources, RS refers to remote sensing, and RA refers to the reanalysis product. Abbreviations for data sources and models can be found in each respective article. The links that might not work in the data access platform column are marked with a superscript asterisk.

Category	Paper	Region	Data type and source / Data access platform	Model variables	Model(s)	Tools
Precipitation	Hu et al. (2025)	Dadu river basin (China)	Gb: National agency; RS/RA: SRTM, CMPAS [1], [2]	P, DEM	ConvLSTM, DConvLSTM, XGBoost, LSTM, OI	ArcGIS 10.8, PyTorch
	You et al. (2025)	Qinghai province (China)	Gb: National agency, RS/RA: IMERG, MODIS, ASTER GDEM, ERA5, GLDAS [1], [2], [3], [4], [5], [6]	P, NDVI, DEM	RF, XGBoost, MLP, CNN, ConvLSTM, MPFM, IEVW, OWA, OORA	Tensorflow
	Kao et al. (2024)	Main island (Taiwan)	Gb: National agency (TCCIP); RS/RA: IMERG, TreAD, MSWEP [1]	P	ConvLSTM, LSTM	Tensorflow, Keras, Numpy, Pandas, Scikit-learn, Matplotlib, Seaborn, [Code]
	Misra et al. (2024)	India	Gb: National agency; RS/RA: NCEP/NCAR, CCCma GCM [1]	T, Patm, SH, WS(U), WS(V)	ConvLSTM, KR, LSTM, Shared ConvLSTM	Tensorflow, Keras
	Xu et al. (2024)	Administrative district of Wuhan city (China)	RS/RA: ERA5-land [1]	P, LMI	ConvLSTM, ConvLSTM-SAC, DConvLSTM, DConvLSTM-SAC, DTR, RF, RNN	PyCharm IDE, Tensorflow, Torch, PIL, Matplotlib, Sklearn, [Code]
	Fang et al. (2023)	Yalong river (China)	Gb: National agency; RS/RA: IMERG, CHIRPS, MODIS, SRTM, ERA5 [1*], [2*], [3], [4], [5], [6]	P, Q, NDVI, DEM, T, WS	A-ConvLSTM, ConvLSTM, GRU, LSTM, MLR, SVR, SWAT, XAJ	ArcGIS 10.2
	Gavahi et al. (2023)	USA	Gb: CPC, GHCNd; RS/RA: IMERG, PERSIANN-CDR, CMORPH, GSMaP, CHIRPS, NLDAS [1], [2*], [3], [4], [5], [6], [7], [8]	P	PDFN	[Code]

Category	Paper	Region	Data type and source / Data access platform	Model variables	Model(s)	Tools
	Kumar et al. (2023)	India	Gb: National agency / [1*]	P	ConvLSTM, UNET, DeepSD, SR-GAN	N.A
	Le et al. (2023)	Mekong river basin (China, Myanmar, Laos, Thiland, Cambodia, Vietnam)	Gb: APHRODITE; RS/RA: TRMM / [1]	P	ConvENDE, ConvINCE, ConvLSTM, ConvUNET	TensorFlow, Keras, Google Colab
	Sheng et al. (2023)	Jianxi basin (China)	Gb: National agency; RS/RA: IMERG / [1]	P	F-SVD, FS-ConvLSTM, IDW, LSTM	N.A
	Tian et al. (2023)	Hanjiang basin (China)	Gb: National agency; RS/RA: IMERG, MODIS, SRTM / [1], [2], [3], [4]	P, NDVI, LST, DEM	ConvLSTM, CBAM-ConvLSTM, RF	N.A
	Cui et al. (2022)	Guangdong and Guangxi provinces (China)	Gb/RS: National agency / [1]	P, REM	A3T-GCN, ConvLSTM, DCRNN, GRAPES_MESO, GWNN, PredRNN, PredRNN-V2	Pytorch
	Kumar et al. (2022)	India	Gb: National agency; RS/RA: TRMM / N.A	P	ARIMA, ConvGRU, ConvLSTM	TensorFlow, Keras
	Gao et al. (2021)	Guangdong province (China)	Gb/RS: National agency / [1]	P	3DCNN, CNN-BiConvLSTM, CNN-ConvLSTM, LI, OF, NN	Tensorflow
	Zhang et al. (2020)	Shenzhen (China)	Gb/RS: National agency / [1]	Rf, REM	ConvLSTM, FC-LSTM, LR, LSTM, Tiny-RainNet	N.A
Soil moisture	Pan et al. (2025)	Hubei province (China)	RS/RA: SMAP, ERA5-land / [1], [2]	Patm, SR, TR, T, W (U), W (V), HV-LAI, LV-LAI, TE, SkT, P	CNN-LSTM, ConvLSTM, GCCL, RF, SARIMAX, TGC-LSTM	PyTorch, [ArcMap], Google Earth Engine
	Zhu et al. (2025)	North China Plain	Gb: CN05.1 (National agency); RS/RA: ERA5	SM, P, RH,	ConvLSTM, CubicRNN, MIM,	CUDA 10.2, PyTorch,

Category	Paper	Region	Data type and source Data access platform	Model variables	Model(s)	Tools
		(China)	[1]	SunHrs, T, Tmax, Tmin, WS	PredRNN	Python 3.8
	Li et al. (2024)	China	Gb: National agency; RS/RA: SMAP, SoMo.ml, GFS (NOAA), ERA5-land N.A	P, LF, SH, Patm, SF, WS, LULC, T, DEM	ConvLSTM, AConvLSTM, ConvLSTM-ED, Hybrid average model, Hybrid condition model	[Code]
	Rabiei et al. (2024)	USA	Gb: SCAN, USCRN; RS/RA: SMAP, NLDAS, SOLUS N.A	TB, ALB, EST, Rough, VOP, VWC, SAND, SILT, CLAY, BD, SM	ConvLSTM	Keras-Tuner
	Habiboullah & Louly (2023)	Sub-Saharan Africa	RS/RA: SMAP, Sentinel N.A	NDVI, NSMI, SM	ConvLSTM, SETR, ViT Encoder–Decoder	Tensorflow
	Huang et al. (2023)	China	Gb: National agency, RS/RA: ERA5-land [1], [2], [3], [4*], [5]	P, WS (U), WS (V), T, SR, TR, SAND, SILT, CLAY, BD	ConvLSTM, RF	Keras, Anaconda, CUDA
	Xu et al. (2023)	Yangtze river basin (China), Europe	RS/RA: ERA5; Other: ECMWF S2S, RESDC, C3S [1], [2], [3]	RZSM, SM, LULC	ConvLSTM, RF, SVR	N.A
	A et al. (2022)	Hailar river basin (China)	Gb: National agency, sampling; RS/RA: MODIS, GLDAS [1], [2], [3]	P, T, SM, ETa, LAI, EVI, NDVI, BD, SOM	ConvLSTM, Hydrus-1D	Keras, Tensorflow, CNTK, Theano, SPSS 16.0, ArcMap 10.6
	Li et al. (2022)	USA	Gb: National agency; RS/RA: SMAP N.A	SM, P, ST, LULC, DEM, TV	AttConvLSTM, ConvLSTM, LSTM, RF, SVR	N.A
			RS/RA:NLDAS			

Category	Paper	Region	Data type and source Data access platform	Model variables	Model(s)	Tools
	Villia et al. (2022)	Idaho & Arkansas (USA)	[1], [2]	SM	ConvLSTM, E-TCN	Tensorflow
	ElSaadani et al. (2021)	South Louisiana (USA)	RS/RA: MRMS, NLCD; Other: HRRR (national agency) [1*], [2], [3], [4]	LF, SF, Q, G, MA, Rf, LULC	CNN, ConvLSTM, LSTM	GDAL, Keras, Tensorflow, Google Colab, [Code]
	Li et al. (2021)	China	RS/RA: SMAP, ERA5-land N.A	SM, P, ST	CNN, ConvLSTM, LSTM	Xesmf Python package, Pycharm, Pytorch, [Code*]
Evapotranspiration	Zheng, Zhang, Yang, et al. (2024)	USA	Gb: FLUXNET2015; RS/RA: TerraClimate, ERA5-land [1]	VPD, WS, P, T, Rn, Patm	ANN, CNN, ConvLSTM, LSTM, MSA-ConvLSTM, RF, SA-ConvLSTM, XGBoost	Google Earth Engine
	Zheng, Zhang, Zhang, et al. (2024)	Shandong Peninsula (China)	RS/RA: ERA5-land, TerraClimate N.A	VPD, WS, P, T, Rn	CNN-LSTM, ConvLSTM, MulSA-ConvLSTM, SA-ConvLSTM	Google Earth Engine
	Babaeian et al. (2022)	Walnut Gulch, Tonzi Ranch, Johnson Creek, Lost Creek (USA)	RS/RA: NCA-LDAS (NASA), MODIS (MYD16A2) [1], [2]	ET, P, Rn, T, SM, WS, ETa, SHF, SoilHF	ConvLSTM, LSTM	Keras, Tensorflow, Google Colab
Surface water	Bassah et al. (2025)	Everglades wetland, USA	Gb: National agency; RS/RA: NEXRAD (NOAA) N.A	WL, Q, Rf	ANN, ConvLSTM, LR	GDAL, Rasterio Library, TensorFlow, Optuna, Pandas, [Code]
	Longyang et al. (2024)	Logan river watershed (USA)	Gb: National agency; RS/RA: NLDAS-2; Other: UEB snow model N.A	SMR	ConvLSTM-FC, ConvLSTM-SA	L-BFGS-B solver in Python, [UEB Model], [Code]
	Xu et al. (2022)	Logan river watershed (USA)	Gb: SNOTEL; RS/RA: NLDAS-2 N.A	SMR, PET	ConvLSTM, LSTM, RF, SAC-SMA	[UEB Model], [Code]
Groundwater			Gb: National agency			

Category	Paper	Region	Data type and source / Data access platform	Model variables	Model(s)	Tools
	Patra & Chu (2024)	Choushui river alluvial fan (Taiwan)	N.A	HH	CNN, ConvLSTM, MLP, LSTM	TensorFlow, Keras
	Pranjal et al. (2024)	North-western part of Indian subcontinent (India)	Gb: National agency; RS/RA: GRACE, TRMM, GLDAS / N.A	GWL, TWS, SM, P, ET, Q	ANN, CNN, ConvLSTM	ArcGIS 10.5, Sklearn, Numpy, Tensorflow, Keras
	Foroumandi et al. (2023)	Iran	Gb: National agency; RS/RA: MODIS, TRMM, GRACE, SRTM, FLDAS / N.A	P, DEM, NDVI, LST, SM, ET, SWE	ConvLSTM, FFNN, RF	Google Earth Engine, Python
	Pang et al. (2023)	Synthetic study site	Other: MODFLOW / N.A	GPR, GWL, SpDist	ConvLSTM	Tigramite Python package, [Code]

Table 2. Abbreviations of variables used in modeling referenced in the reviewed studies.

Abbreviation	Full Term	Abbreviation	Full Term
ALB	Albedo	RZSM	Root Zone Soil Moisture
BD	Bulk Density	SAND	Sand Content
CLAY	Clay Content	SF	Shortwave Flux (shortwave radiation)
DEM	Digital Elevation Model	SH	Specific Humidity
EST	Effective Soil Temperature	SHF	Sensible Heat Flux
ET	Evapotranspiration	SILT	Silt Content
ETa	Actual Evapotranspiration	SM	Soil Moisture
EVI	Enhanced Vegetation Index	SMR	Snowmelt and Rainfall
G	Groundwater Flow	SOM	Soil Organic Matter content
GPR	Groundwater Pumping Rate	SoilHF	Soil Heat Flux
GWL	Groundwater Level	SpDist	Spatial Distance
HH	Hydraulic Head	SR	Solar Radiation
HV-LAI	High Vegetation Leaf Area Index	ST	Soil Temperature
LAI	Leaf Area Index	Skt	Skin Temperature
LF	Longwave Flux (longwave radiation)	SunHrs	Sunshine Hours
LMI	Local Moran Index	SWE	Soil Water Storage
LST	Land Surface Temperature	T	Air Temperature
LULC	Land Use / Land Cover	TB	Brightness Temperature
LV-LAI	Low Vegetation Leaf Area Index	TE	Total Evaporation
MA	Moisture Availability	Tmax	Maximum Temperature
NDVI	Normalized Difference Vegetation Index	Tmin	Minimum Temperature
NSMI	Normalized Soil Moisture Index	TR	Net Surface Thermal Radiation
P	Precipitation	TV	Time Variables (month, day)
Patm	Atmospheric Pressure	TWS	Terrestrial Water Storage
PET	Potential Evapotranspiration	VOP	Vegetation Opacity
Q	Runoff / Discharge / Streamflow	VWC	Vegetation Water Content
REM	Radar Echo Map	VPD	Vapor Pressure Deficit
Rf	Rainfall	VWC	Vegetation Water Content
RH	Relative Humidity	WL	Water Level
Rn	Net Radiation	WS(U/V)	Wind Speed
Rough	Roughness coefficient		

4.1 Precipitation

Precipitation serves as the immediate source of water for the land surface hydrological budget, and it is the most important information regarding water balance calculations (Fekete et al., 2004; Pham et al., 2015). Moreover, accurate precipitation information is essential for agricultural planning and helps farmers to make informed decisions about planting and harvesting (Alexander & Block, 2022), as rainfall patterns influence soil moisture conditions, machinery access to fields, and crop readiness for harvesting, which together determine the feasibility of field operations. With the availability of different precipitation datasets with varying spatial and temporal resolution, evaluating their accuracy and spatiotemporal coverage is crucial. These datasets range from satellite-based products to ground-based gauges, radar products, and reanalysis data. The increasing spatiotemporal variability and non-stationarity of precipitation, as observed across diverse hydroclimatic regions, pose challenges for accurate modeling and prediction (Nazeri Tahroudi, 2025). In this subsection, a selection of the studies where ConvLSTM is used to simulate precipitation is briefly presented.

In recent years, calibrating satellite-derived precipitation estimates with ground-based observations has become a common approach to reduce errors and improve accuracy. However, differences in spatial resolution between satellite products and in situ measurements often introduce biases (Li & Shao, 2010; Tian et al., 2023). While satellite data typically provide only moderate accuracy in capturing precipitation, rain gauges, although precise at specific locations, cannot represent the continuous spatial distribution of rainfall or precipitation (B. Tian et al., 2023). These limitations underscore the growing emphasis on fusing multiple satellite products and bias correction of the available satellite products to generate more reliable precipitation estimates. In this regard, Fang et al. (2023) proposed an attention-enhanced ConvLSTM (A-ConvLSTM) for fusing multiple precipitation products—IMERG, ERA5, and CHIRPS—and short-term precipitation prediction in a high-latitude region. The attention mechanism was used to extract the most relevant input features and reduce input dimensionality. This model was then compared to multiple linear regression (MLR), support vector regression (SVR), LSTM, and gated recurrent unit (GRU). Results showed that the A-ConvLSTM model outperformed both the standalone products (IMERG, ERA5, CHIRPS) and the baseline models, particularly in detecting high-intensity rainfall. It achieved a higher correlation coefficient (CC) of 0.85, while the root mean squared error (RMSE) and mean absolute error (MAE) decreased to 3.53 mm/d and 1.33 mm/d, respectively. Furthermore, hydrological validation using the Xinánjiang (XAJ) model and the soil and water assessment tool (SWAT) confirmed its effectiveness for rainfall–runoff modeling. Kao et al. (2024) applied a multi-source weighted-ensemble precipitation fusion method to merge different sources of precipitation. The method integrated gauge-, satellite-, and model-based products using both LSTM and ConvLSTM architectures. These DL models were used to bias-correct satellite precipitation data (IMERG). A weighting map approach was adopted to determine the contribution of each dataset in generating the final merged product, which was then compared against gauge-only interpolated precipitation derived from inverse distance weighting (IDW) and Kriging. The results showed that both LSTM and ConvLSTM effectively corrected daily satellite precipitation estimates, improving correlation with gauge-based data by about 10%. Tian et al. (2023) developed a downscaling–merging framework to obtain spatially continuous precipitation data. The framework integrated random forest (RF), ConvLSTM, and a convolutional block attention module (CBAM) to generate high-resolution monthly precipitation data by effectively merging satellite- and gauge-based observations. In the proposed approach, monthly IMERG precipitation data were first downscaled using the RF model. The downscaled outputs were then merged with in situ observations through a ConvLSTM network. To enhance the model's ability to focus on salient spatial and temporal features within the IMERG data, CBAM was embedded within the ConvLSTM architecture. CBAM is a lightweight attention module that sequentially applies channel and spatial attention to refine feature maps by emphasizing important features and suppressing irrelevant ones. Results demonstrated that this fusion approach improved the accuracy of IMERG estimates, with the correlation coefficient (CC) increasing from 0.55 to 0.69, RMSE reduced by 31%, and MAE reduced by 27.8%. Le et al. (2023) performed bias correction of the satellite-based precipitation product (TRMM) using four DL models: Convolutional encoder–decoder (ConvENDE), ConvUNET, ConvINCE, and ConvLSTM. Ground-based observations were used as reference targets, with TRMM serving as the input, and the output of each model represented a bias-corrected version of the TRMM data. The results demonstrated that ConvLSTM achieved the lowest predictive performance compared to other models. Notably, the study also found that increasing model complexity did not necessarily lead to improved efficiency, highlighting the importance of balancing model architecture with task-specific requirements.

Enhancing spatial resolution, coherence, or reconstructing incomplete precipitation data has been another key area where researchers have employed ConvLSTM-based models. In this context, Misra et al. (2024) introduced a modified ConvLSTM architecture, termed Shared ConvLSTM, for downscaling General Circulation Model (GCM) precipitation data to higher spatial resolution. The Shared ConvLSTM framework was used to apply a single ConvLSTM model across multiple neighboring regions, allowing it to capture similarities in rainfall patterns while adapting to individual grid points. Unlike region-specific models, it downscaled precipitation for all of India in an end-to-end manner without feature engineering or dimensionality reduction, thereby preserving the full predictor dataset and better representing regional rainfall variability. Results were then compared to LSTM, ConvLSTM, and kernel regression (KR). Findings indicated that Shared ConvLSTM performed better than other models in terms of predictive accuracy by a mean squared error (MSE) of 225.58 and MAE of 7.18. Gao et al. (2021) proposed a CNN-BiConvLSTM model to reconstruct missing precipitation data from radar imagery. The model was trained on randomly generated missing patterns and evaluated across six distinct scenarios. In fact, missing radar frames were simulated by masking images in each 10-frame sequence while ensuring at least two real frames exist, which enabled the model to effectively handle incomplete sequences and maintain prediction accuracy under real-world missing-data conditions. The proposed CNN-BiConvLSTM model was compared to linear interpolation (LI), optical flow (OF), nearest neighbor (NN), CNN-ConvLSTM, and 3DCNN. Results indicated that although the performance of all models declined with an increasing number of consecutive missing frames, CNN-BiConvLSTM consistently outperformed baseline models in terms of reconstruction accuracy. The study also highlighted the importance of including valid first and last frames in the input radar sequences to improve reconstruction quality. Xu et al. (2024) proposed a deformable ConvLSTM equipped with spatial auto correlation named DConvLSTM-SAC to improve short-term precipitation forecasting. Deformable convolution enhanced standard convolution by enabling kernel sampling points to shift adaptively, rather than remain fixed on a regular grid. This flexibility enabled the model to better capture irregular shapes and patterns, which ordinary CNNs often missed. The spatial autocorrelation module was designed to integrate the statistical correlation of precipitation between nearby regions into the prediction process. Using measures such as the global and local Moran indices, it captured clustering patterns to represent spatial dependencies in rainfall. The DConvLSTM-SAC model was evaluated against RNN, RF, ConvLSTM, decision tree regressor (DTR), DConvLSTM, and ConvLSTM-SAC. Results showed that, compared to ConvLSTM, the DConvLSTM-SAC improved first-hour predictions by an average of an R^2 increase of 4.96%, while RMSE and MAE decreased by 15.21% and 9.01%, respectively.

The selected precipitation studies listed in Table 1 were conducted in recent years (2020–2025) and focused mainly on precipitation-dominant regions and mostly in Asia. A majority of the studies used multiple data sources, including ground-, satellite-, and reanalysis-based datasets, while some went beyond single-source learning by incorporating environmental variables (e.g., NDVI, DEM, WS) to better capture precipitation-terrain-climate interactions. Various ConvLSTM variants (e.g., attention mechanisms and deformable structures) were implemented to enhance the model's capability. Moreover, most ConvLSTM-based models were compared against other statistical, ML, and DL approaches. Several studies employed open-source tools such as TensorFlow, Pytorch, and Keras; however, only a few provided open code publicly.

4.2 Soil Moisture

Soil moisture is the hydrological state variable controlling ecosystem functioning, and its spatiotemporal variability is linked with infiltration, runoff, evapotranspiration, and rainfall partitioning (Daly & Porporato, 2005; Singh et al., 2021). It is a critical determinant of plant growth, nutrient cycling, and crop yield prediction. Accurate soil moisture information supports the optimization of irrigation schedules, helps prevent both water stress and overwatering, and promotes healthier plant development, ultimately contributing to increased yields and agricultural sustainability (Abdoli, 2025; B et al., 2025). In this subsection, selected studies of soil moisture prediction using ConvLSTM are briefly reviewed.

In predicting soil moisture, some studies have focused on using physical models and cross-source fusion to improve prediction accuracy. For instance, A et al. (2022) to estimate the root-zone soil moisture at 10 (cm) and 40 (cm) depths, calibrated and verified a physical model named Hydrus1-D based on the in-situ data. The generated spatiotemporal continuous vertical soil moisture values were then used as a target for the ConvLSTM model. Results showed that ConvLSTM substantially improved the ability to capture root-zone moisture dynamics compared to GLDAS products, yielding an increase in R^2 from 0.37 to 0.78 for 0-10 (cm) and from 0.02 to 0.60 for 10-40 (cm) soil moisture. Li et al. (2024) and Xu et al. (2023) have also considered the integration of physics-based models/outputs with DL models. Beyond the use of physical model outputs within the ConvLSTM workflows, cross-source transfer learning provides a related method that enables knowledge transfer from data-rich sources to data-limited targets. In this regard, Li et al. (2021) proposed a framework for improving soil moisture prediction based on limited data. They used CNN, LSTM, and ConvLSTM, organized into two pipelines: one without transfer learning, focusing solely on the target domain (SMAP) to assess model performance with limited data, and another with transfer learning, using both source (ERA5-land) and target domains. In the latter, models were pre-trained on ERA5-land and fine-tuned on SMAP to evaluate whether knowledge transfer could enhance predictive performance. Results showed that the proposed transfer ConvLSTM model improved prediction accuracy across different horizons, with R^2 increasing by 3.39%-4.35% and RMSE decreasing by 15.55%-18.18% compared with ConvLSTM without transfer learning.

Other soil moisture studies have focused on the spatiotemporal and explainability aspects of the ConvLSTM. In this regard, Pan et al. (2025) proposed a model for short-term forecasting of soil moisture based on the graph ConvLSTM (GConvLSTM) and ConvLSTM, named GCCL. GCCL built the connectivity matrix using the Pearson correlation coefficient and incorporated both local and broader spatial information along with temporal correlations, which enabled it to capture heterogeneous long-range soil moisture dependencies. The proposed GCCL was compared against temporal graph convolutional LSTM (TGC-LSTM), ConvLSTM, CNN-LSTM, SARIMAX, and RF. Since RF and SARIMAX were not able to directly predict grid image data, predictions for these two models were made pixel by pixel in a loop. The findings showed that, compared to ConvLSTM, GCCL reduced the RMSE for 1-, 3-, 5-, and 7-day-ahead predictions by 14.3%, 8.8%, 7.9%, and 7.5%, respectively. Moreover, assessment under complex spatiotemporal scenarios, such as variable topographic, rainy, and drought conditions, showed GCCL's high performance. Zhu et al. (2025) modelled soil moisture and compared the performance of ConvLSTM against three DL models, including Memory in Memory (MIM), Predictive Recurrent Neural Network (PredRNN), and CubicRNN. The PredRNN model introduced a spatiotemporal LSTM (ST-LSTM) unit with a gated dual-memory structure that simultaneously captured temporal dependencies and spatiotemporal patterns that enabled a more effective modeling of dynamic sequences than standard ConvLSTM. On the other hand, the MIM model extended ST-LSTM by introducing two cascaded modules, MIM-N for capturing non-stationary dynamics through differences between consecutive states, and MIM-S for modeling stationary patterns, to better handle complex spatiotemporal variations. Finally, the CubicRNN model incorporated separate temporal and spatial states through three Cartesian-branch structures. Results showed that while all models successfully captured the spatial patterns of soil moisture, only ConvLSTM accurately captured the temporal trend of soil moisture. ConvLSTM showed the lowest MAE of 0.0058 (m^3/m^3) and structure similarity index measure (SSIM) of 0.95. Models were also assessed during a flood recession event, and only ConvLSTM accurately captured the gradual decline trend of soil moisture. Huang et al. (2023) developed an interpretation of soil moisture predictions and used ConvLSTM with two data scenarios: the first one, which only had dynamic attributes, and the second with dynamic and static attributes. Moreover, two explainable artificial techniques—permutation importance and smooth gradient—were used to explain the model's behavior and outputs. Permutation importance was used to estimate feature importance by measuring the drop in model performance when a given feature was randomly permuted. Smooth gradient was applied to interpret the ConvLSTM model locally by averaging saliency maps over multiple noisy inputs, reducing gradient variability and improving attribution clarity. Results of permutation importance analysis showed that precipitation and soil properties are the most crucial factors affecting soil moisture prediction. Smooth Gradient analysis confirmed physical consistency, revealing stronger variable effects in low latitudes and clearer seasonality in high latitudes. Moreover, findings showed that incorporating static variables (i.e., land cover, soil properties, and elevation) enhanced the ConvLSTM predictive accuracy and increased R^2 from 0.84 (without static variables) to 0.92.

According to Table 1, ConvLSTM has been applied for soil moisture prediction across diverse regions, including the USA, Europe, Africa, and Asia. Nearly all selected studies incorporated at least one remote sensing or reanalysis dataset, with the SMAP and ERA5 being the most common. The models typically used a combination of meteorological variables (P, T, RH, WS), land surface indices (NDVI, LAI, EVI), and geophysical attributes (soil texture, DEM, land cover). The inclusion of both static and dynamic variables highlights the importance of considering the coupling of soil moisture with climate and terrain conditions. A few variants of ConvLSTM, including attention mechanisms and encoder–decoders, were used. Also, some studies used traditional models such as RF and SVR. Python-based packages and libraries were widely adopted, though only a small number of studies shared their code openly.

4.5 Evapotranspiration

Evapotranspiration determines the amount of water lost to the atmosphere, directly influencing soil moisture dynamics, irrigation requirements, and crop productivity (Allen et al., 1998). Its spatial variability reflects differences in precipitation patterns, vegetation cover, topography, and soil properties (Fisher et al., 2017), while its temporal variability responds to climatic drivers such as temperature, humidity, solar radiation, and wind speed. Given its critical role and dynamic behavior, accurate spatiotemporal prediction of evapotranspiration is essential for effective agricultural planning and hydrological modeling. In this subsection, relevant studies on evapotranspiration prediction using ConvLSTM are reviewed.

Babaeian et al. (2022) applied LSTM and ConvLSTM to predict short- and mid-term actual evapotranspiration across seven U.S. climatic zones with diverse topography, land cover, and soil types. Multivariate LSTM models were built using point-scale time series and meteorological variables from the NCA-LDAS dataset, while the univariate ConvLSTM models incorporated spatiotemporal actual observations from the MODIS/Aqua product to predict weekly actual evapotranspiration. Results showed that, at the watershed scale, ConvLSTM achieved accurate forecasts (mean normalized RMSE (NRMSE) < 6.4%, Nash-Sutcliffe efficiency (NSE) > 0.66) with greater computational efficiency across different climatic conditions. Zheng, Zhang, Yang et al. (2024) proposed a new variant of the ConvLSTM model, called Multi-head Self-Attention ConvLSTM (MSA-ConvLSTM), to predict actual evapotranspiration and overcome the limitation of using a single convolutional kernel for feature extraction. The model incorporated a spatial pyramid pooling module and a multi-head self-attention mechanism to capture multi-scale feature information. Moreover, RF, ANN, and XGBoost were used to fill gaps in net radiation data, while the Recursive Feature Elimination method with RF was applied for feature selection. Additionally, LSTM, CNN, and ConvLSTM were used to predict evapotranspiration at the site-scale. Results showed that for site-scale evapotranspiration prediction, LSTM outperformed CNN since convolution offered no advantage without spatial features, while SA-ConvLSTM and MSA-ConvLSTM were better suited for regional-scale evapotranspiration prediction but not for site-scale applications. For regional prediction, MSA-ConvLSTM achieved an average R^2 of 11.6% and 5.5% higher than ConvLSTM and SA-ConvLSTM, respectively. Its average RMSE was 21.5% and 13.7% lower, and the MAE was 21.3% and 13% lower compared to ConvLSTM and SA-ConvLSTM, respectively. In addition, by extending the prediction horizon from 1- to 7- and 30- days ahead, and by an increase in the elevation of the study area, the predictive accuracy declined. Zheng, Zhang, Zhang et al. (2024) aimed to improve actual evapotranspiration prediction accuracy and proposed a MulSA-ConvLSTM model, which combined the multiheaded self-attention module with the Pyramidally Attended Feature Extraction (PAFE) method. PAFE enabled the model to capture multi-scale spatial information through pyramid-based feature extraction, improving sensitivity to variations such as extreme evapotranspiration events. MulSAM replaced the original self-attention with multi-head attention, allowing the model to capture diverse spatial correlations more comprehensively across different subspaces. The model was compared with CNN-LSTM, ConvLSTM, and Self-Attention ConvLSTM (SA-ConvLSTM), and results showed that MulSA-ConvLSTM outperformed all of them, achieving a 2% improvement over SA-ConvLSTM. However, prediction accuracy generally declined with increasing elevation differences in the study area.

A lower number of studies in Table 1 have applied ConvLSTM to predict evapotranspiration compared to precipitation and soil moisture, and the available works are concentrated in regions in the USA and China. MODIS and ERA5 are commonly used large-scale data sources for this purpose. Typical model inputs include meteorological variables (P, T, WS, Rn, Patm), SM, and vegetation/land surface parameters (ET, SHF, VPD). The inclusion of SHF, Rn, and VPD shows the importance of considering energy availability and atmospheric demand in evapotranspiration modeling. Only two studies explored ConvLSTM variants. Although Python packages and Google Earth Engine were used, none of the studies shared their code.

4.3 Surface water

Surface water bodies can be dynamic and exhibit substantial seasonal and interannual variability. Accurate spatiotemporal data is essential for efficient water resources management, ensuring a reliable supply for agricultural, industrial, and domestic sectors (Nyberg et al., 2024; Tulbure & Broich, 2019). Moreover, precise runoff prediction (as a state of surface water in this study) is critical for managing drainage systems and regulating discharges in urban areas, which can aid in reducing flood risks and associated damages (Zahmatkesh et al., 2015). In this subsection, selected studies related to surface water prediction are briefly reviewed.

Bassah et al. (2025) used a ConvLSTM model to forecast regional-scale water levels, capturing both spatial and temporal dependencies. Two types of models were developed: a local model, which predicted water levels at two gauging stations, and a global model, which predicted water levels across the entire study area. The model's forecasting performance for the global model was compared by ConvLSTM to two local ANN and LR models. All models were trained to forecast water levels with a two-day lead time. Results showed similar accuracy for global and local models, with mean absolute relative error (MARE) values ranging from 0.38% to 1.4%. The global model (ConvLSTM) demonstrated strong potential as a single forecasting solution for the entire region and reduced the need for multiple local models. Longyang et al. (2024) used a fully connected ConvLSTM (ConvLSTM-FC) alongside a ConvLSTM with a spatial attention mechanism (ConvLSTM-SA) to predict rainfall–runoff in a snow-dominant karst watershed. Snow accumulation and melt were first simulated using the Utah Energy Balance (UEB) model, which accounts for both mass and energy balances of ground and canopy-intercepted snow. The rainfall–runoff task was then formulated as a sequence-to-sequence problem, where time series of gridded snowmelt and rainfall served as inputs, and streamflow sequences at watershed outlets or tributaries were predicted as outputs. Within this framework, the ConvLSTM processed the spatiotemporal inputs to generate grid-wise discharge contributions, which represent both surface runoff and subsurface lateral flow. Moreover, an attention mechanism refined the hidden states to better emphasize relevant spatial features before aggregating grid-level discharges into watershed-scale streamflow. Results demonstrated that ConvLSTM-SA outperformed the fully ConvLSTM-FC across all evaluation metrics, showing a notably better fit to observed hydrographs. During the test period, ConvLSTM-SA achieved higher Kling–Gupta efficiency (KGE) values compared to ConvLSTM-FC in runoff (0.92 vs. 0.86), recession (0.96 vs. 0.78), and low-flow (0.60 vs. 0.21) periods.

Similar to evapotranspiration, only a very small number of studies in Table 1 have used ConvLSTM to predict surface water-related variables, and all of them are limited to case studies in the USA, with two focusing on snow-driven watersheds. The models typically relied on a combination of ground-based and satellite/reanalysis datasets, and the input variables were generally restricted to WL, Q, Rf, snowmelt-related variables, and PET. Python was the primary programming environment across these studies, and all of them made their code publicly available.

4.4 Groundwater

Groundwater resources are a critical component of water infrastructures and play a significant role in sustainable development and agricultural production. Effective management and accurate estimation of groundwater budgets are essential to address the growing pressures of climate change and population expansion (Ren et al., 2018; Sousa & Fussi, 2021). Capturing groundwater variability across space and time aids in ensuring long-term availability despite increasing demands from urbanization, agriculture, and industry (Alabdulkreem et al., 2023; Liang et al., 2025). Because in some cases groundwater is typically measured at sparse monitoring locations, predicting its spatiotemporal dynamics remains a major challenge. To address these challenges, recent studies have applied ConvLSTM to learn complex groundwater patterns from multi-source datasets. This subsection reviews selected studies on groundwater prediction.

Foroumandi et al. (2023) applied ConvLSTM, RF, and Feed Forward Neural Network (FFNN) models to downscale GRACE-derived terrestrial water store anomaly and generate an estimate of ground water storage using remote sensing data. A Growing Neural Gas method was used on data by clustering correlated pixels into meaningful groups to improve the ability of the models to learn spatiotemporal relationships. High-resolution predictor datasets were first resampled to the coarse GRACE resolution (via linear interpolation) for model training, and then resampled to a finer 10 km resolution for terrestrial water storage anomaly estimation. In addition, GRACE drought severity index (GRACE-DSI), groundwater storage (GWS), and standardized precipitation index (SPI) maps were generated. Comparison with in-situ groundwater wells showed that ConvLSTM improved prediction accuracy, raising R^2 from 0.81 (RF) and 0.70 (FFNN) to 0.88, while reducing RMSE from 0.64 cm (RF) and 0.78 cm (FFNN) to 0.52 cm. Pang et al. (2023) used ConvLSTM to predict groundwater fluctuations influenced by collective pumping activities from multiple pumping stations in a synthetic site. MODFLOW, a physics-based groundwater model, was employed to generate synthetic data for training the ConvLSTM model. The Peter-Clark momentary conditional independence (PCMCI) method was applied to identify time-lagged causal links between pumping and groundwater drawdown, separate them from natural autocorrelation, and quantify their strength by comparing actual and counterfactual scenarios. The causal inference results obtained from PCMCI were validated against those from the classical Shapley value method. Results showed that ConvLSTM effectively modeled groundwater drawdown variations caused by pumping activities, achieving R^2 values above 90% and RMSEs smaller than 0.11 m across different scenarios. Moreover, the findings indicated that the causal relationship between a pumping station and an observation well was stronger when they were spatially closer and/or when the volume of water abstraction was larger. Patra & Chu (2024) used ConvLSTM to predict hydraulic heads and compared its performance with CNN, MLP, LSTM, and RNN. They also evaluated a Masked ConvLSTM model designed to handle missing data by reconstructing incomplete spatiotemporal input images. Results showed that ConvLSTM outperformed the other models, while the Masked ConvLSTM performed especially well under the scenario with up to 80% missing data, demonstrating strong capability in solving the spatiotemporal reconstruction problem. Finally, Pranjal et al. (2024) applied ConvLSTM to predict groundwater level fluctuations across four seasons: late post-monsoon (January), pre-monsoon (May), monsoon (August), and early post-monsoon (November). To address the limitation of data size, data augmentation techniques such as random flipping, color enhancement, rotation, and zoom were employed. Results showed that while all models performed with high accuracy, ConvLSTM achieved relatively lower prediction errors compared to CNN and ANN.

According to Table 1, only a few studies have applied ConvLSTM for groundwater level prediction, with case studies spanning Iran, Taiwan, India, and one synthetic test site. Except for the synthetic site, the others relied on ground-based datasets, and when remote sensing data were used, GRACE and TRMM were the most common sources. The models incorporated a range of hydrological, meteorological, and geospatial variables as inputs. MODFLOW, a well-established groundwater flow model, was used in one study to generate training data, which shows the potential for hybrid modeling approaches. In most cases, the predictive performance of ConvLSTM was compared against traditional ML/DL models such as RF, ANN, LSTM, and CNN. Python-based tools, including TensorFlow, Keras, and Scikit-learn, were used, although some studies employed ArcGIS and Google Earth Engine. Finally, only one study provided public code, which shows room for improvement in transparency and reproducibility.

4.5 Spatial and Temporal Resolution

Figure 3 shows the temporal and spatial resolutions applied in the reviewed ConvLSTM-based studies. The vertical axis lists the articles, grouped and ordered by hydrometeorological variable categories as defined in Table 1, and the horizontal axis shows the years. Temporal resolution is classified into hourly, daily, monthly, and seasonal, while spatial resolution is indicated for each study using reported kilometre or degree values. Where spatial or temporal resolution was not explicitly provided, studies are marked as N.A. Studies lacking information on modelling duration were excluded from this figure. The synthesis indicates that daily temporal resolution dominates ConvLSTM applications, whereas spatial resolution shows variability influenced by data availability and measurement scale. Precipitation studies exhibit a large diversity in temporal coverage. In contrast, soil moisture studies cluster after 2015, which reflects the increased availability of satellite missions providing spatiotemporal data suitable for soil moisture prediction. Evapotranspiration studies are fewer and mostly use daily or monthly intervals, and surface water studies are uniformly daily. Groundwater studies adopt monthly or seasonal scales, which is consistent with the slower variability and longer memory associated with groundwater systems.

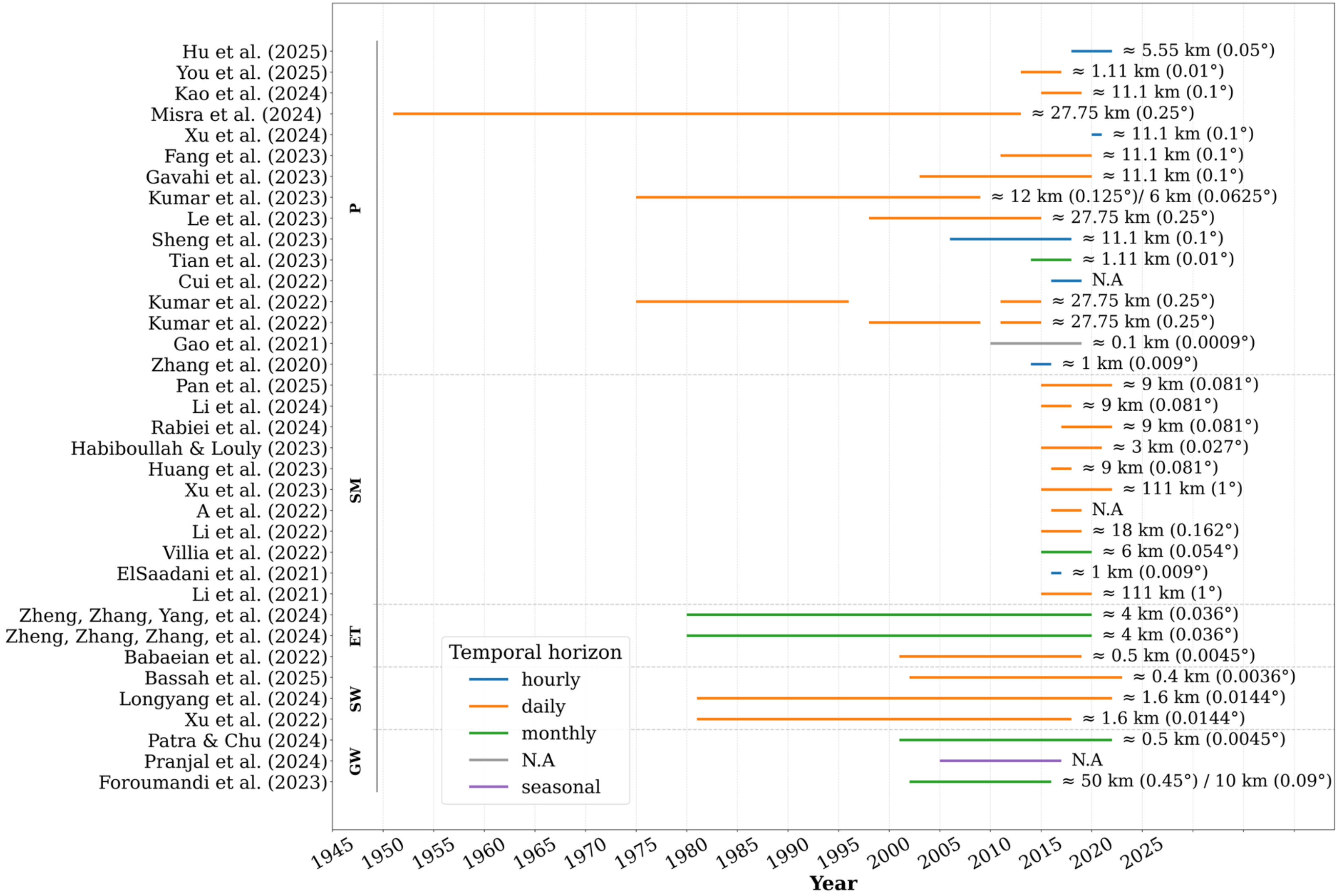

Figure 3. Modeling horizons across ConvLSTM studies.

5. Research Gaps, Challenges, and Future Directions

ConvLSTM applications in hydrometeorological studies typically involve three stages: data preprocessing, model construction, and postprocessing. Each step has specific considerations that require careful design choices to ensure accurate spatiotemporal prediction. Despite recent advancements, several critical topics remain that require more exploration. These include advanced techniques for managing missing values in spatiotemporal datasets, methods for achieving spatial and temporal resolution alignment and harmonization, the development of physics-guided architectures, the incorporation of explainability frameworks, the implementation of uncertainty quantification, and the use of transfer learning to improve model generalization. This section discusses these issues and provides potential directions for future research.

5.1 Managing missing values in spatiotemporal datasets

ConvLSTM model relies on spatiotemporal data, typically obtained from remote sensing products, reanalysis products, or ground-based measurements. To achieve high predictive performance, the availability and quality of data across both spatial and temporal dimensions must be sufficient. A critical challenge arises from missing values in hydrometeorological records that hinder model training, bias statistical measures, and distort flow variability analyses (Hamzah et al., 2020). Patterns of missing values in spatiotemporal datasets can occur along different dimensions (Son & Jang, 2020). In the spatial domain, observations and missing values may be distributed unevenly across locations. In the temporal domain, measurements may be recorded at inconsistent or arbitrary time intervals, which results in an incomplete time series. Finally, missingness may occur spatiotemporally, where data is irregularly distributed in both space and time. Because ConvLSTM models depend on continuous data sequences to learn spatiotemporal dependencies, missing values can disrupt hidden state representations and memory updates, which lead to inaccurate transitions and impaired memory dynamics (Chen et al., 2023; Courtney & Sreenivas, 2020; Son & Jang, 2020). Especially when temporal gaps occur in clusters, the model’s ability to capture underlying patterns can be further weakened (Liu et al., 2023; Liu et al., 2025). Therefore, addressing missing values in ways that preserve both temporal and spatial dependencies is essential for maintaining model accuracy (Wai et al., 2025; Weilisi & Kojima, 2022). A practical ConvLSTM-based solution for handling missing values, a method known as DL inpainting, was proposed by Son & Jang (2020). They trained a partial ConvLSTM on the incomplete spatiotemporal data, without imputation or interpolation, to predict missing values spatiotemporally. They designed a network in which the hidden state is updated only at observed locations. Moreover, since ground-truth data may not be available in real-world scenarios, a training technique was proposed that does not require ground-truth.

Within the water balance components domain, the sensitivity of the ConvLSTM model to spatial and temporal data gaps requires careful consideration. As stated earlier, given its architecture, ConvLSTM is designed to capture spatiotemporal dependencies, but it remains vulnerable to missing data. Spatial gaps can disrupt convolution operations by interfering with the extraction of local spatial features (Asadi & Regan, 2019; Lin et al., 2020), while temporal gaps compromise memory continuity in the recurrent units (Lin et al., 2020; Eum & Yoo, 2022). Among the studies reviewed, various gap-filling strategies have been employed. These include traditional interpolation techniques (Cui et al., 2022; Fang et al., 2023; B. Tian et al., 2023; Bassah et al., 2025), ML models such as RF, ANN, and XGBoost (Zheng, Zhang, Yang, et al., 2024), and the use of continuous recurrent units (Rabiei et al., 2025). In terms of DL solutions, masked ConvLSTM (Patra & Chu, 2024) and CNN-BiConvLSTM variants (Gao et al., 2021) have been applied to reconstruct spatiotemporal sequences. Other approaches include convolution-based data transformations to address NaN values in regions without observations (Kumar et al., 2022) and inter-observation prediction using ConvLSTM (ElSaadani et al., 2021). Some studies adopted a threshold-based exclusion approach, removing stations with more than 5% missing data. While there are various methods for addressing missing data, quantifying the spatiotemporal uncertainty associated with imputating missing values in hydrometeorological datasets is an area, which remained less explored. These imputed values may introduce biases and reduce model performance and should be addressed properly (Muhaime et al., 2022). This task is necessary for ensuring the reliability and accuracy of subsequent predictions and analysis while using ConvLSTM.

5.2 Spatial harmonization and resolution alignment for ConvLSTM inputs

An important consideration when applying ConvLSTM models is ensuring consistency in the spatial resolution of input variables (e.g., satellite precipitation at 0.1°, MODIS evapotranspiration at 500 m, and in-situ groundwater at point scale). Maintaining uniform spatial resolution across datasets is critical for effective integration, which contributes to the model coherence. When input data exhibit varying spatial resolutions, convolutional layers may struggle to extract consistent spatial features across time steps, which can lead to degraded performance and diminished reliability in capturing spatiotemporal patterns (Fang et al., 2021; Nie et al., 2021; Oddo et al., 2024). Therefore, spatial harmonization and resolution alignment prior to ConvLSTM prediction are essential, and suitable interpolation or resampling techniques must be applied. In this regard, a DL-based approach was proposed by Noh & Ahn (2025), in which they implemented a ResU-Net architecture and used each dataset at its inherent spatial and temporal resolution as input to generate predictions. By effectively merging multiple datasets with varying spatiotemporal characteristics, their method demonstrated promising potential for improving prediction accuracy while preserving the original data integrity. The main contribution of this method can be preserving the original resolution of data as input for ConvLSTM.

Among the reviewed studies, various approaches have been used to achieve uniform resolution across datasets or make gauge-measured data spatially distributed. Some studies used deterministic techniques such as inverse distance weighting (IDW)(Fang et al., 2023; Kao et al., 2024; Patra & Chu, 2024; Pranjal et al., 2024; Bassah et al., 2025), Shepard interpolation (Kumar et al., 2022), and nearest neighbor (Gavahi et al., 2023; Habiboullah & Louly, 2023; Z. Pan et al., 2025; You et al., 2025). Spline and polynomial-based approaches, such as linear interpolation (Foroumandi et al., 2023), bilinear interpolation (B. Tian et al., 2023; Kao et al., 2024; Li et al., 2024; Misra et al., 2024; Zheng, Zhang, Yang, et al., 2024; Zheng, Zhang, Zhang, et al., 2024; Hu et al., 2025), and bicubic interpolation (Rabiei et al., 2025) were also used in the reviewed studies. Geostatistical method, kriging (A et al., 2022; Kumar et al., 2023; Pranjal et al., 2024), and DL-based approaches, CNNs (Kumar et al., 2023; Le et al., 2023), and F-SVD (Sheng et al., 2023), were also used for this purpose. While most studies used classical techniques to make input datasets spatially consistent in resolution, it is recommended to benchmark interpolation-induced uncertainty by evaluating how different interpolation methods affect the reliability and accuracy of ConvLSTM predictions.

5.3 Integrating physical knowledge into the ConvLSTM model

One inherent limitation of ConvLSTM, and DL models broadly, is the lack of embedded physical knowledge about hydrological and atmospheric processes. Because these models operate as data-driven systems, they inherently neglect underlying physical laws. To bridge this gap, the inclusion of meaningful auxiliary variables related to the investigated phenomena in the model input can help make the approach more *physics-guided* (Harilal et al., 2021; Oyama et al., 2023). In addition to this strategy, running a physical model and using its output as input to DL models is often considered a form of *physics-guided* modeling (B. Liu et al., 2022). While these approaches may enhance the predictive accuracy of the models, they do not guarantee adherence to physical principles. A robust definition of *physics-guided* modeling involves explicitly incorporating physical laws into the model architecture or its training objective. This approach was successfully applied in a study conducted by Shi et al. (2024), where a *physics-informed* ConvLSTM was developed for sea surface temperature prediction. They introduced a physical constraint module to mimic fluid transport dynamics, using data assimilation techniques typically applied to solve partial differential equations. Incorporating such constraints into more sophisticated architectures entails greater engineering complexity and necessitates careful consideration of which physical laws should be preserved (Shen & Lawson, 2021). In the case of predicting water balance–related components, integrating water balance–based constraints into the ConvLSTM loss function can guide the model with hydrological laws, which, in turn, improves its physical consistency.

5.4 Advancing transparency in ConvLSTM

The complexity of the ConvLSTM architecture, with its multiple layers and a large number of neural weights and biases, poses challenges for interpreting the prediction process and understanding the influence of individual features on model outputs. Therefore, ConvLSTM falls into the category of black box models. In recent years, explainable artificial intelligence (XAI) has shown potential in making DL models more transparent (Bramm et al., 2025). XAI methods can be categorized into three groups (Maier et al., 2024): (1) identifying decisive features, in other words, inputs that have the most influence on the model's predictions, (2) apportioning and quantifying each feature's contribution to the prediction, and (3) assessing the model's robustness against perturbations in the input features. While various XAI methods have been developed for DL models, explainability in ConvLSTM requires approaches that are designed for its spatiotemporal characteristics. In the hydrological domain, where features used in the model can be interdependent, interpreting the contribution of each across both space and time becomes particularly complex. For instance, effects of temporal lag (e.g., between precipitation and soil moisture) and spatial heterogeneity (e.g., due to diverse land cover types) must be captured without introducing interpretative bias. Therefore, explainability techniques should account for these multiscale dependencies to ensure physically meaningful and unbiased insights. Gradient-weighted Class Activation Mapping (Grad-CAM) is a method that helps to make DL models explainable. In fact, this method highlights the parts of an input image of a neural network that most influence its predictions (Selvaraju et al., 2020). Similarly, vanilla gradient and smoothgrad can be used (Simonyan et al., 2014; Smilkov et al., 2017). These XAI methods enable understanding of what a ConvLSTM is learning spatially and make this black box model more interpretable.

5.5 Uncertainty quantification in ConvLSTM prediction

In addition to the standard performance metrics, conducting uncertainty analysis provides valuable insight into the reliability of ConvLSTM predictions. Uncertainty analysis focuses on understanding and quantifying the sources and impacts of uncertainties in model predictions (Camacho & Martin, 2013; Alimohammadi et al., 2018). It is primarily concerned with the variability and limitations in model inputs, parameters, and structural assumptions. Specifically, aleatoric uncertainty refers to uncertainty inherent in the data itself, arising from noise or randomness in observations, which cannot be reduced by collecting more data. In contrast, epistemic uncertainty arises from the model's lack of knowledge, structure, or parameter limitations (Kendall & Gal, 2017; Brown et al., 2020; Choi et al., 2020). Addressing these uncertainties within ConvLSTM is particularly important, especially when interpolation or resampling is applied, or when physics-based constraints are embedded in its architectures. Within the spatiotemporal prediction, Bayesian and frequentist methods offer distinct capabilities in quantifying the uncertainties (D. Wu et al., 2021). Despite some recent progress in applying uncertainty quantification to DL models for spatiotemporal data (He & Jiang, 2023), its application within ConvLSTM-based modeling requires more Investigation. Future research should prioritize developing and benchmarking uncertainty quantification techniques that are both scalable and hydrologically meaningful.

5.6 Transfer learning for enhancing ConvLSTM generalization

Achieving robust generalization across diverse hydrological regions remains a fundamental challenge, particularly when models trained for one watershed are applied to another with differing climatic, topographic, or land use conditions. Transfer learning is a DL technique that involves taking advantage of a pre-trained model on one task and adapting it to a new but related task. Different tasks may share underlying mathematical structures or require similar types of responses, which results in transferable internal representations within the neural network. In other words, transfer learning enables reusing parts of the original model while fine-tuning others for the target task, which is particularly beneficial when data availability is limited (S. J. Pan & Yang, 2010; Ouyang et al., 2025). The applicability of transfer learning has been explored in hydrology (Ma et al., 2021; Yao et al., 2023; Y. Xu et al., 2023) and showed promise for improving model generalizability. In the context of ConvLSTM-based models, the reliability of transfer learning can be systematically evaluated across varying degrees of regional similarity, including climatic zones, topographic features, and land cover types, to establish guidelines for effective transferability. Moreover, transfer learning has the potential to offer a scalable solution for extending spatiotemporal ConvLSTM models to data-scarce or ungauged basins. Integrating physics-informed constraints during the transfer process is recommended to ensure that model outputs remain physically plausible in the new region.

6. Conclusions

The systematically reviewed studies pinpoint recent advances in spatiotemporal prediction of water balance–related variables, including precipitation, soil moisture, evapotranspiration, surface water, and groundwater. The findings demonstrated that ConvLSTM has been applied across these domains and is capable of capturing complex spatiotemporal dependencies that are often difficult for traditional ML and DL models to represent. The integration of attention mechanisms, encoder–decoder structures, and deformable convolutions highlights the architectural flexibility of ConvLSTM. Overall, ConvLSTM has been used for diverse purposes, including multisource data fusion and satellite bias correction, spatial downscaling, missing data reconstruction, and, most prominently, spatiotemporal prediction of hydrometeorological variables. Recent progress has revealed remaining challenges and new research gaps. The presence of missing values in spatiotemporal datasets, as well as mismatches in the spatial resolution of satellite and reanalysis products, are issues that must be addressed before feeding inputs to a ConvLSTM model. However, it is equally important to quantify uncertainties introduced by these preprocessing steps, an area that still requires more exploration. Additionally, the lack of embedded physical knowledge and the black-box nature of ConvLSTM restricts interpretability and physical consistency. Integrating hydrological constraints into ConvLSTM's architecture and employing XAI techniques can help address these issues. Transfer learning also offers a promising strategy to improve scalability by adapting models trained in data-rich basins to data-scarce or ungauged regions.

Looking forward, future efforts should focus on developing integrated frameworks that couple ConvLSTM with hydrological models, advancing ConvLSTM architectures capable of multiresolution learning for hydrometeorological purposes, and designing basin-transferable ConvLSTM models. Continued interdisciplinary collaboration will be essential to unlock the full potential of these approaches for sustainable water resource management.

Statements & Declarations

Ethical Approval

The authors declare that all data and materials, as well as software applications or custom codes, are in line with published claims and comply with field standards.

Consent to Participate

All authors contributed to the study and agreed to participate in the preparation and submission of this manuscript.

Consent to Publish

All authors have read and approved the final manuscript and consent to its publication.

Authors Contributions

Seyed Hossein Hosseini: Conceptualization; Methodology; Formal Analysis; Investigation; Data Curation; Writing – Original Draft; Visualization. Henrikki Tenkanen: Conceptualization; Methodology; Writing – Review and Editing; Supervision; Funding Acquisition. Harri Koivusalo: Conceptualization; Writing – Review and Editing; Supervision. Jussi Nikander: Conceptualization; Writing – Review and Editing; Supervision.

Funding

This work was a part of the Ministry of Education and Culture's Doctoral Education Pilot under Decision No. VN/3137/2024-OKM-6 (Digital Waters (DIWA) Doctoral Education Pilot related to the DIWA Flagship (decision no. 359248) funded by the Research Council of Finland's Flagship Programme. The work was further supported by Maa- ja vesitekniikan tuki ry.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and materials

All the data used have been presented in the paper.

Generative Artificial Intelligence Use Disclosure

ChatGPT was employed solely to assist with grammar, language flow, and typographical corrections. Its use was limited to language refinement, and all outputs were critically reviewed, checked, and approved by the authors.

References

A, Y., Wang, G., Hu, P., Lai, X., Xue, B., & Fang, Q. (2022). Root-zone soil moisture estimation based on remote sensing data and deep learning. *Environmental Research*, *212*, 113278. https://doi.org/10.1016/j.envres.2022.113278

Abdoli, S. (2025). Remote Sensing Methods in Agrogeophysical Investigations. In *Remote Sensing for Geophysicists*. CRC Press.

Alabdulkreem, E., Alruwais, N., Mahgoub, H., Dutta, A. K., Khalid, M., Marzouk, R., Motwakel, A., & Drar, S. (2023). Sustainable groundwater management using stacked LSTM with deep neural network. *Urban Climate*, *49*, 101469. https://doi.org/10.1016/j.uclim.2023.101469

Alexander, S., & Block, P. (2022). Integration of seasonal precipitation forecast information into local-level agricultural decision-making using an agent-based model to support community adaptation. *Climate Risk Management*, *36*, 100417. https://doi.org/10.1016/j.crm.2022.100417

Ali, M., Prasad, R., Xiang, Y., & Yaseen, Z. M. (2020). Complete ensemble empirical mode decomposition hybridized with random forest and kernel ridge regression model for monthly rainfall forecasts. *Journal of Hydrology*, *584*, 124647. https://doi.org/10.1016/j.jhydrol.2020.124647

Alimohammadi, S., Behrouz, M., & Noorzad, A. (2018). Uncertainty Analysis of Flood Control Levees Design Considering Correlation of Input Parameters*. In *Twenty-Sixth International Congress on Large Dams / Vingt-Sixième Congrès International des Grands Barrages*. CRC Press.

Allen, R., Pereira, L., & Smith, M. (1998). *Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56* (Vol. 56).

Althoff, D., & Rodrigues, L. N. (2021). Goodness-of-fit criteria for hydrological models: Model calibration and performance assessment. *Journal of Hydrology*, *600*, 126674. https://doi.org/10.1016/j.jhydrol.2021.126674

Amen, E. M., & Calvache, M. L. (2025). Hydrological model and integrated GIS techniques for simulation and analysis of the long-term water balance in a coastal aquifer, Spain. *Scientific Reports*, *15*(1), 27148. https://doi.org/10.1038/s41598-025-07543-z

Ardabili, S., Mosavi, A., Dehghani, M., & Várkonyi-Kóczy, A. R. (2020). Deep Learning and Machine Learning in Hydrological Processes Climate Change and Earth Systems a Systematic Review. In A. R. Várkonyi-Kóczy (Ed.), *Engineering for Sustainable Future* (pp. 52–62). Springer International Publishing. https://doi.org/10.1007/978-3-030-36841-8_5

Asadi, R., & Regan, A. (2019). *A convolution recurrent autoencoder for spatio-temporal missing data imputation* (No. arXiv:1904.12413). arXiv. https://doi.org/10.48550/arXiv.1904.12413

B, S. S. K., Immanuel, R. R., Mathivanan, S. K., Jayagopal, P., Rajendran, S., Mallik, S., & Li, A. (2025). Smart Irrigation System Using Soil Moisture Prediction with Deep CNN for Various Soil Types. *Artificial Intelligence and Applications*, *3*(2), 200–210. https://doi.org/10.47852/bonviewAIA42021514

Babaeian, E., Paheding, S., Siddique, N., Devabhaktuni, V. K., & Tuller, M. (2022). Short- and mid-term forecasts of actual evapotranspiration with deep learning. *Journal of Hydrology*, *612*, 128078. https://doi.org/10.1016/j.jhydrol.2022.128078

Baroni, G., Schalge, B., Rakovec, O., Kumar, R., Schüler, L., Samaniego, L., Simmer, C., & Attinger, S. (2019). A Comprehensive Distributed Hydrological Modeling Intercomparison to Support Process Representation and Data Collection Strategies. *Water Resources Research*, *55*(2), 990–1010. https://doi.org/10.1029/2018WR023941

Bassah, R., Corzo, G., Bhattacharya, B., Haider, S. M., Swain, E. D., & Aumen, N. (2025). Forecasting water levels using the ConvLSTM algorithm in the Everglades, USA. *Journal of Hydrology*, *652*, 132195. https://doi.org/10.1016/j.jhydrol.2024.132195

Beven, K., & Binley, A. (1992). The future of distributed models: Model calibration and uncertainty prediction. *Hydrological Processes*, *6*(3), 279–298. https://doi.org/10.1002/hyp.3360060305

Beven, K., & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology*, *249*(1), 11–29. https://doi.org/10.1016/S0022-1694(01)00421-8

Bramm, A. M., Matrenin, P. V., & Khalyasmaa, A. I. (2025). A Review of XAI Methods Applications in Forecasting Runoff and Water Level Hydrological Tasks. *Mathematics*, *13*(17), 2830. https://doi.org/10.3390/math13172830

Brown, K., Bhuiyan, F. A., & Talbert, D. (2020). *Uncertainty Quantification in Multimodal Ensembles of Deep Learners*.

Camacho, R., & Martin, J. (2013). Bayesian Monte Carlo for evaluation of uncertainty in hydrodynamic models of coastal systems. *Journal of Coastal Research*, *Special Issue 65*, 886–891. https://doi.org/10.2112/SI65-150.1

Chen, Y., Shi, K., Wang, X., & Xu, G. (2023). MTSTI: A Multi-task Learning Framework for Spatiotemporal Imputation. In X. Yang, H. Suhartanto, G. Wang, B. Wang, J. Jiang, B. Li, H. Zhu, & N. Cui (Eds.), *Advanced Data Mining and Applications* (pp. 180–194). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-46677-9_13

Choi, J., Kim, D., & Byun, J. (2020, October 11). *Uncertainty estimation in impedance inversion using Bayesian deep learning*. SEG International Exposition and Annual Meeting. https://doi.org/10.1190/segam2020-3428098.1

Courtney, L., & Sreenivas, R. (2020). Using Deep Convolutional LSTM Networks for Learning Spatiotemporal Features. In S. Palaiahnakote, G. Sanniti di Baja, L. Wang, &

W. Q. Yan (Eds.), *Pattern Recognition* (pp. 307–320). Springer International Publishing. https://doi.org/10.1007/978-3-030-41299-9_24

Cristiano, E., ten Veldhuis, M.-C., & van de Giesen, N. (2017). Spatial and temporal variability of rainfall and their effects on hydrological response in urban areas – a review. *Hydrology and Earth System Sciences*, *21*(7), 3859–3878. https://doi.org/10.5194/hess-21-3859-2017

Cui, Y., Qiu, Y., Sun, L., Shu, X., & Lu, Z. (2022). Quantitative short-term precipitation model using multimodal data fusion based on a cross-attention mechanism. *Remote Sensing*, *14*(22), 5839.

Daly, E., & Porporato, A. (2005). A Review of Soil Moisture Dynamics: From Rainfall Infiltration to Ecosystem Response. *Environmental Engineering Science*, *22*(1), 9–24. https://doi.org/10.1089/ees.2005.22.9

Dastorani, M. T., & Poormohammadi, S. (2012). Evaluation of Water Balance in a Mountainous Upland Catchment Using SEBAL Approach. *Water Resources Management*, *26*(7), 2069–2080. https://doi.org/10.1007/s11269-012-9999-y

dos Santos, F. M., de Oliveira, R. P., & Mauad, F. F. (2018). Lumped versus Distributed Hydrological Modeling of the Jacaré-Guaçu Basin, Brazil. *Journal of Environmental Engineering*, *144*(8), 04018056. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001397

ElSaadani, M., Habib, E., Abdelhameed, A. M., & Bayoumi, M. (2021). Assessment of a Spatiotemporal Deep Learning Approach for Soil Moisture Prediction and Filling the Gaps in Between Soil Moisture Observations. *Frontiers in Artificial Intelligence*, *4*. https://doi.org/10.3389/frai.2021.636234

Eum, Y., & Yoo, E.-H. (2022). Imputation of missing time-activity data with long-term gaps: A multi-scale residual CNN-LSTM network model. *Computers, Environment and Urban Systems*, *95*, 101823. https://doi.org/10.1016/j.compenvurbsys.2022.101823

Fang, W., Pang, L., Yi, W., & Sheng, V. (2021). AttEF: Convolutional LSTM Encoder-Forecaster with Attention Module for Precipitation Nowcasting. *Intelligent Automation & Soft Computing*, *30*(2), 453–466. https://doi.org/10.32604/iasc.2021.016589

Fang, W., Qin, H., Liu, G., Yang, X., Xu, Z., Jia, B., & Zhang, Q. (2023). A Method for Spatiotemporally Merging Multi-Source Precipitation Based on Deep Learning. *Remote Sensing*, *15*(17), 4160.

Fekete, B. M., Vörösmarty, C. J., Roads, J. O., & Willmott, C. J. (2004). *Uncertainties in Precipitation and Their Impacts on Runoff Estimates*. https://journals.ametsoc.org/view/journals/clim/17/2/1520-0442_2004_017_0294_uipati_2.0.co_2.xml

Feltrin, R. M., de Paiva, J. B. D., de Paiva, E. M. C. D., & Beling, F. A. (2011). Lysimeter soil water balance evaluation for an experiment developed in the Southern Brazilian

Atlantic Forest region. *Hydrological Processes*, *25*(15), 2321–2328. https://doi.org/10.1002/hyp.7971

Fisher, J. B., Melton, F., Middleton, E., Hain, C., Anderson, M., Allen, R., McCabe, M. F., Hook, S., Baldocchi, D., Townsend, P. A., Kilic, A., Tu, K., Miralles, D. D., Perret, J., Lagouarde, J.-P., Waliser, D., Purdy, A. J., French, A., Schimel, D., ... Wood, E. F. (2017). The future of evapotranspiration: Global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. *Water Resources Research*, *53*(4), 2618–2626. https://doi.org/10.1002/2016WR020175

Foroumandi, E., Nourani, V., Jeanne Huang, J., & Moradkhani, H. (2023). Drought monitoring by downscaling GRACE-derived terrestrial water storage anomalies: A deep learning approach. *Journal of Hydrology*, *616*, 128838. https://doi.org/10.1016/j.jhydrol.2022.128838

Gao, L., Zheng, Y., Wang, Y., Xia, J., Chen, X., Li, B., Luo, M., & Guo, Y. (2021). Reconstruction of missing data in weather radar image sequences using deep neuron networks. *Applied Sciences*, *11*(4), 1491.

Gardiya Weligamage, H., Fowler, K., Peterson, T. J., Saft, M., Peel, M. C., & Ryu, D. (2023). Partitioning of Precipitation Into Terrestrial Water Balance Components Under a Drying Climate. *Water Resources Research*, *59*(5), e2022WR033538. https://doi.org/10.1029/2022WR033538

Gavahi, K., Foroumandi, E., & Moradkhani, H. (2023). A deep learning-based framework for multi-source precipitation fusion. *Remote Sensing of Environment*, *295*, 113723.

Gemechu, T. M., Zhao, H., Bao, S., Yangzong, C., Liu, Y., Li, F., & Li, H. (2021). Estimation of Hydrological Components under Current and Future Climate Scenarios in Guder Catchment, Upper Abbay Basin, Ethiopia, Using the SWAT. *Sustainability*, *13*(17), 9689. https://doi.org/10.3390/su13179689

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Convolutional networks. *Deep Learning*, *2016*, 330–372.

Habiboullah, A., & Louly, M. A. (2023). Soil Moisture Prediction Using NDVI and NSMI Satellite Data: ViT-Based Models and ConvLSTM-Based Model. *SN Computer Science*, *4*(2), 140. https://doi.org/10.1007/s42979-022-01554-7

Hamzah, F. B., Mohd Hamzah, F., Mohd Razali, S. F., Jaafar, O., & Abdul Jamil, N. (2020). Imputation methods for recovering streamflow observation: A methodological review. *Cogent Environmental Science*, *6*(1), 1745133. https://doi.org/10.1080/23311843.2020.1745133

Harilal, N., Singh, M., & Bhatia, U. (2021). Augmented Convolutional LSTMs for Generation of High-Resolution Climate Change Projections. *IEEE Access*, *9*, 25208–25218. https://doi.org/10.1109/ACCESS.2021.3057500

He, W., & Jiang, Z. (2023). *Uncertainty Quantification of Deep Learning for Spatiotemporal Data: Challenges and Opportunities* (No. arXiv:2311.02485). arXiv. https://doi.org/10.48550/arXiv.2311.02485

Herrera, P. A., Marazuela, M. A., & Hofmann, T. (2022). Parameter estimation and uncertainty analysis in hydrological modeling. *WIREs Water*, *9*(1), e1569. https://doi.org/10.1002/wat2.1569

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hu, B., Zhang, X., Fang, Y., Mou, S., Qian, R., Li, J., & Chen, Z. (2025). Multisource Precipitation Data Merging Using a Dual-Layer ConvLSTM Model. *Remote Sensing*, *17*(3), 546.

Huang, F., Zhang, Y., Zhang, Y., Shangguan, W., Li, Q., Li, L., & Jiang, S. (2023). Interpreting Conv-LSTM for Spatio-Temporal Soil Moisture Prediction in China. *Agriculture*, *13*(5), Article 5. https://doi.org/10.3390/agriculture13050971

Huntington, J. L., & Niswonger, R. G. (2012). Role of surface-water and groundwater interactions on projected summertime streamflow in snow dominated regions: An integrated modeling approach. *Water Resources Research*, *48*(11). https://doi.org/10.1029/2012WR012319

Husic, A., Al-Aamery, N., & Fox, J. F. (2022). Simulating hydrologic pathway contributions in fluvial and karst settings: An evaluation of conceptual, physically-based, and deep learning modeling approaches. *Journal of Hydrology X*, *17*, 100134. https://doi.org/10.1016/j.hydroa.2022.100134

Jaderberg, M., Simonyan, K., Zisserman, A., & Kavukcuoglu, K. (2016). *Spatial Transformer Networks* (No. arXiv:1506.02025). arXiv. https://doi.org/10.48550/arXiv.1506.02025

Kao, Y.-C., Tsou, H.-E., & Chen, C.-J. (2024). Development of multi-source weighted-ensemble precipitation: Influence of bias correction based on recurrent convolutional neural networks. *Journal of Hydrology*, *629*, 130621.

Kendall, A., & Gal, Y. (2017). What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision? *Advances in Neural Information Processing Systems*, *30*. https://proceedings.neurips.cc/paper/2017/hash/2650d6089a6d640c5e85b2b88265dc2b-Abstract.html

Kumar, B., Abhishek, N., Chattopadhyay, R., George, S., Singh, B. B., Samanta, A., Patnaik, B. S. V., Gill, S. S., Nanjundiah, R. S., & Singh, M. (2022). Deep learning based short-range forecasting of Indian summer monsoon rainfall using earth observation and ground station datasets. *Geocarto International*, *37*(27), 17994–18021.

Kumar, B., Atey, K., Singh, B. B., Chattopadhyay, R., Acharya, N., Singh, M., Nanjundiah, R. S., & Rao, S. A. (2023). On the modern deep learning approaches for precipitation downscaling. *Earth Science Informatics*, *16*(2), 1459–1472.

Latif, S. D., & Ahmed, A. N. (2023). A review of deep learning and machine learning techniques for hydrological inflow forecasting. *Environment, Development and Sustainability*, *25*(11), 12189–12216. https://doi.org/10.1007/s10668-023-03131-1

Lauenroth, W. K., & Bradford, J. B. (2006). Ecohydrology and the Partitioning AET Between Transpiration and Evaporation in a Semiarid Steppe. *Ecosystems*, *9*(5), 756–767. https://doi.org/10.1007/s10021-006-0063-8

Le, X.-H., Nguyen, D. H., & Lee, G. (2023). Performance comparison of bias-corrected satellite precipitation products by various deep learning schemes. *IEEE Transactions on Geoscience and Remote Sensing*, *61*, 1–12.

Li, L., Dai, Y., Shangguan, W., Wei, N., Wei, Z., & Gupta, S. (2022). *Multistep Forecasting of Soil Moisture Using Spatiotemporal Deep Encoder–Decoder Networks*. https://doi.org/10.1175/JHM-D-21-0131.1

Li, L., Dai, Y., Wei, Z., Shangguan, W., Wei, N., Zhang, Y., Li, Q., & Li, X.-X. (2024). Enhancing Deep Learning Soil Moisture Forecasting Models by Integrating Physics-based Models. *Advances in Atmospheric Sciences*, *41*(7), 1326–1341. https://doi.org/10.1007/s00376-023-3181-8

Li, L., Dai, Y., Wei, Z., Shangguan, W., Zhang, Y., Wei, N., & Li, Q. (2023). *Enforcing Water Balance in Multitask Deep Learning Models for Hydrological Forecasting*. https://doi.org/10.1175/JHM-D-23-0073.1

Li, M., Liang, X., Xiao, C., & Cao, Y. (2020). Quantitative evaluation of groundwater-surface water interactions: Application of cumulative exchange fluxes method. *Water (Switzerland)*, *12*(1). https://doi.org/10.3390/w12010259

Li, M., & Shao, Q. (2010). An improved statistical approach to merge satellite rainfall estimates and raingauge data. *Journal of Hydrology*, *385*(1), 51–64. https://doi.org/10.1016/j.jhydrol.2010.01.023

Li, Q., Wang, Z., Shangguan, W., Li, L., Yao, Y., & Yu, F. (2021). Improved daily SMAP satellite soil moisture prediction over China using deep learning model with transfer learning. *Journal of Hydrology*, *600*, 126698. https://doi.org/10.1016/j.jhydrol.2021.126698

Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2022). A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(12), 6999–7019. https://doi.org/10.1109/TNNLS.2021.3084827

Li, Z., Liu, H., Zhao, W., Yang, Q., Yang, R., & Liu, J. (2019). Quantification of soil water balance components based on continuous soil moisture measurement and the

Richards equation in an irrigated agricultural field of a desert oasis. *Hydrology and Earth System Sciences*, *23*(11), 4685–4706. https://doi.org/10.5194/hess-23-4685-2019

Liang, X. X., Gloaguen, E., Claprood, M., Paradis, D., & Lauzon, D. (2025). Graph Neural Network Framework for Spatiotemporal Groundwater Level Forecasting. *Mathematical Geosciences*, *57*(6), 1071–1093. https://doi.org/10.1007/s11004-025-10194-5

Lin, Z., Li, M., Zheng, Z., Cheng, Y., & Yuan, C. (2020). Self-Attention ConvLSTM for Spatiotemporal Prediction. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(07), Article 07. https://doi.org/10.1609/aaai.v34i07.6819

Liu, B., Tang, Q., Zhao, G., Gao, L., Shen, C., & Pan, B. (2022). Physics-Guided Long Short-Term Memory Network for Streamflow and Flood Simulations in the Lancang–Mekong River Basin. *Water*, *14*(9), 1429. https://doi.org/10.3390/w14091429

Liu, M., Huang, H., Feng, H., Sun, L., Du, B., & Fu, Y. (2023). PriSTI: A Conditional Diffusion Framework for Spatiotemporal Imputation. *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, 1927–1939. https://doi.org/10.1109/ICDE55515.2023.00150

Liu, X., Gao, J., He, X., Deng, L., Duh, K., & Wang, Y.-Y. (2015). *Representation Learning Using Multi-Task Deep Neural Networks for Semantic Classification and Information Retrieval*. https://www.microsoft.com/en-us/research/publication/representation-learning-using-multi-task-deep-neural-networks-for-semantic-classification-and-information-retrieval/

Liu, Z., Zhao, X., & Song, Y. (2025). RDPI: A Refine Diffusion Probability Generation Method for Spatiotemporal Data Imputation. *Proceedings of the AAAI Conference on Artificial Intelligence*, *39*(12), Article 12. https://doi.org/10.1609/aaai.v39i12.33335

Longyang, Q., Choi, S., Tennant, H., Hill, D., Ashmead, N., Neilson, B. T., Newell, D. L., McNamara, J. P., & Xu, T. (2024). An Attention-Based Explainable Deep Learning Approach to Spatially Distributed Hydrologic Modeling of a Snow Dominated Mountainous Karst Watershed. *Water Resources Research*, *60*(11), e2024WR037878. https://doi.org/10.1029/2024WR037878

López López, P., Sutanudjaja, E. H., Schellekens, J., Sterk, G., & Bierkens, M. F. P. (2017). Calibration of a large-scale hydrological model using satellite-based soil moisture and evapotranspiration products. *Hydrology and Earth System Sciences*, *21*(6), 3125–3144. https://doi.org/10.5194/hess-21-3125-2017

Ma, K., Feng, D., Lawson, K., Tsai, W.-P., Liang, C., Huang, X., Sharma, A., & Shen, C. (2021). Transferring Hydrologic Data Across Continents – Leveraging Data-Rich Regions to Improve Hydrologic Prediction in Data-Sparse Regions. *Water Resources Research*, *57*(5), e2020WR028600. https://doi.org/10.1029/2020WR028600

Marcinkowski, P., Kardel, I., Płaczkowska, E., Giełczewski, M., Osuch, P., Okruszko, T., Venegas-Cordero, N., Ignar, S., & Piniewski, M. (2023). High-resolution simulated water balance and streamflow data set for 1951–2020 for the territory of Poland. *Geoscience Data Journal*, *10*(2), 195–207. https://doi.org/10.1002/gdj3.152

Mihaela, P., Gabriel, E., Minda Codruta, B. –, & Daniela, P. (2019). Sustainable Water Resources Development as Part of the Integrated Water Resource Management for Mureş River. *IOP Conference Series: Materials Science and Engineering*, *603*(4), 042022. https://doi.org/10.1088/1757-899X/603/4/042022

Misra, S., Sarkar, S., Mitra, P., & Shastri, H. (2024). Statistical downscaling of high-resolution precipitation in India using convolutional long short-term memory networks. *Journal of Water and Climate Change*, *15*(3), 1120–1141.

Mohebzadeh, H., & Fallah, M. (2019). Quantitative analysis of water balance components in Lake Urmia, Iran using remote sensing technology. *Remote Sensing Applications: Society and Environment*, *13*, 389–400. https://doi.org/10.1016/j.rsase.2018.12.009

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Muhaime, N. A. D. A., Arifin, M. A., Ismail, S., & Shaharuddin, S. M. (2022). Comparative Performance of Various Imputation Methods for River Flow Data. In R. Ghazali, N. Mohd Nawi, M. M. Deris, J. H. Abawajy, & N. Arbaiy (Eds.), *Recent Advances in Soft Computing and Data Mining* (pp. 111–120). Springer International Publishing. https://doi.org/10.1007/978-3-031-00828-3_11

Nandi, S., & Reddy, M. J. (2024). Investigating the projected changes in water balance components under climate change considering the effect of storage structures. *Journal of Water and Climate Change*, *15*(5), 1981–2000. https://doi.org/10.2166/wcc.2024.371

Nannawo, A. S., Lohani, T. K., & Eshete, A. A. (2021). Exemplifying the Effects Using WetSpass Model Depicting the Landscape Modifications on Long-Term Surface and Subsurface Hydrological Water Balance in Bilate Basin, Ethiopia. *Advances in Civil Engineering*, *2021*(1), 7283002. https://doi.org/10.1155/2021/7283002

Nazeri Tahroudi, M. (2025). Comprehensive global assessment of precipitation trend and pattern variability considering their distribution dynamics. *Scientific Reports*, *15*(1), 22458. https://doi.org/10.1038/s41598-025-06050-5

Nie, T., Ji, X., & Pang, Y. (2021). OFAF-ConvLSTM: An Optical Flow Attention Fusion-ConvLSTM Model for Precipitation Nowcasting. *2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST)*, 283–286. https://doi.org/10.1109/IAECST54258.2021.9695635

Niemi, T. (2017). *Improved Precipitation Information for Hydrological Problem Solving-Focus on Open Data and Simulation*.

Niswonger, R. G., Panday, S., & Ibaraki, M. (2011). MODFLOW-NWT, a Newton formulation for MODFLOW-2005. *US Geological Survey Techniques and Methods*, *6*(A37), 44.

Noh, G.-H., & Ahn, K.-H. (2025). Enhancing Multiple Precipitation Data Integration Across a Large-Scale Area: A Deep Learning ResU-Net Framework Without Interpolation. *IEEE Transactions on Geoscience and Remote Sensing*, *63*, 1–16. https://doi.org/10.1109/TGRS.2025.3538829

Nolz, R. (2016). A review on the quantification of soil water balance components as a basis for agricultural water management with a focus on weighing lysimeters and soil water sensors / Ein Überblick über die Ermittlung von Wasserhaushaltsgrößen als Basis für die landeskulturelle Wasserwirtschaft mit Fokus auf Lysimeter und Bodenwassersensoren. *Die Bodenkultur: Journal of Land Management, Food and Environment*, *67*(3), 133–144. https://doi.org/10.1515/boku-2016-0012

Nourani, V., Baghanam, A. H., Adamowski, J., & Gebremichael, M. (2013). Using self-organizing maps and wavelet transforms for space–time pre-processing of satellite precipitation and runoff data in neural network based rainfall–runoff modeling. *Journal of Hydrology*, *476*, 228–243. https://doi.org/10.1016/j.jhydrol.2012.10.054

Nyberg, B., Sayre, R., & Luijendijk, E. (2024). Increasing seasonal variation in the extent of rivers and lakes from 1984 to 2022. *Hydrology and Earth System Sciences*, *28*(7), 1653–1663. https://doi.org/10.5194/hess-28-1653-2024

Oddo, P. C., Bolten, J. D., Kumar, S. V., & Cleary, B. (2024). Deep Convolutional LSTM for improved flash flood prediction. *Frontiers in Water*, *6*. https://doi.org/10.3389/frwa.2024.1346104

Olah, Christopher. (2015). *Understanding LSTM Networks*. https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Oliveira, P. T. S., Nearing, M. A., Moran, M. S., Goodrich, D. C., Wendland, E., & Gupta, H. V. (2014). Trends in water balance components across the Brazilian Cerrado. *Water Resources Research*, *50*(9), 7100–7114. https://doi.org/10.1002/2013WR015202

O'Neill, M. M. F., Tijerina, D. T., Condon, L. E., & Maxwell, R. M. (2021). Assessment of the ParFlow–CLM CONUS 1.0 integrated hydrologic model: Evaluation of hyper-resolution water balance components across the contiguous United States. *Geoscientific Model Development*, *14*(12), 7223–7254. https://doi.org/10.5194/gmd-14-7223-2021

O'Shea, K., & Nash, R. (2015). *An Introduction to Convolutional Neural Networks* (No. arXiv:1511.08458). arXiv. https://doi.org/10.48550/arXiv.1511.08458

Ouyang, W., Zhang, C., Ye, L., Zhang, H., Meng, Z., & Chu, J. (2025). Dive into transfer-learning for daily rainfall-runoff modeling in data-limited basins. *Journal of Hydrology*, *657*, 133063. https://doi.org/10.1016/j.jhydrol.2025.133063

Owuor, S. O., Butterbach-Bahl, K., Guzha, A. C., Rufino, M. C., Pelster, D. E., Díaz-Pinés, E., & Breuer, L. (2016). Groundwater recharge rates and surface runoff response to land use and land cover changes in semi-arid environments. *Ecological Processes*, *5*(1), 16. https://doi.org/10.1186/s13717-016-0060-6

Oyama, N., Ishizaki, N. N., Koide, S., & Yoshida, H. (2023). *Deep generative model super-resolves spatially correlated multiregional climate data* (No. arXiv:2209.12433). arXiv. https://doi.org/10.48550/arXiv.2209.12433

Pan, S. J., & Yang, Q. (2010). A Survey on Transfer Learning. *IEEE Transactions on Knowledge and Data Engineering*, *22*(10), 1345–1359. https://doi.org/10.1109/TKDE.2009.191

Pan, Z., Xu, L., & Chen, N. (2025). Combining graph neural network and convolutional LSTM network for multistep soil moisture spatiotemporal prediction. *Journal of Hydrology*, *651*, 132572. https://doi.org/10.1016/j.jhydrol.2024.132572

Pang, M., Du, E., & Zheng, C. (2023). A data-driven approach to exploring the causal relationships between distributed pumping activities and aquifer drawdown. *Science of The Total Environment*, *870*, 161998. https://doi.org/10.1016/j.scitotenv.2023.161998

Patra, S. R., & Chu, H.-J. (2024). Convolutional long short-term memory neural network for groundwater change prediction. *Frontiers in Water*, *6*. https://doi.org/10.3389/frwa.2024.1471258

Pham, H. X., Shamseldin, A. Y., & Melville, B. W. (2015). Assessment of Climate Change Impact on Water Balance of Forested and Farmed Catchments. *Journal of Hydrologic Engineering*, *20*(10), 04015009. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001169

Phukan, P. K. (2023). Water Balance Equation for Rivers of Assam, India. In N. Shahzad (Ed.), *Water and Environment for Sustainability: Case Studies from Developing Countries* (pp. 45–54). Springer International Publishing. https://doi.org/10.1007/978-3-031-27280-6_3

Porporato, A., Daly, E., & Rodriguez-Iturbe, I. (2004). Soil Water Balance and Ecosystem Response to Climate Change. *The American Naturalist*, *164*(5), 625–632. https://doi.org/10.1086/424970

Pranjal, P., Kumar, D., Soni, A., & Chatterjee, R. S. (2024). Assessment of groundwater level using satellite-based hydrological parameters in North-West India: A deep learning approach. *Earth Science Informatics*, *17*(3), 2129–2142. https://doi.org/10.1007/s12145-024-01263-0

Rabiei, S., Babaeian, E., & Grunwald, S. (2024). *Surface and Subsurface Soil Moisture Estimation Using Fusion of SMAP, NLDAS-2, and SOLUS100 Data with Deep Learning*. https://www.preprints.org/frontend/manuscript/4e69a4ae33c0de7eef98a40660597d67/download_pub

Rabiei, S., Babaeian, E., & Grunwald, S. (2025). Surface and Subsurface Soil Moisture Estimation Using Fusion of SMAP, NLDAS-2, and SOLUS100 Data with Deep Learning. *Remote Sensing*, *17*(4), Article 4. https://doi.org/10.3390/rs17040659

Ren, D., Xu, X., Huang, Q., Huo, Z., Xiong, Y., & Huang, G. (2018). Analyzing the Role of Shallow Groundwater Systems in the Water Use of Different Land-Use Types in Arid Irrigated Regions. *Water*, *10*(5), 634. https://doi.org/10.3390/w10050634

Robert Maier, H., Rosa Taghikhah, F., Nabavi, E., Razavi, S., Gupta, H., Wu, W., Radford, D. A. G., & Huang, J. (2024). How much X is in XAI: Responsible use of “Explainable” artificial intelligence in hydrology and water resources. *Journal of Hydrology X*, *25*, 100185. https://doi.org/10.1016/j.hydroa.2024.100185

Sadhwani, K., & Eldho, T. I. (2023). Assessing the Vulnerability of Water Balance to Climate Change at River Basin Scale in Humid Tropics: Implications for a Sustainable Water Future. *Sustainability*, *15*(11), 9135. https://doi.org/10.3390/su15119135

Sainath, T. N., Vinyals, O., Senior, A., & Sak, H. (2015). Convolutional, Long Short-Term Memory, fully connected Deep Neural Networks. *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 4580–4584. https://doi.org/10.1109/ICASSP.2015.7178838

Salem, A., Abduljaleel, Y., Dezső, J., & Lóczy, D. (2023). Integrated assessment of the impact of land use changes on groundwater recharge and groundwater level in the Drava floodplain, Hungary. *Scientific Reports*, *13*(1), 5061. https://doi.org/10.1038/s41598-022-21259-4

Schilling, K. E., Jha, M. K., Zhang, Y.-K., Gassman, P. W., & Wolter, C. F. (2008). Impact of land use and land cover change on the water balance of a large agricultural watershed: Historical effects and future directions. *Water Resources Research*, *44*(7). https://doi.org/10.1029/2007WR006644

Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2020). Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. *International Journal of Computer Vision*, *128*(2), 336–359. https://doi.org/10.1007/s11263-019-01228-7

Shen, C. (2018). A Transdisciplinary Review of Deep Learning Research and Its Relevance for Water Resources Scientists. *Water Resources Research*, *54*(11), 8558–8593. https://doi.org/10.1029/2018WR022643

Shen, C., & Lawson, K. (2021). Applications of Deep Learning in Hydrology. In *Deep Learning for the Earth Sciences* (pp. 283–297). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119646181.ch19

Sheng, S., Chen, H., Lin, K., Zhou, N., Tian, B., & Xu, C.-Y. (2023). An integrated framework for spatiotemporally merging multi-sources precipitation based on F-SVD and ConvLSTM. *Remote Sensing*, *15*(12), 3135.

Shi, B., Feng, L., He, H., Hao, Y., Peng, Y., Liu, M., Liu, Y., & Liu, J. (2024). A Physics-Guided Attention-Based Neural Network for Sea Surface Temperature Prediction. *IEEE Transactions on Geoscience and Remote Sensing*, *62*, 1–13. https://doi.org/10.1109/TGRS.2024.3457039

Shi, X., Chen, Z., Wang, H., Yeung, D.-Y., Wong, W., & WOO, W. (2015). Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. *Advances in Neural Information Processing Systems*, *28*. https://proceedings.neurips.cc/paper/2015/hash/07563a3fe3bbe7e3ba84431ad9d055af-Abstract.html

Shu, X., Ding, W., Peng, Y., Wang, Z., Wu, J., & Li, M. (2021). Monthly Streamflow Forecasting Using Convolutional Neural Network. *Water Resources Management*, *35*(15), 5089–5104. https://doi.org/10.1007/s11269-021-02961-w

Silvestro, F., Gabellani, S., Delogu, F., Rudari, R., & Boni, G. (2013). Exploiting remote sensing land surface temperature in distributed hydrological modelling: The example of the Continuum model. *Hydrology and Earth System Sciences*, *17*(1), 39–62. https://doi.org/10.5194/hess-17-39-2013

Šimůnek, J., & van Genuchten, M. Th. (2008). Modeling Nonequilibrium Flow and Transport Processes Using HYDRUSAll rights reserved. No part of this periodical may be reproduced or transmitted in any form or by any means, electronic or mechanical, including photocopying, recording, or any information storage and retrieval system, without permission in writing from the publisher. *Vadose Zone Journal*, *7*(2), 782–797. https://doi.org/10.2136/vzj2007.0074

Simonyan, K., Vedaldi, A., & Zisserman, A. (2014). *Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps* (No. arXiv:1312.6034). arXiv. https://doi.org/10.48550/arXiv.1312.6034

Singh, N. K., Emanuel, R. E., McGlynn, B. L., & Miniat, C. F. (2021). Soil Moisture Responses to Rainfall: Implications for Runoff Generation. *Water Resources Research*, *57*(9), e2020WR028827. https://doi.org/10.1029/2020WR028827

Sit, M., Demiray, B. Z., Xiang, Z., Ewing, G. J., Sermet, Y., & Demir, I. (2020). A comprehensive review of deep learning applications in hydrology and water resources. *Water Science and Technology*, *82*(12), 2635–2670. https://doi.org/10.2166/wst.2020.369

Smilkov, D., Thorat, N., Kim, B., Viégas, F., & Wattenberg, M. (2017). *SmoothGrad: Removing noise by adding noise* (No. arXiv:1706.03825). arXiv. https://doi.org/10.48550/arXiv.1706.03825

Son, H., & Jang, Y. (2020). Partial Convolutional LSTM for Spatiotemporal Prediction of Incomplete Data. *IEEE Access*, *8*, 164762–164774. https://doi.org/10.1109/ACCESS.2020.3022774

Sophocleous, M. (2002). Interactions between groundwater and surface water: The state of the science. *Hydrogeology Journal*, *10*(1), 52–67. https://doi.org/10.1007/s10040-001-0170-8

Sousa, R., & Fussi, F. (2021). The Role of International Cooperation in Sustainable Groundwater Development. In M. Abrunhosa, A. Chambel, S. Peppoloni, & H. I. Chaminé (Eds.), *Advances in Geoethics and Groundwater Management: Theory and Practice for a Sustainable Development* (pp. 339–343). Springer International Publishing. https://doi.org/10.1007/978-3-030-59320-9_70

Sun, Z., & Zhao, M. (2020). Short-Term Wind Power Forecasting Based on VMD Decomposition, ConvLSTM Networks and Error Analysis. *IEEE Access*, *8*, 134422–134434. https://doi.org/10.1109/ACCESS.2020.3011060

Tian, B., Chen, H., Yan, X., Sheng, S., & Lin, K. (2023). A Downscaling–Merging Scheme for Monthly Precipitation Estimation with High Resolution Based on CBAM-ConvLSTM. *Remote Sensing*, *15*(18), 4601.

Tian, S., Tregoning, P., Renzullo, L. J., van Dijk, A. I. J. M., Walker, J. P., Pauwels, V. R. N., & Allgeyer, S. (2017). Improved water balance component estimates through joint assimilation of GRACE water storage and SMOS soil moisture retrievals. *Water Resources Research*, *53*(3), 1820–1840. https://doi.org/10.1002/2016WR019641

Tripathy, K. P., & Mishra, A. K. (2024). Deep learning in hydrology and water resources disciplines: Concepts, methods, applications, and research directions. *Journal of Hydrology*, *628*, 130458. https://doi.org/10.1016/j.jhydrol.2023.130458

Tulbure, M. G., & Broich, M. (2019). Spatiotemporal patterns and effects of climate and land use on surface water extent dynamics in a dryland region with three decades of Landsat satellite data. *Science of The Total Environment*, *658*, 1574–1585. https://doi.org/10.1016/j.scitotenv.2018.11.390

Villia, M. M., Tsagkatakis, G., Moghaddam, M., & Tsakalides, P. (2022). Embedded Temporal Convolutional Networks for Essential Climate Variables Forecasting. *Sensors*, *22*(5), Article 5. https://doi.org/10.3390/s22051851

Wai, K. P., Koo, C. H., Huang, Y. F., Chong, W. C., El-Shafie, A., Sherif, M., & Ahmed, A. N. (2025). A practical temporal transfer learning model for multi-step water quality index forecasting using A CNN-coupled dual-path LSTM network. *Journal of Hydrology: Regional Studies*, *60*, 102553. https://doi.org/10.1016/j.ejrh.2025.102553

Wang, G., Xia, J., & Chen, J. (2009). Quantification of effects of climate variations and human activities on runoff by a monthly water balance model: A case study of the Chaobai River basin in northern China. *Water Resources Research*, *45*(7). https://doi.org/10.1029/2007WR006768

Waqas, M., & Humphries, U. W. (2024). A critical review of RNN and LSTM variants in hydrological time series predictions. *MethodsX*, *13*, 102946. https://doi.org/10.1016/j.mex.2024.102946

Weilisi, & Kojima, T. (2022). Investigation of Hyperparameter Setting of a Long Short-Term Memory Model Applied for Imputation of Missing Discharge Data of the Daihachiga River. *Water*, *14*(2), Article 2. https://doi.org/10.3390/w14020213

Wu, B., Zeng, H., Yan, N., & Zhang, M. (2018). Approach for Estimating Available Consumable Water for Human Activities in a River Basin. *Water Resources Management*, *32*(7), 2353–2368. https://doi.org/10.1007/s11269-018-1933-5

Wu, D., Gao, L., Xiong, X., Chinazzi, M., Vespignani, A., Ma, Y.-A., & Yu, R. (2021). *Quantifying Uncertainty in Deep Spatiotemporal Forecasting* (No. arXiv:2105.11982). arXiv. https://doi.org/10.48550/arXiv.2105.11982

Xu, L., Yu, H., Chen, Z., Du, W., Chen, N., & Huang, M. (2023). Hybrid Deep Learning and S2S Model for Improved Sub-Seasonal Surface and Root-Zone Soil Moisture Forecasting. *Remote Sensing*, *15*(13), Article 13. https://doi.org/10.3390/rs15133410

Xu, L., Zhang, X., Yu, H., Chen, Z., Du, W., & Chen, N. (2024). Incorporating spatial autocorrelation into deformable ConvLSTM for hourly precipitation forecasting. *Computers & Geosciences*, *184*, 105536.

Xu, T., & Liang, F. (2021). Machine learning for hydrologic sciences: An introductory overview. *WIREs Water*, *8*(5), e1533. https://doi.org/10.1002/wat2.1533

Xu, T., Longyang, Q., Tyson, C., Zeng, R., & Neilson, B. T. (2022). Hybrid Physically Based and Deep Learning Modeling of a Snow Dominated, Mountainous, Karst Watershed. *Water Resources Research*, *58*(3), e2021WR030993. https://doi.org/10.1029/2021WR030993

Xu, Y., Lin, K., Hu, C., Wang, S., Wu, Q., Zhang, L., & Ran, G. (2023). Deep transfer learning based on transformer for flood forecasting in data-sparse basins. *Journal of Hydrology*, *625*, 129956. https://doi.org/10.1016/j.jhydrol.2023.129956

Yao, Y., Zhao, Y., Li, X., Feng, D., Shen, C., Liu, C., Kuang, X., & Zheng, C. (2023). Can transfer learning improve hydrological predictions in the alpine regions? *Journal of Hydrology*, *625*, 130038. https://doi.org/10.1016/j.jhydrol.2023.130038

You, S., Zhang, X., Wang, H., Quan, C., Zhao, T., Liu, C., Huo, W., Zhang, Q., & Hu, N. (2025). A Multisource Precipitation Data Fusion Model for Qinghai Province Based on 3D CNN and Bidirectional ConvLSTM. *Journal of Hydrometeorology*, *26*(3), 327–343.

Zahmatkesh, Z., Karamouz, M., & Nazif, S. (2015). Uncertainty based modeling of rainfall-runoff: Combined differential evolution adaptive Metropolis (DREAM) and *K*-means clustering. *Advances in Water Resources*, *83*, 405–420. https://doi.org/10.1016/j.advwatres.2015.06.012

Zhang, C.-J., Wang, H.-Y., Zeng, J., Ma, L.-M., & Guan, L. (2020). Tiny-RainNet: A deep convolutional neural network with bi-directional long short-term memory model for short-term rainfall prediction. *Meteorological Applications*, *27*(5), e1956.

Zhang, L., Schlaepfer, D. R., Chen, N., Gu, S., & Lauenroth, W. K. (2021). Comparison of AET partitioning and water balance between degraded meadow and artificial pasture in Three-River Source Region on the Qinghai-Tibetan Plateau. *Ecohydrology*, *14*(7), e2329. https://doi.org/10.1002/eco.2329

Zhao, X., Wang, H., Bai, M., Xu, Y., Dong, S., Rao, H., & Ming, W. (2024). A Comprehensive Review of Methods for Hydrological Forecasting Based on Deep Learning. *Water*, *16*(10), 1407. https://doi.org/10.3390/w16101407

Zheng, X., Zhang, S., Yang, S., Huang, J., Meng, X., Zhang, J., & Bai, Y. (2024). Predicting future evapotranspiration based on remote sensing and deep learning. *Journal of Hydrology: Regional Studies*, *56*, 102023. https://doi.org/10.1016/j.ejrh.2024.102023

Zheng, X., Zhang, S., Zhang, J., Yang, S., Huang, J., Meng, X., & Bai, Y. (2024). Prediction of Large-Scale Regional Evapotranspiration Based on Multi-Scale Feature Extraction and Multi-Headed Self-Attention. *Remote Sensing*, *16*(7), Article 7. https://doi.org/10.3390/rs16071235

Zhou, X. (2020). Application of Deep Learning in Ocean Big Data Mining. *Journal of Coastal Research*, *106*(SI), 614–617. https://doi.org/10.2112/SI106-139.1

Zhu, L., Dai, W., Huang, J., & Luo, Z. (2025). A comparative analysis of deep learning models for accurate spatio-temporal soil moisture prediction. *Geocarto International*, *40*(1), 2441382. https://doi.org/10.1080/10106049.2024.2441382